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# COB-2021-0249 Reservoir characterization comparing different ensembles methods

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***Abstract.*** *The estimation of reservoir properties with a high level of certainty is essential to guarantee an efficient reservoir management. To minimize the associated uncertainties with estimated properties, different data sources can be, individually or in combination, analyzed. Well test is an important source of dynamic data during reservoir exploration. Normally the bottom hole pressure (BHP) and the flow rate from the reservoir are post-processed to calibrate the model that represents the reservoir dynamics. The procedure of using the response from the reservoir to calibrate the model is called history matching. The estimated properties can be associated with a local minimum on the objective function used to find the reservoir/well parameters. Finding a local minimum in the residual function is a goal of an inverse problem. History matching is a type of inverse problem that is highly non-linear, therefore there are several combinations of parameters that can generate profiles that have good data matching with the observed data from the reservoir. To solve this inverse problem, several methods can be used to create a set of models generating a distribution of the parameters. Those methods are called ensemble-based methods. In this work, we applied Genetic Algorithm (GA), Ensemble Smoother (ES), and Ensemble Smoother with multiple data assimilation (ES-MDA) to estimate reservoir properties using pressure and/or temperature dynamic data and make a probability distribution of the parameters in the analysis. Results indicate that for a cylindrical homogenous single layer reservoir and assuming the same quantity of assimilations and/or generations, the ES-MDA produced a better history matching of the data and a better uncertainty quantification of the porosity and permeability. It also indicates that both the pressure and the temperature data can be used separately or combined to estimate reservoir parameters.*

***Keywords:*** *Reservoir characterization, Inverse Problem, Genetic Algorithm, Ensemble Smoother, ES-MDA*

## 1. INTRODUCTION

Reservoir characterization is an important tool for reservoir management. The estimation of reservoir properties with a high level of certainty is essential to guarantee efficient reservoir management. Well testing is fundamental because it is the only source of dynamic data during the exploitation step. It typically consists of measuring the pressure and temperature responses at the well, during production, injection, or static conditions. Usually, only pressure data is post-processed to estimate reservoir characteristics and improve the reservoir model. Most analyses of well tests assume isothermal flow. In the past, an isothermal flow hypothesis was considered and accepted, because the resolution of temperature gauges was insufficient to detect small variation during the flow. However, with the technical evolution of temperature sensors, the quality of the measured data has improved considerably and it is becoming common to have temperature sensors permanently in the wells. Recent studies by Galvao *et al.* (2019a) show that considering only pressure data can lead to misinterpretations due to thermal effects neglected specifically in high transmissibility reservoirs such as in the Brazilian Pre-Salt reservoir. The availability of data increases as the technology improves in parallel with the growing number of smart wells. Li *et al.* (2011) presented a procedure to characterize reservoirs taking into account temperature data and showed that including it improves the result of the analysis.

The characterization of the reservoir properties by using pressure and temperature transient data obtained from well tests is a classical inverse problem. The procedure of using the response from the reservoir to calibrate the model is called history matching. The estimated properties can be associated with a local minimum on the objective function used to find the parameters. Finding a local minimum is normal since history matching is an inverse problem that is highly non-linear, there are several combinations of parameters that can generate profiles that have good data matching with the observed data from the reservoir. Therefore, several methods can be used to create a set of models generating a distribution of the parameters. Those methods are called ensemble-based methods. In this work, we applied Genetic Algorithm (GA), Ensemble Smoother (ES), and Ensemble Smoother with multiple data assimilation (ES-MDA) to estimate reservoir properties using pressure and/or temperature dynamic data and make a probability distribution of the parameters in the analysis.

Figure 1 represents a homogenous cylindrical reservoir with the wellbore with the respective components, those model was used to provide the pressure and temperature evolution in order to use as observed data in this work. Preliminary, the genetic algorithm and the ES-MDA were used to solve the inverse problem and make a comparison with the estimates found by each method as well as the number of times the method used the simulator to make its estimates.

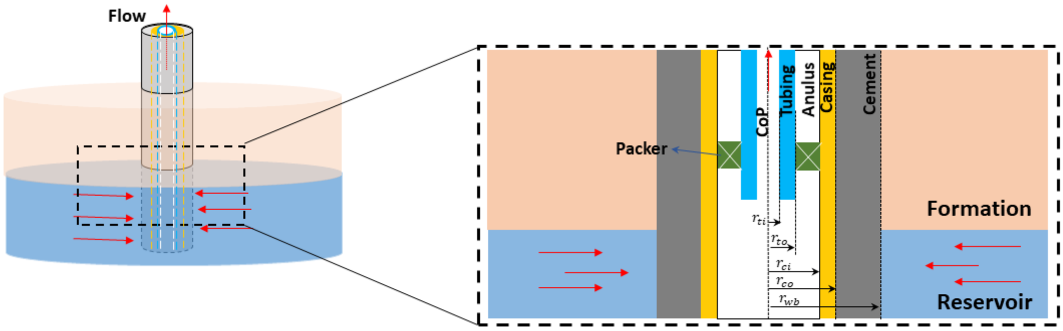


Figure 1. Wellbore reservoir scheme, with the wellbore components.

## 2. Mathematical formulation

This work is divided into two stages. First, the direct problem is solved, in which all the physics of the problem is being represented in order to generate pressure and temperature data. Secondly, the inverse problem is solved, by using genetic algorithm and ES-MDA method in order to estimate reservoir parameters such as permeability and porosity, as shown in Fig. 1.

### 2.1 Direct problem

The direct problem consists in solving mass, momentum, and energy conservation equations in a coupled wellbore-reservoir system, described in Onur *et al.* (2017). To solve the system of equations that compose the direct problem, a finite difference method is used. The validation of the method, as well as better explanations of its implementation, can be seen in Mattoso *et al.* (2020b) and Mattoso *et al.* (2020a).

Reservoir properties and well parameters used in this work are listed in table 1 and table 2, respectively. These data were also used in Galvao *et al.* (2019b) and Galvao *et al.* (2020).

| | | | | | |
|---|---|---|---|---|---|
| $K$[m$^2$] | $9.87 \times 10^{-14}$ | $C_o$ [Pa$^{-1}$] | $1.12 \times 10^{-9}$ | $\beta_o$ [K$^{-1}$] | $1.11 \times 10^{-3}$ |
| $\phi$ | 0.12 | $C_w$ [Pa$^{-1}$] | $4.04 \times 10^{-10}$ | $\beta_w$ [K$^{-1}$] | $5.27 \times 10^{-4}$ |
| $T^o$[K] | 334.0 | $C_r$ [Pa$^{-1}$] | $3.06 \times 10^{-10}$ | $\beta_r$ [K$^{-1}$] | $9.0 \times 10^{-5}$ |
| $H$[m] | 50 | $c_{po}$ [J/kgK] | 2252.9 | $\rho_o$ [kg/m$^3$] | 770.0 |
| $p^o$[MPa] | 49.033 | $c_{pw}$ [J/kgK] | 4209.35 | $\rho_w$ [kg/m$^3$] | 998.2 |
| $r_w$[m] | 0.156 | $c_{pr}$ [J/kgK] | 888 | $\rho_r$ [kg/m$^3$] | 2643.05 |
| $r_e$[m] | 25000 | $B_o$ [m$^3$/std m$^3$] | 1.4 | $\mu_o$ [Pa.s] | $0.9 \times 10^{-3}$ |
| $s_w$ | 0.15 | $\lambda_t$ [J/msK] | 3.44 | $\alpha_t$ [m$^2$/s] | $1.484 \times 10^{-6}$ |

Table 1. Input data used to validate the numerical model and also used in Galvao *et al.* (2019b); Galvao *et al.* (2020).

| | | | |
|---|---|---|---|
| $L$ [m] | 1100 | $z_{tubbing}$ [m] | 100.0 |
| $\alpha$ | 90° | $z_{gauge}$ [m] | 513 |
| $r_w$ [m] | 0.156 | $\lambda_{cement}$ [W/mK] | 1.898 |
| $r_{co}$ [m] | 0.12224 | $\lambda_{wall}$ [W/mK] | 44.917 |
| $r_{ci}$ [m] | 0.10839 | $\lambda_{an}$ [W/mK] | 0.162 |
| $r_{to}$ [m] | 0.06985 | $\lambda_{rock}$ [W/mK] | 3.8773 |
| $r_{ti}$ [m] | 0.05931 | $g_G$ [K/m] | -0.03 |

Table 2. Input data of well parameters.

### 2.2 Inverse problem

This inverse problem is well known in the oil industry and is called history matching (Oliver *et al.* (2008)). This history matching process aims to estimate parameters that produce pressure and temperature data and fit to the observed data. Due to the high non-linearity of the problem, there may be more than one combination of parameters of interest that when introduced into the flow simulator produce a similar response to the observed data. In order to obtain a range of values for each parameter as estimation, this work chooses ensemble-based methods to solve the history matching problem.

In the literature, there are many works that solved history matching problems by using genetic algorithm (GA), Ensemble Smoother (ES), Ensemble smoother with multiple data assimilation (ES-MDA), and others ensemble methods. Maurya *et al.* (2019) and Xavier *et al.* (2013) used the genetic algorithm to make the reservoir characterization with different data sources. The ES-MDA was introduced by Emerick and Reynolds (2012) and applied in different works. Emerick and Reynolds (2013) compare different ensemble-based methods to evaluate the performance.

The ES-MDA method is used to estimate and perform the uncertainty analysis of the parameter vector **m**, that contains reservoir properties, listed in the following vector:

$$\mathbf{m} = [log(K), and\ \phi]^T \tag{1}$$

It is common to use the permeability in a log scale in order to reduce the amplitude of the initial range. The variable $K$ is the permeability of the reservoir, as shown in Fig.1. The variable $\phi$ represents the homogenous porosity of the reservoir.

When the parameter vector (**m**) is introduced in the flow simulator ($g$) a pressure and temperature response (**d**) is generated. The pseudo-measured data is called $\mathbf{d}_{obs}$. To approximate to a real data, is introduced Gaussian noises for sandface pressure ($\epsilon_1$) and sandface temperature ($\epsilon_2$) data. Therefore, depending on the case the observed data ($\mathbf{d}_{obs}$) is defined as:

$$\mathbf{d}_{obs} = g(\mathbf{m}_{true}) + (\epsilon_1\ or\ \epsilon_2) \tag{2}$$

In the ES-MDA, the observed data ($\mathbf{d}_{obs}$) is perturbed by adding another Gaussian distribution in each assimilation originating the $\mathbf{d}_{uc}$:

$$\mathbf{d}_{uc} = \mathbf{d}_{obs} + \sqrt{\alpha_i C_D^{1/2} Z_d}\,, \quad on\ which\ Z_d = N(0, Id_{N_d}) \tag{3}$$

According to Emerick and Reynolds (2012), in nonlinear cases, this recurrent procedure tends to reduce the sampling problems caused by matching outliers that may be created when the observed data ($\mathbf{d}_{obs}$) is perturbed. The variable $C_D$ is the covariance of measurement errors matrix, and $\alpha_i$ is the inflation coefficient that satisfies:

$$\sum_{i=1}^{N_i} \frac{1}{\alpha_i} = 1 \tag{4}$$

The update process of the vector parameters $m$ is defined as follow:

$$\mathbf{m}_j^a = \mathbf{m}_j^p + [C_{MD}(C_{DD} + \alpha_i C_D)^{-1}](\mathbf{d}_{uc} - \mathbf{d}_j^p) \tag{5}$$

Where the superscripts "*a*" means the present ensemble and "*p*" means the prior. The subscript "*j*" is the ensemble counter that goes from 1 to $Ne$ individuals. The $C_{MD}$ is the cross-covariance matrix between the parameters and the simulated data and $C_{DD}$ is the auto-covariance matrix of the simulated data and defined as follow:

$$C_{MD} = \frac{1}{N_e - 1} \sum_{j=1}^{N_e} (\mathbf{m}_j^f - \overline{\mathbf{m}}^f)(\mathbf{d}_j^f - \overline{\mathbf{d}}^f)^T \tag{6}$$

$$C_{DD} = \frac{1}{N_e - 1} \sum_{j=1}^{N_e} (\mathbf{d}_j^f - \overline{\mathbf{d}}^f)(\mathbf{d}_j^f - \overline{\mathbf{d}}^f)^T \tag{7}$$

The ES method has similar update formula of ES-MDA, expressed in the Eq.(5). The difference between them is that ES has only one global assimilation.

$$\mathbf{m}^u = \mathbf{m}^p + [C_{MD}(C_{DD} + C_D)^{-1}](\mathbf{d}_{uc} - \mathbf{d}^p) \tag{8}$$

In the Genetic Algorithm, the quadratic error is adopted as fitness function ($f(M)$).

$$f(M) = \sum_{j=1}^{N} (\mathbf{d}_{obs} - \mathbf{d}_j)^2 \tag{9}$$

For Eq.(9), M is the chromosome and the parameters are the gens. The $N$ is the number of points into the evolution in analysis ($\mathbf{d}_{obs}$). The variable $\mathbf{d}_j$ is the evolution calculated by the flow simulator when introduced the parameters of one chromosome. Equal to the parameter vector $m$ from the ES-MDA, the chromosome is composed of the log of the permeability and the porosity.

The initial population and the number of generations will be controlled, in order to be able to compare the times that the flow simulator is required when the GA and the ES-MDA are applied. For the crossover fraction, some percentiles were tested, and $80\%$ was the best option.

## 3. Results

Application results of ES-MDA and GA methods are discussed next; they were used to estimate the properties of a synthetic homogenous reservoir, as shown in Fig. 1. In order to compare the methods, the size of the population and the ensemble size was set to 100. For the ES-MDA method, 4 assimilations were performed, this means that the flow simulator was used 400 times during the estimation process. However, using the GA method, the estimation result , when the simulator was used 4 generations (400 times), showed dispersed results. It was necessary to increase the number of generations to 12, 16, and 20. Increasing the number of generations causes an increase in CPU time. Table 3 contains the times that the flow simulator was used by each analysis.

| Analysis | Simulator run times |
|---|---|
| $Press_1$ or $Temp_1$ | 1200 |
| $Press_2$ or $Temp_2$ | 1600 |
| $Press_3$ or $Temp_3$ | 2000 |
| $Temp_{ES-MDA}$ | 400 |
| $Comb_{ES-MDA}$ | 400 |

Table 3. Table with the times that the flow simulator was used by each test.

As already mentioned, for the GA method, tests were performed with different numbers of generations and these tests received the sub-index 1, 2, and 3 , being 1 to 12 generations, 2 to 16, and 3 to 20 generations. For the genetic algorithm, the observed data was divided into two, the first one containing only temperature data ($Temp$) and the other only pressure data ($Press$).

In the ES-MDA method, two configurations of observed data were also used. First, only the temperature data was considered ($Temp_{ES-MDA}$). Secondly, the observed data was built with a combination of pressure and temperature data ($Comb_{ES-MDA}$).

Figure 2 shows the responses for applying the Genetic algorithm considering pressure as an observed data. On the left side of the fig.(2) is the initial distribution of the parameters, the range of values for permeability is reduced because it is being used in the log scale. In the millidarcy (mD) scale the initial range of the permeability is between 7mD to 1000mD.

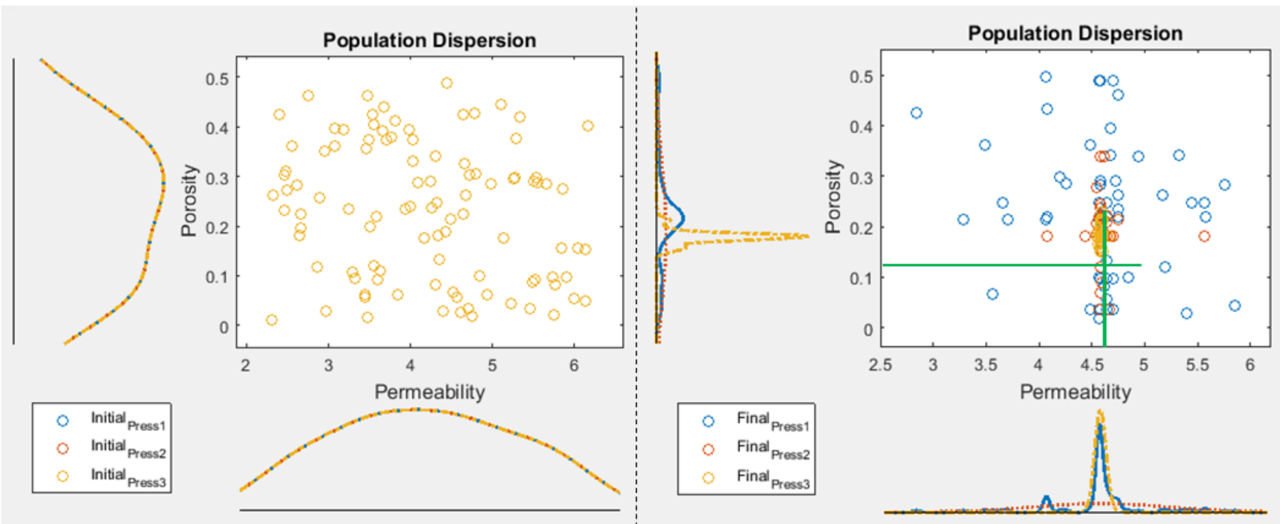


Figure 2. Genetic Algorithm results considering the pressure as observed data.

The pair of parameters to be estimated is 4.605 (100 mD) for permeability and 0.12 for porosity (target values). On the right side of Fig.(2) is observed the pressure estimation considering 12 generations (blue circles) and it still has a large dispersed data for porosity and permeability. Already, those results present a higher concentration of values close to the target value. However, when the number of generations is increased it is possible to see that the value of permeability quickly converges towards the expected value. On the other hand, the porosity estimation achieves is $\sim 50\%$ higher than the expected value.

Figure 3 shows the result for the Genetic Algorithm method considering temperature data in a similar way to the pressure data. Results considering 12 generations still show spread data around the target value and increasing the number of generations the convergence to the expected values is observed. It is noteworthy that when considering only the temperature data the permeability estimate similarly when considering only pressure data, but the porosity value is estimated much better.

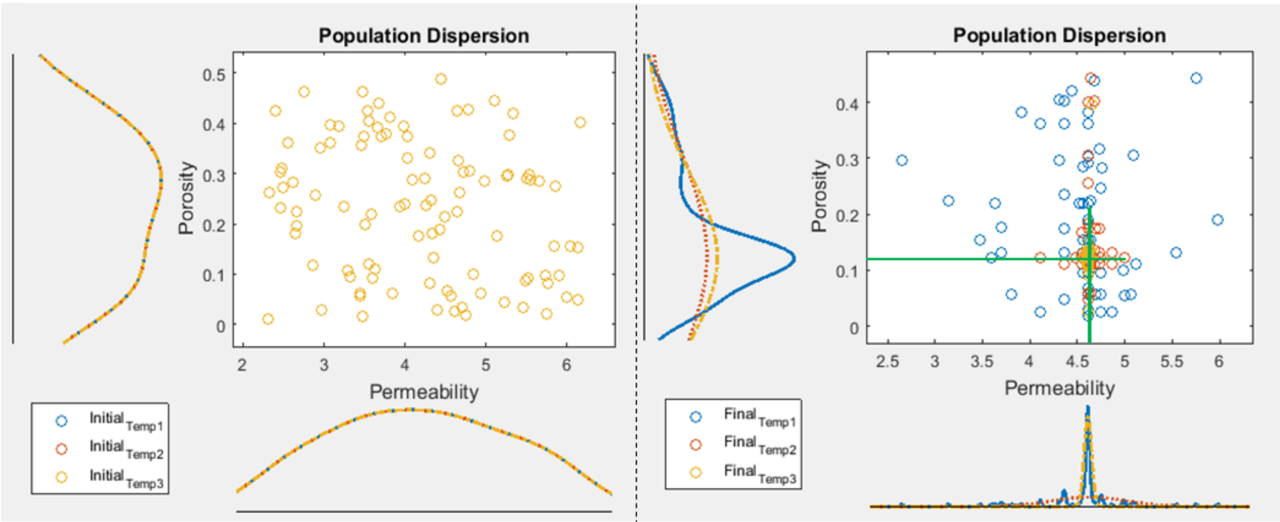


Figure 3. Genetic Algorithm results considering the temperature as observed data.

Finally, Figure 4 shows the comparison of results of the ES-MDA method and genetic algorithm method by using temperature data considering 20 generations. On the left side is the initial population, the limits of the initial population are the same. However, the initial ensemble for the ES-MDA must be in a Gaussian shape that reduces the number of parameters at the extremes of the variable values. On the right side, results of those three analysis show similar results, however in the analysis done with GA method the results for the permeability was a little spread when compared to results obtained with the ES-MDA method.

Although both methods show a good parameters estimation, in the ES-MDA the flow simulator was used 400 times to generate the estimates present on the right side of Fig.(4). While for the GA produce the result shown in Fig.(4), it was necessary to use the simulator 2000 times. With these results, it is possible to conclude that to perform parameter estimation, the GA method requires a great number of generations, and it produces a high CPU time consumption, compared to the ES-MDA method.

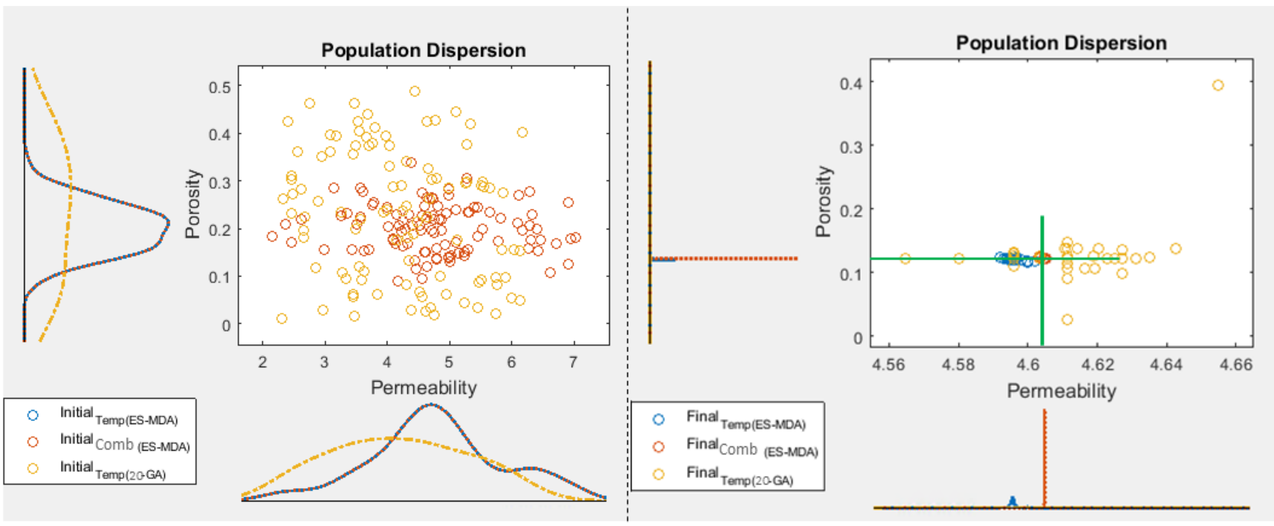


Figure 4. Comparison of the GA method results considering only the temperature data with the ES-MDA method results.

## 4. ACKNOWLEDGEMENTS

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