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Integrating a robust model for predicting surfactant–polymer flooding performance

Arash Kamari [a], Farhad Gharagheizi [a], Amin Shokrollahi [b], Milad Arabloo [b,*], Amir H. Mohammadi [a,c,d,**]

[a] Thermodynamics Research Unit, School of Engineering, University of KwaZulu-Natal, Howard College Campus, King George V Avenue, Durban 4041, South Africa

[b] Young Researchers and Elites Club, North Tehran Branch, Islamic Azad University, Tehran, Iran

[c] Institut de Recherche en Génie Chimique et Pétrolier (IRGCP), Paris Cedex, France

[d] Département de Génie des Mines, de la Métallurgie et des Matériaux, Faculté des Sciences et de Génie, Université Laval, Québec (QC), G1V 0A6, Canada

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ABSTRACT

The combination of surfactant and polymer in injecting water will improve the oil recovery during a water flood. The surfactant–polymer (SP) flooding would be more effective if economic policies are considered in addition to technical issues. The present communication introduces two reliable models for the performance evaluation of surfactant–polymer flooding in terms of both technical and economical approaches. To this end, a promising methodology called least square support vector machine (LSSVM) is applied for the accurate determining both recovery factor (RF) and net present value (NPV) related to SP flooding. The results obtained in this study reveal that there is an acceptable agreement between the data estimated by LSSVM approach and the actual data of RF and NPV. Moreover, to perform a comprehensive modelling to predict RF and NPV properly, an analysis is conducted on the different assignments of data for training, validation and testing phases. The results display that the value/percentage of data assigned for training set must be balanced and reasonable to avoid over-fitting problem, and also achieve an accurate and tested prediction. Finally, in order to show the importance degree of each input parameter on RF and NPV, a sensitivity analysis is conducted in this study. The results demonstrate the positive and negative impacts of those variables on both RF and NPV.

1. Introduction

Scale deposition in pipelines as well as the robust emulsification related to the fluids produced are two important drawbacks faced with alkaline–surfactant–polymer (ASP) flooding technology (Hongyan et al., 2009; Zhang et al., 2007). In order to overcome such disadvantages, alkali-free surfactant–polymer flooding technique has been proposed (Hongyan et al., 2009). As a result, the chemical enhanced oil recovery (EOR) techniques, in particular surfactant–polymer (SP) flooding, has demonstrated its key role in decreasing the saturation of residual oil in both scales of experimentally tests/measurements and field developments. As a matter of fact, SP flooding decreases the mobility ratio and interfacial tension (IFT) between water and oil phases. In other words, SP flooding method increases the production rates by injecting a surface/external agent (surfactant), regarding two important mechanisms including the IFT and mobility ratio which should be reduced (Lake, 1989).

To forecast the results of EOR techniques, representative methods have been utilized already as an accurate and reliable tool (Crane et al., 1963; Giordano, 1987; Koval, 1963; Patton et al., 1971; Paul et al., 1984; Paul et al., 1982). Paul et al. (1982) developed the chemical flood predictive model to recognise best reservoirs for considering SP flooding. On the basis of fractional flow theory, the proposed method estimates the production rates and ultimate oil recovery efficiency vs. time. Lake et al. (1981) introduced an efficient method for the estimation of performance of a large-scale SP flooding project. As a result, their predictive method includes the sequential utilize of a finite difference tool for simulation target. Wang et al. (1981) proposed a simulator for evaluation of micellar/polymer flooding. Therefore, a streamline generator has been utilized to set up the flow and balance the concentration.

* Corresponding author: Tel: +98 9171405706.
** Corresponding author at: Institut de Recherche en Génie Chimique et Pétrolier (IRGCP), Paris Cedex, France.
E-mail addresses: milad.arabloo@gmail.com (M. Arabloo), a.h.m@irgcp.fr (A.H. Mohammadi).

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Nomenclature

ANN	artificial neural network
SVM	support vector machine
LSSVM	least square support vector machine
SA	simulated annealing
CSA	coupled simulated annealing
RBF	radial basis function
IFT	interfacial tension
EOR	enhanced oil recovery
RF	recovery factor
NPV	net present value
SP	surfactant–polymer
ASP	alkaline–surfactant–polymer
MSE	mean square error
R^2	correlation coefficient
AARD	average absolute relative deviation, %
RMSE	root mean square errors
SDE	standard deviation errors
γ	relative weight of the summation of the regression errors
σ^2	squared bandwidth
r	relevancy factor

As a result, it is well known that EOR methods have been strongly influenced by economic policies (Alvarado and Manrique, 2010), so that an economic analysis can improve their profitability (Kamari et al., 2014d). Therefore, it seems necessary to predict the net present value (NPV) obtained by using EOR methods. Regarding the risk analysis, Costa et al. (2008) acquired predictive method, and then combined it with economical analysis to increase the production prediction in a Brazilian reservoir. Wyatt et al. (2008) presented the economic effects of some important variables such as the injected chemical cost and recovery factor, *etc*., on the performance of ASP flooding method. Moreover, they compared the ASP flooding method with micellar flooding technique and alkaline–polymer flooding. They found that the rate of return and payout time is associated with the process rate, and/or pore volume per year of injection. Wu et al. (1996) focused on the economic conditions in the USA through study of a light-oil, onshore, and sandstone reservoir. To this end, they utilized the UTCHEM compositional simulator. They also validated the results obtained with field data for a SP flooding project.

To evaluate the performance of an EOR method technically and economically, the typical evaluation technique for calculation of recovery factor (RF) is conventional simulator and to calculate the NPV is Excel spreadsheet or value and risk management software (Karambeigi et al., 2011). Generally, these aforementioned methods are not economic and take long time once uncertainty of various variables/parameters is included (Ghorbani, 2008; Qingjun et al., 2004; Silva et al., 2007). In last decades, the intelligent modelling of EOR methods has gained much interest due to their fast-prediction capability, reliability and applicability.

Shafiei et al. (2013) developed a novel model for EOR screening targets on the basis of artificial neural networks (ANN) for evaluating the performance of steam flooding in naturally fractured heavy oil carbonate reservoirs. To evaluate the performance, they used recovery factor and cumulative steam oil ratio as outputs parameters. The results indicated that the developed model could be employed successfully for screening of steam flooding method in naturally fractured heavy oil carbonate reservoirs. In another study, Hou et al. (2009) established quantitative characterization models of oil increase and water-cut variation in polymer flooding method. To this end, they applied automatic solution technique on the basis of genetic algorithm (GA). Additionally, Hou et al. (2009) developed a quantitative model for performance prediction of polymer flooding method on the basis of numerical simulation of this EOR method. During simulation study of polymer flooding, impact of some efficient factors have been studied within the coupling the support vector machine (SVM) as well as orthogonal design approaches.

The method of least square support vector machine (LSSVM) (Suykens and Vandewalle, 1999) is an improvement of the SVM methodology version. In this progressed version, a set of linear equations has been applied using support vectors (SVs) instead of quadratic programming problems for simplifying the solutions associated with the SVM version. Thus far, the LSSVM version has been applied successfully for various applications in oil and gas disciplines (Arabloo et al., 2013; Esfahani et al., 2015; Farasat et al., 2013; Fazavi et al., 2014; Kamari et al., 2015a; Kamari et al., 2015c; Kamari et al., 2014a; Kamari et al., 2013; Kamari et al., 2014b; Kamari et al., 2015d; Rafiee-Taghanaki et al., 2013; Shokrollahi et al., 2013). Nevertheless, the LSSVM technique has not so far been implemented for forecasting the performance of EOR methods technically and economically, in particular NPV and RF related to the surfactant–polymer flooding.

In the present study, two representative models have been proposed for the estimation of SP flooding performance (RF and NPV) for sandstone oil reservoir based on LSSVM modelling approach. The model was built and tested using a comprehensive data set collected from the literature. Moreover, to perform a comprehensive modelling to predict RF and NPV properly, an analysis is conducted on the different assignments of data for training, validation and testing phases. In addition, in order to show the importance degree of each input parameter on RF and NPV, a sensitivity analysis is conducted in this study. Finally, leverage technique has been presented simultaneously to discover the measured possible doubtful data of RF and NPV.

2. Investigational databank

The applicability, reliability and accuracy of predictive/representative methods are normally associated with the comprehensiveness and validity of the databank utilized for their advancement (Gharagheizi et al., 2008; Mohammadi and Richon, 2008; Rafiee-Taghanaki et al., 2013; Scalabrin et al., 2006). Therefore, the most important parameters which affect RF and NPV should be selected. The data used in this study have been presented by Prasanphanich (2009) and gathered by Karambeigi et al. (2011) wherein SP flooding method had been modelled using UTCHEM simulator. Furthermore, NPV had been calculated utilizing Excel spreadsheet. The dataset includes surfactant slug size, surfactant concentration in surfactant slug, polymer concentration in surfactant slug, polymer drive size, polymer concentration in polymer drive, ratio of vertical permeability to horizontal permeability (K_v/K_h), and salinity of polymer drive as inputs parameters, and RF and NPV as outputs parameters. Here it is worthwhile to note that the importance of above variables for accurately prediction of RF and NPV has previously been confirmed by Karambeigi et al. (2011). To calculate the amount of NPV, Prasanphanich (2009) reported some economic assumptions as summarized in Table 1. Normally, the main problem of predictive economic