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Inversion of fractures with combination of production performance and in-situ stress analysis data

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A B S T R A C T

Successful identification of the fractures in fractured reservoirs is important to guarantee an effective development. Considering that the production performance of fractured reservoirs contains important information of the distribution of fractures, the production performance can be applied for the inversion of fractures. However, the inversion of fractures is difficult to achieve because it is an inverse problem with an inherent defect of multiplicity of solutions. In order to alleviate the defect, we estimate the possible distribution ranges of fractures which can be obtained by analyzing the correlation of fractures and in-situ stress, and the ranges are used as constraint conditions when the production performance is applied for obtaining the accurate distribution of fractures. Firstly, we choose the geometric parameters of fractures such as midpoint coordinate, azimuth and extension length of fractures as inversion parameters and use production data as inversion indexes. Secondly, we simulate the flow behavior in fractured reservoirs based on the Discrete Fracture Matrix (DFM) module of Matlab Reservoir Simulation Toolbox (MRST) to explicitly describe the effect of fractures on the flow behavior of fluid. Thirdly, the possible distribution ranges of fractures which can be obtained by analyzing the correlation between fractures and in-situ stress based on Griffith failure criterion are used as the constraint conditions of inversion parameters. Finally, Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm is adopted to minimize the inversion objective function to obtain the accurate distribution of fractures. Theoretical cases verify that the method is effective for the accurate inversion of fractures while the inversion results of more fractures become worse because more fractures make the sensitivities of production performance to individual fractures decrease greatly.

1. Introduction

The flow behavior and mechanism in fractured reservoirs are much complicated because of the existence of fractures. In order to effectively develop oil and gas in fractured reservoirs, it is necessary to realize the accurate identification of fractures. Conventional identification techniques which are used to identify or predict natural fractures, such as core analysis, outcrop data, logging and seismic exploration, are inappropriate to obtain the accurate distribution of fractures because of ignoring the effect of fractures on the flow behavior. Therefore, the production performance of fractured reservoirs which includes the flow information determined by both matrix and fractures is a crucial information for the inversion of fractures (Gang and Kelkar, 2006; Suzuki et al., 2005). In order to directly connect the distribution of fractures with the dynamic flow behavior, the midpoint coordinate(x_0, y_0), azimuth α and extension length L of fractures are chosen as inversion parameters instead of conventional petro-physical parameters such as permeability or porosity. When it comes to the mathematical flow models of simulating the flow behavior in fractured reservoirs, there are two main flow models: dual medium model and discrete fracture model. Dual medium model was proposed by Barenblatt et al. and has been widely used (Zheltov et al., 1960; Lim and Aziz, 1995). However, the simulation results of the dual medium model for the fractured reservoirs in which the fractures are poorly developmental, especially when there are several large-scale fractures dominating the flow behavior, are much different with the actual flow behavior. Therefore, in order to more accurately simulate the effect of individual fractures on the flow behavior in

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fractured reservoirs, Noorishad et al. proposed discrete fracture model, in which the realistic geometry of fractures is represented explicitly (Noorishad, 1982; Hægland et al., 2009; Jiang and Younis, 2015; Mia et al., 2014). DFM model has the advantage of simulating the fractured reservoirs in which a small number of fractures dominate the reservoirs. In 2012, Sandve et al. developed the Discrete Fracture Matrix (DFM) module based on an open-source Matlab Reservoir Simulation Toolbox (MRST) and used the multi-point flux approximation (MPFA) Finite Volume method to handle unstructured grids to calculate numerical simulation values (Lie et al., 2012; Sandve et al., 2012). The numerical simulation of all the fractured reservoirs involved in the paper is calculated by the DFM module of MRST.

Essentially, applying the production information for the inversion of fractures is an inverse problem: on the basis of Bayesian theory, the inversion objective function which represents the difference between the real production of fields and the numerical simulation is established; then an effective optimization algorithm is used to minimize the difference to obtain the optimal distribution of fractures which is consistent with the real distribution of fractures in fractured reservoirs (Zhao et al., 2013). However, the inversion of fractures has an inherent defect of multiplicity of solutions, which makes it much difficult to get the optimal distribution of fractures. Therefore, effectively alleviating the multiplicity of solutions is a crucial step to achieve the successful inversion of fractures. Considering that fractures are the products of in-situ stress, the possible distribution ranges of fractures can be estimated by studying the correlation between fractures and in-situ stress based on rock failure criteria such as Griffith failure criterion (Zhang, 2008; Zongzhen et al., 2010). Then the estimated ranges can be used as the constraint conditions of inversion parameters to mitigate the multiplicity of solutions. Generally, the optimization algorithms which are applied for the inversion process involve gradient and non-gradient methods. The gradient methods include Gauss-Newton method, Adjoint method and so on (Kalogerakis and Tomas, 1995; Wu et al., 1999; Rodrigues et al., 2006). However, the complicity of calculating high-dimensional Jocabian Matrix limits the application of gradient methods for the inversion problems in large-scale reservoirs. In order to overcome the defect, some non-gradient methods have been used, such as Genetic Algorithm, Evolutionary Algorithm, Particle Swarm Optimization, EnKF and SPSA, etc. (Sen et al., 1995; Abdelkhalik et al., 2012; Mohamed et al., 2011; Gu and Oliver, 2006; Gao et al., 2004a). Although there is no need to calculate gradients when using non-gradient methods, there are other disadvantages: when genetic algorithm is used to minimize objective function, the optimal results are obtained at the expense of thousands of simulation operations; EnKF is unavailable for the inversion problems when the flow behavior in reservoirs is highly nonlinear. In order to make the inversion process easily achieved and guarantee the high efficiency of operation, SPSA algorithm (Simultaneous Perturbation Stochastic Approximation) is adopted to minimize the inversion objective function. In 2004, Gao et al. introduced SPSA algorithm to solve the optimization problems in reservoirs (Gao et al., 2004b). The advantages of SPSA are that it can guarantee the calculated gradient to be invariably descent direction in terms of minimization problems and it can be easily combined with numerical simulators. Besides, in order to guarantee the search results to be in accord with the conditions of reservoirs, the covariance matrix of inversion parameters is added to the standard SPSA to improve the stability of it (Zhang et al., 2015).

2. Establishment of inversion objective function

In order to achieve the inversion of fractures successfully, it is necessary to establish a proper inversion objective function which can reflect the difference between the production performance and the numerical simulation.

2.1. Bayesian inverse objective function

Reservoir parameters are usually considered to be random variables conforming to the multivariate Gaussian distribution, and there is a probabilistic relationship between reservoir parameters and production performance of fields (Tarantola, 2005). On the basis of Bayesian theory, when production datad_{obs} is given, the conditional probability distribution function of reservoir parameters m is given by:

$$f(m|d_{\text{obs}}) \propto f(d_{\text{obs}}|m) f(m) \tag{1}$$

The probability distribution function of reservoir parameters m is defined as:

$$f(m) \propto \exp\left[-\frac{1}{2}(m - m_{pr})^T C_M^{-1} (m - m_{pr}) \right] \tag{2}$$

Where m is a vector of N_m dimension with mean value as m_{pr} and covariance matrix as C_M; m_{pr} is the prior estimate of the reservoir parameters.

When reservoir parameters m is given, the conditional probability distribution function of production data is given by:

$$f(d_{\text{obs}}|m) \propto \exp\left[-\frac{1}{2}(d_{\text{obs}} - g(m))^T C_D^{-1} (d_{\text{obs}} - g(m)) \right] \tag{3}$$

Where d_{ods} is a vector of N_d dimension, containing the production data such as oil production rate and water production rate; C_D is the covariance of the production data. $g(\cdot)$ represents the numerical simulation results of a reservoir simulator.

Therefore, when production data d_{obs} is given, the probability distribution function of reservoir parameters m is defined as:

$$\begin{aligned} f(m|d_{\text{obs}}) &\propto f(d_{\text{obs}}|m) f(m) \\ &\propto \exp\left[-\frac{1}{2}(d_{\text{obs}} - g(m))^T C_D^{-1} (d_{\text{obs}} - g(m)) - \frac{1}{2}(m - m_{\text{pr}})^T C_M^{-1} (m - m_{\text{pr}}) \right] \end{aligned} \tag{4}$$

The goal of the inversion is to search for the optimal parameters m which can make the probability calculated by Eq. (4) maximal. Eq. (4) can be simplified as:

$$O(m) = \frac{1}{2}(m - m_{\text{pr}})^T C_M^{-1} (m - m_{\text{pr}}) + \frac{1}{2}(d_{\text{obs}} - g(m))^T C_D^{-1} (d_{\text{obs}} - g(m)) \tag{5}$$