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Dynamic Productivity Prediction Method of Shale Condensate Gas Reservoir Based on Convolution Equation

Ping Wang [1,*], Wenchao Liu [2,*], Wensong Huang [1], Chengcheng Qiao [2], Yuepeng Jia [1] and Chen Liu [2]

[1] PetroChina Research Institute of Petroleum Exploration and Development, Beijing 100083, China
[2] School of Civil and Resource Engineering, University of Science and Technology Beijing, Beijing 100083, China
* Correspondence: wp2011@petrochina.com.cn (P.W.); wcliu_2008@126.com (W.L.)

Abstract: The dynamic productivity prediction of shale condensate gas reservoirs is of great significance to the optimization of stimulation measures. Therefore, in this study, a dynamic productivity prediction method for shale condensate gas reservoirs based on a convolution equation is proposed. The method has been used to predict the dynamic production of 10 multi-stage fractured horizontal wells in the Duvernay shale condensate gas reservoir. The results show that flow-rate deconvolution algorithms can greatly improve the fitting effect of the Blasingame production decline curve when applied to the analysis of unstable production of shale gas condensate reservoirs. Compared with the production decline analysis method in commercial software HIS Harmony RTA, the productivity prediction method based on a convolution equation of shale condensate gas reservoirs has better fitting affect and higher accuracy of recoverable reserves prediction. Compared with the actual production, the error of production predicted by the convolution equation is generally within 10%. This means it is a fast and accurate method. This study enriches the productivity prediction methods of shale condensate gas reservoirs and has important practical significance for the productivity prediction and stimulation optimization of shale condensate gas reservoirs.

Keywords: shale condensate gas reservoirs; multi-stage fractured horizontal wells; flow-rate deconvolution; Blasingame production decline typical curve; productivity prediction

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1. Introduction

Despite the strong trend of zero carbon, the world still needs a lot of fossil fuels [1]. Compared with traditional fossil energy, natural gas produces less carbon dioxide when releasing the same calorific value. The shale gas reservoir is an unconventional reservoir, which has self-generation, self-storage, and a large area of continuous accumulation [2]. Global shale gas resources are abundant, and with continuous exploration and development, the amount of resources is increasing. At present, the global resource of shale gas is 4.57×10^{14} m^3 which is equivalent to conventional natural gas resources, and is mainly distributed in North America, Central Asia, China, Latin America, the Middle East, North Africa, and the former Soviet Union [3]. With the progress of exploration technology, the exploration and development of shale condensate gas reservoirs have gradually become a hot research topic. As an important growth point of condensate oil reserves, the global technology's recoverable resources of shale oil are 738×10^8 t, and the recoverable resources of associated condensate oil is predicted to be $(140\sim192) \times 10^8$ t. It can be seen that the condensate oil formed by condensation of shale condensate gas reservoirs contributes greatly to global oil and gas resources [4]. Increasing the proportion of shale condensate gas in energy consumption can effectively reduce carbon emissions. Although shale condensate gas reservoirs are abundant, the overall pore structure scale of shale reservoirs is extremely low, and effective shale gas seepage channels within micro-scale pore throats are difficult to be formed. Then, ultra-low porosity and permeability are exhibited [2]. Therefore, the reservoir is stimulated in order to achieve economic exploitation of shale gas through

horizontal wells and volume fracturing technology [5]. With research in recent years, the multi-stage fractured horizontal well technology has been greatly improved and has been widely applied. The production of shale gas is effectively improved. Production of shale gas reservoirs is the core index to evaluate the development effect of shale gas reservoirs. How to predict it accurately and efficiently is a hot and key issue in shale gas development.

At present, there are four main methods for predicting the production of shale gas reservoirs. The first is the empirical method, including the Arps production decline analysis method [6], power exponential decline model [7], extended exponential decline (SEPD) model [8], Duong decline model [9], and universal exponential decline model [10]. The empirical method has the advantages of simple and convenient calculation. However, the empirical method lacks theoretical basis and is greatly affected by some factors such as geographical location, basic geological conditions of gas reservoirs, mining schemes, mining tools, and on-site operators. Therefore, the empirical method has obvious limitations. Not only that, but the empirical model also has the defect of limited applicable conditions. It must be ensured that the production data meet the conditions of the model before using the empirical method to predict the productivity of shale gas reservoirs. The second is a method for predicting the productivity of shale gas reservoirs based on artificial intelligence. In 2017, Zhu et al. established a neural network that predicts shale gas production with better accuracy and stability than traditional BP neural networks [11]. In 2021, according to hydraulic fracturing data, production data, and evaluation of final recoverable reserves (EUR) of 282 wells in WY shale gas reservoirs, an EUR evaluation algorithm for shale gas wells based on deep learning has been obtained by Liu et al. [12]. In 2022, Song et al. has established a model for the productivity prediction of shale gas reservoirs, which combines the BP neural network and genetic algorithm [13]. The productivity after horizontal wells fracturing has been predicted by forward and reverse training and parameter correction by error identification. In 2022, a hyper-parameters optimized long short-term memory (LSTM) network to effectively forecast daily gas production has been proposed by Qiu et al. [14]. The production data analysis method based on artificial intelligence is adopted to improve the reliability of prediction results. However, its interpretability is poor, and it cannot explain which factor was the main influencing factor. In addition, some learning samples are needed. Numerical modeling is also often used to explain engineering problems [15]. Considering the influence of shale gas adsorption and desorption, Wei et al. has obtained the Blasingame typical curve of shale gas reservoirs by the numerical method [16]. The study expands the understanding of shale gas flow characteristics and can be used for reserves prediction. Considering the multi-scale flow characteristics of shale gas, a 3D numerical model for the seepage of shale gas has been established discretely using the finite volume method, and the production performance of multi-stage fractured horizontal wells in shale gas reservoirs have been simulated by Chen et al. [17]. Zhang et al. have established a continuum-discrete fracture network coupling model considering the multi-scale seepage mechanism of shale, and have used the controlled volume finite element method and unstructured triangular prism grid for numerical solution. The numerical simulation model has successfully been applied to comprehensive and field examples [18]. Although numerical simulation can directly represent shale gas seepage characteristics, it also has high accuracy for productivity prediction. However, the mathematical modeling, grid division, and numerical solution of shale reservoirs after hydraulic fracturing are relatively difficult. The fourth is the typical curve analysis method. In 2020, considering the adsorption/desorption, diffusion, threshold pressure gradient, and stress sensitivity of gas flow in shale, Wang et al. have established a five-linear seepage mathematical model for multi-stage fractured horizontal wells in shale gas reservoirs. Then, the flow regime is divided by using the typical curve, which provides a scientific basis for single well productivity prediction [19]. Jiang et al. have established a matrix fracture fluid flow model considering the stress-sensitive effect, and have obtained the Blasingame typical curve to predict the productivity of multi-stage fractured horizontal wells in tight reservoirs [20]. The typical curve analysis method is widely used in engineering, but the use of the model

is closely related to the mining stage, as the choice of the model has higher requirements. In summary, the methods for the productivity analysis of shale gas reservoirs have some defects. Not only that, but most methods for productivity prediction are aimed at shale dry gas, but now shale condensate gas also has great development value. At present, the productivity prediction methods of shale condensate gas reservoirs based on characteristic curve analysis are relatively few.

The special seepage mechanism and complex development methods for shale condensate gas reservoirs lead to serious fluctuations in production data. In addition, the special seepage law and production mechanism of shale condensate gas reservoirs lead to the pressure data and production data measured on site, which are constantly changing with time. However, the internal boundary conditions of the mathematical model used for production data analysis are generally constant pressure (or constant flow-rate) conditions. Shut-in is usually used to solve the problem that production data do not match the theoretical mathematical model in conventional oil and gas reservoirs. However, for shale gas development, the production of shale gas wells will be greatly affected by shut-in and economic losses will be caused. Therefore, when analyzing the production data of shale gas reservoirs, the normalization method is often used to process the production data. The traditional normalization method extracts equivalent discrete flow-rate data corresponding to constant pressure from variable pressure production by introducing material balance time or converting the flow rate corresponding to variable pressure into the flow-rate corresponding to constant pressure by the pressure normalized rate (PNR) and superposition time combination method [21]. However, for the production data of shale gas with rapid changes, the production data processed by the traditional normalization method still has the defects of scattered distribution of characteristic data points and poor smoothness, which leads to great uncertainty in data fitting. The smooth characteristic data curve generated after processing production data by deconvolution algorithm can improve the fitting effect of data, reduce the uncertainty of interpretation results, and eliminate the influence of data errors. A series of progress on deconvolution has been made. In 2007, using the cumulative flow-rate data and the second-order B-spline function weight sum, the flow rate corresponding to unit pressure difference has been reconstructed by ILK et al. [22]. However, the accuracy of the algorithm is not high, and the error in the initial stage and the final stage is large. In 2016, the von Schroeter deconvolution model [23] has been improved by Wang et al. [24]. The formation flow rate is converted with the surface flow rate and the wellbore flow rate so that the wellbore storage effect can be removed by the transient pressure response after deconvolution. However, there are also defects of low accuracy. In 2018, inspired by the ILK deconvolution algorithm with high calculation accuracy, the flow rate data are used to replace the cumulative flow rate data of the original algorithm for the deconvolution calculation by Liu et al. [25]. A fast solution method has been presented, which greatly improves the computational efficiency and accuracy, and significantly improves the fitting effect of data.

In order to evaluate the shale gas and condensate oil productivity of multi-stage fractured horizontal wells in shale condensate gas reservoirs, this study proposes a set of typical curve analysis processes for dynamic production data. Firstly, a trilinear seepage mathematical model for multi-stage fractured horizontal wells is introduced in this work. The linearization of mathematical model and Laplace transformation have been used to obtain the flow rate solution of the model corresponding to per unit pseudo bottom hole flowing pressure drop. Secondly, a calculation method is used to convert condensate oil into equivalent gas. The condensate oil and gas two-phase production data of shale condensate gas reservoir are converted into equivalent gas production data. The pressure data is calculated as pseudo pressure data to realize the linearization of production data. On this basis, the improved flow-rate deconvolution algorithm [25] is introduced to normalize the production data. Then, the normalized dynamic production data and the Blasingame production decline typical curve are fitted with the flow rate solution corresponding to per unit pseudo bottom hole flowing pressure drop, and some of the reservoir and fracture

parameters are explained. Finally, according to the explained parameters and the flow-rate solution corresponding to variable pseudo bottom hole flowing pressure calculated by the seepage mathematical model, the shale gas and condensate oil predicted recoverable reserves results of multi-stage fractured horizontal wells in shale condensate gas reservoirs are obtained. It has important reference value for studying the main controlling factors of the productivity of shale condensate gas reservoirs and optimizing production systems.

2. Dynamic Productivity Prediction Method of Shale Condensate Gas Reservoir Based on Convolution Equation

2.1. Seepage Model of Multi-Stage Fractured Horizontal Well in Shale Condensate Gas Reservoir

After the hydraulic fracturing of shale condensate gas wells, a very complex fracture network will be formed in shale reservoirs. According to Brown et al. [26], it is a very effective way of simplification to deal with the complex fracture network of the stimulated reservoir volume (SRV) of the fractured zone. After staged fracturing of shale condensate gas reservoirs, the reservoir will show obvious linear flow, which can last for one year or even several years. Therefore, the mining process of shale condensate gas reservoirs is simplified as a trilinear flow from the main fracture flow zone to the wellbore, from the inter-fracture flow zone to the main fracture flow zone, and from the reservoir flow zone to the inter-fracture flow zone. The established trilinear seepage physical model is shown in Figure 1. It is considered that all the main fractures are of equal length and equal spacing distribution. Without considering the flow in the horizontal well, the horizontal well is considered to be infinitely conductive; the confinement effect of micro-nano pores in shale reservoirs is not considered [27].

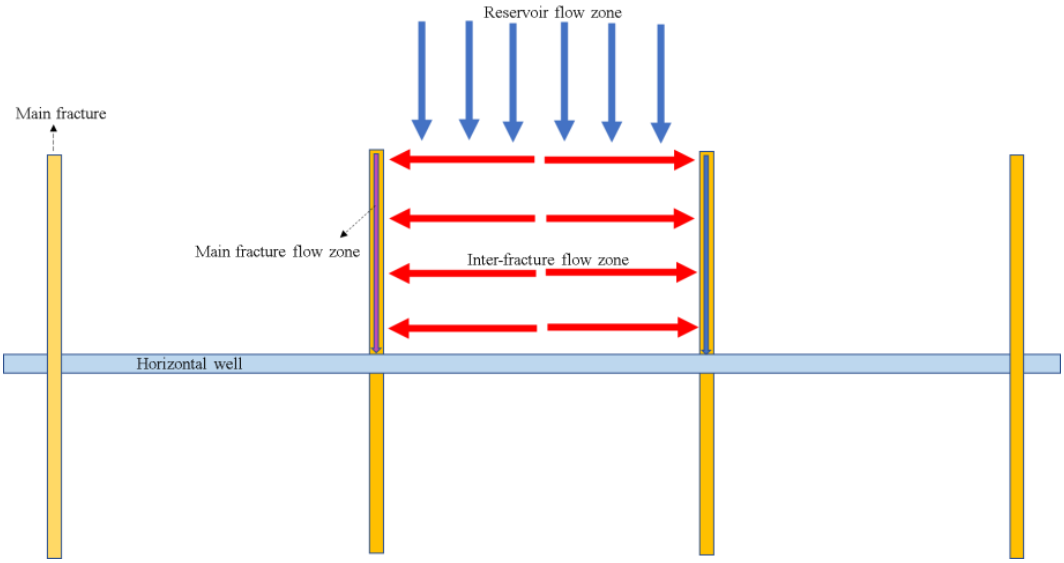


Figure 1. Trilinear seepage physical model of staged fracturing horizontal wells in shale condensate gas reservoirs.

Based on the trilinear seepage physical model of multi-stage fractured horizontal wells in shale condensate gas reservoirs, the unsteady seepage mathematical models of reservoir flow zone, inter-fracture flow zone, and main fracture flow zone are established as follows.

For the linear flow area of the reservoir [26], the linearized seepage mathematical model is as follows:

$$\frac{\partial^2 m_O}{\partial x^2} = \frac{1}{\eta_O}\frac{\partial m_O}{\partial t} \tag{1}$$

$$m_O|_{t=0} = m_i \tag{2}$$

$$\left.\frac{\partial m_{\mathrm{O}}}{\partial x}\right|_{x=x_{\mathrm{e}}}=0 \tag{3}$$

$$m_{\mathrm{O}}|_{x=x_{\mathrm{F}}}=m_{\mathrm{I}}|_{x=x_{\mathrm{F}}} \tag{4}$$

where, the subscript O represents the reservoir flow area; subscript I represents the flow area between main fractures; the subscript i represents in the initial state; η_{O} is the diffusion coefficient of the matrix area, cm^2/s, defined as Equation (5); x is the distance from the horizontal wellbore, cm; x_{e} is the size of the reservoir in the x direction, cm; x_{F} is the fracture half length, cm; t is time, s; m represents the pseudo pressure, $\mathrm{atm}^2/\mathrm{cp}$, defined as Equation (6):

$$\eta_{\mathrm{O}}=\frac{K_{\mathrm{O}}}{\phi_{\mathrm{O}}\left(\frac{1}{P_{\mathrm{O}}}-\frac{1}{Z}\frac{\partial Z}{\partial P_{\mathrm{O}}}\right)\mu} \tag{5}$$

$$m=2\int_0^p\frac{P}{\mu Z}dP \tag{6}$$

where, K is the permeability, D; ϕ is the porosity; P represents the pressure, atm; p represents the real production pressure, atm; μ is the viscosity of shale gas, cp; Z is the compression factor of shale gas, dimensionless.

It can be seen from Equation (5) that the diffusion coefficient is a variable related to pressure. It has strong nonlinearity. In order to make the model suitable for the deconvolution algorithm, the diffusion coefficient of this study is averaged and considered to be approximately constant.

For the linear flow area between main fractures [26], the linearized seepage mathematical model is as follows:

$$\frac{\partial^2 m_{\mathrm{I}}}{\partial y^2}+\frac{K_{\mathrm{O}}}{K_{\mathrm{I}}x_{\mathrm{F}}}\left.\frac{\partial m_{\mathrm{O}}}{\partial x}\right|_{x=x_{\mathrm{F}}}=\frac{1}{\eta_{\mathrm{I}}}\frac{\partial m_{\mathrm{I}}}{\partial t} \tag{7}$$

$$m_{\mathrm{I}}|_{t=0}=m_{\mathrm{i}} \tag{8}$$

$$\left.\frac{\partial m_{\mathrm{I}}}{\partial y}\right|_{y=\frac{d_{\mathrm{F}}}{2}}=0 \tag{9}$$

$$m_{\mathrm{I}}|_{y=\frac{w_{\mathrm{F}}}{2}}=m_{\mathrm{F}}|_{y=\frac{w_{\mathrm{F}}}{2}} \tag{10}$$

where, subscript F represents the flow area of main fracture; y represents the distance in the y direction, cm; η_{I} is the diffusion coefficient of the flow area between main fractures, cm^2/s, defined as Equation (11); w_{F} is the width of hydraulic fracture, cm; d_{F} is the distance between two adjacent main fractures, cm.

$$\eta_{\mathrm{I}}=\frac{K_{\mathrm{I}}}{\phi_{\mathrm{I}}\left(\frac{1}{P_{\mathrm{I}}}-\frac{1}{Z}\frac{\partial Z}{\partial P_{\mathrm{I}}}\right)\mu} \tag{11}$$

For the linear flow area of main fracture [26], the linearized seepage mathematical model is as follows:

$$\frac{\partial^2 m_{\mathrm{F}}}{\partial x^2}+\frac{2K_{\mathrm{I}}}{K_{\mathrm{F}}w_{\mathrm{F}}}\left.\frac{\partial m_{\mathrm{I}}}{\partial y}\right|_{y=\frac{w_{\mathrm{F}}}{2}}=\frac{1}{\eta_{\mathrm{F}}}\frac{\partial m_{\mathrm{F}}}{\partial t} \tag{12}$$

$$m_{\mathrm{F}}|_{t=0}=m_{\mathrm{i}} \tag{13}$$

$$\left.\frac{\partial m_{\mathrm{F}}}{\partial x}\right|_{x=x_{\mathrm{F}}}=0 \tag{14}$$

$$\left.\frac{\partial m_{\mathrm{F}}}{\partial x}\right|_{x=0}=\frac{q_{\mathrm{F}}P_{\mathrm{sc}}T}{k_{\mathrm{F}}w_{\mathrm{F}}hT_{\mathrm{sc}}} \tag{15}$$

where, η_F is the diffusion coefficient of hydraulic fracture, cm^2/s, defined as Equation (16); h represents the reservoir thickness, cm; T_{sc} is the temperature under standard conditions, K; P_{sc} is the pressure under standard conditions, atm; q_F is the flow in the fracture, cm^3/s.

$$\eta_F = \frac{K_F}{\phi_F\left(\frac{1}{P_F} - \frac{1}{Z}\frac{\partial Z}{\partial P_F}\right)\mu} \tag{16}$$

The linearized mathematical model of the three linear flow area can be solved by Laplace space [26], and then the flow-rate solution corresponding to the production condition of constant pressure in Laplace space can be obtained as follows:

$$\widetilde{q} = \frac{1 + Cs^2\widetilde{m}_w}{\widetilde{m}_w} \cdot \frac{1}{s^2} \cdot m_{w,const} \tag{17}$$

where, ~ represents the corresponding variable in Laplace space; q is the flow-rate corresponding to constant pressure production condition, cm^3/s; m_w is the pseudo bottom hole pressure solution corresponding to the constant production rate, atm^2/cp which is equal to m_F at $x = 0$; C is wellbore storage coefficient, cm^3/atm; s is the Laplace transform parameter; $m_{w,const}$ is the pseudo bottom hole flowing pressure corresponding to constant production pressure, atm^2/cp.

2.2. Consider the Production of Condensate Oil in Model Solution

The mathematical model of multi-stage fractured horizontal wells in shale condensate gas reservoir established in Section 2.1 is based on single-phase flow with only shale gas flow. However, in actual production, with the formation pressure of shale condensate gas reservoirs gradually lower than the dew point pressure, condensate will be precipitated near the wellbore [28]. When the formation pressure is lower than the critical flow pressure, the precipitated condensate oil forms a continuous phase, and then forms a seepage state of oil and gas two-phase flow. Therefore, shale gas and condensate oil will be produced simultaneously in real conditions. This paper uses a gas equivalent conversion method [29]. The production of shale condensate is equivalently converted to the production of shale gas so that only single-phase gas production data analysis is required. The conversion method of gas equivalent is as follows.

It is assumed that the relative density of the condensate oil is γ_o and the molecular weight is M_o; assuming that the volume of 1 cm^3 condensate oil in the standard state (p = 0.101 MPa, T = 293 K) before liquefaction is V (cm^3); since the weight of 1 cm^3 condensate oil is γ_o g, then:

$$n = \frac{\gamma_o}{M_o}(g \cdot mol) \tag{18}$$

$$V = \frac{nZRT}{p} = \frac{\gamma_o}{M_o} \times \frac{1 \times 8.314 \times 10^{-6} \times 293}{0.101} = 0.0241\frac{\gamma_o}{M_o}\left(cm^3\right) \tag{19}$$

where, n is the mole number of gas, g·mol. That is to say: before the liquefaction of 1 cm^3 condensate oil with a relative density of γ_o and molecular weight of M_o, the volume of condensate oil in standard state is shown in Equation (20), which is the conversion coefficient of converting condensate oil volume into shale gas volume in standard state. Therefore, if the condensate oil production of the gas well is q_o cm^3/s, the converted gas production is as follows:

$$q_{GE} = 0.0241\frac{\gamma_o}{M_o} \cdot q_o\left(cm^3/s\right) \tag{20}$$

If only the relative density of condensate oil is known, and the molecular weight of condensate oil is unknown, the Gragoe equation [29] can be used to replace M_o:

$$M_o = \frac{44.29\gamma_o}{1.03 - \gamma_o} \tag{21}$$

Substituting Equation (21) into Equation (20), we can obtain that:

$$q_{GE} = 5.367 \times 10^{-4}(1.03 - \gamma_o) \cdot q_o \tag{22}$$

The total gas production equivalent is as follows:

$$q_{total} = 5.367 \times 10^{-4}(1.03 - \gamma_o) \cdot q_o + q_g \tag{23}$$

where, q_{total} is the total gas production equivalent, cm^3/s; q_g is the production of shale gas, cm^3/s.

2.3. Flow-Rate Deconvolution

In order to solve the problem that the dynamic production data of shale condensate gas reservoirs do not match the internal boundary conditions of the mathematical model of the productivity prediction theory, and to solve the defect that the traditional normalization method of production data is not suitable for the production data with sharp changes in shale gas reservoirs, an improved ILK flow rate deconvolution algorithm [25] is introduced in this study. Based on Duhamel's principle, the algorithm converts the flow rate data corresponding to variable bottom hole pressure drop into the flow rate corresponding to per unit bottom hole pressure drop by Equation (24):

$$q(t) = \int_0^t \Delta p(t - \tau) \cdot q'_u(\tau) d\tau \tag{24}$$

The implementation process of the improved ILK flow rate deconvolution algorithm is as follows: first, based on Equation (24), the second-order B-spline function weight and the flow-rate derivative corresponding to unit pressure drop are used to reconstruct. Then, using the mathematical properties of the convolution integral, the sensitivity matrix in the deconvolution calculation process is solved analytically and quickly by using the technique of piecewise integral according to the pressure drop segment. Then the dichotomy method is used to quickly find the pressure drop segment of each group of flow rate data points to further improve the computational efficiency.

The integral derivative of regularized production in unsteady seepage segments will be affected by the error of dynamic production data of shale condensate gas reservoirs, and the data fluctuating is caused. The direct use of original flow rate data will result in the poor effect of typical curve fitting, and the error of the parameters of the reservoir and fracture obtained by inversion is large. The flow rate data corresponding to variable bottom hole pressure drop can be transformed into the flow rate data corresponding to unit bottom hole pressure drop by using the improved ILK flow rate deconvolution algorithm, so as to match the inner boundary conditions of the theoretical seepage model, and the processed flow-rate data is smoother, which conforms to the law of flow rate decline corresponding to unit bottom hole pressure drop. Therefore, the effect of the Blasingame production decline typical curve [30] fitting is better; the inverted reservoir and fracture parameters are more accurate and the accuracy of productivity prediction is improved. In addition, when using the improved ILK flow-rate deconvolution algorithm to normalize the dynamic production data, the long-time shut-in operation of the traditional production data normalization method can be avoided; the impact of the shut-in test on shale gas production is avoided and the economic losses are reduced. Moreover, the improved ILK flow rate deconvolution algorithm has fast calculation speed and high stability, and a large number of field data can be processed quickly and accurately.

Although the improved flow rate deconvolution algorithm has the above advantages, there are some limitations in the calculation of flow rate deconvolution: first, the flow rate deconvolution algorithm can only be used in linear problems or linearization problems (such as single-phase flow, Darcy flow, material balance, etc.) and must be applied to the Duhamel's principle. Second, it must be ensured that the interpretation model does not change from beginning to end in the process of interpreting the production history data.

2.4. Dynamic Production Data Analysis Method for Shale Condensate Gas Reservoir Based on Flow-Rate Deconvolution

First, the trilinear seepage physical model for shale condensate gas reservoirs and the corresponding mathematical model are established. The unsteady seepage mathematical model is linearized and the flow rate solution corresponding to constant pseudo bottom hole pressure drop is obtained. Second, the production data of shale gas and condensate oil are transformed into the total equivalent gas production data by using Equation (23). The data of bottom hole flowing pressure is transformed into the data of bottom hole pressure by using Equation (6) of the pseudo pressure in the theoretical mathematical model. The method of Lee et al. [31] is used to calculate the viscosity of shale gas. The method of Yarborough and Hall [32] is used to calculate the compressibility factor of shale gas. The linearization of the nonlinear dynamic production data measured in the field is realized. Then, based on Equation (24), based on Duhamel's principle, the improved ILK flow rate deconvolution algorithm is used to convert the flow rate data corresponding to the variable pseudo bottom hole pressure drop into the flow rate data corresponding to the constant pseudo bottom hole pressure drop, and the normalization of production data is realized. Finally, the typical curve fitting of Blasingame production decline is performed on the flow rate solution corresponding to the pseudo bottom hole pressure drop and the normalized dynamic production data. Based on the basic data of reservoir and the construction data of fracturing in the developed analysis program of flow instability, by adjusting the main fracture conductivity, fracture half length, outer boundary distance, matrix permeability, matrix porosity, the matrix comprehensive compression coefficient. and other parameters, the real data points of normalized production, normalized production integral, and normalized production integral derivative are fitted with the data points of the same type of the theoretical model flow rate solution, and some parameters of the fracture and reservoir are explained. The flow chart of the dynamic production data analysis method for shale condensate gas reservoirs based on flow deconvolution is shown in Figure 2:

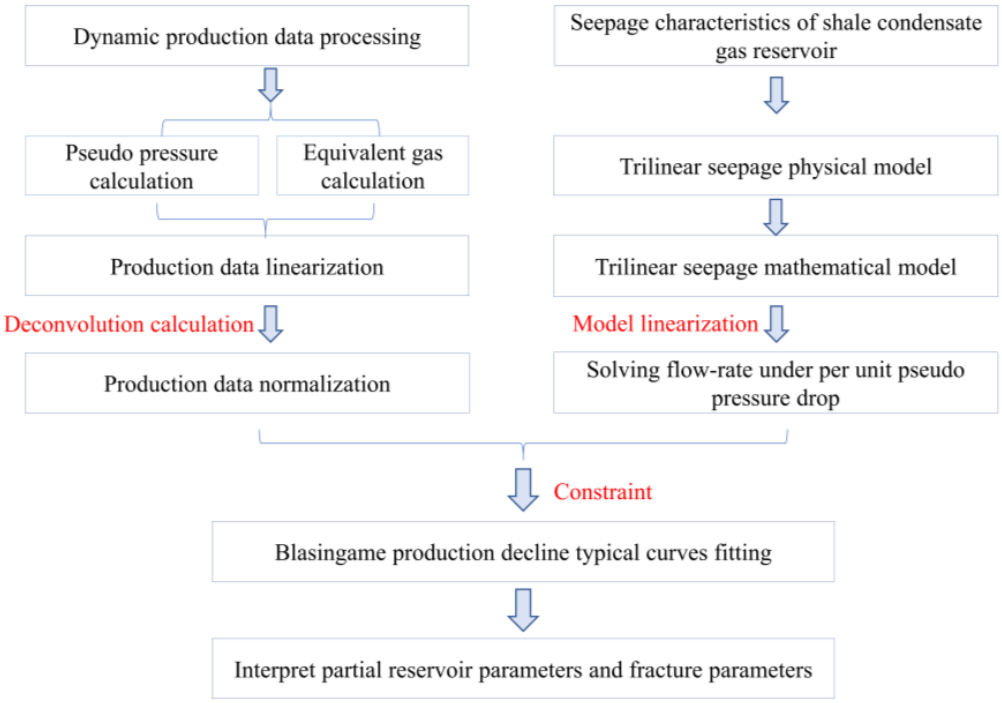


Figure 2. The flow chart of the production dynamic data analysis method for shale condensate gas reservoirs based on flow rate deconvolution.

The typical curve fitting of Blasingame production decline is realized by adjusting the main fracture conductivity, fracture half length, outer boundary distance, matrix permeability, matrix porosity, the matrix comprehensive compression coefficient, and other parameters. In the process, the known data of fracturing construction and the basic data of the reservoir are used as condition constraints, and the normalized parameter debugging of flow rate deconvolution calculation and the model parameter debugging of seepage theory model calculation are mutually restricted in the process of typical curve fitting. Therefore, more reliable parameter results can be analyzed. Not only that, but the analytical method used in the flow rate deconvolution algorithm is used in this dynamic production data analysis method; the calculation speed is faster and a large number of dynamic production data can be processed quickly. In addition, the flow rate deconvolution algorithm is used for normalization to make the typical curve fitting better, and the parameter results analyzed by the dynamic production data are more accurate.

2.5. Proposal of Dynamic Productivity Prediction Method for Shale Condensate Gas Reservoir Based on Convolution Equation

The dynamic productivity prediction method of shale condensate gas reservoirs is of great significance to the evaluation of the fracturing effect of staged fracturing horizontal wells and the analysis of the main control factors of productivity. The basis for the formulation of reasonable development technology policy of shale condensate gas reservoirs and the optimization suggestion of staged fractured horizontal wells can be provided. Therefore, a dynamic productivity prediction method for shale condensate gas reservoirs based on the convolution equation is proposed, and the recoverable reserves of shale gas and condensate oil can be predicted.

The dynamic productivity prediction process of shale condensate gas reservoirs is as follows: first, based on the Duhamel principle, the convolution Equation (24) is used to calculate the flow rate solution corresponding to the pseudo bottom hole flowing pressure obtained in Section 2.1, and the flow rate solution corresponding to variable pseudo bottom hole flowing pressure is obtained. Then, the parameter results of the analysis and inversion of the dynamic production data in Section 2.4 are brought into the flow-rate solution corresponding to the variable pseudo bottom hole flowing pressure, and the total gas equivalent flow rate can be predicted. For the later production stage of horizontal wells, it is set to continue production corresponding to constant pressure, and CGR is approximately a fixed value [33,34]. Therefore, after the predicted total gas production equivalent flow rate is obtained, the recoverable reserves of shale gas and condensate oil of staged fractured horizontal wells in shale condensate gas reservoirs are predicted by using Equations (25) and (26), according to the method of condensate oil converted gas equivalent and condensate oil-gas ratio CGR.

$$q_{\mathrm{g}} = \frac{q_{\mathrm{tot}}}{1 + 5.367 \times 10^{-4} \times (1.03 - \gamma_{\mathrm{o}}) \times \mathrm{CGR}} \tag{25}$$

$$q_{\mathrm{o}} = \mathrm{CGR} \times q_{\mathrm{g}} \tag{26}$$

The flow chart of the dynamic productivity prediction method for shale condensate gas reservoirs based on the convolution equation is shown in Figure 3.

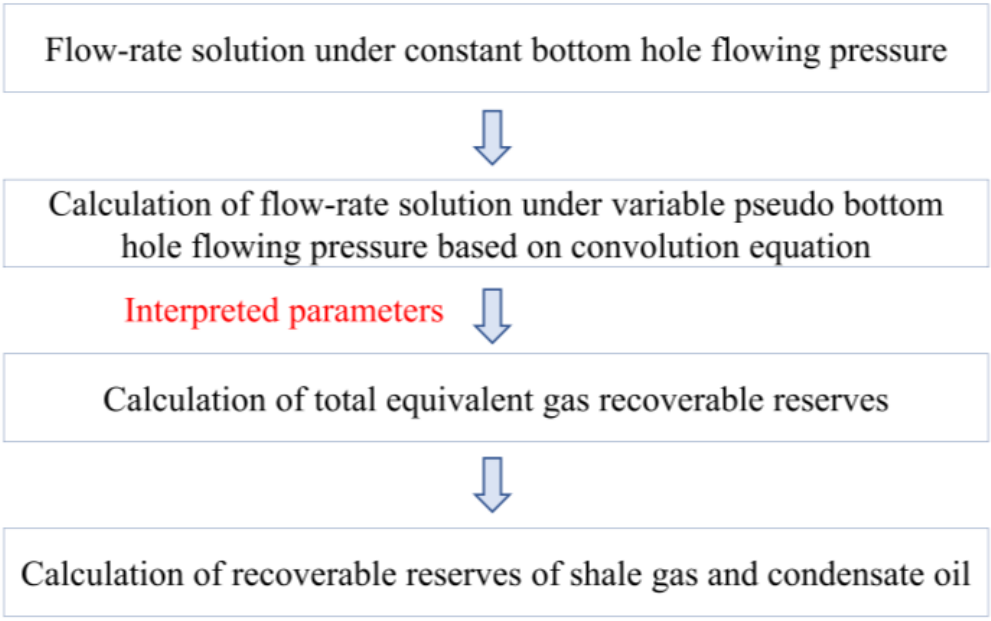


Figure 3. The flow chart of the dynamic productivity prediction method for shale condensate gas reservoirs based on the convolution equation.

3. Practical Application

The horizontal well length of a multi-stage fractured horizontal well in the Duvernay shale reservoir is 1962 m, the wellbore radius is 0.107 m, the number of hydraulically fractured segments is 21, and the distance from the nearest well is about 3700 m. The reservoir where the well is located has a thickness of 41 m and a reservoir temperature of 115 °C. The initial gas reservoir pressure is 62 MPa. The multi-stage fractured horizontal well has been put into production for about 2500 days with a cumulative shale gas production of 36.39 $\times$ 10^6 m^3 and a daily average shale gas production of 13.07 $\times$ 10^3 m^3/d. The cumulative production of condensate oil is 26.91 $\times$ 10^3 m^3, and the average daily production of condensate oil is 9.66 m^3/d. The dynamic monitoring data of daily production of condensate oil and shale gas are shown in Figure 4. The pseudo bottom hole flowing pressure vs. bottom hole flowing pressure curve is shown in Figure 5. The bottom hole flowing pressure and CGR of the well are shown in Figure 6. It can be seen that the relationship between bottom hole flowing pressure and CGR is consistent with that described in Section 2.5. CGR is closely related to the bottom hole flowing pressure. When the bottom hole flowing pressure remains constant, CGR is also approximately a constant value. Therefore, after predicting the recoverable reserves of gas equivalent, the recoverable reserves of condensate oil corresponding to constant pressure can be predicted by using constant CGR. According to Equation (23), the condensate oil production is converted into equivalent gas production, and the shale gas production is added. Then the total cumulative equivalent gas production is calculated to be 40.36 $\times$ 10^6 m^3. The converted daily equivalent gas production data and bottom hole flowing pressure data are shown in Figure 7.

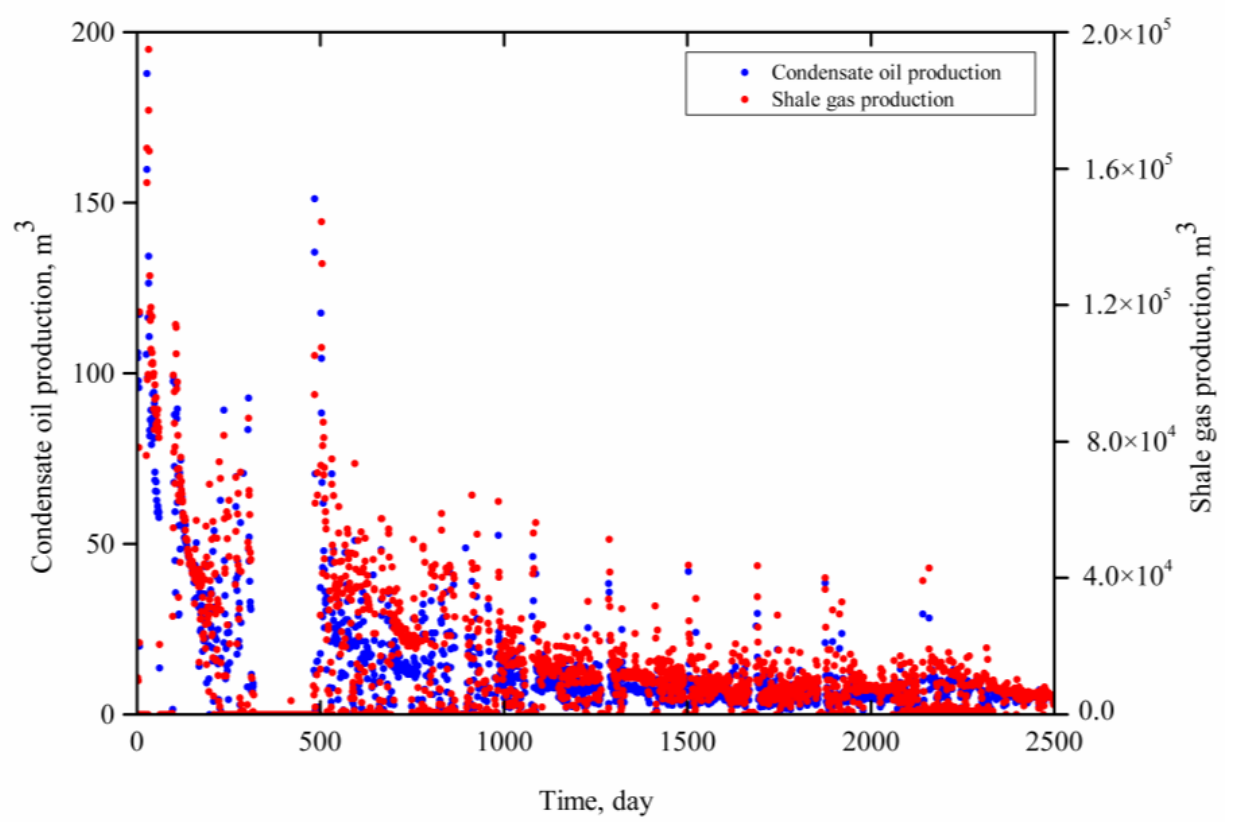


Figure 4. Daily output of condensate oil and shale gas in a multi-stage fractured horizontal well.

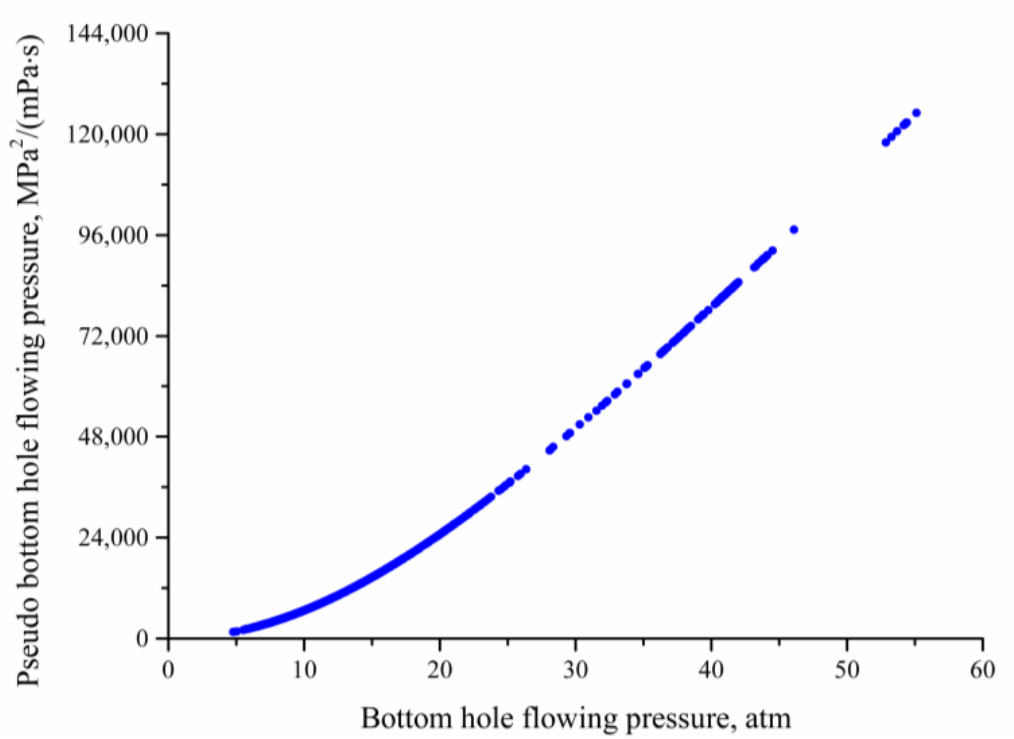


Figure 5. Pseudo bottom hole flowing pressure vs. bottom hole flowing pressure curve.

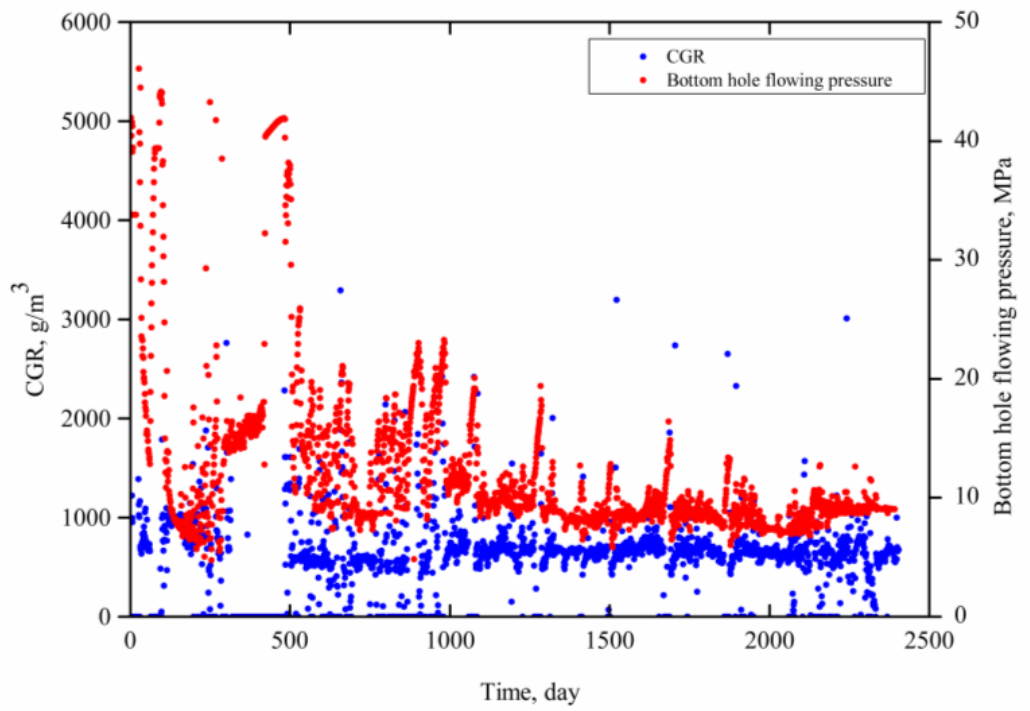


Figure 6. Bottom hole flowing pressure and CGR of the multi-stage fractured horizontal well.

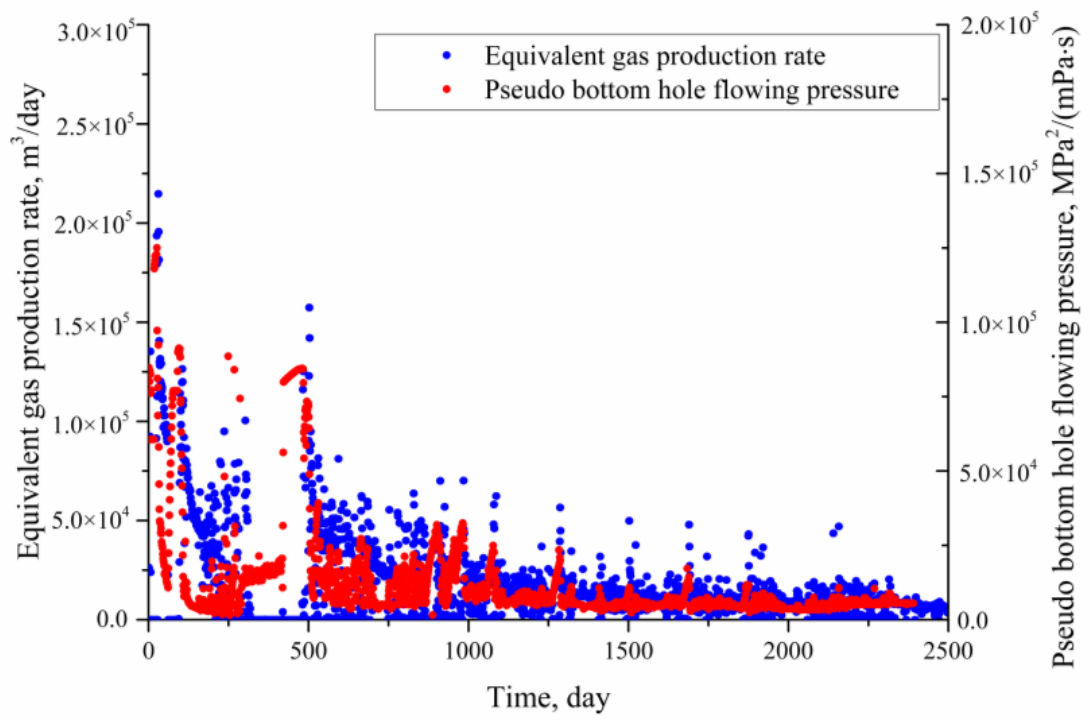


Figure 7. Equivalent gas production rate and pseudo bottom hole flowing pressure of the multi-stage fractured horizontal well.

It can be seen from Figure 7 that the daily production rate data and the bottom hole flowing pressure data are seriously fluctuated, and the data error is large. In addition, the shut-in operation has carried out during the period, and the production data are intermittent. The traditional pressure normalized rate and material balance time combination method is used to normalize the production data, and the obtained Blasingame production decline typical curve is shown in Figure 8. The improved ILK flow-rate deconvolution algorithm [25] is used to normalize the production rate data. Figure 9 shows the production rate data corresponding to unit pseudo bottom hole flowing pressure drop calculated by the deconvolution algorithm. The Blasingame production decline typical curve of the deconvolution algorithm output is shown in Figure 10. It can be seen that the flow rate deconvolution algorithm eliminates the noise of the dynamic production data and the calculated output Blasingame production decline typical curve is smoother. Then, based on the basic reservoir data and fracturing construction data, the normalized dynamic production data is fitted to the Blasingame production decline typical curve of the seepage theoretical model by adjusting the fracture half-length, fracture conductivity, matrix permeability, and other parameters. It is interpreted that the fracture half-length is 45 m, the main fracture conductivity is 16.5 mD·cm, the reservoir matrix permeability is 0.0006 mD, and the reservoir porosity is 0.04. Figure 11a shows the fitting results of the Blasingame production decline typical curve calculated by traditional PNR-MBT method and the ones calculated by the seepage theoretical model. Figure 11b shows the fitting results of the Blasingame production decline typical curve calculated by the flowrate deconvolution algorithm and the ones calculated by the seepage theoretical model. Obviously, the dynamic production data processed by the flowrate deconvolution algorithm is smoother, and the Blasingame production decline typical curve fitting effect is better. The equivalent gas production corresponding to the setting pressure can be obtained by putting the parameters interpreted from the Blasingame production decline typical curve fitting into the flow rate solution corresponding to the variable bottom hole flowing pressure, calculated according to the seepage theoretical model. The pressure setting diagram of the whole production stage is shown in Figure 12. In the later stage of the setting, the constant bottom hole flowing pressure of 9 MPa is used for 30 years of production, and the CGR is 0.6 L/m^3. Figure 13 shows the equivalent gas production calculated by the mathematical model and the real equivalent gas production. It can be seen that the equivalent gas production calculated by the seepage theoretical model and the real equivalent gas production are well fitted. Even in the shut-in stage, the fitting effect is also good, which proves the accuracy of later production prediction. At this time, the output of the late constant pressure production is calculated by the mathematical model, while the output of the early stage is measured by the field data. This further improves the accuracy of predicting equivalent gas recoverable reserves over 30 years of production. After obtaining the predicted equivalent gas recoverable reserves, the predicted recoverable reserves of shale gas and condensate oil can be calculated by using the contents in Section 2.5. The recoverable reserves of equivalent gas are 5.5050×10^7 m^3, the recoverable reserves of shale gas are 4.9679×10^7 m^3, and the recoverable reserves of condensate oil are 3.4794×10^4 m^3.

In addition to the dynamic productivity prediction of single well, the dynamic production prediction method of shale condensate gas reservoirs based on the convolution equation is used to predict the production of 10 multi-stage fractured horizontal wells in the Duvernay area. Moreover, the business software HIS Harmony RTA is used to analyze the production data of these wells by the multi-stage Arps production decline curve, and then the predicted shale gas production and condensate oil production are obtained. The results and errors of the two methods are shown in Table 1.

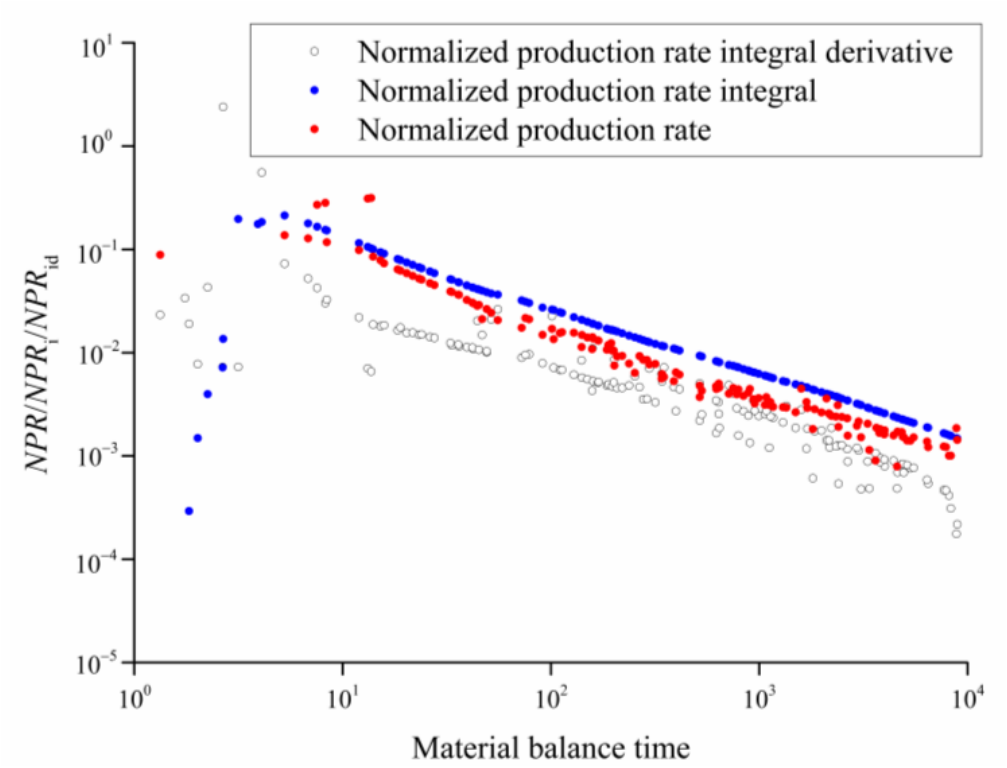


Figure 8. Blasingame production decline typical curve of the single well corresponding to PNR-MBT method.

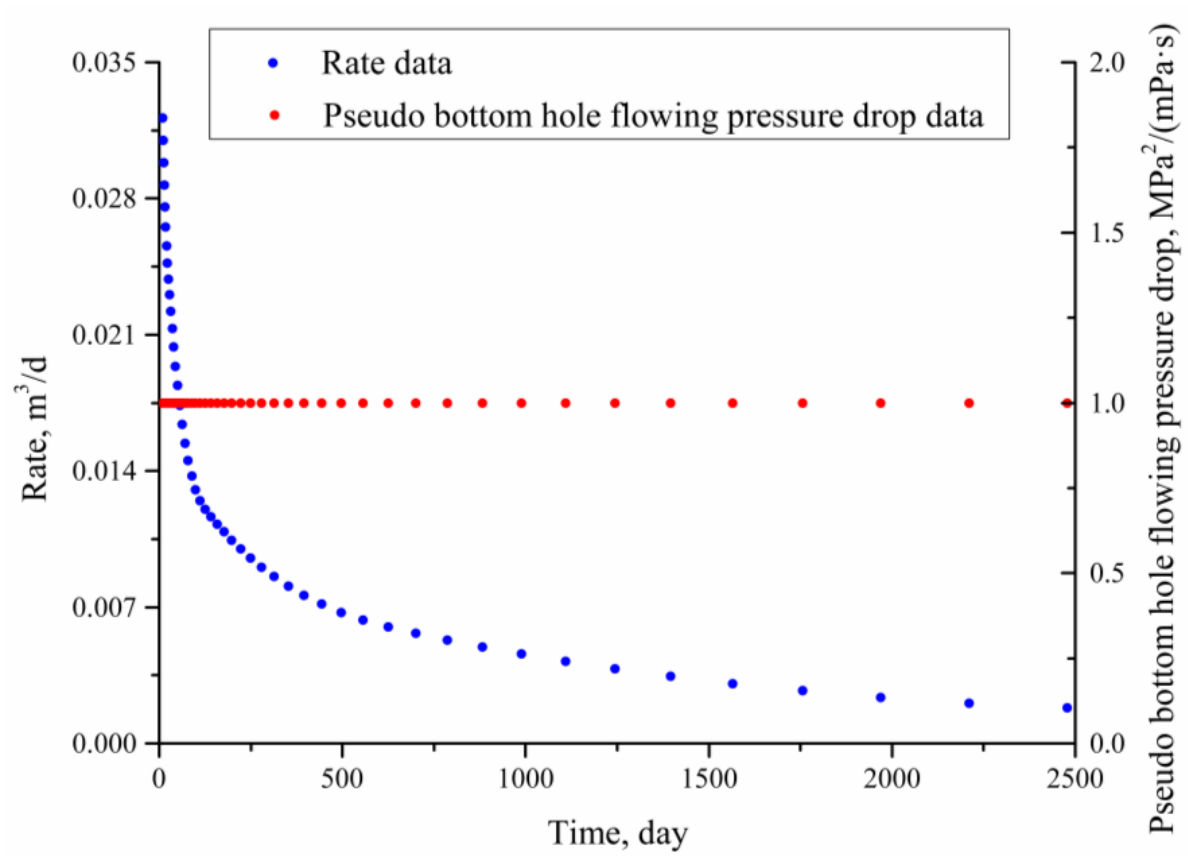


Figure 9. Flow rate data per unit pseudo bottom hole flowing pressure drop.

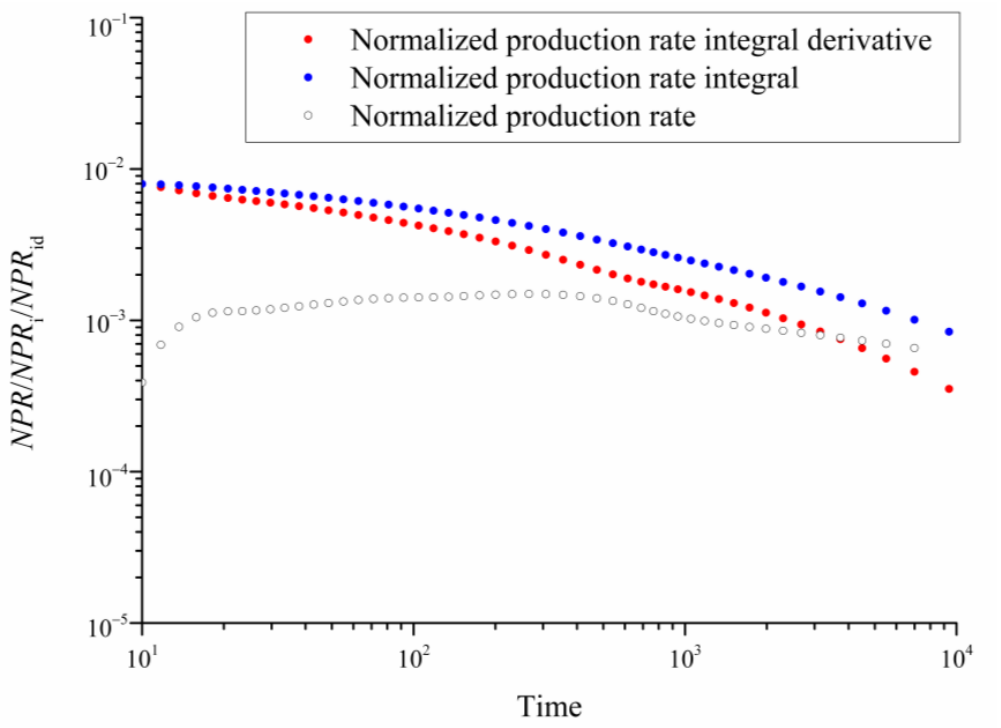
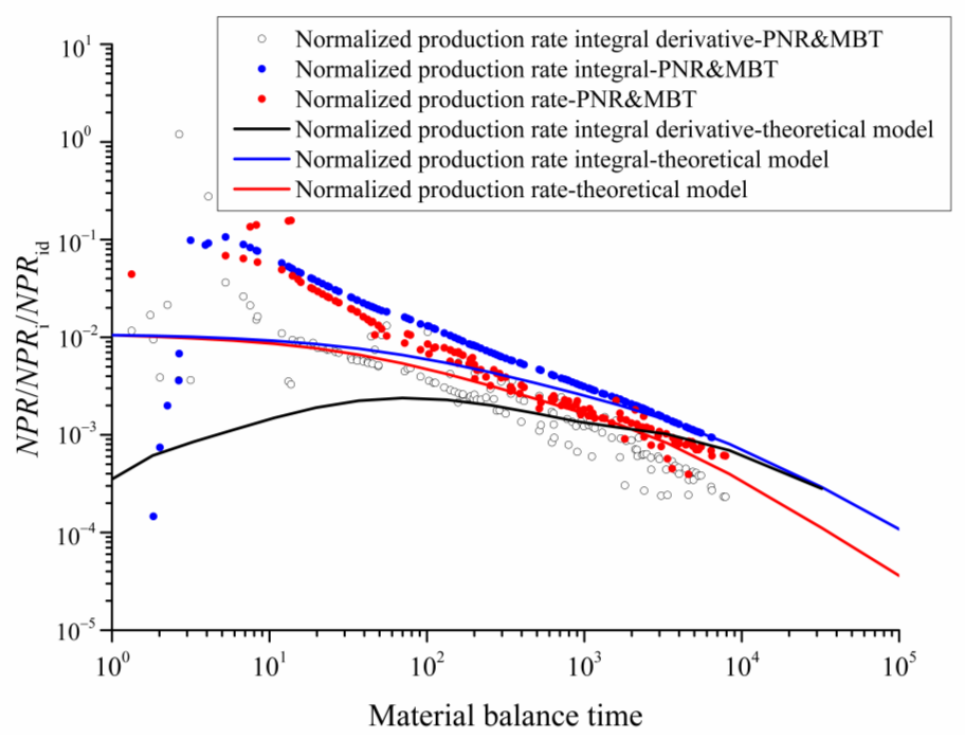


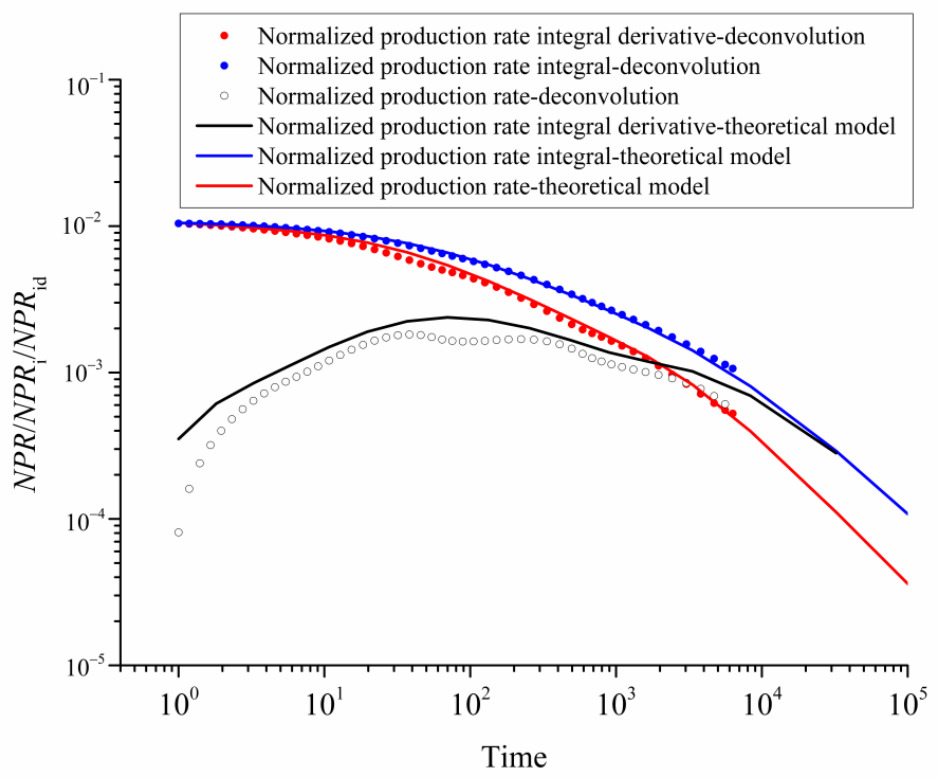
Figure 10. Blasingame production decline typical curve of the single well corresponding to flow rate deconvolution algorithm.

Table 1. Comparison of prediction results between the two methods.

Well Number	Actual Production ($10^4 \times m^3$)			Decline Curve Analysis Method ($10^4 \times m^3$) & Error (%)			Method Based on Convolution Equation ($10^4 \times m^3$) & Error (%)		
	Equivalent Gas	Shale Gas	Condensate Oil	Equivalent Gas	Shale Gas	Condensate Oil	Equivalent Gas	Shale Gas	Condensate Oil
Well 1	4036.24	3564.95	2.6369	6267.51 (55.3%)	5573.6 (38.1%)	3.88252 (47.2%)	3901.14 (3.4%)	3635.23 (2.0%)	2.25646 (14.4%)
Well 2	3663.72	3253.88	2.4906	4238.35 (15.7%)	3768.03 (15.8%)	2.85809 (14.8%)	3653.61 (0.3%)	3356.13 (3.1%)	2.12563 (14.6%)
Well 3	3242.82	2893.69	2.1216	3718.84 (14.7%)	3358.36 (16.1%)	2.19074 (3.3%)	3538.81 (9.1%)	3224.65 (11.4%)	2.09555 (1.2%)
Well 4	3631.22	3272.39	2.1805	4621.96 (27.3%)	4215.65 (28.8%)	2.46904 (13.2%)	3354.19 (7.6%)	2995.52 (8.5%)	1.97988 (9.2%)
Well 5	4480.10	4026.30	2.7577	4987.70 (11.3%)	4477.17 (11.2%)	3.10243 (12.5%)	4653.17 (3.9%)	4225.09 (4.9%)	2.64729 (4.0%)
Well 6	6128.55	5633.07	3.0109	6224.16 (1.6%)	5727.29 (1.7%)	3.01939 (0.3%)	5820.20 (5.0%)	5320.48 (5.5%)	2.82470 (6.2%)
Well 7	4307.33	3898.02	2.2694	4981.07 (15.6%)	4127.80 (5.9%)	2.99860 (32.1%)	3924.89 (8.9%)	3594.27 (7.8%)	1.83308 (19.2%)
Well 8	2633.71	2390.25	1.3622	3277.84 (24.4%)	3039.89 (27.2%)	1.33133 (2.3%)	2839.40 (7.8%)	2593.71 (8.5%)	1.37467 (0.9%)
Well 9	4162.75	3823.97	1.8955	4741.44 (13.9%)	4368.07 (14.2%)	2.08903 (10.2%)	4415.87 (6.1%)	4053.64 (6.0%)	2.02681 (6.9%)
Well 10	3850.55	3481.67	2.0639	4281.17 (11.2%)	3869.36 (11.1%)	2.30411 (11.6%)	3917.84 (1.7%)	3567.19 (2.5%)	1.96195 (4.9%)



(**a**)



(**b**)

Figure 11. Blasingame production decline typical curve fitting results of the production data processed by two different normalization methods and the seepage theoretical model: (**a**) PNR-MBT method; (**b**) flow rate deconvolution algorithm.

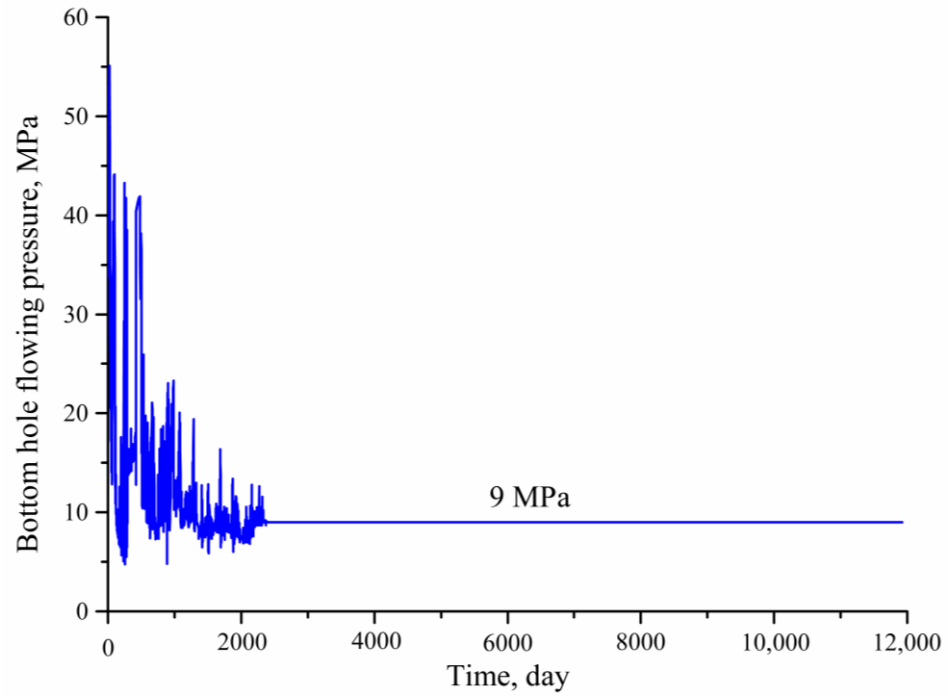


Figure 12. Schematic diagram of production pressure settings.

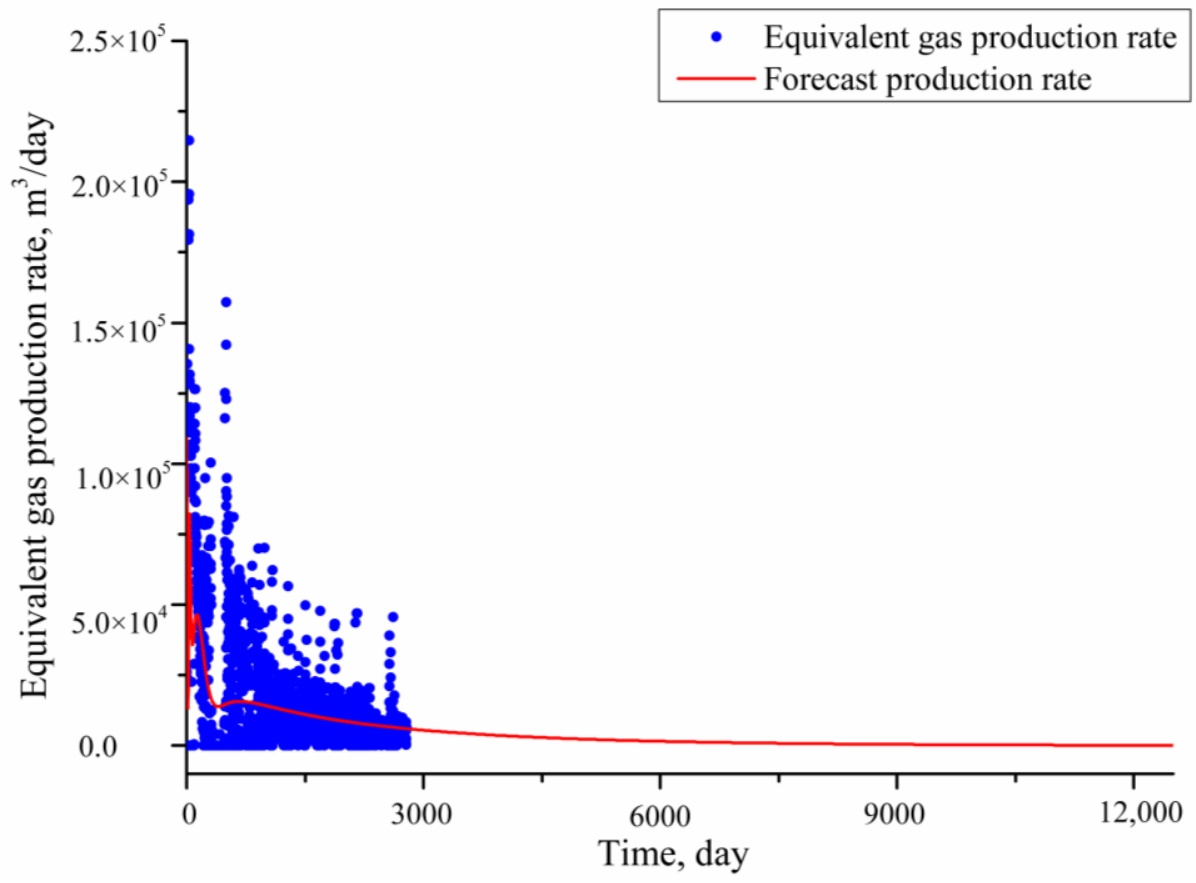


Figure 13. The fitting effect between the equivalent gas production calculated by the mathematical model and the real equivalent gas production.

For equivalent gas, the error of production predicted by the convolution equation is within 10%. In particular for well 2 and well 10, the errors are only 0.3% and 1.7%, respectively. For shale gas and condensate, the error of production predicted by the convolution equation is generally within 10%, too. Especially for well 1, the error of shale gas production is only 2%. For well 8, the error of condensate oil production is only 0.9%. The calculation results of two production prediction methods show that the production decline curve fitting effect of the method based on the convolution equation is better. Compared with the traditional production decline curve method, the predicted cumulative recoverable reserves of this method are more accurate. Moreover, the production prediction method based on the convolution equation uses the flow rate deconvolution algorithm to normalize the production data. Therefore, especially for the wells with serious production data oscillation, the Blasingame production decline typical curve fitting effect is much better than the traditional normalization method. The accuracy of the predicted cumulative recoverable reserves of shale gas and condensate oil is much higher than that predicted by the traditional production decline analysis method. By comparing the production predicted by the convolution equation with the actual production, the accuracy of the gas equivalent conversion method in Section 2.2 is also partially confirmed. This also confirms that the assumption that the relative density of condensate is constant has little influence on the prediction results of recoverable reserves.

4. Conclusions

In this paper, a method for predicting dynamic productivity of shale condensate gas reservoir based on convolution equation is proposed. It aims to obtain some reservoir parameters and hydraulic fracturing parameters through the analysis of production rate data and bottom hole flowing pressure, so as to predict the accumulative recoverable reserves of shale gas and condensate gas. It provides an accurate and efficient method for the production prediction of shale gas condensate reservoirs. Firstly, a trilinear seepage mathematical model for multi-stage fractured horizontal wells has been introduced in this paper. Linearization of mathematical model and Laplace transformation have been used to obtain the flow rate solution of the model corresponding to unit pseudo bottom hole flowing pressure drop. Secondly, a calculation method has been used to convert condensate oil into equivalent gas. The condensate oil and gas two-phase production data of shale condensate gas reservoirs were converted into equivalent gas production data. The pressure data was calculated as pseudo pressure data to realize the linearization of production data. On this basis, the flow rate deconvolution algorithm has been introduced to convert the production rate data corresponding to variable pseudo bottom hole flowing pressure into the production rate data corresponding to per unit pseudo bottom hole flowing pressure drop, which realizes the normalization of dynamic production data. Then, in the process of typical curve fitting, some reservoir parameters and fracture parameters have been adjusted with the basic reservoir parameters and fracturing construction data as constraints. The normalized dynamic production data and the Blasingame production decline typical curve have been fitted with the flow rate solution corresponding to per unit pseudo bottom hole flowing pressure drop, and some of the reservoir and fracture parameters have been explained. Finally, according to the explained parameters and the flow rate solution corresponding to variable pseudo bottom hole flowing pressure calculated based on the Duhamel's principle, the shale gas and condensate oil predicted recoverable reserves results of multi-stage fractured horizontal wells in shale condensate gas reservoirs are obtained.

This method has been used to predict the dynamic productivity of 10 multi-stage fractured horizontal wells in the Duvernay shale condensate gas reservoir. The results show that compared with the production decline analysis method in commercial software HIS Harmony RTA, the dynamic productivity prediction method based on the convolution equation of shale condensate gas reservoirs has better fitting effect and higher accuracy of recoverable reserves prediction. For equivalent gas, the error of production predicted

by convolution equation is within 10%. In particular for well 2 and well 10, the errors are only 0.3% and 1.7%, respectively. For shale gas and condensate, the error of production predicted by convolution equation is generally within 10%, too. Especially for well 1, the error of shale gas production is only 2%. For well 8, the error of condensate oil production is only 0.9%. It proves the accuracy of this method.

The convolution equation-based dynamic productivity prediction method of shale gas condensate reservoirs can effectively evaluate the hydraulic fracturing effect. It can accurately and efficiently predict the recoverable reserves of multi-stage fractured horizontal wells in shale condensate gas reservoirs. Compared to empirical methods, it is much more accurate. Compared to previous methods of typical curve analysis, due to the introduction of the deconvolution algorithm in this method, the data processing speed is faster and the fitting effect is better. Compared to artificial intelligence analysis methods, it does not require a large sample of production data. In addition, some reservoir and fracture parameters can be explained to facilitate the analysis of productivity factors. In addition, compared with the numerical simulation method, this method is simpler and more efficient. It enriches the production decline analysis method of shale condensate gas reservoirs and has important practical significance for the production prediction and stimulation optimization of shale condensate gas reservoirs.

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References

1. Jia, B.; Xian, C.; Tsau, J.-S.; Zuo, X.; Jia, W. Status and Outlook of Oil Field Chemistry-Assisted Analysis during the Energy Transition Period. *Energy Fuels* **2022**, *36*, 12917–12945. [CrossRef]
2. Liu, Y.; Gao, D.; Li, Q.; Wan, Y.; Duan, W.; Zeng, X.; Li, M.; Su, Y.; Fan, Y.; Li, S.; et al. Mechanical frontiers in shale-gas development. *Adv. Mech.* **2019**, *49*, 1–236.
3. Zhou, D. Continuous deepening of world shale gas exploration and development. *Sino-Glob. Energy* **2019**, *24*, 64.
4. Wang, Z.; Wen, Z.; He, Z.; Song, C.; Liu, X.; Chen, R.; Liu, Z.; Bian, H.; Shi, H. Global condensate oil resource potential and exploration fields. *Acta Pet. Sin.* **2021**, *42*, 1556–1565.
5. Lei, Q.; Xu, Y.; Cai, B.; Guan, B.; Wang, X.; Bi, G.; Li, H.; Li, S.; Ding, B.; Fu, H.; et al. Progress and prospects of horizontal well fracturing technology for shale oil and gas reservoirs. *Pet. Explor. Dev.* **2022**, *49*, 191–199. [CrossRef]
6. Arps, J.J. Analysis of decline curves. *Pet. Trans.* **1945**, *160*, 228–247. [CrossRef]
7. Ilk, D.; Rushing, J.A.; Perego, A.D.; Blasingame, T.A. Exponential vs. hyperbolic decline in tight gas sands: Understanding the origin and implications for reserve estimates using Arps' decline curves. In Proceedings of the SPE Annual Technical Conference and Exhibition, Denver, CO, USA, 21–24 September 2008.
8. Valko, P.P. Assigning value to stimulation in the Barnett Shale: A simultaneous analysis of 7000 plus production hystories and well completion records. In Proceedings of the SPE Hydraulic Fracturing Technology Conference, The Woodlands, TX, USA, 19–21 January 2009.
9. Duong, A.N. An unconventional rate decline approach for tight and fracture-dominated gas wells. In Proceedings of the SPE Canadian Unconventional Resources and International Petroleum Conference, Calgary, AB, Canada, 19–21 October 2010.
10. Chen, Y.; Xu, L.; Wang, L. Applications of the generic exponential production decline model on estimating well-controlled recoverable reserves of shale gas fields in the United States. *Pet. Reserv. Eval. Dev.* **2021**, *11*, 469–475.

11. Zhu, H.; Kong, D.; Qian, X. Shale Gas Production Prediction Method Based on Adaptive Threshold Denoising BP Neural Network. *Sci. Technol. Eng.* **2017**, *17*, 128–132.
12. Liu, Y.Y.; Ma, X.H.; Zhang, X.W.; Guo, W.; Kang, L.; Yu, R.; Sun, Y. A deep-learning-based prediction method of the estimated ultimate recovery (EUR) of shale gas wells. *Pet. Sci.* **2021**, *18*, 1450–1464. [CrossRef]
13. Song, L.; Wang, J.; Liu, C. BP-GA algorithm assisted intelligent horizontal well fracturing design. *Fault-Block Oil Gas Field* **2022**, *29*, 417–421, +426.
14. Qiu, K.; Li, J.; Chen, D. Optimized long short-term memory (LSTM) network for performance prediction in unconventional reservoirs. *Energy Rep.* **2022**, *8*, 15436–15445. [CrossRef]
15. Alberti, L.; Angelotti, A.; Antelmi, M.; La Licata, I. Borehole Heat Exchangers in aquifers: Simulation of the grout material impact. *Rend. Online Soc. Geol. Ital.* **2016**, *41*, 268–271. [CrossRef]
16. Wei, M.; Duan, Y.; Dong, M.; Fang, Q. Blasingame decline type curves with material balance pseudo-time modified for multi-fractured horizontal wells in shale gas reservoirs. *J. Nat. Gas Sci. Eng.* **2016**, *31*, 340–350. [CrossRef]
17. Chen, X.; Tang, C.; Du, Z.; Tang, L.; Wei, J.; Ma, X. Numerical simulation on multi-stage fractured horizontal wells in shale gas reservoirs based on the finite volume method. *Nat. Gas Ind. B* **2019**, *6*, 347–356. [CrossRef]
18. Zhang, R.-H.; Chen, M.; Tang, H.-Y.; Xiao, H.-S.; Zhang, D.-L. Production performance simulation of a horizontal well in a shale gas reservoir considering the propagation of hydraulic fractures. *Geoenergy Sci. Eng.* **2023**, *221*, 111272. [CrossRef]
19. Wang, Q.; Ye, Y.; Dong, J.; Wan, J. Unsteady flow model of fractured horizontal well in shale gas reservoir. *Sci. Technol. Eng.* **2020**, *20*, 10225–10234.
20. Jiang, L.; Liu, J.; Liu, T.; Yang, D. Semi-analytical modeling of transient rate behaviour of a horizontal well with multistage fractures in tight formations considering stress-sensitive effect. *J. Nat. Gas Sci. Eng.* **2020**, *82*, 103461. [CrossRef]
21. Clarkson, C.R.; Yuan, B.; Zhang, Z. A new straight-line analysis method for estimating fracture/reservoir properties using dynamic fluid-in-place calculations. *SPE Reserv. Eval. Eng.* **2020**, *23*, 606–626. [CrossRef]
22. Ilk, D.; Valko, P.P.; Blasingame, T.A. A deconvolution method based on cumulative production for continuously measured flowrate and pressure data. In Proceedings of the SPE Eastern Regional Meeting, Lexington, KY, USA, 17–18 October 2007.
23. Von Schroeter, T.; Hollaender, F.; Gringarten, A.C. Deconvolution of well test data as a nonlinear total least squares problem. *SPE J.* **2004**, *9*, 375–390. [CrossRef]
24. Wang, F.; Pan, Z. Deconvolution-based well test model for the fractured horizontal wells in tight gas reservoirs. *Acta Pet. Sin.* **2016**, *37*, 898–902+938.
25. Liu, W.; Liu, Y.; Zhu, W.; Sun, H. Improvement and application of ILK flow-rate deconvolution algorithm based on the second-order B-splines. *Acta Pet. Sin.* **2018**, *39*, 327–334.
26. Brown, M.; Ozkan, E.; Raghavan, R.; Kazemi, H. Practical solutions for pressure-transient responses of fractured horizontal wells in unconventional shale reservoirs. *SPE Reserv. Eval. Eng.* **2011**, *14*, 663–676. [CrossRef]
27. Du, F.; Nojabaei, B. Estimating diffusion coefficients of shale oil, gas, and condensate with nano-confinement effect. *J. Pet. Sci. Eng.* **2020**, *193*, 107362. [CrossRef]
28. Mirzaie, M.; Esfandyari, H.; Tatar, A. Dew point pressure of gas condensates, modeling and a comprehensive review on literature data. *J. Pet. Sci. Eng.* **2021**, *211*, 110072. [CrossRef]
29. Liu, N. Condensate oil conversion processing in condensate gas well test interpretation. *Well Test.* **1994**, *3*, 19–21.
30. Lu, T.; Li, Z.; Lai, F.; Meng, Y.; Ma, W.; Sun, Y.; Wei, M. Blasingame decline analysis for variable rate/variable pressure drop: A multiple fractured horizontal well case in shale gas reservoirs. *J. Pet. Sci. Eng.* **2019**, *178*, 193–204. [CrossRef]
31. Lee, A.L.; Gonzalez, M.H.; Eakin, B.E. The Viscosity of Natural Gases. *JPT* **1966**, *18*, 997–1000. [CrossRef]
32. Yarborough, L.; Hall, K.R. How to Solve EOS for Z-factors. *Oil Gas J.* **1974**, *72*, 86.
33. Whitson, C.H.; Sunjerga, S. PVT in liquid-rich shale reservoirs. In Proceedings of the SPE Annual Technical Conference and Exhibition, San Antonio, TX, USA, 8–10 October 2012.
34. Barzin, Y.; Walker, G.J. Choke management—The driver of liquid yield trends in shale reservoirs. In Proceedings of the Unconventional Resources Technology Conference, Unconventional Resources Technology Conference (URTeC), Houston, TX, USA, 20–22 June 2022; pp. 960–976.

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