

Article

Radial Basis Function Neural Network and Response Surface Methodology-Based Optimization of Glue Breakage in Waste Drilling Fluids

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Abstract: This paper aims to solve the problems of difficult breakage and low water yield of wastewater-based drilling fluids. The effects of breakage agent dosage, reaction temperature, stirring speed, and pumping time on the water yield of wastewater-based drilling fluids were analyzed through one-way experiments, and these parameters were optimized by Response Surface Methodology (RSM). A Radial Basis Function Neural Network (RBF) model was also introduced to compare its performance with that of RSM in predicting optimal process conditions. To further improve the accuracy of the model, a combination of Genetic Algorithm (GA) and RBF was used for optimization. The results show that both RSM and RBF models can predict the water yield of wastewater-based drilling fluids with high accuracy, in which the coefficient of determination of the RSM model is 0.9939, which is better than that of the RBF model (0.9778). The optimal operating conditions are determined through numerical optimization: the amount of glue breaker added is 3.97 kg/m³, the reaction temperature is 51 °C, the stirring speed is 419 rpm, and the maximum water yield is 62.37%, which is the best-predicted water yield. The GA-RBF coupled model performed better in terms of root mean square error (RMSE), coefficient of determination ($R^2 = 0.998$), and mean absolute error (MAE), and the *t*-test verified that there was no significant difference between the predicted and actual values. The maximum value of the water yield of the waste mud could reach 61.97% when the gum breaker was added at 3.83 kg/m³, the reaction temperature was 53 °C, and the stirring speed was 424 rpm, which provided an accurate and reliable theoretical basis and technical support for the harmless treatment of deep and complex drilling fluids.



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Keywords: wastewater-based drilling fluids; gum breaking; response surface methodology; radial-based neural network; genetic algorithm

1. Introduction

As a significant fossil fuel resource, oil and gas represent a fundamental component of the national economy. In order to ensure stable and high production levels in the oil and gas field, there has been an improvement in the level of oil and gas exploration and development in China in recent years [1,2]. In the context of oil and gas exploration and development, drilling fluid assumes a pivotal role [3]. Its function encompasses vortex pressure injection, which utilizes pressure to propel drilling tools while dislodging rock

chips generated during drilling. Additionally, it facilitates cooling and lubrication of the drill bit and drilling tools, safeguarding the well wall, and maintaining equilibrium in downhole air pressure, thereby mitigating the risk of blowout [4,5]. However, it should be noted that drilling fluids inevitably generate a large volume of hazardous waste during their utilization [6]. The environment is also susceptible to contamination due to the presence of water sources, forests, sandy areas, and nature reserves in the oilfield operation area, which is characterized by deep mountains, ravines, beams, and mounts. Consequently, the risk to safety and environmental protection is high. Therefore, it is imperative to explore effective methods for the reuse of drilling waste fluids, as this issue is of great importance and urgency [7–10].

Currently, compared with oil-based drilling fluids, water-based drilling fluids (WBFs) possess greater advantages in terms of environmental protection and cost [11]. Spent WBFs form a stable system containing clay, various chemical treatment agents, contaminated oils, etc., characterized by complex composition, high mineralization, deep coloration, and high solid content. If not treated and discharged arbitrarily, they will cause significant harm to the ecological environment [12,13]. Traditionally, the disposal of spent WBFs primarily relies on tanker trucks to transport the drilling waste fluids from the mud pits at the well site to centralized pits for subsequent solidification treatment [14]. In contrast, the non-landing mud technology mainly employs a “broken glue + press filtration” process to treat the spent drilling fluids. This technology offers notable advantages by enabling immediate on-site processing of the spent mud at the drilling location, effectively preventing environmental pollution. Additionally, it facilitates the recycling and reuse of the drilling mud, thereby reducing costs and enhancing resource utilization efficiency [15]. However, when applying non-landing mud technology to treat spent drilling fluids, several challenges remain. Firstly, it is difficult to precisely control the dosage of glue breaker agents. Due to the complex and variable on-site environment, and given the significant differences in the composition of different drilling fluids, an improper dosage of glue breaker agents not only increases treatment costs but may also pose environmental risks. Secondly, the mixing process is also problematic. The high-viscosity property of waste drilling fluid easily leads to uneven mixing, especially when the mixing speed is insufficient to provide enough shear force to fully disperse the components, thus affecting the effective contact between the breaker and drilling fluid and the breaking effect. Furthermore, the fluctuation of the reaction temperature during the breaking process will also have a certain impact on the breaking effect. Finally, in the filtration link, the waste drilling fluid often contains clay and other impurities, which makes the filtration time long and unstable, not only does the frequency of equipment maintenance increase, but even leakage may occur. Therefore, a large number of domestic and foreign scholars have paid attention to and favored the above problems [16–19].

Pereira et al. [20] have investigated the use of centrifugation for enhanced solid-liquid separation to achieve oil recovery from water-based drilling fluid muds, and experiments have shown that the use of gel-breaking agents at lower temperatures and centrifugal forces (50 °C and 2200 rpm) allows the separation of the liquid phase from the waste drilling fluid; Li Jinming et al. [21] developed a solid-liquid separation and reuse technology suitable for the purification and treatment of low-solid-phase waste drilling mud, and achieved good treatment results in the Sulig block test; Jian Huang et al. [9] who formulated shallow inhibitory anti-collapse drilling fluids based on the mechanism of well wall instability, developed deep drilling fluid formulations by adding and replacing agents in the base fluid to achieve the reuse of multi-layer waste drilling fluids. Zhan Feng [22] et al. systematically explored the effects of a single reagent, two or three reagents compounded gel-breaker on the solid-liquid separation effect of mud through experimental studies, which can provide

technical support for the efficient and harmless treatment of wastewater-based drilling mud generated from drilling platforms. In the process of breaking rubber in waste drilling fluids, it is not feasible to carry out experiments that cover all the factors that affect the effectiveness of breaking rubber in practice, in view of the variety of factors that affect the effectiveness of breaking rubber. In response to the above problems, Yang Bin et al. [23] studied the effect of breaking agent dosage on the treatment of drilling mud, and Qiao Sanyuan et al. [24] evaluated the effect of temperature on the treatment effect of seawater-based waste drilling fluids, Ji Ting et al. [25] studied the effect of mixing speed on the treatment of waste drilling fluids, and Jiu Weipeng et al. [26] studied the effect of filtration time on the treatment of extracted water from the oilfield. Although the above research has achieved certain results in the treatment of waste drilling fluids, it is still facing problems such as the unstable effect of breaking rubber and treatment efficiency to be improved, especially in the Longdong block, the existing treatment technology and research results are difficult to be universally applied and cannot effectively meet the actual production needs. Moreover, at present, there is no research in this field, on the RSM, RBF, and GA-RBF methods for the systematic integration of the application of wastewater-based drilling fluids to break the optimization of the process of rubber research.

Relying on the abundant research results, this study was conducted on the wastewater-based drilling fluids in the Longdong block of Changqing oilfield, and the core factors such as the amount of glue breaker, reaction temperature, stirring speed and filtration time, etc., which have a significant potential influence on the experimental results, were comprehensively considered and screened. Given that this experiment is an indoor study simulating field conditions, the range of values of each factor is closely based on the actual working conditions in the field. Through single-factor experiments, the changing rules of these factors were studied to determine their suitable working intervals, and then the response surface method and artificial neural network model were used to optimize them in depth to obtain the optimal operating conditions. This study provides an accurate and reliable theoretical basis and data source for the harmless treatment of deep and complex drilling fluids and helps to improve the application level and effect of waste drilling fluid treatment technology in actual projects.

2. Materials and Methods

2.1. Sources of Wastewater-Based Drilling Fluids

The low-solid polymer water-based drilling muds under scrutiny in this study were obtained from a well site in the Longdong block. Their composition included amphoteric ionic polymers, strong encapsulants, viscosity-increasing and lifting cuttings, plugging agents, and bentonite clay.

2.2. Experimental Apparatus and Reagents

Reagent: Calcium chloride type glue breaker.

Instruments: METTLER TOLEDO AG285 density balance, Qingdao Hengtaida (Qingdao, China) ZNN-D6 six-speed rotational viscometer, Qingdao Hengtaida martensitic funnel viscometer, China Youke PHS-3C pH detector, Xi'an Taikang Biotechnology Company SHB-III (Xi'an, China) circulating water multi-purpose vacuum pump, and glass instruments.

2.3. Experimental Methods

2.3.1. Component and Performance Testing of Wastewater-Based Drilling Fluids

In order to determine the physical properties of the wastewater-based drilling fluids, the following methods were used in this study: firstly, the density of each wastewater-based

drilling fluid was measured using a density balance; next, 1500 mL of wastewater-based drilling fluids were measured, and their funnel viscosities were measured by a Martell's funnel viscometer; lastly, the plastic viscosities of the wastewater-based drilling fluids were measured and calculated using a six-speed rotational viscometer. All measurements were carried out in accordance with the standard GB/T 16783 «Petroleum and natural gas industries—Field testing of drilling fluids» [27]. Total suspended solids content, total dissolved solids content, pH, and mineralization were carried out concerning the standard SY/T 5523-2016 «Method for analysis of oil-filed water» [28].

2.3.2. Response Surface Model Analysis and Optimization

In the field of wastewater-based drilling fluids glue-breaking process research, it is crucial to explore efficient and accurate optimization methods. Response Surface Methodology (RSM) has shown unrivaled advantages in this process and has become a good choice for this study.

The breaking process of wastewater-based drilling fluid is affected by multiple factors, such as the amount of breaking agent added, reaction temperature, stirring speed, and filtration time, and there are complex interactions among these factors. Traditional single-factor experiments are unable to consider such interactions, but RSM can investigate the effects of the interactions between multiple independent variables on the response values of the breakthrough effect and water yield and comprehensively analyze the intrinsic connection between the factors. By constructing the response surface model, the trend of the glue-breaking effect under different combinations of factors can be visualized.

From the perspective of optimizing process conditions, RSM has significant advantages. By constructing multivariate high-order regression curve equations, it fits the implicit functional relationship between the influencing factors and the response values and realizes the combination and tuning of multivariate variables based on the different degrees of influence of each factor on the non-independent variables [29]. Based on this, the method can accurately predict the glue-breaking effect under the combination of different factor levels, quickly locate the optimal process parameter combinations, greatly improve the optimization efficiency, and avoid the waste of resources caused by the traditional blind attempts of different parameter combinations.

Compared with the traditional orthogonal design, RSM can not only analyze the continuity of the different levels of the influencing factors but also reasonably analyze and predict the optimization results [30]. RSM adopts a scientific and reasonable way to obtain rich information with fewer experiments, reduce the experimental workload, make full use of the experimental data to carry out a systematic analysis, effectively reduce the error, and improve the reliability and accuracy of the result.

The observed value Y in response analysis can be expressed by Equation (1):

$$Y = f(x_1, x_2, \dots, x_i, \dots, x_n) + \varepsilon \quad (1)$$

In response to surface analysis, the initial step involves the fitting of multiple quadratic regression and quadratic terms to the experimental data. This process yields a multiple quadratic regression response surface model for the response value and a higher-order regression equation for the response value, as depicted in Equation (2):

$$\hat{Y} = a + \sum_{i=1}^m b_i x_i + \sum_{j < i} b_{ji} x_j x_i + \sum_{i=1}^m b_{ii} x_i^2, \quad j = 1, 2, \dots, m-1 (i \neq j) \quad (2)$$

Subsequently, the independent variable, x_i , is to be specified as the independent variable in the above equation, with the objective of taking the first-order partial derivatives

to zero. This is to be followed by the solution of the joint system of equations. The final step is to determine the extreme value of the higher-order regression equation, as well as the corresponding value of the independent variable factors. The form of the extreme value is shown in Equation (3), under the conditions of the extreme value.

$$\frac{\partial \hat{Y}}{\partial i} = 0, \quad i = 1, 2, \dots, n \quad (3)$$

In this paper, Design-Expert 13.0.1.0 software is utilized for the analysis and optimization of response surface models.

2.3.3. Calculation of Water Yield

The quantity of water resulting from the utilization of a wastewater-based slurry subsequent to the fragmentation of rubber can be calculated through the application of Equation (4).

$$Y = \frac{V_0 - V_1}{V_0} \quad (4)$$

In this study, the water output rate, expressed as a percentage (%), is represented by the variable Y . The volume of the wastewater-based drilling fluid prior to the rupture of the gum, denoted by L , is designated as V_0 . The volume of the pressurized filtrate subsequent to the rupture of the gum, denoted by L , is designated as V_1 .

2.3.4. Artificial Neural Network Analysis

The Radial Basis Neural Network (RBF) model consists of three layers, as illustrated in Figure 1.

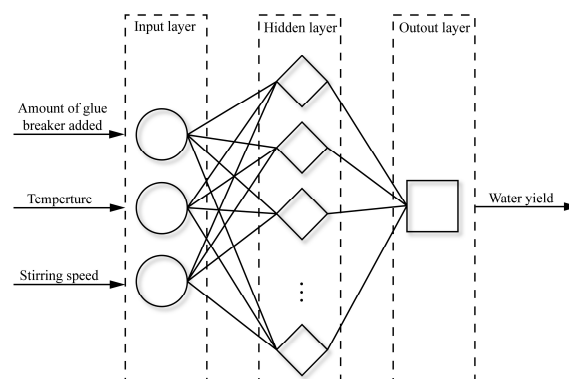


Figure 1. Topology of the neural network model.

As with the three-layer structure of the Back Propagation (BP) model, both the BP model and the Radial Basis Function (RBF) model are feed-forward neural networks. The hidden layer of the RBF model is a radial basis activation function, which is characterized by a radially symmetric centroid and a function that gradually decreases and is non-negative, and which is characterized by a non-linear as well as a local response. The transfer function of the hidden layer in the model is predominantly a Gaussian function, defined by Equation (5):

$$a_j(x) = \exp\left(-\frac{\|x_i - c_j\|^2}{2\sigma_j^2}\right) \quad (5)$$

In this equation, the width of the j th neuron (σ_j) is considered, along with the input node (x_i) and the centre point of the radial basis function (RBF) unit (c_j). The j th unit's

output (a_j) is also of relevance, as is the output layer, which is a linear function. This function can be expressed by Equation (6):

$$y_k(x) = \sum_{j=1}^n w_{jk} a_j(x) + b_k \quad (6)$$

In this equation, y_k denotes the output of the input variables, w_{jk} and b_k represent the weights and deviations, respectively, between the output variables and the implicit layer.

Before building the neural network model, the input and output sample data must be normalized between 0 and 1 to ensure the accuracy of the prediction, and the calculation of the normalized value (y_n) for each original input and output dataset (y_i) is represented by Equation (7).

$$y_n = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \quad (7)$$

In this study, three parameters, root mean square error (RSME), coefficient of determination (R^2), and mean absolute error (MAE) are used for evaluation through the model prediction results as an indicator, and the formulas for each parameter are as follows.

Root mean square error (RSME):

$$\text{RMSE} = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}} \quad (8)$$

where y_i and $\hat{y}_i$ are the actual and model predicted values, respectively.

Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (9)$$

where y_i is the input data, $\hat{y}_i$ is the predicted value, and $\bar{y}_i$ is the mean value of the input data.

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n} \quad (10)$$

where y_i and $\hat{y}_i$ are the actual value and model predicted value respectively.

For these three parameters, RMSE reflects the error between the predicted value and the real value, the smaller the value indicates that the error between the expected value and the real value is smaller, the better the prediction network effect. R^2 is the degree of fit of the network, the closer the value is to 1 indicates that the network fits better. MAE also reflects the error between the predicted value and the real value, the smaller the value indicates that the model's prediction accuracy is better.

3. Results and Discussion

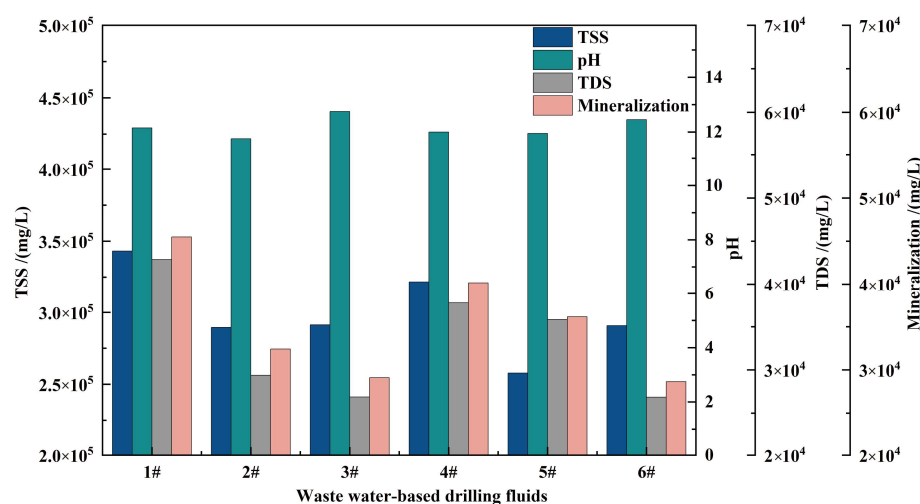
3.1. Analysis of the Properties of the Waste Drilling Fluid

The waste drilling fluids studied in this paper are all from a well field in the Longdong area, and 1–6# waste drilling fluids are all the waste drilling fluids produced at different stages of the well field, and their densities, plastic viscosities, and funnel viscosities and other keys are shown in Table 1.

Table 1. Comparison of the working performance of each waste drilling fluid with the required.

Name	Unit	1#	2#	3#	4#	5#	6#	Indicator Requirements
Density	g/cm ³	1.4281	1.2365	1.3366	1.3816	1.1972	1.3354	1.0300~1.0800
Plastic viscosity	mPa·s	14.5	12.5	16.0	14.5	13.0	15.5	8.0~10.0
Funnel viscosity	s	87.21	79.04	76.23	85.17	82.25	74.68	35.00~55.00

As demonstrated in Table 1, the working properties of the wastewater-based drilling fluids, including density, plastic viscosity, and funnel viscosity, failed to meet the stipulated design indexes for drilling fluid. Specifically, the density, plastic viscosity and funnel viscosity of 1~6# wastewater-based drilling fluids range from 1.1972~1.4281 g/cm³, 12.5~16.0 mPa·s and 74.68~87.21 s, respectively, which exceed the index requirements of 1.0300~1.0800 g/cm³, 8.0~10.0 mPa·s and 35.00~55.00 s. In order to further find out the root cause of the failure of the drilling fluids, the total suspended solids (TSS), pH, total dissolved solids (TDS), and mineralization of six more drilling fluids were systematically measured in this paper, and the results are shown in Figure 2.

**Figure 2.** Determination of TSS, pH, TDS, and mineralization in wastewater-based drilling fluids.

As can be seen in Figure 2, the TSS content of the wastewater-based drilling fluid was $2.5 \times 10^5 \sim 3.5 \times 10^5$ mg/L, the pH was about 12, the content of TDS was $2.3 \times 10^4 \sim 4.5 \times 10^4$ mg/L, and the mineralization was $2.5 \times 10^4 \sim 4.5 \times 10^4$ mg/L. The high density of the wastewater-based drilling fluid was initially attributed to its substantial content of suspended solids, such as sediment and drill cuttings. The elevated pH of the drilling fluid hinders the dispersion of clay within the solution system, resulting in its high plastic viscosity. The abundant anions and cations present in the drilling fluid significantly increase the mineralization of water samples, thereby elevating the funnel viscosity. These characteristics increase the complexity of waste drilling fluid treatment and significantly affect the effectiveness of the breaking process. The high density and viscosity of the drilling fluid result in difficulties for the breakers to be uniformly dispersed and to effectively act on the colloidal structure in the drilling fluid. In addition, the high pH may inhibit the activity of the breakers or cause them to fail prematurely. Consequently, these factors must be considered during the execution of the breaking process, and critical parameters such as the quantity of breaking agent incorporated, the reaction temperature, and the mixing velocity must be optimized to ensure the effectiveness and efficiency of the breaking process.

3.2. Single Factor Analysis

In view of the fact that this study aims to deeply explore the key parameters in the drilling fluid waste treatment process, considering that 2# waste drilling fluid is mainly generated in the first opening section, and the amount of waste drilling fluid generated in this stage is significantly higher than that in other drilling stages, this study chooses to take 2# waste drilling fluid as the main object of study. In order to systematically optimize the break-bulk treatment process of waste drilling fluids, this study adopted a one-way experimental method, focusing on the effects of an additive amount of break-bulk agent, reaction temperature, stirring rate, and pumping time on the water output rate. The value ranges of each factor are determined based on previous studies and field conditions to ensure that the experimental conditions are close to the actual application environment. As an important index to measure the effect of gum breaking, the water yield was quantitatively evaluated according to Equation (4).

3.2.1. Influence Law of Addition of Gum Breaker

The gel-breaking agent was added to the wastewater-based drilling fluid in quantities of 1.0000 g, 2.0000 g, 3.0000 g, 4.0000 g, 5.0000 g, 6.0000 g and 7.0000 g, respectively. The mixture was then pumped and filtered at 30 °C and 500 rpm with sufficient stirring for 30 min.

As demonstrated in Figure 3, the water yield of the wastewater-based drilling fluid increases in proportion to the amount of rubber breaker added. Once the amount of rubber breaker reaches 3.0000 g, the water yield of the wastewater-based drilling fluid remains relatively constant at approximately 60%. This phenomenon can be attributed to the fact that the magnitude of the gel-breaking reaction of the wastewater-based drilling fluid increases with the increase of the amount of rubber breaker added. Once the amount of rubber breaker added approaches a state of saturation, the water yield of the wastewater-based drilling fluid gradually stabilizes. Consequently, a working interval of 2.00~4.00 kg/m³ of wastewater-based drilling fluid is deemed appropriate for the incorporation of a gel breaker.

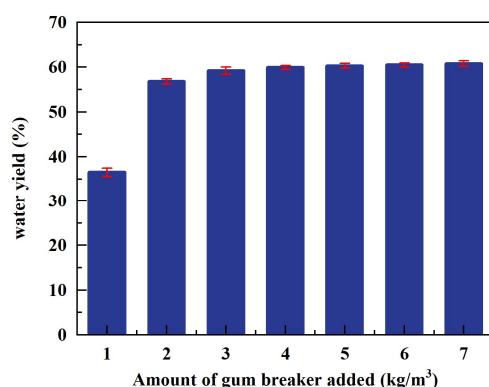


Figure 3. The effect pattern of gum breaker addition on the water yield of wastewater-based drilling fluid.

3.2.2. Influence Law of Reaction Temperature

A quantity of 3.0000 g of the gel-breaking agent was added to 500 mL of water-based drilling fluid, and then gel-breaking experiments were carried out at temperatures of 10 °C, 20 °C, 30 °C, 40 °C, 50 °C, 60 °C and 70 °C, under a rotational speed of 500 rpm and a pumping filtration time of 30 min, respectively. The change in the water output rate was observed, and the results of the experiments are shown in Figure 4.

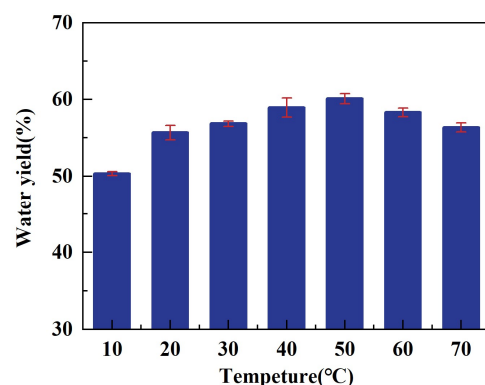


Figure 4. Role of reaction temperature on the water yield of wastewater-based drilling fluid.

As can be seen in Figure 4, when the reaction temperature in the breaking process is 10 °C, the water yield of the wastewater-based drilling fluid is only 50.32%, and as the temperature increases to 20–70 °C, the water yield is gradually increased and then decreased, and reaches the maximum value at 5 °C. This is because the increase in temperature promotes the molecular thermal movement, which makes the wastewater-based drilling fluid and the breaker particles micro-mixed more fully, thus significantly increasing the water yield; however, if the temperature continues to increase, the hydrolysis degree of carbonate in the solution increases, which leads to an increase in the pH value of the suitable colloidal system, which in turn causes the breaker to partially precipitate, and ultimately results in a slow decline in the water yield. Therefore, after comprehensive consideration, it is reasonable to take 40–60 °C as the appropriate interval of the reaction temperature in the gel-breaking process. This temperature range not only covers the typical conditions of on-site treatment of water-based waste drilling fluids in the Longdong block of Changqing oilfield but also avoids the influence of low reaction efficiency due to too low temperature or the influence of pH value change on the effect of gel breaker caused by too high temperature.

3.2.3. Influence Law of Stirring Speed

A quantity of 500 mL of wastewater-based drilling fluid was combined with 3000 milligrams of gel-breaking agent. The mixture was then subjected to a temperature of 30 °C for a duration of 30 min. The gel-breaking experiments were conducted at a range of speeds, including 0 revolutions per minute (rpm), 200 rpm, 400 rpm, 600 rpm, 800 rpm, 1000 rpm and 1200 rpm. The duration of the pumping and filtering process was set at 30 min. The outcomes of these experiments are presented in Figure 5.

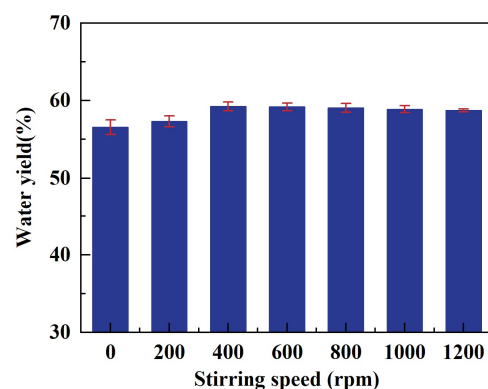


Figure 5. Role law of stirring speed on water discharge rate of wastewater-based drilling fluid.

The stirring speed has a significant effect on the mass transfer and reaction kinetics in the gum-breaking process. As can be seen in Figure 5, the effluent rate of the wastewater-based drilling fluid increases as the stirring speed increases because higher stirring speeds enhance the mixing of the gel-breaking agent with the drilling fluid and promote the gel-breaking reaction. However, when the stirring speed exceeds 400 rpm, although the dispersibility of the gel-breaker continues to increase, the effective contact time between it and the drilling fluid at the phase interface decreases, which inhibits the continuation of the gel-breaking reaction, leading to a slow decreasing trend in the water yield, which eventually stabilizes at about 60%. Therefore, considering the mass transfer effect and avoiding mechanical degradation, 200 to 600 rpm was taken as the optimized zone for the stirring speed during the breaking process.

3.2.4. Influence Law of Pumping Time

In the course of the experiment, 500 mL of wastewater-based drilling fluid was combined with 3.0000 g of gel-breaking agent. The reaction was conducted at a temperature of 30 °C, a stirring speed of 500 rpm, and a pumping time of 30 min, 40 min, 50 min, 60 min, 70 min, 80 min, and 90 min for the gel-breaking experiments. The results of the experiments are presented in Figure 6.

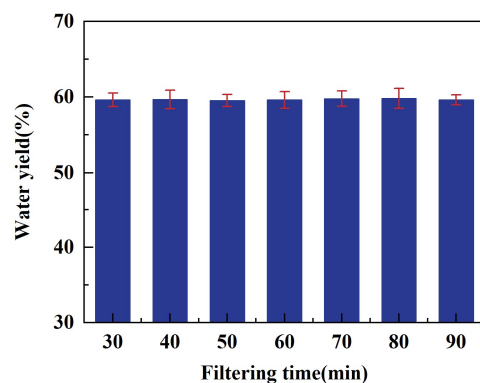


Figure 6. Role of filtration time on the water yield of wastewater-based drilling fluid.

As demonstrated in Figure 6, when the filtration duration is set at 30 min, the water yield of the wastewater-based drilling fluid is recorded at 59.6%. With an extension in the filtration duration, there is a negligible change in the water yield of the wastewater-based drilling fluid, which remains at approximately 60%. This phenomenon can be attributed to the capacity of the gel-breaking agent to form a network structure that adsorbs and envelops the solid phase in a brief period, thereby expediting the formation of the filter cake during the filtration process. Consequently, the water yield of the wastewater-based drilling fluid remains relatively constant with the prolongation of the filtration time.

In view of the negligible effect of pumping time on the water yield of waste-water-based drilling fluids, the aforementioned experimental results were utilized to determine the quantity of gel-breaking agent to be added, the reaction temperature, and the stirring rate for the response surface experimental design.

3.3. Response Surface Experiment Design and Optimization

3.3.1. Response Surface Experiment Design

In this paper, a response surface experimental design was conducted utilizing the Box-Behnken Design (BBD), with the significant influencing factors being taken into consideration. The model's accuracy and reliability were examined through analysis of variance (ANOVA), and the interaction effects between the influencing factors were investigated. The experimental scheme was devised with the amount of glue breaker added (A), the

reaction temperature (B), and the stirring speed (C) as the influencing factors, and the water yield (Y) as the response value. The factors and levels are enumerated in Table 2, and the results of the response surface experimental design are listed in Table 3.

Table 2. Factors and levels.

Level	Experimental Factors		
	A (kg/m ³)	B (°C)	C (rpm)
−1	2	40	200
0	3	50	400
1	4	60	600

Table 3. Results of response surface experimental design.

No.	A (kg/m ³)	B (°C)	C (rpm)	Y/%
1	3	40	600	60.58
2	4	50	200	61.92
3	3	50	400	61.61
4	4	50	600	61.91
5	3	60	600	61.15
6	4	60	400	61.87
7	3	50	400	61.6
8	2	60	400	58.65
9	2	50	600	58.85
10	3	50	400	61.6
11	2	50	200	58.7
12	3	40	200	60.32
13	3	50	400	61.59
14	2	40	400	58.67
15	3	60	200	60.56
16	4	40	400	61.89
17	3	50	400	61.62

3.3.2. Response Surface Model Analysis and Optimization

Response surface analyses were performed on the experimental data using Design-Expert 13.0.1.0 software, and the statistical results of the analysis of variance (ANOVA) and response surface design fitting are shown in Tables 4 and 5, respectively.

As demonstrated in Tables 4 and 5, given that the F value of the model (127.33) exceeds the critical value $F_{0.01}(9, 7) = 0.1782$ and the p -value is less than the confidence interval of 0.01, it can be concluded that the model possesses two key characteristics. Firstly, it is capable of accurately depicting the interrelationships between the factors and the response values. Secondly, it can be relied upon to determine the key optimization operating parameters under the maximum water output rate. Meanwhile, the influence of each factor on the water discharge rate of wastewater-based drilling fluid is in the following order: glue breaker addition (A) > mixing speed (C) > temperature (B). Subsequent to the incorporation of each of the aforementioned factors through the implementation of a high-order polynomial, the resultant regression equation is presented in Equation (11):

$$Y = 34.71925 + 6.59450A + 0.506375B + 0.007921C - 0.0002AC + 0.000041BC - 0.82075A^2 - 0.005133B^2 - 0.000011C^2 \quad (11)$$

Table 4. Response surface design analysis of variance.

Source	Sum of Square	df	Mean Square	F-Value	p-Value
Model	25.71	9	2.86	127.33	<0.0001
A	20.22	1	20.22	901.48	<0.0001
B	0.0741	1	0.0741	3.30	0.1120
C	0.1225	1	0.1225	5.46	0.0521
AB	0.0000	1	0.0000	0.0000	1.0000
AC	0.0064	1	0.0064	0.2853	0.6098
BC	0.0272	1	0.0272	1.21	0.3071
A ²	2.84	1	2.84	126.42	<0.0001
B ²	1.11	1	1.11	49.44	0.0002
C ²	0.8087	1	0.8087	36.05	0.0005
Residual	0.1570	7	0.0224		
Lack of Fit	0.1565	3	0.0522	401.35	0.0001
Pure Error	0.0005	4	0.0001		
Cor Toal	25.87	16			

Table 5. List of response surface design fitting statistics.

Name	Value	Name	Value
Standard Deviation	0.1498	R ²	0.9939
Mean	60.77	Adjusted R ²	0.9861
C.V.%	0.2465	Predicted R ²	0.9032
		Adequate Precision	29.9012

The coefficient of determination of the model is 0.9936, and its correction coefficient of determination and prediction coefficient of determination are 0.9861 and 0.9032, respectively. The difference between them is less than 0.2, and their signal-to-noise ratio is 29.9012, which is much larger than the critical value of 4. This indicates that the model has a certain degree of reliability, as shown in Figure 7, where the distribution of its residual values and the normal probability distribution diagram are shown.

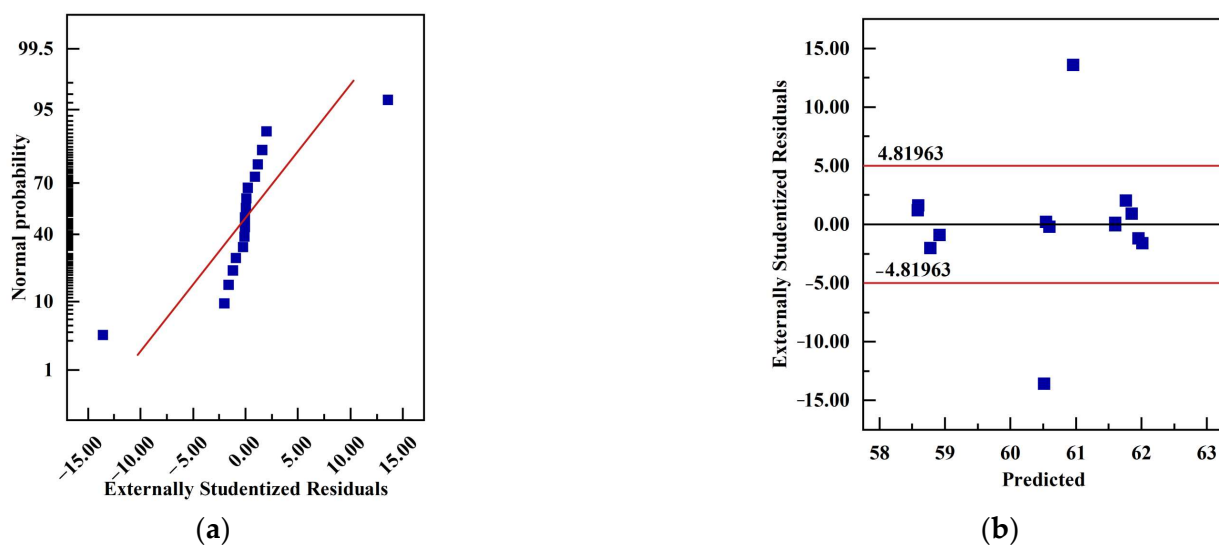


Figure 7. Plot of residuals against normal probability distribution. (a) Probability plot of residual distribution; (b) Plot of residual vs. predictive analysis.

As demonstrated in Figure 7, the arrangement of all data points is found to be irregular, thereby satisfying the criteria for a residual normal distribution. Furthermore, the data points are observed to be uniformly dispersed on the diagonal, signifying that the experimental data possesses authenticity. This is consistent with the requirement of normal distribution of residuals, and the data points are uniformly distributed on the diagonal, which indicates that the experimental data have good authenticity. Furthermore, the existence of a linear relationship between predicted and real values, in conjunction with their uniform distribution on both sides of the diagonal, serves to substantiate the efficacy and precision of the model. Consequently, it can be employed for subsequent optimization processes.

As demonstrated in Figure 8, the interaction surface between the variables is depicted. It is evident from Figure 8 that the interaction surfaces of gel-breaker addition and temperature, and gel-breaker addition and mixing speed, exhibit a steeper gradient, and the contours of their vertical transmission in the XY plane are highly dense; in contrast, the interaction surfaces of temperature and mixing speed demonstrate a flatter gradient. Consequently, the interactions of gel breaker addition and temperature, and gel breaker addition and mixing speed, exert a more substantial influence on the water yield of wastewater-based drilling fluids, while the interactions of temperature and mixing speed demonstrate a less pronounced effect.

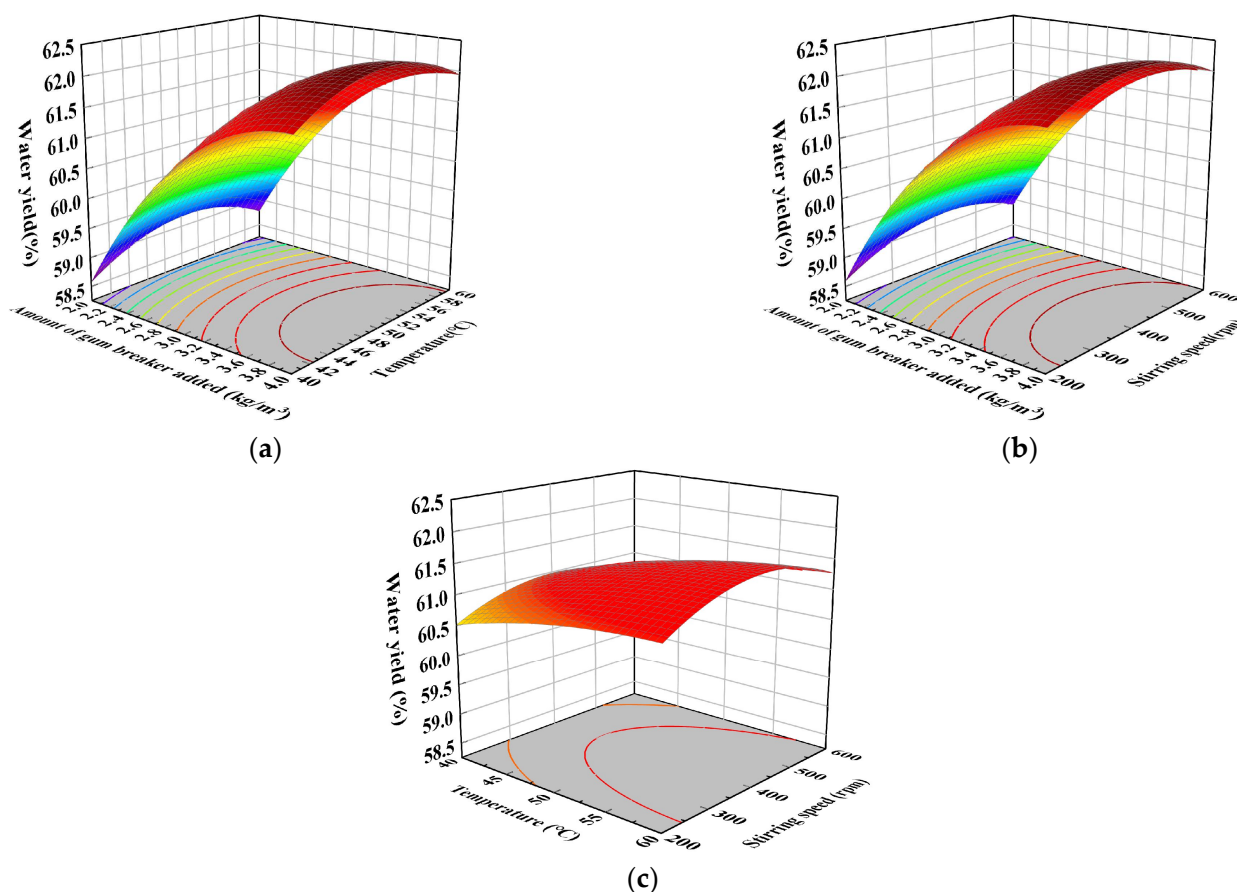


Figure 8. Interactive surfaces in two variables. (a) Gum breaker dosage versus temperature; (b) Gum breaker dosage versus stirring speed; (c) Relationship between temperature and stirring speed.

In order to ascertain the maximum value of the higher-order fitted regression equation of the response surface model, the first-order partial derivatives of the equation were taken to be equal to zero, and the system of equations was solved by association based on the necessary conditions for obtaining the extreme value at the stationary point. The amount

of glue breaker added, the temperature of the reaction, and the speed of stirring were taken as the independent variables, respectively, as shown in Equation (12):

$$\begin{cases} \frac{\partial Y}{\partial A} = 6.59450 - 0.0002C - 1.6415A = 0 \\ \frac{\partial Y}{\partial B} = 0.506375 + 0.000041C - 0.010226B = 0 \\ \frac{\partial Y}{\partial C} = 0.007921 - 0.0002A + 0.000041B - 0.000022C = 0 \end{cases} \quad (12)$$

The aforementioned system of linear equations was resolved through the utilization of the MATLAB 9.9.0.1467703 software, employing the `inv()` function to facilitate this process. The maximum predicted value for the water yield of the wastewater-based drilling fluid was determined to be 62.37%, which was achieved under specific conditions. These conditions included the incorporation of 3.97 kg of glue breaker per m³ of wastewater-based drilling fluid, a reaction temperature of 51 °C, and a stirring speed of 419 rpm.

3.4. Neural Network Optimisation Analysis

3.4.1. RBF Neural Network Model

The artificial neural network was subjected to training, testing, and validation using input, hidden, and output data from 17 datasets. The input layer consists of three neurons, the output layer contains a single neuron, and the number of neurons in the hidden layer is selected between three and 12. The quantity of nodes constituting the hidden layer is determined in accordance with the calculation outlined in Equation (13) [31].

$$h = \sqrt{m + n} + z \quad (13)$$

In the given equation, the number of nodes in the implicit layer is denoted by h , the number of nodes in the input layer by m , and the number of nodes in the output layer by n . The term z is defined as a conditioning constant, which takes values from 1 to 10.

The number of neurons utilized during the training of the network is determined on an individual basis, with the quantity of nodes constituting the hidden layer of the network being ascertained under conditions of elevated output accuracy and adequate generalization capability, in conjunction with a minimal number of training steps. The coefficient of determination is utilized to identify the optimal neural network configuration, and when the coefficient of determination attains its maximum value, the optimal neural network topology is attained [32]. In this particular model, the coefficient of determination attains its maximum value when the number of implied nodes is 10, thereby indicating that the 3-10-1 type neural network structure is ultimately selected for the subsequent training and comparison phases.

3.4.2. RBF Neural Network Model Prediction

The Box-Behnken test data was utilized as the dataset for the RBF neural network, with 70% of the data randomly selected for training and 30% for testing. In this case, the data was utilized to verify that the value of the coefficient of determination R^2 indicates the fit of the RBF neural network model to the output [33]. The Box-Behnken test values were then compared with the model training and verification values.

The efficacy of the RBF neural network training, testing, and overall dataset is demonstrated in Figure 9, where the red line indicates the result of linear fitting to these data points, and the fitting equation is $y = a + b \times x$, the specific coefficients of the fitting equation have been marked in the figure; the red shaded portion indicates the 95% confidence band, which means that the true regression line will fall within this region at the 95% confidence level, and the confidence band has a range that is narrower, indicating a higher degree of certainty in the estimation of the fitted line; The light pink shaded portion of the graph

indicates the 95% prediction interval, i.e., the range within which there is a 95% probability that the new observation will fall. It is evident that the prediction interval is wider than the confidence interval, reflecting the uncertainty surrounding the prediction of the new data point.

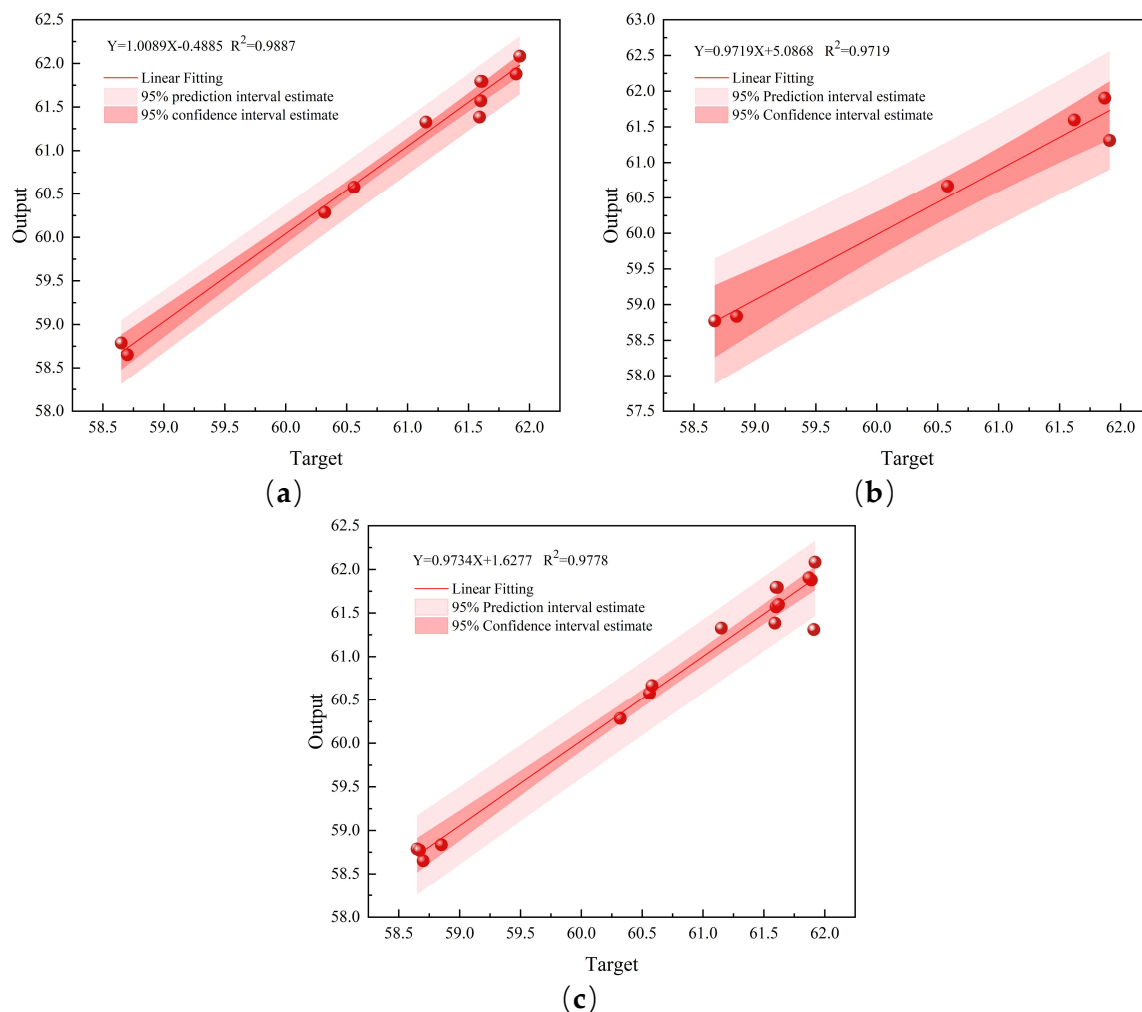


Figure 9. Train, test, and overall data set fit of the RBF model. (a) Train set; (b) Test set; (c) Overall data set.

As demonstrated in Figure 9, the coefficient of determinations (R^2) of the neural network's training layer, testing layer, and overall data are 0.9887, 0.9719, and 0.9778, respectively. The neural network model demonstrates excellent performance on various datasets, exhibiting a robust fitting ability and effective generalization capability. The high coefficient of determination indicates a strong agreement between the model output and the true value, which is crucial for predicting the effluent rate of the waste drilling fluid during gum breakage. This ensures that the model can provide reliable and accurate predictions, providing a solid basis for optimizing the process parameters.

As demonstrated in Figure 10, a comparison is made between the experimental values, the predicted values of the RBF model, and the predicted values of the RSM model. A comparison of the correlation between the predicted and experimental results of both methods, the RSM model and the RBF model reveals that both exhibit very high coefficients of determination ($R^2 \geq 0.95$). This finding suggests that both the RSM model and the RBF model are effective in measuring and predicting performance.

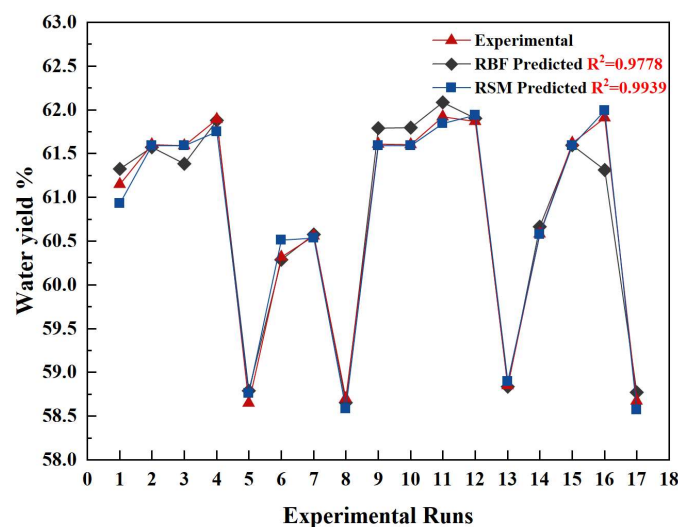


Figure 10. Comparison of experimental and predicted values of water discharge by RSM and RBF models.

3.4.3. RBF Neural Network Coupled Genetic Algorithm Optimization

Although the RBF neural network model has demonstrated good fitting ability and high correlation coefficients on the training set, the test set and the overall dataset suggest that it is able to better simulate the water discharge rate in the process of breaking gums in waste drilling fluids. However, in order to further improve the accuracy and generalization ability of the model, more advanced optimization techniques need to be introduced to fine-tune the model parameters. A genetic algorithm, as a global search algorithm, can effectively explore the parameter space and find the optimal solution, thus enhancing the performance of the RBF neural network [34].

Assuming the amount of glue breaker addition, reaction temperature, and stirring speed to be the input parameters x , and the water yield y to be the optimization objective, the initial populations are first randomly generated under the effect of bounding constraints, in which the i th initial population group $p_i(0) = [x_1^{(0)}, x_2^{(0)}, \dots, x_n^{(0)}]^T$; secondly, let $t = 0$, and each individual in $p_i(t)$ is genetic coding, gets their chromosome information, and uses the regression coefficient after standardization as the fitness function to calculate the fitness of the individuals in $p_i(t)$; The output of the RBF artificial neural network y is then used to determine the optimal one sub-population from $p_i(t)$ as the parent population that produces offspring. The next step is to make $p_i(t)$ produce offspring through hybridization, and then use the mutation action of each offspring to produce the new offspring set. The fitness of the new offspring set is then calculated. Finally, make $t = t + 1$, select the next generation population $p_i(t + 1)$ from each generation population and the offspring population, and so on repeatedly, and finally achieve the optimization of the offspring population, the flowchart of GA-RBF neural network, as shown in Figure 11.

The hybridization probability of this population was set to be 0.7 and the mutation probability to be 0.05. Following 86 iterations and crossovers, the most suitable conditions were produced, and the graphs of the changes in the rate of waste drilling mud outflow and the number of iterations are shown in Figure 12.

As illustrated in Figure 12, the genetic algorithm delineates the constraints of gum breaker addition, reaction temperature, and stirring speed. The maximum water yield of waste slurry is determined to be 61.97% when the gum breaker addition is 3.83 kg/m³, the reaction temperature is 53 °C, and the stirring speed is 424 rpm.

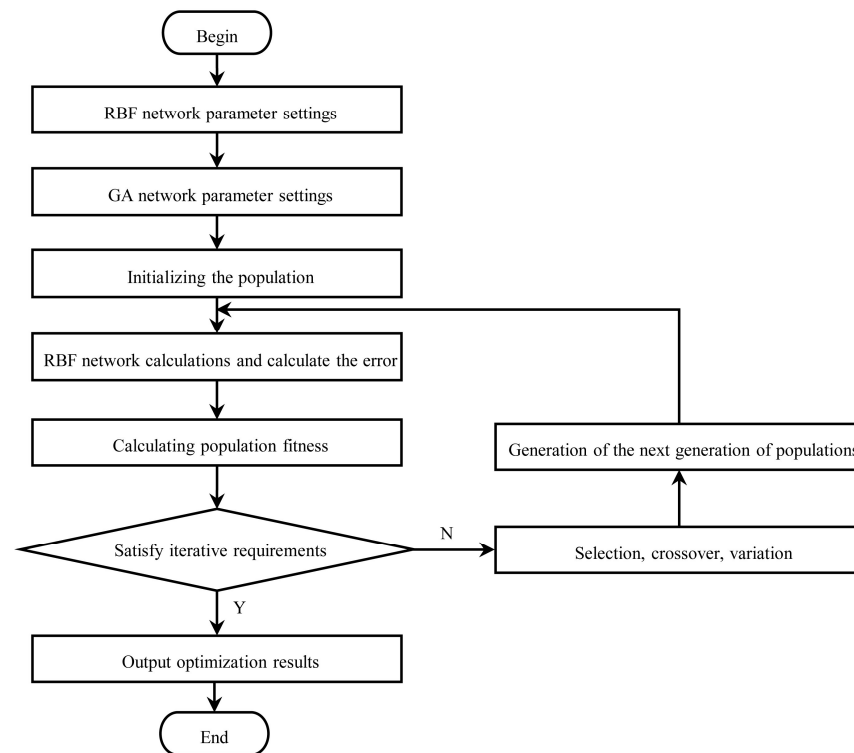


Figure 11. Flowchart of GA-RBF network.

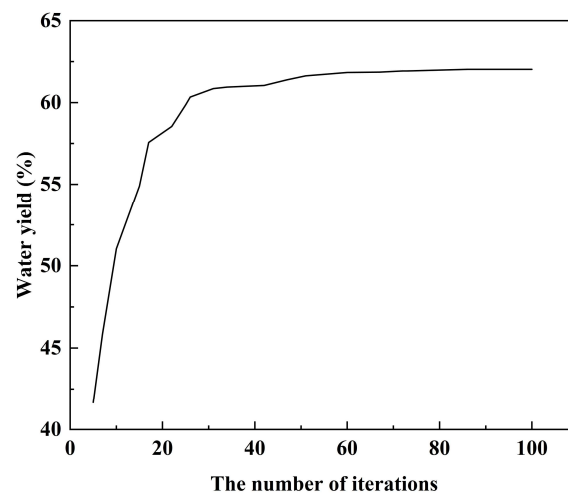


Figure 12. GA-RBF optimization process.

3.4.4. Comparison of Models

In order to accurately assess the performance of the constructed models and determine whether they have achieved substantial optimization improvement, the root mean square error (RMSE), the coefficient of determination (R^2), and the mean absolute error (MAE) are chosen as the evaluation indexes in this study. Response surface model (RSM), radial basis function neural network model (RBF), back propagation neural network model (BP), support vector machine model (SVM), and radial basis function neural network model optimized by genetic algorithm (GA-RBF) are compared. These indicators can comprehensively measure the performance of the models in terms of the degree of fit, prediction accuracy, and stability of the results, providing solid data support and a strong basis for selecting the most appropriate models.

Specifically, the structure of the BP neural network (BPNN) is set as 3-10-1, i.e., there are three nodes in the input layer (corresponding to the amount of glue-breaking agent

added, the reaction temperature, and the stirring speed), 10 nodes in the hidden layer, and one node in the output layer (predicting the water output rate). For the activation function, the hidden layer uses a Tanh function to ensure nonlinear mapping capability, while the output layer uses a linear activation function. The learning rate is initially set to 0.01 and an adaptive learning rate adjustment strategy is used with the maximum number of iterations set to 100, or until the training error and validation error stabilize.

For the support vector machine (SVM), the RBF kernel function was chosen to deal with the nonlinear problem. The starting values of the penalty parameter C and the γ parameter were set to 1.0 and $1/3$, respectively. These two parameters were optimized by grid search or random search combined with cross-validation to find the best combination to ensure that the models have good generalization ability.

In order to fairly compare different models, all models were trained and tested on the same dataset, including the same training, validation, and test set divisions. In addition, the input data were standardized or normalized to eliminate scale differences between features.

As shown in Figure 13, the GA-RBF model performs well in all three key indicators. Specifically, it has the lowest RMSE value, indicating that the model produces the least error in the prediction process; the R^2 of 0.998 is close to 1, which implies that the model is capable of interpreting the data with high fitting accuracy; and the lower MAE further confirms the accuracy of the GA-RBF model in predicting individual data points.

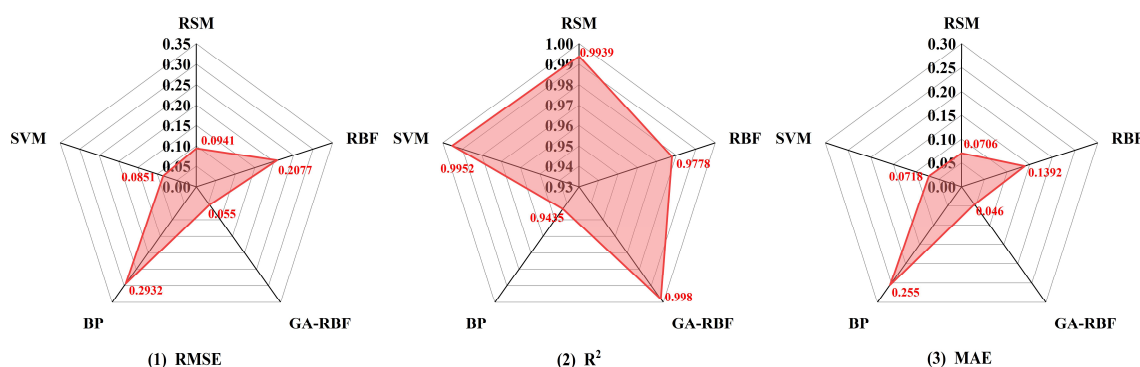


Figure 13. Model evaluation results.

In order to further verify the reliability of the GA-RBF prediction model, the above prediction model was validated using the t -test method, and the results are detailed in Table 6.

Table 6. Validation of optimized process conditions for the glue-breaking process.

Predictive Modelling	No.	Water Yield/%	Degrees of Freedom	Sample Standard Deviation	t -Value	p -Value	t -Critical Value
RBF-GA	1	62.16	2	0.0247	0.55	0.318	4.303
	2	62.05					
	3	61.85					

As can be seen from Table 6, for a given significance level $\alpha = 0.05$, when the degree of freedom of the above validation test is 2 and the standard deviation of the sample is 0.0247, the GA-RBF prediction model has a statistically validated value that is less than the critical value of $t_{0.05}(2) = 4.303$ and the probability of p is greater than the critical value of 0.05, therefore, there is no significant difference between the optimized prediction value obtained by using GA-RBF and the validation value difference and their accuracy are consistent, indicating that the optimization using the GA-RBF model is accurate and reliable.

4. Conclusions

- (1) In this study, a response surface experimental design was conducted utilizing the BBD experimental method to investigate the interactions between the influencing factors. The bivariate interaction surface demonstrates that the interactions of the gum breaker addition and temperature, and the interaction of the gum breaker addition and mixing speed, have a greater effect on the water discharge rate of the wastewater-based drilling fluids, while the interactions of the temperature and the mixing speed have a lesser effect.
- (2) A Box-Behnken Design (BBD) design of experiments was conducted to determine the effects of gum breaker addition, reaction temperature, and stirring speed on the water yield of wastewater-based drilling fluids. The optimum conditions were gum breaker addition of 3.97 kg/m³, reaction temperature of 51 °C, and stirring speed of 419 rpm, at which the maximum water yield predicted was 62.37%. The high coefficient of determination ($R^2 = 0.9939$) and ANOVA results of the model indicated its significance and reliability.
- (3) By comparing with BP, RSM, BP, and SVM models, the RMSE, R^2 , and MAE of the GA-RBF model were 0.055, 0.998, and 0.046 respectively, which were better than other models, and it was verified that there was no significant difference between the predicted and actual values by t-test, which proved that the model had higher prediction accuracy and stability. The optimization analysis based on the GA-RBF model showed that the maximum water yield of the waste slurry could reach 61.97% when the gum breaker was added at 3.83 kg/m³, the reaction temperature was 53 °C, and the stirring speed was 424 rpm. These results provide a reliable basis for optimizing the process parameters.

Author Contributions: Y.L.: Ideas; formulation or evolution of overarching research goals and aims. Z.X.: Conducting a research and investigation process, specifically performing the experiments. J.X.: Management activities to annotate, scrub data, and maintain research data for initial use and later reuse. H.Z.: Preparation, creation, and presentation of the published work, specifically writing the initial draft. Z.F.: Acquisition of the financial support for the project leading to this publication. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Due to privacy concerns and the sensitivity of the data, the datasets in this study are not publicly available at this time. We are committed to protecting the confidentiality and integrity of personal and sensitive information. As a result, access to these datasets is currently restricted. However, we recognize the importance of data sharing for the advancement of science. Reasonable requests for access may be considered on a case-by-case basis by contacting the corresponding author. Such requests will be assessed in accordance with relevant ethical and legal guidelines and it is possible that access may be provided in the future on appropriate terms.

Conflicts of Interest: Author Yan Li, Ziqiang Xu and Jiabin Xi were employed by the Oil and Gas Technology Research Institute of PetroChina Changqing Oilfield Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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