HIERARCHICAL OPTIMIZATION IN SHORT-TERM AND LONG-TERM OF RESERVOIR MANAGEMENT THROUGH SURROGATE MODELS

Jefferson Wellano Oliveira Pinto

Silvana Maria Bastos Afonso

wellano@gmail.com

smb@ufpe.br

Federal University of Pernambuco – Dept. Eng. Civil

Rua Acadêmico Hélio Ramos, s/n, 50740530, PE, Recife, Brazil

Ramiro Brito Willmersdorf

ramiro@willmersdorf.net

Federal University of Pernambuco – Dept. Eng. Mecânica

Rua Acadêmico Hélio Ramos, s/n, 50740530, PE, Recife, Brazil

Abstract. *Optimization techniques have been extensively used to achieve feasible and economical designs in most varied fields of engineering. Nowadays the approaches have become gradually more realistic, having been commonly used to solving non-trivial problems of practical engineering, including the optimum management of reservoirs through computational simulation. One point only recently tackled concerns the short-term objective, which in most production optimization studies is neglected. As a result, the production and injection flow obtained from optimization often results in a considerable reduction of short-term production performance. And it is generally these objectives that define the course of the operational strategy, especially due to reservoirs geological and economic uncertainties. A hierarchical optimization structure with multiple objectives is adopted to handle short-term and long-term optimization. Since the numerical simulation has a high computational cost, it is not practicable to use it directly to guide the search, hence to overcome this inconvenience accurate surrogates, based on radial-basis functions, with low computational costs will be used herewith the Sequential Approximate Optimization (SAO) technique that minimize the number of function evaluations.*

Keywords: *Optimal Management, Hierarchical Optimization, Short-term, Long-term optimization, Sequential Approximation Optimization.*

INTRODUCTION

In most production optimization studies, the short-term goal is neglected. As a result, production and injection flows obtained from the optimization often result in a considerable decrease in the yield indices in the short term (Van Essen et al, 2009).

From an operational point of view, the decision on how to operate the wells is quite critical, since the optimization strategies adopted by reservoir engineers and production engineers may differ significantly. Using an analogy, a reservoir engineer approach is geared towards optimizing the reservoir throughout its concession time, while the production engineer looks for a faster attempt at opening the wells. In operational terms, it means that the reservoir engineer tends to produce the oil at a lower flow in the beginning and gradually increases the production rate, since the production engineer adopts a more aggressive strategy initially, producing the oil the maximum flow in initial control cycles and as time goes by the production rate of oil decreases (Hasan, 2013). Each option has pros and cons, the strategy of producing more oil in the short term can leave an appreciable amount of oil in the reservoir, however this option is not so affected by the present uncertainties, such as in the oil price that occurs in a long-term production.

It was observed (Jansen et al, 2009) that different control variables of water injection and liquid production result in practically equal values of NPV in the end of concession period. In this reference it is concluded that the optimization problem along the control cycles is ill-posed and contain more variables than necessary. As a result, there are multiple solutions to the optimization problem, i.e., different optimal controls that must reach at similar optimal results in a subset of the space of the control variables.

To solve the problem, a hierarchical optimization structure is adopted. In this work two approaches are used. The first one considers only the NPV as objective function and in its calculation different annual discount rates are used as a parameter to emphasize a short or long term optimization. In the second approach, NPV is optimized with a fixed discount rate and with the solution obtained, a least squares method is applied on oil production in a short pre-established time interval.

Two reservoir problems are analyzed, both are black-oil models and they are simulated by CMG's commercial IMEX simulator. To reduce the computational cost of simulation, surrogate models based on data fitting using radial basis functions (RBF) are constructed. In this case the surrogate model is applied in an iterative process called Sequential Approximate Optimization (SAO).

1 WATERFLOODING PROBLEM

Waterflooding is the most commonly used method to improve oil recovery and maintain the reservoir at a proper pressure level. Optimization techniques can be applied to improve waterflooding sweep efficiency through the propagation of the water front. In this sense, one problem of great interest is the dynamic optimization of producing scheduling, leading to optimal rate allocation to the injectors and producers. In this problem, the net present value (NPV) is considered as the objective function and the constraints are related to the rates: total filed, limit values and voidage-type replacement (Horowitz, Afonso, & Mendonça, 2013).

The NPV function can be seen as a weighted sum of the cumulative oil production and cumulative water injection function. The objective function and constraints for the Waterflooding problem can be written as shown in Eq. (1):

$$\text{Maximize}: NPV = J = \sum_{t=1}^{n_t}\left[\frac{1}{\left(1+d\right)^{\tau_t}}\cdot F\left(\mathbf{q}_t\right)\right]$$

$$\text{subject to} = \begin{cases} \sum_{p\in P} q_{p,t} \le Q_{l,\max} \\ \sum_{p\in I} q_{p,t} \le Q_{inj,\max} \\ q_{p,t}^{l} \le q_{p,t} \le q_{p,t}^{u} \quad ; \quad p = 1 \ldots n_w \\ \sum_{p\in P} q_{p,t} \le \sum_{p\in I} \alpha \cdot q_{p,t} \le \delta \cdot \sum_{p\in P} q_{p,t} \\ t = 1 \ldots n_t \end{cases} \tag{1}$$

where $\mathbf{q} = \left[\mathbf{q}_1^T\ \mathbf{q}_2^T \cdots \mathbf{q}_{n_t}^T\right]^T$ is the vector of the maximum flows in the wells for all control cycles; $\mathbf{q}_t = \left[q_{1,t} \cdots q_{n_w,t}\right]^T$ is the vector of maximum well rates at control cycle t; n_t is the total number of control cycles; n_w is the total number of wells; d is the discount rate and τ_t is the time at the end of the t^{th} control cycle. The cash flow in the control cycle t, which represents the difference between oil revenue and the cost of injection and water production, is given by Eq. (2):

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

where is the time interval of t^{th} control cycle; P and I are producers and injectors wells platform, respectively; and are the average oil and water rates at the p^{th} production well at t^{th} control cycle; is the oil price; is the cost of producing water, and is the costs of injecting water. In Eq. (1), $Q_{l,\max}$ is the maximum allowed total production liquid rate and $Q_{inj,\max}$ is the maximum allowed total injection rate of the field. Superscripts l and u refer to the lower and upper bounds of design variables, respectively. The last constraint in Eq. (1) requires that, for all cycles, the total injection rate belong to an interval that goes from the total production rate to δ times this value, where $\delta \geq 1$ is the over injection parameter and α is the ratio between $Q_{inj,\max}$ and $Q_{l,\max}$. This is a more general form of the so-called voidage replacement constraint used by many researchers as a means to maintain the reservoir properly pressurized (Brouwer & Jansen, 2004; Naevdal; Asadollahi, 2012).

The commonly used approach to waterflooding problems is to subdivide the concession period into a number of control cycles, n_t, whose switching times are fixed. The design variables are the well rates in each control cycle. Scaling them by their respective maximum allowable platform, it follows that design variables ($x_{p,t}$) are the allocated rate for well p at time cycle t:

$$\boldsymbol{x}_{p,t} = \frac{q_{p,t}}{Q_{l,\max}},\ p \in P;\ \boldsymbol{x}_{p,t} = \frac{q_{p,t}}{Q_{inj.\max}},\ p \in I \tag{3}$$

Computation of the objective functions of the above problem requires a complete reservoir simulation. As simulations can take several hours to run, the optimization algorithm is coupled to surrogate models constructed as described in the following section.

2 OPTIMIZATION ALGORITHM

In the last decades great advances in computer software and hardware have been achieved, which greatly improved the reservoir simulation speed. However, the availability of computational resources is still a limiting factor for several types of reservoir optimization (Fedutenko et al., 2013). The use of surrogate models, such as Kriging, Radial Basis Function, and Neural Networks, has been suggested to reduce the number of simulations required in the optimization (Afonso, Horowitz & Wilmersdorf, 2008; Naidu, 2004; Gutmann, 2001; Forrrester, Sobester & Keane, 2008).

In the present work, a data fitting approach will be used, which in turn has several fitting models, of which radial basis functions (Gutmann, 2001; Forrrester, Sobester & Keane, 2008) will be used.

The optimization strategy used is sequential approximate optimization (SAO), which will operate on surrogate model, instead of making use of real simulations.

2.1 Surrogate Construction – Radial basis functions

Surrogate models are built to provide smooth functions accurate enough to capture the general trends of the high fidelity model at a considerably lower computational cost. These properties make them especially adequate for optimization purposes.

In this paper, the chosen surrogate model is Radial Basis Function (RBF) approximator (Gutmann, 2001; Forrrester, Sobester & Keane, 2008; Wild, Regis & Shoemaker, 2008; Elsayed et al., 2012). It was originally developed by Hardy (1971) in 1971 to fit irregular topographic contours of geographical data. Krishnamurthy (2003) added a polynomial to the definition of RBF to improve the performance. Wu (1995) provided criteria for positive definiteness of the basis functions with compact support which produced series of positive definite basis functions. The first step on the construction of surrogate model is to design the sampling points in the design space, which can be performed using Design of Experiments (DoE) techniques (Giunta & Eldred, 2000; Giunta, Wojtkiewicz & Eldred, 2003). Latin hypercube sampling (LHS) (Forrester, Sobester & Keane, 2008; Giunta, 2002) is the DoE technique used here.

The Radial Basis Function (RBF) is a method to approximate multivariate functions in terms of more basic functions, with known properties and easier analysis (Forrester, Sobester & Keane, 2008).

Let $\hat{f}\left(\boldsymbol{x}\right)$ be a Radial Basis Function (RBF) of the form (Gutmann, 2001):

$$\hat{f}\left(\boldsymbol{x}\right) = p\left(\boldsymbol{x}\right) + \sum_{i=1}^{m} \lambda_i \phi\left(\left\|\boldsymbol{x} - \boldsymbol{x}_i\right\|\right), \qquad \boldsymbol{x} \in \mathbb{R}^n \tag{4}$$

where $\boldsymbol{x}^i$ denotes the i^{th} of the m basis function centers and is a real valued function called the basic function. The coefficients λ_i, i = 1, …, m, are real numbers, and the norm $\|\bullet\|$ is the Euclidean norm in $\mathbb{R}^n$, p is a low degree polynomial function, typically linear. A RBF consists of a weighted sum of a radially symmetric basic function ϕ located at the centers $\boldsymbol{x}^i$ and a low degree polynomial p.

The basic function, in this context, is a real function of a positive real r, where r is the distance (radius) from the origin. Popular choices for this function are:

- linear $\phi(r) = r$
- cubic $\phi(r) = r^3$
- thin plate spline $\phi(r) = r^2 \ln r$

The RBF interpolant $\hat{f}\left(\boldsymbol{x}\right)$ is defined by the coefficients of the polynomial p and the weights λ_i. Given the interpolation values $y = (y^1, ..., y^m)$, the goal is to find the weights λ_i so that the RBF satisfies Eq. (5):

$$\hat{f}(\boldsymbol{x}^{(i)}) = y^{(i)}, \; i = 1, ..., m \tag{5}$$

Since this equation gives an underdetermined system, i.e., there are more parameters than data, the orthogonality conditions or lateral conditions given by Eq. (6) are additionally imposed on the coefficients $\boldsymbol{\lambda} = \left(\lambda_1, ..., \lambda_m\right)^T$.

$$\sum_{i=1}^{m} \lambda_i \pi\left(\boldsymbol{x}_i\right) = 0 \tag{6}$$

Let $\{\pi_1(\boldsymbol{x}), \ldots, \pi_l(\boldsymbol{x})\}$ be a basis for polynomials of degree at most k and let $\boldsymbol{c} = \left(c_1, \ldots, c_l\right)$ be the coefficients that give π in terms of this basis. Then equations Eq. (5) and Eq. (6) can be written in matrix form as:

$$\begin{pmatrix} A & P \\ P^T & 0 \end{pmatrix} \begin{pmatrix} \boldsymbol{\lambda} \\ \boldsymbol{c} \end{pmatrix} = \begin{pmatrix} F \\ 0 \end{pmatrix} \tag{7}$$

where $A_{i,j} = \phi\left(\left|x_i - x_j\right|\right)$, $i, j = 1, ..., m$, and $P_{i,j} = \pi_j\left(x_i\right)$, $i = 1, ..., m,\; j = 1, ..., l$. By solving this linear system of equations, $\boldsymbol{c}$ and $\boldsymbol{\lambda}$ are determined, hence $\hat{f}\left(\boldsymbol{x}\right)$ is determined (Elsayed, 2012).

2.2 Sequential Approximate Optimization

A local strategy named Sequential Approximate Optimization (SAO) is used in this study. It decomposes the original optimization problem into a sequence of optimization subproblems, confined into small subregions of optimization design space called trust regions, whose extents are adaptively managed by the SAO strategy depending on surrogate accuracy (Alexandrov et al., 1998; Eldred, Giunta & Collis, 2004). Surrogate functions (low-cost) are created and used by the optimizer. Mathematically each subproblem, at the k^{th} SAO iteration, is defined as

$$\begin{aligned} \text{Minimize} \quad & \hat{f}^{k}(\boldsymbol{x}) \\ \text{subject to:} \quad & \hat{g}_i^{k}(\boldsymbol{x}) \le 0, \quad i = 1, \ \ldots, \ m \\ & \mathbf{A}\boldsymbol{x} \le \mathbf{b} \\ & \left\| \boldsymbol{x} - \boldsymbol{x}_c^{k} \right\|_{\infty} \le \boldsymbol{\Delta}^{k} \\ & \boldsymbol{x}_l \le \boldsymbol{x} \le \boldsymbol{x}_u \end{aligned} \tag{8}$$

In the above equations, $\hat{f}^{k}(\boldsymbol{x})$ and $\hat{g}_i^{k}(\boldsymbol{x}), i = 1 \ldots m$ are respectively the surrogate objective and the *m* constraints functions constructed for the current iteration, *A* and *b* are the matrix and right-hand side of linear constraints, $\boldsymbol{x}_c^{k}$ is the center point of the trust region, $\boldsymbol{\Delta}^{k}$ is the size of the trust region at the current iteration; $\boldsymbol{x}_l$ and $\boldsymbol{x}_u$ are respectively the lower and upper bounds of the design variables.

Each subproblem formulated in Eq. (8) defines a SAO iteration. At each iteration the optimum candidate is validated against the high fidelity model at the center of the trust region. If a sufficient decrease is obtained the trust region is re-centered on this new point. The extent of new trust region is expanded, maintained or shrunk depending on the accuracy of the surrogate model. If a sufficient decrease is not attained the new point is rejected and the trust region is shrunk. The main steps of the SAO algorithm are schematically given below (Giunta & Eldred, 2000):

1. Compute the expensive and/or nonsmooth objective function and constraints at the designated samples sites in the subregion;

2. Construct surrogate model in the subregion of objective and nonlinear constraints;

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 convergence. If it is achieved stop the SAO procedure; otherwise return to step 1.

Convergence test is based on maximum number of consecutive iterations with high fidelity objective function improvement less than the convergence tolerance. There is also a limit on the total number of SAO iterations and on the minimum size of the trust region.

In step 2 the samples are obtained using the chosen DOE technique. The number of samples to be used is set at $s = 2n + 1$, where n is the number of dimensions of the problem;

To update the trust region size of $\boldsymbol{\Delta}^k$ for each optimization subproblem we considered the approach described in (Eldred, Giunta & Collis, 2004). A parameter ρ^k controls the trust region size. This parameter measures the accuracy of the surrogate function at $\boldsymbol{x}_*^k$, the candidate optimum obtained in Step 3 of the SAO algorithm, and is calculated as:

$$\rho^k = \min\left(\frac{f(\boldsymbol{x}_c^k) - f(\boldsymbol{x}_*^k)}{\hat{f}(\boldsymbol{x}_c^k) - \hat{f}(\boldsymbol{x}_*^k)}, \frac{g_i(\boldsymbol{x}_c^k) - g_i(\boldsymbol{x}_*^k)}{\hat{g}_i(\boldsymbol{x}_c^k) - \hat{g}_i(\boldsymbol{x}_*^k)} \right), \quad \text{for } i = 1\ldots m \tag{9}$$

where f and g_i, i=1…m, are the high fidelity objective and m constraint functions.

The next trust region size is updated as follows:

$$\begin{aligned} \boldsymbol{\Delta}^{k+1} &= 0.5\boldsymbol{\Delta}^k, \ \text{ if } \ \rho^k \le 0,.25 \\ &= \boldsymbol{\Delta}^k, \ \text{ if } \ 0.25 \le \rho^k \le 0.75 \text{ or } \rho^k > 1.25, \\ &= 2\boldsymbol{\Delta}^k, \ \text{ if } \ 0.75 \le \rho^k \le 1.25. \end{aligned} \tag{10}$$

The next iterate, $\boldsymbol{x}_*^{k+1}$, is given by:

$$\begin{aligned} \boldsymbol{x}_c^{k+1} &= \boldsymbol{x}_*^c \ , \ \text{ if } \ \rho^k > 0 \\ &= \boldsymbol{x}_c^k \ , \ \text{ if } \ \rho^k \le 0 \end{aligned} \tag{11}$$

3 HIERARCHICAL OPTIMIZATION

A hierarchical optimization structure with multiple objectives is adopted. One of the objective function is the NPV, given by Eq. (1). Two approaches are used to conduct hierarchical optimization.

In the first approach, for long-term optimization, the discount rate considered for the NPV calculation is not changed, focusing on recovery. The short-term objective is similar to the long-term, but with the addition of a high annual discount rate, for example 25%. Thus, short-term production is weighted much more intensely than future production (Van Essen et al, 2009, Hasan, 2013).

The steps for conducting hierarchical optimization can be described as follows:

1. The NPV is maximized by local search using the SAO methodology, using the real discount rate d for the calculation of NPV. This is called the "true" long-term NPV and the flow strategy will be denoted by q_{LT};

2. The NPV is maximized in short-term using a discount rate d_{ST} = 25%, to be applied in the NPV. In this optimization an additional constraint is imposed such that at the end of the concession time, T, the NPV of the short-term optimization must be greater than or equal to the NPV found in the long-term optimization, $NPV_{ST}^T \ge NPV_{LT}^T$;

3. At the end of the hierarchical procedure the optimal control obtained is used in the NPV expression considering the true discount rate.

In step 2, to decide which rate to use in d_{ST}, we can make multiple optimizations at different discount rates, e.g. 25%, 50% and 75%, and take the one that obtained the best NPV in the short-term to continue with the hierarchical optimization. In step 3, for calculation of $NPV_{ST}^{T} \geq NPV_{LT}^{T}$ constraint is used the true discount rate for both short and long-term NPV.

The second approach does not change the value of the discount rate, d. The long-term optimization strategy is to optimize the NPV, given by Eq. (1), just like the previously approach. To conduct short-term optimization, the solution obtained in the previous step is considered. The objective function considered for the short-term optimization is to increase the difference between the oil production in a short pre-established time interval $n_{t_{ST}}$ and the oil production obtained from the long-term strategy in this same interval $n_{t_{ST}}$. The short-term objective function is given by Eq. (12).

$$f_{ST} = \sum_{t=1}^{n_{t_{ST}}} \left[q_t^o - q_{LT,t}^o \right] \tag{12}$$

Where f_{ST} is the short-term objective function, q_t^o is the current cumulative oil rate, $q_{LT,t}^o$ is the cumulative oil rate resulting from long-term optimization.

The goal of both approaches is to obtain a final NPV equal or close to that found by the long-term strategy and to increase the NPV in the short and medium term. For this aim, a hierarchical optimization structure is used, in which two consecutive optimizations are performed, the long-term NPV, given by Eq. (1), serves as the primary objective. Then, the short-term optimization is conducted using Eq. (12) as objective function, subject to the optimality of the first objective is constrained by the secondary optimization problem, i.e. at the end of the concession time, *T*, the NPV of short-term optimization has to be greater than the NPV found in long-term optimization, see Eq. (13).

$$VPL_{ST}^{T} \geq VPL_{LT}^{T} \tag{13}$$

The formulation of the hierarchical approach is given by:

$$\begin{aligned}
&\text{Maximize } J_{VPL} \\
&\text{subject to:} \\
&\sum_{p \in P} q_{p,t} \leq Q_{l,\max}; \quad \sum_{p \in I} q_{p,t} \leq Q_{inj,\max}; \; t = 1 \ldots n_t \\
&q_{p,t}^{l} \leq q_{p,t} \leq q_{p,t}^{u}, \; p = 1 \ldots n_w, \; t = 1 \ldots n_t
\end{aligned} \tag{14}$$

Subsequently,

$$\begin{aligned}
&\text{Maximize } f_{ST}\\
&\text{sujeito à:}\\
&J_{VPL_{ST}} \geq J^{*}_{VPL_{LT}};\\
&\sum_{p\in P} q_{p,t} \leq Q_{l,\max}; \ \sum_{p\in I} q_{p,t} \leq Q_{inj,\max}; \ t = 1 \ldots n_t\\
&q^{l}_{p,t} \leq q_{p,t} \leq q^{u}_{p,t}, \ p = 1 \ldots n_w, \ t = 1 \ldots n_t
\end{aligned} \tag{15}$$

where $J_{VPL_{ST}}$ is the NPV value with the controls used in f_{ST}, J^{*}_{VPL} is the optimization result of Eq. (14).

4 EXAMPLE AND RESULTS

The simulations use data from the synthetic model Brush Canyon Outcrop (BCO) presented by (Oliveira, 2006). This model is widely used in researchs at UFPE (Horowitz et al, 2013; Oliveira, 2013; Pinto, 2014; Tueros, 2015). Main characteristics of BCO model are presented in Table 1.

Table 1. Summary of BCO model characteristics

Simulation mesh	43x55x6
Porosity	16% a 28%
Horizontal permeability (k_h)	157 a 2592 mD
Vertical permeability (k_v)	30% de k_h
Saturation Pressure (P_{sat})	101.97 kgf/cm²
Viscosity @ T_{res} , P_{sat}	0.77 cP
Oil in place (m³)	8,1881 x 10^7
Concession period	24 years
Maximum platform liquid production rate (m³/d)	Max 900
Maximum platform production rate (m³/d)	Max 6300
Maximum water rate at injectors (m³/d)	Max 1500
Maximum platform injection rate (m³/d)	Max 6750

The permeability map of this model is shown in Fig. 1. The operating condition considered is non-full capacity operation with three control cycles. The total number of wells is twelve, being seven production and five injectors.

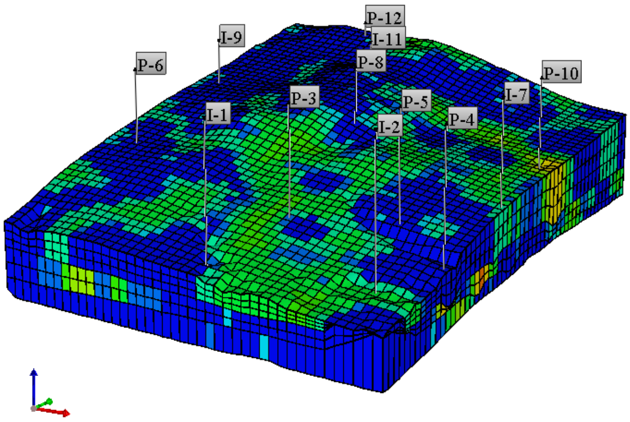

Figure 1. Permeability field and well location of BCO model

The two approaches viewed in previously section are here applied.

First Approach

To show the distinction in production rates of different discount rates, Fig. 2 shows liquid production in continuous lines and water injection in dashed lines, for long-term optimizations (red curves), considering the discount rate d = 0.093, and for short-term optimization (blue curves), considering the discount rate d_{ST} = 0.25. It may be noted that long-term optimization emphasizes higher oil recovery from the reservoir through increased water injection, while short-term optimization focuses on maximum oil production in the early years with a low injection of water, as can be seen in Fig. 2. This result is consistent with the short-term and long-term production analogy with production and reservoir engineers, presented at the introduction section.

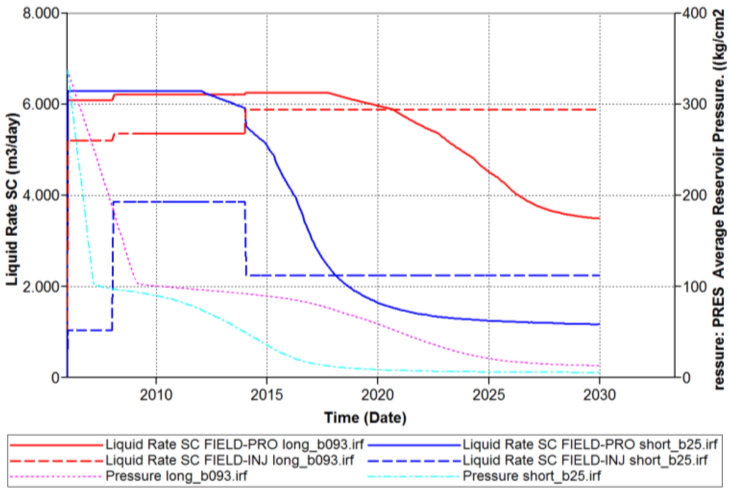

Figure 2. Curves of liquid production, water injection and field pressure

Proceeding the hierarchical optimization, Fig. 3 shows the NPV for the isolated short-term (in blue), long-term (in red) optimization and the result of the hierarchical optimization, in green. In this case, the optimized solution is not feasible, because the constraint, Eq. (13), was violated.

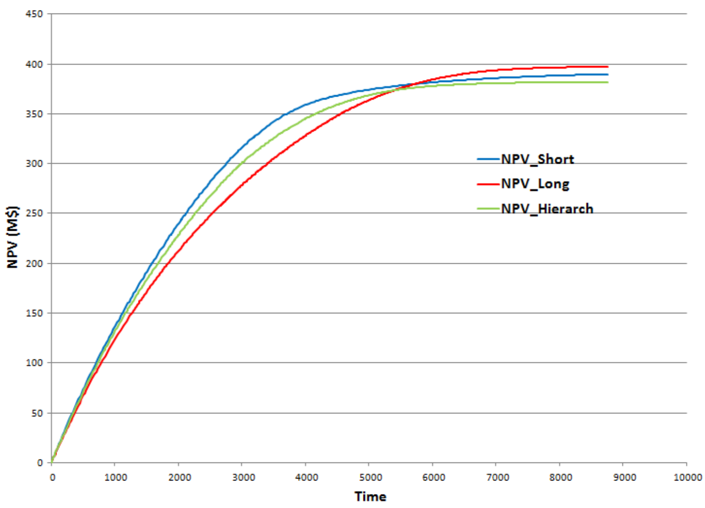

Figure 3. Oil and water cumulative production, d_{ST} = 0.25

The same procedure was repeated considering now a discount rate d_{ST} = 0.5.

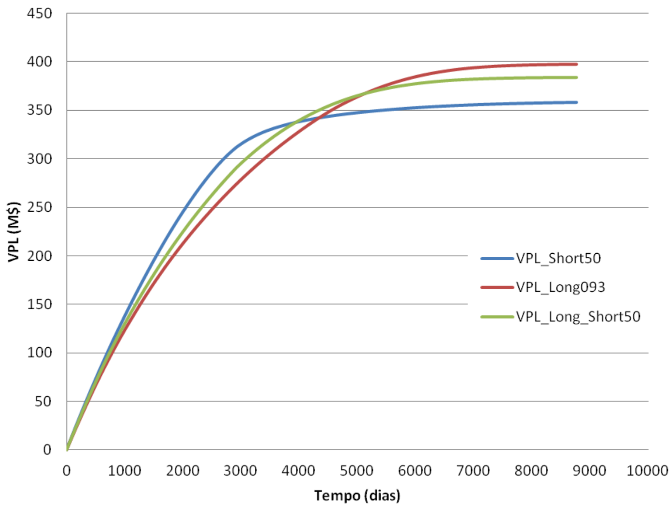

Figure 4 shows the NPV of the three optimizations conducted. The stopping criterion reached by SAO scheme was the small size of the region of confidence, but as the previous solution, this one is also not feasible because of the violated constraint. Table 2 shows the NPV results in short-term (8 years) and long-term (24 years). This short-term isolated optimization had a lower NPV result compared to that with d_{ST} = 0.25, shown in Fig.3, although the hierarchical optimization using either d_{ST} = 0.25 or d_{ST} = 0.50 were similar, as can be seen in Table 2, however both results were infeasible.

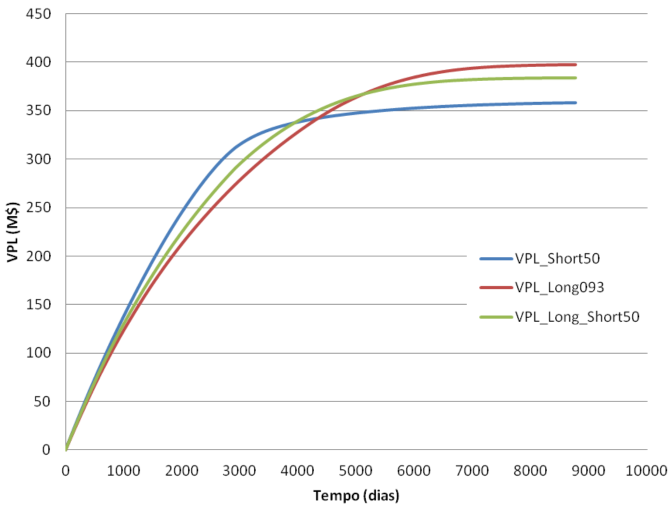

Figure 4. NPV optimizations: short term (blue); Long-term (red), hierarchical (green)

Table 2. NPV optimizations results of the first approach

Strategy	NPV (M$) in 8 years	NPV (M$) in 24 years
Short-term (d = 0.25)	311,30	389,82
Short-term (d = 0.5)	312,30	358,53
Long-term (d=0.093)	274,00	397,3
Hierarchical (d=0.25)	295,99	381,86
Hierarchical (d=0.5)	291,00	383,96

Second Approach

In the second stage of hierarchical optimization, the objective function consists of the difference between the current oil production and that obtained by the optimization of the first stage (maximization of NPV) in a time interval, $n_{t_{ST}}$, equal to eight years.

Figure 5 shows the NPV curves for short-term (in blue), long-term (red), and hierarchical (green). Analyzing the results of short-term and long-term optimization strategies, it can be noted that, over a horizon up to 5500 days, the NPV of the short-term strategy is largest, while the long-term strategy has a higher NPV at the end of the concession period.

Applying the hierarchical optimization, we can see that the final NPV is equal to that found by the long term strategy and it has an improvement in NPV in the medium term. Table 3 shows the numerical results of the NPV in eight and twenty-four years, representing the short and long term, an increase of 7.7% of the NPV in 8 years is observed, resulting from the hierarchical optimization in relation to the long-term optimization.

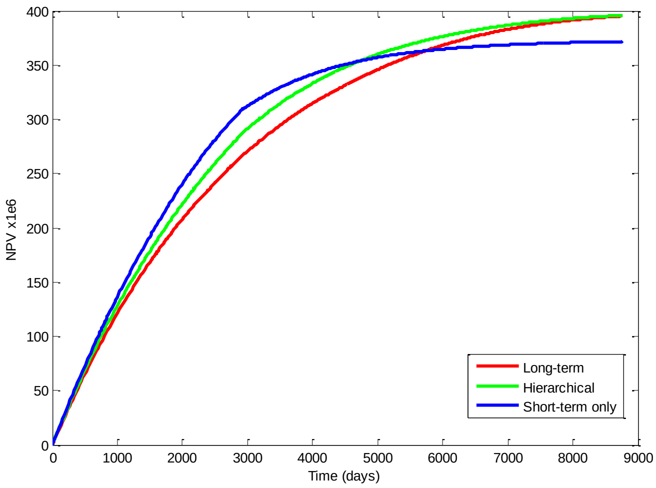

Figure 5. NPV optimizations: short term (blue); Long-term (red), hierarchical (green)

Table 3. NPV optimizations results of the second approach

Strategy	NPV (M$) in 8 years	NPV (M$) in 24 years
Short-term	309,0	371,7
Long-term	266,6	395,3
Hierarchical	287,1	395,9

5 CONCLUSIONS

The aim of this study was optimize NPV of long-term and short-term. To do this, we used two approaches with the same goal to find the best controls that benefit both term analyzed.

The result of the first hierarchical optimization approach, which considers two different discount rates, violated the constraint imposed on the final NPV. By increasing the discount rate, in this first approach, from 0.25 to 0.5 the results of hierarchical optimization were almost the same.

In the second approach, the results show that the hierarchical optimization was able to increase the NPV in short-term in 7,7%, maintaining the NPV in the long-term.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support of CNPq, the Foundation CMG, and UFPE.

REFERENCES

Afonso, S. M., Horowitz, B., & Wilmersdorf, R. B., 2008. Comparative Study of Surrogate Models for Engineering Problems. *ASMO-UK* (Association for Structural and Multidisciplinary Optimization in the UK), Bath, UK.

Alexandrov, N., Dennis Jr, J., Lewisand, R., & Torczon, V., 1998. A Trust Region Framework for Managing the Use of Approximation Models in Optimization. (Springer-Verlag, Ed.) *Structural Optimization*, 15, pp. 16-23.

Asadollahi, M., 2012. *Waterflooding Optimization for Improved Reservoir Management*. Ph.D. thesis. NTNU, Norway.

Brouwer, D., & Jansen, J., 2004. Dynamic Optimization of Waterflooding with Smart Wells Using Optimal Control Theory. SPE 78278-PA. *SPE Journal*,, 9, No. 4, pp. 391-402.

Computer Modeling Group LTD., 2006. *IMEX: User´s Guide*. Calgary – Canada.

Eldred, M. S., Giunta, A. A., & Collis, S. S., 2004. Second-Order Corrections for Surrogate-Based Optimization with Model Hierarchies, Paper AIAA-2004-4457 in Proceedings of the *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*. Albany, NY.

Elsayed, K., Vucinic, D., d'Ippolito, R., & Lacor, C., 2012. Comparison between RBF and Kriging surrogates in design optimization of high dimensional problems. Proceeding of *3rd international conference on engineering optimization conference*, (pp. 1-5). Rio de Janeiro, Brazil.

Fedutenko, E., Yang, C., Card, C., & Nghiem, L., 2013. Optimization of SAGD Process Accounting for Geological Uncertainties Using proxy Models. Presented at *GeoConvention 2013: Integration*, Calgary, Alberta.

Forrester, A., Sobester, A., & Keane, A., 2008. *Engineering Design Via Surrogate Modelling: A Practical Guide.* 228 p. Chichester: Wiley, ISBN 0470060689.

Giunta, A., 2002. Use of Data Sampling, Surrogate Models, and Numerical Optimization in Engineering Design. Paper AIAA-2002-0538 in Proceedings of the *40th AIAA Aerospace Sciences Meeting and Exhibit*, Reno, NV.

Giunta, A., & Eldred, M., 2000. Implementation of a Trust Region Model Management Strategy in the DAKOTA Optimization Toolkit. *8th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*. AIAA-2000-4935. Long Beach, CA.

Giunta, A., Wojtkiewicz, S., & Eldred, M., 2003. Overview of Modern Design of Experiments Methods for Computational Simulations. Proceedings of the *41st AIAA Aerospace Sciences Meeting and Exhibit*. Reno, NV: AIAA-2003-0649.

Gutmann, H. M., 2001. A Radial Basis Function Method for Global Optimization. *Journal of Global Optimization*, 201–227.

Hardy, R., 1971. Multiquadric equation of topography and other irregular surfaces. *Journal of geophysical research*, 76(8), pp. 1905-1915.

Hasan, A., 2013. *Optimization and Control of Petroleum Reservoirs*. Doctoral Thesis. Norwegian University of Science and Technology.

Horowitz, B., Afonso, S. M., & Mendonça, C., 2013. Surrogate Based Optimal Waterflooding Management. *Journal of Petroleum Science and Engineering*, vl. 112, pp. 206–219.

Jansen, J. D., Brouwer, R., & Douma, S. G., 2009. Closed loop reservoir management. *SPE Reservoir Simulation Symposium*. Society of Petroleum Engineers.

Krishnamurthy, T., 2003. Response surface approximation with augmented and compactly supported radial basis functions. Proceeding of the *44 th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*. AIAA Paper (Vol. 1748).

Naevdal, G., Brouwer, D., & Jansen, J., 2006. Waterflooding using Closed-Loop Control. *Computational Geosciences*, 10, pp. 37-60.

Naidu, S. L., 2004. *Neural Network Surrogate Model For Multidisciplinary Design Optimization*. M. Tech. Dissertation, Indian Institute of Technology.

Oliveira, D., 2006. *Técnicas de Otimização da Produção para Reservatórios de Petróleo: Abordagens Sem Uso de Derivadas para Técnicas de Alocação Dinâmica das Vazões de Produção e Injeção*, Master Thesis (in Portuguese). Recife, Brazil: Civil Engineering Department, UFPE.

Oliveira, L., 2013. *Hibrid Strategy Applied to the optimum reservoir management* (Ph.D. Thesis). Recife: Federal University of Pernambuco.

Pinto, J. W., 2014. *Uso da Otimização Sequencial Aproximada a Problemas Uni e Multiobjetivos de Gerenciamento de Reservatórios*. Master Thesis (in Portuguese). Universidade Federal de Pernambuco, Recife, PE.

Tueros, J. H., 2015. Numerical experience with an ensemble-based method for constrined waterfloonding optimization. Rio Janeiro: *CILAMCE 2015. XXXVI Congresso Ibero Americano em Métodos Computacionais em Engenharia*.

Van Essen, G., Van den Hof, P., & Jansen, J. D., 2009. Hierarchical long-term and short-term production optimization. *SPE Journal*, 16(01), pp. 191-199.

Wild, S. M., Regis, R. G., & Shoemaker, C. A., 2008. ORBIT: Optimization by Radial Basis Function Interpolation in Trust-Regions. Cornell University, School of Operations Research and Information Engineering Technical Report: #ORIE-1459, To appear in *SIAM Journal on Scientific Computing*.

Wu, Z., 1995. Compactly supported positive definite radial functions. *Advances in Computational Mathematics*, 4(1), 283-292.