THE INFLUENCE OF THE PARAMETER SPACE AND THE OBJECTIVE FUNCTIONS DEFINITION IN THE HISTORY MATCHING

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Abstract. *History matching is the process of calibrating a reservoir model to reproduce the observed data. Reservoir parameters are perturbed such the best combination minimizes the distance between simulated and observed data, such as field pressure, field water and oil rate, well water cut, well bottom hole pressure, etc. Two important steps of the history matching are (1) to identify the parameters that have influence on the performance of the reservoir, and (2) to choose the objective function. This paper investigates, through an assisted history matching methodology, the influence of the parameters and selected objective function in the process. The optimization algorithm used in the methodology is based on the parameters discretization, in which a tolerance for the reservoir parameters is defined instead of a tolerance for the objective function, as occurs in the derivative-based methods. Regarding to the matching parameters, the aspects investigated are: the choice of the parameters, different grid size settings based on its minimum and maximum limits, that is, several discretization levels are evaluated. Furthermore, the influence of the objective function definition is also evaluated. Results showing important insights in the relationship between parameters space and objective function are presented.*

Keywords. Reservoir Simulation, History Matching, Direct Optimization, Parameter Space

1. Introduction

Even with the modern reservoir characterization techniques, the available information in a reservoir study is rarely sufficient to construct a model that represents faithful the reservoir. History matching is an important process used to improve reservoir simulation models, in order to reproduce the past behavior of the reservoir. The goal of the history matching is to build reliable models for production forecasting. It is an iterative process that consists of successive changes in the reservoir model and comparison of the simulation results with the observed data. History matching is an inevitable process that is present practically in the entire field life. However, in the initial stage of the production, when a few data is available, it is more critical. The greater the uncertainties degree on the reservoir properties, and the greater the scarcity of production data, the greater the difficulties to outline the problem.

For complex cases, history matching is characterized by a great amount of control variables: a lot of reservoir uncertain properties, several data series to be adjusted, such as field and well pressures, well productivity, field and well productions, such as oil rate, water rate, gas-oil ratios, water cut, etc. For such cases, an overall matching stage is very difficult. It is necessary to divide the process in several stages. In each stage, the choice of matching parameters and the definition of the objective function in very important.

Besides the difficult intrinsically related to the history matching process, the amount of tasks involved makes it more complicated when manual process, based on trial and error procedures, is used. Thinking in the difficult associated to the manual process, several automatic history matching methodology are proposed in the literature. Automatic history matching uses an optimization algorithm to find the best combination of parameters that minimize a given objective function. A set of reservoir properties forms the parameter space and a set of data series form the target of the matching.

In order to use an automatic history matching procedure, the process needs formalizing, quantifying and putting the target of the matching into mathematical terms that a computer program can deal with. This is called objective function. Objective function can be composed not only by production and pressure data. Other type of data, such as seismic-derived data (as for example fluids saturation maps) can compose the objective function (Kretz, 2002; Gosselin, 2003).

Actually, for complex cases, completely automatic history matching is not feasible. Important decisions based on the experience and based on the knowledge of the overall process are required. In this context, it is more reasonable to think in a process that uses the advantages of automatic tasks, but the main decisions, such as what parameters to change and how to change it, as well as how to compose the objective function, when stop the process, etc, are responsibility of the specialist. This procedure is called Assisted History Matching. The algorithms applied in Assisted History Matching can be divided in two main categories. The first one is based on gradient methods and the second one is based only on the objective function value.

The gradient-based methods (Brun, 2001; Gomez, 2001), also called local optimization, require the computation of the gradients of the solution (pressure in a well, water rate, for example) with respect to the matching parameters. Some advantages of this method are: (1) a relatively large number of parameter can be evaluated at a time; (2) for cases where the topology of the objective function in not very complicated, the gradient method have high convergence rates. As disadvantages, one can to mention: (1) implementation difficulties: to take gradient calculation, the method must be implemented inside the flux simulator code, that is, it is necessary to have access to the simulator code. Moreover, there is the intrinsic difficulty to implement the method; (2) for complicated objective function, with several local minima, the search in the parameter space can be locally trapped.

The other category of algorithm, also called global optimization, has the advantage of implementation facility. Since they require only the objective function value, only output simulations to compute objective function are necessary. Examples of global optimization techniques are: evolutionary algorithms (Romero, 2000; Schulze-Riegert, 2002), also called genetic algorithms, and simulated annealing (Ouenes, 1993). Some methodologies combine global end local optimization (Gomez, 2001; Mantica, 2002). Besides the implementation facility, another advantage of these methods is that they generally work better in problems with more complicated objective function (characterized by local minima). The disadvantage is that the number of iterations increase fast with the increase of the number of matching parameters.

In this paper, a global optimization (direct search) method is used. An Assisted History Matching methodology is utilized in order to evaluate some important steps of a history matching process, such as definition of the objective function and the choice of the matching parameters.

2. Methodology

The methodology used in this paper is an assisted history matching procedure. The parameter space is formed through the discretization of the reservoir properties included in the matching process. To minimize the objective function, a direct search method is used. The dimension of the solution space depends on the number of parameters and on the discretization level of the parameters. The search method is performed by successive exploratory and linear search. An initial point pertaining to solution space is selected (point “0” in Fig. 1) and the neighboring points are evaluated. Each evaluated point implies in a flux simulation. The point of smaller objective function defines the direction of the linear search done subsequently. The point of the linear search with smaller objective function is used to a new exploratory search and so on, until a minimum is founded (point “4” green, in the example).

The algorithm described above was designed for parallel environment, that is, flux simulations are distributed in a computer network. Therefore, the algorithm perhaps is not optimized for efficiency, in terms of number of iterations, but is more robust in parameter space with complicated topology (with several local minima).

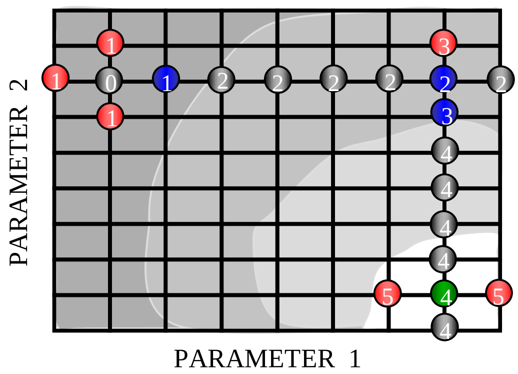


Figure 1. Schematic representation of the direct search algorithm (example for two generic parameters)

The objective function (OF) is defined as follows:

$$OF = \frac{\sum_{j=1}^{s} w_j A_j^N}{\sum_{j=1}^{s} w_j}, \text{ where } A_j^N = \frac{\sum_{i=1}^{n} (obs_i - sim_i^M)^2}{\sum_{i=1}^{n} (obs_i - sim_i^B)^2} \tag{1}$$

In the equations above, obs_i is the observed data, n is the number of observed data, sim_i^B is the simulation data for base case, sim_i^M is the simulation data for modified models; s is the number of data series, w_j is the weight for each data series and j is the number of data series.

3. Application

The reservoir model studied in the present work was generated from Tenth SPE Solution Project - Model 2 (Christie, 2001). The original model is a reservoir represented by 60 x 220 x 85 active simulation cells. For this work, 10 layers (from layer 71 to 80) were extracted from original model. Another changing was the number of wells used. In the original model, 4 producers in the corners and 1 injector in the center were used. In the model used in this work 6 producers and 5 water injectors wells were defined. The simulation of the resulting model, composed by 60 x 220 x 10 (132000 active cells), originated a synthetic history of production and pressure data for 3600 days.

To generate the initial model (to be adjusted), others 10 layers were extracted from another portion of the original model (from layer 11 to 20). This model was upscaled to 20 x 44 x 5 simulation cells. To upscale the porosity map, arithmetic average was used. To upscale horizontal and vertical permeability maps, the DP method, proposed by Maschio and Schiozer (2003) was employed. The same 11 wells, in the same positions, were used in the coarse model.

In Fig. 2 is shown three-dimensional porosity maps for fine grid model used to generate the history (a) and for the initial (base) model.

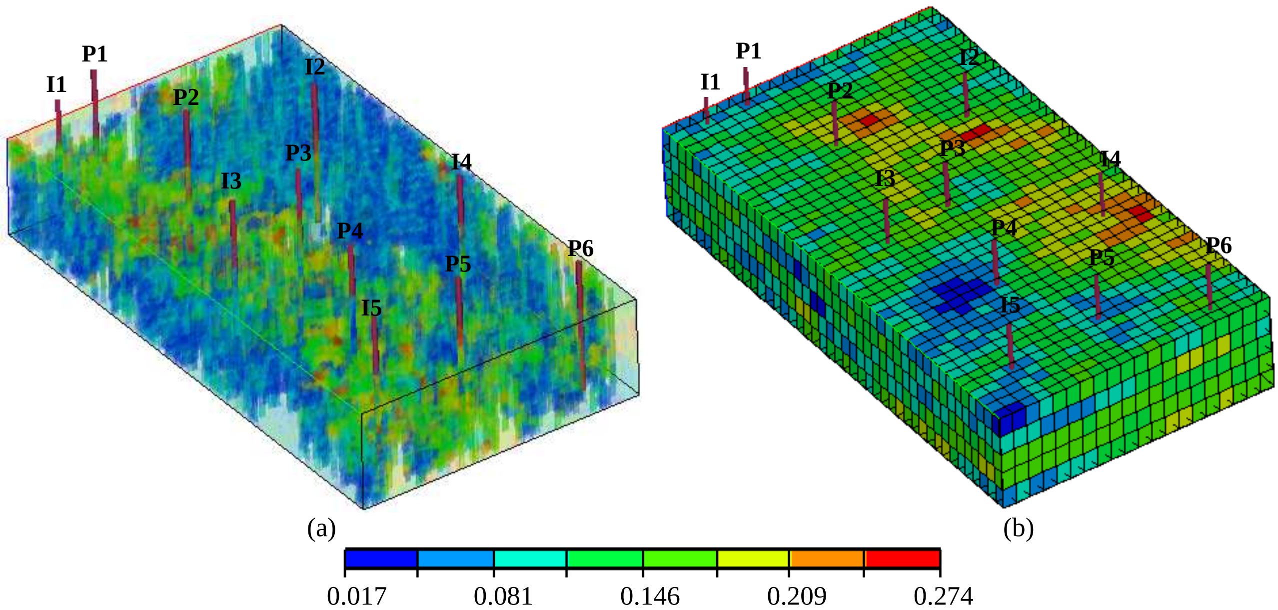


Figure 2. Three-dimensional porosity map of the model used to generate the history (a) and base model (b)

4. Matching procedures

Firstly, in order to evaluate the influence of the objective function composition, two matching process using four entire field parameters were carried out. The matching parameters were: rock compressibility, between 2.069×10^{-9} and 1.233×10^{-6}; porosity multipliers, between 0.6 and 1.4; horizontal and vertical permeability multipliers, between 0.25 and 2.5. For all parameters, 10 intervals equally spaced between minimum and maximum values were used. In the first matching process (Match 1), the objective function was composed by bottom-hole pressure and water cut of the six producer wells, that is, 12 data series were used to form the objective function. In the second matching process (Match 2), only well pressure data series were included in the objective function.

After well pressure matching, two others matching processes were performed in order to match producer wells water cut. One of them was using horizontal permeability of the 5 layers, with 11 multipliers (10 intervals) between 0.25 and 2.5 (Match 3), and the other was using vertical permeability, also for the 5 layers, with the same parameters bounds and numbers of intervals (Match 4). Three derived process from Match 3 (Match 3-b, 3-c and 3-d) were also performed with the objective to test different discretization and different bounds of the parameters.

The analysis of the results showed that two wells were not adjusted yet, PROD3 and PROD4. Therefore, a regional match was necessary for these wells (Match 5). Two regions around the wells were defined and the permeabilities (horizontal and vertical) were again included as matching parameters. In Tab. 1 is a summary of the matching processes carried out.

Table 1. Description of the history matching processes

Process	Parameters							Domain	Objective Function
1		CPOR	POR	PERMI	PERMK			Field	BHP + WCUT (6 wells)*
	Min.	2.07×10^{-9}	0.6	0.25	0.25				
	Max.	1.20×10^{-6}	1.4	2.5	2.5				
	Intervals	10	10	10	10				
2	Similar to Process 1							Field	BHP (6 wells)
3_a	PERMI (5 parameters)							Layers	WCUT (6 wells)
		Min.	Max.	Intervals					
		0.25	2.5	10					
3_b	PERMI (5 parameters)							Layers	WCUT (6 wells)
		Min.	Max.	Intervals					
		0.5	1.5	10					
3_c	PERMI (5 parameters)							Layers	WCUT (6 wells)
		Min.	Max.	Intervals					
		0.25	2.5	5					
3_d		PERMI Layer 1	PERMI Layer 2, 3 and 4	PERMI Layer 5				Layers	WCUT (6 wells)
	Min.	1.25	0.575	0.35					
	Max.	3.0	1.725	1.05					
	Intervals	7	10	10					
4	PERMK (5 parameters)							Layers	WCUT (6 wells)
		Min.	Max.	Intervals					
		0.25	2.5	10					
5	PERMI			PERMK				Region	WCUT (PROD3, PROD4)
		Min.	Max.	Intervals	Min.	Max.	Intervals		
		0.5	1.5	10	0.5	1.5	10		

* Producer wells

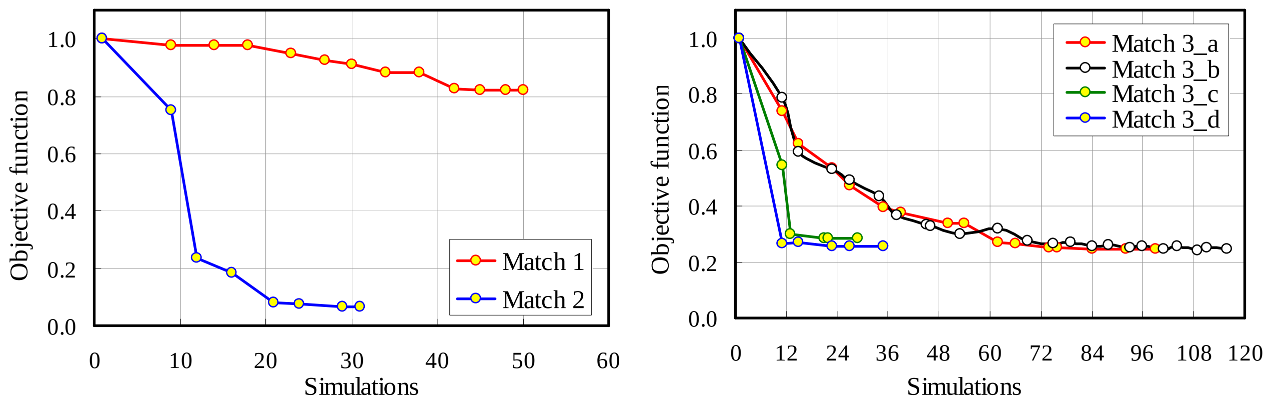
5. Results and Discussion

In Fig. 3, is presented a comparison of the objective function evolution for Match 1 and Match 2. Clearly, it is possible to observe that the process using wells bottom-hole pressure and water cut do not converge. The maximum reduction of the objective function was 20 % after approximately 50 simulations. On the other hand, the reduction of the objective function for Match 2 was practically 95 % with only 31 simulations. Figure 3-b shows the evolution of the objective function for Match 3_a, 3_b, 3_c and 3_d. Match 3_a and 3_b are the cases where the bounds of parameters are different, but the discretization level is the same. It can be seen that for the case with nearest bounds, and therefore, lower parameter variation between two consecutive nodes, the process took more simulations and reached the same objective function reduction level (76 %). Match 3_c is the process where 5 intervals for each parameter were defined. The number of simulation for this process was only 29, while for Match 3_a the number of simulation was 99 and Match 3_b took 116 simulations. Match 3_c reduced the objective function to a level similar to Match 3_a and 3_b, using much less simulations.

It is noted that in the Match 3_c and 3_d, the convergence is much faster than Match 3_a and 3_b. For Match 3_d, the behavior of the objective function is similar to Match 3_c. For all process, the reduction of the objective function reached the limit of approximately 75 %. One can observe that processes 3_c and 3_d had advantage over process 3_a or 3_b, because converged faster, using less simulation.

In Fig. 4 are matching results for producers PROD3 and PROD4 before regional match. It can be observed that global and layers matching processes were not sufficient to adjust all wells.

Table 2 summarizes all presented matching process in terms of final reduction of objective function and number of simulations. In this table, the total number of simulations do not represents the total effort of overall matching process. Some process was repeated with different options in order to show the influence of different parameter and objective function configuration. The final match and the comparison with the two initial match processes are shown in Fig. 5. For the period of 3600 days, no water is produced in the producer PROD6. Therefore, this well was not showed.



(a) (b)

Figure 3. Evolution of the objective for Match 1 and Match 2 (a) and Match 3 (b)

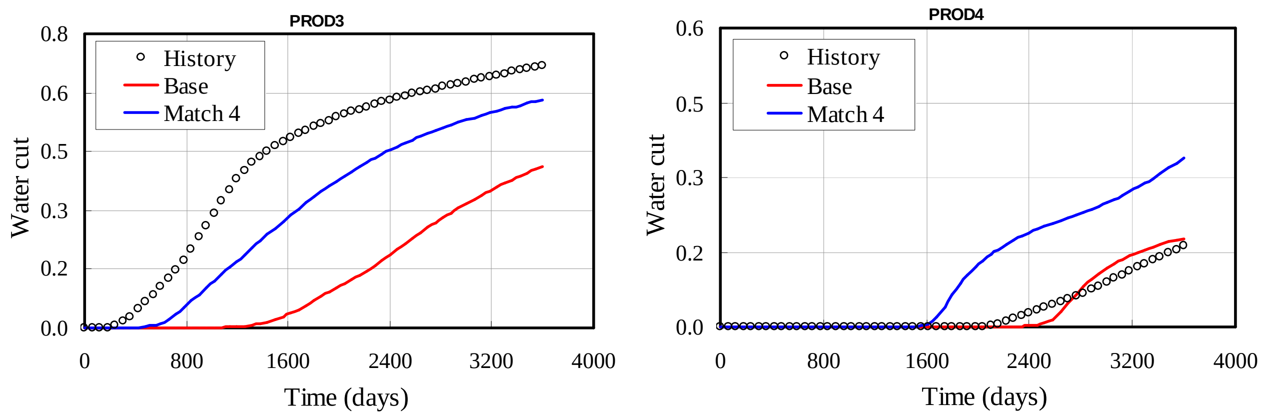
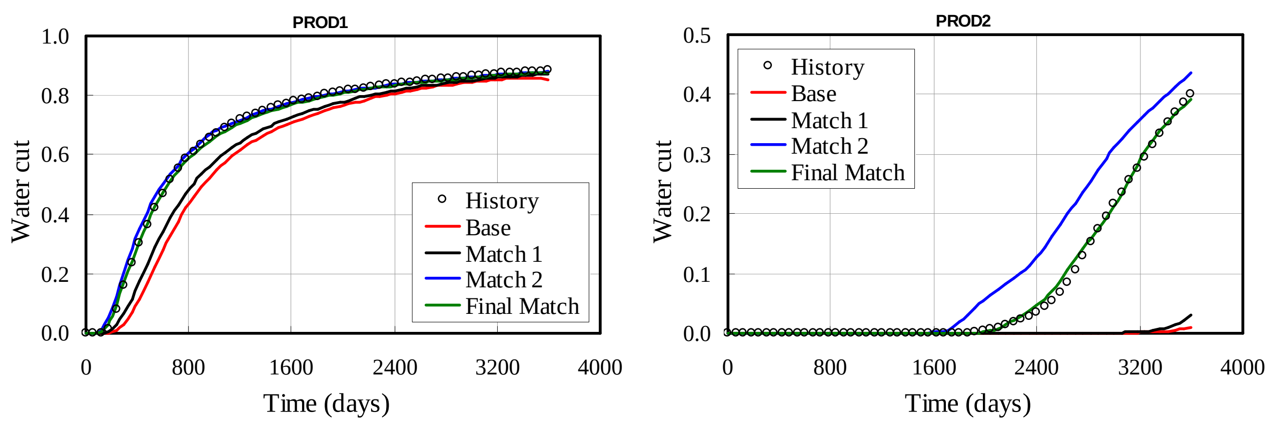


Figure 4. Wells PROD3 and PRD4 before regional matching

Table 2. Summary of the history matching processes

Process	1	2	3_a	3_b	3_c	3_d	4	5
Simulations	50	31	99	116	29	35	71	41
OF Reduction (%)	28	92	76	76	72	75	22	71



(a) (b)

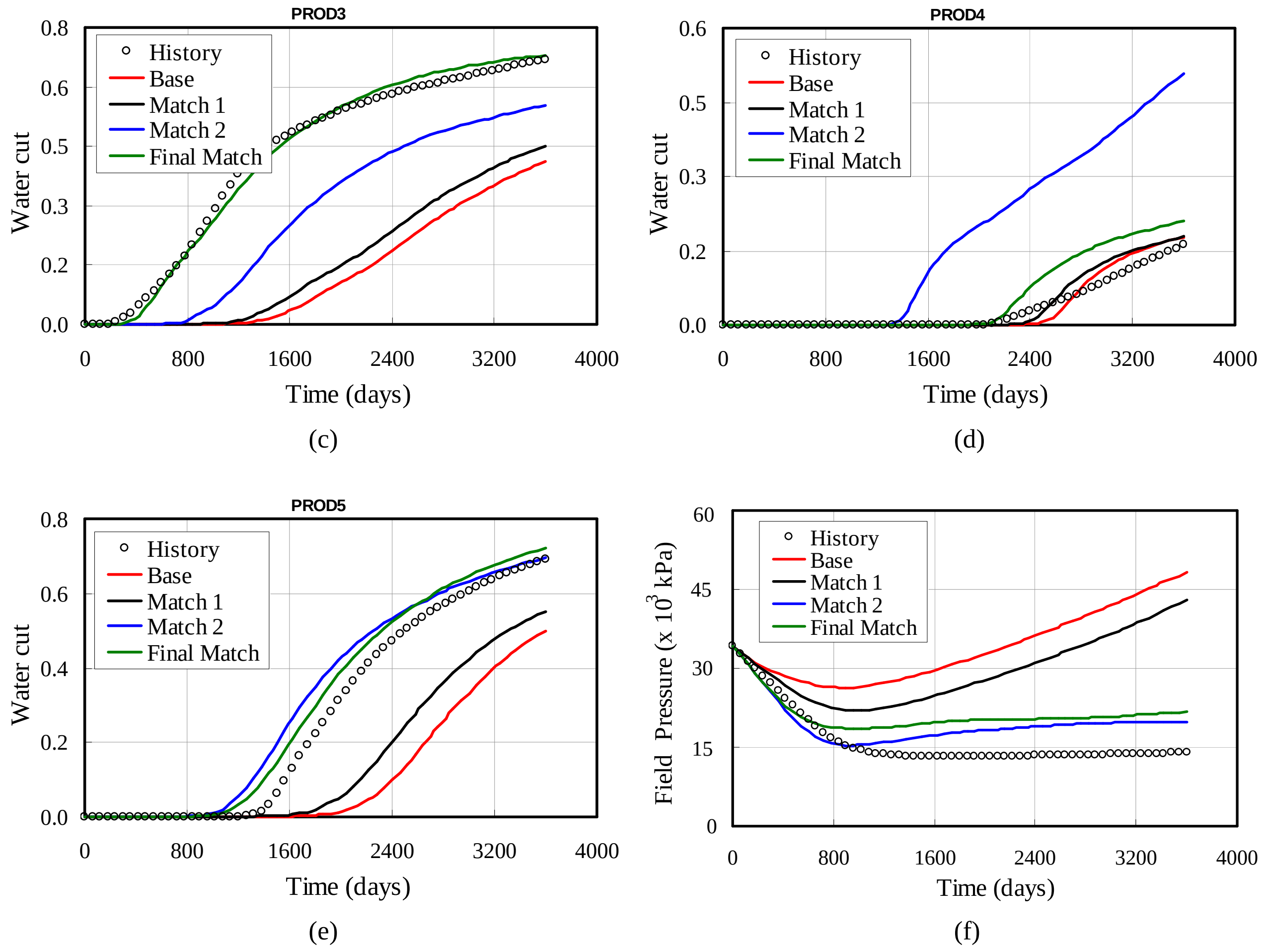


Figure 5. Comparison of two initial matching process and final match results for water cut producer (a-e) and average field pressure (f)

6. Conclusions

History matching is a complex process that requires the experience of the specialist. In order to outline the problem, a good knowledge of the analyzed reservoir model is necessary. This work showed that several important control variables influence the process. The correct parameter space definition and the composition of the objective function are important and decisive procedures. The results showed that is very difficult to get match in a unique step. It was shown that is necessary to solve the problem in several steps. In each step, the parameter space, the domain in which the parameters will be defined and the objective function must be correctly selected.

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