Energy Proceedings
Vol 28, 2022
ISSN 2004-2965

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 data. Hence, history matching is exactly an inverse modeling process. A lot of methods have been proposed to carry out history matching research in different kinds of reservoirs [7-8], such as gradient-based method [9], streamline-based method [10], gradient free method [11] and data assimilation method [12]. Among these history matching methods, the gradient-based method needs to be embedded into a numerical simulator so as to process the Jocabian Matrix which may be up to millions of dimensions. This makes the gradient-based method effective for only small-scale history matching problems [13]. Gradient-free method needs expensive computational cost and cannot utilize the latest observed data to improve the history matching results. The data assimilation method avoids the disadvantages of the gradient-based method and the gradient-free method. This method therefore has been widely applied, and a typical example is the Ensemble Karman Filter (ENKF) [14]. However, ENKF contains an implicit linearization in the updating step and requires the assumption of white Gaussian noise for the underlying prediction model [13].

Unlike the ENKF, particle filter approximates the posterior distribution of the reservoir state by a set of particles [15]. Therefore, particle filter can be applied in any nonlinear system with any arbitrary shape of stochastic distribution. It is obvious that shale oil simulation system is a typical nonlinear system and the distribution of fracture and related parameters may not follow the Gaussian distribution. However, there are still few researches focused on the application of particle filter in the parameter's inversion of fractured shale oil reservoir.

In this paper, a history matching method based on the embedded discrete fracture model (EDFM) and particle filter is proposed to evaluate the reservoir and invert the fracture's physical parameters. To validate the performance of the proposed history matching method, a reference fractured shale oil reservoir model is established, and the results show that the proposed model is efficient.

2. MATHEMATICAL MODEL

2.1 Embedded discrete fracture model

In order to explore the production performance of fractured reservoirs, several numerical simulation methods are proposed, such as Discrete Fracture Model (DFM) [16], Equivalent Continuum Model (ECM) [17], Embedded Discrete Fracture Model (EDFM) [18]. Among these widely applied models, EDFM avoids the generation of unstructured grid and is able to describe the complex distribution of fractures. In this research, EDFM was adopted to simulate the production performance of multi-fractured shale oil reservoir to capture the distribution characteristics of generated fractures. In EDFM, the mass transfer conservation equations for matrix system and fracture system can be expressed as [18]:

$$\nabla\left(\frac{k}{\mu B}\nabla p\right)_m + \delta q_{mf} = \frac{\partial}{\partial}\left(\frac{\varphi}{B}\right)_m \tag{1}$$

$$\nabla\left(\frac{k}{\mu B}\nabla p\right)_f + \delta q_f = \frac{\partial}{\partial}\left(\frac{\varphi}{B}\right)_f \tag{2}$$

$$q_f = q_{mf} + q_{ff} + q_{fw} \tag{3}$$

where μ is the viscosity; δ is the Dirac function; k is the permeability; B is the volume factor; p is the pressure; q_{mf} is the mass transfer between fracture and matrix; q_{ff} is the mass transfer between fractures; q_{fw} is the mass transfer between well and fracture; t is the time; φ is the porosity; subscript f represents the fracture; the subscript m represents the matrix.

Due to the ultralow permeability and porosity of shale oil reservoirs, oil flow behavior in shale matrix does not follow the Darcy law. That is to say that the flow velocity is not proportional to the pressure gradient. The oil transport behavior in shale matrix can be described by Huang's model [19]:

$$v = -\frac{k}{\mu}\nabla p\left(1 - \frac{c_1}{\left|\nabla p\right| - c_2}\right) \tag{4}$$

where c_1 and c_2 are the coefficients to describe the nonlinear flow.

It can be found from Eq. (4) that there is a nonlinear multiplier incorporated to modify the mass transfer equation:

$$M = \left(1 - \frac{c_1}{\left|\nabla p\right| - c_2}\right) \tag{5}$$

By introducing Eq. (5) into Eq. (1), the mass conservation equation can be modified to be:

$$\nabla\left(\frac{k}{\mu B}M\nabla p\right)_m + \delta q_{mf} = \frac{\nabla}{\nabla t}\left(\frac{\varphi}{B}\right)_m \tag{6}$$

2.2 Particle filter

Based on the EDFM, the effect of fractures on the production performance of shale oil reservoir can be obtained. However, numerical simulation process alone is not enough to obtain the fracture physical parameters and their distribution. Therefore, an effective inversion method is required. Particle filter approximates the posterior distribution $p\left(X_t \middle| z_{1:t}\right)$ by a set of random samples $\boldsymbol{X}_t = \left\{\boldsymbol{x}_1, \cdots, \boldsymbol{x}_N\right\}_t$ with associated weights $\boldsymbol{w}_t = \left\{w_1 \cdots w_N\right\}_t$ and estimates the system state (fracture distribution parameters and fracture physical parameters, such as fracture length, fracture permeability, fracture azimuth, fracture position) as [20]:

$$p\left(\boldsymbol{x}_t \middle| \boldsymbol{z}_t\right) = \sum_{i=1}^{N} w_t^i \delta\left(\boldsymbol{x}_t - \boldsymbol{x}_t^i\right) \tag{7}$$

where $\boldsymbol{X}$ is the state vector; N is the particle size; $\boldsymbol{Z}$ is the measurement vector; W is the particle weight.

The i_{th} state vector $\boldsymbol{x}_t^i$ at time step t obeys a proposal distribution:

$$\boldsymbol{x}_t^i \sim p\left(\boldsymbol{x}_t^i \middle| \boldsymbol{x}_{t-1}^i, \boldsymbol{z}_t\right) \tag{8}$$

The weight of particle is obtained by:

$$\tilde{w}_t^i \propto \tilde{w}_{t-1}^i \frac{p\left(\boldsymbol{z}_t \middle| \boldsymbol{x}_t^i\right) p\left(\boldsymbol{x}_t^i \middle| \boldsymbol{x}_{t-1}^i\right)}{q\left(\boldsymbol{x}_t^i \middle| \boldsymbol{x}_{t-1}^i, \boldsymbol{z}_t\right)} \tag{9}$$

where $p\left(\boldsymbol{z}_t \middle| \boldsymbol{x}_t^i\right)$ is the likelihood function; $p\left(\boldsymbol{x}_t^i \middle| \boldsymbol{x}_{t-1}^i\right)$ is the state transition density function; $q\left(\boldsymbol{x}_t^i \middle| \boldsymbol{x}_{t-1}^i, \boldsymbol{z}_t\right)$ is the proposal distribution, which is usually equal to $p\left(\boldsymbol{x}_t^i \middle| \boldsymbol{x}_{t-1}^i, , \boldsymbol{z}_t\right)$. The estimated state is:

$$\hat{\boldsymbol{x}}_t = \sum_{i=1}^{N} w_t^i \boldsymbol{x}_t^i \tag{10}$$

However, when the filter process is being executed, a significant weight is concentrated on only one particle. This results in a significant computational effort being spent on some particles with low weights. The effective sample size N_{eff} is usually applied to measure the degeneracy [15]:

$$N_{eff} = \frac{1}{\sum_{i=1}^{N} \left(w_t^i\right)^2} \tag{11}$$

Once the effective sample size is smaller than a threshold value N_e, the particle will be resampled by the Sampling Importance Resampling (SIR) method [20]. The threshold is usually set to be 0.3~0.7 of the effective sample size. In this research, the threshold is 0.5 times the effective sample size.

Based on the EDFM and the particle filter, a history matching method is established. Its flowchart is presented in Fig. 1.

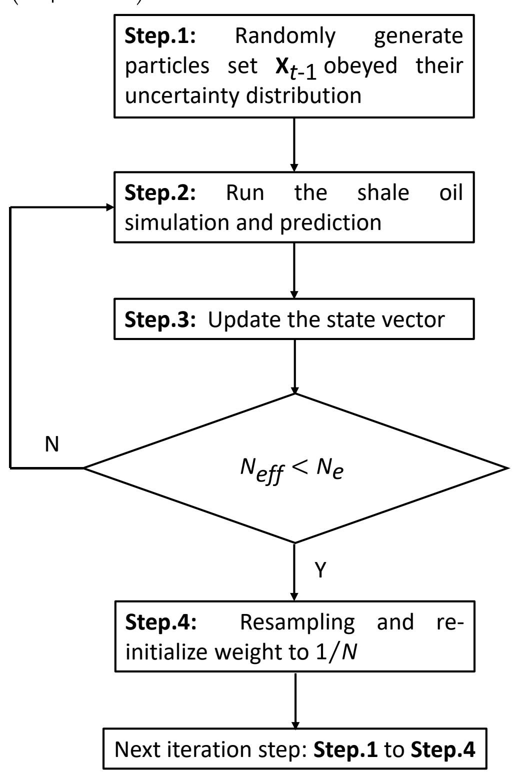


Fig. 1 Flowchart of the proposed automatic history matching method.

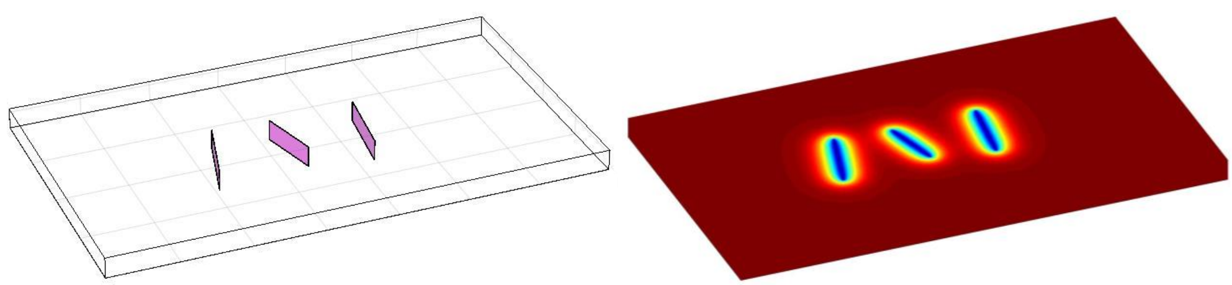
3. RESULTES

3.1 Reference model

To illustrate the workflow and the performance of the proposed automatic history matching method, a reference model was applied. The reference model is composed of three fractures with different azimuth angles, as shown in Fig.2(a). The dimensions of the shale oil reservoir are 1400m×800m×60m and the model is discretized into 140×80×6. The other parameters as well as the uncertainty parameters applied in the reference model are presented in Table. 1. In the reference model, the hydraulic fractures are assumed to penetrate the entire thickness, and the dip angle is assumed to be 90°. The pressure distribution after 200 days' production is presented in Fig.(2b). In the history matching process, the fracture length, the fracture permeability, the fracture azimuth angle, the fracture central points, and the matrix permeability are set as the uncertainty parameters. The initial guesses of all the uncertainty parameters are listed in Table 2.

Table. 1 The parameter values and the uncertainty parameters.

Parameters	Value	Unit	Is uncertainty parameter?
Reservoir Area	1400×800×60	m^3	×
Discretization	140×80×6	-	×
Number of fractures	3	-	×
Fracture central points	(438.7,388.4); (649.4,395.5); (859.1,382.7)	-	√
Initial Pressure	45	MPa	×
Bottom Hole Pressure	20	MPa	×
Matrix Permeability	0.05	mD	√
Matrix Porosity	0.07	-	×
Nonlinear coefficient c_1	0.01	MPa/m	×
Nonlinear coefficient c_2	0	MPa/m	×
Fracture Permeability	5	D	√
Fracture Width	0.005	m	×
Half-Length	107;87.5;107.5	m	√
Fracture Porosity	0.3	-	×
Well Length	1000	m	×
Fracture Dip Angle	90	°	×
Fracture Azimuth	75;105;83	°	×



(a) (b)

Fig. 2 The reference model of shale oil reservoir with three discrete fractures. (a) the distribution of fractures; (b) the pressure distribution after 200 days' production.

Table. 2 Initial guess of the uncertainty parameters.

Parameter	Minimum value	Maximum value	Unit	Distribution	Abbreviation
Fracture center points x_c	250; 350;450;550; 650; 750; 850;950	450;550;650;750; 850;950;1050;1150	-	Uniform	Frac_C_x
Fracture center points y_c	300	600	-	Uniform	Frac_C_y
Matrix Permeability	0.0001	1	mD	Gauss	Matrix_P
Fracture Permeability	0.1	50	D	Gauss	Frac_P
Half-Length	20	160	m	Lognormal	Frac_HF
Fracture Azimuth	30	150	°	Lognormal	Frac_A

3.2 Determination of particle size

Determination of particle size is of great significance. A smaller particle size will result in a lower filtering accuracy, while too large a particle size will lead to the huge computational cost. In this case, the mean production was chosen as the indicator to evaluate the stability of the proposed automatic history matching method. The results are shown in Fig. 3. It is observed from Fig.3 that the change of the mean production was more drastic when the particle size was small. With an increase in particle size, the obtained mean production gradually stabilized. Based on Fig.3, the particle size in this case was set as 400 due to the insignificant changes observed in the filtering results.

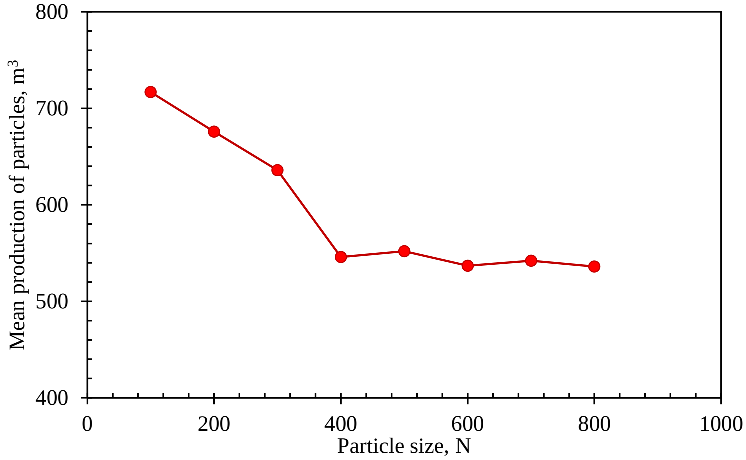


Fig. 3 Stability of mean production obtained by the particle filter with different particle size

3.3 Performance of PF

In order to evaluate the performance of the particle filter, the most notable parameters were selected. Hence, the parameters that are evaluated can be set as:

$$\boldsymbol{x}' = \left\{Frac\_P, Frac\_HF, Frac\_C_x, Frac\_C_y, Frac\_A, Matrix\_P\right\} \quad (12)$$

For the initialization of the proposed automatic history matching workflow, 400 of particle's uncertainty parameters were sampled from the given distribution based on the Monte Carlo sampling method. The distribution is presented in Table 2. To initialize the proposed history matching workflow, the 400 samples were selected based on the Monte-Carlo sampling method, as shown in Fig. 4.

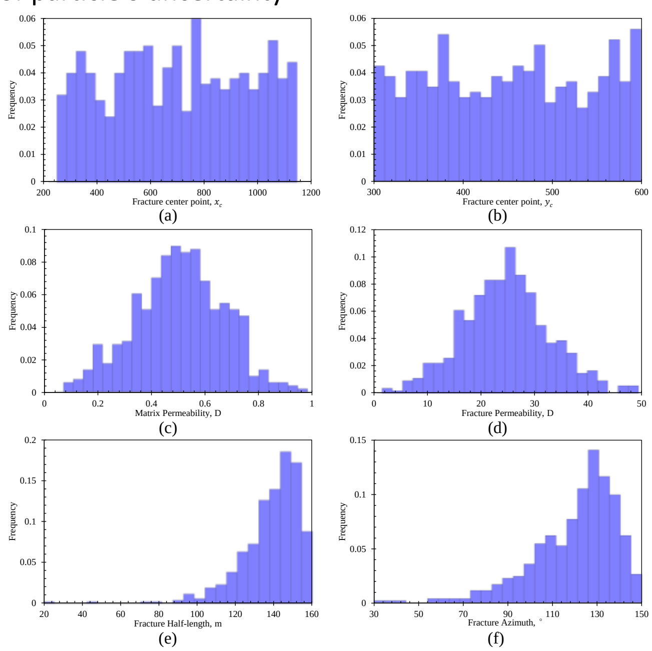


Fig. 4 Distributions of the uncertain model parameters at the initialization stage.

Fig. 5 shows the parameter inversion results after 13 steps' estimation by using the proposed history matching workflow. The red dashed lines in Fig. 5 are the true values in the reference model. One can see from

Fig.5 that the tendency of change is different from the commonly used ENKF. Due to the Gaussian distribution assumption, the posterior distribution obtained by the ENKF at each iteration step usually tends to be normally distributed [21]. Meanwhile, the proposed history matching workflow based on particle filter can represent the multimodal distribution of the uncertain parameter. This illustrates that the particle filter is not limited by the Gaussian distribution assumption and it may be more accurate than ENKF. The most significant changes occur on the matrix permeability, fracture permeability and fracture half-length, illustrating that these three parameters are the most sensitive parameters for the shale oil well production performance. For parameters fracture center points and fracture azimuth, the obtained posterior distribution changes are not as notable as the matrix permeability, fracture permeability and fracture half-length, but the particles with high probabilities are still located around the reference values, which illustrates that the uncertainties of these parameters are improved.

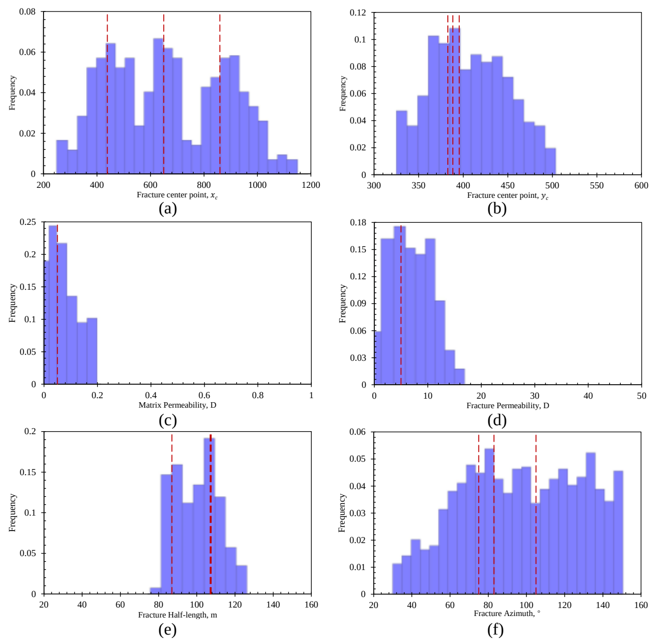


Fig. 5 Distributions of the uncertain parameters at the 13th iterative step.

The filter results with a particle size of 400 is presented in Fig. 6. Fig.6(a) is the predicted production performance at the initial stage, given the fact that the true production data is not incorporated into the history matching process. The prediction results were very divergent, which illustrated that strong uncertainties existed and this needed to be assimilated in the process. From Fig. 6(b) and Fig .6(c), it is observed that the filtering accuracy gradually increased, and at the final iterative step, the uncertainty of the predicted production performance decreased significantly. This showed that the accurate reservoir state and the uncertainty parameters had been obtained.

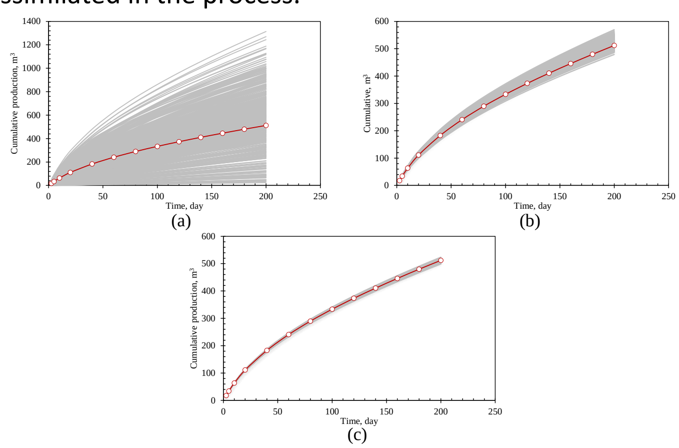
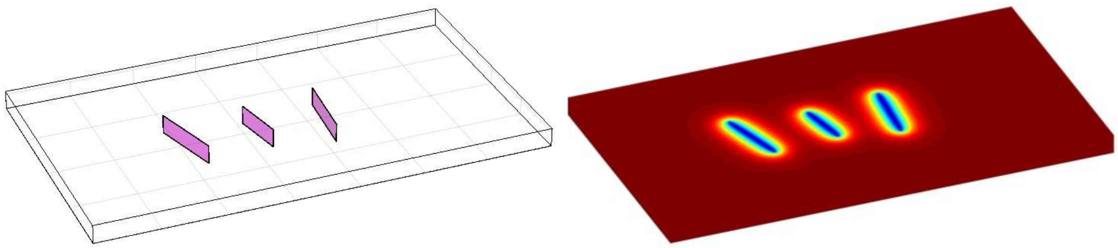


Fig. 6 Predicted production performance of the proposed history matching method: (a) initial stage; (b) 7th iterative step; (c) 13th iterative step.

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
1	True value	438.74	388.40	107.00	5.00	75.00
	Inversion value	414.21	466.71	106.20	4.72	107.40
	Error	2.56%	4.74%	0.07%	5.90%	42.93%
2	True value	649.40	395.52	87.50	5.00	105.00
	Inversion value	634.72	376.45	82.06	5.32	101.32
	Error	2.26%	4.85%	6.22%	7.90%	3.50%
3	True value	859.13	382.73	107.50	5.00	83.00
	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.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the National Basic Research Program of China (No. 2015CB250900) and financial support from China Scholarship Council (No. 202106440068).

REFERENCE

[1] Zhang T, Li X, Shi J, Sun Z, Yin Y, Wu K, Li J, Feng. An apparent liquid permeability model of dual-wettability nanoporous media: A case study of shale. Chem Eng Sci 2018;187:280-291.

[2] Luo Y, Zhao Y, Chen H, Su H. Fracture characteristics under the coupling effect of tectonic stress and fluid pressure: A case study of the fractured shale oil reservoir

in Liutun subsag, Dongpu Sag, Bohai Bay Basin, Eastern China. Pet Explor Dev 2015;42(2):196-205.
[3] Fan Y, Durlofsky L, Tchelepi H A. Numerical Simulation of the In-Situ Upgrading of Oil Shale. Spe J 2009;15(02):368-381.
[4] Xu C, Li P, Lu Z, Lu J, Lu D. Discrete fracture modeling of shale gas flow considering rock deformation. J Nat Gas Sci Eng 2018;52:507-514.
[5] Zhang Y K. Stochastic Methods for Flow in Porous Media. Vadose Zone J 2006;5(3):908.
[6] Ping J, Zhang D. History matching of fracture distributions by ensemble Kalman filter combined with vector-based level set parameterization. J Pet Sci Eng 2013;108:288-303.
[7] Oliver D S, Yan C. Recent progress on reservoir history matching: a review. Comput Geosci 2011;15(1):185-221.
[8] Jafarpour B, Mclaughlin D. History matching with an ensemble Kalman filter and discrete cosine parameterization. Comput Geosci 2008;12(2):227-244.
[9] Chang H, Liao Q, Zhang D. Surrogate model based iterative ensemble smoother for subsurface flow data assimilation. Adv Water Resources 2017;100:96-108.
[10] Stenerud V, Kippe V, Lie K. Adaptive Multiscale Streamline Simulation and Inversion for High-Resolution Geomodels. Spe J 2008;13(01):99-111.
[11] Sun X, Mohanty K. Estimation of Flow Functions During Drainage Using Genetic Algorithm. SPE Annu Tech Conf and Exhib 2003.
[12] Luo X, Stordal A, Lorentzen R, Nævdal G. Iterative Ensemble Smoother as an Approximate Solution to a Regularized Minimum-Average-Cost Problem: Theory and Applications. Spe J 2015;20(05):962-982.
[13] Zhang K, Luo R, Zhang L, Zhang X, Yao J. A two-stage efficient history matching procedure of non-Gaussian fields. J Pet Sci Eng 2016;138(05):189-200.
[14] Jafarpour B, Mclaughlin D. History matching with an ensemble Kalman filter and discrete cosine parameterization. Comput Geosci 2008;12(2):227-244.
[15] Guan R, Ristic B, Wang L, Palmer J. KLD sampling with Gmapping proposal for Monte Carlo localization of mobile robots. An Int J Inf Fusion 2019;49:79-88.
[16] Zhao Y, Jiang H, Rahman S, Yuan Y, Zhao L, Li J, Ge J, Li J. Three-dimensional representation of discrete fracture matrix model for fractured reservoirs. J Pet Sci Eng 2019;180:886-900.
[17] Wu Y, Guan Q. A Generalized Numerical Approach for Modeling Multiphase Flow and Transport in Fractured Porous Media. Commun Comput Phys 2009;6(1):85-108.
[18] Xu J, Chen B, Sun B, Jiang R. Flow behavior of hydraulic fractured tight formations considering Pre-Darcy flow using EDFM. Fuel 2019;241:1145-1163.
[19] Huang S, Yao Y, Zhang S, Ji J, Ma R. A fractal model for oil transport in tight porous media. Transp Porous Media 2018;121(3):725–39.
[20] Chopin N. A Sequential Particle Filter Method for Static Models. Biometrika 2002;89(3):539-551.
[21] Chang H, Zhang D. History matching of facies distribution with varying mean lengths or different principle correlation orientations. J Petrol Sci Eng 2014;124:275–292.