Journal of Petroleum Science and Engineering 71 (2010) 147–159

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

Research paper

A dual scale approach to production data integration into high resolution geologic models

Jong Uk Kim [a], Akhil Datta-Gupta [a,*], Eduardo A. Jimenez [b], Detlef Hohl [c]

[a] Petroleum Engineering Department, TAMU 3116, Texas A&M University, College Station, TX 77843-3116, USA
[b] Shell E&P Inc, Houston, TX 77001-0481, USA
[c] Shell International E&P B.V., The Hague, The Netherlands

ARTICLE INFO

Article history:
Received 18 May 2009
Accepted 11 January 2010

Keywords:
dual scale
'optimal' coarsening
coarse-scale inversion
generalized travel time inversion
history matching

ABSTRACT

Inverse problems associated with reservoir characterization are typically under-determined and often have difficulties associated with stability and convergence of the solution. A common approach to address this issue is through the introduction of prior norm constraints, smoothness regularization or reparameterization to reduce the number of estimated parameters.

We propose a dual scale approach to production data integration that relies on a combination of coarse-scale and fine-scale inversions while preserving the essential features of the geologic model. To begin with, we sequentially coarsen the fine-scale geological model by grouping layers in such a way that the heterogeneity measure of an appropriately defined 'static' property is minimized within the layers and maximized between the layers. Our coarsening algorithm results in a non-uniform coarsening of the geologic model with minimal loss of heterogeneity and the 'optimal' number of layers is determined based on a bias-variance trade-off criterion. The coarse-scale model is then updated using production data via a generalized travel time inversion. The coarse-scale inversion proceeds much faster compared to a direct fine-scale inversion because of the significantly reduced parameter space. Furthermore, the iterative minimization is much more effective because at the larger scales there are fewer local minima and those tend to be farther apart. At the end of the coarse-scale inversion, a fine-scale inversion may be carried out, if needed. This constitutes the outer iteration in the overall algorithm. The fine-scale inversion is carried out only if the data misfit is deemed to be unsatisfactory.

We demonstrate our approach using both synthetic and field examples. The field example involves waterflood history matching of a structurally complex and faulted offshore turbiditic oil reservoir. Permeability and fault transmissibilities are the main uncertainties. The geologic model consists of more than 800,000 cells and 10 years of production data from 8 producing wells. Using our dual scale approach, we are able to obtain a satisfactory history match with a finite-difference model in less than a day in a PC. Compared to a manual history matching, the dual scale approach is shown to better preserve the geological features and the pay/non-pay juxtapositions in the original geologic model.

1. Introduction

Geologic models now routinely consist of several hundred thousands to millions of grid cells. Reconciling such high-resolution geological models derived from static data to the field production history is critical for reliable reservoir performance forecasting. Several methods have been proposed in the literature for this purpose. These include gradient-based methods (Brun et al., 2004), stochastic approaches such as simulated annealing and genetic algorithms (Quenes et al., 1994) and more recently the Ensemble Kalman Filter (Devegowda et al., 2007). The integration of production data typically requires the solution of an inverse problem. It is well known that such inverse problems are typically ill-posed and can result in non-unique and unstable solutions. A common approach to at least partially alleviate the problem is through incorporation of prior information or regularization such as 'norm' or 'roughness' constraints. However, there are additional outstanding challenges that have deterred the routine integration of production data into reservoir models using inverse modeling. First, the computational cost is still extremely high, particularly when the number of parameters is very large. Second, the relationship between the production response and reservoir properties can be highly non-linear. This often causes the solution to converge to a local minimum with an inadequate match to the data. Furthermore, the solution itself can be unstable, leading to a loss in geologic realism.

* Corresponding author. Fax: +1 979 845 1307.
E-mail address: datta-gupta@pe.tamu.edu (A. Datta-Gupta).

0920-4105/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.petrol.2010.01.006

One approach to address the ill-posed nature of the inverse problem and the difficulties with the existence of local minima is through decomposing the inverse problem by scale. The scale-decomposition approach to inversion offers a number of advantages. First, computational efficiency is significantly enhanced compared to direct fine-scale inversion of production data because typical fine-scale models can consist of several hundred thousands to millions of parameters. Second, we can avoid over-parameterization and the subjectivity arising from introduction of artificial regularization terms as discussed before. Finally, the iterative minimization is much more effective because at larger scales there are fewer local minima and those tend to be farther apart. Thus, the solution is more likely to reach the global minimum or at least a local minimum that is in the close vicinity of the global solution. The coarse-scale solution can then be recursively refined by using it as the initial solution for the fine-scale.

Yoon et al. (2001) proposed a multiscale history matching method that starts with the largest scale and successively progresses to smaller scale. This approach explicitly accounts for the resolution of the production data by refining the parameterization only up to a level sufficient to match the data. However, the refinement was carried out uniformly throughout the domain without consideration of the available data. The approach was subsequently modified by Grimstad et al. (2004) through introduction of an adaptive multiscale inversion whereby the parameterization is introduced via local refinement rather than global refinement. Furthermore, the new degrees of freedom are introduced only in places where it is warranted by the data. Both of these methods rely on recursive refinement based on the production data. No consideration of the prior model or static information is taken into account during reparameterization. As a result these methods pose challenges in preserving prior geologic information which is typically incorporated using post-processing of the solution to the inverse problem.

In this paper we propose an approach to history matching that relies on sequential coarsening rather than sequential refinement. Starting with the fine-scale geologic model, first an 'optimal coarsening' of the model is carried out. The coarsening is designed to preserve the features of the geologic model to the maximum possible extent. It follows the approach proposed by King et al. (2005) and combines cells in the fine-scale model in such a manner that the variation of a 'properly defined' heterogeneity measure is minimized within the coarsened cells and maximized between the coarsened cells. A well defined statistical measure is used to determine the optimal level of coarsening. The history matching and model updating is carried out primarily at the coarse-scale and the updates are then mapped onto the fine-scale. When production data misfit is sufficiently reduced, an outer iteration allows for direct updating of the fine-scale model to further improve convergence, if necessary.

One important distinguishing feature of our approach is that the coarsening is primarily driven by the static model and thus, the method naturally preserves the important characteristics of the initial geologic model. Also, unlike the previous works, the coarsening is carried out in the vertical direction while taking into account property variations both in the areal and vertical directions. Our approach preserves all the advantages of the previously proposed multiscale methods in terms of computational efficiency, stability and convergence of the solution. In addition, because the parameterization is driven by the initial geologic model rather than production data, the approach naturally preserves geologic realism.

2. Approach

Multiscale approaches are getting increasing attention both for the forward and inverse modeling applications of flow through porous media. For history matching applications, the previous works on multiscale methods (Yoon et al., 2001; Grimstad et al., 2004) mainly focused on dynamic parameterization of the permeability distribution based on the production data. More recently, Stenerud et al. (2008) presented an adaptive multiscale approach for history matching using streamline models. Their approach used a mixed multiscale finite element forward model to resolve the pressure and velocity variations and streamline-based sensitivities for inverse modeling. In our approach, we adopt many of the concepts from these previous works. However, the major difference is that our approach relies on a sequential coarsening of a fine-scale geologic model rather than a sequential refinement of a coarse-scale model. Thus, our approach is able to better preserve the geology embedded in the fine-scale model. The main steps of our approach are outlined below.

(1) *Optimal coarsening of the geologic model.* The fine-scale geologic model is sequentially coarsened until an 'optimal' level of coarsening is achieved. We follow the approach of King et al. (2005) to coarsen the geologic model by grouping layers in such a way that the heterogeneity measure of an appropriately defined 'static' property is minimized within the layers and maximized between the layers. However, our approach differs from that of King et al. (2005) in the choice of the static parameter as discussed later. The optimal number of layers is then selected based on an analysis resulting in the minimum loss of heterogeneity because of the coarsening.

(2) *Flow simulation and sensitivity computations.* We use a finite-difference or a streamline simulator for modeling multiphase flow in the reservoir. If a finite-difference simulator is used, then the cell fluxes are used to trace the streamlines and the time of flight (Datta-Gupta and King, 2007). The streamline trajectories and time of flight are then used to analytically compute the sensitivity of the production data with respect to permeabilities (Oyerinde et al., 2007).

(3) *Coarse-scale inversion.* History matching is carried out primarily at the coarse-scale. This constitutes our inner iteration in the overall inversion scheme. The coarse-scale permeabilities are updated via inverse modeling which proceeds in two steps: (i) a generalized travel time inversion that matches the production response based on an optimal travel time shift (Cheng et al., 2005), followed by (ii) an amplitude matching that further refines the match (Vasco et al., 1999). The coarse-scale inversion proceeds much faster compared to a direct fine-scale inversion because of the significantly reduced parameter space. Furthermore, the iterative minimization is much more effective because at the larger scales there are fewer local minima and those tend to be farther apart. (Bunks et al., 1995) The inversion is terminated when no further improvement in data misfit is observed. The permeability updates are then transferred to the fine-scale model. Because our 'optimal' coarsening method groups fine-scale cells with similar attributes, the coarse-scale updates are simply added back to the corresponding fine-scale cells.

(4) *Fine-scale inversion.* At the end of the coarse-scale inversion, a fine-scale inversion may be carried out, if needed. This constitutes the outer iteration in the overall algorithm. The fine-scale inversion is carried out only if the data misfit is deemed to be unsatisfactory.

Fig. 1 shows overall workflow of the dual scale inversion. It is comprised of two major loops. The inner loop consists of a coarse-scale inversion and majority of the data misfit reduction is accomplished at this stage. The coarse-scale inversion can be carried out very efficiently because of the reduced parameterization. The optimal design of the coarse-scale preserves most of the initial heterogeneity and important geologic continuity. Since the coarse-scale inversion has fewer tendencies to converge to a local minimum, it is more stable compared to the direct fine-scale inversion (Bunks et al., 1995), and