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Research on Quantitative Evaluation and Optimization Method of Multi-Scheme Drilling Engineering Design Parameters

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Abstract

The reasonable selection of drilling engineering design parameters is related to the success or failure of drilling operations. Traditional parameter optimization mostly relies on experience and single-index decision-making, and therefore fails to satisfy multi-dimensional engineering constraints such as drag and torque, wellbore trajectory and casing running, and lacks a systematic quantitative evaluation mechanism. To address the above problems, this paper proposes a quantitative evaluation and optimization method for drilling engineering design parameters based on multi-dimensional coupling. First, this method establishes a parameter system for drilling engineering design and analyzes the coupling relationships and constraint conditions among various parameters. The parameter system covers not only wellbore trajectory, drill string and casing parameters but also drilling fluid properties (density, yield point and gel strength) and formation rock strength (uniaxial compressive strength, UCS), which are treated both as model inputs and as feasibility constraints. On this basis, an exhaustive strategy is adopted to systematically traverse and discretely combine key design parameters, generating all possible parameter combination schemes. Subsequently, four engineering calculation modules, including wellbore trajectory design, drag and torque calculation, casing running capacity evaluation and a drilling fluid hydraulics and wellbore stability constraint module, are integrated to provide multi-dimensional quantitative analysis for each parameter combination scheme. Finally, a comprehensive evaluation model combining the analytic hierarchy process with the entropy weighting method is constructed to perform weighted scoring on the calculation results of each scheme and realize automatic scheme ranking and optimal scheme recommendation. Verified with a field case of a complex horizontal well, and after validating the calculation modules against measured hook loads, torques and casing running loads, the results show that reasonable parameter combinations can significantly improve engineering performance, effectively reducing the risk of drag and torque and casing running, with the comprehensive score increased by 18.0%. The practicability and effectiveness of the method are verified, providing a new idea and method for quantitative optimization of drilling engineering design parameters.

Keywords: drilling engineering design; parameter optimization; quantitative evaluation; friction torque; comprehensive evaluation model

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1. Introduction

With the continuous expansion of global oil and gas exploration and development towards deep wells, ultra-deep wells, and complex structural wells, drilling engineering is facing more and more complex geological conditions and engineering challenges, and the requirements for the rationality and reliability of drilling engineering design are also increasing [1]. The widespread application of complex well types such as horizontal wells, extended-reach wells and multi-target wells has made the coupling between drilling engineering design parameters increasingly prominent, and parameter optimization has become an important way to improve drilling efficiency and reduce engineering risks and economic benefits [2]. Drilling engineering design parameters cover multiple dimensions, including wellbore trajectory parameters, drilling fluid parameters, drill string parameters, and casing parameters, among which complex coupling relationships exist [3]. In particular, the drilling fluid properties (density, yield point and gel strength) and the formation rock strength (uniaxial compressive strength, UCS) directly control the feasible window of the mechanical design: the fluid density determines the equivalent circulating density (ECD) and the buoyed string weight, the yield point and gel strength govern the annular pressure loss and the cuttings-carrying capacity, and the UCS limits the allowable mud weight and the dogleg severity that can be drilled without wellbore instability [4–6].

Traditional drilling engineering design parameter optimization mainly relies on engineers' personal experience and engineering analogy, and has the following prominent problems: first, the experience-based method has strong subjectivity, and different engineers may give quite different design schemes, lacking consistency and repeatability [1]; second, traditional methods usually take a single engineering index as the optimization objective, making it difficult to balance multi-dimensional constraints such as drag and torque, casing running capacity and the hydraulic and stability envelope [3,7]; third, there is a lack of rapid and quantitative evaluation means for the engineering impact after parameter adjustment, making it difficult for engineers to compare the advantages and disadvantages of a large number of parameter combination schemes in a short time [8].

In recent years, with the development of computer technology and numerical simulation methods, drilling engineering calculation software has been widely used. Internationally, commercial software such as Schlumberger's DrillPlan and Halliburton's DecisionSpace provides integrated trajectory, hydraulics and torque-and-drag modules, and digital-twin-based advisory systems have been developed to recommend drilling parameters in real time [8,9]. In China, CNPC, Sinopec and universities have also actively explored parameter optimization [10,11].

However, existing commercial software and methods still have the following three specific limitations in parameter optimization. First, optimization is module-local: trajectory, torque-and-drag, casing running, hydraulics and stability are evaluated in separate modules, and the coupling between them is handled by manual iteration rather than by a single evaluation mechanism. Second, the optimizers are either gradient-based local methods or stochastic heuristics, for which global coverage of the feasible design space is not guaranteed for the parameter-optimization problem addressed here [7,12]. Third, there is no unified mechanism for quantitatively scoring and ranking the multi-module results of a large number of candidate designs [13].

Meanwhile, big data technology and quantitative evaluation methods have achieved remarkable results in other engineering fields. Multi-criteria decision making (MCDM) provides a general framework for the comprehensive evaluation of alternatives under conflicting criteria. The analytic hierarchy process (AHP) [14] derives criterion weights from structured pairwise comparisons, the technique for order preference by similarity to an ideal solution (TOPSIS) [15] ranks alternatives by their distance to an ideal solution, and

the entropy weighting method (EWM) [16] and the CRITIC method [17] derive objective weights from the information content of the data. Because subjective and objective weighting methods have complementary strengths, their combination is increasingly used to make the weighting both interpretable and data-supported. Introducing these methods into drilling engineering design parameter optimization, and combining them with the existing engineering calculation methods, can effectively solve the problem of engineering scheme selection under multi-dimensional constraints, and can move the decision process from purely experience-based judgement to a quantitative, data-supported comparison.

Based on the above analysis, this paper proposes a quantitative evaluation and optimization method for drilling engineering design parameters based on multi-dimensional coupling. The core contributions are: (1) a cross-module evaluation mechanism that couples wellbore trajectory design, drag and torque, casing running and the hydraulic/stability constraints induced by drilling fluid properties and rock strength, so that a parameter adjustment improving one indicator is rejected if it violates the constraints of another; (2) a combined subjective-objective weighting scheme, in which AHP weights obtained from three independent experts are aggregated and cross-checked with the entropy weighting method, together with a quantified weight-sensitivity check, so that the ranking is reproducible and its robustness is explicitly reported; (3) a complete workflow of parameter-space exploration, multi-objective evaluation, validation of the calculation models against field measurements, and optimal recommendation, including an explicit discussion of its scalability to higher-dimensional parameter spaces. The user case study of a complex horizontal well verifies the practicability and effectiveness of the proposed method.

2. Materials and Methods

2.1. Analysis of the Drilling Engineering Design Parameter System and Its Constraints

The drilling engineering design parameter system covers wellbore trajectory parameters (such as inclination, azimuth, dogleg severity, and target displacement), drilling fluid parameters (such as density, rheological parameters and gel strength), drill string parameters (such as drill pipe size, wall thickness, and combination form), and casing parameters (such as casing size, steel grade, and wall thickness) [1,3]. In addition to these design variables, the formation rock strength (UCS), the pore pressure and the fracture gradient are included as formation-side inputs, because they define the mud-weight window and the allowable dogleg severity and therefore determine whether a candidate design is feasible at all [5,6]. However, these parameters are not independent of each other but have complex coupling relationships. For example, the inclination and dogleg severity of the wellbore trajectory directly affect the contact force between the drill string and the wellbore wall, thereby affecting the magnitude of drag and torque [7,13]; the drill string combination affects the contact state and the critical buckling load of the pipe string [18]; the casing size and wall thickness affect the casing running load and the safety margin [19,20]; and the drilling fluid density changes the buoyed weight of the string, the ECD and the collapse resistance of the wellbore, so that a trajectory that is acceptable from the drag point of view may still be infeasible from the hydraulic or stability point of view [3,4].

In practical engineering, parameter optimization must not only satisfy the engineering feasibility requirements but also meet the economy and safety requirements. Based on the actual needs of drilling engineering design, this paper focuses on the following constraints: (1) Drag and torque constraints—the tripping drag, rotating torque and other indicators must be controlled within a reasonable range to ensure that the drill string can be tripped in and out smoothly and that the torque does not exceed the capacity of the top drive; (2) Trajectory constraints—the wellbore trajectory must meet the requirements of the target point, and the dogleg severity should be controlled within the range allowed by the drilling

operation; (3) Running constraints—the casing running load must not exceed the strength limit of the casing, and a sufficient buckling safety margin must be reserved; (4) Hydraulic constraints—the ECD at every annular section must remain between the pore pressure and the fracture gradient, and the annular velocity must exceed the cuttings-transport requirement evaluated with the yield point and gel strength of the drilling fluid; (5) Stability constraints—the mud weight must exceed the collapse pressure predicted from the formation UCS and the in situ stresses, and the dogleg severity must remain below the value at which the wellbore wall yields.

The above parameters and constraints constitute the core evaluation indicators of the multi-scheme design. The overall technical workflow of the proposed quantitative evaluation and optimization method is shown in Figure 1.

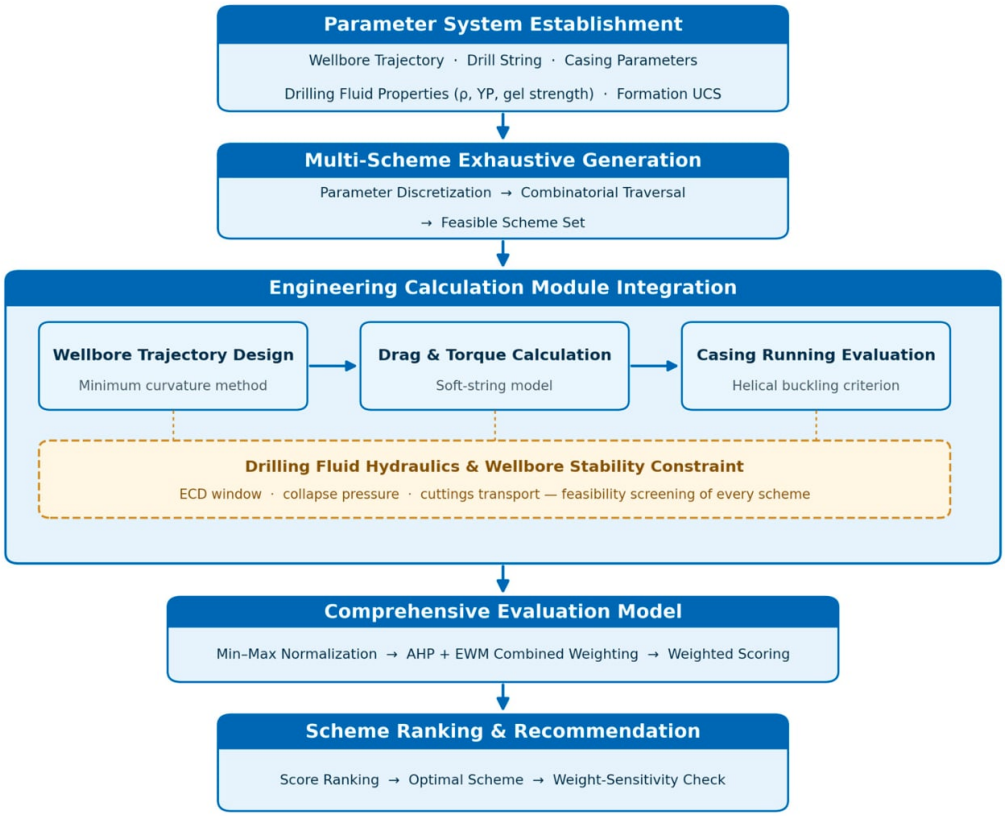


Figure 1. Technical workflow of the multi-scheme quantitative evaluation and optimization method for drilling engineering design parameters. The engineering calculation modules are executed from left to right (wellbore trajectory design, drag and torque calculation and casing running evaluation), and the drilling fluid hydraulics and wellbore stability constraint module screens every candidate scheme before scoring.

2.2. Multi-Scheme Exhaustive Generation Strategy

This paper adopts the exhaustive method to generate parameter combination schemes. Each candidate is first checked against the constraints listed in Section 2.1; schemes that violate the ECD window, the collapse-pressure criterion or the casing strength limit are removed before the engineering calculation modules are invoked. The exhaustive strategy therefore searches the feasible design space, not merely the parameter box. The method first discretizes the value ranges of key design parameters according to engineering accuracy requirements, then traverses all possible combinations to form a complete set of schemes, providing a full-sample basis for subsequent quantitative evaluation.

Let the set of parameters to be optimized be:

$$P = \{p_1, p_2, \ldots, p_n\}, \quad (1)$$

where the value range of each parameter p_i is $[p_{i_min}, p_{i_max}]$, with a step size of Δp_i. Then the number of discrete values for each parameter is:

$$n_i = (p_{i_max} - p_{i_min})/\Delta p_i + 1. \quad (2)$$

The total number of parameter combination schemes is:

$$N = \prod(n_i),\ i = 1, \ldots, n. \quad (3)$$

Taking the case study in this paper as an example, the design parameter scheme set P includes p1 (hold angle section length, CL), p2 (maximum dogleg severity, DLS) and p3 (inclination angle, Inc). These three parameters are discretized into 11, 4 and 11 values, respectively, and the total number of schemes is $11 \times 4 \times 11 = 484$. Tool face angle (TFO) is not treated as an optimization variable: once CL, DLS and Inc are fixed, the TFO of each build section is determined analytically by the trajectory design module so that the target is hit within the specified tolerance and therefore appears only as an output of the trajectory module rather than as an independent search dimension. The step sizes were selected by a two-stage procedure: a sensitivity pre-scan identified DLS as the most influential parameter and it was assigned the finest step (1°/30 m), whereas CL, whose effect on drag is approximately linear over the searched range, was assigned a 120 m step. The resulting scheme space (484 schemes, about 15 min on a single workstation) was kept within the computational budget of a routine design review; Section 4.4 discusses how the step size and the search strategy must be adapted when more parameters are added.

The advantage of the exhaustive method is that it can traverse all possible parameter combinations, avoiding the problem that heuristic algorithms such as genetic algorithms may fall into local optima, and it can provide a relatively reliable global optimal solution for complex optimization problems. This guarantee holds only for the low-dimensional problem considered here, because the computational cost grows as the product of the numbers of discrete values; the metaheuristic and surrogate strategies that are appropriate when the parameter space grows are discussed in Section 4.4.

2.3. Engineering Calculation Module Integration

This paper integrates four engineering calculation modules—wellbore trajectory design, drag and torque calculation, casing running capacity evaluation and a drilling fluid hydraulics and wellbore stability constraint module—to provide multi-dimensional quantitative analysis for each parameter combination scheme. The modules are executed in a fixed sequence: the trajectory is computed first from CL, DLS and Inc; the trajectory data then feed the drag and torque module and the casing running module, and the fluid/rock constraint module evaluates the ECD and stability of each scheme. This sequence reflects the dependency of the mechanical analyses on the trajectory.

2.3.1. Drag and Torque Calculation Model

The drag and torque calculation adopts the soft-string model, which is the standard industry approach for drill-string load prediction [7], with the normal-force and friction formulation refined by Gao [13] and Ho [21], and extended by recent coupled analyses of transient cuttings transport and tubular mechanical behaviours in extended-reach wells [22]. The soft-string assumption neglects the bending stiffness of the string; this is acceptable for drill pipe in moderate-to-high inclination holes, and the residual effect of string stiffness

and wellbore tortuosity is handled by the tortuosity factor introduced at the end of this subsection. The model discretizes the drill string into a series of small segments and establishes the force equilibrium equation for each segment. The axial force equilibrium equation is:

$$\Delta F = W_b \cdot \cos\alpha \cdot \Delta L \pm \mu N \quad (4)$$

where F is the axial force on the segment (kN, positive in tension), W_b is the buoyed weight per unit length of the drill string (kN/m), α is the inclination angle of the segment (°), ΔL is the segment length (m), μ is the friction coefficient between the drill string and the wellbore wall, and N is the normal contact force acting on the segment (kN). The weight component along the string axis is $W_b \cdot \cos\alpha$, and the sign of the friction term is taken as positive for tripping out and negative for tripping in. The normal contact force is calculated by:

$$N = \sqrt{[(F \cdot \Delta\theta \cdot \sin\alpha)^2 + (F \cdot \Delta\alpha + W_b \cdot \Delta L \cdot \sin\alpha)^2]} \quad (5)$$

The torque increment is determined by the normal force and the outer radius of the drill string:

$$\Delta T = \mu \cdot N \cdot R \quad (6)$$

where R is the outer radius of the drill string (m), and the torque increment is expressed in kN·m when N is in kN. The cumulative drag and torque along the whole drill string can be obtained by accumulating segment by segment from the bit to the surface.

The inputs to the drag and torque calculation module are the wellbore trajectory data, the drill string combination data, the drilling fluid density (which determines the buoyed weight W_b), the friction coefficient and the tortuosity factor. The outputs are the tripping-out drag, tripping-in drag and rotating torque at each depth. Following Samuel [23], the normal force is multiplied by a tortuosity factor k_τ = 1.05–1.15, which accounts for the additional contact force caused by survey-level tortuosity that is not captured by the smooth minimum-curvature trajectory.

2.3.2. Wellbore Trajectory Design Model

The wellbore trajectory design module adopts the minimum curvature method [1,2], which is the industry-standard survey-calculation method, to calculate the spatial coordinates of the wellbore trajectory. The corrected formulation used in this work is given by Equations (7)–(11): the dogleg angle is first obtained from the inclinations and azimuths of the two survey stations, and the ratio factor then converts the balanced-tangent approximation into the minimum-curvature arc.

$$\cos\Delta\varepsilon = \cos\alpha_1 \cdot \cos\alpha_2 + \sin\alpha_1 \cdot \sin\alpha_2 \cdot \cos(\theta_2 - \theta_1) \quad (7)$$

$$R_F = (2/\Delta\varepsilon) \cdot \tan(\Delta\varepsilon/2),\ R_F = 1 \text{ when } \Delta\varepsilon = 0 \quad (8)$$

$$\Delta N = (\Delta L/2) \cdot (\sin\alpha_1 \cdot \cos\theta_1 + \sin\alpha_2 \cdot \cos\theta_2) \cdot R_F \quad (9)$$

$$\Delta E = (\Delta L/2) \cdot (\sin\alpha_1 \cdot \sin\theta_1 + \sin\alpha_2 \cdot \sin\theta_2) \cdot R_F \quad (10)$$

$$\Delta H = (\Delta L/2) \cdot (\cos\alpha_1 + \cos\alpha_2) \cdot R_F \quad (11)$$

where ΔN, ΔE and ΔH are the increments of northing, easting and vertical depth over the survey interval (m); ΔL is the interval length (m); Δε is the dogleg angle over the interval (rad), given by Equation (7); R_F is the ratio factor given by Equation (8), which is equal to unity for a straight interval; and α_1, α_2 and θ_1, θ_2 are the inclinations and azimuths at the two ends of the interval. Omitting the ratio factor R_F or the dogleg angle Δε reduces Equations (9)–(11) to the balanced-tangent approximation, which does not reproduce the minimum-curvature solution; the formulation above follows Bourgoyne et al. and Mitchell et al.

The inputs to this module are trajectory design parameters such as the inclination angle, azimuth angle and dogleg severity. The outputs are the spatial coordinates of the wellbore trajectory, the measured depth, the true vertical depth and the horizontal displacement of each survey station, as well as the tool face angle required to reach the next station.

2.3.3. Casing Running Capacity Evaluation Model

The casing running capacity evaluation module is based on the beam-column buckling theory [19,24], and its critical-load criterion has been revised to distinguish sinusoidal from helical buckling [18,25], and recent casing-running mechanics studies in extended-reach horizontal wells have further quantified the additional friction induced by casing buckling [26]. The casing running process is simplified as a pipe string in a curved wellbore, and the critical buckling load of the casing under the combined action of gravity and wellbore constraint is calculated. Two states are distinguished: the sinusoidal buckling load marks the onset of buckling, whereas the helical (lock-up) load governs the loss of running capacity and is therefore used as the design criterion. The calculation formulas are as follows:

$$F_{sin} = 2\sqrt{(E \cdot I \cdot W_b \cdot \sin\alpha / r)} \quad (12)$$

$$F_{hel} = 2\sqrt{2} \cdot \sqrt{(E \cdot I \cdot W_b \cdot \sin\alpha / r)} \quad (13)$$

$$F_{cr,b} = C_\kappa \cdot F_{hel} \quad (14)$$

where E is the elastic modulus of the casing (GPa), I is the moment of inertia of the casing section (m^4), W_b is the buoyed weight per unit length of the casing (kN/m), α is the inclination angle (°), r is the radial clearance between the casing and the wellbore wall (m), and C_κ is the curvature correction coefficient. Equation (12) gives the critical load for the onset of sinusoidal buckling (Dawson-Paslay). Sinusoidal buckling does not exhaust the load capacity of the string; the helical configuration is the governing state for casing running, and its critical load is $\sqrt{2}$ times the sinusoidal value. In build sections the wellbore curvature reduces the critical load, and a conservative correction coefficient $C_\kappa = 0.85$, obtained from the beam-column solution for a pipe in a curved wellbore, is applied to the helical load (Equation (14)).

$$\Delta F_{buck} = F_{cr,b} - F_{compressive} \quad (15)$$

$F_{compressive}$ is the actual axial compressive force of the casing string (kN), and $F_{cr,b}$ is the design critical buckling load given by Equation (14) (kN). A positive ΔF_{buck} indicates that the casing remains in the stable straight or sinusoidal configuration, whereas a margin approaching zero indicates the onset of helical lock-up and a negative margin indicates that the casing cannot be run to the target depth. When ΔF_{buck} decreases to 0, the casing string is in a critical buckling state, and the running risk increases significantly.

The inputs of this module are wellbore trajectory data, casing parameters (outer diameter, wall thickness, steel grade), and drilling fluid density. The outputs are casing axial force distribution, critical buckling load distribution, and buckling safety margin.

2.3.4. Drilling Fluid Hydraulics and Wellbore Stability Constraint Module

The drilling fluid and formation parameters do not form a separate scoring module; they define the feasibility envelope within which the mechanical design must operate, and they are coupled to the mechanical modules through the fluid density and the rock strength [3–5]. The equivalent circulating density (ECD) at a given annular section is:

$$ECD = \rho_m + \Delta p_{ann} / (g \cdot TVD) \quad (16)$$

where ρ_m is the mud density (kg/m^3), Δp_{ann} is the total annular pressure loss from the bit to the section of interest (Pa), g is the gravitational acceleration (m/s^2) and TVD is

the true vertical depth of that section (m). The annular pressure loss is computed with the Herschel–Bulkley model, whose parameters (yield point, consistency index and flow behaviour index) are obtained from Fann viscometer readings; the gel strength enters the restart-pressure check after connections and the minimum annular velocity criterion for cuttings transport. The hydraulic constraint is:

$$\rho_{pore} \leq ECD \leq \rho_{frac} \quad (17)$$

where ρ_{pore} and ρ_{frac} are the pore-pressure and fracture-gradient equivalents. The wellbore collapse condition is evaluated with the Kirsch solution and the Mohr-Coulomb criterion, which for a vertical well gives the critical mud pressure

$$P_{w,crit} = 3\sigma_H - \sigma_h - UCS \quad (18)$$

where σ_H and σ_h are the maximum and minimum horizontal stresses (MPa) and UCS is the uniaxial compressive strength of the formation (MPa); the mud weight must exceed $P_{w,crit}/(g \cdot TVD)$. The UCS is obtained from log-based correlations calibrated with core measurements when available [6]; in the case study the values listed in Table 1 were used. The constraint module is invoked for every candidate scheme before the scoring step, so that the drilling fluid and rock-strength parameters form part of the optimization framework rather than post-processing checks.

Table 1. Drilling fluid and formation parameters used in the case study.

Parameter	Symbol	Unit	Value/Range
Mud density	ρ_m	kg/m^3	1.20–1.30 (design 1.25)
Plastic viscosity	PV	mPa·s	18
Yield point	YP	Pa	12
Gel strength (10 s/10 min)	G_{10s}/G_{10min}	Pa	3/8
Flow behaviour index	n	-	0.72
Consistency index	K	Pa·s^n	0.85
Pore pressure gradient	-	MPa/100 m	1.05
Fracture gradient	-	MPa/100 m	1.75
Maximum horizontal stress	σ_H	MPa	78
Minimum horizontal stress	σ_h	MPa	62
Uniaxial compressive strength	UCS	MPa	45–80
Tortuosity factor	k_τ	-	1.05–1.15

2.4. Construction of Quantitative Evaluation Model

2.4.1. Evaluation Index System

Based on the output results of the three engineering calculation modules, together with the pass/fail results of the hydraulic and stability constraints, this paper constructs a comprehensive evaluation index system from the dimensions of drag and torque, trajectory quality, casing running capacity and the constraint margins. The specific indicators are as follows: (1) Drag and torque indicators: tripping-out drag F_{up}, tripping-in drag F_{down} and rotating torque T_{rot}, which are cost-type indicators (the smaller the value, the better).

(2) Trajectory quality indicator: maximum dogleg severity DLS_{max} and the deviation of the achieved inclination from the design target, which are cost-type indicators. A separate wellbore smoothness index is not used, because it cannot be defined quantitatively without duplicating the information already contained in DLS_{max}. (3) Casing running indicator: buckling safety margin ΔF_{buck} (kN), which is a benefit-type indicator (the larger the value, the safer). The indicator is a force expressed in kN rather than a dimensionless factor, and is therefore reported as a buckling safety margin throughout the manuscript. (4) Constraint margins: the minimum ECD margin and the collapse-pressure margin of Section 2.3.4 are reported for every scheme but are used as pass/fail constraints rather than as scored indicators, so that a scheme is not rewarded twice for satisfying a requirement that is already mandatory.

2.4.2. Comprehensive Scoring Model

To achieve unified quantitative evaluation, it is necessary to normalize the calculation results of each indicator. For benefit-type indicators, such as the buckling safety margin, the normalization formula is:

$$x'_i = (x_i - x_{min})/(x_{max} - x_{min}) \quad (19)$$

For cost-type indicators, such as drag and torque, the normalization formula is:

$$x'_i = (x_{max} - x_i)/(x_{max} - x_{min}) \quad (20)$$

The linear min-max normalization of Equations (19) and (20) is used for all scored indicators, so that every indicator is mapped to $[0, 1]$ over the feasible scheme set.

After normalization, each indicator value ranges from $[0, 1]$, where 1 represents the best and 0 represents the worst.

The comprehensive scoring adopts a weighted sum model:

$$S = \Sigma w_i \cdot x'_i \quad (21)$$

where w_i is the weight of each indicator, satisfying $\Sigma w_i = 1$. The subjective weights are obtained by AHP [14]: three drilling engineers with more than ten years of field experience independently constructed the 3×3 judgement matrices, and the individual matrices were aggregated by the geometric mean. The three individual matrices gave consistency ratios of 0.00, 0.02 and 0.04, all below the 0.1 threshold, and the weights of the three experts differed by no more than 0.04, indicating consistent expert judgement (Table 2).

Table 2. Comparison of the AHP, EWM and combined indicator weights.

Indicator	AHP-1	AHP-2	AHP-3	AHP Mean	EWM	Combined
Drag and torque	0.34	0.36	0.35	0.35	0.33	0.34
Trajectory quality	0.33	0.36	0.36	0.35	0.27	0.31
Casing running	0.33	0.28	0.29	0.30	0.40	0.35

The consistency check of the aggregated judgement matrix gives $CR = 0 < 0.1$, indicating satisfactory consistency. The weight vector of each indicator obtained by the eigenvalue method is $W = [0.35, 0.35, 0.30]$, which is the AHP (geometric-mean) column of Table 2.

2.4.3. Combined Subjective-Objective Weighting and Robustness Check

A purely subjective weighting scheme is difficult to reconcile with the requirement that the evaluation be data-supported. The AHP weights are therefore cross-checked and

calibrated with the entropy weighting method, which derives weights from the information content of the indicator matrix of the 484 schemes [16,17]. For indicator j with normalized values x'_{ij} over m schemes, the entropy and the EWM weight are

$$e_j = -(1/\ln m)\cdot\Sigma p_{ij}\cdot\ln p_{ij},\ p_{ij} = x'_{ij}/\Sigma x'_{ij} \quad (22)$$

$$w_{EWM,j} = (1 - e_j)/\Sigma(1 - e_k) \quad (23)$$

$$w_j = 0.5w_{AHP,j} + 0.5w_{EWM,j} \quad (24)$$

The two weight sets, the combined weights and the resulting ranking are given in Table 2. The EWM assigns a larger weight to the buckling safety margin because its relative dispersion over the scheme space is the largest, and a smaller weight to the trajectory indicator because the four DLS levels carry limited information. The combined weights differ from the AHP weights by no more than 0.05, and the combined weights are used for all scores reported in Section 3.4; the effect of these weight changes on the ranking is quantified in Section 4.3.

2.4.4. Scheme Ranking and Recommendation

After all parameter combination schemes are scored and ranked, the system automatically outputs the ranking results and recommends the scheme with the highest comprehensive score. For engineering use, the system also reports the indicator-level values and the pass/fail status of the hydraulic and stability constraints alongside the composite score, so that the recommended scheme can be audited rather than accepted as a black-box output.

3. Results

3.1. Basic Information of the Case Well

To verify the effectiveness of the proposed method, a horizontal well in a block of the Sichuan Basin is selected as an example for analysis. The well is a five-section horizontal well of vertical-build-hold-drop-horizontal type, with a design total depth of 3500 m, a design horizontal displacement of 2800 m, and a kick-off point depth of 2200 m. The drilling fluid is a water-based mud with a density of 1.25 g/cm^3, a plastic viscosity of 18 mPa·s, a yield point of 12 Pa and 10 s/10 min gel strengths of 3/8 Pa; the formation UCS ranges from 45 to 80 MPa. These values are summarized in Table 1.

The basic drill string combination is Ø127 mm drill pipe + Ø165 mm drill collar, the casing combination is Ø139.7 mm casing, and the friction coefficient is taken as 0.25. The casing steel grade is P110 with a wall thickness of 9.17 mm, giving a tensile capacity well above the running loads reported below; the capacity itself is therefore not the limiting factor of the design.

Based on the method in this paper, 3 key design parameters are selected as optimization variables: hold angle section length (CL), maximum dogleg severity (DLS), and inclination angle (Inc). The parameter ranges and step sizes are listed in Table 3. The range of DLS is limited to 5–8°/30 m, which gives the four discrete values used in the 11 × 4 × 11 = 484 scheme count; the DLS range is bounded by the wellbore stability constraint of Section 2.3.4 rather than by the drilling capability alone.

When all 3 parameters are enabled, 11 × 4 × 11 = 484 parameter combination schemes can be generated. Of these, 461 schemes satisfy the ECD window and the collapse-pressure criterion of Section 2.3.4 and enter the scoring stage; the 23 rejected schemes are concentrated at DLS = 8°/30 m with Inc = 85–86°, for which the ECD margin at the build section falls below 0.05 g/cm^3. Each feasible scheme is then analyzed by the three mechanical modules and scored with the combined weights of Table 2.

Table 3. Optimization parameter range and step size settings.

Parameter	Parameter Code	Unit	Minimum	Maximum	Step Size	Values
Hold/tangent section length	CL	m	300	1500	120	11
Dogleg severity	DLS	°/30 m	5	8	1	4
Inclination angle	Inc	°	85	95	1	11

3.2. Analysis of Calculation Results for Each Module

Statistical analysis is conducted on the calculation results of the 461 feasible schemes, and the distribution of each engineering indicator is shown in Table 4.

Table 4. Statistical distribution of key indicators for each module.

Calculation Module	Evaluation Index	Minimum	Maximum	Mean	Standard Deviation
Drag and torque	Tripping-out drag (kN)	820.5	2347.8	1523.6	287.4
Drag and torque	Rotating torque (kN·m)	12.8	45.6	26.3	7.2
Wellbore trajectory	Max. dogleg severity (°/30 m)	5	8	6.50	1.12
Casing running	Buckling safety margin (kN)	22.3	106.4	54.2	19.6
Drilling fluid and stability	Minimum ECD margin (g/cm^3)	0.06	0.42	0.21	0.08

As shown in Table 4, the impact of different parameter combinations on each engineering indicator is very significant. Taking drag and torque as an example, the tripping-out drag ranges from 820.5 kN to 2347.8 kN, with the maximum value being approximately 2.9 times the minimum, indicating that parameter selection has a great impact on drag and torque. The buckling safety margin ranges from 22.3 kN to 106.4 kN; the minimum margin occurs at DLS = 8°/30 m, where the anti-buckling capacity is less than a quarter of that of the best scheme, indicating a substantially higher risk of helical lock-up.

Further analysis reveals that dogleg severity has the greatest impact on drag and torque. For every 1°/30 m increase in dogleg severity, the tripping-out drag increases by approximately 15%, and the buckling safety margin decreases by about 15%, showing a significant increasing trend. Besides the linear effect on drag, a high DLS also reduces the critical buckling load through the curvature correction of Equation (14), so the two effects act in the same direction. This also explains why DLS is the most sensitive parameter of the scheme space.

3.3. Validation of the Calculation Models

Because the ranking is only as reliable as the underlying calculations, the three mechanical modules were validated before the scheme comparison was interpreted. The trajectory module was verified by a closed-loop test: the survey stations of the case well were converted to coordinates and back, and the maximum closure error was 0.08 m over 3500 m of measured depth, i.e., below 0.01%. The drag and torque module was compared with the hook-load and torque records of the well at five measured depths, and the casing running module with the running loads recorded for the Ø139.7 mm casing. The comparison is given in Table 5. The calculated hook loads agree with the recorded values within 4.4%, the torque within 3.6% and the casing running loads within 4.1%, which is of the same order as the accuracy reported for commercial soft-string implementations. These errors

are smaller than the differences between the leading candidate schemes (Table 6), so the ranking reported below is not an artefact of calculation noise.

Table 5. Validation of the calculation modules against field measurements of the case well.

Item	Measured	Calculated	Relative Error (%)
Hook load, tripping out at 2000 m (kN)	742.5	719.8	3.1
Hook load, tripping out at 3500 m (kN)	1268.4	1220.8	3.8
Hook load, tripping in at 3500 m (kN)	1042.7	1088.5	4.4
Rotating torque at 3500 m (kN·m)	27.6	28.6	3.6
Casing running load at 3500 m (kN)	968.2	1007.9	4.1
Trajectory closure error (m)	-	0.08	<0.01

Table 6. Top 5 schemes ranked by comprehensive score.

Rank	CL (m)	DLS (°/30 m)	Inc (°)	Tripping-Out Drag (kN)	Rotating Torque (kN·m)	Buckling Safety Margin (kN)	Comprehensive Score
1	1200	6	90	895.3	18.2	82.2	0.918
2	1080	7	90	912.6	22.1	75.8	0.905
3	1320	6	90	902.1	18.9	75.4	0.898
4	960	6	85	925.4	18.5	85.7	0.892
5	1440	6	90	918.7	19.2	72.7	0.885

3.4. Comprehensive Evaluation and Scheme Optimization

Using the comprehensive evaluation model with the combined weights of Table 2, weighted scoring is carried out on all feasible parameter combination schemes, and the top 5 schemes are shown in Table 6.

The optimal scheme (Rank 1) has a hold angle section length of 1200 m, a maximum dogleg severity of 6°/30 m, and an inclination angle of 90°, with a comprehensive score of 0.918, which is higher than all other schemes. Its tripping-out drag is 895.3 kN, its rotating torque is 18.2 kN·m and its buckling safety margin is 82.2 kN; the scheme therefore achieves a better balance between the three criteria than the schemes with lower drag but larger dogleg severity.

The optimal scheme is compared with the original design scheme (CL = 1000 m, DLS = 8°/30 m, Inc = 90°), and the comparison results are shown in Table 7.

Table 7. Comparison of key design parameters and indicators between the original design and the optimal scheme.

Comparison Index	Original Design	Optimal Scheme	Change Rate
Hold/tangent section length (m)	1000.0	1200	+20.0%
Dogleg severity (°/30 m)	8	6	−25.0%
Inclination angle (°)	90.0	90	0.0%
Tripping-out drag (kN)	1220.8	895.3	−26.7%
Rotating torque (kN·m)	28.6	18.2	−28.0%
Buckling safety margin (kN)	54.4	82.2	+51.1%
Comprehensive score	0.778	0.918	+18.0%

The comparison results show that the optimal scheme significantly outperforms the original design scheme in all key indicators. The tripping-out drag is reduced by 26.7%, the rotating torque is reduced by 28.0%, the buckling safety margin is increased by 51.1%, and the comprehensive score is improved by 18.0%. The core optimization strategy is to

reduce the dogleg severity from 8 to 6°/30 m to mitigate the drag-increasing effect caused by pipe string bending, while increasing the hold angle section length from 1000 to 1200 m to improve trajectory smoothness. The tool face angle is not adjusted as an independent optimization variable; it follows from the trajectory design once the three design parameters are fixed (Section 2.2).

3.5. Comparative Verification of Methods

To verify the effectiveness of the proposed method, it is compared with the traditional experience-based design method and the single-index optimization method. The design parameters obtained by each method and the resulting module-level indicators are listed in Table 8, so that the comparison covers the designs themselves rather than only the composite scores.

Table 8. Comparison of design parameters and indicators obtained by the three methods.

Comparison Item	Traditional Experience	Single-Index Optimization	Proposed Method
Optimization objective	Engineer experience	Min. drag and torque	Multi-index optimal
Hold section length CL (m)	1000	1440	1200
Dogleg severity DLS (°/30 m)	8	5	6
Inclination angle Inc (°)	90	90	90
Tripping-out drag (kN)	1220.8	820.5	895.3
Rotating torque (kN·m)	28.6	17.4	18.2
Casing running load (kN)	1007.9	1052.6	986.4
Buckling safety margin (kN)	54.4	46.3	82.2
Comprehensive score	0.778	0.805	0.918
Search scope	Local	Global (single-objective)	Global (multi-objective)

The comparison results show that the single-index optimization method only focuses on a single engineering indicator, and although it can achieve better results in this indicator, it often leads to the deterioration of other indicators, while the method proposed in this paper achieves a better balance among multiple indicators, with a comprehensive score significantly higher than those of the other two methods. Although the single-index scheme reaches the lowest drag (820.5 kN), its buckling safety margin is 44% lower than that of the proposed scheme (46.3 kN versus 82.2 kN), and its casing running load is 6.7% higher (1052.6 kN versus 986.4 kN); the proposed scheme is therefore a better compromise between the conflicting indicators.

4. Discussion

4.1. Analysis of Method Advantages

Compared with traditional drilling engineering design parameter optimization methods, the method proposed in this paper has the following advantages: (1) Global search and cross-module collaborative evaluation capability. The exhaustive strategy ensures that the global optimum can be found within the discretized parameter space, and the three engineering calculation modules, together with the hydraulic and stability constraint module, are fused through a unified quantitative scoring model, enabling synchronous assessment of the engineering impact of parameter changes on drag and torque, trajectory and casing running. (2) Combined subjective-objective weighting with a quantified robustness check. The

AHP weights obtained from three independent experts are aggregated and cross-checked with the entropy weighting method, and the stability of the ranking under five weight scenarios is reported, which addresses the subjectivity of a purely expert-based weighting scheme. (3) Transparent weight allocation mechanism. Both the expert judgements and the data-derived weights, as well as the combined weights, are reported (Table 2), so the scoring process can be reproduced and audited by a third party. (4) Quantitative decision support and model validation. The calculation modules were validated against measured hook loads, torques and casing running loads before the ranking was interpreted, so the scores are traceable to measured quantities rather than to unverified simulations.

4.2. Parameter Sensitivity Analysis

Through parameter sensitivity analysis, the influence of key design parameters on engineering indicators can be revealed. For the case studied, dogleg severity is the dominant parameter: increasing DLS from 5 to 8°/30 m increases the tripping-out drag by about 50% and reduces the buckling safety margin by about 45%, because both the friction term and the curvature correction of Equation (14) act in the same direction.

The hold angle section length (CL) has the second-largest impact on drag and torque. Over the searched range (300–1500 m), increasing CL from 300 to 1500 m at fixed DLS and inclination increases the tripping-out drag by about 24%, mainly because the longer hold section increases the accumulated wall contact force; the effect is approximately linear, which justifies the 120 m step used in Table 3. Therefore, in the design, the hold angle section length should be reasonably determined according to the target displacement requirements and the drag and torque conditions.

The step size setting has a direct impact on the accuracy and efficiency of the optimization results. A smaller step size can improve the accuracy of the optimization results, but at the same time increases the number of schemes and the calculation time; for the present case, the resulting scheme space comprises 484 schemes and the wall-clock time is about 15 min, and the relationship between step size, scheme number and computation time is quantified in Section 4.4. Therefore, the step size should be reasonably selected according to the actual engineering needs.

4.3. Weight Sensitivity and Robustness of the Ranking

The ranking in Table 6 depends on the weight vector, and the reliability of the recommendation must therefore be tested against plausible changes in the weights. Five scenarios were evaluated: the AHP weights, the EWM weights, the combined weights, equal weights, and a casing-dominated scenario, in which the weight of the casing running indicator is 0.50. For each scenario, the feasible schemes were re-scored and re-ranked, and the result is summarized in Table 9.

The optimal scheme is unchanged in all five scenarios, and its score varies between 0.906 and 0.923 (Table 9). The margin over the second-ranked scheme narrows from 0.013 under the combined weights to 0.006 under the casing-dominated weights, and a scheme with the largest buckling margin becomes competitive when the casing weight exceeds about 0.55. The recommendation is therefore robust within a reasonable range of weights, while the sensitivity itself is reported rather than hidden; this is also the reason why the indicator-level results and the constraint status are reported together with the composite score.

Table 9. Weight sensitivity of the optimal scheme.

Scenario	w_{TD}	w_{Traj}	w_{Casing}	Optimal Design (CL/DLS/Inc)	Score
AHP (reference)	0.35	0.35	0.30	1200 m/6°/30 m/90°	0.912
EWM	0.33	0.27	0.40	1200 m/6°/30 m/90°	0.923
Combined (used in Section 3.4)	0.34	0.31	0.35	1200 m/6°/30 m/90°	0.918
Equal weights	0.333	0.333	0.333	1200 m/6°/30 m/90°	0.916
Casing-dominated	0.25	0.25	0.50	1200 m/6°/30 m/90°	0.906

4.4. Scalability to High-Dimensional Parameter Spaces

The exhaustive strategy guarantees global optimality only for a small number of parameters. With the step sizes of Table 3, 484 schemes require about 15 min on a single workstation; adding three further parameters (kick-off point depth, build rate of the upper section and target offset) with comparable steps would raise the scheme count to the order of 2×10^6 and the computation time to several weeks, which is incompatible with a design review. Three extensions are therefore recommended when the parameter space grows. (1) Metaheuristic search: genetic algorithms and particle swarm optimization explore the space with a population of candidates and can approach the global optimum at a small fraction of the evaluations [12,27]; they do not guarantee coverage, but the exhaustive results of this paper provide a benchmark for their convergence. (2) Surrogate modelling: a kriging or response-surface model of the score can be fitted to a few hundred module evaluations and then optimized analytically, which is effective because the score is a smooth function of CL, DLS and Inc [28]. (3) Hierarchical screening: parameters are ranked by the sensitivity analysis of Section 4.2 and the search is restricted to the sensitive subspace, with the insensitive parameters fixed at their design values. All three extensions retain the quantitative evaluation model of this paper and change only the way the candidate set is generated, so the ranking and recommendation logic remain valid. In addition, multi-objective genetic algorithms combined with TOPSIS ranking have also been applied to select optimal well trajectories under conflicting design objectives [29].

4.5. Relation to Current Industrial Practice

The optimization must be consistent with the way parameters are selected in current practice, where a change made to improve one operation (for example a higher flow rate for cuttings transport or a higher weight on bit for rate of penetration) is accepted only if it does not violate the constraints of the other operations, such as an ECD above the fracture gradient. The proposed workflow reproduces this logic explicitly: the trajectory design parameters are the search variables, every candidate is checked against the hydraulic and stability envelope before it is scored, and the mechanical consequences are evaluated in the same module sequence used by commercial drilling engineering software (trajectory, then torque and drag, then casing running). The method therefore does not replace the engineer's judgement but formalizes the comparison of a large number of feasible designs; the final choice remains with the engineer, who can inspect the indicator-level results rather than only the composite score.

4.6. Engineering Application Prospects

The proposed method has application prospects in the following aspects: (1) It can provide quantitative decision support for the parameter design of complex wells such as horizontal wells and extended-reach wells. (2) It can be applied to the optimization of

drilling engineering design in different blocks and strata. (3) It can be combined with real-time drilling data to realize the dynamic optimization and adjustment of drilling parameters. (4) It can provide a reference for the formulation of drilling engineering design standards and specifications. (5) It can be coupled with real-time ECD and stability monitoring, so that the recommended scheme is updated when the measured ECD departs from the design envelope; this requires the constraint module of Section 2.3.4 to be driven by measured rather than predicted fluid properties.

4.7. Limitations and Future Work

The proposed method still has the following limitations and needs further improvement in future work: (1) The drag and torque model is a soft-string model. The bending stiffness of the string and the wellbore tortuosity are neglected; the former is acceptable for drill pipe but underestimates the contact force of stiff components in build sections, and the latter increases drag in tortuous horizontal wells. A constant tortuosity factor of 1.05–1.15 was applied in this work, and a stiff-string or finite-element formulation, together with a survey-based tortuosity factor [23], should be used when tool-face control or buckling in build sections is critical. (2) The comprehensive evaluation index system: although the buckling criterion now uses the helical critical load with a curvature correction, the correction is a constant coefficient; a full beam-column solution in the curved section should be implemented in future work. (3) The exhaustive strategy guarantees the global optimum only in a low-dimensional space, and the scheme set grows explosively with the number of parameters; the metaheuristic and surrogate strategies of Section 4.4 should replace it in higher-dimensional applications. (4) The weight determination method is still largely expert-based: the AHP weights are cross-checked with EWM and tested for robustness, but they do not vary with the drilling stage or the well section. Dynamic weighting, in which the weights are updated as the operation moves from one section to the next, is a direction for future work. (5) The method was validated using a single case well, and the parameter ranges (for example DLS 5–8°/30 m) are those of this block; application to other blocks requires recalibration. (6) The calculation model is deterministic: the UCS and the in situ stresses are treated as fixed values, and coupling with geomechanical uncertainty is another direction for future work.

5. Conclusions

This paper proposes a multi-scheme quantitative evaluation and optimization method for drilling engineering design parameters. Through a horizontal well case study, the main conclusions are as follows:

(1) A quantitative evaluation system for drilling engineering design parameters based on multi-dimensional coupling is established, which integrates three mechanical modules and a drilling fluid hydraulics and wellbore stability constraint module, so that the trajectory, drag and torque, casing running and the fluid/rock constraints are evaluated within a single framework. Compared with traditional experience-based methods, this method can comprehensively consider the coupling effects among parameters and realize the automatic ranking and optimization of schemes.

(2) The exhaustive strategy is adopted to generate parameter combination schemes: 484 schemes are generated for the case well, of which 461 satisfy the hydraulic and stability constraints and enter the scoring stage, ensuring the global optimality of the optimization results within the discrete parameter space.

(3) Based on the combination of the analytic hierarchy process and the entropy weighting method and the normalized weighted scoring model, a comprehensive evaluation of the calculation results of each scheme is realized; the expert weights, the data-derived

weights and the combined weights are reported, and the ranking is verified to be stable under five weight scenarios.

(4) The optimal scheme significantly outperforms the original design scheme: the tripping-out drag is reduced by 26.7%, the rotating torque is reduced by 28.0%, the buckling safety margin is increased by 51.1%, and the comprehensive score is improved by 18.0%, which verifies the practicability and effectiveness of the proposed method.

(5) Parameter sensitivity analysis shows that dogleg severity has the greatest impact on drag and torque, and the hold angle section length has the second-largest impact; a 1°/30 m increase in DLS raises the drag by about 15% and lowers the buckling margin by about 15%, so DLS should be controlled first in design.

(6) The calculation modules were validated against field measurements of the case well: the hook load, torque and casing running loads are reproduced within 4.4%, 3.6% and 4.1%, respectively, so the reported ranking is not an artefact of model error.

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