Comparison of different experimental data inputs in history matching procedure for relative permeability and capillary pressure determination

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Abstract

In order to determine relative permeability (K_r) and capillary pressure (Pc) curves, several laboratory tests are performed, for instance, Core Flooding (CF) experiments using one or two fluids, from which experimental data such as pressure drop (DP), net produced volume (NP), and Computed Tomography (CT) scans of saturation profiles (SP) may be derived, and input into a history matching software. History matching is a technique used to approximate unknown numerical properties of a model based on the knowledge of experimental data. It is usually performed by solving the inverse problem upon the physical modeling of a system. The SCAS module of the software RFDAP, developed by ESSS, was used to compare the curves obtained using several combinations of experimental data inputs: (1) Only DP, (2) Only NP, (3) DP and NP, (4) DP and SP, and (5) DP, NP and SP. The purpose is to compare the quality of the solutions, in relation to a reference. The synthetic data used for the studies is based on an CF experiment performed by LRAP (UFRJ).

Keywords: History matching, Relative permeability, Reservoir characterization

1 Introduction

Understanding the behaviour of a rock-fluid system of a reservoir is an important piece of the process of designing an exploitation strategy that aims to maximize hydrocarbon recovery. This requires a detailed investigation of such system, consisting of measurements of its fluid and rock properties and, specially, the interaction between them. In this process of understanding rock-fluid behaviour, the determination of relative permeabilities (Kr) and capillary pressures (Pc) are key for the characterization of the reservoir and thus for the optimization of the development strategy, since they are one of the main inputs for the reservoir simulators.

Core flooding (CF) laboratory experiments are often used to obtain pressure drop and production curves of a real rock-fluid system, indirectly telling how is the interaction between the rock surface and its minerals with the fluids and their compositions (generally brine and hydrocarbon). Such curves are then used as the target for the history matching software, that will solve the inverse problem using a core flooding simulator that models the flow through the porous media using K_r and P_c curves.

Such experiments are conducted by sealing and saturating a rock sample with a fluid and trying to reproduce the reservoir conditions (Ambrus [1]) of temperature and pressure. Unsteady State (USS) experiments are performed by injecting one fluid through a core sample to displace the saturated fluid, either by constant pressure or flow rate (Ambrus [1]). An additional bump flow can be employed at the end of the test, to minimize laboratory artifacts (Santos [2]). Lenormand [3] suggests that USS experiments require 7 to 10 steps of injection to be accurate. The reason for this is that single-injection experiment is based on transient flow dominated by viscous fingering and channeling. Steady State (SS) experiments may also be employed, by injecting oil and water simultaneously. From those experiments, Net Production (NP), Pressure Drop (DP), and/or Saturation Profiles (SP) curves through

CT scan are commonly measured.

A 2-phase porous media simulator based on the Darcy equations is used to reproduce the CF experiment and retrieve NP, DP, and/or SP curves. An inverse model (also termed "History Matching") iteratively searches for solutions of K_r and Pc that better fit the simulated NP, DP, and SP curves against the experimental data. These kind of inversion processes are very non-unique or, in the presence of noise in the measurements, there may be no solution that matches the experimental data exactly. For those cases, the definition of "solution" may be relaxed to identify a "best estimate" (Oliver [4]).

Das [5] investigated the non-uniqueness of the solutions associated with different rock properties such as the particle or pore size distributions. Their work show how the micro-heterogeneities can affect K_r and Pc curves. But even for noiseless data and assuming homogeneous rock sample properties, multiple solutions may arise. Typically, the uniqueness can be improved by considering more and different types of experimental data (Berg [6]).

In this work, it is performed an investigation of how the selection of different combinations of experimental NP, DP, and SP curves, for the same rock-fluid system, affects the uniqueness of the solution during the history matching process. To achieve this, the RFDAP SCAS simulator is used to solve the porous media flow model and the least squares problem associated with the history matching process, using a gradient-based optimizer.

2 Two phase flow in porous media modeling

Immiscible 2-phase flow in homogeneous porous media is formulated from the conservation of mass, with Darcy's velocity (Ambrus [1]), and the LET model (Lomeland [7] [8]) is used for K_r and Pc parametrization.

$$\phi\rho_\alpha \frac{\partial S_\alpha}{\partial t} = \rho_\alpha \nabla \cdot \left(k \frac{k_{r\alpha}}{\mu_\alpha} \nabla P_\alpha \right) \qquad \alpha = w, o \tag{1}$$

With the volumetric restriction of saturations $S_o + S_w = 1$. Pressures P_w and P_o are related by the capillary pressure Pc, defined as $Pc = P_o - P_w$. K and ϕ are the porosity and the absolute permeability, respectively, which can have spatial variations in the rock sample. ρ_α and μ_α are the specific gravity and the viscosity of fluid α. Finally, $K_{r\alpha}$ are the relative permeabilities.

To solve the equation for the unknowns P and S, the finite volume method (FVM) is used with fully implicit discretization (Maliska [9], Patankar [10]), which leads to a nonlinear system of equations to be solved. K_r and Pc curves are assumed to be functions of saturation. The LET model is summarized as follows.

$$K_{ro} = K_{ro@S_{wi}} \frac{(1-S_{wn})^{L_o}}{(1-S_{wn})^{L_o} + E_o S_{wn}^{T_o}} \qquad K_{rw} = K_{rw@S_{or}} \frac{S_{wn}^{L_w}}{S_{wn}^{L_w} + E_w (1-S_{wn})^{T_w}} \tag{2}$$

$$S_{wn} = \frac{S_w - S_{wi}}{1 - S_{wi} - S_{or}} \tag{3}$$

Where L_α, E_α and T_α are the model parameters in relation to each fluid. $K_{ro@S_{wi}}$ is the relative permeability of oil in the irreducible saturation of water and $K_{rw@S_{or}}$ is the relative permeability of water in the residual saturation of oil. The Pc model for secondary imbibition process is given by

$$P_c = (P_c^s - P_c^t) F_c^s + (P_c^f - P_c^t) F_c^f + P_c^t \tag{4}$$

$$F_c^s = \frac{(1-S_{wn})^{L^s}}{(1-S_{wn})^{L^s} + E^s {S_{wn}}^{T^s}} \qquad F_c^f = \frac{{S_{wn}}^{L^f}}{{S_{wn}}^{L^f} + E^f (1-S_{wn})^{T^f}} \tag{5}$$

Where L^s, E^s, T^s, L^f, E^f and T^f are adjustable parameters and P_c^t is a threshold pressure.

3 History matching modeling

Estimating the K_r and Pc curves involves the solution of an inverse problem (here denoted "History Matching"). Since the curves are parametrized, the problem is, therefore, to find a set of values of $\Phi = [L_\alpha, E_\alpha, T_\alpha, ...]$ that minimizes the cost function:

$$\min_{\Phi} \sum_{c} \sum_{t} w_t^c (y_t^c - f_t^c(\Phi))^2 \qquad c = \{NP, DP, SP^i\} \tag{6}$$

$$\text{s.t.} \quad \phi\rho_\alpha \frac{\partial S_\alpha}{\partial t} - \rho_\alpha \nabla \cdot \left(k \frac{k_{r\alpha}}{\mu_\alpha} \nabla P_\alpha \right) = 0 \qquad \alpha = w, o \tag{7}$$

Parameters for the models in equations (2) and (4) are approximated by solving a least squares minimization problem (6) from which simulated data $f_t^c(\Phi)$ is compared to the available experimental data y_t^c for each one of the experimentally obtained curves $c = \{NP, DP, SP^i\}$. The index i refers to a spatial position where the saturation profile is being measured. Each index t refers to the temporal index from which the data is being retrieved from. Φ is a vector composed with the L, E and T parameters being optimized. The function f refers to the data retrieved from the simulated experiment, and w_t^c are weight factors.

The problem is solved with a Levenberg-Marquardt based method with additional linear restrictions that avoid spurious K_r or Pc curves. The algorithm stops either by a minimum error tolerance or a number of maximum iterations passed.

4 Objective function analysis

The objective function is affected by the choice of relative permeability models, and also by the selection or availability of experimental data. For example, It is common to take in consideration differential pressure (DP) and net production (NP) curves, but the saturation profiles (SP) data may not be available due to the absence of necessary laboratory apparatus. Common sense may give the intuition that providing more information about the system (e.g. by providing more experimental data for the History Matching) should add more restrictions to the optimization process and, thus, ease the determination of the relative permeability and capillary pressure curves. However, it is also possible that some of the provided data are redundant, and don't provide any relevant information about the system. Thus, it is not clear how the selection of experimental curves of NP, DP and SP would affect the objective function and the history matching procedure.

In order to analyse the effects of changing the objective function (6) with different experimental data inputs for the history matching procedure, a synthetic experiment has been produced based on real experimental data provided by the "Laboratório de Recuperação Avançada de Petróleo" (LRAP).

The simulation represents an imbibition USS experiment with 5 steps of brine injection. K_r and Pc model parameters were obtained by running the RFDAP SCAS history matching tool against the NP and DP experimental data (since experimental SP curves were not available). Then, RFDAP SCAS was used to generate the synthetic NP, DP, and SP curves with the best fit from the previous solution. Since this synthetic data is obtained numerically, the obtained parameters for K_r and Pc are certainly the global minimum for the optimization problem, and are used as a ground truth solution.

The experiment at LRAP used an injection brine with 0.47 cP viscosity and 0.988 g/cm³ to displace a 3 cP viscosity oil with 0.83 g/cc density. A rock sample of 5.03 cm length and 3.83 cm diameter was used, that has measured porosity of 14.8% and measured absolute permeability of 321 mD. Total CF experiment time is 23 hours and 46 minutes, and the change of injection flow rate is summarized in the table below. $K_{ro@swi}$, $K_{rw@sor}$, S_{wi} and S_{or} are assumed to be known, and were not optimized.

Time (s)	Flow Rate (cc/min)
14781	1
16801	2
19201	4
18002	8
16802	10

The objective function from the history matching problem is a multidimensional function mapping n parameters into a scalar value, making it difficult to plot and visually compare the potentially various local minimum positions that the different combinations of experimental data inputs produced. Thus, two different approaches have been tackled to investigate how the objective function is affected by different inputs. At first, a set of plots have been produced around a known solution of K_r, only considering L_α, E_α, and T_α parameters. For each pair of parameters a contour plot is generated by fixing all the other parameters at the known solution. This results in a matrix of slices of the objective function around the solution, making it possible to investigate how the objective function is affected near the global minimum. The slices related to E_w x E_o is shown for different experimental data inputs in Figure 1. Other slices produced similar behavior, with a large area of small values around the global minima, which may be a source of convergence struggle for the evolution of gradient based methods. Results show that the objective function is affected by the addition of different experimental data inputs. Mainly, the addition of the DP curve alters the shape of the objective function. It is not clear, only considering the landscape plots, if those changes in the objective function would improve the history matching results in any way.

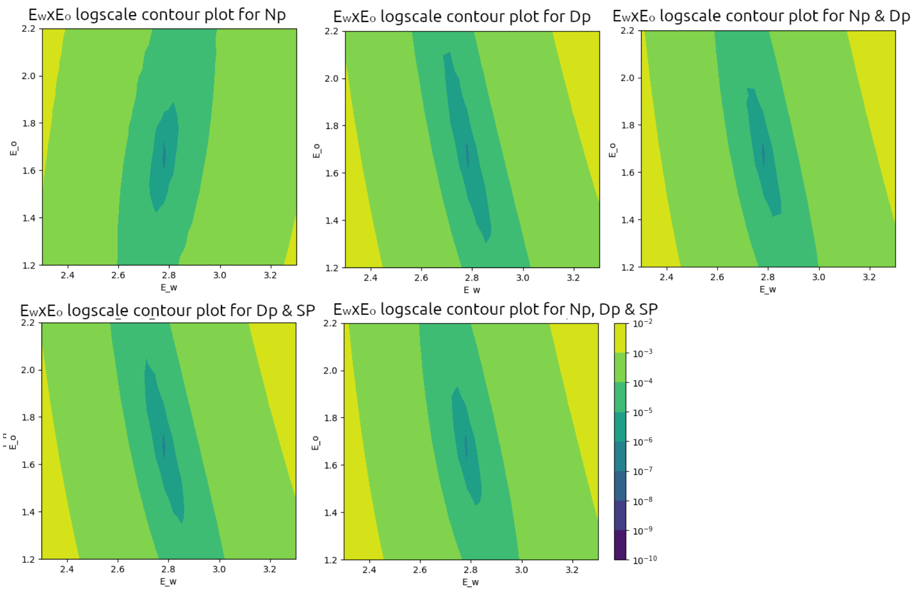

Figure 1. Landscape plot of E_w x E_o variables around global minimum for the numerical experiment, in logarithm scale, considering the following experimental data on objective function: (a) Only NP, (b) Only DP, (c) NP and DP, (d) DP and SP and (e) NP, DP and SP.

However, using the previous approach, it is not possible to observe how the objective function changes far from the solution. To overcome this issue, a second approach has been evaluated: Given a set of 60 initial guesses generated using a Latin Hypercube Sampling in a space of suitable solutions, a batch of optimizations is executed using RFDAP SCAS History Matching module for each configuration. Each initial guess is generated within a range of +/-25% perturbation for each model parameter, around the known solution space. Both K_r and Pc LET model parameters are optimized. A shadow of curves is plotted against the ground truth to evaluate the comparisons, considering: (1) Only DP, (2) Only NP, (3) DP and NP, (4) DP and SP, and (5) DP, NP and SP. Results for K_r and Pc for cases (4) and (5) are shown in Figure 2, and comparison against experimental data for all cases is shown in Figure 3.

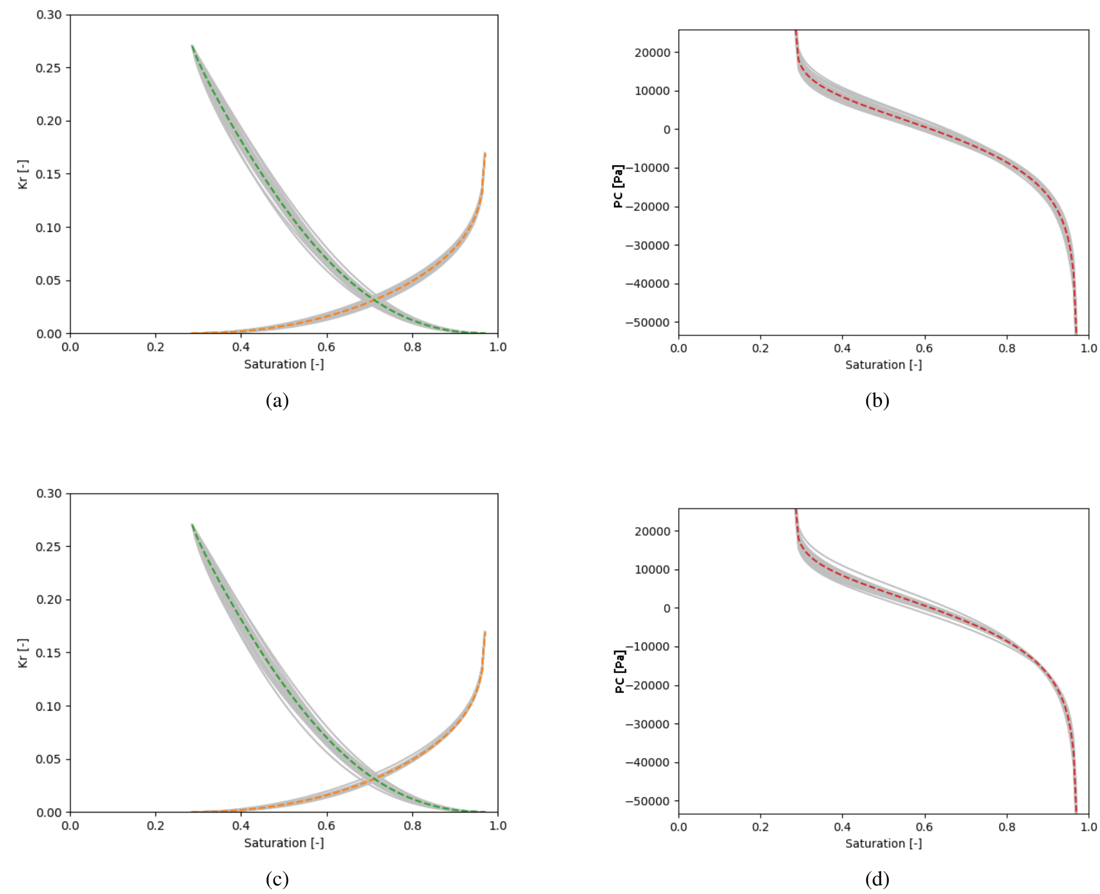

Figure 2. K_r and Pc solution cloud for each initial guess (in gray), and ground truth solution (dashed colored) for numerical experiments (4) and (5)

For the synthetic case presented in this work, it can be seen that cases (1) and (2) produces a set of solutions around NP and DP curves that are more spread out. With the addition of the DP curve, case (3) seems to give a better match for NP than case (1). Cases (3) and (4) matches the saturation profiles well (quantitatively), but case (3) did not take into consideration the SP curves. It may be the case that the relation between NP and SP curves generates redundant data, in the scope of the HM algorithm, at least for the type of rock being used. Different synthetic cases (e.g. which different rock properties) would be necessary to validate if this is true for any case. Finally, case (5) gives similar results to case (3), indicating that the addition of the SP curves does not add extra relevant information for the History Matching, in relation to the NP and DP curves. This also makes sense from the point of view of the results obtained in the landscape plots. Figure 2 shows the comparison between the generated K_r and Pc solution cloud for cases (4) and (5).

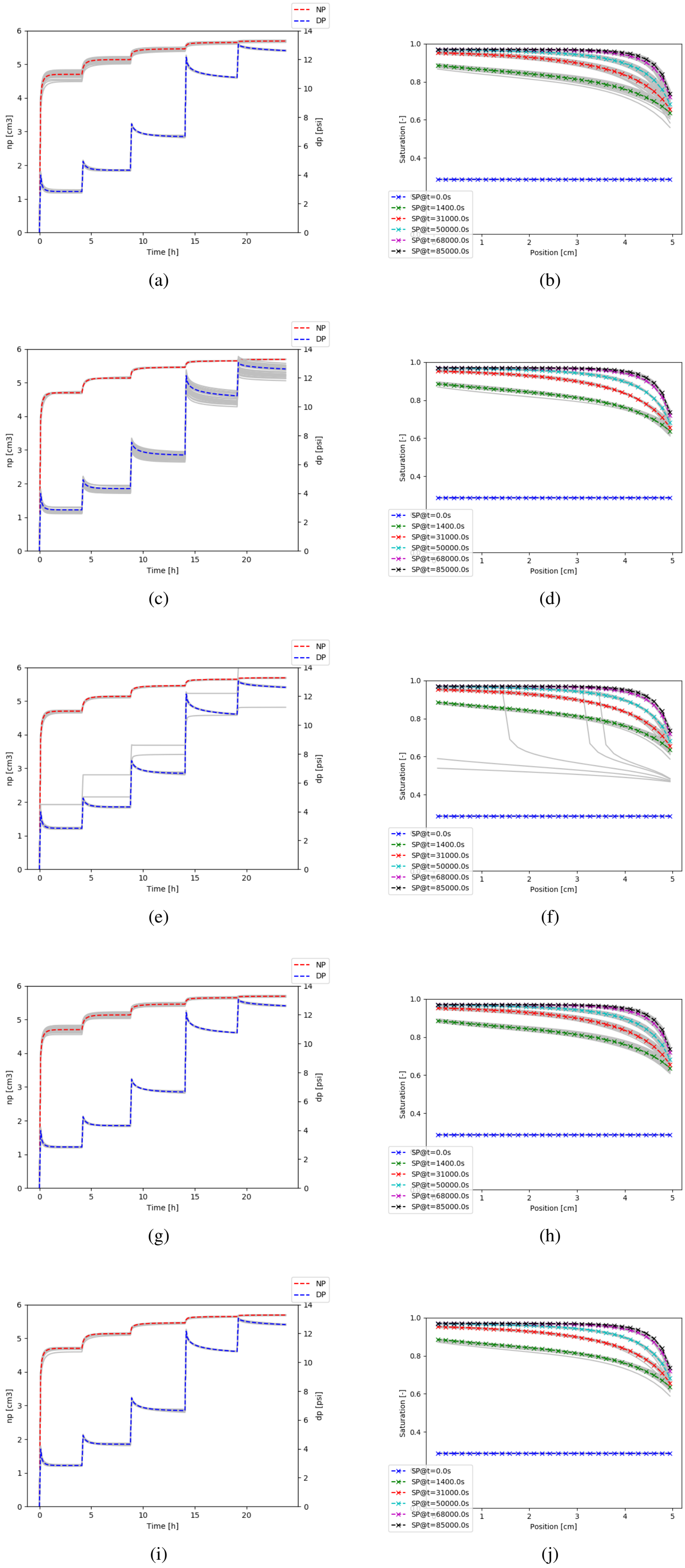

Figure 3. NP, DP and SP solution cloud for each initial guess (in gray), and synthetically generated experimental data (dashed colored) for numerical experiments (1) to (5)

5 Conclusions

The relative permeability is the variable that models the behaviour of multiphase flow in a porous media, and it is one of the main inputs for reservoir simulators. It dictates the fluid movement within the reservoir and affects production profiles, impacting directly in the reservoir management strategy. Due to its importance, it is critical that its determination procedure has a small uncertainty, at least from the numerical point of view. To understand such variation on the probable answers, a numerical simulation experiment using RFDAP SCAS has been performed using a synthetically generated data based on a real case experiment provided to ESSS by LRAP and a comparison between several data inputs in the history matching procedure has been performed. Results seem to indicate that the use of only NP or only DP is not sufficient to correctly derive K_r and Pc curves from USS experiments. Also, the addition of SP curves in addition to NP and DP data inputs for History Matching does not seem to provide better results. Finally, results seems to indicate a relationship between NP and SP curves, which may be explained, as SP curves are a measurement of fluids inside the sample, and the NP curves are the measurement of fluids extracted from the sample. This will be investigated further in the ongoing research. For the experimental standpoint, the measurement of SP curves may be much more difficult than the measurement for NP and DP. The results obtained in this work indicate that such measurements may not have enough impact on the history matching results. However, further work must be employed in other types of samples to better validate this hypothesis.

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