COBEM-2021-1864-OPTIMUM WELL LOCATION AND RATES USING GENETIC ALGORITHMS CONSIDERING SURROGATES

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Abstract. *This work focuses on solving an optimization problem of Reservoir Engineering considering the positions of the wells and its flow rates as variables. The main objective is to maximize the Net Present Value (NPV). The problem is divided into two parts: the first part is the well placement definition, where the Genetic Algorithm (GA) is used to define the position of the wells across the reservoir; the second part is the flow rates definition, where Sequential Approximate Optimization (SAO) determines the optimal flow rates for each well. The optimization process requires a bunch of function evaluation which uses a Reservoir Simulator. This is a high-cost process and to overcome this, a methodology with adaptive surrogate models is adopted. The problem also presents some constraints, and to enable the GA to work smoothly an Adaptive Penalty Method is considered. The case studied here consists of a reservoir presented in the literature, The Egg Model. It is performed 20 optimizations to check the consistency of the approach. The best solution increased the NPV by 75.46% when compared with the base case.*

Keywords: *Reservoir Engineering, Optimization, Combined Strategies, Surrogate Models, Well placement and flow rate*

1. INTRODUCTION

During the exploitation of a reservoir, one of the steps that most impact the economic return of the field is the definition of the location of the wells and their flow-related controls. The definition of an optimal design for the development of the field is one of the most challenging and complex steps in the management process of reservoirs in the oil and gas industry. This is mainly due to its non-linear nature of problem formulation, involving several decision variables, production and injection rates, well allocation constraints, multiple scenarios, and multiple local optimums. Furthermore, complex reservoir, generally, provides high costs in its analysis due to the computational effort for the massive number of simulations required, for instance, in an optimization process. In the face of such complexity, the approach only based on the operators' technical knowledge can ignore profitable production scenarios. Therefore, using an algorithm that is fast, efficient, and handles the complexities that involve an optimization problem of this type is crucial. This aspect motivated the development of this work.

The central reference for this work was a study about adaptive surrogate models using a genetic algorithm (GA) (Holland, 1984) to optimize the location in fractured reservoirs proposed by Redouane *et al*. (2019). However, there are plenty of other researches that have been developed about the optimization of well placement. Among them, the following can be mentioned: Alrashdi and Sayyafzadeh (2019) in which the authors compare the evolution strategy (ES) algorithm with GA and other optimization algorithms for well placement, trajectory, control, and joint optimization in the same work; Optimum well location using a basic genetic search heuristics algorithm and a Black Oil Simulator was presented by Onuh *et al*. (2017); Islam *et al.* (2020) conducted a holistic review based on artificial intelligence techniques for well placement optimization; Semnani *et al*. (2021) considered a joint optimization of constrained well placement and control parameters using teaching-learning based optimization and an inter-distance algorithm; Han *et al.* (2021) studied well placement and control optimization of horizontal steamflooding wells using derivative-free algorithms.

In the present work, a combined approach is used to optimize the position and the flow rate of the wells in a specific reservoir reported in the literature. For a specified lifetime, its Net Present Value (NPV) is to be maximized. The optimization process has two stages. In the first stage, a genetic algorithm from MATLAB global optimization toolbox (The Mathworks, Inc., 2018) is used to optimize the allocation of the wells. Then, the global search using GA considers an adaptive substitute model in an adapted proposal from Redouane *et al*. (2019). Surrogate-based optimization (SBO) includes surrogate models (SM) on its interactive process to minimize the computational cost that involves such a proceeding. The substitute model quality influences the trade-off between precision and CPU time cost of the optimization process. The better the quality of the surrogate model, the better the results in terms of accuracy and CPU time consumption. The high computational cost intrinsic to the GA global search, including all the function evaluations in the simulator, can become a hard task for reservoir management problems. Therefore, it is fundamental to apply a substitute model in these situations to act in the algorithm's performance in the entire design domain. Also, for constraint

optimization, the requirements increase for that reason, so the substitute model must represent the function behavior on the feasible space and the unfeasible region as well, on a reasonable mode, taking to account that, usually, the best solution is found in the border of the feasible region.

An alternative to be considered is creating a "weak" surrogate model that is improved as the search process is accomplished. (Souza, 2010) studied a scheme with a model where new points are added, and it was applied to a water injection problem at a petroleum reservoir using Particle Swarm Optimization (PSO). Oliveira (2013) implemented a similar strategy to the Genetic Algorithm. Redouane *et al.* (2019) indicated a way to build the surrogate model based on optimization by exploiting a restricted budget of reservoir simulations. This technique makes use of the existing solution aiming to find more promising regions around it. Thus, this study uses one of the adaptative sampling methods: Minimizing an Interpolating Surface (MIS) (Jones, 2001). This choice is because MIS is excellent in the region containing the optimum and is not concentrated on a complete response surface. All these strategies are adapted, combined, and employed in this paper.

In the second optimization stage, the flow rates of the producer and injector wells are optimized through a local search strategy, the Sequential Approximate Optimization (SAO) strategy (Horowitz *et al.*, 2013). The well locations for SAO are the best solution found by GA.

2. MATHEMATICAL FORMULATIONS

For an optimization problem to be formulated, it is necessary to define its constraints, design variables, and the objective function to be improved. These characteristics are important and determine the complexity of the problem.

In this paper, optimization will be performed in two sequential steps: the first step aims to optimize the placement of the wells. The second stage uses the best locations found in the first step and optimizes the production and injection flow rates. The Net Present Value (NPV) of the field cash flow is the objective function considered for both stages. The values of the objective functions, NPV, are calculated from numerical simulations using the IMEX simulator (COMPUTER MODELLING GROUP LTD, 2016).

2.1 Well placement

The first stage of the combined optimization is the well placement problem. It aims to define the optimum coordinates associated with the NPV maximization on the field. For this problem, the constraints are imposed by the low and up limits of the reservoir spatial coordinates, by a minimum distance between wells, and by verifying the reservoir's active cells. The latter is represented by an index for each cell indicating whether it is active or inactive and the specification about the variables domain that must be integers. Although there is no definition of control cycles during the well placement optimization, i.e., there is no interference by the optimizer in this process, the flow rate results are valid as all restrictions for wells and platforms are controlled internally by the simulator.

The well location optimization for oil fields is a problem usually formulated with discrete, integer, and positive design variables. When using a centered block scheme, the reference for the topographic positioning of the wells is made with the coordinates i and j in the reservoir grid, where known wells configurations are initially assumed. The problem formulation for wells location optimization was adapted from Garrido (2019) and is presented by Eq. (1) as follows:

$$\text{Maximize} \quad \text{NPV} = f(\boldsymbol{x}) = \frac{1}{(1+d)^{\tau_t}} \cdot F(\boldsymbol{x})$$

$$\text{subject to:} \quad x_{i,w} \leq n_{cI} \qquad w = 1\ldots n_w \qquad x_{i,w} \in N^*$$

$$x_{j,w} \leq n_{cJ} \qquad w = 1\ldots n_w \qquad x_{j,w} \in N^*$$

$$\left\| (x_{w_a}, x_{w_b}) \right\| \geq dist_w \qquad a,b = 1\ldots n_w \quad \text{with} \qquad a \neq b \tag{1}$$

$$\prod_{w=1}^{n_w} \left(\prod_{block=1}^{n_{cK}} id_{block} \right) = 1$$

$$id_{block} = \begin{cases} 0, & \text{for inactive blocks} \\ 1, & \text{otherwise} \end{cases} \qquad block = (x_{i,w}, x_{j,w}, x_{k,w}) \quad k = 1\ldots n_{cK}$$

Where $f(\boldsymbol{x})$ is the objective function (Net present Value); $\boldsymbol{x} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_w, \ldots, \boldsymbol{x}_{n_w}]$ is the design variable vector, where $\boldsymbol{x}_w = [\boldsymbol{x}_{i,w}, \boldsymbol{x}_{j,w}]$, i.e., i and j are design variables represented by coordinates of the wells and define the *block* position at the grid with $\boldsymbol{x}_w$ belonging to naturals, excluding zero (N^*); n_{cI}, n_{cJ} and n_{cK} are, in this order, the maximum number of blocks in the i, j, and k directions of the reservoir grid; n_w is the total number of the wells on the reservoir; $dist_w$ is a constant that establishes the minimum Euclidean distance between the well a and any well b; id_{block} is an

index that defines if a *block* is located in an active or inactive cell; $x_{i,w}$, $x_{j,w}$ and $x_{k,w}$ are integers and real. In this study, for $x_{k,w}$ it is considered that the drilling of the well is done up to the n_{cK} limit keeping a topographic optimization as a general characteristic. Therefore, n_{cK} was used only to determine if the well with all its cells is located in an active zone.

In the objective function, the discount rate applied to capital is represented by d. The cash flow F at control cycle t represents the oil revenue minus the cost of water injection and water production and is given by Horowitz *et al.* (2013) and is described by Eq. (2) as:

$$F(\boldsymbol{x}_t) = \Delta\tau_t \left[\sum_{w \in P} \left(r_o q_{w,t}^o - c_w q_{w,t}^{wt} \right) - \sum_{w \in I} c_{wi} q_{w,t} \right] \tag{2}$$

Where in general formulation $\Delta\tau_t$ is the time size of the tth control cycle. In this study, it is equal to the field concession time; P and I indicates the producer and injector wells, respectively; $q_{w,t}^o$ and $q_{w,t}^{wt}$ are the average oil and water rates at the wth production well at tth control cycle; r_o is the oil price; c_w and c_{wi} are the production and water injection costs, in this order; $q_{w,t}$ is the flow of water injected into the wth injector well during the concession time t (single control cycle).

2.2 Production and injection flow rates

The flow control of the wells at each time interval is made through the relation between flow rates of the wells and the production capacity of the group where the wells are connected. The problem of production and injection flow rate optimization is already known in the literature and has a classic formulation. In the last optimization stage, to obtain the best operation of the wells in the reservoir, it will be adopted a formulation of non-full capacity operation (NCO) with a constant chosen control cycle (Horowitz *et al.*, 2013). After the first optimization step, the flows will be optimized using the wells' new (best) coordinates. Then, three control cycles of flow controls are defined. In the example to be studied, a total of 20 optimization runs were performed. After that, numerical simulations using IMEX are analyzed for each optimized case, including its flow rate results.

The studied case will consider three control cycles. The times of each control cycle are determined as follows: the first one is the initial concession time, the second one is defined as the average period of water breakthrough calculated from 20 optimum solutions. The time for the last control cycle is defined as the average between the second cycle time and the final reservoir concession time. For the studied case of this paper, this results in $T_{C1} = 0$ days (at the beginning); $T_{C2} = 600$ days and $T_{C3} = 2010$ days.

3. SURROGATE MODELS

In most optimization problems, difficulties can be found in obtaining the answer to the functions considered in representing the physical problem. Therefore, high-fidelity computer simulations are often used instead of controlled experiments to reduce total time, costs, and risks. These simulations are used by engineers to understand and interpret the system's behavior under study and to identify promising regions in the design space. They are also used to understand the relationships between the different input parameters and how they affect the output parameters.

Schmit and Farshi (1973) demonstrated that the use of substitute models can be very efficient when searching to optimize some complex engineering problems. The substitute functions have been used to aim a fast computational response and obtain a smoother and simplified behavior of the functions of high computational cost (high fidelity models), i.e., free of numerical noises, still allowing to obtain their gradients. The essential aspect in the approximation is to replace the high-fidelity function evaluations with functions that are simpler to calculate (substitute functions) and to use during the optimization process.

3.1 Sampling plan

The first step to construct a substitute model based on data adjustment is generating a sample of points. The Design of Experiments (DoE) is the sampling plan used to define the initial values of the input data in the project space (Jin *et al.*, 2001). This data set, where information is calculated using the high-fidelity model, is needed to create a suitable substitute model. Several sampling techniques are available. Among them, the Latin Hypercube Sampling (LHS) is used in this paper because this method, generally, performs a better uniform distribution of points (Romero *et al.*, 2006).

3.2 Constructing the surrogate model

Various techniques can be used for the construction of substitute models. They are grouped into two categories, functional and physical (hierarchical fidelity). The functional technique encompasses different approaches such as methods based on data fitting, polynomial series, and reduced order methods. The physical category involves models based on the physics of the problem studied. The functional category was used in the present work with the data fitting

approach, which has several adjustment models. Here, is used the Radial Basis Function (RBF). Foroud *et al.* (2012) evaluated the quadratic, multiplicative and radial function models applied to the well location problem, concluding that the last metamodel was the one that presented the best response to the optimization process using the genetic algorithm. This method is a way to approximate multivariable functions in more basic functions, with known properties and easier to analyze (Forrester *et al.*, 2008). The RBFs are, therefore, an efficient tool to solve multivariable data interpolation problems.

Sometimes, in constrained optimization problems, part of the design space may not be feasible. Thus, ensuring that the samples, or a portion thereof, are in the feasible space is fundamental, especially for algorithms that are more dependent on these positions, such as metaheuristics (Silva, 2019). In problems such as the location of the wells, whose feasible space is severely limited, given the restrictions and a high number of variables, it is crucial to ensure, for better performance of the substitute model, that a portion of the samples is positioned in the feasible design space. Oliveira (2013) recommends that 60% of the population be initialized in this way. This strategy is adopted in this work. The LHS technique is used with an initial size of $5n$ for the first optimization stage, which is the location of wells, where n is the total number of design variables in the problem. For the problem to be analyzed here, each well presents two design variables associated with its location. As a total of 12 wells is shown in the reservoir, this results in sampling with 120 points. New samples are inserted throughout the optimization process to enrich and increase the accuracy of the model.

4. OPTIMIZATION STRATEGIES

In this paper, a combined optimization approach is built for NPV improvement. First, the location of the wells is obtained by a Genetic Algorithm (GA), considering an adaptive substitute model procedure. Then, the production and injection flows are optimized through a local search through the Approximate Sequential Optimization (SAO) strategy.

4.1 Genetic algorithm

Genetic Algorithms (GA) are search algorithms based on Darwin's Theory of Species Evolution that primarily involves natural selection and genetics in the Evolutionary Algorithms (EA). It was introduced and studied by Holland (1984). The GA is used because it is an efficient resource and a robust heuristic optimization technique for constrained problems such as Well Placement Optimization. This initial problem needs a good algorithm that should find global optimums or optimums groups; therefore, a stochastic process is required. The GA also has a good performance in a range of multiobjective problems and does a search that modifies, simultaneously, a population of points, not a single point for interaction, as deterministic algorithms. All these features make the GA an algorithm fully able to overcome the limitations of the other traditional methods.

The flowchart (Figure 1) shows the GA's implementation with its overall procedure.
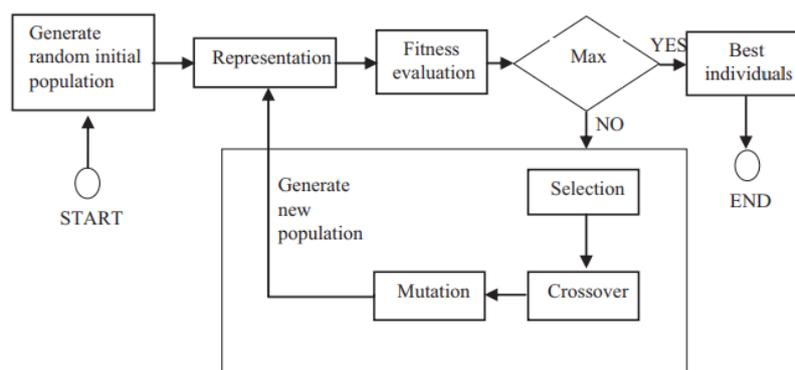

Figure 1. Basic GA method procedure.

The GA from the MATLAB toolbox (The Mathworks, Inc., 2018) has a range of convergence options. In this paper, the stopping criteria for the global search are the maximum number of generations and minimum changes value related to improvement in the objective function at the population. For better tracking the fitness function value changes, it is fixed the number of consecutive generations where the accumulated changes in your valuation do not exceed a defined tolerance. In this work, the value considered to that tolerance is $1e^{-6}$ and the maximum number of generations is 100.

4.1.1 Constraints manipulation

In this paper, two constraint manipulation techniques are considered: chromosome repairing and adaptive penalty function. These methods are the most popular and are used in the optimization process at different moments. The

chromosome repairing is used in the early stage of the search, whereas the adaptative penalty approach is applied in the remaining of the process.

Chromosome repairing

Chromosome repairing arises from the necessity to have feasible individuals in the GA's initial population and the constraints imposed on the problem. Based on Oliveira (2013), here is considered a procedure for correcting the genes of the individuals created. In the beginning, the individuals are randomly generated, and then their violations are verified. In the assessed generation, the number of generated individuals must be greater than the population size (*ps*) used in GA. Afterward, all the individuals of the random sample go through a constraint violation test and, if they are not feasible, they are discarded. Therefore, in the end, only feasible individuals remain. If the number of feasible individuals is less than *ps*, a new random sample must be generated and tested again as done at the beginning. However, if the number of feasible points is greater than *ps*, the group with size *ps* with feasible individuals are randomly chosen to compose the sample. Finally, if the group of feasible individuals is equal to the size of the population *ps*, then the GA's initial population will be this set.

Adaptive penalty method (APM)

Most engineering problems are subject to constraints. However, genetic algorithms were developed to optimize unconstrained problems. The penalization methods are needed to execute operations during the optimization process. Lemonge and Barbosa (2004) introduced a technique that does not require defining penalization parameters. An adaptive scheme is elaborated to make this possible, where uses population data, such as the average of the objective function value and the violation level of each constraint during the optimization process.

In the present work, a simultaneous verification for all constraints is carried out, consisting of examining the activity of the blocks and evaluating the distance between the wells. If any of these constraints is violated, the penalization by Lemonge and Barbosa (2004) is applied.

4.1.2 Adaptive surrogate reservoir model (ASRM)

Initially, a sample is created with a representative number of individuals in the feasible region. Then, unfeasible individuals are converted into feasible by repairing the chromosomes (Oliveira, 2013) in sequence, and the sample is updated through coordinates perturbations around the best (four new points are generated). Finally, these points are evaluated by the simulator and used to build the new substitute model.

One contribution of this paper is to combine the strategy presented by Redouane *et al.* (2019) that defines a new way to build the surrogate model for optimization using an established budget of reservoir simulations (*i*) with a different approach. Here, this work presents a procedure that perturbs the best point from the optimizer and creates new points around it. Here, the proposed ASRM framework that uses the GA as an optimizer is illustrated by the flowchart in Figure 2 and is outlined in the following steps.
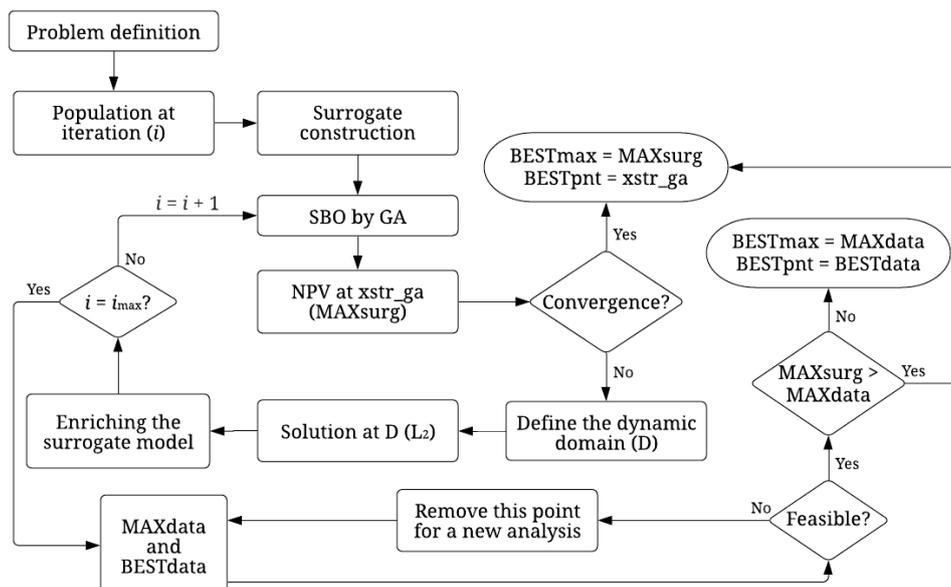

Figure 2. Optimization scheme using an adaptive surrogate model.

The main steps of the procedure are:

Step 1: Optimizes the surrogate model by the GA and finds the best individual (xstr_ga).

Step 2: Evaluates xstr_ga in the simulator (MAXsurg) and verify the convergence. If there is convergence, BESTmax and BESTpnt are updated.

Step 3: Defines the dynamic domain (D) where new points based on the best point are created. Here, 4 different points (n_p) are generated around xstr_ga through random perturbations in the coordinates of 5 random wells (n_{dw}). Each new point is created by calculating the Euclidean distance between the well to be disturbed and the center of the reservoir. Due to the square shape of the reservoir, taking into account the complete area involving active and inactive cells, it was defined a circular influence region, diameter (d) equal to half size of the reservoir. It is set like this to standardize the configuration of movement of the coordinates. Such action has a small size, one or two blocks, and is selected randomly between both mentioned sizes. Thus, if the Euclidean distance calculated is greater than the defined radius (d/2), the coordinate movement is done toward the center. Otherwise, it is moved toward the borders, e.i., it depends on where they are initially located.

Step 4: Computes the objective function at the new set of individuals, generating L_2 group.

Step 5: Enriches the substitute model adding the points: the best from the genetic algorithm and the new points created around it. Next, adds these points to the initial population for the next search.

Step 6: Applying the loop (L_2) i times until reaching the maximum number of iterations (i_{max}) or obtaining the determined convergence with $i = 1$ at the beginning and $i = i + 1$ every time that passes by the loop.

Step 7: Continue the process (step 6) until one of the stopping criteria is reached. The stopping criteria are the maximum iterations number ($i_{max} = 48$), representing a total number of function evaluations equal to 240 (10n) for model enrichment, and the convergence represented by Eq. (3):

$$convergence = \frac{MAXsurg - fit\,(GA)}{MAXsurg} < 1e^{-6} \tag{3}$$

MAXdata and BESTdata represent, in this order, the best value of the objective function corresponding to its respective variables contained in the enriched substitutive model. At the end of the procedure demonstrated in the steps and the flowchart above, the best individual found is the optimized solution.

4.2 Sequential Approximate optimization

To tackle the problem formulated is employed the Sequential Approximate Optimization (SAO) (Horowitz *et al.*, 2013) methodology. It decomposes the original optimization problem into a sequence of optimization subproblems, confined into small subregions of optimization design space, Δ^k. Surrogate functions, $\hat{f}(\mathbf{x})$, are created and used by the optimizer. A trust region-based method is used to update the design variable space for each subproblem, i.e., SAO iteration (Horowitz *et al.*, 2013). Mathematically each subproblem, at the kth SAO iteration, is defined by Eq. (4) as:

$$\begin{aligned} &\text{Maximize} \quad \hat{f}^k(\mathbf{x}) \\ &\text{subject to: } \mathbf{Ax} \leq \mathbf{b} \\ &\qquad \|\mathbf{x} - x_c^k\|_\infty \leq \Delta^k \\ &\qquad x_{lb} \leq \mathbf{x} \leq x_{ub} \end{aligned} \tag{4}$$

Where A and b are, respectively, the matrix and right-hand side of linear constraints, x_c^k is the center point of the trust-region; x_{lb} and x_{ub} are the lower and upper bounds of the design variables.

To update the trust-region size for each optimization subproblem, we considered the approach described in Eldred *et al.* (2004), which considers the accuracy of surrogate functions against the true functions. The main steps involved in the computations are:

1. Compute the objective function and constraints at the central point in the subregion;
2. Construct a surrogate model in the subregion;
3. Optimize within the subregion using the surrogate objective function and constraints;
4. Compute the true objective function and constraints at the optimum identified in step 3;
5. Check for convergence;
6. Move/shrink/expand the subregion according to the accuracy of the approximated model compared to the true function and constraint values;
7. Check for overall optimization convergence. If it is achieved, stop the SAO procedure; otherwise, return to step 3

The chosen surrogate model is a cubic Radial Basis Function (RBF) (Gutmann, 2001), where Latin Hypercubic Sampling (LHS) is the DoE technique used for its training (Horowitz *et al.*, 2013).

4.2.1 Stopping criteria

Three stopping criteria were considered in the SAO strategy divided as follows.

1. It refers to the global convergence that defines the end of the optimization process. So, to stop if the optimum value of the substitute model does not show significant changes for the last three iterations ($k = 3$), i.e., the absolute difference between this value and its average in the previous three iterations is less than a certain tolerance. The tolerance value $1.5e^{-5}$ was adopted in the study cases. Equation (5) below seeks to represent, mathematically, this condition:

$$tol = \left| \hat{f}^k(\boldsymbol{x}) - \frac{\sum_{i=k-2}^{k} \hat{f}^i(\boldsymbol{x})}{k - i + 1} \right| \leq 1.5e^{-5} \tag{5}$$

2. It is defined based on local convergence during the optimization of the subproblems confined in the subregions, i.e., trust regions of the space project. It is linked to the minimum size of the trust regions (Horowitz *et al.*, 2013). The Δ^k tolerance value adopted was $1e^{-3}$;

3. The optimization process stops if the maximum number of iterations is reached. This maximum was defined in twenty iterations.

5. EXAMPLE: EGG MODEL

5.1 Reservoir description

The proposed method is tested in a benchmark reservoir named Egg Model (Jansen *et al.*, 2014). The standard reservoir is three-dimensional (3D) channelized and has a two-phase flow (oil-water). The grid is modeled with 60 by 60 by 7 blocks (directions i,j,k), resulting in 25,200 cells where 18,553 active. Each cell size has 8 m in length (directions i and j) and 4 m of depth (direction k). The reservoir is defined as underwater flooding circumstances, and it has 12 vertical wells in total which 4 are producers and 8 are injectors (Figure 3). The concession time to exploit the reservoir is 3,600 days. The standard model parameters employed in this paper have been listed in Jansen *et al.* (2014).
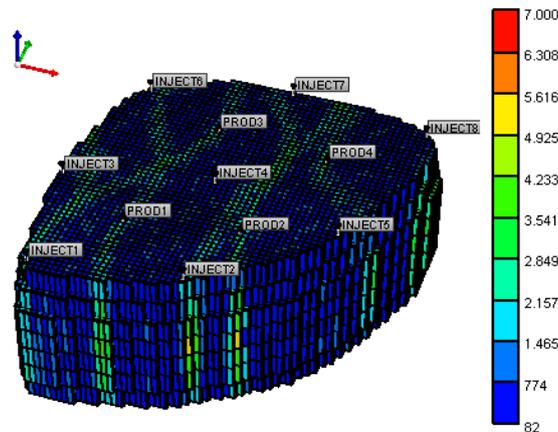

Figure 3. Egg model with permeability and well placement scheme (PROD: production well, INJECT: injection well).

The economic parameters are based on Siraj *et al.* (2015). Thus, water injection cost, water produced costs, and produced oil price are fixed at $\$6/m^3$, $\$19/m^3$, and $\$126/m^3$, respectively, for all simulations.

5.2 Results and discussion

For the first stage, the formulation of the problem considered 2 variables of location for each well. The depth is fixed for all wells as previously described. For the last stage, flow rate optimization was defined by three control cycles with one variable for each well per cycle. To this study, 20 optimization runs were performed using MATLAB's GA and SAO. It was set $5n$ for the size of the initial surrogate model and $10n$ for model enrichment, where n is the number of variables. For the SAO, the maximum number of iterations adopted was 20.

The initial location of the wells was previously defined and provided in the literature. The initial point to the flow rate values to be optimized was defined based on the rates controlled internally by the simulator in the first stage and was extracted in the time corresponding to each control cycle determined for this last stage. The optimizations changed the initial configuration for positions and flow rates of all wells. The best solution for well placement in this work is presented

in Figure 4 through a comparative superposition. The old (base case) and new (optimized case) positions for producers (left) and injectors (right) wells in the studied reservoir are shown below.
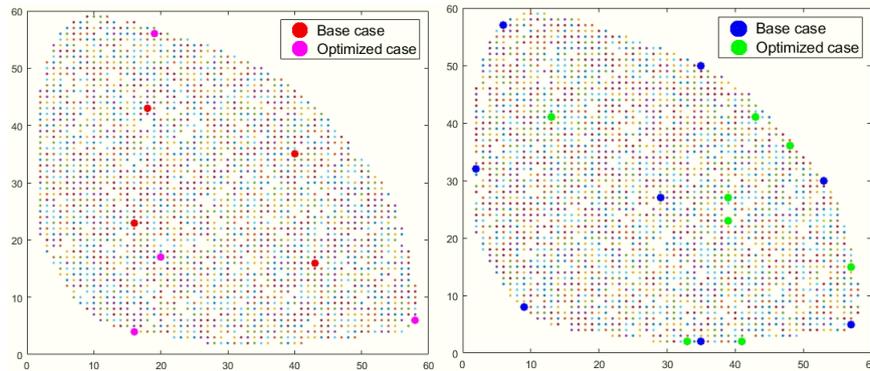

Figure 4. Demonstration of the well positions: producers (left), injectors (right).

The best result obtained in the combined approach involving GA to well placement and SAO to flow rates increased the NPV by 75.46% compared to the base case. This water decrease is due to the recovery methodology utilized here which significantly impacts the NPV increase. The cumulative water and water cut parameters demonstrated this reduction. The water cut is kept for long in lower levels and at the end of the simulation time, there is a difference of about 13.32% between the original case (94.18%) and the optimized case (80.86%). The cumulative water at the end of 10 years of field exploration showed a reduction of over 84% in the optimized case with relation to the base case. All these mentioned considerations can be seen in Figure 5.
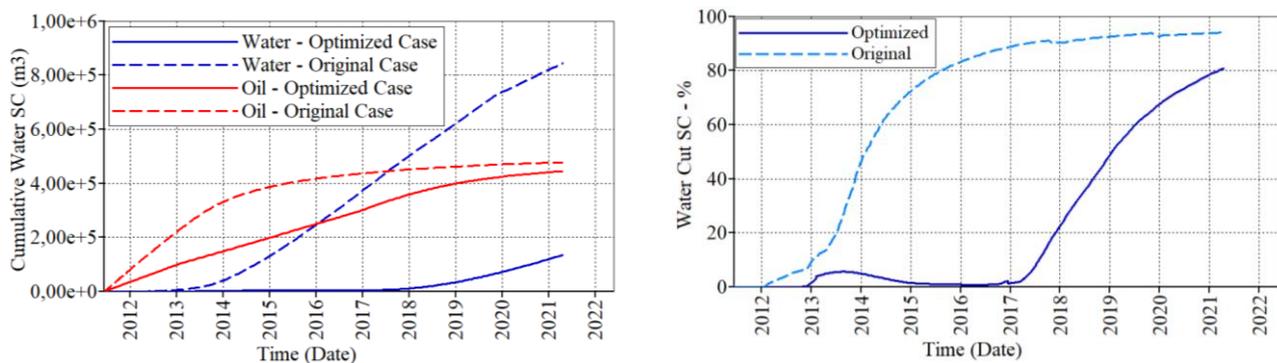

Figure 5. Oil and water cumulative production (left) and the water cut (right) for the original case and the optimized case to Egg model.

The late water breakthrough in the optimized case was determinant in the optimization process. The Figure 6 presents the water saturation maps comparison between the base case and the best optimized case.
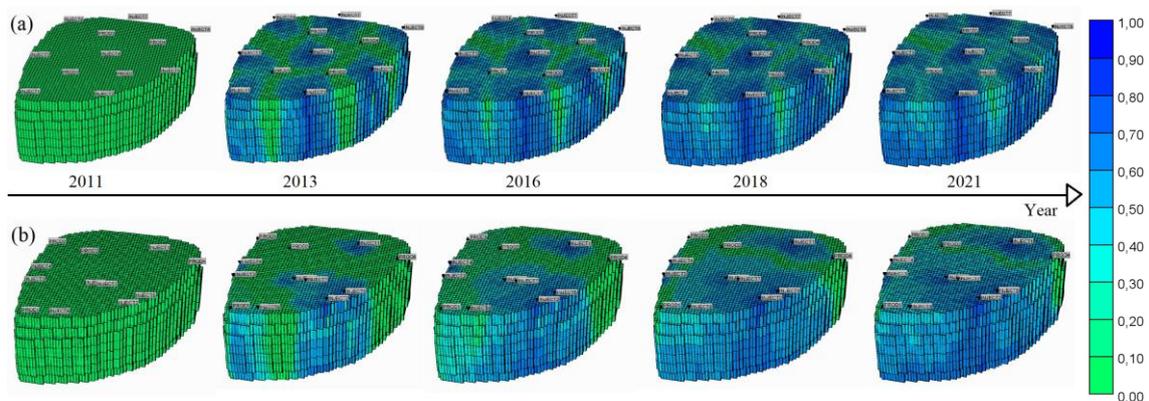

Figure 6. Water saturation in the reservoir over the concession time: (a) base case, (b) optimized case.

Some observations must be made about the stages of optimization. In the first stage, all of the optimizations increased the objective function value (NPV). However, in the second stage, 2 out of 20 solutions were not improved, i.e., the results were worse than those of the first stage. These results are due to the application of only one flow control cycle in the initial optimization stage. The summary of optimization results of these two stages is organized in Table 1. It contains the improvement data for the first stage considering just GA and the final optimization result with the two strategies (GA and SAO) combined. The analysis for the second stage only considers the results where the NPV was improved.

Table 1. Optimization results summary.

Strategy	Number of optimizations	Best solution (%)	Worst solution (%)	Average improvement wrt base case (%)	Standard deviation of the solutions (%)	Number of objective function evaluations (best solution)	Number of objective function evaluations (average)
GA	20	68.70	35.04	48.01	9.46	361	361
GA + SAO	18	75.46	46.96	61.84	8.23	1768	1398

6. CONCLUSIONS

A combined optimization methodology to maximize the Net Present Value (NPV) was developed in this paper. Genetic Algorithms (GA) and Sequential Approximate Optimization (SAO) were the strategies employed to optimize the positions and flow rates of the wells of the Egg Model reservoir sequentially. The optimization process was carried out in two steps: in the first, GA was used to obtain the best configuration of location of the wells. The last, the SAO was utilized to manage the flow rate of the wells. The well placement for SAO was the best solution found by GA.

The combination of strategies showed meaningful and satisfactory increases in the NPV, the main objective of this paper. The best solution increased by 75.46% the NPV with relation to the base case. The standard deviation improved from 9.46% in the optimization with GA to 8.23% in the optimization with both strategies (GA and SAO), a decrease of 1.23%, demonstrating more homogeneous results. In the stage of the combined strategies, the average improvement in optimizations went from 48.01% to 61.84%, representing a difference of 13.83%. All these data show the efficiency of the strategy employed. This improvement is, noticeably, due to the decrease in water production over the time of exploitation of the reservoir, the primary recovery methodology used here. Such reduction can be observed in the results of the cumulative water and water cut. The first one showed a reduction of about 84% in the water produced for the optimized case compared to the base case. The last one demonstrated a percentual difference of approximately 13.32% between the original case, (94.18%), and the optimized case, (80.86%). Unlike this, the results of cumulative oil demonstrated a reduction in production. It is known that this situation is not attractive and not ideal to Oil and Gas Industry because one of its principal interests is also to improve the oil recovery, not just to increase the NPV. Because of this, it is feasible to consider and suggest that the joint optimization of well positions and control of well flow rates be a more efficient alternative to increase oil production and the NPV simultaneously. To the objective of this paper, the methodology proposed shown an effective performance and brought significant results of improvement to the NPV.

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8. RESPONSIBILITY NOTICE

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