SPE 115911

A Multistage MCMC Method with Nonparametric Error Model for Efficient Uncertainty Quantification in History Matching

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This paper was prepared for presentation at the 2008 SPE Annual Technical Conference and Exhibition held in Denver, Colorado, USA, 21–24 September 2008.

Abstract

Uncertainty quantification is generally carried out in a Bayesian framework whereby multiple reservoir models can be evaluated by sampling from a posterior distribution that incorporates the observed production data and the prior parameter distribution. Rigorous sampling methods such as the Markov Chain Monte Carlo (MCMC) method provide accurate sampling but at a high cost because of their high rejection rates and the need to run flow simulation for every proposed candidate.

We propose a methodology that combines coarse- and fine-scale information to improve the efficiency of MCMC methods without loss of its rigorousness in sampling. Our proposed method employs off-line computations for establishing a mathematical relation between coarse- and fine-scale error responses. This relation is modeled using non-parametric approaches that correlate the error responses via optimal transformations. The resulting statistical models are then used in efficient sampling within an MCMC framework. We propose a multi-stage MCMC where inexpensive coarse-scale simulations are performed to determine whether or not to run the fine-scale simulations. The latter is determined based on the non-parametric error model developed off-line. Our proposed method substantially improves the efficiency of existing multi-stage MCMC methods that only rely on coarse-scale or other approximate models. Most importantly, our proposed method does not depend on the proximity of the coarse and fine-scale models and thus, can employ much coarser and inexpensive models to guide the fine-scale simulations.

We will present a synthetic and a field example involving three-phase flow to demonstrate that the proposed approach is both robust and computationally efficient. In these examples, water cut and GOR are integrated to generate multiple reservoir models and assess uncertainty in the production forecasts.

Introduction

Uncertainty exists inherently in dynamic reservoir modeling because of several factors, the primary ones being the modeling error, data noise, and the non-uniqueness of the inverse problems that causes several models to fit the dynamic data. By understanding and quantifying the uncertainty in production forecast, financial investment risks can be reduced and decision quality can be improved. A common practice to quantifying uncertainty is to generate multiple reservoir model realizations that are conditioned to static and dynamic data, and then perform flow simulation for future performance predictions. The validity of the uncertainty quantification will strongly depend upon the distribution of these realizations, that is, whether they adequately represent the underlying uncertainties. In the context of the Bayesian inversion, the solution to the inverse problem is the posterior probability distribution itself. Therefore, the problem of uncertainty quantification is closely tied to the correct sampling of multiple reservoir models from the posterior distribution. Such sampling is nontrivial because the posterior distribution has very high dimension (equal to the number of parameters) and is known only within a proportionality constant (un-normalized). Furthermore, the posterior distribution can be both nonGaussian and multimodal. This makes rigorous sampling from the posterior distribution extremely computationally demanding. The common practice is to resort to approximate sampling methods.

One of the rigorous approaches to sample the posterior distribution is through the use of the Markov Chain Monte Carlo or briefly, MCMC algorithm (Omre and Lødøen 2004). The MCMC methods are designed to generate a sequence of realizations that are samples from a target probability distribution. The difficulties with MCMC are that it might require long transitions or many iterations before the Markov chain converges to the target distribution. Because each iteration in traditional MCMC typically involves a flow simulation, if the acceptance rate is low, this will further increase the computational requirements. Kitanidis (1995) and Oliver et al. (1996) proposed a method for generating multiple realizations of reservoir