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A Neuro-Fuzzy Approach to Screening Reservoir Candidates for EOR

Lateef Akanji[a],*; Rafael Sandrea[b]

[a] School of Engineering, College of Physical Sciences, University of Aberdeen, UK.
[b] IPC Petroleum Consultants, Oklahoma, USA.
*Corresponding author

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Abstract

The challenge of discovering new reserves coupled with the current dwindling oil price has necessitated the need to generate and sustain long-term production from existing fields through improved or enhanced oil recovery (IOR/EOR) processes. There is however, no established mechanism to match the thousands of candidate reservoirs worldwide to the subtle and critical variations in reservoir properties that control the success of the many different EOR options. We present a neuro-fuzzy approach to screening potential hydrocarbon reservoirs for enhanced oil recovery (EOR) applications. First, reservoir field data from multiple successful thermal, miscible, chemical and biological EOR projects across different petroleum systems worldwide were trained to establish knowledge pattern and represent it using fuzzy rules. This is achieved by combining fuzzy technique with neural network learning capability to deduce knowledge from the EOR data in a form akin to linguistic rules. Then, the extracted knowledge pattern was validated and used to determine the combination of reservoir properties which could best characterise the key heterogeneities that control EOR success. The model output can be used in screening potential reservoir for EOR application.

Key words: Neuro-fuzzy; EOR; Reservoir screening; Artificial intelligence; Training and learning

INTRODUCTION

Crude oil is the vital component of the 11 million m^3/D (90 million *B/D*) of petroleum liquids that the world consumes every day. It accounts for 82%, the rest being split among Natural Gas Liquids (NGLs) (11%) and other liquids (biofuels, refining gains, and so forth). Today, barely 15% of world oil production comes from IOR and 3% from EOR. The top example of success is the North Sea. Its recovery factor was 17%−18% in the 1970s and is now nearing 50%. This has been achieved through intensive efforts in IOR; re-injection of stranded gas and waterflooding, both from the onset of the development of the fields.

Our goal should be to increase the recovery factor of our existing oil fields by at least one-percentage point each year, which is very attainable. There are more than 1,500 world class oil fields and thousands of smaller fields worldwide that are prime candidates for EOR. Each field has multiple reservoirs and every reservoir is different. There is however, no established mechanism to match the thousands of candidate reservoirs worldwide to the subtle and critical variations in reservoir properties that control the success of the many different EOR options. Furthermore, data that could be used for matching and predicting the performance of such EOR processes are sparse.

The primary objective of this study is to develop a neuro-fuzzy model to screen potential reservoirs for EOR applications. This study analyses reservoir field data from multiple successful thermal, miscible, chemical and biological EOR projects across different petroleum systems worldwide to determine what combination of reservoir properties could best characterise key reservoir heterogeneities that control EOR success. The data used are drawn from the very limited successful EOR operations that have been carried out at various locations around the world.

1. IOR AND EOR BACKGROUND

While this study focuses on the broader sense of improving oil recovery and more specifically enhanced oil recovery (EOR), it is nonetheless important to clarify what is meant; in a more technical sense, by the terms IOR and EOR. Historically, EOR denotes tertiary oil recovery processes such as chemical, miscible gas and thermal processes. The IOR term followed and now generally comprises all but primary recovery technologies including waterflooding and gas pressure maintenance, as well as infill drilling and horizontal wells for improving sweep efficiency. These definitions are not trifling; they are of prime importance in determining contract details and government fiscal and regulatory parameters regarding both company and country reserves assessments.

In this study, we analyzed 365 active field projects covering 10 different EOR technologies from 16 major oil producing countries (Table 1). Steam and CO_2 projects are the most ubiquitous and together account for more than three-quarters of the total projects. Steam is generally associated with heavy oil (less than 25°API) reservoirs while CO_2 predominates the light oil (25°API and greater) reservoir category.

Successful EOR projects are quite a challenge both technically and economically. They are also influenced strongly by oil prices because projects are longlived, manpower intensive and need long lead times to do the research and development vital to the tailoring of the processes and require constant sophisticated engineering monitoring. Overall they require high upfront investments with a long pay-out period. For screening purposes, this study focuses on the technical aspects, analysing principally the limits of reservoir lithology and oil quality.

Table 1
Attributes of Successful EOR Projects Worldwide[1]

Type of EOR	Number of projects	Formation type	Depth, * (feet)	Porosity φ, (%)	Permeability κ, (mD) ‡	Oil gravity, (°API)	Oil viscosity μ_o, (cp) ‡	S_o, at start-up (%)	EOR, production † (B/D)
	113	Sandstone	250-5,750	15-39	100-10,000	8-22	18-500,000	20-90	62-86,000
Steam	26	Unconsolidated sands	175-3,150	25-40	300-15,000	9 - 25	175-200,000	48-90	500-190,000
	6	Carbonates	550-1,500	20-65	1-2,000	10-29	26-4,000	45-85	25-1,200
	50	Sandstone	1,600-11,950	10-28	9-2,300	27-45	0.3-3.0	26-77	205-15,000
Miscible CO_2	-	Unconsolidated sands							
	83	Carbonates	4,000-11,100	4-24	0.1-5,000	28-45	0.32-6.0	30-89	25-28,300
	17	Sandstone	4,000-13,750	8-26	20-1,500	19-41	0.3-73	25-80	200-80,000
Miscible HC	-	Unconsolidated sands							
	20	Carbonates	4,040-9,150	8-18	3-5,000	37-48	0.1 4-0.83	30-90	10 - 8,810
	24	Sandstone	625-5,450	15-34	7-5,000	13-34	5-5,000	45-82	14-55,000
Polymer	-	Unconsolidated sands							
	-	Carbonates							
	1	Sandstone	400-2,065	32	650	19	660	94	240
Combustion	3	Unconsolidated sands	3,120-3,450	28-30	8,000-15,000	9.8-17	100-550	70-80	
	11	Carbonates	8,300-9,500	17-20	10-15	31-38	1.4-2	50-85	100-12,733
	2	Sandstone	625-14,500	12-17	45-50	27-39	0.5-3	36-51	70-350
Surfactants	-	Unconsolidated sands							
	1	Carbonates	4,800	14	20-60	34	2.6	50	

To be continued

Continued

Type of EOR	Number of projects	Formation type	Depth, * (feet)	Porosity φ, (%)	Permeability κ, (mD)‡	Oil gravity, (^{o}API)	Oil viscosity μ_o, (cp) ‡	S_o, at start-up (%)	EOR, production † (B/D)
Nitrates	1	Sandstone	7,500-8,100	25-30	20-2,500	33	0.14		8,800
	-	Unconsolidated sands							
	1	Carbonates	2,000-3,000	50	0.1-1	30	2	50	860
Microbial	3	Sandstone	200-1,572	17-26	180-200	23-31.5	19-31	54	
	-	Unconsolidated sands							
	-	Carbonates							
Hot water	2	Sandstone	1,350-2,100	32-34	1,500-2,000	12-14	900-3,350	15-48	226-1,450
	-	Unconsolidated sands							
	-	Carbonates							
Miscible acid gas	-	Sandstone							
	-	Unconsolidated sands							
	1	Carbonates	4,900	8	10-100	32-40	0.6-1.5	40	1,000
All	213	Sandstone							
	29	Unconsolidated sands							
	123	Carbonates							
	365								

Note. Carbonates include limestone, dolomite, diatomite, tripolite, and conglomerates.
*1 foot ≈ 0.3048 metres
*1 mD (milliDarcy) ≈ $10e^{-16}$ m^2
‡1 cp ≈ 0.001 Pa•s
†1 *B/D* ≈ 0.16 m^3/D

In order to embark on an EOR project, quite a number of factors have to be taken into consideration. Applicability of CO_2 is mostly dependent on its availability in commercial quantities, the cost of setting up infrastructure, reservoir characteristic including size of attached aquifer (if any) and existence of natural fracture. These data are however sparse and usually not available particularly in regions where implementation of EOR techniques is relatively new. In order to determine whether a specific EOR method would be compatible with the reservoir characteristics, limited data from regions where such techniques or methods have been successfully applied could be used as the basis for the screening and selection process.

Table 1 summarises the contents of our survey EOR database which consists of 365 reservoirs utilising ten (10) different EOR technologies. The statistics define their reservoir lithology through nine (9) basic parameters: Formation type, porosity, permeability, depth, oil gravity, oil viscosity and oil saturation at the start of the project. Formation type is further classified into: Sandstones, carbonates and unconsolidated sands. An additional column gives the current EOR oil production of the project; this provides an insight to the size range of projects in each EOR category. For example, low-end EOR oil production values generallyreflect projects that are nearing termination or small scale pilot projects.

Here are some highlights of the 365 field EOR projects analysed:

- Miscible CO_2 (133) and steam (145) projects represent three-quarters (76%) of the total. Miscible hydrocarbon gases (37), polymers (24) and combustion (15) together account for 21%. The remaining 3% correspond to surfactants (3), microbial (3), hotwater (2), Nitrate waterflooding (2) and miscible acid gas (1). Overall, ten (10) EOR technologies are field active worldwide. The *US* accounts for more than half (55%) of the total projects that cover seven of the ten (10) genres of EOR methods.
- Almost 60% of all projects are realised in sandstone reservoirs, another one-third in carbonates and the rest in unconsolidated sands. Miscible CO_2, miscible hydrocarbon gases and combustion projects are very common in carbonate reservoirs. Steam projects are

successful in all of the formation types: sandstones, carbonates and unconsolidated sands. Polymer flooding is being applied only in sandstone reservoirs. Surfactants and microbials are very few - only three projects each - while Nitrate waterfloods are beginning to pick up as the cost of Nitrates has dropped drastically for reasons discussed previously. Many projects have oil saturation at start-up values less than 50%; generally these EOR projects went into operation following waterflooding.

- It is very encouraging to see individual steam projects producing 22,296 m^3/D (190,000 B/D) of EOR oil, miscible hydrocarbon projects producing 9,388 m^3/D (80,000 B/D), polymers 6,454 m^3/D (55,000 B/D) and miscible CO_2 3,286 m^3/D (28,000 B/D). Hopefully, this is a prelude of many more and bigger EOR projects to come.

2. NEURO-FUZZY SIMULATION APPROACH

Application of screening technique in identifying candidate reservoirs for EOR processes is helpful when a large number of reservoirs needs to be analysed. Screening criteria are now used in many field applications as well as laboratory and numerical simulation studies[2-3]. Analytical models and computer programs (for instance artificial intelligence technique) have also been developed to select feasible EOR methods and predict their oil recovery potentials based on reported screening criteria (e.g. [4-6]). Typical selection criteria are shown in Table 1. Petroleum reservoirs are complex systems with high degree of uncertainty associated with the description of important parameters.

The capabilities of neural networks to learn from given data allow for combination with fuzzy rules in order to automate the process of developing a fuzzy system for a set of task[7]. This is achieved by classifying data based on supervised structure and parameter learning using simple heuristic procedures. Neural networks are used where little is known about the relationship between input and output variables and a lot of training data is available[8].

Fuzzy systems are used when the relationship between input and output can be easily described linguistically or if there is a need to interpret the solution by simple ”*if*” ”*then*” rules[9]. Identifying an appropriate fuzzy system for a given problem requires the specification of membership functions (parameters) and a rule base (structure) through prior knowledge, or by learning or combination of both prior knowledge and learning. If a learning algorithm is applied that uses local information and causes local modifications in a fuzzy system, this approach is usually called neuro-fuzzy system[8].

Neuro-fuzzy approach is unique in its method of classifying survey data with its inherent uncertainties, which is the source of our database. The core of this framework is based on knowledge extraction procedure that is aimed at identifying the structure as well as the variables of a fuzzy rule-base, through a neuro-fuzzy network. Structure and parameter of the fuzzy rule base are identified through definition, adaptation and optimisation of the topology and parameters of the neuro-fuzzy network based on available data only.

Due to the non-linearity of the data involved in the screening process of candidate reservoir for EOR processes, a multi-layered genetic fuzzy perceptron based on ANFIS system is hereby implemented[8,10-11]. This approach makes it easy to define constraints for the neuro-fuzzy learning procedure. This permits to impose the rule that fuzzy sets must intersect at some point (e.g. 0.5). Data training will continue until the error decay over the validation dataset does not decrease any further.

The aim of this work is therefore to develop a systematic fuzzy modelling mechanism which is capable of automatically generating a rule-base from worldwide EOR database (without making any assumption about the structure of the data), finding a suitable rule number, optimising the variables of the fuzzy membership functions and providing readily interpretable models.

2.1 Neuro-Fuzzy Relational Systems

In a multi-input single-output (MISO) system with a prescribed vector $\hat{A}$ of J membership values $\mu_{AJ}(\boldsymbol{x})$ for an observed input value $(\boldsymbol{x})$, the output vector $\hat{B}$ of M crisp memberships μ_m can be obtained thus[12],

$$\hat{B}=\hat{A}oR, \tag{1}$$

where set A is defined as:

$$A=\{A^1,A^2,\ldots,A^J\}, \tag{2}$$

and the $J\times M$ relational matrix R can be defined as:

$$R_{j,m}=\begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,M} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,M} \\ \vdots & \vdots & r_{j,m} & \vdots \\ r_{m,1} & r_{m,2} & \cdots & r_{J,M} \end{bmatrix}. \tag{3}$$

This can be implemented by a generalised form of maximum-minimum (max−min) composition, thus:

$$\mu_m = \underset{j=1}{\overset{J}{S}}\left[T\left(\mu_A j(x), r_{jm}\right)\right]. \tag{4}$$

The crisp output of the relational system is computed by the weighted mean given by:

$$\bar{y} = \frac{\sum_{m=1}^{M}\{\bar{y}^m\mu_m\}}{\sum_{m=1}^{M}\mu_m}, \tag{5}$$

where $\overline{y}^m$ is the centroid (centre of gravity) of the fuzzy set B^m or the mean−of−maximum (MOM) defuzzification method which computes the average of the fuzzy outputs that have the highest degrees. This will produce the same result for those membership functions with different shapes but the same highest degrees (Figure 1). The (MOM) defuzzification method may be expressed as

$$y^{m}_{\mathrm{MOM}} = \sum_{j=1}^{m} \frac{z_j}{m}, \tag{6}$$

where, m is the number of values and z_j is the value at which the membership function reaches the maximum value $\mu_C(z_j)$.

2.2 Membership Functions

Two types of membership functions are implemented in this work viz: (a) linear and (b) sinusoidal (Figure 1).

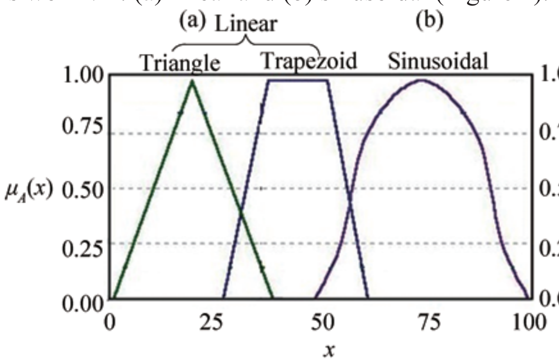

Figure 1
Typical Membership Functions; With Different Shapes, Used in Fuzzy Models (a) Linear (e.g. Triangle and Trapezoidal) (b) Sinusoidal (e.g. Bell Shaped and S-Shaped Curves)

2.2.1 Linear Membership Functions

In a typical linear membership function (e.g. Figure 1), four parameters are used to determine the shape of the function. Depending on the choice of parameter values *a, b, c,* and *d*, we can further classify linear membership functions into four categories: S-shaped, trapezoidal, triangular and L-shaped. A linear membership function can be described by the equation:

$$f(x) = \begin{cases} 0 & \text{if } x < a \\ \dfrac{x-a}{b-a} & \text{if } a \leqslant x \leqslant b \\ 1 & \text{if } b < x < c. \\ \dfrac{d-x}{d-c} & \text{if } c \leqslant x \leqslant d \\ 0 & \text{if } x > d \end{cases} \tag{7}$$

2.2.2 Sinusoidal Membership Functions

Sinusoidal membership function is usually adopted in cases where a rounded shape is deemed more appropriate in modelling the system behaviour. Similarly, by making an appropriate choice of four parameter values a, b, c, and d, three (3) membership functions S-shaped, bell-shaped and L-shaped can be identified. An example of a Gaussian membership function (a special case of bell-shaped function) is shown in Figure 1 and it can be expressed as

$$\mu_A(x) = \exp^{-\frac{(x-c)2}{2\sigma 2}}, \tag{8}$$

where, the parameters c and σ are the mean and standard deviation of the probability density function of the normal distribution.

2.3 Neuro-fuzzy Model for EOR Screening

In this work, we model the adaptive-network-based fuzzy inference system[10] using both Mamdani's direct method, the Sugeno's approach[13] and the structure of a feed-forward neural network implemented in a *C/C++* object oriented programming platform.The schematic diagram of the Neuro-Fuzzy System (NFS) is shown in Figure 2. It consists of five layers viz: "Layer 1" represents input variables with K multidimensional fuzzy membership functions (input layer); "Layer 2" (fuzzification layer); "Layer 3" (AND operation implementing layer); "Layer 4" (fuzzy inference layer); and "Layer 5" represents output variables for the realisation of center average defuzzification (defuzzification layer).

Each neuron in "Layer 1" corresponds typically to each of the different variables investigated in this work. Each variable in turn has ten 10 EOR categories as input variables of the neuro-fuzzy system. This 5 "layer" feed-forward neural network allows for system parameter learning or fine-tuning through the back-propagation algorithm.

In "Layer 2", corresponding to all the four (4) inputs, there exist three (3) different neurons separately, which represent three 3 different grades of the inputs, namely low (L), medium (M) and high (H). In all the three 3 cases, we tested the algorithm on each of the three (3) membership functions triangular, trapezoidal and Gaussian (a special case of the bell-shaped function), Figure 1. The membership function with the minimum error is then implemented in the Neuro-fuzzy model. For a bell-shaped membership function, we have

$$f = \exp^{-\frac{(\mu_j^{(2)} - m_{i,j})2}{\sigma_{ij}^2}}. \tag{9}$$

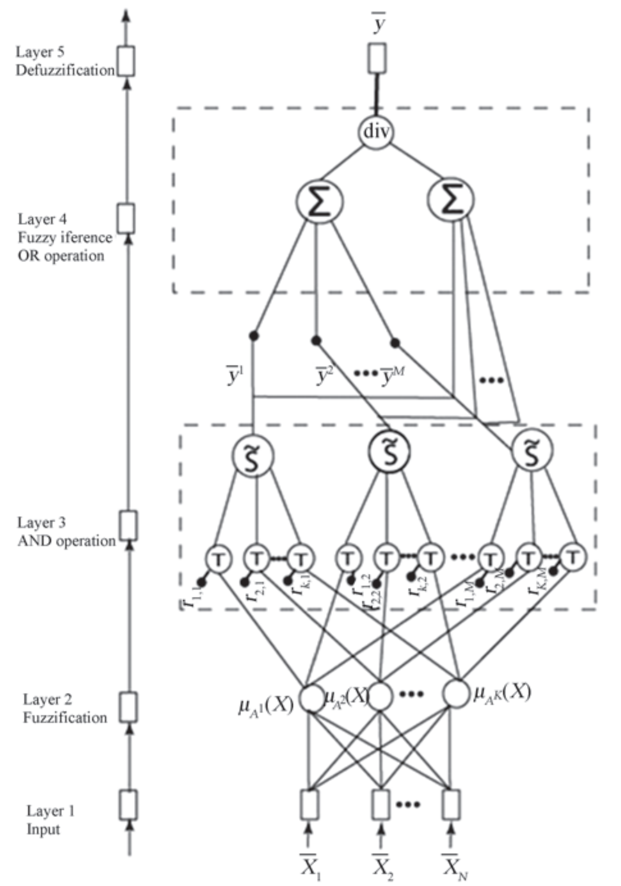

Figure 2
A Typical Neuro-Fuzzy System Representing a 5-Layer Feed-Forward Neural Network

Where $m_{i,j}$ and are the mean and variance of the bell-shaped function of the j^{th} term of i^{th} input linguistic variable x_i. Hence, the link weight ($w_{ij}^{(2)}$) can be interpreted as m_{ij} at "Layer 2". Since there are 3^{10} (i.e. 59,049) possible rules for the three 3 input variables, 59049 different neurons are considered in the "Layer 3".

In "Layer 3", the task of logical AND operation is performed with each neuron connected to ten 10 neurons of the previous layer. Membership function values computed in the previous layer are considered as the inputs of a particular neuron (say m^{th}) present in this layer. These ten (10) membership function values are then compared and the minimum taken as the output of that m^{th} neuron. Each neuron therefore represents an appropriate fuzzy rule.

In "Layer4", three neurons indicating three different grades (i.e., "*L*", "*M*" and "*H*") of the EOR output are considered.The connectivity between a neuron lying in the third layer and another one lying in the fourth layer represents the output of a particular rule. The links in this layer perform the fuzzy OR operation to integrate the fired rules having the same consequent:

$$f = \Sigma_{j=1} \mu_j^{(4)}. \tag{10}$$

In the "Layer 5", there exists only one neuron representing the EOR output. Having known the membership function distributions, the output of all the rules are calculated in relation to the area of membership function distributions. The outputs are then superimposed to obtain the crisp value corresponding to the fuzzified output (i.e. defuzzification) thus:

$$f = \Sigma_{j=1} w_{ij}^{(5)} \mu_{ij}^{(5)}. \tag{11}$$

2.4 EOR Data Training and Learning

Neuro-fuzzy system (NFS) knowledge can be expressed in the form of fuzzy rules where certainty weights, number of rules and fuzzy set parameters are computed during learning. These parameters are also determinable by engineers in the field. We compute these parameters by machine learning from the EOR data with the input fuzzy sets determined by the fuzzy clustering algorithm.

Then, all parameters are tuned by the backpropagation-like algorithm where the error is propagated from the output units towards the input units[10]. Given learning EOR data set of pair $(\bar{x}, d)$ where d is the desired value, the mean squared deviation error is computed thus:

$$E(\bar{x}, d) = \frac{1}{2}[\bar{y}(\bar{x}) - d]^2. \tag{12}$$

Every relational neuro-fuzzy system parameter, p, can be determined by minimising the associated error in an iterative procedure. For each iteration i, the parameter value is computed thus:

$$w(t+1) = w(t) - \alpha \frac{\partial E(\bar{x}, d; t)}{\partial w(t)}. \tag{13}$$

Where α is a learning rate coefficient, set in simulations to 0.01 after error validation sensitivity.

The $\frac{\partial E}{\partial w}$ for the input and output of the "Layer 5" can be computed thus:

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial E_C}\frac{\partial E_C}{\partial O_5}\frac{\partial O_5}{\partial I_5}\frac{\partial I_5}{\partial w}. \tag{14}$$

Similarly, for the "Layer 2",

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial E_C}\frac{\partial E_C}{\partial O_5}\frac{\partial O_5}{\partial I_5}\frac{\partial I_5}{\partial O_4}\frac{\partial O_4}{\partial I_4}\frac{\partial I_4}{\partial O_3}\frac{\partial O_3}{\partial I_3}\frac{\partial I_3}{\partial O_2}\frac{\partial O_2}{\partial I_2}\frac{\partial I_2}{\partial w}. \tag{15}$$

Therefore, the updated value of w can be calculated.

The prediction error was further evaluated using the non-dimensional error index (NDEI) defined as:

$$\text{NDEI} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}[\bar{y}(\bar{x}) - d]^2}}{\sigma(d)}, \tag{16}$$

where d is the desired output, $\bar{y}(\bar{x})$ is the predicted output and $\sigma(d)$ is the standard deviation of the target series.

2.5 Neuro-Fuzzy Architecture

The training data were created using a Runge-Kutta procedure with step width 0.1[10]. For this study, 365 data from active field projects covering 10 different EOR techniques from 16 major oil producing countries were analysed. We used 80% of the data for training and the rest as validation set by random selection in multiple simulation run. The set of validation data with consequent minimal error is then identified and selected for use against any future EOR field test data. Each simulation dataset consisted of four input variables; representing four major regions (US, Canada, South-America, Europe) from which the data have been obtained and one output. Each EOR variable in each set was initially partitioned into seven (7) uniformly distributed membership (e.g. bell-shaped) fuzzy sets, where the leftmost and rightmost membership functions were shouldered. A max−min inference (Equation 4) and mean−of−maximum defuzzification (Equation 6) was implemented due to speed advantage in comparison to center−of−gravity (CoG) defuzzification and produces almost the same results after learning.

Considering an X input and Y output neuro-fuzzy (NF) system, the input vector $w(t)$ measured at time t, is composed of N components, $w_i(t)$, $i = 1, ..., N$. Further, each crisp input variable corresponds to a linguistic variable x_i and is partitioned into several overlapping regions labelled with linguistic values. We use a system of fuzzy rules to approximate each of the variable function based on prior knowledge. This allows for an appropriate initialisation of the NFS with the remaining rules determined by learning. In order to apply the neuro-fuzzy architecture to the screening of EOR dataset, run two categories of simulation based on: (a) variable and (b) techniques.

2.6 EOR Variable-Based Learning

Using the NFS algorithm flowchart shown in Figure 2, we run the simulation as described in section 2.5 on the EOR dataset variables (depth, oil gravity, porosity, permeability, saturation and viscosity); to obtain trained and validated output. This is aimed at providing a screened and validated output data that could be used against test data from any prospective EOR project from brown or green fields. Other variables like thickness, temperature, pressure and salinity which are also important in screening EOR processes can also be studied in a similar manner if these data are available. In order to initialise the training process, each variable is split and analysed based on randomised dataset which serves as the basis for the rapid testing in the neuro-fuzzy algorithm.

3. RESULTS AND DISCUSSION

The data base was optimised by tuning for the number of patterns, epochs, mean and standard deviation (SD) of each of the variables associated with the EOR projects. First, we run several simulations using 80% of the EOR variables as training dataset and the rest as validation dataset. For each EOR variable consisting of API, depth, permeability, porosity, saturation and viscosity, we select at random, five (5) different configuration corresponding to options 1-5 from the dataset and run simulations to determine the validation dataset. Since the data were selected at random, we used four indicators; root mean square error (RMSE), non-dimensional error index (NDEI), mean and SD, Figures 3-8, to identify the validation data. The validation dataset corresponds to those with consequent minimal RMSE and/or NDEI; options 4, 2, 4, 2, 1, and 1 for API, depth, permeability, porosity, saturation and viscosity respectively (Figures 3 -8).

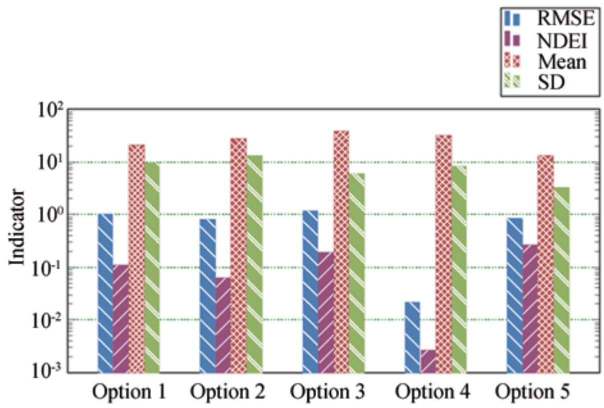

Figure 3
Root Mean Square Error (RMSE), Nondimensional Error Index (NDEI), Mean and Standard Deviation (SD) for the ^{o}API of Trained EOR Data

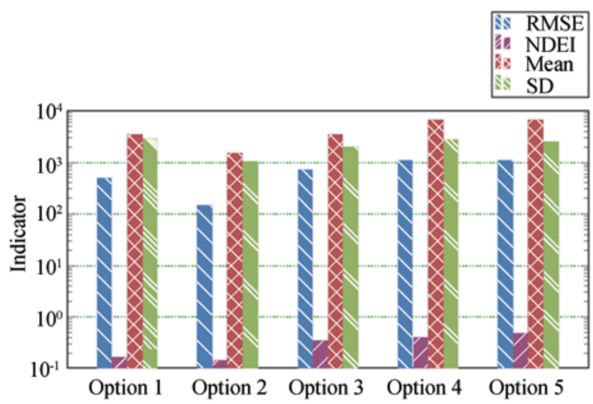

Figure 4
Root Mean Square Error (RMSE), Nondimensional Error Index (NDEI), Mean and Standard Deviation (SD) for the Depth of Trained EOR Data

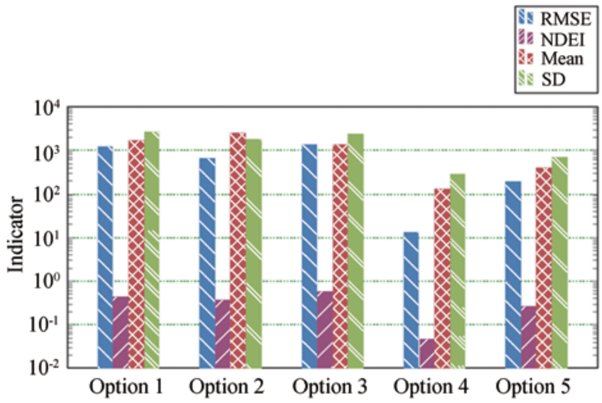

Figure 5
Root Mean Square Error (RMSE), Nondimensional Error Index (NDEI), Mean and Standard Deviation (SD) for the Permeability of Trained EOR Data

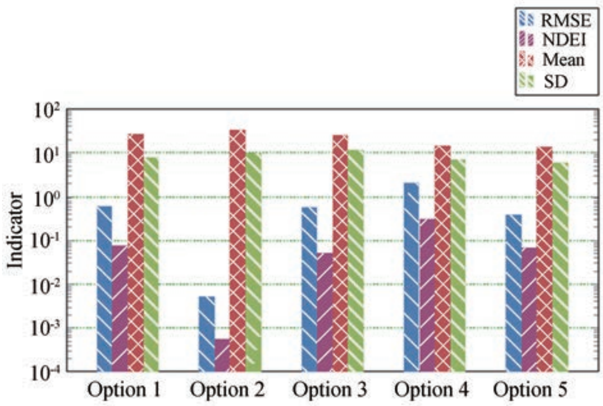

Figure 6
Root Mean Square Error (RMSE), Nondimensional Error Index (NDEI), Mean and Standard Deviation (SD) for the Porosity of Trained EOR Data

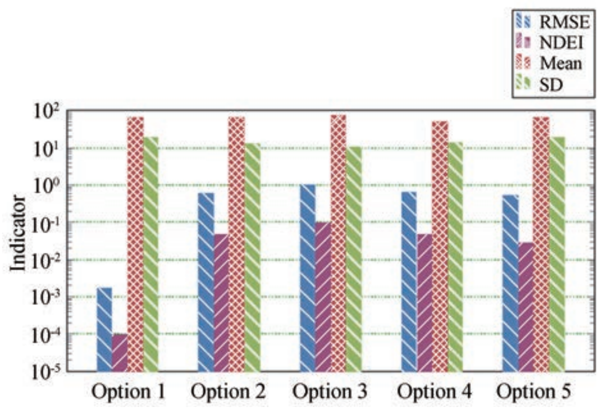

Figure 7
Root Mean Square Error (RMSE), Nondimensional Error Index (NDEI), Mean and Standard Deviation (SD) for the Oil Saturation of Trained EOR Data

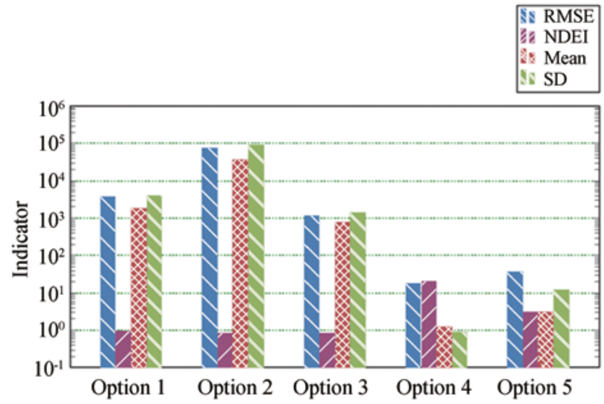

Figure 8
Root Mean Square Error (RMSE), Nondimensional Error Index (NDEI), Mean and Standard Deviation (SD) for the Viscosity of Trained EOR Data

Having identified the validation dataset, variable based simulation runs were then carried out. In a separate investigation, we considered simulation based on different EOR techniques. This will be published in another manuscript. For each variable, five 5 unique values of mean and standard deviation, based on the identified patterns underpinned by the number of actual data available, were computed. Since the computed weights are based on the number of data available from each of the identified regions in the EOR projects, availability of data becomes critical to the minimisation of error and optimisation of the neuro-fuzzy simulation.

The training data for the depth, API gravity, permeability, porosity, saturation and viscosity match the predicted data within certain error limits as shown in Figures 9-17. Figure 9 shows the plots of the API gravity for the weighted training data, prediction data and associated error versus number of patterns. The neuro-fuzzy model matches the predicted API data with RMSE and NDEI as shown in option 4, of Figure 3. Figure 11 shows the plots of the EOR project depths for the training and prediction data versus number of patterns.The neuro-fuzzy model matches the predicted injection depth with RMSE and NDEI as shown in option 2, of Figure 4. The range of the formation permeability data is up to five orders of magnitude (Figure 13) with RMSE and NDEI as shown in option 4, of Figure 5. Figure 14 shows the weighted training data, prediction data and associated error for the formation porosity in EOR projects versus number of patterns. The computed RMSE and NDEI are as shown in option 2, of Figure 6. The training and prediction data for oil saturation plots at start-up are shown in Figure 16 and RMSE and NDEI as shown in option 1 of Figure 7.

Table 2
Number of EOR Technique / Variable Data Available Based on Successful Projects Around the World

EOR technique	Depth, feet	Porosity, %	Permeability, mD	Oil gravity, ^{0}API	Oil viscosity, cp	Oil saturation at start-up, %
Steam	145	145	134	145	141	138
Miscible CO_2	130	130	129	131	128	107
Miscible HC	37	37	36	37	36	33
Polymer	24	24	24	24	21	18
Combustion	16	15	14	16	15	15
Surfactants	3	3	3	3	3	3
Nitrates	2	2	2	2	2	2
Microbial	3	3	3	3	3	2
Hot water	2	2	2	2	2	2
Miscible acid gas	1	1	1	1	1	1
Total	363	362	348	364	352	321

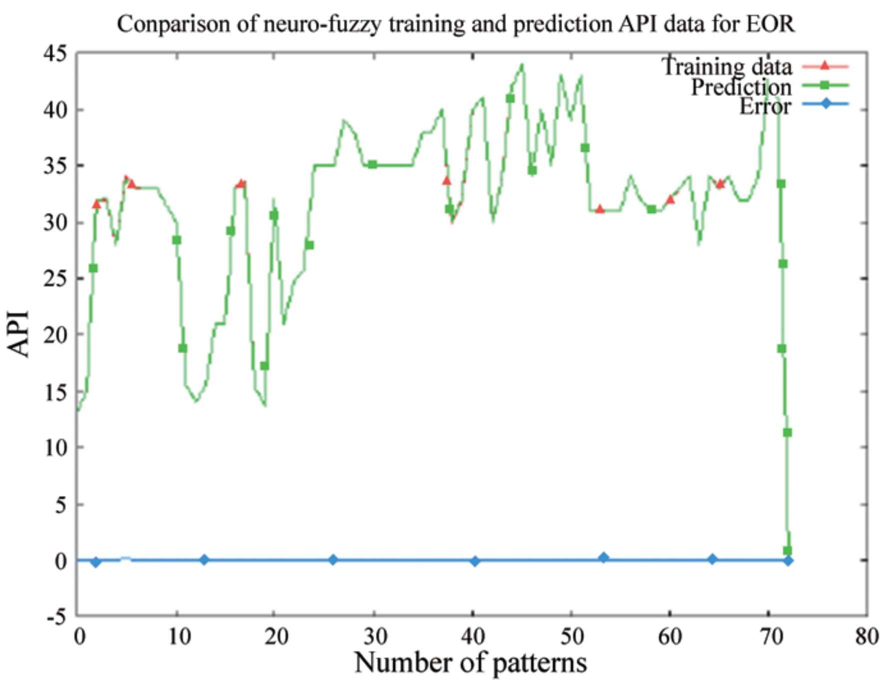

Figure 9
Plots of the ^{0}API Gravity for the Weighted Training Data, Prediction Data and Associated Error Versus Number of Patterns

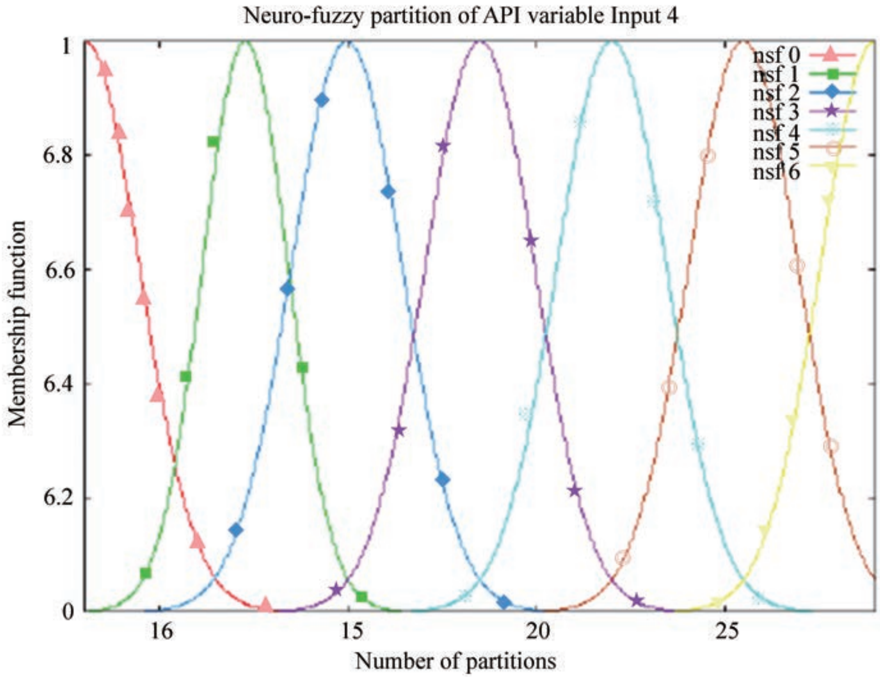

Figure 10
Plot of the Membership Function for the ^{o}API Gravity Data

The viscosity data varies by up to 7 orders of magnitude ranging from $1.4e^{-4}$ Pa•s (0.14 cp) in miscible hydrocarbon / Nitrate injection projects to 500 Pa•s (500,000 cp) in steam assisted projects (Figure 17). The computed RMSE and NDEI are shown in option 1, of Figure 7. Typical learning curves and membership function for the ^{O}API gravity and porosity data are shown in Figures 11, 10 and 15.

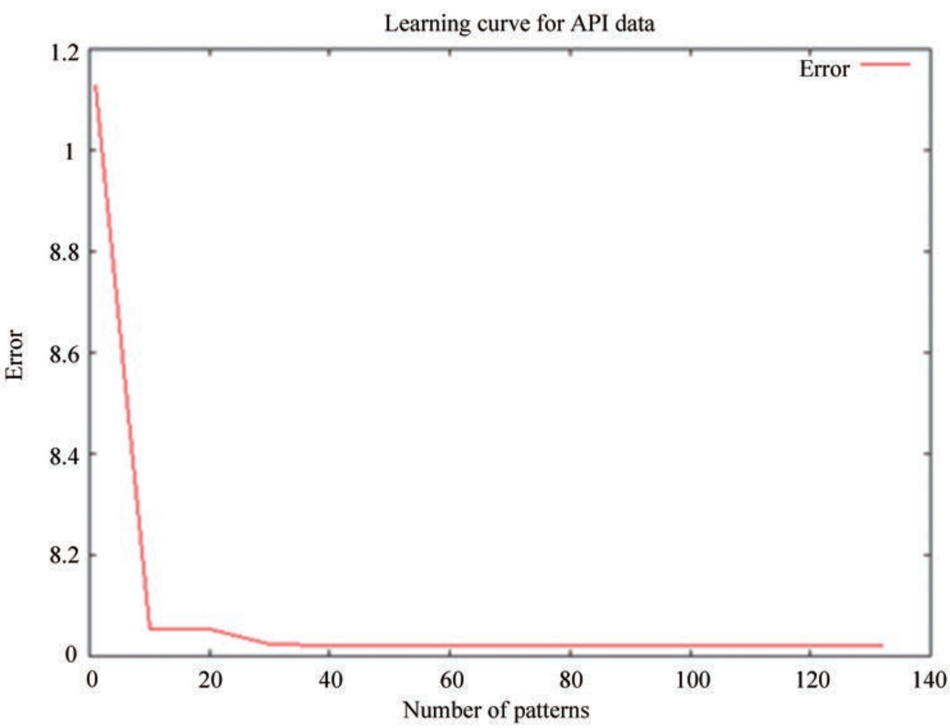

Figure 11
Learning Curve for the API Neuro-Fuzzy Data

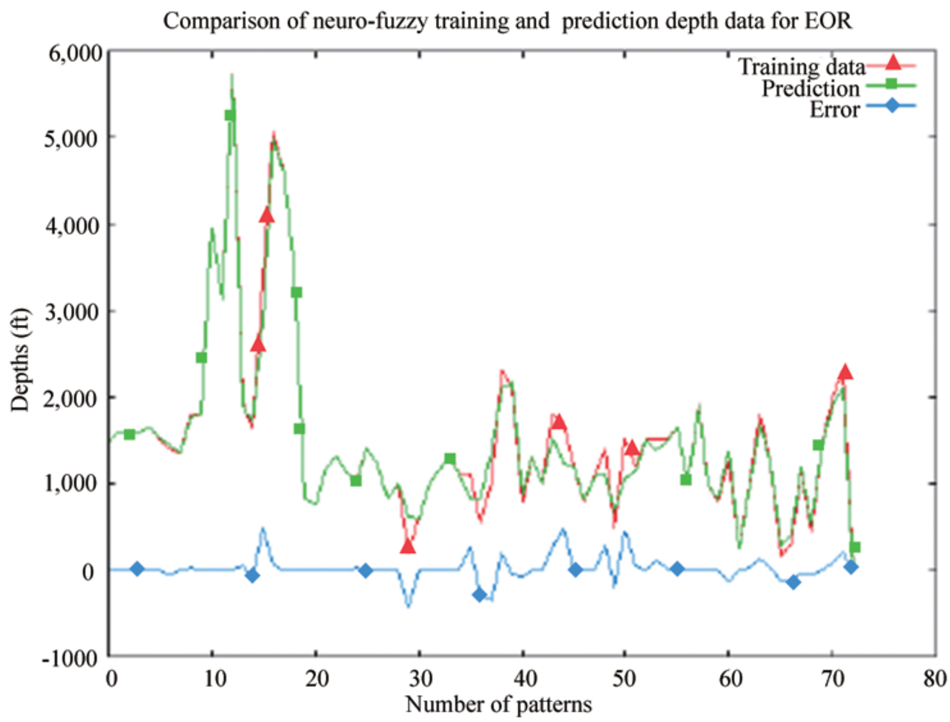

Figure 12
Plots of the EOR Project Depths (Feet) for the Weighted Training Data, Prediction Data and Associated Error Versus Number of Patterns

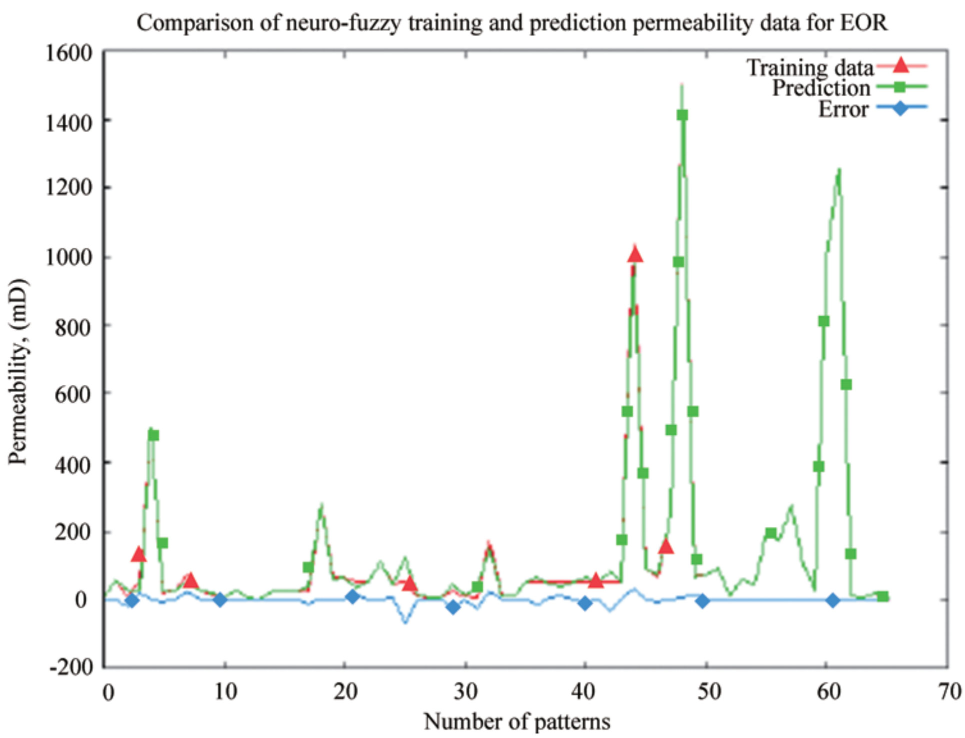

Figure 13
Plots of the Permeability κ(mD) for the Weighted Training Data, Prediction Data and Associated Error Versus Number of Patterns

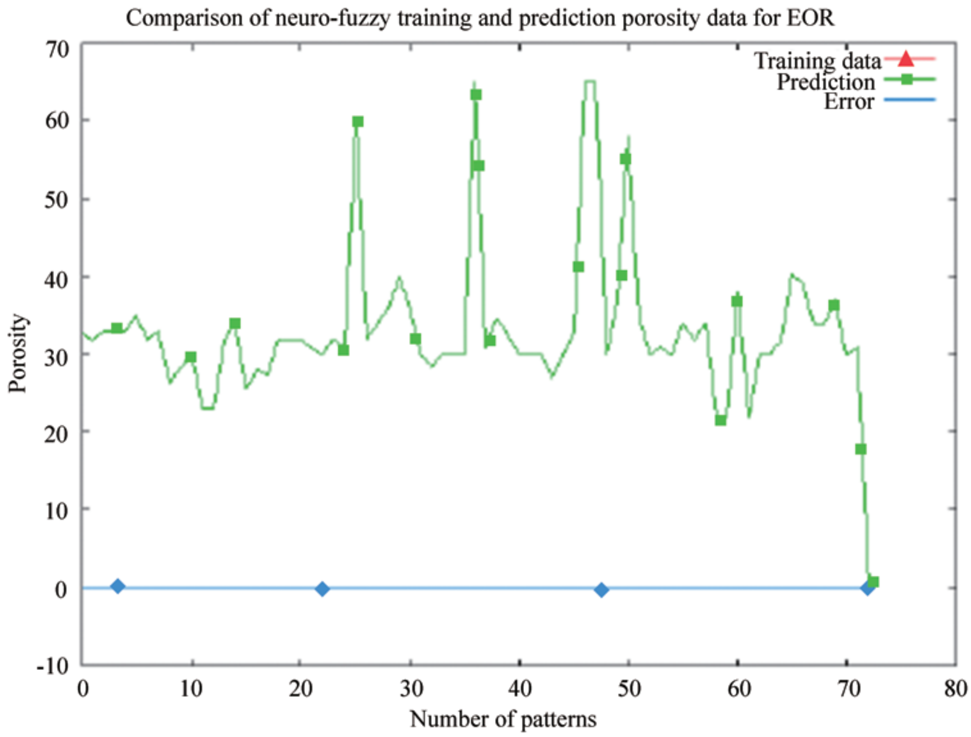

Figure 14
Plots of the Porosity φ(%) for the Weighted Training Data, Prediction Data and Associated Error Versus Number of Patterns

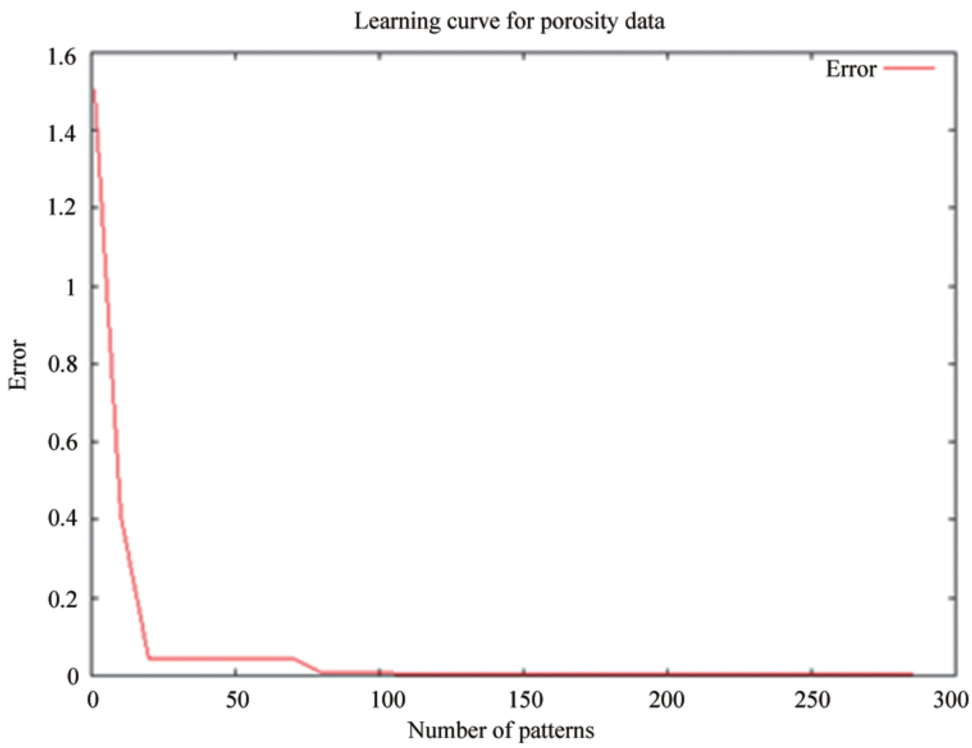

Figure 15
Learning Curve for Porosity Data

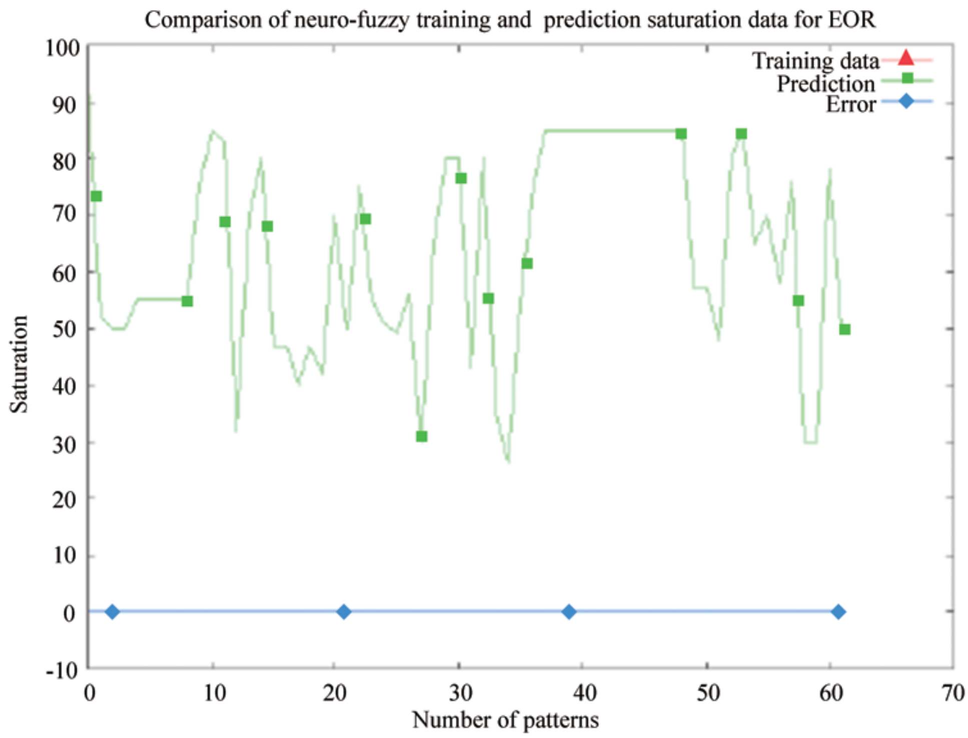

Figure 16
Plots of Oil Saturation at Start up, for the Weighted Training Data, Prediction Data and Associated Error Versus Number of Patterns

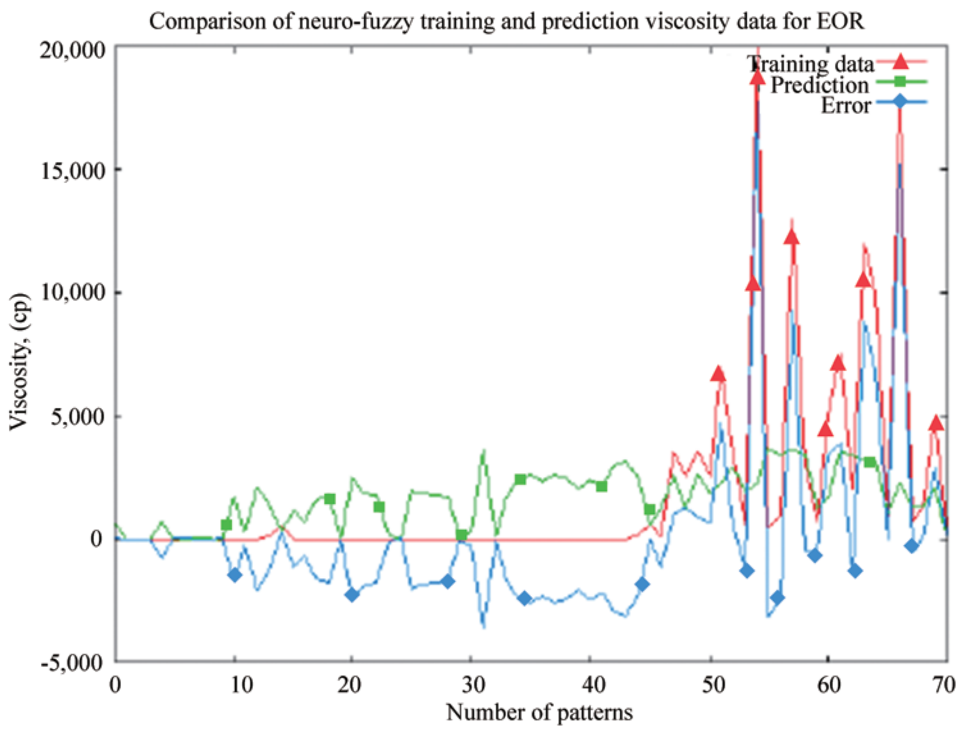

Figure 17
Plots of Oil Viscosity, μ_o(cp) for the Weighted Training Data, Prediction Data and Associated Error Versus Number of Patterns

Low percentage error ensures that this neuro-fuzzy (NF) technique is suitable for the current investigation. Little deviation can occur either due to the insufficient data or inconsistency for the training process. However, any inconsistency will be identified during the training process and more subtle reservoir characteristics that may impact on EOR projects can be isolated. In order to use the technique we have developed in this project in field application, data from the field (test data) will be required. Data from such brown fields can be tested against this trained and validated model thereby providing a means of effectively screening candidate reservoir for EOR application.

CONCLUSION

As much as 90% of all conventional light crude oil discovered in fields worldwide is still in the ground. Under current operational practices, we will produce an additional 12%, leaving behind more than three-quarters of the original discoveries; roughly 9 trillion barrels. EOR is the only option to recover, hopefully, another 25%. It is known that in order to enhance recovery from hydrocarbon reservoirs, a number of techniques could be applied, although mostly based on assertive judgement. A neuro-fuzzy model was developed to provide a screening tool for the thousands of reservoirs that are potential candidates for EOR.

The model uses survey data obtained for 365 successful EOR projects worldwide, covering 10 genres of EOR technologies. This technique provides a screening approach in determining the potentials of reservoirs as EOR candidate based on 5 parameters for each case. Data from such fields can be tested against this trained and validated model thereby providing a means of screening candidate reservoir for EOR application. The model can also be extended to accommodate other reservoir or field data, where available, for similar training and validation process.

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