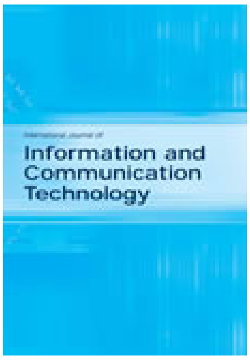

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Research on dynamic parameter identification method of shallow reservoir based on Kalman filter

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Abstract: The identification method of reservoir parameters has the problems of low recognition accuracy and timeliness. A dynamic parameter identification method of shallow reservoir based on Kalman filter is proposed. The history fitting method is used to establish and adjust the shallow reservoir model, and the parameters and range of the reservoir model are continuously adjusted according to the actual observation data of the shallow reservoir. Kalman filter is used to filter the data of shallow reservoir and to filter out the noise and interference information. Then the dynamic parameters of shallow reservoir are identified by the method of water resistivity shale content discrimination, and the state of shallow reservoir is reflected by the shallow water resistivity. The comparison shows that the average recognition accuracy of the method can reach 95.2%, the recognition process takes only 22 seconds at most, and its recall precision value level is always high.

Keywords: historical fitting; least squares objective function; reservoir model; Kalman filtering; parameter identification.

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1 Introduction

The shallow reservoir area refers to the reservoir in the same reservoir area where the reservoir resistivity growth rate is less than 2 and the boundary between reservoir resistivity and water-oil resistivity is not clearly distinguished, and it is difficult to accurately identify the reservoir in logging. With the deepening of oil and gas exploration and the development of reservoir layer recognition technology, the potential of such reservoirs has far-reaching significance for oil and gas development (Ma and Wang, 2017; Lu, 2020). With the rapid development of social economy, an increasing demand for energy, in the process of development of natural reserves of energy declining, economic development cannot leave the support of energy, in the shallow reservoir area development contribute to the supply of energy, therefore, related geological worker's pay more and more attention to the value of the shallow reservoir layer. In the identification of shallow reservoirs, the identification of reservoir dynamic parameters is crucial (Guang et al., 2018).

In Duan and Zhu (2018), a parameter identification method for shallow low-contrast reservoirs is designed. Considering the complexity of the sedimentary environment of shallow reservoirs, comprehensive factors such as high bound water saturation and conductivity of formation minerals are comprehensively analysed, and effective identification of reservoir parameters is achieved through the identification of spontaneous potential amplitude difference. However, it is found in practical application that the accuracy of this method is low. In Chen et al. (2018), design based on the origin of low resistivity reservoirs of shallow reservoir parameter identification method, the first analysis of shallow reservoir forming reasons of low resistance characteristics, and combining with the actual situation of drilling, logging, through summarising the test data and the corresponding relationship between the logging response, complete the recognition of shallow reservoir dynamic parameters. Design in Wang et al. (2019), the reservoir parameter identification method based on fuzzy comprehensive evaluation method, this method is mainly aimed at the shallow reservoir area of the big growth of channel and channel identification parameters, select six static dynamic index, index, and then using the method of fuzzy comprehensive evaluation of reservoir macroscopic throats launches the analysis judgement, and combining the theory of fluid seepage establish macroscopic throats permeability, pore size and large hole volume calculation model, so as to realise the recognition of reservoir parameters. However, due to the complexity of the calculation process, the above two methods often lead to time-consuming parameter identification process.

In view of the shortcomings of traditional methods, this study designed a shallow reservoir dynamic parameter identification method based on Kalman filter, which can realise the ability of optimal estimation of system state and realise the rapid and high-precision identification of shallow reservoir dynamic parameters. The idea of the article is as follows:

1 Establish a shallow reservoir model using historical fitting method, and adjust the parameters of the model and the range of parameters according to the actual observation data of shallow reservoirs.

2 The method of Kalman filtering was used to filter the shallow reservoir data, and the state equation was established to reduce the error between the observed value and the actual value, so as to filter out the interference information existing therein.

3 The dynamic parameters of shallow reservoirs were identified by the water resistivity and shale content discrimination method.

4 Experiments verify that the above methods have the characteristics of high recognition accuracy, short recognition process time and high reactor-precision value level.

2 Dynamic parameter identification method of shallow reservoir based on Kalman filter

2.1 Adjustment of shallow reservoir model based on historical fitting method

Before the Kalman filter is used to identify the dynamic parameters of shallow reservoir, the historical fitting method is first used to construct the shallow reservoir model. The process of historical fitting is the process of reinterpreting shallow reservoirs (Almedallah and Walsh, 2018). This process needs to reverse reservoir parameters according to the reservoir observation data, reservoir parameter can reflect the characteristics of shallow reservoir, and then will get the reservoir parameters as the input of the model, and then re-use optimisation way to modify reservoir model, the simulation result of model and shallow reservoir as much as possible close to the observed values. If the gap between the larger, the need to use the existing data of shallow reservoir, the reservoir model is adjusted ceaselessly expand, thus reduce model error between the calculation results and the observed values, to a certain extent, improve the shallow reservoir dynamic parameters to predict the accuracy of the results, as far as possible consistent with the actual situation to that of the shallow reservoir; When the error between the two is within the rated threshold, a set of model parameters conforming to the actual dynamics of shallow reservoir can be generated automatically (Jumin et al., 2018; Oyeyemi et al., 2018).

The process of historical fitting effectively avoids the subjectivity and complexity of manual calculation, reduces the workload of reservoir workers to a great extent, and also solves the problem of complex calculation process (Chen et al., 2019).

In the process of historical fitting, the objective function should be defined to reasonably quantify the error between the calculated result and the measured result. First, the least squares objective function is established as follows:

$$f(x)=\sum_{i=1}^{n} w_i\left(D_{obs}^{1}-D_{sim}^{i}(x)\right)^2 \tag{1}$$

In equation (1), w_{i} represents the weight of the i^{th} time point; x represents the shallow reservoir model parameters to be measured. Due to the large number of parameters in the shallow reservoir model, it is often necessary to select the main parameters of the author's model which have a great influence on the target quantity according to the actual situation. D_{obs}^{i} represents the actual observed value of shallow reservoir at time point i, $D_{sim}^{i}(x)$ represents the simulation value of shallow reservoir at time point i, n represents the total number of points in time.

It can be seen from equation (1) that $f(x)$ is the weighted error sum of squares between the simulated value of the model and the actual observed value of shallow reservoir.

According to equation (1), a set of parameters of actual dynamic changes in the loading shallow reservoir model can be found to minimise the least-squares objective function $f(x)$.

The process of historical fitting requires the automatic matching of reservoir model parameters by means of computer. The process is as follows:

Step 1 Establish a shallow reservoir model, determine the model parameters that need to be fitted according to the actual situation of the shallow reservoir, and then establish a constraint relationship that meets the conditions.

Step 2 Use the actual observation data of shallow reservoir to allocate the weight factor of time point for the observed data.

Step 3 According to the objective function shown in formula (1), constantly adjust the parameters and parameter range of the reservoir model to reflect the situation of shallow reservoirs as truly as possible (Creon et al., 2018; Bin et al., 2018).

2.2 Kalman filter processing of shallow reservoir data

In the use of historical fitting constantly adjust the shallow reservoir, on the basis of model parameters, using Kalman filtering approach to shallow reservoir data filtering processing, filter out noise and interference information, there is a way similar to the data reduction using shallow reservoir data, fundamentally improve the precision of the dynamic parameter identification.

Kalman filter overcomes the deficiency of the early Wiener filter and supplements the state space model on the basis of the traditional filtering process (Baptista et al., 2018; Fariz et al., 2018). Kalman filtering method is divided into two parts, namely, the equation of state and the equation of observation, which are mainly as follows:

a The equation of state can be expressed as follows:

$$A_{N+1} = \varphi_{N+1,N} A_N + \mu_1 \tag{2}$$

In formula (2), the state variable A_N represents a set of m-dimensional vectors, and $\varphi_{N+1,N}\,\varphi_{N+1,N}$ represents the transition matrix in $m \times m$ dimensions.

b The expression of the observation equation is as follows:

$$B_N = C_N A_N + \mu \tag{3}$$

In equation (3), the state quantity B_N represents a set of m'-dimensional vectors, and C_N represents the transition matrix of $m' \times m$-dimensional vectors. In equations (2) and (3), the parameters μ_1 and μ_2 satisfy the following equation:

$$\begin{cases} \dfrac{E\left\{\mu_1\mu_1^T\right\} = T_1}{E\left\{\mu_2\mu_2\right\} = T_2} \end{cases} \tag{4}$$

In equation (4), T represents the error variance matrix of reservoir model. On this basis, y_0^v represents the initial input state vector of shallow reservoir, and e_0^v represents the initial error variance matrix. Accordingly, the processing process of Kalman filtering is designed as follows:

Step 1 The predicted value y_{t+1}^{u} and error variance matrix e_{t+1}^{u} of shallow reservoir state variables at time $t + 1$ are calculated as follows:

$$y_{t+1}^{n} = f y_{t}^{u} \tag{5}$$

$$e_{t+1}^{u} = f e_{t}^{u} f^{T} + T \tag{6}$$

In the above formula, y_{t}^{u} represents the state quantity of shallow reservoir at time t after update, e_{t}^{u} represents the error variance matrix of state quantity y_{t}^{u}, and f represents the linear factor.

Step 2 The calman gain matrix K_{t+1} at time $t + 1$ is calculated as follows:

$$K_{t+1} = \frac{e_{t+1}^{u} H^{T}}{H e_{t+1}^{u} + J} \tag{7}$$

In formula (7), H represents the measured value matrix, and J represents the error variance matrix of the observed value.

Step 3 The state quantity Y_{t+1}^{q} and error variance matrix E_{t+1}^{q} of the analysis field at time $t + 1$ are calculated as follows:

$$Y_{t+1}^{q} = y_{t+1}^{u} + K_{t+1}\left(d_{t+1} - H y_{t+1}^{u}\right) - E_{t+1}^{q} \tag{8}$$

$$E_{t+1}^{q} = \left(i - K_{t+1} H\right) e_{t+1}^{u} \tag{9}$$

In the above formula, d_{t+1} represents the observed value of the analysis field at time $t + 1$, and i represents the identity matrix.

Step 4 Iterate Step 1 to Step 3, and calculate the state vector of the shallow reservoir model at the corresponding time.

Based on the above process, it can be seen that Kalman filtering and error variance analysis are used to adjust and supplement the observed data of shallow reservoir model, thus completing the preliminary processing of the observed data of shallow reservoir model and laying a foundation for the next step of reservoir dynamic parameter identification.

2.3 *Dynamic parameter identification based on Kalman filtering*

In general, shallow reservoir areas are characterised by low contrast, for the following reasons:

1 The shallow reservoir area is characterised by fine lithology and strong hydrophilicity, resulting in an increase in the surface area of clay particles. At the same time, due to the action of argillaceous materials filling pores, the number of micro-pores on the surface of the rock increases, leading to an increase in the content of bound water to more than 30% (Hidayat and Abdurrahman, 2018; Liu et al., 2018).

2 In the shallow reservoir area, the autogenous clay layer is relatively thick, which contains a lot of mineral data. The additional conductivity of minerals including montmorillonite is relatively obvious, so that the resistivity of sandstone in the shallow reservoir area rich in clay is far lower than that of pure sandstone.

3 In the sandstone reservoirs with gravel and different grains, the resistivity and logging density of the conglomerate are relatively high, which weakens the characteristics of different fluids on the logging curve (Mehrabi et al., 2018; Jun et al., 2019).

4 Dissolution and cementation of carbonate minerals exist in shallow reservoirs, but hydrocarbon embeds inhibit these two kinds of USES, resulting in significant differences in carbonate content in different oil-bearing reservoirs. Because of the relatively high carbonate content in the water layer, the resistivity of the water layer also increases, which is also the important reason for the low contrast in the shallow reservoir area.

In view of the low contrast characteristics of shallow reservoirs, this study USES the water resistivity – shale content discrimination method to identify the dynamic parameters of shallow reservoirs.

The conventional single factor reservoir parameter identification method is shown in Figure 1.

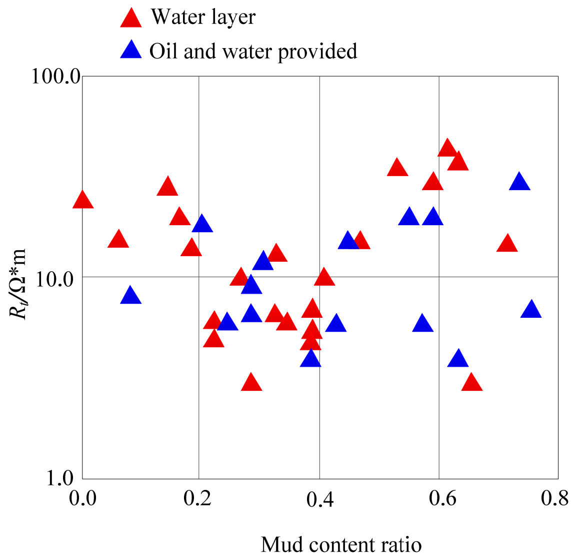
In Figure 1, R_t represents the resistivity of the oil-bearing formation. It can be seen from Figure 1 that conventional single-factor reservoir parameter identification method is difficult to effectively identify water layer and water-oil layer in shallow reservoir area. Therefore, the key to identify shallow oil reservoirs is to find the sensitive information parameters that carry fluid properties. According to the analysis of main control origin, the dynamic identification parameters of shallow reservoirs should be characterised by lithology, oil bearing, physical property and electrical property (Hong and Jun, 2018; Sharma et al., 2018). Therefore, the water resistivity of the bottom layer of shallow reservoir can be used as a comprehensive parameter to identify shallow reservoir.

According to Archie's formula, water resistivity in shallow reservoir area is related to rock resistivity, rock porosity, lithologic parameters and cement coefficient. The calculation process is as follows:

$$r = \frac{r_0 \times \omega^g}{\lambda} \Rightarrow r_a\left(R_t\right) = \frac{R_t \times \omega^g}{\lambda} \tag{10}$$

In formula (10), r represents water resistivity of shallow reservoir area, r_0 represents saturated formation water resistivity, r_a represents water resistivity of apparent formation, λ represents lithologic parameters, ω represents porosity of rock, and g represents cementation coefficient. According to equation (10), $r_a(R_t)$ contains saturation, formation water salinity and argillaceous content, etc.

Figure 1 Conventional single factor reservoir parameter identification results (see online version for colours)



In addition, water resistivity of apparent formation in shallow reservoir area can also be calculated by equivalent resistivity of drilling fluid, difference of spontaneous potential amplitude and coefficient of spontaneous potential. The process is as follows:

$$
\begin{aligned}
& NAP = -\eta \lg\left(\frac{r_f}{r}\right) \Rightarrow NP \\
& = -\eta \lg\left(\frac{r_a}{r}\right) \Rightarrow r_a(NP) \\
& = r_f \times 10^{\frac{NP}{\eta}} \Rightarrow r_a(\Delta NP) \\
& = r_f \times 10^{\frac{\Delta NP}{\eta}}
\end{aligned}
\tag{11}
$$

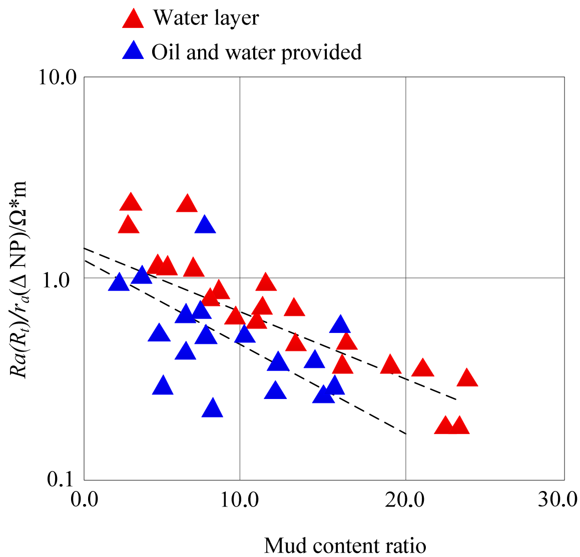
In formula (11), NAP represents the static SPONTANEOUS potential of 100% water-bearing pure rock, η represents the SPONTANEOUS potential coefficient, r_f represents the mud filtrate resistivity, NP represents the spontaneous potential, and ΔNP represents the spontaneous potential amplitude difference. For shallow reservoir area, when the salinity of shallow water is similar to that of oil drilling mud, the spontaneous potential amplitude can reflect the oil saturation, lithology and porosity of shallow oil.

On this basis, the above calculation results can be fused to reflect the information fusion of low contrast in the shallow reservoir area, so as to analyse multiple sample points in the shallow reservoir area. The results are shown in Figure 2.

Combined with the results in Figure 2, under the condition of similar lithology in the shallow reservoir area, the double water ratio $\frac{r_a(R_t)}{r_a(\Delta NP)}$ decreases with the increase of shale content, resulting in lower oil content and obvious boundary of oil-water zone.

Oil-water zone is located in the upper part of the shallow reservoir area, while water-water zone is located in the lower part of the shallow reservoir area.

Figure 2 Results of water resistivity – mud content discrimination method (see online version for colours)



In the identification of shallow reservoir dynamic parameters, the least square objective function is established to adjust the parameters and parameter range of the reservoir model, and the historical fitting method is constructed to construct the shallow reservoir model. Kalman filter was used to filter the shallow reservoir data to remove the noise and interference information, and the preliminary treatment of the observed data of the shallow reservoir model was completed. The water resistivity and mud content discrimination method was used to identify the dynamic parameters of the shallow reservoir.

3 Experimental research

3.1 Experimental design

In order to verify the application performance of the shallow reservoir dynamic parameter identification method based on Kalman filter designed in this study, the following experiments are designed to prove it. The experiment was carried out in MATLAB simulation platform. The hardware of the simulation platform includes controller (2060Max-Q), graphics card (NVIDIA) and network (wireless routing), and the software of the simulation platform includes database (underground gas storage project database) and operating system (Wins 10). During the experiment, the data transmission was 2,000 Mbps and the network speed was 160 MHz. The number of iterations is 200.

To improve the accountability and the comparative experiment results, Chen et al. (2018) is based on the analysis of the low resistivity reservoir formation in the shallow reservoir parameter identification method [method of Chen et al. (2018) and Wang et al. (2019)] in the reservoir parameter identification method based on fuzzy comprehensive evaluation method [method of Wang et al. (2019)] as contrast method, and in this paper, the identification method of design (method in this paper) to performance contrast test and verify. The indexes selected for the experiment are as follows:

1. Identification accuracy. This index can be used to reflect the recognition ability of different parameter identification methods. The higher the identification accuracy, the more practical the parameter identification method is.
2. Time to identify the process. This index can be used to reflect the identification efficiency of different parameter identification methods. The shorter the time of the identification process, the higher the identification efficiency of the parameter identification method, that is, the higher the timeliness of the method.
3. Rear-precision value. In this index, recall represents the recall rate of reservoir parameter identification results, and Precision represents the accuracy of reservoir parameter identification results. This index can effectively reflect the adaptive performance of different parameter recognition methods. The closer the reactor-precision curve slope is to 45°, the stronger the adaptive performance of parameter recognition method is, the more significant its application scope and advantages are.

3.2 Experimental results and analysis

3.2.1 Comparison of recognition accuracy

First, the identification accuracy is taken as the test index to verify the identification ability of different parameter identification methods. The results are shown in Table 1.

Table 1 Comparison of recognition accuracy of different methods (%)

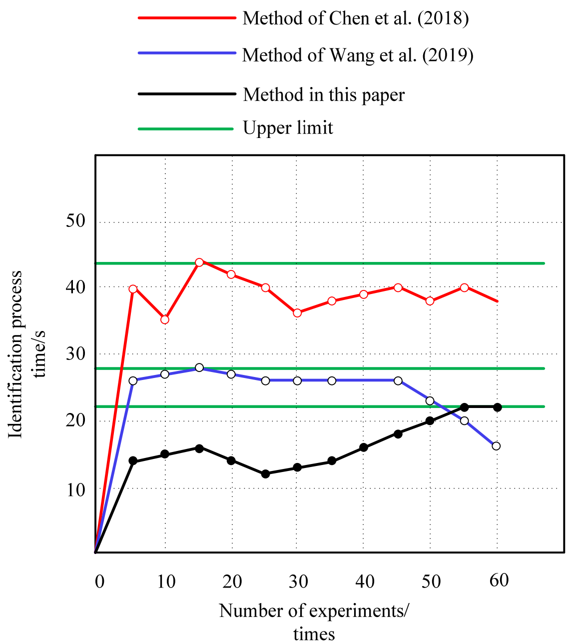
	Method	*Method of Chen et al. (2018)*	*Method of Wang et al. (2019)*	*Method in this paper*
Number of experiments/times	10	72.3	83.5	92.2
	20	75.0	87.2	94.9
	30	70.5	75.4	95.1
	40	73.1	85.6	96.8
	50	75.5	75.8	97.0
	Average	73.3	81.5	95.2

As shown in Table 1, with the increase of the number of experiments, the recognition accuracy of different parameter identification methods presents obvious changes. Among them, the identification accuracy range of the shallow reservoir parameter identification method based on the genetic analysis of reservoir low resistance is 70.5%~75.5%, and the average identification accuracy is 73.3%. The accuracy range of reservoir parameter identification based on fuzzy comprehensive evaluation method is 75.4%~87.2%, and the average accuracy is 81.5%. However, the identification accuracy range of the dynamic parameter identification method based on Kalman filter designed in this paper is 92.2%~97.0%, and its average identification accuracy is 95.2%. By comparing the above results, it can be seen that the method presented in this paper has a higher accuracy in identifying the dynamic parameters of shallow reservoirs, indicating that the method has a strong recognition ability.

3.2.2 Identify process time comparisons

Further test the identification process of different parameter identification methods. The results of the recognition process are automatically counted by the experimental operating platform. The comparison results are shown in Figure 3.

Figure 3 Time comparison of different identification methods (see online version for colours)

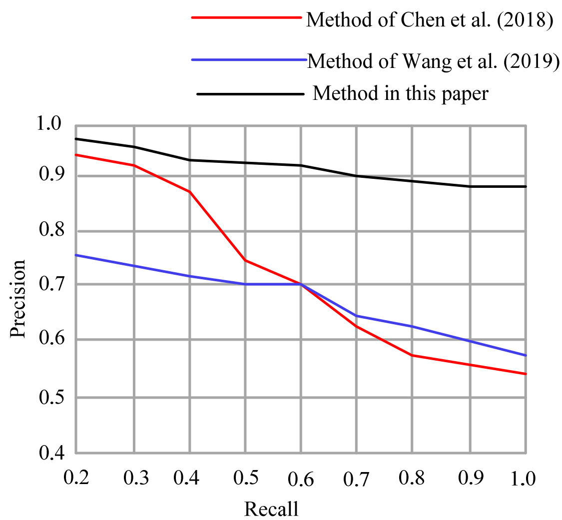


By analysing the results shown in Figure, it can be seen that with the increase of the number of experiments, the time of the identification process of different parameter identification methods also presents obvious changes, and there is no obvious rule of such changes. Among them, the identification process of shallow reservoir parameter identification method based on the genetic analysis of reservoir low resistance takes at least 36 s and at most 44 s. The identification process of reservoir parameter identification based on fuzzy comprehensive evaluation method takes at least 16 s and at most 27 s. However, the identification process of the shallow reservoir dynamic parameter identification method based on Kalman filter designed in this paper takes at least 12 s and at most 22 s. By comparing the above results, it can be seen that the method presented in this paper has the fastest identification speed, which indicates that the method presented in this paper has a higher identification efficiency for the dynamic parameters of shallow reservoirs and a higher timeliness.

3.2.3 Recall and precision value contrast

In the verification of this step, firstly, the database of underground gas storage project is retrieved, and dimensionality reduction of different degrees is carried out for the identified shallow reservoir dynamic data by means of dimensionality reduction. Then, recall values and precision of different parameter identification methods are settled respectively, and reactor-precision is plotted according to the calculated results. The reactor-precision value comparison results are shown in Figure 4.

Figure 4 Comparison of reactor-precision values of different parameter recognition methods (see online version for colours)



In Figure 4, the horizontal axis represents the calculated result of recall and the vertical axis represents the calculated result of precision.by comparing and observing the results shown in Figure 3, it can be seen that in the shallow reservoir parameter identification method based on the genetic analysis of low resistivity reservoir, with the increase of recall value, the precision value changes in a large range and is at a high level in the early stage. When the recall value is 0.5, the precision value drops to 0.75, and then keeps a rapid downward trend until the precision value drops to 0.55. In the reservoir parameter identification method based on fuzzy comprehensive evaluation method, the reactor-precision value presents a downward trend as a whole, and the recall and precision results are always at a low level. In the Kalman filter-based method designed in this paper, the precision result is always higher as the Recall result changes. Although it has a certain downward trend, compared with the two comparison methods, the reactor-precision value level of the method in this paper is higher. Through the above comparison, it can be seen that the dynamic parameter identification method based on Kalman filter designed in this paper has strong adaptive performance and can realise effective identification of reservoir parameters in different application environments.

4 Conclusions

In this paper, a dynamic parameter identification method for shallow reservoir based on Kalman filter is proposed. On the basis of adjusting the parameters of the shallow reservoir model by using the historical fitting method, the parameters of the shallow reservoir model and the range of parameters are determined according to the real observation data. Based on this, the method of Kalman filtering was used to filter and process the shallow reservoir data, so as to reduce the influence of noise and interference information in the data on the parameter identification results in the later stage and fundamentally improve the identification accuracy. Finally, the dynamic parameters of shallow reservoir are identified by using the water resistivity – shale content discrimination method. The simulation results show that the average recognition accuracy of this method can reach 95.2%, the time of the recognition process does not exceed 22 s, and its reactor-precision value is always high, which proves that this method has a high application advantage. In the following research, the application scope of this method will be further expanded, so that it can be applied to the parameter identification process of more oil and gas reservoirs.

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