Contribution ID: **749** Type: **Poster (+) Presentation**

Comparison of Response Surface and Artificial Neural Network Model for Relative Permeability using Saturation and Phase Connectivity

Thursday, 3 June 2021 20:00 (1 hour)

Hysteresis in transport properties such as relative permeability remains a challenge for reservoir simulations of multiphase processes such as CO2 sequestration as well as chemical enhanced oil recovery (EOR). Modeling relative permeabilities as a state function with the knowledge of the parameters that affect relative permeabilities has shown promise in mitigating hysteresis.

In this research, we advance the development of the relative permeability equation-of-state (kr–EOS) by considering quadratic and cubic polynomial forms for relative permeability (kr) in the space of state parameters, namely, phase saturation (S) and phase Euler connectivity ($\hat{\chi}$). We maintain other state parameters, such as wettability, pore structure, and capillary number, to be constant. We consider numerical data sets of nonwetting phase kr, S, and $\hat{\chi}$ for two different contact angles in the water-wet regime using pore-network modeling (PNM). These data sets include multiple sets of primary drainage, imbibition, and secondary drainage scanning curves. We constrain the polynomial functions of kr in the physical $\hat{\chi}$-S space traversed by the PNM data. Next, we use linear regression to fit the models to the numerical data and analyze the behavior of the kr response as well as the partial derivatives of kr in the $\hat{\chi}$-S space. These are also compared to the numerically calculated kr partials. A comparison of the tradeoffs between the quadratic versus the cubic response is presented. Furthermore, using these regression models, we extend the EOS approach and couple with machine learning algorithms. We develop a physics-based Artificial Neural Network (ANN) algorithm to provide a practical estimate of the values and paths of kr, using the numerical data sets and polynomial variables as the designated inputs. A comparison of the accuracy between the polynomial functions and the ANN model is presented.

Our results show that a cubic or higher-order response function is needed to capture reasonably well the behavior of kr over the entire physical $\hat{\chi}$-S space for different cycles of injections. This is because only a cubic or higher-order polynomial can capture the complex behavior of the locus where relative permeability is zero (the locus of residual saturation and residual phase connectivity). The cubic response also allows us to capture the behavior of the kr partial derivatives as defined by the EOS in the $\hat{\chi}$-S space. Lastly, the machine learning framework helps implement a hybrid approach which incorporates a data-driven model while still honoring the physics-driven polynomial responses. This method provides further improvement compared to both the response surface approach and conventional estimation methods of kr. The described methodology and functions will aid in modeling complex hysteresis that occur in both CO2 storage and in EOR processes.

Time Block Preference

Time Block B (14:00-17:00 CET)

References

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Session Classification: Poster +

Track Classification: (MS15) Machine Learning and Big Data in Porous Media