



Society of Petroleum Engineers

SPE-177255-MS

Short-Term and Long-Term Optimizations for Reservoir Management with Intelligent Wells

Marcio Augusto Sampaio Pinto, Santa Catarina State University; Eduardo Gildin, Texas A&M University; Denis José Schiozer, State University of Campinas

Copyright 2015, Society of Petroleum Engineers

This paper was prepared for presentation at the SPE Latin American and Caribbean Petroleum Engineering Conference held in Quito, Ecuador, 18–20 November 2015.

This paper was selected for presentation by an SPE program committee following review of information contained in an abstract submitted by the author(s). Contents of the paper have not been reviewed by the Society of Petroleum Engineers and are subject to correction by the author(s). The material does not necessarily reflect any position of the Society of Petroleum Engineers, its officers, or members. Electronic reproduction, distribution, or storage of any part of this paper without the written consent of the Society of Petroleum Engineers is prohibited. Permission to reproduce in print is restricted to an abstract of not more than 300 words; illustrations may not be copied. The abstract must contain conspicuous acknowledgment of SPE copyright.

Abstract

Short-term optimization of an oil field has been used to increase economic value of oil recovery as compared to reactive control (shutting the well when water cut limit is reached, for instance), especially in the case of short-term production strategies. One way to improve the management of a field involves adjusting the production flow rates over a short time, maximizing the overall NPV during the life cycle of the field. Using intelligent wells (IW), the challenges include not only the optimization of well flow rates, but also the simultaneous adjustment of flow in each valve, controlling each aperture in a given production time. These optimal control strategies are often difficult to be realized in practice due to the large number of control variables involved in the optimization process, especially with larger number of wells and valves. To this end, this work proposes an efficient optimization framework employing a fast genetic algorithm (FGA) in order to adjust simultaneously the flow rates of wells and the valves aperture. We have used a commercial reservoir simulator whereby the flow rates of wells were optimized with an option available that calculates well rates when there is production constraint on the wells (platform capacity or other operational constraint) using production parameters in real time; and at the same time the flow in each valve was controlled through a keyword associated with the control of the aperture of valves by monitoring the pressure drop around of them. The FGA optimization algorithm employed is a global optimization method, which is robust and efficient for sweeping the solution space with many variables, and it is able to work with continuous and discrete variables simultaneously. We demonstrate the power of the FGA strategy by applying the methodology to a heterogeneous reservoir model based on Brazil's Namorado field, with four horizontal producers and four horizontal injector wells. Two producers were tested as intelligent, using two valves of continuous variation type. The rate of wells was determined using water cut values while there were constraints on the production of the platform. The valves were adjusted each 60 days, during the first four years of production, closing in the optimal time at the end of production. The results showed an improvement in reservoir management, increasing 3.7% of NPV, with additional gains around US\$ 20 million (already discounted the costs of intelligent completion), increasing oil production and reducing water production. The combination of the tools available in a commercial simulator jointly with global optimization algorithm showed advantages of the operation of the wells and valves simultaneously.

Introduction

The management of a field can be improved finding optimal production strategies by means of dynamically adjusting the production flow rates over the reservoir production time. This optimization of the well flows may indicate the best way to maximize the economic output of the field, very often indicated by the net present value (NPV) of the operations. As it is known, realistic field production is not set as the operator will, but it is driven by operations constraints defined by the capacity of the platform and the surface facilities required to separate, process and store (or drain) all production (oil, water and gas). A major difficulty occurs in optimizing production of all wells, according to these constraints along the production of a field.

For this reason, designing optimal well control strategies taking into account realistic production constraints and well allocation rates is paramount for the increase in reservoir recovery factor and, in turn, the NPV of the project. To this end, this article aims at developing a fast methodology for the optimization of the well flows over the production life-cycle of a realistic field with several wells and constraints.

Production optimization in waterflooding processes can be considered a mature research area. Many developments in the last decade have proven to validate the closed-loop reservoir paradigm, i.e., combining production optimization and history matching in a seamless fashion. However practical implementations of the entire concept is still making its way to full realization in the industry. One of the main reason for the slow acceptance is due to the computational cost associated with the optimization processes involved. Methodologies to mitigate this cost has been evolving in both in numerical optimization and fast reservoir simulation strategies. In what follows we summarize some of the old and new accomplishments in these areas.

We start with the seminal work on the closed-loop paradigm in Brouwer et al. (2004). In this paper, the authors demonstrated the effect in improving the NPV in waterflooding processes by combining the Ensemble Kalman filter, to continually update the model, with the adjoint-based optimization technique to control water rates of wells. In this case, the static parameters (permeabilities) and dynamic (pressures and saturations) could be updated in the reservoir through the new production data of the model using the Kalman filter. Based on updated parameters, an optimal strategy of water injection could be determined for the rest of the production process. The methodology was applied in two synthetic cases, thus allowing comparison with traditional production strategies. Significant increases of the NPV, accelerating oil production, oil recovery and reduce water production were obtained. For example, the oil recovery increase was about 40%, a value very close to the increase obtained in a previously a priori known reservoir.

Liang et al. (2007) presented a methodology for optimizing the oil production by adjusting the water injection flow rates in a mature field, considering the production capacity of the model. To this end, the method considered oil and water production and injection flow-rates parameters, taking into account the revenue from oil produced and the cost of water injected and produced. A non-linear programming method was used to maximize the future economic return. Emphasizing that the optimal flow injection depend on the cost of the water injected, leading some injectors to close due to low contribution, while others operate in maximum rate defined. The proposed method can be used to control real-time production and is suitable for the simultaneous optimization of the wells flow rates in a field where the injectors frequently close.

Van Essen et al. (2009) highlighted that the optimizations of oil and water injection rates are usually neglected, decreasing the performance of short-term production. To circumvent this problem, they proposed a hierarchical structure optimization with multiple objectives, using the NPV of the long-term (J_1) as a primary objective and operational performance (undiscounted NPV) of short-term (J_2) as a secondary objective. Thus, the proposed method performs optimization of short-term (maximizing J_2) with the constraint that the NPV values remain very close to the optimum value of the NPV of long-term

(minimizing $J_1 - J_2$). For this, a method based on gradients comprising a set of equations to determine the adjoint gradients was used, thus optimizing the long-term production. As for the optimization of short-term, used as parameters of water injection rates in each period of 900 days in a total time of 3600 days, employing the method of steepest descent. The methodology was applied in a reservoir with aquifer in the bottom. The results showed a significant increase in the production of short-term (increased undiscounted NPV of 28.2%), driving the first year of production by a factor 2, without significantly compromising the primary objective, showing a small decline in the NPV of only 0.3%. Thus, the study was able to perform the optimization of short-term, without significantly prejudice the long-term optimization.

Cardoso and Durlofsky (2010) proposed a trajectory piecewise linear procedure (TPWL) to reduce the order of a two-phase flow model. This method represents new pressure and saturation states using linear around previously simulated and saved during a series of preprocessing training runs. The model obtained by TPWL was applied to two examples, one containing 24,000 and another 79,200 gridblocks in the loop simulation. The results of the reduced model were quite accurate when the controls (BHP for producer wells) applied in tests simulation are within the general range of the controls applied in the training runs. The model was shown to reduce the computational power significantly, by a factor of 100-2000, depending on the size of the model, for the cases considered. Subsequently, the model was applied to a problem of multi-objective optimization to determine the Pareto frontier using a gradient-based (using *fmincon* of Matlab) method, maximizing the accumulate oil production and minimizing the accumulate water injection. The results showed high accuracy and applicability of TPWL for this type of optimization over models of high fidelity (conventional simulation).

Dehdari et al. (2012) tested the use of three different optimization algorithms to evaluate the efficiency in finding the optimal value of NPV in management of a field with restrictions, by adjusting the flow rates of the producer and injector wells. The algorithms employed were: steepest ascent (SA), sequential quadratic programming (SQP) and interior point (IP). Although the SA method does not require much computational effort, was unable to achieve a high value of the NPV because of the neglect of constraints in the gradient. Since the method of SQP often find the maximum NPV, but with substantial computational cost for each iteration due to the need to identify the active constraints. On the other hand, the IP method, though not able to obtain the maximum NPV that SQP was able to achieve greater NPV than SA with similar computational cost. These analyzes could be made by studying the Brugge field with constraint on total flow of liquids. In all methods, the control gradients were calculated using ensemble based method.

Asadollahi et al. (2012) proposed a methodology to perform the optimization of water injection to reduce considerably the variables of problem through a simple procedure for low cost, using concepts of reservoir engineering to efficiently initialize the local search for algorithms of optimization. The initialization strategy is applied to history matching the Brugge Field model, prepared for the management of short-term reservoir. Three algorithms of optimization were also evaluated and compared: the standard search of Hooke-Jeeves, the simplex method of Nelder-Mead and sequential quadratic programming. The methodology presented many advantages. First, it is simple and easy to program in any reservoir simulator. Second, only one simulation is needed after the initial for a reasonable initial solution. Third, it is not necessary to connect the non-linear constraints in a complex implementation of non-linear inequalities. Among the algorithms of optimization, the standard search of Hooke-Jeeves showed the best performance.

Gildin et al. (2013) proposed the use of proper orthogonal decomposition (POD) to perform the reduction of reservoir model, and thus reduce the computation time spent in the simulations. To reduce the complexity of the nonlinear terms and increase the speed of each run, the POD was modified by adding a discrete empirical interpolation method (DEIM), forming the POD-DEIM method. Performed a comparison with the trajectory piecewise linear (TPWL), but this approach modestly reduced the computational time as preserving all states of the model, unlike the POD-DEIM where the nonlinearities

are approximations based on interpolation taken by DEIM. The results showed a high correlation between a reservoir model and the reduced model using POD-DEIM, indicating a promising technique that deserves further investigation.

Genetic algorithms (GA) were used in the optimization framework in (Almeida et al., 2010; Sampaio et al., 2011; Sampaio et al., 2012), showing significant progress compared to classical optimization methods. In (Sampaio et al., 2015a), GA and model reduction by means of the POD-DEIM were coupled to yield even faster computations solutions. However, the full closed-loop framework was not tested in that case. In this paper, we attempt to couple short- and long-term production in a constrained reservoir setting. The optimization process is accounted for after some of the production strategies is established, i.e., after the project variables (number of wells, type, placement and schedule of wells, and capacities constraints of liquid, oil and water production and also water injection) are defined. This work employs a reservoir model well suited to represent a realistic oil field in the offshore of Brazil (in deterministic condition), therefore, without the need to realize the history matching of the model. For the optimization method, we employ a fast genetic algorithm (FGA), which is a robust and efficient method for sweeping the solution space with many variables and it has been used in some studies (Almeida et al., 2010; Sampaio et al., 2011; Sampaio et al., 2012), outperforming classical optimization techniques.

The main objective of this paper is optimize the control variables, adjusting well flow rates and valves aperture of IW, in the short-term fashion, aiming to maximize the NPV of the field, improving the reservoir management and observing the effects of long-term. To this end, we organized this paper as follows: we start by introducing the fast GA methodology and its algorithm. We then show how this can be implemented in a commercial reservoir simulation software and apply it to several test cases. Results and conclusions are discussed in the end.

Methodology

The optimization methodology is divided in two main strategies, acting simultaneously: (1) short-term and (2) long-term. The former is embedded in the latter and comprises four years of production. The long-term strategy accounts for 30 years of production, which is considered the life-time of the reservoir production. The general framework is showed in Figure 1.

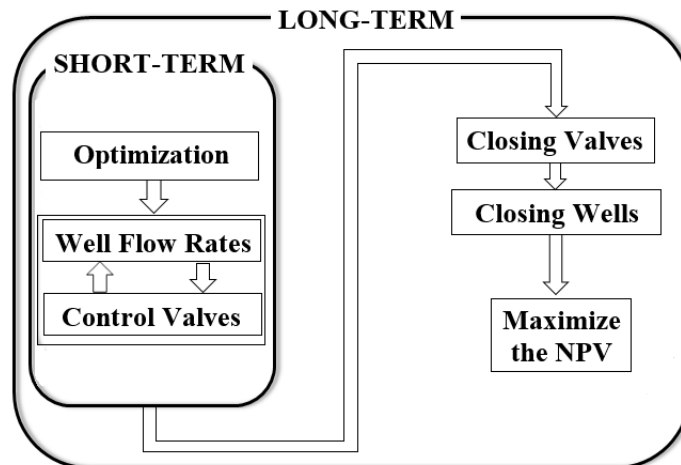


Figure 1: Flowchart of the general methodology framework.

Optimization Process: Fast Genetic Algorithm

Due to the limitations of the classical methods of optimization to work with many variables, this paper employs a genetic algorithm, which is a global-optimization method that performs the search for an optimal (or suboptimal) solution using concepts of the theory of evolution and natural selection

(Goldberg, 1989, Koza, 1992, Mitchell, 1996). This method is based on the simulation of evolution of species through selection, mutation and reproduction. It uses a population of structures called chromosomes or individuals, which are then subjected to genetic operators such as recombination and mutation, among others, that simulate reproduction and genetic mutation, respectively. Each individual is submitted to an evaluation that determines its quality as a solution to the problem. This evaluation determines which chromosomes will apply genetic operators to generate offspring. This optimization comprises global optimization step. In this work, we use GA, with advanced genetic operators called fast genetic algorithm (FGA). These advanced operators aim to accelerate the search for the maximum global. Next, we describe how to this method is used in the production optimization scenario and we detail its implementations.

To solve the problem proposed in this work, an external program was coupled with a commercial reservoir simulator. The genes in this study are: (1) the apertures of valves (5 positions) during the short-time (4 years), (2) parameters of the GUIDERAT control, that is, the allocation of fluids, and (3) the values of water cut in each intelligent wells (IW) valve or for the entire conventional well (CW). Valves operate in a continuous variation system, determined by the optimal closing found by the FGA to maximize the NPV of the field. Thus, the methodology used can be considered an optimal strategy of the control of valves in the beginning of production and closing of valves and wells at different times over the exploitation of the field in order to maximize the profitability of production.

Initially, the FGA creates a random initial population, and these values are written into files (input) which are simulated to provide production data. The program then reads the results (output) generated by the simulator to calculate the NPV. The algorithm makes the selection of individuals with higher NPV, storing the best ones. This is done so that the algorithm seeks out the best solutions, but also preserves those solutions over succeeding generations. The determined NPV values are ordered using Sigma Scaling, a modified evaluation function (Mitchell, 1996). With the assessment of each individual, the selection of parents is performed to be used in the crossover. The selection of parents is done by Uniform Stochastic Sampling (Mitchell, 1996). Once the parents are selected, the crossover is done through another operator, the Uniform Crossover. After the crossover, the mutation operator is applied, which is a random selection of individuals from the current population and genes, randomly exchanging these genes for others. With the mutation carried out, a new population is created. These created individuals are tested against a database to check if those individuals have already been previously used. If so, it generates a new individual to replace this individual by applying the operator of mutation. Figure 2 shows the flowchart, which summarizes the steps taken to optimize the all variables. In this work, as described above, three independent populations are evolving with time, due to each of the three types of variables employed in the optimization process.

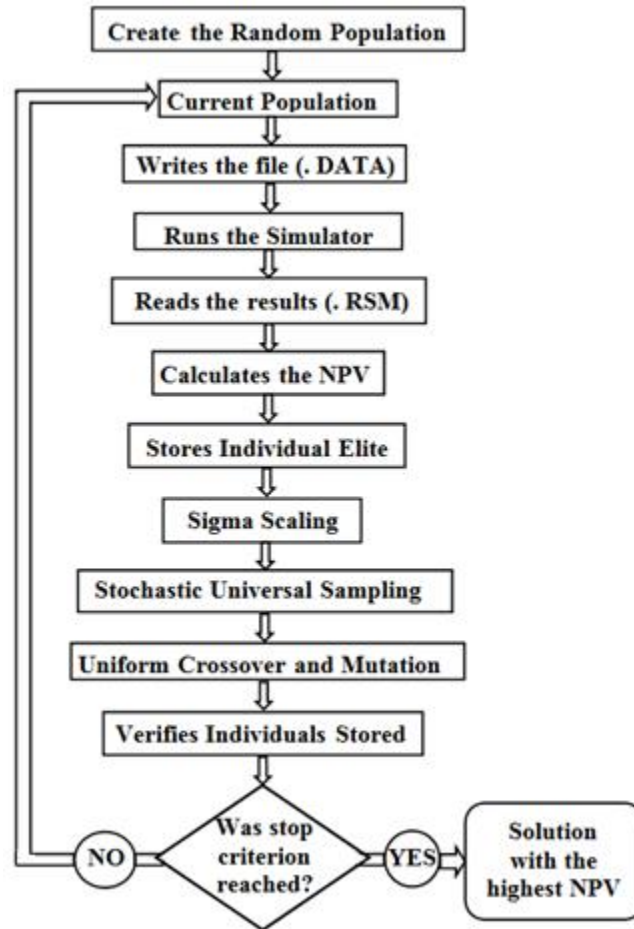


Figure 2: Flowchart of the FGA optimization framework.

Well Flow Rates: GUIDERAT

In order to determine the individual flow rates of each well, a systematic way to distribute the rates need to be obtained. In the case of the Eclipse simulator, GUIDERAT command can be used for that purpose. It basically distributes flow rates, during the constraint of platform production, through a user-defined formula. The simulator makes this distribution of flow during the period in which production is being (apportionment) limited by the maximum production. In this case, the simulator needs to calculate a flow rate for every well that is limited (Schlumberger, 2006).

This formula can be used to calculate the flow rates of the wells as a function of the potential of production of wells and ratios such as GOR (gas-oil ratio) and OWR (oil-water ratio). Thus, in the beginning of the next timestep, the flow rate for a given phase p is calculated by the equation:

$$GR_p = \frac{(POT_p)^A}{B+C(R_1)^D+E(R_2)^F} \quad (1)$$

where POT_p is the potential of well or group for the phase p ; A , B , C , D , E and F are coefficients of weights and exponents; R_1 and R_2 are the ratios for the potential of the phases according to the phase p .

The users can determine the coefficients by trial and error, through information obtained from the reservoir production or found through optimization methods in order to maximize the NPV or oil recovery, depending on the company's interests. In this paper, we apply the genetic algorithm to determine the parameters that maximize the NPV.

For this, we applied the control of wells based on values of water cut. The Equation 1, used the descending order of the values of the inverse of water cut to be used in the apportionment (or ascending order of the water cut values). Thus, the wells with lower values of water cut were prioritized in relation to wells with higher values of water cut. In this way, the parameters have the following values: $A = B = 1$, $E = F = 0$, C and D were also variables of the optimization process, with constraints of $-3 \leq C \leq 3$ and $-3 \leq D \leq 3$.

Control Valves

The modeling of IW operation is performed with proactive control, using operation mode of the continuous type (five positions of aperture of the valves: 0%, 25%, 50%, 75%, and 100%). Here we used the intelligent completions tools provided by the commercial reservoir simulator.

IW can be represented in a simulator, grouping blocks to form independent completions with a valve that will control the flow through the segment, with independent oil and water productions, but united by production tubing to form the well. In the Eclipse simulator, this grouping of the layers can be done by using the keyword COMPLUMP.

For short-term, the continuous mode is used to control valves by monitoring the pressure drop due to flow in the area of the cross section, using the keyword WSEGVAlV. This type of control involves adjusting areas of valve aperture, such as settings of ICV that act as subsurface chokes. Then, the problem is to find the optimum ICV configuration. This study uses four valves in two horizontal producers (two valves for each well). To perform the optimization, the long-term period considered was the simulation time of 30 years. The short-term was considered the first four years, divided into intervals of 60 days. So, every 60 days, it was necessary to determine the aperture of each valve in order to maximize the NPV of the field. This results in 24 intervals. Thus, the problem is to optimize four valve apertures in 24 time intervals for each IW used in each case. At the end of production, the valves were closed in the optimal time, to achieve the water cut limit.

The pressure drop across an ICV is calculated for a single-phase flow considering the sum of effects of constriction and any additional friction pressure loss due to flow through the ICV (Schlumberger, 2006). Mathematically:

$$\delta P = \delta P_{cons} + \delta P_{fric} \quad (2)$$

where δP_{cons} is the pressure drop due to flow through constriction and is given by:

$$\delta P_{cons} = C_u \frac{\rho v_c^2}{2 C_v^2} \quad (3)$$

where C_u is a unit conversion constant, ρ is the density of the fluid mixture, v_c is the flow velocity of the mixture through the constriction and C_v is a dimensionless flow coefficient for the valve.

And δP_{fric} is additional friction pressure loss in the segment containing the valve, given by:

$$\delta P_{fric} = 2 C_u f \frac{L}{D} \rho v_p^2 \quad (4)$$

where f is the Fanning friction factor, L and D represent the length and diameter of the pipe segment and v_p is the flow velocity of the mixture through the pipe. In this work, it was not considered a component of friction. Therefore, the ICV configuration depends on total pressure drop, which is a function of the cross section area of the valves. These areas changed between five positions during short-term and open/closed at the end of production, in order to maximize the NPV.

Case Study

This section presents the application of the methodology using a realistic reservoir model, with four producers and four injectors, under water injection recovery process. The maximum simulation time was defined as 30 years.

Reservoir Model

The simulation models used are synthetic, where rock and fluid properties are based on Brazil's Namorado field. The dimensions of the grid are of 50 x 90 x 10 blocks, with each block 50m x 50m x 10m in size. The grid used in the models is Cartesian. Table 1 presents the data of rock and fluid properties of the model. The oil used was light oil with 27.72 °API and residual saturation of 20%. The bubble pressure was approximately 206 bar and the initial pressure of the field was 330 bar. This model was created through the combination of different arrangements of high permeability channels and different arrangements of sealant faults.

Table 1: Properties of Rock and Fluids

<i>Parameter</i>	<i>Value</i>	<i>Unity</i>
Permeability (outside of channels)	mean of 200	mD
Permeability (inside of channels)	4000	mD
Porosity	0.15 ~ 0.30	----
Reference pressure of rock	283.91	bar
Compressibility of rock	4.514×10^{-5}	bar ⁻¹
Reference pressure of water	315.75	bar
Compressibility of water	4.351×10^{-5}	bar ⁻¹
Density of water	1.06	----
Top of reservoir (mean)	3160	m
Oil-water contact (mean)	3265	m

Well Configurations

Four producer and four injector wells were used, all horizontal with 500 m of length. The producer wells were completed in the second layer of the model, and the injectors in the tenth and last layer of the model. The optimization of well placement was done by Silva and Schiozer (2009). The model is shown in the Figure 3.

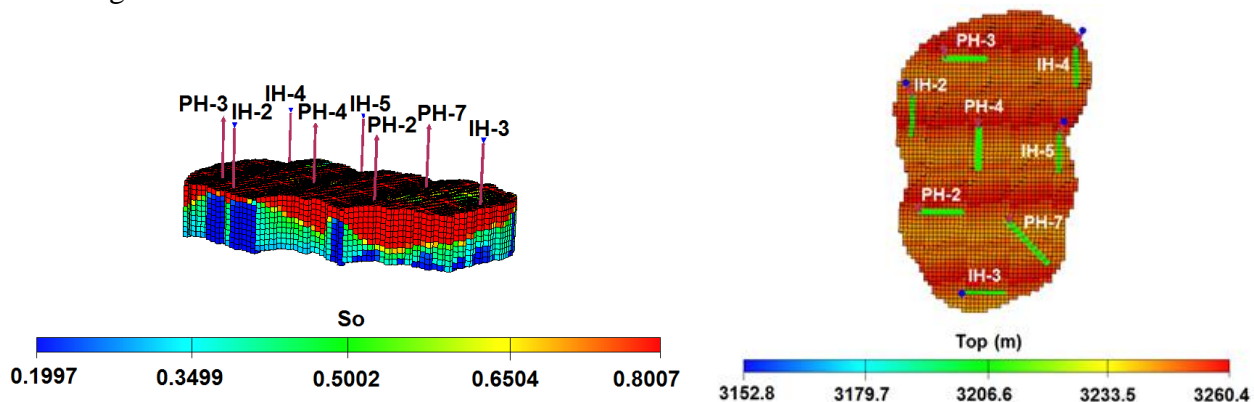


Figure 3: Model employed in this work.

The schedule of well entry was two months, alternating between producer and injector. In our model, we only tested IW in the producer wells. The operational restrictions of the wells are listed in Table 2. For injectors, the maximum rate of water injection is equivalent to the fluid production volume, considering reservoir conditions to avoid high pressurization.

Table 2: Operational restrictions of the wells

<i>Producer Wells</i>		<i>Injector Wells</i>	
Control Mode	Liquid Production	Control Mode	Surface Rate
Maximum Rate	3500 m ³ /day	Maximum Rate	5500 m ³ /day
Minimum BHP	210 bar	Maximum BHP	400 bar

It should be pointed out that these values remained fixed throughout the optimization process. The injection system used was peripheral. An operating condition was also used that limits the maximum amount of water injected to the total volume of fluid produced, so as to avoid the high pressurization of the reservoir. Another operational constraint results from the maximum capacity of the platform, a limitation imposed on the group of producer wells. The platform used in this work had a maximum capacity of 9062 m³/day of liquid (approximately 57,000 barrels/day).

Fast Genetic Algorithm Parameters

Table 3 presents the FGA parameters used in each case. There are 6 variables for the water cut values (one variable for each valve and one for each conventional well), 2 variables for parameters of Equation 1 (C and D parameters) and 96 variables for control valves during 4 years (four variables for each interval time).

Table 3: Genetic algorithm parameters

<i>Parameters</i>	<i>Values</i>
Number of Generations	100
Size of Population	312
Number of Elite Individuals	1
Mutation Rate	0.1
Crossover Rate	0.9

Economic Scenarios

The chosen platform with the desired production capacity was estimated to cost US\$ 572 million. This value was found by taking into account the maximum capacity of liquid processing. The values for economic scenario are shown in Table 4.

Table 4: Economic data

<i>Economic Scenarios</i>	<i>Discount Rate (% p.a.)</i>	<i>Oil Price (US\$/bbl)</i>	<i>Oil Production Cost (US\$/bbl)</i>	<i>Water Production Cost (US\$/bbl)</i>	<i>Water Injection Cost (US\$/bbl)</i>
Probable	8.80	50.00	8.00	1.00	1.00

The economic base model was selected following a simplified Brazilian fiscal regime, assuming: 25% corporate tax rate, 10% in royalties, 9% in social benefits contributions, and 10 years of linear depreciation.

The investments were distributed in the following manner: US\$ 100 million for exploration, US\$ 15 million for evaluation, US\$ 40 million for conventional perforation of the wells, and US\$ 115 of

abandonment cost. For the IW, the values of Table 5 below are considered, for the additional investment of intelligent completion for continuous type of valves. With these values, one IW with 2 valves of continuous type has a cost of USD 2.5 million. Therefore, in this work the total investment in intelligent completion was USD 5 million.

Table 5: Additional Cost for Intelligent Completion

	<i>Cost of Intelligent Completion (USD millions)</i>
Intelligent completion	1.00
Additional for each valve of continuous type	0.75

Results and Discussions

The main results are presented in this section. The base case was the optimization of all producers as standard wells (no intelligent completions). For the case with intelligent wells, we used two intelligent producers and two conventional. The rationale for this choice was based on the work of Sampaio et al. (2015b), which took into account which wells had the potential to become intelligent, to thereby determine the best number and placement of valves.

Short-Term Analysis

Table 6 shows the results obtained for the optimization with two cases described above. These results refer to the end of the short-term, i.e., the end of four years. Although the optimization has been made taking into account the NPV of the field during the 30 years, these results can help us to analyze the effects of optimization in the short-term. As can be seen, the optimization process was able to increase oil production and reduce water production and injection, showing that the optimization of the valves just in the early years of production can bring benefits in the oil production, and reducing water production and injection. This type of control, for being proactive type, requires that the reservoir manager has good knowledge of the reservoir characteristics to operate the valves appropriately (Sampaio et al., 2015b).

Table 6: Results for short-term optimization (4 years)

<i>Short-Term (4 years)</i>	<i>Cumulative Oil Production (10⁶ std m³)</i>	<i>Cumulative Water Production (10⁶ std m³)</i>	<i>Cumulative Water Injection (10⁶ std m³)</i>
Conventional Wells	11.13	1.16	15.69
With Intelligent Wells	11.21	1.08	15.64
Δ	+ 0.08	- 0.08	- 0.05
%	+ 0.73	- 7.08	- 0.35

Figure 4 shows the regions in which the oil production was increased, and the periods in which water production was reduced, clearly showing the benefits of optimization in the short-term.

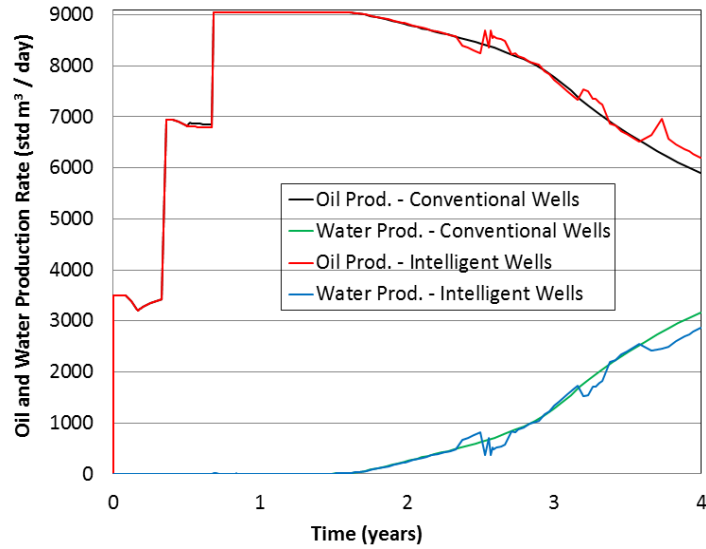


Figure 4: Oil and water production for two cases optimized in the short-term.

Long-Term Analysis

Now the Table 7 shows the optimization effects of long-term (30 years). As can be seen, the short-term effects in the long-term also intensified, increasing the oil production and NPV, also reducing the water production. Highlight for the increase of the NPV of USD 20.19 million, already discounted the costs of intelligent completion. These results show that we can enhance the short-term and long-term production simultaneously.

Table 7: Results for long-term optimization (30 years)

<i>Long-Term (30 years)</i>	<i>Cumulative Oil Production (10⁶ std m³)</i>	<i>Cumulative Water Production (10⁶ std m³)</i>	<i>Cumulative Water Injection (10⁶ std m³)</i>	<i>NPV (US\$ millions)</i>
Conventional Wells	28.28	70.06	107.92	522.14
With Intelligent Wells	28.48	69.86	107.92	542.33
Δ	+ 0.20	- 0.20	0.00	+ 20.19
%	+ 0.71	- 0.28	0.00	+ 3.72

Figure 5 shows the periods when the oil flows increased and water flows decreased. We can also see that the optimization process has been beneficial for the entire production period, highlighting the importance of optimizing the short-term but while benefiting also the long-term. These results also show the advantages of optimizing the flow rates of wells and valves simultaneously, using the proposed methodology.

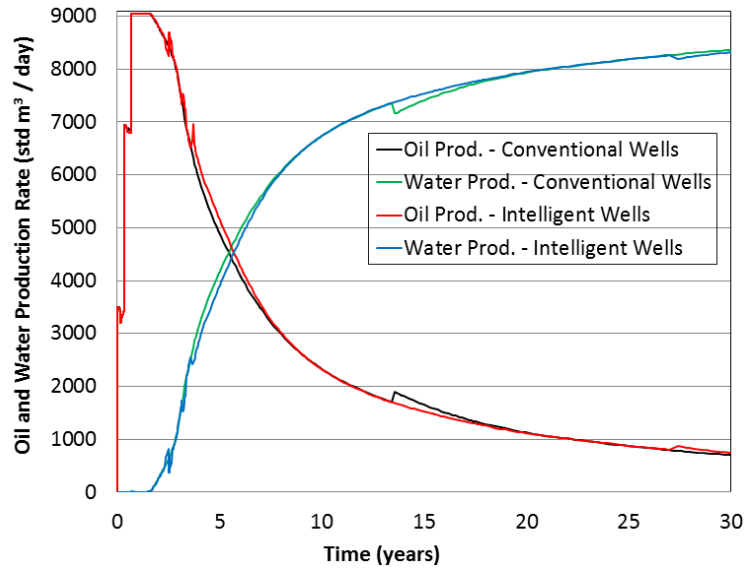


Figure 5: Oil and water production for two cases optimized in the long-term.

Optimization Process

Figure 6 shows the results of the optimization process. For the base case, all producers as conventional, it is necessary to maximize NPV, having 4 variables for wells to establish the water cut limit for each one. In this case, the maximum value of NPV was reached with only 135 simulations. For the case with two intelligent producers and two conventional producers, 104 variables were necessary, corresponding to the optimal apertures of each valve of IW every 60 days over 4 years (four valves optimized in each 60 days during 4 years, 96 variables in total), 2 variables for two parameters for Equation 1 and 6 variables for water cut limit for each valve and two conventional producers. The maximum value of NPV was reached, in this case, with 10079 simulations. From the graph, it can also be seen that the parameters of the genetic algorithm chosen are sufficient to achieve the convergence for a better solution (optimal or suboptimal). It can be clearly seen that the choice of replacing two conventional producers by two intelligent producers, in this case, brought advantages to increase the NPV of the field.

The set of FGA with GUIDERAT command showed to be efficient in maximizing the objective-function, once this command allows to reduce the number of variables in the process, since it uses production data in real time (water cut values), needing only two variables to determine the flow rates of wells. The methodology proved to be robust to optimize both the flow rates of wells and the flow of valves (controlling the aperture of valves). The choice of a global optimization algorithm proved to be essential in the application of our case, since 104 control variables (with three different types of variables) were used in the optimization process, once the application of the gradient-based methods would be unfeasible in practice.

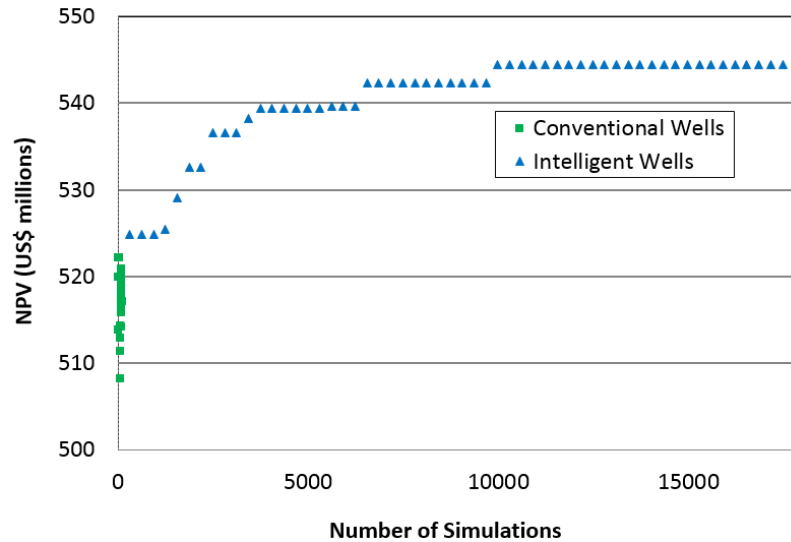


Figure 6: Number of simulations required to achieve maximum NPV with FGA.

Conclusions

The results presented here show that the short-term optimization also aiming to optimize the long-term can bring benefits to both periods analyzed. Also shows these benefits by employing IW, exploiting the flexibility of the valves. These results were based on the maximization of the NPV but other options can be selected depending on the objectives of the company.

In the cases tested, the results have shown the advantages of employing the configuration of the case with IW (option with two intelligent producers and two conventional injectors). This can be explained by the fact that in this case, simultaneous optimization of flow rates of wells and valves can be improved the oil recovery, increasing oil production and NPV. The GUIDERAT control was also important to reduce the number of variables in the process.

The optimization process although has showed global efficiency, many simulations needed to start convergence. This problem can be minimized in the future by employing so-called model order reduction such as POD and TPWL, which can be speed up the simulation time.

Many articles have shown the benefits of short-term optimization, but without taking into account the long-term effects. This paper showed that we can increase oil production in the short-term and also in the long-term, maximizing the NPV of the field.

Another important point to note is the fact that short-term optimization, carried out in this work in the first four years, unfortunately requires a high level of knowledge of the characteristics of the reservoir from the beginning of development of the field, since we apply a proactive control of valves of IW. And as we know, the level of knowledge of the reservoir characteristics will expand along time production. An alternative to overcome this difficulty is the use of representative models (Schiozer et al. 2004), using EMV instead NPV, which can be tested in future work.

Nomenclature

BHP – Bottom Hole Pressure

CW – Conventional Well

DEIM - Discrete Empirical Interpolation Method

EMV- Expected Monetary Value

FGA – Fast Genetic Algorithm

GOR – Gas-Oil Ratio

ICV – Inflow Control Valves

IP - Interior Point
IW – Intelligent Well
NPV – Net Present Value
OWR – Oil-Water Ratio
POD - Proper Orthogonal Decomposition
SA - Steepest Ascent
SQP - Sequential Quadratic Programming
TPWL - Trajectory Piecewise Linear

Acknowledgments

The authors would like to thank Santa Catarina State University, Texas A&M University, UNISIM, CEPETRO, UNICAMP, PETROBRAS, CMG and Foundation CMG for supporting this research and development project.

References

- Almeida, L. F.; Vellasco, M. M. B. R.; Pacheco, M. A. C; Optimization system for valve control in intelligent wells under uncertainties, *Journal of Petroleum Science and Engineering*, Elsevier, Amsterdam, 73 (2010) 129 – 140, 2010.
- Asodollahi, M., Naevdal, G., Shafieirad, A., Efficient Workflow for Optimizing Well Controls. *Journal of Petroleum Science and Engineering*, 82-83 (2012) 66-74.
- Brouwer, D. R., Naevdal, G., Jansen, J. D., Vefring, E. H., Van Kruijsdijk, Improved Reservoir Management Through Optimal Control and Continuous Model Updating. SPE 90149. 2004 SPE Annual Technical Conference and Exhibition; Houston, EUA; 2004.
- Cardoso, M. A., Durlafsky, L.J., Linearized Reduction-Order Models for Subsurface Flow Simulation. *Journal of Computational Physics*, 229 (2010) 681-700.
- Gildin, E., Ghasemi, M., Protasov, A., Efendiev, Y., Nonlinear Complexity Reduction for Fast Simulation of Flow in Heterogeneous Porous Media. SPE 163618. 2013 SPE Reservoir Simulation Symposium; Texas, EUA; 2013.
- Goldberg, D. E., Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley Longman Publishing Co., Inc., USA, 1989.
- Dehdari, V., Oliver, D.S., Deutsch, Comparison of Optimization Algorithms for Reservoir Management with Constraints – A Case Study. *Journal of Petroleum Science and Engineering*, 100 (2012) 41-49.
- Liang, X., Changsha, H., Weber, D. B., Edgar, T. F., Lake, L. W., Sayarpour, M., Al-Yousef, Optimization of Oil Production Based on A Capacitance Model of Production and Injection Rates. SPE 107713, 2007 SPE Hydrocarbon Economics and Evaluation Symposium, Dallas, USA, 2007.
- Koza, J. R., Genetic Programming: On the Programming of Computers by Means of Natural Selection. MIT, Press, USA, 1992.
- Mitchell, M., An Introduction to Genetic Algorithms. MIT, Press, USA, 1994.

- Sampaio, M. A., Barreto, C. E. A. G., Ravagnani, A. T. F. S. G., Schiozer, D. J., Comparison between Smart and Conventional Wells Optimized under Economic Uncertainty. OTC 22426, 2011 Offshore Technology Conference Brasil, Rio de Janeiro, Brazil, 2011. doi: 10.4043/22426-MS
- Sampaio, M. A., Barreto, C. E. A. G., Schiozer, D. J., Optimization of Proactive Control Valves of Producer and Injector Intelligent Wells under Economic Uncertainty. SPE 154511, 2012 EAGE Annual Conference & Exhibition incorporating SPE Europec, Copenhagen, Denmark, 2012. doi: 10.2118/154511-MS
- Sampaio, M. A., Ghasemi, M., Sorek, N., Gildin, E., & Schiozer, D. J. (2015, February 23). Hybrid Optimization for Closed-Loop Reservoir Management. 2015 SPE Reservoir Simulation Symposium, Houston, Texas, USA, February, 2015. doi:10.2118/173278-MS
- Sampaio, M. A., Barreto, C. E. A. G., Schiozer, D. J., Assisted optimization method for comparison between conventional and intelligent producers considering uncertainties. *Journal of Petroleum Science and Engineering*, 133 (2015) 268-279. doi: 10.1016/j.petrol.2015.06.023
- Schiozer, D. J.; Ligerio, E. L.; Suslick, S. B. ; Costa, A. P. A. Use of representative models in the integration of risk analysis and production strategy definition. *Journal of Petroleum Science & Engineering*, Amsterdam, v. 44, n.1-2, p. 131-141, 2004. doi: 10.1016/j.petrol.2004.02.010
- Schlumberger, 2006. Eclipse Reference Manual - Multi-Segment Wells 2006.2.
- Silva, J.P.Q.G., Schiozer, D.J., Methodology to compare smart and conventional wells. In: Proceedings of 2009 Annual Technical Conference and Exhibition, SPE 124949, New Orleans, USA, 2009.
- Van Essen, G. M.; Jansen, J. D.; Brouwer, D. R.; Douma, S. G.; Rollett, K. I.; Harris, D. P.; Optimization of Smart Wells in the St. Joseph Field, SPE 123563, 2009 SPE Asia Pacific Oil and Gas Conference and Exhibition, Jakarta, Indonesia, August, 2009.