ELSEVIER

Journal of Petroleum Science and Engineering 35 (2002) 83–93

JOURNAL OF PETROLEUM SCIENCE & ENGINEERING

www.elsevier.com/locate/jpetscieng

Surrogate modeling-based optimization of SAGD processes

Nestor V. Queipo*, Javier V. Goicochea, Salvador Pintos

Applied Computing Institute, Faculty of Engineering, University of Zulia, Zulia, Venezuela

Accepted 12 February 2002

Abstract

This paper presents a solution methodology for the optimization of geometrical and operational parameters of SAGD processes in a heterogeneous and multiphase petroleum reservoir. The optimization refers to the maximization or minimization of performance measures such as net present value, cumulative oil production, or cumulative steam injected. The solution methodology includes the construction of a "fast surrogate" of an objective function whose evaluation involves the execution of a time-consuming mathematical model (i.e. reservoir numerical simulator) based on neural networks, DACE modeling, and adaptive sampling. Using adaptive sampling, promising areas are searched considering the information provided by the surrogate model and the expected value of the errors. The proposed methodology provides a global optimization method, hence avoiding the potential problem of convergence to a local minimum in the objective function exhibited by the commonly Gauss–Newton methods. Furthermore, it exhibits an affordable computational cost, is amenable to parallel processing, and is expected to outperform other general-purpose global optimization methods such as simulated annealing, genetic algorithms, and pattern search methods. The methodology is evaluated using a case study with vertical spacing, steam-injected enthalpy, injection pressure, and subcooling as the sought parameter values in a SAGD process that optimize a weighted sum of cumulative oil production and cumulative steam injected for a selected reservoir. From the results, it is concluded that the methodology can be used effectively and efficiently for the optimization of SAGD processes. In addition, the optimization approach holds promise to be useful in the optimization of objective functions involving the execution of computationally expensive reservoir numerical simulators, such as those found not only in oil recovery processes, but also in other areas of petroleum engineering (e.g. hydraulic fracturing).

Keywords: Thermal oil recovery; Steam oil recovery; SAGD; Surrogate modeling-based optimization; SAGD optimization

1. Introduction

There is considerable interest in effective oil recovery mechanisms for heavy oil and bitumen due to the decline of conventional oil reserves, and the estimated magnitude of these resources worldwide (approximately 6 trillion bbl). A major part of these resources are located in Venezuela, Canada, and the United States (Singhal et al., 1996).

While the use of horizontal wells has improved the recovery of heavy oil, the ultimate oil recovery remains unsatisfactory due to the low mobility of the crude at reservoir conditions. Different alternatives have been proposed in the last three decades for improving the flowing capacity of heavy oil and

* Corresponding author. Tel.: +58-261-7598408; fax: +58-261-7598411.

E-mail address: nqueipo@luz.ve (N.V. Queipo).

0920-4105/02/$ - see front matter
PII: S0920-4105(02)00167-5

improve oil recovery. Examples of these alternatives are cyclic steam stimulation (CSS), steam drive, in situ combustion, and SAGD. The latter could be effective even in reservoirs containing highly viscous oil or bitumen (Jiang et al., 1998) and have proven to be economically viable at a variety of pilot (Butler, 1994; Mendoza et al., 1999) and commercial recovery projects (Butler, 1994), typically achieving oil recoveries of over 50% from the well pattern with a steam/oil ratio of 2.5 to 4 (Jiang et al., 1998). See the work by Butler (1994) and the references contained in it for details of the SAGD concept and mechanisms.

The performance of the SAGD process can be significantly affected by the selection of the geometrical and operational parameters. Examples of the former are the vertical spacing, lengths of the producer and injector wells, and the horizontal separation between well pairs; the latter include parameters such as steam-injected enthalpy, injection pressure, and subcooling. Even though there have been significant contributions regarding screening of reservoir candidates (Singhal et al., 1996; Edmunds and Suggett, 1995), theoretical aspects (Butler, 1987, 1994), analytical and numerical modeling (Butler, 1985; Reis, 1992; Scott Ferguson and Butler, 1988), laboratory experiments (Yang and Butler, 1992; Nasr et al., 2000), the optimal or near optimal selection of the aforementioned parameters have been addressed only by a few sensitivity studies (Kamath and Hatzignatiou, 1993; Kisman and Yeung, 1995).

Kamath and Hatzignatiou (1993), using a numerical two-dimensional model that accounts for reservoir heterogeneities, conducted a sensitivity study of a SAGD process which considers the relative influence with respect to a base case of different parameters such as porosity, absolute permeability, steam temperature, steam quality, horizontal well length, injector/producer spacing, shale barriers, and lateral well spacing, among others. The study establishes percent recovery and oil/steam ratio as performance measures. Kisman and Yeung (1995) performed a similar study using a two-dimensional base case numerical model that quantifies the relative influence of factors such as thermal conductivity, flow barriers, oil viscosity, relative permeability, solution gas, well placement, among others. Note that these are both sensitivity studies that do not address the formal optimal setting of geometrical and operational parameters.

This paper presents a solution methodology called neural network-based efficient global optimization (NEGO) for the optimization of the geometrical and operational parameters in a SAGD process, such that a given performance measure is minimized. The solution methodology includes the construction of a "fast surrogate" of an objective function whose evaluation involves the execution of a time-consuming mathematical model (i.e. reservoir numerical simulator) based on neural networks, DACE (Sacks et al., 1989) modeling, and adaptive sampling. Using adaptive sampling, promising areas are searched considering the information provided by the surrogate model and the expected value of the errors.

The DACE surrogate model is initially constructed using sample data generated from the execution of mathematical models with parameters given by a latin hypercube experimental (LHC) design and a neural network, and provides error estimates at any point. Additional points are obtained balancing the exploitation of the information provided by the surrogate model (where the surface is minimized) with the need to improve the surface (where error estimates are high). The proposed methodology provides a global optimization method, hence avoiding the potential problem of convergence to a local minimum in the objective function exhibited by the commonly used Gauss–Newton methods (Tan, 1995; Landa and Horne, 1997), and computational cost involved in numerically estimating derivatives, and in the step by step movement along given trajectories. Furthermore, it exhibits an affordable computational cost, is amenable to parallel processing, and is expected to outperform other general purpose global optimization methods such as simulated annealing, genetic algorithms (Huang and Kelkar, 1994; Datta Gupta et al., 1992), and pattern search methods (Lewis and Torczon, 1999).

2. Problem definition

The optimization of SAGD processes is a complex task. The complexity is associated with a time consuming and limited number of objective function (performance measure) evaluations, a potentially high number of parameters, and a nonlinear solution space. Performance measures such as net present value,

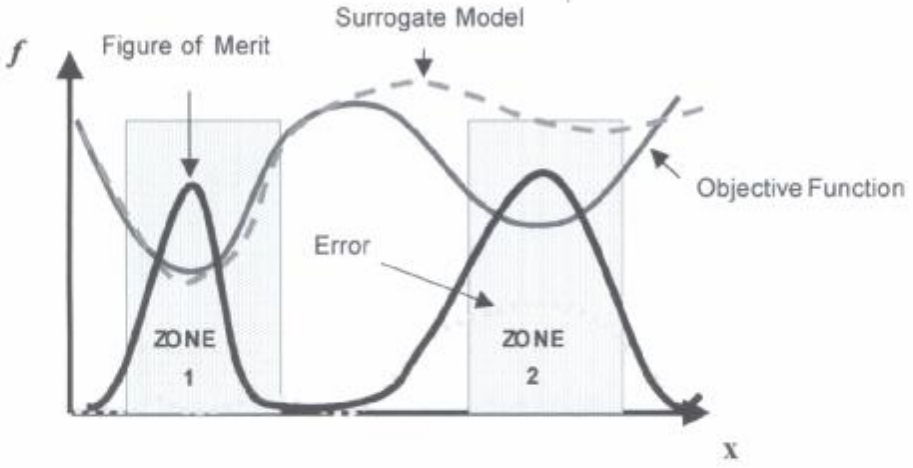

Fig. 1. Illustration of the purpose of the figure of merit.

cumulative oil production, and cumulative steam injection require computationally expensive reservoir numerical simulations restricted in number given the time constraints typically present in the oil industry. The number of geometrical (e.g. vertical and horizontal spacing, and wells length) and operational parameters (e.g. subcooling, steam-injected enthalpy, injection temperature, etc.) to be considered may be significant, and solutions may be needed under different economic and reservoir/oil property scenarios. In addition, the nonlinear nature of the process makes the identification of optimal settings through sensitivity studies (as it is usually performed) not possible. Formally, it can be written as:

find $x \in X \subseteq R^p$ such that $f(x)$ is minimized

where f is a mathematical function (objective function) of x, the geometrical and operational parameter vector, and X is the set constraint. Hence, the problem of interest is one of finding the vector of parameters that minimized a given performance measure of a SAGD process subject to a set constraint.

3. Solution methodology

The proposed solution approach called NEGO (Queipo et al., 2000) is an improved version of the EGO algorithm (Jones et al., 1998) for the optimization of computationally expensive black-box functions.

The proposed solution methodology involves the following four steps.

(1) Construct a sample of the parameter space using the latin hypercube method. The latin hypercube sampling procedure has been shown to be very effective for selecting input variables for the analysis of the output of a computer code (McKay et al., 1979).

(2) Conduct mathematical simulations using the sample from the previous step and obtain the objective function values.

(3) Construct a parsimonious neural network (multilayer perception) using the data from the previous step. The purpose of this neural network is to capture the general trends observed in the data; no rigorous performance criterion is placed on the neural network.

Table 1
Parameter restrictions (case study)

Parameter	Description	Range		Units
		Min	Max	
x_1	Vertical spacing of wells	3	15	m
x_2	Injection pressure	1000	4000	kPa
x_3	Steam-injected enthalpy	1980	2580	kJ/kg
x_4	Subcooling	5	30	°C

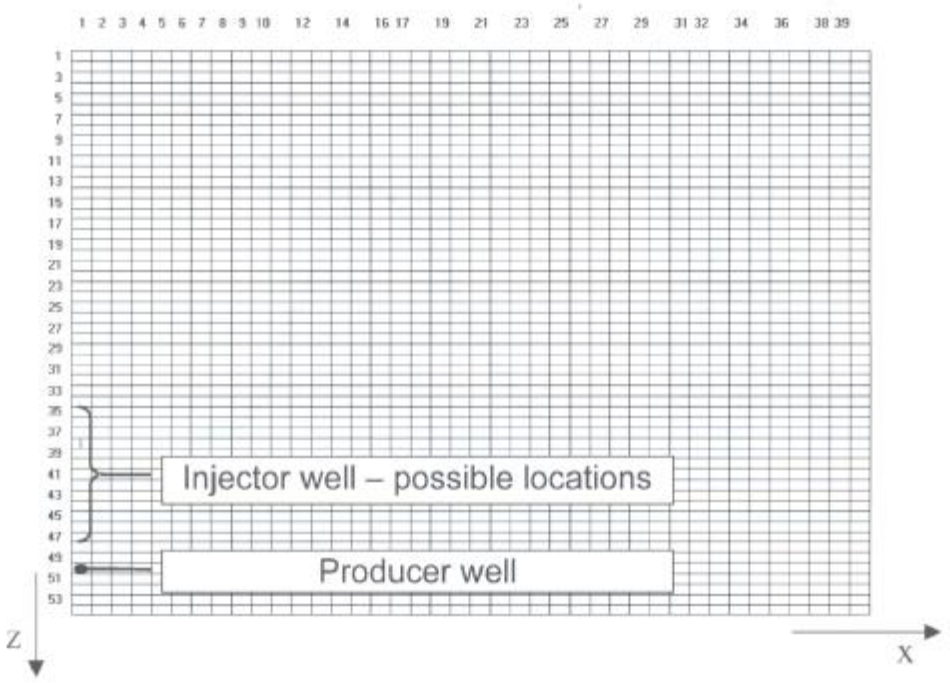

Fig. 2. Illustration of the grid used in the numerical simulations (case study).

(4) Construct a DACE model for the residuals, that is, the difference between the observed objective function values, and the neural network responses using the sample data. These models provide not only estimates of the residuals value but also of the respective errors. The surrogate model for the evaluation of the objective function is the sum of the neural network and DACE models. Details of this step will be given later in this section.

(5) Additional points are obtained balancing the exploitation of the information provided by the surrogate model (where the surface is minimized) with the need to improve the surface (where error estimates are high), until a stopping criterion has been met. This balance is achieved by sampling where a figure of merit is maximized. Details of the figure of merit will be given later in this section.

Table 2
Reservoir data and petrophysical properties (case study)

	x	y	z	Units
Gridblocks	40	1	54	
Gridblock size	1.5	1500	1	m
Reservoir size	60	1500	54	m
Rock compressibility			1.00E − 7	kPa^{-1}
Rock heat capacity			2390.00	$kJ/m^3/K$
Rock thermal conductivity			147	kJ/D m K
Gas–Oil contact depth			160	m
Reservoir initial temperature			15	°C
Reservoir initial pressure			500	kPa
Oil				
Thermal Capacity			1.88	kJ/kg/K
Thermal Expansion			7.0E − 4	$°C^{-1}$
Density			1029	kg/m^3
Compressibility			7.2E − 7	kPa^{-1}

3.1. DACE models

These models owe their name, design, and analysis of computer experiments to the title of an article that popularized the approach (Sacks et al., 1989). These models suggest to estimate deterministic functions as shown in Eq. (2).

$$y(x_j) = \mu + \varepsilon(x_j) \tag{2}$$

where y is the function to be modeled, μ is the mean of the population, and ε is the error with zero expected

Table 3
Geological model (case study)

Layer	Horizontal permeability	Vertical permeability	Porosity	Thickness (m)	Initial S_w	Initial S_o
1	1500	450	0.2	54	0.15	0.85

value, and with a correlation structure given by Eq. (3).

$$\mathrm{cov}(\varepsilon(x_i),\varepsilon(x_j)) = \sigma^2 \exp\left(-\sum_{h=1}^{p} \theta_h (x_i^h - x_j^h)^2\right) \tag{3}$$

where p denotes the number of dimensions in the vector x, σ identifies the standard deviation of the population, and θ_h is a correlation 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). Having estimated these values, the function estimate for new points is given by Eq. (4).

$$\hat{y}(x) = \hat{\mu} + r' R^{-1}(y - L\hat{\mu}) \tag{4}$$

where the line above the letters denote *estimates*, r' identifies the correlation vector between the new point and the points used to construct the model, R is the correlation matrix among the n sample points, and L denotes an n-vector of ones.

The mean square error of the estimate is given by Eq. (5).

$$s^2(x^*) = \sigma^2\left[1 - r' R^{-1} r + \frac{(1 - L' R^{-1} r)}{L' R^{-1} L}\right] \tag{5}$$

The model is validated through a cross-validation procedure that essentially makes sure that the estimates using all but the point being tested and the actual response values are within an specified number of standard deviations. The original EGO algorithm may not cross-validate properly if there are trends in the data, in contrast to NEGO, which is expected to subtract any significant trends in the data.

The benefits of modeling deterministic functions using this probabilistic approach are: (i) represents a best linear unbiased estimator; (ii) interpolates the data; and (iii) provides error estimates.

3.2. Figure of merit

With reference to Fig. 1, there are two zones where it is desirable to add additional points. The left zone is where the objective function is minimized, whereas the right zone is where there is a significant error in the prediction. Hence, the figure of merit for adding sample points should be high in either of these

Table 4
Overburden and underburden characteristics (case study)

	Thickness (m)	Temperature (°C)	Heat capacity (kJ/m^3/K)	Thermal conductivity (kJ/D m K)
Overburden	60	15	2390	146.88
Underburden	60	15	2390	233.28

Table 5
Relative permeability data (case study)

Water–oil			Liquid–gas		
S_W	K_{RW}	K_{ROW}	S_L	K_{RG}	K_{ROG}
0.15	0.000	1.000	0.15	0.850	0.000
0.20	0.000	0.882	0.20	0.750	0.000
0.25	0.002	0.800	0.25	0.680	0.003
0.30	0.006	0.720	0.30	0.612	0.008
0.35	0.013	0.600	0.35	0.510	0.020
0.40	0.025	0.470	0.40	0.400	0.038
0.45	0.044	0.350	0.45	0.298	0.056
0.50	0.070	0.240	0.50	0.204	0.056
0.55	0.104	0.165	0.55	0.140	0.069
0.60	0.148	0.093	0.60	0.119	0.075
0.65	0.204	0.000	0.65	0.096	0.090
0.70	0.271	0.000	0.70	0.057	0.137
0.75	0.352	0.000	0.75	0.052	0.199
0.80	0.447	0.000	0.80	0.038	0.257
0.85	0.559	0.000	0.85	0.019	0.311
0.90	0.687	0.000	0.90	0.010	0.454
0.95	0.834	0.000	0.95	0.005	0.628
1.00	1.000	0.000	1.00	0.000	1.000

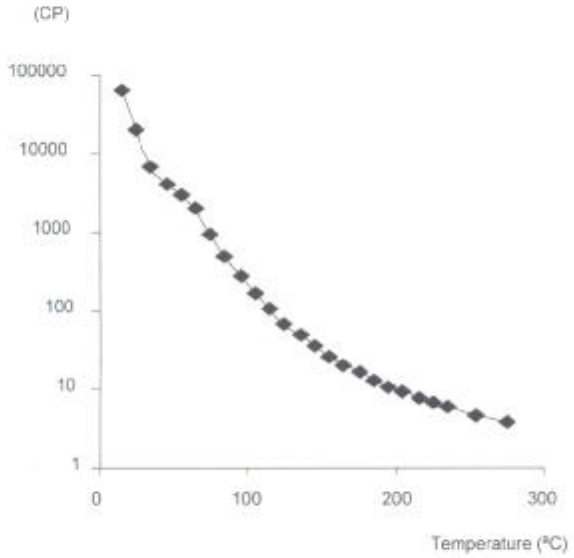

Fig. 3. Illustration of oil viscosity vs. temperature.

situations. Specifically, the figure of merit (Jones et al., 1998) used in this work is given by Eq. (6).

$$\mathrm{fom}(x) = (f_{\min} - \hat{f})\Phi\left(\frac{f_{\min} - \hat{f}}{s}\right) + s\phi\left(\frac{f_{\min} - \hat{f}}{s}\right) \tag{6}$$

where Φ and ϕ are the cumulative and density normal distribution functions, respectively, and $f_{\min}$ denotes the minimum current objective function value. Eq. (6) establishes the desired balance of sampling where the response surface (the predictor) is minimized (left term) and in zones where error estimates are high (right term). Note that the figure of merit makes reference to the objective function so it includes the sum of the output of both the neural network and the residual models.

3.3. Final remarks

This surface response approach for global optimization is expected to outperform competing methods, in terms of necessary computationally expensive objective function evaluations, to meet a stopping criterion. It can identify promising areas without the need of moving step by step along a given trajectory. In addition, by providing estimates of the errors at unsampled points, it is possible to establish a reasonable stopping criterion. Furthermore, it provides a fast surrogate model that could be used to visualize the relationship between the sought parameters and the objective function values, and to identify the relative significance of each of the parameters.

3.4. Implementation

The following case study was solved using an implementation of the NEGO algorithm developed

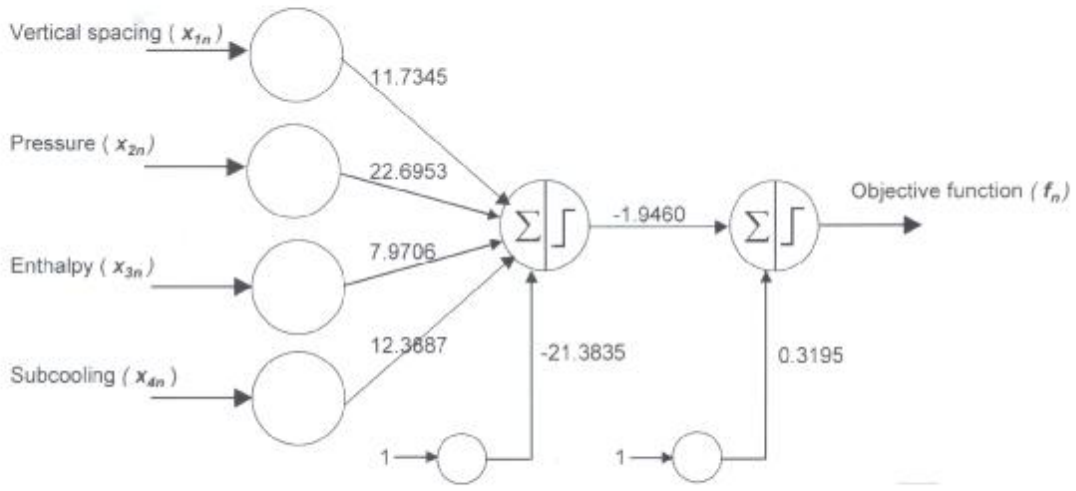

Fig. 4. Neural network architecture and weights (case study).

by the authors (Queipo et al., 2000) in MATLAB (The MathWorks). The subproblems of finding near optimal values for maximizing likelihood and the figure of merit were solved using the DIRECT method (Jones et al., 1993). Note that the solution of these subproblems does not require additional computationally expensive objective function evaluations. The reservoir numerical simulations were conducted using a commercial reservoir numerical simulator EXOTHERM (T.T. & Associates).

4. Case study

The NEGO algorithm was evaluated using a synthetic problem having geometrical and operational

Table 6
Initial sample (case study)

Run	Vertical spacing (m)	Pressure (kPa)	Enthalpy (kJ/kg)	Subcooling (°C)	COP (1.0E3 m^3)	CSI (1.0E3 m^3)	f
1	11	3756.6000	2578.4000	29.7490	154.7980	592.4600	−0.5418
2	4	1649.7000	2144.1000	11.2180	62.8010	286.2200	−0.1981
3	7	3166.3000	2450.0000	20.8050	125.8620	546.9400	−0.4157
4	5	1395.4000	2421.6000	7.4305	63.1220	257.9800	−0.2097
5	12	2606.5000	2317.1000	21.3130	95.2280	328.7300	−0.3425
6	9	1916.0000	2507.2000	14.4160	81.1630	242.9800	−0.3037
7	12	1827.7000	2477.0000	27.0210	45.5830	147.5400	−0.1626
8	9	1006.1000	2228.0000	18.7080	10.5460	43.1000	−0.0274
9	14	3388.8000	2095.9000	21.9140	126.4960	660.5200	−0.3786
10	11	1325.5000	2436.0000	18.9150	9.0780	38.3000	−0.0219
11	14	3285.0000	2285.4000	8.7497	122.4640	562.4500	−0.3935
12	9	2718.5000	1984.3000	25.1320	119.8020	600.8400	−0.3668
13	5	1092.1000	2068.0000	9.6865	51.8880	246.8900	−0.1584
14	14	1514.7000	2199.4000	11.4320	3.1230	9.8500	−0.0027
15	10	3224.2000	2178.6000	22.9200	139.2840	608.6200	−0.4599
16	15	3091.8000	2369.7000	6.2237	86.2820	350.2400	−0.2909
17	4	2386.6000	2124.6000	12.9790	68.5600	417.5600	−0.1799
18	7	3024.4000	2403.4000	23.5410	125.6590	465.4100	−0.4436
19	6	1553.0000	2380.2000	25.7070	68.9870	273.4200	−0.2331
20	10	2239.9000	2545.0000	11.9350	101.4690	368.9500	−0.3589
21	13	1163.6000	2072.0000	20.0090	2.2260	4.9900	0.0000
22	9	2762.6000	2295.3000	7.6801	99.7930	401.1200	−0.3393
23	13	3656.7000	2013.9000	13.6350	136.3700	694.9600	−0.4149
24	13	2924.5000	2491.7000	29.3660	106.3280	376.8700	−0.3800
25	13	3825.5000	2341.0000	24.3860	153.5680	683.6300	−0.5035
26	11	1746.8000	2472.8000	26.7620	58.4750	194.8400	−0.2092
27	3	1989.4000	2252.7000	14.1380	49.2910	284.1300	−0.1325
28	10	2808.3000	1995.5000	19.7250	123.7260	710.5500	−0.3473
29	8	1267.4000	2051.0000	17.6530	56.3310	257.6600	−0.1764
30	12	1822.7000	2153.0000	10.5140	52.3570	214.7800	−0.1721
31	8	3476.8000	2524.1000	5.1645	138.9060	547.9400	−0.4795
32	4	2115.3000	2555.5000	16.0960	72.9800	287.2300	−0.2478
33	7	2427.0000	2265.2000	16.6620	107.8590	414.0900	−0.3743
34	3	3889.0000	2338.3000	17.0090	72.4230	450.8800	−0.1871
35	5	2514.4000	2398.0000	27.8760	92.0440	355.0100	−0.3175
36	5	3453.7000	2163.8000	9.1281	104.1080	646.1200	−0.2737
37	7	2293.8000	2213.5000	15.4120	104.6670	451.7500	−0.3453
38	14	3620.0000	2027.4000	23.8650	138.6820	666.5700	−0.4364
39	8	3935.3000	2243.9000	28.5230	148.6800	622.4500	−0.5011
40	6	2164.1000	2105.0000	6.3564	90.8320	390.4000	−0.2990

Table 7
DACE model parameters corresponding to the initial sample (case study)

θ_1	θ_2	θ_3	θ_4	σ^2	μ
0.0099	1.0435E − 5	1.0907E − 5	0.0021	0.0134	0.0083

parameters: vertical spacing, injection pressure, steam-injected enthalpy, and subcooling, with ranges as specified in Table 1. The objective function (given by Eq. (7)) to be minimized is a weighted sum of normalized values of cumulative oil production (COP) and cumulative steam injected (CSI).

$$f(\vec{x}) = -\frac{3}{4}\mathrm{COP} + \frac{1}{4}\mathrm{CSI} \tag{7}$$

The weights (-0.75 for COP and $+0.25$ for CSI) reflect a preference structure and the intend to maximize COP and minimize CSI. The values of COP and CSI are calculated after a 5-year production period.

An illustration of the 2D reservoir simulation grid under consideration and the coordinate system is depicted in Fig. 2. The grid is composed of $40 \times 1 \times 54$ blocks in the x-, y-, and z-directions, respectively, with symmetry with respect to the z-axis. The producer well is placed in the block denoted as (1,1,49), while the injector well is placed in a block within the blocks (1,1,35) to (1,1,47); both wells are of 1500 m length. The reservoir is at a depth of 500 m, has an initial pressure of 500 kPa, and initial oil and water saturation of 0.85 and 0.15, respectively. Furthermore, the porosity is assumed to be constant throughout the reservoir and equal to 0.2, the horizontal permeability is isotropic and equal to 1500 md and vertical permeability is equal to 450 md. The initial temperature of the reservoir is 15 °C. Further details of the reservoir and fluid data are presented in Tables 2–5 and Fig. 3.

The neural network (Fig. 4) and DACE model were constructed using an initial sample of 40 points (Table 6) selected using a latin hypercube sampling procedure. The DACE model parameters corresponding to the initial sample can be found in Table 7. Fifteen additional points were added in the search of the optimum parameters. The weights in the neural network resulted from the application of a learning algorithm (Levenberg–Marquardt) on the normalized initial sample. The input and output variables in the neural network were normalized using a standard statistical and linear transformations, respectively.

5. Results and discussion

With reference to the case study, the parsimonious neural network has a $4 \times 1 \times 1$ architecture with a mean square normalized error of 3.657E − 2; all the points in the DACE model cross-validated within three times of the standard deviation.

The initial sample also shows (Table 8) the sensitivity of the objective function to the parameter selection with COP and CSI in the intervals [2.2E3 m^3,154.8E3 m^3], and [5.0E3 m^3,710.6E3 m^3], respectively. The minimum objective function value found within the initial sample (40 points) was -0.5418 which corresponds to a COP of 154.8E3 m^3 and a CSI of 592.5E3 m^3; the associated parameters values for vertical spacing, injection pressure, steam-injected enthalpy, and subcooling are 11 m, 3756.6 kPa, 2578.4 kJ/kg, and 29.7 °C, respectively.

Additional 15 points maximizing the figure of merit were added (see Table 9). From those points, the best solution found (second additional sampled point) observed an objective function value of -0.5537, which is slightly better than that corresponding to the initial sample (2.19% lower) with a COP of 156.9E3 m^3 and a CSI 589.0E3 m^3 with similar parameter values. Changing parameter values with respect to the overall best solution found or extending the optimization process of the figure of merit did not improve the objective function value; all of which suggest the cited solution is in fact near optimal.

The parameters associated with the optimal or near optimal solution found could not have been anticipated because of the complex nonlinear interaction among the selected parameters and the objective function.

Table 8
Characterization of objective function values within the initial sample (case study)

	Min (1.0E3 m^3)	Max (1.0E3 m^3)	Mean (1.0E3 m^3)	Standard deviation (1.0E3 m^3)
COP	2.23	154.80	89.30	42.07
CSI	4.99	710.55	392.62	200.83
f	0	−0.5418	−0.2907	0.1427

Table 9
Additional sampled points (case study)

Run	Vertical spacing (m)	Pressure (kPa)	Enthalpy (kJ/kg)	Subcooling (°C)	COP (1.0E3 m^3)	CSI (1.0E3 m^3)	f
NEGO1	10	3759.2593	2480.0000	28.0967	154.1330	641.9000	−0.5211
NEGO2	11	3759.2593	2577.9424	28.1310	156.9660	589.0300	−0.5537
NEGO3	11	3746.9136	2578.7654	25.3189	155.5530	603.1300	−0.5418
NEGO4	11	3759.2593	2576.2963	27.6852	141.6320	460.3600	−0.5239
NEGO5	15	3730.4527	2561.2071	28.9769	117.3830	436.5300	−0.4132
NEGO6	7	2425.9259	2265.1852	16.6770	110.6570	434.1600	−0.3809
NEGO7	12	3722.2222	2487.4074	24.9074	153.4730	620.4700	−0.5254
NEGO8	7	3166.6667	2450.0960	13.3276	129.8720	494.7100	−0.4539
NEGO9	10	3168.8005	2450.6752	5.0019	143.5830	615.9600	−0.4784
NEGO10	4	3167.5812	2450.1875	5.0019	95.0670	451.9400	−0.2980
NEGO11	15	3165.2949	2462.3503	5.0019	89.8760	347.1900	−0.3096
NEGO12	10	3165.2949	2451.6507	5.0019	146.5280	611.9200	−0.4943
NEGO13	10	3166.6667	2450.4618	5.0019	121.3610	442.6300	−0.4306
NEGO14	12	3167.7336	2455.7252	7.7776	123.1230	419.4200	−0.4475
NEGO15	14	3161.1797	2456.5280	5.0006	112.1580	452.0100	−0.3820

Selecting maximum parameter values results in 70% lower COP and 72% lower CSI; maximum parameter values for injection pressure, steam-injected enthalpy and subcooling, and minimum vertical spacing translates in 52% lower COP and 36% lower CSI; maximum parameter values for injection pressure, steam-injected enthalpy and subcooling, and the frequently used vertical spacing of 5 m resulted in 22% lower COP and 16% lower CSI; finally, mean parameter values provided 30% lower COP and 20% lower CSI. All of these alternatives provide higher objective function values.

6. Conclusions

- A global optimization method for the evaluation of the operational parameters of SAGD process called NEGO has been proposed. The method includes the construction of a "fast surrogate" of an objective function whose evaluation involves the execution of a time-consuming mathematical model (i.e. reservoir numerical simulator) based on neural networks, DACE modeling, and adaptive sampling. Using adaptive sampling, promising areas are searched considering the information provided by the surrogate model and the expected value of the errors.
- The results suggest that the NEGO algorithm can be used effectively and efficiently for improved oil recovery purposes. In addition, the optimization approach holds promise to be useful in the optimization of objective functions involving the execution of computationally expensive mathematical models (e.g. reservoir numerical simulators), such as those found not only in oil recovery processes, but also in other areas of petroleum engineering (e.g. hydraulic fracturing).
- The NEGO algorithm is expected to outperform competing methods in terms of computationally expensive objective function evaluations necessary to meet a stopping criterion. This is because it can identify promising areas without the need of moving step by step along a given trajectory. Furthermore, it provides a fast surrogate model that could be used to visualize the relationship between the sought parameters and the objective function values, and to identify the relative significance of each of the parameters.

Nomenclature

DACE	Design and analysis of computer experiment
x	Parameters vector
X	Set constraint
f	Objective function
$\hat{f}$	NEGO objective function predictor
w_i	Weighting coefficients
μ	Mean of the population
ε	Error in the DACE model
p	Number of dimensions in the vector x
σ	Standard deviation of the population
θ_h	Correlation parameter

r	Correlation vector between the new point and the points used to construct the model
R	Correlation matrix between the n sample points
L	n-vector of ones
fom	Figure of merit
Φ	Cumulative normal distribution function
ϕ	Density normal distribution function
y	Residual function
$\bar{y}$	DACE residual predictor
$f_{\min}$	Current best function value
$s^2(x^*)$	Mean square error of the predictor
COP	Cumulative oil production (m^3)
CSI	Cumulative steam injected (m^3)
cov	Covariance
BIS	Best initial solution
LHC	Latin hypercube

Subscript

h	Coordinate directions

Superscript

*	New point
'	Transpose

Acknowledgements

The authors gratefully acknowledge the financial support provided by the Consejo Nacional de Investigaciones Petroleras (CONIPET) and the Consejo Nacional de Investigaciones Cientificas (CONICIT), Venezuela, to execute this project. We also thank T.T. & Associates for providing the compositional thermal reservoir simulator Exotherm, Ver. 4.0.

References

Butler, R.M., 1985. A new approach to the modeling of steam-assisted gravity drainage. JCPT 24 (3), 42–51, May–June.

Butler, R.M., 1987. Rise of interfering steam chambers. JCPT 26 (3), 70–75, May–June.

Butler, R.M., 1994. Horizontal wells for the recovery of oil, gas and bitumen. Petroleum Society Monograph, vol. 2. Prentice-Hall, Englewood Cliffs, NJ, pp. 169–200.

Datta Gupta, A., Stoffa, P.L., Lake, L.W., Pope, G.A., 1992. Stochastic reservoir modeling using simulated annealing and genetic algorithm. Paper SPE 24754, presented at the 67th SPE Annual Technical Conference and Exhibition held in San Antonio, TX, USA, October 4–7.

Edmunds, N.R., Suggett, J.C., 1995. Design of a commercial SAGD heavy oil project. Paper SPE 30277, presented at the SPE International Heavy Oil Symposium held in Calgary, Alberta, Canada, June 19–21.

EXOTHERM, Ver. 4.0. T.T. & Associates.

Huang, X., Kelkar, M., 1994. Application of combinatorial algorithms for description of reservoir properties. Paper SPE/DOE 27803, presented at the 9th SPE Symposium on Improved Oil Recovery, Tulsa, OK, USA, April 17–20.

Jiang, Q., Butler, R.M., Yee, C.T., 1998. Development of the Steam and Gas Push (SAGP) process. The 7th UNITAR International Conference of Heavy Crude and Tar Sands, October 27–30, Beijing, China. paper #1998.59.

Jones, D., Perttunen, C., Stuckman, B., 1993. Lipschitzian optimization without the Lipschitz constant. Journal of Optimization Theory and Applications 79 (1), 157–181, October.

Jones, D., Schonlau, M., Welch, W., 1998. Efficient global optimization of expensive black–box functions. Journal of Global Optimization 13, 455–492.

Kamath, V.A., Hatzignatiou, D.G., 1993. Simulation study of steam assisted gravity drainage process in Ugnu Tar sand reservoir. Paper SPE 26075, presented at the Western Regional Meeting held in Anchorage, AK, USA, May 26–28.

Kisman, K.E., Yeung, K.C., 1995. Numerical study of the SAGD process in the Burnt Lake oil sands lease. Paper SPE 30276, presented at the International Heavy Oil Symposium held in Calgary, Alberta, Canada, June 19–21.

Landa, J., Horne, R., 1997. A procedure to integrate well test data, reservoir performance history and 4-D seismic information into a reservoir description. Paper SPE 38653, presented at the SPE Annual Technical Conference and Exhibition held in San Antonio, TX, USA, October 5–8.

Lewis, R., Torczon, V., 1999. Pattern search algorithms for bound constrained optimization. SIAM Journal on Optimization 9 (4), 1082–1099.

MATLAB, Ver. 5.3. The MathWorks.

McKay, M., Beckman, R., Conover, W., 1979. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 21 (2), 239–245, May.

Mendoza, H.A., Finol, J.J., Butler, R.M., 1999. SAGD, pilot test in Venezuela. Paper SPE 53687, presented at the Latin American and Caribbean Petroleum Engineering Conference held in Caracas, Venezuela, April 21–23.

Nasr, T.S., Law, D.H.-S., Golbeck, H., Korpany, G., 2000. Counter—current aspect of the SAGD process. JCPT 39 (1), 41–47, January.

Queipo, N., Pintos, S., Contreras, N., Rincon, N., Colmenares, J., 2000. Surrogate modeling-based optimization for the integration of static and dynamic data into a reservoir description. Paper SPE 63065, presented at the SPE Annual Technical Conference and Exhibition held in Dallas, TX, USA, October 1–4.

Reis, J.C., 1992. A steam-assisted gravity drainage model for tar sands: linear geometry. JCPT 31 (10), 14–20, December.

Sacks, J., Welch, W., Mitchell, T., Wynn, H., 1989. Design and

analysis of computer experiments. Statistical Science 4, 409–435.

Scott Ferguson, F.R., Butler, R.M., 1988. Steam-assisted gravity drainage model incorporating energy recovery from a cooling stream chamber. JCPT 27 (5), 75–83, September–October.

Singhal, A., Das, S.K., Leggitt, S.M., Kasraie, M., Ito, Y., 1996. Screening of reservoir for exploitation by application of Steam Assisted Gravity Drainage/Vapex processes. Paper SPE 37144, presented at the SPE International Conference on Horizontal Well Technology held in Calgary, Alberta, Canada, November 18–20.

Tan, T., 1995. A computationally efficient Gauss–Newton method for automatic history matching. Paper SPE 29100, presented at the 13th SPE Symposium on Reservoir Simulation held in San Antonio, TX, USA, February 12–15.

Yang, G., Butler, R.M., 1992. Effects of reservoir heterogeneities on heavy oil recovery by steam-assisted gravity drainage. JCPT 31 (8), 37–43, October.