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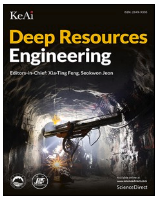

Full Length Article

Artificial intelligence technology in rock mechanics and rock engineering

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ABSTRACT

The scope and scale of rock engineering activities have witnessed continuous expansion, which makes the geological conditions of rock engineering increasingly complex, and there are more and more types of disasters occurring during the construction and operation processes. The uncertainty of engineering geological information and the unclear nature of rock mass failure and disaster mechanisms pose increasingly prominent challenges to the study of rock mechanics and engineering problems. The artificial intelligence technology develops driven by data and knowledge, especially the proposal of digital-twin technology and metaverse ideas. This has injected new innovative impetus for the development of rock mechanics and engineering intelligence, where data and knowledge have been greatly enriched and updated in recent years. This article proposes the construction idea of a rock mechanics and engineering artificial intelligence system based on the metaverse, including intelligent recognition of three-dimensional (3D) geological structures, intelligent recognition of 3D geostress, intelligent recognition of rock mechanical behavior, intelligent evaluation, monitoring and early warning of rock engineering disaster, intelligent design of rock engineering, and intelligent construction of rock engineering. Two typical engineering applications are used as case studies to illustrate the integrated method of applying this system to solve engineering problems with multiple tasks.

1. Introduction

To meet the needs of socio-economic and technological development, the scope and scale of rock engineering activities in areas such as resources, energy, transportation, water conservancy and hydropower, environment, and safety are increasing, with the maximum depth of underground mines being 4350 m, the longest length of transportation tunnels being 57.6 km, the maximum size of underground powerhouse being 453 m × 88.7 m × 34 m, and with a tunnel group consisting of over seven tunnels with a length of 17 km and a maximum diameter of 13 m. Consequently, the geological conditions are becoming increasingly complex, with the ground stress being as high as 100 MPa, the water pressure exceeding tens of MPa, the high temperature exceeding 90 ℃, and the unfavorable geological structures involving structural knots, suture zones, active faults, folds, compression fracture zones, ductile shear zones, hard structural planes, and complex rock types such as altered rocks and mixed rocks. The types of rock engineering disasters caused by excavation are increasing, from shallow engineering wedge failure, fractured zone collapse, large deformation of soft rock, to large-scale rock spalling, deep fracturing, large deformation of hard rock, large-volume stress-structural collapse in deep engineering [24], especially different types of rockburst such as strain rockburst, strain-structure slip rockburst, fault rockburst, and “chain” rockburst [15,48,86]. This poses the following challenges to the study of rock mechanics and engineering problems: ① Information on rock engineering geological conditions is incomplete, with significant uncertainty, mainly manifest in: high cost and difficulty of on-site testing, mostly local point/hole testing with limited data and high randomness, strong interference and high noise in the construction environment, the high uncertainty of empirical judgment results, complex conversion relationships of indirect measurement, *etc.* ② The mechanism of rock failure and disasters such as rockburst, large deformation, collapse, deep cracking, and spalling remains unclear. The effects of three-dimensional (3D) excavation stress path, the heterogeneity, discontinuity and anisotropy of rock mass, as well as the mechanism of tensile/shear fracture, localization of failure and energy accumulation and release are complex with highly nonlinear relationships among them. These make it difficult to describe rock mechanics and engineering behavior using

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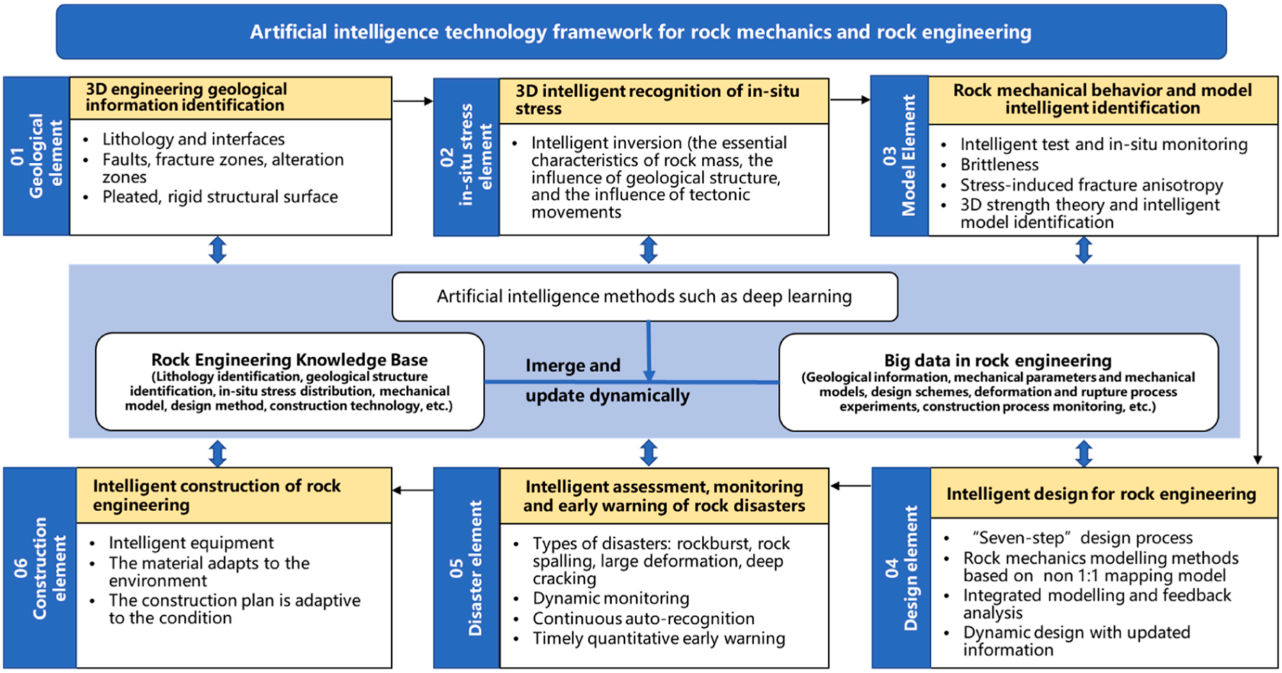


Fig. 1. Systematic composition of rock mechanics and engineering in the view of the metaverse under the backdrop of artificial intelligence technology.

deterministic mathematical, physical, and mechanical equations. Therefore, it is necessary to utilize modern information science, systems science and technology, integrating and intersecting them with the traditional disciplines of engineering geology and rock mechanics, and explore new problem-solving solutions.

In response to such issues, artificial intelligence can leverage many advantages such as intelligent perception, high-precision sensors and wireless sensors used to achieve dynamic adaptive monitoring and continuous monitoring of the behavior of rock during engineering work [92]. Another example is intelligent interconnection, which uses the Internet of Things, 5 G networks, edge computing, and other technologies to realize unmanned collaborative operation of intelligent equipment through cloud edge end interconnection of everything [74]. There is also intelligent decision-making, which utilizes powerful GPU computing power, deep learning, big model and other technologies to elucidate complex non-linear relationships in a data-driven manner. In doing so, the deep features and essential trends contained in big data could be explored, promoting the formation of new theories and iterative updates of knowledge through knowledge reasoning, induction, and decision-making [3,91]. Furthermore, there is intelligent interaction, combining technologies such as metaverse, digital twins, virtual reality, and simulation deduction to construct a metaverse space that continuously interacts with the real space, achieving real-time information updates and remote interactive control of rock engineering behavior across all scenarios [71].

These significant advantages of artificial intelligence provide intelligent solutions for the aforementioned rock mechanics and engineering problems. Through interdisciplinary analysis with geology, mechanics, materials, machinery, information, control, *etc*., based on intelligent perception of big data (including engineering experience, various monitoring and testing data, and rock mechanics and engineering knowledge), feedback analysis, deep learning and uncertainty reasoning, the engineering geology and stress conditions can be reasonably identified from uncertain information. The rock mechanical behaviors and parameters that best match reality can be learned from chaotic and complex data, and to achieve intelligent monitoring, early warning, and adaptive control of rock engineering disasters. In addition, the development of rock mechanics and engineering has laid a solid foundation for this:① The monitoring, testing, and testing methods of rock mechanics and rock engineering are advanced and multi-faceted, with high accuracy of test results and strong ability to achieve continuous collection of data, providing sensing and control technology support for intelligent perception, as well as a large amount of available data; ② The automation, digitization, and intelligence of rock engineering construction materials and equipment have significantly improved, providing diversified networking equipment and materials for intelligent interconnection; ③ Rock engineering cases are numerous and diverse, with richer engineering geological conditions, disasters, and engineering design and construction plans. The knowledge of rock mechanics and rock engineering is continuously updated, offering rich cases and a good foundation for intelligent decision-making; ④ The level of rock engineering geological identification, engineering design, construction analysis and simulation software has significantly improved, and the human-machine interactive ability has been significantly enhanced, providing a high-performance software platform for intelligent interactions.

The intelligent development of rock mechanics and rock engineering lays a solid foundation and shows a strong trend. As early as the 1990 s, new directions of intelligent mining science [16] and intelligent rock mechanics and rock engineering [26,14] were proposed. A series intelligent technologies have been developed, such as identification of rock mechanical models based on neural network self-learning [18] and based on global search of model structure according to mechanism understanding [21], intelligent back-analysis and determination of mechanical parameters of rock masses [28,31,60], intelligent modelling and forecasting of ground pressure, acoustic emission and displacement time series during the disaster-development process [25,17,32], and intelligent evaluation, monitoring and warning of rockbursts [37,56]. Furthermore, rock engineering design methods based on intelligent dynamic design have been established [20,22,23,58]. These have been successfully applied in rock slope engineering [30], deep-buried hard rock tunnels [36], and high-stress underground cavern groups [35].

In summary, rock engineering activities involve more and more fields, with a larger scope and scale, more complex geological conditions , and consequently more kinds of disasters, which poses both challenges and opportunities for rock mechanics research. The new round of artificial intelligence development has injected an innovative impetus for this, and the deep integration of artificial intelligence and

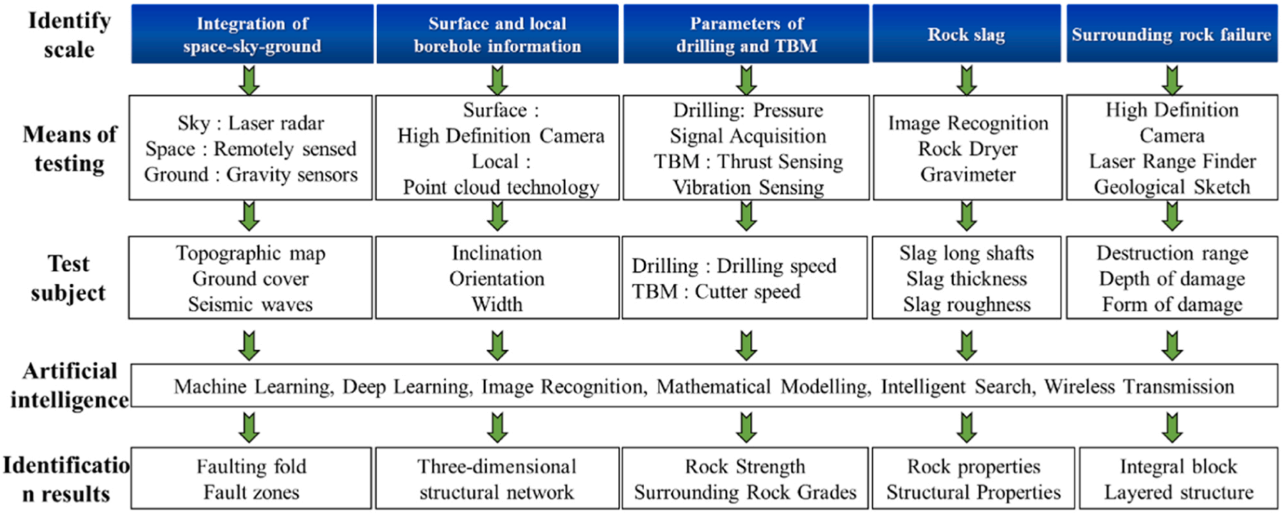


Fig. 2. Intelligent recognition of 3D geological information.

rock mechanics and rock engineering has become an inevitable trend. Based on this, the present work provides an artificial intelligent technical system for rock mechanics and rock engineering. Combined with typical engineering cases, we systematically elucidate the connotation and development trends of engineering geological condition recognition, rock mechanical behavior identification, engineering design, and construction. The findings provide guidance and suggestions for the development of this interdisciplinary field.

2. An artificial intelligence technology system for rock mechanics and rock engineering

According to the classic working flow of a deep rock engineering work, there are generally six working phases step by step for implementation. These six working phases are investigation of engineering geological conditions, in-situ stress instrumentation, rock mechanical behavior description by rational models, rock engineering design, construction site assessment, monitoring and disaster early warning, and the construction by excavations. These working phases have contributed to form the knowledge base and big data in rock engineering. The knowledge base includes the lithology identification, geological structure identification, in-situ stress distribution, mechanical model, design method, construction technology in rock engineering. The big data refers to the data of geological information, mechanical parameters and mechanical models, design schemes, deformation and failure process experiments, construction process and monitoring, etc.

Recently, a new system (Fig. 1) was established for rock mechanics and rock engineering in the view of metaverse under the backdrop of artificial intelligence technology. The new system networks the working phases of classic working flow of rock engineering by emerging and

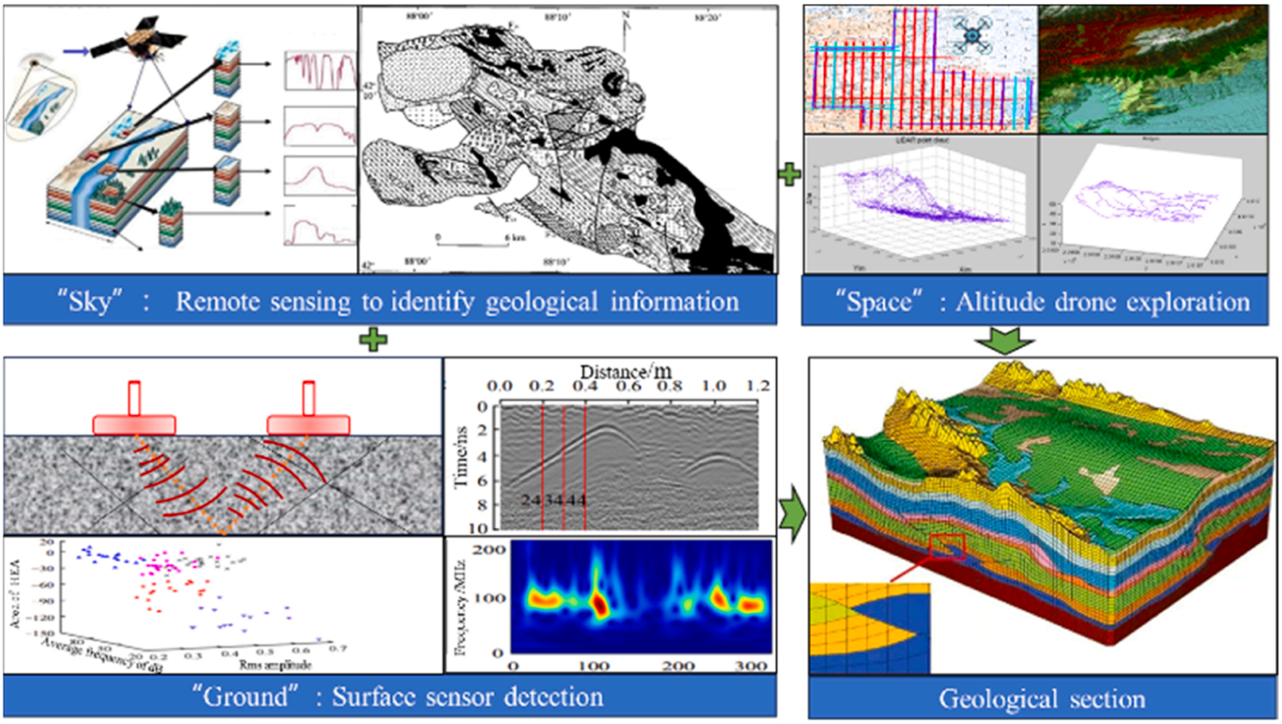


Fig. 3. The monitoring model of space-ground integration (modified from [65,69,67]).

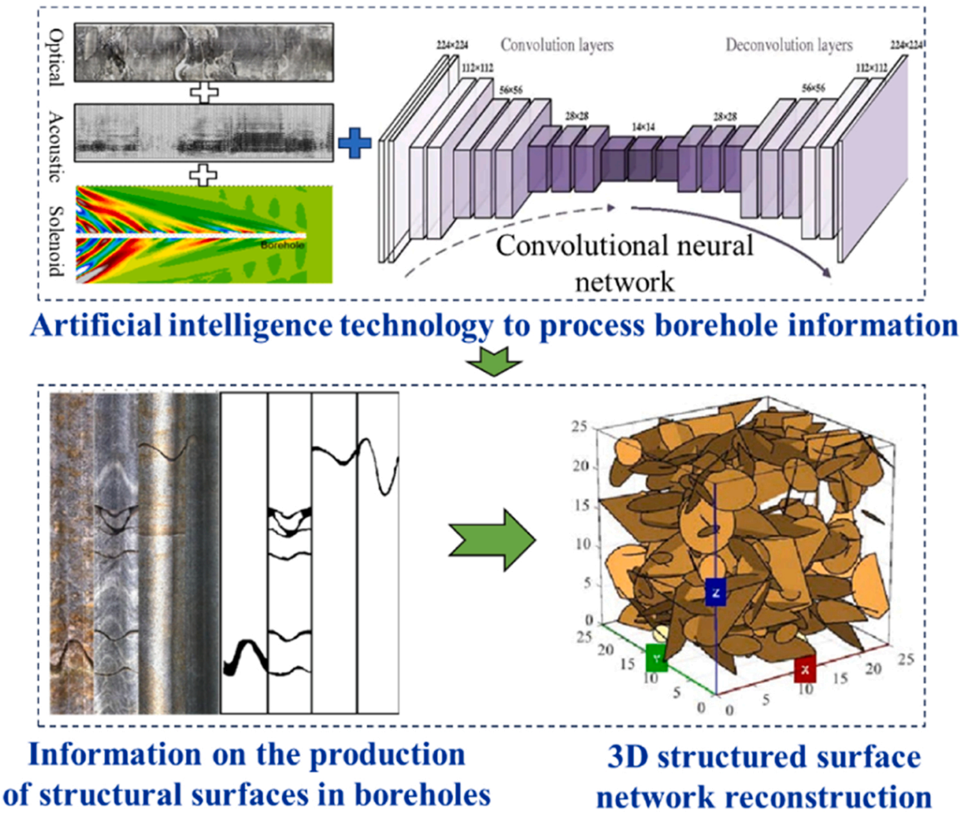


Fig. 4. Optically constrained joint acoustic-electromagnetic inversion for hard structural surface identification (modified from [87]).

updating dynamically the knowledge database and the big data of rock engineering with artificial intelligence method such as deep learning. The system primarily comprises six major technical elements according to the working flow of a deep rock engineering project: (1) geological element, (2) in-situ stress element, (3) model element, (4) design element, (5) disaster control element, and (6) construction element. The technical aspects of each element are as follows:

(1) The geological element includes 3D engineering geological intelligent identification of lithology and interfaces, faults, fracture zones, alteration zones, folds, and hard structural planes;
(2) The *in-situ* stress element refers to the intelligent recognition of in-situ stress, both the magnitude and direction, by intelligent inversion of *in-situ* stress in three dimensions considering the essential characteristics of rock masses and the influences of geological structure and tectonic movements;
(3) The model element denotes the intelligent identification of rock mechanical behavior and models. It encompasses the intelligent measurement of mechanical properties in the laboratory and field-based intelligent monitoring, including the brittle and ductile nature of rock, the stress-induced fracturing and deformation anisotropy, 3D strength theory, and intelligent model identification.
(4) The design element refers to the intelligent design of rock engineering works. It is mainly reflected in a “seven-step” design process, including modeling method based on so-called non 1:1 mapping model, integrated modelling and feedback analysis and dynamic design with information updated timely;
(5) The disaster element refers to the intelligent assessment, monitoring and early warning of rock engineering disasters. It includes mainly the dynamic monitoring, continuous automatic identification and timely quantitative early warning of rockburst, rock spalling, large deformation, deep cracking, *etc*.;
(6) The construction element refers to intelligent construction of rock engineering works. It includes the smartification of equipment, intelligent material adaptive to the environment, construction plans adaptive to evolving dynamic conditions.

3. Intelligent recognition of 3D engineering geological features

The geophysical field, attitude of the structural plane, tunnelling information pertaining to construction equipment, physical properties of rock slag, and the failure mode of surrounding rock were assessed through recording space-sky-ground integrations, surface and local borehole cameras, drilling and TBM parameters, slag information, and surrounding rock damage characteristics.

To achieve less human and 3D engineering geological intelligence recognition (Fig. 2), pre-construction geological survey, rock fracture during the construction period, working performance of the boring equipment, and rock slag were monitored, covering the large-scale regional geology to small-scale working surfaces.

3.1. Prediction of the geological section with space-sky-ground information

Low-altitude aviation, space observation, ground detection, and intelligent technologies were used to infer subsurface geological structures (Fig. 3). “Sky”: UAV aerial observation and mathematical 3D model reconstruction methods were utilized to obtain regional topography, geomorphology, and other geological information [53]. “Space”: automatic interpretation of remote sensing images using artificial intelligence techniques to monitor geological changes and identify geological structures [52]. “Ground”: setting up a sensor network on the ground, and using image recognition technology to reduce data noise accurately and quickly to acquire geological parameters such as seismic activity and geomagnetic field strength [10]. Combining the above 3D data lead to analysis using artificial intelligence to predict intelligently

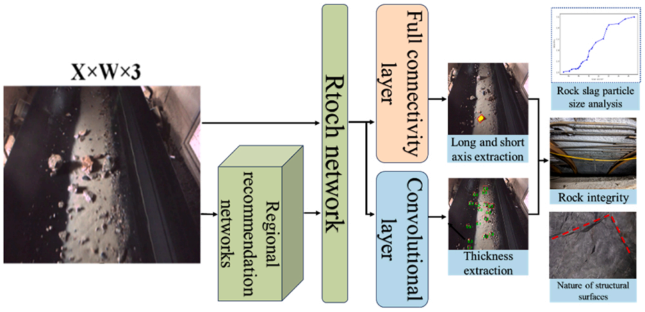


Fig. 5. The rock slag feature extraction method.

the local geological sections [54]. Based on the aforementioned information, geologic structures are identified, including faults, folds, and so on in the region. In the future, with the continuous expansion of engineering projects, the prediction of geological profiles by the information of space-sky-ground for special regional geological conditions (high field stress areas, undersea tunnels, *etc.*) will require the development of new technologies based on the current research to overcome the interference of special geological areas for the collection of information in the space-sky-ground framework.

3.2. Identifying 3D information about structural planes from surface and local borehole data

The identification of internal 3D structural planes [40] involves utilizing surface rock and local drilling data. This process can be achieved through the working face advance borehole or radial surrounding rock borehole camera observation in tunnel sections. Optical, acoustic, electromagnetic, and other means can be used to acquire the borehole rock fissure information [61]. A recognition model can be established using deep learning in the image recognition module to extract the borehole structural surface location, attitude, and other 3D information in an intelligent manner [51]; 3D laser scanning is used to gather information on the surface of the surrounding rock and working face. This information is then used to create a mathematical model with artificial intelligence to extract data pertaining to the surface structure of the surrounding rock (*e.g.*, hard structural surfaces, lithology, and faults). The extracted data processed by artificial intelligence technology are then used to reconstruct the 3D structural surface network in front of the working face, by using information from drilling holes and knowledge of the geologic structure. This process enables the reconstruction and visualization of 3D geological information (Fig. 4). By analyzing and organizing the 3D visualization information, it is possible to predict small-scale geological structures such as hard structural surfaces in front of the working face.

3.3. Geological information recognition based on rock slag

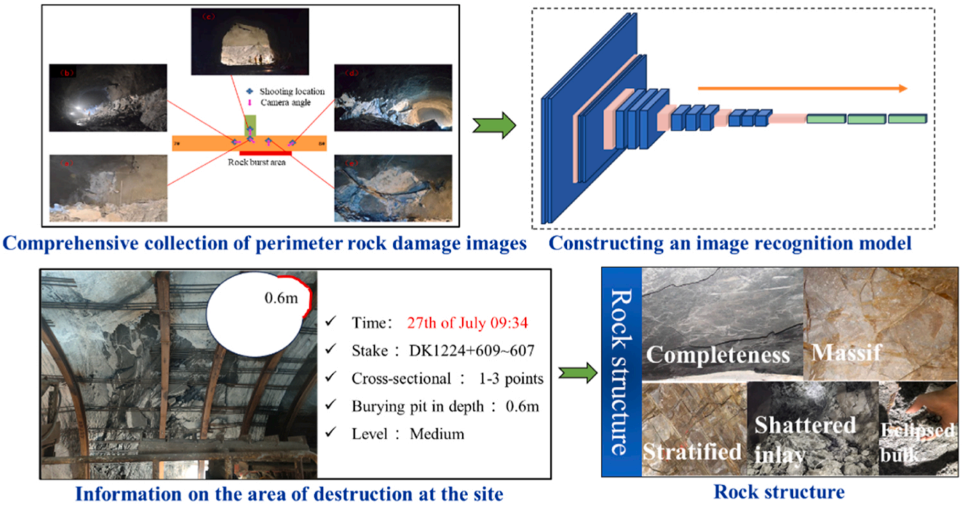
Rock slag, a byproduct of excavation, provides a comprehensive representation of geological characteristics in the working face [57]. The mineral composition, size and shape of the slag can be used to quickly predict the lithology and some physical and mechanical properties of the rock ahead. Video acquisition can be used during the slagging process, using artificial intelligence image recognition methods to calibrate the location, size, lithology, and overall particle size distribution of the slag. Statistical methods for big data are used to correlate slag information with the rock bulk integrity and surface structure to intelligently identify geological information in the working face (Fig. 5). Future work will involve classifying and recognizing excavation products from various construction methods, expanding the range of recognizable information and improving recognition accuracy for swiftly predicting geological information.

3.4. Geological information identification based on surrounding rock failure

When addressing damage caused by surrounding rock during excavation, high-definition cameras were used to capture the characteristics of the damaged area from multiple angles. An image recognition module was then applied for automatic calibration and damage area segmentation[50]. Simultaneously, 3D laser scanner measurements generate point cloud data for a rockburst area, which is used to establish a 3D surface model [75]. This model, in combination with site-specific destruction characteristics collected manually, determines the surrounding rock structure of the failure areas (Fig. 6). By summarizing the damage patterns brought about by different engineering disasters, we can achieve the purpose of identifying different type of geological information. In the future, artificial intelligence technology will identify types of disaster intelligently and integrate disaster information, which enables automated and intelligent disaster information collection and collation, minimizing the need for human involvement.

3.5. Geological identification based on drilling and TBM parameters

Intelligent geological identification, centered on drilling and tunnel boring machine (TBM) parameters, is currently a primary direction for many researchers [84]. The correlation between drilling and TBM



✓ Time: 27th of July 09:34
✓ Stake : DK1224+609~607
✓ Cross-sectional : 1-3 points
✓ Burying pit in depth : 0.6m
✓ Level : Medium

Fig. 6. The geological information recognition method based on surrounding rock failure.

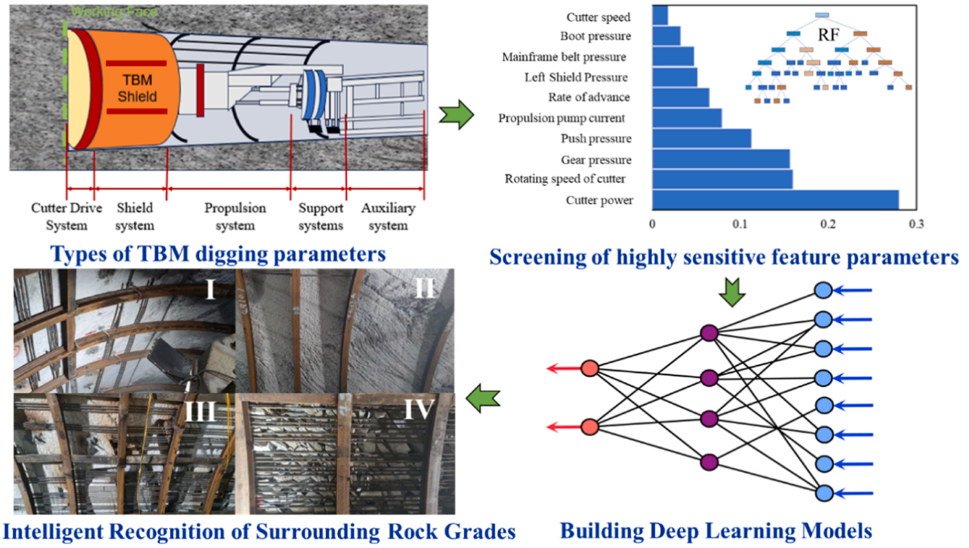


Fig. 7. Recognition of geological information based on TBM boring parameters.

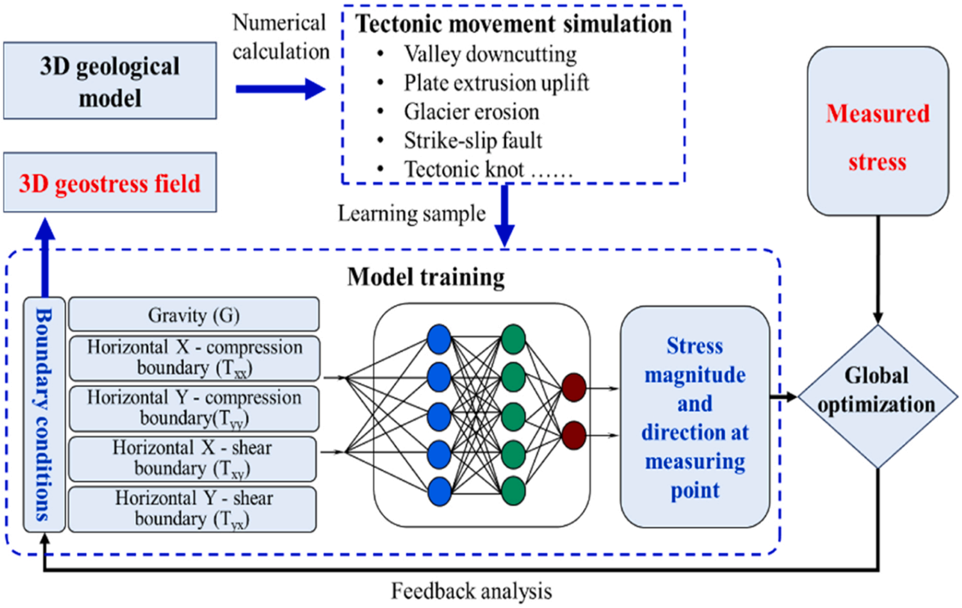


Fig. 8. The method of intelligent recognition of 3D geostress.

parameters and the geological information in front of the working face is notably high. The excavation parameters of TBM in different rock structures have been analyzed in order to predict the type as well as the size of the undesirable geological body in front [64,68]. However, not all parameters exhibit significant correlations with geological information. To address this, random forests can be used to identify parameters that are highly sensitive to the geological conditions in front of the face. Subsequently, machine learning classification algorithms can predict the grade of the surrounding rock, facilitating rapid, efficient, and intelligent rock grading (Fig. 7). The aim is to achieve automatic screening and extraction of parameters as engineering construction experience accumulates. This will help construction personnel refine parameters and receive feedback more quickly [2].

4. Intelligent recognition technology applied to 3D geostress states

Affected by topography, tectonic movement and geological transformation, and so on, the 3D geostress field of rock mass is highly heterogeneous, non-linear, uncertain, and spatio-temporal variability. The limited *in-situ* stress measurement data cannot reflect the complicated and changeable geostress field in the engineering area making it necessary to identify the 3D in-situ stress field intelligently combining the tectonic geological characteristics of rock mass and artificial intelligence technology (Fig. 8). On the basis of 3D geological model, the tectonic movements, such as valley downcutting, plate extrusion uplift, glacier erosion, strike-slip fault and tectonic knot etc., are simulated by numerical calculations. By using the artificial intelligence method, the artificial intelligence model between the boundary conditions of the 3D geological model and the stress of the measured point, can be constructed. The intelligent back-analysis is conducted to obtain the optimal boundary conditions using the trained model and global optimization. The 3D regional geostress field can be determined based on the optimal boundary conditions.

Fig. 9 shows the detailed nonlinear intelligent inversion method of 3D geostress field considering tectonic movement. Firstly, a 3D

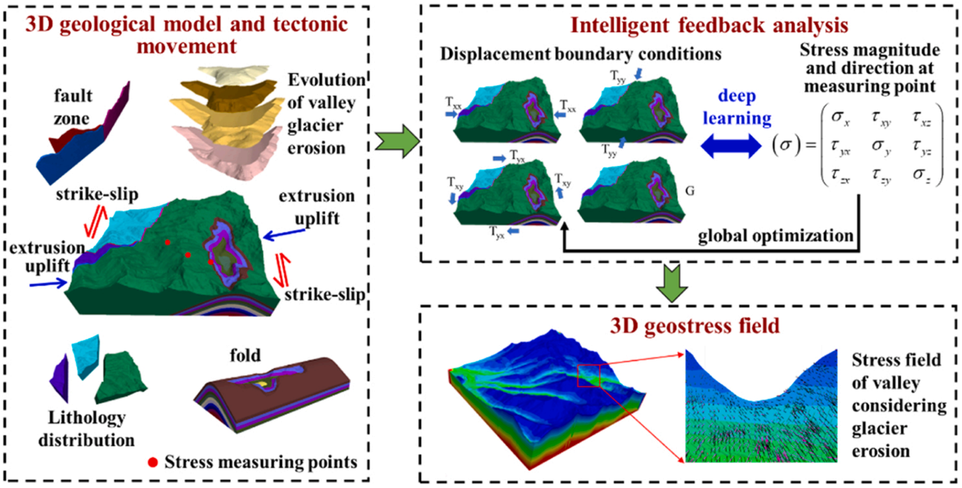


Fig. 9. Non-linear intelligent inversion method of 3D geostress field considering tectonic movement.

geological model is established considering landform, geological structure (such as faults, folds, *etc*.), lithology distribution, and historical tectonic processes (such as riverine erosion, glacial erosion, *etc*.). Secondly, considering plate extrusion uplift and strike-slip, the historical development of the geostress field is divided into gravity, extrusion, and shear displacement conditions, and the displacement boundary conditions are applied step-by-step to simulate the successive processes of historical tectonics, and the geological transformation associated with formation denudation is considered. Then, the neural network model between displacement boundary condition and measuring point stress is constructed by using deep learning algorithm. Finally, a genetic algorithm or particle swarm optimization algorithm is used to seek the optimal displacement boundary conditions, the 3D ground stress field is then obtained by applying optimal displacement boundary conditions to the 3D geological model.

5. Intelligent identification of rock mechanical behavior and mechanical models

Intelligent recognition of rock mechanical behavior and mechanical models is to develop intelligent devices for testing the real fracture and deformation process information of rocks, then use artificial intelligence, deep learning, and other methods to model and predict the mechanical properties and behavior from the measured results. This methodology enables independent learning and identification of intricate patterns within rock mechanics, leading to more reasonable forecasts of rock deformation and failure behaviors. It encompasses intelligent testing of the mechanical characteristics of rock, intelligent identification of mechanical models, and intelligent back-analysis of the mechanical parameters of rock.

5.1. *Intelligent measurement of the mechanical characteristics of rock*

Intelligent testing of rock mechanical properties aims to observe the mechanical behavior of rocks considering in-situ factors such as stress and temperature. This involves utilizing intelligent sampling techniques [77,80], intelligent testing equipment [38,41,46,44,78,89], and data acquisition and analysis systems. These tools enable the measurement of characteristics and patterns, including peak failure processes, time-dependent failure processes, disturbance-induced failure processes of rock blocks and structural planes, along with attributes such as strength, brittleness, fracture, and energy. For example, a system based on fracturing information collected through acoustic emission is employed to control intelligently the post-peak fracture behavior of hard rocks under true triaxial compression. This enables the measurement of the entire deformation process and the fracturing process after reaching the peak strength of brittle hard rock (Fig. 10).

5.2. *Intelligent identification of mechanical models for rock*

Intelligent identification of rock mechanics models is to depict the high non-linear constitutive or in-situ response relationship from extensive rock mechanics and rock engineering test data (such as stress-strain, loading-deformation, excavation-displacement, *etc*.), using

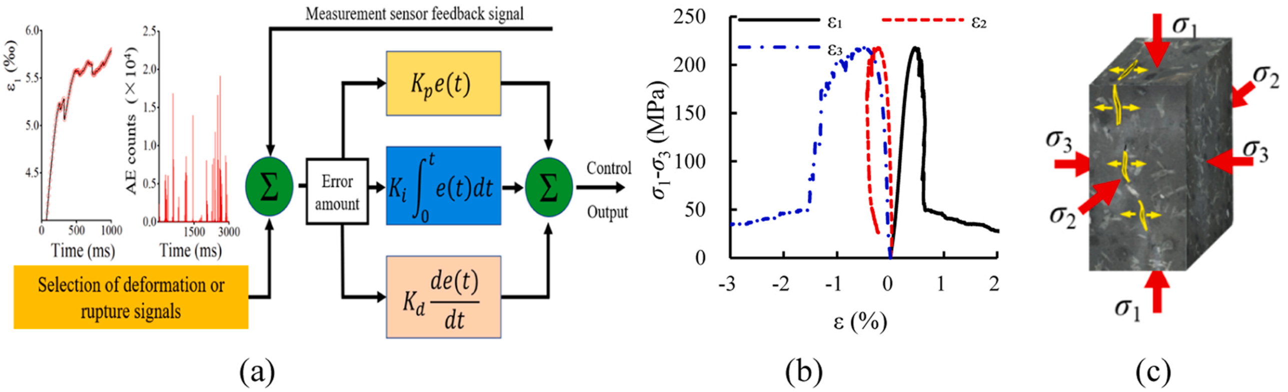


Fig. 10. Intelligent feedback control technology for post-peak fracturing process of hard rock based on fracture information: (a) Intelligent control method; (b) The measured stress-strain curves throughout the process; (c) Failure mode with mainly tension fractures.

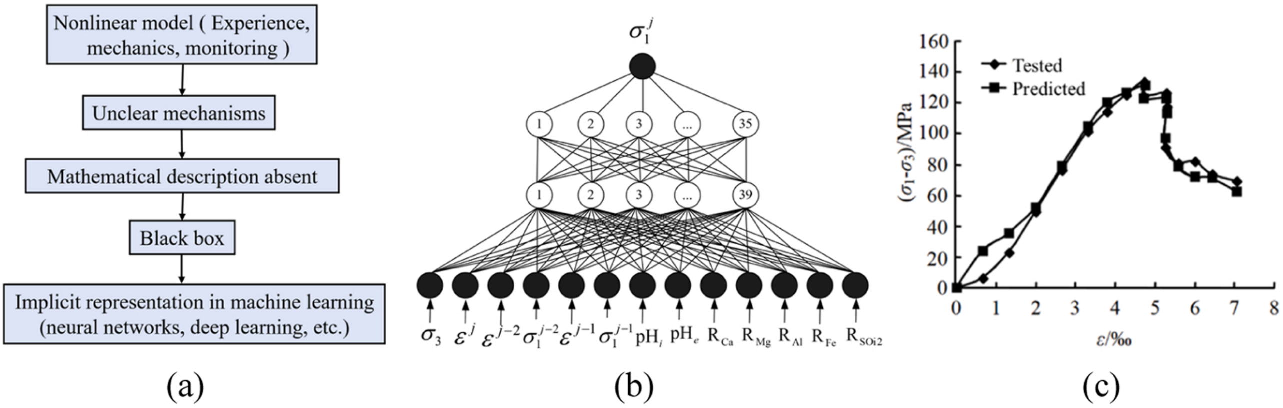


Fig. 11. Neural network expression of non-linear models of rock under chemical corrosion conditions: (a) Modelling method for the black box problem; (b) Neural network expression of non-linear models; (c) Results compared [7].

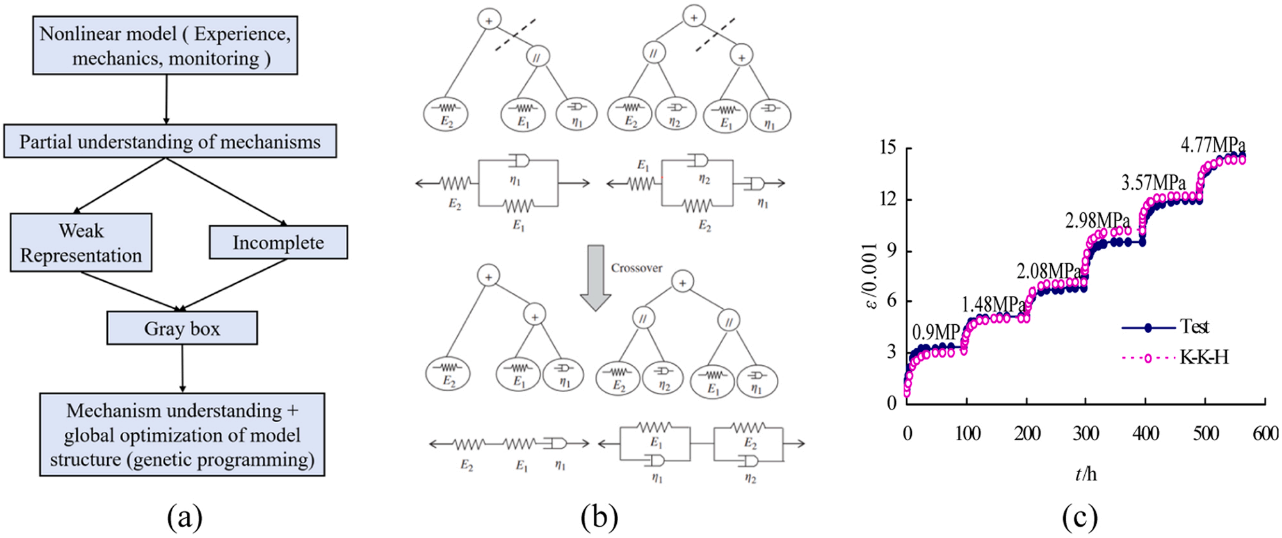


Fig. 12. Genetic programming of rheological model for celadon clay rock based on a grey-box problem: (a) Modelling method for the grey-box problem; (b) Model structure optimization combination operation; (c) Comparison of prediction and creep test results [33].

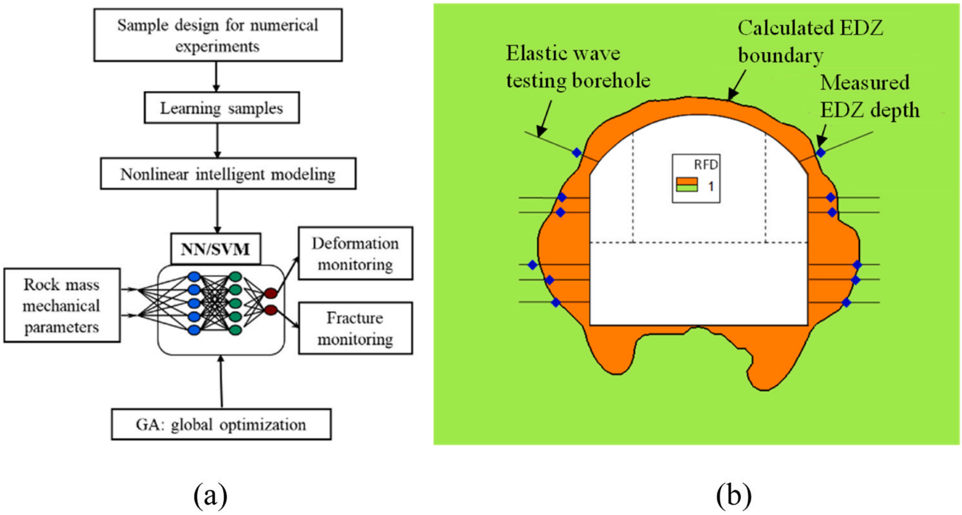
techniques such as artificial intelligence and deep learning. Advances in identifying rock mechanics models have involved the integration of artificial intelligence and optimization algorithms [19,29,21,32,33,81].

The methods for intelligent identification of rock mechanical models can be generally categorized into two groups: the first, termed the black-box problem, arises due to the unclear non-linear characteristics and failure mechanisms of rocks, making it challenging to describe them accurately with mathematical methods. In such scenarios, neural networks and deep learning (*inter alia*) can be used to derive implicit representations (Fig. 11a). For instance, a stress-strain-chemical neural network constitutive model (Fig. 11b) is trained from the testing data when investigating the effects of various chemical erosion conditions on rock mechanical behavior, evincing substantial agreement with experimental data (Fig. 11c) [7].

The other category is termed the grey-box problem, which differs from the black-box problem in that some of its mechanisms are known, but their mathematical descriptions might be incomplete or weak (Fig. 12a). For example, when identifying rock rheological models, optimal combinations are achieved by continuously employing genetic programming methods to navigate through the series and parallel relationships among fundamental components (such as elastic and viscous elements). This iterative process aims to derive specific mechanical models tailored for particular rocks (Fig. 12b). By using this approach, as depicted in Fig. 12c, the visco-elastic mechanical model of a type of claystone is established, exhibiting a close match with experimental values after several iterations to derive the K-K-H model [33].

5.3. *Intelligent back-analysis of rock mechanical parameters*

Intelligent back-analysis of rock mechanical parameters is used to search for reasonable parameters of rock mass for numerical calculation through an iterative parameter optimization procedure by minimizing the discrepancies between field-measured and numerically calculated results, instead of in-situ testing methods or empirical estimation methods which are usually cost and time-consuming with the results confusing to use because of many uncertainties and disparities. Intelligent global optimization methods [14,34,5,82] and hybrid intelligent methods [28,31,60] have been extensively employed for more efficient analysis, with numerical models extended from 2D to 3D and the back-analysis information extended from single to multiple items. For example, for the mechanical parameters of marble in the China Jinping Underground Laboratory Phase II (CJPL-II), a training database is established through numerical experiments, and the non-linear mapping relationship between the parameters to be back-analyzed and the excavation damage zone (EDZ) size and displacement of surrounding rock is deeply learned. Based on the representative displacement and



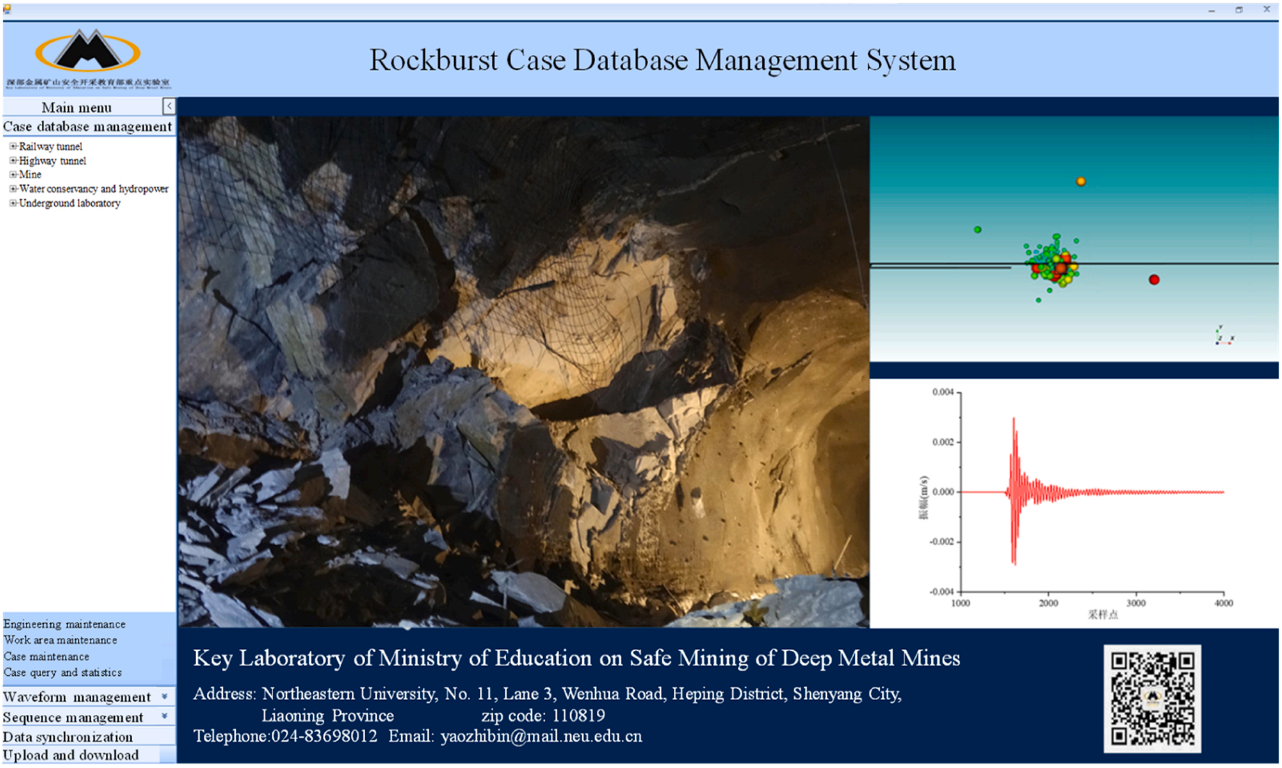
(a) (b)

Fig. 13. Comparison of mechanical parameter inversion process and results of marble in Phase II of the Jinping underground laboratory: (a) Back-analysis procedure; (b) Comparison between measured results calculated results using back-analyzed parameters.

EDZ information and its spatial distribution pattern obtained from on-site monitoring, the parameters were intelligently sought through global approximation of the measured information, and validated against the 3D spatio-temporal evolution of the internal displacement and EDZ of the surrounding rock during excavation. The calculated EDZ depth based on the back analyzed results is found to well coincide with the measured values in terms of both quantity and distribution (Fig. 13).

6. Intelligent assessment, monitoring, and warning of rock engineering disasters

Geological hazards (such as rockbursts, large-scale spalling, collapse, large deformations, deep fractures, *etc.*) are key factors that constrain the safe and efficient construction of rock engineering [73]. The intelligent assessment, monitoring, and warning technology for rock engineering disasters is advancing, including intelligent risk assessment before excavation, continuous monitoring and intelligent analysis of disaster development processes, intelligent identification of disaster types and intensity warning, and adaptive mitigation of disaster development process. Artificial intelligence techniques can describe the highly non-linear relationship between the development process and the type, intensity, and time of occurrence of disasters. While improving the accuracy of analysis and warning, researchers have significantly enhanced its level of automation. A rockburst is a dynamic phenomenon whereby the elastic deformation potential energy accumulated in the rock mass is suddenly released during excavation or other external


Rockburst Case Database Management System

Key Laboratory of Ministry of Education on Safe Mining of Deep Metal Mines

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Fig. 14. Rockburst database management system.

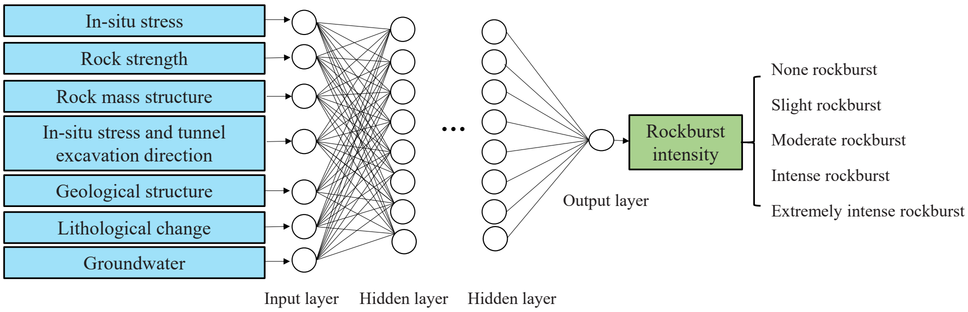


Fig. 15. The intelligent assessment model for the rockburst intensity.

Fig. 16. The wireless MS monitoring system for rockbursts.

disturbances, leading to the bursting and ejecting of the surrounding rock [15]. These events are intense, occur suddenly, and are random and damaging. Taking rockburst as an example, we introduce the implementation process of intelligent assessment, monitoring, and warning technology to prevent accidents and disasters.

6.1. *Classification and intensity of rockbursts*

According to the relationship between the occurrence characteristics of a rockburst and the construction program, rockbursts can be divided into immediate rockbursts, time-delayed rockbursts, and chain rockbursts (which can be divided into axial chain rockbursts and radial chain rockbursts) [13,42,48]. According to the rockburst development mechanism, they can be divided into strain rockbursts, strain structure-slip rockbursts, and fault rockbursts [55,87,88]. Rockburst intensities are generally divided into: slight, moderate, intense, and extremely intense rockbursts [9].

6.2. *Intelligent assessment of rockburst intensities before excavation*

Before excavation, it is necessary to conduct intelligent assessment of rockburst intensities to provide a basis for monitoring and warning of rockburst risk at various sections. A rockburst database has been established (Fig. 14), containing over 2000 rockbursts of different intensities and types [83]. The main factors controlling rockburst intensities and geological correction factors can be acquired through in-depth data mining of these cases. Using these factors as the inputs, an intelligent assessment model for rockburst intensity based on deep learning was established (Fig. 15), which can automatically output the rockburst intensity.

6.3. *Continuous micro-seismic monitoring of a rockburst development process*

Micro-seismic (MS) monitoring is the most widely used monitoring method for rockburst [59,8,79]. To ensure the continuity of MS monitoring, the current MS sensors have evolved from wired to wireless transmission (Fig. 16). Their data transmission stability has been greatly improved, and the installation and maintenance time has been reduced by 80%, with the number of obtained MS events is increased by 40% in the tunnel excavated using the drilling and blasting (D&B) method. Its longer transmission distance is also conducive to long-term continuous monitoring of time-delayed rockbursts.

6.4. *Intelligent analysis of rock fracture signals during the rockburst development process*

The MS monitoring data during the rockburst development process should be further analyzed for rockburst warning, including waveform recognition, arrival time picking, and MS source locating. The suddenness and harmfulness of rockbursts impose more onerous requirements on the rapid and accurate processing of MS monitoring data. Then, a full-process intelligent analysis technology for MS monitoring data has been established facing this situation. Besides, the further to improve the

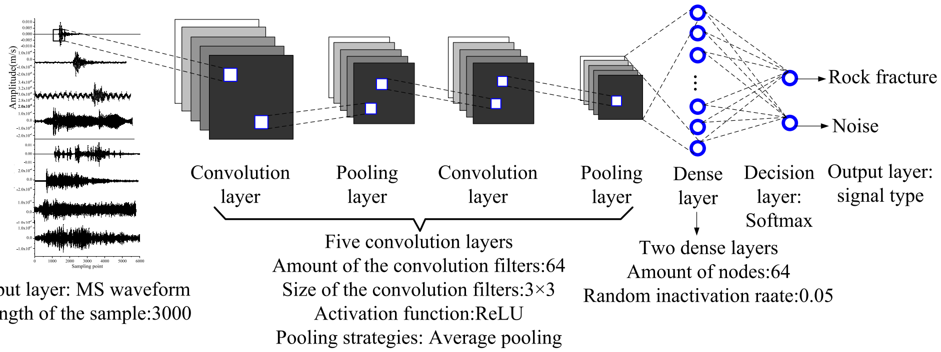


Fig. 17. An automatic recognition method of MS waveform based on deep learning convolution neural network [4].

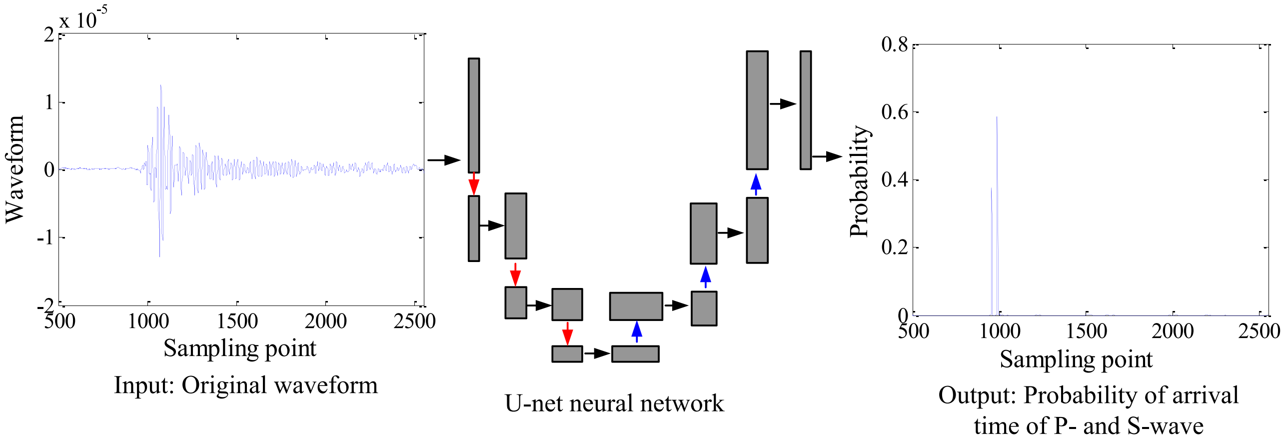


Fig. 18. Automatic detection of waveform arrival-time using a U-net neural network [85].

generalization ability and applicability of the technology in different scenarios, *i.e.*, different excavation methods, lithology, surrounding rock conditions and so on, a large model for MS monitoring data analysis remains to be established.

6.4.1. Intelligent recognition of rock fracture waveform

Due to the similarity to, and interweaving with, extremely complex noise signals on site, it is difficult to recognize rock fracture signals with any accuracy, especially those with a low signal-to-noise ratio (SNR). An intelligent recognition method based on deep convolutional neural network has been established (Fig. 17). The original waveforms are taken as the input and the signal type, i.e., rock fracture signal or noise signal, is output directly. This model can achieve real-time recognition of MS signals, with a 95% accuracy rate [4].

6.4.2. Intelligent detection of arrival time of rock fracture signals

To locate the source of fracturing within the rock mass, it is necessary to detect the arrival time of the rock fracture signals in a reasonable and timely manner, which is very difficult for the rock fracture signals with low SNR. An intelligent arrival time picking model for rock fracture signals was established using a U-net neural network. As shown in Fig. 18, the original waveforms were taken as input and outputs the probabilities of P-wave and S-wave arrival times, respectively. It can accurately pick up the arrival time of both P-wave and S-wave simultaneously, with an accuracy rate of over 85%, without manually setting thresholds and time-window lengths, and can process a large number of waveforms in real time [85].

6.4.3. Intelligent localization of rock fracture sources

The rock fracture sources can be located using rock fracture signals and their arrival time information. Complex geological and construction environments, pathological sensor arrays, and other factors can affect the location of MS sources. An intelligent location algorithm for MS sources was established, with a sectional velocity model [12] and a hierarchical solution and particle swarm global optimization approach [6], considering diffraction of elastic waves in empty spaces. This significantly improves the location accuracy of rock fracture sources, especially for MS source location in near-field monitoring outside the array. The rock fracture MS source location error is less than 5 m in a TBM tunnel.

6.5. Intelligent warning of rockbursts

Rockburst warning refers to the pre-judgment of the location, intensity, and time of potential rockburst in the rock engineering based on on-site monitoring data (such as MS data, *etc.*), providing guidance for the subsequent construction and rockburst prevention measures, to avoid or reduce the risk of rockbursts [42]. D&B and TBM methods induce different disturbances and damages to the surrounding rock, leading to differences in the characteristics of rockbursts under these two methods. Moreover, different types of rockburst have diverse conditions of occurrence and mechanisms of development, resulting in the differences in the spatio-temporal evolution characteristics and rules of relevant monitoring information during their development. Therefore, to provide more targeted warnings and improve their effectiveness, it is necessary to distinguish between construction methods and types of rockburst.

Intelligent warning of rockbursts relies on intelligent methods to process and analyze multi-source monitoring information closely related to the development of the rockburst, excavating the deep-seated characteristics of its development, performing non-linear mapping between multi-source monitoring information and potential rockburst information (location, type, intensity, time, *etc.*). Hence, an intelligent warning model capable of delivering an automatic quantitative warning of an imminent rockburst was established. Taking the intelligent identification of rockburst types as an example, a large number of rockburst cases were analyzed. The results indicated that the conditions for different types of rockburst and the spatio-temporal evolution of MS activity during the development process, *etc.* differ. For example, a strain rockburst mainly occurs in hard, intact rock masses with no structural planes, and the process is mainly controlled by stress, and its MS time-series tends to be concave upward during the development process. On the other hand, a strain-structure slip rockburst mainly occurs in hard rock masses with a few structural planes, which is jointly controlled by stress and structure, and its MS time-series tends to be linear during the development process. Under the guidance of this *a priori* knowledge, an intelligent identification model for types of rockburst based on deep learning is established (Fig. 19). This model can intelligently identify the type of potential rockburst by inputting MS time-series type, lithology, rock mass integrity, spatial relationship between geostress, geological structure and tunnel, excavation information and support information [27,49,70]. In the future, when different types and intensities of rockburst cases of various projects accumulate to a certain number, a large-scale intelligent rockburst warning model can be established. Through fine-tuning, migration learning and reasoning, the model can be used to conduct efficient rockburst warning in newly-built projects, overcoming the limitation whereby the corresponding rockburst warning model can only be established after a certain number of rockburst cases are collected on newly-built projects. Compared with traditional rockburst warning methods, intelligent warning of rockburst can improve the accuracy and timeliness of the warning. In recent years, intelligent warning of rockburst has developed rapidly, especially in the field of intelligent warning of rockbursts in a tunnel, and has achieved rich research results.

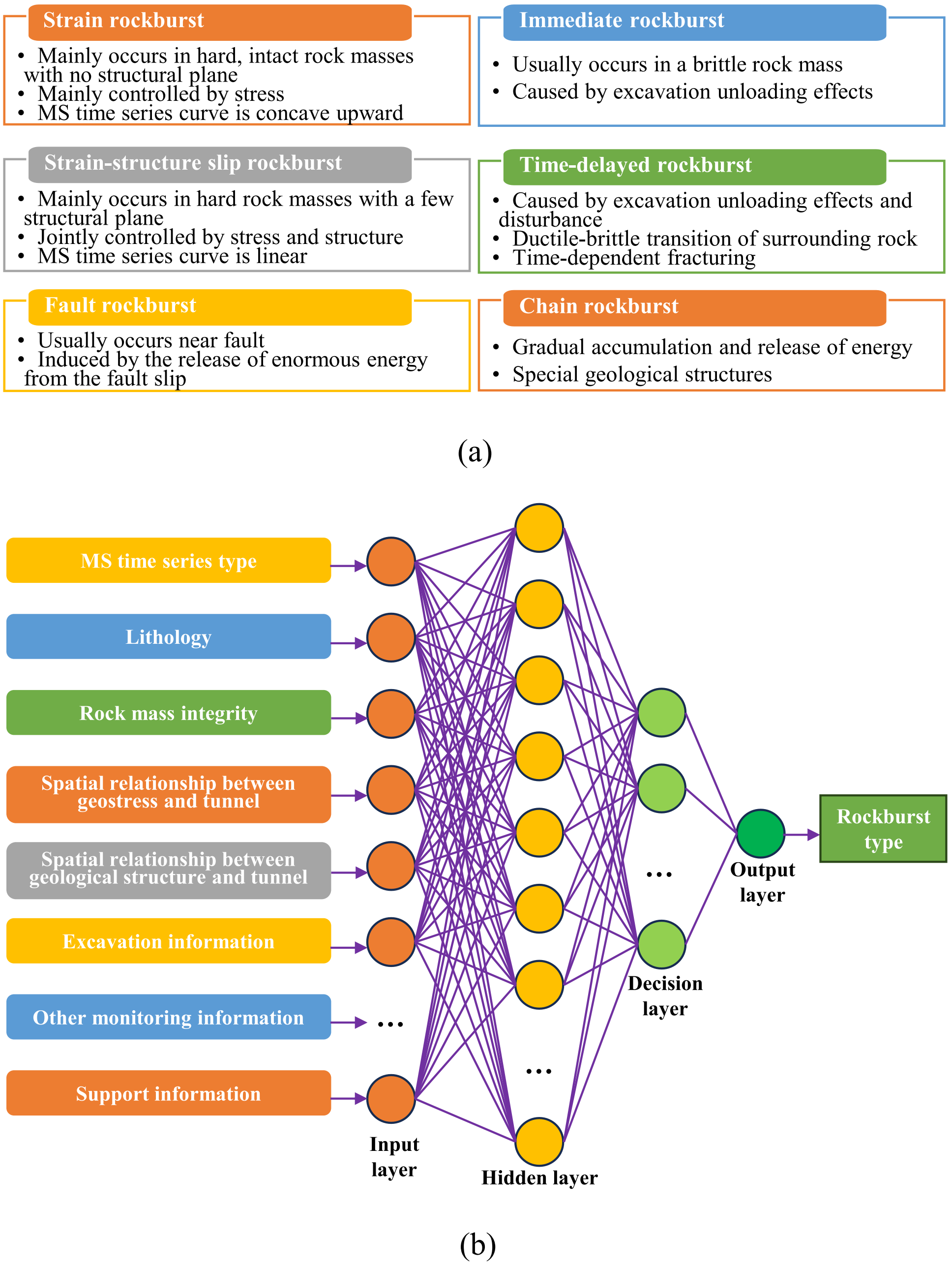


Fig. 19. The intelligent identification model of types of rockburst based on multi-source information: (a) Prior knowledge; (b) Intelligent identification model of rockburst type based on deep learning.

6.5.1. *Intelligent warning method of rockburst in a tunnel excavated by the D&B method*

The most significant characteristic of a tunnel excavated by the D&B method is that the construction process consists of blasting cycles, each of which is mainly composed of drilling, charging, blasting, ventilation, slag removal, removal of danger, and implementation of primary support measures. In addition, multi-source monitoring information during rockburst development processes is closely related to the blasting. Therefore, when establishing an intelligent warning method for rockburst in the tunnel excavated by the D&B method, the multi-source monitoring information can be discretized according to the blasting cycle, and then arranged in the actual blasting cycle sequence to form a time-series of multi-source monitoring information based on the blasting cycle. Based on Long Short-term Memory (LSTM) neural networks, the time series of multi-source monitoring information from historical blasting cycles can be used as the input vector, and the potential rockburst intensity and its probability in subsequent blasting cycles are used as the output vector to establish an intelligent warning model for rockburst (Fig. 20). This intelligent warning model can achieve intelligent warning for rockburst, and also can realize warning of the time of a rockburst with a blasting cycle as the unit [56].

The further to identify the construction procedure in which a rockburst is most likely to occur within the blasting cycle, the time-series data containing MS information for rockbursts occurring during different construction procedures were analyzed. The results show that the time series of MS information can be roughly divided into four types (Fig. 21). The fore shock, fore-main-aseismic shock, and fore-aseismic-main shock time series correspond to the most likely occurrence of rockburst during the ventilation and slag removal stage, danger removal, and primary support stage and drilling and charging stage in the next blasting cycle, respectively, while the swarm shock time series corresponds to any construction procedure in which a rockburst may

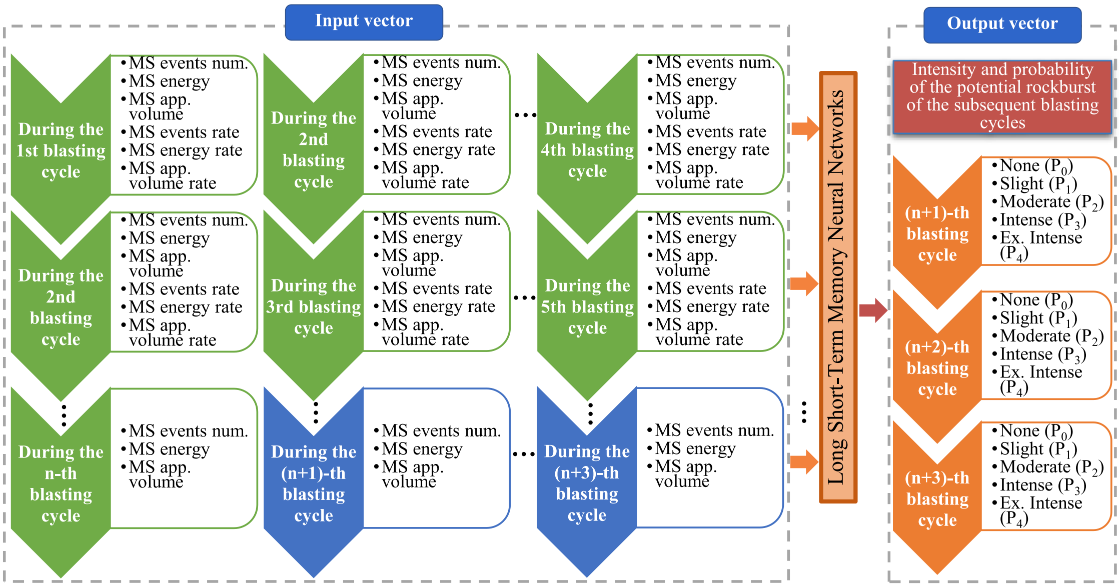


Fig. 20. The intelligent warning model for time of a rockburst with a blasting cycle as the unit. (Note: A. The n^{th} blasting cycle is the current cycle; B. MS information about the n+1, n+2, and n+3 blasting cycles are predicted values calculated from historic MS information; C. Num. denotes number, App. denotes apparent, Ex. denotes extremely).

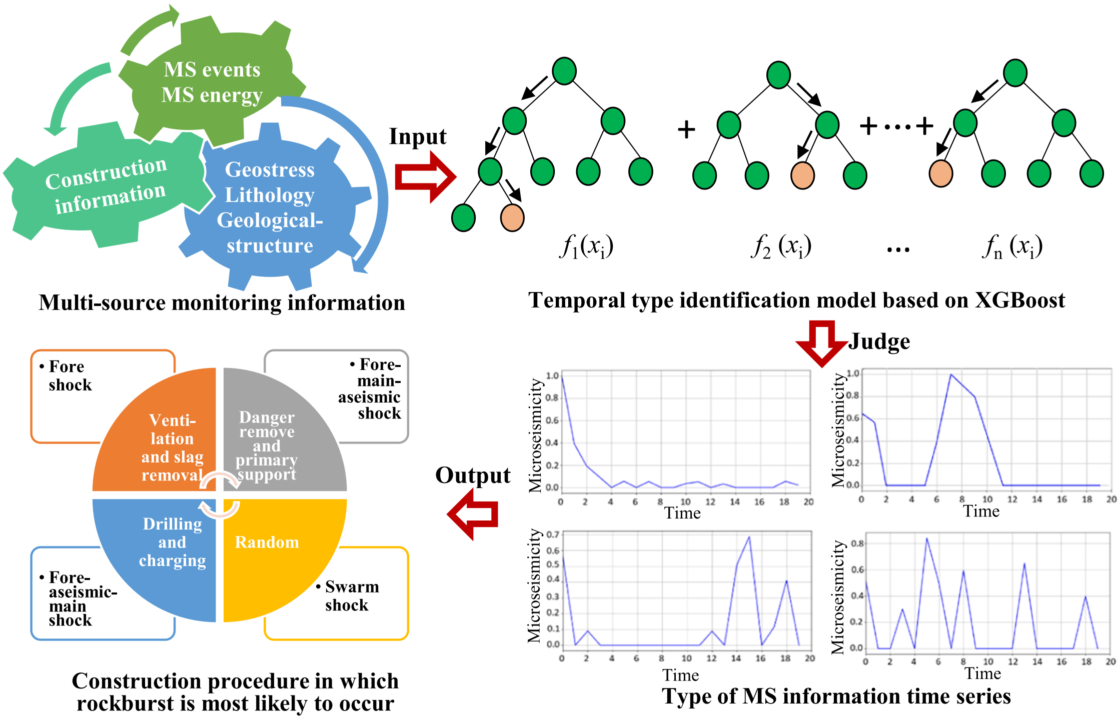
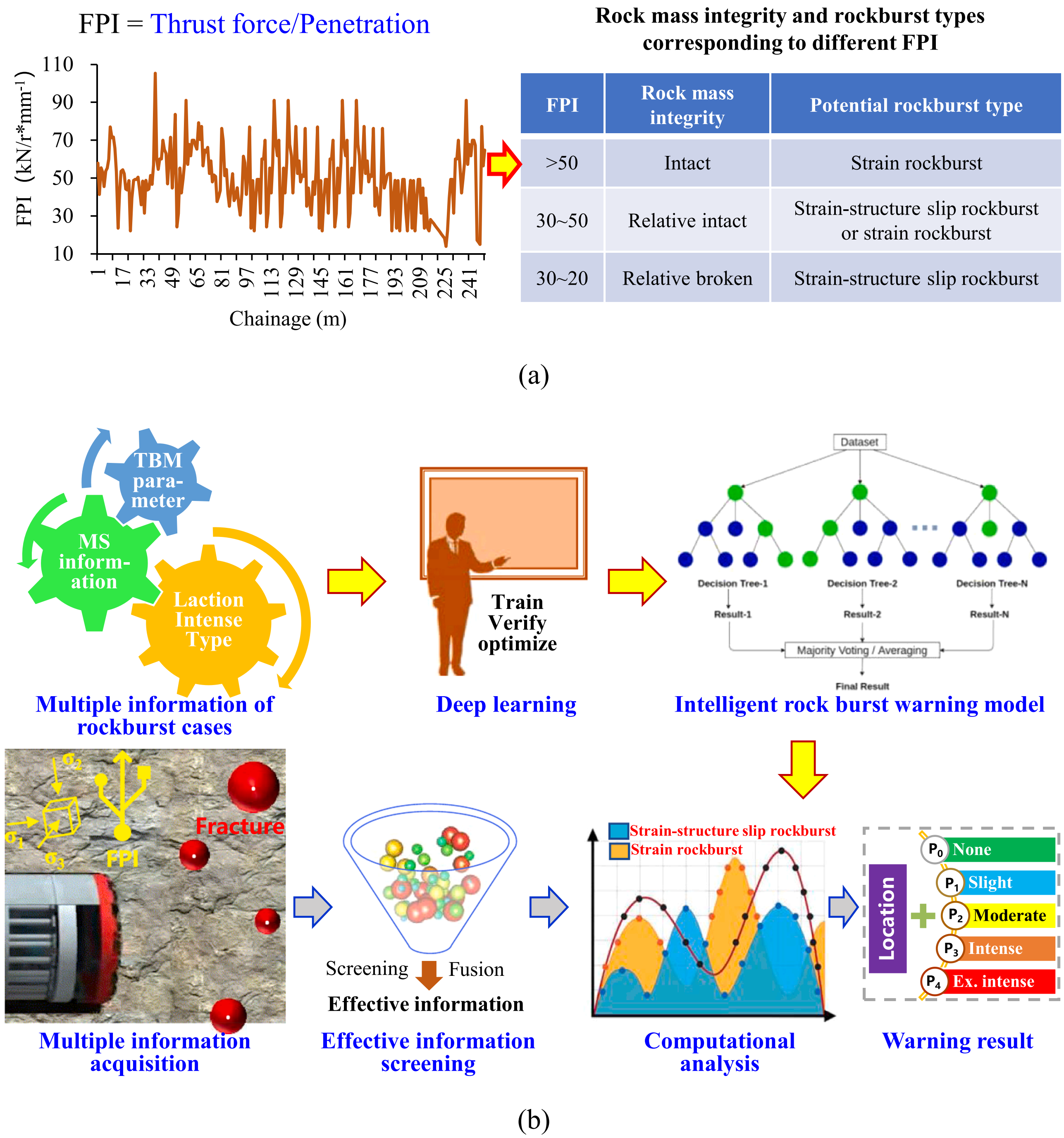


Fig. 21. The intelligent warning model for the occurrence time of rockburst with construction procedure as the unit.

occur in subsequent blasting cycles. That is, there is a good correspondence between the type of MS information time series in the blasting cycle and the rockburst occurrence time [72]. Therefore, establishing an intelligent warning model for rockburst based on the type of MS information time series in the blasting cycle (Fig. 21) can realize intelligent warning of rockburst time with the construction procedure as the unit.

6.5.2. Intelligent warning method of rockbursts in a tunnel excavated by the TBM method

Compared with the intelligent warning method for a rockburst in a tunnel excavated by the D&B method, the main feature of the intelligent warning method for a rockburst in a tunnel excavated by TBM method is to introduce some monitoring information from the TBM itself into the warning index system. These TBM monitoring information can partially reflect the basic situation of the surrounding rock near the working face. Combined with MS information, it can predict the type of potential rockburst, and then distinguish between the types of rockburst for warning, thus improving the pertinence and accuracy of rockburst warning. The TBM monitoring information closely related to the surrounding rock conditions mainly includes the thrust force and penetration. Therefore, the index of the ratio of thrust force to penetration (FPI) can be introduced to characterize the surrounding rock conditions.



Rock mass integrity and rockburst types corresponding to different FPI

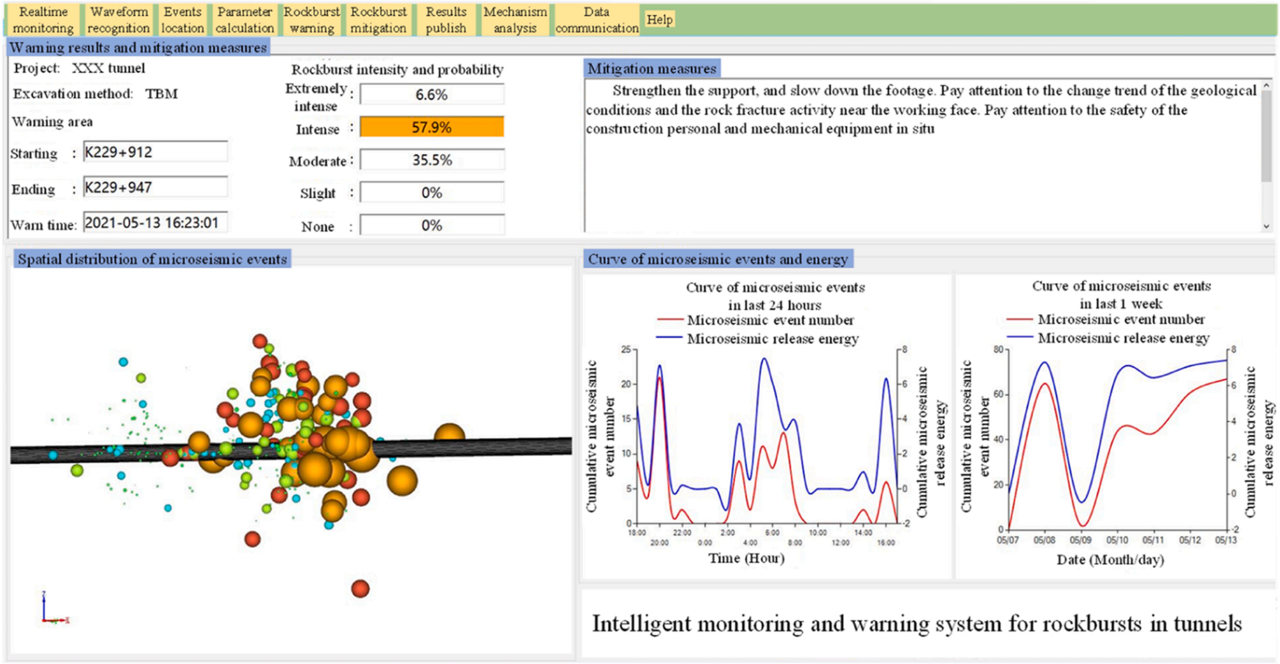
FPI	Rock mass integrity	Potential rockburst type
>50	Intact	Strain rockburst
30~50	Relative intact	Strain-structure slip rockburst or strain rockburst
30~20	Relative broken	Strain-structure slip rockburst

Fig. 22. The intelligent warning method for rockburst by distinguishing between types of rockburst in a TBM tunnel: (a) Prior knowledge; (b) Intelligent rockburst warning model based on TBM parameters and MS information.

For example, for granite tunnels, generally, when the median FPI is greater than 50, the surrounding rock near the working face is relatively intact, and any potential rockburst is likely to be a strain rockburst. When the median of FPI is less than 50, the structural plane of the surrounding rock near the working face is relatively developed, and the potential rockburst is mainly strain-structure slip rockburst. When the median FPI is between 30 and 50, the surrounding rock near the working face is relatively intact, and the potential rockburst may be a strain rockburst or strain-structure slip rockburst. Under the guidance of such *a priori* knowledge, establishing an intelligent warning model for rockburst that integrates TBM monitoring information and MS information (Fig. 22) can achieve quantitative warning of a rockburst, distinguishing between types of rockburst in TBM tunnels.

6.5.3. *Intelligent monitoring and warning system for rockbursts in tunnels*

Based on the aforementioned results, comprehensive utilization of artificial intelligence, big data, cloud technology, and other means, an intelligent monitoring and warning system for rockbursts in tunnels has been developed (Fig. 23) [24]. The system can realize the automation and intelligence of the whole process of fracture perception, waveform recognition, arrival-times picking, MS source location, data analysis, quantitative warning, prevention and control suggestions, report generation, and information reminders. It can improve the accuracy and timeliness of rockburst warning, realize unattended monitoring and warning of tunnel rockbursts, and is of importance in ensuring the safe and efficient construction of rockburst-prone tunnels.



Project: XXX tunnel

Excavation method: TBM

Warning area

Starting : K229+912

Ending : K229+947

Warn time: 2021-05-13 16:23:01

Rockburst intensity and probability

Extremely intense	6.6%
Intense	57.9%
Moderate	35.5%
Slight	0%
None	0%

Mitigation measures

Strengthen the support, and slow down the footage. Pay attention to the change trend of the geological conditions and the rock fracture activity near the working face. Pay attention to the safety of the construction personal and mechanical equipment in situ

Intelligent monitoring and warning system for rockbursts in tunnels

Fig. 23. Intelligent monitoring and warning system for rockbursts in a tunnel [24].

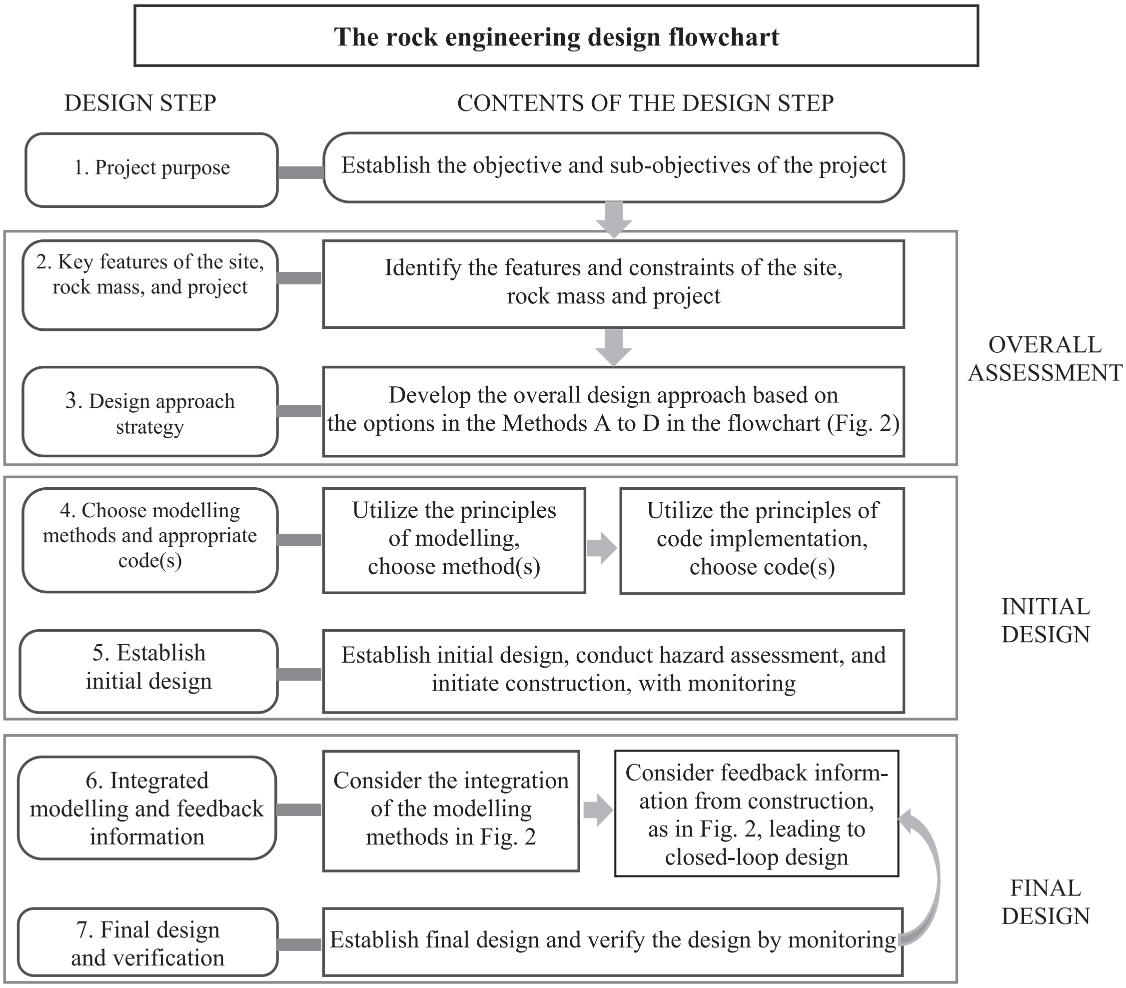


Fig. 24. Flowchart: the rock engineering design process [58].

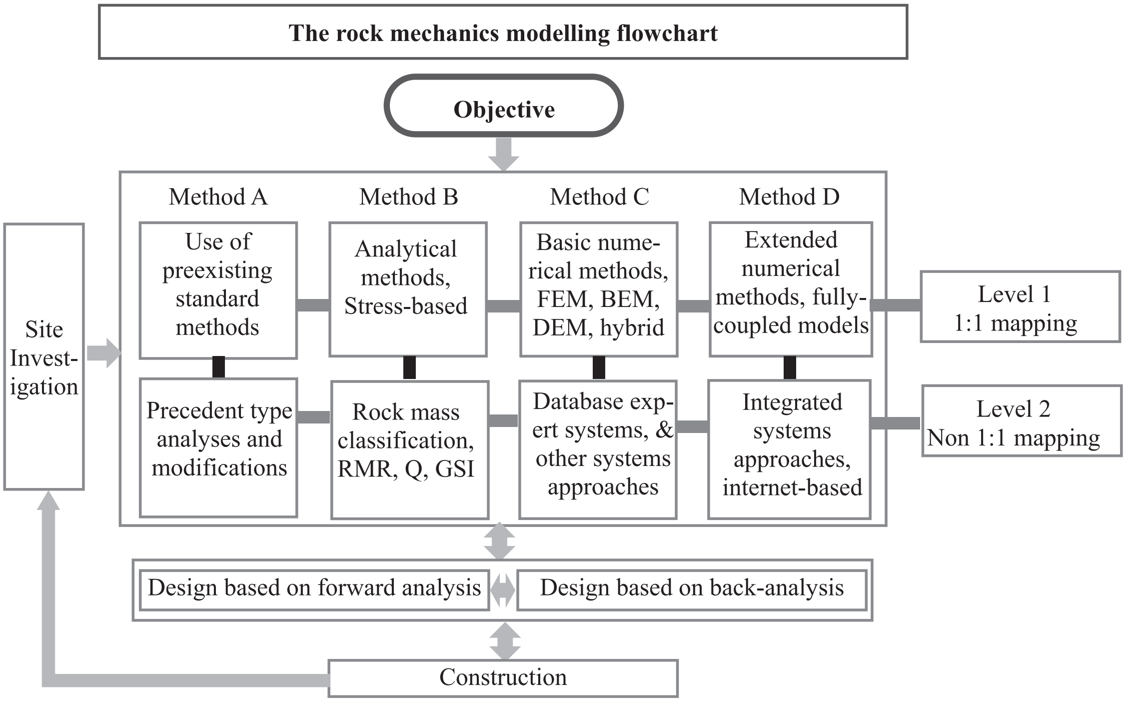


Fig. 25. Flowchart: rock mechanics modelling techniques [58].

7. Intelligent design of rock engineering works

The overall idea of intelligent design in rock engineering, is mainly reflected in a “seven-step” process, which divides the design into three stages, that is, overall assessment, initial design and final design respectively (Fig. 24) [58]. It includes seven steps: specifying project purpose; identifying key features of the site, rock mass, and project; establishing a design approach strategy; choosing modelling methods and appropriate code(s); establishing an initial design, integrated modelling and feedback analysis; and establishing final design and verification. Among them, the modelling methods and appropriate code (s) are selected based on the so-called 1:1 mapping model and non 1:1 mapping model (Fig. 25) [58]. The intelligent optimization design method is mainly applied in the initial design stage and integrated modelling and feedback analysis step in the final design stage.

Based on the flowcharts in Figs. 24 and 25, detailed design methods have been developed according to the characteristics of different types of engineering operation and their potential for different types, and degrees of severity of disasters. For example, design methods such as axial optimization, prevention and control of rockburst and high-pressure water hazard, and high temperature protection have been proposed to ascertain the characteristics of tunnel engineering such as long chainage, large burial depth, crossing multiple strata along the line, the high-stress and high-temperature environment in deep-buried tunnels; based on the characteristics of large underground caverns with large spans, high side walls, multiple connected caverns, and layered and segmented excavation, design methods such as optimizing the layout of the axis of large caverns, optimizing the spacing between caverns, optimizing the excavation sequence and dynamic feedback of layered distribution, and preventing large deformation of the high side walls were proposed; based on the shape of steep rock slopes and the characteristics of excavation construction from top to bottom, design methods based on slope functional requirements, excavation support methods considering natural environment, and operation and maintenance monitoring and design methods considering the overall safety of engineering slopes were proposed.

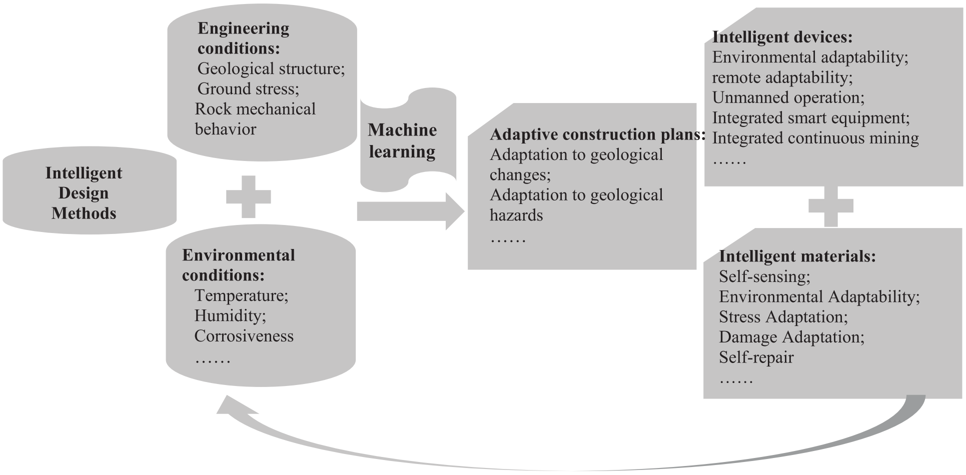


Fig. 26. Intelligent construction technology system in rock engineering.

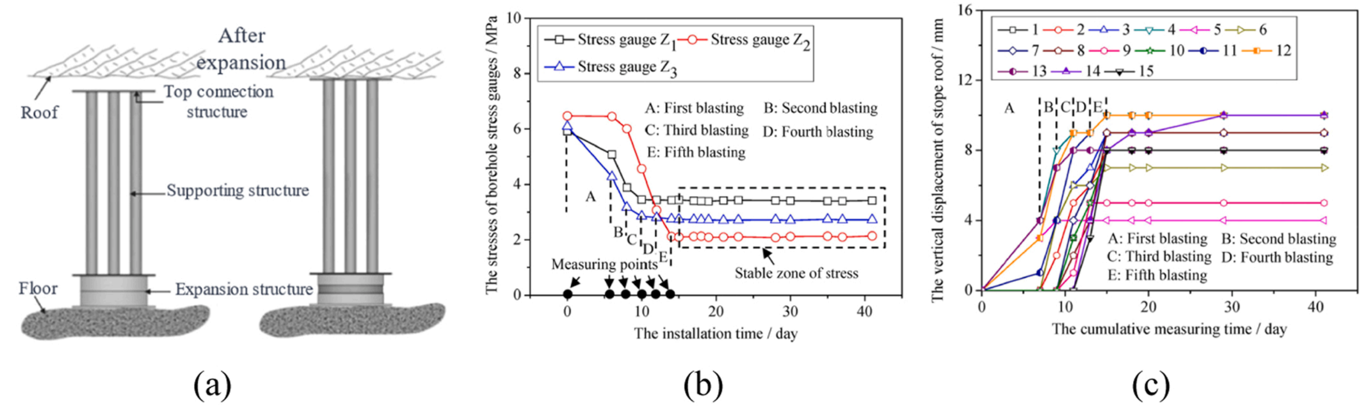


Fig. 27. A novel pre-stressed expanding column and variations in axial bearing capacity [66]: (a) Diagram of pre-stressed expanding column; (b) Variation of stress in the roof of the support area; (c) Variation of axial force in the expanding support within the supported area.

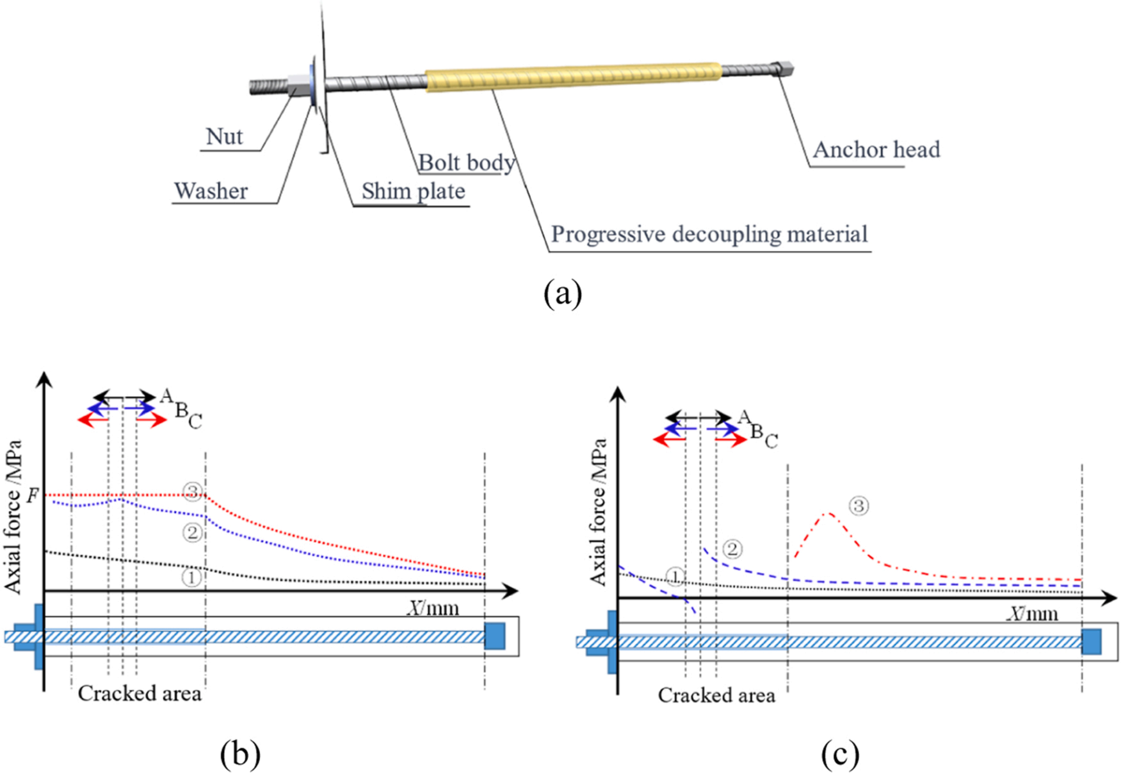


Fig. 28. Diagram illustrating the progressive decoupling bolt and its principle [43]: (a) Progressive decoupling anchor bolt structure; (b) The axial force distribution on the surface of the rod body; (c) The shear stress distribution on the surface of the rod body. Note: A - Initiation of cracks; B - Expansion of cracks; C - Displacement or rebound.

8. Intelligent construction in rock

Intelligent construction in rock engineering refers to methods capable of adapting to environmental and engineering conditions. It integrates intelligent design approaches and machine learning techniques to achieve intelligent, safe, and efficient construction practices in rock engineering. This primarily includes intelligent materials, intelligent equipment, and intelligent construction decision-making (Fig. 26).

8.1. Intelligent materials

Rock engineering intelligent materials refer to materials that possess functions such as self-sensing, self-adaptation, self-repair, or self-absorption capabilities, enhancing engineering reliability and lifespan [11,76]. For instance, incorporating carbon fibers into concrete to produce strain-sensitive carbon fiber-reinforced concrete enables the measurement of changes in the environment or condition of the concrete by monitoring changes in electrical resistance [76]. Similarly, chemical materials can autonomously adapt to various environmental changes from surface to subsurface environments by introducing permeability, temperature, salinity, CO_2, and pH-adaptive polymers or surface-active agents [47]. Microorganism-mediated self-healing concrete employs the mineralization activity of certain bacteria, requiring no external intervention, as it can autonomously engage in partial or complete repair of damage [1].

Some intelligent materials can adapt to variations in stress during excavation and the fracturing of rock masses in geotechnical engineering operations. For instance, stress-adaptive novel pre-stressed

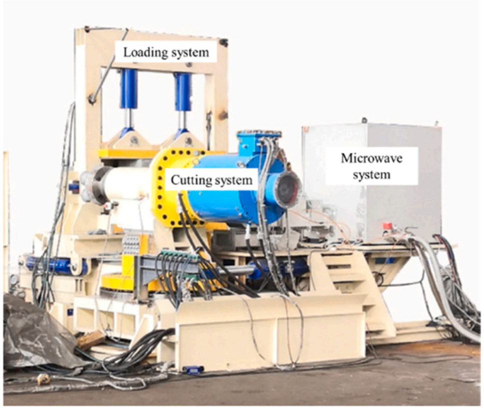


Fig. 29. High-power microwave mechanical integrated continuous mining device [45].

expanding columns for surrounding rock use a base expanding material to rapidly hydrate, generating approximately 2800 kN of active supporting force. With alterations in ground stress, the force within the expanding columns is adjusted accordingly, enabling pressure-relieving support to the roof of the excavation area. These columns offer advantages such as shorter construction periods, adjustable support timing (Fig. 27) [63,62,66]. The stress-adaptive novel progressive decoupling bolt consists of a threaded steel rod body and a progressively decoupling isolating material, offering cost-effectiveness and easy installation. This bolt functions during three stages — initiation, propagation, and displacement (or rebound) — of rock mass fracturing. Its length adjusts with the increasing extent and depth of rock fracturing, enabling the overall structure to undergo a brittle-to-ductile transition. This design allows the structure to undergo significant displacement while exhibiting energy absorption, adapting to the process of rock mass failure (Fig. 28) [43].

8.2. *Intelligent equipment*

Intelligent equipment refers to equipment that integrates advanced manufacturing technology, information technology, and intelligent technology, giving it the ability to perceive, analyze, reason, make decisions, and control. Compared to traditional equipment, intelligent equipment has the following characteristics: it can autonomously perceive and identify various items of physical information, enabling autonomous learning, decision-making, and execution; it integrates various intelligent technologies, allowing it to adapt rapidly to various environments and tasks; it has a high level of intelligence and autonomous collaboration, enabling a certain degree of autonomous coordination. Multi-functional integrated intelligent equipment has gradually begun to be used in tunnel engineering, such as fully computerized three-arm rock drilling trolleys and boom-type road-header used in the excavation process, three-arm three-basket steel arching installing machine and wet shotcrete trolleys used for support, and digital lining trolleys and vehicle-mounted tunnel lining quality inspection vehicles used for lining. Unmanned driving and remote-control functions are used in underground mines, open-pit mines, dams, and other engineering projects.

Research into integrated continuous mining equipment for metal ores will be a disruptive technology. The world's first high-power microwave mechanical integrated continuous mining device has been independently developed, which can achieve synchronous cutting and breaking of rocks using microwave and mechanical methods (Fig. 29) [45]. This device has initially improved dust reduction and rock breaking efficiency during the rock-breaking process. The development of this device is key to achieving continuous mechanical mining in metal mines.

8.3. *Adaptive construction planning*

Adaptive construction planning is based on a comprehensive perception of rock engineering information, and through intelligent decision-making based on the acquired information, corresponding applicable construction plans are proposed. For example, intelligent prevention and control of rockbursts based on MS monitoring information can adjust support parameters (*inter alia*) in D&B tunnels based on MS monitoring early warning results to reduce rockburst risks. In TBM tunnels, rockburst risks can be reduced by lowering excavation rates and increasing support strength.

Integrated intelligent construction technology for TBM tunnelling and rockburst risk control is shown in Fig. 30. This allows determination of control measures based on rockburst risk assessment and acceptable loss, along with the intelligent prediction model of excavation

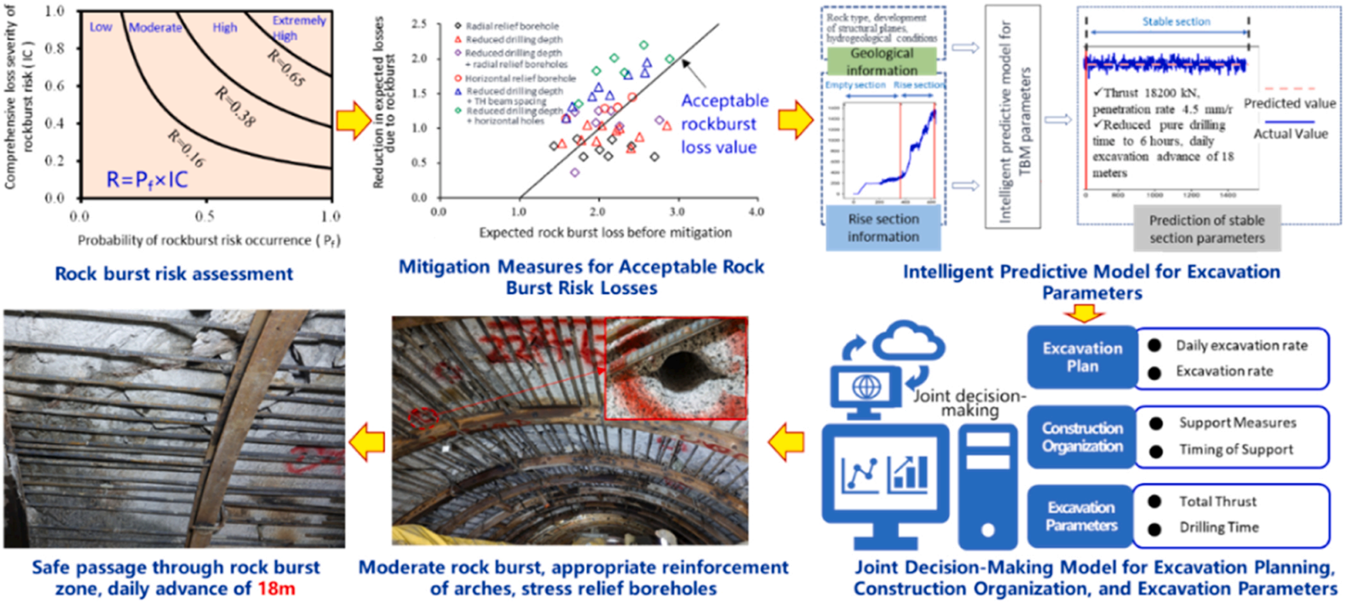


Fig. 30. Integrated intelligent construction technology for rockburst risk control in a TBM tunnel.

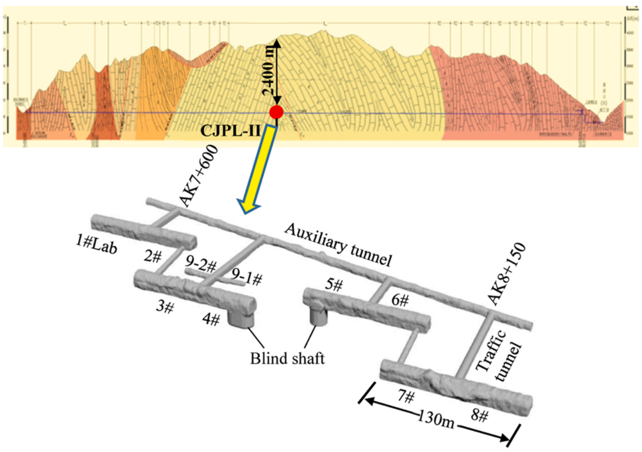


Fig. 31. The layout of the China Jinping Underground Laboratory (Phase II).

parameters and rockburst early warning grade, jointly determining excavation plans, construction organization, and excavation parameters. The excavation rate of sections with moderate rockburst risks is decreased, support is appropriately reinforced, and stress release holes are arranged, enabling safe passage through the rockburst zone with a daily advance of 18 m.

9. Applications

Two typical case examples are presented to illustrate the comprehensive application of intelligent technologies in rock mechanics and rock engineering. In the CJPL-II project, the deepest underground physical laboratory in the world, the identification of the complex geological conditions, recognition and prediction of the rock mechanical behavior, and the monitoring of the rockburst were conducted to ensure the construction safety. For the powerhouse cavern of the Baihetan hydropower station project, China, with the largest cavern size in the world, intelligent identification of 3D geostress and intelligent back-analysis of rock mass parameters were conducted for the design of measures implemented to prevent deep cracking during excavation.

9.1. CJPL-II

9.1.1. Engineering context

The CJPL-II is currently the deepest laboratory in the world. The

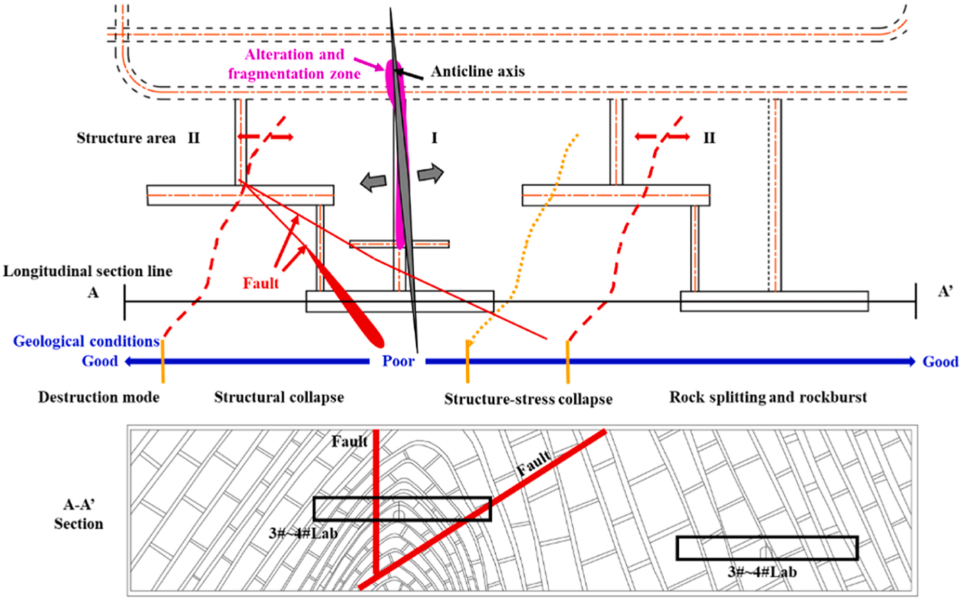


Fig. 32. Macroscopic geological structure of the engineering area of interest [39].

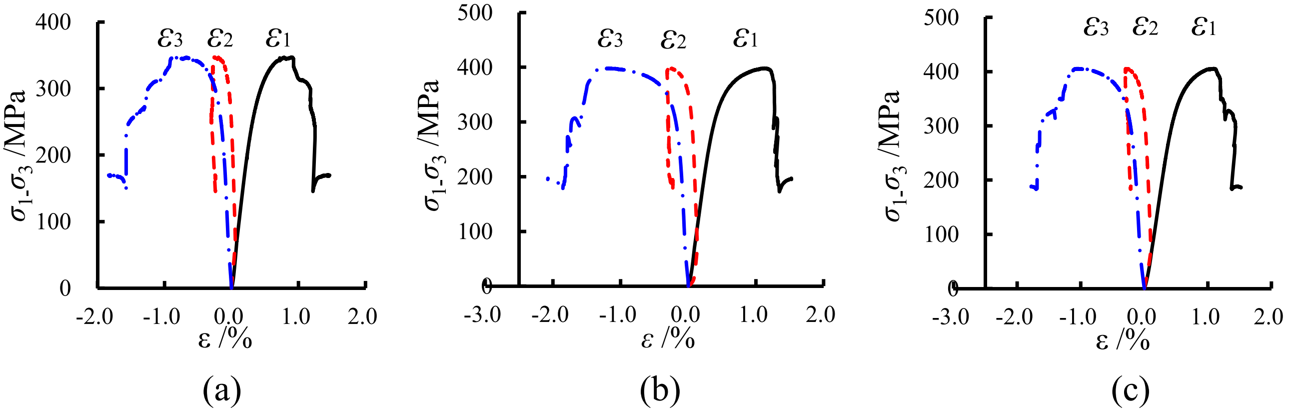
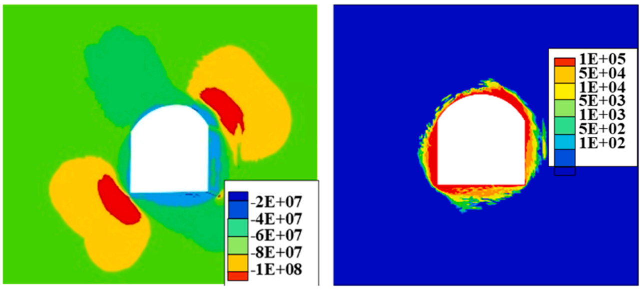


Fig. 33. The stress-strain curves under true triaxial compression for the three types of marble ($\sigma_2 = 100$ MPa, $\sigma_3 = 30$ MPa): (a) White marble; (b) Grey marble; (c) Grey interlayered with white striped marble.



(a) (b)

Fig. 34. The maximum principal stress and local energy release rate of Lab. 8: (a) The maximum principal stress (unit: Pa); (b) Local energy release rate (unit: J/m^3).

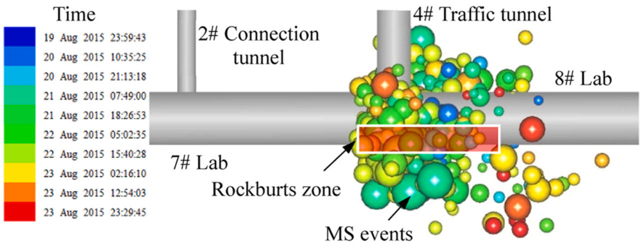


Fig. 36. Spatial distribution of MS activities in the area from Lab. 7 to Lab. 8 (chainages K0+010 of Lab. 7 to K0+040 of Lab. 8).

overall layout of the underground laboratory consists of nine tunnels and two blind shafts (Fig. 31). Among the nine laboratories, Labs 1–8 are physical laboratories, and Lab. 9 is a deep rock-mechanics laboratory. The axis of the laboratory is parallel to the auxiliary tunnel of the Jinping diversion tunnel, with an azimuth of N58°W. After the excavation of Labs 4 and 5, a blind shaft was excavated in the bottom of each laboratory. The maximum principal stress was measured to be 69.2 MPa, with an angle of 55.6° relative to the vertical direction. The intermediate principal stress was 67.32 MPa, very close to the maximum principal stress, and the minimum principal stress was 25.54 MPa [90].

Based on the geological information obtained from integrated drilling and exposed surrounding rock, the geological structures of the engineering area are intelligently identified (Fig. 32) [39]. The engineering area is located in a syncline zone with a predominant north-south orientation. The axis of the No. 2 traffic tunnel is located in the core area of the syncline. Two faults, which extend relatively long and exhibit overall shearing syncline structures with a maximum width of about 1 m, are developed between Labs 2 and 4. According to the types of structures, the surrounding rock of the engineering area can be divided into two zones: Zone I is the core area of the syncline and the local fault structure zone, while Zone II is that area affected by the syncline on both sides. In terms of the overall classification of the surrounding rock in the engineering area, the rock mass in the core area of the synclines demonstrates the worst integrity, mainly classified as Class III, with some areas classified as Class IV. The integrity of the rock mass gradually increases from the core area of the syncline towards the northwest and southeast, transitioning to Class II.

The rock type in the engineering area is predominantly the Dali Formation (T2b) marble of the Middle Triassic. As shown in Fig. 32, significant variations in rock types were observed in Labs 2, 3, and 4, including white, grey, and grey interlayered with white striped marbles. The stress-strain curves under true triaxial compression using an intelligent test device [38] for the three types of marble were plotted as shown in Fig. 33. Under the same stress ($\sigma_2 = 100$ MPa, $\sigma_3 = 30$ MPa), the strength of the grey marble is significantly higher than that of white marble. Both white and grey marbles exhibit significant ductility during the pre-peak stage, but the post-peak brittleness of white marble is less pronounced compared to grey marble, indicating that grey marble is more brittle. The strength and post-peak brittleness drop of the grey interlayered with white striped marble are similar to those of grey marble.

9.1.2. Intelligent prediction and analysis of surrounding rock failure

An intelligent back-analysis method for rock mass mechanical parameters and numerical analysis software were used to calculate, analyze, and evaluate the rock mass fracture, deformation, and energy release during laboratory excavations. Taking Lab. 8 as an example, the calculated maximum principal stress and local energy release rate are shown in Fig. 34. After excavation, the maximum principal stress is found to exceed 160 MPa, and the depth at which the RFD value exceeds 1 reaches 2.6 m. The maximum value of the local energy release rate exceeds 500 kJ/m^3, indicating that Lab. 8 has a high risk of high-stress failures such as roof fall and rockburst.

9.1.3. Intelligent monitoring and early warning of rockbursts

To capture the rock mass fracture and rockburst development processes during excavation, MS sensors were pre-embedded before excavation. The MS monitoring system was focused on Labs 7 and 8, equipped with two data-acquisition servers, ten MS monitoring stations, and sixty-two MS sensors (Fig. 35).

On August 23, 2015, the spatial distribution of MS activity and the specific values of MS information in the area from K0+010 of Lab. 7 to

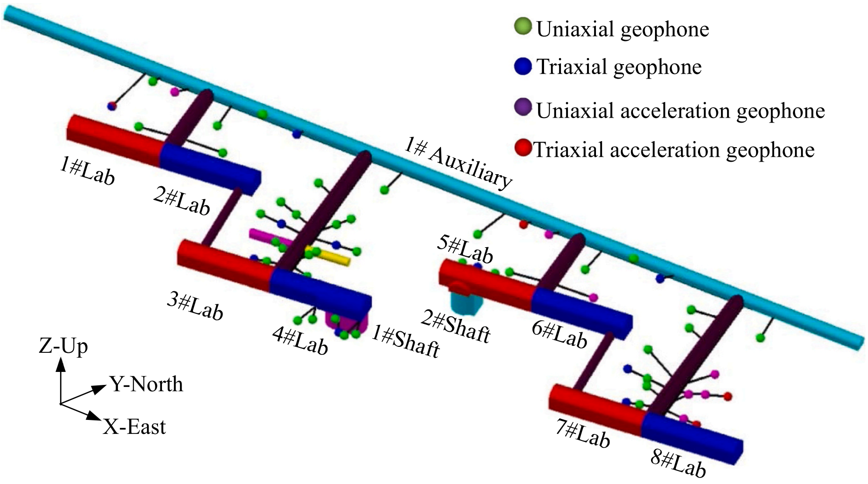


Fig. 35. Schematic diagram of the overall arrangement of MS monitoring sensors.

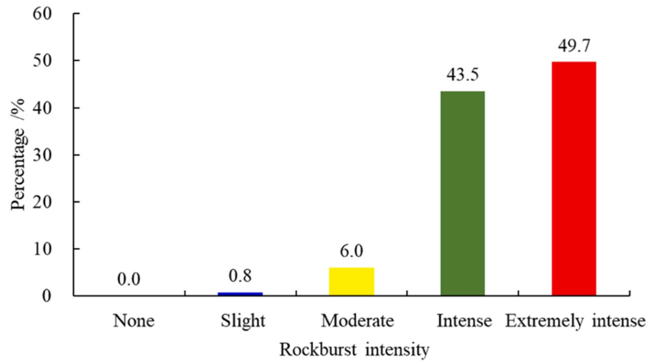


Fig. 37. Rockburst warning results based on MS information before the “8.23” extremely intense rockburst.

K0+040 of Lab. 8 were obtained, as shown in Fig. 36. The cumulative number of MS events in this area reached 475. The rockburst intelligent early warning system displays the rockburst risk in this area as illustrated in Fig. 37, indicating a high risk of strong rockburst occurrence.

Between 23:39 and 23:58 on August 23, 2015, an extremely intense rockburst occurred at the intersection of Labs 7 and 8 (Fig. 38). The rockburst zone was approximately 44 m long and 5 m to 6 m high, with a maximum rockburst pit depth of 3.2 m. The largest ejected rock block reached a size of 2.4 m × 2.4 m × 1 m, with a maximum ejection distance of 7 m to 10 m. The total volume of ejected rock blocks was approximately 350 m^3. The rockburst caused severe damage to the south-side wall support system of the upper part of Labs 7 and 8, with anchor bolts being fractured and pulled out, and steel mesh and initial sprayed concrete being ejected.

9.2. Underground powerhouse caverns of the Baihetan hydropower station in China

9.2.1. Engineering context

The scale of the underground tunnel group, span of the main power house, and size of the tail water regulating chamber of the Baihetan Hydropower Station in China are all the world’s largest, with the main and auxiliary power houses measuring 438 m in length, 34 m in width, and 88.7 m in height, and the tail-water regulating chamber measuring 93 m in height. However, constrained by complex geological conditions, the project faces engineering challenges such as brittle failure of basalt under high ground stress (> 30 MPa), time-dependent relaxation of columnar jointed rock masses with dense fractures, and more than 10 long, large fault zones such as C3, C4, and C5 intersecting underground cavern groups (Fig. 39).

9.2.2. Intelligent optimization analysis and design of the underground powerhouse cavern group on the right bank

During construction of the underground cavern group, the stability analysis of the left and right bank underground caverns was integrated with the optimization of the excavation and support design. The aforementioned intelligent recognition method for 3D geostress, intelligent back-analysis method for rock mechanical parameters, intelligent monitoring, and cracking-restrain design for deep cracking in the basalt cavern based on the seven-step rock engineering design method, were comprehensively implemented to ensure the safety and efficient construction of the cave group. Taking the underground powerhouse cavern group on the right bank as an example, the details are as follows.

1) Intelligent recognition of 3D geostress in the engineering area of interest

Numerical models reflecting the mountains and erosion process of deep valleys are established based on the terrain and landform characteristics of the engineering area. Based on regional tectonic activities and measured stress characteristics, a uniform design with small displacement gradient loading method is adopted to numerically establish training samples for the relationship between displacement boundary conditions and calculated geostress at measurement points. Then a neural network mapping model is trained to back-analyze the displacement boundary conditions and gravity correction coefficient of the numerical model based on measured stress values. Furthermore, the distribution of the geostress field was obtained through numerical calculations with the back-analyzed boundary conditions (Fig. 40). The intelligent recognition results are in good agreement with the measured geostress values.

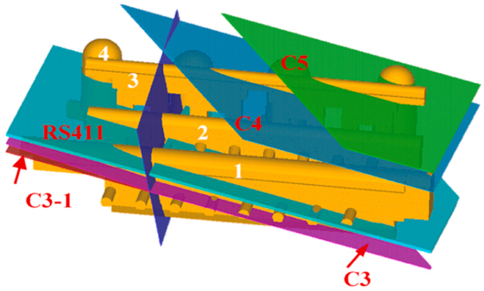
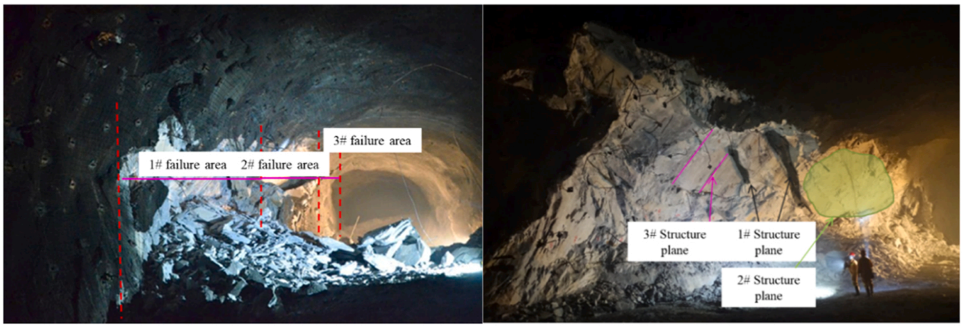


Fig. 39. Layout of the underground powerhouse caves of the Baihetan Hydropower Station in China and its typical geological structures. (1 - Main power house; 2 - Transformation chamber; 3 - Draft tube gate chamber; 4 - Surge shaft; C3, C3-1, C4, C5 - Interlayer fracture zone).



(a) (b)

Fig. 38. On-site damage after the “8.23” rockburst: (a) Characteristics of damage zones during the “8.23” rockburst; (b) Photograph of the rockburst site after treatment.

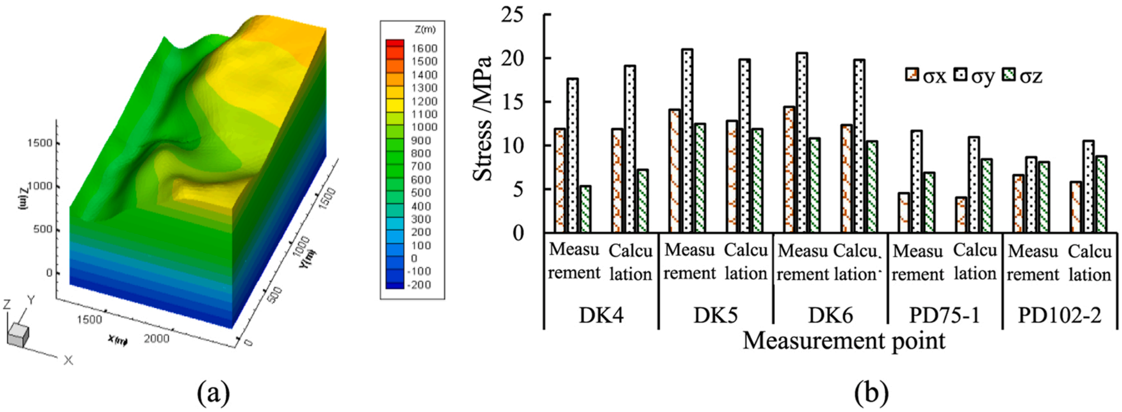


Fig. 40. Intelligent back-analysis of 3D geostress in the engineering area of the underground power house: (a) Numerical model and (b) Back-analyzed results.

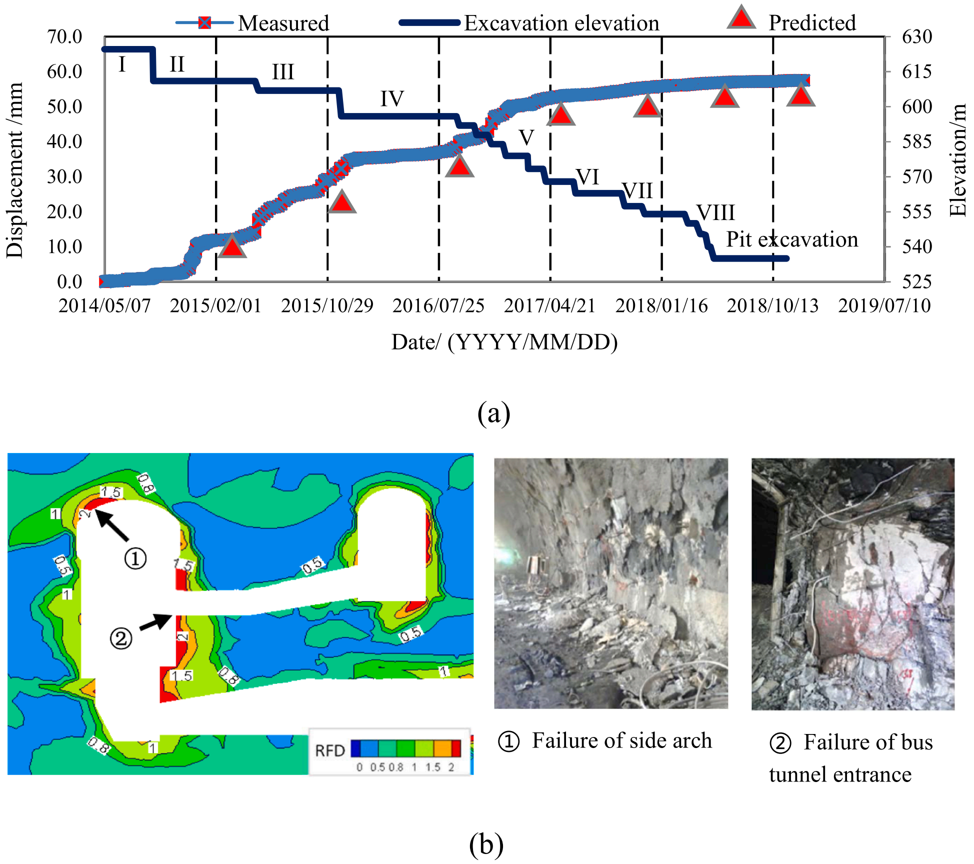
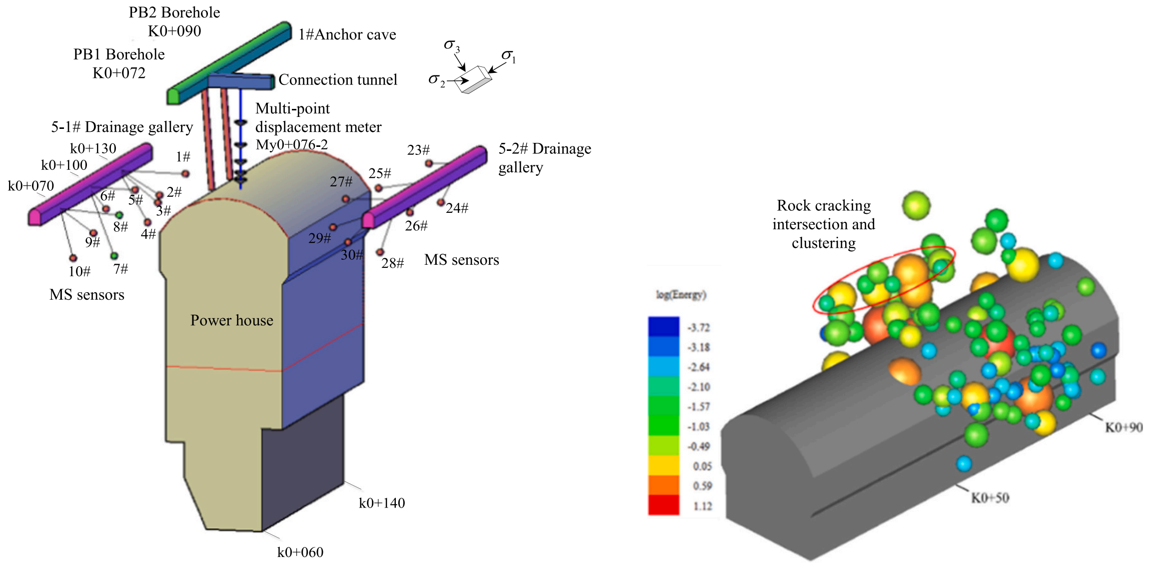


Fig. 41. Comparison between the predicted deformation and failure of surrounding rock using back-analyzed parameters and the on-site observation results: (a) Comparison between calculated and measured displacement; (b) Comparison between the predicted and the on-site failure location of surrounding rock.

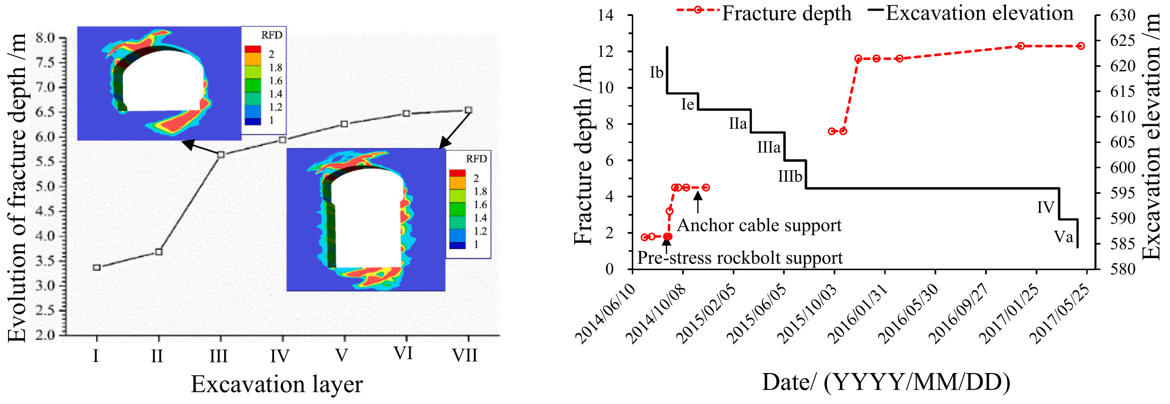
2) Dynamic intelligent back-analysis of rock mechanical parameters during excavation

Taking the back-analysis of parameters of rock mechanics after excavation of the second floor of the underground power house as an example, a corresponding 3D numerical calculation model is established based on the latest revealed geological conditions and the excavated structure. By monitoring analysis, two displacement monitoring data for the top and side arches of two cross-sections, as well as two EDZ testing data for the side walls, were selected as back-analysis information. The rock mass parameters to be back-analyzed were determined the as elastic modulus and initial internal friction angle through parameter sensitivity analysis. Using the orthogonal design method to numerically construct training samples, a neural network model for mapping the selected rock mechanical parameters and the back-analysis information was established, and then the rock mechanical parameters were obtained through global optimization inversion based on measured values. The back-analyzed parameters were used in the numerical model for prediction analysis, and the results were in good agreement with the measured values (Fig. 41a). In addition, the obtained rock mechanical parameters were also used to predict the location of rock fracture, which is consistent with the stress-induced failure location on-site (Fig. 41b). This finding indicates that the back-analyzed parameters can be used for stability calculation analysis and optimization design of subsequent excavation.



(a) (b)

Fig. 42. MS monitoring and analysis of deep cracking in the surrounding rock during excavation of underground power house: (a) Layout of the MS sensors and (b) MS analysis of deep cracking.



(a) (b)

Fig. 43. Prediction analysis and design optimization of deep fracture development in the top arch of cavern and observed results: (a) Numerical prediction; (b) On-site measured fracture depth.

3) Intelligent monitoring and control of deep cracking during excavation

MS monitoring was conducted during excavation of the cavern group, and the layout of the MS sensors is shown in Fig. 42a. Through intelligent analysis and spatial positioning of rock micro-fracture signals, high-risk areas of deep cracking in the surrounding rock of the cavern were identified (Fig. 42b). Numerical simulations were then conducted to study the relationship between the rock fracture depth and the excavation of underground chambers in layers and sections. The area with calculated rock fracture degree (RFD) index [24] being greater than 1.4 was used as the range of obvious rock fracture. As shown in Fig. 43, when the working face passes through the monitoring section by 16 m, the depth of rock mass fracture increases more significantly, indicating that the optimal support timing for the excavation of layer I of the cavern is 16 m. To avoid instability of the arch caused by deep cracking, the original design support scheme was optimized based on the cracking-restraint concept. The original design plan was to apply cross anchor cables after excavation layer III, the arch bolts at the upstream side were installed at intervals of ordinary mortar bolts and pre-stressed bolts, and the support timing was 30 m behind the working face. The optimized support plan had been adjusted to apply the cross-anchor cables after the excavation of layer I, and only use prestressed bolts in the upstream side arch, with the support timing being 16 m behind the working face.

10. Prospects

Artificial intelligence is an important driving force for a new round of technological revolution and industrial transformation, and has strong complementarity with rock mechanics and engineering problems. It is necessary to accelerate the construction of a rock mechanics and engineering artificial intelligence technology system. The knowledge base of rock mechanics and engineering is constantly improving, and big data is constantly accumulating. It is necessary to innovate using data-knowledge-driven development models with rock engineering characteristics. The intelligent analysis theory and design methods of rock mechanics and engineering have made significant progress, and it is necessary to deepen the research into engineering geological condition identification and intelligent construction theory and technology: establishing a global rock mechanics and engineering model to solve rock engineering problems is a worthwhile goal.

Declaration of Competing Interest

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

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