

Article

Multi-Objective Optimization of Annular Flow Structure for Coring Drilling Tools in Ultra-Deep Wells

Lianbin Xia ¹, Jie Wu ^{1,*}, Xi Zhang ¹, Fei He ¹, Ye Chen ¹, Xiangmin Guo ¹ and Kun Zhan ²¹ Oil and Gas Technology Research Institute, Southwest Oil & Gasfield Company, PetroChina, Chengdu 610017, China² School of Mechanical and Electronic Information Engineering, China University of Geosciences, Wuhan 430074, China

* Correspondence: 18613206159@163.com

Abstract

Conventional coring drilling tools suffer from suboptimal annular flow design, leading to excessive pressure loss and hydraulic torque in ultra-deep well coring operations. To address this issue, we propose a systematic multi-objective optimization framework for the annular flow structure of single-acting double-tube coring tools, with the dual objectives of minimizing annular pressure loss and local circumferential hydrodynamic torque exerted on the outer pipe surface. Four key design variables, including the inner diameter and angle of the flow distribution sub, the number of water outlets on the centralizer, and the distance between the slip seat and the inner step surface of the drill bit, were selected. 81 sample points were generated via L81 orthogonal experiments combined with 3D CFD simulations. High-precision XGBoost surrogate models were established, and PAWN global sensitivity analysis was performed to identify dominant factors. The improved non-dominated sorting whale optimization algorithm was used to obtain the Pareto optimal solution set. The results show that the number of water outlets on the centralizer is the most significant factor affecting annular pressure loss, while the distance between the slip seat and the drill bit's inner step dominates hydraulic torque. Compared with the original design, the optimized structure reduces annular pressure loss by 32.36% and local hydraulic torque by 4.02%, an absolute decrease of approximately 9.46 N·m. This study provides a reusable optimization method and clear parameter direction for ultra-deep well coring tools.

Keywords: coring drilling tool; annular flow field; CFD; XGBoost; PAWN; NSWOA; multi-objective optimization



Academic Editor: Francesco Zirilli

Received: 19 May 2026

Revised: 17 June 2026

Accepted: 29 July 2026

Published: 4 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The global push for deep hydrocarbon resources has accelerated the advancement of ultra-deep and ultra-ultra-deep drilling technologies over the past decade [1,2]. In China's Tarim Basin, notable engineering milestones have been achieved in 10,000 m class well drilling, which exposes drilling systems to unprecedented downhole conditions [3,4]: extremely high temperature and pressure (HPHT), extremely narrow safe drilling fluid density windows, and extended circulation paths spanning several kilometers. Under such severe operating scenarios, the combined effect of formation temperature and pressure severely compromises wellbore integrity, while complex lithologies including salt-gypsum beds, fractured mudstones, and unconsolidated sandstones exhibit pronounced viscoelastic-plastic deformation and erratic pore pressure fluctuations [5,6]. Additionally,

the temperature-dependent rheological degradation and density stratification of drilling fluids during long-distance circulation introduce significant uncertainties in frictional pressure drop calculations, creating critical challenges for efficient cuttings transport and precise bottom-hole pressure regulation [7,8]. The circumferential hydrodynamic torque generated by the annular flow field under the action of outer pipe rotation and non-uniform shear will be superimposed on the mechanical load, causing uneven stress and additional torsional load on the outer pipe, increasing the probability of vibration and failure, and adversely affecting coring stability and core integrity [9–11].

To meet the special needs of ultra-deep well drilling, the design and optimization of coring drilling tools have always been a research focus [12,13]. Although traditional wireline coring drilling tools and single-acting double-tube coring drilling tools have improved coring quality and drilling efficiency to a certain extent, meaning they generally have high adaptability requirements for mud systems, drill bit structures and formation conditions, which is why their application effects under complex working conditions are still limited [14,15]. Aiming at complex geological conditions such as broken mudstone and poor wellbore stability, existing studies have proposed and verified a variety of structural and technological improvement measures [16,17], such as improving coring effects by increasing water passing area, coordinating wellbore protection and casing following, side jetting, and innovating core withdrawal mechanisms [18,19]. At the same time, in terms of the internal flow field characteristics and pressure drop prediction of drilling tools, methods such as three-dimensional numerical simulation, laminar flow pressure drop calculation, annular response modeling, and gas drilling flow channel analysis have provided an important theoretical basis for the optimization of drill tool structural parameters [20–22].

Furthermore, with the development of multiphase flow numerical simulation methods, the CFD-DEM coupling method has shown obvious advantages in the research of particle transport, flow loss and structural optimization [22,23]. Existing studies have shown that this method can better reveal the internal laws of particle movement, local flow field evolution and wall interaction in complex fluid–solid two-phase flow systems [24,25]. In relevant studies, Wang et al. [26] revealed the correlation between flow irreversibility and local wear for the flow process of gas–solid two-phase flow in elbow–reducer connection structures, providing a basis for the structural optimization of vulnerable parts in pipes under particle-containing flow conditions; Guo et al. [27] reconstructed the shape of irregular pebble particles combined with 3D scanning technology, analyzing the particle transport and blockage mechanism in the reverse circulation system of a mud shield, which has certain reference value for the design of return flow channels under complex particle systems; and Han et al. [28] established a cuttings–air two-phase flow model inside a drill pipe during coal seam drilling and systematically studied the effects of cuttings discharge air velocity and cuttings mass flow rate on flow characteristics and cuttings discharge effect, providing direct reference for the analysis of return flow cuttings carrying and discharge laws inside drilling tools. Nygaard and Nævdal [29] proposed a nonlinear model predictive control scheme for stabilizing annular pressure during drilling, providing an advanced control strategy for managed pressure drilling. Kaasa et al. [30] developed a simplified hydraulic model for the managed pressure drilling system to realize the intelligent estimation of downhole pressure. Jin et al. [31] established a casing annular pressure prediction model for deepwater drilling and completion operations, considering the influence of temperature on annular pressure. Liu et al. [32] carried out a systematic study on the casing annular pressure problem in deepwater drilling and completion, and derived the annular temperature calculation formula. Overall, relevant studies show that the CFD-DEM method has strong applicability in revealing particle microscopic behavior, evaluating flow performance and analyzing local erosion and blockage risks, as well as

providing a reference analysis idea for the research of return-flow cuttings transport, local wear and flow stability inside drilling tools [33–35]. In terms of optimization methodology, multi-objective optimization theory, orthogonal experimental design based on CFD simulation and intelligent optimization algorithms provide effective means for multi-index collaborative trade-off under complex working conditions [36–38]. Therefore, existing studies not only provide theoretical support for the structural design and performance evaluation of coring drilling tools for ultra-deep wells in complex flow environments, but also lay a relatively solid methodological foundation for the reconstruction of tool internal flow structure and multi-objective optimization in this paper. Although certain progress has been made in existing studies, under HPHT and long-circulation conditions of ultra-deep wells, the research on the mapping of “structural parameters—pressure loss and torque response” and multi-objective collaborative optimization for the down–return channel–annular flow organization of coring drilling tools is still relatively insufficient. The management of annular pressure loss is crucial in ultra-deep well drilling, which is not only related to the efficient removal and return of deep cuttings, but also directly acts on the core surface pressure and shear environment. Optimizing the bottom-hole and annular flow fields and reducing the along-the-way pressure drop and the core contact pressure difference are of great significance for preventing core plugging and secondary core crushing and for improving the fidelity of core structural information. However, the influence of key structural parameters on pressure loss and torque often shows strong nonlinear and coupling characteristics, and the empirical adjustment of a single factor makes it difficult to account for both. At the same time, the high cost of high-precision CFD calculation also limits the rapid search in a larger design space and the acquisition of a Pareto solution set.

Despite significant progress in coring tool design, two critical research gaps remain: (1) previous studies have primarily focused on single-objective optimization and lack systematic investigation of the nonlinear coupling relationship between structural parameters and dual responses; (2) traditional single-factor adjustment methods cannot balance the trade-off between these two conflicting objectives, and high-fidelity CFD simulations are computationally expensive, limiting large-scale design space exploration. The main contributions of this work are: (1) establishment of a complete engineering optimization process combining orthogonal experiments, CFD, surrogate modeling, sensitivity analysis, and multi-objective optimization; (2) quantitative identification of parameter priority and underlying physical mechanisms through PAWN sensitivity analysis; and (3) obtainment of a manufacturable optimal parameter combination that achieves synchronous improvement of both pressure loss and hydraulic torque, with direct engineering application value.

Based on this, this paper takes the single-acting double-tube coring drilling tool as the research object, focuses on the joint action mechanism of water distribution and return flow channel structures on annular pressure loss and hydraulic torque, and aims to establish a set of multi-objective optimization processes for engineering design. This study will first select the inner diameter and angle of the water distribution joint, the number of water outlets of the centralizer ring, and the distance between the slip seat and the inner step surface of the drill bit as the core design variables based on the single-acting double-tube coring drilling tool, and adopt the L81 orthogonal design method to obtain the pressure loss and torque data set. Then, an XGBoost surrogate model is constructed to realize the rapid prediction of the two responses from structural parameters, and the PAWN global sensitivity analysis is introduced to identify the main control parameters and risk intervals. Finally, with the surrogate model as the objective function, the improved non-dominated sorting whale optimization algorithm (NSWOA) is used for multi-objective optimization. The algorithm performance is verified using the ZDT2 benchmark test, yielding the Pareto

solution set of annular pressure loss and hydraulic torque. This study aims to provide a reusable method framework for parameter configuration, performance trade-off and engineering design of the annular flow structure of coring drilling tools in ultra-deep wells.

2. Study on the Influence of Key Structural Parameters of Single-Acting Double-Tube Coring Drilling Tool

2.1. Improved Design of Single-Acting Double-Tube Coring Drilling Tool for Ultra-Deep Wells

The single-acting double-tube drilling tool achieves high-quality collection of cores in complex formations through the collaborative design of the outer assembly and the inner assembly. The drilling tool includes an outer assembly and an inner assembly, where the outer assembly consists of an upper sub, an upper reamer, an outer pipe, a lower reamer and a drill bit, and the inner assembly is mainly composed of a water distribution joint, an adjusting nut, a connecting shaft, a sealing ring, a single-acting mechanism, a quick-release mechanism, an inner pipe, a centralizer ring, a slip seat and a slip. The main function of the upper sub is to connect the drill pipe with the drilling tool or other measurement subs, and transmit rotational torque and axial pressure. The upper and lower reamers mainly function to ream the wellbore to form a stable annular gap, reduce the frictional resistance between the outer pipe and the wellbore wall, and form a drilling fluid circulation channel. The outer pipe protects the inner assembly from wellbore wall collision and forms a drilling fluid down–return circulation channel. The drill bit mainly cuts the formation to form a core and guides the drilling fluid to flow out from the diversion hole. The main function of the water distribution joint is to dynamically redirect the drilling fluid flow to make the core stress more uniform. The adjusting nut is mainly used to accurately adjust the distance between the slip seat and the step surface of the drill bit. The single-acting mechanism keeps the inner pipe stationary when the outer pipe rotates, protecting the integrity of the core, and is equipped with an alarm valve plate to judge whether the core is in place by the sudden rise of pump pressure. The quick-release mechanism realizes the quick disassembly of the inner pipe and improves operation efficiency. The inner pipe accommodates and protects the core. The main function of the centralizer ring is to keep the inner pipe centered, reduce the disturbance of the outer pipe to the core, and is provided with diversion holes to guide the drilling fluid to the bottom of the drilling tool. The slip seat fixes the position of the slip, provides a supporting platform for core breaking, and adopts a conical shrinkage structure to enhance core guidance. The slip has an elastic structure with a multi-tooth array, which clamps the core adaptively according to core strength to prevent excessive core crushing. The specific structure is shown in Figure 1.

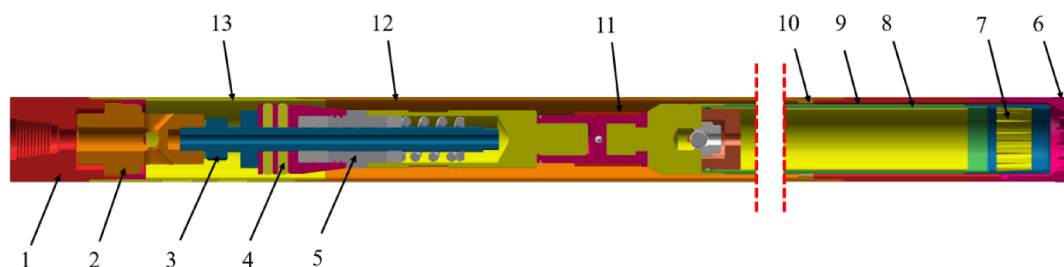


Figure 1. Schematic diagram of drilling tool structure. 1—upper sub, 2—water distribution joint, 3—adjusting nut, 4—alarm valve plate, 5—single-acting mechanism, 6—drill bit, 7—slip, 8—inner pipe, 9—lower reamer, 10—centralizer ring, 11—quick-release mechanism, 12—outer pipe, 13—upper reamer.

As shown in Figure 1, threaded connections are adopted between the upper sub and the outer pipe, the outer pipe and the upper and lower reamers, and the lower reamer and the drill bit. When the upper sub rotates, it drives the outer pipe, upper and lower reamers

and the drill bit to move to realize the drilling process. When the upper sub moves axially, it drives the water distribution joint and the single-acting mechanism to move. Under the action of the thrust bearing of the single-acting mechanism, the bearing seat and the components below remain stationary. To ensure the stability of the relative position of the inner pipe when it is stationary, a centralizer ring is installed in the gap between the inner and outer pipes to ensure coring quality. When drilling is completed, during the tripping process, the slip moves downward relative to the slip seat, causing the slip to shrink and cut off the core.

Drilling fluid passes through the middle flow channel of the upper sub, then flows into the gap between the inner and outer pipes through four water distribution holes in the middle of the water distribution joint, and finally flows to the periphery of the drill bit, so as to cool the drill bit, remove cuttings and protect core samples. Further, under the action of pressure, the drilling fluid carries waste residue out to the wellhead along the gap between the wellbore wall and the outer pipe, completing the circulation process. The drilling fluid circulation process is shown in Figure 2.

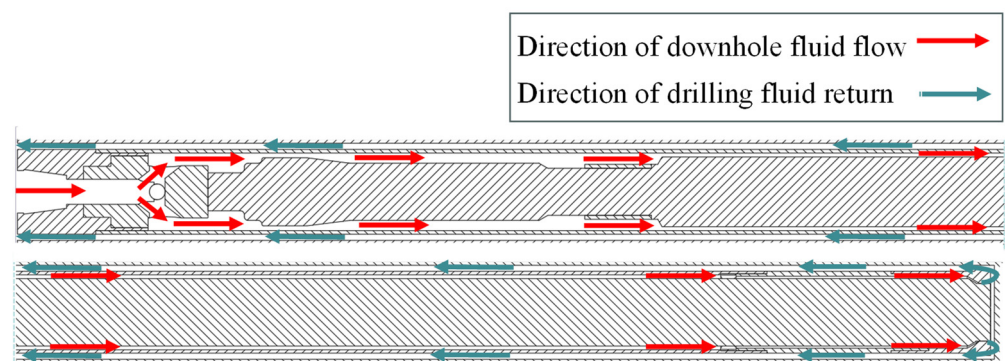


Figure 2. Physical diagram of hydraulically driven cordless coring drill tool.

2.2. Analysis of Structural Parameters Affecting Annular Pressure Loss and Fluid Torque

In the single-acting double-tube drilling tool, the annular pressure loss is defined as the total pressure drop from the inlet of the upper sub to the annulus exit at the drill bit; the fluid torque refers to the circumferential hydrodynamic torque of the fluid in the annulus acting on the outer surface of the drilling tool outer pipe. Structural parameters such as the inner diameter D and water distribution angle θ of the water distribution joint, the number N of water outlets of the centralizer ring, and the distance d between the slip seat and the drill bit step surface will simultaneously change the flow distribution mode of drilling fluid entering the annulus, local contraction and expansion loss, and circumferential uneven flow in the annulus, thus jointly determining the magnitude of annular pressure loss and outer pipe fluid torque. The selection of these four variables was based on comprehensive preliminary single-factor CFD simulations and decades of field engineering experience in ultra-deep well coring. Parameters with negligible influence on both objectives were excluded. Each selected parameter directly affects the flow distribution, local resistance, and circumferential flow uniformity in the annulus. The inner diameter of the flow distribution sub (D) controls the flow velocity and jet intensity entering the annulus. The flow distribution angle (θ) determines the radial-axial flow distribution and impact intensity on the outer pipe. The number of water outlets on the centralizer (N) affects the uniformity of circumferential flow distribution and local turbulence dissipation. The distance between the slip seat and the drill bit's inner step (d) governs the geometric constraint of the return flow channel near the bit, which is critical for vortex formation and circumferential shear stress distribution.

As shown in Figure 3a, if the inner diameter of the flow distribution sub (D) is too small, it will increase the flow velocity inside and at the outlet of the water distribution joint, increase the jet kinetic energy entering the annulus, increase local contraction loss and turbulent

dissipation, and lead to an increase in the total pressure drop from the inlet to the return outlet. At the same time, if the high-speed jet forms drift flow or a vortex in the annulus, the circumferential shear stress distribution on the outer surface of the outer pipe is uneven, and the fluid torque increases accordingly. As shown in Figure 3b, θ determines the flow direction and diffusion mode of drilling fluid entering the annulus. When θ is too large, the radial component is enhanced, which is easy to form impact flow and cyclone structure near the outer pipe, resulting in uneven circumferential pressure/shear and increased torque; when θ is too small, the fluid diffusion is insufficient, the high-speed zone near the annulus wall is more obvious, the proportion of along-the-way friction resistance increases, and the annular pressure loss increases. As shown in Figure 3c, the distance between the slip seat and the drill bit's inner step (d) essentially illustrate the geometric constraint of the annular return flow channel near the drill bit. If D is too small, it causes obvious contraction of the flow channel in this area, increases the local resistance coefficient, leads to an increase in the pressure drop near the drill bit and transmits it upstream, thereby raising the system annular pressure loss; at the same time, the restricted channel is more likely to induce asymmetric vortex or drift flow, resulting in uneven circumferential stress on the outer pipe and increased torque fluctuation. When d is too large, the return flow channel expands, the development space of local return flow and vortex structure increases, and the circumferential flow inhomogeneity may be enhanced, which will also cause an increase in the outer pipe fluid torque and manifest as return pressure fluctuation. As shown in Figure 3d, N affects the annular flow pattern through the uniformity of flow distribution. When the number of water outlets is insufficient, the single-hole flow rate and outlet velocity are too large, which is easy to generate strong shear layers and local vortices after entering the annulus, which not only increases the local pressure drop but also easily causes uneven circumferential shear of the outer pipe and increased torque. Although an excessive number of water outlets can reduce the single-hole velocity and local loss, the fluid kinetic energy is excessively dispersed, the organization of annular return flow becomes weak, pressure fluctuation and torque instability may occur, and this is unfavorable for the effective scouring of the drill bit bottom. In engineering, orthogonal experiments can be used to set factor levels, evaluate annular pressure loss and outer-pipe fluid torque based on CFD, and determine parameter combinations with multi-objective optimization to achieve low pressure loss, low torque and stable circulation.

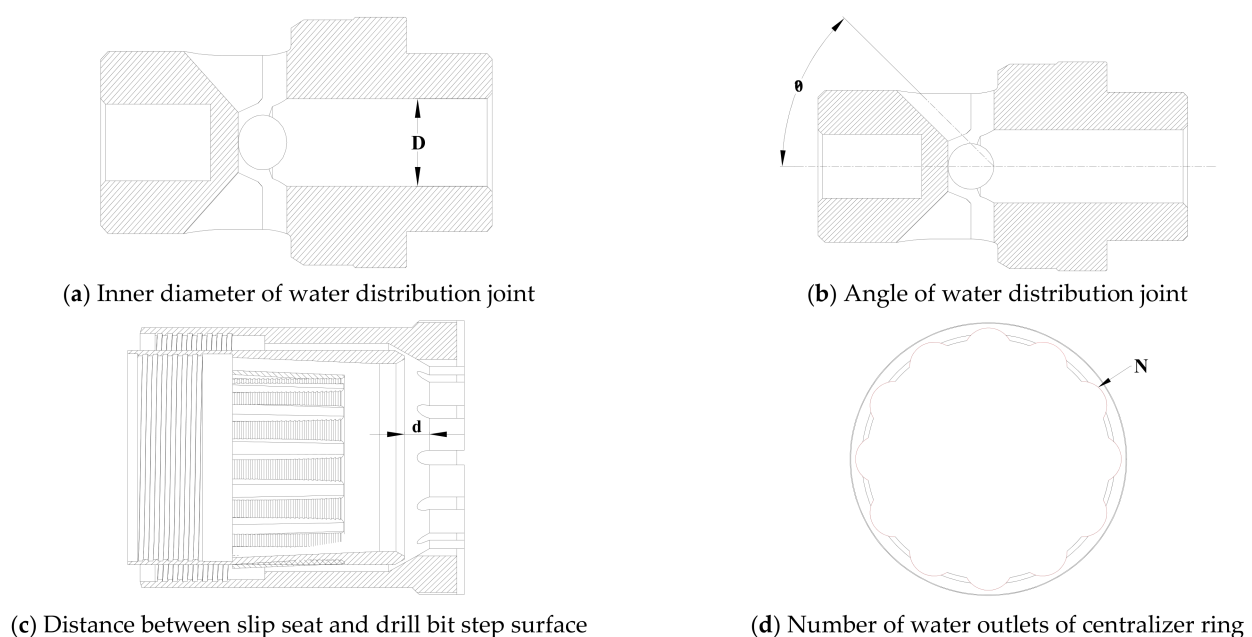


Figure 3. Structural schematic diagrams of each influencing factor.

3. Numerical Calculation

3.1. Orthogonal Experimental Design

There are many structural parameters affecting annular pressure loss and hydraulic torque, mainly including the inner diameter D of the water distribution joint, the water distribution angle θ of the water distribution joint, the number N of water outlets of the centralizer ring, and the distance d between the slip seat and the inner step surface of the drill bit, and each factor includes multiple levels. If the full test method is adopted, the number of test combinations is large, the calculation and analysis workload is high, and the time required and cost consumption are large. In contrast, orthogonal experimental design can investigate the influence of multi-factor and multi-level parameters on annular pressure loss and hydraulic torque, with fewer test times, on the premise of ensuring the reasonable and balanced distribution of factor levels, and is convenient for analyzing the primary and secondary relationships of each factor and the optimal combination. Therefore, this paper selects the standard orthogonal table L_{81} to carry out the experimental design, and its factor and level settings are shown in Table 1. The L_{81} (9^4) orthogonal table is a fractional orthogonal design that can effectively evaluate both main effects and all second-order interaction effects between parameters.

Table 1. Factor and level settings of the standard orthogonal test table.

	1	2	3	4	5	6	7	8	9
Inner diameter D of water distribution joint (mm)	26	28	30	32	34	36	38	40	42
Water distribution angle θ of water distribution joint ($^\circ$)	20	25	30	35	40	45	50	55	60
Number N of water outlets of centralizer ring (pcs)	7	8	9	10	11	12	13	14	15
Distance d between slip seat and inner step surface of drill bit (mm)	3	4	5	6	7	8	9	10	11

3.2. Establishment of Simulation Model and Mesh Generation

In this paper, Fluent is used to establish the flow channel model inside the drilling tool, which can accurately simulate the flow of fluid in the drilling tool and provide data support for optimizing the drill tool structure and improving coring quality.

To reduce the amount of calculation, according to the structural characteristics of the outer and inner assemblies of the drilling tool, a three-dimensional geometric model including the following key components is established—a drill bit, an outer pipe, an inner pipe, a water distribution joint, a centralizer ring, a gap between the slip seat and slip, and a wellbore wall—ignoring the details of threaded connections. To establish the flow channel model, the model is created in SolidWorks 2022R1, and the flow channel is extracted using the combination command. Before import into Fluent, the geometry is cleaned to ensure there are no small faces, overlapping faces or open boundaries, so as to improve the accuracy and efficiency of subsequent mesh generation and calculation. A comprehensive grid independence study was conducted using five progressively refined mesh configurations to eliminate numerical discretization errors. The results indicated that once the total element count surpassed 4.0 million, the relative deviations in both annular pressure loss and hydraulic torque predictions dropped below 1%, satisfying engineering accuracy requirements. Consequently, the 4.0-million-element mesh scheme was selected for all subsequent numerical computations. The final computational domain was discretized into approximately 4.02 million elements, comprising 3.95 million tetrahedral elements for the bulk flow region and 0.07 million hexahedral elements for the near-wall boundary layers.

The mesh quality metrics were strictly controlled: average cell orthogonality exceeded 0.85, and the maximum aspect ratio was limited to 5. All solid walls were treated with the standard wall function, and the first grid layer height was calibrated to ensure near-wall y^+ values fell within the logarithmic law range of 30–50.

In the process of mesh generation for the drill tool fluid domain based on ANSYS 2022R1 Fluent Meshing, this paper adopts the patch-conforming method based on the Pave algorithm to generate unstructured meshes. The basic element size is set to 3mm, and the tetrahedron is selected as the mesh topological structure to adapt to the complex geometric shape. To optimize calculation accuracy and efficiency, adaptive sizing technology is introduced to realize the intelligent gradient adjustment of mesh density through local curvature and proximity criteria. In the mesh quality optimization link, the high-order smoothing algorithm is used to carry out iterative optimization of node positions, which effectively improves the cell orthogonality to more than 0.85. Aiming at the boundary layer flow characteristics, the inflation layer parameters are set in smooth transition mode, the transition ratio is set to 0.272 to control the thickness change rate between adjacent layers, the maximum number of inflation layers is limited to five layers, and a geometric growth rate factor of 1.2 is configured to ensure that the y^+ value in the near-wall area is stable within the applicable range of the turbulence model. The specific process is shown in Figure 4.

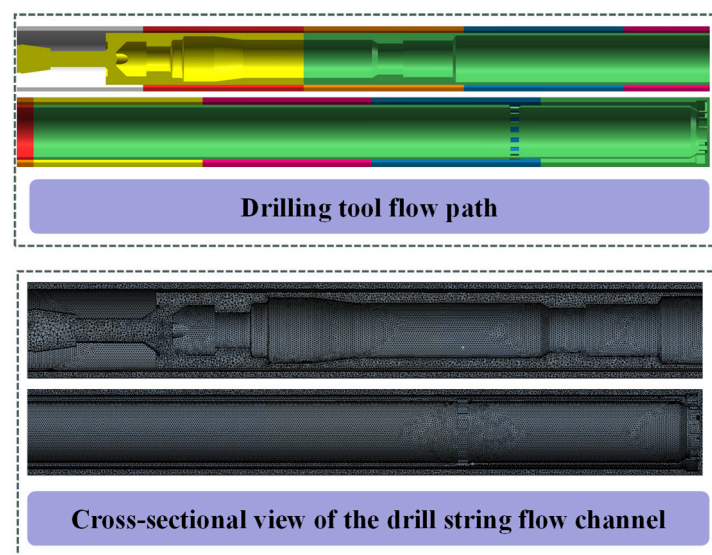


Figure 4. Schematic diagram of model establishment and mesh generation.

3.3. Setting of Boundary Conditions and Related Parameters

The drilling fluid was modeled using the Herschel–Bulkley non-Newtonian fluid model, which accurately describes the rheological behavior of water-based drilling fluids used in ultra-deep wells. The rheological parameters were obtained from field measurements of drilling fluids used in 9500m ultra-deep wells in the Tarim Basin: yield stress τ_0 : 5.2 Pa, consistency index K : 0.08 Pa·s^{*n*}, and flow behavior index n : 0.75. A fully parameterized boundary condition system was established based on field-measured data from 9500 m ultra-deep wells in the Tarim Basin. The Herschel–Bulkley constitutive model was employed to characterize the non-Newtonian rheological properties of the water-based drilling fluid, which has been proven to provide superior accuracy for high-pressure, high-shear flow conditions in annular spaces. The inlet velocity boundary was derived from the field pump displacement using the continuity principle: with a measured pump rate of 1441.2 L/min and an inlet cross-sectional area of 2290.22 mm², the

time-averaged inlet velocity was calculated to be 10.48873 m/s, and the velocity profile was assumed to be uniform. The outlet pressure reference is set to the drilling fluid pressure at 9500 m (111,834 kPa) to simulate the open-flow environment. The RNG k- ϵ turbulence model was adopted, which is suitable for simulating rotating flows and high-shear flows in annular spaces. A pressure-based segregated solver was used, with the SIMPLEC algorithm for pressure-velocity coupling. The convective terms of the momentum and turbulence equations were discretized using the second-order upwind scheme. The simulation was considered converged when the residuals of the continuity equation dropped below 1×10^{-5} and the residuals of the momentum equations dropped below 1×10^{-6} . Additionally, the inlet–outlet pressure difference and hydraulic torque were monitored, and convergence was confirmed when their fluctuations were less than 0.5% over 100 consecutive iterations. The rotational dynamic boundary conditions are processed differently according to the structural characteristics of the drilling tool: the outer wall surface of the inner pipe is defined as a stationary wall surface, and the rotational motion boundary is applied to the inner and outer wall surfaces of the outer pipe, whose angular velocity is converted from the measured linear velocity $v = 1$ m/s by $\omega = v/r$ to 18.52 rad/s. The rock formation contact surface adopts fixed-constraint conditions, and all wall surfaces adopt the standard wall function and apply the no-slip condition to ensure the accurate solution of the shear stress of the near-wall flow. The accuracy of our CFD model was validated against the annular friction pressure loss experimental data published by Saasen et al. [21]. Validated by comparison with published annular pressure loss data under comparable rheological and flow conditions, the relative error between our CFD calculation results and the experimental data was 4.2%, which is within the acceptable engineering error range (<10%). This confirms the reliability of our CFD model for simulating annular flow in coring tools. The value of 0.01 is the minimum apparent viscosity used to ensure numerical stability. The simulation parameters are shown in Table 2. According to the setting of the above parameter conditions, the simulation data of annular pressure loss and hydraulic torque under four influencing factors of 81 groups are obtained, as shown in Appendix Table A1.

Table 2. Simulation parameter setting table.

Name	Value	Name	Value
Density (kg/m ³)	1200	19.5 Temperature (°C)	25
Viscosity (kg/(m·s))	0.01	Outlet pressure (kPa)	111,834
Rotational speed (rad/s)	18.52	13.5 Inlet velocity (m/s)	10.48873

4. Sensitivity Analysis and Optimization Based on Annular Flow Structure Parameters

4.1. Evaluation of Structural Parameter Sensitivity Based on PAWN Algorithm

To quantitatively identify the influence intensity of key parameters of the annular flow structure on annular pressure loss and hydraulic torque, this study adopts the PAWN (moment-independent) global sensitivity analysis method to carry out parameter sensitivity evaluation [37,39]. The PAWN global sensitivity analysis approach, a moment-independent method, quantifies the influence of input parameters on output responses by measuring the discrepancy between the unconditional cumulative distribution function (CDF) of the output variable and the conditional CDF obtained when a specific input parameter is fixed to a constant value. This discrepancy is numerically characterized using the Kolmogorov–Smirnov (KS) statistic, which represents the maximum vertical distance between the two CDF curves.

$$KS(X_i) = \sup_y |F_y(y) - F_{y|x_i}(y)| \quad (1)$$

For each parameter X_i , multiple conditional distributions are obtained through random sampling, the corresponding KS values are calculated, and the median or maximum value is used to characterize the overall sensitivity:

$$S_i^{\text{median}} = \text{median}(KS(X_i)), S_i^{\text{max}} = \max(KS(X_i)) \quad (2)$$

The median reflects the sensitivity level of the parameter under typical conditions, and the maximum value reveals its potential impact on the extreme fluctuation of the output. This study conducts a comprehensive analysis from these two dimensions to avoid engineering decision-making deviations caused by a single index.

The comparison results of the unconditional CDF and conditional CDF of annular pressure loss are shown in Figure 5. When the number of water outlets of the centralizer ring and the distance between the slip seat and the inner step surface of the drill bit are fixed, the separation degree between the conditional CDF curve and the benchmark (unconditional) CDF curve is the most obvious. This indicates that these two parameters have the most significant impact on annular pressure loss and are key sensitive parameters.

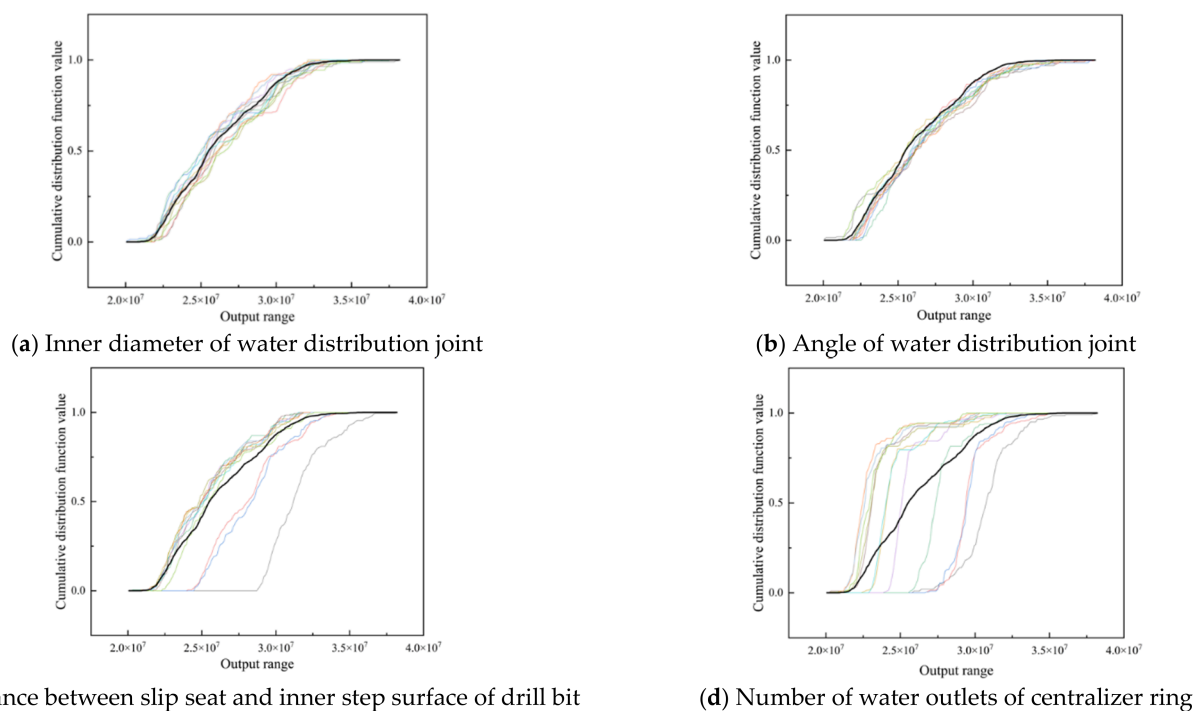


Figure 5. Comparison of unconditional CDF and conditional CDF of annular pressure loss.

The results of the parameter sensitivity analysis of annular pressure loss using the KS statistic are shown in Figure 6. The number of water outlets of the centralizer ring is the most significant in both overall and local sensitivity, which is the key factor affecting the pressure loss level. And the sensitivity of the step surface distance ranks, while the sensitivity of the inner diameter and angle of the water distribution joint is low. Therefore, in structural optimization, the number of water outlets should be regulated first, and the synergistic effect of the step surface distance should be monitored, so as to realize the effective control of annular pressure loss.

A comparison of the unconditional CDF and conditional CDF of hydraulic torque is shown in Figure 7. The separation degree of the curve of the distance between the slip seat and the inner step surface of the drill bit is high, so the distance between the slip seat and the inner step surface of the drill bit has strong sensitivity to hydraulic torque.

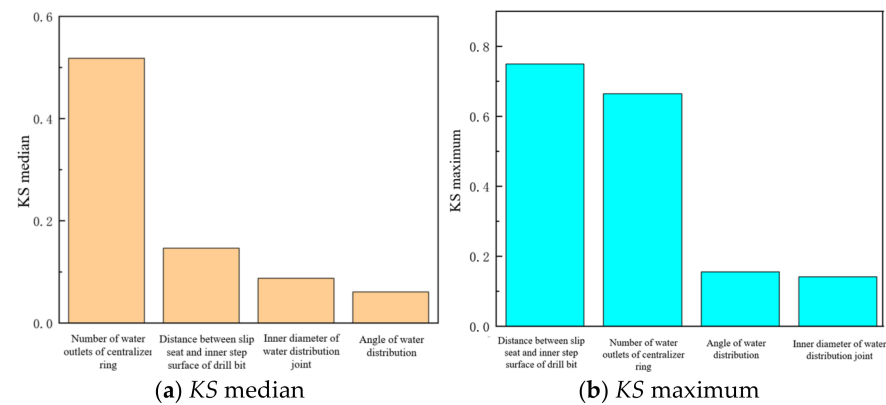


Figure 6. KS statistical chart of annular pressure loss.

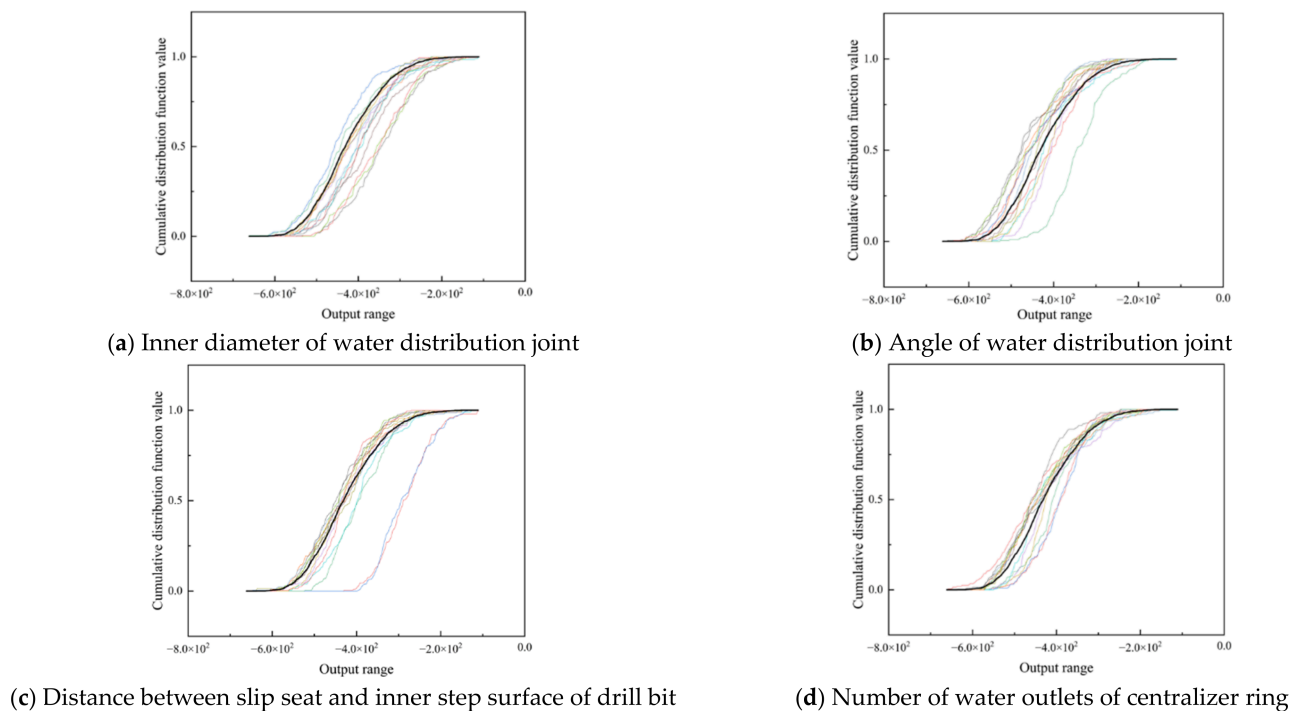


Figure 7. Comparison of unconditional CDF and conditional CDF of hydraulic torque.

The results of the parameter sensitivity analysis of hydraulic torque using the KS statistic are shown in Figure 8. The distance between the slip seat and the inner step surface of the drill bit is the most significant in both overall and local sensitivity, which is the key factor affecting hydraulic torque, and the water distribution joint angle is the second most sensitive factor. Therefore, it is necessary to monitor the high-risk value ranges of the step surface distance and the water distribution joint angle to realize the effective control of torque. For annular pressure loss, the number of water outlets on the centralizer N has the most significant influence because it directly determines the circumferential uniformity of flow distribution and single-hole flow velocity. Too few outlets lead to excessively high single-hole velocity, resulting in severe local turbulence dissipation and impact loss. For hydraulic torque, the distance between the slip seat and the drill bit's inner step d is dominant because it controls the geometric constraint of the return flow channel near the bit. An excessively small distance causes sharp flow channel contraction, leading to the formation of asymmetric vortices and uneven circumferential shear stress distribution on the outer pipe, which generates large additional hydraulic torque.

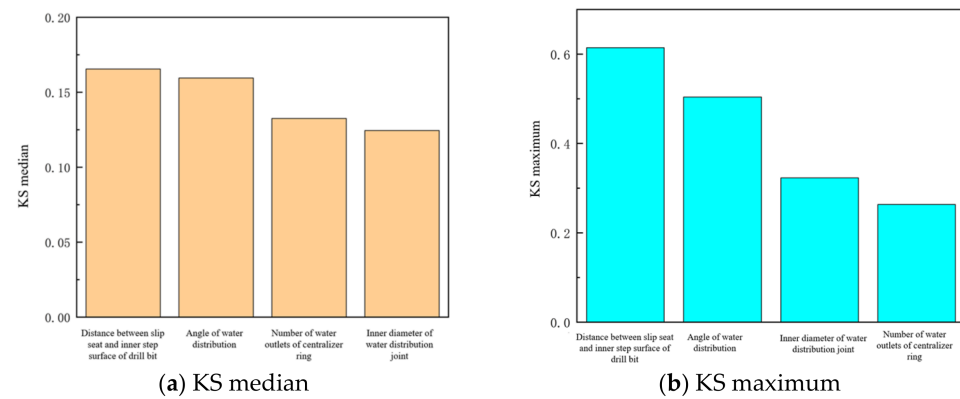


Figure 8. KS statistical chart of hydraulic torque.

4.2. Prediction of Annular Pressure Loss and Hydraulic Torque Based on XGBoost

XGBoost is a state-of-the-art gradient-boosting ensemble learning framework that builds predictive models through the sequential addition of decision trees, each of which is trained to correct the residual errors of the previous ensemble. By integrating both first- and second-order gradient information into the objective function and incorporating L1/L2 regularization terms to penalize model complexity, XGBoost achieves exceptional predictive accuracy for high-dimensional, highly nonlinear regression problems while mitigating overfitting risks. Its core idea is to iteratively construct multiple decision trees, each tree fits the residual of the previous tree, and the objective function consists of a loss function and a regularization term, which can be expressed as:

$$\mathcal{L}^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (3)$$

in which l is the loss function, f_t is the t -th tree, and Ω is the regularization term, defined as:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|w\|^2 \quad (4)$$

In the formula, T is the number of leaf nodes, w is the leaf weight, and γ and λ are regularization coefficients. The final predicted value of the model is the sum of the prediction results of each tree:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (5)$$

By minimizing the objective function, XGBoost can efficiently handle high-dimensional nonlinear regression problems. This study applies the methodology to predict annular flow structure parameters, aiming to establish a quantitative mapping relationship between the water distribution joint diameter, angle, slip seat distance, number of water outlets of the centralizer ring and annular pressure loss and hydraulic torque.

A data set is constructed from 81 groups of structural model combinations (L_{81} mixed orthogonal table) generated by orthogonal experimental design, and divided into a training set (57 groups) and a test set (24 groups) at a ratio of 7:3 to ensure the uniformity of data distribution and the reliability of generalization verification. Figure 9 shows the function fitting of the correlation between the dependent variable annular pressure loss and the independent variables such as water distribution joint diameter, water distribution joint angle, distance between slip seat and drill bit step surface, and number of water outlets of the centralizer ring, with a correlation coefficient $R^2 = 0.9868$. R^2 is the correlation coefficient, and the larger the R is, the higher the fitting accuracy is.

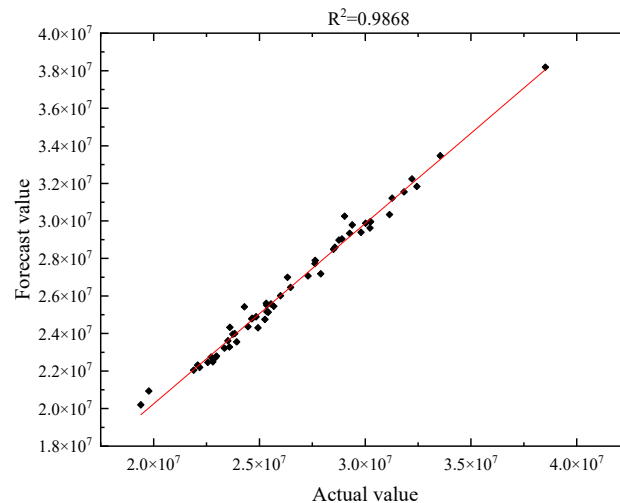


Figure 9. Training results of annular pressure loss.

Figure 10 shows the function fitting of the correlation between the dependent variable hydraulic torque and the independent variables including water distribution joint diameter, water distribution joint angle, distance between slip seat and drill bit step surface, and number of water outlets of centralizer ring, with a correlation coefficient $R^2 = 0.8921$.

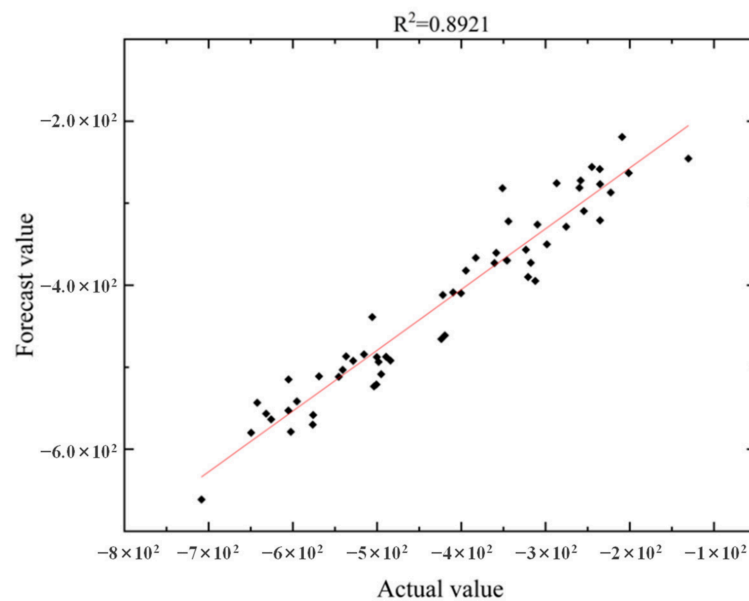


Figure 10. Training results of hydraulic torque.

According to the established XGBoost prediction model for annular flow structure parameters, the predicted values of annular pressure loss and hydraulic torque of the drill tool flow channel under different structural parameters can be obtained, and this prediction model is also used as the input of multi-objective optimization to obtain the predicted values of the annular flow structure under the optimal objective.

4.3. Principle of NSWOA

The Non-dominated Sorting Whale Optimization Algorithm (NSWOA) integrates the robust global search capability of the Whale Optimization Algorithm (WOA) with the Pareto-based non-dominated sorting mechanism, making it well-suited for solving constrained multi-objective optimization problems [40]. In this work, three targeted enhancements were implemented to adapt the standard NSWOA for drilling tool structural

optimization. First, an external archive mechanism was introduced to preserve elite non-dominated solutions generated across successive generations, preventing high-quality solutions from being lost during the evolutionary process. Second, a dedicated integer-constraint-handling module was developed to accommodate discrete design variables, such as the number of water outlets, ensuring that all generated solutions comply with the practical parameter value requirements of engineering applications. Finally, a hybrid crowding distance metric was proposed, which integrates diversity information from both the objective space and decision space to effectively improve the distribution uniformity of the Pareto front and avoid solutions clustering in local regions. The algorithm proceeds as follows:

- (1) An initial population is randomly generated within the predefined parameter ranges, and integer constraints are enforced on all discrete variables during the generation process. The objective function values of all individuals are then calculated using the XGBoost surrogate model. The fitness of each individual is defined as:

$$Fitness(i) = \frac{1}{rank(i)} + crowding_distance(i) \quad (6)$$

in which $rank(i)$ represents the non-dominated sorting rank of individual i , and the smaller the value, the more advanced the non-dominated front where individual i is located and the higher the quality of the solution; $crowding_distance(i)$ represents the crowding distance, which is used to measure the distribution density of individual i in its front. The larger the crowding distance, the sparser the solutions around individual i and the better the diversity of the solutions.

- (2) For each individual p , compute the set S_p of individuals it dominates and the number n_p of individuals that dominate it. The population is then stratified into Pareto fronts. The first front consists of all individuals with $n_p = 0$. Subsequent fronts are generated by removing the current front and repeating the dominance check on the remaining population until every individual is assigned to a front.
- (3) Sort the objective function values corresponding to the individuals on the Pareto front by size. For each objective function, calculate the crowding distance of each individual at its sorted position. The improved crowding distance calculation formula is:

$$d_i = \sum_{m=1}^M \frac{|f_m(i) - f_m(j)|}{f_{max,m} - f_{min,m}} + \alpha \sum_{k=1}^D \frac{|x_k(i) - x_k(j)|}{x_{max,k} - x_{min,k}} \quad (7)$$

where $f_m(i)$ and $f_m(j)$ denote the objective function values of individuals i and j for the m -th objective, respectively; $f_{max,m}$ and $f_{min,m}$ denote the maximum and minimum values of the m -th objective function in the current population, respectively. $x_k(i)$ and $x_k(j)$ denote the values of individuals i and j for the k -th decision variable, respectively; and $x_{max,k}$ and $x_{min,k}$ denote the maximum and minimum values of the k -th decision variable in the current population, respectively.

- (4) Generate offspring using the three core behaviors of the WOA: encircling prey, random search, and spiral update. Merge the parent and offspring populations, perform non-dominated sorting again, and select individuals of the original population size to form the next generation. Update the external archive with non-dominated solutions from the current generation.

Assume there are two individuals—A and B—whose Pareto ranks are $rank(A)$ and $rank(B)$, respectively, and whose crowding distances are $distance(A)$ and $distance(B)$, respectively. The selection rule can be expressed as:

$$\begin{cases} A, \text{Ifrank}(A) > \text{rank}(B) \\ B, \text{Ifrank}(A) < \text{rank}(B) \\ A, \text{Ifrank}(A) = \text{rank}(B) \text{ and distance}(A) > \text{distance}(B) \\ B, \text{Ifrank}(A) = \text{rank}(B) \text{ and distance}(A) < \text{distance}(B) \\ \text{Randomly select } A \text{ or } B, \text{Ifrank}(A) = \text{rank}(B) \text{ and distance}(A) = \text{distance}(B) \end{cases} \quad (8)$$

- (5) Repeat steps 2 to 4 until the maximum number of iterations is reached, and output the non-dominated solution set from the external archive as the optimization result.

4.4. Test and Application of NSWOA

To validate the effectiveness of the proposed improvements to the NSWOA, the classic ZDT2 multi-objective benchmark function is selected for performance testing. The ZDT2 function is a standard two-objective optimization problem with a known analytical true Pareto front, making it an ideal candidate for objectively comparing the convergence accuracy and solution diversity of different multi-objective optimization algorithms [41]. The performance of the improved NSWOA is compared head-to-head with the standard NSWOA.

The first and second objective functions of the ZDT2 test function are:

$$f_1(x) = x_1 \quad (9)$$

$$f_2(x) = g(x)(1 - (\frac{x_1}{g(x)})^2) \quad (10)$$

respectively, in which $g(x)$ is a function calculated from the second to n -th elements of the vector:

$$g(x) = 1 + \frac{9}{n-1} \sum_{i=2}^n x_i \quad (11)$$

In the test function, the default is $n = 30$, and the decision variable is $x_i \in [0, 1]$.

The Inverted Generational Distance (IGD) metric was adopted to simultaneously assess both the convergence accuracy and solution diversity of the obtained Pareto optimal fronts. IGD calculates the average of the minimum Euclidean distances from a set of uniformly distributed reference points on the analytical true Pareto front to the nearest solution in the algorithm-generated approximate front. A lower IGD value signifies that the approximate front is closer to the true optimal front (better convergence) and that the solutions are more evenly spread across the front (better diversity). The mathematical definition of the IGD is:

$$IGD(A, P^*) = \frac{1}{|P^*|} \sum_{v \in P^*} \min_{u \in A} d(u, v) \quad (12)$$

where P^* denotes the uniformly sampled reference set from the true Pareto front, A represents the approximate Pareto solution set generated by the algorithm, u is an arbitrary approximate solution in set A , v is a reference point sampled from the true front P^* , $d(u, v)$ represents the Euclidean distance between individual $u \in P^*$ and the nearest individual on A , and $\min d(u, v)$ represents the minimum distance from the reference point to A .

To validate the performance improvement in the proposed algorithm, the modified NSWOA and the original standard NSWOA are benchmarked using the ZDT2 multi-objective test function introduced earlier. The Pareto optimal fronts generated by the two algorithms are illustrated in Figure 11a and Figure 11b, respectively. From the Pareto front comparison chart, the Pareto front of the improved NSWOA performs better in terms of overall uniformity and convergence, while the Pareto front of the ordinary NSWOA is unevenly distributed on the true Pareto front and has a segmented phenomenon, performing

poorly in uniformity. In general, the performance of the improved NSWOA is superior to that of the ordinary NSWOA in terms of convergence and uniformity.

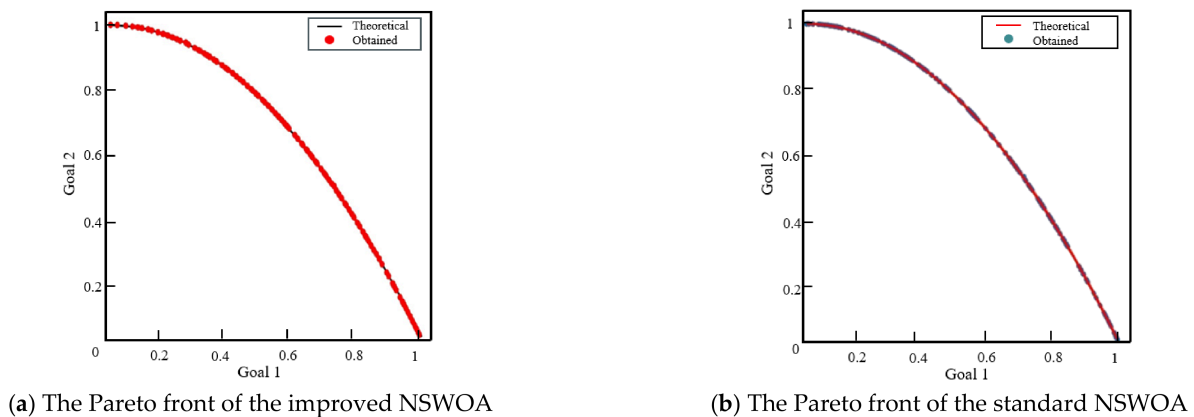


Figure 11. Pareto fronts before and after improvement.

The IGD metric is used to quantitatively compare the performance of the improved NSWOA and standard NSWOA. The ZDT2 test function is selected for the comparison experiment, and each algorithm runs independently 30 times. The average IGD value and standard deviation are calculated and presented in Table 3. The results show that the improved NSWOA exhibits better convergence and a more uniform Pareto front distribution than the standard algorithm.

Table 3. Mean and variance of IGD indexes of the two algorithms.

Test Function	Index	Improved NSWOA	Ordinary NSWOA
ZDT2	Mean (IGD)	4.9×10^{-3}	5.3×10^{-3}
	Std (IGD)	8×10^{-4}	1.59×10^{-2}

The improved NSWOA program is run for 100 iterations, and all multi-objective optimization results of NSWOA for the four structural parameters of the single-acting double-tube drilling tool regarding annular pressure loss and hydraulic torque within the parameter range are obtained, as shown in Figure 12a. By definition of Pareto optimality, every point on the Pareto front shown in Figure 12b represents a non-dominated optimal solution, meaning no single objective can be further improved without deteriorating the other. Each point on the front corresponds to a unique trade-off between the two conflicting objectives, with different positions reflecting different priority weights assigned to annular pressure loss reduction and local hydraulic torque reduction. The corresponding values of the four key structural parameters of the single-acting double-tube coring tool for each optimal solution can be directly extracted from the normalized decision space coordinates of these points.

4.5. Simulation Verification of Optimized Structural Parameters of Single-Acting Double-Tube Coring Drilling Tool

Based on the above optimization results, an optimal set of structural parameters is selected and set in the numerical simulation model. The selected structural parameters are: inner diameter of the water distribution joint, 30mm; water distribution joint angle, 50°; distance between the slip seat and the inner step surface of the drill bit, 10mm; and number of water outlets of the centralizer ring, 8. The simulation results are shown in Figure 13a,b. The corresponding hydraulic torque is −225.82 N·m, and the annular pressure loss is 20,457,501 Pa. After calculation, the optimized hydraulic torque is reduced by 4.02%, and

the annular pressure loss is reduced by 32.36%. The above simulation data show that the optimized structural parameters can achieve the expected performance improvement goals. Although the absolute reduction in local hydraulic torque is approximately 9.46 N·m, it still has non-negligible engineering value for ultra-deep well coring operations. This local torque reduction directly alleviates the uneven circumferential shear stress distribution on the outer pipe surface caused by asymmetric annular flow, which helps reduce local flow-induced torque fluctuations, decrease local stress concentration on the outer pipe, and lower the risk of fatigue failure at the outer pipe connection threads. Combined with the significant 32.36% reduction in annular pressure loss, which effectively relieves ground pump pressure load and reduces the risk of well leakage and kick in ultra-deep wells with narrow safe density windows, the dual performance improvements greatly enhance the long-term operational stability and safety of coring tools.

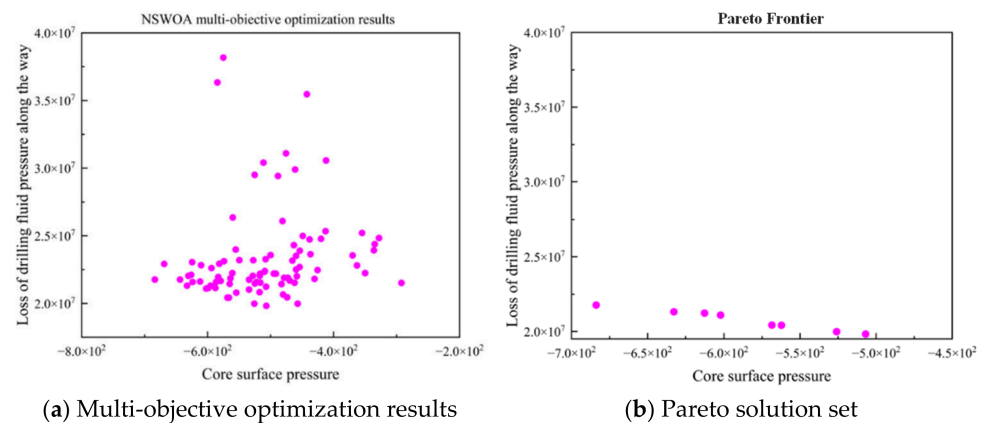


Figure 12. Schematic diagrams of multi-objective optimization results and Pareto solution set.

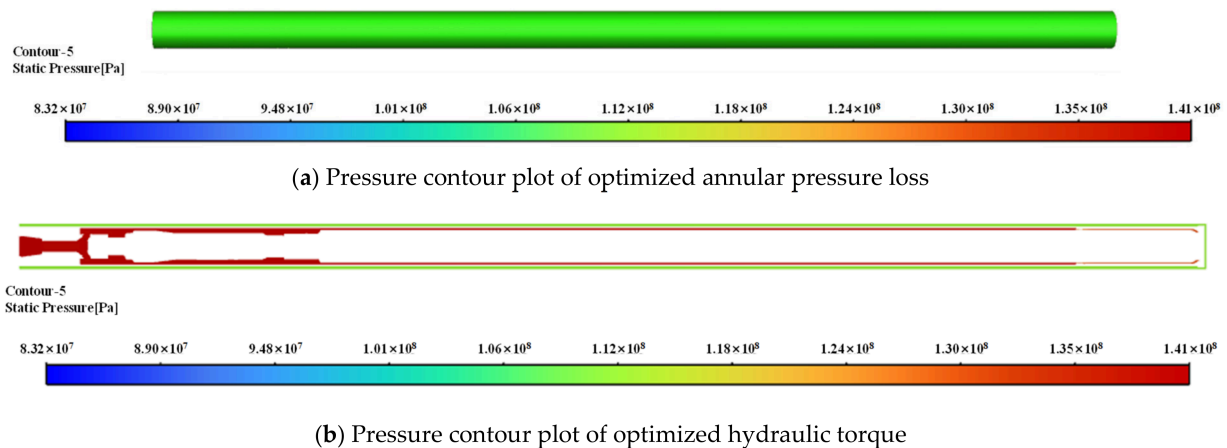


Figure 13. Pressure contour plot.

5. Conclusions

The following conclusions can be drawn from this study:

- (1) An improved single-acting double-tube coring drilling tool for ultra-deep wells is proposed, which features a quick-release structure for improved operational efficiency and an alarm device in the single-acting mechanism for core-in-place detection.
- (2) A systematic engineering optimization workflow integrating orthogonal experimental design, high-fidelity CFD simulation, machine learning-based surrogate modeling, global sensitivity analysis, and improved multi-objective evolutionary optimization was developed. The XGBoost surrogate model constructed in this study achieved excellent predictive performance, with coefficient of determination (R^2) values of

0.9868 for annular pressure loss and 0.8921 for hydraulic torque, respectively, making it a reliable and computationally efficient objective function for large-scale multi-objective parameter search.

- (3) The PAWN global sensitivity analysis quantitatively identified the relative importance ranking of the four key structural parameters: the number of water outlets on the centralizer ring exerts the dominant influence on annular pressure loss and should therefore be the primary design variable for pressure drop reduction; the distance between the slip seat and the drill bit's inner step surface is the most sensitive parameter affecting hydraulic torque, followed by the water distribution angle, and these two parameters should be prioritized in torque optimization efforts.
- (4) The improved NSWOA shows superior convergence and diversity compared to the standard version. A representative optimal parameter combination is obtained, which achieves significant performance improvements.

This study provides a reusable optimization path and clear parameter direction for ultra-deep well coring tools. However, the presented methodology still has the following limitations:

- (1) Fluid model limitation: Only single-phase water-based drilling fluid flow was considered, and the influence of cuttings particles was not taken into account. In actual drilling processes, cuttings will change the fluid rheological properties and flow field distribution.
- (2) Temperature field coupling limitation: This study assumed a constant fluid temperature and did not consider the variation law of drilling fluid rheological parameters with temperature in the high-temperature environment of ultra-deep wells.

Future research will introduce the CFD-DEM coupling method to investigate the effect of cuttings transport on annular flow characteristics, establish a temperature–flow field coupling model, and conduct full-scale laboratory experiments and field tests to further validate the performance of the optimized tool.

Author Contributions: Conceptualization, L.X. and F.H.; Methodology, L.X. and F.H.; Software, J.W. and X.G.; Validation, L.X.; Formal analysis, L.X.; Investigation, J.W. and K.Z.; Resources, J.W., Y.C., X.G. and K.Z.; Data curation, J.W. and X.Z.; Writing—original draft, L.X. and X.Z.; Writing—review & editing, Y.C.; Visualization, L.X., X.G. and K.Z.; Supervision, F.H. and K.Z.; Project administration, F.H.; Funding acquisition, F.H. All authors have read and agreed to the published version of the manuscript.

Funding: This project is funded by the General Program of Sichuan Provincial Natural Science Foundation (2026NSFSC0343).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors Lianbin Xia, Jie Wu, Xi Zhang, Fei He, Ye Chen, and Xiangmin Guo were employed by the Oil and Gas Technology Research Institute, Southwest Oil & Gasfield Company, PetroChina. The remaining author, Kun Zhan, declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest. The authors declare that this study received funding from the General Program of the Sichuan Provincial Natural Science Foundation. The funder was not involved in the study design; collection, analysis, or interpretation of the data; the writing of this article; or the decision to submit it for publication.

Appendix A

Table A1. 81 sets of simulation data of annular pressure loss and hydraulic torque.

Serial Number	Inner Diameter of Water Distribution Joint (mm)	Angle of Water Distribution Joint (°)	Distance from Step Surface (mm)	Number of Water Outlets of Centralizer Ring (pcs)	Hydraulic Torque (Nm)	Annular Pressure Loss (Pa)
1	36	25	11	15	−320.79775	23,924,190
2	26	55	10	9	−282.14373	29,562,570
3	28	60	10	7	−308.12239	32,643,630
4	42	25	8	13	−351.0942	23,344,680
5	30	45	6	11	−498.14111	25,357,700
6	32	30	11	13	−275.56248	25,260,810
7	26	30	5	15	−259.82179	24,463,140
8	30	50	10	8	−225.82	20,457,501
9	42	30	6	8	−235.62811	30,224,760
10	30	20	4	10	−235.28101	30,244,680
11	42	55	5	11	−605.20155	27,294,790
12	30	35	7	15	−360.06314	22,547,430
13	40	25	6	7	−317.60962	24,287,200
14	34	40	3	11	−130.40283	29,024,700
15	28	50	11	11	−280.99373	25,015,300
16	32	35	3	10	−642.41225	32,209,620
17	42	20	7	12	−254.47773	23,831,870
18	42	60	3	15	−422.01789	30,022,300
19	36	45	3	12	−605.41932	31,147,880
20	32	40	4	14	−209.0859	25,412,930
21	32	60	8	11	−385.42863	24,499,520
22	42	40	11	9	−300.82971	26,450,180
23	38	30	8	14	−201.2004	22,717,180
24	26	60	11	10	−271.88837	27,443,360
25	28	25	3	8	−282.6999	27,141,690
26	40	55	3	14	−346.16234	28,754,860
27	36	35	4	13	−309.70119	25,679,380
28	34	45	4	15	−286.75344	23,743,780
29	36	50	7	9	−400.40291	26,326,660
30	28	45	7	14	−268.41284	22,075,010
31	42	35	10	14	−358.51469	22,174,030
32	32	45	5	9	−345.68297	27,623,510
33	36	20	10	11	−481.39188	25,262,570
34	32	55	7	7	−409.6492	31,269,530
35	28	20	5	13	−423.63657	19,393,940
36	40	60	4	9	−244.936	28,498,890
37	40	40	9	12	−222.56494	23,583,560
38	40	45	10	13	−426.60833	21,163,850
39	28	40	6	10	−500.25197	24,639,750
40	34	35	5	7	−323.25199	29,266,100
41	36	55	8	10	−419.48291	25,544,990
42	36	60	6	14	−545.53065	19,775,260
43	34	30	10	10	−394.60867	25,995,730
44	38	55	4	8	−273.23359	31,397,780
45	38	45	11	7	−575.93157	32,442,340
46	30	55	11	12	−484.18678	23,599,950
47	30	60	9	13	−602.39201	22,562,790
48	38	40	10	15	−536.84207	22,079,250

Table A1. Cont.

Serial Number	Inner Diameter of Water Distribution Joint (mm)	Angle of Water Distribution Joint (°)	Distance from Step Surface (mm)	Number of Water Outlets of Centralizer Ring (pcs)	Hydraulic Torque (Nm)	Annular Pressure Loss (Pa)
49	38	20	6	9	−631.79692	27,899,040
50	38	60	5	12	−312.19708	24,932,150
51	34	60	7	8	−258.38917	29,800,450
52	26	40	7	13	−436.98036	23,233,100
53	32	50	6	15	−556.18348	22,179,160
54	32	20	9	8	−503.7142	28,901,770
55	34	55	6	13	−495.19241	22,798,340
56	38	35	9	11	−382.85139	24,840,300
57	42	50	4	7	−489.28159	33,546,860
58	26	35	6	12	−610.6915	24,629,520
59	28	30	4	12	−344.06584	26,471,100
60	30	30	3	9	−583.07205	32,883,540
61	28	35	8	9	−593.13776	27,790,070
62	34	50	8	12	−568.9828	23,509,930
63	26	20	3	7	−576.36326	38,515,990
64	26	25	4	11	−599.58324	26,454,590
65	30	40	8	7	−625.78674	31,833,170
66	26	50	9	14	−500.72706	22,795,620
67	42	45	9	10	−298.3507	25,343,090
68	34	20	11	14	−595.14484	21,892,260
69	26	45	8	8	−360.72792	29,381,420
70	40	20	8	15	−683.39259	21,995,920
71	36	40	5	8	−505.75229	28,567,050
72	38	50	3	13	−307.90171	29,864,920
73	40	50	5	10	−540.87531	25,322,390
74	40	35	11	8	−515.52277	27,634,480
75	34	25	9	9	−391.61171	27,532,760
76	38	25	7	10	−526.75108	26,053,370
77	40	30	7	11	−500.80276	22,872,520
78	30	25	5	14	−528.50701	22,930,500
79	36	30	9	7	−550.07393	31,582,680
80	28	55	9	15	−708.47409	22,970,530
81	32	25	10	12	−649.57483	24,666,010

References

1. Wang, C.; Feng, S.; Zhang, Z.; Zhou, B.; Wang, X.; Lv, X.; Liu, J.; Zhou, B. Drilling Design and Optimization Technology for Ultra Deep Wells in Tarim Oilfield: A Case Study of Well Take-1, the Deepest Well in Asia. In *Proceedings of the ARMA US Rock Mechanics/Geomechanics Symposium*; ARMA: Alexandria, VA, USA, 2024; D042S058R002.
2. Zhang, J.; Wang, H.; Ji, G.; Cui, M.; Chen, L.; Li, W.; Liu, L. Technologies and Achievements for Drilling and Completion of Onshore Deep and Ultra-Deep Wells in China. In *Proceedings of the International Petroleum Technology Conference*; IPTC: Kuala Lumpur, Malaysia, 2025; D032S009R016.
3. Li, B.; Zhou, B.; Fang, P.-L.; Yu, J.; Bi, W.-X.; Zhou, C.-P. Progress And Challenge of Deep Oil And Gas Resource Drilling Technology in China. In *Proceedings of the International Field Exploration and Development Conference*; Springer: Singapore, 2024; pp. 131–144.
4. Li, Z.; Tao, L.; Xi, J.; Fu, C.; Jin, N.; Ma, H. Study on the Influence of High-Temperature Environment on Dynamic Characteristics of Drill String in Ultra-Deesp Wells. *Chem. Technol. Fuels Oils* **2025**, *61*, 760–773. [[CrossRef](#)]
5. Sun, J.; Yang, J.; Bai, Y.; Lyu, K.; Liu, F. Research progress and development of deep and ultra-deep drilling fluid technology. *Pet. Explor. Dev.* **2024**, *51*, 1022–1034. [[CrossRef](#)]
6. Song, H.; Guo, J.; Li, J.; Zhang, S.; de Oliveira, A.J.S.; He, A. Application of multifunctional wellbore cleaning fluid in the removal of residual drilling fluids in ultra-deep wells: Research progress and prospects. *Geoenergy Sci. Eng.* **2024**, *243*, 213329. [[CrossRef](#)]

7. Epelle, E.I.; Gerogiorgis, D.I. A multiparametric CFD analysis of multiphase annular flows for oil and gas drilling applications. *Comput. Chem. Eng.* **2017**, *106*, 645–661. [\[CrossRef\]](#)
8. Dvoynikov, M.V.; Sidorkin, D.I.; Yurtaev, S.L.; Grokhotov, E.I.; Ulyanov, D.S. Drilling of deep and ultra-deep wells for prospecting and exploration of new raw mineral fields. *J. Min. Inst.* **2022**, *258*, 945–955. [\[CrossRef\]](#)
9. Fang, X.; Zhang, C.; Li, C.; Chen, L.; Li, J.; Yang, X.; Xie, H. Structural Design and Numerical Analysis of an All-Metal Screw Motor for Drilling Applications in High-Temperature and High-Pressure Environments in Ultra-Deep Wells. *Appl. Sci.* **2023**, *13*, 8630. [\[CrossRef\]](#)
10. Liu, J.; Wang, J.; Guo, X.; Dai, L.; Zhang, C.; Zhu, H. Investigation on axial-lateral-torsion nonlinear coupling vibration model and stick-slip characteristics of drilling string in ultra-HPHT curved wells. *Appl. Math. Model.* **2022**, *107*, 182–206. [\[CrossRef\]](#)
11. Kaneko, T.; Inoue, T.; Wada, R.; Katsui, T.; Suzuki, H. Torsional Vibration of Drill String Induced by Heave Motion in Deepwater Drilling. *J. Offshore Mech. Arct. Eng.* **2025**, *147*, 061801. [\[CrossRef\]](#)
12. Zhang, S.; Mao, Y.; Liu, F.; Xu, H.; Qu, Z.; Liao, X. Multi-objective optimization and evaluation of PEMFC performance based on orthogonal experiment and entropy weight method. *Energy Convers. Manag.* **2023**, *291*, 117310. [\[CrossRef\]](#)
13. Tian, J.; Li, J.; Cheng, W.; Zhu, Z.; Yang, L.; Yang, Y.; Zhang, T. Working mechanism and rock-breaking characteristics of coring drill bit. *J. Pet. Sci. Eng.* **2018**, *162*, 348–357. [\[CrossRef\]](#)
14. Ma, L.; Yin, D.; Ren, J.; Han, B.; Qin, S. A novel thixotropic structural dynamics model of water-based drilling fluids. *Geoenergy Sci. Eng.* **2024**, *234*, 212585. [\[CrossRef\]](#)
15. Chen, L.; Li, W.; Guo, J.; Li, K.; Cai, Z.; Wu, J.; Xu, W.; Zhu, X. Optimal bit selection for large-diameter wellbore drilling in an ultra-deep well. *Pet. Explor. Dev.* **2025**, *52*, 807–816. [\[CrossRef\]](#)
16. Wang, J.; Qian, D.; Sun, Y.; Peng, F. Design of diamond bits water passage system and simulation of bottom hole fluid are applied to seafloor drill. *J. Mar. Sci. Eng.* **2021**, *9*, 1100. [\[CrossRef\]](#)
17. Shi, Y.; Li, C. Flow Field Simulation of a Hydrogeological Exploration Drill Bit for Switching between Coring Drilling and Non-Coring Drilling. *Appl. Sci.* **2024**, *14*, 4893. [\[CrossRef\]](#)
18. Bo, K.; Ji, F.; Zhao, Z.; Fan, L.; Wang, M. Optimum design of large-diameter reverse circulation drill bit for drilling rescue wells using orthogonal experimental method and CFD simulation. *Energies* **2023**, *16*, 3913. [\[CrossRef\]](#)
19. Zhang, Y.; Xu, Y.; Zheng, Y.; Fernandez-Rodriguez, E.; Sun, A.; Yang, C.; Wang, J. Multiobjective optimization design and experimental investigation on the axial flow pump with orthogonal test approach. *Complexity* **2019**, *2019*, 1467565. [\[CrossRef\]](#)
20. He, M.; Wang, Z.; Chen, H.; Cao, Y.; Ma, L. Multi-Objective Evolutionary Algorithm Based on Decomposition With Orthogonal Experimental Design. *Expert Syst.* **2025**, *42*, e13802. [\[CrossRef\]](#)
21. Saasen, A.; Ytrehus, J.D.; Lund, B. Annular frictional pressure losses for drilling fluids. *J. Energy Resour. Technol.* **2021**, *143*, 053201. [\[CrossRef\]](#)
22. Guo, D.; Chen, L.; Zhou, Z.; Wang, D.; Zhang, Y.; Yang, X.; Fang, X.; Wang, X.; Lu, H.; Dai, L.; et al. Development of a pressure coring system for the investigation of deep underground exploration. *Int. J. Min. Sci. Technol.* **2023**, *33*, 1351–1364. [\[CrossRef\]](#)
23. Zhou, W.; Huang, J.; Li, L. Numerical simulation of bottomhole flow field structure in particle impact drilling. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2018; p. 032080.
24. Chierigati, A.C. Validation of reverse circulation drilling rig for reconciliation purposes. In *Proceedings of the TOS Forum*; International Organization for Standardization (ISO): Geneva, Switzerland, 2015.
25. Liu, J.; Sun, J.; Jiang, G.; Yu, Y. A Study on the Influence of Core Stability on the Coring Process of Long-Barrel Coring Tools. *Processes* **2024**, *12*, 2847. [\[CrossRef\]](#)
26. Wang, C.; Liu, M.; Yan, J. Flow irreversibility versus wear of elbow-reducer connection with gas-solid two-phase flow: A numerical study via CFD-DEM coupling method. *Powder Technol.* **2023**, *428*, 118835. [\[CrossRef\]](#)
27. Guo, Y.; Li, X.; Jin, D.; Liu, H.; Yang, Y.; Fang, Y.; Cui, L. Assessment on the reverse circulation performance of slurry shield pipeline system assisted with CFD-DEM modeling under sandy cobble stratum. *Powder Technol.* **2023**, *425*, 118573. [\[CrossRef\]](#)
28. Han, X.; Li, P.; Li, J. CFD-DEM Simulation of Reverse Circulation Pneumatic Cuttings Removal during Coal Seam Drilling. *Math. Probl. Eng.* **2020**, *2020*, 3707864. [\[CrossRef\]](#)
29. Nygaard, G.; Nævdal, G. Nonlinear model predictive control scheme for stabilizing annulus pressure during oil well drilling. *J. Process Control* **2006**, *16*, 719–732. [\[CrossRef\]](#)
30. Kaasa, G.O.; Stamnes, Ø.N.; Imsland, L.; Aamo, O.M. Simplified Hydraulics Model Used for Intelligent Estimation of Downhole Pressure for a Managed-Pressure-Drilling Control System. *SPE Drill. Complet.* **2012**, *27*, 127–138. [\[CrossRef\]](#)
31. Yang, J.; Tang, H.; Liu, Z.; Yang, L.; Huang, X.; Yan, D.; Tian, R. Prediction model of casing annulus pressure for deepwater well drilling and completion operation. *Pet. Explor. Dev.* **2013**, *40*, 661–664. [\[CrossRef\]](#)
32. Liu, B.; Yang, J.; Zhou, B.; Yan, D.; Tian, R.; Liu, Z.; Luo, J.; Huang, X. Study of Casing Annulus Pressure for Deepwater Drilling and Completions. In *Proceedings of the SPE Deepwater Drilling and Completions Conference*; Society of Petroleum Engineers: Richardson, TX, USA, 2014.

33. Jing, W.; Zhang, H.; Chen, Y. Collaborative optimization of the wet screening process: A CFD-DEM based modeling approach with bi-objective optimization. *Powder Technol.* **2024**, *443*, 119930. [[CrossRef](#)]
34. Ning, C.; Li, Y.; Huang, P.; Shi, H.; Sun, H. Numerical Analysis of Single-Particle Motion Using CFD-DEM in Varying-Curvature Elbows. *J. Mar. Sci. Eng.* **2022**, *10*, 62. [[CrossRef](#)]
35. Xu, Z.; Mao, X.; Gu, Y.; Chen, X.; Kuang, W.; Wang, R.; Shao, X. Analysis of hydrodynamic filtration performance in a cross-step filter for drip irrigation based on the CFD-DEM coupling method. *Biosyst. Eng.* **2023**, *232*, 114–128. [[CrossRef](#)]
36. Chen, T.; Guestrin, C. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM Sigkdd International Conference on Knowledge Discovery and Data Mining*; ACM: New York, NY, USA, 2016; pp. 785–794.
37. Pianosi, F.; Wagener, T. Distribution-based sensitivity analysis from a generic input-output sample. *Environ. Model. Softw.* **2018**, *108*, 197–207. [[CrossRef](#)]
38. Pianosi, F.; Sarrazin, F.; Wagener, T. A Matlab toolbox for global sensitivity analysis. *Environ. Model. Softw.* **2015**, *70*, 80–85. [[CrossRef](#)]
39. Puy, A.; Piano, S.L.; Saltelli, A. A sensitivity analysis of the PAWN sensitivity index. *Environ. Model. Softw.* **2020**, *127*, 104679. [[CrossRef](#)]
40. Tian, Q.; Shi, X.; Lo, F.; Lin, X. Application of multivariant optimization algorithm in multiobjective optimization. *Preprints* **2023**. [[CrossRef](#)]
41. Saha, I.; Maullik, U.; Łukasik, M.; Plewczynski, D. Multiobjective differential evolution: A comparative study on benchmark problems. In *Man-Machine Interactions 3*; Springer: Cham, Switzerland, 2014; pp. 529–536.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.