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Water flooding performance prediction by multi-layer capacitance-resistive models combined with the ensemble Kalman filter

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ABSTRACT

In this study, a system of multi-layer capacitance resistive models (MLCRMs) is established for water flooding performance prediction in a layered reservoir. Three different types of observation data are considered for a layered reservoir: (1) both injection and production rates of each layer; (2) only production rates of each layer; and (3) only injection rates of each layer. The cross flow among layers and the bottom-hole pressure are considered in the models. A modified power law model is used to describe the ratio of water to oil production. The ensemble Kalman filter (EnKF) method is applied to estimate the connectivity coefficients for each layer and the well index numbers in the MLCRMs. Synthetic examples of a layered reservoir with different types of observation data are performed to validate the proposed models. The results show a good match of historical data and a reasonable prediction for future oil and liquid production.

1. Introduction

Conventional reservoir simulation is usually based on the finite difference method, which requires detailed information of various parameters, such as porosity, permeability, relative permeability, and saturation in each grid block. Since information about those parameters is usually limited by measuring techniques, reservoir characterization using history-matching tools becomes one of the most significant problems for petroleum engineers. Historical data of injection and production rates are usually used for characterizing inter-well connectivity of a reservoir.

An alternative to reservoir simulation, the capacitance resistive model (CRM), is generally based on signal-processing techniques, in which the injection and production rates are treated as input and output signals, respectively. The CRM is analogous to a resistor-capacitor (RC) circuit (Thompson, 2006). Similar to a grid-based numerical simulation approach, the CRM is based on a total mass balance equation with compressibility. However, the CRM describes the reservoir flow behavior through some model parameters, such as connectivity coefficients and time constants, which are evaluated based on historical data of injection and production rates (Yousef et al., 2006).

To some extent, the CRM is comparable to streamline simulation (e.g., Datta-Gupta and King, 2007), which has gained substantial popularity because of its fast computation speed. The inter-well connectivity coefficients are analogous to the relative numbers of streamlines of an injector that support a certain producer. The advantage of the CRM is its computational efficiency and capability for reservoir performance prediction. History-matching algorithms can also be combined with the CRM for characterizing inter-well connectivity.

Through injection/production data, Albertoni and Lake (2003) used a linear multivariate regression technique with diffusivity filters to estimate the inter-well connectivity coefficients between pairs of injection/production wells. Gentil (2005) subsequently interpreted the inter-well connectivity coefficients in terms of a sole function of reservoir transmissibility. Yousef et al. (2006) developed an improved CRM method to include generic mathematical features of resistance and capacitance. This model introduces two parameters for each injector/producer pair: a weight that quantifies the connectivity between wells and a time constant that characterizes the time delay of the injection signal at the producers. Lake et al. (2007) later introduced an approach to optimize oil production through the CRM by adjusting injection rates.

The ensemble Kalman filter (EnKF), introduced by Evensen (2003), is an ensemble-based method for data assimilation. The EnKF is able to compute gradients through a Monte Carlo evaluation over an ensemble of state variables corresponding to their uncertainties.

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SI Metric Conversion Factors

Ft × 3.048 E − 01 = m
Psi × 6.894 75 E + 00 = kPa
STB × 6.2901 E − 01 = m^3
Day × 1.1574 E − 05 = s

This enables the EnKF to deal with sequential data assimilation in large-scale nonlinear dynamics (e.g., Verlaan and Heemink, 2001; Mitchell et al., 2002; Bertino et al., 2003). The EnKF has been widely applied in reservoir engineering for history-matching (e.g., Gu and Oliver, 2005, 2007; Liu and Oliver, 2005; Chang et al., 2010; Heidari et al., 2013). Jafroodi and Zhang (2011) used the EnKF to incorporate nonlinear effects in the CRM model for reservoir characterization and optimization. And different versions of the EnKF have been developed, such as the standard ensemble Kalman filter (Aanonsen et al., 2009), iterative ensemble filters (Chen and Oliver, 2013), and local ensemble Kalman filter (Ott et al., 2004). In this study, the standard ensemble Kalman filter is used.

However, in the above-mentioned studies, only single-layer reservoirs are considered for the CRM. Mamghaderi et al. (2013) applied the CRM to study the effects of layers of a reservoir using the data from production logging tools (PLT). In their work, the effects of the cross flow between the layers and the bottom-hole pressure change are neglected. The genetic algorithm (GA) method is used to evaluate model parameters as a history-matching tool in their work. As an extension of their work, an improved CRM for a layered reservoir, which takes the cross flow between the layers into consideration, is introduced (Mamghaderi and Pourafshary, 2013). However, the effect of bottom-hole pressure is still neglected.

In this study, a system of multi-layer capacitance resistive models (MLCRMs) is established to deal with three different types of observation data of a layered reservoir: (1) both injection and production rates of each layer; (2) only production rates of each layer; and (3) only injection rates of each layer. In addition to the connectivity coefficients and time constants, the effects of cross flow across the layers and bottom-hole pressure are taken into consideration. The influence of different geological conditions for each layer on the well index numbers for different producers is also investigated. A power law model (Gentil, 2005; Lake et al., 2007) is used to describe the relationship between the ratio of water to oil production and the cumulative water injected in the production well. The EnKF is used as a history-matching tool to efficiently estimate the parameters in the models. Detailed procedures of the MLCRMs and the EnKF are discussed in the following sections.

2. Methodologies

2.1. Multi-layer CRM

2.1.1. Background of CRM

We first provide a brief background of CRM. The CRM is based on a total mass balance equation considering compressibility. It is assumed

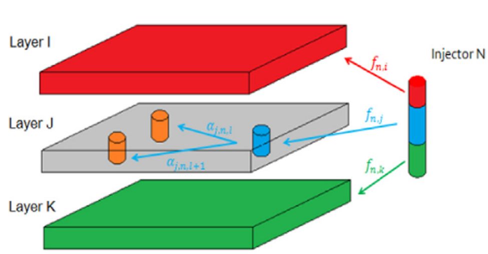

Fig. 1. Drainage area of a layered reservoir with one injector and two producers in each layer.

that there are m injectors acting simultaneously on n producers. The governing material balance equation for the control volume around a certain producer j is given by the following differential equation (e.g., Sayarpour et al., 2009):

$$q_j(t) = \sum_{k=1}^{m} \lambda_{kj} i_k(t) - c_t V_p \frac{d\bar{p}_j(t)}{dt}, \tag{1}$$

where $\{\lambda_{kj}\}$ defines the connectivity coefficient between (k, j) pair of injector k and producer j; c_t is the total compressibility around the control volume; V_p is the pore volume around each producer; $\bar{p}_j$ is the average pressure in the volume drained by producer j; i_k is the injection rate of each injector k; and q_j is the total production rate of producer j. Then a productivity index model is introduced to relate Eq. (1) more directly to the rates:

$$q_j(t) = J_j(\bar{p}_j(t) - p_{wf,j}), \tag{2}$$

where p_{wfj} and J_j are the flowing bottom-hole pressure and productivity index number of the producer j, respectively. Eliminating the average reservoir pressure $\bar{p}_j(t)$ in Eq. (1) and Eq. (2) subsequently leads to the basic differential equation of the CRM model:

$$q_j(t) = \sum_{k=1}^{m} \lambda_{kj} i_k(t) - \tau_j \frac{dq_j(t)}{dt} - \tau_j J_j \frac{dp_{wf,j}(t)}{dt} \tag{3}$$

where the time constant $\{\tau_j\}$ for the volume drained by each producer j is defined as:

$$\tau_j = \frac{c_t V_p}{J_j} \tag{4}$$

2.1.2. Derivation of CRM for a layered reservoir

The above derivation acts as the theoretical basis of the governing equations for the MLCRMs. We introduce layered connectivity $\{\alpha_{kij}\}$ to replace integral connectivity $\{\lambda_{ij}\}$ for each pair of injector i and producer j, where k indicates the k-th layer of the reservoir. Fig. 1 illustrates the drainage area for a layered reservoir, where $f_{l,i}$ represents the fraction of injected water from injector i that is allocated to layer l. Then, Eq. (1) is modified as

$$q_{kj}(t) = \sum_{i=1}^{N_I} I_{ki} \alpha_{kij} - c_{kt} V_{kp} \frac{d\bar{p}_j(t)}{dt}, \tag{5}$$

where I_{ki} indicates the injection rates that are assigned to the k-th layer from injector i; q_{kj} indicates the production rates in the k-th layer for producer j; c_{kt} stands for c_t in layer k; and V_{kp} stands for V_p in layer k, respectively. Eq. (5) has been applied for a layered reservoir (Mamghaderi et al., 2013). However, Eq. (5) neglects the effect of cross flow, which means that the adjacent layers in the reservoir are not connected, which is obviously not practical for the purposes of this study.

It is necessary to introduce the cross flow term Qc_{kj}, which stands for the production rates of well j in the k-th layer that are from its adjacent layers. Then Eq. (5) can be modified as

$$q_{kj}(t) = Qc_{kj}(t) + \sum_{i=1}^{N_I} I_{ki} \alpha_{kij} - c_{kt} V_{kp} \frac{d\bar{p}_{k,j}(t)}{dt}, \tag{6}$$