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Short Communication

Fast high-resolution prediction of multi-phase flow in fractured formations

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ABSTRACT

The success of a thermal water flood for enhanced oil recovery (EOR) depends on a detailed representation of the geometrical and hydraulic properties of the fracture network, which induces discrete, channelized flow behavior. The resulting high-resolution model is typically computationally very demanding. Here, we use the Proper Orthogonal Decomposition Mapping Method to reconstruct high-resolution solutions based on efficient low-resolution solutions. The method requires training a reduced order model (ROM) using high- and low-resolution solutions determined for a relatively short simulation time. For a cyclic EOR operation, the oil production rate and the heterogeneous structure of the oil saturation are accurately reproduced even after 105 cycles, reducing the computational cost by at least 85%. The method described is general and can be potentially utilized with any multiphase flow model.

1. Introduction

Efficient numerical approaches are needed to lower the computational barrier for performing optimization and uncertainty quantification using models that accurately represent complex multi-phase flow processes in fracture networks, with considerable impact on our ability to sustainably manage and optimize energy and water resource systems, and to effectively remediate contaminated sites. For example, a reliable evaluation of the economic viability of thermal water flood—a common enhanced oil recovery (EOR) technique—depends on whether we can predict the oil production rate accurately. Prediction of the oil production rate is typically obtained by constructing a numerical model that accurately captures the geometrical and hydraulic details of the fracture network, which induces discrete, channelized flow behavior. The network also determines the effectiveness with which heat and brine penetrates the rock matrix, mobilizing and displacing the oil. Simulating an EOR operation using a discrete fracture network embedded in a low-permeability matrix is computationally very demanding, mainly because the detailed representation of the fracture network and the complex geometry of the matrix blocks bounded by randomly oriented fracture planes require high-resolution meshes.

In this paper, we apply a reduced order modeling (ROM) technique known as the Proper Orthogonal Decomposition Mapping Method (PODMM)—first proposed by Robinson et al. [1]—which allows us to reconstruct the solutions from a high-resolution model representing the fracture network as a heterogeneous medium based on solutions obtained using low-resolution models that only have upscaled, effective properties of the fracture network and thus can be efficiently simulated. This technique was recently enhanced and applied to land surface models to accurately reconstruct hydrological states, heat fluxes, and carbon fluxes [2,3]. However, the suitability of the method for modeling multiphase non-isothermal subsurface problems with significant nonlinear temporal and spatial dynamics has yet to be demonstrated. This work evaluates the accuracy of PODMM for a multiphase problem (an enhanced oil recovery problem).

PODMM can be viewed as a regression-based downscaling technique. Overviews of empirical downscaling techniques have been presented before (see, e.g., Wilby et al. [4], Fowler et al. [5], Gutmann et al. [6]). Previous work on regression-based downscaling methods focuses on constructing empirical parametric models between the predictors and variables of interest [7,8]. In the context of reduced order models (ROMs), regression models can also be constructed between model parameters and the variables of interest [9,10]. PODMM differs from the above regression approaches in that proper orthogonal decomposition (POD) is not just used to obtain a dimensionally reduced representation of the high-dimensional data. Instead, a least-square minimization problem that utilizes portions of the singular vectors obtained through the POD procedure [11] is solved to directly map low-resolution solutions to the high-resolution solutions. More details are provided in Section 2.2.

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PODMM also differs from the projection-based POD methods that were previously applied to subsurface flow problems [12–15] and other engineering fields [16–18]. Specifically, the projection-based POD method is an intrusive approach that requires projecting the governing partial differential equations onto a linear space spanned by the singular vectors, and implementing the resulting discrete equations. For a multiphase non-isothermal model, the complicated nonlinear terms require additional approximations [19–21] in order to obtain a set of discrete equations that can be solved efficiently. PODMM is considerably simpler since it only requires solving the low-resolution models once the ROMs have been trained. Thus, it does not require intrusive changes to the simulation software, making it an attractive method for complex multiphase flow problems.

2. Methods

2.1. Mapped fracture network models

We demonstrate the proposed PODMM model-reduction approach for an EOR operation conducted in a fractured hydrocarbon reservoir with a single injection-extraction well. An individual cycle of the operation consists of four phases: (1) injection of hot water at 10 kg/s for 3 days, (2) an inactive soaking period of 4 days, (3) production of oil and water for 6 days at a total rate of 5 kg/s, and (4) an inactive rest period of 1 day. This two-week cycle is repeated 105 times for a total simulation time of 1470 days. The distribution of oil in the reservoir and the oil production rates are the key prediction variables of interest.

We consider a discrete fracture network within a model domain of dimensions $100 \times 50 \times 30$ m. Fractures are generated by randomly sampled values for size, orientation, and aperture from appropriate, truncated probability distributions. Two fracture sets with an average fracture spacing of 4 m are generated using the code ThreeDFracMap [22]. In our modeling approach, the fracture network is then represented by a heterogeneous continuum model. The fractures are first mapped onto a structured, uniform mesh, before upscaled, heterogeneous, anisotropic permeabilities are calculated based on the number, aperture, and orientation of the fractures intersecting the given element. Elements that do not contain any fractures are assigned a low matrix permeability of 10^{-18} m^2. The procedure is described in detail in Parashar and Reeves (2011).

Based on this heterogeneous, high-resolution continuum model representing a network of discrete features embedded into a low-permeability matrix, we use the “dead-oil” (EOS8) module of TOUGH2 [23] to simulate the response of the reservoir to cyclic injection of hot water and production of a multi-phase mixture of oil and water. Simulating a long sequence of injection-production cycles is computationally expensive, especially if a high-resolution continuum representation of the discrete network is needed to capture the exchange of fluids between the reservoir rock (which contains most of the oil) and a network of discrete fractures (whose main role is to provide the pathways for oil extraction) embedded in that matrix. Moreover, the resolution also affects the system behavior and computational costs. The PODMM approach described below predicts the high-resolution behavior using a computationally efficient low-resolution model (LRM), combined with a mapping procedure for downscaling the simulation results. Two basic grids with different resolutions are thus developed: a high-resolution model (HRM) with an element size of 2 m, and a low-resolution model (LRM) with an element size of 5 m (see Fig. 1(a)). The LRM thus has about 15 times fewer elements than the HRM, making it significantly more efficient at the expense of loss of accuracy in representing discrete flow behavior in the fractures and fluid exchange with the matrix. The HRM provides simulation data for a relatively short training phase; it is also used in this study as the reference solution needed to demonstrate the accuracy of the proposed approach. The LRM provides approximate, efficient solutions for the entire simulation period; these solutions are then downscaled to provide high-resolution predictions of the cyclic EOR operation based on the mapping procedure in PODMM.

We examine three alternative LRMs: (1) an upscaled heterogeneous model (LRM-HET), using the exact same conceptualization as the HRM with the exception that it uses a coarser discretization, (2) a simple homogeneous model (LRM-HOM) with a permeability of 10^{-13} m^2, and (3) a dual-porosity model (LRM-DPM) [24] with fracture- and matrix-continuum permeabilities of 10^{-13} m^2 and 10^{-18} m^2, respectively. Key parameters are summarized in Table 1. Note that the number of elements of LRM-DPM is twice that of LRM-HOM and LRM-HET. The permeabilities of LRM-HOM and LRM-DPM are chosen to approximately represent the fracture network permeability such that they produce some of the behaviors seen in the HRM. However, no rigorous upscaling technique is used to determine the permeabilities of the LRMs, e.g., by matching the oil production rate obtained from the HRM through an inverse modeling procedure. A calibrated LRM will likely improve the performance of the PODMM. However, the goal of this work is to demonstrate that the accuracy of the PODMM is not due to the calibration of LRM model parameters to fit the outputs of the HRM.

Fig. 1(b) shows the oil saturation after 3 days. The solutions obtained from LRM-HET is a smoother representation of the considerably more intricate distribution obtained with the HRM. Fig. 1(c) and (d) compares oil production rate (Q_{oil}) determined using the HRM and the 3 LRMs at the 55th, and 105th cycles, respectively. For the parameters given in Table 1, LRM-HET over-predicts the Q_{oil} while LRM-HOM and LRM-DPM under-predict the Q_{oil}.

2.2. Proper orthogonal decomposition mapping method

We summarize the Proper Orthogonal Decomposition Mapping Method (PODMM) here; details can be found in [2]. The method consists of a training stage and a prediction stage. During the training stage, we determine the solutions (e.g., oil saturations and fluxes at all locations) to the low- and high-resolution models (denoted as $\mathbf{g}$ and $\mathbf{f}$, respectively) at N time points. These N solutions constitute the training set. In our example, snapshots are obtained at 1-day intervals from multiple consecutive EOR cycles. We then perform a singular value decomposition (SVD) of the following matrix **W:**

$$\mathbf{W} = \begin{bmatrix} \mathbf{f}_1 - \bar{\mathbf{f}} & \cdots & \mathbf{f}_N - \bar{\mathbf{f}} \\ \mathbf{g}_1 - \bar{\mathbf{g}} & & \mathbf{g}_N - \bar{\mathbf{g}} \end{bmatrix} \tag{1}$$

where $\mathbf{f}_i$, and $\mathbf{g}_i$ are the high- and low-resolution solutions at the ith time point,

$$\bar{\mathbf{f}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{f}_i, \quad \bar{\mathbf{g}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{g}_i \tag{2}$$

The POD bases, $\zeta_i, i = 1, \ldots M$, are given by the resulting singular vectors and can be decomposed into

$$\zeta_i = \begin{bmatrix} \zeta_i^{\mathbf{f}} \\ \zeta_i^{\mathbf{g}} \end{bmatrix} \tag{3}$$

where $\zeta_i^{\mathbf{f}}$ and $\zeta_i^{\mathbf{g}}$ are components associated with the HRM and LRMs, respectively, and M is the chosen number of POD bases to use in an approximation.

During the prediction stage, we first determine a coarse-resolution solution $\mathbf{g}$, and solve

$$\boldsymbol{\alpha}(\mathbf{g}) = \arg\min_{\gamma} \left\| \mathbf{g} - \bar{\mathbf{g}} - \sum_{i=1}^{M}\gamma_i\zeta_i^{\mathbf{g}} \right\|_2 \tag{4}$$