Use of Artificial Neural Network to Select the Appropriate EOR Method for a Reservoir Field

Steffones K, Dr Pushpa Sharma **Paper ID- 2011180**

University of Petroleum & Energy Studies, Dehradun. P.O. Bidholi Via-Prem Nagar Dehradun-248007.Uttrakhand , India.

Presenting Author E-mail- cephanos26@gmail.com

Abstract

Enhanced Oil Recovery (EOR) has gained great attention as a result of higher oil prices and increasing oil demands. Extensive researches have been conducted to develop various EOR methods, evaluate their applicability and optimize operation conditions. One of the principal areas is to develop an effective tool for selection of a suitable EOR method according to oil field characteristics. The main objective of the studies is to screen various EOR methods based on field characteristics and evaluate their technical/economic applicability in an efficient way instead of predicting the field performances of all possible competing strategies and comparing their economics. In this paper, we present an Artificial Neural Network (ANN) approach to enable the petroleum engineer to select an appropriate EOR method with the given reservoir properties. The ANN developed in this study is a four-layered feed-forward Back Propagation (BP) network consisting of one input and output layer with two hidden layers. The input layer is composed of the key reservoir parameters (reservoir depth, temperature, porosity, permeability, initial oil saturation, oil gravity, and in-situ oil viscosity) while the output layer is composed of the five EOR methods to be evaluated (steam, CO2 miscible, hydrocarbon miscible, in-situ combustion, polymer flooding). The number of hidden layers and neurons are optimized during the training by repeated trial and error. After trained successfully, the ANN is tested and applied to other fields which are not used for the training. A series of the test results show that the ANN developed in this study can be used to select the most appropriate EOR process according to reservoir rock and fluid characteristics in a time and cost effective way.

Introduction

Higher oil prices and concerns about future oil supply are leading to increased interest in Enhanced Oil Recovery (EOR) around the world. Because EOR projects are generally more expensive and involve higher front end costs than conventional secondary projects, effective planning takes on added importance (Hite *et al.*, 2004). A large number of studies have been conducted to help the petroleum engineer select efficient EOR methods with limited field information. The main objective of the studies is to select the suitable EOR method in an effective way without predicting the reservoir performance of all possible competing strategies and comparing their economics.Most of early studies in the EOR selection were to establish the technical screening criteria of each EOR method (Taber and Martin, 1983; Goodlett *et al.*, 1986; Taber *et al.*, 1996a; Taber *etal.*, 1996b). Based on laboratory experiments and field experiences, the applicable ranges of the reservoir rock and fluid properties were presented in these studies. The effort has been added in several studies to update the applicable ranges with the current technical and economic conditions (Aladasani and Bai, 2010; Dickson and Wylie, 2010). The problem of selection and implementation of proper EOR techniques was also addressed in some papers as a guide for petroleum engineers (Zerafat *et al.*, 2011).The improvement of computer technology introduced the artificial intelligence technique into EOR selection (Guerillot, 1988; Elemo and Elmtalab, 1993; Surguchev and Li, 2000; Shokir *et al.*, 2002; Lee and Lim, 2008). Because the values of these models strongly depend on the accuracy of the input data, it should be continuously updated with up-to-date operation data.In this paper, we developed the Artificial Neural Network (ANN) incorporating the recent database published in the industry. The main goal of the study is to develop the ANN model that can estimate the best EOR method according to the given reservoir rock and fluid properties in a time and cost effective way and evaluate applicability of the model.

Artificial Neural Network

ANN is an information-processing system that has certainperformance characteristics in common with biological neural networks. A typical neural network is a multilayered system consisting of single input layer, single or double hidden layer, and single output layer. Each layer is composed of basic processing elements called neurons. Each neuron is connected to the neurons of the adjacent layer with the connection eights between 0 and 1. The signals between the neurons are multiplied by the associated connection weights and added up together as Eq. (1), and then used as the net input of the neuron.

$NET = \sum_{k=1}^{n} I_k W^k$ (1)

Where *NET* is the net input of the neuron, *I* is the input variable, *W* is the connection weight, *k* is the index, and *n* is the number of input variables. Each neuron applies an activation function to its net input to determine its output signal and the signal is transmitted to the next neuron. The sigmoid function in Eq. (2) is a activation function commonly used.

$f(NET) = \frac{1}{1+e^{NET}}$ (2)

The connection weights between the neurons are adjusted during the training. There are two ways of the training; supervised and unsupervised. For most typical neural network, the connection weights are adjusted by the given input and corresponding output. This process is called as supervised training. One of the widely used supervised networks is the feed-forward Back Propagation (BP) network which adjusts the connection weights during the back propagation process. In this study, the BP network with the training algorithm of Scaled Conjugate Gradient (SCG) which is a new variation of the conjugate gradient method is used. SCG allows the avoidance of the line search per training iteration of Levenberg-Marquardt approach in order to scale the step size.

Data Source and Preparation

The data used for training and testing the networks are extracted from the special reports, Worldwide EOR Survey published by Oil and Gas Journal (Moritis 2010). The reports include the field name, reservoir rock and fluid properties, project maturity, and project evaluation of the field where the EOR was being applied. In this study, the data of those fields were evaluated where application of EOR was successful. Neurons of the input layer are designed to be the main reservoir properties. The seven reservoir properties which are reservoir depth, temperature, porosity, log permeability, initial oil saturation, oil gravity, log oil viscosity are selected as the input variables of the ANN model

Step 1	Divide the input variables into two groups by their effects on the selection ·Group 1 : porosity, log permeability, oil saturation, log oil viscosity ·Group 2 : depth, temperature, oil gravity
Step 2	Multiply the variables for each group ·V1 = porosity × log permeability × oil saturation × log oil viscosity ·V2 = depth × temperature × oil gravity
Step 3	Generate the group variable by dividing V1 by V2
Step 4	Rank each data by group variable and group each three data
Step 5	Sample two data for each group

Table 1. *Data sampling method by group variable*

A new variable is generated by grouping the input reservoir parameters to sample the data to be used for the training and two-thirds of the total data are selected based on this group variable as summarized in Table 1. For training efficiency, the sampling ratio increases to three-fourths if the number of sampling data is less than ten. The remaining data which are not included in the training are used for testing the developed ANN model. Table 2 shows the number of data for the training and the applicability test.

EOR type	Total	Training	Testing
Steam	103	70	33
Carbon dioxide miscible	65	45	20
Hydrocarbon miscible	32	22	10
In-situ combustion	15	11	4
Polymer flooding	15	11	4
Total	230	159	71

Table 2. *The number of data used for the training and the applicability test*

Reservoir parameters	Minimum	Average	Maximum
Reservoir depth, ft	200.0	4,079.0	13,750.0
Reservoir temperature, ℉	45.0	126.9	290.0
Porosity, %	3.0	23.3	65.0
Permeability, md	0.1	1,283.6	11,500.0
Initial oil saturation, % of OOIP	26.5	62.8	98.0
Oil gravity, °API	8.0	24.9	57.0
In-situ oil viscosity, cp	0.1	26,594.4	200,000.0

Table 3. *Ranges of the input reservoir parameters*

The ranges of the input reservoir parameters are summarized in Table 3. Each input variable is normalized between 0 and 1 before the training for numerical stability as defined in Eq. (3). The normalized input variables are then entered into the input neurons to train the network.

$$X_{norm} = \frac{X_{actual} - X_{min}}{X_{max} - X_{min}} \quad (3)$$

Where X_{norm} is the normalized input variable, X_{actual} is the original value of the variable, X_{min} is the minimum value of the variable and X_{max} is the maximum value of the variable. The ranges of the input reservoir parameters are summarized in Table 3. The neurons of the output layer are composed of the EOR methods to be selected. The five EOR methods (steam, carbon dioxide miscible, hydrocarbon miscible, in-situ combustion, polymer flooding) which are being applied in more than ten fields consist the output layer. The target value of the output neurons are designed to be +1 in the neurons indicating the successfully applied EOR methods and -1 in other neurons indicating other EOR methods.

Development of ANN Model

Design and training of the ANN is done in the software developed by our team in Visual Studio (.NET IDE) The object function in the training is the mean square error as defined in Eq. (4) and the convergence tolerance is initially designed to be 0.001.

$Error = \frac{1}{N}\sum_{i=1}^{N_p}(y_i - f(x_i))^2$ (4)

Where N_p, y_i, and $f(x_i)$ indicate the number of data, the measured output, and estimated output by the model respectively.

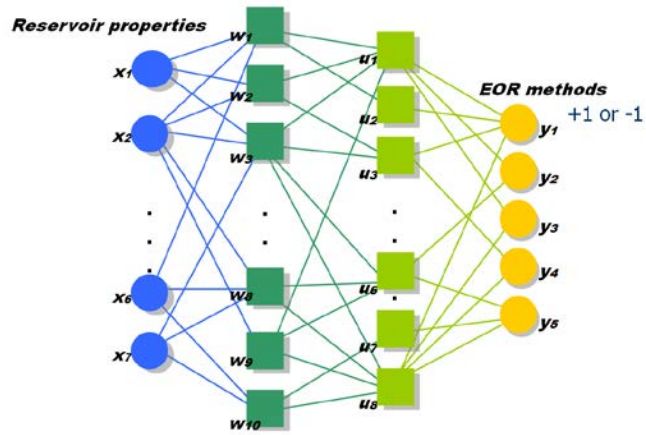

Fig. 1. *Structure of the ANN model developed in this study*

As an activation function, the tangent sigmoid function is used for the first hidden layer and the logistic sigmoid function is used for the second hidden layer. For the output layer, the linear function is used (Lee and Lim, 2008). The structure of the ANN model, that is the number of neurons of the hidden layers, is optimized during the training by repeated trial and error. Maximum number of iteration is set to 10,000.

Conclusion

- A four-layered ANN model is developed to select the most suitable EOR method based on the field characteristics. The input layer consists of the seven reservoir parameters and the output layer consists of the five EOR methods to be selected. The number of neurons in the hidden layers is optimized during the training; ten for the first hidden layer and eight for the second hidden layer.
- After trained successfully with the successful EOR field data, the ANN model is tested against the data excluded in the training. The model correctly selected the best EOR method with the accuracy greater than 95%.

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