Research progress and prospects of intelligent technology in underground mining of hard rock mines

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ABSTRACT

Minerals are the material foundation for advancing human civilization, the starting point of the manufacturing supply chain, and strategic resources essential for national security and economic progress. In recent years, deep learning and big data have strongly supported improving mining efficiency and safety in underground hard rock mines. Against this backdrop, this paper focuses on the production processes and vital auxiliary aspects of underground mining in hard rock mines. It delves into six aspects: drilling, blasting, transportation, hoisting, ventilation, and support and filling. The paper elaborates on the latest advancements in intelligent technology research for each aspect and provides a summary and outlook on the key technologies relevant to these processes. Research results show that the current intelligent technology used in underground mining not only improves production efficiency but also further improves the safety production level of mining enterprises. To achieve intelligent unmanned mining, bottleneck problems in each primary process must be further addressed.

1. Introduction

Mineral resources are the material basis for the survival of human civilization and an essential guarantee for social and economic development. In terms of solid minerals, mining methods can be divided into open-pit mining and underground mining according to the occurrence conditions of the ore body. Open-pit mining refers to directly excavating ore by removing the topsoil and surrounding rock covering the upper part of the ore body and the surrounding rock. In this process, the ratio of the amount of rock and soil stripped to the amount of mining is called the stripping ratio. Open-pit mining may increase the stripping ratio when the deposit is buried deep, resulting in excessive mining costs. In contrast, underground mining refers to the vertical shaft digging process, inclined shafts, ramps or tunnels to access the ore body and transporting the mined ore to the surface to reduce costs when the ore body is buried deep. With the gradual depletion of resources in the shallow parts of the earth, the mining of metal minerals will continue to extend downward. In the future, the most critical mining methods will be underground mining and even deep mining.

In underground mining of hard rock mines, the production processes mainly include drilling, charging, blasting, ventilation, transportation, hoisting, support and filling, as shown in Fig. 1 [1]. Compared with soft rock mines, achieving automation and continuity in hard rock mines is more difficult. Because of the low strength of soft rock represented by coal mines, mechanical equipment can cut and separate the ores during mining, facilitating the implementation of mechanized continuous mining. In hard rock mining, because of the high strength of the ore rock, rock drilling and blasting must be used to break the rock, resulting in interruptions in the production process, low production efficiency, and poor safety. Particularly as the mining depth increases, the ground stress increases linearly or nonlinearly, the ground temperature rises, and the rock mass becomes hard and brittle, which brings about many technical problems in transportation, ventilation and cooling, and filling processes, further increasing the difficulty of making hard rock

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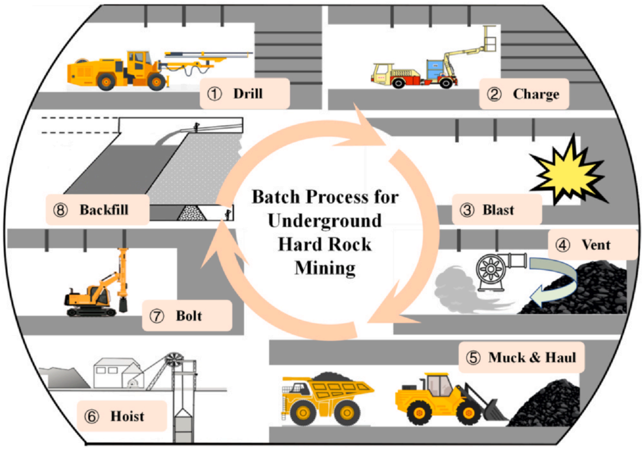

Fig. 1. Batch progress for underground hard rock mining (Note: modified based on the original version in Ref. [1]). Reproduced with permission from Ref. [1]. Copyright (2022) Elsevier.

mines intelligent.

This article focuses on the abovementioned main production links and describes the latest progress in intelligent technology research. Section 2.1 mainly describes the intelligent sensing of borehole lithology and intelligent drilling rig control technology in tunnel excavation drilling and production drilling; Section 2.2 combines the charging and blasting links and describes the intelligent technology in blasting design, charging and detonation, blasting effect evaluation and prediction, and blasting parameter optimization; Section 2.3 divides horizontal transportation and vertical hoisting into transportation links and describes the progress of intelligent technology in vehicle positioning and dispatching and transportation safety monitoring; Section 2.4 provides a narrative analysis of the intelligent sensing, fault diagnosis, and intelligent control of the ventilation system; Section 2.5 summarizes the intelligent evaluation of rock mass quality, intelligent support equipment, and intelligent monitoring of surrounding rock deformation related to the support link; Section 2.6 investigates and summarizes the intelligent technology in the filling process. Finally, the content of the full text is summarized in Chapter 3.

2. Research progress of intelligent mining technology

2.1. Drilling

During the underground mining process of hard rock mines, whether it is the excavation process of the mine passages or the production process of ore mining through blasting, the drilling process is indispensable. In addition to continuous improvements in drilling tools, recent research has also made progress in using intelligent technology to assist drilling operations. This research primarily focuses on the intellectual perception of rock properties during drilling and automation control of drilling rigs.

2.1.1. Intelligent perception of drillings

In the drilling operation process, the drilling parameters and the rock layer lithology are closely correlated, and using advanced technology to obtain the properties of the rock layer and adjust the working parameters of the drilling rig promptly can substantially improve the drilling efficiency. Generally, in engineering, direct or indirect methods such as drilling core testing and geophysical exploration are used to obtain the physical and mechanical characteristics of the strata and rock mass. However, these methods are usually cumbersome, expensive, and have significant errors. Recently, the development of technologies such as measurement while drilling (MWD) and digital panoramic imaging technology for drilling has provided new means for intelligent perception of drilling lithology.

MWD is a technology that continuously measures and records drilling data, which can measure the situation of the rock mass on-site in real-time during production and achieve comprehensive, continuous, and accurate real-time acquisition of various drilling parameters such as rotation speed, torque, drilling pressure, and drilling speed during the drilling process. Recently, many scholars have researched using MWD technology to achieve intelligent perception of drillings. Van Eldert *et al.* [2–4] filtered and normalized large amounts of complex data obtained from MWD technology. Wang and He [5] predicted rock compressive and tensile strengths based on friction characteristics parameters obtained from MWD measurements. Khorzoughi *et al.* [6] used MWD technology to monitor permeability, pulling force, rotational torque, rotation speed, and bail air pressure data to determine the presence of open and partially open fractures with different inclinations. Park and Kim [7] used penetration rate parameters measured by MWD to estimate complete rock properties and predict the crushing efficiency that directly affects the energy consumption of pulverization. Navarro *et al.* [8] indicated over- and under-excavation areas based on MWD measurement parameters. Meanwhile, the rise of technologies such as machine learning has also promoted the development of intelligent perception technology for lithology. Galende-Hernández *et al.* [9] employed machine learning techniques to intelligently predict the mass quality grade (Rock Mass Rating, RMR value) of surrounding rocks based on parameters measured during drilling. Liaghat *et al.* [10] applied machine learning to the measurement technology during drilling, achieving ore grade prediction. Gao *et al.* [11] employed intelligent sensing of rock strength by combining a multi-feature fusion of drilling vibration response with the backpropagation (BP) neural network. Fernández *et al.* [12] used machine learning in drilling measurements to predict rock structure by identifying discontinuities within the rock formations inside a borehole. Fig. 2 is a flowchart of a classic case using MWD and machine learning technology to realize intelligent rock property sensing. First, the information monitored during drilling is recorded in the drilling and geological database. Second, the obtained drilling data is filtered and normalized to correlate it with the discontinuities observed, and binary sequences are used to quantitatively describe whether the rock mass has discontinuities. Finally, machine learning methods are used to classify and correct these data to obtain the final rock structure model.

Digital panoramic imaging technology for boreholes [13] is a novel, practical, and effective detection technique that provides visual information for complex geological issues. It uses sound waves, light signals, and various image processing methods to generate panoramic three-dimensional images, planar unfolded images, and virtual rock core images within a borehole. The panoramic three-dimensional images reconstructed using borehole imaging technology can accurately represent rock formation structural morphology. Therefore, borehole imaging technology can be used to monitor the evolution of rock fractures and deformation response characteristics within a section, enabling the prediction of surrounding rock damage [14]. In addition, the direction of the earth's stress can be estimated by analyzing the morphological features of the borehole and their relationship with the *in-situ* stress [15]. Additionally, combining borehole fracturing theory allows for measuring the magnitude of *in-situ* stress [16]. Digital panoramic imaging technology can also be combined with deep learning algorithms, such as convolutional neural networks (CNNs). Jin *et al.* [17] applied borehole imaging technology with U-Net to achieve intelligent and rapid segmentation of ore and waste rock boundaries. Researchers have combined borehole imaging technology with semantic segmentation models such as Faster R-CNN [18] and DeepLabV3+ [19], achieving automatic detection and characterization of internal fractures in boreholes. Digital panoramic imaging technology can provide more accurate and comprehensive drilling parameter information during drilling, which is crucial for subsequent rock assessments.

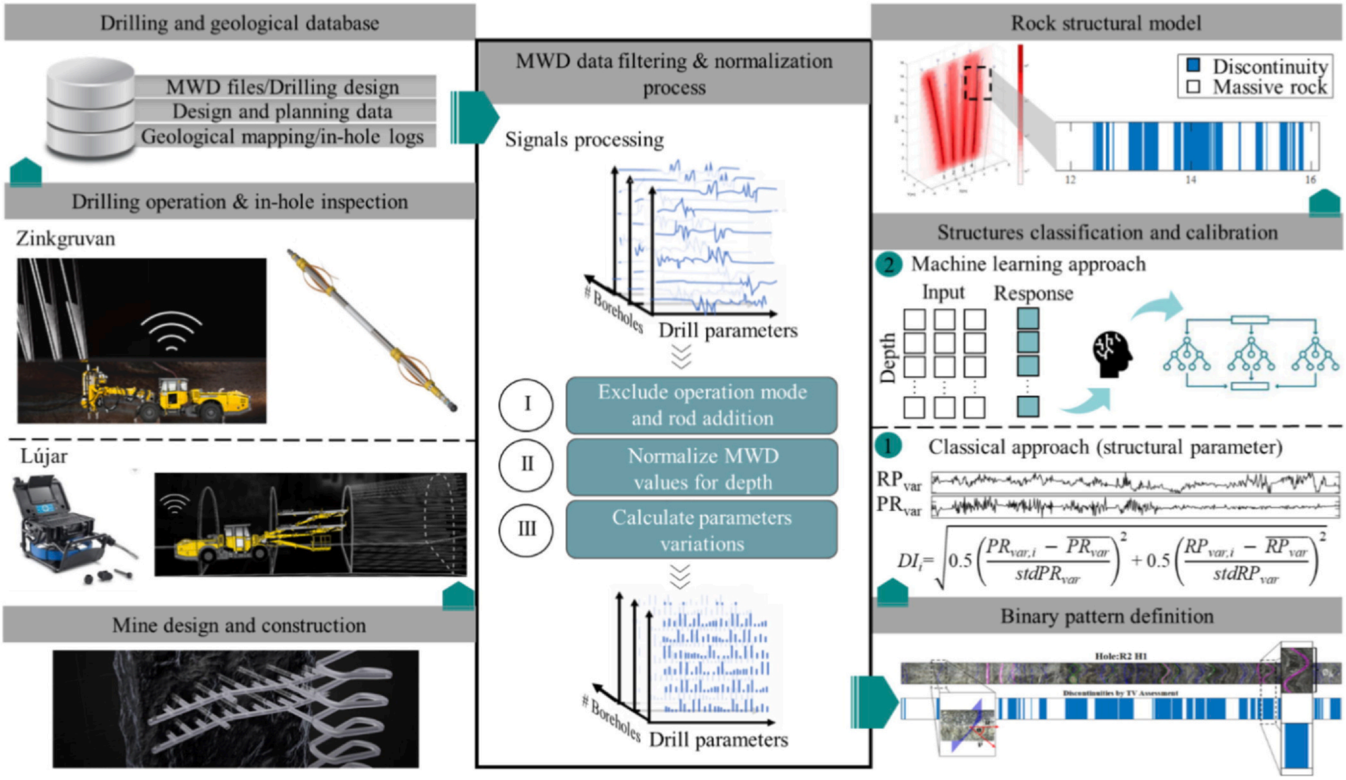

Fig. 2. Methodology for rock structural model generation [12].

In the future, with the rapid development of artificial intelligence technology, computer vision technology will be increasingly used for measuring rock properties during drilling, and digital imaging will improve work efficiency and ensure work safety.

2.1.2. Drilling rig monitoring and intelligent control

As an essential component of underground mining perforation and rock drilling equipment, the drilling bit plays a crucial role in the drilling process. Monitoring and evaluating the wear condition of the drilling bit is a critical task. Kalhori *et al.* [20] studied the relationship between drilling bit wear and the sound and vibration signals generated during rock drilling operations, thereby analyzing and monitoring the wear of the drilling bit; furthermore, Kalhori *et al.* [21] investigated a method for measuring wear rate and used nonlinear regression techniques to predict the wear of rock drilling bits based on the geological and mechanical properties of rocks; Yang *et al.* [22] combined mechanical specific energy, principal component analysis (PCA), and wavelet analysis to achieve real-time monitoring and prediction of drilling bit wear levels.

In addition, to automate perforation equipment operation, the digital autonomous perception of the surrounding environment must also be realized during drilling machine operation. Specifically, using computer vision [23], GNSS (Global Navigation Satellite System) [24], radar, three-dimensional laser [25], sonar [26], and other data perception technologies, the dynamic perception of equipment position, status, and operating environment can be achieved, which can be effectively integrated with mining geography, mining production, and safety management. Using three-dimensional laser scanning technology can obtain accurate parameters of tunnel section profiles [25] and information on surrounding rock mass structures [27], which can help achieve automatic hole drilling and equipment positioning in subsequent stages. Currently, machine vision technology is widely applied to perceive equipment operating environments, which is a necessary technical means to ensure the safe operation of equipment. Using deep neural networks for image classification realizes the classification of surrounding obstacles and image-ranging. Technology can calculate the distance between equipment and obstacles, helping realize automatic equipment movement.

Drill intelligent control is a highly integrated combination of technologies, including the Internet of Things (IoT), big data, automatic control, and information processing. To achieve the automatic control of drilling equipment, wireless communication technology must be used to transmit real-time monitored data to the rear [28]. By relying on the centralized control of the drilling equipment control terminal IoT platform [29] and with the high-precision GNSS positioning module on the equipment, functions such as automatic drilling sequence planning [30], drilling path planning [31], automatic positioning and alignment [32], navigation and automatic movement [33], intelligent hole position planning [34], and automatic leveling [35] can be achieved. Fig. 3 shows the process of intelligent control of drilling speed. According to different geological conditions, different drilling speeds can be obtained by adjusting parameters such as the drilling rig's shock pressure, shock frequency, rotational speed, and push pressure. The best parameter combination can be selected by comparing the designed drilling diameter and drilling depth requirements.

In short, drilling intelligent sensing technology is developing rapidly, but reports related to the development of intelligent drilling

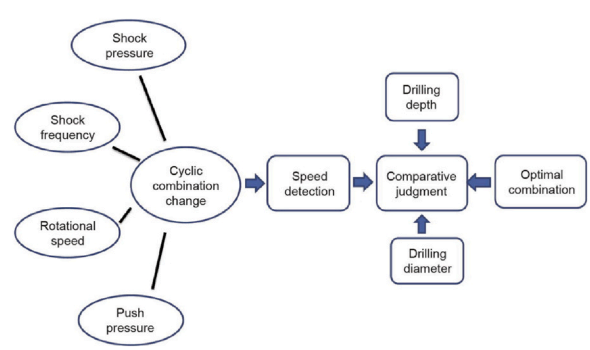

Fig. 3. Intelligent control flow diagram of hydraulic drilling [36].

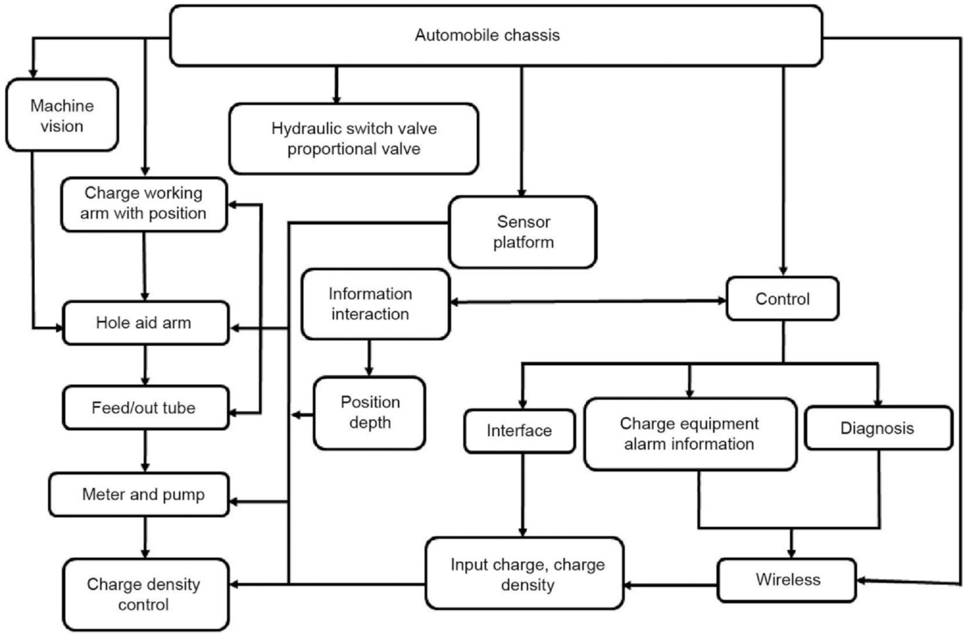

Fig. 4. Design of an intelligent charging vehicle system [36].

equipment are scarce. In the future, data transmission methods must be studied to increase data transmission speed, process a large amount of working condition data, and further improve the intelligent sensing function of equipment in complex environments. At the same time, equipment intelligent systems must be developed and integrated to combine artificial intelligence with drilling intelligent sensing technology and drilling rig automatic control technology to achieve genuinely unmanned and intelligent drilling.

2.2. Blasting

Blasting operation is the next critical step after rock drilling. With the rapid development of the new generation of information technologies represented by 5G, artificial intelligence, cloud computing, big data, etc., intelligent design and management of blasting have become an inevitable trend. Specifically, this topic includes intelligent blasting design, intelligent charging and initiation, prediction of blasting effects, and parameter optimization.

2.2.1. Intelligent design of blasting

Recently, many scholars have integrated professional knowledge of engineering blasting, expert experience, and technologies such as artificial intelligence to develop intelligent blasting system designs, providing considerable assistance for efficient mining blasting design. For example, Zhou *et al.* [37] addressed the characteristics of large-diameter deep-hole blasting, such as a heavy workload, cumbersome operation, and error-prone results in actual production processes. By analyzing the blasting process and the structure of segmented and layered interval charging, they developed intelligent identification and auxiliary design software for large-diameter deep-hole blasting parameters using Visual Lisp. Wu *et al.* [38] addressed the issues existing in intelligent design systems for blasting excavation. On the basis of the T–S fuzzy neural network model, they constructed smart search rules for excavation blasting system data. They developed a new intelligent design system for tunnel blasting excavation based on software tools such as Oracle and VB.NET. Aiming at the problem that the design of shaft blasting is affected by multiple factors, Ma *et al.* [39] proposed an intelligent decision-making system for shaft blasting plans based on the integration of the knowledge base and artificial intelligence and developed an intelligent visual design system for shaft blasting.

In short, most current research on intelligent blasting design systems focuses on neural networks and expert systems, and a big gap still exists between truly realizing intelligent blasting design. In the future, more profound research must be conducted by combining rock property data obtained from drilling and professional large language models.

2.2.2. Smart charging and detonation

The construction process of mining blasting mainly includes two critical procedures: loading explosives and initiating detonation. The development and application of digital electronic detonators, on-site mixed explosive trucks, and intelligent initiation technology have considerably advanced the automation and intelligence of blasting construction, making blasting projects more scientific, precise, safe, environmentally friendly, and economically reasonable.

Traditionally, underground mining blasting processes mainly involved the manual loading of explosives, but today, they have evolved to be performed by intelligent mixed explosive trucks. For example, Bonchis *et al.* [40] from Australia proposed a brilliant loading scheme based on visual hole-seeking. In this process, a three-dimensional laser scans the tunnel environment, and a visual algorithm selects blast holes, calculates three-dimensional coordinates, assists in hole positioning, and then controls a precise automated robotic arm for accurate loading. The BGRIMM Technology Group [41] independently developed an underground intelligent explosive loading truck with strong maneuverability and flexibility. This truck has a high degree of automation and can perform all-around automatic hole-seeking and loading for blast holes at different angles in mines. To enhance the automation and intelligence of mixed explosive trucks, Li *et al.* [42] developed an intelligent mixed explosive truck. This vehicle can achieve automatic hole-seeking, remote hole targeting, real-time extraction of loading parameters, and intelligent adjustment of loading density. Overall, innovative explosive loading equipment for underground mines should be capable of automatic positioning, hole-seeking, and loading blast holes. This equipment should control loading parameters and adjust loading density. Various aspects of explosive truck operations, such as coiling speed, pipe delivery speed, and loading speed, should be digitally and intelligently controlled. Moreover, the loading system of intelligent explosive trucks needs to meet online monitoring and fault diagnosis requirements. Additionally, a smart scheduling system should be on the surface to enable remote fault diagnosis, remote scheduling, remote

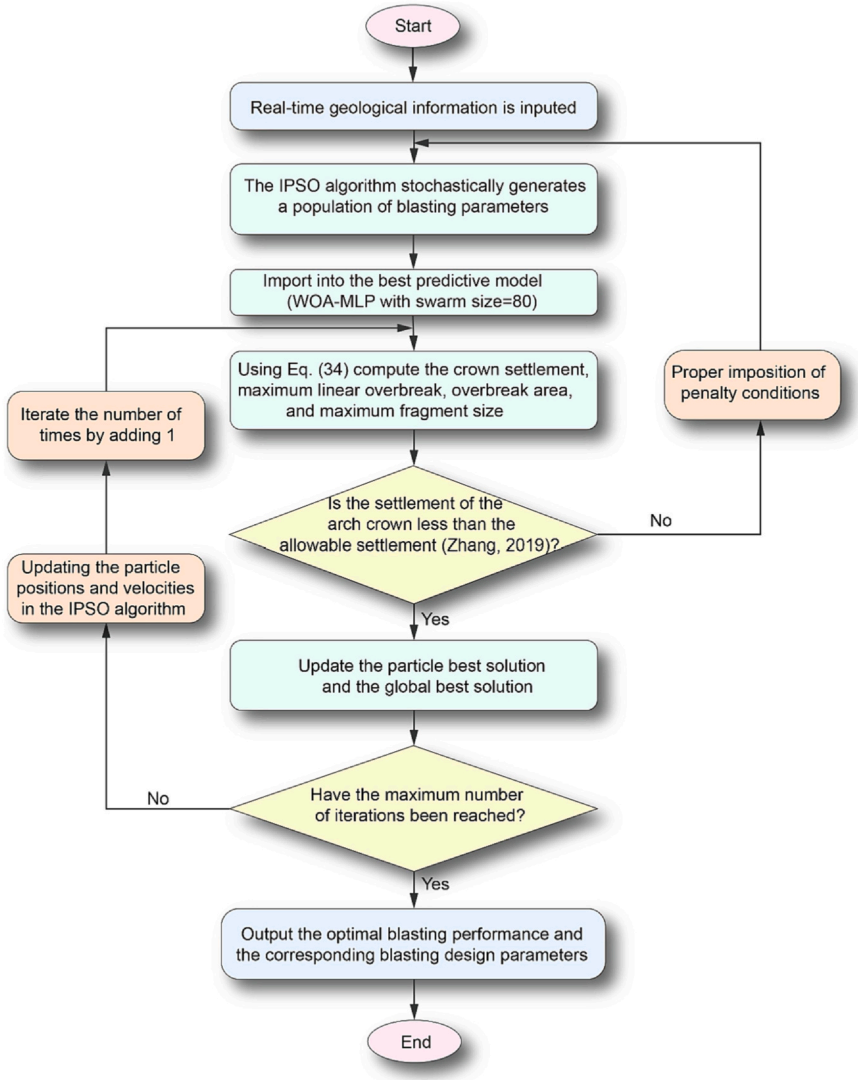

Fig. 5. Flowchart of IPSO for finding optimal blasting parameters [54]. Reproduced with permission from Ref. [54]. Copyright (2024) Elsevier.

management, production tasks, and data uploading for underground bright explosive trucks [36]. An intelligent charging vehicle system is shown in Fig. 4. The robotic arm outside the charging truck has positioning and visual recognition functions. With the help of sensors and control systems, this arm can realize automatic positioning of the blast hole, intelligent control of charging speed and density, unmanned driving, and remote control.

The intelligence of the initiation system refers to using new digital electronic detonators and electronic initiation systems. This system employs precise control of the ignition sequence of explosive points to achieve accurately delayed blast hole initiation. Researchers have also studied this aspect. For instance, Branch *et al.* [43] investigated an underground mining explosive initiation system based on long-range (LoRa) relays. This system uses LoRa as a multi-hop information transmission system, transferring signals from the initiator to detonators through multiple relays, thereby initiating explosives. Chi *et al.* [44] developed an underground, remote detonation system based on wireless networks comprising surface detonation control units and undercover field control units. The development of these systems has played an important role in the intelligence of the blasting process.

2.2.3. *Blasting effect prediction and parameter optimization*

Blasting is performed to achieve specific blasting effects. When the ore block size is large, mining shovel production will encounter considerable obstacles, and the amount of secondary blasting will increase accordingly; if the ore block is too small, the consumption of explosives is excessive, increasing blasting costs. Therefore, evaluating, predicting, and optimizing the blasting effects is essential.

Recently, with the widespread application of machine learning methods in various fields, numerous scholars have conducted extensive research on using machine learning for blasting evaluation and prediction. Ma *et al.* [45] proposed a blasting hole utilization coefficient prediction model based on the random forest algorithm, which predicts the utilization rate of blasting holes. Referring to the predicted values can optimize the blasting parameters. Yue *et al.* [46] compared the prediction accuracy of borehole utilization rates using traditional models such as grid search–SVM and particle swarm optimization–support vector machine (PSO–SVM) models established on the basis of the radial basis function kernel function. Xie *et al.* [47] aimed to improve the prediction accuracy of smooth blasting effects in tunnel excavation by constructing a support vector regression (SVR)-based soft blasting effect prediction model. The optimization results of genetic algorithms (GAs) were used as the final parameters of the SVR prediction model. Lei *et al.* [48] established a tunnel blasting effect neural network evaluation model with blasting block size and excessive excavation volume as prediction targets to address issues such as excessive over-excavation and inappropriate slag block size in mountain tunnel blasting excavation. Yu *et al.* [49] combined GAs and BP algorithms to analyze the principles of intelligent image recognition, image pattern recognition, and BP neural network learning algorithms. They established a genetic algorithm–BP (GA–BP) network image recognition model to predict and analyze the quality of mine blasting.

The selection of blasting parameters affects the cost and quality of blasting and impacts the production costs of other production processes, such as drilling. The best way to improve quality and lower production costs is by selecting the optimal blasting parameters. Gao *et al.* [50] established a dual-hole blasting model based on the actual conditions of deep underground mining in a particular mine. They used its stress damage changes to conduct a simulation analysis of blasting parameters and demonstrated the optimization scheme through corresponding blasting experiments. Ke *et al.* [51] used single-hole, variable-hole spacing, and inclined-hole blasting experiments to determine the parameters of deep-hole blasting and used the inversion method to determine the optimal deep-hole blasting parameters. They proposed and used the particle swarm optimization–BP (PSO–BP) neural network method to predict the blocking rate after optimizing the parameters of deep-hole blasting, with high prediction accuracy, verifying that the optimized blasting parameters can reduce the occurrence of large ore blocks after blasting. Chen *et al.* [52] proposed a parameter optimization calculation model for smooth blasting (SWB) based on a GA and BP. By controlling the SWB objectives to automatically search for the best blasting design parameters, the optimal design parameters can be obtained according to the specific geological conditions of the surrounding rock and the specified control targets. Xu *et al.* [53] proposed a blasting vibration prediction method combining PCA and a support vector machine (SVM). Using the PCA–SVM model, they successfully adjusted and optimized the blasting parameters of the No. 21 mining area of the Hongtoushan copper mine. Liu *et al.* [54] developed a hybrid model (namely, improved particle swarm optimization (IPSO)) based on multilayer perceptron (MLP) combined with metaheuristic algorithms to improve the blasting performance during tunnel excavation. They optimized the blasting parameters by combining the optimal prediction model with metaheuristic algorithms. The process is shown in Fig. 5.

Overall, the current popular research methods mainly involve predicting, evaluating, and optimizing blasting effects through various machine learning algorithms and numerical simulation methods, substantially improving the effectiveness of blasting compared to traditional empirical methods. In the future, the overall progress of intelligent blasting operations in mines will be greatly promoted by closely integrating blasting design, simulation, prediction, evaluation, and parameter optimization.

2.3. Transportation

After blasting and ore extraction, the minerals must be transported to the surface or other locations underground for subsequent processing. The transport capacity plays a crucial role in determining the production efficiency of a mine; therefore, it holds an important position in the underground mining process. Depending on the different stages of the process, transportation in underground hard rock mining is mainly divided into horizontal transport within tunnels and vertical lifting transport through shafts.

2.3.1. Horizontal transport

The primary methods for horizontal transport include rail locomotives, trackless equipment, and conveyor belts, among which trackless transport is considered the mainstream direction for future development. With continuous technological advancements, most mines are now equipped with mining transport equipment that has undergone automation transformation. The research focus has shifted toward the development of unmanned transport systems. To this end, the positioning and scheduling technology of transport vehicles and the safety assurance of underground transport systems are two crucial components.

Ensuring the smooth operation of an underground transportation system relies on applying stable and reliable communication and positioning technologies, along with effective scheduling and planning. Unlike surface environments, confidential communication is complex and often disrupted by geological structures, necessitating the construction of specific communication networks tailored to individual circumstances. Recently, wireless communication and positioning technologies used underground include WIFI, Bluetooth [55], ultra-wideband (UWB) [56], radio frequency identification (RFID) [57,58], sensors [59], 3D laser radar technology [60,61], and ZigBee [62,63]. To address the challenges of coordinating and controlling vehicles in the dark and narrow conditions underground, researchers have proposed optimization and scheduling methods such as GAs [64], particle swarm optimization (PSO) algorithms [65], improved distribution estimation algorithms [66], and simulation methods [67] for trackless trucks to solve transportation traffic issues underground. With the rapid development of artificial intelligence technology, researchers have also used deep learning algorithms to address truck scheduling problems, such as stacking integrated learning algorithms [68], improved RRT* (Rapidly-Exploring Random Tree Star) algorithms [69], or reinforcement learning algorithms [70] for intelligent planning of underground unmanned vehicle transportation.

Safety in underground transportation systems is a crucial focus of mining production, and many scholars have conducted extensive research in this area. For example, Zhang *et al.* [71] proposed using cellular vehicle-to-everything and vehicular edge computing to retrofit tramcars, enabling them to rapidly and accurately detect and identify obstacles. Kim *et al.* [72] developed a wearable personnel proximity warning system (PWS) based on intelligent helmets to address collisions between underground transport vehicles and personnel. The design of PWS based on Bluetooth beacons and smart helmets is summarized in

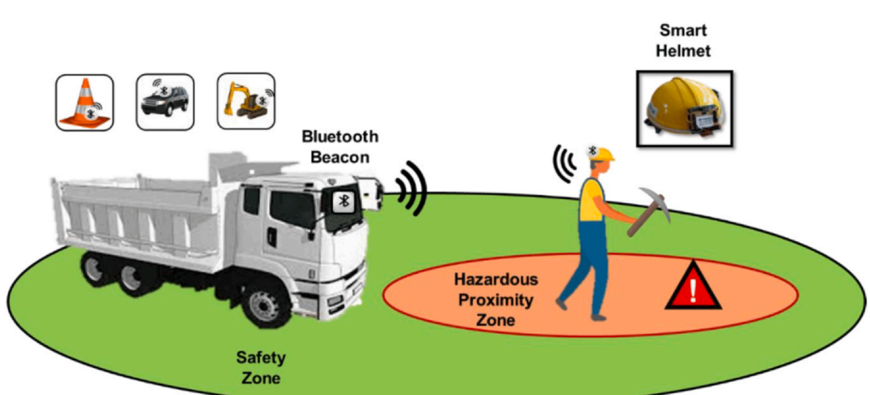

Fig. 6. Overview of a personal proximity warning system (PWS) using a smart helmet [72].

Fig. 6. Pedestrians receive warning messages when approaching heavy equipment, light vehicles, or hazardous areas. Regarding the conveyor belt maintenance inspection of traditional belt conveyors, Szrek *et al.* [73] used a mobile detection platform based on autonomous user-generated content and equipped with corresponding sensors to inspect belt conveyors using mobile robots. In addition to using intelligent technology to retrofit existing transportation equipment, virtual reality technology is used in some cases to allow operators to adapt to the on-site environment in advance to ensure the safety of underground transportation. For example, Tang *et al.* [74] used virtual reality technology to enable drivers to control virtual scene mine cars, simulating on-site driving environments and reducing the inadequacy of on-site driving.

2.3.2. Vertical hoisting

Vertical transportation systems are divided into two main categories based on the method of material lifting: wire rope hoisting (such as wire rope hoists) and ropeless hoisting (such as belt conveyor hoisting [75], hydraulic hoisting, and pneumatic hoisting), among which wire rope hoisting is more widely used. A system of wire rope hoists includes a hoist drive device, head frame, hoist wire rope, transportation equipment (cage or skip), and control and safety devices. The safe and stable operation of the hoisting system is crucial for underground mining production. Therefore, the intelligent transformation of hoisting systems has recently been mainly focused on enhancing their safety. For instance, Fan *et al.* [76] invented a portable vibration monitoring device to identify the types and characteristics of mechanical faults by analyzing different vibration signals during hoist operation. He *et al.* [77] proposed a novel sensor based on flexible printed circuits and designed a corresponding wear detection system to address the wear detection issue of hoist cage sliding sleeves. Zhang and Cao [78] proposed a vision-based measurement framework to obtain dynamic rope displacement for fault diagnosis in hoisting systems. In extreme cases of sensor failure, Chen *et al.* [79] proposed a novel encoder fault detection, isolation, and fault-tolerant control strategy based on finite-time observers and constrained fault-tolerant controllers to ensure the safe operation of mine hoists. Yang *et al.* [80] developed a safety monitoring algorithm based on visible light for mine cage safety, enabling the tracking of personnel overload and limbs protruding from the cage, thus further enhancing the safety performance of underground mining hoisting systems. Kalinowski *et al.* [81] used 3D structural digital models, building information modeling, and digital twinning concepts to diagnose and monitor vertical shaft infrastructure to ensure the safety of hoisting systems. Liang *et al.* [82] modeled the mine hoisting system based on digital twin technology. They used the information obtained by the sensor to monitor and predict the temperature changes of the hoist motor in real time. The technical details are shown in Fig. 7.

In general, research on the intelligence of rope hoisting systems primarily focuses on intelligent perception and using perceptual data. Intellectual perception involves the installation of sensors for real-time monitoring of critical components of the hoisting system, with efforts directed toward predictive maintenance. This aspect has gradually matured. The data obtained through perception is then used for safety renovations or the construction of more intelligent monitoring facilities to coordinate the management of underground mine operations, another essential component of intelligent mine construction.

2.4. Ventilation

Underground hard rock mines often use dynamite blasting for mining because of the hardness of the ore rock, producing smoke and harmful gases. Thus, timely ventilation is necessary to facilitate the loading and transportation of the ore. Moreover, as underground mining progresses to a certain depth, the temperature of the working face gradually increases. Therefore, only through a well-designed ventilation system can cooling be achieved for regular production. Because of the continuous development of emerging technologies, mine ventilation is progressively transitioning toward intelligent systems [83]. Currently, research on intelligent ventilation technology primarily focuses on four main areas: intelligent monitoring of mine ventilation, fault diagnosis in mine ventilation systems, intelligent decision-making processes, and the intelligent regulation and control of mine ventilation.

2.4.1. Ventilation intelligent sensing

Intelligent perception of mine ventilation primarily involves monitoring and addressing ventilation system parameters, including wind volume, wind pressure, temperature, humidity, and the concentrations of harmful gases. Rapid and precise acquisition of ventilation parameters forms the foundation for achieving real-time problem-solving and intelligent regulation of the ventilation network. Currently, research on the intelligent perception of mine ventilation primarily centers on optimizing the arrangement of ventilation system sensors and monitoring and addressing shaft wind speed.

Designing a ventilation system sensor layout involves analyzing the mine structure and airflow dynamics to strategically position sensors for high-precision, comprehensive monitoring of parameters such as wind speed, wind pressure, temperature, humidity, and gas concentration. Yan *et al.* [84] proposed an optimal sensor layout method based on the DETMAX and forbidden search algorithms. According to the calculated airflow data of each branch, this method can effectively select an optimal set of branches to arrange the sensors, considering the air resistance error and sensor error. This method efficiently selects the optimal branches, maximizing their number while considering air resistance and sensor errors, ultimately minimizing airflow errors. Liu *et al.* [85] introduced the concept of an independent cut-set, which determines the minimum number of sensors and their locations using the underlying graph structure. This approach ensures reliable ventilation data monitoring and addresses airflow reconstruction challenges.

After obtaining ventilation data, correctly solving ventilation network parameters becomes paramount. Shao and Wen [86] employed neural networks to predict the average air velocity of roadways, offering intelligent data and robust prediction capabilities crucial for accurate ventilation network solutions and optimization. Jia *et al.* [87] utilized sensitivity theory to rank active branches and calculate the regulation range of practical branches based on the sensitivity decay rate and the principle of minimum airflow. Subsequently, the determination of the active branch and regulation range relies on the total airflow of the passive branch. Zhang *et al.* [88] introduced a local regression fuzzy C-clustering algorithm for processing mine air velocity data. This algorithm facilitates local outlier processing and overall state analysis. Yang *et al.* [89] proposed a remote intelligent air conditioning method based on machine learning. This approach involves analyzing key performance indicators using mine ventilation theory, constructing an intelligent model, and achieving high-precision prediction with a least squares SVM. Bian *et al.* [90] employed a computational fluid dynamics method to simulate tunnel wind flow numerically. On the basis of the theory of approximate constancy of velocity field structure, he proposed a GA–BP neural network-based model for testing tunnel average wind speed. Li *et al.* [91] proposed a real-time calibration method using wind speed sensors to collect airflow data accurately, enabling ventilation network calculations independent of wind resistance measurements. Additionally, he employed an improved Kalman filter to dynamically adapt and correct errors, thereby enhancing correction effectiveness and convergence rates.

Overall, the advancement of intelligent perception technology in mine ventilation will persist through research, development, and application of new high-precision sensors and intelligent solutions for ventilation networks. Ultimately, this progress will enable remote real-time monitoring and intelligent, accurate prediction, offering more dependable technical support for mine safety and production.

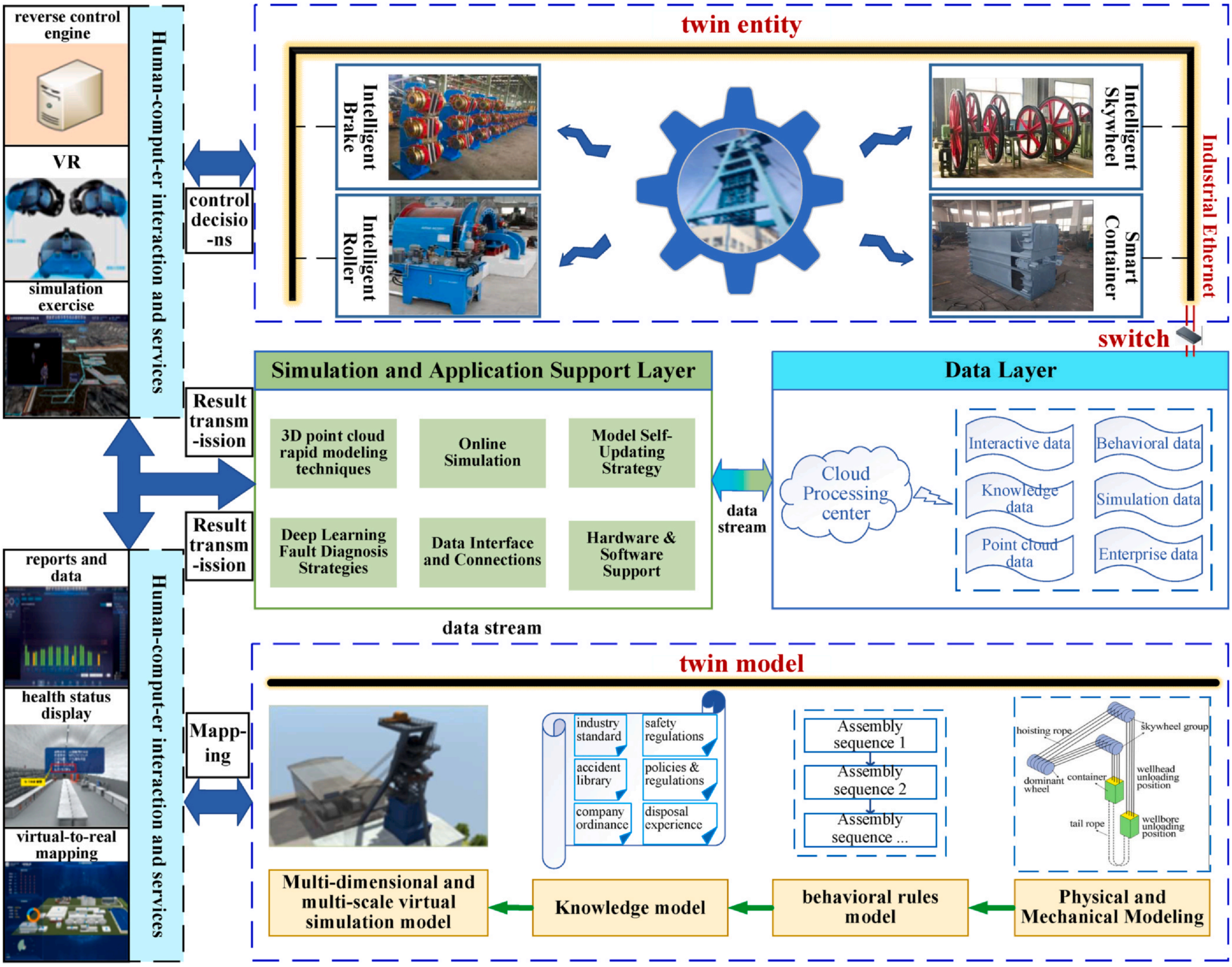

Fig. 7. Digital twins structure of mine hoist [82].

2.4.2. Ventilation fault diagnosis

Mine ventilation fault diagnosis technology employs sensors and data processing technology to monitor and analyze a ventilation system in real time, ascertain the presence of faults based on predefined rules and algorithms, and offer corresponding solutions. Ni *et al.* [92] proposed a decision tree (DT)-based intelligent diagnosis method for mine ventilation faults, integrating embedded sensor optimization techniques, dimensionality reduction, and pruning to enhance diagnostic accuracy and model generalization. Additionally, he proposed a random forest-based diagnosis method for determining fault location and volume within a ventilation network [93], which can rapidly and precisely identify resistive-type faults in mine ventilation systems. Dong *et al.* [94] proposed a supervised machine learning model utilizing a DT, MLP, and ranked support vector machines (Rank-SVMs) for RVMFL (resistance variable multi-fault location) diagnosis in mine ventilation systems. Fig. 8 shows the flow of the diagnosis method for the RVMFL of the mine ventilation system. Liu *et al.* [95] developed an unsupervised learning model for diagnosing resistive-variable faults in mine ventilation systems without sample participation. This model is optimized using a covariance matrix adaptive evolutionary strategy method, integrating classification and regression prediction. Wei *et al.* [96] designed MIVDEDP software architecture for real-time problem-solving, anomaly diagnosis in mine ventilation networks, disaster assessment, wind flow emergency regulation, and judgment.

Mine ventilation fault supervision and diagnosis technology will be developed leveraging big data, artificial intelligence, and the IoT. An efficient and dependable fault diagnosis model will be established by deploying and interconnecting diverse sensors, artificial intelligence algorithms, and cloud computing platforms, enabling intelligent diagnosis and prediction.

2.4.3. Ventilation control method

The ventilation intelligent regulation method relies on intelligent perception, using real-time data analysis and intelligent optimization for autonomous decision-making in regulating ventilation parameters. This technology ensures that air quality meets safety standards and enhances ventilation system efficiency. Wu *et al.* [97] proposed a mine airflow intelligent regulation method using a multi-strategy fusion sparrow search algorithm. The optimization objective is to establish a mathematical model and employ multi-strategy fusion for improved optimization, aiming to achieve fast and effective airflow regulation. This approach achieves fast and effective wind flow regulation. He proposed an intelligent emergency wind regulation scheme to promptly meet the air demand requirements at an underground wind location [98]. This scheme selects different regulating branches based on the expected value of the branch airflow, with the differential evolutionary (DE)–grey wolf optimization (GWO) algorithm proposed in this study showing considerable improvements in optimization performance and stability. Wang *et al.* [99] developed intelligent emergency regulation

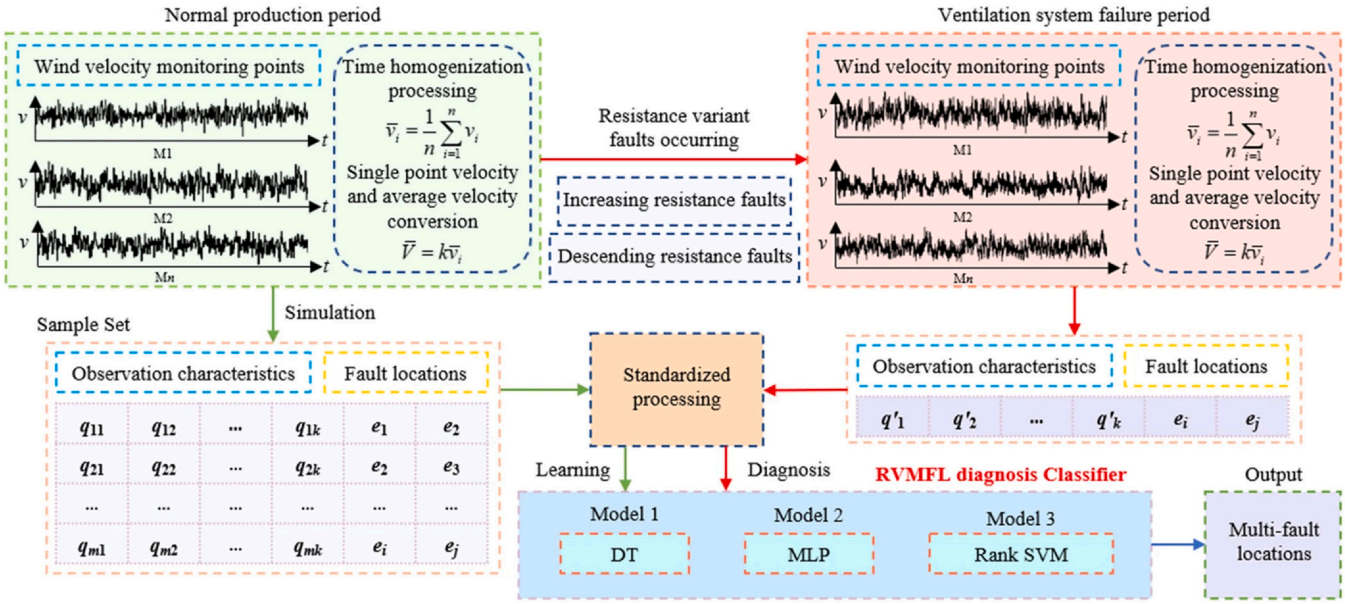

Fig. 8. Ventilation system RVMFL diagnosis method process [94].

software based on a mathematical model for multivariate feature fusion. This software operates on the supply–demand matching and linkage regulation method and reliably predicts toxic and hazardous gas outpouring to regulate ventilation supply–demand deviation. Rodriguez-Diaz *et al.* [100] used experimental benchmarks to explore modeling and control strategies for small mine ventilation networks. This study considered available sensors and actuators under constrained conditions, comparing three classical control strategies and presenting experimental and simulation results.

In general, ventilation intelligent regulation and control technology will evolve with a focus on data-driven intelligent algorithms, optimized decision-making based on IoT and cloud computing, the establishment of intelligent sensor networks, the development of human–machine collaborative decision-making systems, and integration with other mine systems. These advancements will facilitate the achievement of more efficient, reliable, and safe ventilation intelligent regulation and control, consequently enhancing miners' working environment and productivity.

2.5. Support

The critical role of perimeter rock support in underground mining must be considered, as it is a pivotal component in ensuring the smooth operation of the entire project [101]. Given the escalating mining depth and the consequent complex and variable geological conditions, integrating intelligent technology to enhance the upgrading and optimization of support systems is a crucial direction in advancing current support technology. Currently, intelligent support technology for rock bodies primarily encompasses intelligent evaluation of rock body quality, intelligent support equipment, and intelligent monitoring of peripheral rock deformation.

2.5.1. Evaluation of rock quality

Precise evaluation of rock mass quality is the prerequisite and foundation for formulating suitable support plans [102,103], and its importance is self-evident. The burgeoning advancements in intelligent technology have propelled the application of cutting-edge technology to evaluate rock mass quality into a prominent research focus. For instance, addressing the technical challenges inherent in traditional rock mass quality evaluation—such as lack of intuitiveness, low efficiency, and extensive manual intervention—Yuan *et al.* [104] optimized the conventional evaluation method. They devised a three-dimensional visual evaluation system grounded in close-range photography. This system, which stores joint information through close-range photography and extracts joint information through human–computer interaction, can accurately estimate undisclosed rock mass quality evaluation indicators. On the basis of a deep learning algorithm, Su *et al.* [105] devised a system capable of core image recognition, segmentation, and rock quality designation (RQD) estimation. This system not only fulfills engineering requirements but also resolves the issue of low RQD calculation efficiency stemming from manual core length measurement. Hasan *et al.* [106] introduced an experience-based resistivity fault scanning (ERT) geophysical method, as shown in Fig. 9. This method facilitates a more accurate evaluation of rock mass quality while minimizing the need for numerous drilling holes, enhancing overall work efficiency. It proves particularly suitable for areas where obtaining many core samples is challenging. Drawing on the analytic hierarchy process and CRITIC (CRiteria Importance Through Intercriteria Correlation) technology of cloud model theory, Jin *et al.* [107] deduced the subjective and objective weights of each engineering rock mass evaluation index. These weights are then recalculated using game theory to evaluate rock mass quality through the GA–CM (game theory–cloud mode). This approach mitigates the impact of subjective factors on rock mass quality evaluation and enhances its reliability.

In summary, applying cutting-edge technology to enhance and optimize traditional rock mass quality evaluation offers novel insights into intelligent rock mass quality evaluation. It establishes a solid groundwork for subsequent support scheme design.

2.5.2. Support equipment

The anchor drilling truck is crucial as a primary support equipment within the support operation. Using the mechanical arm, the anchor drilling trolley must meticulously control the direction, angle, and distance between the drill bit and the roadway wall. This task demands exceptional precision and adjustment capabilities from the mechanical arm. Consequently, the intelligent retrofitting of the anchor cart holds immense importance in enhancing support quality and construction efficiency [108].

Currently, the complexity of the equations governing the motion of the robotic arm, coupled with limitations in control strategies, results in its limited adjustment capability and significant positioning errors. Addressing these challenges, Zhang and Huang [109] introduced a

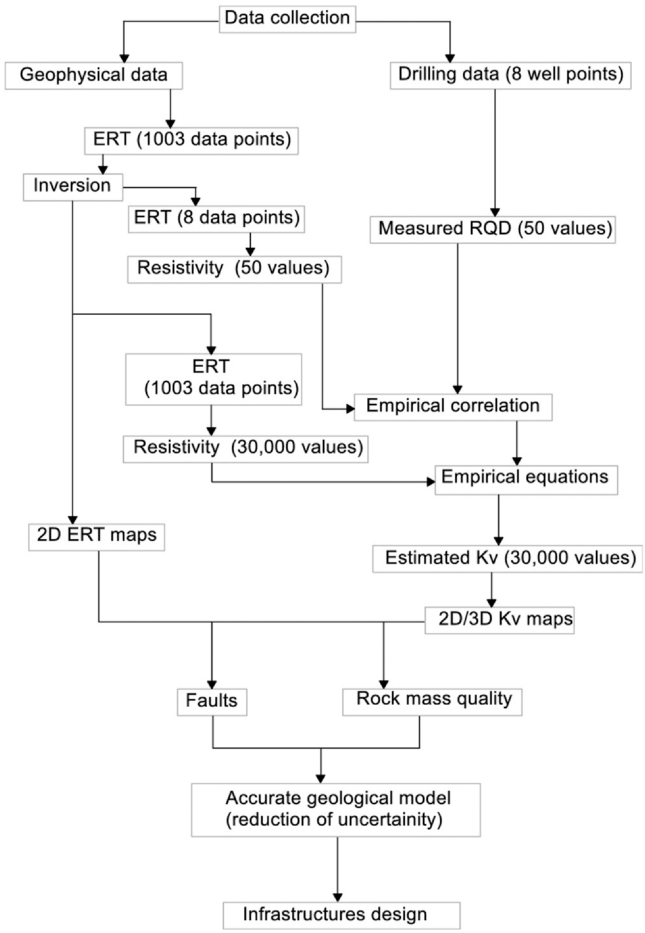

Fig. 9. Flowchart summarizing the methodology for obtaining an accurate geological model using ERT and RQD [106]. Reproduced with permission from Ref. [106]. Copyright (2022) Springer Nature.

composite control method comprising a fractional-order proportional-derivative controller + input shaping technology. This method effectively suppresses the maximum swing amplitude of the robotic arm and showcases its superiority in steady-state accuracy, offering ample theoretical support for precise robotic arm positioning. Zhang *et al.* [110] devised a mechanical arm position parameter adjustment system for anchor drilling rigs using intelligent control technology and electro-hydraulic proportional control technology. This system offers high control accuracy for adjusting mechanical arm position parameters, effectively enhancing the efficiency of preparatory work and ensuring construction safety before support operations. It also furnishes technical support for the intelligent development of the anchor drilling rig's mechanical arm. To improve the positioning accuracy of the robotic arm and achieve optimal efficiency of the robotic arm, Zhang *et al.* [111] achieved faster response speed and better trajectory tracking ability using the DH (Denavit–Hartenberg) method and intelligent parameter setting method to optimize the robotic arm structure and motion control strategy. This study provides a reference basis for designing precise positioning control of the robotic arm.

In conclusion, enhancing and upgrading the anchor trolley is vital for the intelligent evolution of underground mining equipment. It stands as a pivotal technology that must be addressed to achieve intelligent unmanned support.

2.5.3. *Monitoring of surrounding rock deformation*

Surrounding rock responds the most directly to changes in its stress state by deforming [112]. Monitoring this deformation is crucial for ensuring the design and safe execution of tunnel support projects. The primary objective of monitoring is to understand changes in the mechanical properties and behavior of surrounding rock, ensuring the stability and safety of the surrounding rock and supporting structures [113]. Consequently, it has garnered considerable attention from scholars. The renowned new Austrian construction method considers this principle as fundamental.

Recently, with the widespread adoption of deep learning and other technologies in tunnel support projects, the monitoring of surrounding rock deformation has advanced systematically and intelligently. For instance, Zhou *et al.* [114] devised a real-time measurement system for surrounding rock displacement using the digital displacement measuring instrument testing system and the V-STARS measurement system. This system enables monitoring and early warning of the surrounding rock's dynamic deformation and crack characteristics, which is particularly suited for projects in complex geological environments. Xu *et al.* [115] devised a real-time monitoring method and system for surrounding rock deformation based on machine vision. They established a multi-index early warning criterion for surrounding rock deformation and damage, capable of reflecting the state and development trend of surrounding rock deformation. This system enables regional, continuous, and real-time monitoring and early warning of surrounding rock deformation. Using the deep learning recurrent neural network algorithm, He *et al.* [116] constructed a long short-term memory (LSTM) network model to analyze and predict surrounding rock deformation. With the extension of the prediction period, the stability of the prediction results increases, offering a reliable basis for integrating deep learning into tunnel support. These studies have propelled the advancement of intelligent monitoring of surrounding rock deformation.

2.6. *Backfill*

Currently, underground mining in mines is characterized by three major trends: intelligence, sustainability, and increasing depth. Mines are increasingly adopting the backfill mining method because of its advantages in sustainability and safety. Integrating filling technology with intelligent methods will undoubtedly emerge as a critical technology for underground mining in hard rock mines. Research on intelligent filling technology primarily centers on filling material proportions, predicting filling body strength, transporting filling slurry pipelines, and monitoring filling bodies.

2.6.1. *Proportioning of filling materials*

The filling process in hard rock mines primarily relies on cemented filling. This method involves preparing filling slurry by blending inert materials such as tailings sand and waste rock with cement and other cementitious materials. The slurry is then conveyed to the underground mining area to form a specific strength and integrity filling body, fulfilling the intended filling function. The cemented filling body must adhere to strength, fluidity, and cost requirements, emphasizing the importance of a proportioning design for the filling material. Direct experiments are costly and time-consuming. Consequently, many scholars are exploring using artificial intelligence technology to simulate the strength of filling bodies with various material ratios. For instance, Sadrossadat *et al.* [117] used the PSO algorithm to design CPB (cemented paste backfill) mixtures that fulfill multiple objectives, thereby reducing costs and ensuring cleaner and more sustainable production. To analyze the combined impact of conventional and fiber variables on compressive properties, Yu *et al.* [118] introduced a new artificial intelligence model that integrates the recently developed meta-heuristic algorithm and extreme learning machine techniques. Ultimately, fiber content and length were shown to considerably influence the unconfined compressive strength of fiber-reinforced CPB. To reduce the cost of filling materials, Mishra *et al.* [119] studied the impact of partially replacing OPC (ordinary Portland cement) with fly ash on the strength of CPB. They employed a Bayesian network to identify the optimal combination most cost-effectively to attain the desired strength.

2.6.2. Estimation of backfill strength

In filling mining methods, accurately determining the filling body strength in each underground quarry is critical for ensuring the safety of neighboring quarries. Predicting the filling body strength involves investigating the relationship between its composition, mixing ratio, age, and other factors and establishing a prediction model using intelligent methods. To enhance filling mining design and evaluate filling effects, Li *et al.* [120] proposed a hybrid artificial intelligence model that integrates an SVM, DE algorithm, and GWO algorithm to predict the compaction characteristics of MGBM (mixed gangue backfill material). Qi *et al.* [121] combined test cycle experiments with machine learning techniques. They employed a DT regression model that effectively captured the complex mapping between tailings sand properties, ash–tail ratio, inlet velocity, solids content, and compaction drop. Additionally, they combined artificial neural networks and differential evolution to enhance compaction drop estimation in 2021, achieving substantial improvements in estimation performance [122]. Cheng *et al.* [123] developed a deeply connected CNN for efficiently extracting input parameters. This CNN served as a fast and accurate prediction model for forecasting the strength of slurry fill materials with various compositions. To comprehend the mechanical response of the backfill–rock interaction system, Zhao *et al.* [124] numerically evaluated the uniaxial compressive behavior of a combined backfill–rock structure using a Karagöz concrete (KCC) model. This approach aids in stabilizing the structural design of the backfill body more rationally and economically.

2.6.3. Filling slurry transportation

Indeed, the conveyancing of filling slurry is a pivotal aspect of the filling process, primarily entailing water use as the conveyancing medium to transport solid materials, including underground filling aggregates and cementitious materials. Addressing this aspect, numerous scholars have delved into the critical issues surrounding the conveying process of filling slurry through intelligent energy methods.

To explore the impact of the particle settling factor on pipeline slurry transport, Wang and Gan [125] developed a pipeline transport model and assessed its influence on settling rate in terms of slurry concentration, particle size, and flow rate. The findings underscored the model's reliability in quantifying the effects of various factors on particle settling. Because existing mathematical models and concentric partial particle size distribution curves inadequately represent tailings material particle size distribution (PSD), Li *et al.* [126] devised a mathematical model with three coefficients (A, B, and K) to characterize the PSD of mine tailings. They also proposed an optimal coefficient solution method based on error analysis. Detecting pipeline abnormalities is crucial for ensuring the continuity and safety of mine backfilling. Xiao *et al.* [127] introduced a long short-term memory deep learning (LSTM-DL) model for diagnosing clogging and leakage in gravity transport high-density backfill (GHB) pipelines, adept at accurately identifying various pipeline states within complex GHB systems. To investigate cemented GHB filling as a requisite solution for mitigating risks associated with underground mining voids and surface tailings ponds, Researchers [128,129] conducted a full factorial ring test to obtain pressure drop observations and rheological parameters of CHB (cemented high-concentration backfill), considering variables such as binder content, solid phase fraction, and flow rate.

In addition to intelligent research on the filling slurry transportation process, the intelligent construction of mine filling stations is another important component. For the time series prediction problem for underflow concentration of deep cone thickener, Yuan *et al.* [130] introduced a dual attention neural network method to model spatial and temporal features of the data collected from multiple sensors in the thickener to predict underflow concentration, and the test results show that this method has favorable prediction accuracy. Lei [131] proposed a new unified optimal prediction control framework (ConFrame) for an industrial mining system. The proposed framework integrates optimal and nonlinear control for an industrial paste-filling system.

Deep mine filling will be a pivotal developmental trajectory for underground mines in the future. Given the high vertical depth, low magnification, and long distances in deep mine filling slurry pipeline transportation, intelligent filling can provide a more efficient and accurate transportation process. To adapt to evolving mining processes, intelligent filling technology must delve deeply into calculating pipeline transport resistance and managing residual pressure head treatment of the paste. Additionally, this technology necessitates establishing a comprehensive pipeline monitoring and early warning system to ensure a safe and dependable filling outcome.

2.6.4. Filling monitoring

Upon entering the void area, the filling slurry initiates the "black box" maintenance stage, characterized by a complex, unpredictable, and uncontrollable curing process. During this phase, employing suitable monitoring methods becomes imperative to establish a foundation for accurately formulating mining and filling strategies.

To investigate the mechanical behavior of the boundary part of the backfill body, Lu *et al.* [132] established a scientific basis for the strength design and support selection of a metal mine by utilizing underground stress monitoring for the backfill mining method. Wei *et al.* [133] employed an independently designed stress monitoring system pre-buried at four segment levels to effectively monitor the flow, deposition of high-stage quarry cemented filling slurry, and the strength development of the filling body in real-time throughout the filling, maintenance, and bearing stages, thus capturing the spatiotemporal evolution law of stress inside the filling body. Shang *et al.* [134] demonstrated the potential of machine learning algorithms for time-delayed 3D ground penetrating radar (GPR) data segmentation and dynamic monitoring by training U-Net, a rapid neural network based on CNNs, effectively segmenting backfilled pits with online profiles. To address the lack of equipment or techniques for accurately monitoring the real-time backfill process in the harsh subsurface environment, Yuan *et al.* [135] developed backfill visualization and soft sensing techniques, offering crucial guidance for subsurface backfill production management. Yang *et al.* [136] proposed an online image analysis

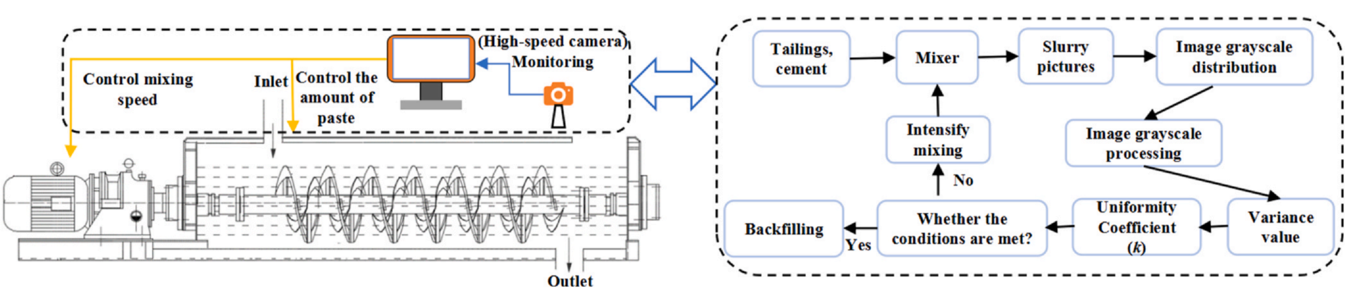

Fig. 10. Online monitoring of CPB undergoing mixing [136].

technique for the intelligent monitoring of the CPB preparation process by applying this technique to the online monitoring of backfill mixing of cemented slurry, capturing vital information about the evolution of different formulations during the mixing process; the operation to realize such an effect is shown in Fig. 10. Additionally, Wang *et al.* [137] conducted continuous monitoring experiments by installing pressure sensors inside a barricade, establishing a barricade pressure prediction model for discontinuous backfilling conditions, and characterizing the relationship between backfill height and barricade pressure using a Gaussian fitting method, thereby addressing the challenge of monitoring the curing process of the backfill and its lateral load on the barricade during the backfilling process.

In conclusion, the advancement of appropriate filling materials, precise prediction of filling body strength, monitoring of filling slurry transportation, and observation of the filling curing stage stand as pivotal areas of current and future research in the field of mine filling. Integrating new technologies such as machine learning and artificial intelligence is poised to aid these endeavors considerably.

3. Conclusions and perspectives

With the rapid development of emerging technologies such as the IoT, big data, and deep learning, all operating aspects of underground mining in hard rock mines are undergoing new transformations. The research and application of these technologies not only improve production efficiency but also further improve the safety production level of mining enterprises and ensure the safety of personnel and equipment. This article briefly summarizes the research progress of intelligent technology in underground mining of hard rock mines. The conclusions and prospects obtained are as follows.

(1) Intelligent research on rock drilling is mainly reflected in the intellectual perception of rock drilling sections and surrounding environments, dynamic monitoring of the position and status of drilling equipment, automatic control and intelligent adjustment of drilling rigs, etc. Integrating measurement-while-drilling technology, borehole digital panoramic imaging technology, the IoT, big data, GNSS positioning, and other technologies has promoted the rapid development of intelligence in the rock drilling process. However, incoherent overall intelligence remains problematic. In the future, a core control model must be established for digital drilling equipment that is standardized, modular, and configurable. This model integrates software and hardware and effectively combines downstream processes, mine geology, mine production, and safety management.

(2) Current research on intelligent blasting technology mainly focuses on developing intelligent design systems before blasting, smart charging and detonation, predicting and evaluating blasting effects, and developing optimization algorithms. These studies have promoted the progress of intelligent blasting. Unfortunately, they are limited to local intelligence and have not yet formed the application of smart technology for the entire blasting process. In the future, we will continue to dig deeper from the acquisition of rock mass data information before blasting-to-blasting scene simulation, blasting design and construction, post-blasting effect prediction and evaluation, blasting parameter optimization, etc., and combine multiple critical aspects of the blasting process to conduct intelligent technology research and apply it to realize the intelligentization of the whole process of mine blasting.

(3) The overall trend of underground mine transportation is comprehensive, unmanned, and intelligent. Horizontal transportation and unmanned, large-load, and trackless transportation are key contents that require continuous research. The key technical points are autonomous operation planning of equipment, real-time positioning of vehicles, stable wireless communications, transportation system optimization, and safety monitoring and control. In terms of vertical transportation, rope lifting is still the primary method for vertical lifting in the short term. Intelligent transformation is essential to building smart mines, including applying sensors and machine vision tools to achieve intellectual perception and remote control. However, as the mining depth increases, new lifting methods, such as magnetic levitation lifts, must be developed to overcome the limitations of mining depth.

(4) Intelligent research on underground ventilation systems mainly includes intelligent sensing of ventilation parameters, intelligent diagnosis of ventilation faults, and on-demand air volume regulation. Although some advanced mines have implemented innovative management of ventilation systems, there are still various problems overall. Future innovative ventilation research mainly includes predictive maintenance of ventilation systems based on artificial intelligence and big data technology. Through real-time data analysis and prediction models, ventilation faults can be discovered in advance, and corresponding measures can be taken; intelligent ventilation monitoring and control combined with IoT technology can realize remote monitoring and intelligent adjustment of a ventilation system to improve the flexibility and efficiency of this system; the intelligent interconnection of the ventilation system and other mining equipment can be explored to achieve collaborative work and information sharing between equipment to further optimize the operating efficiency of the entire mine production system and security.

(5) Support technology combined with intelligent means is an essential guarantee of safe mining in underground mines. It is also a critical technology that requires continuous breakthroughs toward deep mining. Its research core includes intelligent evaluation of rock mass quality, intelligent upgrade of support equipment, and accurate monitoring of surrounding rock deformation. Future support technology must be deeply integrated with innovative technologies such as artificial intelligence, big data, and cloud computing to create more accurate intelligent evaluation methods for rock mass quality, develop more advanced smart support components and systems, and develop multi-information fusion tunnel stability. The monitoring and early warning platform effectively achieves early intelligent evaluation of tunnel-surrounding rocks, unmanned support construction, and continuous stability monitoring to ensure the safe production of mines.

(6) Intelligent filling of hard rock underground mines is a complex system engineering involving multiple disciplines and is a main method for future underground mining. The current intelligent research on cement filling technology is mainly reflected in filling material proportions, prediction of filling body strength, filling slurry transportation, and intelligent monitoring of the filling solidification process. In the future, it will be necessary to continue to make breakthroughs in the research and development and optimization of filling materials, precise control of the filling process, waste processing and reuse, etc., and ultimately realize intelligent perception based on innovative filling materials through the self-learning, self-decision-making, and self-control of the intelligent control system—execution to achieve intelligentization of the entire mine filling process.

This article summarizes the latest research progress in intelligent technology for underground mining of hard rock mines from six processes: rock drilling, blasting, transportation, lifting, ventilation, and support and filling. The survey mainly focused on papers published by scholars, and more summary of the intelligent equipment developed by mining machinery manufacturers was needed to provide a more comprehensive understanding of the current progress of mine intelligence.

CRediT authorship contribution statement

Xiaobo Liu: Conceptualization, Supervision, Writing – review & editing. **Xingfan Zhang:** Writing – original draft. **Liancheng Wang:**

Writing – review & editing, Supervision. **Fuming Qu:** Writing – review & editing, Supervision. **Anlin Shao:** Funding acquisition, Supervision. **Lingyu Zhao:** Writing – review & editing. **Huaiyuan Wang:** Writing – original draft. **Xingtong Yue:** Writing – original draft. **Yizhuo Li:** Writing – review & editing. **Wenzhen Yan:** Writing – original draft. **Jiang He:** Writing – original draft.

Declaration of Competing Interest

Anlin Shao and Xiaobo Liu are editorial board members for this journal and were not involved in the editorial review or the decision to publish this article. 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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