

Original Paper

A physics-data hybrid model for energy consumption prediction of hydraulic rock drills with applications in petroleum engineering

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ABSTRACT

To address the issue of high energy consumption in electro-hydraulically driven rock drills, a hybrid energy consumption prediction model integrating physics-informed and data-driven approaches is proposed. First, a physical model of energy transfer is established based on the working principle of the hydraulic rock drill. Rock drilling experiments reveal the influence of the pressure parameter matching mechanism on energy consumption. Excessively high impact pressure significantly increases both the rate of penetration (ROP) and energy consumption, insufficient propulsion pressure tends to cause idle drilling thereby increasing energy consumption, and excessively high buffer pressure reduces impact efficiency and increases energy consumption. Meanwhile, rock properties significantly affect pressure regulation strategies. Soft sandstone exhibits an optimal pressure range, medium-hard limestone achieves the best energy efficiency in the low-pressure range, and hard granite requires high pressure to activate efficient fragmentation. Finally, with the physical model serving as the core framework, a hybrid data-driven compensation model is constructed using Least Squares Support Vector Machine (LSSVM) optimized by the sine cosine algorithm (SCA). Experimental results show that the hybrid model achieves a coefficient of determination (R^2) of 0.99, a mean absolute percentage error (MAPE) of 2.18%, and a root mean square error (RMSE) of 59.45 kJ, outperforming both pure data-driven models LSSVM, Random Forest (RF), Multi-Layer Perceptron (MLP), and Gaussian Process Regression (GPR), as well as the pure physical model. By ensuring interpretability through the physical framework and dynamically correcting unmodeled errors with a data-driven compensation mechanism, the model achieves synergistic improvement in accuracy and reliability.

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1. Introduction

In mining, tunneling, and petroleum drilling (Guo et al., 2016), carbon emissions present a critical challenge. Traditional hydraulic rock drills, powered by fossil fuels, incur high energy consumption

and carbon intensity, impeding the green transition of resource extraction. The advent of pure-electric drilling rigs (Guo et al., 2024) utilizing electric-drive hydraulic systems mitigates direct carbon emissions at source. However, in complex geological conditions such as hard rock or deep tight reservoirs, these systems exhibit considerable energy efficiency fluctuations (Long et al., 2015), compromising overall performance and economic viability. Given that drilling constitutes a substantial portion of energy consumption in petroleum engineering, enhancing system energy efficiency is vital for reducing the carbon footprint of oil and gas production. Accurate prediction of energy consumption in

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pure-electric rigs and analogous electro-hydraulic systems is therefore imperative. Developing robust and adaptive prediction models for complex environments (Kozłowski and Bołoz, 2021) facilitates energy optimization (Halim et al., 2022) and cost reduction, while accelerating the industry's transition toward green, intelligent, and sustainable operations, notably in petroleum and geothermal drilling.

Established methodologies for calculating rock drill energy consumption are well documented. Hu et al. (2014) modeled internal energy transfer using bond graph theory. Song et al. (2019) determined that square wave pulses maximize efficiency under fixed loads, whereas sine waves perform optimally with fixed input energy, with efficiency (Song et al., 2022) rising alongside impact hammer speed. Ma et al. (2019) formulated a coupled piston-valve model and computed rebound energy through stress wave theory. Li (2021) introduced a dimensionless impact coefficient correlating impact energy with system performance. Given the analogous operating principles of rock drills and drilling rigs, mechanical specific energy serves as a fundamental efficiency indicator, though current models lack parameter comprehensiveness. Jia et al. (2021a) proposed sub-power modeling for energy assessment; Shen et al. (2022) introduced the “rate-energy ratio”, identifying propulsion and impact pressures as primary determinants of drilling rate, with rock-breaking energy deriving principally from impact energy. Yu et al. (2021) compared rock drillability index and specific energy for evaluating surrounding rock strength. He et al. (2021) established a linear relationship between drilling energy and fracture frequency, subsequently refining (He et al., 2019) modulus and strength parameters using Rock Quality Designation (RQD). Oparin et al. (2022) developed an energy efficiency framework for percussion-rotary drilling. Khoshouei and Bagherpour (2023) constructed correlation models linking specific energy to rock parameters via regression analysis. Abu et al. (2018) generated prediction models for drilling rate and specific energy utilizing cutting characteristics and geomechanical parameters. Deng et al. (2022) optimized weight-on-bit and hydraulic parameters to create a rotary impact specific energy model and bit optimization framework, demonstrating that roller cone bits combined with hydraulic impactors enhance drilling rate by approximately 10% and efficiency by about 8% relative to PDC bits.

Advances in artificial intelligence have established data-driven methods as essential for predicting drilling parameters, including the rate of penetration (ROP) and drilling energy. These approaches offer high accuracy, robust generalization, and capacity to capture complex nonlinear relationships among multivariate inputs and outputs. In ROP prediction, numerous machine learning algorithms surpass traditional empirical models. Hegde et al. (2017) demonstrated that random forest achieves superior accuracy and fit compared to empirical formulas. Backpropagation neural networks (Liao et al., 2020), support vector regression (Kor and Altun, 2020), and Gaussian process regression (Chen et al., 2021) have also proven effective. Researchers have further integrated prediction models with drilling optimization objectives. Hassan et al. (2020) combined ROP predictions with mechanical specific energy (MSE) via neural networks to formulate a comprehensive metric reflecting both efficiency and energy consumption. Alali et al. (2021) developed a hybrid data-driven optimization system that recommends optimal parameters from historical data and dynamically adjusts them through real-time automated testing. Regarding optimization strategies, Hegde and Gray (2018) compared ROP, torque on bit (TOB), and MSE models, revealing that ROP-only optimization, while significantly increasing drilling speed, may elevate energy consumption and torque; conversely, MSE optimization reduces specific energy and torque while improving ROP, enabling more balanced

(Khalilidermani and Knez, 2022) and economical drilling operations. These investigations collectively emphasize the considerable potential of data-driven methods for intelligent drilling parameter prediction and multi-objective optimization.

Gao et al. (2022) developed a hybrid physics-data-driven model for predicting drilling energy consumption. By integrating power flow theory with optimization algorithms, they achieved a prediction error of 2.44% and enhanced energy efficiency by 26.71%. Subsequently, their team incorporated human energy consumption to formulate a comprehensive “rig-operator” system energy model (Gao et al., 2025). In directional drilling optimization, Kunshin et al. (2022) combined strength theory with machine learning to establish a mechanical specific energy distribution prediction model, enabling identification of inefficient rock-breaking states and dynamic parameter adjustment. Delavar et al. (2023) employed random forest and multi-objective optimization methods to simultaneously improve drilling rates and reduce bit torque. Riazi et al. (2022) compared multiple intelligent models using extensive field data, identifying gradient boosting decision trees as optimal for ROP prediction, with depth and pump pressure as key influencing factors. Bizhani and Kuru (2022) systematically evaluated deterministic and probabilistic model performance on drilling data. Liu et al. (2025) substantially enhanced mechanical specific energy prediction accuracy by integrating CNN-LSTM-Attention models incorporating spatiotemporal features. Jia et al. (2021b) proposed an improved method for rapid drilling power prediction, enhancing practicality while maintaining accuracy.

Current research on rock drill energy consumption predominantly employs either purely physical or purely data-driven models, each possessing inherent limitations. Physical models provide interpretability but suffer from reduced accuracy owing to oversimplified assumptions. Data-driven models, though flexible, exhibit strong dependence on data quality and demonstrate compromised robustness under noisy or data-limited conditions. To address these shortcomings, this paper proposes a hybrid physical-data-driven methodology. Initially, a physical model characterizing energy transfer mechanisms is developed, with key influencing factors identified experimentally. To compensate for prediction errors arising from model simplifications and parameter uncertainties, an SCA-optimized LSSVM is implemented as a data-driven correction module. LSSVM reduces computational complexity by solving linear equations rather than quadratic programming problems while effectively capturing nonlinear relationships through high-dimensional mapping. This hybrid model integrates physical interpretability with data-driven adaptability, preserving the physical essence of the drilling process while learning from data to correct deviations. The approach ensures computational efficiency while substantially improving prediction accuracy and robustness.

The remainder of this paper is organized as follows. Section 2 investigates the physical model of energy consumption during the drilling process of a rock drill. Section 3 examines the influence of different operating pressures and rock properties on energy consumption parameters. Section 4 evaluates the energy consumption prediction accuracy of various models.

2. Energy consumption mechanism model for rock drills

2.1. Working principle of the rock drill

As shown in Fig. 1, the rock drill is an impact-rotary type of equipment. Under high-power drilling conditions, the influence of its rotary system can be neglected, and its dynamic behavior is predominantly governed by impact motion. The device advances under the drive of an external propulsion mechanism, ensuring

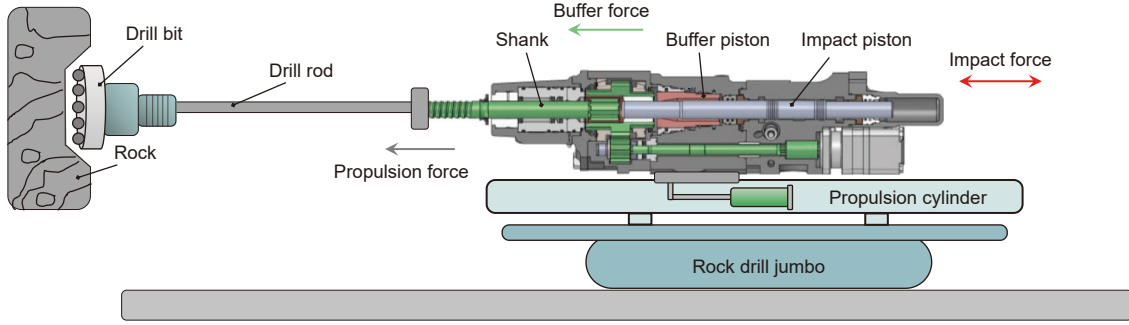


Fig. 1. Working principle of the rock drill.

tight contact between the drill bit and the rock surface. The internal directional valve periodically switches the hydraulic oil circuit, controlling the impact piston to achieve high-frequency reciprocating motion under the pressure difference between the front and rear chambers. When the impact piston accumulates sufficient kinetic energy, it strikes the drill tools assembly, creating a rigid collision. This impact energy is transmitted through the drill tools (Gan et al., 2022)—bit assembly to the rock mass, completing the rock fragmentation process. The buffer piston is arranged in a nested configuration outside the impact piston, with its end consistently in contact with the drill tools. After the impact action is completed, the moving assembly consisting of the drill bit, drill tools, and buffer piston undergoes a rebound motion under reaction forces and rapidly resets through the damping effect of the buffer system, preparing for the next working cycle. In this study, the drill tools and buffer piston are treated as an integrated moving component, with localized collision effects between them being neglected.

2.2. Global drilling dynamics model

A global dynamic model is established based on the working principle of rock drilling, as shown in Fig. 2. In this model, X_1 denotes the displacement of the impact piston, X_2 represents the displacement of the buffer piston and the drill tools moving together, X_3 corresponds to the displacement of the drill bit, and X_4 indicates the penetration into the rock. F_{a1} , F_{a2} , and F_{a3} represent the external impact hydraulic pressure, buffer hydraulic pressure, and propulsion hydraulic pressure, respectively. The meanings and values of other parameters can be found in the Appendix.

The overall dynamic model integrates lumped parameter modeling, rigid impact modeling, rock contact modeling, and internal fluid dynamics modeling.

(1) Lumped parameter model

Based on the established mechanical model, the equations of motion for the impact piston, drill tools, and bit are given in Eq. (1).

$$\begin{cases} m_1 \ddot{X}_1 = F_{a1} - k_1 X_1 - c_1 \dot{X}_1 \\ (m_2 + m_3) \ddot{X}_2 = F_{a2} - c_2 \dot{X}_2 - k_2 X_2 - c_3 (\ddot{X}_2 - \ddot{X}_3) - k_3 (X_2 - X_3) \\ m_4 \ddot{X}_3 = F_{a3} + c_3 (\ddot{X}_2 - \ddot{X}_3) + k_3 (X_2 - X_3) \end{cases} \quad (1)$$

(2) Rigid collision model

During normal operation of a rock drill, the impact piston undergoes a rigid collision with the drilling tool once per complete motion cycle, transferring energy to the drill bit. After the collision, the velocity of the impact piston reverses direction with reduced magnitude. By introducing the coefficient of restitution e , the system of equations describing the motion of the components before and after the collision is established, as is shown in Eq. (2).

$$\begin{cases} X_{1+} = X_{2-} + G_1 \\ X_{2+} = X_{2-} \\ \dot{X}_{1+} = \frac{m_1 - (m_2 + m_3)e}{m_1 + m_2 + m_3} \dot{X}_{1-} + \frac{(1+e)(m_2 + m_3)}{m_1 + m_2 + m_3} \dot{X}_{2-} \\ \dot{X}_{2+} = \frac{(1+e)m_1}{m_1 + m_2 + m_3} \dot{X}_{1-} + \frac{(m_2 + m_3) - m_1 e}{m_1 + m_2 + m_3} \dot{X}_{2-} \end{cases} \quad (2)$$

In this context, X_{1-} and $\dot{X}_{1-}$ denote the displacement and velocity of the impact piston before collision, while X_{1+} and $\dot{X}_{1+}$

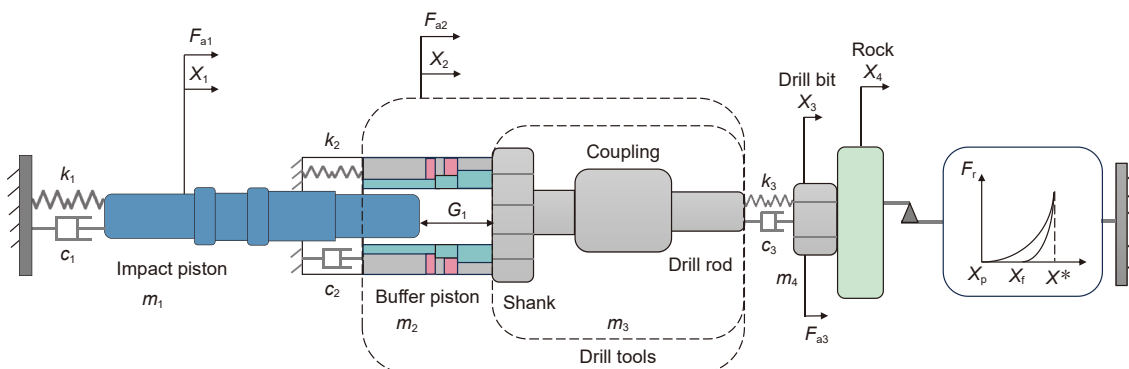


Fig. 2. Mechanical model of the rock drill.

represent the displacement and velocity of the impact piston after collision. e denotes the coefficient of restitution. X_{2-} and $\dot{X}_{2-}$ indicate the displacement and velocity of the drill tools before collision, whereas X_{2+} and $\dot{X}_{2+}$ correspond to the displacement and velocity of the drill tools after collision.

(3) Nonlinear rock contact model

Ajibose et al. (2015) proposed a nonlinear dynamic model based on the microscopic contact mechanism, which clearly distinguishes the penetration process during the loading phase from the rebound behavior during the unloading phase, as shown in Fig. 3. The primary governing equations are given by Eq. (3). F_r represents the force acting on the rock. F_f represents the static friction threshold during rock fragmentation.

$$k_L(X_n^* - X_{pn})^{n_L} = k_U(X_n^* - X_{fn})^{n_U} \quad (3)$$

$$\begin{cases} m_1 \ddot{X}_1 = F_{a1} - k_1 X_1 - c_1 \dot{X}_1 \\ (m_2 + m_3) \ddot{X}_2 = F_{a2} - c_2 \dot{X}_2 - k_2 X_2 - c_3 (\dot{X}_2 - \dot{X}_3) - k_3 (X_2 - X_3) \\ m_4 \ddot{X}_3 = F_{a3} + c_3 (\dot{X}_2 - \dot{X}_3) + k_3 (X_2 - X_3) - H_{1a} H_{2a} k_L (X_3 - X_p)^{n_L} - H_{1a} (1 - H_{2a}) H_{3a} k_U (X_3 - X_f)^{n_U} \\ \dot{X}_4 = [H_{1a} H_{2a} + H_{1a} (1 - H_{2a}) H_{3a}] \dot{X}_3 \\ \dot{X}_p = H_{1a} (1 - H_{2a}) H_{3a} \left[1 - \frac{k_U n_U (X_3 - X_f)^{n_U-1}}{k_L n_L (X_3 - X_p)^{n_L-1}} \right] \dot{X}_3 \\ \dot{X}_f = H_{1a} H_{2a} \left[1 - \frac{k_L n_L (X_3 - X_p)^{n_L-1}}{k_U n_U (X_3 - X_f)^{n_U-1}} \right] \dot{X}_3 \end{cases} \quad (6)$$

Here, k_L represents the loading stiffness and k_U represents the unloading stiffness. X_{pn} , X_{fn} , and X_n^* denote the initial loading position, the final unloading position, and the maximum penetration point of the rock surface during the n -th impact, respectively. For the single impact illustrated in Fig. 3(b), the calculation of the endpoint position during the unloading stage is given in Eq. (4).

$$X_{fn} = X_n^* - \left[\frac{k_L (X_n^* - X_{pn})^{n_L}}{k_U} \right]^{1/n_U} \quad (4)$$

Specifically, during the unloading phase, the bit velocity reverses direction at the penetration position X_c , while the displacement has not yet reached the predicted endpoint X_{f1} of the previous cycle. As defined in Eq. (5), the virtual starting point of the second impact, X_{p2} , does not coincide with X_{f1} . This positional lag phenomenon directly leads to residual deformation.

$$X_{p2} = X_c - \left[\frac{k_U (X_c - X_{f1})^{n_U}}{k_L} \right]^{1/n_L} \quad (5)$$

According to the above theory, the rock drilling process can be divided into three motion modes: non-penetration mode, loading penetration mode, and unloading penetration mode. By synthesizing Eqs. (1)–(5), Eq. (6) is obtained.

Among them, $H_{1a} = h(X_3 - X_p)$, $H_{2a} = h(\dot{X}_3)$, and $H_{3a} = h(X_3 - X_f)$. h represents the Heaviside function, and H_{1a} , H_{2a} and H_{3a} are used to adjust the formulation of the equation under different drilling conditions.

(4) Internal dynamic model of a rock drill

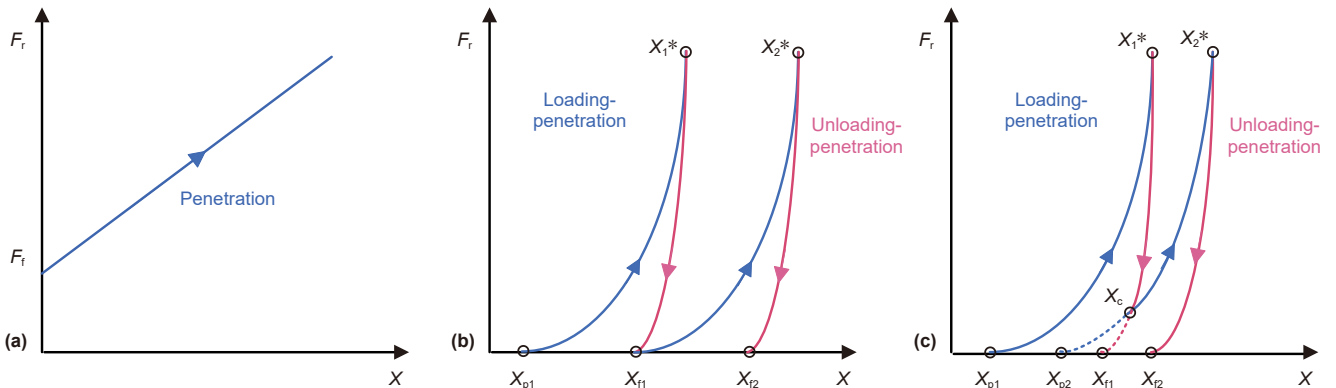


Fig. 3. Relationship between force and penetration in different bit-rock interaction models. (a) Dry friction rock model; (b) nonlinear rock contact model under single impact; (c) nonlinear rock contact model under multiple impacts.

chamber volume, and ΔQ_c indicates the net flow rate change into the chamber. Thin-walled orifices are widely used in impact systems, and their flow rate calculation is given by Eq. (9).

$$Q_t = C_d A_t \sqrt{\frac{2}{\rho} \Delta P_t} \quad (9)$$

Here, Q_t represents the orifice flow rate, C_d denotes the flow resistance coefficient determined by the Reynolds number, A_t indicates the cross-sectional flow area of the orifice, ρ stands for the hydraulic oil density, and ΔP_t is the pressure differential across the orifice. The pressure loss along internal pipelines is calculated using Eq. (10).

$$\Delta P_{cb} = \frac{128 \mu l_{cb}}{\pi d_{cb}^4} Q_{cb} \quad (10)$$

Here, ΔP_{cb} represents the pressure loss between two chambers connected by the pipeline, Q_{cb} denotes the flow rate in the pipeline, μ indicates the dynamic viscosity of the hydraulic oil, l_{cb} is the length of the pipeline, and d_{cb} stands for the diameter of the pipeline. Integrating Eqs. (8)–(10), the pressure and flow rate in each chamber of the system can be modeled, as is shown in Appendix.

2.3. Energy distribution model

The energy consumption of rock drills during the drilling process primarily concentrates on three systems: impact, propulsion, and buffer. Given that the rotary and flushing systems have minimal influence on energy consumption during drilling, they are temporarily not considered in this study. Fig. 5 illustrates the power flow distribution across these systems, where the impact power curve exhibits a distinct pulse-like pattern. This reveals the intermittent drilling mechanism dominated by impact in rock drills: energy (Davoodi et al., 2023) is accumulated during the non-drilling phase and released at the moment of impact. In contrast, the power fluctuations in the buffer and propulsion systems are relatively smoother. Therefore, the drilling process can be distinguished into “drilling states”, where energy is released, and “non-drilling states”, where energy is accumulated, with significant differences in power consumption between the two.

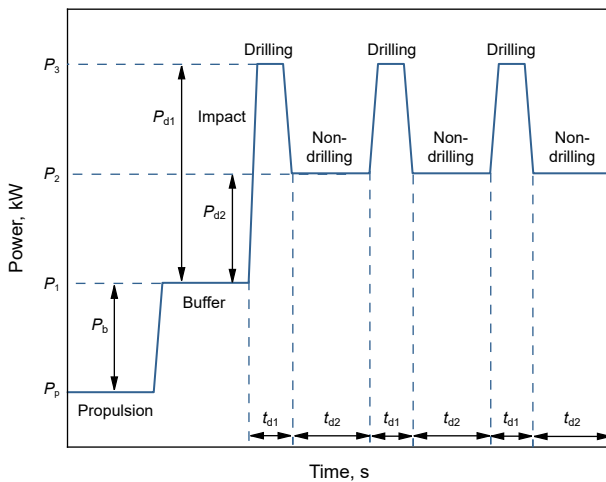


Fig. 5. Power flow during drilling process.

During the drilling state, the total energy consumed by the impact system, propulsion system, and buffer system is given by Eq. (11).

$$E_{d1} = \int_0^{t_{d1}} [P_p(t) + P_b(t) + P_{d1}(t)] dt \quad (11)$$

Here, E_{d1} is the total energy consumed by the system during the drilling state, t_{d1} is the drilling time in one working cycle, P_p is the power consumed by the propulsion system, P_b is the power consumed by the buffer system, and P_{d1} is the power consumed by the impact system during the drilling state. The total energy consumed by each system in the non-drilling state is given by Eq. (12).

$$E_{d2} = \int_0^{t_{d2}} [P_p(t) + P_b(t) + P_{d2}(t)] dt \quad (12)$$

Here, E_{d2} represents the total energy consumed by the system during the non-drilling state, t_{d2} is the non-drilling time within one working cycle, and P_{d2} is the power consumed by the impact system in the non-drilling state. Each system is powered by the hydraulic system, and its power can be calculated based on the pressure and flow output from the pump, as given by Eq. (13).

$$P_i = P_j Q_j \quad (13)$$

Here, P_i represents the hydraulic output power of each system, P_j denotes the real-time pressure of different systems, and Q_j indicates the real-time flow rate of different systems. Considering the inherent measurement errors associated with hydraulic power calculations based on pressure and flow, while the monitoring of electrical systems offers significant advantages such as low cost and easy implementation, the input electrical power for each hydraulic subsystem can be directly calculated using voltage and current signals, as given by Eq. (14).

$$P_k = U_k I_k \quad (14)$$

Here, P_k represents the electrical power consumed by different systems, U_k denotes the voltage consumed by different systems, and I_k indicates the current consumed by different systems. Once the system state stabilizes, the total energy for both the drilling and non-drilling states is calculated as given by Eq. (15).

$$E_t = E_{d1} + E_{d2} = \int_0^{t_{d1}} [P_p(t) + P_b(t) + P_{d1}(t)] dt + \int_0^{t_{d2}} [P_p(t) + P_b(t) + P_{d2}(t)] dt \quad (15)$$

Here, E_t represents the total energy consumed by the system. Since the energy losses caused by environmental factors during the drilling process cannot be calculated, the actual energy consumption model for the drilling process is given by Eq. (16).

$$E_a = E_t + \Delta E \quad (16)$$

Here, E_a represents the total energy consumed by the system after accounting for environmental factors, and ΔE denotes the energy error. The impact energy generated at the instant the impact piston strikes the drill tools is a critical factor determining the drilling rate. By quantifying the mechanical energy transmitted per impact, it is directly linked to and indirectly characterizes the rock-breaking efficiency and overall drilling effectiveness during the process. The physical origin of this energy lies in the kinetic energy of the impact piston at the end of its stroke, where the piston's velocity reaches its maximum value. The calculation for impact energy efficiency is given by Eq. (17).

$$\eta_{p1} = \frac{E_{p1} f_{p1}}{P_{d1}} \quad (17)$$

Here, η_{p1} is the impact energy efficiency, E_{p1} is the impact energy, and f_{p1} is the impact frequency. The calculation of impact energy is given by Eq. (18).

$$E_{p1} = \frac{1}{2} m_1 v_{p1}^2 \quad (18)$$

Here, m_1 is the mass of the impact piston and v_{p1} is the velocity at the impact point. Additionally, this paper introduces a global drilling dynamics physical model for the rock drill to predict energy consumption, as detailed in the Appendix. This numerical model integrates lumped parameter modeling, collision modeling, rock contact modeling, and internal fluid dynamics modeling. Using pressure and flow parameters of the hydraulic system as inputs, it solves the governing equations to obtain drilling speed as a function of time, thereby enabling energy consumption prediction. The ROP is a key indicator of the drilling process, as given by Eq. (19).

$$ROP = \frac{X_{p2} - X_{p1}}{t_{p2} - t_{p1}} \quad (19)$$

Here, X_{p2} is the displacement of the machine body after drilling, X_{p1} is the displacement of the machine body before drilling, t_{p1} is the time point before drilling, and t_{p2} is the time point after drilling.

3. Rock drilling experiment

3.1. Experimental procedure

This study established a comprehensive testing platform for hydraulic rock drill drilling performance based on synchronous and precise measurement. The schematic diagram of the test setup is shown in Fig. 6. The platform employs a programmable industrial control console as the integrated core, a hydraulic power unit as the power source, and a hydraulic rock drill as the actuating unit (Yu et al., 2026). Multiple sets of sensors are configured to form a complete measurement chain. A laser displacement sensor is used for non-contact, high-frequency real-time acquisition of the impact piston's displacement. Pressure and flow sensors are deployed in key circuits of the hydraulic system to synchronously capture the working parameters of the impact, buffer, and propulsion circuits. All sensor signals are connected via shielded cables to an NI high-speed data acquisition board integrated into the industrial control console. Programming control is implemented

based on the LabVIEW software (Zhao et al., 2025a) platform to achieve synchronous triggering, high-speed acquisition, and real-time digitization of multi-channel signals. A constant-flow pump controls the output flow, while a relief valve controls the output pressure.

Before initiating the impact function, the buffer and propulsion systems first act cooperatively to drive the rock drill and the entire drill tools assembly forward until the drill bit presses firmly against the rock surface, establishing the necessary axial preload. After preload is completed, the impact system is activated. The impact piston accelerates under hydraulic drive and strikes the drill tools. The stress wave generated by the impact propagates along the drill tools to the bit, subjecting the rock to an instantaneous high-pressure impact, thereby achieving local rock fragmentation. Following the impact, due to rock breakage and system rebound, a minute gap may appear between the drill bit and the rock. At this point, under the continuous action of the propulsion cylinder, the rock drill drives the drill tools forward again, re-compressing against the rock surface in preparation for the next impact, thus forming a continuous “preload-impact-propulsion” working cycle. A photograph of the rock drilling experiment site is shown in Fig. 7.

The specifications of the COP1838 rock drill are listed in Table 1. The experimental conditions are presented in Table 2. Three types of rock, namely sandstone, limestone, and granite, are used in the experiments, and their characteristic parameters are provided in Table 3. The rock stiffness is estimated through linear fitting of the contact force and penetration depth. The loading and unloading stiffness depend not only on the elastic modulus of the rock but also on the drill bit geometry and Poisson's ratio of the rock.

3.2. Experimental data analysis

By continuously adjusting the impact pressure, experimental data for impact system pressure and piston displacement were synchronously acquired, as shown in Fig. 8(a) and (b). The rock drill operates in a high-frequency, high-power state with intense vibrations, introducing significant background noise into the pressure signals. After stabilization, increasing the impact pressure from 3.1 MPa to 11.2 MPa substantially boosted energy output, directly enhancing drilling speed, with ROP rising from 2.93 mm/s to 6.26 mm/s. In Fig. 8(b), the outer envelope of the displacement curve shows a steady upward trend, reflecting actual bit penetration into the rock.

Fig. 9 shows time-domain response curves of buffer and propulsion pressure, impact piston displacement, and velocity

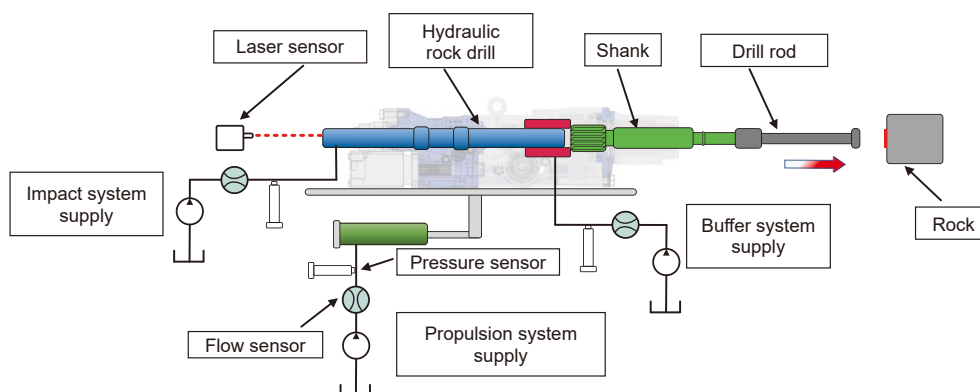


Fig. 6. Schematic diagram of the test system.

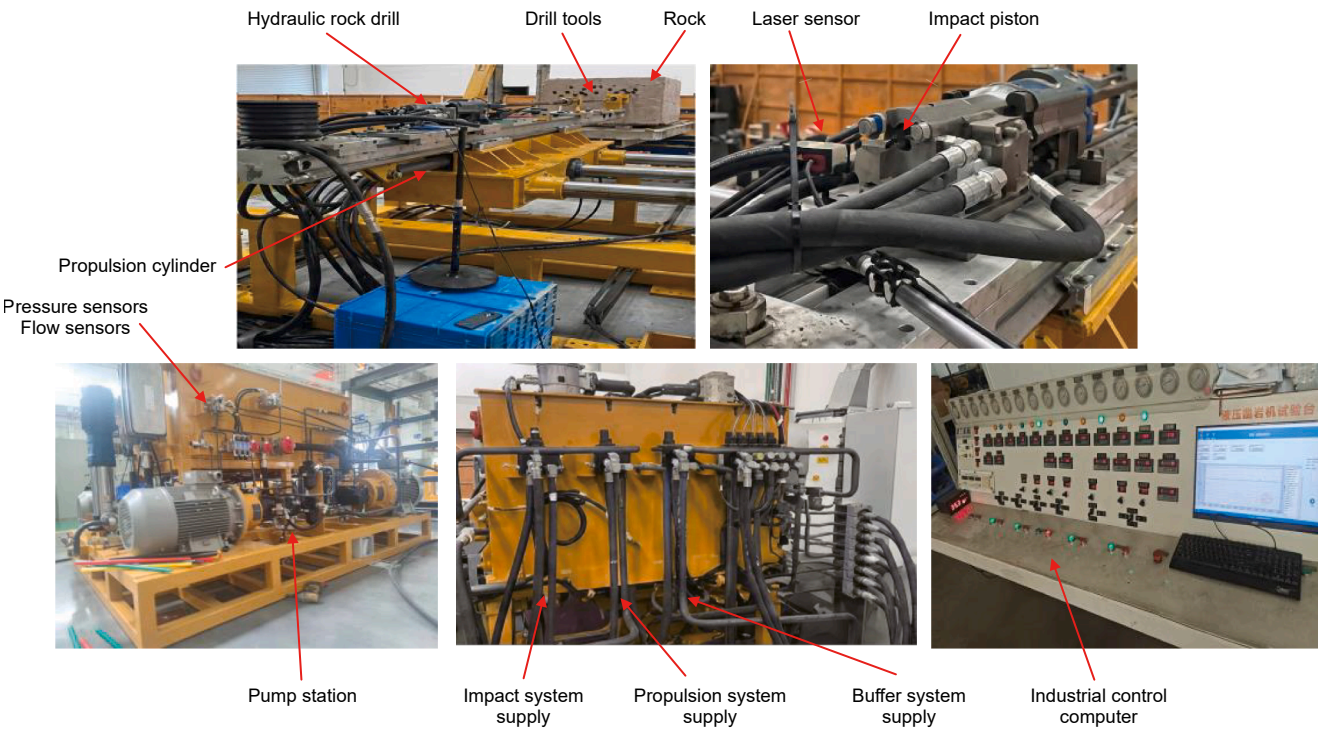


Fig. 7. On-site rock drilling experiment photograph.

Table 1
Parameters of the Epiroc COP1838 hydraulic rock drill.

Maximum output power of the impact system	Maximum input power of the impact system	Impact flow rate	Impact frequency	Application	Drilling diameter
19 kW	32 kW	45–90 L/min	40–65 Hz	Drilling in open-pit mining, quarries, and petroleum engineering	60–110 mm

Table 2
Experimental conditions.

Drilling depth	Data sampling frequency	Impact pressure P_{a1}	Propulsion pressure P_{a2}	Buffer pressure P_{a3}
1 m	10 kHz	7–22 MPa	3–9 MPa	3–9 MPa

under three impact pressures. Mean propulsion and buffer pressures are 5.78 MPa and 4.03 MPa, respectively. Under low pressure, severe fluctuations occur due to fragile balance between system dynamics and load damping. Low energy input barely exceeds the motion threshold, making the system highly sensitive to disturbances like load variations or backpressure fluctuations. As impact pressure increases, energy input

strengthens and pressure curves smooth, indicating improved dynamic stability.

The impact pressure curve shows intermittent peaks corresponding to drilling states. During drilling, the bit receives sudden impact energy and advances, reducing propulsion and buffer pressure. In non-drilling states, the tools rebound and reset, increasing these pressures. Displacement and velocity

Table 3
Rock characteristic parameters.

Index	Rock elastic modulus, GPa	Rock type	Uniaxial compressive strength, MPa	Cohesion, MPa	Internal friction angle, °	Measured parameters	Stiffness, kN/mm Average value
1	39.16	Sandstone	78.32	8–12	35–40	k_L	191.38
						k_U	390.11
2	42.14	Limestone	84.28	12–16	38–43	k_L	248.65
						k_U	422.43
3	51.08	Granite	102.16	15–20	35–40	k_L	300.74
						k_U	439.60

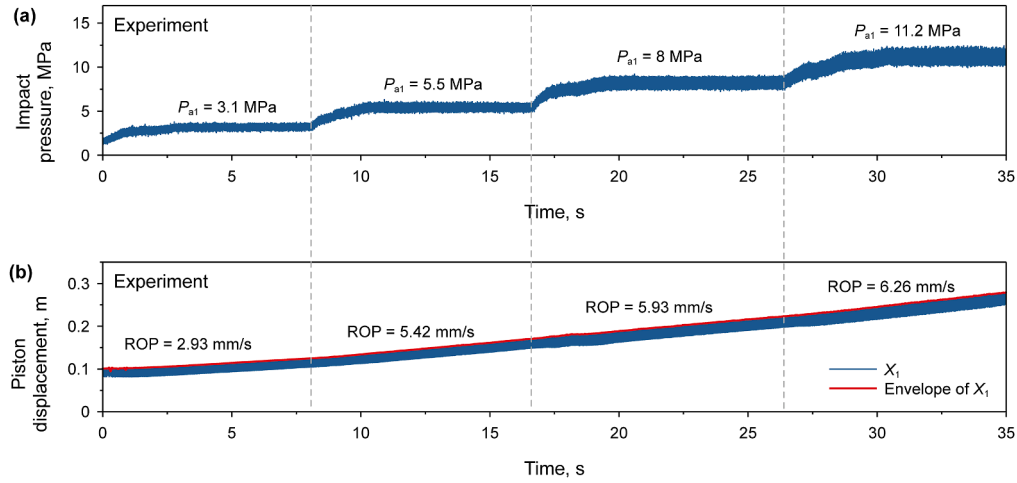


Fig. 8. Time-series diagrams of impact pressure and impact piston displacement. **(a)** Impact pressure time-series diagram; **(b)** impact piston displacement time-series diagram.

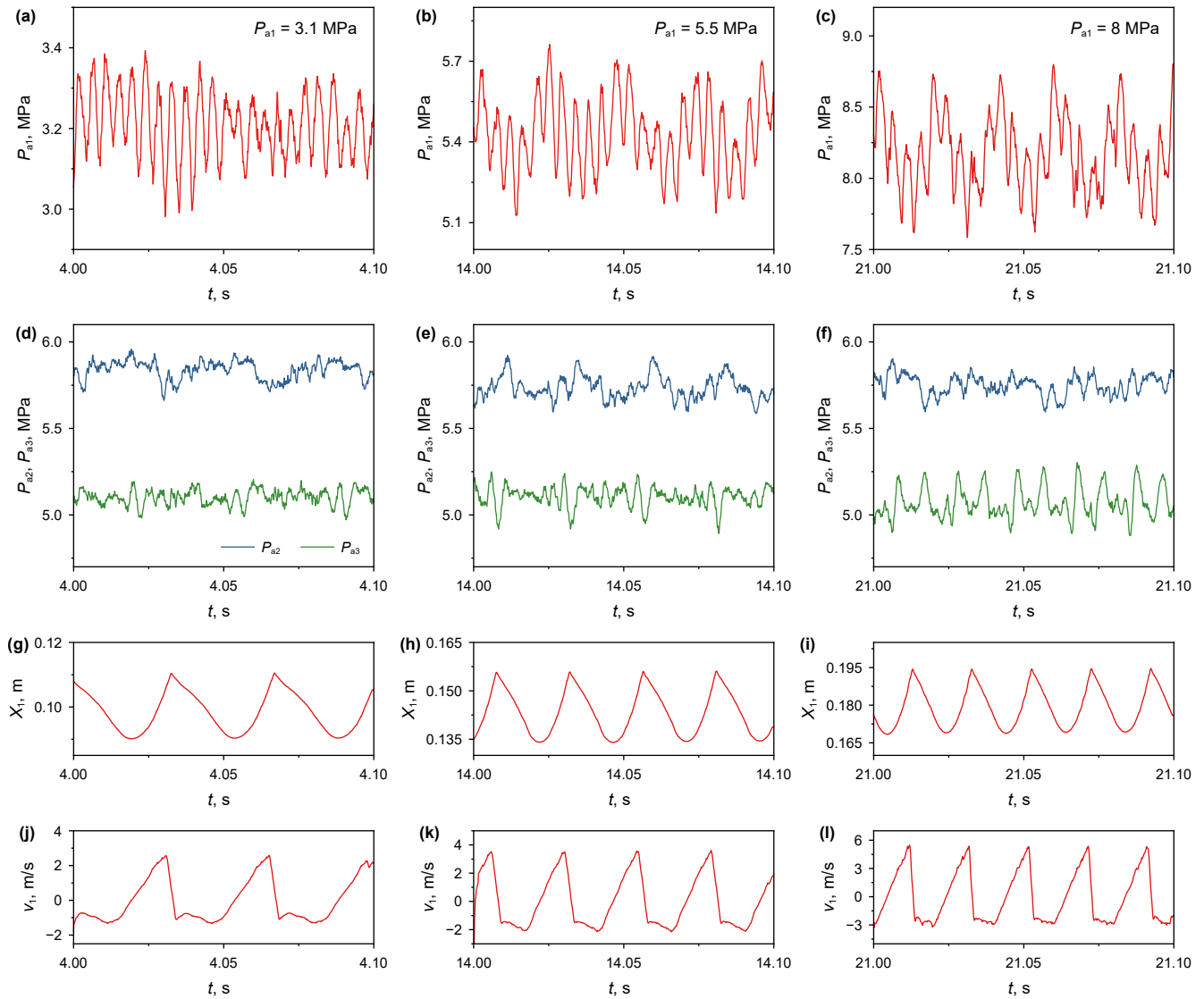


Fig. 9. Curves of propulsion pressure, buffer pressure, impact piston displacement, and velocity under various impact pressure conditions.

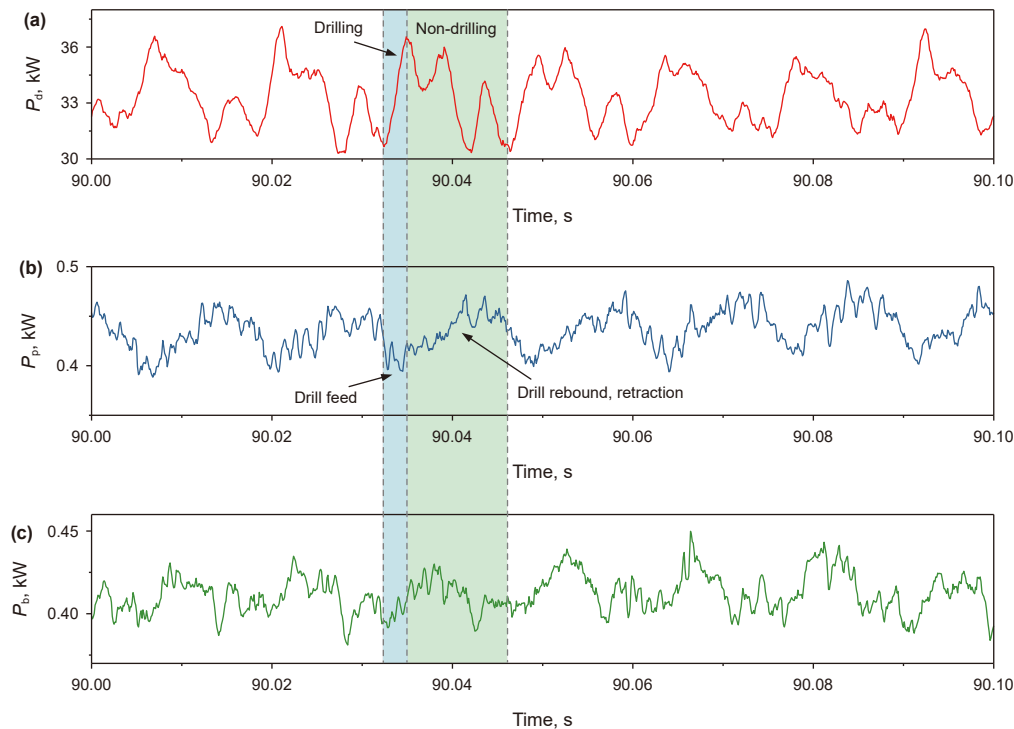


Fig. 10. Time-series diagram of input power for the impact, propulsion, and buffer systems. (a) Time history of impact power; (b) time history of propulsion power; (c) time history of buffer power.

curves indicate the impact piston maintains near-harmonic motion. Higher impact pressure increases impact energy, frequency, and piston stroke. Rigid impact occurs at peak velocity, followed by rebound and a complete cycle of return acceleration, return deceleration, and stroke acceleration. Fig. 10 shows power curves at 21 MPa impact pressure. All systems exhibit periodic fluctuations. The impact system dominates with peak power of 36.5 kW and a 6.1 kW range. Average propulsion and buffer power is only 0.43 kW. Blue and green shaded areas indicate drilling (17% of cycle) and non-drilling states. During drilling, the bit load increases, which boosts impact power while reducing the demand on propulsion and buffering. After rock fragmentation, the tool rebounds, causing impact power to decrease; propulsion and buffering power then rise to reset the system for the next cycle.

3.3. Effect of different system pressures on energy consumption

To further investigate the energy consumption mechanism during the rock drill's operation, the pressure parameters of the impact, propulsion, and buffer systems are adjusted through 15 sets of experiments, as shown in Table 4. To ensure accuracy under the influence of external disturbances, each working condition is repeated five times consecutively. For ease of energy consumption analysis, data from the interval where the cumulative drilling displacement reaches 1 m are selected. The input and output parameters in Tables 4 and 5 are presented as mean values. The “parameter combinations 1–15” are uniformly labeled as “C1–C15”.

The relationship between system energy consumption and each pressure parameter is analyzed as follows. For parameters C1–C5, as the impact pressure increases, both the ROP (Brenjkar

Table 4
Average input parameters in rock drilling experiments.

Index	Rock type	Impact pressure, MPa	Impact flow, L/min	Propulsion pressure, MPa	Propulsion flow, L/min	Buffer pressure, MPa	Buffer flow, L/min
1	Limestone	7.78	41.73	6.14	4.30	5.65	3.96
2	Limestone	13.10	66.29	6.14	4.30	5.65	3.96
3	Limestone	15.19	80.27	6.14	4.30	5.65	3.96
4	Limestone	19.22	82.18	6.14	4.30	5.65	3.96
5	Limestone	21.99	93.71	6.14	4.30	5.65	3.96
6	Limestone	10.31	47.25	4.59	3.21	5.55	3.89
7	Limestone	10.31	47.25	5.45	3.82	5.55	3.89
8	Limestone	10.31	47.25	6.58	4.61	5.55	3.89
9	Limestone	10.31	47.25	7.51	5.26	5.55	3.89
10	Limestone	10.31	47.25	9.24	6.47	5.55	3.89
11	Limestone	9.96	47.63	5.86	4.10	3.58	2.51
12	Limestone	9.96	47.63	5.86	4.10	4.14	2.90
13	Limestone	9.96	47.63	5.86	4.10	5.93	4.15
14	Limestone	9.96	47.63	5.86	4.10	6.39	4.47
15	Limestone	9.96	47.63	5.86	4.10	7.59	5.31

Table 5
Average output parameters in rock drilling experiments.

Index	ROP, mm/s	Operating time, s	Impact energy, J	Impact frequency, Hz	Impact output power at impact point, kW	Total EC, kJ	Impact efficiency, %
1	5.25	190.26	70.91	51.66	3.66	1181.54	58.94
2	12.08	82.80	101.55	62.70	6.37	1265.14	41.69
3	13.65	73.25	146.12	63.68	9.30	1546.29	44.05
4	18.90	52.90	150.68	65.05	9.80	1433.64	36.16
5	21.15	47.28	167.74	69.65	11.68	1664.84	33.19
6	8.52	117.43	85.08	56.93	4.84	1024.36	55.50
7	9.28	107.71	88.63	58.18	5.16	950.03	58.50
8	9.45	105.79	89.42	58.46	5.23	949.97	58.24
9	10.34	96.74	93.50	59.88	5.60	883.23	61.34
10	9.15	109.29	91.09	60.11	5.47	1036.07	57.72
11	3.67	272.48	62.69	49.10	3.08	2305.18	36.41
12	9.09	110.01	87.75	57.87	5.08	936.19	59.69
13	9.01	111.10	85.91	55.15	4.74	968.79	54.36
14	8.59	116.41	85.35	53.39	4.56	1022.08	51.94
15	7.59	131.75	75.39	51.19	3.86	1183.12	42.98

and Delijani, 2022) and energy consumption (EC) show a significant rise. The maximum and minimum ROP values differ by 15.9 mm/s, while the maximum and minimum EC values differ by 483.3 kJ. Since the impact system accounts for the largest proportion of total system power demand, EC increases noticeably. This reflects that higher impact energy enhances rock-breaking effectiveness but simultaneously accompanies greater power consumption. However, the output power of the impact system increases at a slower rate than its input power, causing the impact energy efficiency to drop from 58.94% to 33.19%.

For C6–C10, as propulsion pressure increases, energy consumption first decreases and then increases, with a maximum-minimum difference of 152.84 kJ. Insufficient propulsion

pressure fails to provide adequate preload, leading to bit detachment and idle drilling, which reduces the rate of penetration and wastes energy. Excessive propulsion pressure compresses the stroke of the buffer piston (Zhang et al., 2025b), impairing the buffering function and affecting tool reset, while dissipating impact energy and increasing energy consumption. For C11–C15, as buffer pressure increases, energy consumption first decreases and then increases, with a maximum-minimum difference of 1368.99 kJ. Excessively high buffer pressure, especially when it exceeds propulsion pressure, alters the impact point and increases the stroke of the impact piston, causing it to brake, thereby reducing energy transfer efficiency. If the pressure is too low, it hinders accumulator recharging and slows tool reset. Therefore,

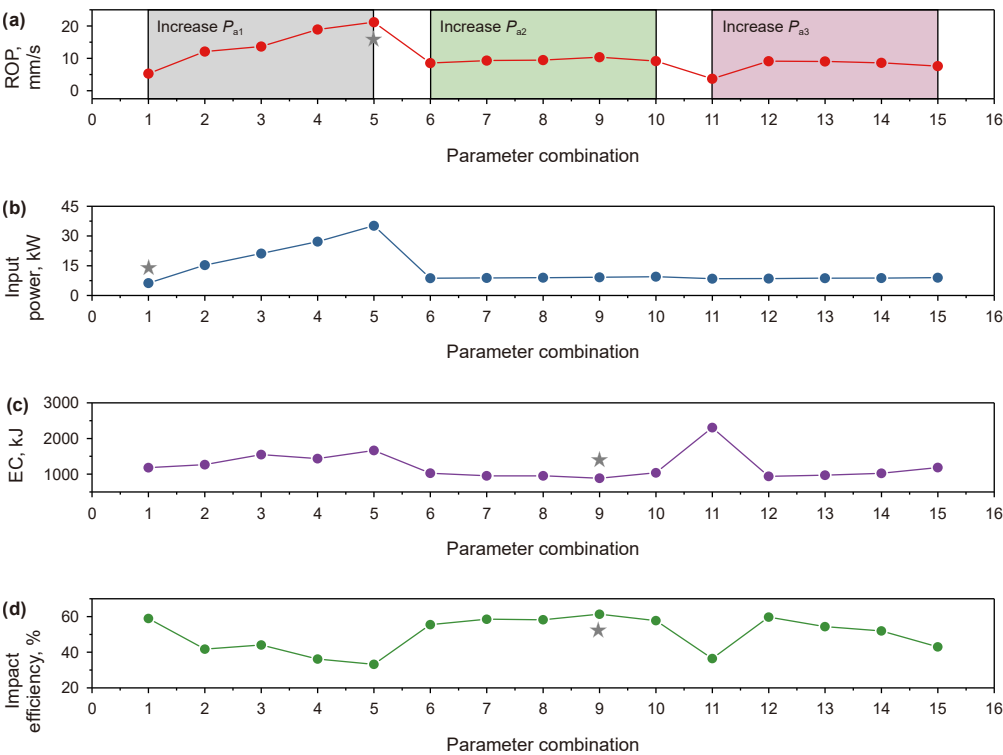


Fig. 11. Sequence line chart of energy parameters under different parameter combinations. (a) ROP sequence plot; (b) input power sequence plot; (c) EC sequence plot; (d) impact efficiency sequence plot.

maintaining an appropriate balance between propulsion pressure and buffer pressure is essential for achieving efficient rock breaking and energy optimization.

Fig. 11 presents the variation curves of ROP, input power, system EC, and impact energy efficiency across these 15 parameter combinations, revealing the following patterns: When system EC is at a relatively low level and impact energy efficiency is high, the system operates in a “moderate impact” state, where the matching among impact, propulsion, and buffer pressures is most effective, and the ROP typically falls within a medium range. This indicates that under conditions with favorable EC, although the system does not achieve the maximum drilling speed, it attains a good balance between energy utilization and cost-effectiveness.

Low input power (Sheng et al., 2026) reduces impact pressure and ROP while extending drilling cycles, but minimizes drill tool wear—ideal when tool longevity is prioritized. The highest ROP combination uses high impact pressure but achieves the lowest energy efficiency, increasing ROP at the expense of conversion efficiency and accelerated tool wear, potentially compromising long-term reliability and cost-effectiveness. Combination C5 achieves maximum ROP, suitable for efficiency-priority conditions. Combination C9 balances low energy consumption with highest impact energy efficiency, performing (Chang et al., 2025) optimally for energy economy. Combination C1 has minimum input power, suited for wear-sensitive operations with low ROP requirements.

3.4. Multi-perspective visualization study

Based on 15 parameter combinations, Fig. 12(a) shows the power proportion distribution among impact, propulsion, and buffer systems. The impact system dominates under all combinations, consistently accounting for 85%–98% of total power, indicating most energy is consumed for impact work. The propulsion system accounts for 1%–11%, primarily maintaining bit-rock contact and providing thrust. The buffer system fluctuates between 1% and 7.5%, absorbing recoil vibration—small in share but critical for stability. Fig. 12(b) compares impact system input power during drilling and non-drilling states. Drilling state power demand is significantly higher (Zhang et al., 2025a), approximately 1.1 times that of non-drilling. The largest power difference occurs between combinations C1 and C5, reaching 31.83 kW.

Given the core function of the impact system, and to more intuitively display its energy utilization rate under different parameter conditions, this study presents a ring chart in Fig. 13, which reflects the impact energy efficiency across all 15 parameter combinations. As the impact pressure increases, the impact energy efficiency generally shows a declining trend. This indicates that although simply increasing the impact energy input can enhance rock-breaking intensity, the energy conversion efficiency actually decreases, with some energy dissipated in other forms during the transmission process. The energy efficiency first rises and then falls as the propulsion pressure increases, exhibiting an optimal range. Excessively low propulsion pressure leads to poor contact between the drill bit and the rock surface. Similarly, energy efficiency shows an initial increase followed by a decrease as the buffer pressure rises. Appropriate buffer pressure helps stabilize the resetting and impact processes of the drill tools.

Impact pressure and buffer pressure significantly affect system energy efficiency. Among all combinations, C9 achieves the highest efficiency (61.34%) with well-matched pressures, while C5 has the lowest (33.19%) due to high impact pressure and poor buffer matching—a 28.15% efficiency gap. Fig. 14 shows EC and impact energy efficiency across combinations, revealing working time and ROP as key influencing factors. C11 has the highest EC (2305.18 kJ) with low efficiency, corresponding to the smallest ROP and longest working time—excessively low buffer pressure slows tool reset and increases losses. C9 achieves the lowest EC (883.23 kJ) with well-matched pressures and reasonable ROP, demonstrating good energy economy. The EC difference between maximum and minimum is 1421.95 kJ, with a corresponding efficiency difference of 24.93%. Thus, working time critically influences EC—appropriate duration controls energy consumption and enhances efficiency, while excessive time significantly increases losses.

The working time, input power, and EC parameters are summarized, and their correlations are studied and visualized in energy bubble charts, as shown in Fig. 15. In Fig. 15(a), (b), and (c), the horizontal and vertical axes represent working time and input power, respectively, with the bubble area indicating EC. In Fig. 15(d), (e), and (f), the horizontal and vertical axes represent input power and EC, respectively, with the bubble area representing working time. When the impact pressure is varied, drilling work shows a negative correlation with input power and also with EC, while input power and EC exhibit a positive correlation.

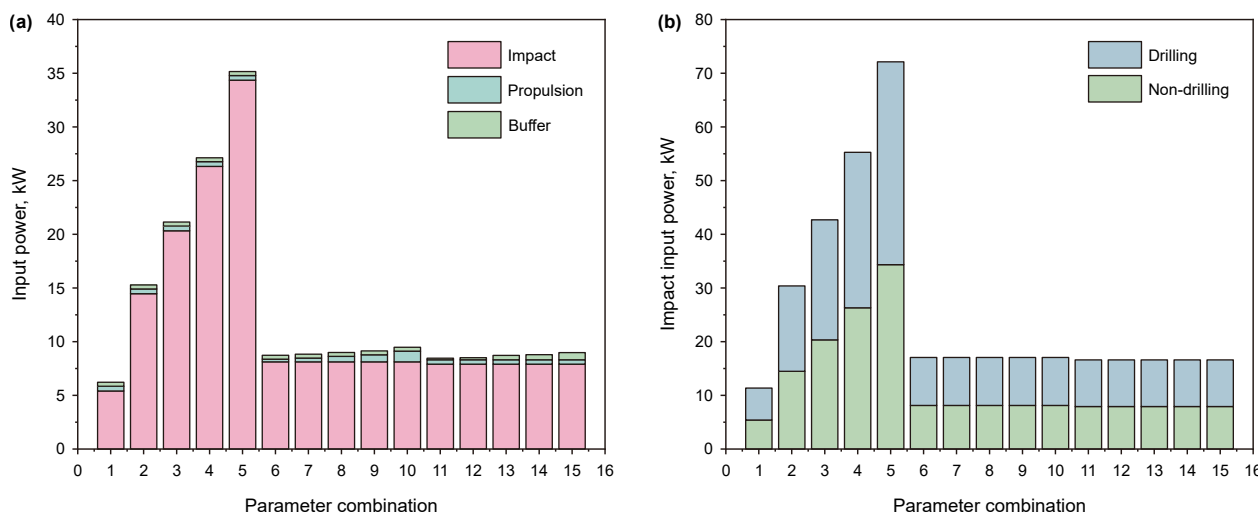


Fig. 12. Histogram of power distribution during the drilling process. (a) Histogram of input power distribution by system; (b) histogram of power allocation in the impact system for drilling and non-drilling states.

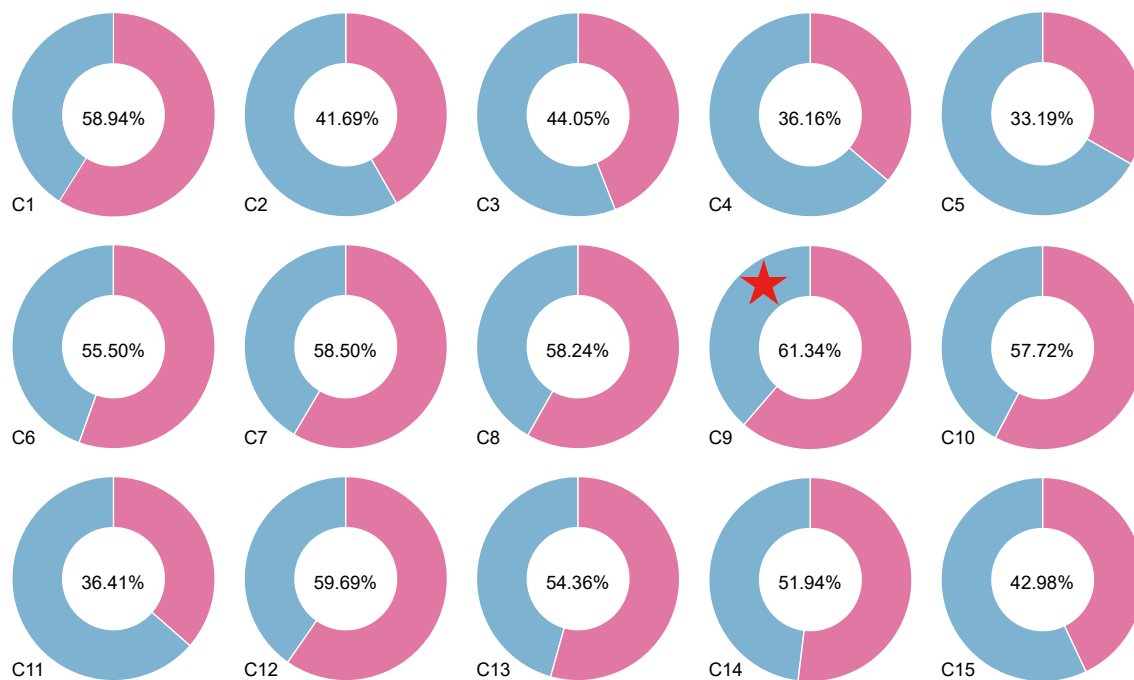


Fig. 13. Ring chart of impact energy efficiency across parameter combinations.

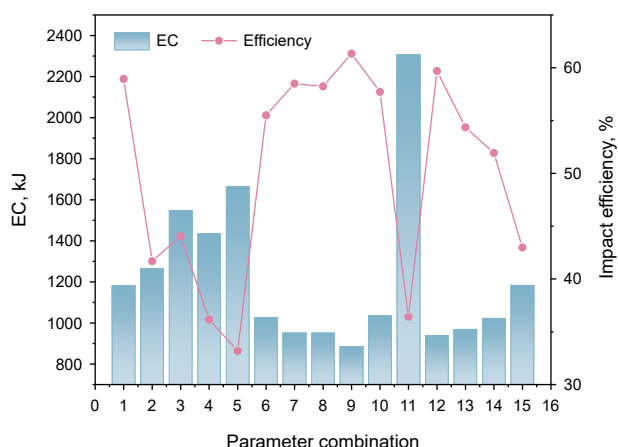


Fig. 14. Comparative histogram of energy consumption and impact energy efficiency.

Changes in propulsion pressure have little effect on EC. Increasing buffer pressure results in a positive correlation between working time and EC. Among these, four parameter sets exhibit notable characteristics: EC for parameter C5 is 483.3 kJ higher than that for C1; EC for parameter C15 is 1122.06 kJ lower than that for C11; working time for parameter C1 is 142.98 s longer than for C5; and working time for parameter C11 is 140.73 s longer than for C15. Impact pressure is the core factor influencing EC and efficiency. Increasing it raises input power but shortens working time and improves rock-breaking, typically reducing EC. Propulsion pressure affects drilling stability, with minor impact on total power and EC—its main role is preventing bit bounce, slightly optimizing working time. Buffer pressure plays an indirect but critical role: though its power share is small, excessively low pressure increases vibration and slows resetting, significantly prolonging working time and raising EC. Thus, buffer pressure is a key variable for energy-saving control.

The multi-perspective energy visualization analysis above indicates that drilling time, input power, and EC are all directly influenced by the input parameters of the rock-drilling system. By analyzing the energy transfer pathways during the drilling process and collaboratively regulating the working parameters, the goal of high energy efficiency and low-carbon-emission drilling can be achieved (Zhao et al., 2025b). Data in Table 5 show that under the condition of drilling 1 m in depth, the largest energy-consumption difference occurs between parameters C9 and C11, reaching 1421.95 kJ. To explore its economic implications, the operational costs of these two parameters under different electricity-price periods in complex working conditions are further compared, as presented in Table 6. The analysis shows that parameter combination C9 minimizes electricity costs during all price periods—peak, normal, and off-peak—while delivering a moderate ROP and the highest impact energy efficiency. In a drilling scenario involving a depth of 4 m and 170 blast holes, the difference in drilling time between parameters C9 and C11 is 33.2 h, and the total energy-consumption difference is 9.69×10^5 kJ. Under peak electricity prices, the cost difference can reach 287.47 RMB, and choosing parameter C9 can save 71.87 RMB per meter of drilling cost. This indicates that by reasonably adjusting the system pressure parameters, it is possible not only to improve drilling efficiency and reduce energy consumption, but also to significantly lower operational costs.

3.5. Effect of different rock types on energy consumption

To investigate the effects of different drilling pressure combinations on the ROP, EC, and impact energy efficiency in sandstone, limestone, and granite, a series of experiments are conducted. Based on the minimum and maximum pressure specifications of the rock drill, the impact, propulsion, and buffer pressures are systematically varied, with 45 tests performed for each rock type. The experimental conditions are presented in Table 7.

Fig. 16 illustrates the effects of impact pressure on drilling parameters. Based on the experimental data, for weak, highly porous,

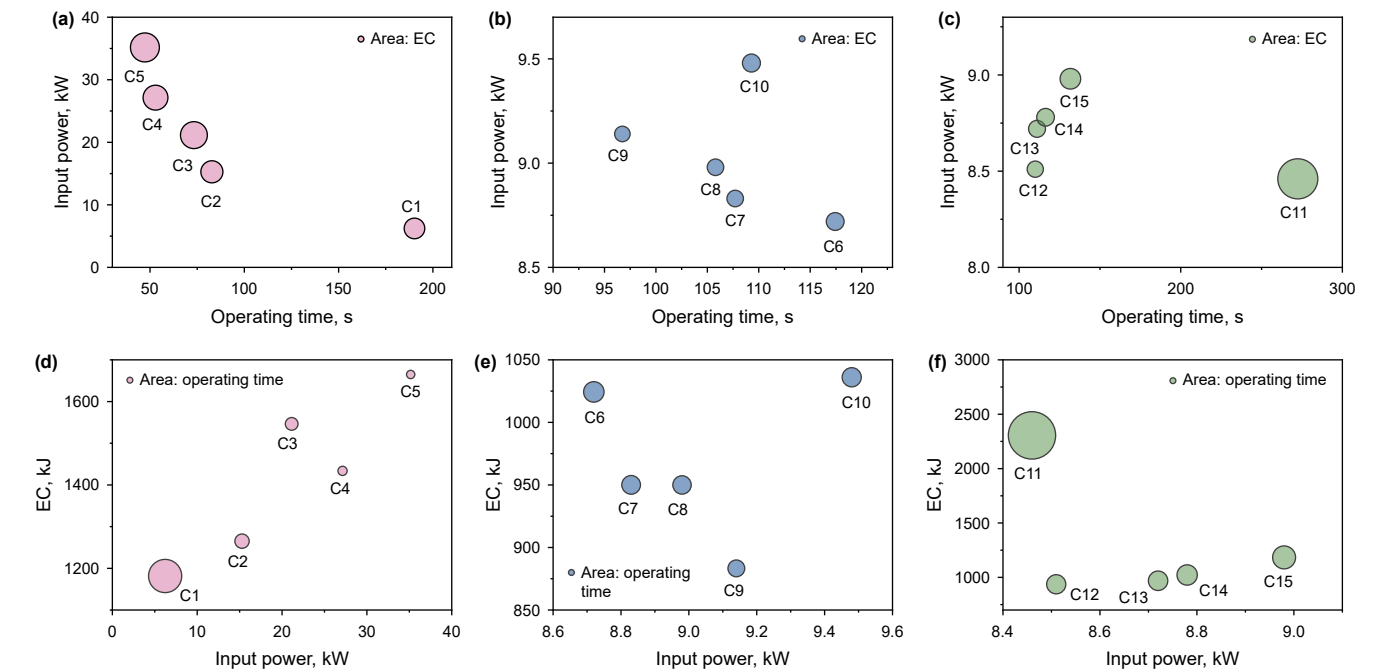


Fig. 15. Bubble charts illustrating the influence among different energy parameters.

Table 6
Cost prediction for the rock drilling process.

Parameter combination	Rock type	Borehole area, m ²	Number of boreholes	Drilling depth, m	Total time, h	Total EC, kJ	Electricity cost, RMB	Electricity tariff, RMB/kW·h
C9	Limestone	100	170	4	18.27	6.01×10^5	178.54	Peak period 1.07
C9	Limestone	100	170	4	18.27	6.01×10^5	106.77	Normal period 0.64
C9	Limestone	100	170	4	18.27	6.01×10^5	55.05	Off-peak period 0.33
C11	Limestone	100	170	4	51.47	1.57×10^6	466.01	Peak period 1.07
C11	Limestone	100	170	4	51.47	1.57×10^6	278.67	Normal period 0.64
C11	Limestone	100	170	4	51.47	1.57×10^6	143.69	Off-peak period 0.33

Table 7
Experimental conditions.

Index	Impact pressure, MPa	Impact flow, L/min	Propulsion pressure, MPa	Propulsion flow, L/min	Buffer pressure, MPa	Buffer flow, L/min
1	7–21, interval 1	38.88–90.12	6.14	4.30	5.65	3.96
2	10.31	47.25	3–10, interval 0.5	2.45–7.01	5.55	3.89
3	9.96	47.63	5.86	4.10	2.5–9.5, interval 0.5	1.75–6.64

elastic-brittle rocks such as sandstone, the fragmentation threshold is low. In the initial stage of increasing impact pressure, the ROP increases rapidly, and the EC is at its lowest, demonstrating favorable energy response characteristics. The maximum energy efficiency can reach 72%. However, once the pressure exceeds 17 MPa, the ROP growth stagnates, stabilizing at 24.8 mm/s. Meanwhile, the EC continues to increase, and the energy efficiency gradually declines, with the excess energy being consumed by the over-crushing of rock cuttings. Among the three rock types, sandstone exhibits the highest ROP, the lowest EC, and the best energy efficiency.

Limestone, a medium-hard rock with a certain degree of plasticity and moderate impedance, shows a continuous increase in ROP and a decrease in EC within the low-to-medium impact pressure range, leading to improved energy efficiency. In the high-pressure range, however, increased energy dissipation due to

plastic deformation results in reduced energy efficiency. Hard, dense granite, characterized by high fracture toughness and high wave impedance, exhibits a distinct threshold effect. When the impact pressure is below 11 MPa, the energy is dissipated through elastic deformation, resulting in a slow ROP and increasing EC, with the maximum EC reaching 3212.6 kJ. Once the pressure threshold is exceeded, the stress wave drives unstable crack propagation, causing the ROP to surge. Concurrently, the fragmentation mode transitions from plastic dissipation to brittle fracture, leading to a reduction in EC.

Fig. 17 shows propulsion pressure effects on drilling parameters. For sandstone, ROP increases rapidly at low-to-medium pressure while EC remains low, achieving peak efficiency of 62.3%—attributed to high porosity enabling rapid crack propagation with optimal weight-on-bit. Excess pressure causes over-penetration, hindering cuttings removal and increasing bit wear,

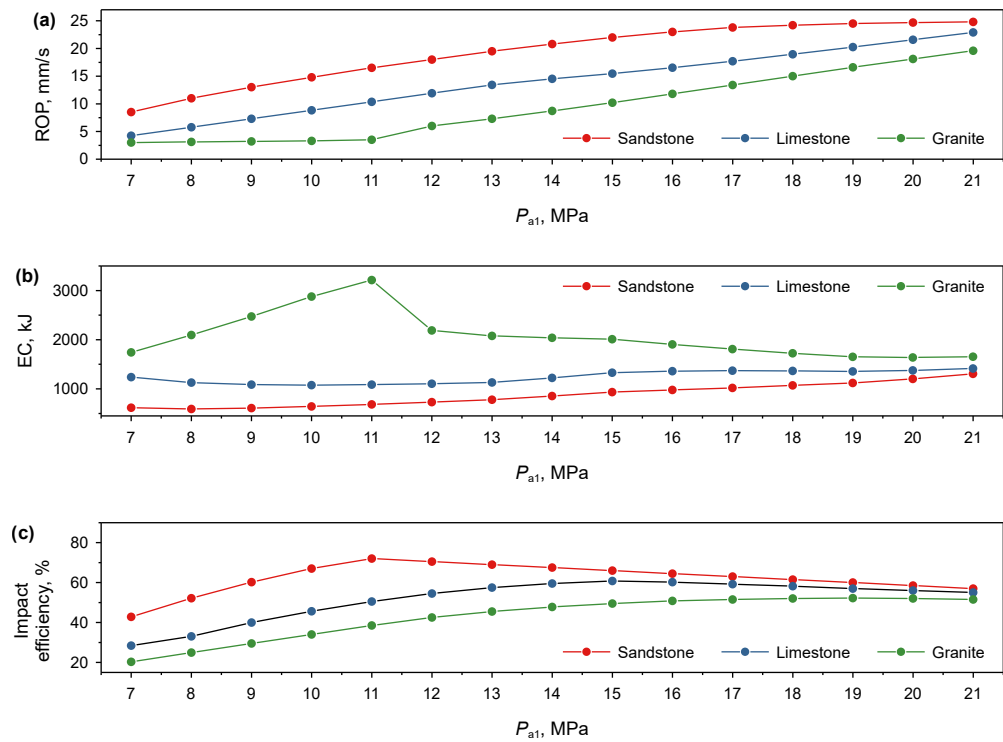


Fig. 16. Effects of varying impact pressure on ROP, EC, and impact energy efficiency during the drilling of three rock types. (a) Variation in ROP; (b) variation in EC; (c) variation in impact energy efficiency.

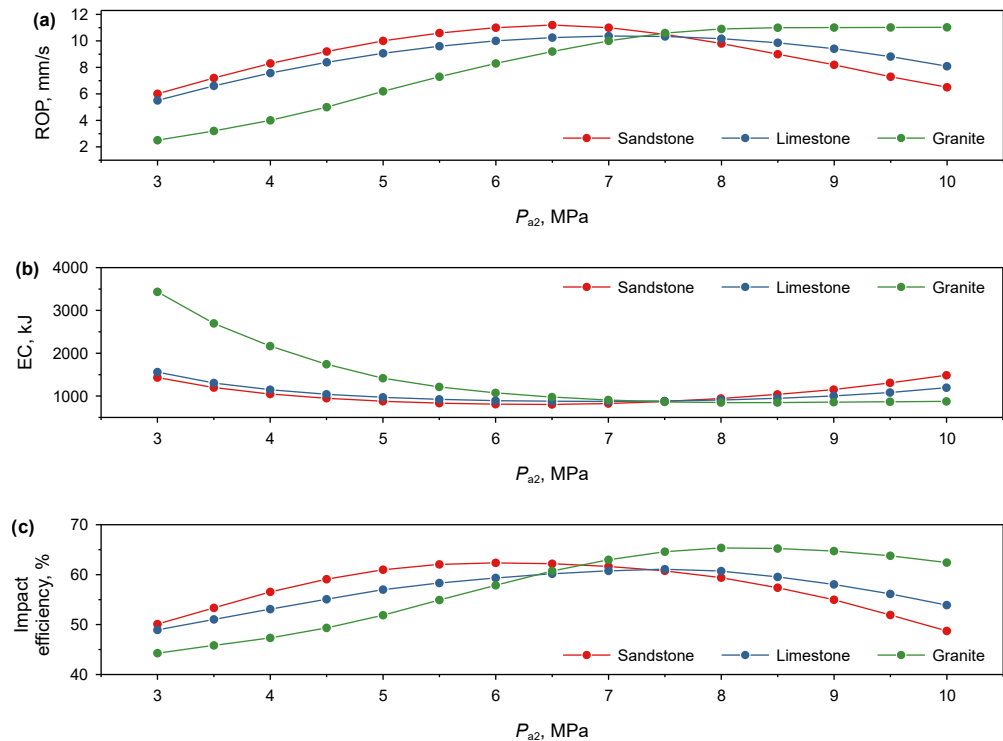


Fig. 17. Effects of varying propulsion pressure on ROP, EC, and impact energy efficiency during the drilling of three rock types. (a) Variation in ROP; (b) variation in EC; (c) variation in impact energy efficiency.

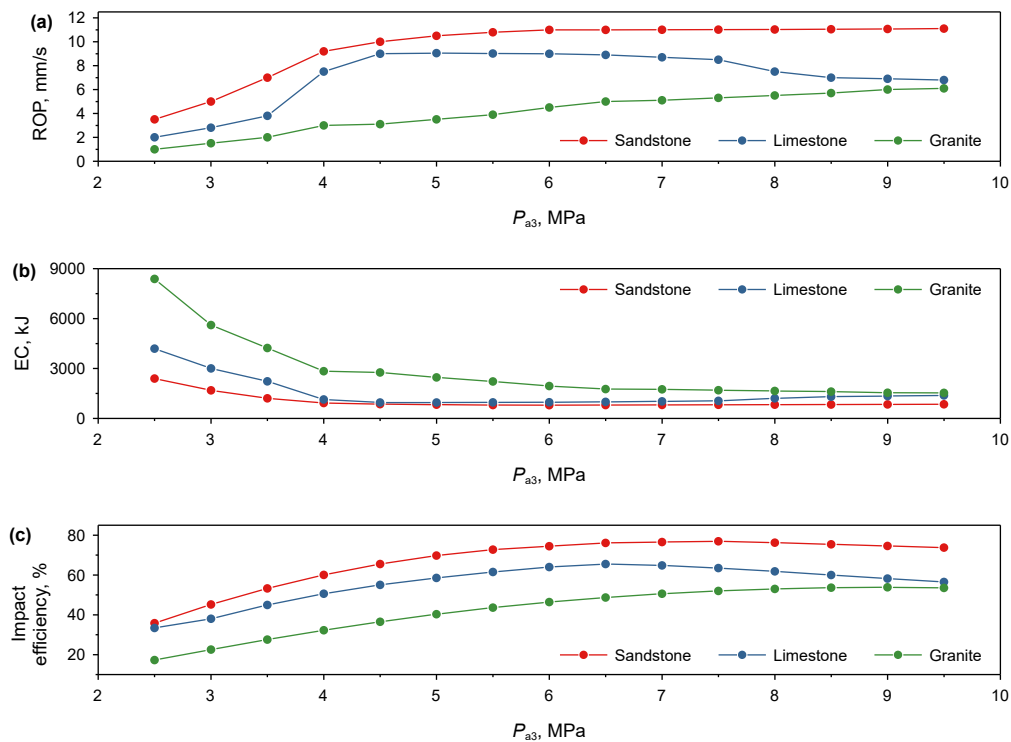


Fig. 18. Effects of varying buffer pressure on ROP, EC, and impact energy efficiency during the drilling of three rock types. (a) Variation in ROP; (b) variation in EC; (c) variation in impact energy efficiency.

dissipating energy through over-crushing and friction, reducing efficiency. Limestone behaves similarly. For granite (high hardness), low pressure causes idle impacts due to bit rebound. As pressure increases, ROP continuously rises and EC declines. In the high-pressure range, granite achieves maximum ROP (11.03 mm/s), minimum EC (874.6 kJ), and highest efficiency—demonstrating high sensitivity to propulsion force.

Fig. 18 shows buffer pressure effects on drilling parameters. For sandstone, ROP and efficiency increase with pressure, while EC decreases—stabilizing above 5 MPa at 11.1 mm/s and 842.8 kJ. Appropriate pressure absorbs rebound energy and reduces vibration; low pressure fails to suppress bit rebound. For limestone, ROP and efficiency first increase then decrease, indicating an optimal pressure range—excessively high pressure accelerates bit wear. For granite, ROP and efficiency continuously rise, and EC declines, due to high hardness and wave impedance causing strong rebound energy. Low pressure prevents proper resetting, wasting impact energy; higher pressure improves performance. In summary, sandstone and limestone have optimal pressure thresholds requiring controlled windows to avoid excess energy. Granite exhibits a threshold effect—pressure provides monotonic benefits, requiring high-pressure operation for effective drilling.

4. Prediction of energy consumption parameters

4.1. Physical model

Before conducting the comparison between the physical model and experiments, a sensitivity study of the model parameters is required. Five structural parameters of the impact system are selected as design variables, including the impact piston damping c_1 , the pipeline diameter d_p , the impact piston mass m_1 , the inner diameter at the rear end of the piston d_{1b} , and the inner diameter at the front end of the piston d_{2b} . The initial values and boundary conditions of these parameters are listed in Table 8. An improved Latin hypercube sampling algorithm combined with a descriptive sampling strategy is adopted to generate 100 parameter combinations within the five-dimensional design space. Numerical simulations are carried out for each parameter combination to calculate the total stroke, a parameter that directly affects drilling efficiency and energy consumption.

The simulation conditions correspond to parameter combination C5 in Table 4. A Pareto chart is generated, as shown in Fig. 19, which allows for a comparison of the contribution rates of each parameter to the total stroke. Among the individual parameters, d_{1b} and d_{2b} have the most significant influence on the stroke, with

Table 8
Initial values and optimization ranges of structural parameters.

Structural parameters	Initial values	Lower bound	Upper bound
Axial motion damping of the impact piston c_1 , N-s/m	1000	300	15000
Pipeline diameter d_p , m	0.01	0.005	0.03
Impact piston mass m_1 , kg	5	4.5	5.9
Inner diameter at the rear end of the impact piston d_{1b} , m	0.037	0.021	0.04
Inner diameter at the front end of the impact piston d_{2b} , m	0.041	0.021	0.042

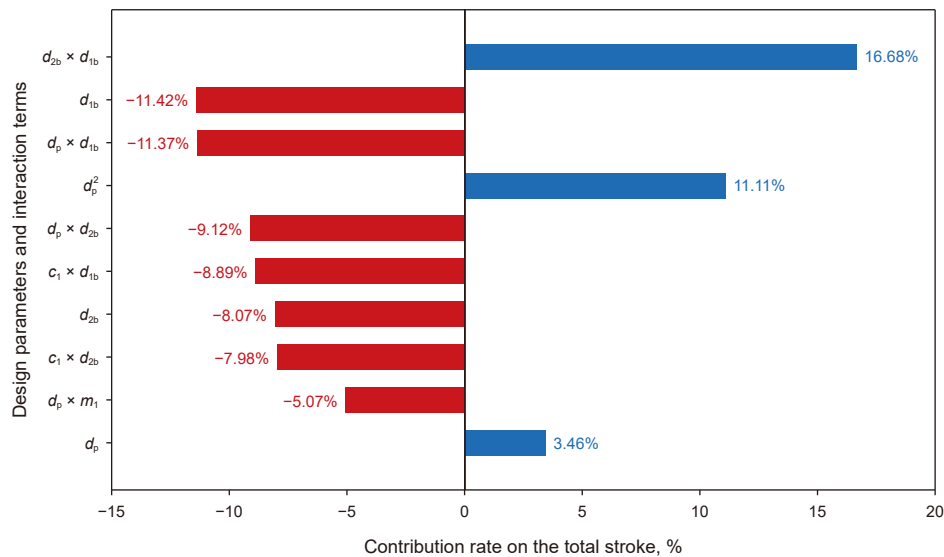


Fig. 19. Pareto chart of contribution rates of design variables to total stroke.

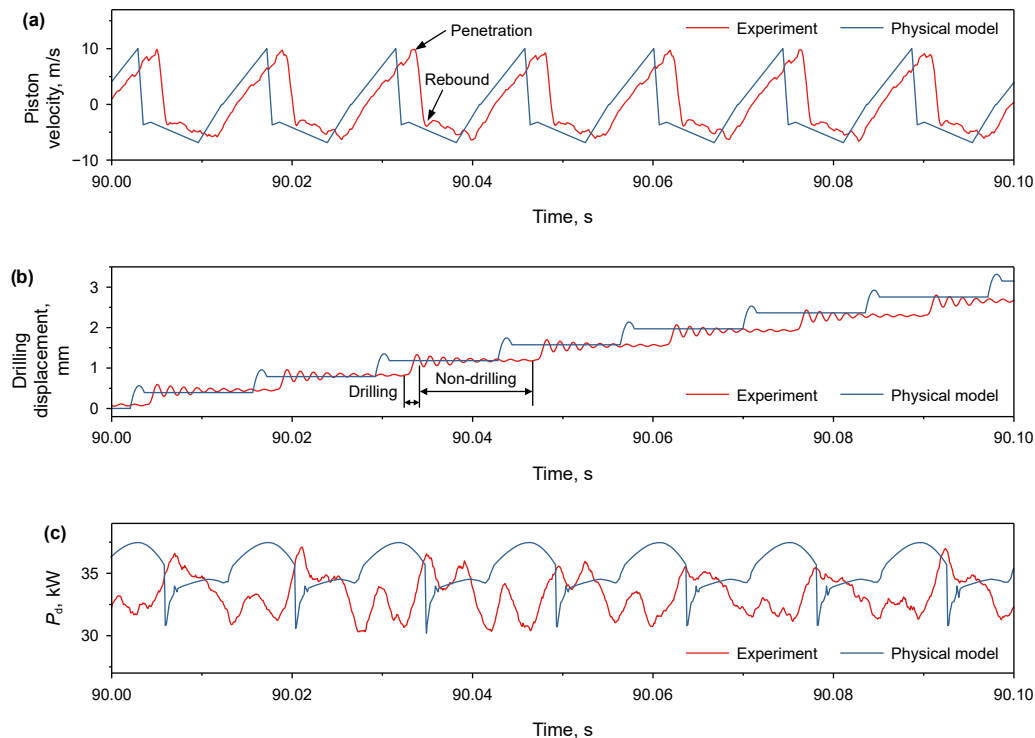


Fig. 20. Comparison between the physical simulation model and experimental data. (a) Comparative plot of impact piston velocity; (b) comparative plot of drilling displacement; (c) comparative plot of impact input power.

contribution rates of -11.42% and -8.07% , respectively, both exhibiting a negative correlation. This is followed by d_p , with a contribution rate of 3.46% , showing a positive correlation. Regarding interaction effects, the interaction between d_{1b} and d_{2b} exhibits the largest contribution rate, reaching 16.68% , followed by the interaction between d_p and d_{1b} , with a contribution rate of -11.37% . When d_{1b} and d_{2b} are increased simultaneously, their combined effect on the stroke demonstrates a positive correlation, which differs from their individual effects. Individually increasing the diameter of a single chamber primarily affects the pressure-

acting area or the return flow on that side, thereby locally altering the piston motion velocity. However, when both chamber diameters are increased synchronously, they collectively reshape the overall force balance under the differential connection by modifying the matching relationship of the pressure-acting areas on both ends of the piston. Consequently, under interactive effects, d_{1b} and d_{2b} produce a superimposed enhancement on the stroke, manifested as a significant positive correlation.

To validate the physical model based on drilling dynamics theory, simulation and experimental data are compared in Fig. 20.

Impact input power P_d consists of drilling power P_{d1} and non-drilling power P_{d2} . Fig. 20(a) shows the piston's three-stage motion during non-drilling and velocity peaking during drilling before rapid rebound. Fig. 20(b) reveals stepwise displacement increases—rising during drilling, stable otherwise—confirming intermittent energy transmission. Fig. 20(c) shows input power rising significantly during drilling, corresponding to high-speed impact. Simulated and experimental power curves show consistent trends, validating the model's ability to capture dynamic characteristics. At 1 m displacement, prediction errors are: impact efficiency 3.66%, ROP 4.01%, and EC 8.49%. These errors stem from simplifications in stress wave and friction loss considerations but remain acceptable. Overall, the model demonstrates good reliability for energy consumption prediction.

4.2. SCA-LSSVM data-driven model

Data-driven modeling effectively captures uncertainties like drilling environments. The SVM algorithm, known for global optimality and strong generalization with small samples, is widely used in classification and regression. It maps input space to high-dimensional feature space via nonlinear transformation to find an optimal hyperplane. Based on statistical learning theory and structural risk minimization, SVM ensures global optima through convex quadratic programming, avoiding local optima issues common in neural networks. However, SVM suffers from high computational complexity. LSSVM (Ahmadi and Bahadori, 2015) improves upon SVM by replacing quadratic programming with linear equations, significantly reducing complexity and enhancing practical applicability.

LSSVM is used for nonlinear function estimation, as shown in Eq. (20). Given a training set $\{x_k, y_k\}, k = 1, 2, \dots, N$, where $x_k \in \mathbb{R}^n$ is the k -th input data point, $y_k \in \mathbb{R}$ is the output value corresponding to the given specific input variable value x_k , and N is the number of training samples. Using a nonlinear mapping function $\phi(\cdot)$ that transforms the training set from the input space into a high-dimensional feature space, the following regression model is constructed.

$$y = \mathbf{w}^T \phi(x) + b \quad (20)$$

Here, $\mathbf{w} \in \mathbb{R}^{n_h}$, $b \in \mathbb{R}$, and $\phi(\cdot) \in \mathbb{R}^n \rightarrow \mathbb{R}^{n_h}$. $\mathbf{w}$ represents the weight vector, b is the bias term, n denotes the dimension of the input data space, and n_h indicates the dimension of the high-dimensional feature space after mapping. When applying LSSVM, a new optimization problem is formulated. The adopted method addresses the following optimization problem.

$$\min_{\mathbf{w}, b, e} J(\mathbf{w}, e) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} \gamma \sum_{k=1}^N e_k^2 \quad (21)$$

Subject to the following equality constraints.

$$y_k = \mathbf{w}^T \phi(\mathbf{x}_k) + b + e_k \quad (22)$$

Here, γ is the regularization parameter used to balance model complexity and training error, while e_k denotes the regression error. The following Lagrange function is constructed to obtain the solution of the constrained optimization problem.

$$L(\mathbf{w}, b, e, \alpha) = J(\mathbf{w}, e) - \sum_{k=1}^N \alpha_k \left\{ \mathbf{w}^T \phi(\mathbf{x}_k) + b + e_k - y_k \right\} \quad (23)$$

Here, α_k represents the Lagrange multiplier. To obtain the solution of the above equations, partial derivatives are taken with respect to $\mathbf{w}$, b , e_k , and α_k , as shown in Eqs. (24)–(27).

$$\frac{\partial L(\mathbf{w}, b, e, \alpha)}{\partial \mathbf{w}} = 0 \rightarrow \mathbf{w} = \sum_{k=1}^N \alpha_k \phi(\mathbf{x}_k) \quad (24)$$

$$\frac{\partial L(\mathbf{w}, b, e, \alpha)}{\partial b} = 0 \rightarrow \sum_{k=1}^N \alpha_k = 0 \quad (25)$$

$$\frac{\partial L(\mathbf{w}, b, e, \alpha)}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k \quad (26)$$

$$\frac{\partial L(\mathbf{w}, b, e, \alpha)}{\partial \alpha_k} = 0 \rightarrow y_k = \phi(\mathbf{x}_k) \mathbf{w}^T + b + e_k \quad (27)$$

After eliminating the variables $\mathbf{w}$ and e , the following Kuhn–Tucker system is obtained.

$$\begin{bmatrix} \mathbf{0} & \mathbf{1}_v^T \\ \mathbf{1}_v & \Omega + \gamma^{-1} \mathbf{I} \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \quad (28)$$

Here, $\mathbf{y} = [y_1 \dots y_N]^T$, $\mathbf{1}_v = [1 \dots 1]^T$ and $\alpha = [\alpha_1 \dots \alpha_N]^T$. $\mathbf{I}$ denotes the identity matrix, $\Omega_{kl} = \phi(\mathbf{x}_k)^T \phi(\mathbf{x}_l) = K(\mathbf{x}_k, \mathbf{x}_l) \forall k, l = 1, \dots, N$, and $K(\mathbf{x}_k, \mathbf{x}_l)$ is the kernel function, which must satisfy Mercer's condition. Eq. (29) corresponds to the linear kernel, Eq. (30) to the polynomial kernel, and Eq. (31) to the radial basis function (RBF) kernel. The function estimate of the LSSVM model is given in Eq. (32).

$$K(x, x_k) = x_k^T x \quad (29)$$

$$K(x, x_k) = (\tau + x_k^T x)^d \quad (30)$$

$$K(x, x_k) = \exp\left(-\|x - x_k\|^2 / \sigma^2\right) \quad (31)$$

$$y(\mathbf{x}) = \sum_{k=1}^N \alpha_k K(\mathbf{x}, \mathbf{x}_k) + b \quad (32)$$

Here, (b, α) represents the solution to the linear system. Considering that the parameters σ and γ significantly affect the learning and generalization capabilities of the LSSVM model, optimizing these two parameters is essential for improving the model's predictive performance. The Sine Cosine Algorithm (SCA) is a meta-heuristic optimization method inspired by trigonometric functions, valued for its reasonable runtime, fast convergence, and effectiveness across domains. Using population-based search (Chen et al., 2025), it initializes random solutions and iteratively improves them via objective functions. While stochastic methods don't guarantee rapid optimal solutions, sufficient initial solutions and iterations increase the probability of finding the global optimum. Population-based algorithms require generating multiple solutions per iteration and balancing exploration (discovering new regions) with exploitation (refining around good solutions). In the SCA (Muniappan et al., 2023), the position is updated using the following mathematical form Eqs. (33) and (34) correspond to two distinct phases.

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t| \quad (33)$$

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_i^t| \quad (34)$$

Here, X_i^t represents the position of the current solution in the i -th dimension at iteration t , r_1 , r_2 , r_3 are random numbers, P_i denotes the position of the destination point in the i -th dimension,

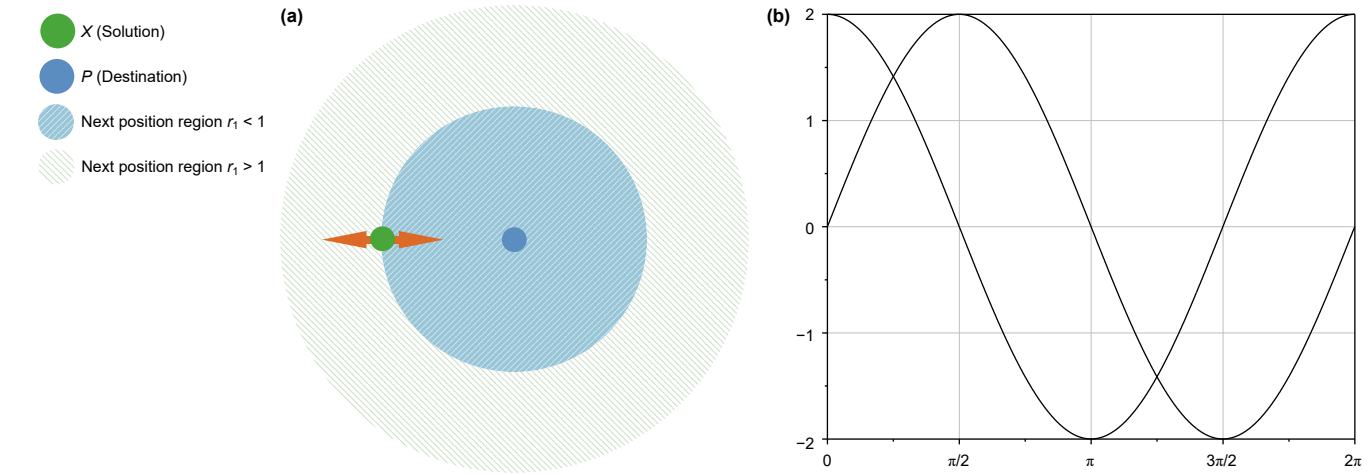


Fig. 21. Core mechanisms and parameter control of the sine cosine algorithm. (a) Schematic diagram of the sine-cosine mechanism for movement in search space; (b) schematic diagram of dynamic search range adjustment based on parameter r_1 .

and $|\cdot|$ indicates the absolute value. These two equations can be combined into the following formula.

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 < 0.5 \\ X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 \geq 0.5 \end{cases} \quad (35)$$

Here, r_4 is a random number in the interval $[0,1]$. SCA's optimization is regulated by four key parameters: r_1 controls position update direction (search between current solution and target or beyond); r_2 defines step size toward target; r_3 assigns random weight to target influence; r_4 switches with equal probability between sine and cosine modes. This design enables flexible balance between local exploitation and global exploration. The algorithm's core mechanism utilizes the periodicity of sine and cosine functions. During the exploitation phase, periodic fluctuations enable fine-grained searches around current solutions, while during the exploration phase, parameter adjustments broaden the search range to escape local optima. This dual mechanism, which combines directed exploitation with stochastic exploration, ensures high convergence efficiency while effectively avoiding local optima. Fig. 21(a) illustrates a two-dimensional model, though the equations can be extended to higher dimensions. The ranges of sine and cosine values in Eqs. (33)–(35) are adaptively adjusted using the following expression.

$$r_1 = a - t \frac{a}{T} \quad (36)$$

Here, t is the current iteration number, T is the maximum number of iterations, and a is a constant. When t is greater than or equal to the maximum iteration count T , the value of t in the current iteration remains unchanged. After a small number of iterations, the range of the sine and cosine values narrows.

The search process of SCA is constrained by the boundary ranges of sine and cosine functions, as illustrated in Fig. 21(b). The algorithm begins by initializing random solutions and then iteratively updates positions based on the current best solution, dynamically narrowing the function ranges to transition from global exploration to local exploitation. The process terminates upon reaching a maximum number of iterations or meeting other criteria such as function evaluations or accuracy thresholds. The algorithm is capable of locating global optima due to the following features: (1) multi-point search with random initialization provides better exploration capability and greater resistance to local optima compared to single-point methods; (2) sine and cosine outputs outside the range $[-1,1]$ facilitate exploration, while outputs within $[-1,1]$ enable exploitation; (3) adaptive range adjustment ensures a smooth transition between exploration and exploitation; (4) continuous retention of the best solution focuses the search on promising regions; (5) as a black-box optimization method, it relies solely on objective function feedback, ensuring broad applicability across different domains.

To improve the quality and efficiency of drilling data processing, an offline preprocessing workflow based on a sliding window is adopted. After acquiring continuous displacement and pressure data, the dataset is divided into 1-m intervals using a fixed-step sliding window. Key indicators—ROP, impact energy, impact frequency, and impact energy efficiency—are calculated within each window, and the results are averaged to obtain representative feature values. Cumulative energy consumption is obtained by integrating power data over the entire segment. An adjacent averaging filter is applied to smooth the data, reducing noise while preserving signal waveform characteristics. Following sample construction and cleaning, all experimental data are aggregated into the final modeling dataset. To ensure objective model evaluation and generalization capability, a batch-based partitioning strategy is adopted. Each complete experiment—i.e., each full set of parameter combinations—is treated as an indivisible unit. These units are randomly assigned to the training and test sets at a 7:3 ratio, ensuring all samples from the same experimental batch remain within the same dataset and preventing information leakage.

During model training and validation, five-fold cross-validation is applied within the training set. All experimental batches in the training set are randomly divided into five equal parts. In each iteration, four parts serve as the training subset and one as the

Algorithm SCA
Initialize population of solutions
Initialize values of r_1 , r_2 , r_3 , and r_4
Do
Evaluate objective function for each solution
Identify current best solution
While $t < \text{maximum iterations}$
Update values of r_1 , r_2 , r_3 , and r_4
Update obtained solutions
Return optimal solution obtained

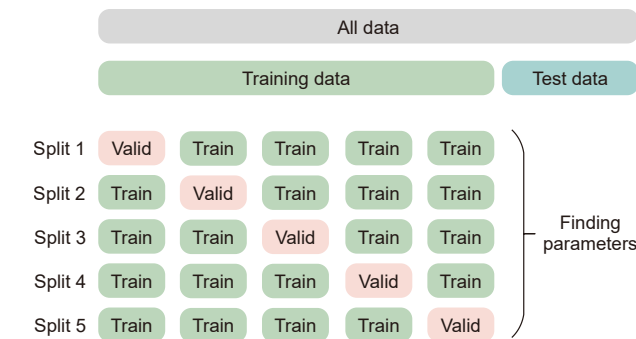


Fig. 22. Schematic diagram of five-fold cross-validation.

validation subset, with the process repeated five times so that each portion participates in validation. This strictly adheres to the group-wise isolation principle, ensuring that samples from the same experimental batch remain entirely within the same fold, preventing information leakage. After validation, an independent test set is used for a one-time evaluation of the final model's generalization ability, as shown in Fig. 22.

During normalization, the mean and standard deviation of each feature are calculated solely from the training set and then applied to the test set. In feature selection, mutual information analysis—which handles strong nonlinear relationships, is computationally efficient, and robust—is employed. Correlation analysis is performed only on the training set to select appropriate input variables, as given in Eq. (37).

$$I(X; Y) = \sum_{y \in Y} \sum_{x \in X} \rho(x, y) \cdot \log \frac{\rho(x, y)}{\rho(x) \rho(y)} \quad (37)$$

Here, $\rho(x, y)$, $\rho(x)$, and $\rho(y)$ denote the joint probability and marginal probabilities of x and y , respectively. A larger $I(X; Y)$ indicates a stronger correlation between x and y . When $I(X; Y) = 0$, it signifies no correlation, and $I(X; Y) = I(Y; X)$. The mutual information between ROP and EC and each input variable is presented in Table 9. It can be observed that all values in the table exceed 0.5, indicating strong correlations. In the mutual information for ROP, the impact parameters exhibit stronger correlations, as they can directly influence drilling efficiency.

In the mutual information for EC, the impact parameters and rock parameters show stronger correlations. The rock parameters fundamentally determine the theoretical lower limit of energy required to crush a unit volume of rock, while the buffer and propulsion systems primarily ensure process stability and vibration control. During this process, the feature importance weights are calculated solely based on the training dataset, with the test set remaining completely isolated throughout the feature selection process and not participating in any decision-making. The prediction process based on the data-driven model is illustrated in Fig. 23.

4.3. Hybrid data-driven model

Aiming to address the issues of high sensitivity to data volume in purely data-driven models and significant inherent errors in

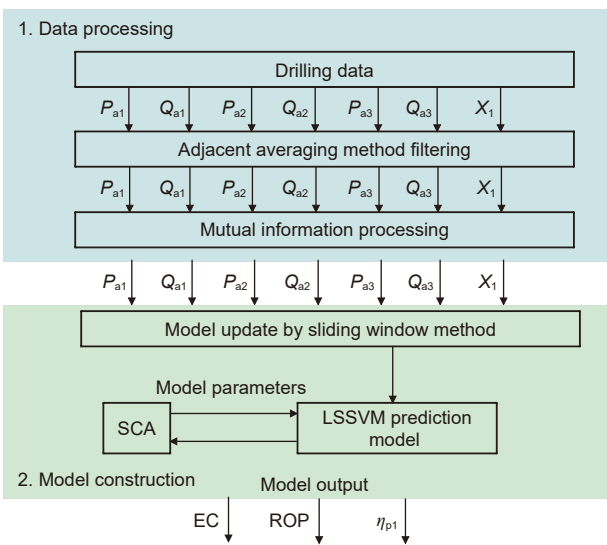


Fig. 23. Flowchart of the drilling parameters prediction modeling based on SCA-LSSVM.

purely physical models, a hybrid model integrating the physical model of the rock drill system with a data-driven model is proposed to enhance the accuracy (Li et al., 2023) of energy prediction. This paper designs a parallel hybrid modeling approach, with the overall structure illustrated in Fig. 24. The method employs the physical model as the main component, with the data-driven model operating in parallel as an error compensation module. The specific process involves training the data-driven model (Wei et al., 2025) based on actual energy consumption data to learn the error patterns between the physical model predictions E_p and actual observed values E_a , subsequently outputting a dynamic error correction term E_d . Ultimately, the energy consumption prediction output of the hybrid model E_t is obtained by summing the output of the physical model and the error correction term, i.e., $E_t = E_p + E_d$. This parallel structure preserves the mechanistic interpretability of the physical model while compensating for systematic errors through the data-driven module, thereby significantly improving the overall accuracy of energy consumption prediction for the rock drill.

4.4. Comparison between single data-driven methods and physics methods

To comprehensively evaluate the predictive performance of the proposed pure LSSVM data-driven model and the pure physical model, the RF model, GPR model, and deep learning MLP model are introduced as comparative benchmarks. To validate the model robustness under different operating conditions, an additional 30 sets of random experiments are designed. Table 10 presents the experimental conditions, and Table 11 summarizes the actual energy consumption values under these conditions along with the prediction results of each model. Based on this dataset, Fig. 25 comprehensively demonstrates the agreement between predicted and actual values, systematic deviations, and dispersion

Table 9
Mutual information between ROP, EC and drilling input parameters.

	Rock type	Impact pressure	Impact flow	Propulsion pressure	Propulsion flow	Buffer pressure	Buffer flow
Mutual information of ROP	0.78671	0.86966	0.9192	0.62563	0.75825	0.61823	0.61618
Mutual information of EC	0.61126	0.69354	0.67173	0.53533	0.55188	0.56302	0.58408

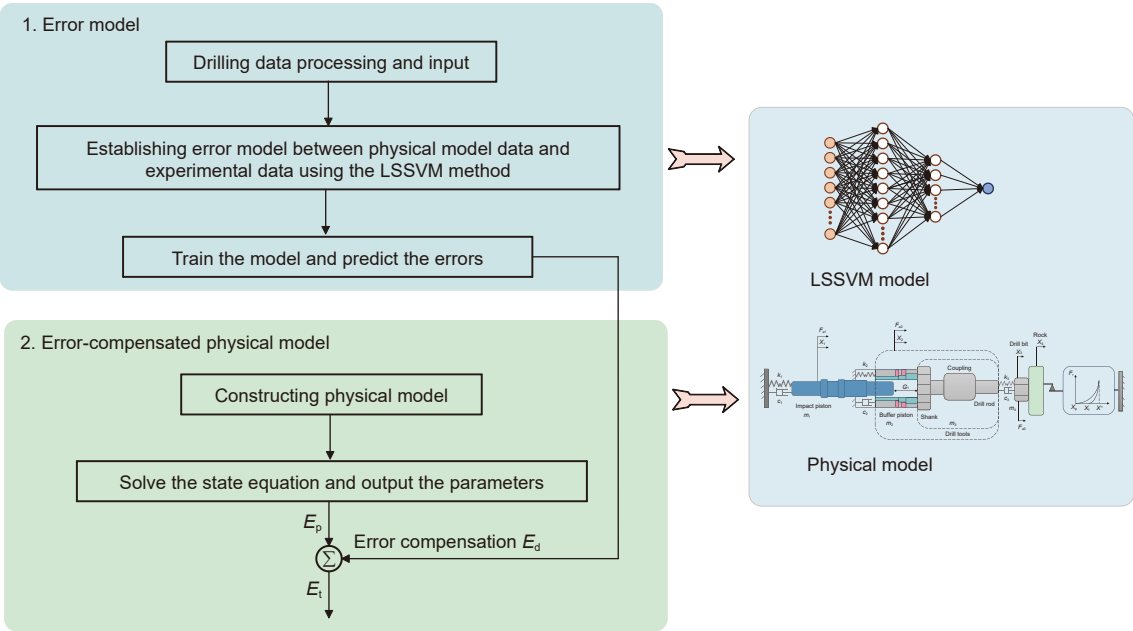


Fig. 24. Schematic diagram of the hybrid data-driven model.

Table 10
Input values of the parameter prediction model.

Index	Rock types	Impact pressure, MPa	Impact flow, L/min	Propulsion pressure, MPa	Propulsion flow, L/min	Buffer pressure, MPa	Buffer flow, L/min
1	Sandstone	7	38.88	6.14	4.31	5.65	3.96
2	Sandstone	15	68.16	6.14	4.31	5.65	3.96
3	Sandstone	21	90.12	6.14	4.31	5.65	3.96
4	Sandstone	10.31	47.25	5	3.53	5.55	3.89
5	Sandstone	10.31	47.25	7	4.91	5.55	3.89
6	Sandstone	10.31	47.25	9.5	6.65	5.55	3.89
7	Sandstone	9.96	47.63	5.86	4.15	3.5	2.45
8	Sandstone	9.96	47.63	5.86	4.15	5	3.50
9	Sandstone	9.96	47.63	5.86	4.15	7	4.89
10	Sandstone	9.96	47.63	5.86	4.15	9.5	6.64
11	Limestone	7	38.88	6.14	4.31	5.65	3.96
12	Limestone	15	68.16	6.14	4.31	5.65	3.96
13	Limestone	21	90.12	6.14	4.31	5.65	3.96
14	Limestone	10.31	47.25	5	3.53	5.55	3.89
15	Limestone	10.31	47.25	7	4.91	5.55	3.89
16	Limestone	10.31	47.25	9.5	6.65	5.55	3.89
17	Limestone	9.96	47.63	5.86	4.15	3.5	2.45
18	Limestone	9.96	47.63	5.86	4.15	5	3.50
19	Limestone	9.96	47.63	5.86	4.15	7	4.89
20	Limestone	9.96	47.63	5.86	4.15	9.5	6.64
21	Granite	7	38.88	6.14	4.31	5.65	3.96
22	Granite	15	68.16	6.14	4.31	5.65	3.96
23	Granite	21	90.12	6.14	4.31	5.65	3.96
24	Granite	10.31	47.25	5	3.53	5.55	3.89
25	Granite	10.31	47.25	7	4.91	5.55	3.89
26	Granite	10.31	47.25	9.5	6.65	5.55	3.89
27	Granite	9.96	47.63	5.86	4.15	3.5	2.45
28	Granite	9.96	47.63	5.86	4.15	5	3.50
29	Granite	9.96	47.63	5.86	4.15	7	4.89
30	Granite	9.96	47.63	5.86	4.15	9.5	6.64

characteristics of each model through point-line comparison plots, regression analysis plots, and error distribution plots. Fig. 26 further provides the histogram distribution of absolute percentage errors for each model.

Table 12 summarizes the predictive performance of five different models for rock drilling machine energy consumption, with evaluation metrics including the coefficient of

determination (R^2), mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), and mean square error (MSE). Overall, data-driven models generally outperform traditional physical models, with the LSSVM model exhibiting the best performance across all metrics. Specifically, the LSSVM model achieves an R^2 as high as 0.98, a MAPE of only 3.91%, RMSE and MAE of 92.34 kJ and 53.94 kJ respectively, and

Table 11
Output values of the parameter prediction model.

Index	Experimental value, kJ	LSSVM model, kJ	RF model, kJ	MLP model, kJ	GPR model, kJ	Physical model, kJ
1	614.4	695.7	613.3	704.9	633.7	638.5
2	932.3	941.9	935.5	904.3	943.9	1115.8
3	1305.6	1295.0	1299.8	1280.4	1308.2	1248.6
4	877.2	893.4	872.3	839.7	890.2	1058.5
5	822.9	826.2	876.3	813.0	1411.5	992.8
6	1305.9	1319.3	1306.2	1269.4	1308.5	1535.8
7	1207.6	1186.8	2299.0	1258.9	1411.5	1175.6
8	819.3	795.9	817.0	811.3	833.6	828.5
9	806.8	821.5	806.5	831.8	821.4	978.5
10	842.8	1027.5	947.5	812.4	1411.5	848.6
11	1237.5	1215.3	1223.3	1108.2	1241.7	1475.8
12	1327.6	1337.7	1337.0	1252.4	1329.6	1278.5
13	1414.3	1423.0	1406.8	1370.9	1414.2	1658.5
14	967.1	944.1	965.5	980.7	977.9	958.5
15	872.9	838.8	876.6	680.9	886.0	1058.5
16	1080.9	1064.4	1124.7	1103.3	1411.5	1078.6
17	2224.5	1909.2	3048.2	2092.0	1411.5	2548.5
18	950.5	936.8	949.9	737.8	961.7	1148.6
19	1020.9	1022.3	1024.8	1226.1	1030.4	1215.8
20	1375.7	1406.4	1375.8	1195.7	1376.6	1328.5
21	1740.7	1810.5	1777.7	2304.5	1732.7	2018.6
22	2011.0	1984.7	2015.2	1986.0	1996.4	1905.8
23	1652.3	1662.8	1658.4	1615.7	1646.5	1915.8
24	1414.8	1293.3	1420.6	1482.2	1414.8	1368.5
25	905.2	1009.2	907.9	968.1	917.5	1088.5
26	865.0	844.3	876.1	926.8	1411.5	868.5
27	4226.5	3980.8	4191.1	4865.8	4158.2	4775.8
28	2457.7	2328.6	2455.5	2358.2	2432.3	2275.6
29	1741.6	1777.9	1743.0	1701.0	1733.6	2015.8
30	1533.6	1534.2	1514.2	1607.0	1411.5	1478.5

an MSE of 8526.26 (kJ)², with all error metrics being the smallest. In comparison, the RF model and MLP model show R^2 values of 0.87 and 0.93, and MAPE values of 5.42% and 7.57% respectively, with error metrics significantly inferior to those of LSSVM. The MLP model's MAE reaches 107.30 kJ, indicating relatively poorer prediction stability.

The lower accuracy of the RF model mainly stems from its Bagging ensemble mechanism based on decision trees. When confronted with geological nonlinear characteristics implicitly present in rock drilling machine energy consumption data, such as rock hardness and fracture development, as well as the complex matching relationships between pressure and flow, the splitting criteria of tree models struggle to achieve the precise global mapping capability of the LSSVM kernel function. Although the MLP model theoretically possesses strong nonlinear fitting capability, its performance heavily depends on data scale and tuning. When facing sample sparsity under different lithological conditions, its complex network structure tends to overlearn noise, resulting in overfitting.

The GPR model and physical model demonstrate relatively weaker performance. The GPR model achieves an R^2 of only 0.87 and a MAPE as high as 10.51%. Although the physical model attains an R^2 of 0.92, its MAPE reaches 11.13%, and its MAE is as high as 149.91 kJ—the worst among all models. Although constructed based on dynamic principles, the physical model struggles to precisely quantify actual factors such as internal leakage in the hydraulic system, time-varying friction losses between moving pairs, energy dissipation caused by impact vibrations, and performance degradation during long-term equipment operation. These unmodeled dynamic losses collectively contribute to significant prediction deviations. The GPR model is relatively sensitive to noise and kernel function selection. These factors collectively limit their performance in precise prediction tasks.

4.5. Comparison of predictive performance of optimized data-driven methods

In this paper, four data-driven methods, including LSSVM, RF, GPR, and MLP, are combined with three optimization algorithms—SCA, Genetic Algorithm (GA), and Particle Swarm Optimization (PSO)—to systematically compare the impacts of different optimization algorithms on model performance. To ensure fairness in the comparison, the parameter settings of the three optimization algorithms are kept consistent. During the model training and optimization process, RMSE is selected as the key evaluation metric. The exploration intervals for each model and the optimal RMSE values are summarized in Table 13. The parameter settings for the three optimization algorithms are presented in Tables 14, 15, and 16, respectively. The convergence curves for each algorithm-model combination are illustrated in Fig. 27.

From the overall trend, all three optimization algorithms can significantly reduce the initial errors of the models, yet distinct differences exist in their optimization effectiveness and convergence characteristics. For the LSSVM model, the PSO algorithm exhibits extremely fast initial convergence, reducing the RMSE to 130 kJ after just 3 iterations, but it falls into a local optimum in the later stages. The SCA algorithm stabilizes at an RMSE of 68.7 kJ after 40 iterations, achieving the global optimum. Meanwhile, the RMSE of the GA algorithm fluctuates around 85.11 kJ during the final iterations. For the RF model, the SCA algorithm achieves rapid convergence, with the RMSE stabilizing at 206.07 kJ after 40 iterations. For the MLP model, the RMSE steadily decreases from an initial 149.1 kJ to 138.72 kJ, displaying a smooth convergence curve without rebound. In contrast, GA and PSO become stuck at 149.9 kJ and 155.96 kJ, respectively. For the GPR model, the SCA algorithm also demonstrates robust performance, ultimately stabilizing at 157.79 kJ, whereas the GA and PSO algorithms exhibit significant

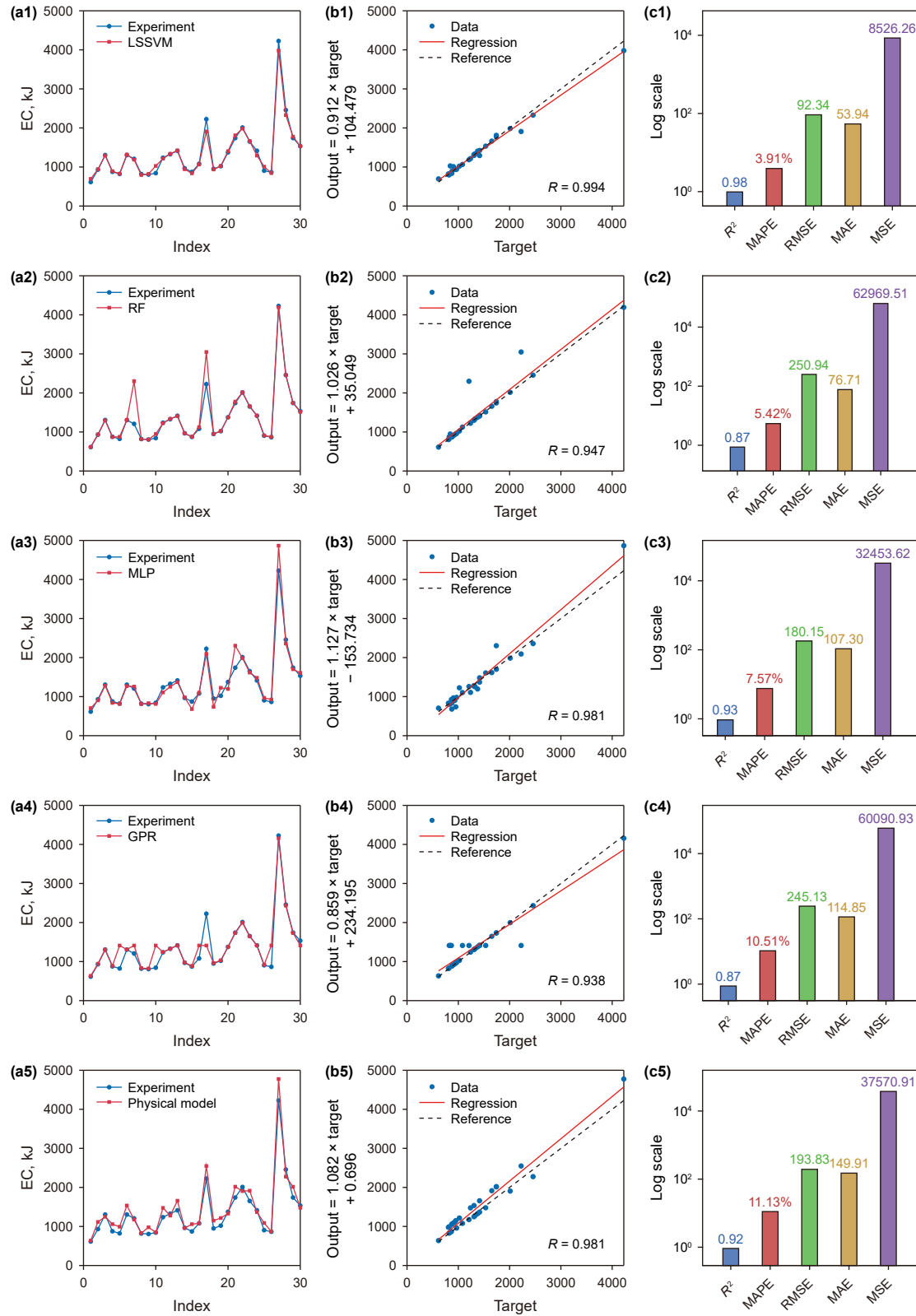


Fig. 25. Point-line comparison plot, regression analysis plot, and error distribution plot of predicted versus actual values for each model.

fluctuations, with PSO even showing abnormal jumps, highlighting SCA's robustness in optimizing probabilistic models.

In summary, the SCA algorithm achieves the best final accuracy across all four models—LSSVM, RF, MLP, and GPR—with smooth

convergence curves and high stability in the later stages. This superior performance is primarily attributed to its sine cosine oscillation mechanism, which effectively balances global exploration and local exploitation, making it suitable for

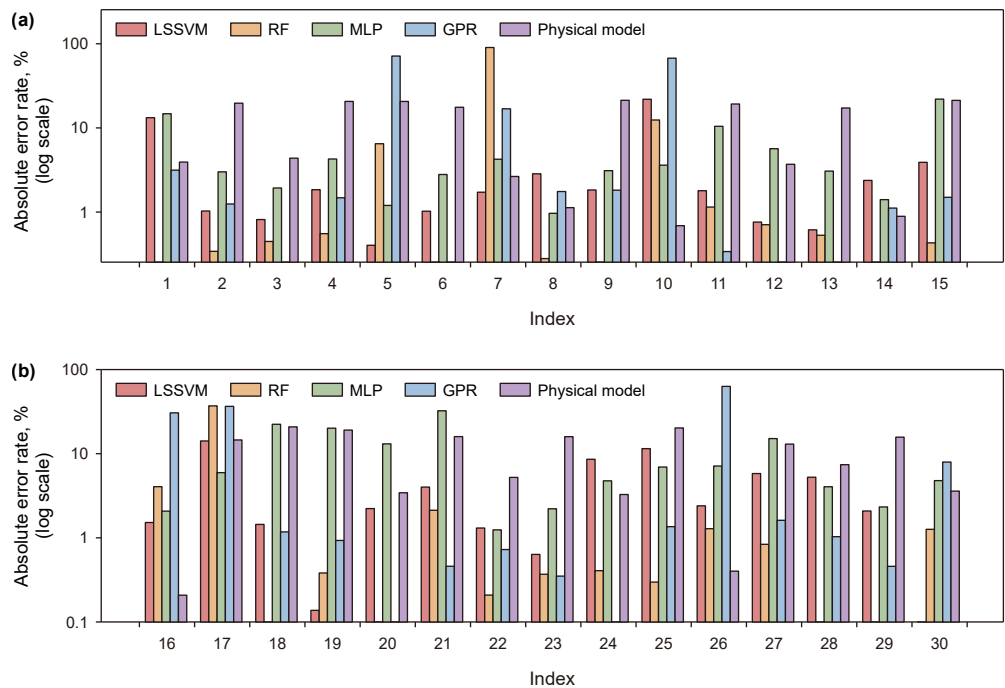


Fig. 26. Histogram distribution of absolute percentage error for each model.

Table 12
Error metrics between each prediction model and the experimental data.

Model	R^2	MAPE, %	RMSE, kJ	MAE, kJ	MSE, kJ ²
LSSVM model	0.98	3.91	92.34	53.94	8526.26
RF model	0.87	5.42	250.94	76.71	62969.51
MLP model	0.93	7.57	180.15	107.30	32453.62
GPR model	0.87	10.51	245.13	114.85	60090.93
Physical model	0.92	11.13	193.83	149.91	37570.91

hyperparameter optimization across various model structures. The gradient-free and parameter-adaptive structural characteristics of SCA endow it with enhanced robustness for kernel function optimization in LSSVM, tree structure splitting in RF, and weight initialization in MLP. In comparison, although the PSO algorithm achieves fast convergence through information sharing among particles (Alsaihati et al., 2022), its inherent “convergence” tendency makes it prone to premature stagnation when dealing with

Table 13
Comparison of exploration interval settings and optimal RMSE for the four models.

Model	Hyperparameter	Exploration interval	Optimal RMSE (SCA)	Optimal RMSE (GA)	Optimal RMSE (PSO)
LSSVM	Regularization parameter	[0.1, 1000]	68.7 kJ	85.11 kJ	74.1 kJ
RF	Kernel parameter	[0.1, 1000]	206.07 kJ	232.5 kJ	207.53 kJ
	Number of trees	[30, 300]			
MLP	Minimum leaf samples	[1, 15]	138.72 kJ	149.9 kJ	155.96 kJ
	Hidden layer structure	[10, 100], [10, 100],			
		[10, 100]			
GPR	Learning rate	[0.0001, 0.01]	157.79 kJ	212.2 kJ	158.76 kJ
	Regularization parameter	[1e-6, 1e-3]			
	Length scale	[0.1, 10]			
	Noise level	[0.1, 10]			

Table 14
SCA algorithm parameter settings.

Population size	Maximum iterations	Control parameter r_1	Direction parameter r_2	Weight parameter r_3	Selection parameter r_4	Stagnation generations	Fitness tolerance
30	100	Linearly decreases from 2 to 0 with iterations	Random in $[0, 2\pi]$	Random in $[0, 2]$	Random in $[0, 1]$	15	1e–6

Table 15
GA algorithm parameter settings.

Population size	Maximum iterations	Crossover probability	Mutation probability	Number of elites	Stagnation generations	Fitness tolerance
30	100	0.8	0.1	2	15	1e–6

Table 16
PSO algorithm parameter settings.

Population size	Maximum iterations	Initial inertia weight	Final inertia weight	Individual learning factor	Social learning factor	Neighborhood size	Stagnation generations	Fitness tolerance
30	100	0.9	0.5	2	2	3	15	1e−6

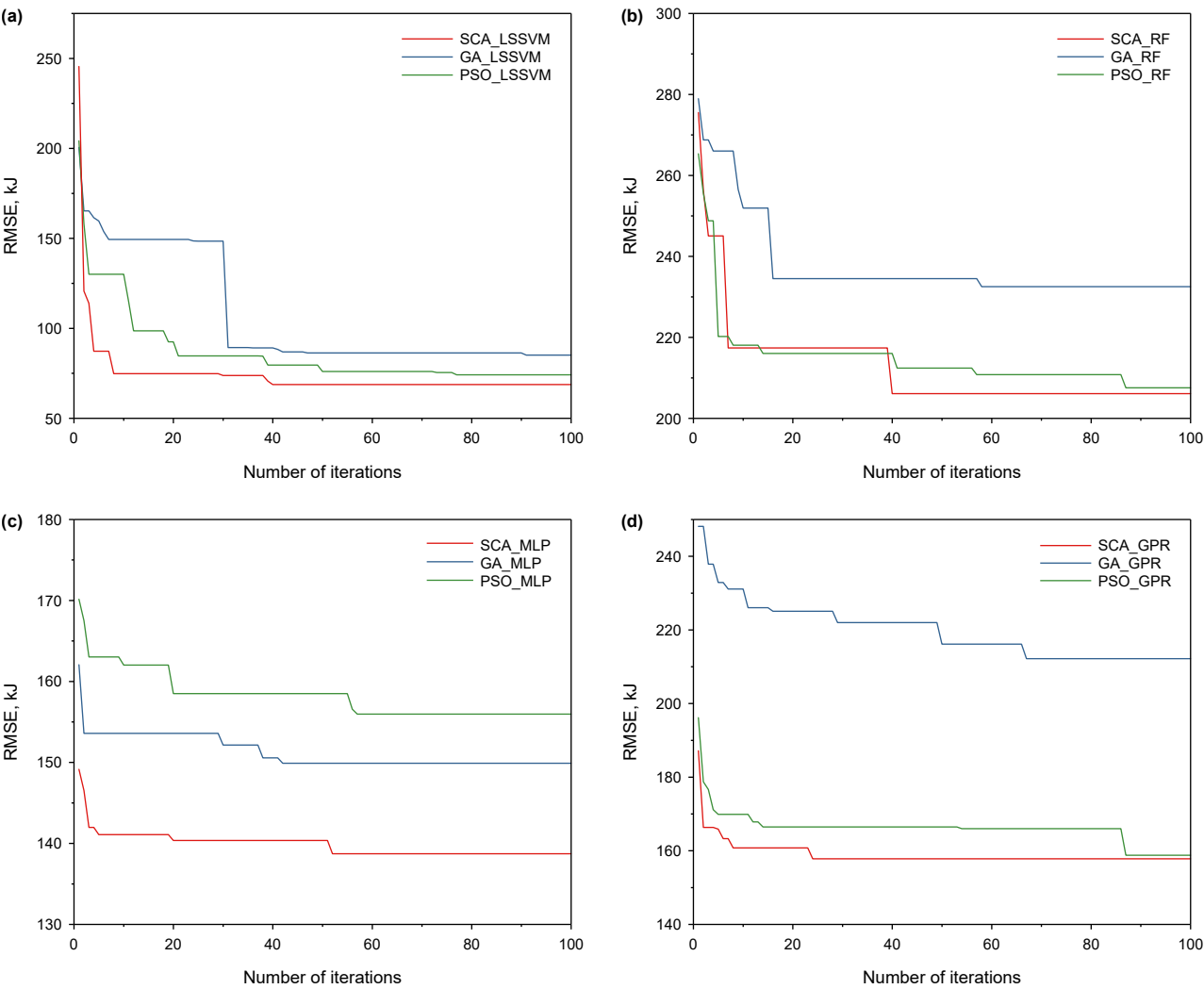


Fig. 27. Comparison of optimized data-driven model prediction performance. (a) LSSVM model; (b) RF model; (c) MLP model; (d) GPR model.

high-dimensional nonlinear models such as LSSVM and RF. Meanwhile, the crossover and mutation operations of the GA algorithm introduce excessive randomness, leading to convergence oscillations, particularly in probabilistic models like GPR. Under SCA optimization, the LSSVM model achieves a minimum RMSE of 68.7 kJ, significantly outperforming the RF, GPR, and MLP models optimized by other algorithms, further validating the superiority of SCA in predicting rock drilling machine energy consumption.

Based on the comprehensive comparative results of the optimized algorithms, the SCA-LSSVM algorithm is ultimately selected as the compensation method for the physical model to predict energy consumption. Fig. 28 illustrates the fitting effect between the predicted values of the constructed hybrid-driven model and the actual energy consumption values. As shown in the figure, the model exhibits high prediction accuracy, yielding an R^2 of 0.99, a MAPE of 2.18%, and an RMSE of 59.45 kJ. Compared with either pure data-driven models or pure physical models, this hybrid

model demonstrates significantly higher prediction accuracy. The hybrid-driven model first establishes the main prediction framework using physical equations, which ensures the interpretability of the prediction process and its consistency with physical laws. On this basis, the SCA-LSSVM algorithm is introduced to dynamically identify and adaptively compensate for the components that the pure mechanism model cannot accurately describe, such as unmodeled dynamic losses and complex nonlinear errors including system time-varying characteristics. The physical model fundamentally constrains the learning space, effectively avoiding the “black box” blindness and overfitting risks common in pure data-driven methods. The data-driven compensation mechanism breaks through the accuracy bottleneck of the pure mechanism model caused by simplifying assumptions. Through this synergistic mechanism, the hybrid-driven model achieves a coordinated improvement in both accuracy and robustness while ensuring the physical credibility of the prediction results.

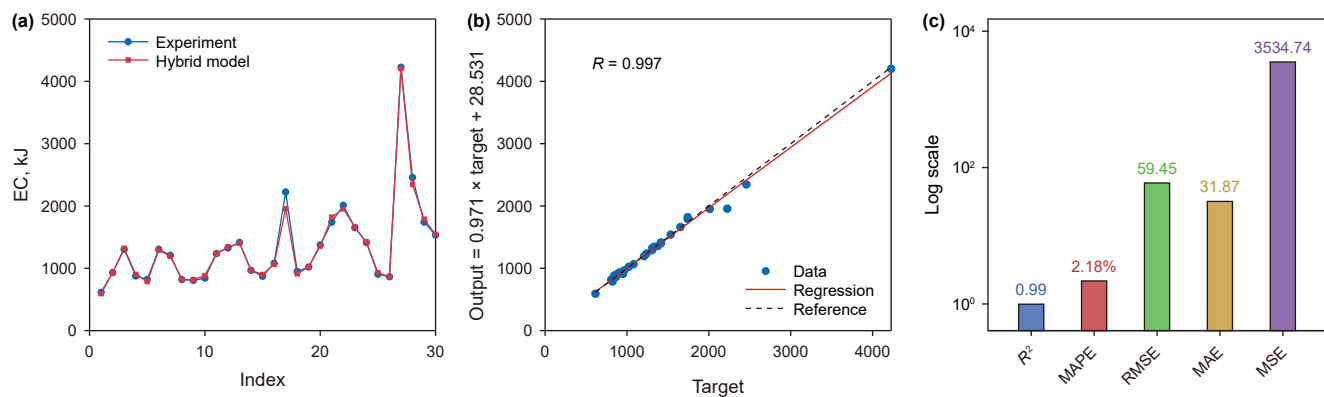


Fig. 28. Point-line comparison plot, regression analysis plot, and error distribution plot of predicted versus actual values for hybrid model.

5. Discussion

This paper's core innovation lies in constructing a full-operating-condition physical model integrating impact, propulsion, and buffering subsystems of a hydraulic rock drill, coupling internal fluid dynamics with external solid dynamics to faithfully reproduce complex drilling characteristics. Orthogonal experiments reveal, for the first time, the energy consumption mechanisms arising from synergistic interactions among the three pressures (impact pressure, propulsion pressure, and buffer pressure).

To address high computational cost, a simulation database is built with reasonable simplifications, and a data-driven method dynamically compensates simulation-experiment discrepancies, establishing a parallel hybrid-driven model characterized as “mechanism-dominant, data-compensatory”. Unlike existing “serial” physics-informed fusion models, this parallel architecture maintains physical model integrity and interpretability: the physical “white box” independently outputs key state variables (piston displacement, impact energy, ROP), while the data-driven module serves solely as a parallel error compensator, enhancing prediction accuracy while preserving mechanistic insight.

In contrast, the Runge–Kutta physics-informed neural network (RK-PINN) method in Zhai et al. (2023) embeds physical information in a “serial” manner, deeply fusing physical laws with data-driven components, making it difficult to independently output intermediate state variables; its interpretability lies mainly in parameter identification rather than transparent internal processes. Similarly, Jia et al. (2021a) and Gao et al. (2022) treated the drill rig as a “black box” based on power flow theory, focusing only on input-output relationships without revealing internal subsystem coupling or error sources, and rely heavily on experimental data, limiting generalizability. Moreover, Gao et al. (2022) optimized energy solely via torque and speed adjustment, without incorporating pressure synergy for matching design.

6. Conclusions

This paper constructs a hybrid data-driven model that integrates physics-informed principles and LSSVM to predict EC during the drilling process. The study first evaluates different energy characterization parameters from multiple perspectives, and then systematically compares the prediction errors of a single physical model, single data-driven models, and the proposed hybrid model. The conclusions drawn from this research are as follows:

- (1) During the rock-drilling process, the impact system serves as the core power source, transmitting high-frequency impact kinetic energy to the rock mass through the drill tools-bit

assembly to directly accomplish rock fragmentation. The propulsion system ensures preload between the drill bit and the rock, while the buffer system rapidly absorbs recoil energy through damping, ensuring quick resetting of all components. Based on the power-flow transmission path of the above process, a key energy parameter model is established.

- (2) The rational matching of impact pressure, propulsion pressure, and buffer pressure is key to reducing energy consumption and improving drilling efficiency. Excessive impact pressure can increase the rate of penetration but at the cost of reduced energy efficiency and accelerated wear. Insufficient or excessive propulsion pressure leads to idle drilling or delayed resetting, respectively. Excessively high buffer pressure weakens the impact energy. Moreover, rock properties significantly influence the regulation strategy for pressure parameters. Soft sandstone exhibits an optimal pressure range. Medium-hard limestone achieves the best energy efficiency in the low-pressure range, while energy consumption increases in the high-pressure range. Hard granite displays a threshold effect, requiring high pressure to activate efficient fragmentation.
- (3) In a drilling scenario with a depth of 4 m and 170 blast holes, the operational costs of the optimal parameter C9 and the worst parameter C11 are compared. The drilling time difference between these two parameters is 33.2 h, and the total energy consumption differs by 9.7×10^5 kJ. During peak electricity hours, using parameter C9 can save 71.87 RMB per meter of drilling cost. By reasonably adjusting system parameters, it is possible not only to improve drilling efficiency but also to reduce energy consumption.
- (4) The performance of different prediction models is compared. Pure data-driven models generally outperform physical models, with LSSVM achieving the best performance. Among the optimization algorithms, SCA attains the highest accuracy across four models with smooth convergence, overcoming the premature convergence of PSO and the oscillation tendency of GA. The hybrid-driven model further improves prediction performance, achieving an R^2 of 0.99, a MAPE of 2.18%, and an RMSE of 59.45 kJ. This model ensures interpretability through a physical framework while employing a data-driven compensation mechanism to dynamically correct unmodeled errors, achieving synergistic improvement in accuracy and reliability.

In subsequent research, this hybrid-driven model can be extended and applied to rock-drilling experiments under complex geological conditions, such as heterogeneous rock formations, to verify its prediction reliability across different rock strata.

CRediT authorship contribution statement

Si-Yuan Chang: Writing – original draft, Software, Project administration, Methodology, Conceptualization. **Ye-Lin Li:** Resources, Project administration, Funding acquisition. **Wei Ma:** Resources. **Jia-Le Zhang:** Resources, Project administration, Funding acquisition. **Bao-Zhou Xia:** Resources. **Min Ye:** Resources, Project administration, Funding acquisition. **Joseph Páez Chávez:** Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

The impact force is generated by the alternating action of the hydraulic oil pressures P_6 and P_5 in the front and rear chambers of the impact piston; the buffering force is produced by the two-stage hydraulic oil pressures P_9 and P_{10} acting on the buffer piston; and the propulsion force is directly provided by the hydraulic oil pressure P_{a2} of the propulsion cylinder, as shown in Eq. (38). A_{a3} represents the area of the rodless chamber of the propulsion cylinder. The impact pressure P_{a1} measured in the experiment corresponds to pressure P_1 in the model, and the buffer pressure P_{a3} corresponds to pressure P_9 in the model. These two pressures can essentially characterize the motion states of the two systems.

$$\begin{cases} F_{a1} = P_6 A_2 - P_5 A_1 \\ F_{a2} = P_9 A_{d1} + P_{10} A_{d2} \\ F_{a3} = P_{a3} A_{a3} \end{cases} \quad (38)$$

(1) Impact system model

During the operation of the rock drill, the gas chamber state in the high-pressure accumulator of the impact system changes very rapidly, which can be approximated as an isentropic process. The flow-pressure parameters in the bond graph are modeled using three governing equations: the flow continuity equation, the thin-walled orifice flow equation, and the frictional pressure loss equation. The pressure and flow between the high-pressure accumulator and the inlet pipeline are described by Eqs. (39)–(41). To reduce the substantial parameter inputs, all internal pipeline diameters and lengths are standardized to a single, constant value.

$$\begin{cases} \frac{dP_1}{dt} = \frac{Q_1 - Q_{1r} - Q_2 - Q_3 - Q_4}{C_{p1}} = \frac{K_e(Q_1 - Q_{1r} - Q_2 - Q_3 - Q_4)}{V_{1a}} \\ \frac{dP_2}{dt} = \frac{Q_2}{C_{p2}} = \frac{1.4P_{2a}V_2^{0.4}Q_2}{V_{2a}^{1.4}} \end{cases} \quad (39)$$

$$\begin{cases} Q_{1r} = \frac{P_1}{R_1} = h(P_1 - P_{1r}) \frac{\pi d_p^4 P_1}{128 \mu L_p} \\ Q_2 = \frac{P_1 - P_2}{R_2} = \frac{\pi d_p^4 (P_1 - P_2)}{128 \mu L_p} \end{cases} \quad (40)$$

Among them,

$$V_2 = V_{2a} \left(1 - \sqrt[1.4]{\frac{P_{2a}}{P_2}} \right) \quad (41)$$

The chamber pressure and flow rate between the impact piston and the directional control valve are calculated using Eq. (42) and Eq. (43), respectively.

$$\begin{cases} \frac{dP_3}{dt} = \frac{Q_3 - Q_5 - Q_{3r}}{C_{p3}} = \frac{K_e(Q_3 - Q_5 - Q_{3r})}{V_{3a}} \\ \frac{dP_4}{dt} = \frac{-Q_4 + Q_6 - Q_{4r}}{C_{p4}} = \frac{K_e(-Q_4 + Q_6 - Q_{4r})}{V_{4a}} \\ \frac{dP_5}{dt} = \frac{Q_5 - Q_8 - \dot{X}_1 A_1}{C_{p5}} = \frac{K_e(Q_5 - Q_8 - \dot{X}_1 A_1)}{V_{5a} + X_1 A_1} \\ \frac{dP_6}{dt} = \frac{-Q_6 + Q_7 + \dot{X}_1 A_2}{C_{p6}} = \frac{K_e(-Q_6 + Q_7 + \dot{X}_1 A_2)}{V_{6a} - X_1 A_2} \\ \frac{dP_7}{dt} = \frac{-Q_7 - Q_{7r}}{C_{p7}} = \frac{K_e(-Q_7 - Q_{7r})}{V_{7a}} \\ \frac{dP_8}{dt} = \frac{Q_8 - Q_{8r}}{C_{p8}} = \frac{K_e(Q_8 - Q_{8r})}{V_{8a}} \end{cases} \quad (42)$$

$$\begin{cases} Q_3 = \frac{P_1 - P_3}{R_3} = h(X_v - L_3) C_d A_{v3} \sqrt{\frac{2(P_1 - P_3)}{\rho}} \\ Q_{3r} = \frac{P_3}{R_{3r}} = h(X_v - L_{3r}) C_d A_{v3r} \sqrt{\frac{2P_3}{\rho}} \\ Q_4 = \frac{P_1 - P_4}{R_4} = h(X_v - L_4) C_d A_{v4} \sqrt{\frac{2(P_1 - P_4)}{\rho}} \\ Q_{4r} = \frac{P_4}{R_{4r}} = h(X_v - L_{4r}) C_d A_{v4r} \sqrt{\frac{2P_4}{\rho}} \\ Q_5 = \frac{P_3 - P_5}{R_5} = \frac{\pi d_p^4 (P_3 - P_5)}{128 \mu L_p} \\ Q_6 = \frac{P_6 - P_4}{R_6} = \frac{\pi d_p^4 (P_6 - P_4)}{128 \mu L_p} \\ Q_7 = \frac{P_6 - P_7}{R_7} = h(X_1 - L_7) C_d A_7 \sqrt{\frac{2(P_6 - P_7)}{\rho}} \\ Q_{7r} = \frac{P_7}{R_{7r}} = h(X_1 - L_{7r}) C_d A_{7r} \sqrt{\frac{2P_7}{\rho}} \\ Q_8 = \frac{P_5 - P_8}{R_8} = h(X_1 - L_8) C_d A_8 \sqrt{\frac{2(P_5 - P_8)}{\rho}} \\ Q_{8r} = \frac{P_8}{R_{8r}} = h(X_1 - L_{8r}) C_d A_{8r} \sqrt{\frac{2P_8}{\rho}} \end{cases} \quad (43)$$

(2) Buffer system model

Table 17
Constant input parameters in the dynamic equations.

Meaning	Value	Meaning	Value
Impact damping c_1	1000 N/(m·s ⁻¹)	Stiffness of impact system k_1	2×10^5 N/m
Buffer damping c_2	9000 N/(m·s ⁻¹)	Stiffness of buffer system k_2	9×10^5 N/m
Damping between the drill tools and the drill bit c_3	2450 N/(m·s ⁻¹)	Stiffness between the drill tools and the drill bit k_3	68850 N/m
Damping of the directional valve c_v	3000 N/(m·s ⁻¹)	Coefficient of restitution e	0.3
Rock loading stiffness k_L	248.65 kN/mm	Mass of impact piston m_1	5 kg
Rock unloading stiffness k_U	422.43 kN/mm	Mass of buffer piston m_2	4.26 kg
Outer diameter of the C_{p5} chamber d_{1a}	0.044 m	Mass of drill tools m_3	32.6 kg
Inner diameter of the C_{p5} chamber d_{1b}	0.037 m	Mass of drill bit m_4	1 kg
Outer diameter of the C_{p6} chamber d_{2a}	0.044 m	Mass of directional valve m_v	0.389 kg
Inner diameter of the C_{p6} chamber d_{2b}	0.041 m	Rock dry friction threshold F_f	68850 N
Outer diameter of the C_{p9} chamber d_{41a}	0.08 m	Impact distance between impact piston and drill tools G_1	0.025 m
Inner diameter of the C_{p9} chamber d_{41b}	0.076 m	Hydraulic oil density ρ	850 kg/m ³
Outer diameter of the C_{p10} chamber d_{42a}	0.076 m	Hydraulic oil dynamic viscosity μ	0.03893 N s/m ²
Inner diameter of the C_{p10} chamber d_{42b}	0.07 m	Clearance between the spool and the valve body h_{2v}	0.0009 m
Outer diameter of the C_{p1} chamber d_{v1a}	0.03 m	Eccentricity of impact piston e	0.2
Inner diameter of the C_{p1} chamber d_{v1b}	0.015 m	Loading exponent n_L	2
Diameter of C_{p7} chamber d_{v2}	0.013 m	Unloading exponent n_U	2
Internal pipeline diameter d_p	0.01 m	Initial length of the C_{p1} chamber L_{1a}	0.0126 m
Internal pipeline length L_p	0.1 m	Initial length of C_{p3} chamber L_{3a}	0.0274 m
Initial length of the C_{p4} chamber L_{4a}	0.0274 m	Initial length of C_{p5} chamber L_{5a}	0.0317 m
Initial length of the C_{p6} chamber L_{6a}	0.0638 m	Initial length of C_{p7} chamber L_{7a}	0.0106 m
Initial length of the C_{p8} chamber L_{8a}	0.005 m	Length of C_{p3} chamber just before oil supply L_3	0.0031 m
Length of the C_{p3} chamber just before oil return L_{3r}	0.0025 m	Length of C_{p4} chamber just before oil supply L_4	0.0025 m
Length of the C_{p4} chamber just before oil return L_{4r}	0.0031 m	Length of C_{p7} chamber just before oil supply L_7	0.03 m
Length of the C_{p8} chamber just before oil supply L_8	0.015 m	Initial length of the C_{p9} chamber L_{9a}	0.019 m
Length of the C_{p9} chamber just before oil return L_{9r}	0.0047 m	Initial length of C_{p10} chamber L_{10a}	0.0018 m
Length of the spool in contact with the valve body L_{v1a}	0.01 m	Length of C_{p9} chamber just before supplying oil to C_{p10} chamber L_{10}	0.0068 m
Length of the C_{p7} chamber just before oil return L_{7r}	0.03 m	Initial charging pressure of the buffer accumulator P_{11a}	9×10^6 Pa
Length of the C_{p8} chamber just before oil return L_{8r}	0.025 m	Initial charging pressure of high-pressure accumulator P_{2a}	9×10^6 Pa
Coefficient related to the compression of the O-ring seal ζ_a	1	Atmospheric pressure P_0	101325 Pa
Drag coefficient C_d	0.6	Cracking pressure of the relief valve P_{1r}	22×10^6 Pa
Input flow rate Q_1	90 L/min	Initial charging volume of buffer accumulator V_{11a}	0.0003 m ³
Buffer flow rate Q_d	9 L/min	Initial charging volume of the high-pressure accumulator V_{2a}	0.0004 m ³

Table 18
Meaning of variable parameters and constant parameters in the dynamic equations.

Parameter	Meaning	Parameter	Meaning
A_2	Effective acting area of C_{p6} chamber	A_1	Effective acting area of the C_{p5} chamber
A_{d2}	Effective acting area of C_{p10} chamber	A_{d1}	Effective acting area of the C_{p9} chamber
A_{v2}	Effective acting area of C_{p7} or C_{p8} chamber	A_{v1}	Effective acting area of the C_{p3} or C_{p4} chamber
A_{1b}	Inner cylinder area of C_{p5} chamber	A_{2b}	Inner cylinder area of the C_{p6} chamber
A_{v3}	Inlet flow area of C_{p3} chamber	A_{v3r}	Return flow area of the C_{p3} chamber
A_{v4}	Inlet flow area of C_{p4} chamber	A_{v4r}	Return flow area of the C_{p4} chamber
A_7	Inlet flow area of C_{p7} chamber	A_8	Inlet flow area of the C_{p8} chamber
A_{9r}	Return flow area of C_{p9} chamber	A_{10}	Flow area between the C_{p9} chamber and C_{p10} chambers
A_{7r}	Return flow area of C_{p7} chamber	A_{8r}	Return flow area of C_{p8} chamber
P_1	Pressure in C_{p1} chamber	P_2	Pressure in the oil chamber of the high-pressure accumulator
P_3	Pressure in C_{p3} chamber	P_4	Pressure in the C_{p4} chamber
P_5	Pressure in C_{p5} chamber	P_6	Pressure in the C_{p6} chamber
P_7	Pressure in C_{p7} chamber	P_8	Pressure in the C_{p8} chamber
P_9	Pressure in C_{p9} chamber	P_{10}	Pressure in the C_{p10} chamber
P_{11}	Pressure in oil chamber of buffer accumulator	Q_3	Inflow to the C_{p3} chamber
Q_{1r}	Relief flow rate	Q_4	Inflow to the C_{p4} chamber
Q_2	Flow rate of high-pressure accumulator	Q_5	Inflow to the C_{p5} chamber
Q_{3r}	Outflow from C_{p3} chamber	Q_7	Inflow to the C_{p7} chamber
Q_{4r}	Outflow from C_{p4} chamber	Q_8	Inflow to the C_{p8} chamber
Q_6	Flow rate between C_{p4} chamber and C_{p6} chamber	Q_{9r}	Outflow from the C_{p9} chamber
Q_{7r}	Outflow from C_{p7} chamber	Q_{11}	Flow rate of the buffer accumulator
Q_{8r}	Outflow from C_{p8} chamber	V_2	Volume of the oil chamber of the high-pressure accumulator
Q_{10}	Flow rate between C_{p9} chamber and C_{p10} chamber	V_{4a}	Initial volume of the C_{p4} chamber
V_{1a}	Initial volume of C_{p1} chamber	V_{6a}	Initial volume of the C_{p6} chamber
V_{5a}	Initial volume of C_{p5} chamber	V_{8a}	Initial volume of the C_{p8} chamber
V_{7a}	Initial volume of C_{p7} chamber	V_{10a}	Initial volume of the C_{p10} chamber
V_{3a}	Initial volume of C_{p3} chamber	V_{9a}	Initial volume of C_{p9} chamber

The buffer system is responsible for providing damping force to the drill tools, reducing its vibration and restoring it to its initial position. The flow rate and pressure in the buffer system are calculated using Eqs. (44)–(46).

$$\begin{cases} \frac{dP_9}{dt} = \frac{Q_d - Q_{9r} - Q_{11} - Q_{10}}{C_{p9}} = \frac{K_e(Q_d - Q_{9r} - Q_{11} - Q_{10})}{V_{9a}} \\ \frac{dP_{10}}{dt} = \frac{Q_d + Q_{10}}{C_{p10}} = \frac{K_e(Q_d + Q_{10})}{V_{10a}} \\ \frac{dP_{11}}{dt} = \frac{Q_{11}}{C_{p11}} = \frac{1.4P_{11a}V_{11}^{0.4}Q_{11}}{V_{11a}^{1.4}} \end{cases} \quad (44)$$

$$\begin{cases} Q_{9r} = \frac{P_9}{R_{9r}} = h(X_2 - L_{9r})C_d A_{9r} \sqrt{\frac{2P_9}{\rho}} \\ Q_{10} = \frac{P_9 - P_{10}}{R_{10}} = h(X_2 - L_{10})C_d A_{10} \sqrt{\frac{2(P_9 - P_{10})}{\rho}} \\ Q_{11} = \frac{P_9 - P_{11}}{R_{11}} = \frac{\pi d_p^4 (P_9 - P_{11})}{128 \mu L_p} \end{cases} \quad (45)$$

Among them, calculation of the gas chamber volume of a buffer accumulator is shown in Eq. (46).

$$V_{11} = V_{11a} \left(1 - \sqrt[1.4]{\frac{P_{11a}}{P_{11}}} \right) \quad (46)$$

The parameters involved in the physical model established in this paper are primarily determined through the following approaches. First, the structural geometric parameters, such as the mass, diameter, area, volume, length, and clearance listed in Table 17, are obtained through the actual mapping (measurement and drawing) of key components of the Epiroc COP1838 hydraulic rock drill. The meanings of other variable parameters and constant parameters are shown in Table 18. Second, regarding the dynamic parameters, the impact stiffness, buffer stiffness, and drill tool connection stiffness are acquired through experimental calibration; meanwhile, the loading and unloading stiffness of the rock are estimated via quasi-static rock deformation tests. Furthermore, the viscous damping c acting on the components, which arises from shear flow, is treated as a constant value to simplify the computational model. Finally, the standard hydraulic coefficients are determined by the Hydraulic Handbook, while system parameters such as the standard input pressure and flow rate are directly sourced from the general manual for the rock drill provided by Epiroc, as detailed in Table 1.

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