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Journal of Petroleum Science and Engineering 47 (2005) 197–208

JOURNAL OF PETROLEUM SCIENCE & ENGINEERING

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An optimization methodology of alkaline–surfactant–polymer flooding processes using field scale numerical simulation and multiple surrogates

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Received 5 June 2004; received in revised form 19 February 2005; accepted 22 February 2005

Abstract

After conventional waterflood processes the residual oil in the reservoir remains as a discontinuous phase in the form of oil drops trapped by capillary forces and is likely to be around 70% of the original oil in place (OOIP). The EOR method so-called alkaline–surfactant–polymer (ASP) flooding has proved to be effective in reducing the oil residual saturation in laboratory experiments and field projects through the reduction of interfacial tension and mobility ratio between oil and water phases.

A critical step to make ASP floodings more effective is to find the optimal values of design variables that will maximize a given performance measure (e.g., net present value, cumulative oil recovery) considering a heterogeneous and multiphase petroleum reservoir. Previously reported works using reservoir numerical simulation have been limited to sensitivity analyses at core and field scale levels because the formal optimization problem includes computationally expensive objective function evaluations (field scale numerical simulations). This work presents a surrogate-based optimization methodology to overcome this shortcoming.

The proposed approach estimates the optimal values for a set of design variables (e.g., slug size and concentration of the chemical agents) to maximize the cumulative oil recovery from a heterogeneous and multiphase petroleum reservoir subject to an ASP flooding. The surrogate-based optimization approach has been shown to be useful in the optimization of computationally expensive simulation-based models in the aerospace, automotive, and oil industries. In this work, we improve upon this approach along two directions: (i) using multiple surrogates for optimization, and (ii) incorporating an adaptive weighted average model of the individual surrogates.

The cited approach involves the coupled execution of a global optimization algorithm and fast surrogates (i.e., based on Polynomial Regression, Kriging, Radial Basis Functions and a Weighted Average Model) constructed from field scale

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0920-4105/$ - see front matter
doi:10.1016/j.petrol.2005.03.002

numerical simulation data. The global optimization program implements the DIRECT algorithm and the reservoir numerical simulations are conducted using the UTCHEM program from the University of Texas at Austin.

The effectiveness and efficiency of the proposed methodology is demonstrated using a field scale case study.

Keywords: Enhanced oil recovery; Chemical flooding; ASP flooding; Global optimization; Surrogate modeling; Surrogate-based optimization

1. Introduction

After conventional waterflood processes the residual oil in the reservoir remains as a discontinuous phase in the form of oil drops trapped by capillary forces and is likely to be around 70% of the original oil in place (OOIP) (Dosher and Wise, 1976). The EOR method so-called alkaline–surfactant–polymer (ASP) flooding has proved to be effective in reducing the oil residual saturation in laboratory experiments and field projects through the reduction of interfacial tension and mobility ratio between oil and water phases. Some ASP pilot tests reported in the literature have reached an oil recovery over 60% OOIP (Clark et al., 1988; Meyers et al., 1992; Vargo et al., 1999; Demin et al., 1999).

In ASP floodings the surfactant is responsible for reducing the interfacial tension between oil and water phases to a level that promotes the mobilization of trapped oil drops. The alkaline agent is intended to react with the acids to generate in situ surfactant (Rivas et al., 1997) to overcome the surfactant depletion in the liquid phases due to retention. The role of the polymer is to increase the viscosity, reducing the mobility ratio and hence allowing a greater volumetric swept efficiency. Details of the physical processes taking place can be found in, for example, Shah and Schechter (1977).

The design of an ASP flooding process must achieve three main objectives: propagation of the chemicals in an active mode, the injection of enough chemicals accounting for the retention, and a complete swept of the area of interest (Lake, 1989). Achieving these objectives is significantly affected by the selection of the chemicals, the concentration of the ASP solution and the slug size, among other factors.

Previous works toward the optimization of ASP processes have concentrated mainly around identifying formulations that will achieve minimum interfacial tension using laboratory experiments and empirical correlations (Salager et al., 1979a,b; Bourrel et al., 1980; Salager, 1996), and sensitivity analyses using numerical simulation at core and field scale levels (Wei-Ju, 1996; Zhijian et al., 1998; Manrique et al., 2000; Qi et al., 2000; Hernández et al., 2001). Table 1 presents a summary of these works and shows that the formal optimization of ASP flooding has not been addressed. The latter is a critical step to find the optimal parameters that will maximize a given performance measure (e.g., net present value, cumulative oil recovery) considering a heterogeneous and multiphase petroleum reservoir.

The cited formal optimization has been limited due to the high computational cost exhibited by the numerical simulations at the reservoir level, which makes impractical the coupled execution of the simulator and optimization algorithms. The surrogate-based optimization approach has been shown to be useful in the optimization of computationally expensive simulation-based models in the aerospace (Giunta et al., 1997; Balabanov et al., 1998), automotive (Craig et al., 2002; Kurtaran et al., 2002), and oil industries (Queipo et al., 2002a,b). Surrogate-based design makes reference to the idea of constructing an alternative fast model (surrogate) from numerical simulation data and using it for optimization purposes. In this work, we improve upon this approach along two directions: (i) using multiple surrogates for optimization, and (ii) incorporating an adaptive weighted average model of the individual surrogates. The rationality of these improvements is described in later sections of the paper.

The proposed methodology estimates the optimal parameters (slug size and concentration of the chemical agents) to maximize the cumulative oil recovery from a heterogeneous and multiphase petroleum reservoir subject to an ASP flooding. The methodology involves the coupled execution of a global optimization algorithm and surrogates (based on Polynomial Regression, Kriging, Radial Basis Functions and a Weighted

Table 1
Summary of previous work towards ASP flooding optimization

Authors	Parameters	Optimum formulation study		Sensitivity		Detailed chemical reactions	Optimization
		Laboratory experiments	Core floods	Core scale	Field scale		
Salager et al. (1978), Salager et al. (1979a,b)	Salinity, ACN, alcohol, surfactant, temperature, WOR	Yes	No	–	–	–	No
Bourrel et al. (1980)	Salinity, ACN, EON of the surf., alcohol, hydrophobic molecular weight of the surf., temperature	Yes	No	–	–	–	No
Zhijian et al. (1998)	Chemical agents, chemical concentrations, slug size, fluid–rock interactions	Yes	No	No	Yes	Yes	No
Manrique et al. (2000)	Salinity, chemical agents, chemical concentration, temperature, fluid–rock interactions	Yes	Yes	Yes	No	No	No
Qi et al. (2000)	Salinity, chemical agents, chemical concentrations, pH, fluid–rock interactions	Yes	Yes	Yes	No	No	No
Hernández et al. (2001)	Salinity, chemical agents, chemical concentration, temperature, fluid–rock interactions	Yes	Yes	Yes	No	No	No
Wei-Ju (1996)	Reservoir properties, chemical agents, chemical concentrations, chemical reactions, fluid–rock interactions, slug size, chemical adsorption	No	No	Yes	Yes	Yes	No
Zerpa et al. (present work)	Chemical concentration, slug size	No	No	No	No	Yes	Yes

Average Model) constructed from field scale numerical simulation data.

The methodology is evaluated using a field scale case study based on an ASP flooding pilot available in the sample data archives of the UTCHEM program of the University of Texas at Austin.

2. Problem of interest

Fig. 1 illustrates the typical stages in an ASP flooding process, namely: a preflush of brine to lower the salinity of the reservoir, an ASP solution used to reduce the interfacial tension between the aqueous and oleic phases, a polymer solution to perform a uniform sweep of the oil and the previous slugs, and chase water to finally drive the oil and the chemicals to the producer wells.

In this study we assume that the chemicals for the EOR process have been already selected, and that a preview design of the ASP flooding process is available. Then, the problem of interest is the optimization of the ASP solution injection stage, which is considered the most important in the design because it is responsible for the oil mobilization and the reduction of the oil residual saturation. More specifically:

find $x \in X \subseteq \mathbf{R}^p$
such that
$f(x)$ is maximized

where f is the cumulative oil recovery (computationally expensive objective function), x represents p

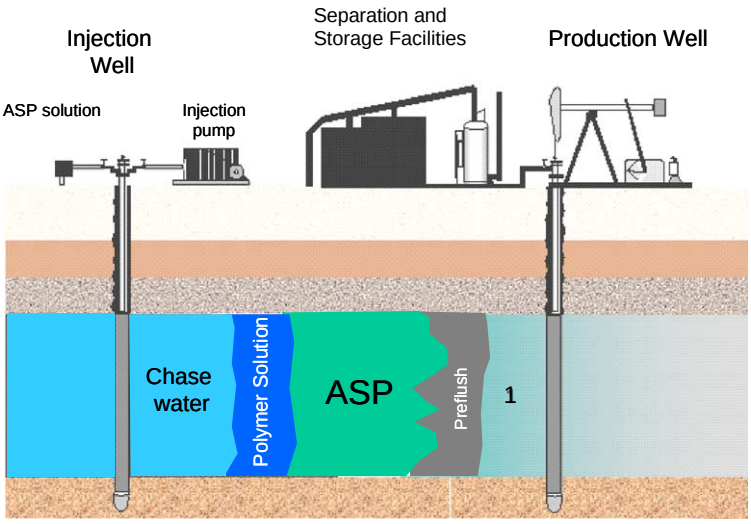

Fig. 1. Typical design of an ASP flooding process.

design variables, namely, slug size and the chemical concentrations, and X is the feasible region that satisfies simple bounds constraints ($x_{i\min} < x_i < x_{i\max}$; with $i = 1, 2, \ldots, p$). Note that the computationally expensive nature of the objective function evaluations limits the possible solution approaches to those satisfying the time restrictions typically present in the oil industry.

3. Solution methodology

With reference to Fig. 2, the proposed methodology involves the following steps:

1. Generate a sample of the design variables space using a modified latin hypercube experimental design. This sampling procedure has been shown to be very effective for selecting values of input variables for the analysis of the output of a computer code (McKay et al., 1979).
2. Conduct numerical simulations (via the program UTCHEM) using the sample (input) from the previous step and obtain the corresponding objective function values (output).
3. Using the input/output pairs obtained in the previous steps, construct multiple surrogate models based on Polynomial Regression, Kriging, Radial Basis Functions and a Weighted Average Model. This surrogate models will be discussed later in this section. In this work the surrogates were coded using MATLAB®.
4. Solve the optimization problem of interest by coupling the execution of a global optimization algorithm (a modified Lipschitzian method called DIRECT developed by Jones et al., 1993) with each of the surrogates constructed in step 3.
5. Conduct numerical simulations using the optimal values obtained in the previous step to confirm their performance level. The designer now selects among the best confirmed design values the solution that satisfies the most his preference structure.

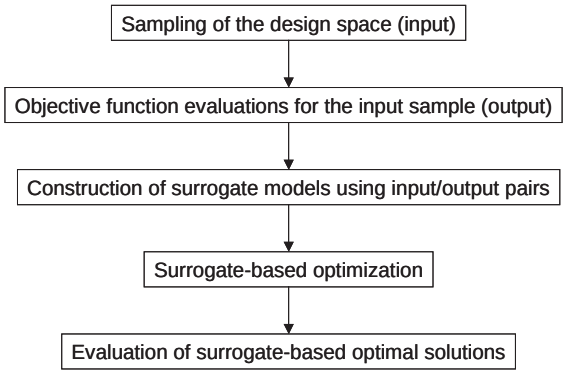

Fig. 2. Architecture of the proposed methodology.

3.1. Surrogate modeling

It is an inverse problem where due to the limited amount of available data: (i) alternative surrogates can provide reasonable approximations to function f, and (ii) each surrogate may offer the best fit to f depending on the region of the design space. Since the location of the optimal design values is unknown we suggest the use of multiple surrogates considering they can be constructed at no significant additional computational cost. Three alternative surrogate models, namely, Polynomial Regression (PRG), Kriging (KRG), and Radial Basis Functions (RBF) are considered. In addition, a Weighted Average Model (WAV) of these surrogates is also included. The WAV can be shown to reduce the variance estimation with respect to that of the individual surrogates (Bishop, 1995). Throughout this section, given the stochastic nature of the surrogates, the available data is assumed a sample of a population.

3.1.1. Polynomial regression model (PRG)

The regression analysis is a methodology that studies the quantitative association between a function of interest y, and m prediction variables z^j, where there are n values of the function of interest y_i, for a set of prediction variable values z_i^j (Draper and Smith, 1966). For each observation i a linear equation is formulated as:

$$y_i = \sum_{i=1}^{m} \beta_j z_i^j + \varepsilon_i \qquad E(\varepsilon_i) = 0 \qquad V(\varepsilon_i) = \sigma^2 \quad (1)$$

where the errors ε_i are independents with expected value equal to zero and variance σ^2. The estimated parameters $\hat{\beta}_j$ (by least squares) are unbiased and have minimum variance.

Eq. (1) is expressed in matrix form as:

$$y = \mathbf{Z}\beta + \varepsilon \qquad E(\varepsilon) = 0 \qquad V(\varepsilon) = \sigma^2\mathbf{I} \quad (2)$$

where $\mathbf{Z}$ is an $n \times m$ matrix with the prediction variable values. The vector of the estimated parameters can be calculated as:

$$\hat{\beta} = \left(\mathbf{Z}^{\mathrm{T}}\mathbf{Z}\right)^{-1}\mathbf{Z}^{\mathrm{T}}y \quad (3)$$

Considering a new set of design values z, the variance of the predicted response $z^{\mathrm{T}}\hat{\beta}$ can be calculated as:

$$V(y(z)) = \sigma^2\left(z^{\mathrm{T}}\left(\mathbf{Z}^{\mathrm{T}}\mathbf{Z}\right)^{-1}z + 1\right) \quad (4)$$

In this work the regression model is a second-order polynomial model of the form:

$$y = \beta_0 + \sum_{i=1}^{p}\beta_i x_i + \sum_{i=1}^{p}\sum_{j=1}^{p}\beta_{ij}x_i x_j \quad (5)$$

3.1.2. Kriging model (KRG)

These models suggest estimating deterministic functions as:

$$y(x_j) = \mu + \varepsilon(x_j) \quad (6)$$

where y is the function to be modeled, μ is the mean of the population, and ε is the error with zero expected value, and with a correlation structure that is a function of a generalized distance among the design values. In this work we use a correlation structure (Sacks et al., 1989) given by:

$$\mathrm{cov}\left(\varepsilon(x_i), \varepsilon(x_j)\right) = \sigma^2\exp\left(-\sum_{h=1}^{p}\theta_h\left(x_i^h - x_j^h\right)^2\right) \quad (7)$$

where p denotes the number of dimensions in the set of design variables x; σ, identifies the standard deviation of the population, and, θ_h is a parameter which is a measure of the degree of correlation among the data along the h direction.

Specifically, given a set of n input/output pairs (x, y), the parameters, μ, σ, and θ are estimated such that the likelihood function is maximized (Sacks et al., 1989). The model estimates for a new set of design values is given by:

$$\bar{y}(x) = \bar{\mu} + r^{\mathrm{T}}\mathbf{R}^{-1}(y - \mathbf{L}\bar{\mu}) \quad (8)$$

where the line above the letters denotes estimates, r identifies the correlation vector between the new set of design values and the points used to construct the model, $\mathbf{R}$ is the correlation matrix among the n sample points, and $\mathbf{L}$ denotes an n-vector of ones.

The estimation variance is given by:

$$V(\bar{y}(x)) = \sigma^2\left[1 - r^{\mathrm{T}}\mathbf{R}^{-1}r + \frac{\left(1 - \mathbf{L}^{\mathrm{T}}\mathbf{R}^{-1}r\right)}{\mathbf{L}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{L}}\right] \quad (9)$$

3.1.3. Radial basis functions (RBF)

This method uses linear combinations of m radially symmetric functions $h(x)$, to approximate response functions as,

$$y_i = \sum_{i=1}^{m} w_i h_i(x) + \varepsilon_i \quad (10)$$

where w are the coefficients of the linear combinations, h is the radial basis functions and ε_i is independent errors with equal variance, σ^2. Radial basis functions are a special class of functions. Their main feature is that their response decreases (or increases) monotonically with distance from a central point. The center, the distance scale, and the precise shape of the radial function are parameters of the model.

A typical radial function is the Gaussian which, in the case of a scalar input is,

$$h(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right) \quad (11)$$

its parameters are its center c and its standard deviation (radius) r. The response of the Gaussian RBF decreases monotonically with the distance from the center, giving a significant response only in the center neighborhood.

An RBF model can be expressed as,

$$y = \mathbf{H}w + \varepsilon \qquad V(\varepsilon) = \sigma^2 \quad (12)$$

where $\mathbf{H}$ is the design matrix given by,

$$\mathbf{H} = \begin{bmatrix} h_1(x_1) & h_2(x_1) & \cdots & h_m(x_1) \\ h_1(x_2) & h_2(x_2) & \cdots & h_m(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ h_1(x_n) & h_2(x_n) & \cdots & h_m(x_n) \end{bmatrix} \quad (13)$$

The optimal weights for the linear model specified in Eq. (12) are estimated using least squares as,

$$\hat{w} = \mathbf{A}^{-1}\mathbf{H}^{\mathrm{T}}y \quad (14)$$

where $\mathbf{A}^{-1}$ is the variance matrix given by,

$$\mathbf{A}^{-1} = \left(\mathbf{H}^{\mathrm{T}}\mathbf{H}\right)^{-1} \quad (15)$$

The variance estimator σ^2 of the error is approximated as,

$$\hat{\sigma}^2 = \frac{y^{\mathrm{T}}\mathbf{P}^2 Y}{trace(\mathbf{P})} \quad (16)$$

where $\mathbf{P}$ is the projection matrix,

$$\mathbf{P} = \mathbf{I} - \mathbf{H}\mathbf{A}^{-1}\mathbf{H}^{\mathrm{T}} \quad (17)$$

The model estimates for a new set of design values is given by,

$$\hat{y}(x) = z^{\mathrm{T}}\hat{w} \quad (18)$$

where z is a column vector with the radial basis functions evaluations,

$$z = \begin{Bmatrix} h_1(x) \\ h_2(x) \\ \vdots \\ h_k(x) \end{Bmatrix} \quad (19)$$

and the estimation variance is the variance of the prediction $z^{\mathrm{T}}\hat{w}$ plus the error variance:

$$V(y) = V\left(z^{\mathrm{T}}\hat{w}\right) + V(\varepsilon) = \left(z^{\mathrm{T}}\left(\mathbf{H}^{\mathrm{T}}\mathbf{H}\right)^{-1}z + 1\right)\frac{y^{\mathrm{T}}\mathbf{P}y}{p-m} \quad (20)$$

The Radial Basis Function approach was implemented using the Matlab functions provided by Orr (1999).

3.1.4. Weighted average model (WAV)

This model suggests to estimate deterministic functions as:

$$y_{\mathrm{WAV}}(x) = \sum_{i=1}^{k} \alpha_i(x) y_{\mathrm{surr}_i}(x) \quad (21)$$

where y_{WAV} is the weighted average model, $y_{\mathrm{surr}\ i}$ is the prediction corresponding to surrogate model i, α_i the weight of the surrogate i, and k the number of surrogates. Note the adaptive nature of the model since the weights are a function of x.

Table 2
Design variable restrictions

Design variable	Range		Units
	Min	Max	
Alkaline concentration (Na_2CO_3)	0	0.5898	meq/ml
Surfactant concentration	0.001815	0.005	vol. fract.
Polymer concentration	0.0487	0.12	wt.%
Injection time	111	326	days

Assuming unbiased and independent predictions, the unbiased weighted average model has minimal variance when the weights are determined as follows,

$$\alpha_i = \frac{\frac{1}{V(i)}}{\sum_{j=i}^{k} \frac{1}{V(j)}} \tag{22}$$

where $V(i)$ is the prediction variance of the i surrogates. In this case the individual surrogates are PRG, KRG and RBF ($k=3$). Details of the WAV approach can be found in Bishop (1995).

4. Case study

As previously stated the problem of interest is to find the values of a set of design variables, namely, concentration of alkaline, surfactant and polymer, and ASP slug size (expressed in the form of injection time) that maximize the cumulative oil production of a heterogeneous and multiphase petroleum reservoir. The ranges of the design variables are presented in Table 2. The cumulative oil production is calculated at 487 days.

As illustrated in Fig. 3, the ASP flooding pilot has an inverted five-spot pattern and a total of 13 vertical wells, 9 producers and 4 injectors. The reservoir is at a depth of 4150 ft, has an average initial pressure of 1770 psi, and the porosity is assumed to be constant throughout the reservoir and equal to 0.3. The numerical grid is composed of $19 \times 19 \times 3$ blocks in the x, y and z directions, respectively. Figs. 4–6 show the initial reservoir pressure, initial water saturation and horizontal permeability fields, respectively. The OOIP is 395,427 bbl, the crude oil viscosity is 40 cP, the initial brine salinity is 0.0583 meq/ml and the initial brine divalent cation concentration is 0.0025

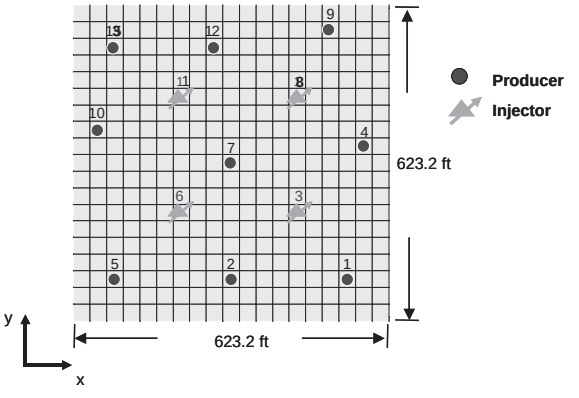

Fig. 3. Well pattern illustration.

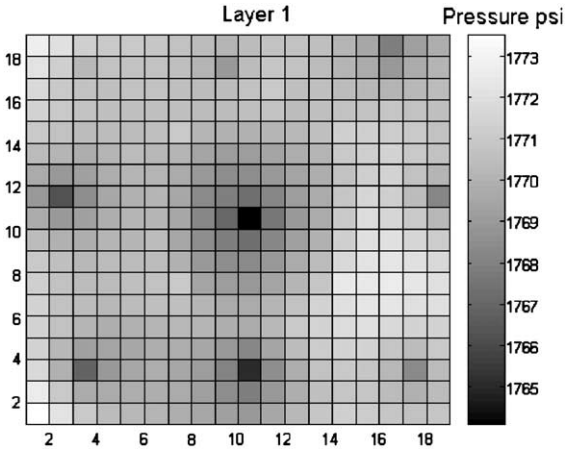

Fig. 4. Initial reservoir pressure distribution.

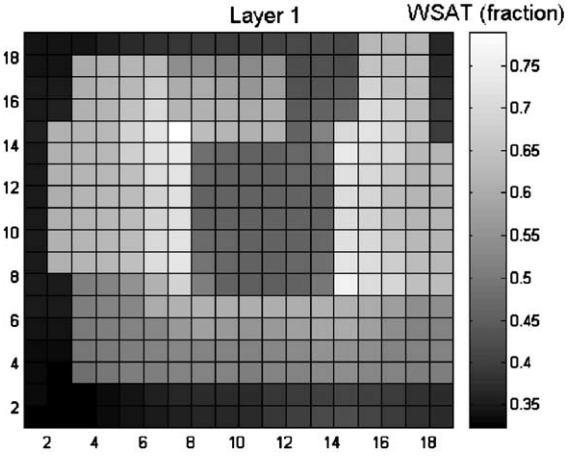

Fig. 5. Initial water saturation field.

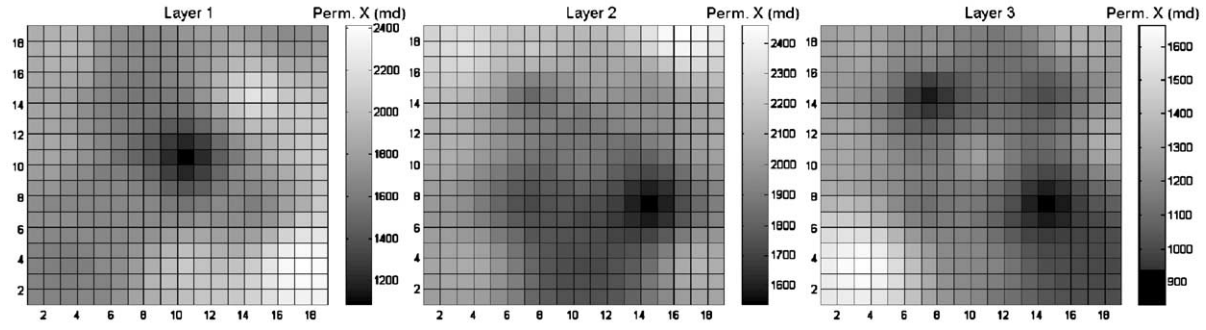

Fig. 6. Horizontal permeability field.

meq/ml. A summary of the reservoir and fluid properties is presented in Table 3. The injection scheme is described in Table 4. This reference configuration is available as sample data files of the UTCHEM program.

Three flowing phases and eleven components are considered in the numerical simulations. The phases are water, oil and microemulsion, while the components are water, oil, surfactant, polymer, chloride anions, divalent cations (Ca^{2+}, Mg^{2+}), carbonate, sodium, hydrogen ion, and oil acid. The ASP interactions are modeled using the reactions: in situ generated surfactant, precipitation and dissolution of minerals, cation exchange with clay and micelle, and chemical adsorption. Note the detailed chemical reaction modeling, and heterogeneous and multiphase petroleum reservoir under consideration.

Two alternative optimization problems are posed (Scenarios I and II) differing in the size of the available data set for the construction of the surrogates. In Scenario I the sample includes 64 input/output pairs obtained through a Latin Hypercube experimental design while in Scenario II the sample in Scenario I was increased to 88 input/output pairs by incorporating the vertices and the center of the faces of the hypercube formed by the design variable bounds.

Table 3
Reservoir and fluid properties

Property		Value	Unit
Reservoir depth		4150 (1265)	ft (m)
OOIP		395,427 (62,868)	bbl (m^3)
Oil viscosity		40	cP
Porosity		0.3	fraction
Average initial pressure		1770	psi
Well ratio		0.49 (15)	ft (m)
Skin factor		0.0	adim
Water salinity	C_{Na}	0.0583	meq/ml
	C_{Ca}	0.0025	meq/ml

5. Results and discussion

Among these input/output pairs considered in Scenarios I and II, the maximum, average, and minimum values for cumulative oil recovery are 33.58% OOIP (132,784 bbl), 24.27% OOIP (95,970 bbl), and 18.06% OOIP (71,414 bbl), respectively. Note that the performance of the ASP flooding is significantly affected by the design variable values, so their optimal specification is a critical issue.

5.1. Scenario I

Table 5 presents the optimal values for the design variables obtained through the coupled execution of DIRECT and each of the surrogate models. For each of these sets of values numerical simulations were conducted to assess its true performance. For the optimal values suggested by the KRG and WAV models the cumulative oil recovery was greater than those obtained within the sample, meanwhile the optimal values corresponding to the PRG and RBF models are less than the maximum of the sample.

The optimization with the KRG model resulted in the greatest objective function, that is, 34.86% OOIP (137,846 bbl), a 3.81% improvement over the maximum value of the sample. This point has maximum values of polymer concentration. The optimal solution obtained with the WAV model is

Table 4
Injection scheme

Slug	Inj. time (days)	PV	Component concentration								
			C_w[a]	C_{surf}[a]	C_{pol}[b]	C_{Cl}[c]	C_{Ca}[c]	C_{Mg}[c]	C_{CO_3}[c]	C_{Na}[c]	C_{H^+}[c]
Polymer preflush	26	0.05	1.0	0	0.0974	0.015667	0.0019	0.004774	0.009122	0.01461	111.0034
AS preflush	25	0.1	0.99574	0.00426	0	0.07168	0.0034	0.0067	0.3339	0.52517	111.0767
ASP slug	715	0.41	0.99637	0.00363	0.0974	0.04948	0.0067	0.00831	0.3351	0.3929	111.839
Polymer drive	50	0.5	1.0	0	0.05	0.03586	0.00665	0.00132	0.0164	0.09	111.0034
Postflush	275	1.0	1.0	0	0	0.0135	0.00185	0.004774	0.008	0.0146	111.0034

[a] Conc. unit=vol. fract.
[b] Conc. unit=wt.%.
[c] Conc. unit=meq/ml.

approximately equal to that of the KRG model. This may be explained by the fact that the KRG prediction variance was found to be significantly lower than for the other approaches so its relative contribution to the WAV model was the highest.

The lowest optimal value corresponded to the PRG model, where in spite of the maximum values of polymer concentration and injection time, the effect of lower surfactant and alkali concentrations has the impact of a lower cumulative oil recovery. The optimal value suggested by the RBF model was negatively affected by a lower polymer concentration in the ASP solution. The results with these models (PRG and RBF) underline the importance of injecting enough surfactant and alkali in order to attain a reduction in interfacial tension to mobilize oil drops, and enough polymer to attain a proper mobility ratio to significantly improve the volumetric swept efficiency.

5.2. Scenario II

Table 6 presents the optimal values for the design variables obtained through the coupled execution of DIRECT and each of the surrogate models. For each of these sets of values numerical simulations were conducted to assess its true performance. Except for the RBF model, the optimal values suggested by the surrogates for cumulative oil recovery were greater than those obtained within the sample.

The optimization using the PRG model resulted in the greatest objective function value (best solution found), that is, 35.69% OOIP (141,128 bbl); a 6.28% improvement over the maximum value of the sample. This point has maximum values of surfactant and polymer concentration and injection time. On the other hand, the interior solution obtained suggested by the WAV model represents a 1.77% reduction with respect to the best solution found, but with a 48% and 13.19% reduction in surfactant concentration and injection time values, respectively, which would result in lower costs. The optimal solution found using the KRG model has an objective function value lower than those suggested by the PRG and WAV models.

Within the context of the case study, increasing the original data set (Scenario II) did not qualitatively altered the location of the optimal solution in the design space; however, cumulative oil recovery in Scenario II is 0.57% higher than the best solution in Scenario I, and 4.22% higher than the best solution within the data set.

Table 5
Optimization results (Scenario I)

Model	Surrogate-based optimal solution				Objective function (COP %OOIP)	
	C_{Na} (meq/ml)	C_{surf} (vol. fract.)	C_{pol} (wt.%)	Injection time (days)	Surrogates	UTCHEM
Polynomial regression	0.1611	0.0018	0.1200	326	34.31 (135,671 bbl)	31.02 (122,661 bbl)
Kriging	0.2898	0.0029	0.1200	280	35.61 (140,812 bbl)	34.86 (137,846 bbl)
Radial basis functions	0.2994	0.0030	0.0931	292	36.71 (145,161 bbl)	32.31 (127,762 bbl)
Weighted average model	0.2866	0.0025	0.1181	282	35.10 (138,795 bbl)	34.81 (137,648 bbl)

Table 6
Optimization results (Scenario II)

Model	Surrogate-based optimal solution				Objective function (COP %OOIP)	
	C_{Na} (meq/ml)	C_{surf} (vol. fract.)	C_{pol} (wt.%)	Injection time (days)	Surrogates	UTCHEM
Polynomial regression	0.3057	0.0050	0.1200	326	32.17 (127,209 bbl)	35.69 (141,128 bbl)
Kriging	0.3167	0.0044	0.1200	283	36.43 (144,054 bbl)	34.73 (137,332)
Radial basis functions	0.2828	0.0030	0.0922	288	36.45 (144,133 bbl)	31.84 (125,904 bbl)
Weighted average model	0.2900	0.0026	0.1200	283	35.04 (138,558 bbl)	35.06 (138,637 bbl)

As expected, in both scenarios the WAV model presents the smallest difference between the surrogate estimations for optimal cumulative oil recovery and the corresponding values obtained using UTCHEM. This confirms the expected better modeling capabilities of the WAV model (through variance reduction) with respect to the individual surrogates (Bishop, 1995).

Note that the use of multiple surrogates have helped identify alternative optimal solutions corresponding to different regions in the design space, providing greater flexibility to match the designer preference structure.

Within the context of the case study, the proposed methodology showed to be effective and efficient (requires a relatively low number of field scale numerical simulations), can benefit from the increasing availability of parallel computing environments, and holds promise to be useful in more general scenarios of ASP flooding optimization.

6. Conclusions

- An optimization methodology of ASP flooding processes has been proposed. The methodology involves the coupled execution of a global optimization algorithm and fast surrogates (i.e., based on Polynomial Regression, Kriging, Radial Basis Functions, and a Weighted Average Model) constructed from field scale numerical simulation data. The global optimization program implements the DIRECT algorithm and the reservoir numerical simulations are conducted using UTCHEM from the University of Texas at Austin.
- For the set of optimal values suggested by most of the surrogates the cumulative oil recovery was greater than those obtained within the sample, and over a 30% greater than the mean value of the sample.
- The optimal values suggested by the PRG and RBF models in Scenario I showed the importance of injecting enough surfactant and alkali in order to attain a reduction in interfacial tension to mobilize oil drops, and enough polymer to attain a proper mobility hence increasing the volumetric swept efficiency. Note that the use of multiple surrogates have helped identify alternative optimal solutions corresponding to different regions in the design space.
- The WAV model presents the smallest difference between the surrogate estimations for optimal cumulative oil recovery and the corresponding values obtained using UTCHEM. This confirms the better modeling capabilities of the WAV model (through variance reduction) with respect to the individual surrogates.
- The proposed methodology showed to be effective and efficient (requires a relatively low number of field scale numerical simulations) within the context of the case study, can benefit from the increasing availability of parallel computing environments, and holds promise to be useful in more general scenarios of ASP flooding optimization.

Nomenclature

α	weights of the WAV model
$\hat{\beta}$	estimated parameters
ε	error
μ	mean of the population
θ	correlation parameter
σ	standard deviation
f	objective function
$\mathbf{I}$	identity matrix
k	number of surrogates
KRG	Kriging model

L	n-vector of ones
p	number of variables
r	correlation vector
R	correlation matrix
PRG	Polynomial regression model
V	variance
x	the design variables
X	constraints set
WAV	Weighted average model
y	function of interest
z	prediction variables
Z	matrix of the prediction variables

Subscripts

surr	surrogate model

Acknowledgements

The authors gratefully acknowledge the financial support provided to this project by Fondo Nacional de Ciencia, Tecnología e Innovación (FONACIT) through Project G-97003899, Venezuela. We also thank the Center for Petroleum and Geosystems Engineering of The University of Texas at Austin for providing the UTCHEM compositional simulator.

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