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Assisted History Matching using Evolution Strategy Algorithm

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Abstract

Predicting the behaviour of oil reservoirs depends crucially on the reliability of their numerical models. However, the latter have great uncertainties that push petroleum engineer to validate them periodically by the commonly known process of "History Matching (HM)". In practice, engineers perform this process manually, which is difficult and tedious. In this article, we aim to assist and accelerate this process using the Evolution Strategy algorithm implemented on Petrel RE software. We are evaluating for the first time the effectiveness of such an algorithm on a real numerical model. The latter is composed of nine production wells under a natural depletion regime with a historical production data of 6 years. For this, we have followed four steps, starting from the definition of an objective function, passing by sensitivity and uncertainty analysis on the model properties and finishing with the optimization process. As a result, the Algorithm was found to successfully match the historical production data of both the field and the wells and in a shorter time compared to the traditional method.

***Keywords**: Numerical Model; Manual History Matching; Assisted History Matching; Evolution Strategy; Optimization.*

1. Introduction

Optimizing the development of an oilfield (number of wells, well type, well location, and design operations, etc.) requires predicting its behavior under different scenarios, this is only possible using numerical models which represent the in-situ properties/conditions and can reproduce its historical production. Several disciplines (geology, geophysics, petrophysics, engineering, etc.) interact to build these numerical models by describing the best estimates of reservoir properties such as porosity, permeability, saturation, etc. Once a model is built, it can be used to predict the reservoir performance under different development strategies. However, a question is always raised: are these properties reliable? To answer this question, a simulation of the behavior of the model for a historical period of production is needed. The simulated results (flow rates, pressures, etc.) are in this case compared to the actual data (i.e., measured flow rates and pressures). However, and unless the engineer is very lucky, the initial model will never reproduce the behavior of the reservoir for the historical period. The estimated properties have always a great uncertainty especially in areas where the engineers have a lack of knowledge (i.e., deep in the reservoir). Therefore, it is necessary to adjust these uncertain properties, so the simulated results and production data are matched to a sufficient degree. This process is called: History Matching (HM).

The HM is an important step in the simulation studies. It allows validating and improving the numerical model and understanding the various phenomena of the reservoir. In practice, the engineer does it manually: he changes iteratively one uncertain parameter at a time and then simulates and evaluates the reduction in the mismatch. This makes the HM process very difficult and time consuming, first because of the multitude uncertainties in the properties of thousands of cells, or even millions of them. Secondly, because of the qualitative evaluations of the mismatch made by the engineer. To overcome these difficulties; the idea is to quantify the existing mismatch in an objective function, and then seeking the adequate values of the reservoir properties for which the objective function is minimal. This makes the history matching a nonlinear, multidimensional and a very complex optimization problem. To solve such a problem, a powerful optimization tool is thus necessary: this methodology is called Assisted History Matching (AHM). In our study, we will apply the Evolution Strategy algorithm in order to assist the process of HM.

The Evolution Strategy (ES) is a stochastic research optimization algorithm based on the population and which uses mathematical operators inspired by the Darwinian evolution theory such as mutation, recombination, and selection. It belongs to the family of metaheuristics Evolutionary Algorithms.

2. Overview of the History Matching

The HM process, as shown in Figure 1, was defined in the literature as "the process of changing the uncertain properties of the reservoir model until the simulated results for a historical period are "fit" with production data [1]".

In other words, it is the adjustment of the reservoir model using production history to reproduce the observed behavior [3]. The purpose is to determine the description of the reservoir (initial spatial distribution of properties) that minimizes the difference between the observed data and the results predicted by the simulator. Matheron was the first to make the initial approaches in the field of HM [4]. Later, Deutsch applied the HM in the oil reservoir models [5]. In recent years, the interest for matching the numerical models of oil reservoirs has increased, and this was expressed by the increase in the annual number of publications related to the HM, published in SPE (Society of Petroleum Engineers) and presented in Figure 2.

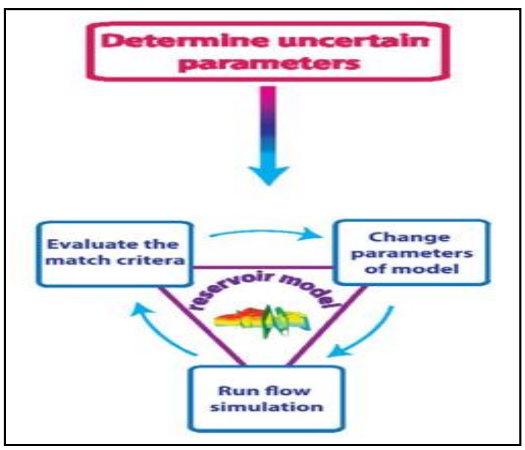


Fig.1. General History Matching process [2]

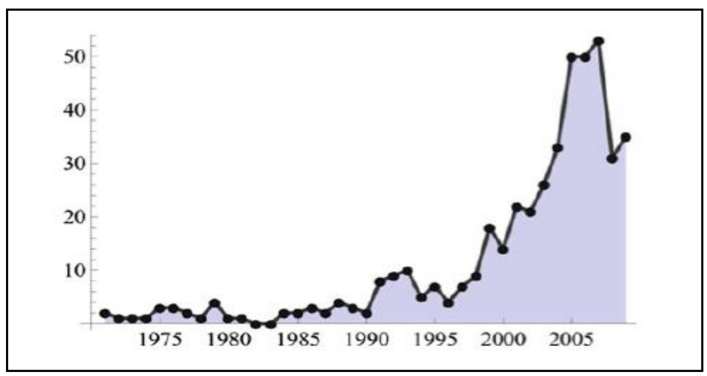


Fig.2. Annual number of publications related to the History Matching, published in the SPE papers and conferences [6]

2.1. Manual history matching

The Manual History Matching (MHM) is a "trial and error" process: the engineer runs the simulation model for a historical period and compares the simulated results with measured data [7]. Once the results are compared, the engineer changes the reservoir properties iteratively and one by one trying to improve the calibration of the model

In general, MHM proceeds through three stages [8]:

- Pressure match phase.
- Saturation match phase.
- Productivity Index (PI) match phase.

Sadly, the MHM consumes up to 40 of the time during a numerical simulation study, which is even higher than the time needed to build the model as shown in Figure 3.

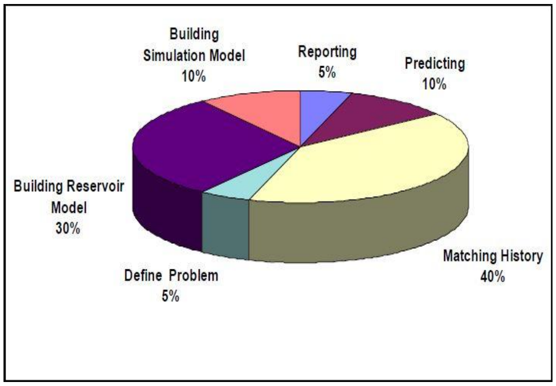


Fig.3 Time consumed by the MHM during a numerical simulation study

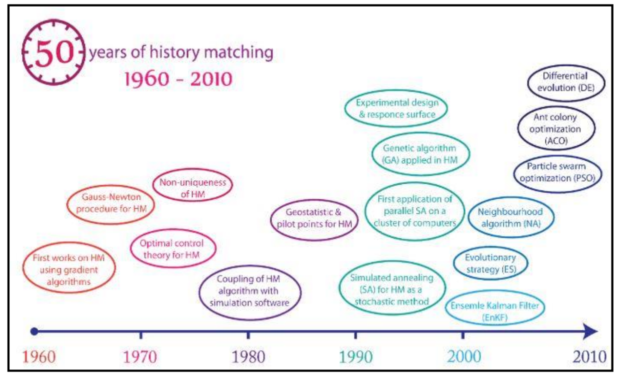


Fig. 4. 50 year of History Matching 1960-2010

2.2. Assisted history matching

The Assisted History Matching (AHM) consists in quantifying the offset (mismatch or misfit) between the observed data and simulated results in an Objective Function called the "error function". This function is then minimized by finding the optimal values of reservoir properties using coded optimization algorithms [7]. Therefore, this process converts the HM to an optimization problem.

Over than 40 successful AHM projects were conducted worldwide by the service company MEPO (Multipurpose Environment for Parallel Optimization) [11]. The time needed for numerical models with over than 600 properties and 1000 wells varied between 1 week to 9 months, according to the cluster's CPU time.

3. Evolution Strategy Algorithm (ES)

Throughout history, several optimization algorithms were used to reduce the time of the HM. Most of these algorithms are metaheuristics stochastic algorithms. Figure 4 shows the different algorithms used in the HM since the sixties until now [2].

The ES was chosen in this case because of its flexibility (resolution of direct or inverse problems, minimizing or maximizing problems) and its ability to find the global optimum. It is a population-based research optimization algorithm that employs operators inspired from the Darwinian evolution theory such as selection, mutation, recombination and it belongs to the family of metaheuristics of Evolutionary Algorithms [9]. The algorithm was first proposed by Ingo Rechenberg in 1965 at Berlin Technical University, Germany. The method was then developed during the late sixties, mainly through the work of Rechenberg *et al*. on designing optimal aerodynamic profiles with the minimal friction with the air [10]. A general algorithm of the SE may be noted by $(\mu/\rho, +\lambda)$-ES, where :

μ: the parents population.

ρ: Parents that will be combined to produce children.

λ: the children population.

, : « *comma* » selection.

+ : « *plus* » selection.

Figure 5 summarizes the steps of the ES Algorithm.

An application example of this algorithm is shown in Figure 6 [12] where the number of individuals of the parents and the children population is fixed at 8.

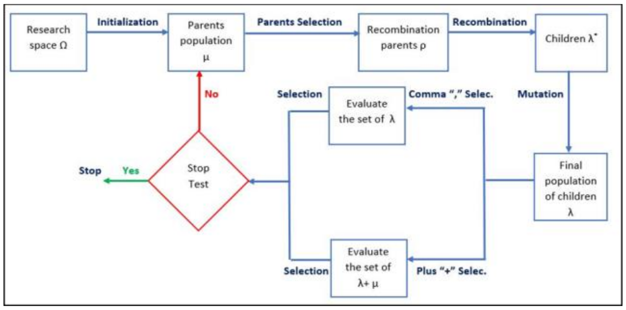


Fig. 5. Representative diagram of the principle of the Evolution Strategy Algorithm [11]

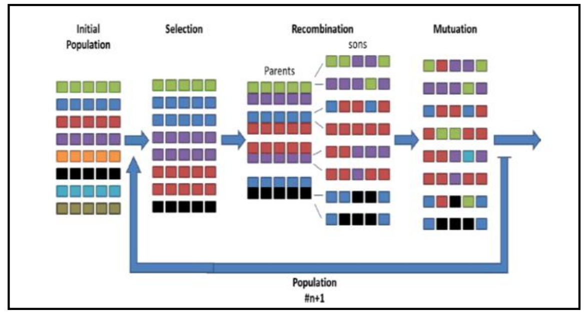


Fig. 6. Application example of the Evolution Strategy Algorithm [12]

To avoid the stagnation of the algorithm in local optimums, recombination and mutation operators allow better exploitation and exploration of the research space. The exploration, provided by the mutation, is to discover new areas in the research space. While exploitation ensured by recombination, is to benefit from the best individuals to achieve better individuals (Models). One should point out that a compromise between these two operators is needed to prevent the exploration-exploitation dilemma explained as follow: "Too exploitation results in convergence to a local optimum known as premature convergence, while too exploration leads to the non-convergence of the algorithm".

4. Case of application

4.1. Reservoir description

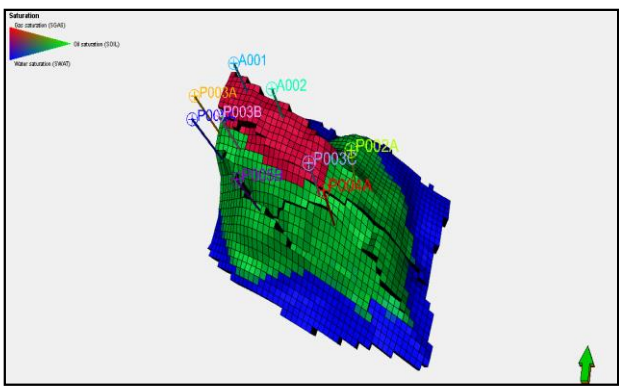


Fig. 7 General View of the reservoir

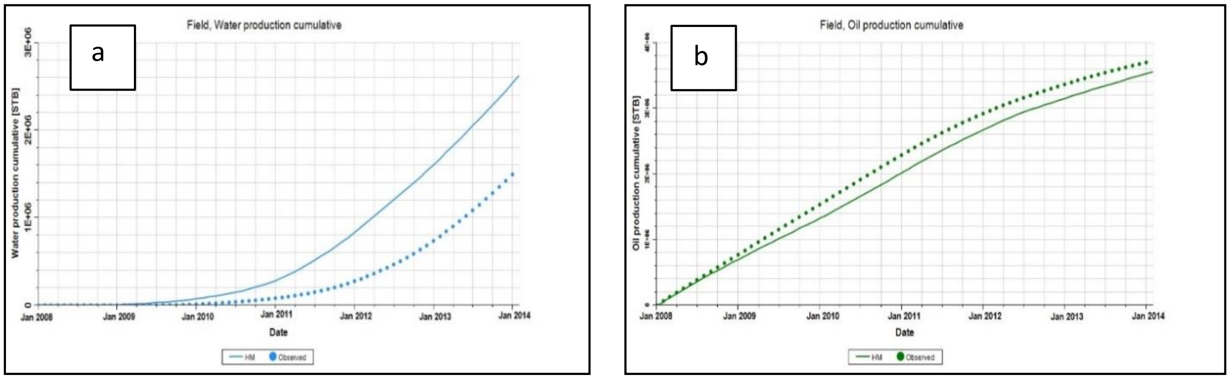
The Agaba reservoir is a sandstone reservoir which began production in January 2008 with 9 wells (A001, A002, P002A, P003A, P003C, P004A, P005A, and P005B). The reservoir (Figure 9) is a highly faulted oil reservoir with a gas cap. It has 4 main faults that divide the reservoir into 5 fault blocks. In some areas, the throw of the fault is so large that there is no sand-to-sand juxtaposition between the fault blocks. Geologists confirmed that fault 1 does not extend completely between fault block 3 and fault block 4. The geologist and geophysicists also agreed that there is very large aquifer connected to the sides of the reservoir and that the uncertainty in the connection between the aquifer and the reservoir is directly related to the connection angle.

4.2. Problematic

The initial simulation of the numerical model (i.e., initial model) has shown (Figure 8) a huge mismatch between simulated and measured field and wells data over the 6 years for the water flow rate (WPR), the oil flow rate (PRO) and the gas flow rate (GPR).

4.3. Numerical model control mode

Each numerical model must have a control mode. This concept involves using the observed data of any parameter (oil flow rate, gas flow rate, water flow rate, reservoir pressure, reservoir volume) as initialization for calculating the results of the other parameters. For this, we have chosen the observed data of oil production as the control mode. The reasons for this choice were first the reliability of the observed oil production data compared to water or gas and secondly to reduce the number of parameters to match to only two parameters (water and gas). The simulator, in this mode, must reproduce the observed data of the oil and will calculate the flow of the other phases (gas and water) according to their mobility ratios. Consequently, as shown in Figure 9, the simulated results and observed for oil production were perfectly superposed. While the mismatch in the production of gas and water were persisted.



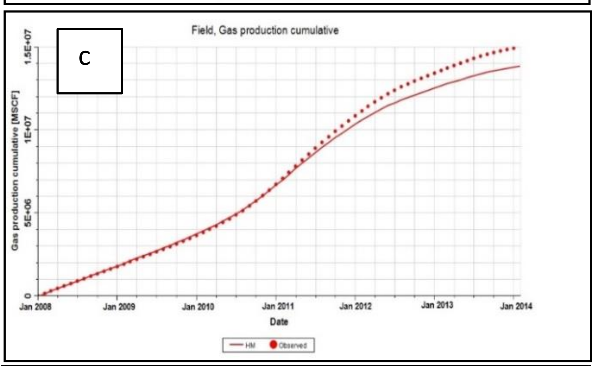


Fig. 8. Field cumulative observed production of water (a), oil (b) and gas (c) [11]

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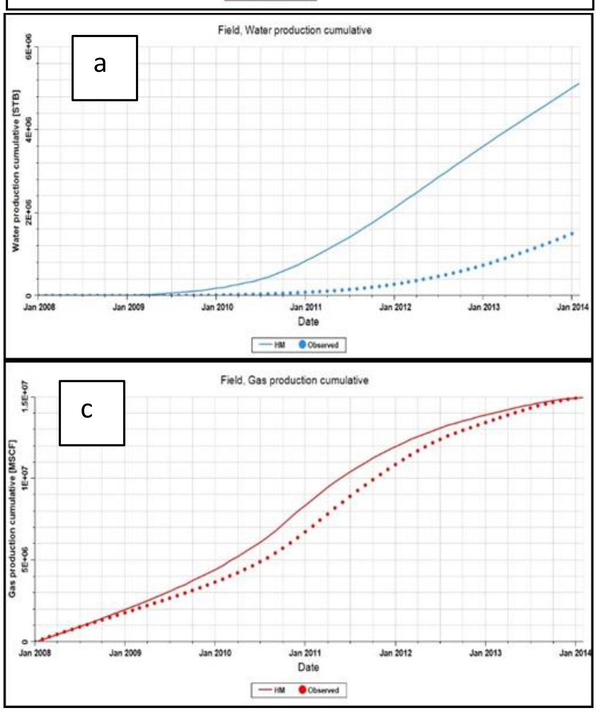

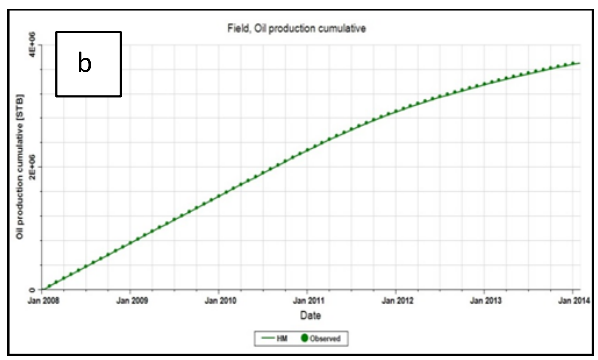

Fig. 9. Field cumulative production of water (a), oil (b), gas (c) in the oil control mode [11]

←

4.4. Assisted history matching

In order to implement an Assisted History Matching process in Petrel RE, we have followed four steps:

4.4.1. Definition of the objective function

The general objective function expresses the overall mismatch that should be minimized. It is defined by the following expression:

$$F = \sum_Q \sum_I w_I w_Q m(I, Q) \quad (1)$$

where: $m(I, Q)$: the mismatch for the quantity Q in the well number I; w_I: weight on the well (higher values are assigned to wells with higher mismatch); w_Q: weight on the quantity (higher values are assigned to quantities with higher mismatch).

The general objective function given by equation (1) is the sum of the partial objective functions. The latter quantifies the mismatch for each quantity Q as shown in the following expression:

$$F_Q = w_Q \sum_I w_I\, m(I, Q) \quad (2)$$

In our case, we have two partial objective functions: one for water production rate and the other for gas production rate.

The observed results should be first inserted in the software, and four parameters should be defined:

- The measurement error "E": used to normalize the mismatch of each quantity, so the partial objective functions can be summed.
- The weight on the well "w_I": higher values are assigned to wells with a higher mismatch.
- The weight on the quantity "w_Q" higher values are assigned to quantities with a higher mismatch.
- The weight on time "w_K": higher values are assigned to times with higher mismatch.

The chosen parameters for this case are resumed in Table.1.

Table 1. Objective function parameters

Quantity	Measurement error "E"	Weight on the well wI	Weight on the quantity wQ	Weight on the time wK
Gas production rate (GPR)	10 MSCF/d	1	1	1
Water production rate (WPR)	5 STB/d	1	1	1

Errors on the gas and water flow rates are relatively high (10 MSCF/d and 5 STB/d) because of the technical and operational conditions such as the gauging conditions, three-phase flow metering, and the back allocation. In addition, these flow rates are not measured periodically as in the case of the oil. On the other hand, we have chosen to fix the weight of different parameters to 1, since the mismatch was observed for all quantities and for all the wells and we are looking to match them all.

After defining the objective function, an estimated value for the base case was obtained by running the first simulation. The results are summarized in Table.2. A value of "803.35" was obtained, and we will try to minimize it.

Table 2. Objective function of the base case

Base case	Objective1	Objective1_WPR	Objective1_GPR
HM	803.35	454.73	348.61
	100%	56.60%	43.40%

4.4.2. Sensitivity analysis

The purpose of a sensitivity analysis is the identification of the properties, which strongly influence the simulated results of the model. In this analysis, known also under the term "One Variable at One Time", one of the model properties is varied while keeping all the other variables constant. This process is then repeated for each uncertain property. The uncertain properties and their intervals are fixed by the engineer based on his analysis on the first simulation results. For this case, we have chosen the following properties:

- Faults Transmissibility (Fault1, 2, 3, 4, 5): FTM1 [0 ; 1], FTM2 [0 ; 1], FTM3 [0 ; 1], FTM4 [0 ; 1], FTM5 [0 ; 1].

- Cells Transmissibility (X, Y, Z): MULTX [0.5; 2], MULTY [0.5; 2], MULTZ [0.5; 2].
- Aquifers contact angle (North/ South): AOF_N [1; 360], AOF_S [1; 360].
- Outer radii of (North/ South) aquifers: Ext_Rad_N [5000; 100000], Ext_Rad_S [5000; 100000].
- Pore volume: PV [0.5; 1.5].

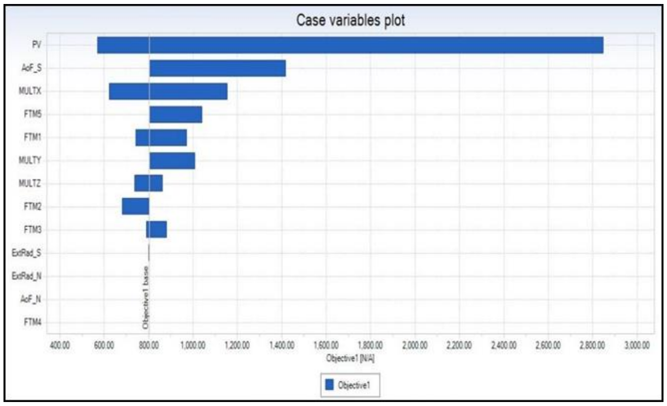

Fig.10. Tornado plot of the sensitivity study [11]

The results of the sensitivity analysis are visualized using a Tornado plot as shown in Figure 10, in this plot the effect of each property, on the objective function, is represented by a bar. As can be seen in this figure: Pore volume, South Aquifer contact angle, Cells Transmissibility in the X direction, Fault 5 Transmissibility, Fault 1 Transmissibility, Cells Transmissibility in the Y and Z directions, Fault 2 Transmissibility and Fault 3 Transmissibility, are the most influencing properties.

4.4.3. Uncertainty analysis

This step involves samples from each sensitive property within the defined research space which are combined and simulated in a random way and then the objective function for the resulted models is evaluated. The samples are chosen using a numerical sampler to try to cover all the research space of each property.

A stochastic sampler "Monte Carlo" with the Latin-hypercube method was selected to choose a random 300 sample from each property. This will allow a better exploration of the research space and will provide us with a set of cases to initialize the optimization algorithm afterwards. The properties and their corresponding intervals that were selected for this analysis are:

- Faults Transmissibility (Fault1, 2, 3, 5): FTM1 [0 ; 1], FTM2 [0 ; 1], FTM3 [0 ; 1], FTM5 [0 ; 1].
- Cells Transmissibility (X, Y, Z): MULTX [0.5; 2], MULTY [0.5; 2], MULTZ [0.5; 2].
- (North/ South) Aquifer contact angle: AOF_N [1; 360], AOF_S [1; 360].
- Pore volume: PV [0.5; 1.5].

The properties "north aquifer outer radii, south aquifer outer radii, Fault 4 transmissibility" were not selected at this level, because of their neglected effect on the simulation results as shown by the tornado plot. However, the north aquifer contact angle was selected despite its minimal effect as we have estimated that it can still affect the simulation results. The simulation was then executed, where 300 numerical model were obtained. The results of the uncertainty analysis for four cases (randomly chosen among 300 cases) are presented in Table 3.

Table 3. Uncertainty analysis results

Case	HM_206	HM_344	HM_272	HM_224
$PV	1.18	1.14	0.53	0.54
$MULTZ	2.48	0.78	0.86	0.98
$MULTY	1.77	0.57	1.76	1.68
$MULTX	0.92	2.25	1.82	1.06
$FTM5	0.87	0.49	0.34	0.25
$FTM3	0.47	0.03	0.54	0.81
$FTM2	0.49	0.54	0.97	0.28
$FTM1	0.00	0.48	0.68	0.49
$AoF_S	93.66	115.78	116.74	75.03
$AoF_N	272.33	255.51	185.08	320.32
$Objective1	416.80	530.82	2 624.78	3 247.80

From this table, one can see clearly that the Monte Carlo sampler has succeeded in exploring the research space by finding some interesting cases: the first two cases had an objective function value below the base case (803.35), and the other two unfavorable cases had an objective function value above the base case.

4.4.4. Optimization

It is the heart of this study. the Evolution Strategy Algorithm is employed to generate numerical models with the lowest objective functions and which can match the observed data. First of all, we had to define the algorithm parameters (listed in table 4) in order to adapt the algorithm to our problem. This was done by running some trial tests. The chosen parameter values were summarized below (Table 4).

Table 4. Evolution strategy algorithm parameters for the optimization process

Parameter	Value	Parameter	Value
Maximum iterations	600	Required improvement	5%
Number of children	20	Improvement window	1 generation
Number of parents	10	Destabilization factor	2
Retain in population	yes	Random seed	1
Mutation standard deviation	0.1	Previous cases	Uncertainty cases
Parents par enfant	2		

The algorithm was then executed. The time needed to simulate all the 600 models was less than 12 hours thanks to the great capacity of the employed computer equipped with 5 CPUs. The results of the four best case obtained after the optimization was presented in Table 5.

Table 5. Best optimization results

Case	\$Obj1 WPR	\$Obj1 GPR	\$Obj1	% of reduction
HM938	102.392	220.425	322.817	60%
HM702	95.579	232.093	327.672	59%
HM751	92.994	236.824	329.818	59%
HM739	96.663	243.400	340.063	58%

According to Table 5, a total reduction of the objective function has reached up to 60% compared to the initial value (803.35) which is very remarkable for an HM process. Furthermore, three other cases reached up to 58% and 59% of reduction. Therefore, one can conclude that the optimization has provided several candidate models that can reflect the actual properties of the reservoir. Figure 11 and Figure 12 show the match obtained after the optimization at the field scale and for some wells (P003B, P004A and P005A) respectively. A perfect match was obtained for the water rate at both the field and well scale and for gas rate at the well scale. While the gas rate at the field scale had a less satisfactory match.

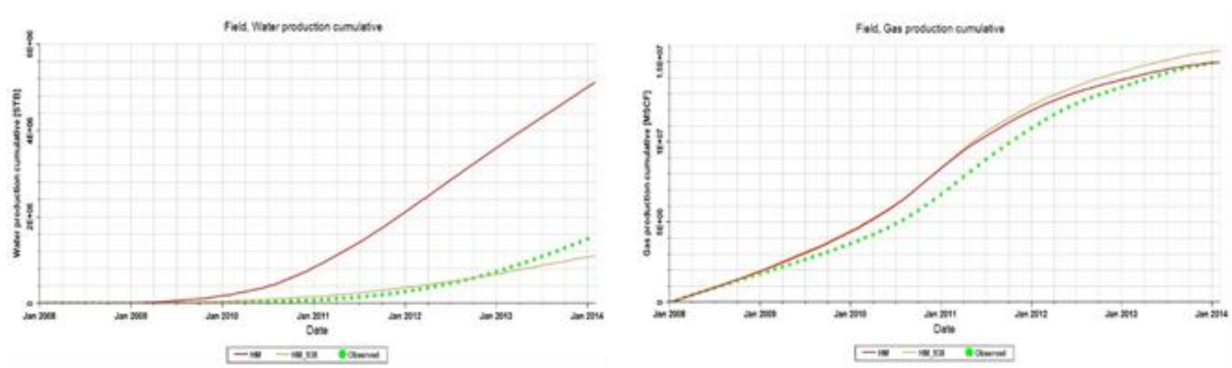

Fig. 11. Optimization results of the field [11].

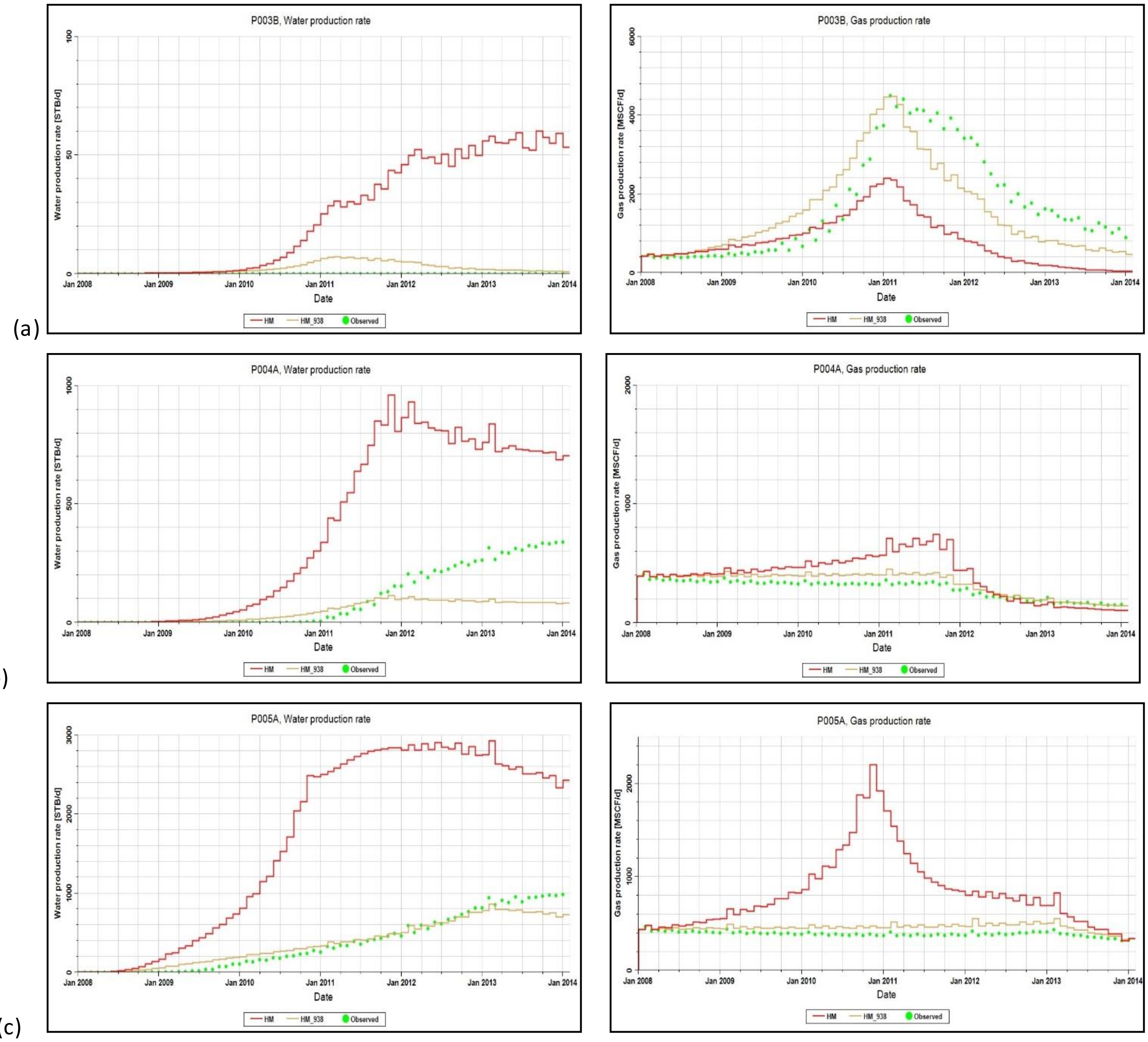

Fig.12. Optimization results at the P3B (a), P4A (b), P5A (c) wells [11]

5. Conclusion

The History Matching (HM) had always required a lot of experience in reservoir engineering and the phenomena governing the reservoir and was always considered as an Art more than as a science; however, evolutionary algorithms can help in this task. In this study, a numerical model with 9 wells and two quantities (water and gas) with up to 13 uncertain properties needed for history matching. The task appeared impossible using the Manuel HM. Nevertheless, An Assisted HM using the Evolution Strategy Algorithm succeeded in matching it in less than 12 hours. At least four matched models were obtained with up to 60% reduction in the objective function. The success of the Evolution Strategy Algorithm in assisting the process of History Matching will certainly promote the use of such algorithms in other complex optimization problems in the oil industry.

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