COBEM 2021 26th International Congress of Mechanical Engineering
ABCM Associação Brasileira de Engenharia e Ciências Mecânicas
November 22-26, 2021, Virtual Congress, Brazil

COB-2021-0255 Reservoir characterization using ES-MDA method combining pressure and temperature data

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Abstract. *Reservoir characterization is an important tool for 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 show that considering isothermal flow and only postprocessing pressure data can lead to misinterpretation due to neglecting thermal effect, leading to errors in the reservoir properties estimation and consequently inefficient reservoir management. This problem becomes more critical in high transmissibility reservoirs, such as in the pre-salt reservoirs in Brazil. In this work, a synthetic reservoir was studied using an in-house flow simulator that considers Joule-Thomson heating and cooling, adiabatic fluid expansion/compression, conduction, and convection effects in the thermal energy balance equation to provide temperature and pressure data. After that, the inverse problem was solved using an ensemble-based method to characterize the reservoir using the pressure and temperature data artificially created by introducing noise in the prediction of the direct problem. To estimate the reservoir properties and evaluate the uncertainties into the variables in the analysis, the ensemble smoother with multiple data assimilation (ES-MDA) is applied creating many models to produce a confidence interval to the parameters. Results show that the ES-MDA method applied with the coupled pressure and temperature transient data provides better reservoir characterization and uncertainty quantification comparatively with only pressure data.*

Keywords: *Thermal model, Reservoir characterization, Ensemble method, Inverse Problem*

1. INTRODUCTION

The use of transient-temperature data for estimating reservoir parameters has been limited in the past. As mentioned by Onur and Cinar (2017), the poor resolution of temperature sensors and the low variation of temperature during well testing contributed to the assumption of isothermal flow. However, recent studies performed by Galvao *et al.* (2020) 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. Sui *et al.* (2008), Duru and Horne (2010), and Li *et al.* (2011) also presented a procedure to characterize reservoirs, taking into account temperature data, and showing that including it improves the result of their analysis.

The characterization of the reservoir properties by using pressure and temperature transient data obtained from well tests can be seen as a classical inverse problem. The ensemble-based method has just been successfully applied to solve an inverse problem similar to reservoir characterization. Specifically, the ensemble smoother with multiple data assimilation (ES-MDA) provides a better data match and a better quantification of uncertainty than other methods, as discussed by Emerick and Reynolds (2013).

In this work, the ES-MDA method is used to reduce uncertainties in the analyzed variables and thereby characterize the reservoir by history matching of pressure data only and compared with coupling pressure and temperature data.

2. Mathematical equations

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 evolution. Second, the inverse problem is solved, by using the ES-MDA method in order to estimate reservoir parameters such as permeabilities, porosity, and skin zone distance, as shown in Fig. 1.

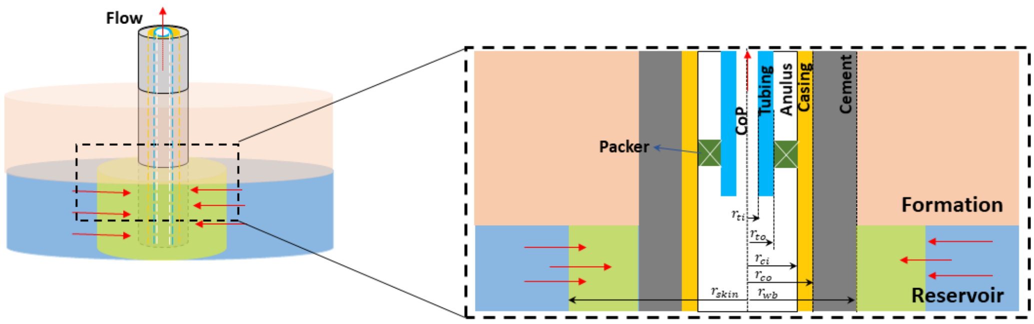

Figure 1. Wellbore reservoir scheme, with the skin region in yellow and the wellbore components.

2.1 Direct problem

The direct problem consists in solving the mass, momentum, and energy conservation equations in the 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 extracted from Galvao *et al.* (2019) and Galvao *et al.* (2020).

K	Permeability[m^2]	9.87×10^{-14}	C_o	Oil Compressibility [Pa^{-1}]	1.12×10^{-9}
ϕ	Porosity	0.12	C_w	Water Compressibility [Pa^{-1}]	4.04×10^{-10}
T^o	Temperature[K]	334.0	C_r	Rock Compressibility [Pa^{-1}]	3.06×10^{-10}
H	Reservoir thickness[m]	50	c_{po}	Oil Heat Capacity [J/kgK]	2252.9
p^o	Pressure[MPa]	49.033	c_{pw}	Water Heat Capacity [J/kgK]	4209.35
r_w	Wellbore radius[m]	0.156	c_{pr}	Rock heat capacity [J/kgK]	888
r_e	External Radius[m]	25000	B_o	Oil formation volume factor [m^3/std m^3]	1.4
s_w	Water saturation	0.15	λ_t	Thermal Conduct. Porous medium [J/msK]	3.44
ρ_w	Water density [kg/m^3]	998.2	β_o	Oil thermal-expansion coefficiet[K^{-1}]	1.11×10^{-3}
ρ_o	Oil density [kg/m^3]	770.0	β_r	Rock thermal-expansion coefficiet[K^{-1}]	9.0×10^{-5}
ρ_r	Rock density [kg/m^3]	2643.05	β_w	Water thermal-expansion coefficiet[K^{-1}]	5.27×10^{-4}
μ_o	Oil viscosity [Pa.s]	0.9×10^{-3}	α_t	Thermal diffusivity total [m^2/s]	1.484×10^{-6}

Table 1. Input data used to validate the numerical model, the properties was extrected from Galvao *et al.* (2019) and Galvao *et al.* (2020).

L	Wellbore length[m]	512.5	$z_{tubbing}$	Tubbing position[m]	100.0
α	Wellbore angle with the horizontal	90°	z_{gauge}	Gauge position[m]	513
r_w	Wellbore radius [m]	0.156	λ_{cement}	Thermal Conduct. Cement [W/mK]	1.898
r_{co}	Chasing external radius [m]	0.12224	λ_{wall}	Thermal Conduct. Wall [W/mK]	44.917
r_{ci}	Chasing initial radius [m]	0.10839	λ_{an}	Thermal Conduct. Anulus [W/mK]	0.162
r_{to}	Tubbing external radius [m]	0.06985	λ_{rock}	Thermal Conduct. Rock [W/mK]	3.8773
r_{ti}	Tubbing initial radius [m]	0.05931	g_G	Geothermal gradient[K/m]	-0.03

Table 2. Input data of well parameters.

2.2 Inverse problem

The estimation of some parameters of the reservoir using the response of this reservoir is a typical inverse problem. This process aims to estimate parameters that produce evolution data of pressure and temperature and converges to the observed data, that comes from the reservoir. This process is known as history matching.

In addition to estimating the value of the parameters of interest, some methods also perform an uncertainty analysis associated with these parameters. The ensemble-based method is a type of method that produces the uncertainty analysis, and the Ensemble Kalman Filter (EnKF) is a popular choice inside the ensemble-based methods. This work uses the Ensemble smoother with multiple data assimilation (ES-MDA) method introduced by Emerick and Reynolds (2013). ES-MDA method provides a better data match than the EnKF and others ensembles methods as discussed in Emerick and Reynolds (2013).

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

$$\mathbf{m} = [log(K_1),\ log(K_2),\ \alpha_{skin}\ and\ \phi]^T. \tag{1}$$

It is common to use the permeability in a log scale in order to reduce the amplitude of the initial range. The variable K_1 is the permeability of the skin zone represented by the yellow color on the reservoir in Fig.1. The variable K_2 is the permeability of the region out of the skin zone represented by the blue color on the reservoir in Fig.1. The variable $\alpha_{skin}(\alpha_{skin} = r_{skin}/r_{wb})$ is a variable that makes the correlation between the wellbore radius (r_{wb}) and the skin zone radius (r_{skin}). Finally, the variable ϕ that 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, we introduced Gaussian noises(ϵ_i).

$$\mathbf{d}_{obs} = g(\mathbf{m}_{true}) + \epsilon_i. \tag{2}$$

In which, the subindex "i" of the observed data (eq. 2) is 1 for the sandface pressure (ϵ_1) or 2 for the sandface temperature (ϵ_2) data. In the ES-MDA, the observed data ($\mathbf{d}_{obs}$) is perturbed by adding another Guassian 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 (2013), in nonlinear cases, this recurrent procedure tends to reduce the sampling problems caused by matching outliers that may be created when the observed data (d_{obs}) is perturbed. The variable C_D is the covariance of measurement errors matrix, and α_i is the inflation coefficient that satisfies:

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

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:

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

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

3. Results

Results for the analyses carried out in the reservoir illustrated in Fig.1 are presented. Initially, a traditional interpretation data analysis are presented and then the results obtained by the ES-MDA method are discussed. The vector $\mathbf{m}_{true}$ represents the expected values for each variable.

$$\mathbf{m}_{true} = [log(32),\ log(100),\ 5,\ 0.12]^T \tag{8}$$

3.1 Pressure and temperature transient analysis

Figure 2 contains the temperature and pressure evolution of the simulated and the observed data. As mentioned previously, the observed data is the simulated data added to a normal distribution with mean zero and standard deviation of 50 KPa for the sandface pressure and 0.005 K for the sandface temperature.

Figure 3 shows the graphical analysis of the pressure data. On the left is the semilog plot in which a single slope is identified. In the right is the pressure derivative, and also a single horizontal level is identified. Both plots indicate that the pressure data perceives only the information of permeability.

Figure 4 contains the temperature response, with the semilog plot in the left which has two slopes, and according to Onur *et al.* (2016) this means the information of two different permeabilities. On the right is the temperature derivative plot identifying two permeabilities regions.

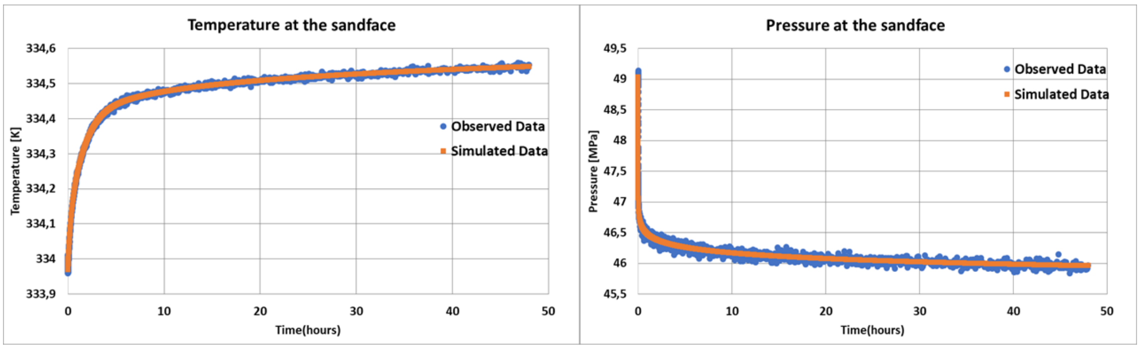

Figure 2. Temperature and pressure evolutions for the simulated Data in blue and the observed data considering a white noise in orange.

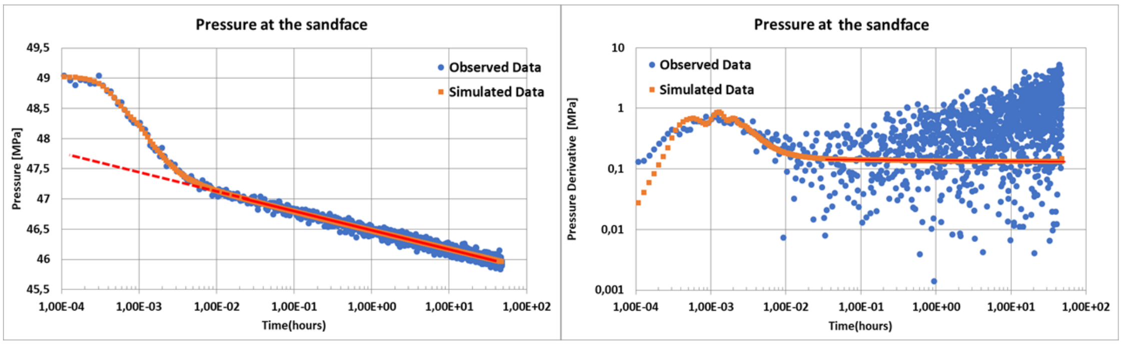

Figure 3. In the left is the semilog of the sandface pressure observed (in blue) and simulated (in orange) data. In the right is the pressure derivative analysis according to Bourdet *et al.* (1989) method.

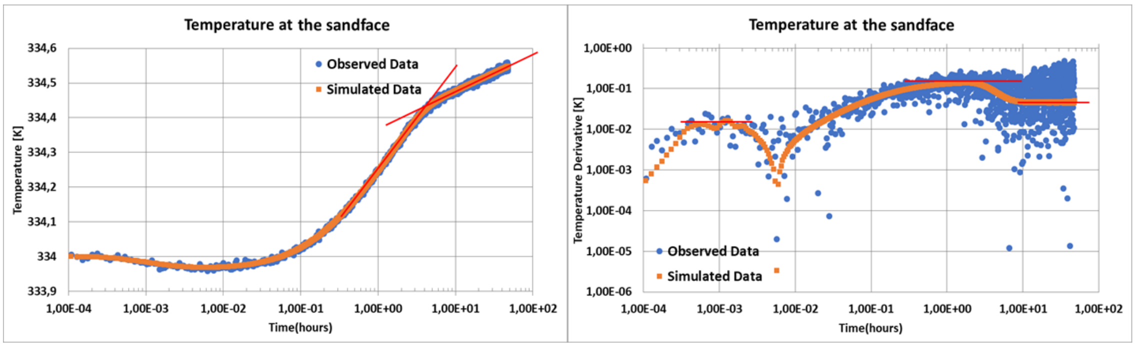

Figure 4. In the left is the semilog of the sandface temperature observed (in blue) and simulated (in orange) data. On the right is the Bourdet derivative for the sandface temperature. In red are the slopes that identified the permeabilites, similarly to the Onur *et al.* (2016).

3.2 ES-MDA results

To perform the ES-MDA method was assumed 4 assimilations ($N_a = 4$), all inflation factors α_i were set to a constant value and equal to N_a, and the ensemble size was 100 ($N_e = 100$). As in this work, the pressure and temperature data are combined and used as observed data, and consequently is necessary to normalize them to avoid errors arising from matrix conditioning. The normalization is done by dividing each evolution data by its respective initial value.

For the chosen C_D matrix, a sensitivity analysis was performed. Two configurations of the C_D matrix were adopted and in both configurations, the C_D matrix is considered a diagonal matrix, this means that the parameters in the analysis are independent. Both configurations of the C_D matrix and the normalization of the observed data are illustrated in Fig.5.

In the first configuration, for the part relative to the pressure data (C_{dp}) the diagonal was filled by a standard deviation of 10 kgf/cm^2 following Silva (2016) and for the temperature (C_{dt}) by a standard deviation of 0.005K similar to Xu (2016), those values were also normalized in the same way that the observed data.

The other configuration of the C_D matrix assumed an identy matrix for the pressure data, and for the temperature data was used the absolute value of the Joule-Thomson coefficient (ε_{Jto}). The reference for this configuration was the work of Sui *et al.* (2008), in which the absolute value of the Joule-Thomson coefficient was used for temperature data, however,

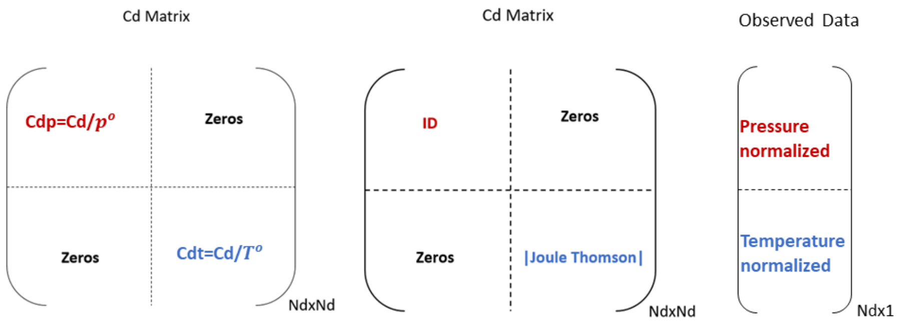

Figure 5. Configurations of the C_D matrix used, and the normalized vector of observed data.

the method used was that of levenberg marquadt and the relation C_{dp}/C_{dt} with has the same magnitude of Joule-Thomson coefficient.

Figure 6 present the initial distribution for each of the parameters of interest of vector m. For both permeability and the α_{skin} value a normal distribution N(5.0,1.0^2) and for porosity N(0.25,0.05^2) were adopted.

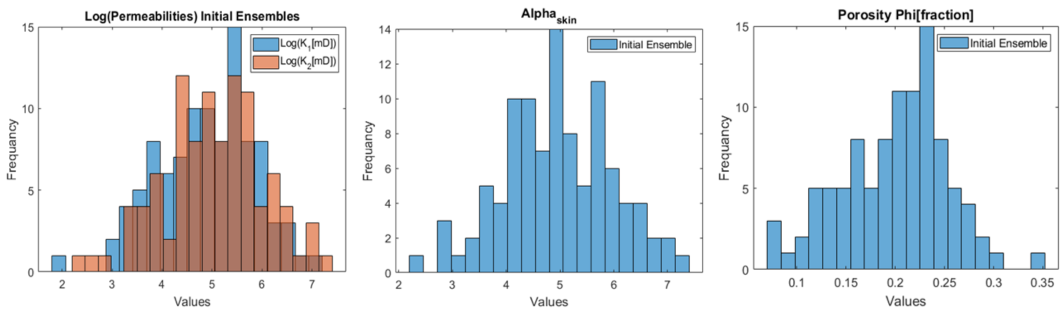

Figure 6. Initial distribution for each parameters that make up the vector m(eq.1)

Figure 7 shows a compilation of the boxplot of skin permeability estimation considering different configurations of the C_D matrix. The red line is the expected value for the skin permeability.

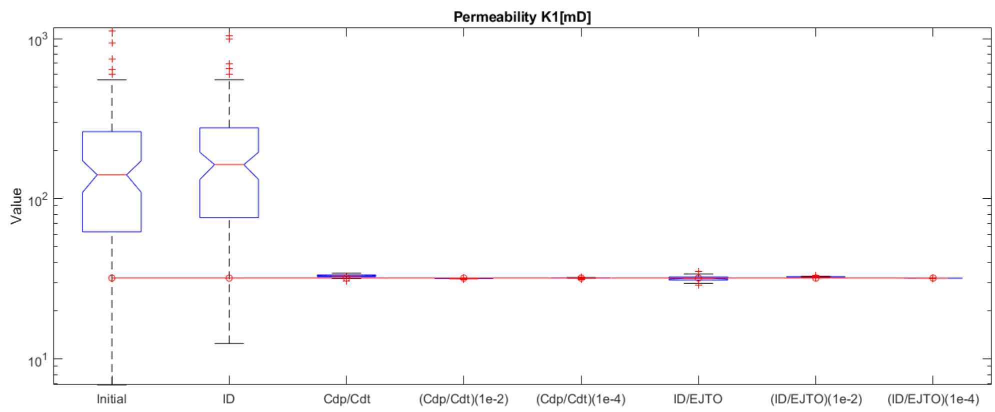

Figure 7. Boxplot for the first permeability considering the initial distribution and all configurations of C_D matrix.

The results from fig.7 show that considering the C_D as an identity matrix, the result showed almost no adjustment when compared to the initial distribution of parameters. For the other adopted C_D matrix configurations, we can see that in all cases the estimates were close to the red line that represents the expected value.

Figure 8 is a zoom of Fig.7, in which all configurations presentes good estimations. Although the configurations multiplied by 10^{-4} obtained a more precise and exact skin permeability distribution than the other configurations.

Figures (9 - 11) show the boxplots with the others parameters estimations for the C_D matrix configurations that made accurate estimations into the skin permeability and the expected values represented by the red line.

With the results presented in the Fig.(8) to Fig.(11), we can conclude that for the C_D matrix configurations that were multiplied by 10^{-4} they presented the most accurate estimates.

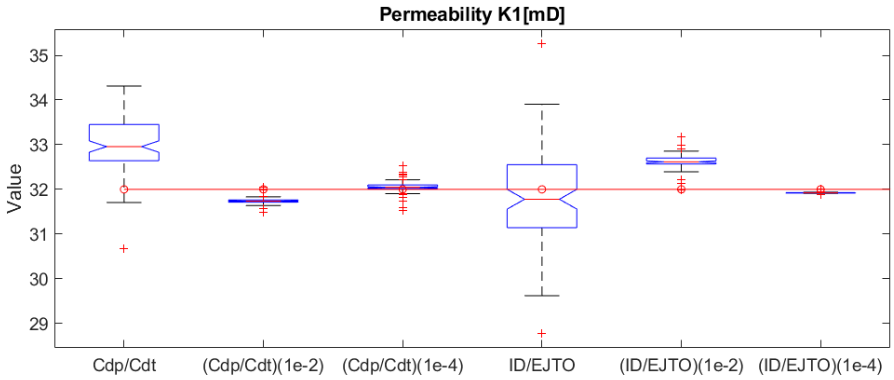

Figure 8. Boxplot for the skin permeability considering the best settings of C_D matrix.

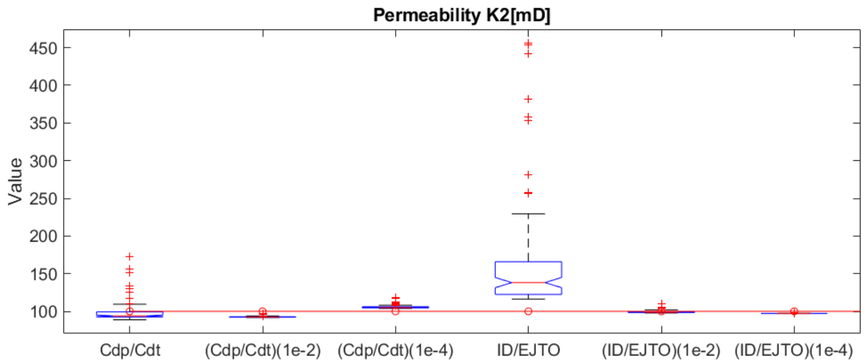

Figure 9. Boxplot for the permeability out of the skin zone considering the best settings of C_D matrix.

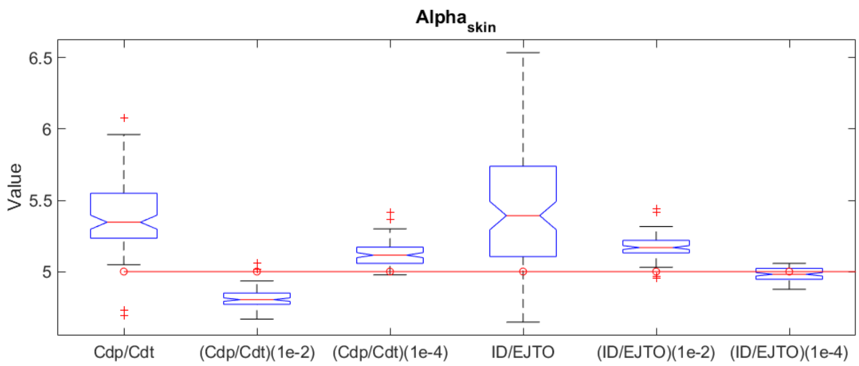

Figure 10. Boxplot for the α_{skin} considering the best settings of C_D matrix.

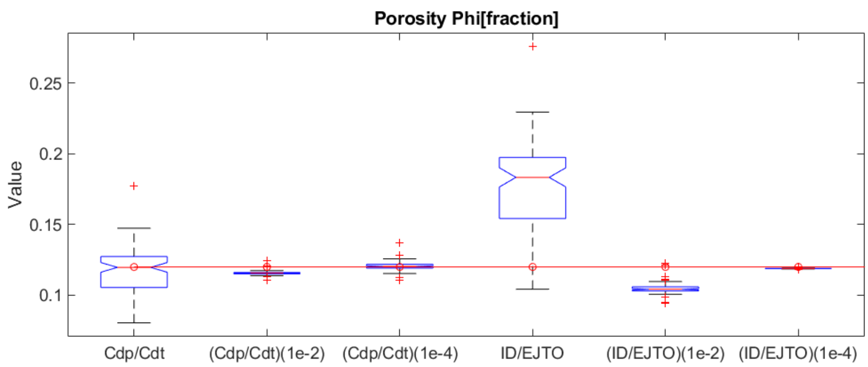

Figure 11. Boxplot for the porosity considering the best settings of C_D matrix.

With this information about the matrix C_D, a comparison was made between the analysis that is commonly done (considering only the pressure data) and the analyzes performed combining pressure and temperature data. Figures 12 and 13 contains the boxplots of comparisons between estimates made considering only pressure data ("Pressure") and when considering combined data ("(Cdp/Cdt)(1e-4)" and "$(ID/EJTO)$(1e-4)").

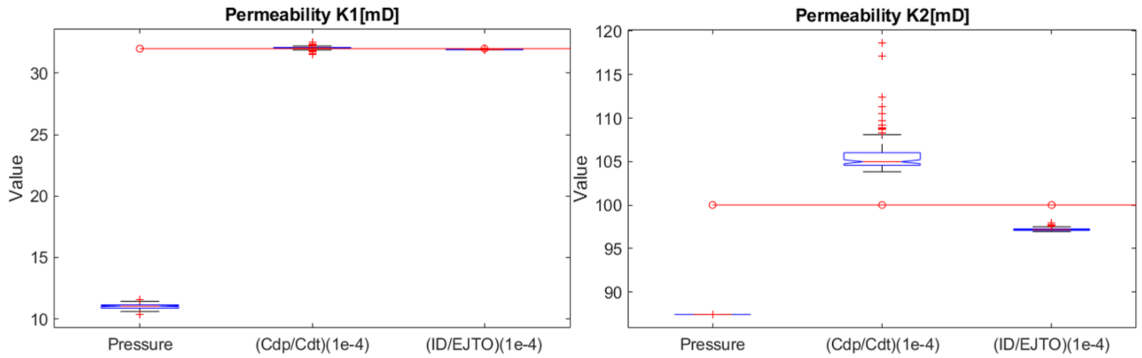

Figure 12. Comparison of estimates made considering only pressure data with those made using combined data. On the left we have the estimated of the skin permeability, and on the right we have the permeability outside of the skin region.

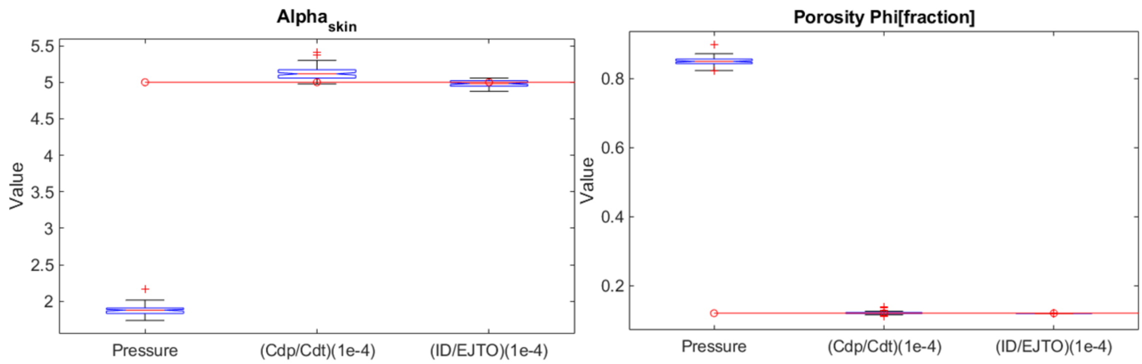

Figure 13. Comparison of estimates made considering only pressure data with those made using combined data. On the left we have the estimated of the α_{skin}, and on the right we have the porosity.

Figures 12 and 13 shows that the use of combined data made more accurate parameters estimations than the estimations made with only pressure data. Thus, being able to better characterize the skin region near the well, generating better management of the same. Figures 15,16 and 14 show the comparison between the time series created with the initial distribution of parameters (grey lines), with the ones generated after the application of the ES-MDA method (blue lines), as well as the observed data (red circles). Figure 14 presents the comparison considering the analysis containing only the pressure data. Figure 15 and 16 presents the comparison for the analysis that consider the combined pressure and temperature data.

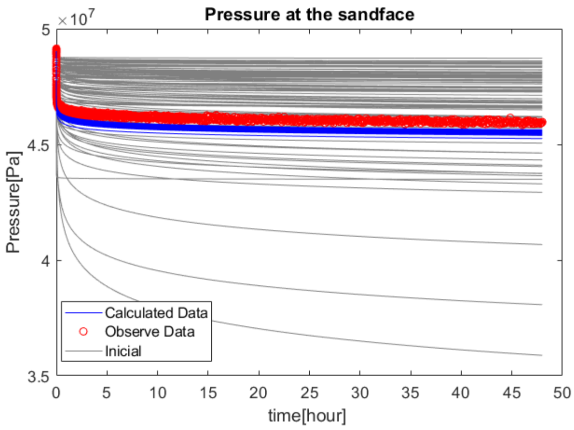

Figure 14. Comparison of the pressure evolution originated with the initial set of parameters (in gray). With the observed data (in red) and with the calculated profiles with the final set of parameters after the 4 assimilations of the ES-MDA method (in blue).

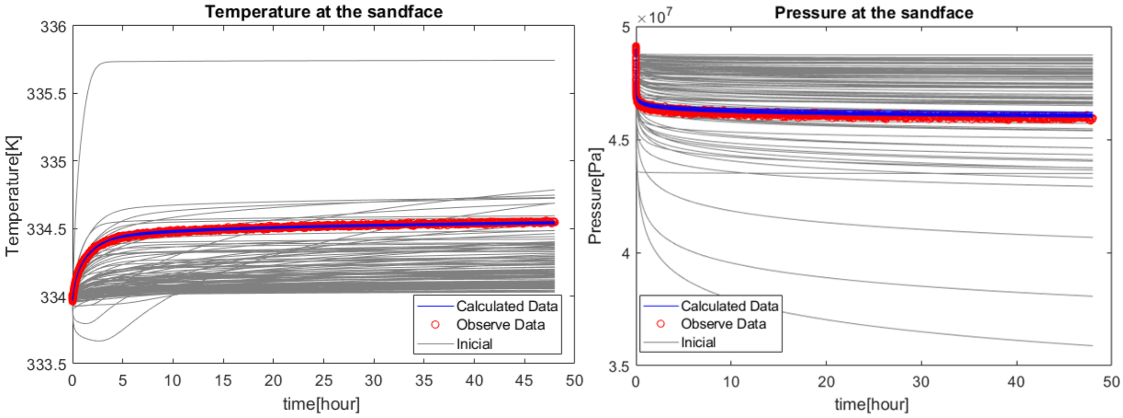

Figure 15. Comparison of the pressure and temperature evolutions from the initial set of parameters (in gray). With the observed data (in red) and with the calculated profiles (in blue) with the final set of parameters after the 4 assimilations of the ES-MDA method, considering the coupled data taking into account the matrix C_D which contains the normalized literature values.

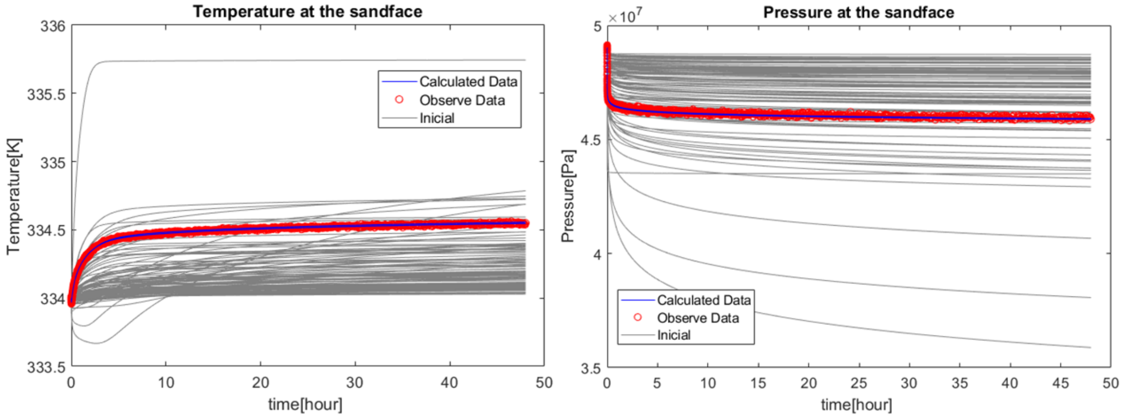

Figure 16. Comparison of the pressure and temperature evolution originated with the initial set of parameters (in gray). With the observed data (in red) and with the calculated evolution (in blue) with the final set of parameters after the 4 assimilations of the ES-MDA method , considering the coupled data taking into account the matrix C_D which contains the value of the Joule Thomson coefficient (ε_{JTO}).

The results that are being presented in this work, show that even obtaining a accurate data matching, the analysis considering only the pressure data information is not able to capture and characterize the skin region. However, with the addition of temperature data, which for new wells is already available data, the skin region can be better characterized.

4. ACKNOWLEDGEMENTS

We would like to acknowledge Petrobras and Capes for financial support.

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