A three-dimensional inverse modelling methodology of two-phase flows at the core scale

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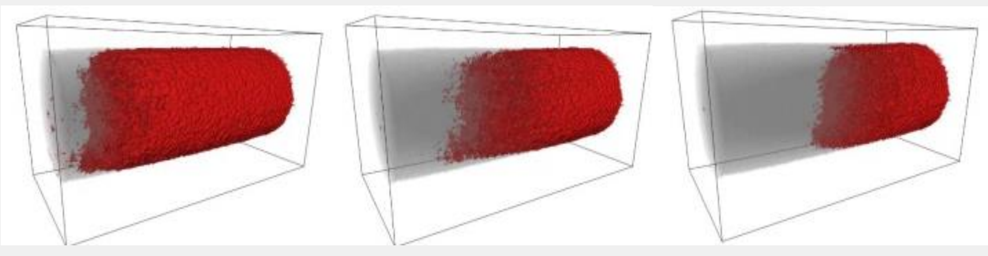
1. INTRODUCTION

- While there are consolidated technologies for the monitoring of temporal and spatial variation of fluid saturations during coreflooading experiments (e.g., Ramskill et al. 2016 and Moghadasi et al. 2016), inverse modeling of transient three-dimensional (3D) two-phase flows introduce new challenges.



(modified from Ramskill et al. 2016)

- We propose an inverse modelling methodology aimed at interpretating measurements conducted during coreflooding experiments. Our methodology is designed for a probabilistic assessment of transient two-phase flow model parameters.
- Our methodology rely on temporal variation of the fluid pressure drop across the sample and the spatiotemporal variation of local saturation of original coreflooding Laboratory-scale experiments.

2. EXPERIMENTAL SET UP

- Our experimental setup includes a rotating core holder, X-ray tomography apparatus for in situ saturation detection, and pressure transducers for the pressure drop monitoring.
- We tested our methodology on two different core flooding laboratory experiments. Both experiments are conducted on a cylindrical core sample made of low-permeability Berea sandstone and involve a synthetic brine. In the first experiment (drainage), a high viscosity (HV) oil is injected into a sample initially saturated with brine. The second experiment (imbibition) brine is injected into a core saturated with low viscosity (LV) oil.

Oils properties	
HV Oil Density (g/mL)	0.859
HV Oil Viscosity (cP)	93.2
LV Oil Density (g/mL)	0.754
LV Oil Viscosity (cP)	1.41

- Local oil saturation is monitored periodically with a voxel resolution of 0.997 x 0.993 x 0.996 mm, and the pressure difference between the inlet and the outlet sample surfaces is monitored continuously.

3. NUMERICAL SIMULATION

- We use the *ad-balckoil* tool of the *MATLAB reservoir simulation toolbox* to solve the two-phase flow black oil equations resting on a finite volume approach.
- The simulation grid used has a coarser resolution than the measurement resolution to reduce the computational burden required by each simulation (voxel dimensions: 6.88x6.88x6.84mm).
- The spatial distribution of absolute permeability ($k(x)$) of the sample is based only on porosity values accordingly to

$$Log_{10}\, k = m\phi + q$$

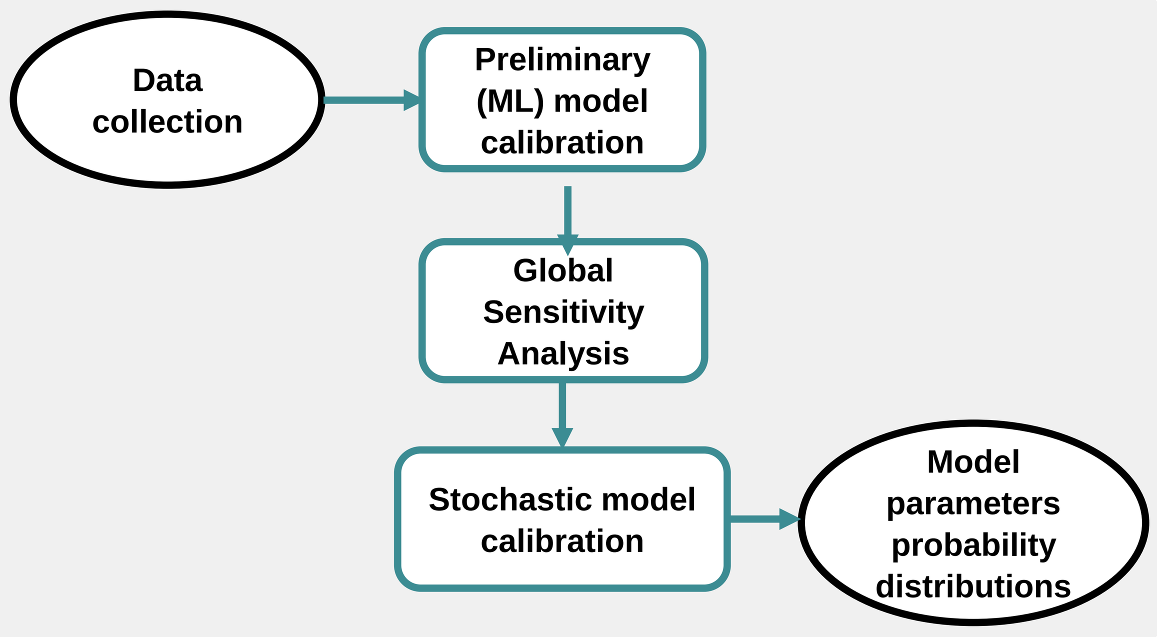
- We couple the Corey model (Corey, 1954) with the Spiteri correlation (Spiteri, 2008) to estimate the distribution of relative permeabilities of oil and brine ($K_{rw}$and K_ro).

$$\begin{cases} K_{rw} = K_{rw}^{o}(S_w^*)^{N_w} \\ K_{ro} = K_{ro}^{w}(1-S_w^*)^{N_0} \\ S_w^* = \dfrac{S_w - S_{wi}}{1 - S_{wi} - S_{or}} \\ S_{or} = \alpha S_{oin} - \beta S_{oin}^2 \\ S_{wi} = F * S_{winitial} \end{cases}$$

- The flow simulation model parameters are 7: m, K_{rw}^{o}, K_{ro}^{w}, N_w, N_0, the contact angle θ (that govern α and β) and F.

4. METHODOLOGY

- The key steps of the methodology can be summarized as follows:
  1. Acquisition of experimental data through X-ray tomography and pressure transucers;
  2. Preliminary ML-based model calibration leading to a reduced parameters space;
  3. Evaluation of the relative importance of uncertain model parameters on simulated state variables through Global Sensitivity Analysis (GSA);
  4. Stochastic model calibration leading to a collection of N_{calib} sets of influential model parameters (influential parameters are pre-selected due to GSA results) and their probability distributions.



OPTIMIZATION

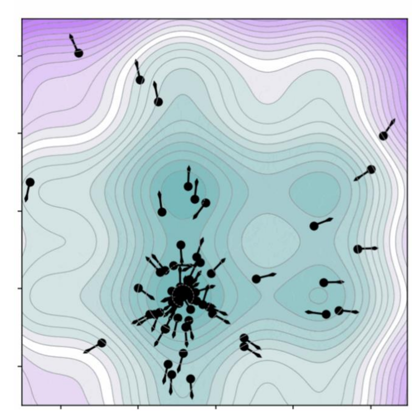
- The second and the fourth steps of the methodology are based on the minimization of the following objective function (J)

$$J = \frac{\sum_t^{N_{\text{time step}}} \sum_i^{N_{\text{celle}}} \left(S_{o,i,t}^* - S_{o,i,t}\right)^2}{N_{\text{time step}} * N_{\text{celle}}} + W * \frac{\sum_t^{N_{\text{time step}}} \left(\frac{\Delta P_t^* - \Delta P_t}{\Delta P_{max}}\right)^2}{N_{\text{time step}}}$$

OIL SATURATION WEIGHT PRESSURE DROP

- J is minimized through an artificial intelligent technique termed Differential Evolution (DE) optimization.
- The DE is a population evolutionary algorithm. It randomly initializes a first population of chromosomes (parameter sets) and then combines existing chromosomes with combinations of other chromosomes with mutated genes (with modified parameters).

The new generation will include only the chromosomes that give the best (lowest) value of J; the comparison is conducted between old and combined chromosomes. New generations are created until a convergence criterion is met.



SENSITIVITY ANALYSIS

- In the third step of the methodology, through a GSA, we identify which uncertain parameters are the most influential on the simulated state variables.
- Our workflow relies on the approach proposed by Morris (1991), it is based on indices that quantify the sensitivity of a quantity of interest with respect to different parameters of the model in use, exploiting the concept of derivative.
- Considering $y(\theta)$ being a generic quantity of interest and θ_j as the j-th parameter of the model, the Elementary Effect EE_j is evaluated as

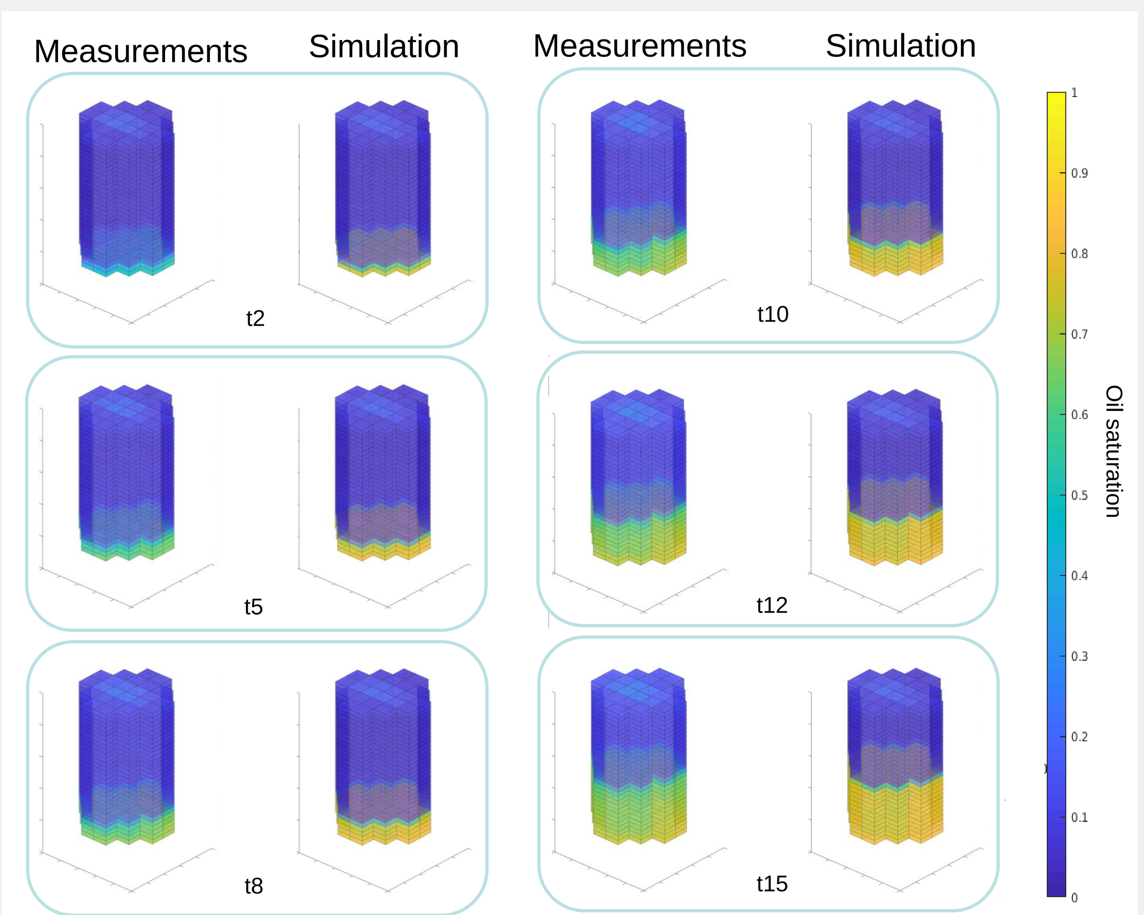
$$EE_j(\boldsymbol{\theta}) = \frac{\Delta y(\boldsymbol{\theta})}{\Delta\theta_j} = \frac{y(\theta_1, \theta_2, \ldots, \theta_j + \Delta, \ldots, \theta_7) - y(\boldsymbol{\theta})}{\Delta\theta_j}$$

- The indices used are the mean and the standard deviation of the absolute values of EEs.

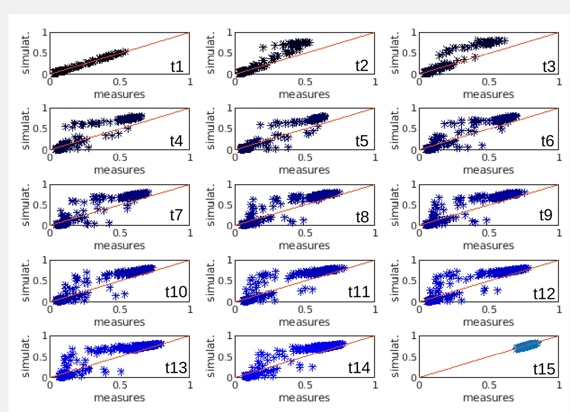
$$\mu^*(\theta_j, y) = \frac{1}{M}\sum_{k=1}^{M} |EE_{j,k}|$$

$$\sigma(\theta_j, y) = \sqrt{\frac{1}{M}\sum_{k=1}^{M}\left(EE_{j,k} - \mu^*(\theta_j, y)\right)^2}$$

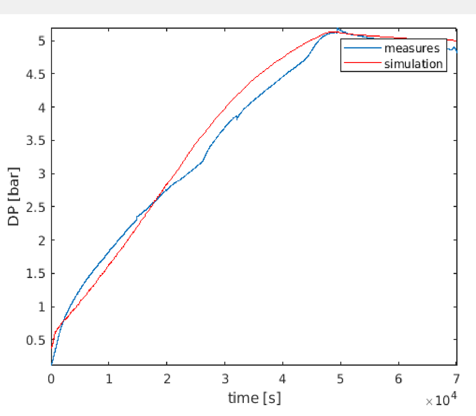
5. RESULTS AND CONCLUSIONS



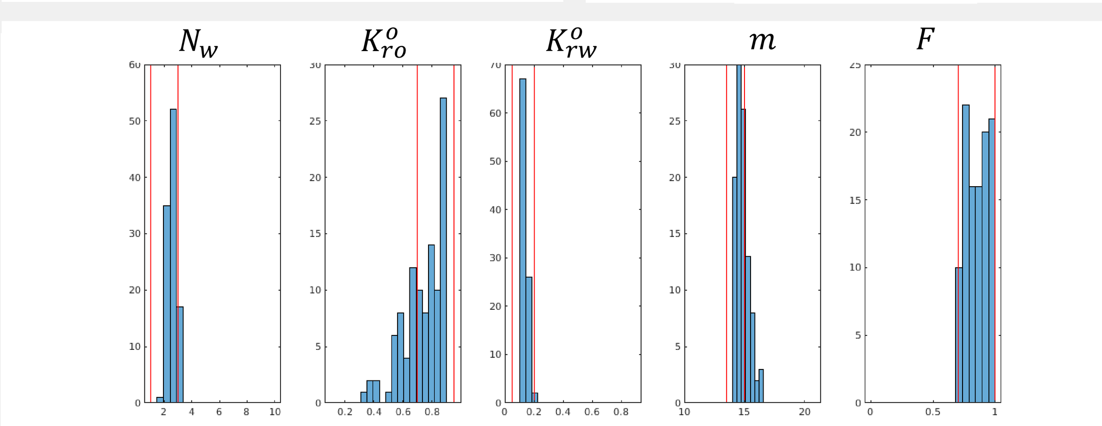
- The probability distributions of the parameters are concentrated within the reduced range of parameters variability used in the sensitivity analysis, even though the stochastic model calibration (step 4) is conducted the full range of variability of the parameters.
- There are two non-influential parameters in both the experiments (N_o and θ in the experiment 1 and K_{romax} and θ in the experiment 2)
- The main drawback of the methodology is the computational cost. We came up with multiple solutions: (i) we select a coarser simulation resolution (ii), we relied on parallel computing of optimizations, and (iii) we estimate the probability distributions only for the most influential parameters.



Saturation Simulation vs Measures



Pressure Drop



Parameters Estimates Probability Distributions