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ORIGINAL ARTICLE

Efficient screening of enhanced oil recovery methods and predictive economic analysis

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Abstract Oil demand for economic development around the world is rapidly increasing. Moreover, oil production rates are getting a peak in mature reservoirs and tending to decline in the near future, which has led to considerable researches on enhanced oil recovery (EOR) methods. Therefore, an efficient technical and economical screening to appropriate selection of EOR methods can make savings in time and cost. The purpose of this communication is to present a method to select an efficient EOR process and investigate its economic parameters. A database of reservoir parameters of rock and fluid properties along with successful EOR techniques has been collected and analyzed. First, an artificial neural network (ANN) was developed to classify the EOR methods technically. Then, an economical EOR screening model was designed, and then, future cash flows on the use of EOR methods were predicted. The results show that the ANN system can select proper EOR methods and classify them. Moreover, the obtained results indicate that the economic analysis performed in this study is efficient and useful to predict future cash flows.

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Keywords Artificial neural network · Screening · EOR data · Economical study · Rock · Fluid characteristics

1 Introduction

Growing global demand for oil and its products, reduction in natural production of oil resources, concerns about future of hydrocarbon reserves and production optimization topics and finally, oil prices in recent years has led considerable researches on enhanced oil recovery (EOR) methods. However, due to high technical sensitivity of these methods and high cost of operation in reservoirs in the second half of their life, new EOR techniques are required.

Basically, screening concept in petroleum engineering is selection of the most appropriate EOR method with respect to rock and fluid properties, and consideration of existing facilities and economic policies. This concept clearly makes savings in time and cost, and reduces the final decision making risk. An appropriate technical and economical screening can provide the context for modeling the project. There are different methods for screening project such as determination of parameters in a specified range, using tables and graphs, fuzzy logic, artificial intelligence (AI), etc.

In the past, various studies have been done on the EOR screening methods that have been published in the papers, conferences and books [3, 6, 7, 11–13, 15, 23]. In one of the first efforts, screening criteria was briefly presented in a series of tables and simple graphs [27]. Then, EOR methods were classified based on field data and EOR mechanisms [28, 29] and were updated in 2011 [4]. Another study examined the impact of oil prices on EOR activities by comparing the EOR oil production to that predicted by earlier National Petroleum Council (NPC) reports [28, 29].

Alvardo et al. [5] collected a series of EOR screening field data in different parts of the world.

In recent years, simulation methods, AI and neural networks have improved the EOR screening methods. Zerafat et al. [30] solved the problem of selecting appropriate EOR methods by Bayesyan network. Ibatullin et al. [14] expressed that available analytical technologies theoretically make it possible to solve the problem of selection of optimum EOR methods. Abbas and Song [1] designed an intelligent system capable for modification of a parameter. Lee et al. [15] developed an ANN model to classify only five types of EOR methods without considering economical issues. Shokir et al. [26] designed a model composed of technical and economical neural networks for EOR screening; however, they could not predict the amount of cash flow in the future by this model. In another study, ANN methodology is used to build a high-performance neuro-simulation tool for screening improved oil recovery (IOR) methods and recognize the relationship between the displacement mechanism and the reservoir characteristics for different reservoirs [22]. Mc Coy and Rubin [18] have developed an engineering-economical model for geological storage of CO_2 through EOR. They briefly described the performance and cost models for CO_2-flood EOR and used them to estimate the breakeven price for CO_2 as a function of significant variables.

As can be seen, most researches on EOR screening have focused on the technical issues; however, economical challenges in EOR studies have not been taken well into account. In this study, both problems of selecting appropriate EOR method and prediction of future cash flows are solved. A database of reservoir parameters of rock and fluid properties along with successful EOR techniques have been collected and analyzed. First, an ANN was developed to classify the EOR methods technically. Then, an economical EOR screening model was designed in an excel sheet, and then, future cash flows on the use of EOR methods were predicted.

2 Data collection

Generally, the data for EOR screening consists of three categories: First, data derived from laboratory studies. Second, data generated from oil reservoirs simulation and third, the most reliable category of information would be the specification of reservoir under successful EOR projects, whose technical and economical capabilities are proved practically [30]. The data used in this study were derived from a series of worldwide EOR surveys [19–21]. This report includes field name, start date, number of production and injection wells, formation type, porosity, area, permeability, depth, start and end saturation, gravity, viscosity, temperature, total and enhanced production, etc. Rock and fluid properties are more important parameters to us.

3 The methodology

This study consists of three main steps:

1. Determination of the range of parameters related to rock and fluid properties of reservoirs under successful EOR techniques.
2. Technically, classification of EOR methods by ANN model.
3. Economical modeling to achieve a profitable and successful project.

3.1 Range of fluid and rock parameters for different types of EOR methods

Basically, there are three main mechanisms that control the efficiency of EOR methods and increase oil recovery such as solvent extraction through miscibility by miscible gas injection methods, reducing oil viscosity by thermal method and decreasing interfacial tension (IFT) by chemical methods [28, 29].

In this study, we present screening criteria for the seven methods that are either the most important or still have some promise. These EOR methods include steam injection, combustion, hydrocarbon miscible flooding, CO_2 miscible injection, chemical flooding, hot water injection and immiscible flooding.

For effective selection of an EOR method, there are several parameters including production, petrophysical, crude oil chemistry, produced water chemistry and field information. But, the most effective parameters were classified into two main groups: rock parameters (porosity, permeability, initial oil saturation and depth) and fluid parameters (gravity, viscosity and temperature). Ranges of all these parameters are given in Table 1. Due to great variation in some parameters, mean values are calculated for all parameters shown in Table 1.

Figures 1, 2, 3, 4, 5, 6 and 7 represent variations of these parameters at different reservoirs under successful EOR production around the world. It is obvious that thermal EOR techniques entail comparatively higher porosity, permeability, viscosity and lower depth, gravity and temperature.

3.2 Artificial neural network

Artificial neural network is an intelligent system to solve the problems of regression and classification. Also, it is a biologically inspired computational model that consists of

Table 1 Range of input rock and fluid parameters

Parameter	Min. value	Average	Max. value
Porosity	3	24.48	65
Permeability	0.1	1,561.95	11,500
Depth	32.8	3,339.86	13,750
Gravity	8	23.75	57
Viscosity	0.097	16,320.1	5,000,000
Temperature	5	120.54	290
Saturation	15	61.17	98

Source: Data from Oil & Gas Journal [19–21]

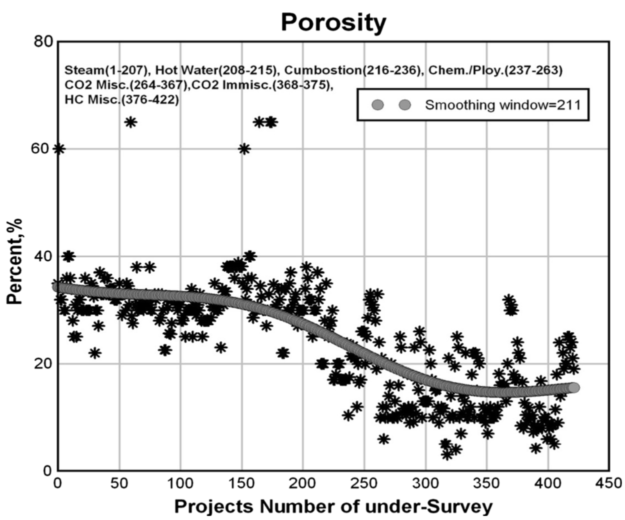


Fig. 1 Ranges of porosity for different types of EOR methods

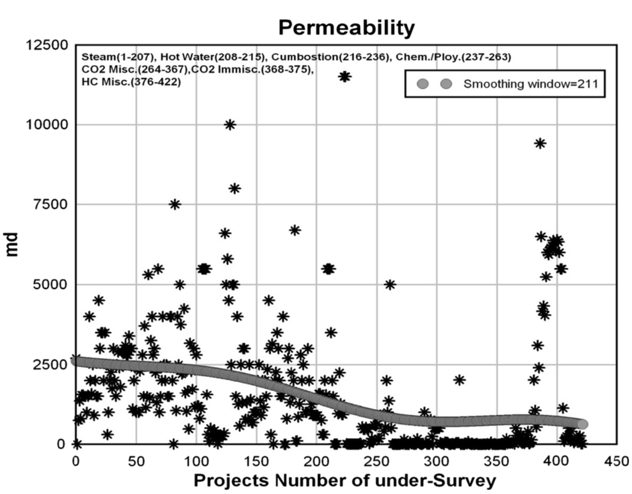


Fig. 2 Range of permeability for different types of EOR method

processing units and connections between them with coefficients bound to the connections, which constitute the neuronal structure, as well as training and recall algorithms attached to the structure [8]. In general, the components of

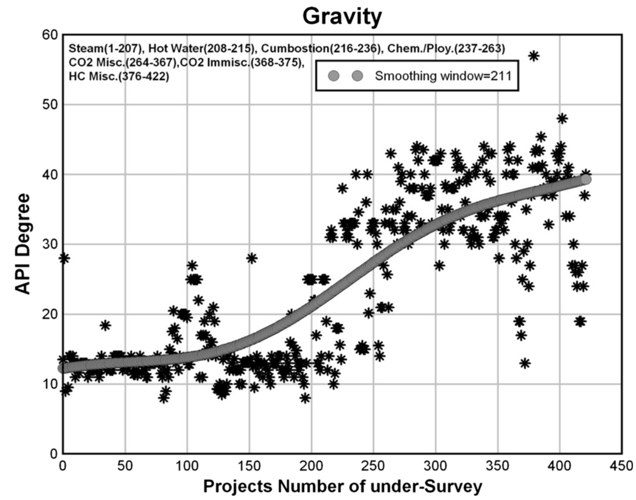


Fig. 3 Range of gravity for different types of EOR

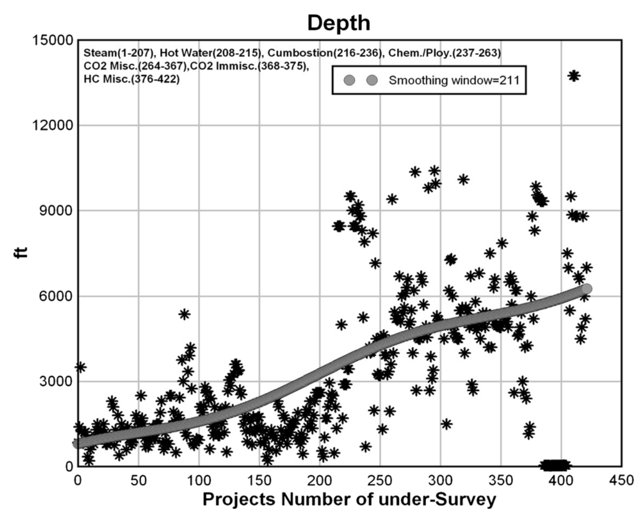


Fig. 4 Range of depth for different types of EOR method

an ANN include input layer, output layer, hidden layer and their neurons. The number of input and output layer neurons depends on the type of problem and the number of input and output variables. But the number of hidden layers and their neurons is selected based on the accuracy of the model. Network input variables have different values which are defined by the weights. Weights are used in calculation before hidden and output layers. They are obtained by training and testing the network. There are several types of ANN that are selected according to the type of neurons connection. The two general types are static and dynamic. Static networks are named as feed forward and dynamic models as feedback. Multi-layer perception and Hopfield networks are the most popular feed forward.

One of the ANN components is transfer functions. These functions are used in the hidden and output layers. Three of

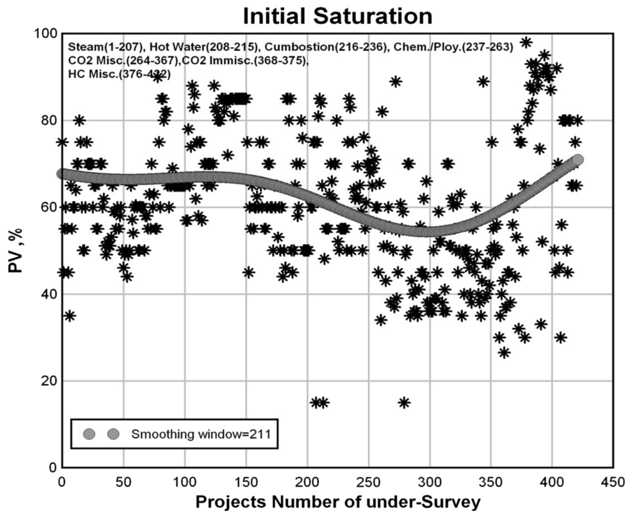


Fig. 5 Range of initial oil saturation for different types of EOR methods

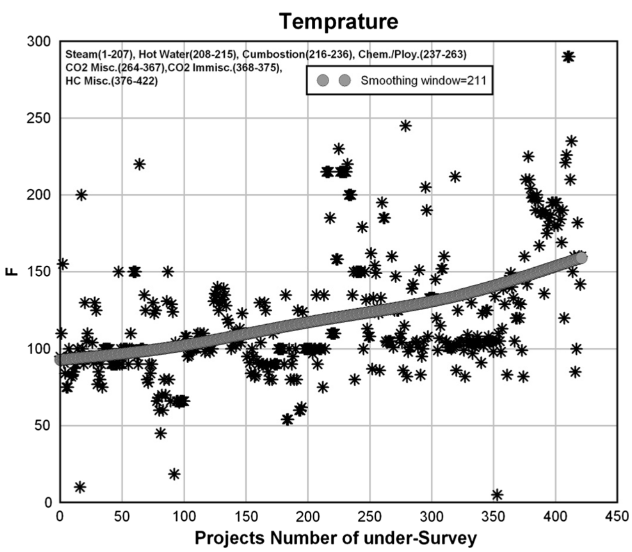


Fig. 6 Range of temperature for different types of EOR methods

the most commonly used functions are shown in Fig. 8. The symbol in the square to the right of each transfer function graph shown in Fig. 8 represents the associated transfer function. Log–Sigmoid transfer function is commonly used in back-propagation networks, because it is differentiable.

3.3 Technical model description

Neurons in the input layer of the network are seven rock and fluid parameters including porosity, permeability, depth, initial saturation, temperature, gravity and viscosity.

Output layer neurons are seven EOR techniques that are classified considering the type of problem. Network was

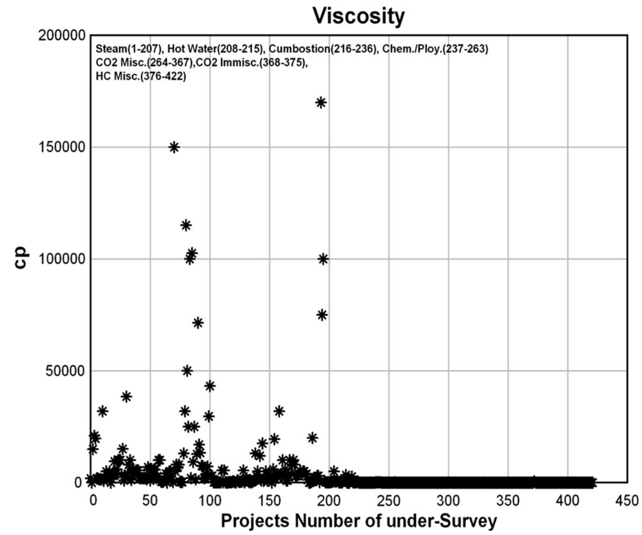


Fig. 7 Range of viscosity for different types of EOR methods (due to high variety, the max value is removed)

trained with 253 data lines. 63 and 106 data lines were allocated to the cross-validation and testing stages, respectively. The number of data used in the model for three steps of training, testing and cross-validation are shown in Table 2.

3.4 Economical model description

An economical model should evaluate various production strategy schemes. Generally, economical models have been designed to simulate the development and operation of actual EOR projects [2]. In this model, the input cash flow is obtained by the rate of oil production and oil price and the output cash flow is lost by costs and pipe line tariffs that both are expressed as dollars per year from the time of project start. The costs consist of capital expenditures (CAPEX), operating expenditures (OPEX), injection material costs and other costs. In this study, a series of financial assumptions are used as follows:

1. During calculation, assumed prices and costs are unchanged for prediction of future years so that an update is needed for future use.
2. In this model, for the calculation of gross revenue, oil price over 105 US$ and pipe line tariff over 7 US$ are set.
3. Operating expenditures include fixed and variable costs. Fixed OPEX and variable OPEX are assumed 8 US$ × bbl and 3 MM US$ per year, respectively.
4. Capital expenditures consist of drilling and completion wells, reworking existing wells and injection costs.
5. The tax rate is 30 % after calculation of the net profit value, and royalty rate is 12 % of after-tax net profit value. Moreover, inflation rate is assumed to be 0.0 %.

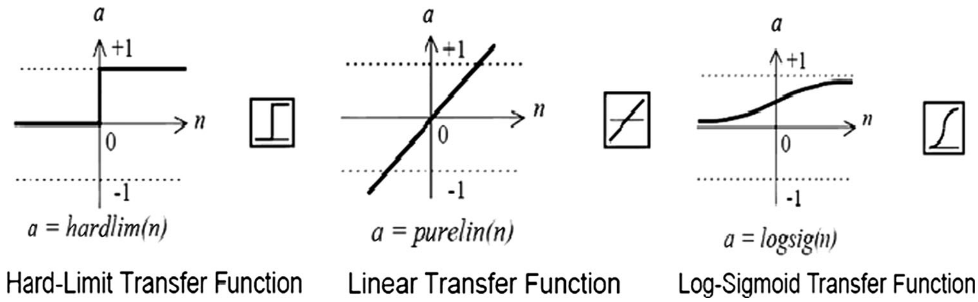


Fig. 8 Scheme of the most commonly used functions [17]

Table 2 Number of data used for training, validation and testing

Parameter	Training	Validation	Testing	Total
Combustion	11	5	5	21
Hot water	6	1	1	8
CO_2 miscible	53	18	33	104
HC miscible	32	5	10	47
Chemical	16	6	5	27
Steam	129	27	51	207
CO_2 immiscible	6	1	1	8
Total	253	63	106	422

Structure of the built economic model in this study is shown in Fig. 9.

4 Results and discussion

First, different types of EOR methods are classified, and their accuracy is calculated by neural network. Then, the two methods with the highest accuracy are chosen as a case study for economical analysis.

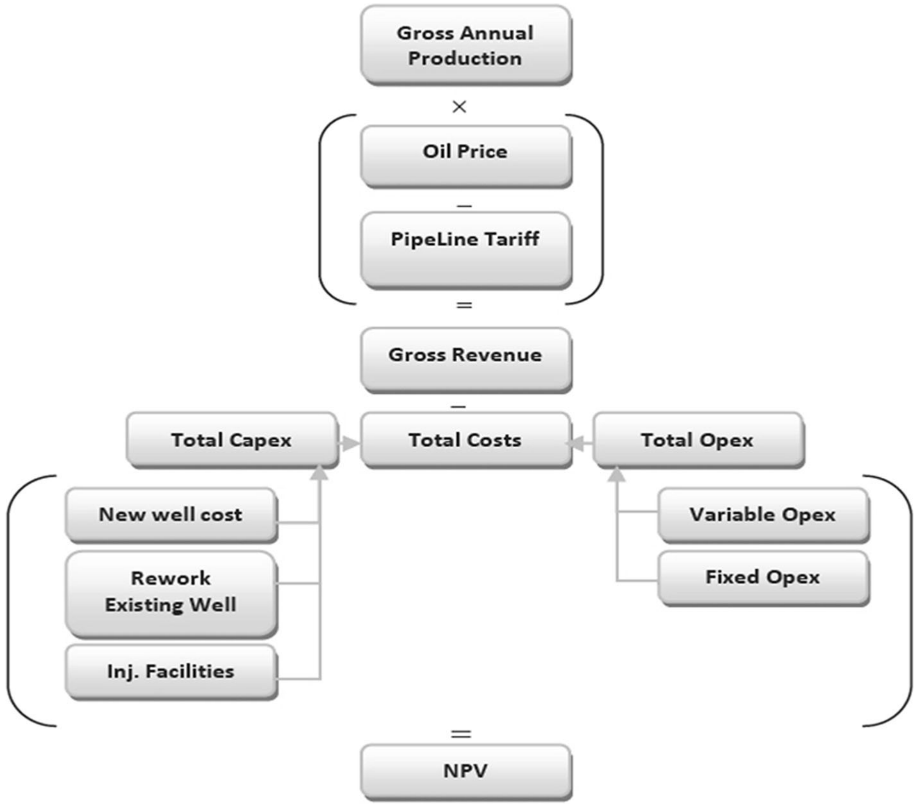
4.1 Selection of the optimal network and classification

In this study, for classification of EOR methods, a multilayer perceptron neural network was used. The tanh-axon was selected as transfer function, and Levenberg–Marquardt back propagation was used in all training steps. The default Mean Square Error performance function, MSE,[1] was used to measure the performance of the model. The threshold is initially designed to be 0.01. The number of epochs per each training case according to the MSE is indicated in Fig. 10. Maximum number of epochs is set to 1,000.

The obtained results indicate that the best network was the one hidden layer network, whose number of neurons was found by trial and error. Various sets of hidden layer neurons, MSE and accuracy were examined to reach the optimum performance of the model (Table 3). As a result, the number of adjustable parameters of an ANN model including weight and bias must be low. Therefore, to ensure this important issue, the process was performed to obtain optimal ANN parameters. Another parameter which is taken into consideration is the number of neurons in the hidden layer (n_h). For this purpose, six ANN modules were developed with n_h. The model with $n_h = 6$ generated the most satisfactory results. Hence, the developed three-layer feed forward ANN has the structure of 7-6-7 (7 neurons are regarded as the inputs of the algorithm, the second layer, viz. hidden layer is composed of 6 neurons, and finally, 7 neurons were assigned for the output layer). Therefore, the ratio of all data points/(parameters of developed ANN model including weight and bias) is reasonable, and the proposed model is valid and is not over-fitted. Consequently, a number of techniques have been developed to further improve ANN generalization capabilities, including: different variants of cross-validation [9], noise injection [10], error regularization, weight decay [9, 25] and the optimized approximation algorithm [16]. A number of cross-validation variants exist, and some of them are of special attention when data are very scarce, i.e., multifold cross-validation or leave-one-out [9]. But probably the most popular in practical applications [16] is the so-called early stopping. To utilize early stopping strategy, apart from the training data set and the testing set, the validation set is required to define stopping criteria of the optimization algorithm. The ANN training terminates when error increases for validation data, although it often continues to reduce for training data set. When error calculated for validation data increases, while calculated for training data reduces, it is considered as fitting to the noise present in the data, instead of signal, in other words over-fitting [24]. In this study, the above-mentioned strategy is considered in addition to limitation of ANN's adjustable parameter issue in order to avoid over-fitting and improve generalization. As can be seen in Table 3, the error values for validation set are more than those for training set at all the developed nets.

[1] $\mathrm{MSE} = \frac{\sum_{i=1}^{n} (\mathrm{EOR}_{\mathrm{pred}_i} - \mathrm{EOR}_{\mathrm{exp}_i})^2}{n}$.

Fig. 9 Layout view of economical model



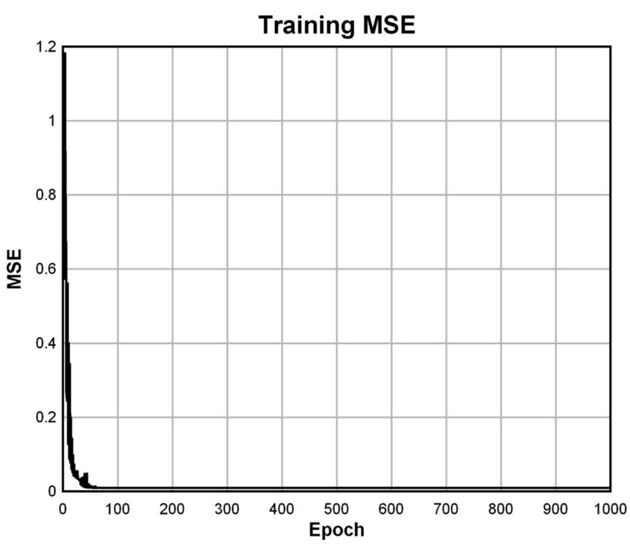


Fig. 10 MSE with standard deviation boundaries and 1,000 epochs

As mentioned above, the obtained results show that the network with 6 neurons has maximum accuracy. Therefore, this network is used technically for classification of EOR methods. Finally, a network with seven input neurons, one hidden layer with 6 neurons and seven output neurons was selected (Fig. 11).

Some thresholds are tested with the model during the training to the improving efficiency of selected network. The test results indicate that the ANN model shows good performance with all given threshold (Table 4). The best performance is shown in the model trained by 0.001, which is eventually selected as the final model. The prediction performance of this model is summarized in Table 5. Here, it is worthwhile to mention that more information regarding this model and its parameters is available upon request to the authors.

4.2 Economical analysis

4.2.1 Predictive performance of economical model for CO_2 miscible injection technique

In this section, the amount of future cash flow is predicted by using our developed economical model. Figure 12 shows the simulated reservoir operation production using technical screening, where miscible CO_2 injection has been detected appropriate.

For reservoir oil recovery, CO_2 injection rate is calculated 813.2 Mscf/day. The purchase of CO_2 is about 30\$–40\$ per Tonne. The number of injection and production wells is 161. First, by using production rates, oil price and pipeline tariff gross profit rate were calculated, then by deduction of expenses, pre-tax net profit value was obtained. As previously mentioned, tax rate is assumed 30 % of net profit value, and royalty rate 12 %

Table 3 Results of topology studies to find optimal ANN configuration with epoch 1,000. The best obtained network is in bold

No.	Hidden layer	Training		Validation		Testing	
	Neuron No.	MSE	Correct (%)	MSE	Correct (%)	MSE	Correct (%)
1	4	0.00353	99.20	0.02449	80.90	0.00645	82.00
2	2	0.01285	92.00	0.03112	84.10	0.01098	84.90
3	1	0.01519	81.00	0.02982	79.30	0.01779	83.00
4	**6**	**0.00081**	**98.80**	**0.06420**	**79.30**	**0.0256**	**93.40**
5	8	0.05197	85.70	0.06997	82.50	0.05943	86.70
6	9	0.05274	79.00	0.07598	80.90	0.06431	83.90
1	4	0.00353	99.20	0.02449	80.90	0.00645	82.00

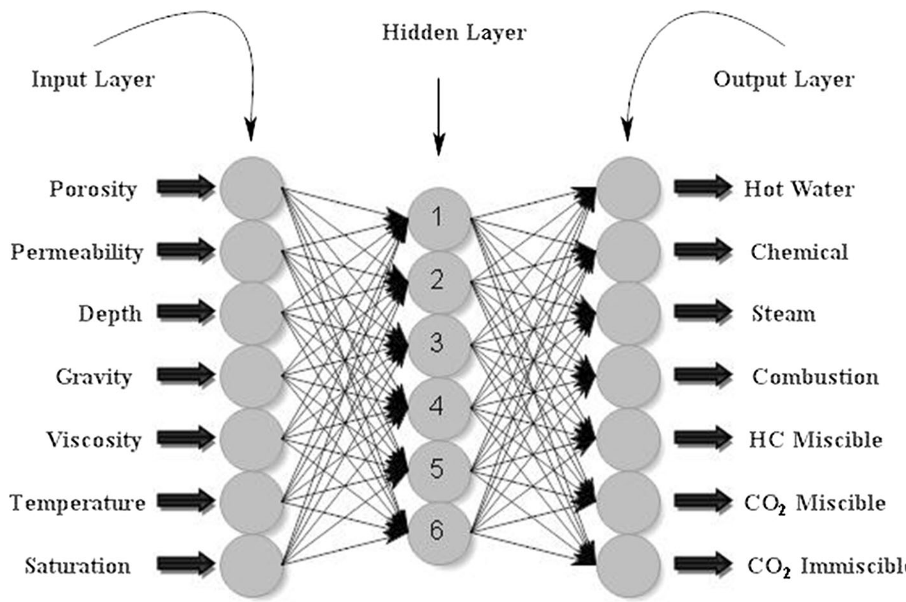


Fig. 11 Schematic diagram of the neural network developed in this study

Table 4 Performance prediction of optimal ANN model (one hidden layer with six hidden neurons) according to the threshold. The best evaluated threshold is in bold

Threshold	0.01			0.001			0.0001			0.00001		
	Train. valid. test.			Train. valid. test.			Train. valid. test.			Train. valid. test.		
No. of rows	253	63	106	253	63	106	**253**	**63**	**106**	253	63	106
MSE	0.00	0.06	0.02	0.01	0.05	0.02	**0.00**	**0.04**	**0.01**	0.00	0.03	0.02
Correlation (r)	0.89	0.40	0.77	0.81	0.68	0.75	**0.82**	**0.70**	**0.78**	0.83	0.71	0.75
No. correct	234	52	99	236	50	98	**240**	**52**	**100**	240	52	98
No. incorrect	19	11	7	17	13	8	**13**	**11**	**6**	13	11	8
% Correct	98.8	79.3	93.4	93.2	79.3	92.4	**94.8**	**81.0**	**93.9**	94.6	80.1	91.3

of after-tax net profit value, e.g., in 2012, the rate of gross profit: 215.5 MM US$, total cost: 342.62 MMUS$, net profit value before tax: −127.028 MM US$, net profit value after tax: −88.91 MM US$ and royalty: −10.67 MM US$ are calculated. Figure 13 shows the cumulative pre-tax net profit value, cumulative after-tax net profit value and cumulative after-tax royalty if using carbon dioxide injection.

4.2.2 *Predictive performance of economical model for steam injection technique*

Figure 14 shows the simulated reservoir operation production in which steam injection has been detected appropriate by using technical screening. Steam injection rate is calculated 2,000 bbl/day. The cost of steam and maximum generator pressure for 60 time steps are assumed

Table 5 Detailed prediction performance (testing step) of the developed ANN model

Performance	Combustion	Hot water	CO_2 miscible	HC miscible	Chemical	Steam	CO_2 immiscible
No. of rows	5	1	33	10	5	51	1
MSE	0.023384506	0.021149352	0.022465203	0.036012084	0.023259313	0.013288549	0.019069683
Correlation (r)	0.700545085	0.592187921	0.952089309	0.932082406	0.618369149	0.9245780343	0.383829719
No. correct	4	0	33	8	4	51	0
No. incorrect	1	1	0	2	1	0	1
% Correct	80	0	100	80	80	100	0

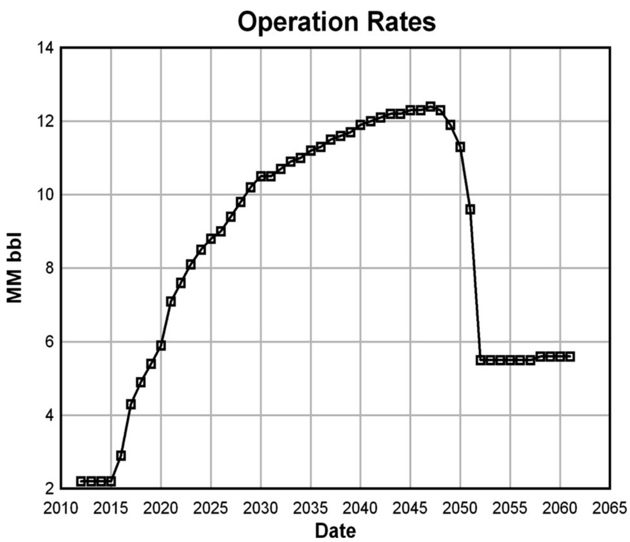


Fig. 12 Predictive operation rates for CO_2 miscible case

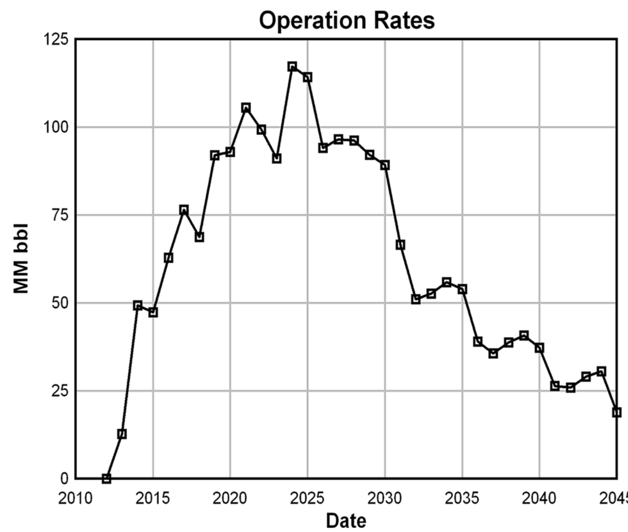


Fig. 14 Predictive operation rates for steam injection case

6.5 M$ per 2,000 bbl steam and 1,500 psi, respectively. The numbers of injection and production wells are 43. First, by using production rates, oil price and pipeline tariff gross profit rate were calculated. Then, pre-tax net profit value was obtained by deduction of expenses, e.g., in 2012, the rate of gross profit: 0 MM$, total cost: 1. MM$, net profit value before tax: −1.5 MM$, net profit value after tax: −1. 05 MM$ and royalty: −0.12 MM$ are calculated.

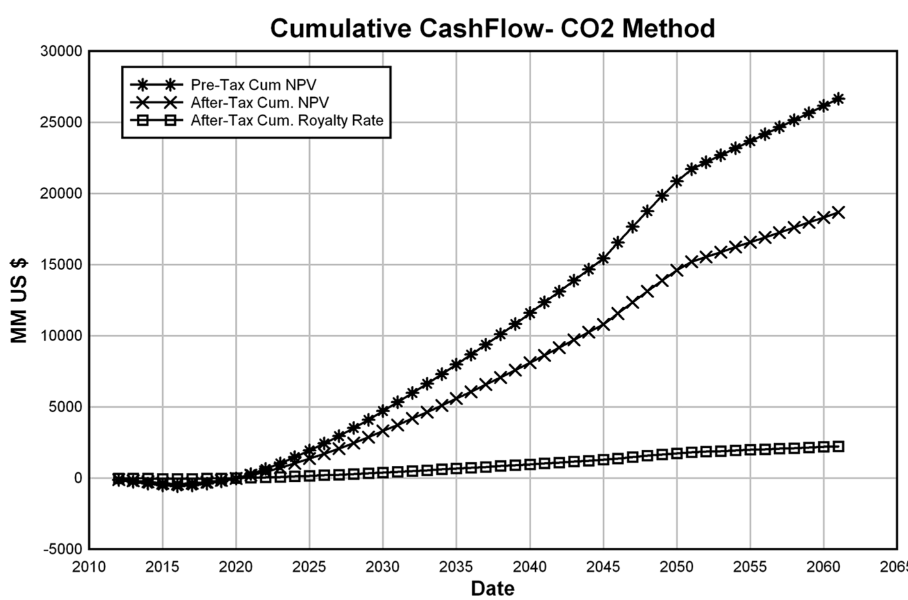


Fig. 13 Predictive cumulative cash flows for CO_2 miscible case

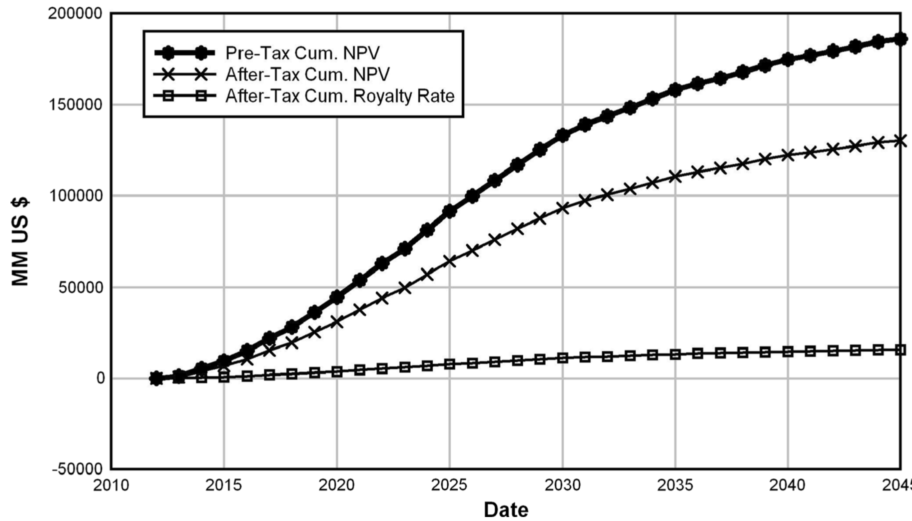


Fig. 15 Predictive cumulative cash flow for steam injection case

Finally, Fig. 15 shows the cumulative pre-tax net profit value, cumulative after-tax net profit value and cumulative after-tax royalty if steam injection is used.

5 Conclusions

1. Rock and fluid properties have direct influence on the selection of EOR methods. Thus, the range of parameters for each EOR method was determined. The results show that thermal methods have the highest viscosity, porosity, and permeability and the lowest gravity, depth, and temperature.
2. Application of ANN system to proper selection of EOR method and classify them is very important and useful. Development of such network shows that ANN systems have important applications that assist experienced reservoir engineers to save time while selecting an appropriate EOR technique on the basis of rock and fluid properties.
3. Economical analysis showed that steam injection and carbon dioxide miscible can be economically profitable and successful in the future.

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