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HISTORY MATCHING OF PRESSURE OR TEMPERATURE DATA USING ES-MDA FOR RESERVOIR CHARACTERIZATION

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Abstract. *Well tests are commonly used to characterize reservoir parameters and estimate oil field performance. These tests typically consist of measuring and interpreting the pressure response at the well to a given change in production or injection conditions. However, in high transmissibility reservoir, using only pressure data can lead to misinterpretations due to thermal effects and consequently to large errors in the estimation of reservoir properties. In the last decades there has been an increase in the use of permanent sensors installed along the wells, which provides a large amount of pressure and temperature data. The use of these sensors, as well as advanced data analysis techniques, has considerably increased the quality of the estimates, contributing to the reduction of uncertainties in the process and to a better production planning in the field. In order to infer reservoir properties by using pressure and temperature transient data obtained from well tests we arrived into the classical inverse problem, in which among several existing methods the Ensemble-based method is being successfully applied. Specifically, the ensemble smoother with multiple data assimilation (ES-MDA) seems to be a good candidate because it provides a better data match and a better quantification of uncertainty than other methods. In this work, synthetic case was created by using an in-house flow simulator that solves the complete coupled system of equations that represent the wellbore/reservoir system. Joule-Thomson heating and cooling, adiabatic fluid expansion/compression, conduction and convection effects are considered in the thermal energy balance equation. Results show how the ES-MDA method applied with the sandface temperature transient data provides better uncertainty quantification comparatively to sandface pressure data to estimate the reservoir properties.*

Keywords: *Inverse problem, ES-MDA, Non-isothermal, Wellbore test, Reservoir characterization*

1. INTRODUCTION

The use of transient-temperature data for estimating reservoir parameters has been limited in the past. As discussed by Onur and Cinar (2017), the poor resolution of temperature sensors and the small variation of temperature during formation tests contributed to the assumption of isothermal flow. However, recent studies 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 data availability increases while the technology improves in parallel with the growing number of smart wells. Li *et al.* (2011) proposed a procedure to characterize the reservoir taking into account the temperature data and showed that including it improved their results.

The characterization of the reservoir properties by using pressure or temperature transient data obtained from well tests is a classical inverse problem. As mentioned by Tarantola (2005) solve an inverse problem is to "*determine plausible values of model parameters given uncertain data and an assumed theoretical model relating the observed data to the model*". In other words, solve the inverse problem is finding possibles values of variables that when introduced into the forward or direct problem, the model, produces good data matching with the data in the analysis. The ensemble-based methods are commonly used in petroleum reservoir history matching, that is a type of inverse problem. Aanonsen *et al.* (2009) and Oliver and Chen (2011) made a bibliographic review of ensembles methods in history matching problems from 2001 to 2010.

"Ensemble Smoother with Multiple Data Assimilation (ES-MDA)" was introduced by Emerick and Reynolds (2012) and recently this method has been commonly applied to solve high-nonlinear problem and compared with other differents ensemble methods (Emerick and Reynolds, 2013) and they concludet that the ES-MDA method presents a better cost-benefit ratio.

Usually, the ES-MDA method was applied to estimate reservoir properties by using pressure data and especificaly, the bottom hole pressure was used as observed data (Silva, 2016; Ranazzi and Sampaio, 2019).

However, recent studies by Xu *et al.* (2017a), Xu *et al.* (2017b) use the temperature data from the sandface region as a part of observed data in a stratified reservoir.

In this work, the direct problem was implemented and then an ensemble-based method has been successfully applied, considering as observed data the sandface pressure or the sandface temperature.

2. MATHEMATICAL AND NUMERICAL FORMULATION

This work was developed in two stages. Initially, a routine to solve the transient flow and heat transfer that occur in the wellbore/reservoir model, consisting of a fully coupled reservoir/casing/tubing system was developed and then the ES-MDA method was applied to estimate the permeability and porosity of the reservoir.

2.1 Direct problem

The equations used in the direct problem were made based on mass and energy conservation equations for the reservoir, and mass, energy, and momentum conservation equations for the well. The detailed formulation can be found in the literature Onur *et al.* (2017). The assumptions considered in this work were as following:

- Flow in the reservoir is 1D radial, single-phase oil with immobile connate water saturation;
- Oil and water are slightly compressible fluids and are immiscible;
- Reservoir is isotropic;
- Fluid flow is governed by Darcy's law;
- Solid matrix, oil, and connate water are in a local thermal equilibrium;
- Well is vertical, fully penetrating the entire formation thickness, which is uniform in the reservoir;
- Inside the well, the flow of slightly compressible single-phase fluid is in the axial direction;
- Density is a function of temperature and pressure. Others fluid properties are constant;
- Heat transfer to the surroundings occurs due to radial diffusion. There is no axial heat diffusion;
- Wellbore material has constant thermal conductivities.

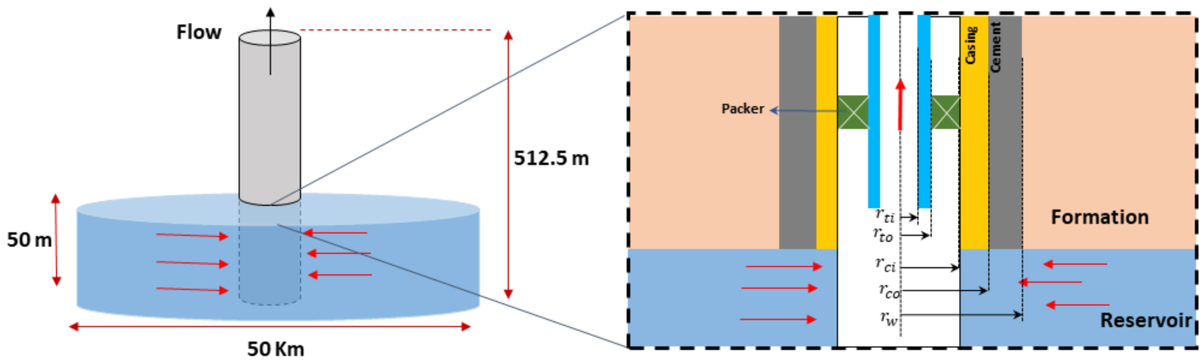

Figure 1. Schematic of the coupled Wellbore/Reservoir system and well components details.

2.1.1 Governing Equations

The mathematical formulation comprises of a coupled wellbore/reservoir model, consisting a fully coupled reservoir/casing/tubing system. In the reservoir, the mass and energy transient conservation equations are solved, as shown in Equation (1) and Equation (2). The wellbore model consists of mass, momentum, and energy transient conservation equation, as shown through Equations (3-5). All those equations with appropriated boundary conditions and initial conditions are solved by using a finite difference method. A second-order method was used to discretize the spatial domain and time integration. In the following equations, the subscribe "o" means the oil phase, and the subscribe "tot" means the total system (fluid+rock). For the mass balance in the reservoir was used the subsequent equation.

$$\phi\left[C_{tot}\frac{\partial p}{\partial t} - \beta_{tot}\frac{\partial T}{\partial t}\right] = \frac{1}{r}\left[\frac{\partial}{\partial r}(rv_{ro}) + rv_{ro}\left(C_o\frac{\partial p}{\partial r}\right) - rv_{ro}\left(\beta_o\frac{\partial T}{\partial t}\right)\right] \tag{1}$$

In Equation (1), the v_{ro} represents Darcy's Law in radial direction C is the compressibility of the phase, and β is the thermal expansion. The energy conservation equation of the reservoir assuming the local thermal equilibrium between the solid matrix and fluid phase and including the Joule-Thomson coefficient(ε_{JTo}) can be expressed as:

$$\frac{\partial T}{\partial t} - \varphi_t^* \frac{\partial p}{\partial t} + u_{co}(r,t)\frac{\partial T}{\partial r} - u_{co}(r,t)\varepsilon_{JTo}\frac{\partial p}{\partial r} = \frac{1}{r}\frac{\partial}{\partial r}\left(r\alpha_{tot}\frac{\partial T}{\partial r}\right) \tag{2}$$

In Equation (2), u_{co} is the velocity of convective-heat transfer and φ_t^* is the effective adiabatic-expansion coefficient of the fluid-saturated porous medium.

In the wellbore system, the mass conservation equation is:

$$\frac{\partial p}{\partial t} + \frac{Q}{AC_o}\frac{\partial p}{\partial z} - \frac{\beta_o}{C_o}\frac{\partial T}{\partial t} - \frac{Q\beta_o}{AC_o}\frac{\partial T}{\partial z} + \frac{1}{AC_o}\frac{\partial Q}{\partial z} = 0 \tag{3}$$

The pipe is considered rigid with a cross-sectional area A shown in Equation (3). The next equation is the momentum, which was also is mentioned in Onur *et al.* (2017).

$$\frac{1}{A}\frac{\partial Q}{\partial t} + \frac{Q}{A^2}\frac{\partial Q}{\partial z} + \frac{1}{\rho_o}\frac{\partial p}{\partial z} + \frac{fQ|Q|}{2A^2D} + g\sin(\alpha) = 0 \tag{4}$$

In Equation (4) the angle (α) is referent to the angle between the wellbore and the horizontal line, in our in-house code a vertical well is being considered, so $\alpha = 90°$. The variable D is the inside diameter of the pipe, and f represents the Darcy Weisbach friction factor. The last equation mentioned here and used in the numerical code is energy conservation.

$$\rho_o AC_{po}(1 + C_T)\frac{\partial T}{\partial t} = \rho_o QC_{po}L_R\Big[T_{ext}(z) - T(z,t)\Big] - \rho_o QC_{po}\left(\frac{\partial T}{\partial z} - \varphi(z,t) + \frac{g\sin(\alpha)}{C_{po}}\right) \tag{5}$$

The term $T_{ext}(z)$ in Equation (5) is correlated with the geothermal gradient and C_T represents the thermal storage. L_R is the relaxation-distance parameter that contains the overall heat-transfer coefficient. The parameter $\varphi(z,t)$ consider the Joule-Thomson effect and the kinetic-energy contribution. More details of those terms are found in Onur *et al.* (2017).

The coupled wellbore/reservoir system was solved by using an accurate finite difference method considering appropriate boundary and initial conditions: The boundary condition related to flow rate is defined at the top of the wellbore. During the drawdown, the flow rate is set to a constant value Q; during the buildup, it is set to zero, Q = 0. The contact region between the wellbore and the reservoir has the same pressure and temperature. As an initial condition, before the wellbore top valve is opened, it is assumed the wellbore is filled with oil, so the geothermal gradient for the temperature and hydrostatic gradient for the pressure are considered.

2.2 Inverse problem

Reservoir history matching is the process of converging an observed data from a reservoir with the simulated data, to infer some parameters of the reservoir in the analysis. The most popular ensemble-based method is the ensemble Kalman filter (EnKF) although in this work is used Ensemble smoother with multiple data assimilation (ES-MDA) that was introduced by Emerick and Reynolds (2012). The results from Emerick and Reynolds (2013) shows that ES-MDA provides a better data match than the EnKF, ES-MDA could be considered an iterative method, with a predefined number of iterations, or assimilation. In this method, the objective is to find the vector m_j that contains the parameters involved in the process such as permeability, porosity, etc. The m_j vector is defined as:

$$m_j = \begin{bmatrix} m_1 & m_2 & . & . & . & m_{Nm} \end{bmatrix}^T \tag{6}$$

Where Nm is the number of parameters to be estimated and the m's are the variables in the analysis. The answer of the simulator d is defined as the response given by the simulator (g) when is introduced the vector m_j:

$$d = g(m_j) \tag{7}$$

The data that comes from a real well test is called d_{obs}. To approximate to a real data, this work used a synthetic data obtained by using the in-house simulator and then is introduced Gaussian noises for pressure and temperature data. For the sandface pressure a Gaussian noise (ϵ_1) was used and for the sandface temperature (ϵ_2). Therefore, depending on the case the observed data (d_{obs}) is defined as:

$$d_{obs} = g(m_{true}) + (\epsilon_1 \; or \; \epsilon_2) \tag{8}$$

According to Emerick and Reynolds (2013), the update process of vector parameters m into the ensemble with j=1,2,3,...Ne individuals is given by:

$$m_j^u = m_j^p + [C_{MD}(C_{DD} + \alpha_i C_D)^{-1}](d_{uc} - d_j^p) \tag{9}$$

Where the superscripts "u" means the updated ensemble and "p" means the previous. In the equation α_i is the inflation factor used in each assimilation, 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:

$$C_{MD} = \frac{1}{N_e - 1} \sum_{j=1}^{N_e} (m_j^p - \overline{m}^p)(m_j^p - \overline{m}^p)^T \tag{10}$$

$$C_{DD} = \frac{1}{N_e - 1} \sum_{j=1}^{N_e} (d_j^p - \overline{d}^p)(d_j^p - \overline{d}^p)^T \tag{11}$$

The inflation coefficients, α_i's needs to obey this formulation rule:

$$\sum_{i=1}^{N_i} \frac{1}{\alpha_i} = 1 \tag{12}$$

In the ES-MDA, the observed data is perturbed in each assimilation using the following definition:

$$d_{uc} = d_{obs} + \sqrt{\alpha_i} C_D^{1/2} Z_d \tag{13}$$

where the Z_d is a normal distribution with mean zero and the variance is an identity with the size of observed data $\approx N(0, I_d N_d)$.

This procedure tends to reduce the sampling problems caused by matching outliers that may be created when the observed data (d_{obs}) is perturbed.

3. RESULTS

Before presenting the application of the inverse problem, the validation results of the direct problem is shown by comparing the in-house code with the commercial software Stars from CMG. Figure 2A shows the sandface pressure evolution from the CMG in a good agreement with the solution obtained with our in-house solver. Plots in Fig. 2B and 2C shows the sandface temperature evolution during the Drawdown and Buildup period, respectively. The inputs properties of the fluids and well parameters for this validation were taken from Onur and Cinar (2017). Finally, Figure 2D and 2E show the wellbore temperature evolution measured at the top of the wellbore during the Drawdown and Buildup period respectively. In this last validation, the input values were taken from Galvao *et al.* (2020).

A heterogeneous reservoir was created considering the properties given by Galvao *et al.* (2020), and here presented in Table (1) and Table (2), and different permeability values as shown in the Fig. 3.

To provide the synthetic data, numerical simulations were performed with the same period (48 hours of production at a constant downhole rate followed by a 48 of static) and the same flow rate ($800m^3/day$) as used by Galvao *et al.* (2020). Preliminary results showed that porosity has more impact during the drawdown period than the buildup period. Therefore, in this work, it was considered only 48 hours of production.

Table 1. Input fluid properties and reservoir parameters.

K$[m^2]$	$variable$	$C_o[Pa^{-1}]$	1.12e-9	$\varphi_o[K/Pa]$	2.324e-7
ϕ [fraction]	0.12	$C_w[Pa^{-1}]$	4.04e-10	$\varphi_w[K/Pa]$	4.213e-8
$T^o[K]$	334.0	$\mu_o[Pa.s]$	0.9e-3	$\rho_o[kg/m^3]$	770.0
$H[m]$	50	$c_{po}[J/kgK]$	2252.9	$\rho_w[kg/m^3]$	998.2
$p^o[MPa]$	49.033	$c_{pw}[J/kgK]$	4209.35	$\lambda_t[J/msK]$	1.238e+4
$r_w[m]$	0.156	$\beta_o[K^{-1}]$	1.11e-3	$\alpha_t[m^2/s]$	5.342e-3
$r_e[m]$	25000	$\beta_w[K^{-1}]$	5.27e-4	$\varphi^*[K/Pa]$	1.874e-7
s_w [fraction]	0.15	$\varepsilon_{JTo}[K/Pa]$	-3.441e-7		
$C_r[Pa^{-1}]$	3.06e-10	$\varepsilon_{JTw}[K/Pa]$	-1.959e-7		

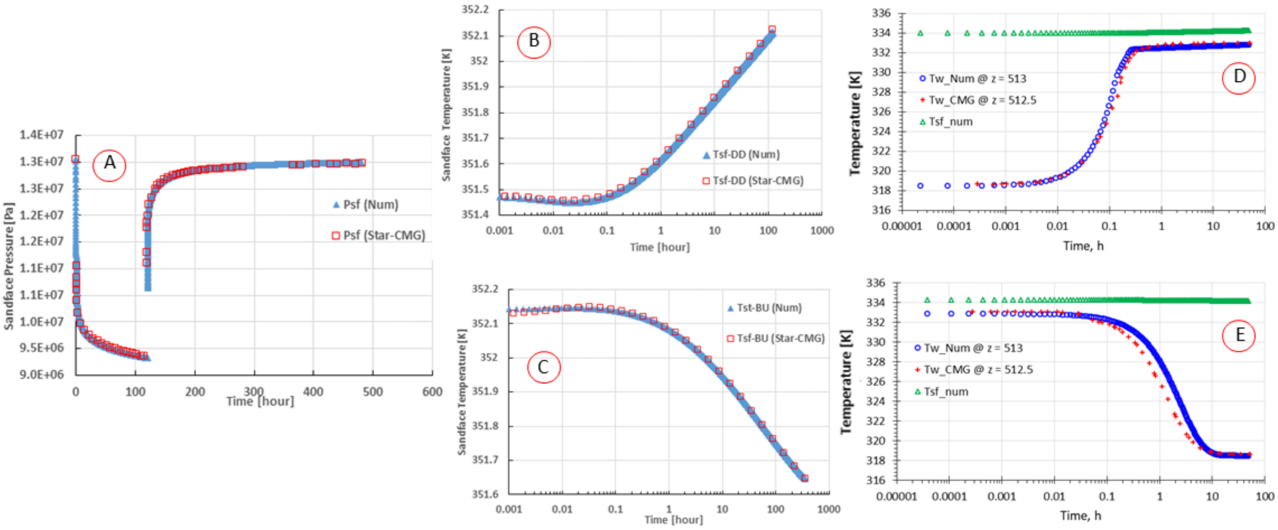

Figure 2. Validation of the direct problem with comercial software (CMG-Stars). (A) is the Sandface pressure evolution during the test, (B) and (C) is Sandface temperature during Drawdown and Buildup period respectively. (D) and (E) is the Wellbore temperature at certain gauge depth during the Drawdown and the Buildup period,respectively.

Table 2. Wellbore parameters.

$L\ [m]$	512.5	z_{gauge} [W/mK]	Depends of the case
α	90°	λ_{cement} [W/mK]	1.898
$r_w\ [m]$	0.156	λ_{wall} [W/mK]	44.917
$r_{co}\ [m]$	0.12224	$\lambda_{wall-cement}$[W/mK]	2.776
$r_{ci}\ [m]$	0.10839	λ_{an} [W/mK]	0.162
$r_{to}\ [m]$	0.06985	C_T	0.0
$r_{ti}\ [m]$	0.05931	$g_G\ [K/m]$	-0.03

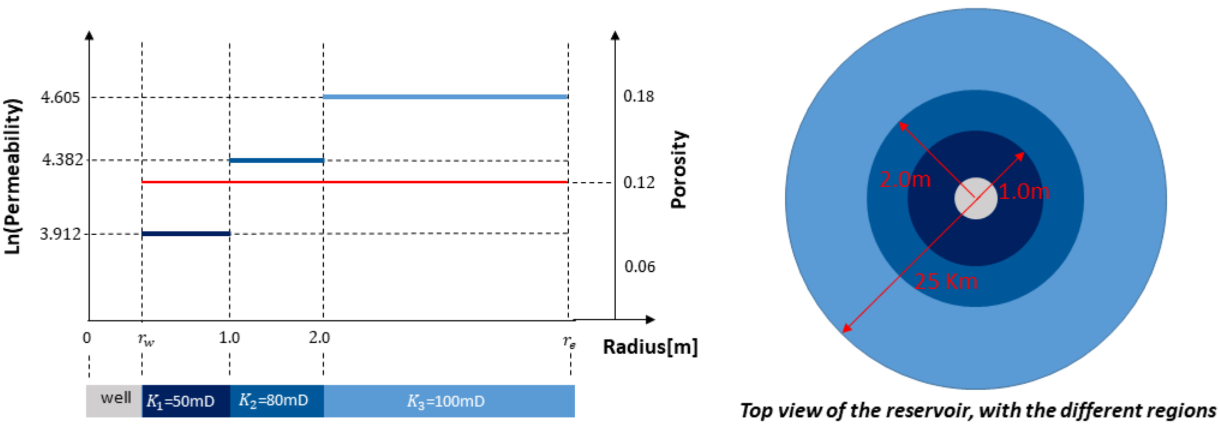

Figure 3. On the left, is the permeability profile with three differents values considering a single porosity value, and on the right is the top view of the reservoir with the heterogeneous region.

For the inverse problem, was used 4 assimilations ($N_a = 4$), all inflation factors α_i's were set a constant value and equal to N_a, and the ensemble size was 100 ($N_e = 100$). As mentioned before, to represent a real field data a Gaussian noise was introduced into the synthetic data obtained from the solver, and it has a normal distribution with mean zero, and the standard deviation was set to 50 KPa for the sandface pressure and two values for the sandface temperature 0.005 K and 0.025 K.

The covariance matrix of observed data measurement errors (C_D) is an important parameter for the ES-MDA method because this matrix defines the confidence level of the data, and as consequence, the weight of the data into the data match. In this work, C_D is a diagonal matrix with the value of the variance of the noise measurement. To define the value of the measurement error to composed the covariance of the C_D matrix, tests were carried out with the value of 5.0 Kgf/cm^2 (490 KPa) as used by Ranazzi and Sampaio (2019) and 10.0 Kgf/cm^2 (980 KPa) as used by Silva (2016), when pressure is considered as observed data. For temperature data was considered the same value as used by Xu *et al.* (2017b), and it was 0.005 Kelvin.

The same initial ensemble were used for pressure and temperature data in order compare the parameter estimations from those data sources. This initial ensemble has a normal distribution with the expected value as mean. A standard deviation of 0.05 was set for the porosity, and for each log-permeability region was apply two standard deviations 0.5 and 1.0. Figure 4 shows the boxplot for the third permeability region considering both standard deviations.

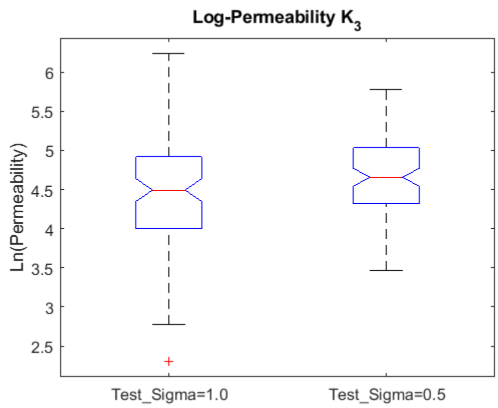

Figure 4. Boxplot of the initial ensemble for the third region permeability considering the mean equal to expected value when a standard deviation is 1 and 0.5.

3.1 SANDAFACE PRESSURE

Synthetic pressure data were generated based on the coupled wellbore/reservoir model corresponding to 2 days of drawdown. This result takes into account a heterogeneous reservoir as shown in Fig. 3. To simulate a real well test was introduced a noise with a normal distribution with mean zero and the standard deviation equal to 50 KPa (0.5 Kgf/cm^2), the result of this observed data is shown in Fig.5 by the red circles.

To create the initial ensemble, as mentioned before, two different standard deviations (sigma or σ) were adopted for the log(permeability): 0.5 and 1. For porosity the normal distribution was fixed with a mean equal to 0.2 and the standard deviation equal to 0.05. The gray lines in Fig. 5 represent the pressure evolution of the initial ensemble considering the standard deviation of 0.5 for each log(permeability).

With the same observed data obtained previously were performed 3 tests. The first one (Test1_P) with the standard deviation equal to 1.0 for all log(permeabilities), and the others (Test2_P and Test3_P) was considering a standard deviation of 0.5. The difference between those last two tests is that they have different initial ensembles.

The blue circles, in Fig. 5, is the result of the data matching from the Test2_P after 4 assimilations by using of the ES-MDA method. The other performed tests taked similar pressure data matches, so it was decided to plot just one of them to do not pollute the graph.

The objective of the inverse problem is not only the data matching but also achieve the best parameters estimations. Because is possible to achieve a good data match with the wrong parameters combination. Figure 6 is a set of boxplot results of the last ensemble for those three tests in order to estimate permeabilities of different regions (Figure 6A, 6B and 6C) and the reservoir porosity (Figure 6D). Here, the black line in each plot represent the expected value, of the parameter, to be estimated.

Figure 6C has a smaller range of values for the Log(Permeability). This shows that the pressure data can estimate better the third region of the reservoir(Fig. 3). On the other hand, observing the Figure 6D, it is possible to observe that using pressure data is not a good option to estimate the reservoir porosity.

Figure. 9A shows the percentual error from the median of the last ensemble for each know parameter. The values

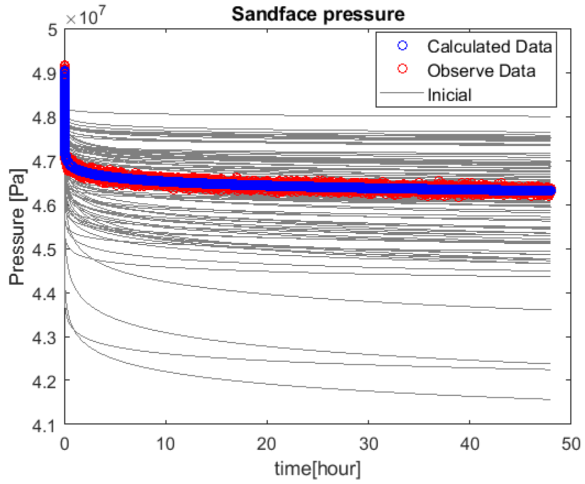

Figure 5. History matching of the pressure data. In blue is the result of the final ensemble, in red is the observed data, and in gray is the response of the initial ensemble.

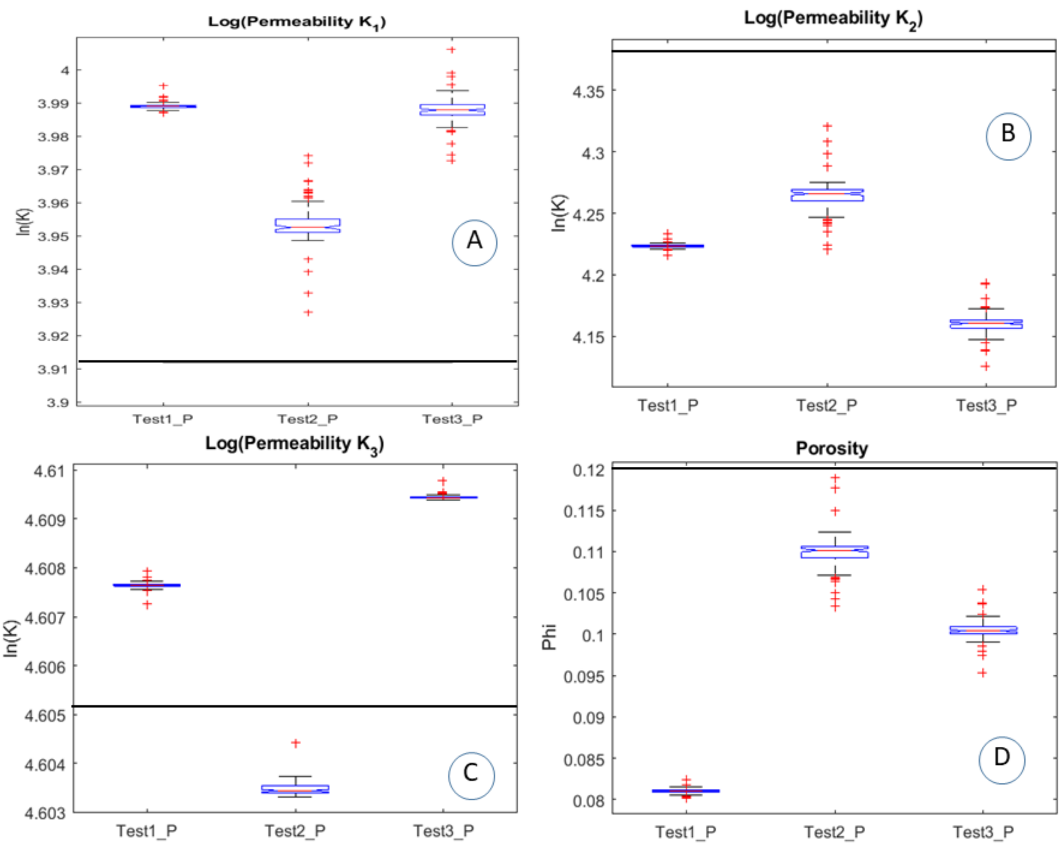

Figure 6. Boxplots of the last assimilation for each experiment considering the pressure as observed data. (A), (B) and (C) for permeability in different region and (D) for reservoir porosity

of the x-axes indicate the log(K_1), log(K_2), log(K_3), and the porosity respectively. As shown into the set of boxplots (fig. 6C) the third parameter, log(K_3), has the smallest percentual error in the log(permeability) estimation, and the fourth (fig. 6D), the porosity, has values that exceed 10%, which indicates a bad parameter estimation by using pressure data.

3.2 SANDFACE TEMPERATURE

Synthetic temperature data were generated in a similar way to pressure data. The noise was also introduced, but to evaluate the impact of the amplitude of the noise into the temperature analysis were created 2 different levels of noises. Both noises have a normal distribution with mean zero but one with a standard deviation of 0.005 K and the other with 0.025 K as a deviation.

The initial ensemble was the same as used in the pressure tests. Because there are two different noises to be considered, 6 tests for the temperature data were performed. The correlations between the initial ensemble for the pressure and temperature tests are:

Table 3. Initial ensemble correlation between the pressure and temperature tests.

Permeability Ensemble Deviation	Pressure	Temperature noise = 0.005K	Temperature noise = 0.025K
$\sigma = 1$	Test1$_P$	Test1$_T$	Test4$_T$
$\sigma = 0.5(1)$	Test2$_P$	Test2$_T$	Test5$_T$
$\sigma = 0.5(2)$	Test3$_P$	Test3$_T$	Test6$_T$

The red circles (observed data) in fig. 7 are the original temperature evolution considering heterogeneous permeability as in fig.3 with the addition of the higher standard deviation of temperature noise.

In the same way, as in the pressure analysis, the grey lines are the temperature evolution for the initial ensemble.

The blue circles, in Fig.7, represent the last ensemble process of data matching using the $Test5_T$ by using of the ES-MDA method. Similar to the pressure tests, the results of the others temperature tests take similars trends, so it was also decided to plot just one of these result to not pollute the graph.

To evaluate the parameter estimations by using temperature data, the Fig.8 were done. It consists of a set of boxplots for each parameter of interest from all temperature tests, and in each boxplot has a black line used as a reference of the expected value. Observing the scale range of the log(permeability) in Fig.8 (A), is possible to see the best parameter estimations by using temperature data. The permeability region close to the well can be better estimated and also it is possible to observe better porosity estimation, as shown in Fig.8 (D).

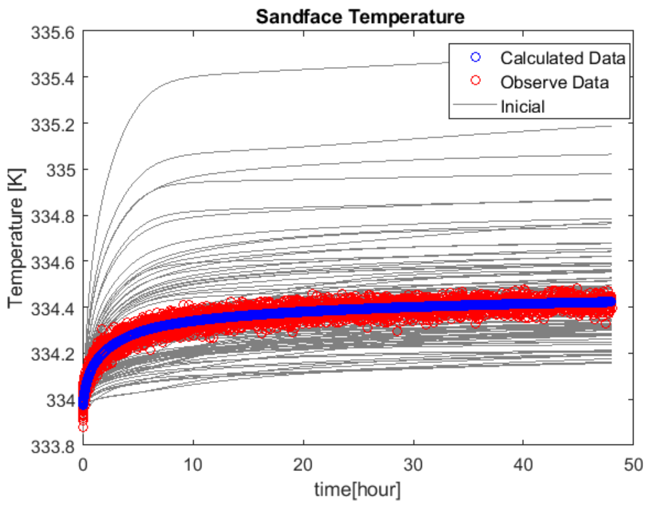

Figure 7. History matching of the temperature data. In blue is the result of the method, in red is the observed data, and in gray is the initial ensemble result.

Figure. 9 (B) shows the percentual error based on the median value of the last ensemble for each parameter and the real value. The values of the x-axes indicate the log(K_1), log(K_2), log(K_3), and the porosity respectively. As shown in the set of boxplots (Fig. 5) log(K_1) has the smallest percentual error, followed by log(K_2) and log(K_3). This suggests that unlike the pressure, the temperature data can achieve better estimation in the region near the well. Analyzing the percentual error of reservoir porosity, results show that temperature data can achieve better estimation with less than 5% of error.

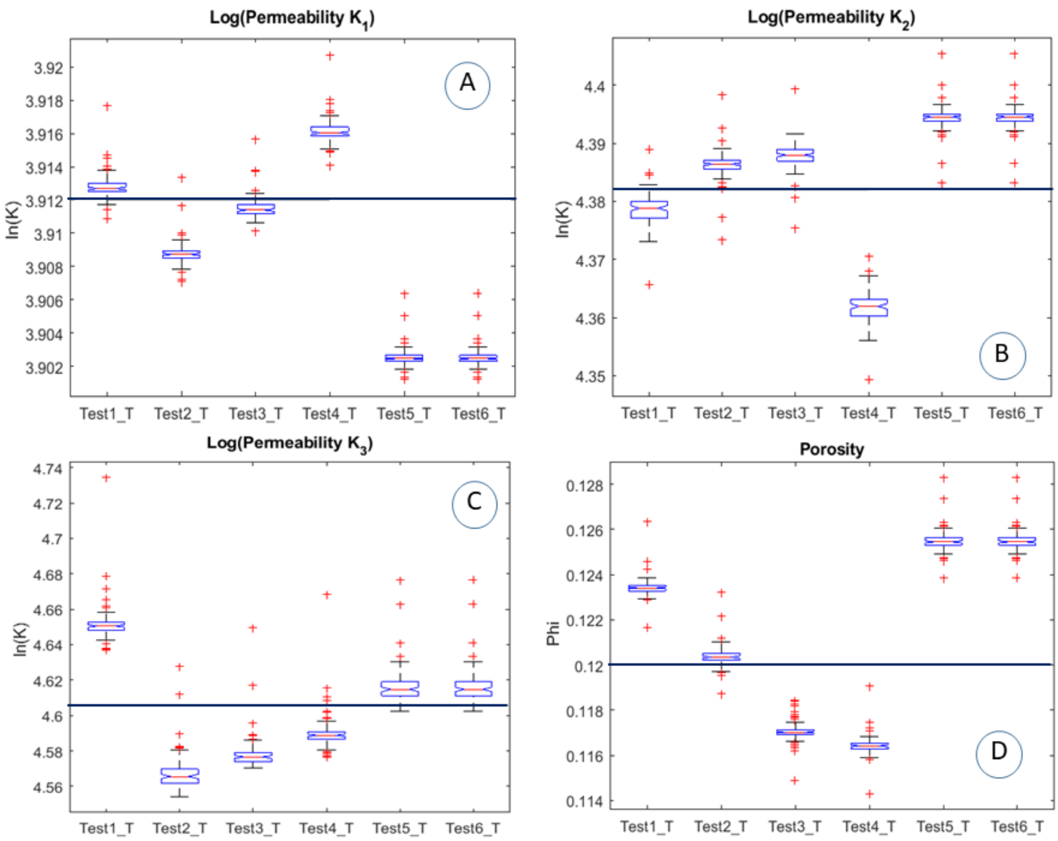

Figure 8. Boxplots of the last assimilation at different test considering the temperature as observed data for different permeability region and reservoir porosity.

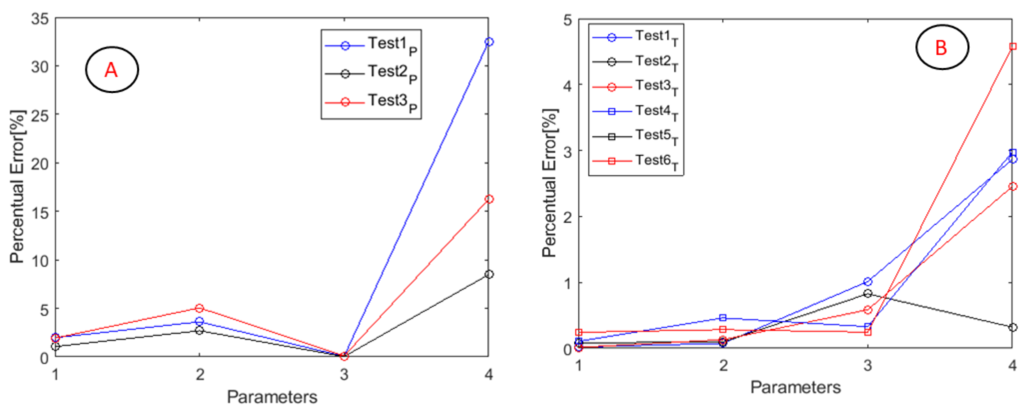

Figure 9. Percentual error into the parameter estimation considering pressure (A) and temperature (B) as observed data.

4. CONCLUSION

This work presented a numerical modeling for a coupled wellbore-reservoir system and the implementation of the inverse problem by using of the ES-MDA method.

An heterogeneous permeability region close to the well was created to test the ES-MDA method in order to comparte the pressure and temperature data as an observed data.

Pressure and temperature data can be used to estimate the permeability with less of 5% of error. Using the ES-MDA method the temperature data was able to estimate better the permeability region close to the well and on the other hand the pressure data result better for permeabilities far away the well region.

Good estimatives for reservoir porosity was achieved by using temperature data with less than 5% of error.

5. ACKNOWLEDGEMENTS

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