Assessing uncertainties and identifiability of foam displacement models employing different objective functions for parameter estimation

InterPore 2022
Abu Dhabi - United Arab Emirates

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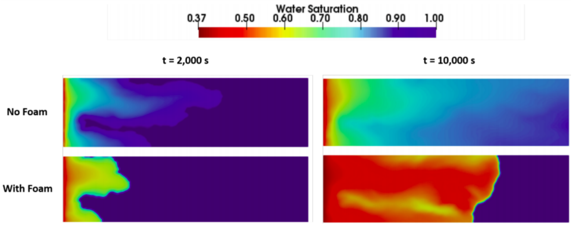
Overview

EOR with Foam Injection

- Water-alternating gas (WAG) injection process can increase the sweep efficiency in EOR
- Gas fingering, channeling, and gravity override, may hamper this technique
- The injection of foam can help by reducing gas mobility and increasing apparent viscosity
- Mathematical models are extensively used for foam flooding in porous media



F. F. de Paula, T. Quinelato, I. Igreja and G. Chapiro, A Numerical Algorithm to Solve the Two-Phase Flow in Porous Media Including Foam Displacement. In: Computational Science - ICCS 2020 pp. 18-31, 2020.

How to model foam injection effects?

- Apparent viscosity (**data**)

$$\mu_{app} = -\frac{\kappa \nabla p}{u_g + u_w}, \tag{1}$$

- The CMG-STARS mathematical **model** for foam flow is given by

$$\mu_{app} = \left(\lambda_w + \frac{\lambda_g}{MRF}\right)^{-1}, \qquad MRF = 1 + fmmob\, F_{water}\, F_{shear}, \tag{2}$$

$$F_{water} = \frac{1}{2} + \frac{1}{\pi}\mathrm{arctg}\left(sfbet(S_w - SF)\right), \quad F_{shear} = \begin{cases} \left(\frac{fmcap}{N_{ca}}\right)^{epcap} & \text{, if } N_{ca} \geq fmcap, \\ 1 & \text{, if } N_{ca} < fmcap, \end{cases}$$

where $N_{ca} = \dfrac{\mu_{app}\, u}{\sigma}$.

CMG STARS. STARS users manual; version 2019.10, 2019.

An expression to obtain data for the MRF

Using the following relations for apparent viscosity and total mobility

$$\mu_{app} = \lambda_T^{-1} = \left(\lambda_w + \frac{\lambda_g}{MRF}\right)^{-1} \quad \text{and} \quad \lambda_T = \lambda_w + \frac{\lambda_g}{MRF} = \frac{\kappa_{rw}}{\mu_w} + \frac{\kappa_{rg}}{\mu_g\, MRF} \tag{3}$$

Rearranging previous equation as $\lambda_T - \lambda_w = \lambda_g / MRF$, and considering that $\lambda_w = f_w \lambda_T$, we have:

$$\lambda_T\,(1 - f_w) = \frac{\lambda_g}{MRF}. \tag{4}$$

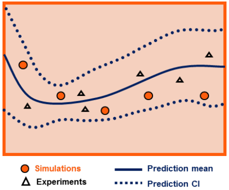
Water and gas fractional flows are defined such that $f_g + f_w = 1$. Using $f_w = 1 - f_g$ in Equation (4) and the relation $\mu_{app} = \lambda_T^{-1}$, we have the following expression to obtain *MRF* **data**:

$$MRF = \frac{\lambda_g}{f_g}\,\mu_{app}. \tag{5}$$

What do we mean by UQ and SA?

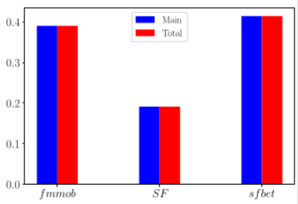
Uncertainty Quantification (UQ)

- UQ is the science of quantitative characterization and reduction of uncertainties in both computational and real world applications.
- Estimation and propagation of uncertainties from input parameters for simulations



Sensitivity Analysis (SA)

- Relation between input (parameters) uncertainties with the variance of the model's response;
- Global sensitivity analysis:
  - Identification of the most influential and non-influential inputs.

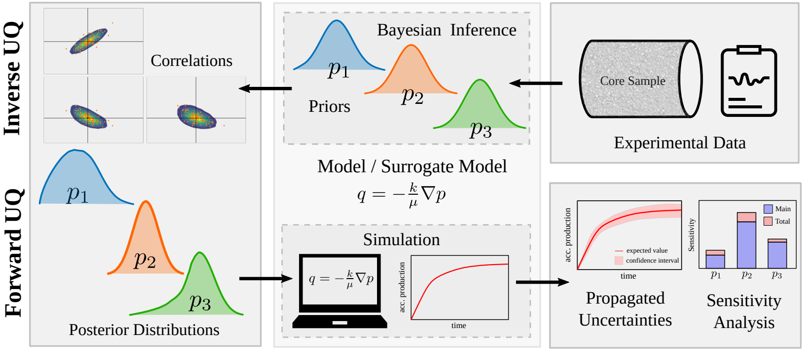


What are the main goals of this work?

- Present a new objective function that can be used for foam flow model calibration. [1]
- The objective function combines the traditional apparent viscosity experimental data with information that reflects the mobility reduction factor.
- Improve parameter estimation and reduce parametric uncertainty.
- Circumvent difficulties such as non-uniqueness in parameter estimation for CMG-STARS model, specially when the non-Newtonian behavior is considered

[1] *Valdez et al.*, Journal of Petroleum Science and Engineering, 2022. doi: 10.1016/j.petrol.2022.110551

UQ and SA in foam-assisted EOR



Methods

- Non-linear least squares
- Profile likelihood for identifiability analysis
- MCMC method for parameter inference
- Sensitivity analysis based on Sobol indices
- Polynomial Chaos Expansion for surrogate modeling

Datasets used in this study

- Synthetic dataset # 1 with sharp transition from LQR to HQR
- Synthetic dataset # 2 with smooth transition from LQR to HQR
- Experimental data from Kapetas et al. (2016)
- Experimental data from Moradi-Araghi et al. (1997)

Table: Overview of input parameters for all investigations of this study.

Dataset	Synthetic	Kapetas (2016)	Moradi–Araghi (1997)
μ_w $[Pa\,s]$	7×10^{-4}	1×10^{-3}	6.5×10^{-4}
μ_g $[Pa\,s]$	2×10^{-5}	2×10^{-5}	5×10^{-5}
σ_{wg} $[N/m]$	3×10^{-2}	2.81×10^{-2}	5×10^{-3}
u $[m/s]$	98.819×10^{-6}	1.383×10^{-5}	1.763×10^{-5}
κ $[m^2]$	5.23×10^{-13}	1.67×10^{-12}	5.44×10^{-13}
ϕ	0.18	0.24	0.18
S_{wc}	0.20	0.25	0.10
S_{gr}	0.20	0.20	0.05
n_w	4.20	2.86	4.00
n_g	1.30	0.70	1.83
κ_w^0	0.20	0.39	0.22
κ_g^0	0.94	0.59	1.00

Objective Functions for Model Calibration

1) OF1 uses μ_{app} data

$$\mathcal{X}^2_{\mu} = \sum_{k=1}^{N_p} \left(\frac{\mu^{exp}_{app,k} - \mu^{model}_{app,k}(\mathrm{x})}{\max(\mu^{exp}_{app})} \right)^2$$

2) OF2 uses MRF data

$$\mathcal{X}^2_{MRF} = \sum_{k=1}^{N_p} \left(\frac{MRF^{exp}_{k} - MRF^{model}_{k}(\mathrm{x})}{\max(MRF^{exp})} \right)^2$$

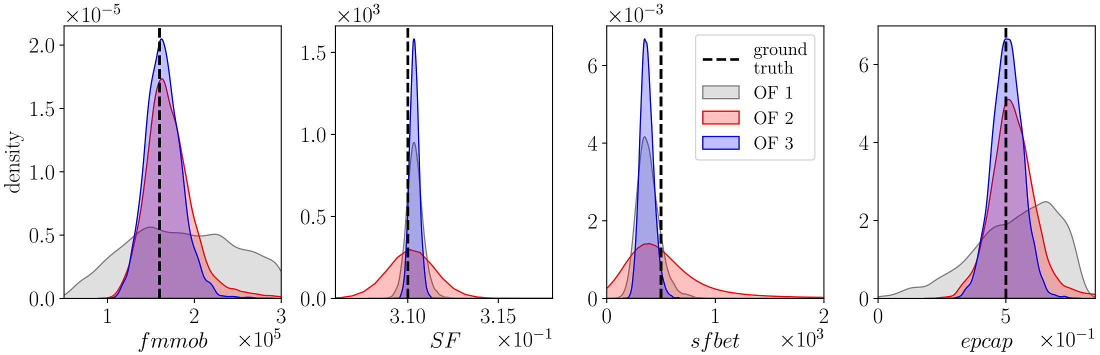
3) OF3 uses (μ_{app}, MRF) data

$$\mathcal{X}^2_{\mu,MRF} = \sum_{k=1}^{N_p} \left(\frac{\mu^{exp}_{app,k} - \mu^{model}_{app,k}(\mathrm{x})}{\max(\mu^{exp}_{app})} \right)^2 + \left(\frac{MRF^{exp}_{k} - MRF^{model}_{k}(\mathrm{x})}{\max(MRF^{exp})} \right)^2$$

- For Bayesian inference (MCMC), these objective functions are defined accordingly.

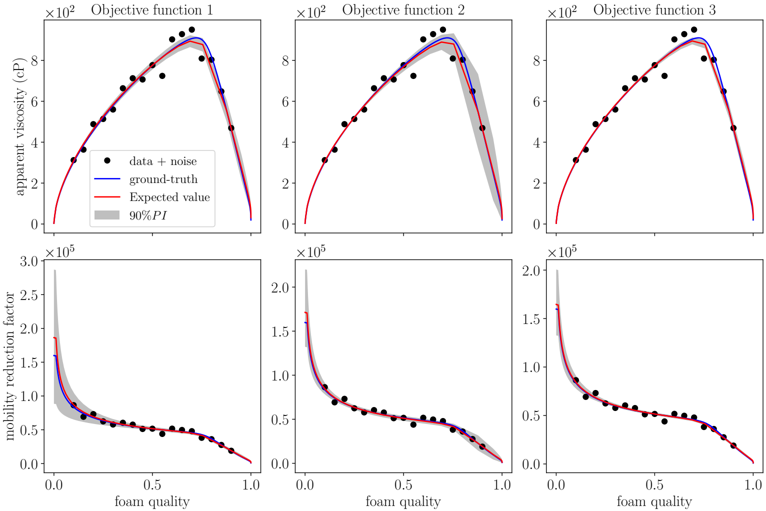
Estimated posterior distributions

Posterior distributions obtained using different objective functions (OF) for MCMC parameter inference for the synthetic dataset #1



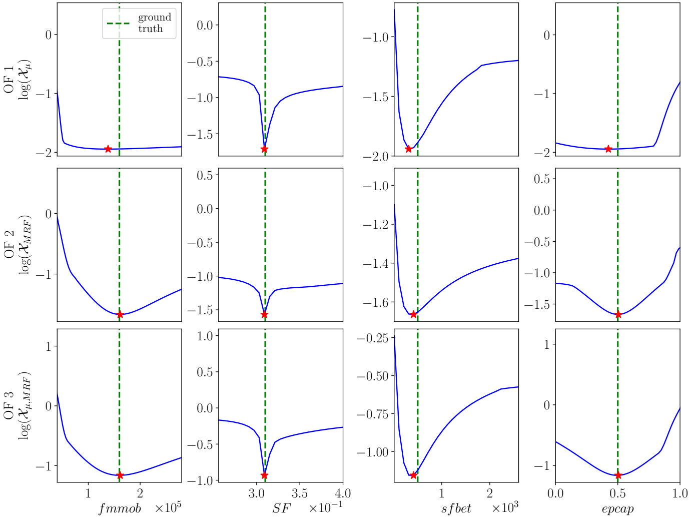
Forward UQ results for μ_{app} and MRF

- OF1 propagates more uncertainty to MRF
- OF2 propagtes more uncertainty to μ_{app} and less to MRF
- OF3 combines the good features of OF1 and OF2



Profile-likelihood analysis

- Identifiability issues for *fmmob* and *epcap* with OF1 propagates more uncertainty to *MRF*
- OF2 improves the identifiability of these parameters
- OF3 combines the features of OF1 and OF2



Variance-based Sensitivity Analysis

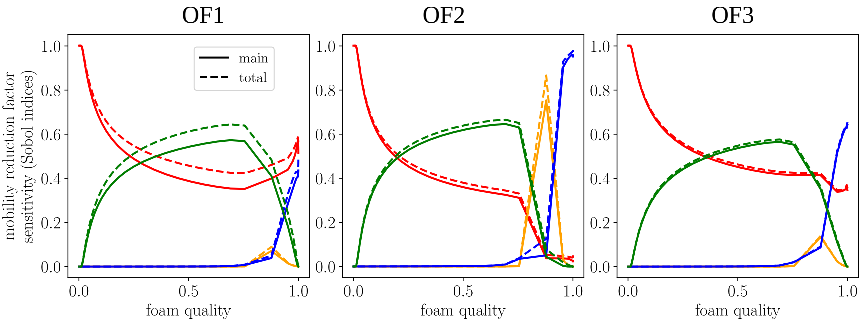
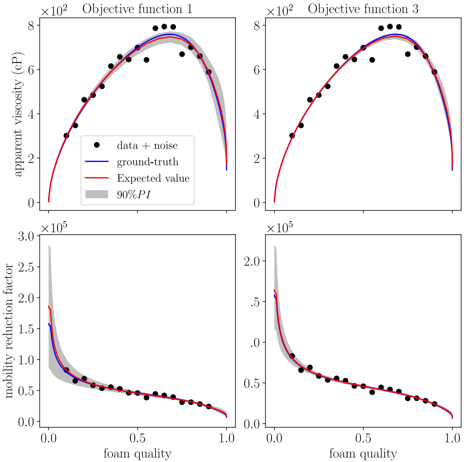


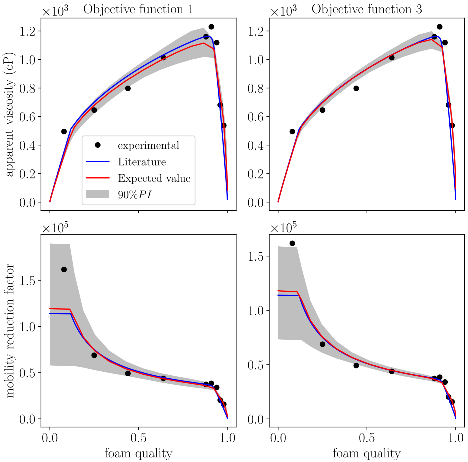
Figure: Sobol indices for *MRF* with respect to parameters: *fmmob*, *SF*, *sfbet*, and *epcap*.

- Results for the OF1 present high-order interactions (see total Sobol indices).
- Parameter interactions can cause model parameters to be not uniquely identifiable.
- This was noticed before in posteriors distributions and shallow profile likelihoods.

Other datasets...

- For the other datasets (synthetic #2 and experimental ones), the results follow the same trend from dataset #1.





Conclusions

- An improved objective function for model calbration of non-Newtonian two-phase flow with foam in porous media was presented.
- The proposed objective function does not require additional experimental observations and can be simply derived from existing two-phase foam flow relations.
- The probability density functions estimated for the parameters were more compact, that is, with lower uncertainty. better estimated with our approach.
- The proposed objective function generated estimates with higher fidelity and lower uncertainties. [2]

[2] Assessing uncertainties and identifiability of foam displacement models employing different objective functions for parameter estimation, *Valdez et al.*, Journal of Petroleum Science and Engineering, 2022. doi: 10.1016/j.petrol.2022.110551

Support from Shell, UFJF, TU Delft, PUC-Rio.

Thank you for your attention!

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