

Review

Optimization of Rock-Cutting Tools: Improvements in Structural Design and Process Efficiency

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Abstract

Rock-breaking cutters are critical components in tunneling, mining, and drilling operations, where efficiency, durability, and energy consumption are paramount. Traditional cutter designs and empirical process optimization methods often fail to address the dynamic interaction between heterogeneous rock masses and tool structures, leading to premature wear, high specific energy, and suboptimal performance. Topology optimization, as an advanced computational design method, offers transformative potential for lightweight, high-strength cutter structures and adaptive cutting process control. This review systematically examines recent advancements in topology-optimized cutter design and its integration with rock-cutting mechanics. The structural innovations in cutter geometry and materials are analyzed, emphasizing solutions for stress distribution, wear/fatigue resistance, and dynamic load adaptation. The numerical methods for modeling rock–tool interactions are introduced, including discrete element method (DEM) simulations, smoothed particle hydrodynamics (SPH) methods, and machine learning (ML)-enhanced predictive models. The cutting process optimization strategies that leverage topology optimization to balance objectives such as energy efficiency, chip formation control, and tool lifespan are evaluated.

Keywords: topology optimization; rock-breaking cutter; rock-cutting mechanics; structural design; numerical simulation; energy efficiency



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1. Introduction

Rock-breaking cutters are indispensable components in tunneling [1], mining [2], and drilling [3] operations, where their efficiency, durability, and energy consumption directly determine the feasibility and cost-effectiveness of large-scale engineering projects. These tools face extreme mechanical loads and abrasive interactions with heterogeneous rock masses [3], which often lead to premature wear, unpredictable failure, and excessive energy expenditure. Traditional cutter designs, which are largely based on empirical modifications of geometric parameters [4], struggle to address the dynamic interplay between tool structures and complex geological conditions. For instance, conventional methods fail to optimize stress distribution under cyclic loading or adapt to anisotropic rock properties, resulting in suboptimal performance and frequent maintenance [5,6]. The performance of rock-cutting tools is governed by multi-domain influencing parameters, including (1) tool-specific factors—geometry, material properties (hardness and fracture toughness), and

structural configuration; (2) rock mass characteristics—strength heterogeneity, abrasiveness, discontinuities, and geological anomalies; (3) operational parameters—cutting depth, penetration rate, tool spacing, and dynamic loading spectra [7]; and (4) environmental constraints—depth-induced geostress, groundwater ingress, and thermal gradients.

Topology optimization, which is a computational design method, has emerged as a transformative approach to overcome these limitations [8,9]. Unlike conventional trial-and-error methods, topology optimization design enables the systematic generation of lightweight, high-strength structures by redistributing material within a design space while satisfying mechanical constraints [10]. This method is particularly advantageous for rock-breaking cutters, where weight reduction can lower inertial forces during operation [11], and stress homogenization can mitigate crack initiation in high-load regions [12]. Topology optimization achieves performance maximization through intelligent material distribution and has been extensively applied across diverse fields such as aerospace [13], automotive manufacturing [14], biomedical engineering [15], and civil engineering [16]. Current cutting-edge approaches focus on interdisciplinary integration, multi-physics coupling optimization [17], encompassing multi-scale topology optimization [18], and data-driven machine learning optimization [19]. These methodologies, by integrating advanced algorithms and manufacturing technologies, significantly enhance structural functionality, lightweight potential, and manufacturability. Recent advancements in additive manufacturing further enhance the applicability of topology optimization, allowing the fabrication of intricate lattice structures that improve energy absorption and wear resistance [20].

The integration of topology optimization with rock-cutting mechanics requires addressing multi-physics challenges, including thermo-mechanical coupling, dynamic fracture propagation, and real-time adaptive control [21]. Numerical frameworks such as the discrete element method (DEM) [22] and smoothed particle hydrodynamics (SPH) [23] have been instrumental in simulating rock–tool interactions, revealing mechanisms like chip formation and crack propagation under varying load conditions. Meanwhile, machine learning (ML) models are increasingly deployed to predict tool wear and optimize cutting parameters [24], bridging the gap between computational design and operational efficiency. Rock-cutting tools endure extreme conditions, including high-impact loads, abrasive wear, and heterogeneous rock interactions, necessitating robust mechanical properties and fatigue resistance [25,26]. Despite the criticality of such tools, research on topology optimization for diverse cutter types (e.g., disk cutters [27] and conical picks [28]) remains underexplored compared to advancements in aerospace or automotive fields. This gap stems from various inherent challenges, as follows: (1) the complex multi-physics coupling during rock fragmentation complicates accurate modeling [29]; (2) dynamic and stochastic loading induces nonlinear material responses, demanding high-fidelity transient simulations; (3) material heterogeneity imposes constraints on isotropic assumptions in conventional optimization frameworks; and (4) the manufacturing feasibility of intricate optimized geometries under harsh industrial conditions remains a practical barrier [30].

This study aims to review recent advancements in topology-optimized cutter design and its synergy with rock-cutting process optimization. We critically analyze structural innovations, numerical modeling techniques, and adaptive control strategies, emphasizing interdisciplinary contributions from mechanics, materials science, and computational engineering. By addressing key challenges this work provides a roadmap for next-generation smart cutting systems that are capable of operating in extreme geological environments. This study is structured as follows: Section 2 examines structural innovations in rock-breaking cutters, analyzing conventional design limitations and emerging topology optimization strategies. Section 3 evaluates numerical modeling techniques for simulating rock–tool interactions and validating optimized designs. Section 4 explores cutting pro-

cess optimization strategies, focusing on energy efficiency, chip formation control, and sustainability. Section 5 proposes future directions.

2. Structural Innovations in Rock-Breaking Cutters

2.1. Conventional Cutter Design Limitations

2.1.1. Continuous Rock-Breaking Equipment and Types of Cutters

As shown in Figure 1a, boom-type roadheaders, driven by telescopic booms to operate rotating cutting heads, employ densely distributed conical picks composed of tungsten carbide tips and alloy steel bodies. These tools fracture medium–hard rock formations (uniaxial compressive strength <80 MPa) through high-speed rotation (20–50 rpm), generating combined shear–impact actions, as well as offering flexibility in adapting to complex cross-sections. As in Figure 1b, full-face tunnel boring machines (TBMs) utilize shield-driven propulsion systems, integrating single- or double-disk cutters on cutterheads. Double-disk cutters employ dual-ring designs to improve load distribution and eccentric resistance, promoting controlled radial crack propagation under high thrust forces. The interaction and subsequent fragmentation processes in rock breaking are directly relevant to the design of the TBM cutterhead and the efficiency of TBM excavation. The spacing between adjacent cutters is a key parameter governing this interaction mechanism. As in Figure 1c, disk-saw rock excavators feature oscillating cutting disks adjusted by hydraulic arms for dynamic radial penetration, combining high-speed rotation with sawtooth trajectory-induced tensile–shear interactions to delaminate stratified rock masses. These three equipment types target distinct scenarios—roadway construction, long-tunnel excavation, and precision rock cutting—yet share common technological challenges in tool wear resistance optimization and intelligent rock-breaking control. Notably, remotely controlled roadheaders play a pivotal role in such contexts, offering enhanced safety and operational efficiency in weakly cracked rock masses that are susceptible to collapses. Table 1 [31] presents the principal classification methods for rock-breaking tools used in this study.

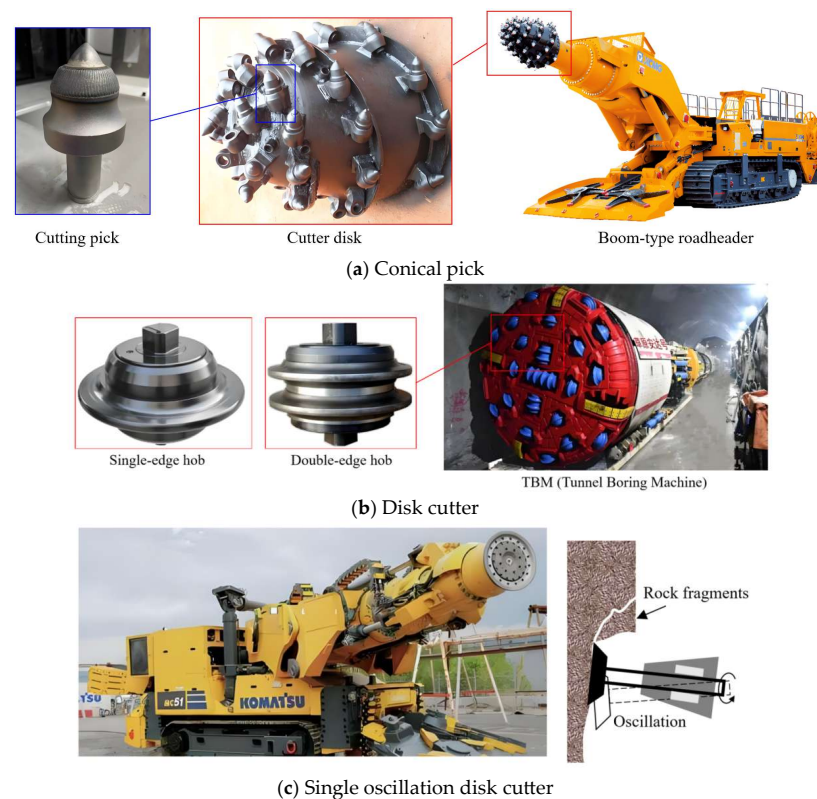


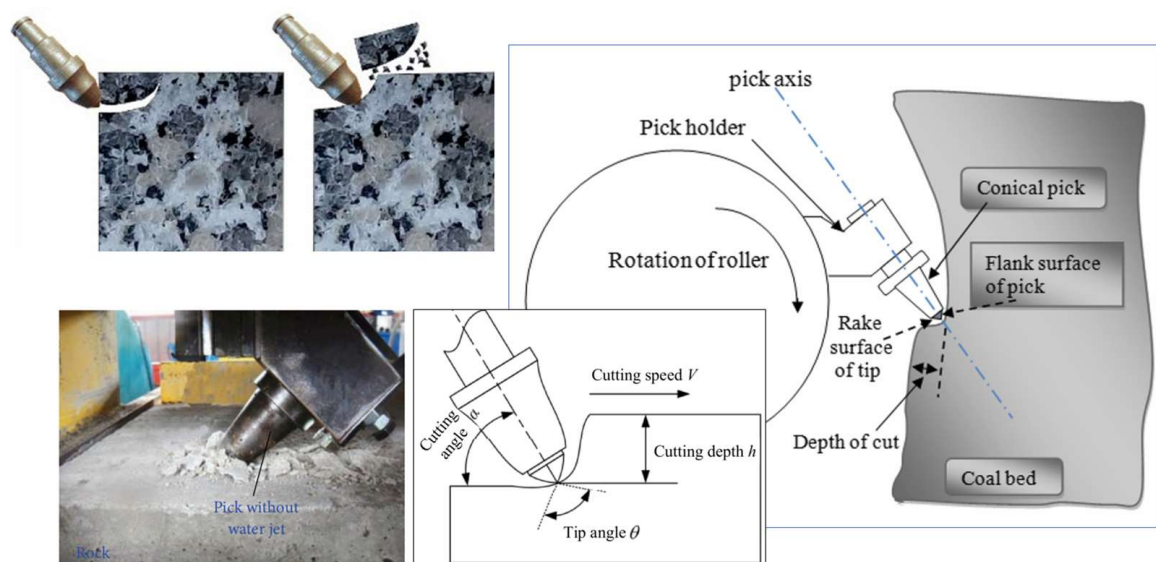
Figure 1. Types of tunnel excavation equipment and cutting tools in mining engineering.

Table 1. Classification methods of rock-breaking tools.

Working Mode	Rock–Tool Interaction	Cutting Tool	Adaptability of Rock Strength
Drag/plowing	Continuous rotation	Cutter tooth	<40~60 MPa
		Scraper	<60~80 MPa
		Conical pick	<40~60 MPa
Rotation	Rolling	Disk cutter	<250 MPa
Impact	Unreal rolling	Roller cone cutter	<200 MPa
	Impact	Beaker hammer	<100 MPa

2.1.2. Rock-Breaking Mechanism and Mechanical Model

Excavation progress is critically governed by geological constraints (rock properties, structure, and groundwater) and mining operational factors (method selection, equipment efficacy, support needs, and logistics). The interaction of these factors ultimately determines the rate of advance and the overall project timeline. Figure 2 (This figure is adapted from reference [32–34]) illustrates the rock-breaking mechanism of cutting picks, including their interaction with the rotating drum during fragmentation. Figure 3 (This figure is adapted from reference [35]) illustrates the relationship between the disk cutter's normal/rolling forces and rock-breaking mechanisms, particularly highlighting the dual-cutter cooperative fracturing effect. The traditional rock-cutting tool design procedure, which is predominantly based on empirical modifications of geometric parameters such as wedge angles and disk diameters [22], faces significant challenges in addressing the dynamic and heterogeneous nature of rock–tool interactions. Conventional approaches often rely on isotropic material assumptions and static load conditions, which fail to account for the anisotropic mechanical properties of rock masses and cyclic loading. For instance, studies on anchored rock joints under constant normal load and constant normal stiffness boundary conditions reveal that stress softening dominates, while stress hardening occurs under constant normal stiffness due to suppressed shear dilation, highlighting the limitations of static design frameworks in adapting to varying boundary conditions [25].

**Figure 2.** Schematic diagram of the rock-breaking mechanism of cutting picks.

The optimized design of rock-breaking tools requires synergistic advancements in both material properties and structural parameters. At the material level, the wear resistance and impact resistance of the tools are balanced through the integration of gradient-structured cemented carbide substrates with ceramic particles or diamond coatings [36,37]. Surface

treatment technologies further enhance surface hardness, while finite element simulations optimize microstructures to inhibit crack propagation [38]. In structural design, tool geometric parameters should be dynamically adjusted according to rock hardness, whereby conical picks with apex angles of $55\text{--}100^\circ$ achieve an optimal balance between economic efficiency and rock-breaking performance [28]. Curved-edge configurations and multi-cutter collaborative layouts effectively reduce ineffective fragmentation while extending service life [39]. The selection of operational parameters (e.g., force and rotational velocity) and tool type involves a fundamental compromise, whereby increasing the force may allow for lower speeds for certain tools, while higher speeds might be viable with specific cutter types under reduced force, all of which are aimed at balancing fragmentation efficiency and tool life. For scaled-up designs, scale effects must be addressed through modified geometric similarity principles, adapted heat treatment and welding processes, and recalibrated dynamic load matching to ensure strength redundancy in large-scale tools and power system stability.

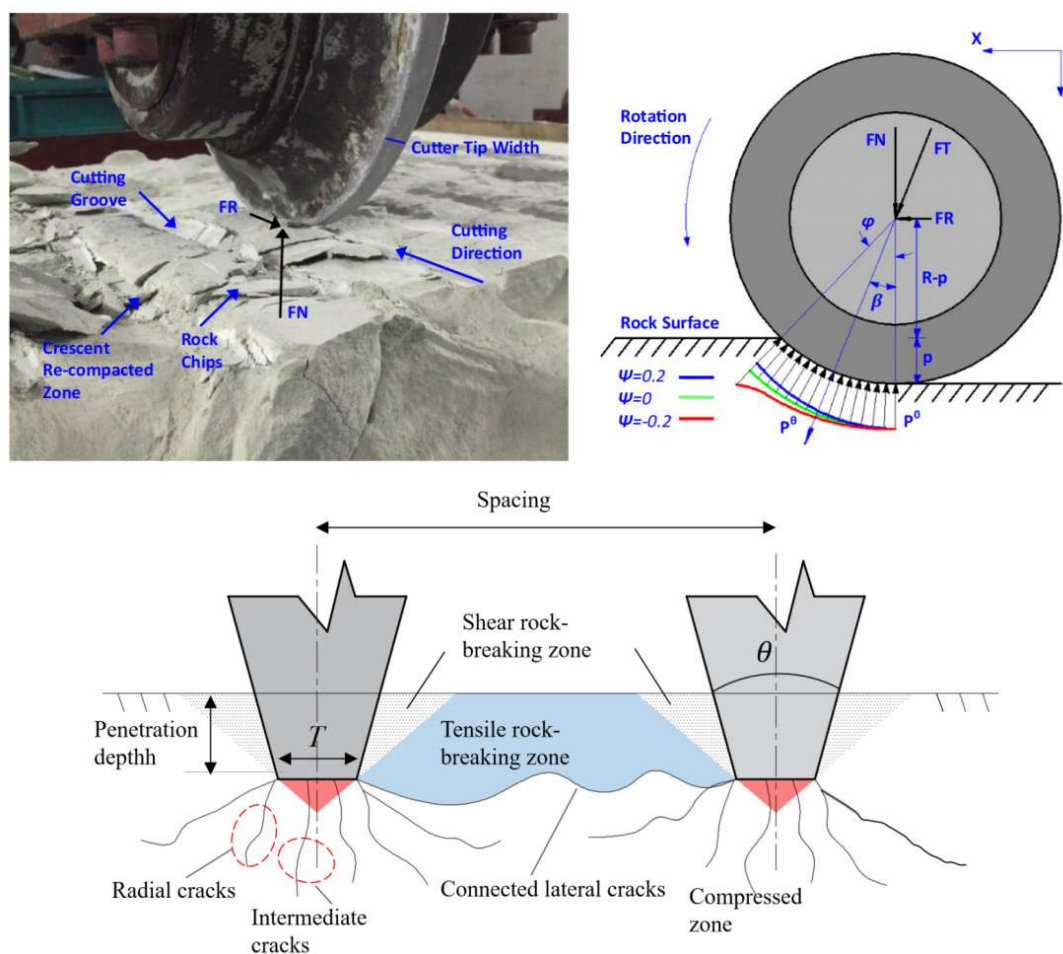


Figure 3. Relation between the disk cutter's normal and rolling forces and rock-breaking mechanisms.

2.1.3. Optimization Objectives and Optimization Methods

Figures 4 and 5 illustrate the influential factors, optimization objectives, and methods for rock-cutting tools aimed at enhancing rock-breaking performance. The optimization focuses on key metrics such as cutting force, specific energy, wear rate, and tool life. By employing topology optimization, finite element analysis, and machine learning, it seeks to improve tool geometry, material distribution, and structural parameters for different rock types and conditions. This enhances cutting efficiency and tool durability, offering a clear guide for subsequent optimization strategies. The optimization process must

integrate practical working conditions with intelligent control strategies. For hard rock or highly abrasive formations, diamond composite coatings and chip removal groove designs mitigate wear. Embedded sensors enable real-time tool condition monitoring, while machine learning-based dynamic adjustments of tunneling parameters facilitate adaptive rock-breaking mechanisms [24,40]. Scaled laboratory tests quantify specific energy consumption and wear rates, whereas field pilot tests optimize cutter arrangements through torque and thrust force monitoring [4,22]. Economic analyses demonstrate that although optimized tools incur 20–30% higher initial costs, their extended lifespan of over 50% significantly reduces the overall operational costs.

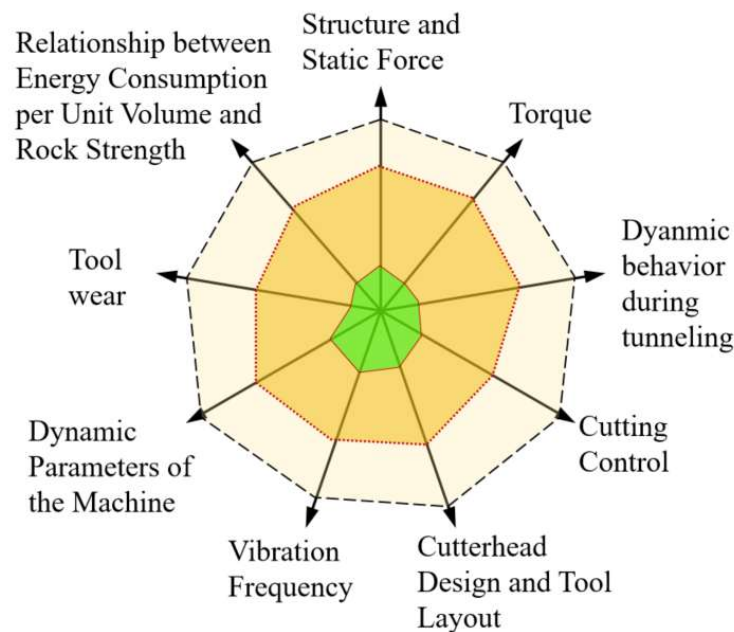


Figure 4. Factors of rock-breaking cutters and rock-cutting process.

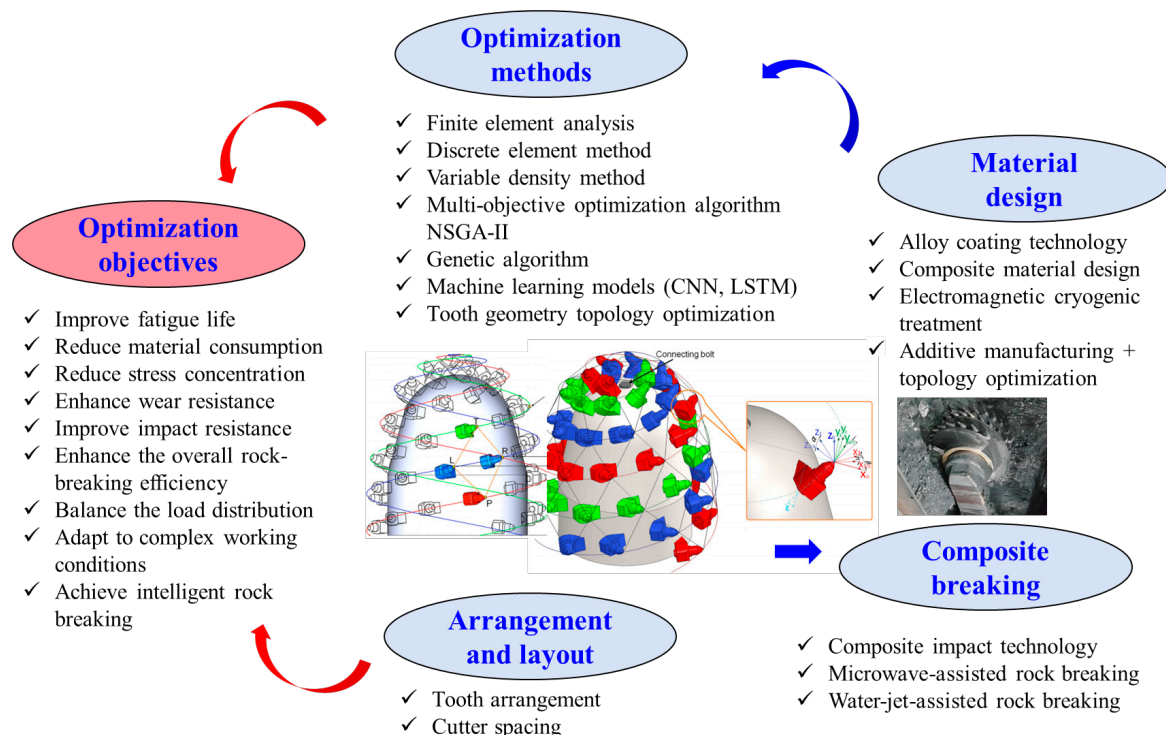


Figure 5. Optimization objectives and methods for improving rock-breaking performances.

Liu et al. [41] proposed an optimization design method for conical pick installation angles based on the coupling of static and kinematic principles. This approach established a geometric relationship model involving impact angle, tilt angle, and skew angle, deriving angular constraints for the resultant force along the pick axis. However, the design process relied solely on rigid-body assumptions and homogeneous rock conditions, limiting its applicability to real-world heterogeneous geological environments. Yasar et al. [32] introduced a semi-theoretical and semi-empirical predictive model for conical pick cutting forces. The model developed a generalized formula incorporating rock uniaxial compressive strength, cutting depth, rake angle, and back-clearance angle. While this model successfully captured the linear relationship between cutting force and depth by addressing limitations in traditional angular functions, it overlooked dynamic interactions between tool geometry and rock brittleness during cutting processes. Consequently, predictions exhibited significant deviations under high-depth cutting or complex operational conditions, highlighting unresolved challenges in balancing theoretical rigor with practical adaptability. Table 2 summarizes the optimization methods and corresponding performance improvements for various rock-cutting tools. A comparative analysis of optimization approaches and their effectiveness is systematically documented in the table.

Table 2. Optimization methods and performance improvements for rock-cutting tools.

Authors and Year	Optimized Component	Optimization Objective(s)	Optimization Method	Performance Improvement
Park et al. (2018), Int. J. Rock Mech. Min. Sci. [5]	Point attack pick cutter and cutter holder assembly	Minimize specific energy; enhance structural stability; extend tool durability	Lab-scale linear cutting tests; finite element analysis; evaluated cut spacing, depth, skew angle, and attack angle	Achieved lower specific energy via optimized skew/attack angles. Positive skew angle linked to slower abrasion rates.
Sun et al. (2018), J. Cent. South Univ. [42]	Cutter layout (assembled radius layout of disk cutters) for TBMs	Optimize cutter layout for balanced forces/moments with coupling and non-interference.	Genetic algorithm; equal life and equal wear principles; comprehensive evaluation model	Assembled radius gap—reduced to 25.8 mm. Unbalanced radial force—decreased by 62.41%.
Palaniappan et al. (2019), Proc. MPES [43]	Conical cemented carbide pick	Reduce the wear rate; analyze cutting forces, cutting efficiency, and specific energy to find the best performance compromise	Coating the pick tip with aluminum titanium nitride; examining wear mechanisms via SEM and X-ray analysis	Hardness improvement: 22.47 GPa; wear rate reduction: 13.9–21.8%.
Kumar et al. (2020), Int. J. Rock Mech. Min. Sci. [44]	Operating parameters of surface miner (depth of cut, cutting speed, and pick temperature)	Minimum pick wear/consumption, higher production, and optimal cutting efficiency	Develop empirical models via Taguchi, MLR, and ANN to study temperature variations in cutting picks	Achieved optimized temperature at 95% confidence level.
Mahmoodzadeh et al. (2021), Autom. Constr. [45]	Prediction of TBM disk cutter life	Develop accurate machine learning models for cutter life prediction	GPR, SVR, DT, and KNN with 200 datasets; five-fold cross-validation	Most accurate model (GPR).

Table 2. Cont.

Authors and Year	Optimized Component	Optimization Objective(s)	Optimization Method	Performance Improvement
Fathipour-Azar (2023), Rock Mech. Rock Eng. [46]	Predictive model for mean cutting force (MCF) of conical picks	Establish quantitative correlation between rock strength, tool geometry, cutting data, and MCF	Fine-tune hyperparameters using grid search, random search, GA, PSO, and DE	Best model (DE-XGBoost).
Zhou et al. (2023), Acta Geotech. [24]	Predictive model for specific energy (SE) in roadheader excavation	Develop accurate SE prediction models considering rock properties, pick geometry, and operation parameters	Six ML algorithms (BPNN, Elman, ELM, KELM, RF, and SVR) optimized by sparrow search algorithm (SSA)	SSA-RF—training set: MAE = 0.7938, MAPE = 12.76%, $R^2 = 0.9632$.
Liu et al. (2024), J. Cent. South Univ. [47]	Prediction model for mean cutting force (MCF) of conical picks	Accurately evaluate MCF for pick design and rock-cutting suitability	Hybrid models (boosting trees + Bayesian optimization (BO))	Best model (BO-CatBoost): outperformed common ML models, especially in handling categorical features (θ with 6 angle types).
Wang et al. (2024), Simul. Model. Pract. Theor. [48]	Disk cutter arrangements and excavation parameters	Reduce cutter wear, minimize specific energy, and balance cutter force during rock-breaking	Enhanced bonding model	Penetration depth ≤ 5 mm; tip width > 20 mm; cutter spacing 80–95 mm.
Du et al. (2025), Rock Mech. Rock Eng. [49]	Working parameters of disk cutter	Rock-breaking mechanism of disk cutter to understand how parameters affect rock-breaking behavior	Brazilian tests; coupled FEM–DEM	Revealed shear–tension failure mechanism; quantified parameter–energy relationships.

Empirical designs often lead to uneven stress distribution, causing localized stress concentrations at cutter edges or joints. This accelerates wear and crack initiation, particularly in hard rock, where abrasive interactions dominate. Conventional designs prioritize mechanical robustness over energy efficiency, resulting in a high specific energy consumption. For example, unoptimized cutter spacing and penetration depth in TBMs generate excessive fines and heat, increasing operational costs [50]. Lu et al. [51] demonstrated that conventional conical picks exhibit excessive material usage due to overestimated fatigue life requirements. Through topology optimization driven by dynamic load spectra and finite element analysis, a 23.83% volume reduction was achieved while maintaining structural integrity under cyclic loading, highlighting the necessity of integrating fatigue constraints in topology optimization frameworks.

2.2. Issues for Topology Optimization for Rock-Cutting Tools

Topology optimization technology, through intelligent material distribution design, plays a significant role in achieving lightweight structures, enhanced strength, and improved fatigue resistance. However, the unique working conditions and functional requirements of rock-breaking tools pose distinct challenges for their topology optimization design. Common construction materials for combining knives and disks include tungsten carbide, high-speed steel, and cemented carbides, which are selected for their ultra-high hardness, fracture toughness, and thermal stability.

Structural Adaptability under Complex Dynamic Loads: Rock-breaking tools undergo asymmetric impact loads, high-frequency vibrations, and multi-axial stresses during operation, rendering conventional static optimization models inadequate for accurately representing real-world working conditions. Dynamic response modeling requires the establishment of multi-physics-coupled models. Existing topology optimization methods predominantly rely on static strength constraints, lacking quantitative control over crack initiation and propagation under cyclic loading. To address this, a dynamic load-sensitive objective function should be developed by integrating transient numerical analysis with data-driven prediction algorithms (such as fatigue life prediction).

Material–Structure Synergistic Optimization in Extreme Wear Environments: Rock-breaking tools rely on composite structures combining hard surface materials for wear resistance with tough substrate materials; however, topological optimization often neglects the impact of material gradients on performance. The parametric representation of continuous/discrete material distributions lacks sufficient compatibility with manufacturing processes. The conflict between lightweight requirements and wear-resistant layer thickness creates competing optimization objectives, necessitating multi-objective analysis. There is a need to develop a multi-scale topology optimization framework integrating material microstructure design with macroscopic geometric morphology optimization.

Data Scarcity in Multi-Condition Adaptive Design: Rock-breaking tools need to adapt to varying working conditions, such as different rock hardness levels. However, the limited amount of experimental data restricts the generalization capability of optimization models. Quantifying the geomechanical properties and tool–rock interactions remains challenging. Machine learning models trained on small datasets face high risks of overfitting, making it difficult to explore high-dimensional design spaces effectively. To address this, a digital twin platform for rock–tool interactions should be established, combined with transfer learning to enhance the cross-condition adaptability of optimization models.

Through response surface methodology, Sun et al. [22] demonstrated that cutting depth (h) exerts the most significant influence on disk cutter wear (contribution weight: 42%), followed by spindle speed and swing arm speed. Their optimized parameters reduced specific energy consumption by 41% (from 29.85 to 17.59 MJ/m³), validating the potential of data-driven parameter tuning in energy efficiency improvement. Lu et al. [51] conducted topology optimization for cantilever roadheader picks driven by fatigue life. A cutting force mathematical model and triaxial load spectrum simulation were used to identify maximum loads for static analysis. Finite element evaluation revealed material redundancy in traditional designs. Volume-minimized topology optimization via the variable density method achieved a 64.42% volume reduction after 43 iterations. Validation demonstrated a maximum stress of 883 MPa (below the permissible 950 MPa), a fatigue life of 1.92×10^4 cycles (meeting the 32-day operational requirements), and a 23.83% material reduction, achieving synergistic improvements in strength, longevity, and lightweight performance.

The topology optimization framework proposed in the reference (Figure 6 [51])—encompassing cutting force simulation, static analysis, and fatigue life prediction—establishes a systematic methodological framework for structural adaptability under complex dynamic loads. The optimized pick achieved a 23.83% reduction in volume while increasing rotational torque by 18% through symmetrical groove design. However, the study did not fully validate the compatibility between the topological configuration and additive manufacturing processes, nor did it investigate the long-term reliability evolution of gradient materials under dynamic service conditions.

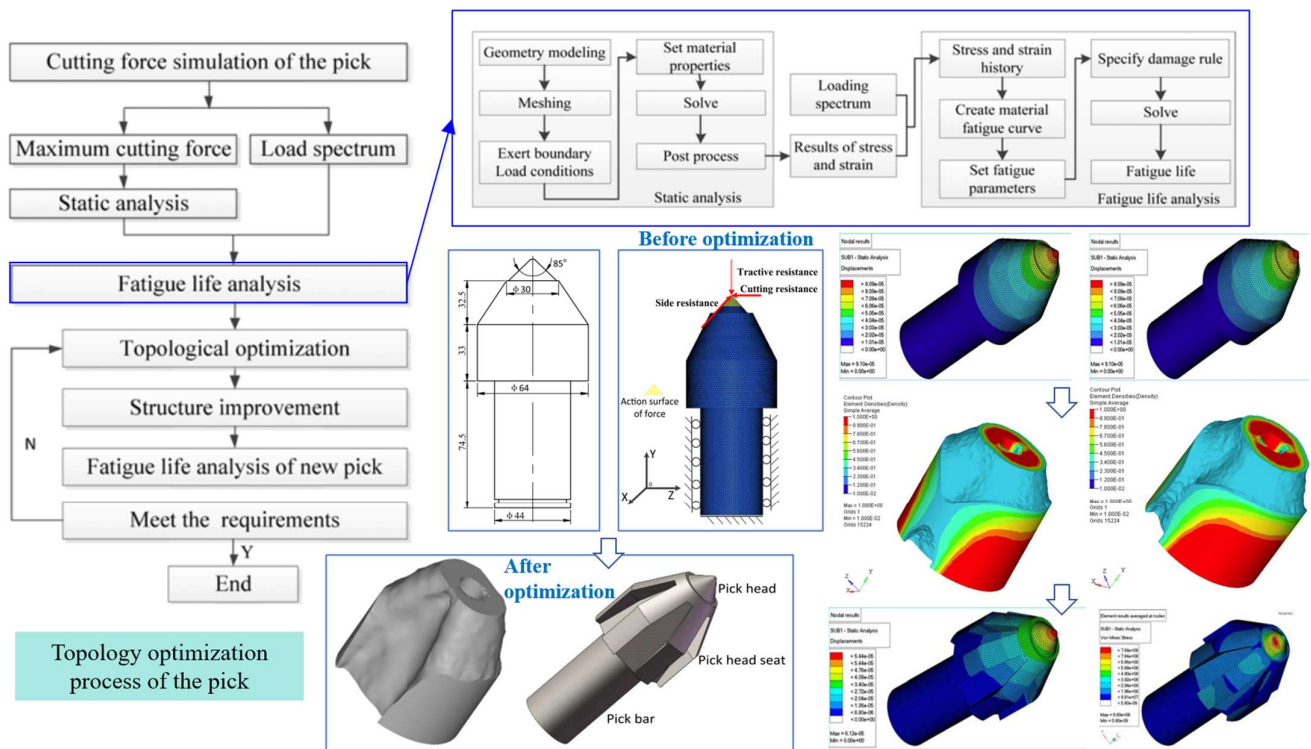


Figure 6. Topology optimization process of the pick cutter.

3. Numerical Modeling of Rock–Tool Interactions

3.1. Numerical Simulation Techniques

Rock fracture evolution represents a quintessential continuum–discontinuum coupling problem. Accurately simulating its complete process requires numerical methods to simultaneously address three critical capabilities—(1) the characterization of continuum mechanical properties, (2) the modeling of discontinuum behaviors, and (3) the resolution of spatiotemporal transition mechanisms between continuum and discontinuum states. However, most existing numerical approaches are confined to specific fracture stages, necessitating hybrid methodologies to achieve full-process simulation [52] (Figure 7 [53]).



Figure 7. Hard alloy disk cutters and the alloy detached after their failure.

Numerical methods for rock fracture simulation are categorized into continuum and discontinuum approaches. Continuum methods (e.g., FEM and XFEM) accurately characterize rock deformation but require mesh refinement or element deletion techniques to model fracture [54]. Discontinuum methods (e.g., DEM) describe discontinuities and large deformations via discrete particle interactions; however, they suffer from computational inefficiency and parameter sensitivity [55] (Figure 8 [56]). Hybrid continuum–discontinuum methods, such as the Continuum–Discontinuum Element Method (CDEM), integrate FEM and DEM to simultaneously simulate continuum deformation and interface fracture. Zhu et al. [57] developed a 3D CDEM hydraulic fracturing model coupling continuum fields with fracture seepage; Yue et al. [58] combined the Material Point Method

(MPM) with CDEM to simulate blast-induced fractures; and Gong et al. [59] combined FEM and Discontinuous Deformation Analysis (DDA) to capture progressive rock failure. While these hybrid approaches enable full-cycle fracture evolution modeling, challenges persist in algorithmic complexity and interfacial transition errors, driving research toward unified numerical frameworks.

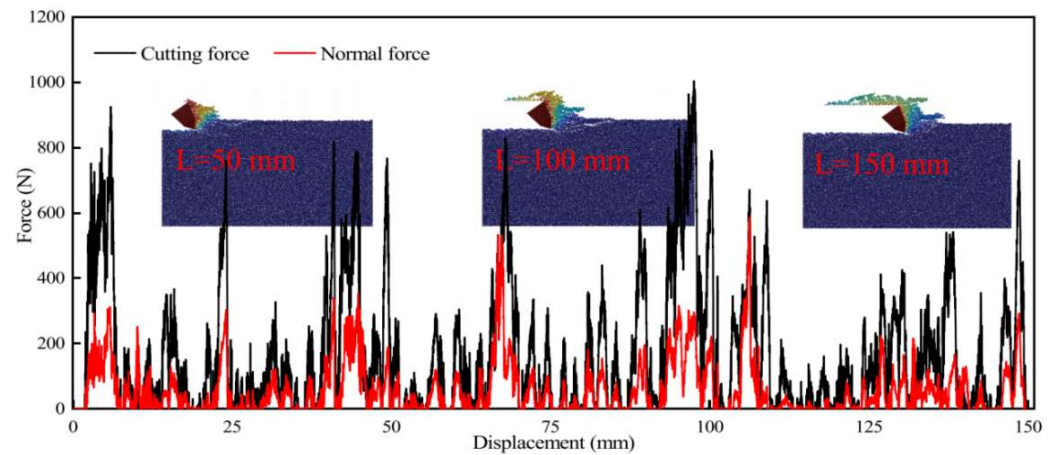


Figure 8. Simulation of the process of a pick cutting rock under confining stress using DEM.

In rock mechanics, numerical methods integrating fracture models and cutter geometries have advanced the understanding of rock-cutting mechanisms. While FEM simulations of disk cutter operations often exhibit over-cutting artifacts in the rock beneath the tip, Geng et al. [60] enhanced cutting force prediction accuracy through optimized element deletion strategies. Li et al. [61] employed PFC3D to analyze lunar rock-cutting loads under shallow depths with varied blade angles. Meshless methods, categorized as continuum approaches (e.g., MPM [62] and SPH [63]), include global weak-form techniques like EFGM [64] (requiring background integration grids) and local weak-form variants such as point interpolation methods and SPM. Leveraging Lagrangian particle properties and mesh-free adaptability, SPM uniquely bridges continuum deformation and discontinuum fracture behaviors, emerging as a robust approach for simulating continuum–discontinuum transitions in rock failure processes (Figure 9).

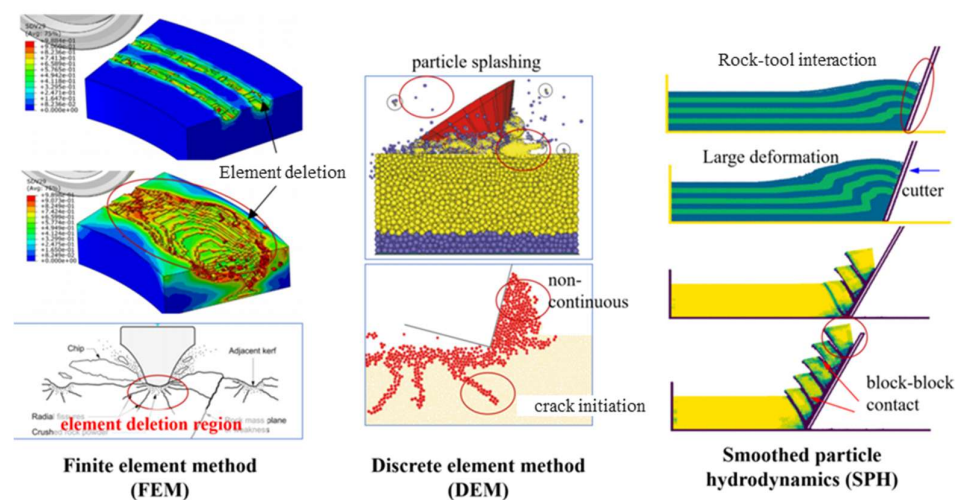


Figure 9. Comparison of different types of rock-cutting models.

3.2. Machine Learning (ML)-Enhanced Predictive Models

Machine learning has revolutionized predictive modeling in rock-cutting optimization by enabling data-driven insights into complex tool–rock interactions. It has been success-

fully applied to assess excavation efficiency in recent studies. E. Avunduk et al. [65] used the artificial neural network technique to predict the instantaneous cutting rate of the road-header. Zhang et al. [66] developed a digital twin-driven method for real-time intelligent control for TBM operation. Liu et al. [67] implemented faster R-CNN with a simplified VGG16 backbone to develop an intelligent rock identification system, achieving a high accuracy for single rock types and >80% for complex lithological mixtures, demonstrating strong robustness for underground mine stability assessment.

Hybrid frameworks, such as Light-GBM coupled with Classification and Regression Trees [68], demonstrate superior accuracy in predicting cutting forces and wear rates under multi-condition scenarios, achieving mean absolute errors below 8% when trained on DEM-simulated datasets. Digital twin platforms further leverage real-time sensor data (e.g., strain and temperature) to dynamically adjust cutting parameters, reducing tool wear prediction latency to <2 s in field trials [69]. However, current ML models remain constrained by their dependency on high-quality labeled data, as well as their limited interpretability in capturing multi-physics interactions. Recent advances in physics-informed neural networks (PINNs) show promise in bridging this gap by embedding the governing equations of rock fracture mechanics into loss functions, enhancing both predictive accuracy and physical plausibility [70].

As a representative ML approach, Physics-Informed Neural Networks (PINNs) integrate physical laws with data-driven modeling to overcome these limitations. Table 3 summarizes the key steps for implementing PINN-based tool optimization, from physics-based problem definition to experimental validation.

Table 3. A general procedure for cutting tool optimization with PINN.

Step 1: Problem Definition and Physics-Based Modeling	
Input Parameters:	Tool geometry (blade angle, edge length), material properties (hardness, elastic modulus), operating conditions (cutting speed, confining pressure).
Output Targets:	Stress field, temperature field, crack propagation path, tool wear rate, specific rock-breaking energy.
Governing Equations:	
Rock Mechanics:	Elastoplastic constitutive equations, as well as Drucker–Prager or Mohr–Coulomb failure criteria.
Heat Transfer:	Energy conservation equation with thermo-mechanical coupling terms.
Tool–Rock Interaction:	Frictional heating model, wear equations.
Step 2: PINN Architecture Design	
Network Structure:	
Input Layer:	Tool parameters (e.g., blade angle α , cutting depth d) and spatial coordinates (x, y, t) .
Hidden Layers:	Multi-layer perceptron (activation: ReLU/Swish).
Output Layer:	Key physical quantities (stress σ , temperature T , damage factor D).
Loss Function:	
$\mathcal{L} = \lambda_{\text{data}}\mathcal{L}_{\text{data}} + \lambda_{\text{phys}}\mathcal{L}_{\text{phys}}$	
Data Loss $\mathcal{L}_{\text{data}}$:	mean square error of experimental or simulation data (such as the cutting tool forces F_x, F_y)
Physics Loss $\mathcal{L}_{\text{phys}}$:	residual of the governing equation, the boundary condition.
Step 3: Model Validation and Uncertainty Quantification	
Validation Metrics:	
	Error between predictions and independent experimental data.
	Norm of physics equation residuals.
Uncertainty Analysis:	Monte Carlo dropout or Bayesian PINN to quantify robustness against input noise.
Step 4: Tool Optimization	
Objective:	Minimize specific energy or maximize tool life.
Optimization Methods:	
Gradient-Based:	Use PINN's automatic differentiation to compute $\partial E_{\text{specific}} / \partial \alpha$ for gradient descent.
Global Search:	Genetic algorithms for multi-objective Pareto optimization (e.g., trade-off between energy consumption and wear rate).
Experimental Validation:	Verify optimized tool designs via experiments or high-fidelity simulations.

3.3. Experimental Validation

In the research, development, and optimization of rock-breaking tools, experimental techniques play an indispensable role. As a mainstream method for rock-breaking experiments, the linear cutting experiment simulates the rock-cutting process under actual working conditions [35]. The experiment is usually carried out in a controlled pressure environment. The rock sample is fixed on the experimental platform, and the cutting tool cuts the rock at a set speed and load. The cutting force, power consumption, and tool wear are monitored in real time (Figure 10 [35]).

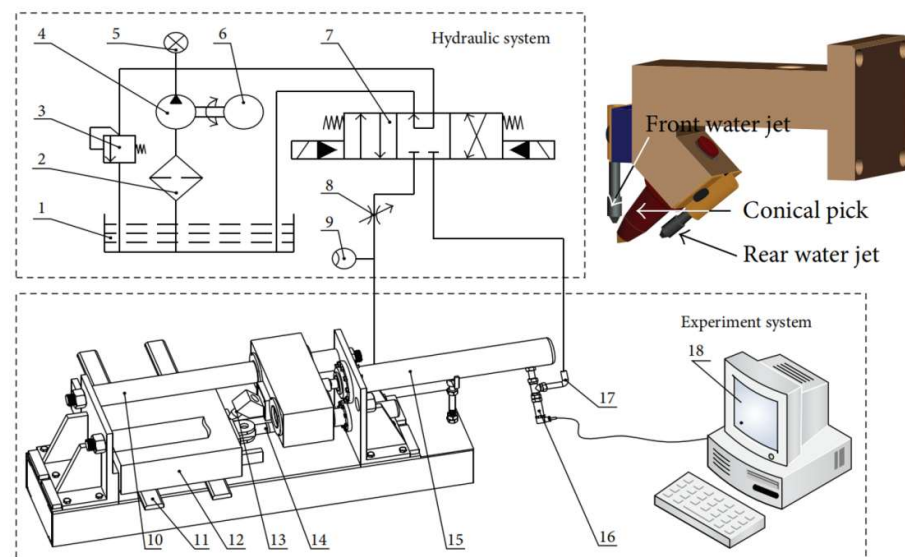


Figure 10. Linear cutting experimental system of water-jet-assisted cutting picks.

Currently, the role of linear cutting experiments is mainly reflected in the following three aspects:

- (1) It provides a basis for the selection of tool materials and geometric optimization;
- (2) It quantifies the performance of tools under different rock conditions;
- (3) It verifies the accuracy of numerical models.

With the evolution of technology, rock-breaking experiments are moving towards automation and digitization. The integration of real-time sensor technology and image recognition systems has significantly improved the accuracy of wear assessment and crack propagation monitoring.

In the future, rock-breaking experiments will be further integrated with artificial intelligence. By leveraging machine learning algorithms, the intelligent analysis and prediction of experimental data can be achieved. At the same time, the improvement in multi-physics field coupling experimental systems will be promoted to more comprehensively simulate the rock fragmentation mechanism under actual working conditions [71]. For example, the development of a thermo-mechanical coupling experimental device will help in understanding the interaction between the cutting tool and the rock in a high-temperature environment, providing crucial support for tool design under extreme working conditions.

4. Cutting Process Optimization

4.1. Energy Efficiency and Specific Energy Reduction

Topology optimization has emerged as a pivotal strategy for enhancing energy efficiency in rock-cutting operations by systematically reducing tool mass while maintaining structural integrity. By redistributing material to minimize stress concentrations and inertial forces, topology-driven designs directly lower the specific energy consumption required

for rock fragmentation. For instance, Lu et al. [51] achieved a 64.42% volume reduction in cantilever roadheader picks through variable density methods, while preserving fatigue life. This was accomplished by optimizing load-bearing paths under dynamic cutting forces simulated via MATLAB-based triaxial spectra. The resultant lightweight structures not only decrease power demands but also mitigate heat generation—a critical factor in high-speed tunneling where unoptimized tools can elevate temperatures by 80–120 °C, accelerating wear [20].

Comparative studies highlight topology optimization's superiority over traditional parameter-tuning approaches. While response surface methods, such as Sun et al.'s gray correlation analysis [22], optimize cutting depth and spindle speed to reduce SEC by 41%, these strategies primarily address operational parameters rather than structural inefficiencies. In contrast, topology optimization concurrently optimizes tool geometry and material distribution, where helical groove designs reduced recirculation energy losses through controlled debris ejection [51]. However, current topology optimization frameworks often neglect thermo-mechanical coupling effects, limiting their ability to predict energy dissipation in high-friction scenarios. Future advancements require hybrid models integrating transient thermal analysis with topology-sensitive objective functions to address energy efficiency across mechanical and thermal domains.

4.2. Chip Formation and Debris Management

The control of chip morphology and debris flow is critical to minimizing energy loss and tool clogging during rock-cutting operations. Numerical frameworks combining SPH and DEM or FEM have proven instrumental in simulating dynamic fracture patterns and granular flow dynamics [72]. SPH captures the fragmentation of soft rock layers under tensile–shear coupling, enabling the prediction of chip sizes and ejection trajectories (see Figure 11), while DEM quantifies inter-particle collisions and frictional forces in debris-laden environments. Recent studies by Yu et al. [72] indicate that the use of the SPH-DEM model can establish a refined coupling model of abrasive particles and rock that is capable of addressing a broader range of multiphase and multifield coupling rock-breaking problems (Figure 12 [73]). However, computational costs remain prohibitive for real-time applications, necessitating reduced-order modeling or surrogate-assisted algorithms to balance accuracy and efficiency.

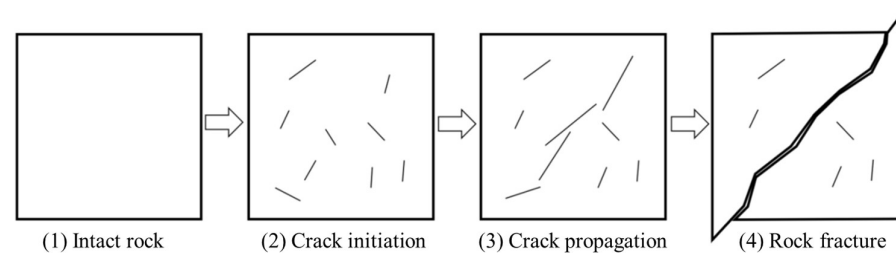


Figure 11. The whole process of rock fracture evolution: a typical continuous–discontinuous problem.

Topology optimization further enhances debris management by tailoring cutter geometries to promote self-cleaning behaviors. Machine learning augments such optimizations, whereby neural networks trained on DEM- or SPH-simulated clogging scenarios identify optimal groove depth-to-width ratios that maximize debris clearance while preserving structural integrity. Nevertheless, field validations under heterogeneous rock conditions remain sparse, highlighting the need for digital twin platforms integrating real-time wear monitoring and adaptive geometry adjustments.

Furthermore, a comprehensive evaluation of TBM performance should also consider the characteristics of the excavated material. Spoil classification provides valuable insights into the fragmentation efficiency, cutter wear, and potential ground conditioning

needs, serving as a direct indicator of the excavation process [74]. Similarly, accurate assessment of the final tunnel profile is crucial for verifying design compliance, evaluating overbreak/underbreak, and ensuring structural stability and lining requirements [75].

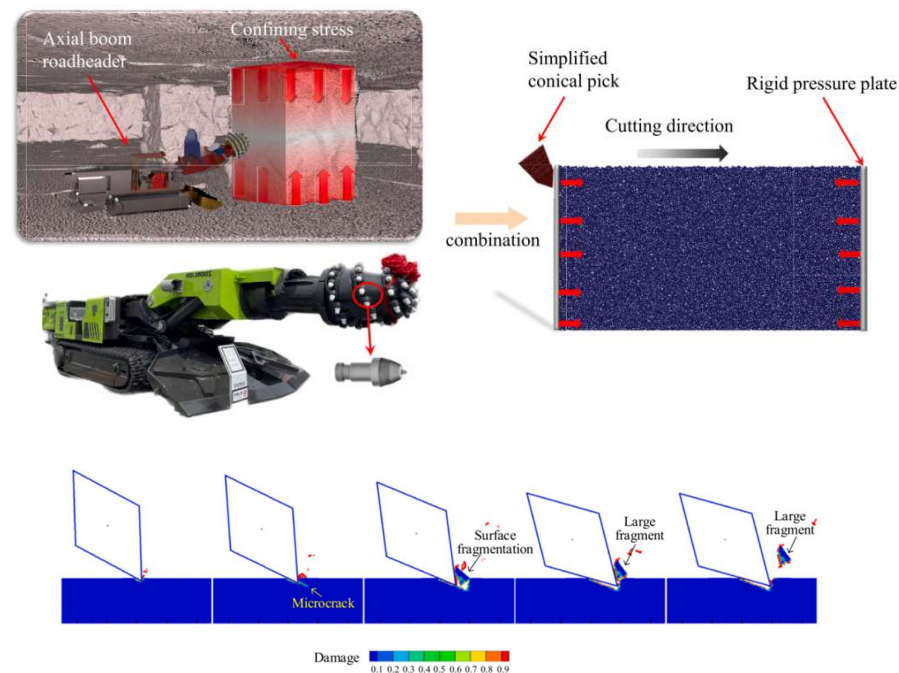


Figure 12. Smoothed particle hydrodynamics (SPH) model for rock-cutting-induced crack propagation and chip separation.

4.3. Sustainability and Scalability

Topology optimization inherently supports sustainability by minimizing material usage while maintaining structural performance. Additive manufacturing further amplifies these benefits by enabling the near-net-shape production of optimized geometries, cutting material waste by up to 45% compared to subtractive methods [76]. Emerging topology optimization algorithms incorporating life-cycle assessment metrics now prioritize designs balancing lightweighting with disassembly feasibility, though industrial adoption remains nascent [77].

Scalability challenges arise when translating lab-scale topology optimization solutions to full-size industrial tools [78]. While small picks (e.g., 50–100 mm in length) achieve 60%+ volume reduction via topology optimization, large disk cutters (>500 mm diameter) face thermo-mechanical instability due to scale effects in heat treatment and residual stress distribution. Multi-scale topology optimization frameworks, which couple macroscopic tool geometry with graded microstructures, mitigate these issues by embedding stress-adaptive lattice patterns in high-stress regions.

4.4. Critical Challenges and Future Directions

Despite significant progress, key challenges persist in topology optimization for rock-cutting applications. Current topology optimization frameworks often simplify dynamic load spectra to mitigate computational burdens in multi-physics coupling, limiting their ability to capture the high-frequency loading effects that are critical for real-time adaptive control. The selection of support systems also directly impacts excavation cycle times. Rigid rock bolt support enables faster installation but requires stable ground conditions, whereas arch-flexible support accommodates deformation at the cost of extended assembly time. Optimizing this trade-off through ground condition prediction can accelerate advance rates while maintaining safety margins. Furthermore, the absence of thermo-mechanical

coupling analysis and in situ wear monitoring in existing studies underscores the gaps in predicting tool degradation under extreme thermal and abrasive conditions. To address these limitations, future research must integrate digital twin platforms with edge computing to enable rapid optimization iterations and real-time geometry adjustments. Additionally, synergizing parameter-level optimizations with structural topology optimization solutions could unlock multi-scale optimization strategies, harmonizing process parameters and tool geometries for holistic energy efficiency gains.

5. Conclusions

This review establishes topology optimization as a paradigm-shifting approach for intelligent rock-cutting tool design, systematically overcoming empirical limitations in structural efficiency, durability, and energy consumption. The principal findings are summarized as follows:

- (1) The transformative potential of topology optimization in rock-cutting tools enables lightweight, high-strength structures that outperform empirical designs, resolving stress concentration, dynamic load adaptation, and wear resistance challenges.
- (2) Integration with advanced methods (DEM/SPH simulations and ML models) achieves the predictive optimization of rock–tool interactions, cutting forces, and tool lifespan.
- (3) Key innovations include multi-physics-coupled frameworks for dynamic loading, ML-enhanced predictive models, and sustainable recyclable designs.
- (4) Persisting challenges involve thermo-mechanical coupling effects, manufacturing feasibility of complex geometries, and scalability across heterogeneous rock conditions.
- (5) Depth-induced difficulties (elevated geostress, rockburst risks, and thermal/water hazards) necessitate intelligent monitoring and adaptive excavation strategies.

Future research directions should focus on multi-scale topology optimization, integrating material microstructures and macro-geometries, digital twin platforms for real-time adaptive control, and AI-driven design frameworks trained on multi-condition datasets. Bridging these gaps will unlock next-generation smart cutting systems that are capable of autonomous adaptation to extreme geological environments, ultimately advancing the sustainability and cost-effectiveness of mining and tunneling operations.

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