Research Article

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Rapid productivity prediction method for frac hits affected wells based on gas reservoir numerical simulation and probability method

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Abstract: As an important unconventional resource, shale gas can alleviate energy shortage, and its efficient development ensures the long-term growth of oil and gas. The prediction of production levels and estimated ultimate recovery with high accuracy is necessary for shale gas development. Conventional methods are widely applied in the oil and gas industry owing to their simplicity and effectiveness; however, none of them can accurately predict the results for frac hits affected wells. In this work, a probability method based on the numerical model of shale gas reservoir has been formed. In view of the impact of frac hits on the productivity of production wells during the development of shale gas reservoirs, an embedded discrete fractured numerical simulation method for gas reservoirs is proposed to simulate the geological engineering parameter range of wells before frac. And aiming at the established numerical model of shale gas reservoir, this method adopts the ensemble smoother with multiple data assimilation automatic history matching technology to carry out the history matching process of the model. Based on the probability theory and numerical simulation results, this study analyses the influence of different distribution functions of parameters on the calculation results of reserves, and obtains the expected curve of reserves through combination calculation. Besides, the effectiveness of this method was verified by comparing with other traditional predicted method.

Keywords: numerical simulation, probability method, automatic history matching, productivity prediction

1 Introduction

Shale gas has seen successful development in Fuling, Changning, Weiyuan, and Zhaotong in the southern Sichuan region as an unconventional oil and gas resource. One of the key indications for shale gas field development, which is best for block development, is the recoverable reserves of shale gas wells. It has a lot of importance.

At present, the calculation methods of recoverable reserves of shale gas mainly include empirical production decline method [1,2], probability method [3], advanced production data analysis method [4], analytical model method [5], material balance method [6], and numerical simulation method [7]. In addition to the commonly used generalized Arps model [1], SEPD model [8], Duong model [2], and YM-SEPD model [9,10], the empirical production decline method also has a EUR evaluation model based on the analysis of data processing methods and an optimization model based on the SEPD and Duong models. The method relies on production dynamic data, and the amount of calculation is small [11,12]. The probabilistic method is based on the uncertainty of geological engineering parameters to predict the production capacity. Its proxy model has two methods: numerical model and analytical model [13,14]. The advanced production data analysis method combines the unsteady percolation theory and empirical method, while the material balance method, the analytical model method, and the numerical simulation method are established based on the percolation mechanism, the geological engineering parameters are considered diverse, the model is complex, and the calculation amount is large [15–19]. The potential of reserves can be more properly reflected by the estimated value of reserves determined using the probability technique. This method is now considered to be one of the
accepted ones for estimating resources and reserves. Chengye et al. [20] used determination method and probability method to calculate geological reserves, respectively, and found that probability method has more advantages in reserve risk assessment by comparison. Lijuan [14] used probability method to estimate the reserves of Weizhou oilfield, and discussed the reliability of the reserves of this oilfield. Yi et al. [21] introduced shape factor into probabilistic reserves evaluation to reduce the influence of structural shape on reserves estimation results, and combined with geological parameters, made sensitivity analysis on reserves results, providing theoretical basis for development schemes.

The quantity of infill wells has continuously expanded as shale gas exploration and development have continued to deepen. Old and modern wells are arranged differently. Frac hits, which occasionally happen during the fracturing process of new wells, have a significant impact on the output of gas fields. The duration of production recovery and the impact on impacted wells following frac hits remain unknown. It is challenging to assess dynamic reserves over time using traditional recoverable reserves estimate methodologies. For this reason, this study uses the embedded discrete-fractured gas reservoir numerical simulation method to establish a numerical model, and calculates the production performance of a single well after frac hits through the automatic history matching of the gas reservoir numerical model and the probability method, and predicts the recoverable reserves of a single well. In reservoir numerical simulation, in order to accurately describe the geometric shape of fracture network in reservoir, Lee et al. [22] combined the advantages of dual-porosity model and discrete fracture model, put forward embedded discrete fracture model (EDFM), and carried out numerical simulation experiments on vertical fractures by using structured grid embedded fracture method, and obtained good matching results. EDFM has been widely used in numerical simulation of various fractured media flow problems, among which the typical ones are: Yu et al. [23] used EDFM to simulate shale gas transportation and production process under the condition of multi-stage fractured horizontal wells. Li et al. [24] applied EDFM simulation to study the influence of wettability inversion on production status under complex fracture grid. Dachanuwatana et al. [25] realized the historical matching of shale gas well production data based on EDFM technology. Compared with the forward problem reservoir numerical simulation, the inverse problem has been the focus of scholars and engineers because of the uncertainty of formation parameters. In 2002, Geir et al. [26] introduced ensemble Kalman filter (EnKF) into reservoir numerical simulation to estimate the permeability field and porosity field. Although EnKF has many advantages, Zafari and Reynolds [27] pointed out that EnKF may not achieve satisfactory results under certain circumstances. In view of the shortcomings of EnKF in reservoir model, Skjervheim et al. [28] first introduced ensemble smoother algorithm (ES) into reservoir history matching, and pointed out that ES algorithm has higher efficiency than EnKF. After that, Maucec et al. [29] used ensemble smoother with multiple data assimilation (ES-MDA) to assist history matching in carbonate oilfield, and achieved good results under geological constraints. Ranazzi and Sampaio [30] used ES-MDA algorithm for history matching in large-scale mines, and analyzed the influence of ensemble size on algorithm performance.

In this work, we developed a productivity prediction method for frac hits affected wells based on shale gas reservoir numerical simulation and probability method. First, an embedded discrete fractured numerical simulation method for gas reservoirs is used to simulate the geological engineering parameter range of wells before frac. And then the gas reservoir numerical model is used to perform automatic history matching based on ES-MDA. After history matching, not only the posterior probability density of reservoir parameters is attained, the knowledge of fracture geometry is more certain. After that, this study analyses the influence of different distribution functions of parameters on the calculation results of reserves and obtains the expected curve of reserves through combination calculation.

2 Numerical model of gas reservoir based on embedded discrete fractures model and automatic history matching

2.1 Embedded discrete fracture modeling

Fractal fracture network model based on fractal theory, extended finite element model based on finite element method, displacement discontinuous numerical model based on boundary element method, and finite element model based on finite element method are the main numerical simulation methods of fracture network in shale gas reservoirs. Additionally, there is the unconventional fracture network model built on the foundation of the discrete fracture network model, which is based on
the dual medium model and the continuity principle. This led to the development of the EDFM, which combines the benefits of dual media and discrete fracture models [31–41].

This approach establishes a shale gas reservoir numerical model based on the gas reservoir numerical model in order to characterize the adsorbed gas and free gas in the shale gas reservoir. The liquid can flow between the matrix and matrix, and also can flow between the matrix and the fractures. The model considers Knudsen diffusion, adsorption and desorption, stress sensitivity, and other mechanisms, and uses the embedded discrete fracture treatment method to characterize the fracture network and natural fractures into the gas reservoir numerical model to generate multi-scale discrete fracture values for shale gas reservoirs simulation model. The reservoir is discretized using Cartesian grids, extra grids are introduced at the fractures to characterize mass transfer across the media, and the conductivity between the grids is used to quantify the effect of fractures on fluid flow.

Conductivity adopts non-adjacent connection method:

\[
q = \lambda_i T_{\text{NNC}} \Delta P, \quad T_{\text{NNC}} = \frac{k_{\text{NNC}} A_{\text{NNC}}}{d_{\text{NNC}}},
\]

where \(q\) is the volume flow of phase \(l\) between non-adjacent connected pairs; \(\lambda_i\) is the relative mobility of phase \(l\); \(T_{\text{NNC}}\) is the conductivity coefficient between non-adjacent connected pairs; \(\Delta P\) is the pressure difference between grids; \(k_{\text{NNC}}\) is NNC penetration rate; \(A_{\text{NNC}}\) is the area of NNC; and \(d_{\text{NNC}}\) is the NNC distance.

1) NNC type I: It is the connection between the fracture segment and the matrix grid through which it passes.

\[
T_{1m} = \frac{2A_f (\mathbf{K} \cdot \mathbf{n}) \cdot \mathbf{n}}{d_{1m}}, \quad d_{1m} = \int \frac{\chi_f dV}{V},
\]

where \(A_f\) is the area on one side of the fracture section; \(\mathbf{K}\) is the permeability tensor; \(\mathbf{n}\) is the normal vector of the fracture plane; \(d_{1m}\) is the average distance from the matrix to the fracture; \(V\) is the volume of the fracture grid; and \(\chi_f\) is the distance between the matrix unit and the fracture unit.

2) NNC type II: It is the connection between different fracture segments of a single fracture.

\[
T_{\text{seg}} = \frac{T_1 T_2}{T_1 + T_2},
\]

where \(T_1\) and \(T_2\) are the openings of fractures 1 and 2, respectively; \(d_{1m}\) and \(d_{2m}\) are, respectively, the weighted average distance from the sub-segment of fractures 1 and 2 to the intersection line of the fracture.

2.2 Automatic history matching of gas reservoir numerical models

The modeling process involves numerous, intricate, and unknown aspects, which cause variations between the gas reservoir model and the actual gas reservoir. The numerical model of the gas reservoir must be corrected and optimized based on the production data history matching, and the reservoir parameters are then reversed and corrected in accordance with the observed actual gas reservoir (well) performance. The automatic history matching technology of the gas reservoir numerical model overcomes the shortcomings of manual trial calculations, and uses the optimization method to automatically correct the model parameters and structure, reducing the fitting time and achieving higher accuracy.

Aiming at the established numerical model of shale gas reservoir, this method adopts the ES-MDA automatic history matching technology to carry out the history matching process of the model [42]. The algorithm updates the model parameters based on the difference between the simulated data and the historical observation data. The multi-iteration set smoothing algorithm is iteratively updated and solved according to the correlation between the simulated data. It
is suitable for high-dimensional situations. With a small number of iterations, the multi-iteration set smoothing algorithm can obtain a better solution.

After completion of the production data history matching gas reservoir numerical model, it is possible to invert fracture conductivity, fracture half-length, reservoir pressure, reservoir permeability, and gas saturation in the artificial fracture network, based on production performance data and other important geological and engineering factors.

2.2.1 Principle of automatic history matching

First, based on Bayesian theory, establish a history matching objective function.

\[
O(m) = \frac{1}{2}(m - m_{pr})^T C_{M}^{-1}(m - m_{pr}) + \frac{1}{2}(d_{obs} - g(m))^T C_{O}^{-1}(d_{obs} - g(m)),
\]  

(9)

where \(m\) is the model parameter; \(m_{pr}\) is the mean of the prior model; \(C_{M}\) is the covariance matrix of the prior model; \(d_{obs}\) is the historical observation data; \(g()\) is the numerical simulator, input the model parameter \(m\) to get the simulated data; and \(C_{O}\) is the error covariance matrix for the history observed data.

In this study, the parameters of each artificial fracture are needed to be adjusted, and other parameters such as natural fractures and phase permeability curves are also included, the number of inversion variables is large, so an automatic history matching algorithm suitable for high-dimensional variables is required. EnKF [43] is widely used in reservoir history matching because it is suitable for updating high-dimensional system state parameters. However, its continuous data peering process requires the model to be restarted continuously, this leads to some limitations in its practical application. The ES-MDA only updates the model parameters, avoiding the tedious process of model restarting. ES-MDA perturbs all available observation data for many times and gradually updates the model parameters, which makes the algorithm convergence more stable. The update formula is as follows:

\[
m_{a}^{t+1} = m_{a}^{t} + C_{M}^{t} (C_{DD} + \alpha_{t} C_{O})^{-1} (d_{uc,j} - d_{f}^{t}),
\]

(10)

\[
d_{uc,j} = d_{obs} + \sqrt{\alpha_{t}} C_{O}^{1/2} z_{d}, z_{d} \sim N(0, I),
\]

(11)

where \(m\) is the model parameter, \(C_{MD}\) is the covariance matrix between the model parameters and the simulated observation data, \(C_{DD}\) is the covariance matrix of the model data, and \(C_{O}\) is the covariance matrix of the model observation data error. \(d_{uc,j}\) is the historical observation data, \(d_{f}^{t}\) is the simulated data, \(\alpha\) is the expansion factor, and \(N\) is the Gaussian distribution function. \(j\) represents the individuals in the set, \(a\) represents the analytical, and \(f\) represents the prediction. The setting of the expansion factor \(\alpha\) must satisfy the following condition:

\[
\sum_{i=1}^{N_{a}} \frac{1}{\alpha_{i}} = 1,
\]

(12)

where \(N_{a}\) is the number of iterations, \(\alpha_{i}\) can be set to \(N_{a}\).

The numerical simulation process of the actual shale gas reservoir model is time consuming, and a single numerical simulation can even take several hours. Therefore, the parallel method is very important to improve the efficiency of history matching of shale gas reservoirs. The ES-MDA algorithm supports parallel computing, that is, multiple models in the ensemble are numerically simulated at the same time, which can reduce the automatic history matching time by several times.

2.2.2 Autoencoder

The ES-MDA algorithm can iteratively update the solution for high-dimensional variables, but it involves the inverse process of model parameters and production data, and the high-dimensional variables will increase the computational consumption, so the model parameters are dimensionally reduced using autoencoder neural network.

Autoencoder neural network is an unsupervised machine learning method that enables data reconstruction or dimensionality reduction through encoding and decoding operations. Its neural network structure is shown in Figure 1. Among them, \(x\) represents the input sample data, \(h\) is the hidden layer node, and \(x'\) is the output data. The loss function of the autoencoder neural network can be expressed as the square of the norm of the difference between the input and output.

\[
\mathcal{L}(x, x') = ||x - x'||^2.
\]

(13)

Through the training of the neural network, the best effect is achieved in the test samples, which can realize the encoding process from the input to the hidden layer, i.e., data dimensionality reduction, and the decoding process from the hidden layer to the output, i.e., data reconstruction. The samples are randomly generated according to the range of shale gas reservoir model parameters, the autoencoder neural network is trained, the samples are input to the self-encoder to get the hidden layer data, and
the hidden layer data are used as parameter variables to achieve the purpose of model parameter dimensionality reduction.

The overall history matching flowchart is shown in Figure 2. First, the shale gas reservoir parameters are characterized, including fractured fractures, natural fractures, relative permeability, stress sensitivity, matrix, etc. Sample data are randomly generated according to the parameter range, and parameter downscaling is performed using a autoencoder to obtain the hidden layer data, which is used as the solution variable. Model parameters are obtained by reconstructing the hidden layer data, and reservoir numerical simulation is performed to obtain the model simulated production data. Termination conditions are judged, and if the termination conditions are met, the history fitting ends; if the termination conditions are not met, the model parameters are updated using an ensemble smoothing algorithm until termination.

3 Probability-based productivity prediction and process of frac hits affected wells

3.1 Probabilistic characterization of frac hits affected wells

Frac hits mainly occurs in the alternate layout of new and old wells. When a new well is being fractured, some of the fracturing fluid will affect nearby production wells, causing their output to drop sharply or cease entirely. The main factor contributing to pressure channeling is that the well that needs to be reformed in this area has been producing next to the old well for a while, which lowers the regional reservoir pressure and alters the reservoir’s original in situ stress field. When new wells undergo fracturing, due to changes in the regional reservoir pressure and in situ stress fields, artificial fracturing fractures are prone to propagate to the pressure-reducing area and cause fracturing fluid to interfere with the neighboring wells [43]. At the same time, part of the new and old wells’ natural fractures are developed, and when the new wells are reformed, they act as channels with high conductivity, which can cause fracturing fluids to flow to adjacent producing wells [44].

Due to uncertainty and the lack of data, the probability approach, also known as the uncertainty method, is frequently used to determine the probability distribution of oil and gas geological reserves. The probability distribution of recoverable reserves can also be computed using this technique in conjunction with the production decline approach and other dynamic methods. The probability technique uses Monte Carlo simulation to complete the probability distribution of the value of the objective function, considering the value of the probability distribution of the uncertainty parameter in the problem to be addressed.

After the occurrence of frac hits, the production of a single well is affected by fracturing fluid interference, and the production cannot be restored within a certain period of time, and its final recoverable reserves will also be
different from before. During the period when the productivity of a single well is not restored, the prediction of the recoverable reserves of a single well becomes a probability distribution problem due to the influence of pressure channeling. During the process of frac hits between wells, the fracturing fluid flow to adjacent production wells through artificial fracturing fractures and natural fractures is disturbed. The water content in the wellbore of the disrupted production well and the nearby formation fractures increases significantly, resulting in water lock in the reservoir near the production well and fluid accumulation in the wellbore, which greatly affects the productivity of production wells. Fluid accumulation in the wellbore will cause changes in bottom hole flowing pressure, and reservoir damage will cause changes in the conductivity of the fracture network, regional permeability, and the number of fracture openings. The influence of pressure channeling on the uncertainty of the bottom hole flow pressure, fracture network conductivity, regional permeability, and the number of fracture openings turns the final recoverable reserves of a single well into a probability prediction problem.

### 3.2 Method and process

1) Because of the uncertainty of the fracture network conductivity, the permeability of the reformed area, bottom hole flowing pressure, and the number of fracture openings in the process of pressure channeling, first establish artificial fractures and natural fractures based on EDFM to characterize single wells. For matrix and micro-fractures in shale gas reservoirs, Multiple interacting continua model is used to characterize the unsteady crossflow between them. For hydraulic fractures formed by artificial fracturing, EDFM is used to explicitly characterize them. The explicit large fracture is directly embedded into the equivalent micro-fracture grid, and the large fracture elements are divided by the intersection point between the large fracture and the grid boundary. By constructing the quasi-steady crossflow between each large fracture element and the corresponding micro-fracture grid, the flow field coupling is realized.

2) The gas reservoir numerical model is then used to perform automatic history matching on the historical production data before frac hits based on the dimensionality.

![Figure 3: Probability-based productivity prediction process for frac hits affected wells.](image)
reduction and ensemble smoother algorithm which is introduced in Section 2.2. Then, we can obtain the conductivity of the fracture network before frac hits, the permeability of the reformed area, the bottom hole flowing pressure, and the number of fracture openings.

3) The probability distribution function is used to quantify the uncertainty of these random variables with a certain range of values. The theoretical distribution model has specific functional expressions, including uniform distribution, triangular distribution, normal distribution, lognormal distribution, and so on. When the parameters can only obtain a range of values and are uniformly distributed in this range, the uniform distribution model is usually satisfied. When parameters have not only range values, but also most probable values, they can be described by triangular distribution. Normal distribution and lognormal distribution are common in the field of oil and gas reserves estimation, which are usually used to describe reservoir area, thickness, porosity, saturation, and other parameters. In this work, the conductivity of the fracture network, the permeability of the reformed area, the bottom hole flow pressure, and the number of fractures opened are quantified using a triangular distribution function, and the permeability of the reservoir outside the reformed area is quantified using a normal distribution function.

4) In the end, based on the quantization function of the uncertainty parameter after frac hits, Monte Carlo simulation is used to extract the probability distribution of the uncertainty parameter in the single well production decline model, and bring it into the model for calculation. After completing multiple iterations, the predicted probability distribution of the final recoverable reserves is obtained, the probability values of P10, P50, and P90 are read from it, and the result of P50 is taken as the final recoverable reserves of the current single well (Figure 3).

4 Application analysis of example wells

In the Weiyuan shale gas development block, after 212 days of production in Well W5, it was disturbed by the frac hits during the fracturing process of the adjacent well, which caused the daily gas production to drop.

Figure 4: Production curve of Well W5.

Figure 5: Pressure distribution before frac hits.
rapidly to zero (Figure 4). Before the gas well resumes production, its single well productivity needs to be recalculated. For this reason, the method proposed in this paper is used to predict the dynamic reserves of this well.

4.1 Establishment and matching of gas reservoir numerical model

A regional gas reservoir numerical simulation model of Well W5 was created using the embedded discrete model modeling technique, and a geological model was developed utilizing geologically related knowledge results (Figure 5). The model covers the area where Well W5 is located in the lateral direction of 3,000 m × 800 m, the length of the coarse grid is 50 m × 50 m in the X and Y directions, and the average thickness in the longitudinal direction is 45 m. It is divided into seven layers according to the thickness of small layers. Under the given production conditions of gas production, the changes in geological engineering parameters of 215 days of well-opening production are simulated. Through the multiphase flow theory in the

Figure 6: Matching curve of bottom hole pressure.

Figure 7: The error distribution of the objective function of automatic history matching.

Figure 8: Probability method capacity prediction results.
Figure 9: Calculation results of three empirical production decline models. (a) Duong method predicted results. (b) YM-SPED method predicted results. (c) WK method predicted results.
wellbore, after converting the historical production data of casing pressure into bottom hole pressure, the automatic history matching technology of gas numerical reservoir simulation is used to fit the production data and simulated data of bottom hole pressure (Figure 6). The parameters set during the matching process include fracturing fracture conductivity, matrix permeability, phase permeability curve, stress sensitivity curve, and other parameters, a total of 368 parameters. Set the number of iterations to 2, the set size to 100, and the total number of simulations is 200. After automatic history fitting, the error between the numerical model bottom hole pressure simulation data and the historical data gradually decreases, and finally reaches a stable state (Figure 7).

After the gas reservoir numerical model is matched with the production data history, the relevant parameters are processed, and the fracture conductivity coefficient of the region near Well W5 before the occurrence of fracturing is 6.25 D*cm, the average equivalent permeability of the reformed zone is 0.0058 mD and the regional. The average permeability of the reservoir is 0.00023 mD. The bottom hole flowing pressure, fracture network conductivity coefficient, the permeability of the reformed area, and the number of fracture openings are brought into the triangular distribution function, and the permeability of the peripheral reservoir of the reformed area is brought into the normal distribution function. Based on the production data before frac hits, using the Monte Carlo simulation random sampling method and substituting the production decline model for 5,000 times, the probability distribution of the final recoverable reserves of Well W5 is obtained, and the final recoverable reserves of P50 are predicted to be 134 million cubic meters (Figure 8). Well W5 resumed production after 71 days of frac hit, and part of the production was restored. As a verification method, after resuming production for a period of time, using the Duong method \( (a = 6.2649, m = 1.4695) \), YM-SPED method \( (n = 0.2634, T = 1.4221) \), and WK method \( (\lambda = 0.0872) \) of the empirical production decline method, the single well EUR is calculated to be 141 million cubic meters, 133 million cubic meters, and 139.5 million cubic meters, respectively (Figure 9). The results are consistent with this article. The error of the prediction results of the method is 4.96, 0.75, and 3.94%, respectively. The accuracy of the prediction of this method has been well verified.

5 Conclusion

1) This article offers a method based on the probability method to quickly predict the production capacity, and the result is similar to the calculation result of the empirical production decline method after the resumption of production. The method is intended to address the issue of inaccurate calculation of the final recoverable reserves in a specific time after the frac hits. And to make sure the method is accurate.

2) The embedded discrete fracture modeling and the dual-medium characterization approach are used to assure the accuracy of the initial parameters of the geological engineering in the proxy model parameter processing of the probabilistic method.

3) The automatic history matching technology of the gas reservoir numerical model enhances the efficiency of the procedure during application and has the ability to swiftly determine the final recoverable reserves of the frac impacts impacted wells.

4) In this work, the basic data used to predict shale gas productivity by probability method is from the numerical simulation results of shale gas reservoir. Because it is difficult to predict the fracture propagation and distribution after hydraulic fracturing, the prediction results in this study cannot be completely conform to the actual situation.

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