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Research Article

Drilling Parameter Optimization of Shale Gas Wells Based on Saw-Tooth Genetic Algorithm to Reduce Drilling Costs

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It is difficult to optimize the drilling parameters, which makes it difficult to reduce drilling costs in the process of drilling shale gas wells in the Fuling region of Chongqing, China. This paper takes the optimization combination of drilling parameters in drilling engineering as the research object and uses a saw-tooth genetic algorithm to perform the objective function. To solve the problem, the algorithm proposes a variable population size with periodic reinitialization, which follows a saw-tooth scheme with unequal amplitude and change period (saw-tooth GA), which can optimize the drilling parameters under constraints. According to the actual situation of the wells in the Fuling region, the three algorithms are compared for the vertical section's drilling parameters. Example calculations show that the algorithm can achieve the best economic benefits at different revolutions per minute and WOB to reduce drilling costs. Compared with other methods, this algorithm has the characteristics of fast convergence, is easy to understand, and is simple to implement. The proposed algorithm is tested for the drilling parameter optimization of shale gas wells and from which it becomes evident that the saw-tooth scheme enhances the overall performance of GAs.

1. Introduction

Optimization of drilling parameters means that in the drilling operation process of an oil and gas field, the optimal combination of various parameters is comprehensively calculated according to the actual situation (bit wear, ROP, etc.), and the normal drilling operation is carried out at a lower cost per unit length to maximize the economic benefits of the whole project.

Several methods for optimizing drilling control parameters are put forward in the literature, including the function extremum method, pattern search method, particle swarm optimization method, and genetic algorithm. According to the description in Okoro Research [1], it can be seen that the mathematical derivation and calculation process of the function extremum method is complicated, with a long design cycle and low efficiency. The pattern search method has great advantages in solving nonlinear problems, but its global search capability is weak. Particle swarm optimization (PSO) and genetic algorithm (GA) have problems of poor stability and local convergence, which limit their search efficiency and accuracy [1]. Self et al. [2] put forward a method of combining particle swarm optimization algorithm with a permeability model and conducted in-depth research on the optimization of dynamic drilling parameters to minimize the total cost of each well. Abbas et al. [3] for the first time, a genetic algorithm was used as an ROP optimizer. In order to determine the optimal controllable drilling parameters, the traditional genetic algorithm was improved, but its searching efficiency and accuracy needed to be improved [3]. Khaleel et al. [4] studied the combination of multiple regression analysis technology and a genetic algorithm, analyzed the field data, and established the equation related to permeability by using the results. As a result, WOB was optimized, the best penetration rate was achieved, the drilling time and cost were effectively reduced, and the drilling problem was alleviated [4]. Toreifi et al. [5], by improving the inappropriate particle swarm optimization algorithm, a new leakage technology was realized, the applicable drilling parameters were improved and selected, and the drilling leakage prediction model was optimized, which minimized leakage and made the prediction accuracy higher. Antil et al.'s [6] particle swarm optimization (PSO) algorithm is used to solve the objective function of drilling parameter optimization of polymer matrix composite (PMC) bit. This algorithm is simple, with few parameters, and it can get good results, but it is easy to fall into local optimization [6]. Zheng et al. [7], based on the multiobjective optimization drilling parameter optimization model of penetration rate, bit life, and bit specific energy, a multiobjective optimization particle swarm optimization algorithm was proposed. In the process of modeling, it is assumed that the effects of the hydraulic purification factor and pressure difference are ideal, which simplifies the model and facilitates the algorithm to solve [7]. Pandey [8] proposed a multiobjective-improved computer-aided genetic formula, which is used to solve the recast layer, heat-affected zone, and microcracks supported by the drilling parameter model, optimized many quality characteristics, and improved drilling quality. Saw et al. [9], combining an adaptive neurofuzzy reasoning system and genetic algorithm, the optimization model of drilling parameters was deeply studied. Li and Cheng [10] proposed a hybrid artificial intelligence model based on an improved genetic algorithm (IGA) and an artificial neural network (ANN) to optimize drilling technology. The algorithm has the advantages of fast convergence, high precision, good stability, and strong robustness, which further deepen the application of the genetic algorithm in drilling parameter optimization [10].

Based on the above research, this paper proposed a saw-tooth genetic algorithm (saw-tooth GA) to solve the drilling parameter optimization problem by analyzing and investigating the related evolutionary algorithms, aiming at ensuring strong global search ability and greatly improving local optimization accuracy.

2. Optimization Model Design of Drilling Parameters

2.1. Determine the Objective Function. The process of optimizing drilling parameters by the genetic algorithm is shown in Figure 1.

There are many functions to measure the overall technical and economic indicators of the drilling process. The more commonly used and intuitive is to use the drilling unit footage cost as an evaluation index for drilling parameter optimization [11], and its expression is:

$$\boldsymbol{C}_{\mathrm{pm}} = \frac{\boldsymbol{C}_{\boldsymbol{b}} + \boldsymbol{C}_{\boldsymbol{r}}(\boldsymbol{t} + \boldsymbol{t}_{\boldsymbol{t}})}{\boldsymbol{H}}. \tag{1}$$

In the formula, $\boldsymbol{C}_{\mathrm{pm}}$ is the footage cost (unit), yuan/m; $\boldsymbol{C}_{\boldsymbol{b}}$ for the drilling cost, yuan; $\boldsymbol{C}_{\boldsymbol{r}}$ for drilling rig operation cost, yuan/h; $\boldsymbol{t}$ for drilling time; $\boldsymbol{t}_{\boldsymbol{t}}$ for the time of tripping and connecting, h; and $\boldsymbol{H}$ for the drill footage.

Formula (1) is to analyze and solve the problem only considering the cost of the drill bit and drilling rig operation, without considering the cost of drilling fluid and drilling tool combination.

The modified drilling rate equation of the F. S. Young model is as follows:

$$\boldsymbol{v}_{\mathrm{pc}} = \mathrm{K}\mathrm{C}_{\boldsymbol{p}}\boldsymbol{C}_{\boldsymbol{H}}(\boldsymbol{W} - \boldsymbol{M})\boldsymbol{n}^{\lambda}\frac{1}{1 + \boldsymbol{C}_2\boldsymbol{h}}. \tag{2}$$

In the formula, $\boldsymbol{v}_{\mathrm{pc}}$ is the rate of penetration, m/h; $\boldsymbol{W}$ and $\boldsymbol{M}$ are the WOB and threshold WOB, respectively, kN; $\boldsymbol{n}$ is the speed, r/min; $\boldsymbol{K}$ is the formation drillability coefficient; $\boldsymbol{C}_{\boldsymbol{p}}$ and $\boldsymbol{C}_{\boldsymbol{H}}$ are the pressure difference influence coefficient and hydraulic purification coefficient, respectively; λ is the speed index; $\boldsymbol{C}_{\boldsymbol{2}}$ is the bit tooth wear coefficient; and $\boldsymbol{h}$ is the amount of tooth wear, $\boldsymbol{0} \le \boldsymbol{h} \le 1$.

Formula (2) can be converted into the relationship between the working time of the drill bit and the footage of the drill bit.

$$\mathrm{dH} = \mathrm{K}\mathrm{C}_{\boldsymbol{p}}\boldsymbol{C}_{\boldsymbol{H}}(\boldsymbol{W} - \boldsymbol{M})\boldsymbol{n}^{\lambda}\frac{1}{1 + \boldsymbol{C}_2\boldsymbol{h}}\mathrm{dt}. \tag{3}$$

Drill tooth wear equation expression:

$$\frac{\mathrm{dh}}{\mathrm{dt}} = \frac{\boldsymbol{A}_{\boldsymbol{f}}\left(\boldsymbol{a}_1\boldsymbol{n} + \boldsymbol{a}_2\boldsymbol{n}^3\right)}{(\boldsymbol{Z}_2 - \boldsymbol{Z}_1\boldsymbol{W})(1 + \boldsymbol{C}_1\boldsymbol{h})}. \tag{4}$$

That is

$$\mathrm{dt} = \frac{(Z_2\text{-}Z_1 W)(1 + C_1 h)}{A_f(a_1 n + a_2 n^3)}\mathrm{dh}. \tag{5}$$

In the formula, $\boldsymbol{A}_{\boldsymbol{f}}$ is the formation abrasive coefficient; $\boldsymbol{a}_{\boldsymbol{1}}$ and $\boldsymbol{a}_{\boldsymbol{2}}$ are the rotational speed influence coefficients, which are determined by the bit type; $\boldsymbol{Z}_{\boldsymbol{1}}$ and $\boldsymbol{Z}_{\boldsymbol{2}}$ are the influence coefficients of WOB, which are related to the diameter of the drill bit; and $\boldsymbol{C}_{\boldsymbol{1}}$ is the tooth wear reduction coefficient.

The above formula integral change, let $\boldsymbol{t}_{\boldsymbol{E}} = \boldsymbol{C}_{\boldsymbol{b}}/\boldsymbol{C}_{\boldsymbol{r}} + \boldsymbol{t}_{\boldsymbol{t}}$, the objective function containing three variables of drilling pressure ($\boldsymbol{W}$), rotation speed ($\boldsymbol{n}$), and bit wear ($\boldsymbol{h}_{\boldsymbol{f}}$) during drilling is obtained.

$$C_{pm} = \frac{C_r\left[t_E A_f\left(a_1 n + a_2 n^3\right)/(Z_2 - Z_1 W) + h_f + h_f^2 C_1/2\right]}{C_H C_p K_d (W - M) n^{\lambda}\left[h_f C_1/C_2 + \ln\left(1 + C_2 h_f\right)(C_2 - C_1)/C_2^2\right]} \tag{6}$$

In the formula, $\boldsymbol{t}_{\boldsymbol{E}}$ is the conversion time of the drill bit and tripping cost, h; $\boldsymbol{h}_{\boldsymbol{f}}$ represents the final amount of tooth wear, that is, the amount of tooth wear corresponding to the life of the drill bit. It can be seen from formula (6) that the values of $\boldsymbol{C}_{\boldsymbol{H}}$ and $\boldsymbol{C}_{\boldsymbol{p}}$ should be as large as possible when optimizing drilling parameters.

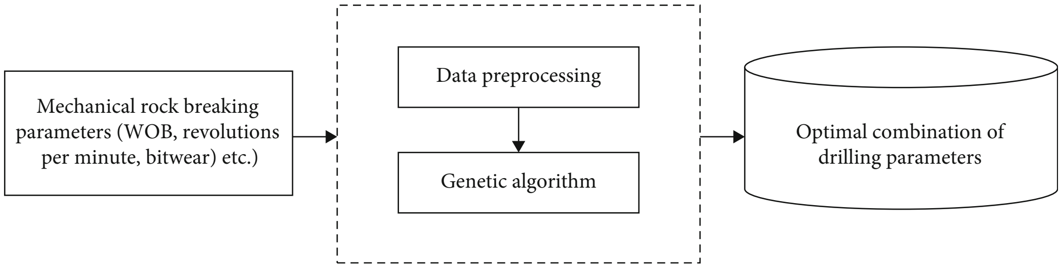

Figure 1: Application of the genetic algorithm to optimize drilling parameters.

According to the above parameters, find the relevant drilling parameter combination when the cost per unit length C_{pm} is the minimum value; that is, find the optimal parameter combination when the objective function formula (6) takes the minimum value. According to classical optimization theory, when the partial derivative of the function on its variables is equal to 0, the minimum value exists, so the point meeting the extreme value condition of the drilling objective function is the minimum point of the objective function. In the objective function determined by formula (6), it is necessary to consider the five variables of W, n, h_f, C_p, and C_H. When the values of C_p and C_H tend to be 1, the drilling cost is the lowest. After determining the optimal values of C_p and C_H, the minimum condition can be expressed as:

$$\begin{aligned} \frac{\partial \boldsymbol{C}_{pm}}{\partial \boldsymbol{W}} &= \boldsymbol{0}, \\ \frac{\partial \boldsymbol{C}_{pm}}{\partial \boldsymbol{n}} &= \boldsymbol{0}, \\ \frac{\partial \boldsymbol{C}_{pm}}{\partial \boldsymbol{h_f}} &= \boldsymbol{0}. \end{aligned} \tag{7}$$

2.2. Constraint Condition. The independent variables contained in the objective function obtained above must have certain constraints under the actual drilling engineering field conditions, including the value range of independent variables and the relationship between them. Constraints set on variables in objective function formula (6) [12]:

(1) WOB (weight on bit) W: $M < W < Z_2/Z_1$, and $W > 0$

(2) Revolutions per minute n: $0 < n < n_{max}$, n_{max} is the maximum revolution per minute of the drilling unit

(3) Amount of bit wear h_f: $0 < h_f < 1$

(4) The bit pressure and revolutions per minute meet the constraints $(W \cdot n) < PD$ (PD is the maximum allowable value recommended by the bit manufacturer; $(W \cdot n)$ can be obtained from the operating manual provided by the bit manufacturer)

(5) Bearing wear B_f: $0 \le B_f \le 1$

2.3. Determine the Fitness Function. When the objective function formula (6) gets the minimum value under the constraint condition, it is the optimal parameter combination of drilling parameters, which is converted into a mathematical problem, that is, the inequality nonlinear programming problem is solved under the constraint condition, and its mathematical model [13–15] is as follows:

$$\boldsymbol{f} = \min \boldsymbol{C}_{pm}(\boldsymbol{W}, \boldsymbol{n}, \boldsymbol{h_f}) \begin{cases} \boldsymbol{M} < \boldsymbol{W} \le \dfrac{\boldsymbol{Z}_2}{\boldsymbol{Z}_1}, \\ \boldsymbol{W} > 0, \\ \boldsymbol{0} < \boldsymbol{n} < \boldsymbol{n}_{max}, \\ \boldsymbol{0} < \boldsymbol{h_f} < 1, \\ \boldsymbol{0} \le \boldsymbol{B_f} \le 1, \\ (W \bullet n) < PD. \end{cases} \tag{8}$$

The higher the fitness of the fitness function, the closer it is to the optimal solution of the objective function. The individual fitness function F selected in this study is

$$\boldsymbol{F} = \boldsymbol{F}[\boldsymbol{f}] = \frac{\boldsymbol{1}}{\boldsymbol{f}}. \tag{9}$$

3. Saw-Tooth Genetic Algorithm

3.1. Characteristics of Improved Saw-Tooth Genetic Algorithm. The probability of individual I being selected in the improved saw-tooth genetic algorithm (GA) is

$$P_i = \frac{F_i}{\sum_{j=1}^{N} F_j}, \tag{10}$$

where F_i is the fitness value of an individual I; N is the number of individuals in the population.

The modified saw-tooth genetic algorithm proposes a variable population size with periodic reinitialization, which follows a saw-tooth variation scheme with unequal amplitude and variation period; that is, the population size decreases linearly in each period, and the randomly generated individuals are added to the population at the beginning of the next period, so it is called a saw-tooth genetic algorithm.

Variable population size can change the population size between successive generations, only affecting the selection operator of the genetic algorithm. n_t and n_{t+1} are the population sizes of current and future generations, respectively.

Individual selection is the repeated process of the n_{t+1} generation selection operation, and P_j is the probability of selecting the jth individual. For most selection operators (such as fixed proportion selection and competitive selection with substitution), the selection probability P_j remains constant for the n_{t+1} generation selection operation. The expected copy number of the selected jth individual can be expressed as

$$\boldsymbol{m}(\boldsymbol{j}, \boldsymbol{t}+1) = \boldsymbol{m}(\boldsymbol{j}, \boldsymbol{t})\boldsymbol{P}_j\boldsymbol{n}_{t+1}. \quad (11)$$

In the formula, $m(j, t)$ is the copy number of the t generation of the j generation individual. The expected number of jth generation individuals is proportional to the population size of the offspring. Therefore, the group part related to the individual after selection [16] can be expressed as

$$\rho(j, t+1) = \frac{m(j, t+1)}{n_{t+1}} = \frac{m(j, t)P_j n_{t+1}}{n_{t+1}} = m(j, t)P_j. \quad (12)$$

The condition of the selected population and population size independent of offspring is that the change in population size is not enough to modify the probability. However, compared with the constant population size genetic algorithm with the same calculation cost (equal average population size), the genetic algorithm with reduced population size has a larger initial population size and a smaller final population size. This prediction method is beneficial because the larger population size at the beginning provides a better initial signal for the evolution process of the genetic algorithm. However, smaller population size is sufficient at the end of the operation, and the genetic algorithm can converge to the optimum.

3.2. Population Initialization of the Saw-Tooth Genetic Algorithm. To study the effect of population reinitialization, the constant population size algorithm proposed in Section 3.1 is compared with the genetic algorithm that reinitializes 8 times every 20 generations, instead of mutations in the 20th, 40th, …, and 180th generations, which is established by using the same average number of modified bits as Goldberg and Richardson's [17] multimodal functions by the following relation

$$t_{\max} n p_{\mathrm{m}} l = 8n' p_{\mathrm{m}}' l, \quad (13)$$

where $t_{\max} = 200$ is the total number of generations, $n = 100$ is the population size, $p_m = 0.019$ is the probability of mutation [17], l is the length of the chromosome. In addition, n' is the number of individuals with a new replacement at each reinitialization, and each bit is changed with probability $p_m{}' = 0.5$.

Solving relation (8) with respect to n', the following relation is obtained:

$$n' = \frac{t_{\max} n p_{\mathrm{m}}}{8p' m}. \quad (14)$$

The population variation scheme of the saw-tooth GA is shown in Figure 2.

3.3. Interlace Operation. Biologically, the crossover of genes can be understood as the DNA at a certain position of the two chromosomes is cut off and the two strings are crossed to form two new progeny chromosomes, also known as gene recombination or hybridization. The individuals in the GA population are paired in pairs, and one or a certain gene segment is crossed and exchanged so that the excellent genes of the parent generation are retained and inherited by the next generation. In this paper, the real number is used to encode the individual, and the crossover operation is carried out by the real number crossover method. The crossover operation method of the k chromosome a_k and the l chromosome a_l at the j position is as follows:

$$\begin{aligned} a_{\mathrm{kj}} &= a_{\mathrm{kj}}(1-b) + a_{\mathrm{lj}} b, \\ a_{\mathrm{lj}} &= a_{lj}(1-b) + a_{\mathrm{kj}} b. \end{aligned} \quad (15)$$

In formula (15), b is a random number in the interval [0,1] [18].

3.4. Variation Operation. Some individuals were randomly selected from the population, and the mutation probability set during initialization was used to make the specific genes located on chromosome loci mutate. According to formula (16), the j -gene a_{ij} variation of the ith individual [19] is as follows:

$$\boldsymbol{a}_{\mathrm{ij}} = \begin{cases} \boldsymbol{a}_{\mathrm{ij}} + \left(\boldsymbol{a}_{\mathrm{ij}} - \boldsymbol{a}_{\max}\right) \bullet \boldsymbol{f}(\boldsymbol{g}), \boldsymbol{r} \geq 0.5, \\ \boldsymbol{a}_{\mathrm{ij}} + \left(\boldsymbol{a}_{\min} - \boldsymbol{a}_{\mathrm{ij}}\right) \bullet \boldsymbol{f}(\boldsymbol{g}), \boldsymbol{r} < 0.5. \end{cases} \quad (16)$$

In formula (16), $a_{\max}$ is the upper bound of gene a_{ij} and $a_{\min}$ is the lower bound of gene a_{ij}. The expression is

$$\boldsymbol{f}(\boldsymbol{g}) = \boldsymbol{r}_2 \left(\boldsymbol{1} - \frac{\boldsymbol{g}}{\boldsymbol{G}_{\max}}\right)^2. \quad (17)$$

In formula (17), g is the current iteration number, r_2 is a random number, and $G_{\max}$ is the maximum number of iterations.

4. Comparative Analysis

4.1. Simulation Experiment. According to the objective function of formula (6) and the rock strength, hydraulic, and bit parameters in Table 1, we programmed to compare the saw-tooth GA with other GAs [20] for simulation calculation.

The genetic algorithm (GA), improved adaptive genetic algorithm (IAGA), and saw-tooth genetic algorithm (saw-tooth GA) are used to solve the problem, and the drilling

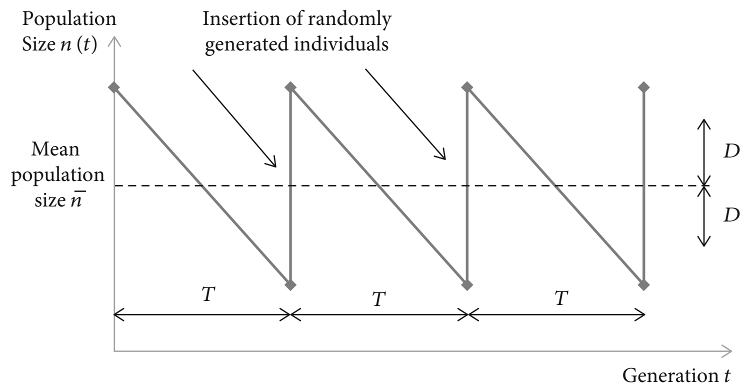

Figure 2: Population variation scheme of saw-tooth GA.

Table 1: Rock strength parameters, hydraulic parameters, and bit parameters.

Rock strength parameters			Hydraulic parameters			Bit parameters						
K_d	A_f	λ	C_2	C_H	C_p	Bit diameter/mm	Z_1	Z_2	a_1	a_2	C_1	C_2
0.0023	2.28×10^{-3}	0.68	3.68	0.9	0.8	251	0.0146	6.44	1.5	6.53×10^{-5}	5	3.68

Table 2: Comparison of simulation results.

Algorithms	Cost per unit length (C_{pm})/(yuan·m^{-1})	WOB/kN	Revolutions per minute/(r·min^{-1})	The rate of convergence
GA	81.43	323.34	60	160
IAGA	85.50	340.00	62	100
Saw-tooth GA	79.80	305.00	85	70

Table 3: Optimal results of different bit wear.

Bit wear(h_f)	WOB/kN	Revolutions per minute/(r·min^{-1})	C_{pm}/(yuan·m^{-1})	Optimal numbers of convergence
0.75	305.00	85.0	79.8	75
0.80	305.00	85.0	79.0	65
0.90	310.68	95.0	77.8	70
1.00	313.47	102.3	77.0	72

parameters are optimized and combined with the goal of cost per unit length. Under the same conditions given in Table 1, different algorithms are used to solve the objective function, and the optimized combination data of drilling parameters obtained by program simulation are shown in Table 2.

It can be seen from Table 2 that the results obtained by the basic genetic algorithm and the improved adaptive genetic algorithm are similar, and the cost C_{pm} obtained by the IAGA method is slightly higher, indicating that the improved adaptive genetic algorithm has a strong local optimization ability, but the global optimization effect is poor, easy to fall into local optimum, and unable to achieve the global optimum. The final unit footage cost C_{pm} obtained based on the zigzag genetic algorithm is slightly lower, and the convergence speed is significantly improved. After only 70 population evolutions, the maximum fitness degree, that is, the minimum value of the objective function, can be obtained. This algorithm can be used to complete the drilling parameter optimization design task.

Furthermore, the saw-tooth GA has calculated the WOB, revolutions per minute combination, and optimal cost under different bit wear, and the results are shown in Table 3.

In the calculation process, record the optimal objective function value and population average function value of each generation in the iterative process, and the trend line is shown in Figure 3.

It can be seen from Figure 3 that the fluctuation amplitude of the saw-tooth GA is attenuated; the solving process is relatively stable, it approaches the optimal solution after less than 100 iterations, and the convergence speed is fast. Combined with Table 2 simulation results, the advantage of using the saw-tooth GA is that it cannot only improve the running speed but also the optimization results of drilling parameters (WOB, rotational speed) are closer to the actual situation and can obtain higher stability and convergence speed.

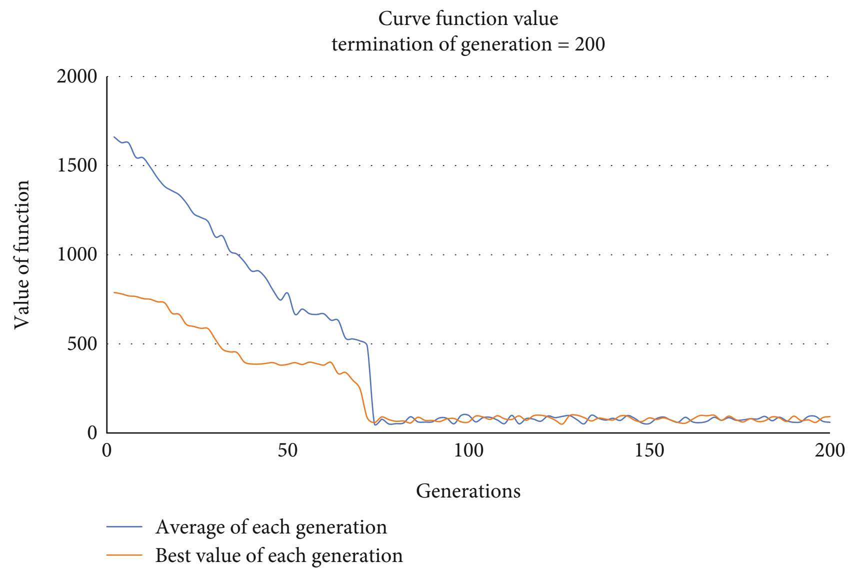

Figure 3: Variation process of saw-tooth GA calculation evolutionary (termination = 200).

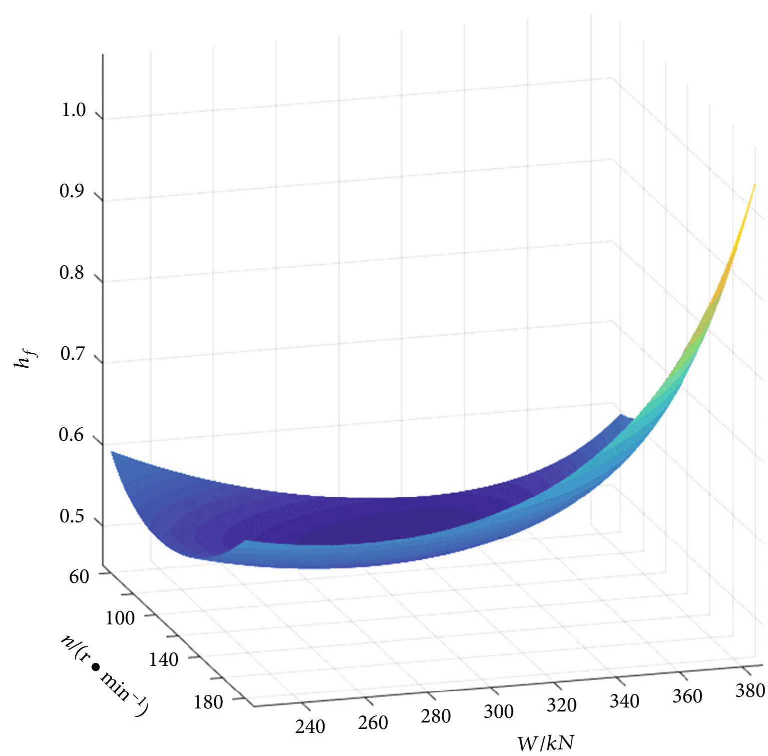

Figure 4: Optimized surface at optimal revolutions per minute and WOB.

In Figure 4, a three-dimensional cost diagram of revolutions per minute (n) in [60,100] and WOB (W) in [220,320], which is an optimal revolution per minute-WOB optimization surface [21] with cost as the objective function, can analyze a more suitable WOB(W) interval ([220,320]). It can be seen from Figure 4 that there is only one optimal solution of the objective function, which will appear at the bottom, and the WOB and revolutions per minute on the optimal solution can be obtained on the three-dimensional diagram. Under the same objective function, the cost per unit length solved by the saw-tooth GA is the lowest, which shows that the saw-tooth GA proposed in this study not only has a strong local optimization ability but also has a good global optimization effect and the shortest convergence time.

Table 4: Bit parameters.

Bit diameter/mm	Z_1	Z_2	a_1	a_2	C_1
311.2	0.0131	7.15	0.5	2.18×10^{-5}	2

Table 5: Actual drilling parameters.

The serial number of bits	Running depth of well/m	Trip-out depth/m	Average bit pressure/kN	Average drilling rate/$r{\cdot}\min^{-1}$	h_f
5	683	886	250	65	0.65
8A	1056	1254	240	55	0.75
9B	1403	1480	240	55	0.60

Table 6: Drilling parameters optimization calculation results of each bit.

The serial number of bits	W_{opt}/kN	h_f	$n_{\text{opt}}/\left(r\cdot\min^{-1}\right)$	$C_{\text{pm}}/\left(\text{yuan}\cdot\text{m}^{-1}\right)$	$C_{\text{pma}}/\left(\text{yuan}\cdot\text{m}^{-1}\right)$
5	256	0.85	42	2 150	
8A	259	0.80	56	1 271	2 238
9B	265	0.90	40	1 259	

4.2. Calculation of Shale Gas Wells in the Jiaoshiba Area. A well in the Jiaoshiba of Fuling region, with a depth of 675~1 357 m, is composed of the Feixianguan Formation of the Lower Triassic, Changxing Formation, and Longtan Formation of the Upper Permian, Maokou Formation, Qixia Formation, and Liangshan Formation of the Lower Permian. The lithology is mainly gray limestone and marlstone, and the formation has poor drillability and strong abrasiveness. Abrasive coefficient $A_f = 2.89\times10^{-3}$. The design uses a three-cone bit with a diameter of φ311.2 mm for drilling [22], and the parameters of the bit are found. The WOB influence coefficients $Z_1 = 0.0131$, $Z_2 = 7.15$, revolutions per minute influence coefficients $a_1 = 0.5$, $a_2 = 0.218\times10^{-4}$, teeth wear slowdown coefficient $C_1 = 2$, bit cost $C_b = 56{,}000$ yuan/piece, cost of drilling rig daily $C_d = 88{,}000$ yuan/d, and cost of drilling rig operation $C_r = 3667$ yuan/h.

The constraint conditions of the objective function are $M < W \le Z_2/Z_1$ and $W > 0$; $0 < n < 100$; $0 \le h_f \le 1$. According to the field drilling data and related data, the values of each coefficient in the penetration rate equation can be determined. The three roller bits are selected from this interval to participate in the drilling. The bit parameters are shown in Table 4, and the actual drilling parameters are shown in Table 5.

After determining the above coefficients and constraints, the improved saw-tooth GA is used to optimize the drilling parameters of each bit working section, and the optimal WOB ($\boldsymbol{W}$), optimal rotation speed ($\boldsymbol{n}$), and optimal bit wear ($\boldsymbol{h_f}$) are obtained. The results are shown in Table 6.

In Table 6, $\boldsymbol{W}_{\text{opt}}$ is the optimal WOB, $\boldsymbol{n}_{\text{opt}}$ is the optimal rotation speed, $\boldsymbol{C}_{\text{pm}}$ is the unit footage cost after the optimization of the well section, and C_{pma} is the actual unit footage cost of the well section.

It can be seen from Table 6 that the optimized unit footage cost is lower than the actual site cost, the optimized WOB is higher than the average value of the actual WOB, and the optimized revolution per minute is lower than the average value of the actual revolutions per minute. It can be seen that the mode of "High WOB-low revolutions per minute" is suitable for drilling in this section, which is consistent with the drilling design scheme of this well before drilling. The optimized rate of bit wear is higher than the actual rate of bit wear, so the drill bit should achieve a relatively high rate of bit wear without considering the influence of hydraulic parameters, and the cost per unit length can be significantly reduced when the value of h_f reaches 0.8~0.9.

To sum up, drilling with reference to the optimized drilling parameters can achieve the lowest unit drilling cost and achieve the purpose of reducing costs and increasing efficiency in the drilling engineering design of shale gas wells.

5. Conclusion

(1) The optimization model of drilling parameters in oil and gas fields constructed by the evolutionary modeling method was studied, and several GAs were compared to determine the optimal revolutions per minute and WOB. In the solution process, a saw-tooth GA is used. The optimization results of drilling parameters are closer to the actual situation, and the convergence speed is fast. It is suitable for complex drilling parameter optimization and can solve the timeliness problem of the algorithm. Compared with the simulation results, the saw-tooth GA effectively solved the problem of drilling parameter optimization and could get the best combination scheme of revolutions per minute and WOB at the lowest cost per unit footage

(2) In the simulation experiment, when the WOB (in the interval [220,320] kN) or the rotational speed (in the interval [60,100] r/min) is relatively stable, increasing the rotational speed or WOB can reduce the unit footage cost, but when it is increased to a certain amount, that is, these two parameters exceed the optimal WOB and rotational speed value, the cost will not be reduced due to factors such as imperfect bottom hole purification and too fast bit wear

(3) The saw-tooth GA algorithm is verified according to the drilling data in the Jiaoshiba area of Fuling, Chongqing. The results show that the optimization

method can be used to optimize the drilling parameters. The optimized WOB is slightly higher than the average value of the actual WOB, the optimized rotation speed is slightly lower than the average value of the actual rotation speed, and the optimized bit wear is larger than the actual bit wear. If the bit is pulled out when the bit wear reaches 0.8~0.9, the bit utilization rate can be improved, and the unit footage cost can be reduced to a certain extent

Data Availability

(1) The parameter data used to support the findings of this study are included within the article. (2) The actual drilling parameter data used to support the findings of this study are available from the corresponding author upon request (Some of the actual drilling parameter data should be kept confidential at the request of the drilling company).

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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