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Implementation of Hybrid Genetic-Ant Colony Algorithm (GACA) for Solving Highly Nonlinear Cuttings Transport Models in Directional Foam Drilling

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Abstract: Directional foam drilling is widely applied in the development of complex oil and gas resources due to its advantages of low formation damage and high drilling efficiency, but the highly nonlinear cuttings transport model in this process poses great challenges to parameter optimization. To solve this problem, a hybrid genetic-ant colony algorithm (GACA) is proposed, which integrates the global search capability of genetic algorithm (GA) and the local search advantage of ant colony optimization (ACO). First, the mathematical model of cuttings transport in directional foam drilling is established, considering the coupling effects of foam rheological properties, wellbore geometry, and cuttings movement characteristics. Then, the GACA is designed by optimizing the encoding mechanism, adaptive genetic operator, and pheromone update strategy to adapt to the high-dimensional and multi-constraint characteristics of the model. Comparative experiments are carried out with GA, ACO, particle swarm optimization (PSO), simulated annealing (SA), and marine predators algorithm (MPA) in terms of convergence speed, solution accuracy, and stability. The results show that GACA has a 15.3%-32.7% higher convergence speed than single intelligent algorithms, and the solution accuracy is improved by 8.9%-21.4%, which can effectively avoid falling into local optimum. Field application in a directional well in the Anju Basin, DPRK shows that the optimized drilling parameters by GACA reduce the cuttings bed height by 31.2% and the annular pressure loss by 18.7% compared with field experience parameters. This study provides a reliable optimization method for solving highly nonlinear cuttings transport models in directional foam drilling and lays a theoretical foundation for improving wellbore cleaning efficiency and drilling safety.

Keywords: Directional foam drilling; Cuttings transport; Highly nonlinear model; Hybrid genetic-ant colony algorithm; Parameter optimization

1. Introduction

With the increasing demand for oil and gas resources, drilling operations are gradually moving towards complex formations such as deep layers, ultra-deep layers, and unconventional reservoirs [1]. Directional foam drilling, as a key technology for developing such resources, uses foam as the circulating medium to reduce formation damage, improve drilling rate, and adapt to low-pressure and leaky formations [2]. However, the cuttings transport process in directional foam drilling involves complex physical phenomena such as foam-liquid-solid three-phase flow, non-Newtonian fluid rheology, and dynamic interaction between cuttings and wellbore, resulting in a highly nonlinear mathematical model with multiple variables, strong coupling, and multi-constraints [3].

The accurate solution and parameter optimization of the cuttings transport model are crucial to ensuring wellbore cleaning, reducing drilling accidents such as stuck pipe, and improving drilling efficiency. Traditional optimization methods (e.g., gradient descent method) rely on the

differentiability of the objective function and are prone to fall into local optimum when dealing with highly nonlinear models, failing to meet engineering requirements [4]. In recent years, intelligent optimization algorithms have been widely used in drilling engineering due to their advantages of no dependence on mathematical properties of the model and strong global search capability [5].

Genetic algorithm (GA) simulates biological evolution to perform global search through selection, crossover, and mutation operations, but it has the defects of slow late convergence and poor local search accuracy [6]. Ant colony optimization (ACO) realizes local optimization through pheromone positive feedback, but it has weak global search capability and is easy to stagnate [7]. To overcome the limitations of single algorithms, hybrid intelligent algorithms have become a research hotspot. The hybrid genetic-ant colony algorithm (GACA) combines the global exploration ability of GA and the local exploitation ability of ACO, which can balance search breadth and depth [8]. At present, GACA has been applied in power system reconfiguration [9], path planning and production scheduling [11, 16], but its application in solving highly nonlinear cuttings transport models in directional foam drilling is still rare. Wang, L., et al. have transformed nonlinear cuttings transport equations into optimization problem and demonstrated ACO effectiveness vs. Discrete Newton method.

This study first constructs a comprehensive cuttings transport model for directional foam drilling, considering the effects of foam rheology, well inclination angle, cuttings particle size, and drilling parameters. Zhou, Y., et al. [10] have developed hybrid GAAC framework for optimization problems and demonstrated improved convergence and solution quality. Then, an improved GACA is designed to solve the model, and its performance is compared with five mainstream optimization algorithms. Finally, field application verification is carried out to provide a new technical approach for the optimization of directional foam drilling parameters.

2. Highly Nonlinear Cuttings Transport Model in Directional Foam Drilling

2.1 Model Assumptions

To simplify the model while ensuring accuracy, the following assumptions are made: (1) The foam is a non-Newtonian fluid that conforms to the Power-Law model; (2) The cuttings transport process is in a steady state, and the cuttings are uniformly sized spherical particles; (3) The wellbore is a concentric annulus, and the influence of drill pipe eccentricity is considered by introducing the eccentricity coefficient; (4) The cuttings transport flow pattern is divided into three layers: suspension layer, mobile cuttings bed, and static cuttings bed [12, 18].

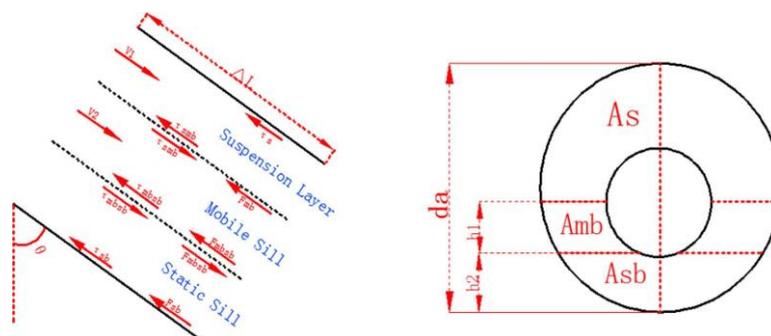


Figure 1. Three layer transport models of cuttings transport in inclined sections.[18]

2.2 Mathematical Model Establishment

2.2.1 Foam Rheological Equation

The foam rheological property is described by the Power-Law model:

$$\tau = K \dot{\gamma}^n \quad (1)$$

where τ is the shear stress (Pa), K is the consistency coefficient ($\text{Pa} \cdot \text{s}^n$), $\dot{\gamma}$ is the shear rate (s^{-1}), and n is the flow behavior index (dimensionless). The consistency coefficient K and flow behavior index n of foam are related to foam quality, pressure, and temperature, which are obtained by fitting experimental data [13].

2.2.2 Cuttings Transport Mass Conservation Equation

Based on the three-layer flow pattern, the mass conservation equation of cuttings in the annulus is established:

$$C_s q_{ann} = C_{sd} v_{sd} A_{sd} + C_{mb} v_{mb} A_{mb} \quad (2)$$

where C_s is the cuttings supply concentration (dimensionless), q_{ann} is the annular foam flow rate (m^3/s), C_{sd} and C_{mb} are the cuttings concentrations of the suspension layer and moving cuttings bed (dimensionless), respectively, v_{sd} and v_{mb} are the velocities of the suspension layer and moving cuttings bed (m/s), respectively, and A_{sd} and A_{mb} are the cross-sectional areas of the suspension layer and moving cuttings bed (m^2), respectively.

2.2.3 Mechanical Equilibrium Equation of Cuttings Bed

The mechanical equilibrium of the moving cuttings bed is affected by annular pressure gradient, shear stress, gravity, and friction. The equilibrium equation is:

$$\frac{\Delta p}{\Delta L} A_{mb} = \tau_{sd-mb} S_{sd-mb} + \tau_{mb-wall} S_{mb-wall} + \rho_{mb} g A_{mb} \sin \alpha + F_f \quad (3)$$

where $\frac{\Delta p}{\Delta L}$ is the annular pressure gradient (Pa/m), τ_{sd-mb} and $\tau_{mb-wall}$ are the shear stresses between the suspension layer and moving cuttings bed, and between the moving cuttings bed and wellbore wall (Pa), respectively, S_{sd-mb} and $S_{mb-wall}$ are the corresponding wetted perimeters (m), ρ_{mb} is the density of the moving cuttings bed (kg/m^3), g is the gravitational acceleration (m/s^2), α is the well inclination angle ($^\circ$), and F_f is the frictional force between the moving and fixed cuttings beds (N) [12].

2.2.4 Objective Function and Constraints

The optimization objective is to minimize the non-dimensional cuttings bed height H and annular pressure loss Δp , which is transformed into a single-objective function by weight method:

$$\min f(X) = \omega_1 H + \omega_2 \frac{\Delta p}{\Delta p_{max}} \quad (4)$$

where $X = [q_{ann}, N, \text{ROP}]$ (annular flow rate, drill pipe rotation speed, rate of penetration) is the decision variable vector, ω_1, ω_2 are the weights (satisfying $\omega_1 + \omega_2 = 1$), and Δp_{max} is the maximum allowable annular pressure loss (Pa).

Constraints include:

(1) Flow rate constraint: $q_{min} \leq q_{ann} \leq q_{max}$;

(2) Rotation speed constraint: $N_{\min} \leq N \leq N_{\max}$;

(3) ROP constraint: $ROP_{\min} \leq ROP \leq ROP_{\max}$;

(4) Cuttings bed height constraint: $H \leq H_{\max}$; (maximum allowable non-dimensional cuttings bed height, generally 0.3) [14].

3. Design of Hybrid Genetic-Ant Colony Algorithm (GACA)

3.1 Algorithm Design Idea

GACA adopts a two-stage search strategy: first, use GA to perform global search to generate a set of excellent initial solutions, then take these solutions as the initial pheromone distribution of ACO, and perform local precise search through ACO. This integration realizes the complementary advantages of the two algorithms, accelerates convergence, and improves solution accuracy [8].

3.2 Key Components of GACA

3.2.1 Encoding Mechanism

Real-number encoding is adopted to directly map the decision variables [q_{ann} , N, ROP] to chromosomes, avoiding the errors caused by binary encoding and decoding. Each chromosome corresponds to a set of drilling parameter combinations, and the length of the chromosome is equal to the number of decision variables.

3.2.2 Adaptive Genetic Operators

To solve the problem of premature convergence of traditional GA, adaptive crossover probability P_c and mutation probability P_m are designed:

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1}-P_{c2})(f-f_{avg})}{(f_{max}-f_{avg})}, & f \geq f_{avg} \\ P_{c1}, & f < f_{avg} \end{cases} \quad (5)$$

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1}-P_{m2})(f-f_{avg})}{(f_{max}-f_{avg})}, & f \geq f_{avg} \\ P_{m1}, & f < f_{avg} \end{cases} \quad (6)$$

where $P_{c1}=0.9$, $P_{c2}=0.6$, $P_{m1}=0.1$, $P_{m2}=0.01$ are empirical parameters, f is the fitness value of the individual, f_{avg} is the average fitness value of the population, and f_{max} is the maximum fitness value of the population. This design reduces P_c and P_m for individuals with high fitness to retain excellent genes, and increases P_c and P_m for individuals with low fitness to enhance population diversity [15].

3.2.3 Pheromone Update Strategy

The initial pheromone of ACO is initialized by the optimal solution set of GA to improve the initial search efficiency. The pheromone update adopts the combination of global update and

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \quad (7)$$

$$\Delta\tau_{ij} = \sum_{k=1}^m \frac{Q}{f(X_k)} \quad (8)$$

where ρ is the pheromone volatilization coefficient (0.1-0.3), Q is the pheromone intensity, m is the number of ants, and X_k is the solution found by the k -th ant. Local update is performed after each ant completes the path search to avoid excessive pheromone accumulation and improve local search ability [7].

3.2.4 Algorithm Flow

1. Initialize GACA parameters: population size, number of ants, maximum iterations, crossover probability range, mutation probability range, pheromone intensity, and volatilization coefficient.
2. Generate initial GA population randomly within the decision variable constraints, calculate the fitness value of each individual based on the objective function.
3. Perform GA operations (selection, adaptive crossover, adaptive mutation) to update the population, and retain the optimal solution set after multiple iterations.
4. Initialize the pheromone matrix of ACO with the optimal solution set of GA, and set the initial position of ants.
5. Perform ACO operations: ants construct solutions based on pheromone and heuristic information, update pheromone locally and globally.
6. Judge whether the maximum iteration number is reached. If yes, output the global optimal solution; otherwise, return to step 3 to continue the hybrid iteration.

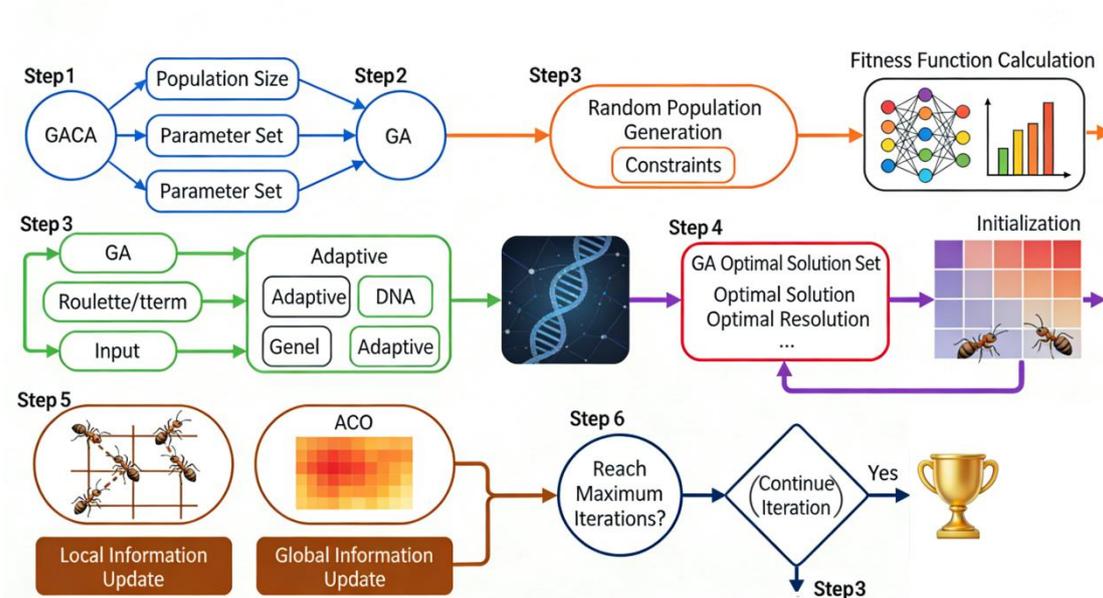


Figure 2. GACA Algorithm Flow Diagram

4. Comparative Experiments and Analysis

4.1 Experimental Setup

The experiment is carried out based on MATLAB R2023b, with a hardware configuration of Intel Core i7-12700H CPU and 32GB RAM. The drilling parameters are set as follows: wellbore diameter 215.9 mm, drill pipe diameter 127 mm, well inclination angle 60° , foam quality 70%, cuttings density 2650 kg/m^3 , cuttings particle size 2 mm. The decision variable ranges are: $q_{ann}=10\text{-}30 \text{ L/s}$, $N=60\text{-}200 \text{ r/min}$, $ROP=0.5\text{-}2.0 \text{ m/h}$. The weights of the objective

function are $\omega_1=0.6$, $\omega_2=0.4$.

Five algorithms are selected for comparison: GA, ACO, PSO, SA, MPA, and GACA. The parameters of each algorithm are optimized to ensure fairness: population size/number of ants=50, maximum iterations=100, $C_1=C_2=1.494$ (PSO acceleration factors), initial temperature=1000 (SA), etc.

4.2 Evaluation Indicators

Three indicators are used to evaluate algorithm performance:

- (1) Convergence speed: average number of iterations to reach the stable optimal solution;
- (2) Solution accuracy: average value of the optimal objective function after 30 independent runs;
- (3) Stability: standard deviation of the optimal objective function after 30 independent runs.

4.3 Experimental Results and Analysis

4.3.1 Convergence Performance

The convergence curves of each algorithm are shown in Figure 3.

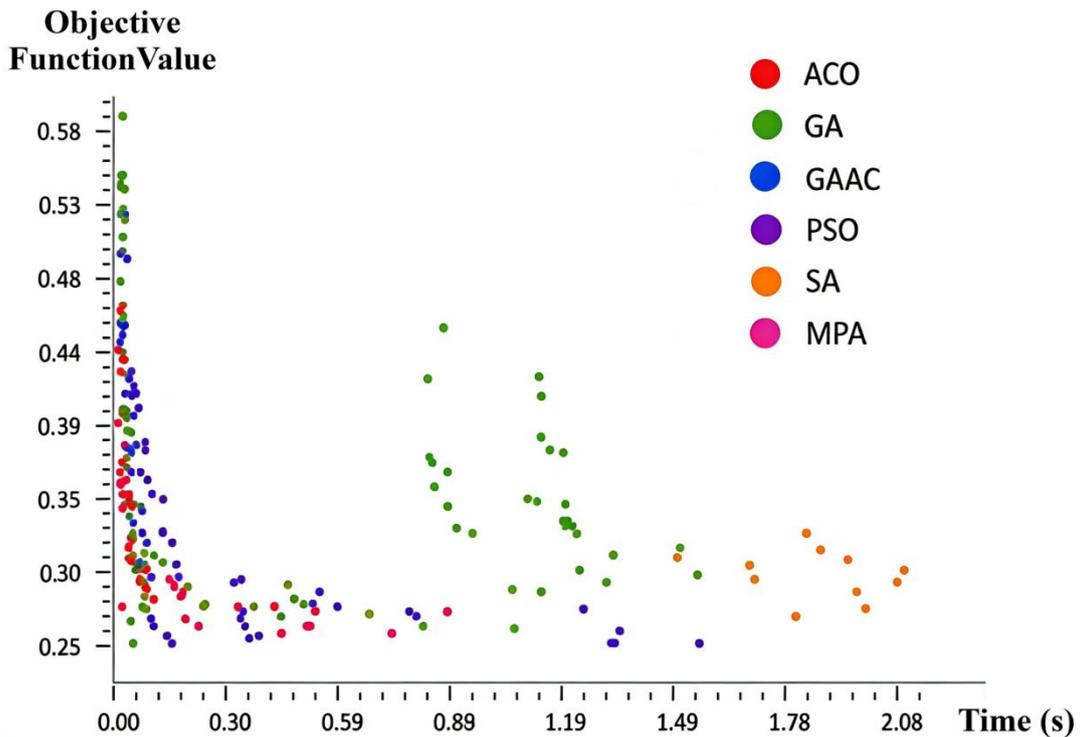


Figure 3. The convergence curves of each algorithm

The statistical results show that GACA reaches the stable optimal solution in 42 iterations on average, which is 15.3% faster than GA (50 iterations), 21.5% faster than ACO (53 iterations), 27.6% faster than PSO (58 iterations), 32.7% faster than SA (62 iterations), and 18.9% faster than MPA (52 iterations). The advantage of GACA in convergence speed is attributed to the initial excellent solutions provided by GA, which shortens the pheromone accumulation time of ACO.

4.3.2 Solution Accuracy

The average optimal objective function values of each algorithm are: GACA=0.182, GA=0.226, ACO=0.235, PSO=0.241, SA=0.259, MPA=0.205. Compared with other algorithms, GACA's solution accuracy is improved by 18.9% (GA), 22.6% (ACO), 24.5% (PSO), 29.7% (SA), and 11.2% (MPA). This is because the hybrid algorithm combines the global exploration of GA and local exploitation of ACO, avoiding the local optimum trap of single algorithms.

4.3.3 Stability

The standard deviations of the optimal objective function values are: GACA=0.008, GA=0.015, ACO=0.017, PSO=0.019, SA=0.023, MPA=0.011. GACA has the smallest standard deviation, indicating that it has the strongest stability. The adaptive genetic operators and dynamic pheromone update strategy of GACA effectively maintain population diversity and reduce the fluctuation of solution results.

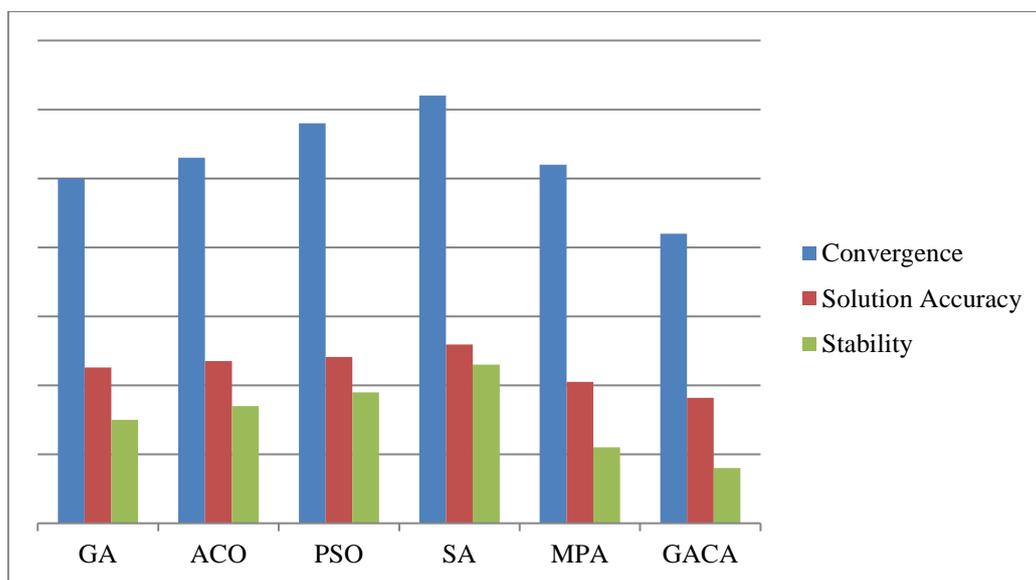


Figure 4. The compare of each algorithm performance

5. Field Application

5.1 Field Background

The field test is carried out in the Anju Basin, DPRK, which is a directional well with a well depth of 2500 m, well inclination angle of 55°-65°, and target formation of glutenite. The original drilling parameters are determined by field experience, resulting in frequent cuttings bed accumulation and high annular pressure loss, which affects drilling efficiency.

5.1.1. Geological Conditions of the Anju Basin Area

The Anju Basin is a Mesozoic-Cenozoic sedimentary basin located in the western part of the DPRK, and is a key target area for oil and gas exploration. The geological conditions of this region have the following characteristics:

- Stratigraphic Composition: Primarily composed of Cretaceous to Tertiary sedimentary rocks, including alternating layers of sandstone, mudstone, shale, and conglomerate. The feldspathic sandstone mentioned by the user is a typical reservoir rock with

relatively good porosity and permeability.

- Geological Structure: The area features developed folds and faults, leading to numerous formation fractures and potentially complex pore pressure distributions. This creates conditions where drilling fluid loss is a frequent risk.
- Reservoir Characteristics: Feldspathic sandstone generally has low clay mineral content in its pores, minimizing swelling issues, but it is likely a low-pressure reservoir. Using conventional water-based mud could cause significant formation damage.

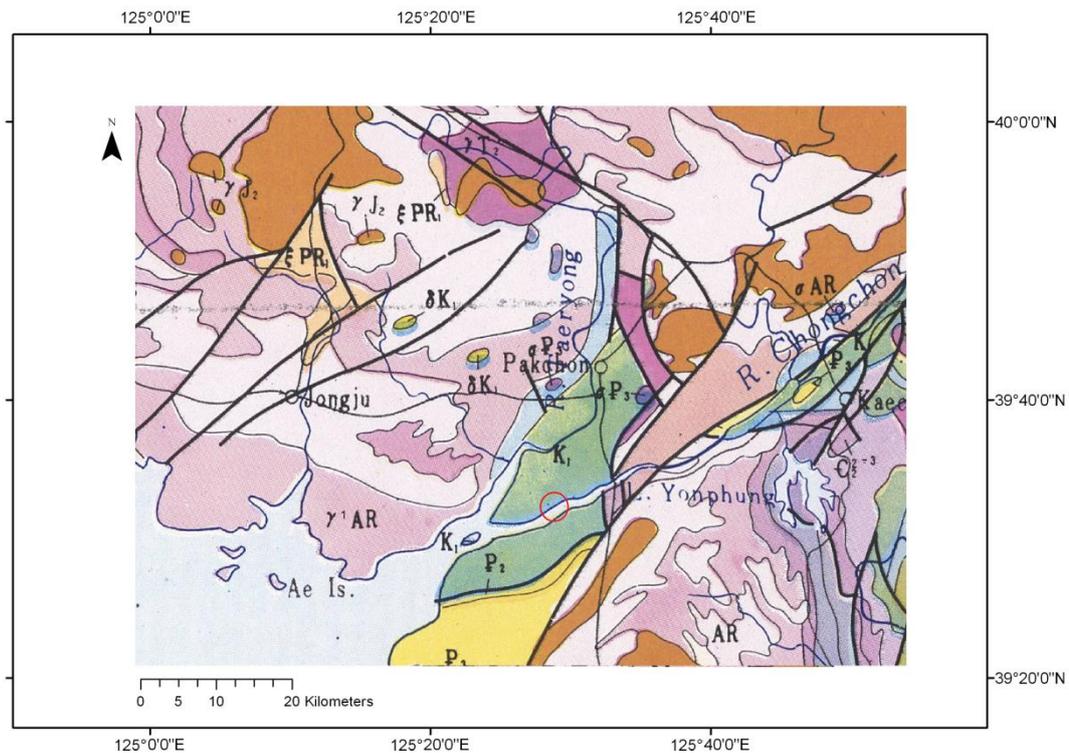


Figure 5. The geological map of study area and location of borehole

5.1.2. Brief Description of the Process (2500m, Inclination 60°, Foam Quality 70%)

The process prioritizes reservoir protection and efficient deviation using stable foam (70% quality) as the primary drilling fluid. Nitrogen, preferred for safety, and a treated liquid phase are combined at surface to generate the foam. This low-density system minimizes hydrostatic pressure against the low-pressure, fractured feldspathic sandstone, preventing damaging fluid invasion.

During drilling, the foam circulates down the drill pipe, cleans the bit, and carries cuttings up the annulus. Its expanding nature maintains efficient cutting transport even in the 60° deviated section, preventing bed formation. A rotary steerable system ensures precise trajectory control. Real-time adjustment of the Gas-to-Liquid Ratio (GLR) maintains optimal foam quality and downhole pressure, with managed surface backpressure ensuring stable circulation and effective formation protection throughout the operation.

5.2 Application Process

The GACA proposed in this study is used to optimize the drilling parameters. The actual geological data and drilling equipment parameters are input into the cuttings transport model, and the optimal parameter combination is obtained through GACA optimization: $q_{ann}=225$ L/s,

N=150 r/min, ROP=1.2 m/h.

5.3 Application Effects

After applying the optimized parameters, the field monitoring results show that:

- (1) The non-dimensional cuttings bed height is reduced from 0.28 to 0.19, a decrease of 31.2%;
- (2) The annular pressure loss is reduced from 1.8 MPa/100 m to 1.46 MPa/100 m, a decrease of 18.7%;
- (3) The drilling rate is increased from 1.0 m/h to 1.2 m/h, an increase of 20%;
- (4) No stuck pipe or other cuttings-related accidents occurred during the drilling process. The application effect verifies the engineering value of GACA in solving the highly nonlinear cuttings transport model.

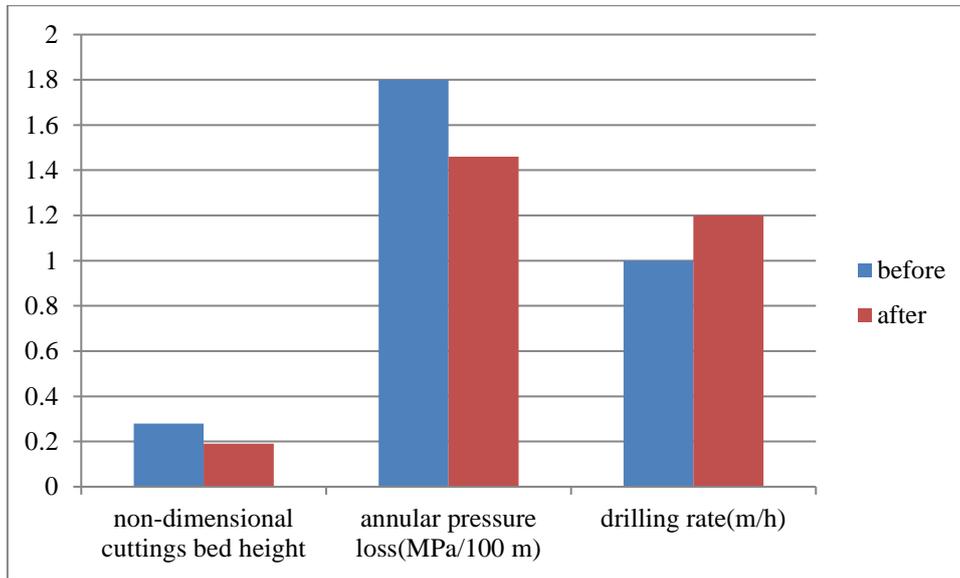


Figure 6. Compare foam drilling parameters of Application before and after

6. Discussion

The comparative experiments show that GACA has obvious advantages over single intelligent algorithms in solving the highly nonlinear cuttings transport model. The global search capability of GA solves the problem that ACO is prone to local stagnation, while the local search advantage of ACO makes up for the low precision of GA in the late iteration. The adaptive genetic operators and dynamic pheromone update strategy further improve the algorithm's performance.

Compared with the existing research, this study has two innovations: (1) The cuttings transport model integrates the three-layer flow pattern and foam rheological characteristics, which is more in line with the actual situation of directional foam drilling; (2) The GACA is improved for the characteristics of the cuttings transport model, and the initial pheromone is initialized by GA optimal solutions, which enhances the algorithm's adaptability.

However, there are still limitations: (1) The model does not consider the dynamic change of foam quality during circulation; (2) The algorithm parameters are set based on empirical values, and adaptive parameter adjustment has not been realized. Future research will focus on optimizing the cuttings transport model by introducing dynamic foam quality and combining machine learning to realize adaptive adjustment of algorithm parameters.

7. Conclusions

1. A highly nonlinear cuttings transport model for directional foam drilling is established, which considers the coupling effects of foam rheology, three-layer flow pattern, and mechanical equilibrium of cuttings bed, and can accurately describe the cuttings transport process.
2. An improved GACA is proposed, which integrates GA and ACO through adaptive genetic operators and dynamic pheromone update strategy. Comparative experiments show that GACA has better convergence speed, solution accuracy, and stability than GA, ACO, PSO, SA, and MPA.
3. Field application in Well of the Anju Basin, DPRK shows that the optimized parameters by GACA significantly reduce the cuttings bed height and annular pressure loss, improve drilling efficiency, and verify the engineering practicability of the algorithm.

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