Data acquisition-interpretation-aggregation for dynamic design of rock tunnel support

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Abstract: During the rock tunnel construction, one of the critical aspects lies on the support design to secure the construction safety. Due to the extreme complex underground geological and geotechnical condition, the support design needs to be dynamic and ideally should consider all related data and information comprehensively and timely. Different Internet of things (IoT) and other related information technologies (IT) have been widely applied during tunnel construction to collect a large amount of monitoring data, which in turn demands real time or just-in-time (JIT) data processing for decision making. To understand the state-of-the-art IoT-based dynamic tunnel support design, a comprehensive review is conducted from the perspectives of real time or just-in-time data acquisition, data interpretation and data aggregation. For different types of technologies, their time consumptions, technology strengths and drawbacks were thoroughly analyzed in a full and seamless "data acquisition-interpretation-aggregation" workflow linking to the dynamic tunnel support optimum design. As a result of the review, three primary research gaps are identified, i.e., the high time consumption of data interpretation, dilemmas of conventional and AI-supported aggregation methods, and long retrieval time for similar design cases. Focusing on these three gaps, three key concepts, namely, time consumption, accuracy, and degree of automation, are proposed as key indicators for the tunnel support design. A conceptual framework, just-in-time tunnel support design is further proposed, where the most appropriate and efficient methods can be conceptually integrated and lead towards technical implementation. This review contributes to the comprehensive understanding of timely dynamic tunnel support design and provides future insights of promoting JIT

tunnel support optimum design.

Key words: rock tunnel, tunnel support design, just-in-time, Internet of things, information technology, drill and blast method

1 Introduction

The drill and blast (D&B) method is a typical and conventional method for the excavation of tunnels in rocks as it enables the flexibility to excavate varying tunnel cross-sections and possibility of adapting to changing rock mass conditions [1,2]. The design of tunnels constructed using the D&B method involves many aspects, including the determination of the geometric layout, and shape and size of the profile; nonetheless, the design of the support used on site is a key issue[3].

Tunneling, as a typical geotechnical engineering, is characterized by a high level of uncertainty, posing a unique challenge to design work compared to other civil engineering projects [4,5]. As the comprehensive interpretation of the geological and geotechnical characteristics of the underground environment is difficult, the design of rock tunnel support is generally composed of preliminary and final design stages [6]. In the preliminary design stage, engineers determine support systems and parameters based on the sparse data collected from geological investigations (e.g., the ground surface survey, borehole investigation). However, owing to the sparsity of the data, inherently, the design scheme of the support may fail when unanticipated geological conditions are encountered during tunneling, which is proved by many accidents arising from incomplete geological knowledge [7]. Hence, engineers must optimize the support parameters according to the data exposed by excavation to complete the final design of the support. In particular, the optimization of the support parameters depends on the geology of the tunnel face, deformation of the surrounding rock and stress-strain in support structures [8]. The design method, which implements the final design of the support by revising the preliminary design using the exposed geological conditions and various unanticipated conditions during the construction process, is also called the dynamic design of the support [6,9]. It is worth mentioning that the concept of the dynamic design of the tunnel support has been suggested by several national standards and specifications [10,11].

The dynamic design of the support of the tunnel excavated by the D&B method faces one critical technical challenges: the quick response of the support, which stems from the fact that untimely support under poor geological conditions may pose a significantly higher risk to the tunnel stability [12]. Hence, the acquisition of the data exposed by excavation, interpretation, and aggregation of the data during the tunnel construction should be fast. Here, the term “aggregation” instead of the term “analysis” is used because the processing of the interpreted data in tunnel engineering includes both the conventional analyses, such as the numerical analysis, and informatics-related methods. Indeed, the term “aggregation” incorporates the meaning of conventional analysis and new-emerging informatics-based processing. The prerequisite for an optimal determination of the support parameters in the construction process is an appropriate estimate of the exposed data as well as the mechanical response [5]. Therefore, firstly, an efficient on-site data acquisition method can significantly contribute to the dynamic design of the tunnel support. Conventionally, the data on or ahead the tunnel face are sketched by field engineers using hand-held equipment, such as a geological compass, measuring tape and roughness profile gauge [13], which is time-consuming and error-prone. With the advancement of IoT in recent years, techniques such as digital photogrammetry (DP) [13,14] and terrestrial laser scanning (TLS) [15,16] have been introduced into the tunnel support design because of their great potential to shorten the data acquisition time and improve the data acquisition accuracy. In addition, many practical engineering cases have demonstrated the advantages of IoT in assisting the efficient acquisition of exposed data on site [16,17]. Based on the acquired raw data, several efficient interpretation methods have been proposed to obtain the required information, such as discontinuity and water inflow information, which can reduce errors in manual interpretations. Another key concern affecting the dynamic design of the support is the aggregation of interpreted data. Conventional aggregation methods include empirical, numerical and analytical analysis, the combination of which has also been adopted in some complex cases, where numerical and analytical methods are used to verify the parameters provided by empirical methods [6]. However, the selection of proper mathematical parameters and sensitivity to the mesh and boundary effects may cost the numerical and analytical models a long period of time to yield [18]. Hence, aggregation methods, such as simplified analytical models [18] and the parallelization of numerical models [19], which are more intuitive and computationally efficient, are gradually developed to assist the design of the tunnel support,. In addition, several artificial intelligence (AI)-based computational methods, such as genetic algorithm (GA) and artificial neural network (ANN), have been used to complement the results from construction sites to optimize the support design in a short period of time, because AI offers predictive capabilities to improve the efficiency and reliability of the design process [20]. Moreover, the advancements in IoT and IT have demonstrated conceivable benefits in the dynamic design of the tunnel support. The focuses on the capabilities of data acquisition, data interpretation and data aggregation have reached an unprecedented level owing to their increasing dependence on IoT and IT. Indeed, IoT-based acquisition approaches integrated with IT-driven interpretation and aggregation solutions provide a new direction for the dynamic design of the tunnel support.

Due to the popularity of applying dynamic design in the construction process of tunnels using the D&B method, several review articles have summarized the state-of-the-art advancements in the rock mass blastability [21], automatic extraction of discontinuity parameters [22] and tunnel ahead prospecting [23]. Although these reviews have summarized some aspects of the dynamic design and information-based tunnel construction, certain limitations exist that (1) none of the existing studies thoroughly summarize the comprehensive aspects of the dynamic design of the tunnel support from data acquisition to data interpretation and aggregation. In addition, the use of IoT in the dynamic design of the tunnel support has brought a paradigm shift to rock engineering design [6]. However, none of the existing reviews were conducted from the perspective of IoT-based dynamic design of the tunnel support; (2) key research directions of the techniques and their applications in the design of the tunnel support have not been discussed. To address these knowledge gaps, this study aims to provide a thorough review of IoT-based dynamic design of the tunnel support, with a focus on the quick acquisition of data during construction, interpretation of the raw data, and aggregation of the interpreted data. In addition, research gaps are discussed, and the conceptual framework of the JIT design of rock tunnel support is proposed.

2 Research methodology

This study provides an in-depth overview and analysis of the recent advances in IoT-based dynamic design of the tunnel support. To address the existing knowledge gaps, the research approach of the study is divided into four steps, as presented in **Fig.1**:

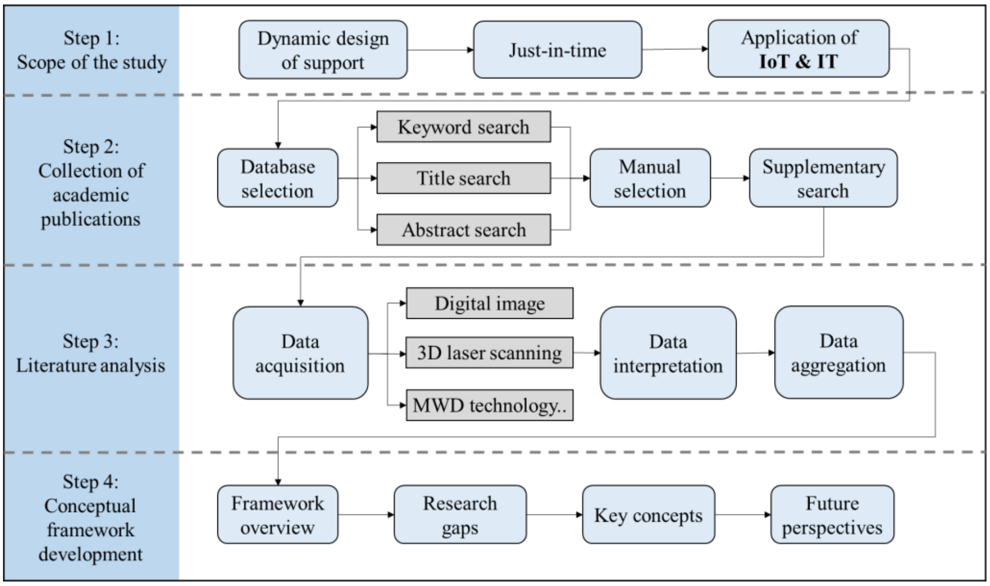


Fig.1 Flow chart of research methodology

1) Clarify the scope of the study: The IoT-based dynamic design of the support in rock tunnels constructed by the D&B method was the primary research aim; therefore, literatures regarding tunnels constructed by a tunnel boring machine (TBM) were not considered. Moreover, the emphasis of the study focused on the optimization of the support parameters using on-site data, so studies that employed data from the

preliminary stage to determine support schemes were not reviewed.

2) Collect academic publications: Studies on the fast acquisition, interpretation, and aggregation of on-site data during tunneling were thoroughly reviewed. Two comprehensive and representative academic databases, Scopus and Web of Science (WoS), were adopted as sources of literature. The first screening of the literature retrieval started with searching keywords and key strings including “tunnel support design”, “information technology”, “Internet of thing”, “artificial intelligence”, “dynamic design” and “tunnel face information”. Subsequently, the search results were analyzed using the title, keywords, and abstract to retain the most appropriate literature within the scope of this study. Moreover, some additional keywords, such as “photogrammetry” and “measurement while drilling (MWD)”, were identified. Hence, a second screening using the new keywords and key strings was performed as a supplementary search. The results of the second search were manually filtered to identify appropriate studies; 83 publications were identified. **Fig.2** shows the yearly distribution of the 83 bibliographic records in the Scopus and WoS databases. Before 2017, few studies were conducted on the quick acquisition, interpretation, and aggregation of data during the tunnel construction. However, the peak points occurred after 2018. With the advancement of IoT, more studies were conducted on the quick acquisition, interpretation, and aggregation of data concerning the dynamic design of the tunnel support.

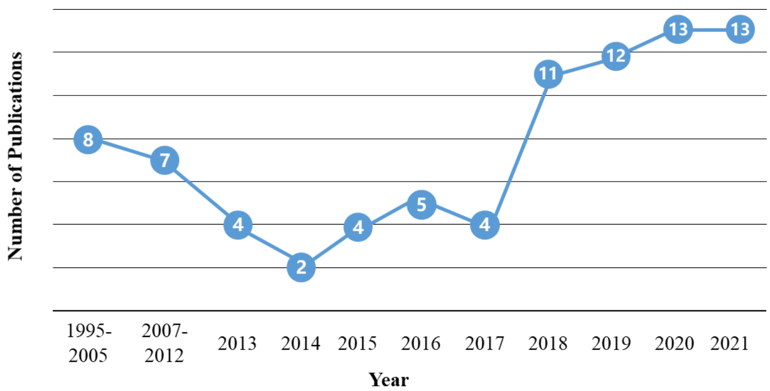


Fig.2 Year and number of reviewed articles on design of tunnel support.

Additionally, we used CiteSpace, a Java application for analyzing and visualizing co-citation networks, to conduct a scientometric analysis [24]. A network of co-occurring keywords was generated using CiteSpace containing 192 nodes and 671 links, as shown in **Fig.3**. In this network, the label size was determined by the frequency of the keyword in the bibliometric record. The top 10 frequently-used keywords are “photogrammetry”, “rock mass”, “prediction”, “light detection and ranging (LiDAR)”, “convolutional neural network”, “3D point cloud”, “stability analysis”, “tunnel face”, “ground penetrating radar” and “crack detection”. It can be seen that keywords, such as the photogrammetry, LiDAR, and ground penetrating radar, that were associated with the fast data acquisition methods appeared most frequently, followed by data aggregation methods, such as the convolutional neural network and stability analysis. Furthermore, the results verified that the literature was dominantly reviewed from the data acquisition, interpretation, and aggregation point of view.

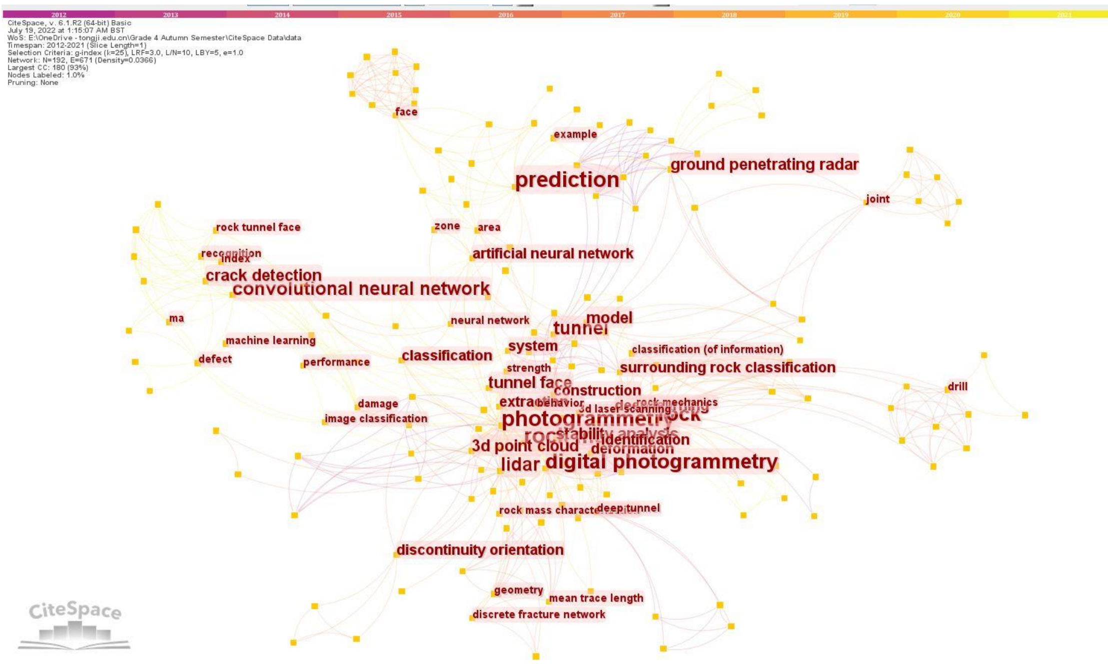


Fig.3 Network of co-occurring keywords in the reviewed papers

3) Conduct the literature analysis: The reviewed studies were analyzed concerning the theme of IoT-based dynamic design of the tunnel support. The analysis included the quick acquisition of on-site data using different IoT-enabled equipment, interpretation of the acquired data, and optimization of the support parameters using

efficient computational aggregation methods.

4) Develop the conceptual framework: First, the framework was defined and overviewed; subsequently, the research gaps of the existing studies were identified. Accordingly, the key concepts influencing the design of the tunnel support were summarized. Finally, a conceptual framework was developed to completely elucidate the steps required for the JIT design of the tunnel support. Additionally, future perspectives of the proposed JIT design of the tunnel support were discussed.

The dynamic design of the support is usually associated with the “information-based construction” and “new Austrian tunneling method (NATM)” terms. Therefore, the relationships and differences between these terms need to be clarified to profoundly comprehend the meaning of the dynamic design of the tunnel support. The relationships between dynamic design of tunnel support, NATM and information-based construction are presented in **Fig.4**.

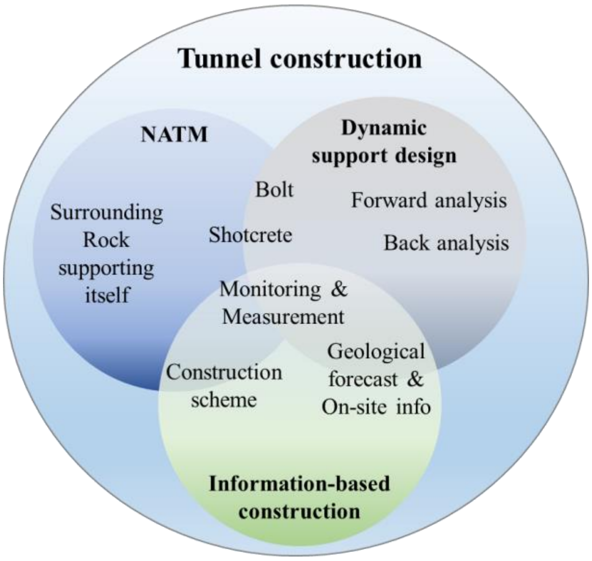


Fig.4 Relationships and differences between the dynamic design of the tunnel support, NATM and information-based construction

NATM was first proposed in 1964 [25] and its fundamental principle is to maximize the capacity of surrounding rock to sustain its own weight in the construction process. After several years of development, NATM has incorporated many existing excavation and support methods. However, one of its core parts is timely monitoring and measurement of the surrounding rock and structure [8].

Moreover, shotcrete, bolts, and monitoring are considered to be the key elements of NATM in the construction of rock tunnels.

Information-based construction refers to the application of IT in tunnel construction to collect, store and process on-site data to provide a decision-making basis for the design and construction processes [26]. Similar to NATM, information-based construction also includes monitoring and measurement using different intelligent sensors. Moreover, advanced geological forecast and on-site data acquisition using different intelligent measuring equipment are within the scope of the information-based construction.

As mentioned above, the dynamic design of the support is a process, in which the preliminary design is optimized based on the data exposed during construction. It relies on the ahead geological prospecting, measurement of tunnel face data, and monitoring data, which are the outcome of information-based construction and NATM. Accordingly, forward and back analysis can be conducted using these data. Moreover, the quick dynamic design of tunnel supports primarily depends on the tunnel face and ahead geological prospecting data, because the monitoring data might need a long duration [27]. In this study, we investigated the quick acquisition of tunnel face and advanced geological data of NATM or information-based construction; in addition, we considered the corresponding efficient interpretation and aggregation methods to provide a profound comprehension of the dynamic design of the tunnel support.

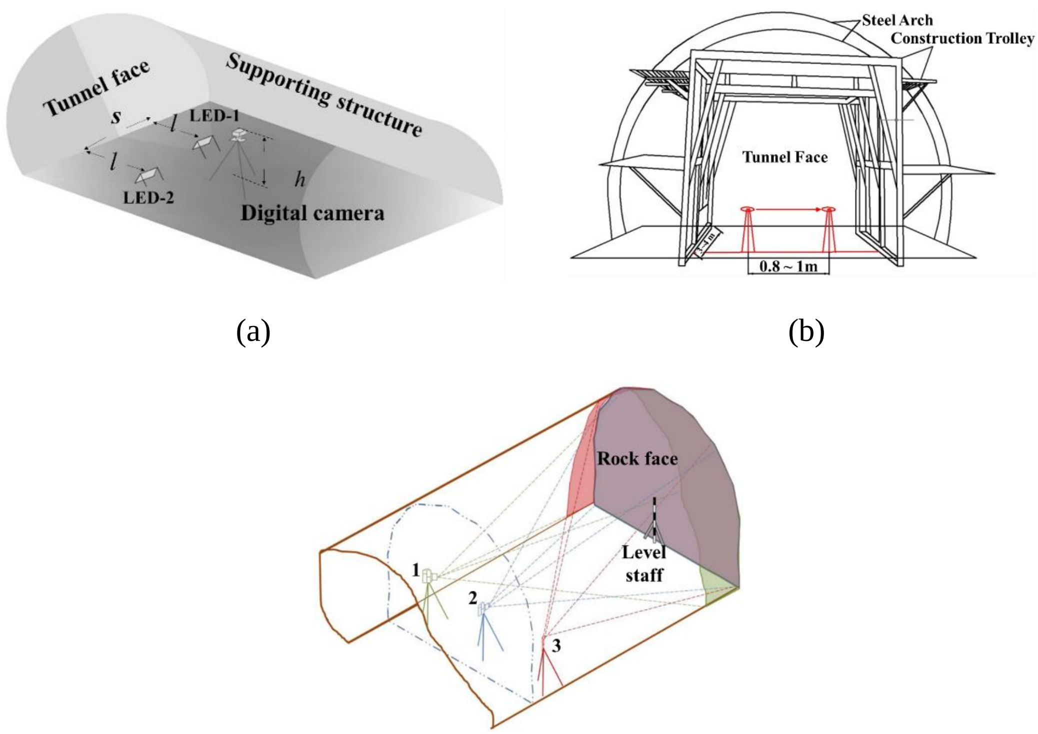
3 Quick acquisition of data during construction

Two types of data acquisition methods have been used to obtain on-site data quickly: noncontact measuring techniques to record tunnel face data, and ahead geological prospecting techniques to reflect geological/hydrogeological conditions in front of the tunnel face. The application of IoT in the quick acquisition of data during the construction process of a rock tunnel from these two aspects are discussed.

3.1 Digital photogrammetry

The recording of on-site tunnel face data typically involves handheld tools, such as measuring tapes and geological compass-clinometers, which need to be operated manually [13]. In most cases, this tedious process is labor-intensive, error-prone and more importantly, time-consuming [28]. Due to the simplicity of obtaining data and the possibility of interpreting data accurately, DP has been employed in rock engineering since the 1970s [29]; in addition, it has been used in tunnel sites in many countries, such as Italy [30], China [17,31], Spain [32]. This approach has been satisfactorily adapted to tunneling activities because uncertain geological conditions require regular and frequent updates to geological surveys. Accordingly, photogrammetry techniques, such as the structure-from-motion technique, and aggregation algorithms have been gradually developed to enable faster and more accurate data acquisition.

In the tunnels constructed using the D&B method, after blasting and mucking, a digital camera is typically placed to the tunnel face to be mapped. Generally, the camera is placed in front of the tunnel face, and images of the tunnel face are recorded from a certain point of view, as shown in **Fig.5** (a). Monocular image systems have been widely adopted in earlier studies, and many image processing algorithms have been introduced to extract the required data accordingly. Due to the simplicity of DP, each image of the tunnel face usually needs less than 1 min to be captured [33]. However, monocular image systems can only record 2-dimensional (2D) data, failing to record relevant 3-dimensional (3D) data of the exposed rock mass. Hence, binocular image system and structure from motion technology, which can acquire 3D data using multiple images from different views [32,34], as shown in **Fig.5** (b) and (c), have been gradually and widely used in the acquisition of the tunnel face data. The entire process, from the preparation to camera displacements and capturing pictures, usually takes approximately 10 ~ 30 min [32,35,36]. Huang et al. [28] demonstrated that the time required to acquire the tunnel face data using DP was approximately 1 h because additional procedures, such as the arrangement of control points and use of a total station to survey the control points, were included. By comparison, the conventional manual sketch of the exposed tunnel face data can take as long as 4 h to acquire the data due to the dark and narrow environment of the underground tunnel [28]. Thus, the application of DP in acquiring the tunnel face data during construction can significantly improve the efficiency of data acquisition.



(a) (b)

(c)

Fig.5 Different layouts of digital cameras: (a) Monocular image system [17]. (b) Binocular image system [37]. (c) Structure from motion technique [30]

3.2 Terrestrial laser scanning

With the advancements in LiDAR, TLS technology has proven to be a useful and efficient noncontact tool for the acquisition of rock mass data, which functions using the controlled steering of a laser beam coupled to a high-speed motorized system that incrementally scans a specific field of view using a rotating mirror [38-40]. In principle, laser pulses transmitted by scanners are reflected off physical objects; thus, they generate a large number of 3D data points (point cloud data) that record the position (*x*, *y*, *z*) in the space and reflectivity (*i*) of the physical objects [41]. Processing and aggregation can be conducted using the generated point cloud data to extract the required information. Compared with DP, TLS is less prone to occlusions, and its measurement accuracy is not affected by lighting conditions [42]. Hence, whilst TLS has far found limited use in the rock tunnel due to the specialist equipment required, the fact that the measurement accuracy can be guaranteed makes it a promising technique for application in rock tunnel construction. Indeed, TLS has been applied in many tunnel construction sites, such as Yuexi [43], Sandvika and Fossvein [16] and Monte Seco [44] tunnels. **Fig.6** depicts the setup of the TLS equipment at a construction site in Norway.

Fig.6 LiDAR scanning of a tunnel face with a diameter of 10m in Oslo, Norway [41].

The time required to scan the tunnel face varies from site to site because the size of the tunnel face to be scanned, distance between the scanner and tunnel face, and resolution of the point cloud can affect the scanning time [45]. Generally, with an acceptable point cloud resolution, the time required to scan a tunnel face can be controlled within 10 min. In [16], the best operational condition was a resolution accuracy of 6 mm, which required 3 min to scan a tunnel face with a diameter of 10 m. Similarly, in [45], the time required to scan a tunnel face with a diameter of 13 m and achieve an appropriate resolution was 5 min and 12 s. In some cases, the scanning time can exceed 30 min to achieve a higher resolution accuracy of 3 mm [39].

3.3 Measurement while drilling technology

In recent decades, the MWD technology has been increasingly used for data acquisition and support optimization during the information-based construction in the D&B tunneling industry. MWD is a technique that captures the responses of drilling parameters on a real time basis, while drilling is underway to expand the knowledge of structural and mechanical properties of the penetrated rock [46-48]. It monitors drilling parameters, such as drilling depth, rotation speed, rotation pressure, penetration rate, percussive pressure, feed pressure, damping/stabilizer pressure, and water/flush pressure [46,47]. Compared with other subsurface exploration methods, such as DP and TLS, MWD (1) offers a lower-cost approach to obtain high-resolution data as both DP and TLS require an expensive camera or scanner to perform the field work; (2) provides a better and more accurate description of the hidden volume of the rock mass because TLS and DP mainly portray the information on the visible portion, which may result in over-estimation of rock mass quality in some cases due to weathering of the tunnel face or poor blasting practices; and, (3) permits faster insight into the structural and mechanical parameters of the rock mass without slowing down the excavation process as data are recorded during the drilling operation [46,49]. Hence, MWD has been increasingly applied to characterize rock masses and provide a basis for the dynamic design of the tunnel support. With these advantages, MWD technologies have been widely used in rock tunnels in many countries, such as Sweden [1,2], Norway [50], Austria [49].

The collection of MWD data relies on machinery for tunnel face drilling, that is, jumbo, during the information-based construction. **Fig.7** shows a jumbo at a construction site in Stockholm. As the acquisition of MWD data is completed during the drilling operation, the time spent to collect and analyze data is greatly reduced, which is primarily owing to data processing and aggregation. Generally, data processing involves data importation, noise reduction, parameters extraction and variation detection [49]. Some recent methods consider all effects of the drilling process [47]. Hence, the time spent during the entire process should depend on the algorithm used and data size; however, none of the reviewed studies specifically reported the consumed time. Nevertheless, the entire time span of MWD-enabled support design is relatively short, as the processing of MWD data is easier than that of images.

Fig.7 Jumbo at a construction site [47]

3.4 Other ahead geological prospecting technologies

Ahead geological prospecting is a technique that predicts lithological and structural heterogeneities in front of the tunnel face within a certain range [23]. During tunnel construction, it has become an essential routine that ahead geological prospecting needs to be performed after the exposure of the new tunnel face to obtain the quantitative and qualitative information of the rock mass, which can provide reliable basis for the optimization of the original support schemes [10]. Likewise, this information-based construction approach should also be a quick-response process from data acquisition to data interpretation, as the time interval between the mucking of the previous round and drilling of the next round at the construction site is often considerably short. Therefore, advanced geological prospecting techniques have been developed and increasingly applied in the construction of D&B tunnels. In general, ahead geological prospecting techniques consist of destructive and nondestructive techniques. MWD is one typical example of destructive-ahead prospecting techniques; thus, the destructive-ahead prospecting techniques were not considered in this study. A detailed and comprehensive overview of the application of advanced geological prospecting techniques in tunneling, with an emphasis on the principles, technical levels, trends, and key problems was summarized by Li et al. [23].Here, different types of ahead geological prospecting technologies and time of acquisition are presented.

Based on the detection range, ahead prospecting techniques can be divided into short-distance prospecting (<30m, e.g., ground penetrating radar (GPR)), moderatedistance prospecting (<60m, e.g., transient electromagnetic method (TEM)), and long-distance prospecting (<120m, e.g., tunnel seismic prediction (TSP)) [23]. The time required for each technique to collect on-site data varies slightly. The use of GPR, TSP, and TEM involves the setup of the instrument, layout of the measuring line/blasting points/measuring point, collection of signals, and processing of the acquired data. None of the literature reviewed mentioned a specific time that each technique requires to acquire data. Thus, we interviewed experienced engineers, and realized that GPR and TEM need less than 2 h to collect data depending on the size of the excavation face, length of the measuring line, and number of measuring points, whereas TSP consumes a longer time to acquire data as the explosion holes need to be drilled on the wall.

4 Interpretation of acquired on-site raw data

Raw data, such as images and waves, can be obtained using the acquisition methods, as described in Section 3. Here, different interpretation methods for extracting the required information from the raw data and contribution of the interpreted data to the dynamic design of the tunnel support are discussed.

4.1 Interpretation of DP data

Table 1 summarizes the application of DP in rock tunnel construction.

Table 1 Summary of the application of DP in data acquisition

Refs	Information extracted	Approach	Time required	Contribution
[14]	Discontinuity length, orientation, separation width, JRC value	Region growing	NA[a]	Calculation of GSI rating
[51]	Discontinuity trace	feature point based, point cloud data	<2min to extract data	Calculation of RMR or Q value
[13]	Discontinuity trace	ravine-line based	NA	NA
[30]	Orientation of joint sets	Rockscan software	Less than 10min to collect the images	Characterization of rock masses
[52]	Position, shape, spacing of joint set, trace length	Siro 6.0 software	NA	NA
[17]	Fracture length, dip angel, intensity and density of the fracture traces	Deep learning	8h 23min to train model and 0.44s/image for testing	Rock mass classification
[37]	Discontinuity orientation, trace, spacing, roughness, aperture	Improved K-means clustering, point	NA	Calculation of RMR and GSI

		cloud data		
[53]	Joint set, joint spacing, joint angle	Edge detection	NA	Calculation of RQD
[54]	Discontinuity orientation	Improved K-means clustering, point cloud data	about 2.5h to extract data from 382,085 facets	NA
[31]	5 types of rock structures	deep learning	2.163s/image for classification	Automated rock classification
[55]	Discontinuity network emplacement	Edge detection	NA	Identification of block geometry
[56]	Geological features such as joints and cracks	Edge detection	NA	Rock mass rating
[29]	Mean trace length, total trace length, total spacing	Edge and line detection	NA	Calculation of RQD
[57]	Joint and bedding spacing, joint condition	Improved K-means clustering, point cloud data	NA	Calculation of RQD and RMR value
[58]	Weak interlayer	Deep learning	0.633s/image for testing	NA
[34]	The location, dip direction and dip angle of joints	Point cloud data, Halcon software	NA	3D stability analysis
[59]	Shotcrete thickness	Comparison of different images	NA	Mapping shotcrete thickness
[60]	Weak interlayers and fracture traces	Machine learning	300s ~ 700s	Assessing the rock mass quality
[61]	Water inflow	Deep learning, CNN	9.85h to train model and 0.428s/image for testing	Calculation of RMR value
[62]	Length and mean spacing of the trace line	Edge detection	NA	Calculation of Rock Block Index
[63]	Deterministic structural planes, joint orientation data	GeoSMA-3D software	Within 10 minutes	Stability analysis of tunnel blocks
[28]	Dip and dip direction of the discontinuity	CAE Sirovision software	About 1h to acquire data and 1.5h for post-processing	Stability analysis
[32]	Dip and dip direction of discontinuity sets	Discontinuity Set Extractor software	About 30 min to photograph and 22h to process 169 photos	Characterization of rock mass
[35]	Dip and dip direction of the discontinuity	Grouping algorithm, point cloud data	10min to collect data and 15min 34s to operate	Characterization of rock tunnel face
[36]	Dip angle, spacing and length of the joints	Manual sketch	About 20min to collect 68 images	Calculation of RQD
[64]	Rock mass structure categories	Deep learning, CNN	NA	Characterization of rock mass

[65]	Number and spacing of rock joint groups	Deep learning	NA	Calculation of basic quality (BQ)value
[66]	Dip, dip direction, trace length and spacing of joints	Manual sketch	NA	Calculation of RBI value
[33]	Dip, dip direction and trace length of joints	ShapeMetriX3D software	1min to collect data	Stability analysis
[67]	Rock mass fractures	Edge detection	NA	Classification of surrounding rock of the tunnel face

[a] NA: not available.

Based on the images obtained using DP, several interpretation algorithms have been developed to extract information accurately and timely. Table 1 shows that two different types of processing methods have been used to interpret the images and extract the required information; some methods use raw images and some methods employ the point cloud data. The former focuses on the direct extraction of information from the obtained images while the latter converts images into a 3D point cloud for extraction. As listed in Table 1, raw-image-based methods include the region-growing [14], ravine-line-based [13], and edge detection [29,53,55,56,62,67] methods. Since the principles of these methods are not the focus of this paper, details of the algorithms, such as the pros and cons, are not discussed here (see [22] for details). In addition, with advancements in AI, different AI branches, such as deep learning, have benefited the timely interpretation of the obtained images. Chen et al. extracted fracture trace (fracture length, dip angle, intensity and density of the fracture traces) [17], weak interlayer [58] and water inflow [61] information on the tunnel face from more than 3000 raw images using convolutional neural network (CNN) methods. The time to train the model in the three cases was more than 8 h; however, the time required to test the model after a successful train was less than 1 s per image, which was computationally efficient. Moreover, Chen et al. [31] used a CNN-based method to classify the rock structure into five categories using approximately 3,000 raw images captured from 150 tunnel faces, where the time to classify a new image after the model training was only about 0.33 s. The latter one, i.e. methods using point cloud data, has also been used by several studies to extract 3D data of the tunnel face for less dependence on the image quality and camera calibration [51]. The images were first converted into point cloud data, and the corresponding aggregation was then conducted based on the point cloud data. Chen et al. [54] used an improved K-means clustering method to extract the discontinuity orientation from tunnel face 3D point clouds; the time consumed to extract information from 382,085 facets was about 2.5 h. To reduce the need for manual intervention and improve computational efficiency, Chen et al. [35] proposed a semi-automatic discontinuity characterization method using 3D point clouds; the operation time was approximately 15 min. Similarly, Zhang et al. [51] extracted the discontinuity trace information using trace feature point; the total processing time was less than 2 min. Meanwhile, commercial software and open-source programs, such as Rockscan [30], GeoSMA-3D [63], CAE Sirovision [28] and Discontinuity Set Extractor (DSE) [32], have been gradually developed and applied in the acquisition and interpretation of tunnel face data,. However, the interpretation of images in some software packages may experience a long time as the generation of a high density point cloud is computationally expensive [32].

In terms of the information extracted, as presented in Tab.1 and **Fig.8** (a), discontinuity-related (including joint and fracture) studies account for 84% of the reviewed publications, where the length, dip angle, dip direction, spacing, density, and number of discontinuity sets are the main parameters to be extracted. Based on the extracted discontinuity information, two typical subsequent analysis are the characterization and stability analysis of the rock mass. As shown in **Fig.8** (b), the characterization of the rock mass accounts for 2/3 of the subsequent analysis of the extracted information. This analysis usually involves the calculation of the rock quality designation (RQD) value [29,36,53,57], rock mass rating (RMR) value [37,51,57], geological strength index (GSI) value [14,37], and other rock mass rating systems. In addition, RMR has been widely used in many rock tunnel projects as a crucial indicator to define the support parameters [68]. In the RMR system, six basic parameters are used to classify the rock mass; these parameters are the uniaxial compressive strength (UCS) of rocks, RQD value, discontinuity spacing, discontinuity condition, groundwater condition, and discontinuity orientation with respect to the opening axis, while the estimation of RQD is related to the spacing and number of the discontinuities [37]:

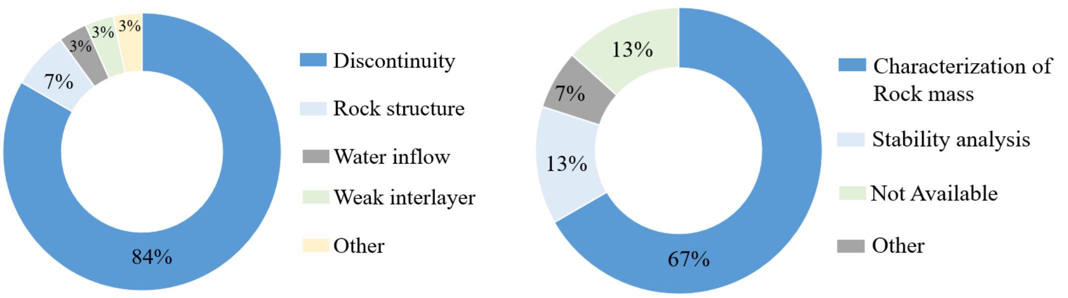
$$RQD = 115 - 3.3J_v \tag{1}$$

$$J_v = \frac{1}{s_1} + \frac{1}{s_2} + \frac{1}{s_3} + ... + \frac{1}{s_n} + N_r(5\sqrt{S}) \tag{2}$$

where s_1, s_2, …, s_n denote the mean spacing of each discontinuity set, N_r denotes the number of discontinuities and S is the measuring area.

Obviously, the extracted discontinuity information can be applied to calculate the value of RQD or RMR, thereby determining the support parameters. For instance, Lemy et al. [29] extracted the trace length and spacing information from images and used them to calculate RQD value. Li et al. [37] conducted research on the automatic extraction of the discontinuity orientation, spacing, trace, roughness, and aperture, which were used to calculate RMR and GSI. The other application of the extracted discontinuity information is to analyze the stability of the surrounding rock mass of the tunnel [28,33,34,63], which accounts for 13% of the subsequent analysis, as shown in Fig.7 (b). Huang et al. [28] used the coordinates and orientations of joints to generate a 3D discrete model and investigate the stability of the surrounding rock of the tunnel; their study results could guide the installation of tunnel supports. Zhu et al. [34] integrated the 3D discontinuous deformation analysis (DDA) with DP to analyze the stability of tunnels in blocky rock mass. The integrated system can support the high-precision design of tunnels in construction. Similarly, Wang et al. [63] performed a 3D stability analysis of tunnel blocks using the discontinuity information and the analysis results provided a guidance for the adjustment of support parameters.

In addition to the discontinuity information, the extraction of water inflow [61] information on the tunnel face during construction has also been studied. The groundwater condition is a key parameter in the RMR system; therefore, after extraction of the water inflow information, calculation of the RMR value was subsequently conducted, which could provide a basis for the determination of the support parameters. Moreover, some studies attempted to directly classify and characterize rock masses without calculating the RMR or other rating system values. Chen et al. [31] employed geological images of tunnel faces and a CNN to present an automated interpretation method for classifying five types of rock structures, including the mosaic, granular, layered, block, and fragmentation structures. The experimental results showed that the proposed method was optimal and efficient for automated classification of rock structures. Similar study has also been conducted by Qin et al. [64]. After classification of the rock mass structure, the support parameters can be determined accordingly.



(a) (b)

Fig.8 (a) Proportion of extracted information from images in the reviewed literature. (b) Different subsequent analysis methods after the extraction of tunnel face data.

4.2 Interpretation of TLS data

Fekete and Diederichs [41] introduced a basic and general processing to interpret the point cloud data collected by TLS. The proposed workflow included 1) reducing the dataset to the zone of interest, 2) creating a surface model, 3) aligning with scans of previous face position or geo-reference to the absolute coordinate system, and 4) interpreting and extracting the data. Similar to the scan time, even based on the same processing workflow, the processing time of the point cloud data can significantly vary for different projects from 1 h [69] to several hours [39], depending on the chosen algorithm and size (up to GBs) of the point cloud data.

A brief summary of different categories of information extracted using TLS during the rock tunnel construction is presented in Table 2. Similar to DP, most of the information extracted using TLS, including the dip, dip direction, spacing, roughness, trace length, and trace density, is related to discontinuity. In addition, the characterization of the rock mass and stability analysis of the tunnel system are the main applications of discontinuity information. Monsalve et al. [45] applied the extracted discontinuity information to characterize the rock mass and generated a discrete fracture network for each discontinuity set for further discontinuous modeling and calculation. Fekete et al. [41] integrated TLS with discontinuous modelling to analyze the stability of a tunnel in blocky rock mass, the result of which can influence the support scheme. Therefore, the usage of the extracted discontinuity using DP and TLS is similar.

Table 2 Examples of literature on different categories of the extracted information using TLS

Category	Detailed information	Refs
Discontinuity information	Orientation, location, spacing	[16]
	Dip, dip direction	[39]
	Location, orientation, joint set spacing, joint roughness	[41]
	Dip, dip direction, trace length, trace area	[45]
	Dip, dip direction	[69]
	Orientation, trace length, frequency, spacing, trace density	[70]
	Traces and orientations	[44]
	Dip, dip direction	[71]
	Discontinuity trace	[43]
Profile information	Tunnel profile geometry	[15]
	Support evaluation	[16]
	Tunnel deformation	[71]
	Overprofile, deformation of the shotcrete	[72]
	Overbreak, contour roughness	[73]

The other scenario where TLS-enabled information can contribute to the dynamic design of the tunnel support is to employ tunnel profile geometry information to evaluate or modify the support schemes. As presented in Table 2, several examples have been listed regarding this topic. Fekete et al. [16] used the scanned data to produce rock and final support profiles, where the rock face was scanned twice (pre- and post-shotcreting) to allow a direct comparison of the shotcrete thickness, as illustrated in **Fig.9**. The shotcrete thickness needs to be optimized if the comparison result is not acceptable or an overbreak is detected. Kim and Bruland [73] proposed Tunnel Contour Quality Index (TCI) based on TLS for the effective management of tunnel contour quality, whose roughness can affect the shotcrete volume or rock bolts. In the studies carried out by Xu et al. [71] and Walton et al. [72], deformation of the excavated section and as-built shotcrete thickness were detected using TLS, the time spent was relatively long, that is, about one month. It should be noted that they do provide valuable instructions on the optimization of the support schemes; however, they are beyond the scope of the study due to the long acquisition time. Such is also the case in some literature using long-term monitoring results of the as-built tunnel structure, as mentioned above in Section 2.

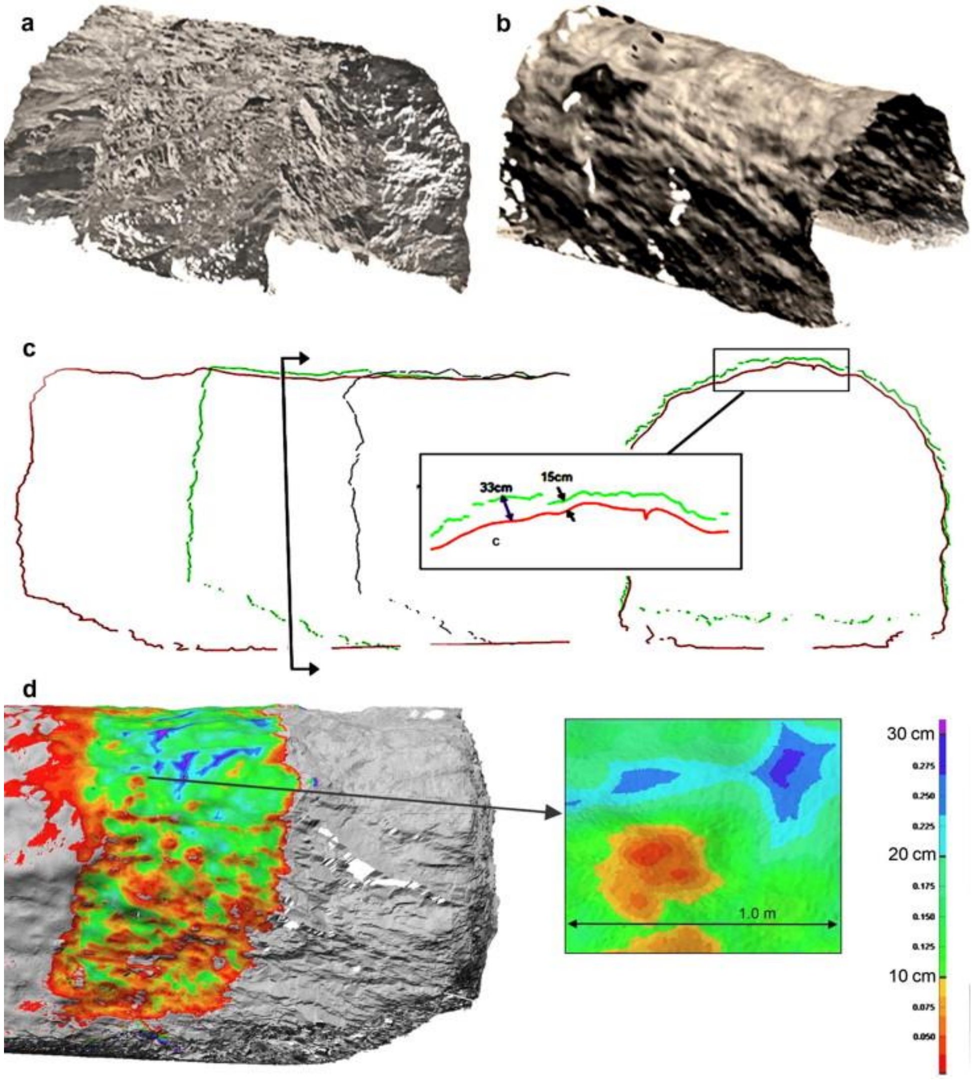


Fig.9 (a) Rock model. (b) Shotcrete Lidar model. (c) Longitudinal and cross-section showing detailed comparison of profiles with shotcrete thickness. (d) Shotcrete thickness contoured onto rock model [16]

4.3 Interpretation of MWD data

One of the most widespread applications where MWD data contribute to the dynamic design of the support during tunnel construction is to characterize the rock mass and provide support parameters accordingly (see Table 3). A case study was reported by Galende-Hernandez et al. [74] where ten kinds of MWD variables, including the penetration rate, hammer pressure, water pressure, and seven other variables, were processed and analyzed using machine learning and computational intelligence techniques to estimate the RMR value. The results were applied to a D&B tunnel and exhibited a satisfactory performance. Similarly, van Eldert et al. [75] used MWD fracturing index (FI) to characterize the rock mass for grouting purposes. However, neither of the studies mentioned the design of the support in the context, nor directly determined the relationship between the rock mass grade and support parameters. To establish correlations between MWD data and installed rock support, van Eldert et al. [1,2] correlated the weighted normalized penetration rate and rotation pressure with the RQD and Q values. Subsequently, the normalized penetration rate and rotation pressure were employed to predict the rock support parameters (bolt spacing, bolt length and concrete thickness), as illustrated in **Fig.10**. The results were compared with those of the Q-value-based method, which exhibited a reasonable correlation. Therefore, the FI value can be used as an indicator to predict the rock support.

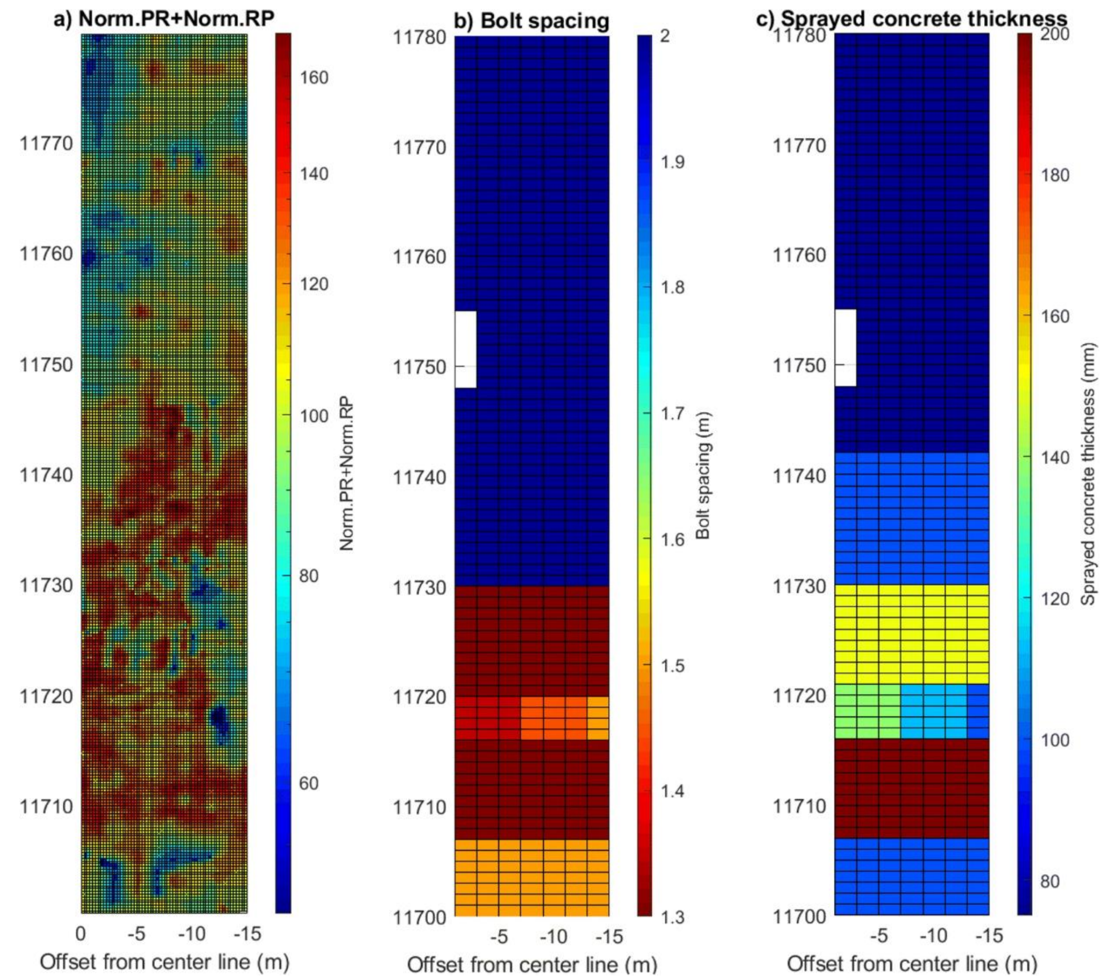


Fig.10 (a)-(c): Visualizations of the MWD parameters, bolt spacing and sprayed concrete thickness [2]. (PR: penetration rate, RP: rotation pressure)

In addition to the characterization of the rock mass, another key application of the MWD data to assist the support design is to detect the potential overbreak zones. Navarro et al. [50] developed a nonlinear multivariable model to predict the excavated mean distance and lookout distance as functions of the normalized penetration rate, rotation speed, hammer pressure, water flow, and rotation pressure parameters. The predicted excavated mean and lookout distances can be considered as a damage measure to predict the high risk of potential over- or under-excavated zones produced by blasting in the contour of a tunnel, thus reinforcing the support if necessary.

Table 3 Examples of literature on different usages of the MWD-enabled data during tunnel construction

Category	Details	Refs

Rock mass characterization	Calculation of RQD and Q value to determine the bolt spacing and concrete thickness	[1]
	Calculation of FI and investigation of relationship with Q system to predict bolt length, bolt spacing and concrete thickness	[2]
	Estimation of RMR value	[74]
	Calculation of FI	[75]
Overbreak zone detection	Prediction of the excavated mean distance and the lookout distance	[50]

4.4 Interpretation of other ahead geological prospecting data

Processing the acquired raw data using the geological prospecting technologies depends on the computational power of the computer, specific software, processing algorithm and size of the data. According to the interviewed domain experts and engineers, data processing can be accomplished in 2 h. As for the acquired data by ahead geological prospecting technologies and its contribution to the dynamic design of the tunnel support, a brief summary of the application of ahead geological prospecting techniques in timely data interpretation during tunnel construction is given in Table 4. Using the high-frequency electromagnetic pulse, GPR satisfactorily responds to rock structures, such as faults, lithological interfaces, and fracture belts [76]. Hence, some studies were conducted using GPR to detect seismic and nonseismic geological features [77], karst geological anomalies [78], and the position and shape of catastrophic geological body [79]. Based on the detection result, the original support schemes can be modified. In addition, Qin et al. [80] introduced an automatic recognition method to directly identify steel ribs, voids, and initial linings from GPR images using CNN methods to control the quality of the support, which is a critical issue in guaranteeing the safety of both tunnel structures and construction operations.

In contrast to GPR, TSP exploits seismic waves that are excited by small-scale artificial blasting to predict unfavorable geology conditions. Parameters of the seismic waves include the longitudinal wave (P-wave) velocity, transverse wave (S-wave) velocity, magnitude of the wave, wave type, wave depth, wave direction and so on, as shown in Table 4. One of the key applications of TSP-based data is the classification and characterization of rock masses. Bu et al. [81] used P-wave velocity, as well as Poison's ratio and Young's modulus, to classify the rock mass ahead of the tunnel face into 5 grades. Shi et al. [82] combined P- and S-wave velocity with Poisson's ratio and Young's modulus to classify the rock mass using the fuzzy analytic hierarchy process method. Moreover, the calculation of the RMR value of the rock mass using TSP data, e.g. P- and S-wave velocity, wave magnitude, wave depth and direction, has been carried out by several studies [83-85], where the rock bolts, shotcrete and steel sets can be determined directly according to the different RMR values. In addition to the characterization of rock masses, TSP has also been integrated with stability analysis to provide a guidance for support design. Fan et al. [86] conducted the discrete element method (DEM) to analyze the deformation and displacement of the rock mass using the discontinuous geological interface information collected by TSP. The analysis results could have practical guiding significance for the design of the support.

Comprehensive prospecting methods have been proposed and applied in construction because each prospecting technique has its advantages and disadvantages. Cao et al. [87] determined the support type and method dynamically during tunnel construction based on the TSP and GPR data. After the detection of well-developed structure planes, such as faults and folds, along with the abundant water, steel frame, steel meshes, and shotcrete thickness were optimized accordingly. Bu et al. [76] and Nie et al. [88] combined GPR and TEM to detect the position and spatial distribution pattern of water-rich areas. These results provide an effective reference for the implementation of dynamic design and construction schemes.

Table 4 Summary of ahead geological prospecting techniques in data acquisition

Techniques	Detected data	Contribution	Refs
GPR	Seismic and non-seismic geological features	NA	[77]
	Different types of karst geological anomalies	NA	[78]
	Steel ribs, voids, and initial linings	Quality control of the support	[80]

	Position and shape of catastrophic geological body	NA	[79]
TSP	P- and S-wave velocity ratio, Poisson's ratio, Young's modulus	Classification of the rock mass	[81]
	P- and S-wave velocity ratio, Poisson's ratio, Young's modulus	Classification of the surrounding rock mass	[82]
	Discontinuous geological interface information	Stability analysis of the surrounding rock	[86]
	Unstable ground conditions	Calculation of RMR value	[83]
	P- and S-wave velocity, wave magnitude, wave depth, direction	Calculation of RMR value	[84]
	P- and S-wave velocity, wave magnitude, wave depth, direction	Calculation of RMR value	[85]
GPR, TSP	Faults, folds, groundwater	Modification of steel frame, steel meshes, shotcrete thickness and bolt	[87]
GPR, TEM	Position and spatial distribution pattern of the water-rich area	NA	[76]
GPR, TEM, ER	Weathered area	NA	[88]

5 Data aggregation for support parameters determination

Sections 3 & 4 focus on the quick acquisition of the data on the construction site and the corresponding interpretation, such as the interpretation of rock mass parameters from images and interpretation of geological anomalies from the TSP waves. Although some studies examined the corresponding aggregation of the interpretation results, such as the calculation of RMR, this study attempted to simplify the process from the interpretation results to support schemes. With the increasing development of IT, multiple computer- and AI-aided aggregations have been applied to optimize support schemes from multiple sources of data. Here, another key issue of the dynamic design of rock tunnel supports, that is, the efficient aggregation of the data exposed by excavation using computer- or AI-aided methods, is discussed. The relationship between Section 4 and Section 5 are shown in **Fig.11**.

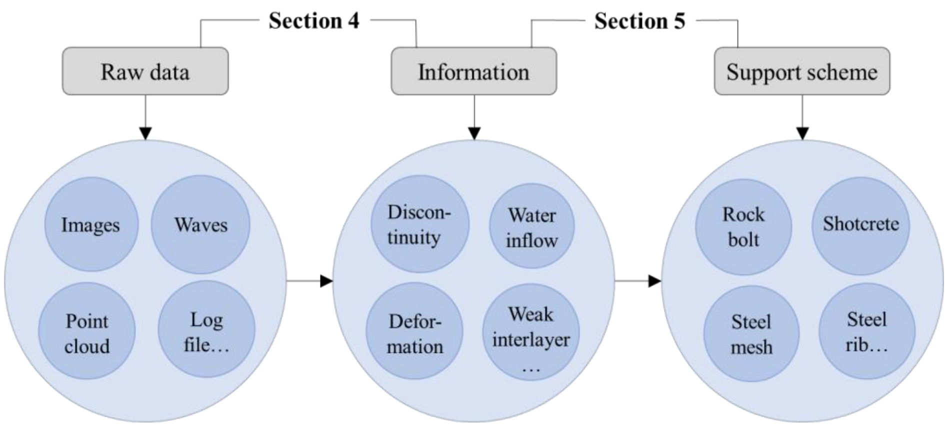
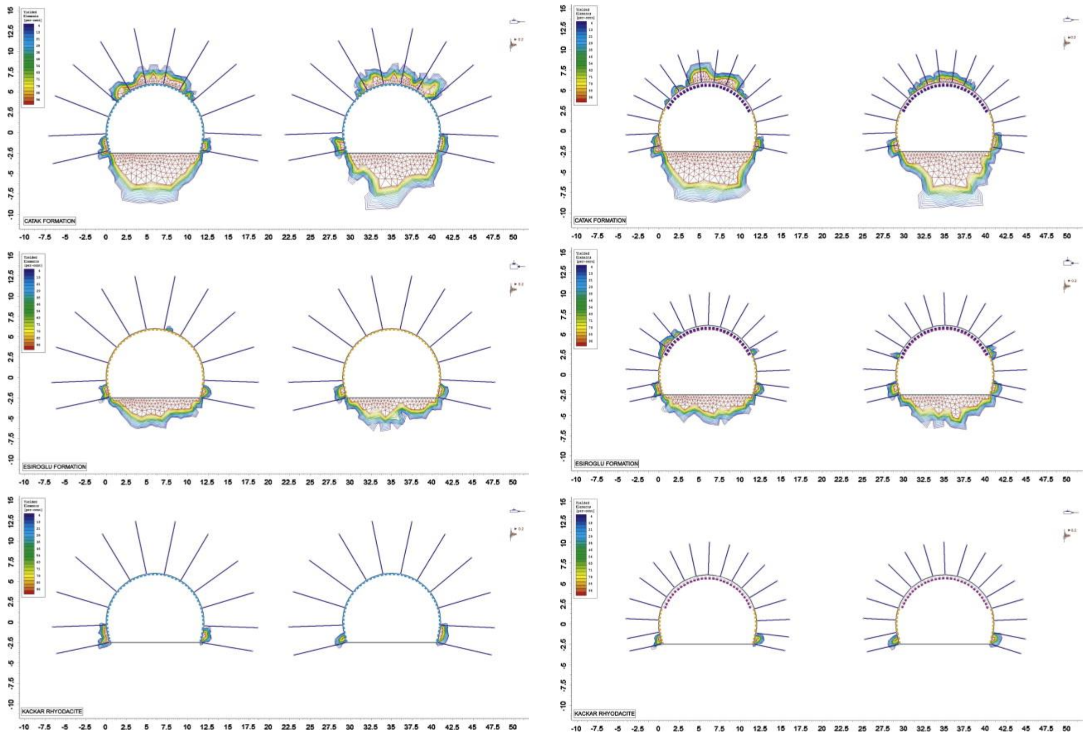


Fig.11 Relationship between Section 4 and Section 5

5.1 Conventional methods

Generally, three traditional methods are mainly used in the determination of the tunnel support parameters: empirical, numerical and analytical methods [89,90]. The empirical method refers to the determination of the design parameters based on the pre-existing standard methods or pre-existing experience [6], which can be quantified by rock mass classification systems such as afore-mentioned RMR and Q value. Upon the classification of the newly exposed rock mass, the corresponding support parameters can be determined. Some examples of using rock mass classification systems to determine support parameters have been discussed in Section 4.

Numerical methods employ both the computational hardware and software to evaluate the rock mass behavior and its effects on the support systems, including the finite element method (FEM) and DEM. Due to its ability to simulate the stresses and deformations that develop in the support system, it has become a powerful and widely used tool to design rock tunnel support [18]. Sopacı and Akgün [91] used a 2D FEM program to analyze the total induced displacement and percentage of yielded elements of the tunnel; the results were used to optimize the empirically determined support parameters. Similarly, Kanik et al. [92] applied a 2D FEM software to calculate the thickness of the plastic zone and total displacements of the tunnel, whose supports were estimated using both RMR_{14} and RMR_{89}. According to the analysis results, as shown in **Fig.12**, the support systems obtained from the RMR_{14} version suggests more realistic support element for fair rock masses and great horizontal stress values. In the study carried out by Aygar and Gokceoglu [93], NATM principles were entirely reflected in the calculations and the input parameters of the numerical models were the interpretation results of the geotechnical monitoring task performed during the construction. Total displacements, vertical displacement, horizontal displacement and the yielding zone were calculated using 2D FEM methods to get the optimal support system.



(a) (b)

Fig.12 Thickness of plastic zone after installation of support systems suggested by: (a) RMR_{14}; (b) RMR_{89}. [92]

However, 2D numerical methods can not accurately solve the support optimization problem as in essence, the support optimization problem is a mechanical problem with three-dimensional effect. The comparison study conducted by Kaya and Sayin [90] revealed that 3D FEM analysis gave the better solution in tunnel support design compared to 2D FEM analysis. Hence, 3D numerical analysis has been carried out by many researchers regarding tunnel support design. Theoretically, Zhang and Zhu [94] proposed a 3D version of the Hoek-Brown strength criterion, i.e. generalized Zhang-Zhu (GZZ) strength criterion, which considered the intermediate principal stress compared with the original 2D Hoek-Brown strength criterion. Based on the GZZ strength criterion, Xu et al. [95] used analytical and numerical methods to investigate the interaction between tunnel support and surrounding rock and predict the deformability of the surrounding rock. With the advancement in the numerical software, many research endeavors have been allocated to 3D numerical analysis based on this approach. Feng et al. [9] and Xing et al. [96] used the 3D numerical analysis to get the optimal length and spacing of the rock bolt, and investigate the displacements and stresses of the tunnel, respectively. Hsiao et al. [97] used the computer program FLAC-3D to simulate the tunnel construction and the numerical results were used for support optimization. In the study carried out by Sun et al. [98], the surrounding rock stress release rate was considered in the calculation to obtain the stability of tunnel lining support, which was also implemented in FLAC-3D. In terms of the time consumed, the computational time of the numerical analysis depends on many factors such as mesh numbers and mesh size, ranging from several minutes to several hours.

Last but not least, analytical methods that use mathematical and mechanical tools to calculate the stress distribution state of the surrounding supported or unsupported rock are widely used in the design of rock tunnel supports. Compared with the numerical methods, analytical methods rely on a number of assumptions and simplifications to formulate the analysis, therefore are simpler, more intuitive, and computationally efficient [18,99]. Su et al. [100] used convergence confinement method (CCM), which is a useful and effective analytical method to simulate the mechanical behavior of the rock mass during tunneling and analyze the stability of the tunnel and its supports. The results provide a guidance for the optimization of the rock bolts and shotcrete parameters, such as elasticity modulus, diameter, longitudinal spacing, bolt length, Young's modulus, Poisson's ratio, bending strength, and shotcrete thickness. To overcome the limitation of hydrostatic loading simplification that CCM may encounter in the tunnel support design, Mitelmam and Elmo [18] adopted equivalent boundary beam (EBB) method to readily compute the distribution of field stresses between the ground and support system, the results of which were used to optimize the lining thickness and rock bolt. In this study, the comparison between the efficiency of the proposed EBB method and the efficiency of the FEM method was also conducted. The results for the proposed EBB method were generated almost instantaneously while the simple FEM models would take about 10 min to be setup and calculated. Hence, it can be seen that in some simple and simplified situation, analytical methods outperform other methods from the perspective of computational efficiency.

5.2 AI-supported methods

Conventional methods are appropriate candidates for designing tunnel support when the available data for projects are sparse [20]. However, the increasing amounts of data collected from the construction site are posing a challenge to conventional analysis methods as the accuracy and efficiency are easily affected [20]. Herein lies an opportunity to integrate AI methods into the existing best practices of the rock tunnel support design to make the best use of the large amount of data, as AI can solve complex engineering problems by learning patterns of data inputs and outputs presented to the models to produce meaningful interpretation [101]. Hence, AI is gaining momentum in the design of rock tunnel support, and different AI techniques have been used in the literature, such as artificial neural network (ANN) [102-105], genetic algorithm (GA) [106-108], particle swarm optimization (PSO) [104,109,110], support vector machine (SVM) [111,112] and so on. For these techniques, the development of the principles and of the mathematic models have been introduced and discussed in the existing studies [101,113], which therefore are excluded in this subsection. Details of the application of AI in the design of the support from the collected literature are summarized in Tab.5.

Table 5 Applications of AI techniques in the design of the rock tunnel support

Refs	AI techniques	Description of applications
[114]	Expert system, Fuzzy set	Prediction of rock bolt, shotcrete, wire meshes parameters
[108]	GA, SVM	Classification of BQ value
[109]	PSO	Optimization of anchoring parameters

[106]	GA	Optimization of steel rib supports
[111]	SVM	Selection of pre-determined support patterns
[115]	SVM, ANN	Calculation of shotcrete thickness, diameter of bolt, and length of bolt
[103]	ANN	Selection of one of the support patterns from 6 pre-determined patterns
[110]	SVM, PSO	Optimization of shotcrete thickness and shotcrete Young's modulus
[107]	GA, SVM	Prediction of RMR value
[112]	SVM	Classification of surrounding rock mass
[104]	ANN, GA, PSO	Characterization of rock mass quality
[105]	ANN	Establishment of relationship between rock quality and support parameters
[116]	Neuro-fuzzy inference system	Prediction of RMR value
[117]	Expert system, machine learning	Establishment of relationship between rock mass quality and support parameters
[102]	ANN	Prediction of shotcrete, rock bolt, steel mesh, steel arch and advanced small pipe
[118]	Expert system, ANN, Case-based reasoning	Prediction of shotcrete, rock bolt, and steel mesh
[119]	Expert system	Prediction of rock bolt, steel mesh and shotcrete

It can be seen from Table 5 that one of the scenarios where AI is applied to solve support design problem is, likewise, the characterization of the rock mass, which is used as the indicator of the corresponding support parameters. Liu et al. [108] introduced GA and SVM coupling algorithm to get the improved BQ value. Similarly, Gholami et al. [107] and Wang et al. [112] also used SVM to predict the RMR value of the rock mass and classify the surrounding rock in a timely manner, respectively. In addition to SVM method, Liu et al. [104] used ANN model to predict the rock mass quality using MWD data and Sebbeh-Newton et al. [116] adopted neuro-fuzzy inference system to predict basic RMR value using on-site data. None specific study reported the time used but it can be speculated that the process to get the results using these AI techniques is timely as it has provided real-time assistance for design alternations in the construction site [112].

Other studies listed in Tab.5 focus on the direct optimization or selection of support patterns without classifying rock mass. Global optimization algorithms such as

PSO and GA are used by Li et al. [109] and Alvarez-Fernandez et al. [106] to optimize the anchorage and steel rib parameters respectively, where little computational cost was needed as the implementation of both GA and PSO is easy and simple. The second type which is usually used in the literature to directly optimize the support parameters is the classification model such as SVM. For example, Liu et al. [115] used 16 factors such as density of joint and discontinuity orientation as input variables of SVM network to get the shotcrete thickness, diameter, length and spacing of rock bolt, diameter and spacing of wire mesh. SVM was also integrated with numerical analysis and PSO by Jiang et al. [110] to represent the nonlinear relationship between the surrounding rock mechanical parameters and displacements, which provided a real-time and quantitative approach to optimize shotcrete parameters.

Given the advantage of computing a mapping from a multivariate space of information to another [120], the ANN model is thus widely used in the support design to describe the end-to-end relationship between rock parameters and support parameters. ANN model has superiority in the support design problem as it is able to consider qualitative descriptive information in tunnel design problems such as rock grade and weathering grade, and the applied data can be imperfect and erroneous [102]. Xia et al. [102] introduced ANN method into tunnel support design earlier and verified the feasibility and reliability of ANN-supported support design. Using 9 parameters including geological factors, tunnel width and buried depth as inputs, 13 kinds of support parameters were outputted by ANN. Similarly, Nie et al. [105] mapped the relationship between rock conditions, the sequential excavation parameters and support parameters using ANN. The results illustrates the feasibility of the proposed ANN-based design method with much less computing time compared with numerical methods. In a different way, Liu et al. [103] explored the correlation between MWD data and support patterns using ANN and found that a neural network with a 6-30-6 topology structure was optimum, whose calculation time was approximately 10 min. The calculation result was to select one of the support patterns from 6 pre-determined patterns.

Last but not least, expert system is also adopted by many researchers to solve the support design problem, as a large amount of historical data and cases within the scope of tunnel support design exist. As early as the last century, Madhu et al. [114] constructed an expert system using rule-based reasoning, i.e., knowledge being represented as “if-then” rules in the system. Data uncertainty was treated using a fuzzy set analysis. The application of the expert system elucidated that the recommended rock bolt, shotcrete and wire mesh parameters were in line with those actually used. Similarly, Wang et al. [119] constructed an expert system which took into account 8 factors such as joint orientations and water inflow information. Later, many researchers endeavor to integrate expert system with other techniques to enhance the robustness and improve the accuracy of the established expert system. Wang [117] combined expert system with machine learning to get the support parameters from 5 types of input data including buried depth, tunnel face stability grade, surrounding rock grade and others. Qiao and Wei [118] integrated expert system with ANN and case-based reasoning to avoid the bias that a single method is prone to. Using this comprehensive method, the shotcrete, rock bolt and steel mesh parameters were determined and were close to the ones in practice.

6 Conceptual framework of JIT design of rock tunnel support

According to the reviewed studies, the advancement of IoT and IT technologies has improved the performance of support design tasks in the rock tunnel construction concerning the time and accuracy. Here, a brief definition and overview of the proposed conceptual framework are presented, and research gaps are identified accordingly. Subsequently, the conceptual framework for the JIT design of tunnel supports, including key concepts and future perspectives, is developed.

6.1 Framework definition and overview

The existing academic and industrial-based studies have proved that an accurate, safe, and particularly JIT design of rock tunnel supports can fulfill the safety, stability, and other requirements for certain underground conditions [3,10,11]. The “just-in-time” concept originates from the manufacturing workflow with an aim to reduce the flow time and costs of production systems and distribution of materials [121], and then has been introduced into computer science industry. For instance, a JIT compiler is used to improve the runtime performance, which gives an equivalent sequence of the native code as soon as the bytecode sequences are given [122]. Similarly, here, we use the term “just-in-time” to denote the intrinsic requirement of the rock tunnel support as the support parameters need to be determined as soon as the hidden volume of the rock mass, the structural surface, the underground water and the mechanical response of surrounding rock, are exposed during tunnel construction. The JIT design of the tunnel support implies that once the data during construction are available in time, the revision of the preliminary design can also be available in time. Hence, in the JIT design of the tunnel support, data acquisition, interpretation and aggregation all need to be in time.

The flowchart of the dynamic design of the support can be seen in **Fig.13**. It can be seen that the dynamic design of the tunnel support focuses on the revision of the preliminary design using the exposed geological and various unanticipated conditions during the construction process. By comparison, the JIT design of the tunnel support is a higher requirement for the dynamic design of the tunnel support, that is, as mentioned above, the revision of the tunnel support schemes should be available in time as soon as the new data are available during the construction process.

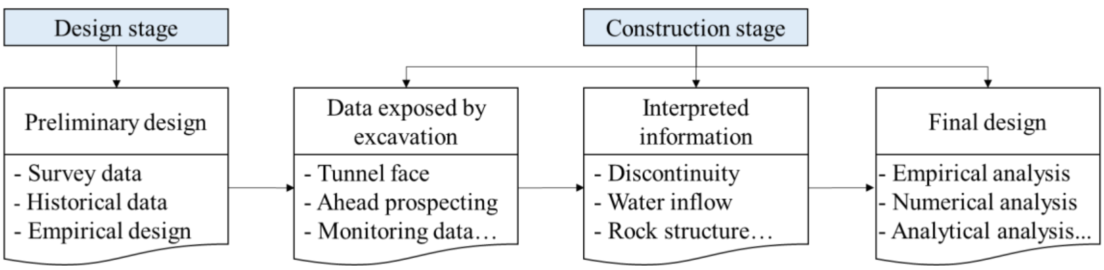


Fig.13 Flowchart of dynamic design of the support in rock tunnel

In this paper, we provide a broad overview of currently state-of-the-art techniques used in the design of the tunnel support during tunnel construction. In previous sections, the contribution of each technique to the JIT design of the rock tunnel support was thoroughly discussed. A brief summary of the workflow and average time requirements for the support design in the current practice is given in **Fig.14**.

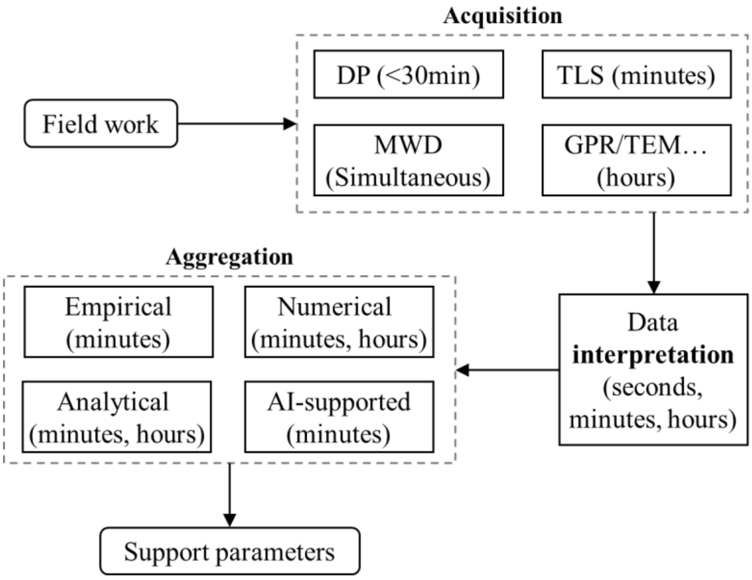


Fig.14 Workflow and average time requirements for support design in current practice.

To sum up, the optimization of the support schemes during rock tunnel construction can be divided into three steps, i.e., acquisition of on-site raw data, interpretation of the data and the aggregation of the interpretation results to obtain new support schemes. As discussed in Sections 4 and 5, one of the key parameters that we consider in the process of JIT design of the tunnel support is the time required to accomplish the task. It can be seen that the time it takes to accomplish each step is closely related to the size of the tunnel face, IoT technique employed to acquire data, and IT technique used to analyze the information, ranging from several seconds to several hours. For instance, generally, it takes less than 30 min for DP to collect on-site data [30] while it may take more than 1 h for TSP to acquire data, as illustrated in **Fig.14**. In addition to time consumption, other important factors that may influence the performance of the JIT design of the tunnel support, such as the information category and algorithm accuracy, have also been discussed. There exist some parallels in the techniques used in each step. As can be seen from Section 4 and 5, the dominant information that each technique extracts from raw data is the discontinuity information, followed by profile information. Then, the majority of the literature samples use these information to conduct rock mass characterization and stability analysis, based on which the support parameters can be determined accordingly.

6.2 Research gaps

Three major shortcomings of current JIT design of the tunnel support have been identified from the literature examples, which are discussed in detail below.

6.2.1 High time consumption of data interpretation

The application of IoT technologies, including DP, TLS and MWD technologies, has enabled the quick acquisition of on-site data, which is the foundation of the JIT design of the tunnel support. However, the corresponding interpretation of the collected raw data may consume a considerable time in some cases, which is typically illustrated in the interpretation of the point cloud data. With a triangular mesh size of 4 cm and 382,085 facets, the interpretation of the point cloud takes about 2.5h in a workstation (the Intel Core i7-2600 CPU and 16GB RAM) [54]. To interpret the point cloud data with the recommended resolution of 7.5mm at 5 m, the processing time of the point cloud was approximately 5 h [39]. The time to process high-density point cloud data in some cases can exceed 20 h, even with a high-powered computer (Intel Core i7-6700 CPU and 16GB RAM) [32]. In addition to the interpretation of point cloud data, the processing of digital images can also take a high computational time, as seen in [28] where 1.5 hours were needed for post-processing. The relatively high time cost can hinder the performance of the JIT design of the tunnel support as the intrinsic quick-response requirement cannot be guaranteed.

6.2.2 Dilemmas of conventional and AI-supported aggregation methods

Empirical, numerical and analytical approaches are the dominant methods which are used in practice to obtain the optimal support parameters. However, through literature examples, some limitations have been identified that can pose challenges to the JIT design of the tunnel support.

(1) Limitation of empirical classification approaches

As discussed, the majority of the literature used the extracted discontinuity or water inflow information to characterize the rock mass, then gave the support scheme from the predefined schemes. This is a one-to-one process, i.e., one class of surrounding rock mass corresponds to a specific type of support parameters. As can be seen from Table 6, the one-to-one relationship between the RMR values and corresponding recommended types of support in a practical tunnel project is obvious [123]. This common practice simply produces a qualitative ranking process for the rock mass and neglects the stresses or deformations that develop in the support system [18], which therefore tends to yield inaccurate and resource-wasting support schemes. Indeed, the newly exposed data, such as the discontinuity information, can be used to not only characterize the rock mass but also to quantitatively evaluate the entire support-rock system stability (see [34]), whose result can be used as an indicator to optimize the support parameters in detail. Unfortunately, most studies using the empirical classification method fail to further integrate the on-site information with more precise analysis methods to improve the accuracy of the JIT design of the tunnel support.

Table 6 Recommended types of support based on RMR system [123]

RMR value	Anchoring Φ 20mm	Shotcrete	Ribs
81-100	-	-	-
61-80	Locally bolts in crown, 3m long, spaced 2.5m, with occasional wire mesh	50 mm in crown where required	-
41-60	Systematic bolts 4m long, spaced 1.5-2 m in crown and walls with wire mesh in crown	50-100 mm in crown, 30 mm in sides	-
21-40	Systematic bolts 4-5 m long, spaced 1-1.5 m in crown and walls with wire mesh	100-150 mm in crown, 100 mm in sides	Light ribs spaced 1.5m where required
<20	Systematic bolts 5-6 m long, spaced 1-1.5 m in crown and walls with wire mesh. Bolt invert	150-200 mm in crown, 150mm in sides and 50 mm in face	Medium to heavy ribs spaced 0.75m with steel lagging and fore poling if required. Close invert

(2) Shortcomings of numerical and analytical approaches

The limitations of empirical methods do not apply to numerical and analytical approaches; thus, both the numerical and analytical approaches have been widely used in practice to improve the accuracy or efficiency of the computation. However, the numerical analysis of the support parameters is sensitive to the mesh and boundary effects, which may require considerable time to yield results [96]. Moreover, the modelling process of numerical analysis can also be time-consuming as various factors need to be taken into account. In comparison, analytical approaches provide a simpler and more computationally efficient way to aggregate data with various simplified hypotheses, which, in turn, limits the application of analytical methods as the simplified conditions are seldom the case in most rock tunnel problems [96].

(3) Scarcity of the AI-supported methods

The use of AI techniques, such as optimization algorithms, ANN and expert system, has greatly improved the performance of the JIT design of the tunnel support concerning the computational time [105] and accuracy [20]. Contrary to our initial expectation that many studies were conducted on the AI-supported JIT design of tunnel supports, actually, only 12 literature using AI to directly optimize support parameters were collected, excluding the studies that used AI to classify the rock mass. Moreover, Published between 2002 and 2005, four of these studies [102,115,118,119] used ANN and an expert system to find the optimal support parameters. Consequently, AI has been widely adopted in the entire process of the JIT design of tunnel supports, such as interpretation of on-site raw data. In addition, it is a powerful tool to describe the end-to-end relationship between the rock and support parameters [120]; however, studies that directly use AI to establish relationships between newly exposed data and support parameters are scarce.

6.2.3 Long retrieval time for similar design cases

According to the current standards and specifications [10,11], the pre-existing experience or cases of rock engineering support design can be reused if the new tunnel project encounters similar geological conditions as before. Therefore, it challenges designers/engineers to recall and search past similar projects and extract associated information [118]. This process is subjective and error-prone, as designers/engineers rely on their own experience and comprehension to retrieve and edit similar cases. Moreover, manual retrieval is time-consuming; therefore, some researchers have attempted to use computer-aided approaches to improve the accuracy the efficiency of the process (see examples in [117,118]). However, the concerns that how to convert the textual cases or knowledge into computer-interpretable data formats and how to retrieve the cases accurately still have not been fully addressed, which influences the performance of the JIT design of the tunnel support.

6.3 Key concepts

Three key performance indicators that can be used to evaluate the performance of the JIT design of tunnel supports during the rock tunnel construction process are discussed.

(1) Time consumption

Support is installed during the construction process after the face is excavated, and the muck is loaded. According to engineering experience, the time for "acquisition-interpretation-aggregation" of the support design is extremely limited [16] as mucking and risk removal can consume approximately 2-3 h, accounting for over 50% of the cycle time; thus, the time allocated to the support design is only approximately 1 h. Hence, under such circumstance, the JIT design of the tunnel support requires the "acquisition-interpretation-aggregation" workflow to be finished within 1 h. Otherwise, the working hours can be increased and the overall construction period can be easily delayed. However, as stated in Section 6.2, in certain cases, some design approaches fail to meet the "time" requirement of the JIT design of the tunnel support.

(2) Accuracy

Inaccurate support parameters adversely affect the safety guarantee in poor rock mass conditions and waste both the support structures and manpower in fair rock mass conditions. As the JIT design of the tunnel support consists of "acquisition", "interpretation" and "aggregation", the accuracy of the JIT design of the tunnel support can be explained by many aspects, such as the resolution of the acquired data [16] and the accuracy of the interpretation [61] and aggregation [103] algorithms. That's to say, higher-resolution data, as well as more appropriate and accurate interpretation and aggregation methods, tends to improve the performance of the corresponding JIT design of the tunnel support.

(3) Degree of automation

Automation in the support design is composed of many aspects in the "acquisition-interpretation-aggregation" workflow, such as the application of automatic machinery [47], automatic model generation [32], automatic information extraction [17,53,54] and automatic information aggregation [117]. The degree of automation significantly affects the performance of the JIT design of the tunnel support. For instance, one of the primary difficulties in the implementation of discontinuous numerical methods for rock mass is generating discontinuous models [34]. If the model is generated automatically and accurately, the overall computational efficiency shall be greatly improved. Hence, higher degree of automation can, to some extent, improve the performance of the JIT design of the tunnel support.

6.4 Conceptual framework and future perspectives

Considering the time, accuracy and automation requirements of the JIT design of the tunnel support, a conceptual framework for the JIT design of the tunnel support is presented in **Fig.15**. The entire framework considers the pros and cons of each technique used in the "acquisition-interpretation-aggregation" workflow. The left part of **Fig.15** shows the workflow of the "acquisition-interpretation-aggregation", whose relationship with the construction site is presented in the right part.

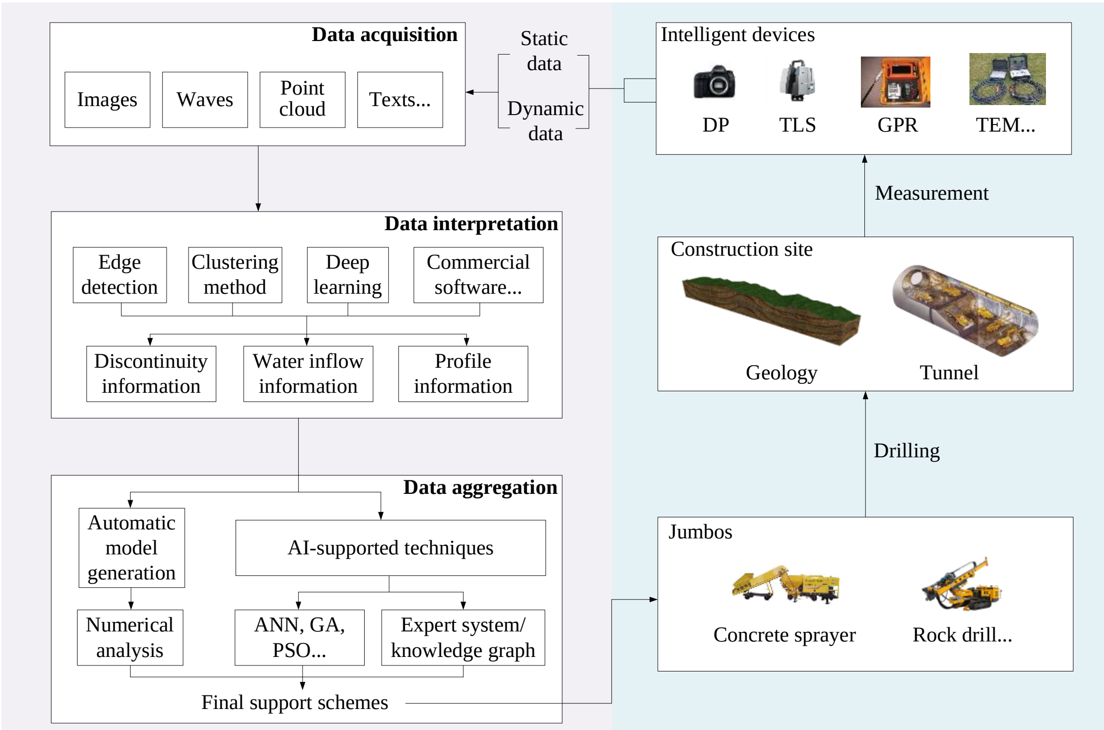


Fig.15 Conceptual framework for JIT design of the tunnel support during rock tunnel construction

Using intelligent acquisition methods such as DP, TLS and GPR, on-site data can be collected in various forms. Then, based on the efficient and accurate methods presented in Section 4, e.g. edge detection and deep learning, the discontinuity, water inflow and profile information can be interpreted. In the third step, the information is used as inputs to automatically generate numerical models or obtain support parameters using AI methods. The final support schemes can be constructed by intelligent jumbos at the construction site. Once again, after the drilling and the measurement, the data on the new tunnel face are collected and a new round of the JIT design of the tunnel support is to be performed. Moreover, the employed techniques and aggregation algorithms in the proposed framework, such as the application of the IoT technique in the rock tunnel construction and performance of the algorithm on construction data, were individually validated in the reviewed studies. Hence, the reviewed studies can be considered as a validation of the proposed framework; thus, they reflect the rationality of the proposed framework.

Regarding the research gaps listed in Subsection 6.2, to accomplish the JIT design of the tunnel support in **Fig.15** with an excellent performance, some possible improvements are needed to remedy the listed limitations.

(1) Adoption of the state-of-the-art deep learning technologies: Our literature review revealed that machine learning and deep learning technologies are particularly successful in tasks associated with the image interpretation as they provide a high accuracy and reasonable computational time [17,31,58,61,80]. Other studies have also demonstrated the effectiveness of deep learning in the interpretation of point cloud data [124]. Hence, regarding the challenge that the interpretation of data in some cases is time-consuming, future researches can explore to use deep learning or other machine learning approaches to accelerate the interpretation of point cloud data.

(2) Automatic generation of numerical models: An important factor affecting the efficiency of numerical simulation is the model generation. Generally, the model is generated manually using multiple pieces of information such as discontinuity information [90,97], which is time-consuming and error-prone. The efficiency can be greatly improved with the automatic generation of the model using certain structural and surrounding rock mass information. In fact, Monsalve et al. [45] used the interpreted information from TLS and generated a discrete fracture network for discontinuous analysis, which indicated that the numerical model could be generated automatically using on-site interpreted information. Further studies are needed to investigate automatic integration of the geological, geotechnical, and hydrological information into numerical models, and improvement of the effectiveness of methods.

(3) Employment of parallel computing and cloud computing: Parallel and cloud computing are the computational methods aiming at improving computational speed to solve complex computing problems. Wang et al. [19,125] used parallelization and cloud computing to solve the problem of contact detection and computational efficiency in 3D DDA, which is considered as one of the most powerful numerical methods. Taking this as an example, further studies can integrate parallel and cloud computing into the "acquisition-interpretation-aggregation" workflow, such as continuous/discontinuous numerical analysis, to improve the computation speed.

(4) Using ANN to directly get optimal support parameters: ANN has been proved to be an effective and powerful tool to model the nonlinear relationship between support parameters and geological information [102,105]. Previous studies using ANN relied on the information that exposed during the preliminary design stage. Hence, the nonlinear relationship between the multi-source information exposed during construction and support parameters can be explored, which can reduce labor cost and improve construction efficiency.

(5) Using ontology to represent knowledge: The structured representation of knowledge forms the basis of knowledge retrieval and reasoning. As an emerging technology, ontology is widely used for knowledge sharing and reuse for its great potential to address the problems related to holistic structural design [126]. Hence, using ontology to represent tunnel design knowledge and design cases can be beneficial for subsequent knowledge retrieval and reasoning. In addition, rule- and case-based reasoning can be conducted to obtain the most appropriate support schemes based on the structured knowledge.

7 Conclusions

This study presents a critical review on the design of the support during rock tunnel construction from three perspectives: acquisition of on-site data, interpretation of raw data and aggregation of interpreted data. The applications of IoT and IT in these three perspectives have been thoroughly reviewed, including the time each technique costs, its strengths and drawbacks, and its contribution to the design of the support. Based on the review results, this study develops a conceptual framework for the JIT design of the tunnel support, where research gaps, key concepts and possibilities of improvement have been identified.

The overall challenges when performing the JIT design of the tunnel support have been discussed. Time consumption, accuracy and degree of automation are three key concepts in the JIT design of the tunnel support. Some appropriate and efficient methods to realize the JIT design of the tunnel support have been highlighted and recommended as follows: DP and TLS approaches for acquisition of tunnel face data, GPR and TEM approaches for acquisition of data in front of the tunnel face, edge detection, clustering and deep learning method for data interpretation, automatic model generation for numerical analysis, and AI-supported techniques for data aggregation.

The adoption of the state-of-the-art AI technologies, such as ANN and deep learning technologies, can significantly improve the efficiency of interpretation and aggregation. Parallel computing and cloud computing are also promising areas that can accelerate the computations involved in interpretation and aggregation. In addition, the ontology technology can be employed in the design of the tunnel support to ease the knowledge representation and reuse, thereby improving the performance of the support design. The proposed framework for the JIT design of the tunnel support is a starting point aiming to lead follow-up researches. The validation of the details in the proposed framework shall be implemented correspondingly in future studies. In addition, the feasibility of the proposed framework should be verified through practical applications in engineering projects. Moreover, this review study contributes to elucidating the current state of the dynamic design of the tunnel support research and providing profound insights into the JIT design of the tunnel support research.

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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