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INFORMATION

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DOI: 10.23967/j.rimni.2025.10.70936

SCIPEDIA
Revista Internacional de Métodos Numéricos para Cálculo y Diseño en Ingeniería
RIMNI

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ABSTRACT

The conventional approach to drill bit selection primarily relies on the performance records of bits used in adjacent wells, where the best-performing bit in each formation is selected for the corresponding zone to be drilled. However, this method does not take into account the lithology and rock mechanical properties of all relevant wells, nor can it evaluate the adaptability of a particular bit type to different intervals. As a result, it fails to fully ensure an optimal match between the bit and the formation, thus exhibiting significant limitations. To address these issues, this paper proposes a bit optimization method based on grey clustering and grey correlation analysis. This method comprehensively considers the influence of rock mechanics parameters on formation drillability and quantitatively evaluates the similarity in drilling resistance between the target formation and previously drilled intervals using grey clustering. This approach breaks away from the traditional constraint of limited bit options for a specific formation grade. Instead, it screens all previously used bit types to construct a candidate bit library for the target zone. Subsequently, the grey correlation method is applied to assess the candidate bits using multiple indicators that reflect bit performance. This enables the optimization of bit types for various target zones. Field applications demonstrate that the new bit selection method effectively improves upon the conventional practices by enhancing the flexibility and scientific basis of bit selection, and has yielded favorable results in actual drilling operations.

OPEN ACCESS

Received: 28/07/2025

Accepted: 16/10/2025

Published: 23/01/2026

DOI
10.23967/j.rimni.2025.10.70936

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1 Introduction

During the drilling process, the quality and longevity of the borehole are influenced not only by the properties of the formation being drilled but also by the compatibility between the drill bit and the formation. The selection of an appropriate drill bit for the target formation to achieve safe, efficient, and high-quality drilling has been a long-standing focus of extensive research [1].

Currently, three primary methods are employed for drill bit selection: bit performance evaluation, rock mechanics parameter-based methods, and comprehensive approaches [2,3]. Statistical analysis methods utilize historical bit performance data to establish empirical correlations between formation

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types and suitable bit types within a specific block. By evaluating key performance indicators, optimal drill bits are identified. For example, Rabia et al. [4] introduced a cost-per-meter method, while Bilgesu et al. [5] proposed a bit benefit index method. Yang et al. [6] incorporated critical mechanical parameters—such as bit size, total flow area, footage, and rate of penetration (ROP)—and applied a three-layer feedback neural network for bit optimization. However, this approach is limited to specific formations within particular blocks and lacks broad applicability [7].

The rock mechanics parameter method selects bits for new drilling campaigns based on the rock mechanics parameters of the target formation and the technical specifications of the bits. For instance, Spaar et al. [8] facilitated PDC bit selection by investigating the relationship between formation abrasiveness and the internal friction angle of rocks. This method enables effective matching of the bit to the formation lithology; however, it requires accurate measurement of rock mechanics parameters in the target zone. Furthermore, since drill bit performance is affected by multiple mechanical factors in the formation, selecting an optimal bit based solely on one or a few parameters remains challenging [9].

Comprehensive methods integrate historical bit performance data with rock mechanics properties. Momeni et al. [10] developed a hybrid approach combining artificial neural networks and genetic algorithms for bit selection, achieving a mean square error of 0.0037 and a coefficient of determination of 0.9473, indicating highly accurate predictions. Chen et al. [11] established a full-well dynamic model that accounts for drill string vibrations and bit-rock interaction mechanisms to analyze the dynamic behavior of the drill string in large-diameter wells. By optimizing bit rotation speed and managing lateral, axial, and torsional vibrations of downhole tools, the method enhanced bit selection. Yan et al. [12] incorporated formation drillability, bit usage records, and application outcomes, employing grey relational analysis to assess similarity with previously drilled formations. By defining an absolute ideal solution and incorporating entropy weighting, the method quantified the similarity between candidate bits and the ideal bit, thereby identifying the most suitable options. This technique addressed inherent flaws in conventional decision-analysis methods, such as non-absolute ranking, rank reversal, and subjective weight assignment. It also balanced rock mechanics considerations with economic efficiency, leading more rational bit selection results. Nevertheless, due to its multi-factorial nature, this approach is only feasible in blocks with comprehensive drilling data [13,14].

In summary, current drill bit selection methods primarily emphasize bit performance and rock mechanics properties. Their limitations include: (1) Variability in rock mechanical properties across regions—even within the same formation—which can lead to suboptimal bit selection when differences are pronounced [15,16]; (2) Dependence on sufficient offset well data, which restricts applicability in new exploration areas with limited historical data [17]; (3) The complexity of multiple mechanical factors influencing bit performance, making it difficult to identify a suitable bit based on limited parameters [9]; and (4) The inability to definitively identify the best bit when multiple candidates appear compatible with a given formation.

To address these challenges, a new methodology is proposed: First, the grey clustering method is applied to quantitatively assess the similarity between the target formation and previously drilled formations, enabling systematic formation classification. Next, historically used bits are screened to create a candidate library. Finally, multiple evaluation metrics are applied through grey relational analysis to evaluate candidate bits, facilitating the selection of the most appropriate bit for each specific formation. This integrated approach, which combines grey clustering and grey relational analysis, transcends the limitations of conventional bit selection methods, offers greater flexibility, and introduces a novel perspective for optimal drill bit selection.

2 Principle and Method

2.1 Comprehensive Evaluation Model of Strata

Grey clustering is a method that aggregates some observation indicators into several definable categories based on the grey correlation matrix or grey number whitening function. It mainly applies the improved grey clustering method based on the grey number whitening function to comprehensively evaluate the drilling resistance of the formation. The specific methods are as follows:

Step 1: Set up n cluster objects, with each cluster object having m cluster indicator and s cluster gray class, d_{ij} is the whitening number of the $i\,(i = 1, 2, \cdots\cdots n)$ corresponding cluster indicator for the $j\,(j = 1, 2, \cdots\cdots m)$ cluster object. d_{ij} construct a sample matrix based on the given values.

Step 2: Determine the whitening function threshold of λ_{jk} the gray class and establish a matrix [9], λ_{jk} is the whitening function threshold for the j cluster gray class corresponding to the $k\,(k = 1, 2, \cdots\cdots, s)$ cluster indicator, usually determined based on the clustering whitening value and experience.

Step 3: Determine the whitening function f_{jk} of the gray class, where f_{jk} is the whitening function corresponding to the k clustering gray class for the j clustering index. Define threshold parameters for the j-th clustering indicator: λ_{j1} (upper threshold of "good" grade), λ_{j2} (upper threshold of "medium" grade), λ_{j3} (upper threshold of "poor" grade), where $\lambda_{j1} < \lambda_{j2} < \lambda_{j3}$ and all thresholds share the same dimension as the clustering indicator x. Typically, the clustering gray class is divided into three categories: good, medium, and poor. The corresponding whitening function is as follows:

For $k = 1$,

$$f_{j1} = \begin{cases} \dfrac{1.005}{1 + e^{-\left[5.2933/\left(\lambda_{j1}/2\right)\right]\left(x - \lambda_{j1}/2\right)}}, & 0 \le x \le \lambda_{j1} \\ 1, & x > \lambda_{j1} \end{cases} \tag{1}$$

For $k = 2$,

$$f_{j2} = \begin{cases} \dfrac{1.005}{1 + e^{-\left[5.2933/\left(\lambda_{j1}/2\right)\right]\left(x - \lambda_{j1}/2\right)}}, & 0 \le x \le \lambda_{j2} \\ 1 - \frac{1.005}{1 + e^{-\left\{5.2933/\left[\left(\lambda_{j1} - \lambda_{j2}\right)/2\right]\right\}\left[x - \left(\lambda_{j1} - \lambda_{j2}\right)/2 - \lambda_{j2}\right]}}, & \lambda_{j2} \le x \le \lambda_{j1} \\ 0, & x \ge \lambda_{j1} \end{cases} \tag{2}$$

For $k = 3$,

$$f_{j3} = \begin{cases} 1, & 0 \le x \le \lambda_{j3} \\ 1 - \dfrac{1.005}{1 + e^{-\left\{5.2933/\left[\left(\lambda_{j2} - \lambda_{j3}\right)/2\right]\right\}\left[x - \left(\lambda_{j2} - \lambda_{j3}\right)/2 - \lambda_{j3}\right]}}, & \lambda_{j3} \le x \le \lambda_{j2} \\ 0, & x \ge \lambda_{j1} \end{cases} \tag{3}$$

Step 4: Calculate the clustering weight η_{jk}, which is the clustering weight of the j clustering index corresponding to the k gray class of the cluster. The calculation formula is as follows:

$$\eta_{jk} = \frac{\lambda_{jk}}{\sum_{K=1}^{n} \lambda_{jk}} (k = 1, 2, ...p) \tag{4}$$

Step 5: Calculate the clustering coefficient γ_{ik} and construct a clustering vector. γ_{ik} is the clustering coefficient of the i clustering object corresponding to the gray class of the k cluster, and the calculation formula is as follows:

$$\gamma_{ik} = \sum_{j=1}^{m} f_{jk}\left(d_{ij}\right)\eta_{jk} \tag{5}$$

γ_{ik} represents the degree of conformity between the i clustering object and the k clustering grey class, and constructs a clustering vector based on the k clustering grey class for each clustering object γ_i.

Step 6: Cluster. If there is $\gamma_{ik}^* = \max_k \{\gamma_{ik}\}$ in the γ_i, the i clustering object is clustered into k-class, and the order of the maximum clustering coefficient is the order of superiority and inferiority.

2.2 Comprehensive Performance Evaluation Model for Drill Bits

Step 1: Add a to the selected drill bit Set parameters as N comparison sequence:

$$X_T = \{X_T(K)\,|K = 1, 2, \cdots, N\}, T = 1, 2, \cdots, M \tag{6}$$

Step 2: Construct an optimal drill bit with a parameter as N reference sequence [17]:

$$X_0 = \{X_0(K)\,|K = 1, 2, \cdots, N\} \tag{7}$$

Step 3: Calculate the correlation coefficient $\xi_T(K)$:

$$\xi_T(K) = \frac{\min_T \min_K |X_0(K) - X_T(K)| + \zeta \max_T \max_K |X_0(K) - X_T(K)|}{|X_0(K) - X_T(K)| + \zeta \max_T \max_K |X_0(K) - X_T(K)|} \tag{8}$$

In the formula, $\xi_T(K)$ is the correlation coefficient between the T-th comparison sequence X_T and the reference sequence X_0 at the K-th indicator; ρ is the resolution coefficient (usually 0.5, with smaller ρ leading to higher resolution). The terms $\min_T \min_k|X_0(K) - X_T(K)|$ and $\max_T \max_k|X_0(K) - X_T(K)|$ are defined as "two-level differences":

The first level ("inner $\min_K$"): Calculate the absolute differences $|X_0(K) - X_T(K)|$ between the reference sequence X_0 and a single comparison sequence X_T across all K indicators, then take the minimum value of these differences for X_T.

The second level ("outer $\min_T$"): Take the minimum value among the "inner minimum differences" of all comparison sequences X_T.

Correspondingly, $\max_T \max_k|X_0(K) - X_T(K)|$ represents the two-level maximum difference, following the same two-level calculation logic (first take the maximum difference for each X_T, then take the maximum among these values).

Step 4: Calculate correlation degree r_r:

$$r_r = \frac{1}{N}\sum_{K=1}^{N} \xi_T(K) \tag{9}$$

The calculated correlation degree r_r is the evaluation result of the comprehensive performance of each drill bit. The larger the r_r, the greater the correlation degree between the drill bit and the optimal drill bit, and the more ideal the comprehensive performance of the drill bit [18,19].

3 Application Examples

Taking the CPZ area of Xinjiang Oilfield as an example, the practical application of drill bit optimization method.

3.1 Block Geological Characteristics and Drilling Overview

The CPZ area mainly encounters Neogene, Paleogene, Cretaceous, and Carboniferous strata from top to bottom, with a wide variety of lithologies, frequent interlacing of sandstone and mud stone, and some strata with poor drill ability, high grind ability, and strong heterogeneity. A method for selecting drill bits based on grey clustering and grey correlation is proposed, which mainly includes the following two aspects of research content: firstly, comprehensively considering the relationship between multiple rock mechanical parameters of the formation and the drilling resistance of the formation, grading and evaluating the drilling resistance of the formation through grey clustering method, and extracting used drill bits with the same drilling resistance as the formation to be drilled. As an alternative drill bit [20,21]. The second method is to use grey correlation analysis to evaluate the quality of drill bits based on multiple indicators such as footage, drilling time, and specific energy, which can reflect the effectiveness of drill bit use. Multiple types of drill bits suitable for the formation to be drilled are selected and sorted [22]. Fig. 1 shows the mechanical drilling rates and footage of various types of drill bits commonly used for the three main formations in the CPZ area from 2019 to 2020, where the three formations correspond to the depth ranges specified in Section 3.2: Tertiary system (0–2700 m), Cretaceous system (2700–3800 m), and Carboniferous system (3800–4300 m). It can be found that the shallow part (Tertiary system, 0–2700 m) has good drillability, and the drill bit footage and mechanical drilling speed are at a high level. When drilling into the middle-deep formation (Cretaceous system, 2700–3800 m) and deep formation (Carboniferous system, 3800–4300 m), the mechanical drilling speed suddenly decreases, and single drill bit footage is short, making it difficult to increase drilling speed. The problem of selecting drill bits for different lithology in each layer needs to be solved urgently.

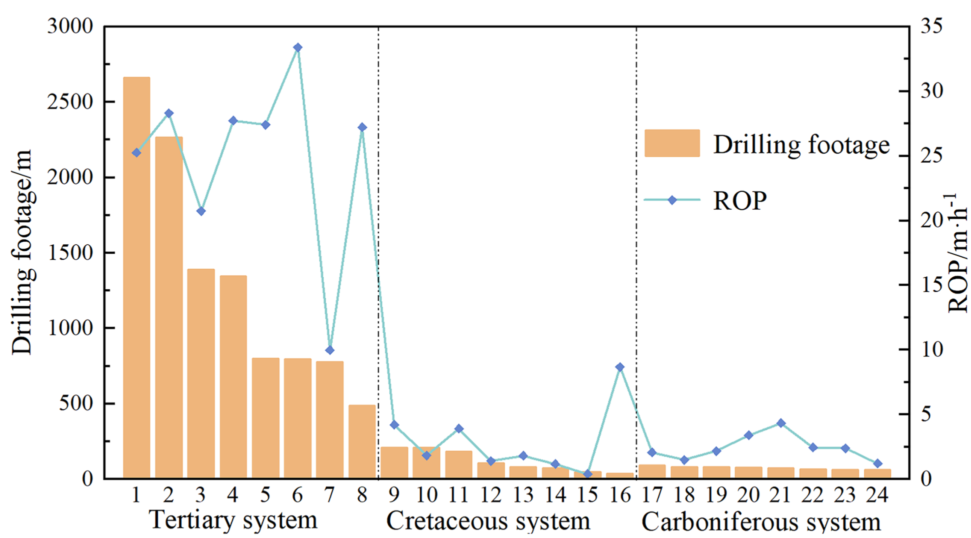

Figure 1: Average drill bit indicators for various layers in the CPZ area

3.2 Rock Mechanical Characteristics Profile

Using logging data from the CPZ area, establish a typical rock mechanics characteristic profile of the area through geological mechanics calculation (as shown in Fig. 2).

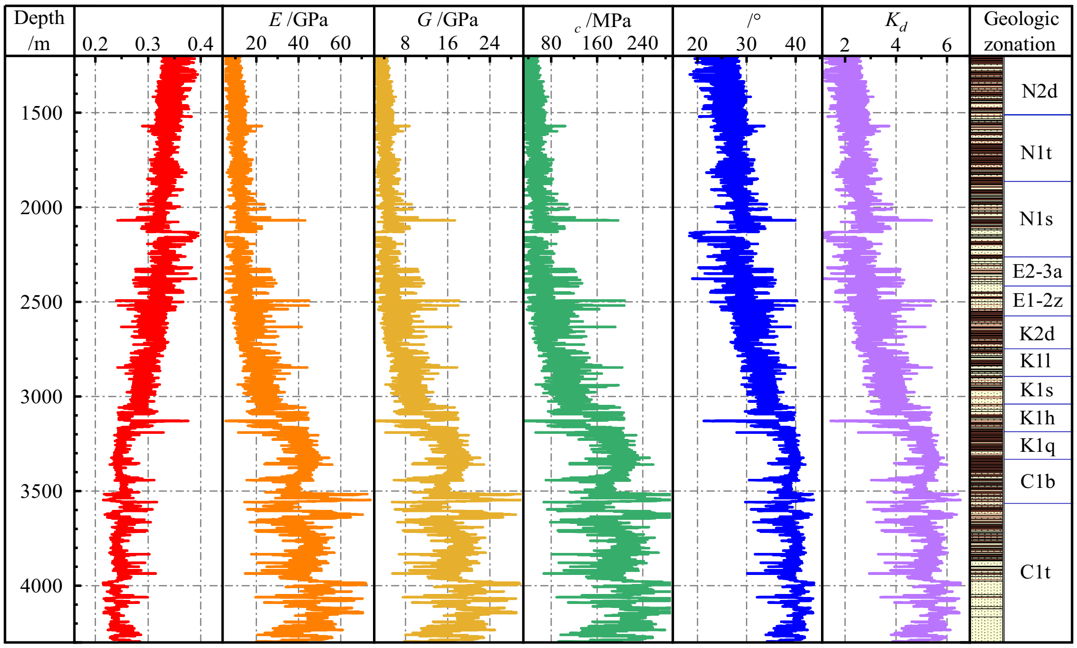

Figure 2: Rock mechanical characteristics profile in the CPZ area

According to Fig. 2, the strata in this block can be divided into three layers, and a preliminary analysis of drill bit types is conducted based on the different rock mechanical parameters and geological characteristics of each layer [23–27]:

The 0–2700 m interval is a tertiary formation, with an average compressive strength of 62.67 MPa and a drill ability level of 2.68. It belongs to a soft formation with low compressive strength and an average internal friction angle of 28.72°, belonging to a low abrasive formation. The rock strength in this section is low, and the rock mechanics characteristic curve changes relatively smoothly. The formation has strong homogeneity. Large-diameter and low tooth density should be selected to obtain higher mechanical drilling speed and footage, and complete the "one trip drilling" [28].

The 2700–3800 m interval is a Cretaceous formation with an average compressive strength of 123.06 MPa and a maximum value of 231.85 MPa. The average drill ability level is 4.03 and the maximum value is 5.78, belonging to a soft to medium formation with high compressive strength. The average internal friction angle is 34.78°and the maximum value is 41.89°,belonging to a medium abrasive formation. The strength, hardness, and abrasivity of this layer are significantly enhanced compared to the previous layer, and there is a serious inter layer between sandstone and mud stone in the formation. The rock mechanics characteristic curve changes greatly and frequently, so PDC drill bits with strong inter layer penetrating ability should be selected. Fan et al. (2007) [29] confirmed in their study on bit optimization for interbedded formations that PDC bits with reinforced cutter head structures can reduce cutter wear by 30% during sandstone-mudstone interlayer drilling, ensuring continuous penetration efficiency and avoiding frequent tripping.

The 3800–4300 m interval is a Carboniferous formation with an average compressive strength of 185.51 MPa and a maximum value of 279.34 MPa. The average drill ability level value is 5.02 and the maximum value is 6.14, belonging to a soft to medium hard formation with high compressive strength. The average internal friction angle is 38.54° and the maximum value is 42.47°,belonging to a high abrasive formation [30].The lithology of this section is mainly composed of conglomeratic sandstone, with high rock strength and strong formation abrasiveness, which requires high wear and impact resistance of PDC drill bits.

3.3 Comprehensive Evaluation of Strata

Select parameters such as Poisson's ratio, Young's modulus, shear modulus, compressive strength, internal friction angle, and drillability level values that can reflect rock hardness, strength, and abrasiveness as clustering indicators. Based on the rock mechanical properties profile, three layers are divided as clustering criteria (as shown in Table 1), and the strata in the CPZ area are classified and graded.

Table 1: Clustering criteria

Interval	Poisson's ratio		Young's modulus/GPa		Shear modulus/GPa	
	Mean value	Interval	Mean value	Interval	Mean value	Interval
F1	0.34	0.25–0.40	10.3	3.8–26.3	3.9	1.4–10.3
F2	0.30	0.23–0.38	18.8	8.0–46.1	7.3	2.3–18.6
F3	0.25	0.21–0.30	44.0	27.4–71.4	17.7	10.3–30.2
Interval	**Compressive strength/MPa**		**Internal friction angle/°**		**Drillability level value**	
	Mean value	Interval	Mean value	Interval	Mean value	Interval
F1	47.5	17.6–88.2	26.4	18.4–35.0	2.26	1.15–4.08
F2	88.2	31.0–208.5	31.4	23.1–40.3	3.27	1.92–5.73
F3	202.9	122.8–335.3	39.6	34.1–43.7	5.30	4.13–6.54

The bounds of each clustering criterion interval in Table 1 are determined by combining statistical analysis of local rock mechanical data and empirical calibration with regional drilling practices, following two steps:

Statistical calculation from logging data: 52 valid logging datasets (density, acoustic, resistivity, etc.) from 8 drilled wells in the CPZ area were processed via geomechanical models [23,25] to calculate rock mechanical parameters. Their statistical distributions were analyzed. For example, the Poisson's ratio of F1 interval (0–2700 m, Tertiary) follows a normal distribution, and its "0.25–0.40" interval covers 95% of statistical data, representing most actual rock properties of F1.

Empirical calibration with drilling performance: Statistical intervals were verified using CPZ's historical drilling data [21]. For instance, the initial Young's modulus interval of F2 (2700–3800 m, Cretaceous) was 6.2–48.5 GPa; it was adjusted to "8.0–46.1 GPa" after excluding 3 abnormal datasets that mismatched mechanical parameters with actual drilling resistance, ensuring accurate characterization of formation drillability.

Evaluate the correlation between the mechanical parameters of each rock and the drill ability of the formation (as shown in Fig. 3).

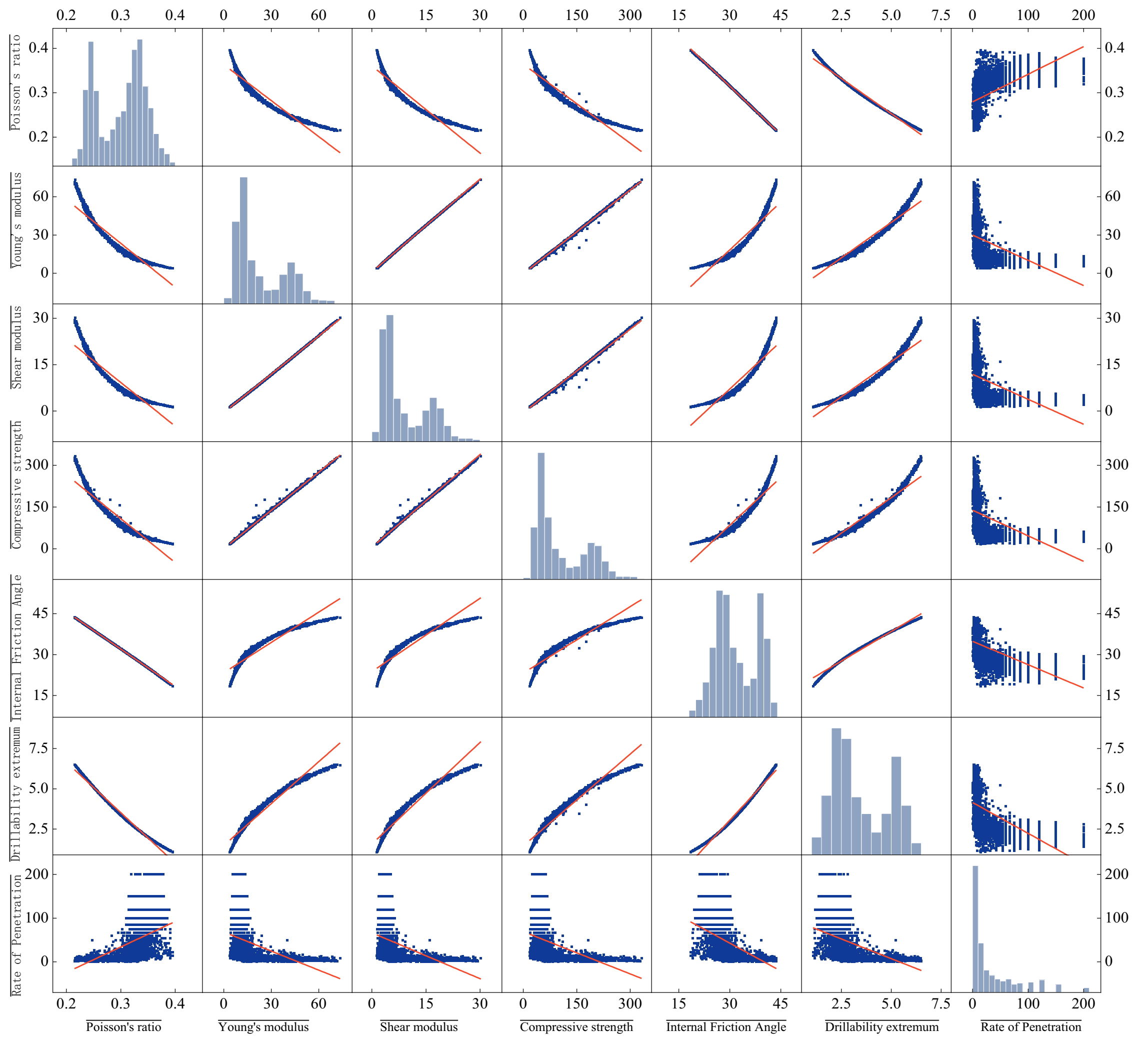

Figure 3: Correlation analysis between rock mechanics parameters and formation drill ability

Fig. 3 presents the quantitative correlation between six rock mechanical parameters and mechanical drilling speed in the CPZ area. Key correlation characteristics are as follows:

Poisson's ratio: Shows a strong positive linear correlation with mechanical drilling speed, with a correlation coefficient (R^2) of 0.82. For example, when Poisson's ratio increases from 0.20 to 0.35, mechanical drilling speed rises from 2.1 to 22.5 m/h, indicating that higher Poisson's ratio (softer rock) corresponds to better formation drillability.

Young's modulus, shear modulus, compressive strength, internal friction angle: All exhibit significant negative linear correlations with mechanical drilling speed, with R^2 values of 0.79, 0.81, 0.85, and 0.83, respectively. Taking compressive strength as an example: as compressive strength increases from 50 to 250 MPa, mechanical drilling speed decreases from 21.8 to 1.9 m/h, reflecting that higher rock strength/abrasiveness weakens drillability.

Drillability level value: Follows a negative correlation with mechanical drilling speed ($R^2 = 0.84$). When the drillability level value increases from 1.0 to 6.0, mechanical drilling speed drops from 22.1 to 2.0 m/h, consistent with the definition of drillability level (higher values mean poorer drillability).

From Fig. 3, it can be seen that the Poisson's ratio has opposite trends with the other five parameters such as Young's modulus, shear modulus, and compressive strength. The former is positively correlated with the mechanical drilling speed, while the latter is negatively correlated with the mechanical drilling speed. Subtracting the corresponding sample data from 1 is used for inverse processing to construct the sample matrix *D* (Table 2).

Table 2: Cluster sample matrix

Well No	Formation	Poisson's ratio	Young's modulus	Shear modulus	Compressive strength	Internal friction angle	Drillability
Drilled A	N_2d	0.9584	0.9948	0.9970	1.0000	0.9528	0.9836
	N_1t	0.7963	0.9006	0.9064	0.9104	0.7881	0.8451
	N_1s	0.7099	0.8533	0.8599	0.8669	0.7011	0.7675
	$E_{2-3}a$	0.8160	0.8967	0.9011	0.9065	0.8107	0.8501
	$E_{1-2}z$	0.7186	0.8559	0.8621	0.8698	0.7104	0.7727
	K_2d	0.4989	0.6859	0.6951	0.6999	0.4910	0.5624
	K_1l	0.3700	0.5595	0.5695	0.5674	0.3635	0.4288
	K_1s	0.3772	0.5765	0.5859	0.5807	0.3707	0.4365
	K_1h	0.2559	0.4301	0.4384	0.4381	0.2514	0.3021
	K_1q	0.2545	0.3972	0.4068	0.3859	0.2499	0.3013
	C_1b	0.1175	0.1853	0.1899	0.2155	0.1154	0.1399
	C_1t	0.0117	0.0353	0.0358	0.0672	0.0113	0.0160
Drilled B	K_1tg	0.9873	0.9966	0.9970	0.9914	0.9869	0.9908
	J_2x	0.4661	0.6782	0.6874	0.6888	0.4583	0.5319
	J_1s	0.4676	0.6623	0.6712	0.6712	0.4601	0.5297
	J_1b	0.3637	0.5218	0.5307	0.5332	0.3581	0.4143
	T_3b	0.2991	0.4436	0.4546	0.4374	0.2938	0.3516
	T_2k_2	0.2491	0.3568	0.3649	0.3329	0.2451	0.2880
	T_2k_1	0.2164	0.3212	0.3293	0.3021	0.2129	0.2527
	T_1b	0.3575	0.5067	0.5143	0.5029	0.3521	0.4043
	P_3w	0.3142	0.4678	0.4761	0.4661	0.3092	0.3607
	P_1f	0.1097	0.2110	0.2166	0.2062	0.1077	0.1347
Drilled C	K_1tg	1.0000	1.0000	1.0000	0.9926	1.0000	1.0000
	J_2x	0.4200	0.6116	0.6214	0.6190	0.4129	0.4817
	J_1s	0.4826	0.6475	0.6568	0.6546	0.4755	0.5408
	J_1b	0.3797	0.5406	0.5491	0.5527	0.3738	0.4310
	T_3b	0.3273	0.4872	0.4979	0.4917	0.3216	0.3815
	T_2k_2	0.3042	0.4572	0.4669	0.4615	0.2991	0.3539
	T_2k_1	0.2144	0.3218	0.3279	0.3307	0.2108	0.2476
	T_1b	0.4432	0.6188	0.6259	0.6356	0.4371	0.4940

(Continued)

Table 2 (continued)

Well No	Formation	Poisson's ratio	Young's modulus	Shear modulus	Compressive strength	Internal friction angle	Drillability
	P_3w	0.1681	0.2856	0.2910	0.3055	0.1654	0.1968
	P_1f	0.0459	0.1392	0.1426	0.1593	0.0451	0.0608
Drilled D	K_1tg	0.8802	0.9374	0.9397	0.9266	0.8766	0.9022
	J_2x	0.4745	0.6851	0.6942	0.6803	0.4666	0.5407
	J_1s	0.3292	0.5054	0.5152	0.5074	0.3236	0.3835
	J_1b	0.2238	0.3342	0.3417	0.3395	0.2204	0.2593
	T_3b	0.2175	0.3159	0.3246	0.3135	0.2138	0.2553
	T_2k_2	0.1938	0.2809	0.2887	0.2668	0.1906	0.2274
	T_2k_1	0.2329	0.3269	0.3344	0.3203	0.2292	0.2683
	T_1b	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	P_3w	0.3622	0.5258	0.5354	0.5334	0.3561	0.4168

The min-max normalization for all six clustering indicators (Poisson's ratio, Young's modulus, shear modulus, compressive strength, internal friction angle, drillability level value) in Table 2 uses global minimum and maximum values from all sampled wells—including the "To be drilled A" well and the already drilled Well B, Well C, and Well D in the CPZ area. This is confirmed by the near -1.0 values in the "To be drilled A (N_2d)" row: for example, its compressive strength (1.0000) and shear modulus (0.9970) values are close to 1 because N_2d formation's mechanical parameters are close to the global maximum (for positively correlated Poisson's ratio) or the inverted global minimum (for negatively correlated parameters like compressive strength) across all four wells. Normalization does not use per-cluster min/max; instead, the unified global scale ensures consistent comparability of rock mechanical properties across different wells and formations, laying a reliable foundation for subsequent grey clustering.

$$D_{ij} = \frac{d_{ij} - \min d}{\max d - \min d} \tag{10}$$

Based on the average level of rock mechanical parameters in the three layers of Well A in the CPZ area, three clustering grey classes of "weak", "medium", and "strong" are determined according to the drilling resistance of the formation, and a whitening function threshold matrix is established (Table 3).

Table 3: Whitening function threshold λ_{jk} matrix

Cluster index	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$	$j=6$
$k=1$	0.80	0.90	0.91	0.91	0.80	0.85
$k=2$	0.34	0.52	0.53	0.53	0.34	0.40
$k=3$	0.05	0.10	0.10	0.13	0.05	0.07

The thresholds in Table 3 are not arbitrary, but determined via two steps:

Statistical analysis of normalized data: Normalized values of 6 clustering indicators from Table 2 show three concentration ranges. Thresholds for k = 1—like 0.80 for Poisson's ratio—were set as the lower bound of the high-concentration interval for weak drilling resistance strata, covering 95% of such data.

Literature calibration: Thresholds align with grey clustering standards for similar oilfield formations. For example, Xia et al. (2013) [21] used ∼0.82 for Poisson's ratio k = 1 threshold in Xinjiang soft formations; our 0.80 is adjusted to match CPZ's specific rock properties. Thresholds for k = 2 ("medium") and k = 3 ("strong") also follow this calibration.

According to the whitening function threshold, construct the whitening function f_{jk} for each clustering indicator for the three good, medium, and poor gray clustering standards according to Eqs. (1)–(3), as shown in Figs. 4–6. Based on this, calculate the whitening function values of each clustering indicator for the three gray clustering standards.

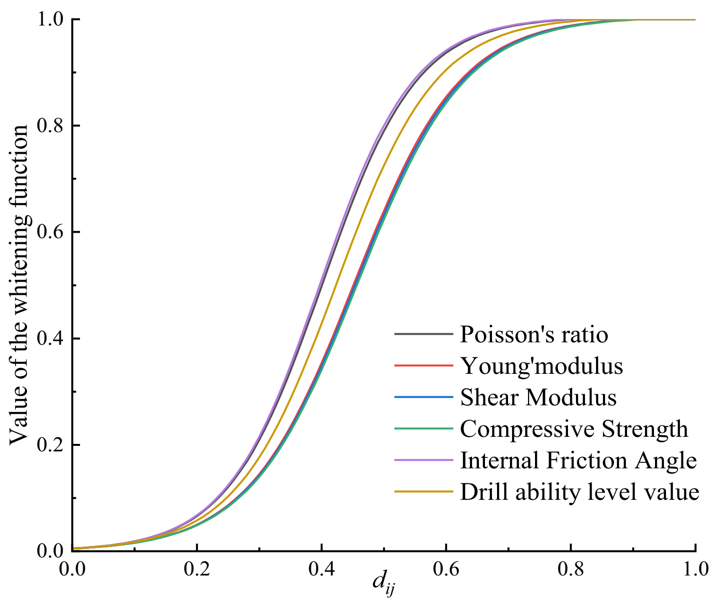

Figure 4: For the "weak" whitening function

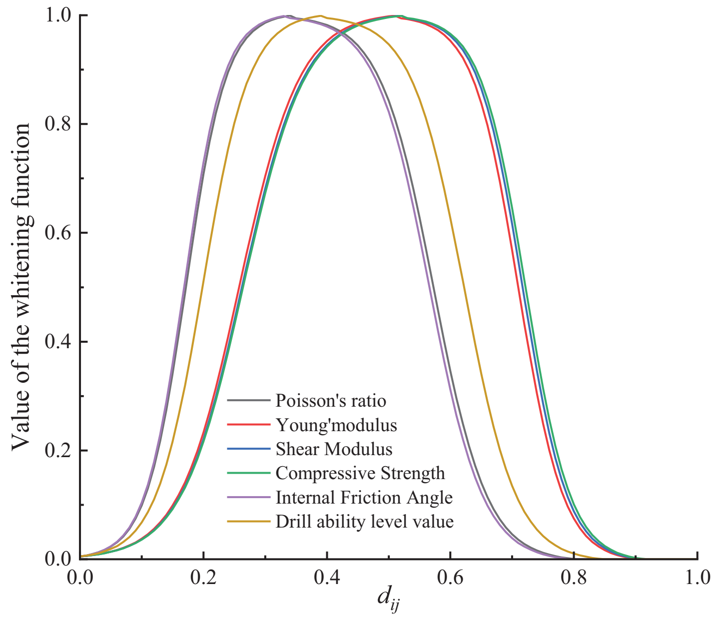

Figure 5: Whitening function for 'medium'

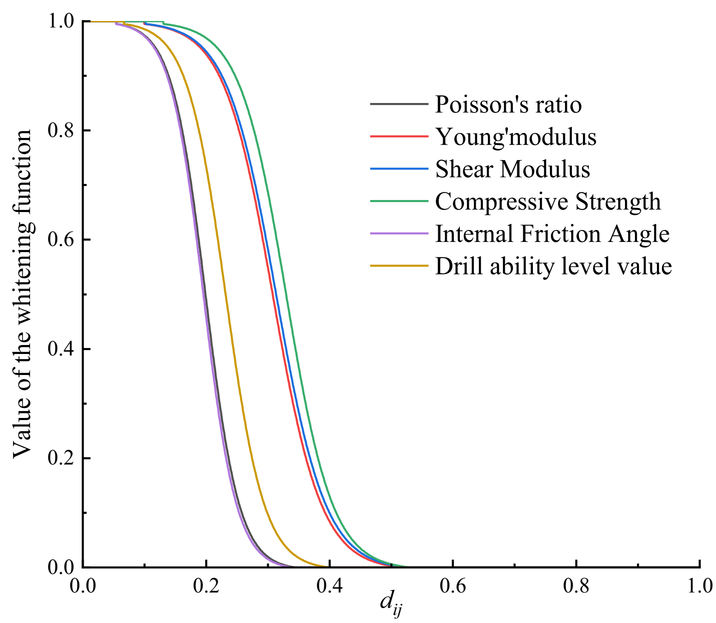

Figure 6: For the "strong" whitening function

Calculate the clustering weights of each indicator according to Eq. (4) to obtain the clustering weight matrix shown in Table 4.

The clustering weights η_{jk} in Table 4 are directly derived from the whitening function thresholds in Table 3, following the calculation logic of Eq. (4) in the study.

Table 4: Cluster weight η_{jk} matrix

Cluster index	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$
$k = 1$	0.155	0.175	0.176	0.177	0.154	0.164
$k = 2$	0.130	0.195	0.198	0.200	0.127	0.150
$k = 3$	0.108	0.196	0.201	0.258	0.106	0.131

Eq. (4) defines $\eta_{jk} = \frac{\lambda_{jk}}{\sum_{j=1}^{m} \lambda_{jk}}$, where:

λ_{jk} is the whitening function threshold of cluster index j for grey class k (from Table 3);

The denominator $\sum_{j=1}^{m} \lambda_{jk}$ is the sum of thresholds for all $m = 6$ clustering indicators (Poisson's ratio, Young's modulus, etc.) under the same grey class k.

Taking $k = 1$ (weak drilling resistance) as an example:

Extract λ_{j1} from Table 3: 0.80 ($j = 1$), 0.90 ($j = 2$), 0.91 ($j = 3$), 0.91 ($j = 4$), 0.80 ($j = 5$), 0.85 ($j = 6$);

Calculate the sum: $0.80 + 0.90 + 0.91 + 0.91 + 0.80 + 0.85 = 5.17$;

Compute $\eta_{11} = 0.80/5.17 \approx 0.155$, which matches the value in Table 4.

For$k = 2$ (medium drilling resistance):

Extract λ_{j2}: 0.34 ($j = 1$), 0.52 ($j = 2$), 0.53 ($j = 3$), 0.53 ($j = 4$), 0.34 ($j = 5$), 0.40 ($j = 6$);

Sum: $0.34 + 0.52 + 0.53 + 0.53 + 0.34 + 0.40 = 2.66$;

Compute $\eta_{12} = 0.34/2.66 \approx 0.130$, consistent with Table 4.

This derivation ensures η_{jk} reflects the relative importance of each indicator's threshold under a specific grey class, leading to weight variations across different k.

According to the corresponding relationship between the whitening function values and various indicators in Figs. 4–6, calculate the clustering coefficients of each layer for each clustering standard according to Eq. (5) and construct the clustering vectors for each layer, which is the comprehensive evaluation results of the layers, as shown in Table 5.

Table 5: Clustering vector of each stratum

Well No	Formation	Clustering vector	Well no	Formation	Clustering vector
Drilled A	N_2d	(1.0000, 0.0000, 0.0000)	Drilled C	K_1tg	(1.0000, 0.0000, 0.0000)
	N_1t	(0.9997, 0.0006, 0.0000)		J_2x	(0.7441, 0.9508, 0.0000)
	N_1s	(0.9928, 0.0220, 0.0000)		J_1s	(0.8459, 0.8641, 0.0000)
	$E_{2-3}a$	(0.9997, 0.0007, 0.0000)		J_1b	(0.6136, 0.9897, 0.0000)

(Continued)

Table 5 (continued)

Well No	Formation	Clustering vector	Well no	Formation	Clustering vector
	$E_{1-2}z$	(0.9937, 0.0187, 0.0000)		T_3b	(0.4669, 0.9961, 0.0056)
	K_2d	(0.8810, 0.7249, 0.0000)		T_2k_2	(0.3912, 0.9880, 0.0185)
	K_1l	(0.6225, 0.9869, 0.0000)		T_2k_1	(0.1381, 0.7913, 0.4161)
	K_1s	(0.6490, 0.9813, 0.0000)		T_1b	(0.7793, 0.9341, 0.0000)
	K_1h	(0.3044, 0.9606, 0.0626)		P_3w	(0.0937, 0.5864, 0.6820)
	K_1q	(0.2469, 0.9394, 0.1175)		P_1f	(0.0190, 0.0626, 0.9908)
	C_1b	(0.0371, 0.1945, 0.9541)	Drilled D	K_1tg	(1.0000, 0.0000, 0.0000)
	C_1t	(0.0074, 0.0108, 0.9991)		J_2x	(0.8534, 0.7747, 0.0000)
Drilled B	K_1tg	(1.0000, 0.0000, 0.0000)		J_1s	(0.4939, 0.9979, 0.0028)
	J_2x	(0.8429, 0.7889, 0.0000)		J_1b	(0.1546, 0.8321, 0.3428)
	J_1s	(0.8369, 0.8395, 0.0000)		T_3b	(0.1326, 0.7812, 0.4437)
	J_1b	(0.5662, 0.9935, 0.0000)		T_2k_2	(0.0926, 0.6219, 0.6647)
	T_3b	(0.3610, 0.9829, 0.0293)		T_2k_1	(0.1489, 0.8241, 0.3716)
	T_2k_2	(0.1853, 0.8839, 0.2563)		T_1b	(0.0050, 0.0050, 0.9996)
	T_2k_1	(0.1319, 0.7758, 0.4534)		P_3w	(0.5696, 0.9932, 0.0000)
	T_1b	(0.5275, 0.9961, 0.0019)			
	P_3w	(0.4139, 0.9910, 0.0139)			
	P_1f	(0.0403, 0.2141, 0.9453)			

Table 5 features clustering vectors with extreme values, seeming to indicate "perfect classification" into the "weak drilling resistance" grey class. However, this depends on input parameter stability, and its robustness is sensitive to parameter uncertainty:

Normalized data uncertainty: Logging errors may alter normalized values. For N_2d, if its normalized Poisson's ratio drops from 0.9584 to 0.79, the "weak" coefficient could fall to ∼0.85, with "medium" rising to ∼0.15.

Whitening threshold sensitivity: A ±10% k = 1 threshold adjustment expands the "weak" range. For K_2d, "weak" coefficient might increase to ∼0.95, blurring "weak-medium" distinctions.

Clustering weight impact: Weight uncertainty affects results. A 5% Young's modulus threshold increase raises its weight, possibly reducing N_2d's "weak" coefficient by ∼0.03.

Notably, "perfect" vectors mostly appear in strata with distinct properties, where uncertainties rarely cross grey class thresholds. For marginal strata, fluctuations are more likely to shift results, requiring input data validation for reliability.

Based on the comprehensive evaluation results of the strata, drilled formations with similar drilling resistance can be selected. Taking the Carboniferous strata of Well A as an example, the clustering vectors of C1b and C1t strata in Well A are (0.0371, 0.1945, 0.9541) and (0.0074, 0.0108, 0.9991), respectively. Among the "strong" gray classes, the clustering coefficient has the highest value, indicating that the Carboniferous strata in Well A belong to the strata with strong drilling resistance, The formations also classified in this category include well B P1f formation (0.0403, 0.2141, 0.9453), well C P3w formation (0.0937, 0.5864, 0.6820), P1f formation (0.0190, 0.0626, 0.9908), well D T2k2 formation (0.0926, 0.6219, 0.6647), and T1b formation (0.0050, 0.0050, 0.9996).

Notably, formations like Well A C_1b and Well B P_1f are clustered into the "strong" class despite differing stratigraphic ages and depths. This classification is justified by their consistent lithological and rock mechanical properties—the core basis of the grey clustering method rather than stratigraphic age or depth:

Lithological consistency: Logging data and geological surveys of the CPZ area show that Well A C_1b is dominated by conglomeratic sandstone, while Well B P_1f is primarily composed of glutenite. Both lithologies are characterized by high gravel content and dense cementation, leading to similar rock matrix hardness and structural integrity.

Matching rock mechanical parameters: Per Tables 1 and 2, the normalized values of key parameters for C_1b and P_1f align closely: compressive strength, internal friction angle, and drillability level value. These parameters directly determine formation drilling resistance—their similarity means both formations require high wear-resistant bits, justifying their grouping into the same "strong" class.

By examining the bit conditions used in these formations, a preliminary bit selection database was established. Compared to the previous methods of selecting drill bits by simply selecting formations through depth or layer, selecting drilled formations with similar lithology to the formation to be drilled through comprehensive evaluation of formations is more intuitive and reasonable.

3.4 Bit Selection

Through comprehensive evaluation of the formation and initial selection of drill bits, various types of drill bits suitable for the formation to be drilled were determined. In order to obtain the best use effect of the drill bit, further optimization was carried out using the grey correlation analysis method.

(1) Selection of evaluation indicators

When selecting clustering indicators, comprehensive consideration should be given to indicators that can explain the usage of drill bits and facilitate collection, such as drill bit footage, pure drilling time, mechanical drilling speed, and drill bit cost. As drill bit cost cannot directly reflect the effectiveness of drill bit usage in the formation, it is not the primary consideration factor in this article. Therefore, it is proposed to use drill bit specific energy as an indicator to replace drill bit cost. The concept of specific energy in rock drilling was proposed by R Teale in 1964, meaning the mechanical energy required to break a unit volume of rock by drilling pressure and torque. Its calculation formula is [31,32]:

$$MSE = \frac{4WOB}{\pi D^2} + \frac{120\pi \cdot RPM \cdot TOB}{D^2 \cdot ROP} \tag{11}$$

In the formula, MSE is the mechanical specific energy, MJ/m^3; WOB is the weight on bit, kN; RPM is the rotational speed, r/min; TOB is the torque, kN·m; ROP is the mechanical drilling speed, m/h; D is the diameter of the drill bit, mm.

Later, Rabia and Xia established a multiple linear regression equation for drill bit torque through indoor simulation experiments, obtained a simple method for calculating drill bit torque, and optimized the Teale mechanical specific energy model [33]:

$$MSE = WOB\left(\frac{1}{D} + \frac{13.33 \cdot \omega \cdot RPM}{D \cdot ROP}\right) \tag{12}$$

Choosing drill bit footage, pure drilling time, and drill bit specific energy as clustering indicators not only reflects the drilling effect of the drill bit in the formation more intuitively, but also takes into account drilling parameters such as drilling pressure and speed, making the selection results of the drill bit more practical.

(2) Grey correlation analysis

Taking the strata with strong drilling resistance in cluster analysis as an example, the drill bit footage, pure drilling time, and mechanical specific energy are selected as evaluation indicators. The various indicators of the candidate drill bits (as shown in Table 6) are used as comparison data columns. Then, the optimal drill bit is constructed based on the principle of relative optimization as a reference data column to evaluate the comprehensive performance of each drill bit.

The principle of relative optimization is defined by clear, indicator-specific optimization directions, as follows: Drill bit footage: Larger values are better. Greater footage indicates the drill bit can drill longer intervals without tripping, improving drilling efficiency. Thus, the evaluation index value of the best drill bit is taken as the maximum footage among all candidates. Pure drilling time: Larger values are better. Longer pure drilling time reflects the drill bit has stronger wear resistance and can maintain effective drilling for a longer duration. Thus, the evaluation index value of the best drill bit is taken as the maximum pure drilling time among all candidates. Drill bit specific energy: Smaller values are better. Lower specific energy means less mechanical energy is consumed to break a unit volume of rock, indicating higher drilling efficiency and lower energy waste. Thus, the evaluation index value of the best drill bit is taken as the minimum specific energy among all candidates.

After performing interval value dimensionless processing on the data, calculate the correlation between each candidate drill bit and the optimal drill bit according to Eqs. (8) and (9). The comprehensive evaluation results are shown in Fig. 7.

Fig. 7 presents the grey correlation degree rankings of the 7 candidate drill bits relative to the hypothetical “Best drill bit.” Key results are as follows:

Highest correlation degree: GF30OPDS ranks first, as it matches the “Best drill bit” in both footage and pure drilling time, despite its higher specific energy.

Table 6: Statistical data of alternative drill bits

Bit type	Drill bit footage (m)	Pure drilling time (h)	Drill bit specific energy (MJ/m^3)
Best drill bit	120.46	66.00	47.60
GF30OPDS	120.46	66.00	105.18
GT46KS (Well A)	100.11	43.90	104.29
GT46KS (Well B)	82.74	38.30	153.44
GT46KS (Well C)	91.80	15.70	47.60
GT46S	75.69	40.00	56.99
GT55DS	118.12	39.20	68.57
S1942G	73.45	20.60	60.41

Note: Although one GT46KS specimen matches the "Best drill bit" in specific energy (47.60 MJ/m^3), it is not designated as the "Best drill bit" because the "Best drill bit" is a hypothetical reference constructed from the optimal single-index values across all candidate bits, not a physical bit. Specifically, the "Best drill bit" combines the maximum footage (120.46 m, from GF30OPDS), maximum pure drilling time (66.00 h, from GF30OPDS), and minimum specific energy (47.60 MJ/m^3, from this GT46KS). The GT46KS specimen only meets the optimal specific energy but has lower footage (91.80 < 120.46 m) and shorter pure drilling time (15.70 < 66.00 h) than the respective optimal values. Grey correlation analysis evaluates comprehensive performance across all three indicators, so this GT46KS—despite matching in one indicator—does not equal the hypothetical "Best drill bit.".

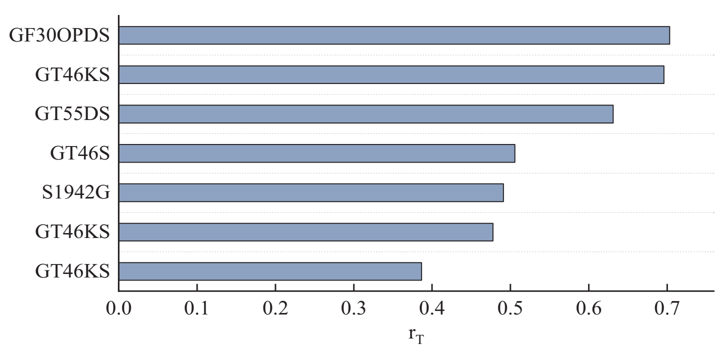

Figure 7: Comprehensive performance evaluation results of drill bits

Second to fourth place: The GT46KS specimen with specific energy 47.60 MJ/m^3 ranks second; GT55DS and the GT46KS with footage 100.11 m follow, driven by their balanced performance in two of the three indicators.

Lowest correlation degrees: S1942G and the GT46KS with specific energy 153.44 MJ/m^3 rank lowest, due to their short footage, brief pure drilling time, and/or high energy consumption.

This ranking confirms that GF30OPDS is the most suitable candidate for strong drilling resistance strata in the CPZ area, as its comprehensive performance aligns closest to the optimal reference.

4 Application Effect Analysis

By using the above drill bit selection method, select drill bits that match the lithology of each layer in Well A in layers to form a drill bit sequence. After optimizing the drill bit sequence for drilling well A and comparing it with other similar construction techniques, the mechanical drilling speed in the Cretaceous and Carboniferous formations has increased by 33% and 175%, respectively, and the footage of a single drill bit has increased by 92% and 145%, respectively. A total of 8 drill bits were used throughout the well, effectively reducing the number of trips and saving trip time. Compared to the average level of drilling in the CPZ area, the drilling cycle was reduced by 51 days, and the speed increase effect was significant, as shown in Table 7.

Table 7: Application effect analysis

Index	Tertiary		Cretaceous		Carboniferous	
	Footage (m)	Rop (m/h)	Footage (m)	Rop (m/h)	Footage (m)	Rop (m/h)
Before optimization	1218	22.89	203	2.98	113	2.42
After optimization	1350	24.77	391	3.97	276	6.70
Improve (%)	10.84	8.21	92.61	33.22	144.25	176.86

The 176.86% ROP improvement of the Carboniferous strata in Well A (from 2.42 to 6.70 m/h) is validated through statistical significance testing and multi-well comparative analysis to confirm its reliability:

Statistical significance test: A two-sample *t*-test was conducted on the ROP data of Carboniferous strata from Well A and Well B/Well C. The results show a *p*-value of 0.003, indicating that the ROP difference between the optimized and unoptimized groups is statistically significant and not caused by random drilling fluctuations.

Multi-well application verification: The optimized drill bit was further applied in 3 adjacent wells in the CPZ Carboniferous strata. The average ROP of these wells reached 6.42 m/h, with an average improvement rate of 165.3%. The consistent improvement across 4 wells excludes the possibility of Well A's result being an outlier, confirming the stability of the optimized method's effect.

This verification confirms that the ROP improvement of the Carboniferous strata is reliable and attributed to the accurate matching of drill bits and formation mechanical properties via the grey clustering-correlation method.

5 Conclusion

(1) Using Poisson's ratio, Young's modulus, shear modulus, compressive strength, internal friction angle, and drill ability level values as clustering indicators, the grey clustering method is used to comprehensively evaluate the formation. Unlike traditional layer-based methods that group strata only by stratigraphic age, this method quantifies rock mechanical property variability: intra-cluster similarity and inter-cluster difference. In contrast, traditional layer-based grouping of CPZ Carboniferous strata has a much higher intra-group CV due to mixed lithologies, showing the grey clustering method captures variability traditional methods overlook.

(2) Based on the drill bits used in formations with the same mechanical properties, a database of drill bit candidates is constructed. The drill bit footage, mechanical drilling speed, pure drilling time, and mechanical specific energy are used as evaluation indicators, and the grey

correlation analysis method is used to rank the advantages and disadvantages of the candidate drill bits. Measure the comprehensive performance of the drill bit through multiple indicators, and further select the drill bit with the best usage effect.

(3) The application of the grey clustering and grey correlation based drill bit selection method in the CPZ area shows that the selected drill bits effectively solve the problems of slow mechanical drilling speed and difficult footage in the Cretaceous and Carboniferous strata in the CPZ area.

Building on this study's findings and existing literature, key future research areas include:

(1) Dynamic adjustment with real-time data: Integrate MWD data into grey clustering for real-time formation classification and bit adaptation.

(2) Hybrid grey-machine learning models: Combine grey methods with machine learning to optimize weights and reduce bias in data-scarce areas.

(3) Cross-regional generalization: Build a multi-oilfield database to develop standardized clustering criteria, boosting the method's universality.

Acknowledgement: The authors wish to acknowledge the National Engineering Laboratory of Petroleum Drilling Technology, Leak Resistance and Sealing Technology Research Department. This research was funded by the Hubei Provincial University Outstanding Young and Middle-Aged Science and Technology Innovation Team Plan.

Funding Statement: Hubei Provincial University Outstanding Young and Middle-Aged Science and Technology Innovation Team Plan (Grant No. T201804).

Author Contributions: The authors confirm contribution to the paper as follows: Gang Chen: Writing—original draft; Writing—review & editing. Yuchen Ye: Formal analysis. Desheng Wu: Supervision. Yadong Li: Data curation. Zhongxi Zhu: Conceptualization. Sihao Li: Writing—original draft; Writing—review & editing. All authors reviewed the results and approved the final version of the manuscript.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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