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An Automatic History Matching Method for Shale Oil Reservoir Based on Particle Filter

Guoxiang Zhao[1], Yuedong Yao[1*], Lian Wang[1]

1 *State Key Laboratory of Petroleum Resources and Prospecting, College of Petroleum Engineering, China University of Petroleum (Beijing), Beijing 102249, China*

*Corresponding author: Yuedong Yao (yaoyuedong@163.com)

ABSTRACT

The key to automatic history matching for fractured shale oil reservoir is its precision. However, traditional widely applied data assimilation methods such as the ENKF is not applicable to a typical nonlinear and non-Gaussian system of shale oil numerical simulation. In this paper, a history matching, based on particle filter is proposed to evaluate the state of the shale oil reservoir and to invert the fracture distribution parameters. The proposed method avoids the disadvantages of the traditional ENKF method. Results showed that the particle size was of great significance to the history matching results. For the established reference model with three discrete fractures, the reasonable particle size was about 400. Meanwhile, the inversion error of the fracture central points, the fracture half length, the fracture permeability and the matrix permeability had low average error of about 4.49%. Meanwhile, the accuracy of inversed fracture azimuth was up to 42.93%, illustrating that the rational application of geological information to decrease the uncertainty as much as possible is of essence. This work explores the feasibility of the application of the particle filter on history matching and aids in the development of shale reservoirs.

Keywords: Shale oil, discrete fracture, history matching, particle filter

NONMENCLATURE

Abbreviations	
Frac_C$_x$	Fracture center points
Frac_C$_y$	Fracture center points
Matrix_P	Matrix Permeability
Frac_P	Fracture Permeability
Frac_HF	Half-Length
Frac_A	Fracture Azimuth
Symbols	
μ	Viscosity
δ	Dirac function
k	Permeability
B	Volume factor
p	Pressure
q_{mf}	Mass transfer between fracture and matrix
q_{ff}	Mass transfer between fractures
q_{fw}	Mass transfer between fracture and well
t	Time
φ	Porosity
c_1	Coefficients to describe the nonlinear flow
c_2	Coefficients to describe the nonlinear flow
$\boldsymbol{x}$	State vector
N	Particle size
$\boldsymbol{z}$	Measurement vector
w	Particle weight
$\hat{\boldsymbol{x}}_t$	Estimated state
N_{eff}	Effective sample size

1. INTRODUCTION

With the increasing demand in energy around the world, efficient development of shale oil has attracted attention in recent years [1]. The application of horizontal well technology and hydraulic fracturing technique make development of shale oil reservoir economically possible [2]. To evaluate the production performance and reasonably design well control parameters, numerical simulation is widely applied [3-4]. However, the input parameters into the numerical simulator are usually based on stochastic modelling [5-6]. Meanwhile, the true reservoir parameters are difficult to obtain, and this results in enormous difficulties while investigating the production performance during shale oil reservoir development.

History matching is a critical method which uses information from observed data, such as production

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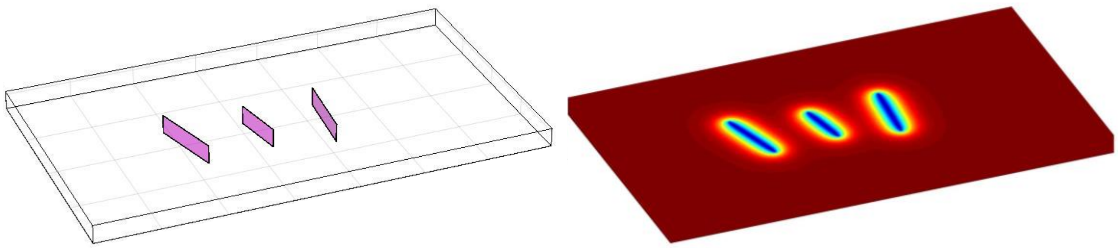
The obtained inversion parameters listed in Table 1 are shown in Table 3. It was found that the fracture half length, fracture permeability and fracture central points had high accuracy with a low average error of about 4.47%. This illustrates that the true value of these parameters can be obtained by the proposed automatic history matching method. However, the obtained fracture azimuth had a relative larger error (the max error was 42.93%); illustrating that the reliability of the proposed method for the azimuth was poor. However, it was also found from Table 3 and Fig. 7 that the unreliable azimuth was symmetrical to the original fracture distribution. Overall, the predicted pressure distribution and the fracture distribution were similar to the reference model. To avoid the inversion error caused by the azimuth, the fracture azimuth can be obtained from a microseismic monitoring results to reduce the uncertainty.



(a) (b)

Fig. 7 The inversion results. (a) the distribution of fractures; (b) the pressure distribution after 200days' production.

Table. 3 Inversion result and comparison with the true value for the primary fractures.

Fracture No.	Value and Error	x_c	y_c	Half-Length	Fracture Permeability	Fracture Azimuth
	True value	438.74	388.40	107.00	5.00	75.00
1	Inversion value	414.21	466.71	106.20	4.72	107.40
	Error	2.56%	4.74%	0.07%	5.90%	42.93%
	True value	649.40	395.52	87.50	5.00	105.00
2	Inversion value	634.72	376.45	82.06	5.32	101.32
	Error	2.26%	4.85%	6.22%	7.90%	3.50%
	True value	859.13	382.73	107.50	5.00	83.00
3	Inversion value	840.87	368.65	113.2	5.16	85.61
	Error	1.80%	8.95%	5.30%	3.10%	3.13%

4. CONCLUCIONS

In this work, an automatic history matching is implemented in a multistage fractured shale oil reservoir and the performance of the proposed model is also investigated. The main research findings can be outlined as follows:

(1) A history matching method for fractured shale oil reservoir based on EDFM and particle filter is proposed. The proposed model can be applied to evaluate the shale oil reservoir state and invert the uncertainty parameters.

(2) The particle size has significant effect on the filtering results. Increased particle size improves the filtering accuracy. In practical applications, an optimal particle size can be obtained by sensitivity analysis to decrease the computational cost as much as possible.

(3) Unlike the widely used ENKF, Particle filter is not limited by Gaussianity and is potentially more accurate when it is applied to solve history matching problems.

(4) Among the uncertainty parameters in this research, the inversion error of fracture azimuth is the largest. To improve the inversion results, geological information such as well logging or microseismic monitoring is necessary.

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