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Original article

A predictive model of chemical flooding for enhanced oil recovery purposes: Application of least square support vector machine

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ABSTRACT

Applying chemical flooding in petroleum reservoirs turns into interesting subject of the recent researches. Developing strategies of the aforementioned method are more robust and precise when they consider both economical point of views (net present value (NPV)) and technical point of views (recovery factor (RF)). In the present study huge attempts are made to propose predictive model for specifying efficiency of chemical flooding in oil reservoirs. To gain this goal, the new type of support vector machine method which evolved by Suykens and Vandewalle was employed. Also, high precise chemical flooding data banks reported in previous works were employed to test and validate the proposed vector machine model. According to the mean square error (MSE), correlation coefficient and average absolute relative deviation, the suggested LSSVM model has acceptable reliability; integrity and robustness. Thus, the proposed intelligent based model can be considered as an alternative model to monitor the efficiency of chemical flooding in oil reservoir when the required experimental data are not available or accessible.

1. Introduction

The oil and gas upstream industries have recently encountered with the difficulties and challenges of dealing with hydrocarbon resources whose productions with conventional technologies are following an upward trend of technical limitations. It is because of achieving the stage of decline phase by most of oilfields around the world. Therefore, how to postpone the abandonment of reservoirs has tuned into the priority of researchers in the worldwide. Their researches normally highlight the concept of great necessities for inventions of new techniques, normally classified as tertiary oil recovery methods, having abilities of maintaining the economic production rate [1–3].

Chemical enhanced oil recovery approaches as one of the most effective subsets of tertiary methods are known as a key to unlock the exploitation of referred resources. Different methods for this process have been developed, such as: polymer, surfactant/polymer (SP), and alkaline/surfactant/polymer (ASP) flooding, microgel, foam, polymer gel and microemulsion flooding. These methods are applied to increase the rate of oil production through focussing on both lowering the interfacial tension and reducing the water mobility. In more details, it has enormously been declared in previous literatures that in order to design, manage and run a chemical enhanced oil recovery operation it is highly required to set very expensive and time-consuming but precise experimental procedures which their generated results must be gained to plan effectively the process of injecting chemical materials [4–9].

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The laboratorial generated outputs are then used to conclude two parameters, RF and NPV, which are used to evaluate the performance of the chemical flooding which is one of the most popular methods of chemical enhance oil recovery. Having knowledge about these two parameters are essentially vital to make decisions if it is beneficial to run the referred operation. Unfortunately, there are no global methods to interpret simultaneously about both aforementioned factors although there are numerous numbers of different software and numerical or analytical method which are capable of making very precise quantitative decisions about the amount of one the RF or NPV [10–12].

Hence, there is a great need in oilfield for having access to a solution or model which can predict the amount of these two parameters at the same time. The major aim of current study is execute new kind of artificial intelligence approaches called "least square support vector machine (LSSVM)" to suggest robust and accurate predictive method to forecast efficiency of the chemical flooding through petroleum reservoirs. To gain successfully this referred goal, LSSVM was executed on the previous literature data bases. The integrity and performance of the proposed predictive approach in estimating RF and NPV from the literature is described in details.

2. Data gathering

The data utilized throughout this research have been gathered from previous attentions [9] in which chemical flooding had been simulated in Benoist sand reservoir, by executing UTCHEM simulator. That reservoir has been produced under primary and secondary processes over fifty years. The Original dataset contained 202 data. Each data had 7 inputs: Surfactant slug size, surfactant concentration in surfactant slug, polymer concentration in surfactant slug, polymer drive size, polymer concentration in polymer drive, Kv/Kh ratio, and salinity of polymer drive. In addition, the outputs were RF and NPV. The ranges of implemented data banks are reported in Table 1 [9].

3. Least square support vector machine (LSSVM)

The least square SVM theorem was proposed and developed by Suykens and Vandewalle in 1999 dedicated to the presumption that the implemented data assortment S = {(x_1,y_1), …, (x_n,y_n)} that deal with a nonlinear function and decision function can be formulated as illustrated in equation (1). Through the addressed equation, w stands for the weight factor, φ denotes the nonlinear function which correlates the input space to a high-dimension characterization area and conducts linear regression while b represents the bias term [13–34]. Following expression was implemented as a cost function of the least square support vector machine (LSSVM) in calculation steps [13–34].

$$Q_{LSSVM} = \frac{1}{2}w^T w + \gamma \sum_{k=1}^{N} e_k^2 \tag{1}$$

Relate to the following restriction [13–23]:

$$y_k = w^T \varphi(x_k) + b + e_k \quad k = 1, 2, \ldots, N \tag{2}$$

To specify function estimation issue the structural risk minimization (SRM) approach is suggested and the optimization issue is implemented to mastermind the addressed R function while C represents the regularization constant and e_i stands for the training error [13–34].

$$R(\omega, e, b) = \frac{1}{2}\left|\left|w\right|\right|^2 + \frac{1}{2}C\sum_{k=1}^{m} e_k^2 \tag{3}$$

To extract routs w and e, the Lagrange multiplier optimum programming approach is performed to solve equation (3); the addressed approach considers impartial and restriction parameters simultaneously. The mentioned Lagrange function L is formulated as following equation [13–34]:

$$L(w, b, e, \alpha) = J(w, e) - \sum_{k=1}^{m} \alpha_i \left\{ w^T \varnothing(x_k) + b + e_k - Y_k \right\} \tag{4}$$

Through above equation, α_i denotes the Lagrange multipliers that may be either positive or negative because LSSVM has equality restrictions. Owing to the Karush–Kuhn–Tucher's (KKT) conditions, conditions for optimum goal are demonstrated in equation (3) [13–23].

$$\left\{ \begin{array}{c} \partial_\omega L = \omega - \sum_{i=1}^{n} \alpha_i \varphi(x_i) = 0 \\ \partial_b L = \sum_{i=1}^{n} \alpha_i = 0 \\ \partial_{e_i} L = Ce_i - \alpha_i = 0 \\ \partial_{\alpha_i} L = w^T \varnothing(x_k) + b + e_k - y_k = 0 \end{array} \right\} \tag{5}$$

Therefore, the linear equations can be demonstrated below expression [13–23]:

$$\begin{bmatrix} 0 & -1^T \\ 1 & \Omega + \frac{1}{\gamma} I_N \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{6}$$

While $y = (y_1, \ldots, y_n)^T$, $1_n = (1, \ldots, 1)^T$, $\alpha = (\alpha_1; \ldots; \alpha_n)^T$ and $\Omega_{il} = \varphi(x_i)^T \varphi(x_l)$ for i, l = 1, …, n. Thanks to the Mercer's theorem, the resulting LSSVM model for function approximation turns to the following equation [13–23]

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{7}$$

Where α and b are the routs to equation (7) as below [13–23]:

$$b = \frac{1_n^T \left(\Omega + \frac{1}{\gamma} I_n\right)^{-1} y}{1_n^T \left(\Omega + \frac{1}{\gamma} I_n\right)^{-1} 1_n} \tag{8}$$

Table 1
Statistical analysis of the implemented chemical flooding data samples [9].

Parameter	Unit	Type	Min	Max	Average	Standard deviation
Surfactant slug size	PV	Input	0.097	0.259	0.177	0.072
Surfactant concentration	Vol. fraction	Input	0.005	0.03	0.017	0.011
Polymer concentration in surfactant slug	wt.%	Input	0.1	0.25	0.177	0.067
Polymer drive size	PV	Input	0.324	0.648	0.482	0.144
Polymer concentration in polymer drive	wt.%	Input	0.1	0.2	0.148	0.044
Kv/Kh ratio	–	Input	0.01	0.25	0.129	0.107
Salinity of polymer drive	Meq/ml	Input	0.3	0.4	0.349	0.045
Recovery factor (RF)	%	Output	14.82	56.99	39.67	9.24
Net present value (NPV)	$ MM	Output	1.781	7.229	4.45	1.53