Reservoir Properties Estimation based on Pressure and Temperature Data using ES-MDA

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Abstract. Well test comprises a set of planned data acquisition activities and interpretation. The acquired pressure and temperature data are used to estimate reservoir properties and oil field performance. The pressure data have several noise sources that may compromise the accuracy of test results. The noise may mask the transient reservoir behavior. Therefore, estimated reservoir properties, such as permeability, porosity, and skin effects, from those acquired field data have a high level of uncertainty.

In this work, we use an in-house flow simulator that solves the complete coupled system of equations representing the wellbore/reservoir system. The thermal energy balance equation considers the Joule-Thomson heating and cooling, adiabatic fluid expansion/compression, conduction, and convection effects. The synthetic measured data was obtained by adding gaussian and harmonics noises to simulate equipment and tidal effects, respectively, to the solution of the problem for different scenarios.

Reservoir properties estimation using pressure and temperature transient data obtained from well tests is a classical inverse problem. We use Ensemble Smoother with Multiple Data Assimilation (ES-MDA) as a non-deterministic method to solve this inverse problem. It provides a better data matching and quantification of uncertainty when compared to other methods.

The results show that the properties of a reservoir with skin are better characterized by using combined pressure and temperature data.

Keywords: Tidal Effect, Reservoir characterization, Ensemble method, Inverse Problem

1 Introduction

Nowadays, a common practice in deep water environment is to install permanent downhole gauges - PDGs (pressure and temperature sensors) in wells completed with intelligent completion valves (ICVs) for the purpose of surveillance and reservoir management. Transient data obtained from those gauges have been used to characterize reservoir properties and monitoring well productivity change and facility operation performance [1, 2]. Pressure and temperature data from a PDGs come to users in a high frenquency and highly accurate, which enable to explore subtle signals in pressure data caused by perturbations of small amplitude such as ocean tides effect in deep water environment. Presence of sinusoidal pressure oscillation was observed in the past during well test. The amplitude of those oscillations are of the order of 1 psi and their frequency suggest the tidal effect [3, 4]. Although these periodic oscillations do not affect the oil production process, they have an important influence in the pressure data interpretation and can lead to errors during static tests and pulse tests. It is well known that during the late time period of a pressure buildup test, the additional pressure change due to tidal effects can be large enough so that it is difficult to determine information about flow regimes from the late-time buildup data [5]. In order to improve the information content of the computed pressure derivative, usually the tidal component is removed from the measured pressure data. Levitan and Phan [5] used signals from either tidal potencial function or sea floor pressure to separate the tidal signals from the pressure data. Fast fourier transform (FFT) is often utilized in analysing the pressure data in a frequency domain [6, 7]. The main advantage is to highlight the major frequency of all tidal constituents. However, most of the times, not all the tidal components are filtered completely, which leaves a few harmonic components in the pressure data. Due to unfiltered tidal signals there are misinterpretations in well test analysis [8]. Therefore, there is a challenge in estimate reservoir properties without filtering these periodic disturbance by using of inverse problem methods.

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. The pressure and temperature transient result is modified by adding of a white gaussian noise in order to represent noise coming from the sensor equipment. To simulate periodic disturbances such as tidal effect it was added also an harmonic noise. After that, the inverse problem was solved using an ensemble-based method to characterize the reservoir using the pressure and temperature data artificially modified taking into account different source of noise coming form the equipment and by the tidal effect. To estimate the reservoir properties and evaluate the uncertainties into the variables of 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 the ES-MDA method applied with the coupled pressure and temperature transient data provides better reservoir characterization and uncertainty quantification even for periodic disturbances introduced in the pressure data.

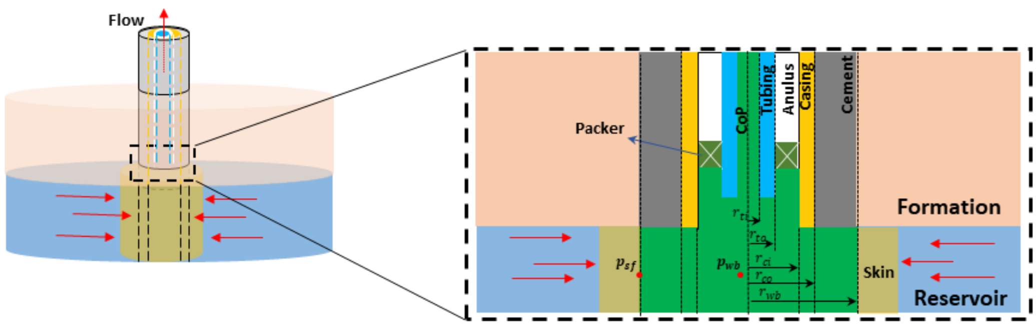

Figure 1. Wellbore-reservoir scheme with the considered components and the respectively geometry.

2 Mathematichal 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 evolution. Second, the ES-MDA is used to estimate the reservoir parameters taken as base the pressure and the temperature data.

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. [9]. 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. [10] and Mattoso et al. [11]. Reservoir properties and well parameters used in this work were also used in Galvao et al. [12] and Galvao et al. [13], unless permeability distribution.

2.2 Inverse problem

The problem of estimating parameters of an unknown system by observing its response to known disturbances is classified as an inverse problem. The procedure of adjusting data to observed data is known in the literature as history matching (HM). The observed data here is the transient bottom hole pressure and temperature during the drawdown period. The Ensamble smoother with multiple data assimilation (ES-MDA) method introduced by Emerick and Reynolds [14] is used to solve the inverse problem. The HM and uncertainty analysis are built by using ES-MDA associated with the parameters of interest. This method was adopted because provides a better data match than the EnKF and others ensembles methods, as discussed in Emerick and Reynolds [15]. The problem of estimating parameters of an unknown system by observing its response to known disturbances is classified as an inverse problem. The procedure of adjusting data to observed data is known in the literature as history matching

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In this work, ES-MDA method is used to estimate and perform the uncertainty analysis of the parameter vector **m**, that contains the properties from the reservoir represented by Fig.1.

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

To reduce the amplitude of the initial range from the permeabilty, the log scale is commonly used. In the vector **m**, the K_1 is the skin zone permeability represented by the yellow color on the reservoir in fig.1. The variable K_2 is the permeability of the region out of skin zone represented by the blue color on the reservoir in fig.1. ϕ is the porosity of the reservoir, which is considered homogenous in this work. And t the skin radius (r_{skin}), is estimated as a multiple of the well radius (r_w), named as α_{skin} and defined as:

$$\alpha_{skin} = r_{skin}/r_{wb} \tag{2}$$

The observed data used in this work were produced by inserting the parameter vector **m** with the pre-defined values (the "likely solution" of the inverse problem) in the direct problem solver, producing as a response a time series of pressure and temperature (**d**). To approximate real field data, white noise was introduced in all analyzes (measurably noise) and the harmonic noise (tidal noise) was introduced only in pressure data for some analysis.

$$\mathbf{d}_{obs} = \mathbf{d} + White\ Noise + Harmonic\ Noise \tag{3}$$

The tidal signal mixed in the bottom hole pressure is assumed to be a damped and shifted version of the tidal signal measured from the sea floor pressure gauges, as we can shown in Fig.2.

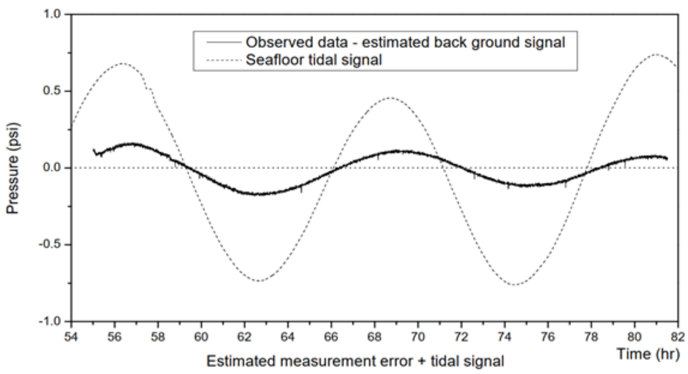

Figure 2. Reference tidal signal measured in the seafloor and the observed data measured in the field case (adapted from Zha [16]).

In the ES-MDA, the observed data ($\mathbf{d}_{obs}$) is perturbed by adding another Guassian distribution in each assimilation originating the $\mathbf{d}_{uc}$, this procedure tends to reduce the sampling problems caused by matching outliers that may be created when the observed data ($\mathbf{d}_{obs}$) is perturbed(Emerick and Reynolds [14]).

$$\mathbf{d}_{uc} = \mathbf{d}_{obs} + \sqrt{\alpha_i C_D^{1/2} Z_d}\ , \quad on\ which\ Z_d = N(0, Id_{N_d}) \tag{4}$$

In the analyzes considering combined observed data, it is necessary the observed data to be normalized. The covariance matrix of measurement errors C_D used is a block-diagonal matrix, which has its diagonal equal to 1 for the part related to the pressure data and the absolute value of the Joule-Thomson coefficient for the temperature data. This matrix was multiplied by a weight of 10^{-4} to improve the estimates. α_i is the inflation coefficient that satisfies:

$$\sum_{i=1}^{N_a} \frac{1}{\alpha_i} = 1 \tag{5}$$

In this work, the α_i was set constante and equal to the number of assimilations N_a. The update process of the vector parameters **m** is defined as follow:

$$\mathbf{m}_j^a = \mathbf{m}_j^p + [C_{MD}(C_{DD} + \alpha_i C_D)^{-1}](\mathbf{d}_{uc} - \mathbf{d}_j^p) \tag{6}$$

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:

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

$$C_{DD} = \frac{1}{N_e - 1}\sum_{j=1}^{N_e}(\mathbf{d}_j^f - \overline{\mathbf{d}}^f)(\mathbf{d}_j^f - \overline{\mathbf{d}}^f)^T \tag{8}$$

3 Results

This work used a synthetic reservoir with a skin zone near the well, represented in Fig.3. The ES-MDA method is tested to estimate reservoir parameters using observed data which has periodic disturbances. We compared the estimation made considering only the pressure data with the white noise and the combined(pressure and temperature) data with the white noise and different magnitude of harmonic noises. The parameter estimation was obtained by using 4 assimilations in the ES-MDA method. The vector $\mathbf{m}_{true}$ represents the expected values for each variable.

$$\mathbf{m}_{true} = [log(32),\ log(100),\ 5,\ 0.12]^T \tag{9}$$

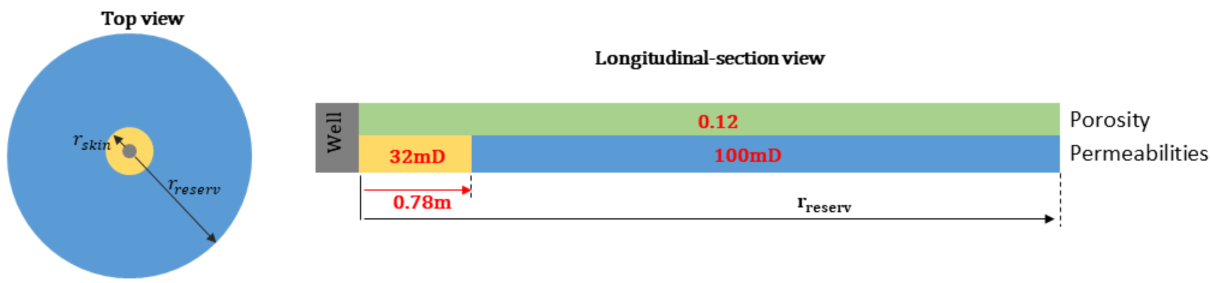

Figure 3. Reservoir configuration, with the top and longitudinal views

Figure 4 shows the pressure and temperature time series in the semi-log scale of time with different combinations of noises. The referencial value for the white noise and the tidal effect was $50KPa$, this means that the blue curve is the simulated data in addition with $50KPa$ from the white noise and $300KPa$ from the tidal effect. The semi-log plot show that the temperatura is detecting two permeabilities regions, while the pressure is detecting only one region.

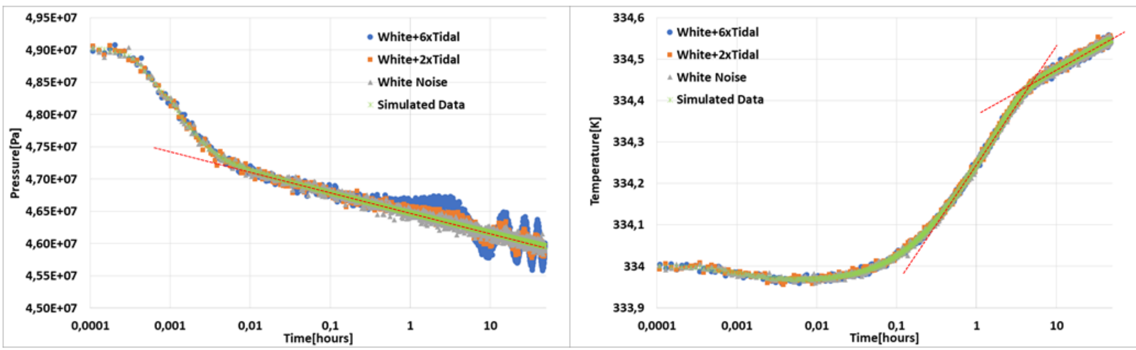

Figure 4. Comparison of the differentes pressure and temperature times series in a semi-log scale.

Figure 5 contains the initial distributions of the parameters **m**. Figure 6 and 7 show the estimation analysis for each parameters, considering only pressure data ("Pressure(White+0xTidal)") and the combined data with multiples amplitudes of the tidal effect.

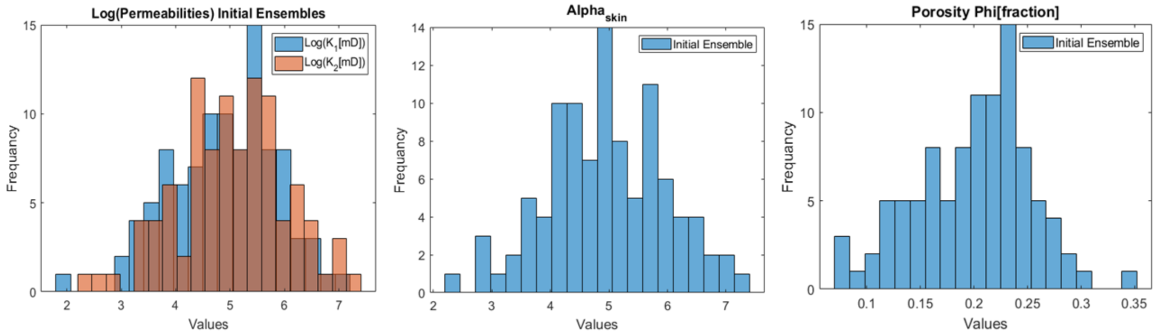

Figure 5. Initial distributions of the parameters

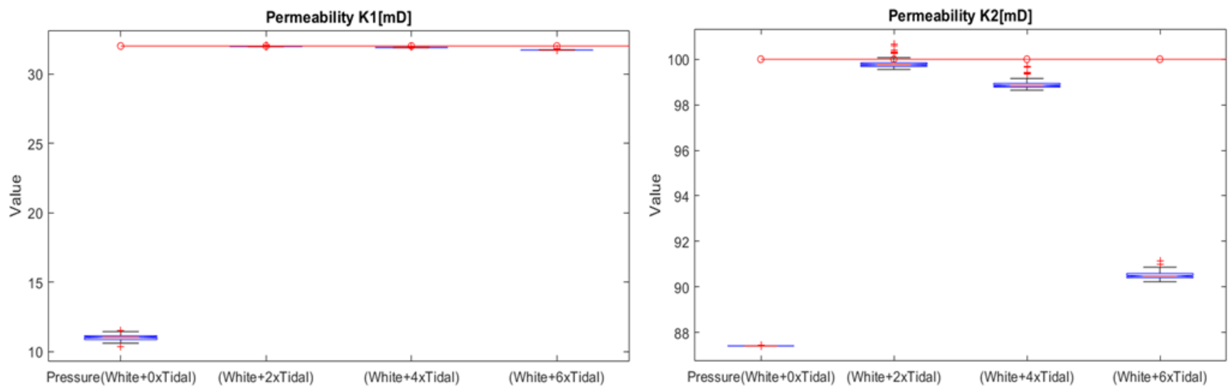

Figure 6. Comparison of estimates made considering only pressure data ('Pressure(white+0xTidal)') with those made using combined data with differents amplitudes of harmonic noise. On the left we have the estimated of the skin permeability, and on the right we have the permeability out of the skin zone.

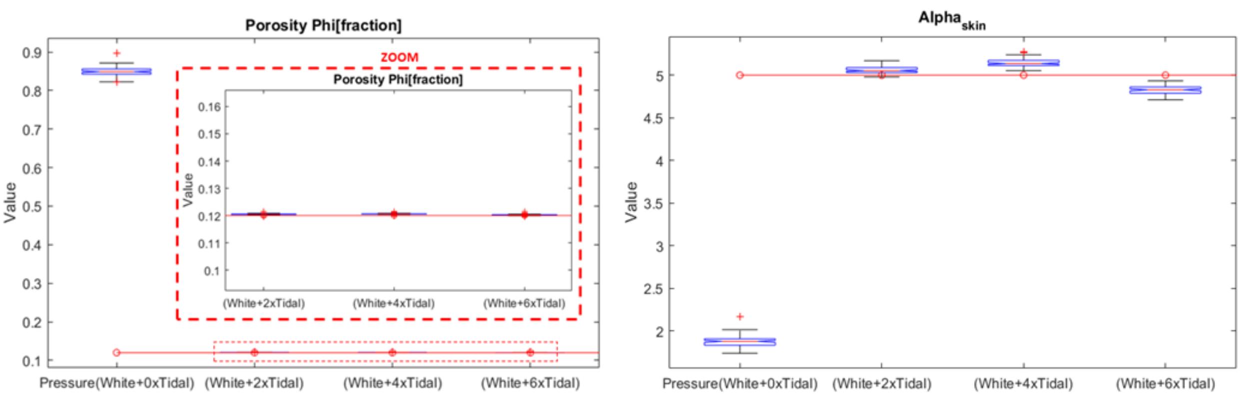

Figure 7. Comparison of estimates made considering only pressure data ('Pressure(white+0xTidal)') with those made using combined data with differents amplitudes of harmonic noise. On the left we have the estimated of the porosity (ϕ), and on the right we have the α_{skin}.

Figure 6 shows that even increasing the harmonic noise, the combined data still provides an accurate estimate of the skin permeability (K_1), better than the simple pressure analysis. For the permeability out of the skin zone (K_2), as we increase the harmonic noise the accuracy of the estimations decreases, but still better than only pressure analysis. Figure 7 contains the estimations for the porosity (ϕ) and α_{skin}, one more time the addition of the temperature data improves the accuracy of the estimations.

Figure 8 and 9 show the comparison between the time series created with the initial distribution of parameters, in grey, with the time series generated with the final ensemble of parameters obtained with the ES-MDA, in blue. The red points are the observed data, ploted together to evaluated the accuracy of the final times series.

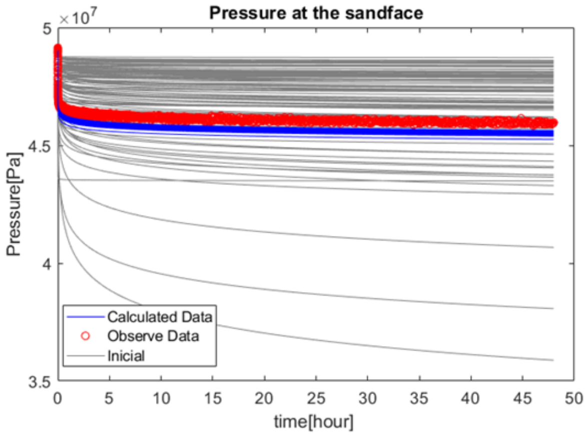

Figure 8. Comparison of the pressure evolution originated with the initial set of parameters (in gray). With the observed data (in red) and with the calculated profiles with the final set of parameters after the 4 assimilations of the ES-MDA method (in blue).

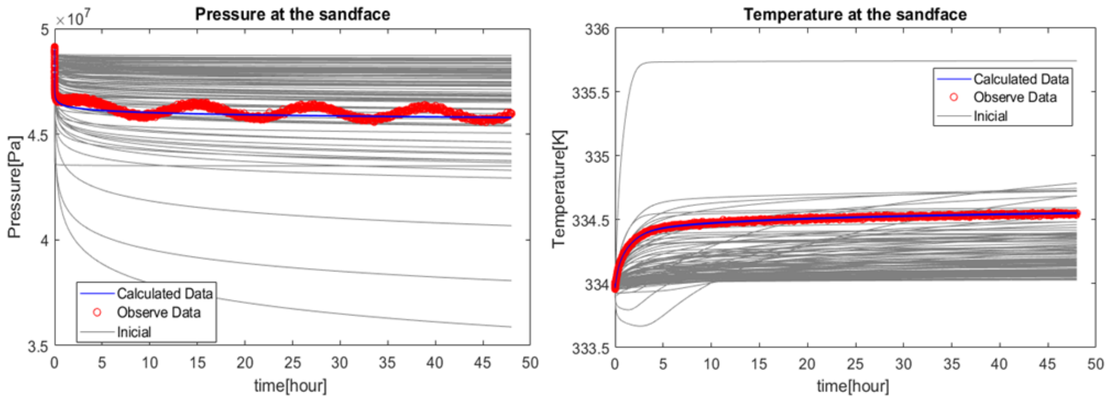

Figure 9. Comparison of the pressure and temperature evolution originated with the initial set of parameters (in gray). With the observed data (in red) and with the calculated evolution (in blue) with the final set of parameters after the 4 assimilations of the ES-MDA method , considering the combined pressure and temperature data. For this case, was considered the highest harmonic noise, with 300KPa of amplitude.

Figure 8 contains the plot of the pressure times series originated with the analysis made with only pressure data. Despite the close fit of the data, the analysis considering only the pressure data could not characterize the skin region near the well. Figure 9 contains the plots of the pressure and temperature times series, originated from the analysis of the combined observe data considering the highest harmonic noise analyzed. Despite containing greater noise, parameter estimates for these cases were more accurate than estimates made with only pressure data without considering harmonic noise.

4 Conclusions

The ES-MDA method with combined pressure and temperature data shows to be more accurately than only considering pressure data. The ES-MDA method seems to be a good candidate to use observed data even with periodic perturbation (tidal effect) without any filtering process to estimate reservoir parameters.

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