Abstract

In this work a methodology of production strategy optimization, based on genetic algorithms (GA) is presented. The process aims to maximize the net present value (NPV) of the field and it is performed in terms of number and placement of wells. Independents optimization stages of quantity and placement of wells are alternated until the procedure convergence. The optimization stages of well placement are performed exclusively by a GA fitted with the goal of reducing the number of simulations needed for maximizing the NPV of the field. The optimization stage of quantity of wells may be carried out both by GA as an enumerative technique. The choice is made, automatically, for the method that requires the lowest number of flow simulations.

The proposed methodology is applied in a selection process of production strategy. A case that aims to check the potential of performance of two production strategies is examined. The first production strategy is composed exclusively by vertical wells while the second one is composed exclusively by horizontal wells. The proposed methodology is used in the optimizations, subsidizing the selection process of the production strategy.

It is possible conclude that the methodology proposed gives a greater efficiency and reliability to optimization processes of production strategy. In addition, with the automated procedure, it is possible to evaluate a greater number of possibilities, increasing the scope of search for the best production strategy.

Introduction

One of most important tasks of a process of production strategy optimization is the definition of the quantity and placements of wells. These items may bring great impacts in project investments and production curves. The well quantity optimization allows defining ideal investment to be carried out in project while the well placement optimization allows maximize the field performance at a fixed investment level.

Generally, the process of production strategy optimization leads to a response surface of high complexity, where the potential for generation of local extreme values is high. In this context, it is interesting the employment of robust search techniques by global extreme value, such as GA. This type of optimization technique exploits better the solution space yielding better results and reliability. However, these techniques tend to require a longer time of processing than others. In this work, it is proposed a methodology for production strategies optimization based on genetic algorithms, which aims to reduce the number of flow simulations necessary to maximize the net present value (NPV) of the project. The main idea is to control the size of solution space through an appropriate design to the chromosome structure and performing specifics stages of optimization.

Genetic Algorithms

The nature has many examples of robust solutions for adaptability of living beings to most different environments (Futuyma, 1989). The key to understand this process is in Darwinism that has progressed since its

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1 Enumerative techniques are those that search the global extreme value through a complete inspection of solution space.
proposition in 19th century by Charles Darwin until the called modern synthesis of evolutionary theory, or neo-Darwinism, in the middle of 20th century, which systemizes the evolutionary process and its mechanisms. Many of these mechanisms may be reproduced to solve engineering problems. GA aim to copy these natural mechanisms to apply them in optimization processes. Frequently, GA are applied in optimization problems involving large solution spaces and with high potential for generation of local extreme values. The application of GA in this kind of problem is justified by the capacity of this kind of algorithm to escape of regions of local extreme values and better exploit the solution space.

GA are based on concepts as selection, crossover, inheritance and mutation (Goldberg, 1989; Mitchell, 1996 and Michalewicz, 1996). A random process guides, in part, these algorithms, that give a greater dispersion to the search, ensuring that the solution space is better exploited. Although the heuristic of GA owns a dispersive character, the procedure is not essentially random. The algorithm uses the built historic to define the next points to be evaluated.

The analogy between the optimization by GA and evolutionary process of living organisms forces the application of characteristic terms of biological sciences to describe the processes of mathematical optimization. An optimization problem can be approached by a GA; it needs a chromosomic representation. All possible solutions (solution space) to the problem must follow a structure, which has similarities with the structure of a chromosome of an organism. In simple cases, where a possible solution to the problem may be represented by a single chromosome, commonly, it is used a simple string of variables to be optimized. Each element of this string receives the designation of gene. Therefore, in such cases, a single chromosome that is composed of various genes defines an individual (possible solution). Each individual has a fitness to solve the problem. This fitness is a measure of relative performance on individuals and it is calculated from the objective-function of the optimization process. In this way, the individuals most suitable are those that have better values of an objective-function.

The set of individuals generated in the same stage of the evolution process is called population and the own stages of evolutionary process is called generations. A number of genetic operators (selection, crossover, mutating etc.) will act in a population aimed at creating a next generation of individuals more suitable.

Selection operators work to form pairs of individuals that should be crossed for the formation of a new generation. Individuals who are more suitable must have a higher probability to participate in the crossover process for their genes have important presence in the next generations. Individuals less suitable must have a smaller probability to participate in the crossover process. The probability is not zero allowing the search far from the best individuals.

The crossover operators carry out the blending of individual's genetic material in order to generate descendants who will form the next generation. The blending of genetic material from two individuals may be performed in various ways. A common used form is to define cutoff points in the string of values that defines the chromosomes of parents to form the son through the concatenation of complementary pieces of parent’s chromosomes. The crossover may be performed also by mathematical operations between the parent’s genes. In this way, the son genes would be mathematical results of operations between the parent’s genes. Therefore, there is flexibility in the definition of the crossover operator to suit the needs of the problem.

The mutations guarantee the genetic diversity to the population, giving greater scope to the search. With no mutation in the process, the algorithm works with the genetic diversity generated in the first population. The mutation process allows that genes different from those generated with the initial population be tested.

The GA performance may be evaluated through the development of the fitness of the best individual of each generation or through the evolution of average of the individual's fitness of the same generation. Obviously, parameters as numbers of individuals in a population, mutation rate, rate of crossover, the mechanisms used by genetic operators and chromosomic representation, have the main responsible for the balance between efficiency and effectiveness of GA and, therefore, they have a vital importance in the process.

Figure 1 shows a flowchart of a classic genetic algorithm as proposes for Goldberg, 1989.

Methodology

General Description

The process aims to maximize the NPV of the field; it is performed in specific and independent optimization stages of quantity and placement of wells. In this intend, computational routines were implemented to perform each optimization stage. These routines are managed by an external routine responsible for alternate the process between the optimization stages of quantity and placement of wells.
The routines implemented were named only to avoid long references in the text, ensuring a better flow of information, therefore, do not have any commercial connotation.

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The flowchart of Figure 2 shows the process in full. Depending on the condition of the initial strategy, certain courses may be skipped.

Two routines for optimization of quantity of wells were implemented (Quantum and Pluvia). The application of each one depends on the quantity of wells expected excluding in this stage. If it is necessary exclude a small quantity of wells, it is appropriate to use the enumerative routine, Quantum, which is based on sequential exclusion of lower performance wells. It is not interesting to use this routine when expected excluding a large numbers of wells, since it can lead to a local extreme value. In this case, it is more interesting the employment of Pluvia routine, which is a GA implementation and, therefore, represents a more robust and reliable searching process. However, generally, this routine needs a greater number of flow simulations than Quantum routine. In this way, the application of these routines in each case must be analyzed.

To start the optimization process, it is necessary the definition of an initial strategy. This strategy must has a reduced spacing between wells, so that the process is efficient always acting to reduce the quantity of wells.

Generally, the optimization process starts by Pluvia routine, since may be have a significant reduction in initial number of wells. The next stage is the placement of wells optimization (Deo routine). In this way, a more efficient arrangement for wells defined on the first stage is obtained. After this stage, even with an efficient arrangement of wells, it is important to test the possibility to exclude one or more wells. As it is expected to exclude a small
quantity of wells in this stage, the proceeding may be alternated for Quantum routine, which requires a smaller number of flow simulations.

The alternation procedure between Deo and Quantum routines continues managed by Optimus routine, until there is no further on improvement of strategy performance and the strategy is considered optimized.

Next, there is a brief description of the optimization mechanism for each routine; Nogueira (2008) gives more details.

**Placement of wells Optimization Stage – Deo routine**

In this optimization stage, it is searched the best arrangement for a specific quantity of wells. This quantity is fixed during this stage. This routine is a GA implementation that aims the placement of wells optimization in a form both effective as efficient. The objective is to reduce the possibility of creating individuals with low performance and thus to accelerate the evolution process. With the goal of reducing the number of possible arrangements and, consequently improve process effectiveness, a reservoir sectorization is generated. Through the nearest neighbor criterion, reservoir sub-regions are defined from the original strategy. In this way, each sector defined embraces some cells of flow simulation mesh as shown in Figure 3. During this optimization stage, it is only possible to locate wells within each sector. This procedure has two important consequences in the optimization process. The first is that the probability of generation of very low performance individuals is reduced, since those are made only small changes in initial strategy. It gives a higher evolution rate for optimization process. The second consequence is that the delimitation of reservoir sectors for placement of wells may restrict the search, yielding a local maximum. To break away this disadvantage, optimization process is led until find placement of wells that overcomes original strategy performance. At this point, a new reservoir sectorization is made based on this new best strategy. This approach provides flexibility to the process because wells in this strategy tend to be centralized in new sectors, giving greater freedom of search. Despite the fact that wells have a restrict placement possibilities in the same population, they tend to have a greater freedom throughout whole process.

![Figure 3 – Chromosomic representation through reservoir sectorization](image)

Similar procedure is used for horizontal wells. In this case, the references to sector definition are the center of wells. The process gets one more degree of freedom that is the well rotation. In this way, it is possible to modify placement of horizontal wells through a translation and a rotation in relation to its center. During the proceeding, well completion layers and lengths are fixed.

The problem may be defined by (following similar notation used by Nemhauser and Wolsey, 1999):

\[
\max \left\{ f(\bar{x}) : \bar{x} = (x_1, \ldots, x_n) \right\} 1 \leq x_i \leq \max \gamma^i_c; \bar{x} \in \mathbb{Z}^n
\]

The chromosome \( \bar{X} \) represents the \( n \) wells positions in the reservoir, defining a production strategy. The function \( f(\bar{X}) \) represents the NPV of the strategy defined by chromosome. Each element in the wells position string (gene) defines the position that a well occupies within its reservoir sector. Figure 3 shows an example of chromosomic representation of a production strategy. The selection process is performed through a stochastic procedure so that the most suitable individuals have a greater probability of participation in a crossover.

An important adjustment of the crossover process allows accelerated the placement of wells optimization. Two different operators perform the crossover. The crossover process chooses which gene the son will inherit from its parents. As a gene represents the position of a same well, the choice is made through the performance measure...
this well. If the NPV of the father is greater than the NPV of the mother, the son shall inherit, the position defined by the father. This procedure allows accelerate the evolution process since the next generation will have the presence of children who are formed by their best parent genes. In order to add diversity to the search, part of the pairs is subjected to a crossover operator that blends randomly the parent's genes to generate the son. Therefore, a random mixture of its parent's genes composes son's chromosome.

Mutation is an important operator in a GA optimization process. It gives greater genetic diversity to a population. In this way, the probability to find better solutions is higher although the number of simulation can increase. In order to get an equilibrium of these characteristics, in this algorithm, the mutation process is activated when the average values of objective-functions of a generation overcomes a limit value for the activation of mutating. This is an artifice assembled to accelerate the evolution process and to establish an effective mutation rate balanced.

**Quantity of wells Optimization Stage (Enumerative) – Quantum routine**

The quantity of wells is optimized through a sequential exclusion of wells that lead to greater increment in objective-function. This optimization stage starts with n wells, and the strategy performance is evaluated with this quantity of wells. Then all possible configurations with n–1 wells are tested. If the project performance with n–1 wells is higher than n wells, adopts the n-1 wells configuration that has the best performance. The stage extends as long as improvement is observed in project performance with the reduction in the quantity of wells.

**Quantity of wells Optimization Stage (GA) – Pluvia routine**

The process of optimization of the quantity is similar to Deo routine. The fundamental difference is in the chromosomal representation for a production strategy, which in this case is a string of binary values. This means that it is not possible to use the crossover operators defined above, it being necessary the construction of new operators. The following is made a procedure description.

The problem may be defined by:

\[
\max \{ f(\bar{X}) : \bar{X} \in \mathbb{R}^n \}
\]

As in the case of Deo routine, function \( f(X) \) represents the NPV of strategy \( X \). The chromosome \( X \) defines a consideration or not of a given well in the production strategy. Figure 4 shows an example of chromosomal representation of a strategy, through a binary values string.

![Figure 4 – Chromosomal representation through string of binary values](image)

The procedures for selection and mutation are identical to those used in Pluvia routine. However, there are differences in the crossover process. In this routine, two other crossover operators are defined. It was adopted two crossover operators to accelerate the evolution process without loss of procedure robustness. The first crossover operator operates only in the differences between parent's chromosomes yielding a tendency to search in regions close to the best individuals trying to accelerate the evolution. If both parents have a well in their strategies, the son generated for the next generation will also have it. In the same way, if both parents do not have a well in their strategies, the son will not have it. In this way, this operator will act only where there are differences between the strategies selected for crossover and, therefore, the son has equal probability of inheriting the gene of the father or mother.
The second operator acts in a distinct form. For each crossover, it is selected a cutoff point from which shall be made the combination between the genetic material of the father with the mother. This operator acts in way to search solutions more distant from the best individuals generated. In this way, more robustness is gives for solution.

**Application and Results**

The proposed methodology is applied in the selection and optimization of a production strategy to a synthetic heterogeneous light oil field. The field has approximately $57.2 \times 10^6$ m$^3$ of OOIP with average permeability of 350mD. The objective is to define the best production strategy. Two kinds of strategies are tested, for vertical and horizontal wells respectively.

Figure 5 represents a reservoir view showing its structure. Figure 6 shows the vertical sections indicated in Figure 5. It indicates that the central region of the reservoir is structurally high.

![Reservoir Perspective - Tops](image1)

![Reservoir vertical sections indicated in Figure 5](image2)

Figure 7 shows the maps of reservoir petrophysics properties. It is clear from the sections shown in Figure 6 and the map shown in Figure 7 that reservoir thickness and horizontal permeability decrease towards the periphery.
The flow model consists of a Cartesian grid formed by 35×35×3 cells with dimensions of 150×150 m and thickness varying according to the geology. There are 2358 active cells in the flow model.

Figure 8 shows the initial strategies adopted. The production strategy that use only vertical wells is composed of 25 producers and 29 injectors wells, in a total of 54 wells in a five-spot system. The initial strategy for horizontal wells is composed by 5 producers and 7 injectors wells, arranged in a peripheral injection with central production system.

The economic scenario adopted in this work is detailed in Table I. The costs considered in the project are detailed in Table II.

**Table I – Main items of Economic Scenario**

<table>
<thead>
<tr>
<th>Item</th>
<th>Incomes (US$/bbl)</th>
<th>Production Costs (US$/bbl)</th>
<th>Inj. Cost (US$/bbl)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil</td>
<td>50.00</td>
<td>4.79</td>
<td>0.82</td>
</tr>
<tr>
<td>Gas</td>
<td>0.314</td>
<td>0.037</td>
<td>0.82</td>
</tr>
<tr>
<td>Oil</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gas</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table II – Investment table**
Vertical Wells Strategy

The optimization process, guided by Optimus routine (Figure 2), was initiated through the Pluvia routine of quantity of wells optimization by GA. In Table III, the control parameters of optimization process by GA are presented.

<table>
<thead>
<tr>
<th>Item</th>
<th>Investment (MM US$)</th>
<th>When</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exploration</td>
<td>100</td>
<td>4 years before the beginning of production</td>
</tr>
<tr>
<td>Evaluation</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Production Facilities</td>
<td>1000</td>
<td>During 3 years before the beginning of production</td>
</tr>
<tr>
<td>Vertical Well</td>
<td>35</td>
<td></td>
</tr>
<tr>
<td>Abandon</td>
<td>100</td>
<td>At the end of production</td>
</tr>
</tbody>
</table>

Table III – Main Parameter of GA

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individuals</td>
<td>12</td>
</tr>
<tr>
<td>Generations</td>
<td>35</td>
</tr>
<tr>
<td>Elite</td>
<td>1</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>0.05</td>
</tr>
<tr>
<td>Mutation Threshold</td>
<td>MM US$ 20.00</td>
</tr>
</tbody>
</table>

The initial strategy has a NPV of MM US$ -195.56. With Pluvia accomplishment, it was possible to exclude 18 wells increasing the NPV for MM US$ 378.57. Figure 8 shows the changes made by routine Pluvia in initial strategy and as was the strategy after this stage accomplishment.

Figure 9 – First Stage of Optimization – Pluvia routine

The strategy defined after Pluvia accomplishment was submitted to Deo routine for placement of wells optimization. In the process, the same GA parameters used in Pluvia routine were adopted. After the accomplishment of this stage, the NPV became MM US$ 471.71. Figure 9 shows the changes made by routine
Deo in previous strategy and as was the strategy after the accomplishment of this stage. This stage, 215 flow simulations were performed throughout the procedure; until this step, 392 flow simulations were performed.

The strategy defined in the stage before was submitted to Quantum routine for quantity of wells optimization by sequential exclusion of low performance wells. After 155 flow simulations were excluded 6 wells, making the NPV reach MM US$ 566.21. Figure 10 shows the changes made by Quantum routine in previous strategy and the strategy after the accomplishment of this stage.

The strategy defined in stage before was submitted to Deo routine to carry out the re-positioning of the wells. After 198 flow simulations, the NPV became MM US$ 587.59. Figure 11 shows the changes made by Deo routine in previous strategy and the strategy after the accomplishment of this stage.
After this stage accomplishment, the strategy was submitted to Quantum routine where it was not possible to exclude any more well. In this point the Optimus routine interrupted the process and the strategy defined in step before was considered optimized.

Table IV summarizes the optimization process. The simulation time was measured in a machine with processor Pentium IV 3.4 GHz with 4 Gb of RAM memory. As the individuals of the same generation are simulated independently, the process is easily breakable, with potential for significant reduction in optimization time. Figure 13 shows NPV evolution in relationship the number of flow simulations. The stabilization at the process end indicates their convergence.

### Table IV – Production Strategy Optimization – Vertical Wells

<table>
<thead>
<tr>
<th>Stage</th>
<th>Routine</th>
<th>NPV (MM US$)</th>
<th>Production Strategy</th>
<th>Wells</th>
<th>Flow Simulation</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Total</td>
<td>Prod.</td>
<td>Inj.</td>
</tr>
<tr>
<td>Initial</td>
<td>-195.56</td>
<td>Figure 8</td>
<td>54</td>
<td>25</td>
<td>29</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>PLUVIA</td>
<td>378.57</td>
<td>Figure 9</td>
<td>26</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>2</td>
<td>DEO</td>
<td>471.71</td>
<td>Figure 10</td>
<td>26</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>3</td>
<td>QUANTUM</td>
<td>566.21</td>
<td>Figure 11</td>
<td>20</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>4</td>
<td>DEO</td>
<td>587.59</td>
<td>Figure 12</td>
<td>20</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>5</td>
<td>QUANTUM</td>
<td>587.59</td>
<td>Figure 12</td>
<td>20</td>
<td>11</td>
<td>9</td>
</tr>
</tbody>
</table>

Figure 12 – Fourth Stage of Optimization – Deo routine
Horizontal Wells Strategy

Differently from the previous case, this case has only 12 wells on its initial strategy, as justified in general description is inappropriate to use the Pluvia routine in these cases. In these circumstances, the ideal is skip the first stages of flowchart Figure 2 and start the optimization process with Deo routine and, throughout the process, alternate with Quantum routine until the end of optimization.

Table V shows the parameters of genetic algorithm used in this case

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individuals</td>
<td>20</td>
</tr>
<tr>
<td>Generations</td>
<td>90</td>
</tr>
<tr>
<td>Elite</td>
<td>1</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>0.05</td>
</tr>
<tr>
<td>Mutation Threshold</td>
<td>MM US$ 20.00</td>
</tr>
</tbody>
</table>

The initial strategy has a NPV of MM US$ 287.17. With Deo accomplishment, it was possible to increase the NPV for MM US$ 607.78. Figure 14 shows the changes made by Deo routine in initial strategy.
The next stage is Quantum routine execution that after 24 flow simulations indicated the exclusion of an injector well (I-05), making the NPV increase for MM US$ 633.82. The exclusion of this well creates the opportunity to hold a new well re-arrangement through Deo routine. Then NPV achieved MM US$ 669.09 after 638 flow simulations. The Quantum routine was accomplished and after 11 flow simulations, it was not possible to exclude any more well.

Figure 15 presents the strategy optimized. There is a change in the initial injection scheme. The initial strategy (Figure 8) was designed for the drainage was made through peripheral injection with central production. The optimization process changed this initial idea alternating injectors and producers wells.

Figure 14 shows NPV evolution in respect to the number of flow simulations. The stabilization at the process end indicates its convergence. As in the previous case, although it is not possible to say that is a maximum global value, the confidence in the process is justified by extensive search carried out in the solution space.
Table VI – Production Strategy Optimization – Horizontal Wells

<table>
<thead>
<tr>
<th>Stage</th>
<th>Routine</th>
<th>NPV (MM US$)</th>
<th>Production Strategy</th>
<th>Wells</th>
<th>Flow Simulation</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td></td>
<td>287.17</td>
<td>Figure 6</td>
<td>12</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>1</td>
<td>DEO</td>
<td>607.78</td>
<td>Figure 14</td>
<td>12</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>QUANTUM</td>
<td>633.82</td>
<td>-</td>
<td>11</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>3</td>
<td>DEO</td>
<td>669.09</td>
<td>Figure 15</td>
<td>11</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>QUANTUM</td>
<td>669.09</td>
<td>Figure 15</td>
<td>11</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>

Conclusions
The production strategy optimization as proposed in this paper allows to speeds up the process of NPV maximization. It is possible to achieve good results, including an extensive search procedure, with less than a thousand of flow simulations. This number is considerably inferior to those reported in literature. This is mainly a consequence of the optimization in specific stages, reducing the space solution, yielding faster responses. Other aspect that is responsible for this behavior is the use of a measurement of the performance of the genes. This allows generating sons with the best genes of its parents.

The two cases presented in this work showed the usefulness of a tool of assisted optimization in a selection of a production strategy for a petroleum field. This kind of tool is useful in the selection of initial production strategy, in the refinement of production strategies and it may also be applied in developed fields because existing wells can be easily be fixed in the procedure.

In this work, two different concepts for the strategy for production were tested in the same field. If the intention would be choose between the uses of horizontal or vertical wells, the results of these would aid in the decision process. In this case, the strategy composed exclusively by horizontal wells has a higher NPV. Other concepts could be tested to ensure a robust decision making process: as adoption of a mixed strategy, that uses vertical and horizontal wells, the use of intelligent wells, multilateral wells, among others. Therefore, the adoption of this kind of tool in a selection process of production strategy enables a larger number of analyzes, providing more robust decisions.

Nomenclature

\( f(X) \)  Objective-function NPV of strategy X
NPV  Net Present Value  
OOIP Original Oil in Place  
X  A production strategy defined by a chromosomal representation

References


