Journal of Petroleum Science and Engineering 138 (2016) 138–152

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

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

Determining the levels and parameters of thief zone based on automatic history matching and fuzzy method

Shuaiwei Ding *, Hanqiao Jiang, Guangwei Liu, Lu Sun, Xiang'an Lu, Lin Zhao

Key Laboratory of Petroleum Engineering of the Ministry of Education, China University of Petroleum, Beijing 102249, China

ARTICLE INFO

Article history:
Received 9 June 2015
Received in revised form
27 July 2015
Accepted 9 September 2015
Available online 18 September 2015

Keywords:
Thief zone
Automatic history matching
Theory of logical analysis
Fuzzy analytic hierarchy process
Fuzzy comprehensive evaluation method
Reservoir numerical simulation

ABSTRACT

Thief zone which evolves from long-term water flooding, has become a subject of concern for reservoir engineers, as they lead to early water breakthrough in oil producers and uneven sweep around water injectors, thus it is essential to select wells which need to be modified injection or production profiles. This article presents a methodology of determining the levels and parameters of thief zone in different areas of the reservoir on the concept of "based on the information from every grid of reservoir model" by using automatic history matching and fuzzy method. Since characterizing the reservoir uncertainty is crucial to the reservoir description and future performance predictions, automatic history matching using ensemble Kalman filter (EnKF) with covariance localization is first proposed. Then according to theory of logical analysis (TLA), fuzzy analytic hierarchy process (FAHP) and Fuzzy comprehensive evaluation (FCE) method, the system to quantitative evaluation of thief zone is presented, and the reservoir can be graded into three categories of severe thief zone, light thief zone and no thief zone. The methodology has been applied to X oilfield in western North China which has 17 layers from the top to the bottom in the stratigraphy, and the results show that 5 layers exist severe thief zones and the volume of severe thief zones is the largest in layer 32, and there are four wells in this layer that their injection or production profiles must be modified. In addition, the interwell tracer test result shows the proposed methodology is more accurate by comparing with other methods in the references which mainly rely on the properties of single well to determine the levels of thief zone. The proposed approach is more accurate and less manpower needs to identify thief zones, which also providing a strong basis for oilfield development adjustment in high water cut stage.

1. Introduction

During long period of water injection, sand production and clay erosion will contribute to the variation of formation structure, which may lead to the widespread formation of thief zones (Bane et al., 1994; Feng et al., 2010, 2011). This phenomenon has serious effect on oilfield development since injected water would circulate inefficiently and sweep out of the reservoir rapidly. Therefore, how to identify and characterize these thief zones effectively and which wells should be modified profile, have been increasingly attracting reservoir engineers' attention.

There are several approaches to detect and characterize the thief zone which involve interwell surveillance (Asadi, 2005), core analysis (Al-Dhafeeri and Nasr-El-Din, 2007; Li et al., 2007), well logging (Li et al., 2008), inverse modeling of geology (Vargas-Guzmán et al., 2009), well testing (Feng et al., 2010) and reservoir engineering method (Feng et al., 2013; Parekh and Kabir, 2013). Although these ways can calculate the specific parameters of thief zones, it is always time-consuming and expensive, and they can not determine the level of the thief zone. Wang and Jiang (2010) first presented a set of index system which is suitable for profile control and water shut-off, then used ISODATA clustering analysis method to determine the existence of thief zone and levels of thief zone in different wells. However, this method mainly relies on the properties of single well which can only describe the situation near the wellbore, and it can not characterize the interwell information. In addition, the selection of the evaluation index is too artificial to lack of corresponding selecting system or method. More importantly, geological uncertainty is not taken into account during the evaluation process.

In fact, proper characterization of the reservoir and the assessment of uncertainty are crucial aspects of any optimal reservoir development plan and management strategy. History matching is a proper way to achieve this goal. Recently, ensemble Kalman filter (EnKF) is a new and most widely used method of

* Corresponding author.
E-mail address: 1-shwding@126.com (S. Ding).

http://dx.doi.org/10.1016/j.petrol.2015.09.010
0920-4105/

automatic history matching because of its advantage. However, for reservoir developed with high permeability channels, it is necessary to implement the EnKF with covariance localization (LcEnKF) (Arroyo et al., 2008).

The objective of this article here is to present a concept of "based on the information from every grid of reservoir model" by extracting information of static geological data and production dynamic data from reservoir numerical simulation model after automatic history matching, then use these information to quantitatively evaluate the thief zone by the system established by theory of logical analysis (TLA), fuzzy analytic hierarchy process (FAHP) and fuzzy comprehensive evaluation (FCE) method. The main feature of this methodology is that it can identify the spatial distribution of thief zones in a reservoir including the near-wellbore and interwell areas, and also take the geological uncertainty into deliberation.

2. Automatic history matching using LcEnKF

Before the comprehensive evaluation of thief zone is performed, the evaluation parameters need to be obtained first. Base on the concept of "based on the information from every grid of reservoir model", the information of static geological data and production dynamic data is extracted from reservoir numerical simulation model. So it is necessary to reconcile geological models to the dynamic response of the reservoir through history matching.

Recently EnKF has gained increasing attention for history matching and continuous reservoir model updating. As EnKF generates multiple history-matched models, it conceptually allows one to characterize the uncertainty in reservoir description and future performance predictions. However, an important deficiency of EnKF is the inaccurate estimation of covariance matrices. Arroyo et al. (2008) proposed a novel approach to overcome this limitation by conditioning the cross-covariance matrix using information gleaned from streamline trajectories. So here we use the LcEnKF for automatic history matching.

2.1. Standard EnKF formulation

The standard EnKF formulation is a sequential data assimilation algorithm which was introduced by Evensen (1994). To present the EnKF equations, the ensemble Ψ can be expressed as

$$\Psi_k = \left[y_{k,1} \cdots y_{k,N_e} \right]^T \tag{1}$$

where Ψ_k is the $N_y \times N_e$ ensemble matrix, and $y_{k,\,N_e}$ is the N_e th ensemble member of state vector at time k.

State variables for each simulation model form a state vector and the ensemble of state variables forms an ensemble matrix. Thus, we have

$$y_{k,N_e} = \left[m_{k,N_e} p_{k,N_e} d_{k,N_e} \right]^T \tag{2}$$

where y_{k,N_e} is the N_e th ensemble member of state vector at time k. m_{k,N_e} is the $N_m \times N_e$ static vectors, and p_{k,N_e} is the $N_p \times N_e$ dynamic vectors, and d_{k,N_e} is $N_d \times N_e$ production data vector.

Here, we define the matrix H by

$$H = \left[O | I_d \right] \tag{3}$$

where H is $N_d \times N_y$ matrix, and O is the $N_d \times (N_y - N_d)$ null matrix, and I_d is the $N_d \times N_d$ identity matrix. Note that the dimension of H depends on the number of data to be assimilated at the kth assimilation step so that we can write the forecast or predicted data vector, $d_{k,i}$, as

$$d_{k,i} = H y_{k,i} \tag{4}$$

The ensemble of sampled observations D_k can be represented as follows

$$D_k = \left\{ d_{k,1} d_{k,2} \cdots d_{k,N_e} \right\} \tag{5}$$

$$d_{k,i} = d_k + \varepsilon_i \tag{6}$$

where d_k represents a vector of production data measured at time k, perturbed by the data noise ε_i assumed to be Gaussian and uncorrelated in time, and $i = 1, \cdots, N_e$.

The EnKF update equation is

$$\Psi_k^u = \Psi_k^p + K\left(D_k - H\Psi_k^p \right) \tag{7}$$

$$K = C_\Psi^p H^T \left(H C_\Psi^p H^T + C_D \right)^{-1} \tag{8}$$

$$C_\Psi^p = \frac{1}{N_e - 1} \sum_{i,j=1}^{N_e} \left(y_i^p - \bar{y}^p \right)\left(y_j^p - \bar{y}^p \right)^T \tag{9}$$

where the superscript u denotes updated and p denotes prior, and K is the Kalman gain, and C_Ψ^p represents the state vector covariance matrix and C_D represents the observation covariance matrix.

2.2. EnKF assisted by streamline (LcEnKF)

The standard EnKF formulation use one sensitivity matrix for all ensembles, even though all ensembles have different static parameters. But reservoir permeability with thief zone usually follows a bimodal distribution, if we utilize the same sensitivity matrix for the whole reservoir, it affects the result of history matching (Jafarpour and McLaughlin, 2009). Therefore, history matching dynamic production data using EnKF with covariance localization which calculates the cross-covariance matrix using information gleaned from streamline trajectories is proposed. That means the cross-covariance calculations that relate reservoir parameters to production data are limited to the regions identified by streamlines.

To account for the conditioning using streamline, the only thing is to redefine the covariance matrix as (Arroyo et al., 2008)

$$C_\Psi^p H^T = \rho^\circ \left(\frac{1}{N_e - 1} \sum_{i,j=1}^{N_e} \left(y_i^p - \bar{y}^p \right)\left(H y_j^p - H\bar{y}^p \right)^T \right) \tag{10}$$

where ρ is a correlation function discussed below and represents the flow path information extracted from the streamlines. The operation ρ° in Eq. (10) denotes the Schur product operator.

We can think of the correlation function ρ as a matrix with the column j filled with ones at the grid locations i selected by streamlines. For other grid blocks in the same column the correlation function is set equal to zero. A similar procedure is repeated for all other producers j until matrix ρ_{ij} is completed. We can build the correlation function at each assimilation time. In fact, it is possible to define different types of the correlation functions depending upon physical considerations.