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Full Length Article

Multi-objective history matching of surfactant-polymer flooding

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ABSTRACT

Surfactant-polymer flooding is an effective process in extracting most of the original oil in place remained after conventional water flooding process. However, this technique is complicated and involves extensive screening and numerous experiments to find the optimum chemical composition, salinity, etc. Surfactant-polymer flood modeling can facilitate the optimization of the process, however, the inherently large parameter space results in great uncertainty and poor predictive capability. Here, by means of a novel approach using global sensitivity analysis, we reduce the parameter space of a typical surfactant-polymer flood model to facilitate model calibration and history matching process.

To inform our analysis, we performed three Berea coreflood experiments with different slug designs and salinity profiles. The results from our coreflood experiments revealed and quantified the high sensitivity to salinity, underlying the importance of accurate phase behavior modeling. In addition to coreflood experimental data, we used an extensive set of laboratory data including polymer rheology, surfactant phase behavior, polymer permeability reduction, and capillary desaturation along with results from sensitivity analysis to build a mechanistic surfactant-polymer flood model.

After modeling of sub-processes such as polymer flood model or phase behavior of our surfactant/oil/water system, through a multi-stage calibration algorithm, coreflood experimental data was used to build a thorough surfactant-polymer flood model where cumulative oil production and pressure profile were history matched simultaneously. Finally, we showed that our surfactant-polymer flood model has predictive capabilities with no need for ad hoc tuning of the model parameters by modeling two additional coreflood experiments where cumulative oil production and pressure profile matched those of experiments.

1. Introduction

Enhanced oil recovery is of great importance as two-third of the original oil in place (OOIP) remains intact after waterflooding of many mature reservoirs [1,2]. Waterflooding becomes ineffective as oil is dispersed and trapped in small pores by strong capillary forces. Surfactant-polymer (SP) flooding is a tertiary oil recovery technique targeting the oil trapped in small pores through reducing the interfacial tension between water and oil, improving mobility control as a result of polymer injection, and avoiding early breakthrough. Despite the elegant mechanism of oil recovery in SP flooding and its high efficacy in controlled laboratory experiments, it has showed poor performances in field-scale experiments [3,4] due to significant uncertainties [5].

Numerical simulations of subsurface flows are subjected to various sources of epistemic uncertainty due to lack of data. This issue is more severe in the case of chemical enhanced oil recovery as such processes are very complicated. A typical SP coreflood model requires about 170 input parameters [6] and extensive screening processes and various experiments. A successful SP process necessitates an optimal design of parameters such as slug sizes, chemical concentration in each slug as well as taking into account uncertain variables such as residual oil saturation to chemical flooding (S_{orc}), chemical adsorption rates, etc. Consequently, the design of a successful SP flood is highly dependent on uncertain parameters.

There exists a large body of literature on SP flooding models [2,7–9]. History matching with coreflood experiments is the first step in developing these models [10], where some model parameters such as relative permeability curves or capillary desaturation curves (CDC) are tuned until a satisfactory match between experiment and simulation results is achieved. AlSofi et al. [8] used data from several SP coreflood

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experiments on carbonates and history matched cumulative oil recovery. In their work, they tuned parameters such as dispersivity, critical micelles concentration, interfacial tension, and capillary desaturation to correctly predict the incremental oil recoveries. Hosseini-Nasab et al. [11] studied the performance of Alkaline-surfactant-polymer (ASP) flooding at sub-optimum conditions in Bentheimer cores and history matched their model for pressure drop profile, cumulative oil recovery, and effluent profile. However, most previous works did not provide a quantitative analysis of performance of their history matched model or did not further validate their models by predicting new coreflood experiments.

After successful history matching, one can use the SP flood model for various purposes such as production forecast or optimization. In literature, much effort has been devoted to sensitivity analysis of design parameters (i.e., slug sizes and concentrations, reservoir characteristics such as porosity and permeability, fluids properties such as viscosity, etc.) [12–17]. One of the most comprehensive studies has been performed in [18] where optimum phase type, effects of salinity profile, oil viscosity, salinity window, and solubilization ratios among other parameters were separately studied on the overall oil recovery. To quantify uncertainty in SP flooding models, a probabilistic collocation method was used to propagate uncertainty in polymer viscosity multiplier, chemical adsorption rates and S_{orc} [19]. In the work of Hou et al. [20], a quasi-Monte Carlo sampling approach was adopted for efficient sampling of uncertain variables and then the effects of medium heterogeneity on CO_2 migration was studied. Douarche et al. [21] carried out sensitivity analysis of SP flooding at the reservoir scale using a response surface methodology (RSM) and Gaussian regression to approximate the reservoir output as a function of time. To avoid large computational costs, Mollaei et al. [17] used Winding Stairs (WS) as a sensitivity analysis method in conjunction with an analytical chemical flood predictive model (CFPM). Although quite important, sensitivity analysis of design parameters facilitates optimization of SP flooding and not history matching. Thus, it is important to perform a separate sensitivity analysis on model parameters to facilitate the history matching process. Sensitivity of SP flood experiments to model parameters in SP floods, however, are well-known to be the main difficulty in scaling up a SP coreflood experiment to field scale [3,22]. Thus, sensitivity of SP floods to model parameters and intrinsic uncertainty associated with them are critically important and must be quantified. Despite the numerous studies on modeling SP flooding, only a few studies have examined sensitivity of important quantities of interest (i.e. cumulative oil production and maximum pressure drop) to key parameters in SP flood model. In the early work of Brown et al. [3], a simple SP flooding model based on a fractional flow theory was employed and the effects of adsorption, relative permeability curves at high capillary numbers, residual water saturation and residual oil saturation were examined. Similar analysis is presented in studies such as [21,23,24] using rather simple models for SP flooding. In those studies oil/water/surfactant phase behavior were disregarded and thus formation of the third phase (i.e. middle phase microemulsion) or solubilization of oil/water in the surfactant-rich phase cannot be captured. Consequently, [21,23] did not focus on successful history matching and further validating it. Inability of those simple models is further clear by relatively poor history matching presented in [24]. In an experimental study, Walker et al. [25] showed that microemulsion viscosity alone has major effects on the pressure gradient and overall recovery efficiency. Recently, AlSofi et al. [8] studied SP flooding in carbonates by means of a 1D coreflood model. They later quantified the sensitivity of their 1D model to some detailed model parameters such as those used in polymer viscosity calculation and surfactant phase behavior. Finally, although in mechanistic modeling studies of SP flooding such as [26,11] good matches between experimental and modeling data have been observed, no systematic history matching algorithm were presented. Furthermore, predictive capability of such history matched models were not further tested.

One can easily notice that in most previous SP flooding studies, (i) there exists an arbitrariness in history matching methodology and thus a systematic approach to history matching of SP flooding is needed, (ii) history matched SP models have not been further tested to assess their predictive capabilities and rather blindly applied at larger scales, (iii) history matching has been performed by matching the cumulative oil production only and other important quantities such as oil-cut, pressure and effluent profiles were ignored, (iv) sensitivity analysis and uncertainty quantification are carried out using simplistic SP models which are far from real processes occurring during a SP flood experiment.

In this work, we aim at addressing two issues we mentioned above namely lack of robust history matching with multiple objectives and determining sensitivity of typical SP flood models to some key physical parameters using a comprehensive SP flood model rather than a simplified one. To do so, we build a mechanistic SP flood model where most of the model parameters are determined prior to coreflood simulation using laboratory measured data and only few parameters are left for the history matching process. Model calibration is greatly assisted by means of global sensitivity analysis to quantify the response of the model to uncertain input parameters taking into account all major physical processes occurring during a SP flood experiment. First, each sub-model in a SP flood model is examined to identify the most important parameters. Next, a sensitivity analysis is done on the entire SP flood model determining the most important processes. Then, we history match the cumulative oil production and pressure profile using a multi-stage calibration algorithm. Finally, we validate the model by predicting new independent experimental results without further tuning the model parameters and we quantify the accuracy of the numerical results.

In the next section, we describe the coreflood experiments, which we used for history matching and calibrating our models. In Section 2, we discuss the modeling approach and how we divide a typical SP flooding process into smaller sub-processes, where model calibration can be robustly performed. In Section 3, we perform a thorough sensitivity analysis of SP flood model to further reduce the parameter space and facilitate the history matching process. Finally, we present the calibrated SP flood model and its validation in Section 3.5.2 obtained via a multi-stage algorithm.

2. Coreflood experiments

In this section, we briefly discuss the coreflood and other experiments used in this study for model calibration and validation. Berea sandstone samples (Length: 12″, diameter: 2″) of similar permeability ($k \approx 400$ mD) and porosity ($\phi = 0.2$) to the reservoir of interest were used for all the flooding experiments under reservoir temperature (24 °C) and pressure (P = 400 psi). Throughout the experiments, a synthetic field brine with total dissolved solid (TDS) of 9400 ppm and reservoir oil (dead oil) were used. A combination of PETROSTEP® S-13D HA (Alcohol Alkoxy Sulfate) and A6 (Alkyl Benzene Sulfonate) and Huntsman SURFONIC® L series co-solvent was used at total chemical concentration of 8000 ppm for the SP slug. Partially hydrolyzed polyacrylamide polymer (SNF Flopam 3330) was used for mobility control. An injection rate of 1 ft/D was used for all the oil recovery experiments. A summary of fluid properties is shown in Table 1. Experiments were performed in secondary and tertiary modes of recovery following the same injection sequence: initial waterflooding (IWF) at reservoir salinity, high total dissolved salt (HTDS) preflush, surfactant-polymer flooding (SP), polymer flooding (P), and finally extended waterflooding (EWF). Experimental data and models used to describe the experiments are provided in the next section.

3. Coreflood modeling

Berea coreflood experiments (BCF) are modeled using UTCHEM-9.0