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ASSISTED HISTORY MATCHING USING COMBINED OPTIMIZATION METHODS

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Abstract. *Numerical simulation is a tool for reservoir management, used to realize the prediction of a field during its productive life. Because the uncertainty parameters, a discrepancy between the real and simulated values may occur, being necessary the validation of the model, which is made through the history matching. In this work, the methodology of this matching was performed in two steps: re-evaluating 1) the uncertain geological petrophysical properties using random search to select the best images; 2) the productivity index of each well using evolutionary algorithm. Using the images found in the first step of the methodology, the second step is performed, with the parameter selected to modify the productivity of the wells being the skin factor. This methodology was applied in the UNISIM-I-H benchmark model to validate it. The fluid model of the field was black-oil with the oil density equal to 28 ºAPI and the data consisting of 11 years of production of 14 producers and 11 injectors. In conclusion, considering the skin factor as uncertain parameter with the objective of altering the wells behavior resulted in improvements in the matching process. This can be observed through of reduction in the objective function from 23 to 7 percent.*

Keywords: *Assisted History Matching, Optimization Methods, Uncertainties*

1 INTRODUCTION

Every oil company must elaborate a development plan to produce a field, since the economic viability of an oil recovery project depends on the performance of the production under current and future conditions. Basically, this plan is to inform how hydrocarbon production will be managed throughout the entire life of a field. To predict its development, technical and economic feasibility studies are required of the various alternatives of how the field can be explored: compare the implementation and maintenance costs, in relation to its expected return due to the production of the field hydrocarbons. Thus, it can be concluded that a fundamental task for the elaboration of a development plan is to determine the prediction of the production of the field during its productive life for all the alternatives that will be studied.

Normally, the most used tool to realize this prediction of the field is the reservoir simulation. Simulation is to “assume the appearance without reality”. In petroleum engineering, mathematical models simulate the reservoir behavior over time, through equations and assumptions, with purpose of estimate field performance. The mathematical reservoir simulator consists basically of sets of partial differential equations that express conservation of mass and/or energy. In addition, the model entails various phenomenological “laws” describing the rate processes active in the reservoir. Required program input data include fluid PVT data, rock relative permeability and capillary pressure data (Coats, 1969). The properties discussed above have uncertainties due to obtaining methods, usually indirect methods. Because of these uncertainties, a discrepancy occurs between the simulated and observed values in the field. The history matching is precisely to carry out the revision of the simulation model, revaluing the properties with uncertainties in such a way that the discrepancy is reduced. It is traditionally performed by trial and error, modifying the values of some parameters in search of a better match (Rwechungura *et al.*, 2011).

The history matching is an inverse problem. One of the first studies was done by Kruger (1961). He presented a calculation procedure for determining the areal permeability in the reservoir. Watson *et al.* (1980) formulated an algorithm based on optimal control approach for joint estimation of permeability, porosity and coefficients of relative permeability in two-phase reservoirs, using pressure and production rate data as observed values. According to Tavassoli *et al.* (2004), the best production-matched model does not necessarily have a good fit for the parameters of the reservoir, and this can provide different values in the forecast period. Schiozer *et al.* (2005) presents a procedure that integrate the history matching with uncertainty analysis, when several possible models are generated based on the probability value of each attribute that constitutes the model. Abrahem *et al.* (2010) presented an assisted approach called “Target Pressure and Phase Method”, where the computer automatically places pseudo wells in the static model to reproduce the measured data and concludes that this method is useful for practical applications. Oliver and Chen (2010) carried out a review of the recent progress on reservoir history matching and conclude that no single best method has emerged and the total computational effort required for history matching is still excessive. Cancelliere *et al.* (2011) discuss the benefits and limitations of assisted history matching and comments it is unlikely to find a reservoir engineer with the mathematical background required to apply more complex optimization algorithms in reservoir models. Random search is a numerical optimization method that not requires the gradient of the function to be optimized, in other words, the differentiability of the function is irrelevant (Baba, 1981).

Bergstra and Bengio (2012) point out some advantages in using random search methods: the experiment can be stopped any time and the trials form a complete experiment. If extra computers become available, new experiments can be add without adjust the algorithm and if the computer carrying out an experiment fails it can be abandoned or restarted without reducing the algorithm efficiency. Another advantage of this is the convergence to the optimum solution as the number of experiments gets large (Spall, 2003). Gentle *et al.* (2012) indicates that the method is a reasonable algorithm when the number of parameters is low.

In evolutionary algorithms methods, biology-inspired mechanisms steps (reproduction, mutation, recombination and selection) are used to find candidate solutions to the optimization problem: randomly initialized points of the search space are chosen and the fitness of each point in the population is evaluated, the bests points are selected for breeding new points through crossover and mutation operations, the new points are then evaluated and the new points population are updated. One of the main advantages of evolutionary techniques is that they do not have much mathematical requirements about the optimization problem (Michalewicz *et al.*, 1996). These techniques usually have difficulties in solving constrained numerical optimization problems, one of the main reasons behind these failures is the inability of evolutionary methods to search precisely the boundary area between feasible and infeasible regions of the search space (Schoenauer and Michalewicz, 1998). However, this type of algorithms has been applied with success in the petroleum area (Sampaio *et al.*, 2015).

The main objectives of this work are: addressing the theoretical concepts involving the history matching procedure, present a new methodology for the adjustment that allow to choose multiple discrete parameters and apply the proposed methodology in a field model.

2 METHODOLOGY

The proposed methodology uses two optimization algorithms: random search and an evolutionary algorithm in two distinct steps. The first optimization step has the purpose of analyze and select the best petrophysical images described in the case study, since they were randomly generated; the second step has the objective of optimizing the scenarios selected in the previous step.

During the construction of the simulation model, loss of information may occur because the process of upscaling, especially in the near-well regions. Because of this, it may be necessary to perform a re-evaluation of the well productivity index. The definition of productivity is expressed in Equation 1:

$$pi = \frac{2\pi\sqrt{k_i k_j}h}{\ln\left(\frac{r_e}{r_w}\right) + s}, \quad (1)$$

where k_i and k_j represents the permeability in the directions i and j respectively, h is the grid block length in k direction, r_e is the well effective radius, r_w is the wellbore radius and s is the skin factor, which represents a damage or stimulus in the near-well formation. This re-evaluation is usually done by creating a permeability modifier around each well. In this work, the well productivity was changed by varying the skin factor and the efficiency of using this parameter was analyzed.

The justification for performing the matching in two optimization steps is due to the fact that if it was performed in a single step, the optimization algorithm would select a single optimum scenario, additionally; the skin factor was added only in the second step, because if it was added in the first, the number of parameters would increase from 6 to 31, reducing the random search efficiency considerably (Spall, 2003). The flow simulator is the Imex® (CMG) and the matching was performed through CMOST® (CMG) optimizer simulator.

Basically, the methodology consists in evaluate the entire domain of petrophysical parameters field using random search and select the bests parameters scenarios using statistics, then optimize them using an evolutionary algorithm in order to obtain multiple adjusted models. The workflow of the methodology can be seen below in the Figure 1:

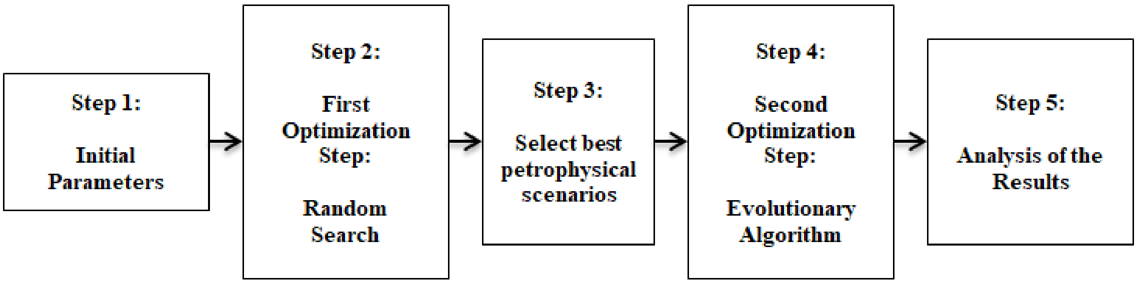

Figure 1 - Workflow of the proposed methodolgy.

2.1 Step 1: Initial Parameters

In this step, the uncertain parameters and their properties are defined. Using the initial parameters provided in the case study section, the case base was built, which will be the starting reference point for the optimization stage (evaluation 0). In this work, all the data used are according to the information provided by the benchmark case study UNISIM-I-H, which will be described later.

2.2 Step 2: Random Search

The algorithm used in the first step of the proposed methodology was the blind random search, where the current sample does not consider the previous experiments.

The blind random search steps for the implementation are presented in Figure 2. Let **P** be the matrix with all parameters defined and **P*** the best solution obtained for objective function F(**P**). We need to choose an initial value of $\mathbf{P_n}$(n=0), calculate F($\mathbf{P_0}$), and defines this as the best solution obtained ($\mathbf{P^*_n}$ = $\mathbf{P_0}$). In next step, generate a new **P** matrix ($\mathbf{P}_{n+1}$), if F($\mathbf{P_{n+1}}$) is less than $\mathbf{P^*_n}$, set the new $\mathbf{P_n}$(n+1) as the new best solution, otherwise, keep the previous one. Stop the algorithm if the number of maximum evaluations (n_{max}) has been reached, otherwise, generate another matrix and proceed with the algorithm (n=n+1).

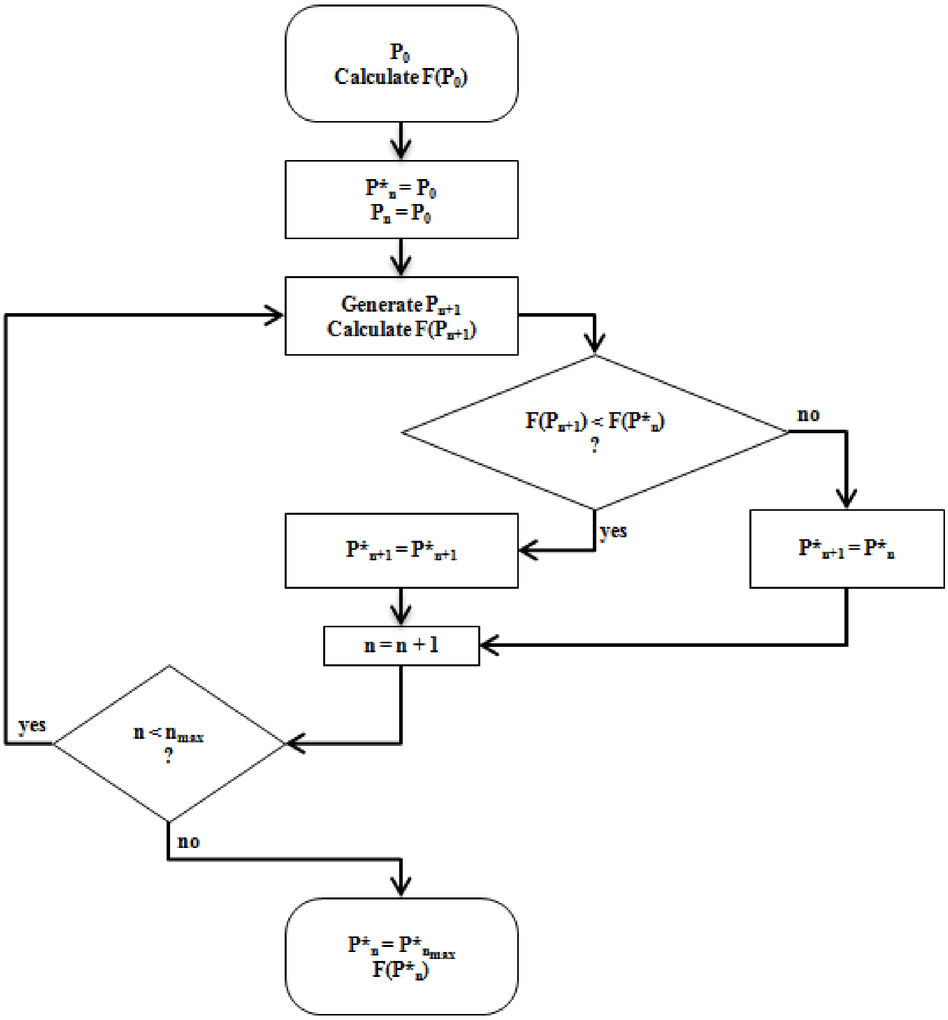

Figure 2 - Methodology of the blind random search algorithm.

During both steps of optimization, the results were compared with the real values using an objective function based on the available CMOST®, which measures the relative difference between the simulation results and observed values.

$$Q_{i,j}(\%) = \frac{\sqrt{\frac{\sum_{t=1}^{T(i,j)}\left(Y_{i,j,t}^{s}-Y_{i,j,t}^{m}\right)^2}{T(i,j)}}}{Scale_{i,j}} \times 100 \; \forall \; i,j, \quad (2)$$

where, i, j, t is the subscripts representing well, production data type and time respectively, $T(i,j)$ is the number of dates that have measurements, $Y_{i,j,t}^{s}$ is the simulated results, $Y_{i,j,t}^{m}$ is the observed values. The term $Scale_{i,j}$ is a normalization parameter, which is the maximum of the following three quantities (Equations. 3, 4, and 5):

$$\Delta Y_{i,j}^{m}, \quad (3)$$

$$0{,}5 \times min\left(\left|max\left(Y_{i,j,t}^{m}\right)\right|, \left|min\left(Y_{i,j,t}^{m}\right)\right|\right), \quad (4)$$

$$0{,}25 \times min\left(\left|max\left(Y_{i,j,t}^{m}\right)\right|, \left|min\left(Y_{i,j,t}^{m}\right)\right|\right), \quad (5)$$

where, $\Delta Y_{i,j}^{m}$ is the measured maximum change.

The total history match error is calculated using the weighted average formula with all errors presented above in the Equation 6:

$$Q(\%) = \frac{\sum_{ij} Q_{i,j}}{\sum_{ij} w_i}, \tag{6}$$

where, $Q_{i,j}$ represents the objective function for well i and production data type j, respectively, and w_i represents the weight of each $Q_{i,j}$ in the calculation (in this work all weights were equal to 1).

The objective function described in this session basically calculates the average of the errors of each well and parameter calculated separately.

2.3 Step 3: Select best petrophysical scenarios

In this step, the method used to select the best scenarios was to calculate the average value of the objective function of each petrophysical image for all the simulations performed in the previous step. The average value of each petrophysical image can be expressed to the equation below (Eq. 7):

$$\overline{F(im_i)} = \frac{\sum_{n=1}^{n} F(im_i)^n}{\sum_{n=1}^{n} 1(im_i)^n} \; \forall \, i, \tag{7}$$

where, im_i is the petrophysical image i and $F(im_i)^n$ is the objective function value in the evaluation *n* (simulation), the overbar denotes average. Basically, this equation expresses the ratio of the sum of all objective functions to the number of occurrences for a scenario in *n* simulations.

2.4 Step 4: Evolutionary Algorithm

The evolutionary algorithm used in this work was the Designed Exploration and Controlled Evolution optimizer (CMOST® DECE). Briefly, this algorithm optimization is composed of two steps: a designed exploration stage and a controlled evolution stage. In the first stage, some search techniques are utilized with objective of explore throughout the space of solutions. In the evolution stage, the evolutionary algorithm is applied with statistical methods in the results obtained previously.

2.5 Step 5: Analysis of the Results

In this step, the results obtained after the use of the evolutionary algorithm were analyzed from two approaches: through the objective function previously defined, and analyzing the time series of the wells for the purpose of making a visual analysis of the matching and verify mismatches in the simulation model. In analysis stage, the engineer's experience is fundamental, since is possible to re-evaluate the decisions made in the previous stages.

3 CASE STUDY

The simulation model used in this work was the benchmark UNISIM-I, more specifically the case study UNISIM-I-H, which consists in perform a history matching with a previously defined production strategy. Avansi and Schiozer (2015) detail the construction of the benchmark model, due to the objective of this work, only a brief description of the model will be presented.

The reference model was build using public data from Namorado Field, Campos Basin, Brazil. The original volume of oil in place is 130 million m^3, and the fluid model is black-oil with the oil density equal to 28 °API, it is composed by a corner point grid (81x58x20 cells). In the most recent work using UNISIM-I-H, Silva *et al.* (2017) proposed a closed-loop reservoir management workflow using ensemble-based methods, presenting consistent results. The dataset contains 11 years of observed data (well rates and pressure, field rates and average pressure) of 4 original vertical producers, 10 horizontal producers and 11 horizontal injector wells. In the simulator, the producer wells are steered on oil rate while the injector wells are steered on water rate.

The uncertainties used in this work were based on the description of the case study. The uncertain parameters are: facies, porosity, net-to-gross, permeability, water relative permeability, black-oil pressure, volume and temperature dependencies, water oil contact depth (WOC), rock compressibility (Cpor) and vertical permeability multiplier (Kz). For the levels, 500 equiprobable petrophysical images (scenarios) were generated containing the facies, porosity, net-to-gross and the permeabilities (Petro). The black-oil properties (PVT) and the water relative permeability (Krw) also have scenarios as uncertainty type, the other parameters have triangular probability density functions. The uncertainties attributes can be viewed in Table 1. The structural model and the location of wells can be viewed in Figure 3.

Table 1 - Uncertainties data description.

		Attributes levels or bounds		
Attribute	Type	Minimum	Most probable	Maximum
Petro	Discrete	500 equiprobable scenarios		
Krw		5 equiprobable scenarios		
PVT		PVT0 (0.34), PVT1 (0.33), PVT2 (0.33)		
WOC	Triangular Continuous	3169	3174	3179
Cpor		10	53	96
Kz		0	1.5	3

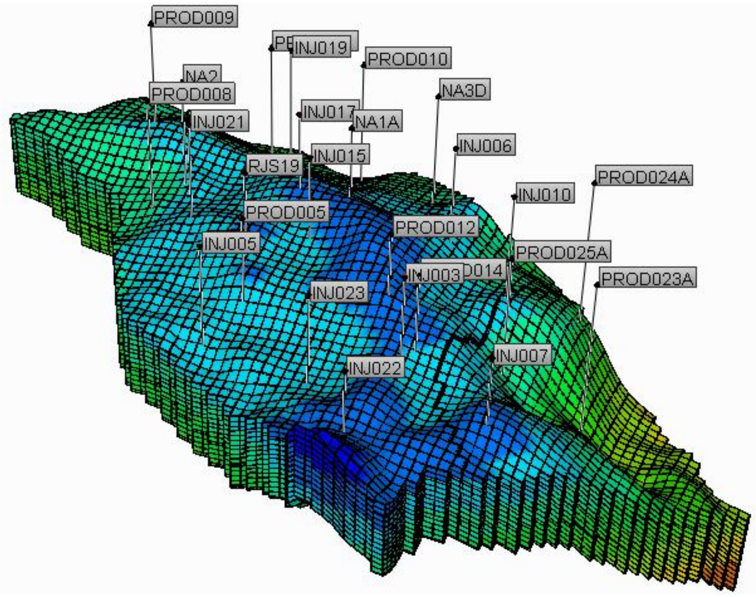

Figure 3 - UNISIM-I-H simulation model.

4 RESULTS AND DISCUSSIONS

4.1 Steps 1 and 2:

For the first stage of the methodology, 5000 experiments were performed using the random blind search as optimization method. The model has been run for 11 years, throughout the period of production history. The results of the simulator were compared with the production history thought the production history data available. The parameters evaluated in the objective function were the oil, gas and water production rates, injection rates and the bottom-hole pressure of the wells.

In Figure 4 and Figure 5 it is possible to verify the randomness of the algorithm by observing the behavior of both parameter and objective function throughout the simulation progress. After the first simulation, the results were analyzed by comparing the average value of the objective function for each petrophysical scenario through the relative frequency histogram, as showed in Figure 6.

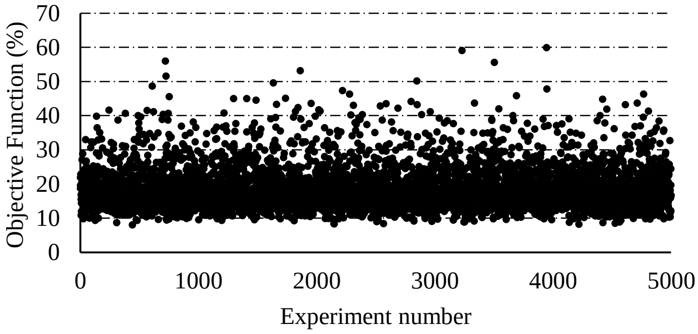

Figure 4 - Objective Function values of the fist optimization step of the methodology.

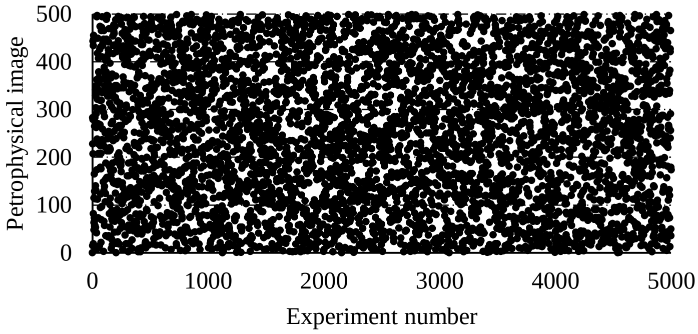

Figure 5 - Petrophysical images as example of the behavior of the parameters of the first optimization step of the methodology.

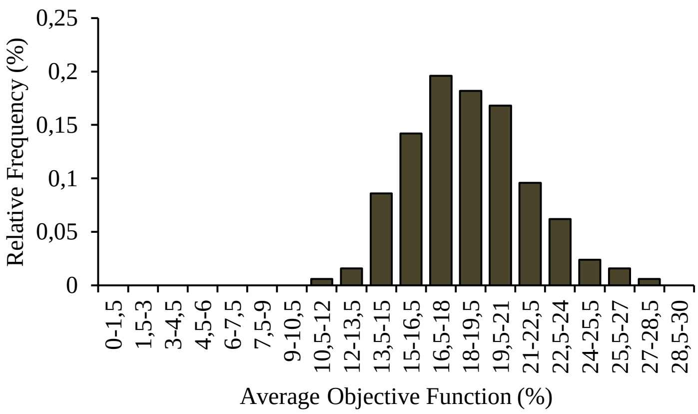

Figure 6 - Relative frequency of the average objective function for each petrophysical scenario.

4.2 Step 3

For the selection of the scenarios, the best petrophysical images were chosen that presented an average error lower than 13.5% (the two columns to the left in Figure 6). In this way, 11 scenarios were selected for the next step. The average objective function values of these scenarios can be viewed in Table 2, which vary between 11% and 13.5%, with mean approximately to 12.5%.

Table 2 - Average Objective Function values for each petrophysical scenario.

Petrophysical Scenario	Average Objective Function (%)
389	11,07
157	11,27
175	11,61
324	12,19
93	12,31
326	12,66
38	13,00

Petrophysical Scenario	Average Objective Function (%)
114	13,14
431	13,15
206	13,23
208	13,31

4.3 Steps 4 and 5

With the petrophysical scenarios, the next step was run with 1000 experiments for each scenario using the evolutionary algorithm as optimization method. The results were compared using the objective function and it was possible to observe the reduction of the objective function throughout the evaluations. The reduction is presented in detail for the higher and lower objective function values before and after the application of the evolutionary algorithm (4 scenarios) and for the average of all 11 scenarios chosen in Figure 7, Figure 8, Figure 9 and Figure 10. In the all figures, the black dots represent the average value of all scenarios for each experiment, and the red dot represents the optimum solution obtained.

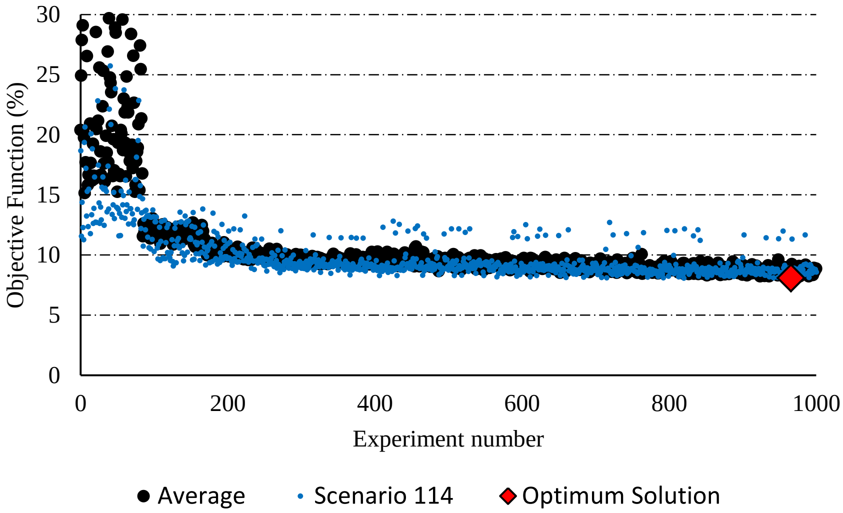

Figure 7- Objective function values for scenario “114”.

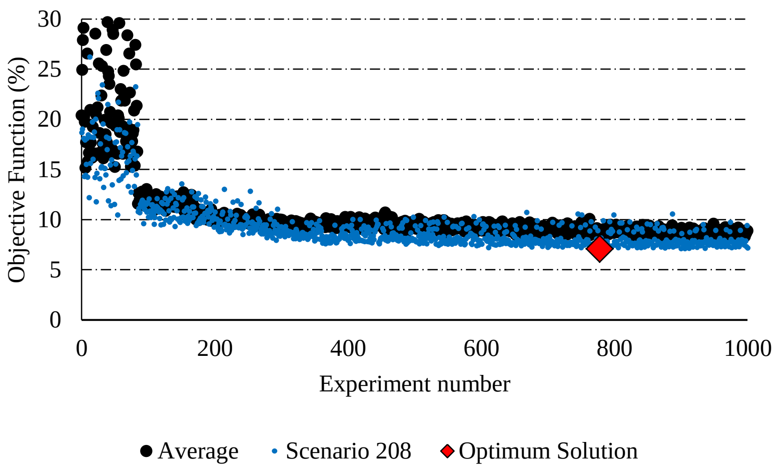

Figure 8 - Objective function values for scenario “208”.

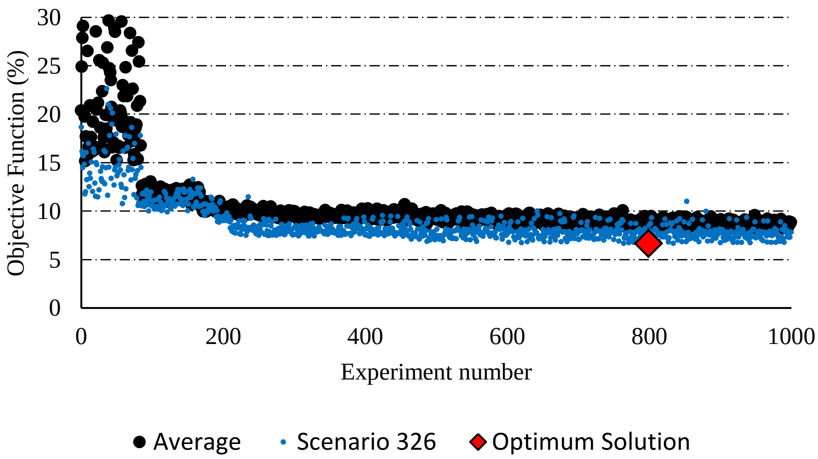

Figure 9 - Objective Function values for scenario “326”.

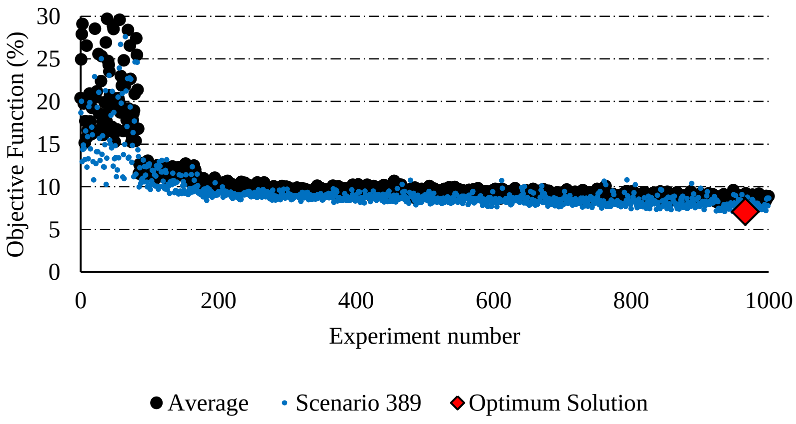

Figure 10 – Objective Function values for scenario “389”.

After the second optimization step, the minimum and maximum values of the objective function were approximately 6.5% (scenario 326) and 8% (scenario 114) respectively.

Redefining a new domain as the 11 selected scenarios, it is possible to compare the values of the objective function before and after the application of the evolutionary algorithm, being possible to verify an improvement in the mean value of the objective functions from 12.5 to 7 percent (Figure 11).

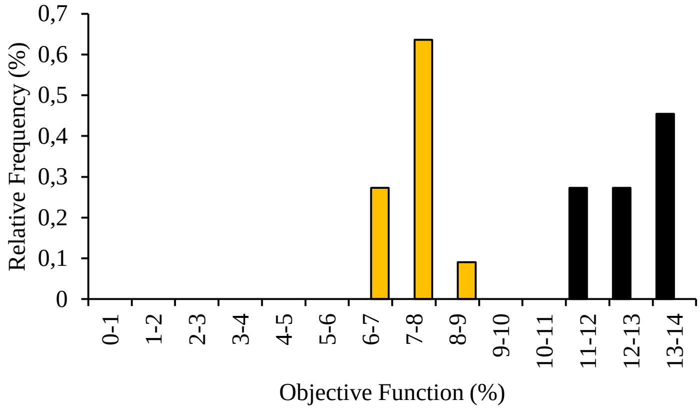

Figure 11 - Relative frequency before (black) and after (yellow) the evolutionary algorithm of the objective function values of the scenarios selected in the first optimization step.

From the matched scenarios, it is possible to check the quality of the matching visually, comparing the time series of wells for each scenario with the observed values. Here, we present the time series for one vertical producer (NA1A), one horizontal producer (PROD021), and one injector well (INJ019).

For the vertical producer, a considerable matching has occurred in the bottom-hole pressure (Figure 12) and the water rate there was only a slight improvement (Figure 13). For the horizontal producer, the bottom-hole pressure matching also obtained a considerable improvement (Figure 14) and for the water rate, the scenarios present deviations around the observed data (Figure 15). The injector showed great improvement in the bottom-hole pressure matching (Figure 16). The deviations in the water rate for some wells need further investigation. The yellow lines represent the values for the 11 scenarios optimized with the evolutionary algorithm. The black dotted line is the base case and the blue dots are the production history data.

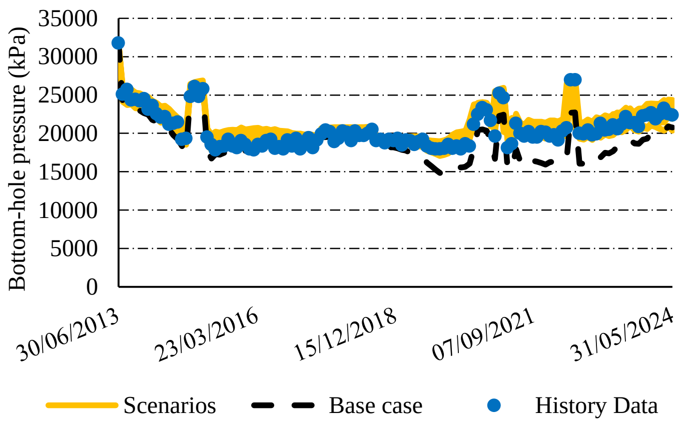

Figure 12 - Bottom-hole pressure for well NA1A during the production history period.

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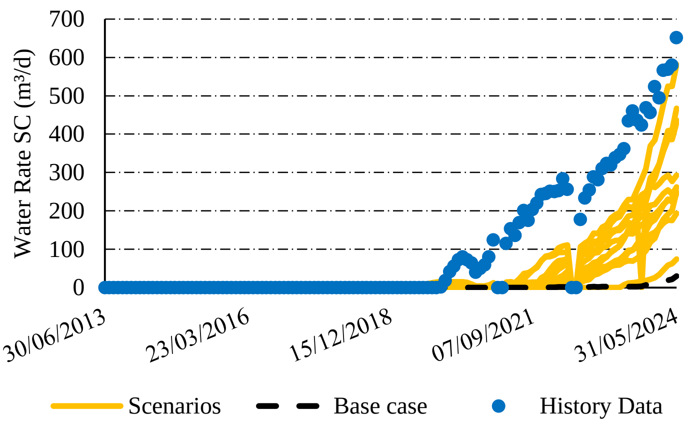

Figure 13 – Water production rate for well NA1A during the production history period.

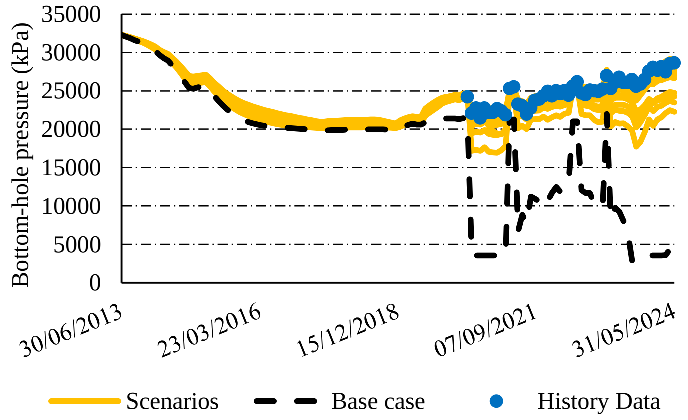

Figure 14 - Bottom-hole pressure for well PROD021 during the production history period

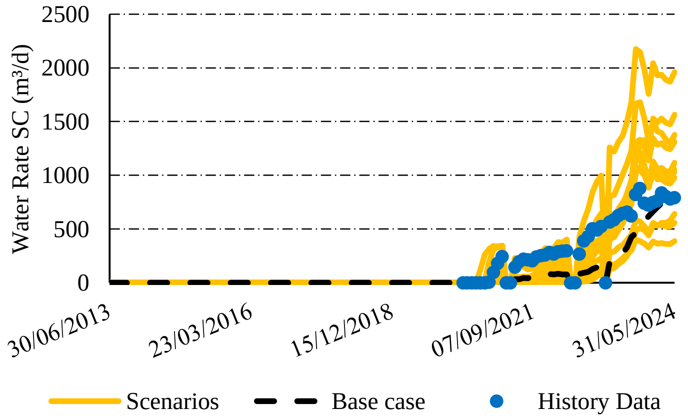

Figure 15 - Water production rate for well PROD021 during the production history period.

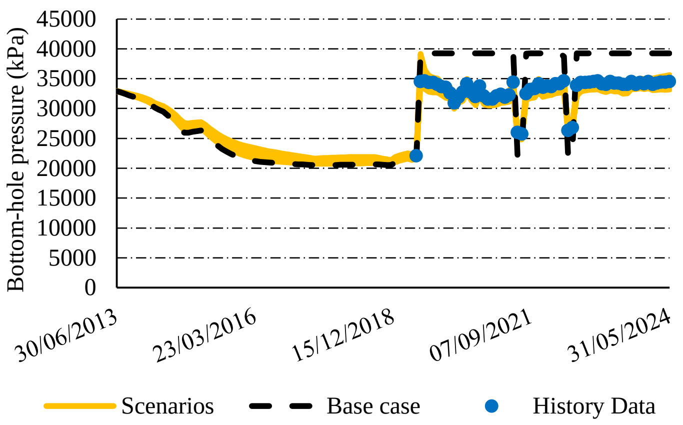

Figure 16 - Bottom-hole pressure for well INJ019 during the production history period.

Analyzing the plots, it is possible to observe a satisfactory quality of the matching for practical purposes. The average value of the objective function after the later step was approximately 7.09%, whereas the base case was equivalent to approximately 22.78%.

5 CONCLUSION

The possibility of improving the procedure of history matching will be beneficial for further field development plans. In this work, a methodology was presented to the realization of the history matching, using two optimizations steps: a random blind search and an evolutionary algorithm.

The random blind search proved to be a useful tool for the selection of the best-matched discrete parameters and the evolutionary algorithm was able to reduce the objective function values for the previously selected scenarios. When evaluating the parameters that influence the productivity of the wells, the skin factor proved to be a viable parameter for changing this productivity, since its implementation as an uncertain parameter is easier than implementing local permeability modifiers. Some wells showed discrepancies in water rate, being necessary further investigation. Finally, this methodology could be valuable, because of easy application and that presented satisfactory results, showing a reduction in the value of the objective function from 22.78 to 7.09 percent approximately.

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