

Article

# A New Model for Discriminating the Source of Produced Water from Cyclic Steam Stimulation Wells in Edge-Bottom Water Reservoirs

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Abstract: Heavy oil reservoirs with edge-bottom water represent a huge portion of the world's reserves, and the effective development of such reservoirs with cyclic steam stimulation (CSS) is significant for the petroleum supply. However, the water cut of some CSS wells increases, and production decreases, with the increase of circulation turns. Discerning the source of the produced water is the basis of targeted treatment measures. In this paper, a new model is established for discriminating the source of produced water from CSS wells in edge-bottom water reservoirs. The model combines traditional hydrochemical characteristics analysis and factor analysis, and considers the quality change in injected water. The coefficient of formation water and injected water in produced water can thus be obtained. In addition, the normal distribution method is used to further divide interlayer water and edge-bottom water. The model was applied to a field case, and the results showed that one well was severely invaded by edge-bottom water. The results are consistent with field production performance, which further verifies the accuracy of the model. This model is of great significance for not only discriminating the source of produced water in an edge-bottom water reservoir, but also providing a basis for further the provision of further treatment measures.

**Keywords:** heavy oil; cyclic steam stimulation; edge-bottom water reservoirs; source discrimination of produced water; factor analysis; hydrochemical characteristics; weight coefficients

# 1. Introduction

Heavy oil and bitumen account for approximately two thirds of the global crude oil resources [1–3]. It is predicted that the production of heavy oil will increase rapidly in the future to meet the increasing energy demand [4–8]. Some heavy oil reservoirs are often surrounded by edge-bottom water, which increases the difficulty of developing such reservoirs [9]. Cyclic steam stimulation (CSS) is the most effective technique to recovery of heavy oil reservoirs with edge-bottom water, and most reserves in such reservoirs have been exploited by this method [10–12]. In CSS, steam is injected into a production well for a period. Then the well is shut in and allowed to soak for several days before it returns to production [13]. CSS has the advantages of a rapid economic return, low capital investment, short economic recovery period, and good economic benefits [14].

For most heavy oil reservoirs, CSS production is in the middle or last stages, which manifests as low daily production per well, high water cut, low cyclic oil-steam ratio, and low utilization of heat [15]. For instance, up until 1998, when the average steam stimulation cycles in the Shan-2 block of Shanjiasi Heavy Oil Field reached ten cycles, the comprehensive water cut was 93.1%, the annual



oil–steam ratio was only 0.36 t/t, the natural decline rate was 30.9%, and the recovery degree was only 11.2% [16]. In addition, in block M, studied in this paper, the oil-steam ratio of a typical vertical well was about 0.91–1.23 t/t in the first to forth cycles, and decreased to 0.42 t/t in the fifth cycle. The water cut increased rapidly, and even reached 100% in the sixth cycle. The large volume of produced water increased the loss of thermal energy injected into the formation. More importantly, it increased the cost of water treatment, resulting in economic losses [17]. Therefore, for CSS wells in block M, it is urgent to discriminate source of produced water and take corresponding treatment measures to improve the production performance.

In edge-bottom water reservoirs, there are two possible reasons accounting for high water cut in CSS wells. On the one hand, due to the difference in permeability, high permeable layer absorbs more steam, and the low permeable layer absorbs less or no steam, which results in the ineffective circulation of injected steam in the high-permeability layer. The produced water is mainly injected steam condensate. In response to this situation, high-temperature resistant chemical profile control agents are usually used to block the high permeability layer and adjust the steam adsorption profile [18]. On the other hand, after the opening to production, the rapid drop of bottom hole pressure will cause the actual production pressure difference to increase rapidly which will lead to water channeling, severely affecting the development effect of CSS wells [19–21]. In this case, the produced water is mainly formation water. The main methods to reduce water intrusion in such reservoirs include mechanical and chemical water plugging [22,23]. For example, the method of injecting nitrogen or nitrogen foam to suppress the invasion of edge-bottom water is one option [24–26]. In short, the first step to propose effective treatment measures for CSS wells with high water cut is to identify the source of the produced water.

At present, the methods for discriminating the source of the produced water in oilfields and mines can be divided into three categories: hydrochemical characteristic analysis, tracer monitoring, and multivariate statistics.

The hydrochemical characteristic analysis method is the earliest comprehensive method used to determine the source of produced water in oilfield, which combines production performance, hydrochemical and electrical characteristics [27]. Subsequently, Li C.Q. supplemented this method, and proposed a multi-ion analysis and identification method based on quartz dissolution, which was effectively applied to the identification of produced water in steam stimulation wells [28]. The hydrochemical characteristic analysis mainly uses the difference in ion content to make empirical judgments on the source of produced water. However, due to various types of ions, the large range of content, and complicated laws, the researcher's subjective knowledge and analysis level will affect the conclusion.

The tracer monitoring method is a commonly used method in oilfields. It plays an important part in judging whether the wells produce formation water and determining the direction of the edge and bottom water as well as the propulsion speed [29,30]. Chai et al. used the tracer method combined with the chemical composition of the produced water, well test analysis, and material balance methods to determine the connectivity between wells [31]. However, it is difficult to apply the tracer monitoring method to the source identification of oilfield produced water on a large scale, due to the high cost. In addition, for oil wells with multi-layer and multi-directional effects, the reasonable and accurate interpretation of the tracer has become a problem. Chai et al.'s analysis of the chemical composition of produced water is only at a qualitative comparison with strong subjectivity.

The multivariate statistics methods include the neural network method [32–35], cluster analysis [36–38], the gray correlation method [39–41], factor analysis [42], and the Bayes multi-class linear discrimination method [43]. Wu et al. employed an improved neural network method to discriminate mine water inrush and obtained a better discrimination result [44]. However, the neural network method requires a large amount of data for training. In addition, the number of samples of water sources may be limited in an actual oilfield. Shi et al. conducted hierarchical clustering analysis to classify water samples into six categories and identified mine water sources [45]. However, cluster

analysis lacks a probability test, which precludes assigning significance to the obtained results, and it does not provide information about the distribution of the chemical constituents forming each group. Gray correlation is a novel algorithm to calculate the degree of correlation through the development trend of time series and find the correlation between data [46]. However, the results obtained are all "gray" relationships, which is not enough for CCS wells to accurately judge the degree of water resource and implement water plugging measures. In addition to the above issues, the above multivariate statistics methods are all used to identify the water inrush in mine and has not been used to determine the source of produced water in the oil field.

In this study, we researched the experience of mine water source identification and pioneered the application of multivariate statistics method to discriminate the source of the produced water in an oil field. This method avoids the subjectivity and blindness of the traditional hydrochemical characteristic analysis method, and reduces the costs compared with the tracer monitoring method. The various methods for discriminating produced water in the past can only judge the produced water sample as a single source, which doesn't meet the speculation of the mixed type of formation water and injection water of steam stimulation wells. In this paper, a new model is established for discriminating the source of produced water in CSS wells. This model combines the traditional hydrochemical characteristic analysis and factor analysis methods and considers the change of injected water quality. The coefficient of formation water and injected water can be obtained by using this model, and normal distribution method is used here to further divide the interlayer water and the edge-bottom water. Finally, a field case is used to show its application. Compared with the traditional empirical method of water source discrimination, the model developed can be effectively applied to new oil fields while avoiding subjective misunderstandings from the researchers. This is a fast and effective model which is of great significance for source identification of the produced water in CSS wells and the provision of treatment measures for the CSS wells with bad performance.

#### 2. Principle of Factor Analysis

Factor analysis is a commonly used method of dimensionality reduction in statistics. The main purposes are to represent the relationship between many indicators with a few factors and evaluate each sample comprehensively.

 $X_1, X_2, \dots, X_n$  are the original variable indices. First, the original data is standardized, and the correlation coefficient matrix of the variables is calculated. The eigenvalues,  $\lambda_1 \ge \lambda_2 \ge \dots \ge \lambda_n \ge 0$ , of the correlation coefficient matrix and the corresponding standard orthogonal vectors,  $\eta_1, \eta_2, \dots, \eta_n$ , are then calculated based on the factor analysis method, where  $\eta_j = [\eta_{1j}, \eta_{2j}, \dots, \eta_{nj}]^T$ . The n principal factors are composed of eigenvectors, as follows [47] (pp. 606–612):

$$\begin{cases} Z_1 = \eta_{11}\widetilde{X_1} + \eta_{21}\widetilde{X_2} + \ldots + \eta_{n1}\widetilde{X_n} \\ Z_2 = \eta_{12}\widetilde{X_1} + \eta_{22}\widetilde{X_2} + \ldots + \eta_{n2}\widetilde{X_n} \\ \vdots \\ Z_n = \eta_{1n}\widetilde{X_1} + \eta_{2n}\widetilde{X_2} + \ldots + \eta_{nn}\widetilde{X_n} \end{cases}$$
(1)

The information contribution rate,  $b_i(i = 1, 2, \dots, n)$  and cumulative contribution rate,  $\partial_i(i = 1, 2, \dots, n)$  of each principal factor are calculated as follows:

$$b_i = \frac{\lambda_i}{\sum_{k=1}^n \lambda_k}, i = 1, 2, \cdots, n$$
<sup>(2)</sup>

$$\partial_i = \frac{\sum_{k=1}^i \lambda_k}{\sum_{k=1}^n \lambda_k} \tag{3}$$

When  $\partial_p \ge 0.95$ , the first *p* principal factors  $Z_1, Z_2, \dots, Z_p$  (p < n) are selected, other unimportant principal factors are omitted. The factor analysis model is established.

After the factor analysis model is established, each sample can be comprehensively evaluated by applying the factor analysis model. The calculation formula of the comprehensive evaluation value of each sample is as follows:

$$X = \sum_{j=1}^{p} b_j Z_j \tag{4}$$

As it is used in this study, the factor analysis method can reduce the dimensionality of the indicators that are used for source discrimination of produced water. Moreover, when we are not certaiin about the hydrochemical characteristic system of water source samples in this oil field, the factor analysis method can find out the indicators that are important to the evaluation results, filter out others, and summarize the principal factors through the logical structures of the data. When the cumulative variance contribution rate of the principal factors is greater than 95%, the principal factors can completely describe the research system and realize information integrity. Finally, a comprehensive evaluation function and comprehensive score value of each sample can be obtained through factor analysis. Therefore, in this paper, the factor analysis is the most suitable method to establish a new model for discriminating source of produced water.

#### 3. Model Establishment

#### 3.1. Analysis Process of Produced Water

As shown in Figure 1, the process to establish a model for discriminating the source of the produced water is as follows: (i) data preparation—determine the typical water source sample and select the appropriate discriminant indicators according to the traditional hydrochemical characteristics analysis process; (ii) factor analysis model and comprehensive evaluation function—process the obtained sample data by using factor analysis method, the factor analysis model is established and the water sample comprehensive evaluation function is further obtained; and (iii) solution of weight coefficients—bring hydrochemical characteristics data of water source samples and produced water into the comprehensive evaluation function and set up the equations. Solve the equations to find the diagram of source proportions.



Figure 1. Flow chart of analysis method of produced water.

#### 3.1.1. Data Preparation

The main task in the data preparation process is to determine the typical water source and select the appropriate discriminant indicators according to the traditional hydrochemical characteristics analysis process. On 28 May 2015, the oilfield detected a quality change in the injected water in the CSS wells. However, the nature of formation water remained basically unchanged, so it could be regarded as one category. Considering the quality change of the injected water, the water sources in the block M could be roughly divided into three categories: injected water 1 (type of injected water before 28 May 2015), injected water 2 (type of injected water after 28 May 2015), and formation water.

According to the traditional hydrochemical characteristics analysis process [27], nine typical indicators were selected: Na<sup>+</sup> + K<sup>+</sup>, Ca<sup>2+</sup>, Mg<sup>2+</sup>, CI<sup>-</sup>, HCO<sub>3</sub><sup>-</sup>, SO<sub>4</sub><sup>2-</sup>, density (20 °C), total salinity, and pH. The hydrochemical characteristics of these water sources are shown in Table 1.

Category	Na <sup>+</sup> /K <sup>+</sup> (mg/L)	Ca <sup>2+</sup> (mg/L)	Mg <sup>2+</sup> (mg/L)	Cl− (mg/L)	HCO <sub>3</sub> - (mg/L)	SO4 <sup>2–</sup> (mg/L)	Density (20 °C) (g/cm <sup>3</sup> )	Total Salinity (mg/L)	pН
Injected water 1	916.6	57.5	32.0	1169.4	277.6	361.8	1.0005	2823.9	6.0
Injected water 2	743.1	2.5	1.0	694.7	297.3	371.95	1.0000	2119.9	7.0
Formation water	2430.0	84.0	47.9	3680.3	408.7	144.7	1.00435	6795.6	7.1

Table 1. Hydrochemical characteristics of different water sources in block M.

3.1.2. Factor Analysis Model and Comprehensive Evaluation Function

After data preparation, the factor analysis model began to be established by SPSS software. The first step was to import the water source data into the SPSS software. The data management window was activated. The indicator names were defined:  $Na^+ + K^+$ ,  $Ca^{2+}$ ,  $Mg^{2+}$ ,  $CI^-$ ,  $HCO_3^-$ ,  $SO_4^{2-}$ , density (20 °C), total salinity, and pH. Their corresponding values were imported into the software, the database was established, and the total variance of the interpretation was obtained and is shown in Table 2.

	]	Initial Eigenvalue		Extract Square Sum and Load Rotate Square Sum and Loa			m and Load		
Component -	Sum	% Variance	Cumulative %	Sum	% Variance	Cumulative %	Sum	% Variance	Cumulative %
1	6.732	74.803	74.803	6.732	74.803	74.803	6.395	71.051	71.051
2	1.836	20.401	95.205	1.836	20.401	95.205	2.174	24.153	95.205
3	0.432	4.795	100.00						
4	$7.254 \times 10^{-16}$	$8.080 \times 10^{-15}$	100.00						
5	$3.577 \times 10^{-16}$	$3.974 \times 10^{-15}$	100.00						
6	$-1.295 \times 10^{-17}$	$-1.439 \times 10^{-16}$	100.00						
7	$-5.958 \times 10^{-17}$	$-6.620 \times 10^{-16}$	100.00						
8	$-3.568 \times 10^{-16}$	$-3.964 \times 10^{-15}$	100.00						
9	$5.045\times10^{-16}$	$5.606\times10^{-15}$	100.00						

Table 2. Total variance of interpretation.

The principal factors were extracted using the factor analysis method. The eigenvalues, contribution rate, cumulative contribution rate, component matrix, and component score matrix of the correlation coefficient matrix were calculated. Since the extraction standard of the principal factors was that the cumulative contribution rate should be more than 95%, two principal factors were selected, and their cumulative contribution rate to the sample variance was 95.205%.

According to the component matrix table, as shown in Table 3, the first principal factor had a large load (greater than 0.9) on Na<sup>+</sup> + K<sup>+</sup>, Mg<sup>2+</sup>, CI<sup>-</sup>, HCO<sub>3</sub><sup>-</sup>, total salinity, and pH, and the second principal factor had a large load on Ca<sup>2+</sup> and SO<sub>4</sub><sup>2-</sup>. It showed that Na<sup>+</sup> + K<sup>+</sup>, Mg<sup>2+</sup>, CI<sup>-</sup>, HCO<sub>3</sub><sup>-</sup>, total salinity, and pH are the main indicators, while Ca<sup>2+</sup> and SO<sub>4</sub><sup>2-</sup> are secondary indicators. The load of the two principal factors on the density was small and similar, which indicates the density had little effect on the results. Therefore, the density can be removed in this factor analysis model.

	Components				
	First Principal Factor	Second Principal Factor			
Na <sup>+</sup> /K <sup>+</sup>	0.989	0.075			
Ca <sup>2+</sup>	0.802	0.933			
Mg <sup>2+</sup>	0.933	0.107			
Čĺ-	0.995	0.031			
HCO <sub>3</sub> <sup>-</sup>	0.946	0.300			
$SO_4^{2-}$	-0.001	0.989			
Density (20 °C)	0.708	0.693			
Total salinity	0.992	0.083			
pH	0.932	0.324			

Table 3. Component matrix.

As shown in Table 4, according to the component score coefficient matrix, the expressions of the first and second principal factors were obtained. The comprehensive evaluation function was obtained based on the respective contribution rate of the first and second principal factors. The comprehensive evaluation value of each water sample was calculated. The discriminant indicators Na<sup>+</sup> + K<sup>+</sup>, Ca<sup>2+</sup>, Mg<sup>2+</sup>, CI<sup>-</sup>, HCO<sub>3</sub><sup>-</sup>, SO<sub>4</sub><sup>2-</sup>, total salinity, and pH were denoted as X<sub>1</sub>, X<sub>2</sub>, X<sub>3</sub>, X<sub>4</sub>, X<sub>5</sub>, X<sub>6</sub>, X<sub>7</sub>, and X<sub>8</sub>. The first and second principal factors are shown as Equations (6) and (7).

$$Z_{1} = (0.152\ 0.149\ 0.138\ 0.178\ 0.154\ 0.180) \begin{pmatrix} X_{1} \\ X_{3} \\ X_{4} \\ X_{5} \\ X_{7} \\ X_{8} \end{pmatrix}$$
(5)

$$Z_2 = (0.241 - 0.520) \begin{pmatrix} X_2 \\ X_6 \end{pmatrix}$$
(6)

	Components				
	First Principal Factor	Second Principal Factor			
Na <sup>+</sup> /K <sup>+</sup>	0.152	-0.001			
Ca <sup>2+</sup>	0.058	0.241			
Mg <sup>2+</sup>	0.149	-0.020			
CĨ-	0.138	0.055			
HCO <sub>3</sub> -	0.178	-0.121			
$SO_4^{2-}$	0.141	-0.520			
Total Salinity	0.154	-0.005			
pН	0.180	0.134			

Table 4. Component score coefficient matrix.

The expressions of the first and second principal factors are shown as follows:

$$Z_1 = 0.152X_1 + 0.149X_3 + 0.138X_4 + 0.178X_5 + 0.154X_7 + 0.180X_8$$
(7)

$$Z_2 = 0.241X_2 - 0.520X_6 \tag{8}$$

Based on the contribution rate of the first and second principal factors mentioned above, the comprehensive evaluation function could be obtained, as follows:

$$Z = 0.1137X_1 + 0.0492X_2 + 0.1115X_3 + 0.1032X_4 + 0.1331X_5 - 0.1061X_6 + 0.1152X_7 + 0.1346X_8$$
(9)

3.1.3. Solution of Weight Coefficients

The comprehensive score values of water source and produced water were obtained by entering the hydrochemical characteristics data in Table 1 into the comprehensive evaluation function, i.e., Equation (10). The results are shown in Tables 5 and 6.

Water Source	Date	Score Symbol	Score
Injected water 1	Before 28 May 2015	$Z^{\prime\prime}$	555.979
Injected water 2	After 28 May 2015	Z'''	401.679
Formation water	/	Zı	1488.426

Table 5. Comprehensive score of water source.

**Table 6.** Comprehensive score of produced water from typical wells.

Well	Date	Score
1	4 March 2015	1040.124
2	16 March 2015	1390.474
3	15 July 2014	1214.433
4	4 March 2015	947.657
5	4 March 2015	1070.265
6	16 March 2015	1293.015
1	5 August 2015	776.543
2	5 August 2015	736.346
3	23 June 2015	1298.610
4	23 April 2016	966.435
7	5 August 2015	1067.901
8	5 August 2015	815.222

In the calculated results, the score of the formation water was denoted Z', and the scores of injected water 1 and 2 were denoted Z'' and Z''', respectively, as shown in Table 5. The score of the produced water from the thermal recovery well under cyclic steam stimulation was Z, as shown in Table 6.

We assumed that the produced water of each CSS well was totally composed of formation water and injected water in different proportions. The following equations were obtained:

$$\begin{cases} (a_1b_1) \begin{pmatrix} Z' \\ Z'' \end{pmatrix} = Z \\ a_1 + b_1 = 1 \end{cases}$$
(10)

$$\begin{cases} (a_2b_2) \begin{pmatrix} Z' \\ Z''' \end{pmatrix} = Z \\ a_2 + b_2 = 1 \end{cases}$$
(11)

In the above equations,  $a_1$  and  $a_2$  are the weight coefficients of the formation water in the produced water before and after 28 May 2015, respectively, and  $b_1$  and  $b_2$  are the weight coefficients of the injected water in the produced water before and after 28 May 2015, respectively.

The comprehensive scores of produced water (*Z*), formation water (*Z*), injected water 1 (*Z''*), and injected water 2 (*Z'''*) were substituted into Equations (11) and (12). The proportions of the injected and

formation water in the produced water of each well before and after 28 May 2015 could be calculated. The results are shown in Tables 7 and 8.

Well	Date Weight Coefficient of Injected Water 1		Weight Coefficient of Formation Water	
1	4 March 2015	0.48	0.52	
2	16 March 2015	0.69	0.31	
3	15 July 2014	0.29	0.71	
4	4 March 2015	0.58	0.42	
5	4 March 2015	0.45	0.55	
6	16 March 2015	0.21	0.79	

Table 7. Weight coefficient of formation and injected water in the produced water before 28 May 2015.

Table 8. Weight coefficient of formation and injected water in the produced water after 28 May 2015.

Well	Date	Weight Coefficient of Injected Water 2	Weight Coefficient of Formation Water	
1	5 August 2015	0.66	0.34	
2	5 August 2015	0.11	0.89	
3	23 June 2015	0.17	0.83	
4	23 April 2016	0.48	0.52	
7	5 August 2015	0.39	0.61	
8	5 August 2015	0.62	0.38	

Based on the weight coefficients of the formation and injected water in the produced water of each well in Tables 7 and 8, the corresponding source proportions of the produced water of each typical well could be drawn, as shown in Figure 2. The criterion of the formation water intrusion is that the formation water weight coefficient in produced water is greater than 0.7. Before 5 August 2015, the weight coefficients of formation water in well 3 and well 6 were high, which indicates that there was water intrusion in well 3 and well 6. After 5 August 2015, the weight coefficients of formation water 5 August 2015, the weight coefficients of formation well 3 and well 6 were high, which indicates that there was water in well 2 and well 3 increased. This indicated that the formation water intrusion in block M became more severe with the production of the CSS wells.



Figure 2. Source proportions of produced water in block M.

### 3.2. Further Analysis Model of Formation Water

In the above, the source of the produced water was analyzed by using the factor analysis method, and the weight coefficients of the formation water and injected water were obtained. However, in some heavy oil reservoirs, there are both interlayer water and edge-bottom water. Therefore, a further analysis model was proposed for determining the composition of the formation water produced by CSS wells. In this model, based on the water recovery rate, the normal distribution method is used to

divide the formation water into three categories: only interlayer water, both the interlayer water and edge-bottom water, and only edge-bottom water.

This model was used to determine the water recovery rate of 34 CSS wells with high weight coefficient of formation water. First, normal distribution processing was carried out on the water recovery rate of each well. The maximum, minimum, and central values, as well as the standard deviation of the data, were calculated, and the water recovery rates were divided into 20 groups at equal intervals. The distance between the upper and lower limits and the central value was set to 3.2. The group distance and the upper and lower limits of the group coordinates were calculated, as shown in Table 9. The group coordinates, frequency, and normal distribution data of 20 groups were calculated, and the normal distribution diagram was created in Figure 3.

Parameter	Value	Parameter	Value
Maximum value	5.78	Group distance	0.3378
Minimum value	0.63	Distance between upper and lower limits and central value	3.2
Central value	2.70	Lower limit of group coordinates	-0.5106
Standard deviation	1.3371	Upper limit of group coordinates	5.9076
Number of groups	20		
6		0.35	5

Frequency 5 0.3 5 Normal distribution curve Normal distribution curve 0.25 4 Frequency 0.2 3 0.15 2 2 0.1 1 1 1 0.05 0 0 0 0 0 0 0.50 `**、**}® , 0<sup>9</sup>8 

Figure 3. Normal distribution of water recovery rate.

By analyzing the normal distribution diagram of the water recovery rate, the water production status of CSS wells was divided into three groups: water recovery rate less than 2, water recovery rate located in the 2–4 range, and water recovery rate greater than 4. When the water recovery rate was less than 2, the main source of formation water was considered to be interlayer water. When the water recovery rate was greater than 2 and less than 4, the main source of the formation water was considered to be interlayer water and edge-bottom water. When the water recovery rate was greater than 4, the main source of formation water was considered to be edge-bottom water. Further determination of the formation water sources of typical wells is shown in Table 10. It can be obtained that the formation water produced from typical wells in block M was mainly a mixture of interlayer water and edge-bottom water. Among these wells, well 2 is the most affected by edge-bottom water intrusion. Moreover, the water recovery rate of typical wells is relatively high, indicating that the edge-bottom water in this block was active.

Category	Well Number	Date	Water Recovery Rate	<b>Classification Basis</b>
Interlayer water	3	15 July 2014	2.98	
and edge-bottom	3	23 June 2015	2.98	2 < Water recovery rate < 4
water	6	16 March 2015	3.40	
Edge-bottom water	2	5 August 2015	4.84	Water recovery rate > 4

Table 10. Source category of formation water.

## 4. Results and Discussion

#### 4.1. Model Validation

The reservoir in this study is a sandstone single-layer heavy oil reservoir with edge-bottom water. The reservoirs are shallow and possess good physical properties, high reserve abundances, high crude oil densities, high crude oil viscosities, small volumes of dissolved gas, and active edge and bottom water. Block M is a conventional heavy oil reservoir. CSS has been adopted in this block, and good development effectiveness was achieved in the early stage of CSS. However, with the increase in the circulation turns, the effectiveness of the CSS wells decreased significantly, which was manifested as a decrease in the daily oil production and increase in the water cut. Due to the particularity of the CSS technology, the produced water from the CSS wells should be the mixture of the condensation of the injected steam and the formation water that was composed of the edge-bottom water and the interlayer water. According to the different main causes of water output, different treatment measures are needed to improve the development effect of the CSS wells in the later stage. In this study, to identify the main source of the produced water, the developed source discriminant model of produced water was applied to the block M. The main source of the produced water for typical wells was obtained, as shown in Figure 2 and Table 10. Among the abovementioned typical CSS wells, the edge-bottom water invasion of well 2 is the most serious. In the following, we will verify the accuracy of the model based on the development history of well 2.

As shown in Figures 4 and 5, in the first cycle of the CSS, well 2 had good development effects with high daily oil production and low water cut. However, with the increase of circulation cycles, the daily oil production of well 2 decreased significantly. By the end of the third cycle, the water cut of well 2 reached 100%. The production performance of well 2 indicates that this well has severe water production and needs corresponding treatment urgently. Since the oil field development is in the early stage, researchers are not familiar with the block, and the corresponding tracer interpretation data is lacking. Therefore, it is difficult to propose corresponding effective treatment measures according to the source of the produced water in well 2. On 5 August 2015, block M applied the model established to well 2 for discriminating the source of produced water and found that the edge-bottom water intrusion in well 2 was severe. Consequently, well 2 was set as a test well, and water plugging measures were taken for this well in July 2016. After water plugging, the daily oil production of well 2 increased significantly, and the water cut declined. The measures for plugging the edge-bottom water in well 2 have shown good results.

In the absence of laboratory experiments and field tracer interpretation data, block M successfully solved the problem of edge-bottom water intrusion based on the results of the developed model, which further proved the accuracy of the model established.



Figure 5. Daily water cut of well 2.

### 4.2. Model Application

Edge-bottom water energy is one of the factors that influences the productivity of single wells. Under the premise of ensuring reasonable productivity, edge-bottom water can supplement the formation energy and increase the productivity of single wells. More importantly, for a reservoir with active edges-bottom water, the edge-bottom water easily enters nearby oil wells during production. The water cut of the oil wells increases rapidly and the production declines or remins at a low level, which affects the productivity of single wells [48,49]. As mentioned above, block M is a reservoir with active edge-bottom water. With the development of the reservoir using CSS, the water cut of the CSS wells generally increased, and the production declined. Therefore, we applied the model established in this paper to block M to obtain information about the produced water source of typical wells, as shown in Table 10 and Figure 2. The next treatment measures will be proposed for the CSS wells based on the combination of model results and dynamic production data.

As shown in Figures 6 and 7, most of the typical CSS wells in block M have undergone 4–5 cycles. As mentioned above, the water cut in well 2 increased and production decreased rapidly in the early stage because of the serious edge-bottom water intrusion. After water plugging, the periodical average water cut decreased and the periodical average daily oil production was restored. With the increase of circulation cycles, the water cut of all the wells, except for well 2, rose in a fluctuating manner. Even the water cut of well 4 and well 6 rose to 100% in the fourth cycle. Correspondingly, as shown in Figure 7, with the increase in circulation turns, the periodical daily oil production of the CSS wells, except for well 2, showed a clear downward trend. Among them, well 3, well 4, well 6, and well 7

were in a serious condition, even the fourth periodical average daily oil production of well 4 and well 6 was reduced to 0. Therefore, corresponding treatment measures are needed for these wells urgently. According to the analysis results of the model developed, the weight coefficients of formation water in well 3 and well 6 are large, which indicates formation water intrusion is serious in these wells, and the water plugging measures should be implemented correspondingly. For well 4 and well 7, the weight coefficients of the formation water are relatively small. Consequently, in these wells, the main problem is the ineffective circulation of the injected steam in the high permeability layer. In this situation, profile control measures should be taken to reduce the permeability of the highly permeable layer.



Figure 6. Periodical average water cut of typical wells in block M.



Figure 7. Periodical average daily oil production of typical wells in block M.

The source discriminant model can quickly and effectively identify the source of the produced water from CSS wells in an edge-bottom water reservoir. This model can be applied not only to source analysis of produced water but also to rapid evaluation of the production performance of oil wells, which provides effective basis and guidance for proposing treatment measures for CSS wells with a high water cut. In addition, this model can also be used in conventional reservoirs developed by water injection. It can not only quantitatively evaluate the connectivity between the production wells and surrounding injection wells, but also identify dominant channels. In short, this model has

important application value and prospects, and provides new ideas for the source discrimination of produced water.

# 5. Conclusions

- 1. In this study, a new source discriminant model for produced water is established that combines the traditional hydrochemical characteristics and factor analysis methods and accounts for the quality change in injected water. The weight coefficients of the formation water and injected water were obtained. Furthermore, the composition of the produced formation water was determined by the normal distribution method.
- 2. According to the results of the model, well 2 was selected as a test well, and water plugging measures were taken for well 2 in the oil field. After water plugging, the water cut of well 2 decreased and the periodical average daily oil production increased significantly, which further verified the accuracy of the model.
- 3. The model developed was applied to block M. It was obtained that the weight coefficient of the formation water in well 2, well 3, and well 6 was high. Therefore, water plugging measures need to be implemented in these wells. For well 4 and well 7, profile control measures are required to reduce the ineffective circulation of injected steam in the high permeability layer.
- 4. This model can be used not only for source analysis of the produced water from CSS wells in edge-bottom water, but also for identification of the dominant channels in a convention reservoir developed by water injection. It provides new ideas for source discrimination of produced water.

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