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Regeneration of channelized reservoirs using history-matched facies-probability map without inverse scheme

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ABSTRACT

Reservoir characterization is a key step to define the facies connectivity in channelized reservoirs. Recently, a new paradigm combining production data with geostatistics has been proposed. Pseudo-hard and -soft data are prepared from production-based techniques, such as ensemble-based methods. However, these methods contain inverse algorithms to integrate dynamic data and have limitations in their uncertainty quantifications on new production wells. In this study, a novel approach for re-static modeling scheme is proposed by history-matched facies-probability map without inverse modeling. Initial static models are realized and selectively simulated for center models, which are chosen by a distance-based method to reduce the number of forward simulation. The average of the selected models, which have a low level of mismatch with the observed data, is used for regeneration of facies models as facies-probability map. Regenerated channelized models are assessed again following the same procedure to select the final models. When the proposed method is applied to a 2D synthetic case, the final models successfully describe the true channel connectivities and facies ratios. Furthermore, the models preserve the bimodal distribution and given well data. Future productions for both the pre-existing production wells and a newly drilled well are properly predicted by the final models. In terms of the simulation time, the proposed method significantly decreases to 30 times from 800 times of the forward simulations over the ensemble smoother case.

1. Introduction

Reservoir characterization is one of the most important steps in petroleum exploration and development. It is the investigation of the distribution of the reservoir properties of interest. Reservoir characterization is an essential process to build reliable reservoir models, which are utilized for dynamic simulations and various decisions, such as the locations of new production wells. In other words, incorrect reservoir properties from a reservoir characterization eventually incur a wrong decision for a new well. Reservoir characterization is implemented by integrating all available data, including static and dynamic data. Static data indicate spatial data, which do not change with time, such as core measurements and well logs, whereas dynamic data refer to information that may change over time, such as the oil production rate (OPR) and bottom-hole pressure (BHP).

In a conventional reservoir characterization, the initial reservoir model is generated from static data by geostatistics, and it is subsequently updated using the dynamic data through history matching based on inverse algorithms. This separated procedure, however, has limitations. First, the updated models cannot preserve the given static data because the optimization algorithms, which are based on mathematical theory, sometimes discard geological and physical meanings, and the changing of support (Jafarpour and Khodabakhshi, 2011; Hu et al., 2013). For example, permeability values from a core analysis at a well location may be changed to match the production history.

Second, long simulation times are necessary because of a large number of forward simulations and extensive iterations for convergence (Queipo et al., 2002; Lee et al., 2014, 2017; Kang et al., 2016). Third, there are application limitations because the equations in the algorithms are derived under certain assumptions. For example, the ensemble-based methods assume that the number of ensembles is infinite and the model parameters follow a Gaussian distribution (Liu and Oliver, 2005; Aanonsen et al., 2009; Chen et al., 2009; Shin et al., 2010; Ping and Zhang, 2013; Lee et al., 2013a, 2013b, 2016; Zhang et al., 2015; Kim et al., 2016a, 2016b).

Recently, a new paradigm has emerged in reservoir characterization to solve these problems, especially the integration of dynamic data. The concept of the extended conditional probability using the permanence

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of ratio hypothesis has been proposed by several previous studies (Caers, 2002; Journel, 2002; Kashib and Srinivasan, 2006). It can preserve geological information and be coupled with multiple-point simulation (MPS) regardless of the distribution of the model parameters. However, it still requires many reservoir simulations corresponding to substantial iterations of inner and outer loops to find an optimal parameter (Kashib and Srinivasan, 2006). Additionally, the differences between the reference and updated models in even simple synthetic cases may still be extensive (Srinivasan and Bryant, 2004).

Conversely, generation schemes of pseudo-hard or -soft data from history matching have been studied (Jafarpour and Khodabakhshi, 2011; Tavakoli et al., 2014; Le et al., 2015; Sebacher et al., 2015; Chang et al., 2016). Instead of modifying the reservoir parameters directly, the results of the inverse modeling are used as the input parameters for geostatistics. Here, the hard (primary) data are directly related to the reservoir parameters, such as well data (core measurements or well logs), whereas soft (secondary) data indicate indirect data, such as facies-probability maps or vertical proportions. These data are used together as input parameters in geostatistics methods.

For history-matched soft data, Jafarpour and Khodabakhshi (2011) used updated models from the ensemble Kalman filter (EnKF) as a probability map in MPS. These researchers successfully applied the map to various channelized reservoirs, although it required many forward simulations. Sebacher et al. (2015) used an iterative adaptive Gaussian mixture filter instead of EnKF to confine the probability map in MPS. However, this followed complex procedures of iterations, parameterization, and resampling. In other previous studies, a truncation map and Gaussian random field are assimilated by history matching in the truncated Gaussian and pluri-Gaussian methods (Agbalaka and Oliver, 2011; Astrakova and Oliver, 2014).

For history-matched hard data, Tavakoli et al. (2014) utilized the updated models from EnKF for generating pseudo-hard data in geostatistics to resample the ensembles. However, it required long simulation times because of the forward simulations on the inverse modeling and resampling procedure for each step. Le et al. (2015) and Chang et al. (2016) used both pseudo-hard and -soft data to regenerate facies models. Chang et al. (2016) successfully characterized the 3D complex channelized reservoir with the concept of a dummy well.

Although the previous studies on the new paradigm partially solved the limitations previously mentioned, these methods mostly needed an inverse scheme or extensive iterations, causing a heavy burden on the reservoir simulation. The originality of this research is to integrate dynamic data into reservoir modeling without inverse algorithms. The proposed method does not use ensemble-based or gradient-based methods for history matching. Dynamic data are utilized for generating history-matched facies-probability maps, which are used for re-static modeling. The novel approach is implemented with a distance-based method to reduce the simulation time.

2. Methodology

2.1. Procedure of the proposed method

A conventional procedure of reservoir characterization is shown in Fig. 1. Reservoir models are first generated from static data, such as a training image (TI), and known well data by geostatistics. Then, initial models become prior models for an inverse model, and forward simulation is implemented. After converging, the posteriori models are used to predict the reservoir performances. In this study, MPS, which was proposed by Guardiano and Srivastava (1993), is used for facies modeling, instead of two-point geostatistics, to embody complex geological patterns. It replaces a variogram with a TI for spatial inference, which is the concept of geological patterns. After Strebelle (2002) proposed the concept of search tree to reduce modeling costs, MPS became a practical tool because of its many advantages: reproduction of realistic geological patterns, easy conditioning of soft data, preservation of hard data, and lack of a need for a variogram modeling for each facies (Caers, 2005).

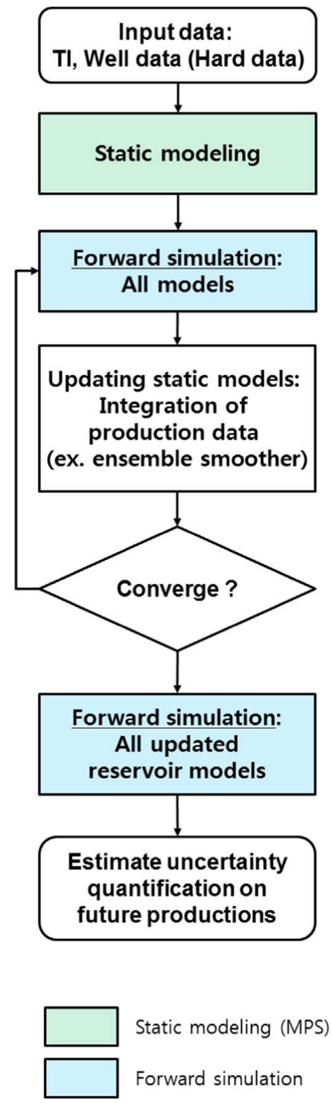

Fig. 1. Flowchart of a conventional reservoir characterization.

The proposed method consists of two times of clustering and simulation procedure (the gray dashed rectangle in Fig. 2) to build a facies-probability map and final models, respectively. For history-matched facies-probability maps, the initial facies models are generated by TI and well data. Based on the distance-based method, the initial models can be grouped into similar models and each cluster has a center (representative) model. Note that the center model is the nearest model from the centroid for each cluster, which is the average point of members in the cluster.

The center models are used for reservoir simulation to choose the best center model, which has the lowest error with the true production observed. Finally, the models surrounding the best model in metric space are selected, and the mean of the selected models becomes a facies-probability map. Here, the number of model selections is determined by the geological uncertainty, and more than 10 models should be selected to make a reasonable facies map. If the training image is reliable, 10 models close to the best center model are enough. This workflow is called the clustering and simulation procedure and is explained with a simple example in Section 2.2.

For final models, re-static modeling is implemented by both the static data given initially (TI and well data) and the history-matched facies-probability map. Then, the clustering and simulation procedure