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From TBM to TBR: Perspectives on intelligent shield machine and its smart operation

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Abstract: Advances in intelligent shield machines reflect an evolving trend from traditional tunnel boring machines to tunnel boring robots. This shift aims to address the challenges encountered by the conventional shield machine industry arising from construction environments and manual operations. This study presents a systematic review of intelligent shield machine technology, with a particular emphasis on its smart operation. Firstly, the definition, meaning, contents, and development mode of intelligent shield machines are proposed. The development status of the intelligent shield machine and its smart operation are then presented. After analyzing the operation process of the shield machine, an autonomous operation framework considering both stand-alone and fleet levels is proposed. Challenges and recommendations are given for achieving autonomous operation. This study offers insights into the essence and developmental framework of intelligent shield machines so as to propelling the advancement of this technology.

Key words: Intelligent shield machine; Tunnel boring machine; Intelligent tunneling robot; Self-driving; Autonomous control; Shield machine; TBM; Intelligent TBM

1 Introduction

A shield machine is a large and complex engineering equipment used for tunnel construction. It combines optical, mechanical, electrical, and hydraulic systems, and belongs to the category of full-face tunnel boring machines (TBMs), as depicted in Fig. 1. The shield machine enables automatic and mechanized tunnel excavation, muck removal, and lining operations by cooperative subsystems under the cover of a steel shield. Compared to traditional tunneling methods such as open excavation, cut-and-cover excavation and drilling-and-blasting methods, the shield method has numerous advantages, such as fast tunneling speed, high geological adaptability, high safety, high automation, low labor intensity, and minimal impact on the construction ground. Therefore, it has become the primary method for modern tunnel construction. Over the past few decades, significant development has been achieved in this field. Nevertheless, as modern tunnels progress towards higher efficiency, smart construction, super-large diameter, super-deep burial, and super-long distance, the traditional shield machine industry confronts immense challenges arising from the construction environment and manual operations.

The construction environment of shield machines is highly complex from a geological standpoint. In engineering practice, geological conditions are primarily obtained from the results of geological exploration conducted prior to tunnel construction. The distance between sampling boreholes for exploration can vary from several tens to hundreds of meters, and the geological information between sampling boreholes is highly uncertain. Moreover, the space available for geological detection in front of the shield is extremely limited, making it difficult to obtain precise geological information using conventional geophysical detection

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Fig. 1 Shield machines

methods. These limitations make it difficult to guarantee construction safety and efficiency.

From an operational perspective, the use of a shield machine involves a complex interaction between humans, the machine, and the environment. In the case of a slurry pressure balance (SPB) shield machine, there are dozens of variables that need to be monitored and controlled by the operator. These parameters are not only numerous, but they are also interdependent, making it challenging to adjust each subsystem's parameters. For example, adjusting the advance speed requires consideration of the current thrust force and cutter-head speed, while adjusting the thrust force has to take into account the advance speed and the attitude deviation from the designed tunnel axis. Additionally, the adjustment of the slurry chamber pressure needs consideration of the cutter-head and the advance speed. Consequently, the operator's decision-making process is considerably complicated. This complexity requires operators to undergo extensive training and to accumulate a significant amount of experience in actual projects before becoming qualified. Also, since human operation mainly relies on experience and is subjective, the level of operation proficiency varies from operator to operator. Due to the complexity of the operation, operational errors are prone to occur, some of which may cause serious accidents.

The complexity and uncertainty of the geological environment surrounding shield construction, as well as the intricate human-machine-environment interaction, present significant challenges for ensuring the safe and efficient operation of shield machines. These challenges are manifested in the following aspects:

(1) Insufficient Autonomous Adaptability: Shield tunneling involves severe working conditions such as strong impact loads, a wide working range, and complex and ever-changing geology with a high degree of uncertainty. Shield machines still lack the ability to sense and self-adjust to the environment and working conditions. This limits the further promotion and application of shield construction methods.

(2) Limited Human-Machine Cooperation and Intelligence: The adjustment of operational parameters in shield tunneling still relies heavily on the experience of human operators. Unfortunately, the theory of optimal decision-making and intelligent control of shield machines is not yet mature. As a result, when faced with strata changes or complex geological conditions, it is difficult for human operators to make timely and effective adjustments to operation parameters and control strategies. This lack of cooperation and intelligence results in a slower

tunneling speed and increased safety risks, with similar accidents occurring repeatedly in shield machine construction.

(3) Inadequate Coordination Between Multiple Subsystems: Shields are complex systems that are coupled with multiple subsystems. The mechanisms of these subsystems are complex, and the working performance of the entire machine is often not fully utilized. This lack of coordination between subsystems reduces the efficiency of tunneling, leading to longer construction time and higher costs.

Moreover, the operation of shield machines involves repetitive pattern working cycles that consist of excavation, segment assembly, and grouting. Long-term and high-intensity repetitive tasks can easily lead to personnel fatigue and negatively impact the physical and mental health of operators. As tunneling is often carried out in remote areas far from cities, young people are increasingly hesitant to engage in such work. Additionally, the high cost of training experienced shield operators, the shortage of personnel, and rising labor costs have become common problems in the industry.

These challenges present significant obstacles to expanding the application range, construction speed, construction quality, and safety of shield machines. As a result, there is a growing need for intelligent shield machines that can operate intelligently, adapt to changing geological conditions, and improve construction efficiency and safety. Fortunately, in recent years, computing power has increased significantly, and new sensing technologies continue to emerge. In particular, artificial intelligence and deep learning have made significant strides, and the development of these enabling technologies has paved the way for the emergence and evolution of intelligent shield machines.

Intelligent shield machines are also referred to as unmanned, automated, self-driving, or autonomous shield machines. Recently, several shield machine manufacturers and research teams such as MMC Gamuda Corporation in Malaysia, Shanghai Tunnel Engineering Corporation, and China Railway Engineering Equipment Group have achieved remarkable progress in the field of intelligent shield machines. Several intelligent shield machine functionalities have already undergone engineering validation. In 2019, the Malaysian contractor MMC Gamuda developed a plug-and-play autonomous TBM operating system and deployed it on 10 TBMs manufactured by Herrenknecht of Germany. These advanced TBMs were employed in the construction of Kuala Lumpur's second mass rapid transit line tunnel, spanning 13.5 kilometers. This system possesses the capability to steer the TBM, regulate air bubble pressure, and control its advance speed, among other functions. According to publicly available information (Gamuda, 2022), this system can maintain the TBM's alignment within a remarkable ±20 mm deviation from the designed tunnel axis, surpassing the ±50 mm deviation observed in human-operated TBMs. In 2022, the Shanghai Tunnel Engineering Corporation in China developed an autonomous earth pressure balance (EPB) shield machine named "Zhiyu" (Hu et al., 2022). The Zhiyu shield was successfully utilized in tunnel construction projects within clayed soil sections in China. It has been confirmed that the cumulative ground settlement caused by the Zhiyu shield is remarkably controlled, ranging from −18.66 to −5.92 mm, which is superior to the −27.98 to −8.81 mm observed during human-operated shield machine operations. Undoubtedly, driven by intelligent technology, the new generation of intelligent shield machines are gradually evolving from tunnel boring machines into tunnel boring robots (TBRs) (Zhang et al., 2023).

There are numerous exciting benefits associated with intelligent shield machines. Firstly, they enhance efficiency and productivity by reducing the number of workers required for tunneling operations. These machines can operate autonomously, enabling them to work continuously without breaks or rest periods. Secondly, they contribute to improved safety by minimizing the risk of accidents and injuries to workers. Operating autonomously allows these machines to handle hazardous environments, such as areas with high dust or gas levels, without putting workers at risk. Thirdly, intelligent shield machines enhance the quality of tunneling operations by minimizing potential human errors. Their autonomous operation enables them to perform tasks with exceptional accuracy and precision, leading to higher quality outcomes. Fourthly, they play a role in reducing the cost of tunneling operations by cutting down on labor requirements and increasing overall efficiency. The ability to operate autonomously allows them to work faster and more effectively, resulting in cost savings for tunneling projects. Finally, the development of intelligent shield machines fosters innovation and research in the tunneling and construction field. Significant investments in research and development are required, leading to the emergence of new technologies and innovations applicable to other areas of construction and infrastructure development. Ultimately, the advancement and implementation of intelligent shield machines have the potential to revolutionize the tunneling and construction industry, offering significant advantages in terms of efficiency, safety, quality, cost-effectiveness, and overall innovation.

Meanwhile, it is crucial to acknowledge that the research on intelligent shield machines is still in an early phase. The realization of fully autonomous shield machines remains a significant challenge, necessitating much further research. During the ongoing research and development of intelligent shield machines, various questions have emerged, including the following:

- What is the general definition of an intelligent shield machine?
- What is the current development status of intelligent shield machines?
- How can autonomous operation be achieved?
- What are the primary technical challenges in achieving autonomous operation?

In order to address these questions, this study presents a comprehensive view of the intelligent shield machine, with a particular focus on its smart operation. This study is organized as follows. Section 2 introduces the fundamental aspects of intelligent shield machines, encompassing their definition, meaning, contents, development mode, and current development status. In Section 3, the state-of-the-art smart operation technology is thoroughly reviewed. Section 4 puts forth an autonomous operation framework, considering both standalone and shield machine fleet levels. Section 5 addresses the challenges encountered in achieving autonomous operation and offers relevant research recommendations. Finally, concluding remarks are presented in Section 6.

The latest literature review techniques can provide a comprehensive and in-depth understanding of technological advances within a specific field, and good examples of these methods are demonstrated in the references (Mourtzis, 2020; Mourtzis et al., 2022). However, due to the distinctive characteristics of intelligent shield machines and their status as a recently emerging technology, the literature is scattered across the specific functionalities of these machines. As a result, the literature review part of this study is structured around the fundamental aspects of shield machine intelligence and its smart operation. To comprehensively explore all aspects of research on intelligent shield machines, we began by clustering the literature based on their titles and abstracts. Subsequently, we meticulously fine-tuned the literature classifications through in-depth readings of the full texts.

2 Fundamental issues of intelligent shield machines

Despite their rapid development, there is still no consensus on the definition, goals, content, and methods of achieving intelligent shield machines. This section aims to address the fundamental issues surrounding intelligent shield machines and presents the current development status of the technology.

2.1 Implications of intelligent shield machines

To date, the definition and meaning of intelligent shield machines remain unclear. Additionally, the term "intelligent" has been overused to some extent. To promote the advancement of intelligent shield machines, we propose a definition as follows.

Definition of intelligent shield machines: An intelligent shield machine is a new generation of high-performance tunnel boring apparatus characterized by its utilization of advanced intelligent technology and its high degree of autonomy. These machines integrate sophisticated sensors, automation, and artificial intelligence to independently perform intricate tunneling tasks, all while intelligently adapting to changing geological conditions. The level of intelligence of an intelligent shield machine increases with its degree of autonomy.

This definition encompasses several key elements of intelligent shield machines. Firstly, an intelligent shield machine must be capable of completing tunneling tasks, which include various

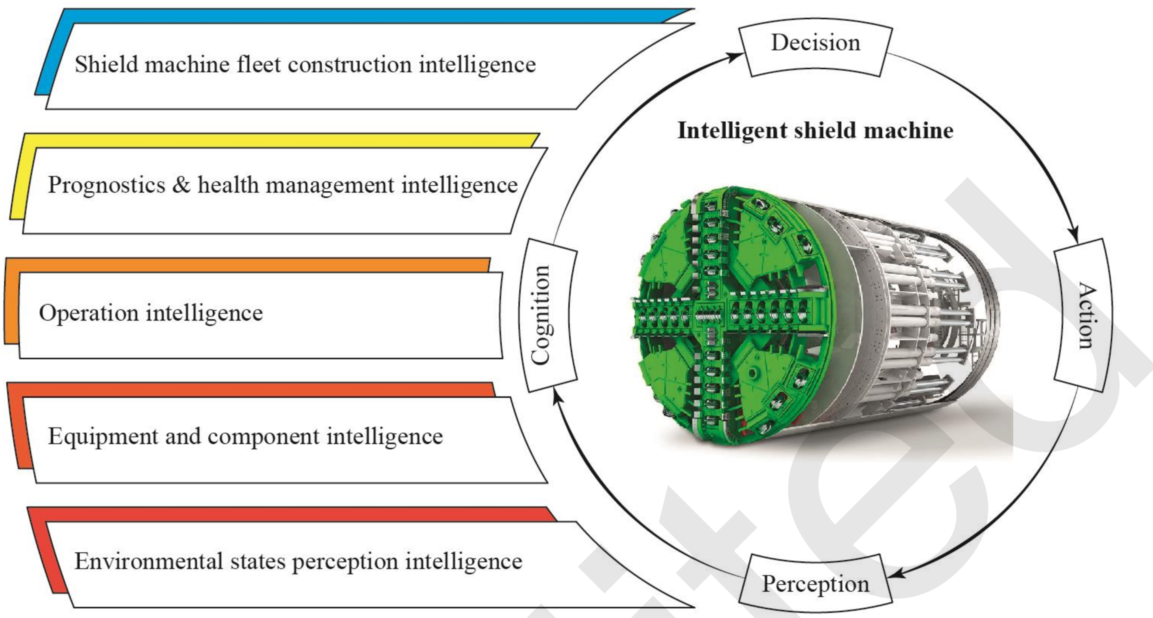


Fig. 2 Contents of shield machine intelligence

sub-tasks such as excavation, supporting pressure balancing on the excavation face, steering, muck removal, lining, condition monitoring, maintenance, and construction management, among others. Secondly, the effectiveness of each task must be evaluated using specific performance metrics. Finally, the definition highlights the importance of the machine's ability to complete tasks with a certain degree of autonomy; the higher the degree of autonomy, the higher the level of intelligence.

Meaning of shield machine intelligence: The meaning of shield machine intelligence, according to the proposed definition of intelligent shield machines, is to enhance the ability of such machines to cope autonomously with uncertainty arising from both the complex geological environment and the machine itself. Additionally, it includes the autonomous completion of tunnel construction operations, minimizing or eliminating the need for human intervention, while ensuring task completion performance.

Compared to existing intelligent ground mobile construction machinery such as excavators (Bradley et al., 1993; Bradley and Seward, 1998; Cui et al., 2022; Eraliev et al., 2022), loaders (Takei et al., 2013; Takei et al., 2015), and tractors (Gonzalez-De-Santos et al., 2020; Sunusi et al., 2020; Shojaei, 2021), shield machines operate underground in a vastly different environment. Intelligent ground mobile construction machinery must navigate dynamically changing environments, avoiding obstacles and even pedestrians that may appear at the construction site. Conversely, the tunnel axis of a shield machine is carefully designed prior to construction and it does not change during excavation. Furthermore, pedestrians are not present in front of the excavation face. The primary environmental uncertainty faced by shield machines is ever-changing complex geological conditions with strong randomness. Therefore, developing dedicated technologies for intelligent shield machines, in addition to the common technologies used for intelligent construction machinery, is crucial.

Contents of shield machine intelligence: Based on the characteristics of shield machines, this paper suggests that shield machine intelligence should encompass at least five aspects: environmental state perception intelligence, equipment and component intelligence, operation intelligence, prognostics and health management intelligence, and shield machine fleet construction intelligence, as shown in Fig. 2. The aim of each aspect should be to increase the degree of autonomy and optimize performance. Different levels of intelligence may be required for each function. Environmental state perception intelligence should include, but not be limited to, geological condition forecasting, geotechnical parameter identification, rock-mechanical parameter mapping and surface subsidence sensing and prediction. Equipment and component intelligence refers to the intelligence of equipment and components such as new types of segment-assembling robots, cutting tool inspection and replacement robots, and intelligent hydraulic components, etc. Operation intelligence aims to assist or replace human operators in controlling basic tunneling processes such as excavation, face pressure balancing, steering, and grouting, etc. Prognostics and health management intelligence should include condition monitoring, fault diagnosis, and predictive maintenance of key components and systems. Shield machine fleet construction intelligence should include, but not be limited to, construction planning and schedule management, construction big data monitoring and storage, and fleet coordination, etc. These aspects may overlap and intersect with each other, and the core of shield machine intelligence is to improve the autonomy of the perception-cognition-decision-action cycle.

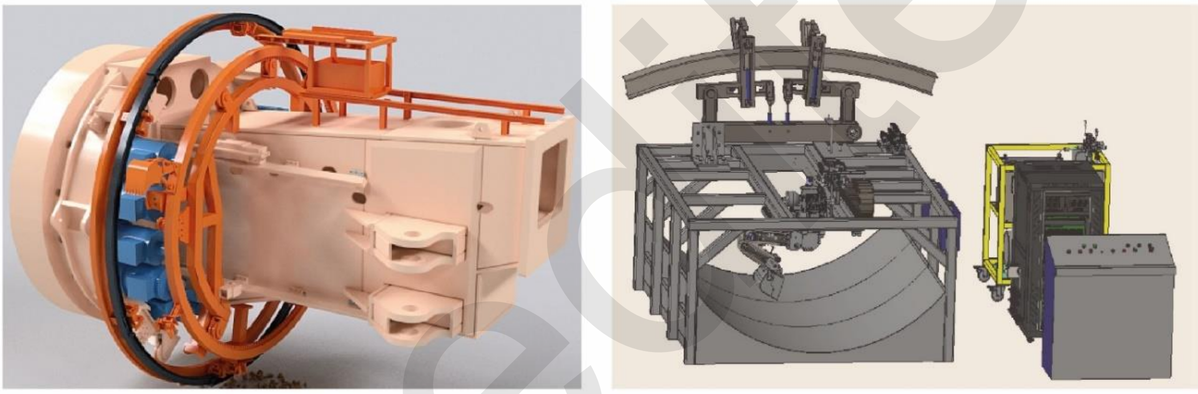
Development modes of intelligent shield machines: The development of intelligent shield machines can be categorized into three modes: teleoperation, semi-autonomy, and full autonomy. In teleoperation, the shield machine is still controlled by human operators, but from a remote location instead of the control cab. Despite appearing unmanned, the machine is fully operated by humans and requires minimal or no operation intelligence for shield machine. However, significant improvements in equipment and component intelligence are needed due to the reduction in the number of people working inside the shield machine. For instance, manual field operation-dependent segment assembly systems need to be upgraded. In semi-autonomous mode, the human operator remains in the cab for control and monitoring, while most of the tasks are performed autonomously by the intelligent shield machine. The human operator only takes control when the machine cannot complete tasks independently or when its operation is deemed unsuitable. In fully autonomous mode, a group of intelligent shield machines can cooperate with each other to complete tunneling tasks independently, without human intervention. From a research perspective, these modes all have great potential, especially the fully autonomous mode. Obviously, achieving full autonomy still requires significant research efforts. We believe the development of intelligent shield machines is evolutionary rather than revolutionary. They evolve from conventional shield machines in a natural way by adding intelligent components to achieve full autonomy. It is worth noting that the above discussion also applies to hard rock TBMs.

2.2 Development status of intelligent shield machines

Although research on intelligent shield machine technology is still in its infancy, it is developing rapidly, and valuable results have already been achieved in various aspects of such machines. In terms of environmental state perception intelligence, Nie et al. (2021) introduced an automated seismic detection system, which is installed on a TBM, enabling rapid imaging of anomalous zones ahead of the tunnel face. Liu et al. (2017; 2018) proposed a novel 3-dimensional observation system for a seismic ahead prospecting method. Li et al. (2017b) proposed integrating the interpretation of collected data to enhance the reliability and accuracy of tunnel ahead prospecting. These works can be considered as sensor-based methods. In recent years, more and more scholars have started to use big data and machine learning methods to achieve forecasting of the geological conditions ahead. For instance, Hu et al. (2023) employed a combination of the k-means and XGBoost algorithms to ascertain the stratum composition of the excavation face, relying on tunnelling parameters. Similarly, Yu et al. (2022) introduced a semi-supervised machine learning framework for the recognition of geological formations on the shield machine tunnel face. Related works can be found in the references (Zhang et al., 2019b; Cheng et al., 2020; Qin et al., 2023a; Xu et al., 2023). However, there is still controversy over whether such methods are effective in engineering. Erharter and Marcher (2021) argued that while machine learning geology ahead prediction models may seem promising at first sight, these forecasts are mostly just delayed and slightly altered versions of the input data, lacking any true predictive value. While Sheil (2021) acknowledged that attempting to forecast geotechnical conditions far ahead of the TBM using TBM operational parameters is likely to be fruitless, that is not due to the incapability of machine learning algorithms to identify this relationship. The reason lies in the fact that such a relationship simply does not exist. Instead, the combination of machine learning forecasting

(a) (b)

Fig. 3 Shield machine cutter inspection and replacement robots: (a) inspection robot, (b) cutter replacement robot



(a) (b)

Fig. 4 TBM steel arch assembly robot operation system: (a) steel arch assembly robot, (b) tunnel bottom muck removal robot

techniques with soil imaging techniques has shown to be a much more promising avenue of research (Schaeffer and Mooney, 2016; Wei et al., 2018). In addition to geological condition forecasting, research efforts have also been focused on surface settlement and surrounding rock deformation. Bouayad and Emeriault (2017) combined the principal component analysis with an adaptive neuro-fuzzy based inference system to model the ground surface settlements induced by EPB shield tunneling while Zhang et al. (2019a) utilized a random forest algorithm to predict tunneling-induced settlement. These studies have laid a strong foundation for realizing environmental state perception intelligence.

In recent years, there has been a rapid development in equipment and component intelligence and various new technologies have emerged, such as cutter replacement robots, segment-assembly robots, and synchronous propulsion and assembly technology. Specifically, replacing the excavation tools for pressurized shields is a highly risky and difficult operation for maintenance personnel. To address this issue, researchers have proposed different robotized cutter replacement methods, such as the 6 degrees-of-freedom (DOF) articulated manipulator with 2 DOF translation stage for cutter replacement (Yuan et al., 2019; Yuan et al., 2020a; Yuan et al., 2020b; Du et al., 2022) and the flexible robot and multi-axis robot developed by Chen (2019) for slurry shield machine cutter wear status detection and robotic cutter replacement operation under pressurized conditions (Fig. 3). Other researchers, such as Zhang et al. (2021a) and Meng et al. (2021), have respectively proposed different types of serial robots and integrated disc cutter designs to simplify the replacement process and facilitate robot operation. In addition to electric drive robots, electro-hydraulic drive robot solutions have also been explored. For instance, Zhu

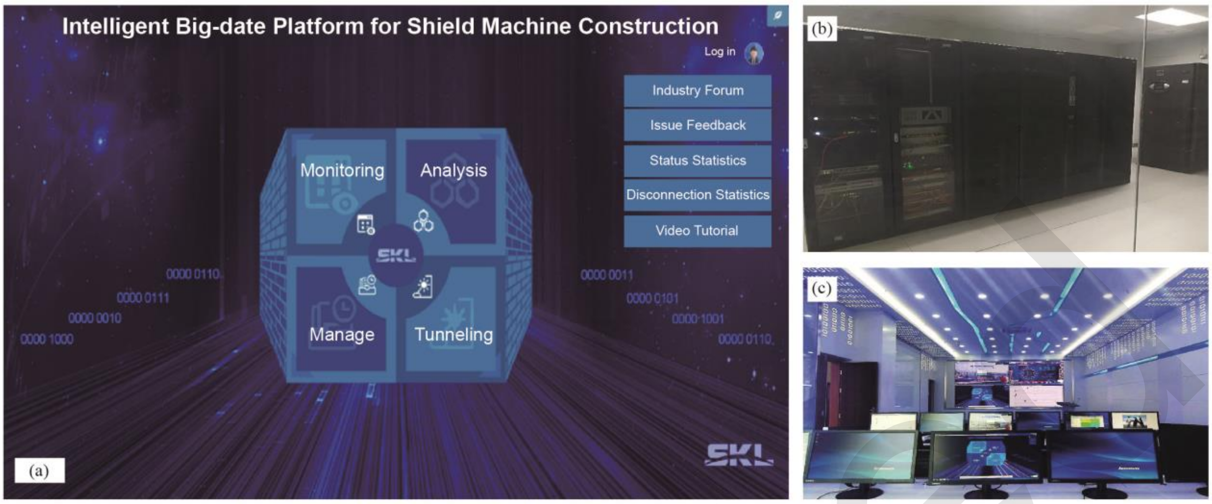


Fig. 5 Big data platform for shield machine construction: (a) platform interface, (b) central computer room, (c) control center

et al. (2022) elaborated a design of an electro-hydrostatic actuator for the disc cutter replacement manipulator. Another breakthrough in equipment and component intelligence is the development of the steel arch assembly robot operation (SAARO) system, led by the China Railway Construction Heavy Industry Group. The SAARO system can realize the intelligent assembly of steel arches with integrated ring/bracing tightening and fast support operation for local collapse and broken surrounding rocks. The system, as shown in Fig.4, consists of a steel arch assembly robot, a steel arch splicing manipulator (He et al., 2022), and a machine vision servo-driven muck removal robot at the bottom of the tunnel (Jiang et al., 2022), which significantly improves the safety and efficiency of TBM construction. Furthermore, the asynchrony between excavation and segment assembly in traditional shield machine construction operations has been a significant hindrance to the construction speed of shield tunneling. To address this problem, researchers have explored synchronous propulsion and assembly methods, such as the continuous shield advance scheme using extruded concrete lining and a steel formwork assembly robot proposed by Braaksma et al. (2006), and the synchronous propulsion and assembly method based on active closed-loop oil pressure control of the shield propulsion system proposed by Zhu et al. (2021). Dai et al. (2022) further analyzed segment interactions and stress concentrations under asymmetric force effects. These works provide valuable exploration in terms of equipment and component intelligence for shield machines.

Extensive research has been conducted in the field of prognostics and health management intelligence, focusing on both the overall shield machine and its key components. Li et al. (2010) developed a back propagation (BP) neural network to identify operational faults such as spewing of the screw conveyer, wear of the disc cutters, and jamming of the shield. Building upon the BP neural network, various methods have been proposed for feature extraction. For instance, Yu and Han (2010) utilized rough set as a feature reduction technique before inputting the data into a BP neural network to diagnose faults in the shield machine, such as motor start failure and clutch overheating. Zhang et al. (2013) and Zou and Liang (2018) respectively combined wavelet packet transforms and self-organizing feature maps with the BP neural network to diagnose construction faults in shield machines. Apart from the BP neural network, Jia and Shi (2014) enhanced the Elman neural network and used it for diagnosing construction faults in the shield machine, including cutterhead caking (also known as clogging), soil occlusion in the pressure chamber, spewing of the screw conveyer, and surface subsidence. In recent years, deep learning techniques have been employed to predict and diagnose construction faults in shield machines. For example, Sun et al. (2019) developed a long short-term memory (LSTM) neural network, while Qin et al. (2023b) proposed a LSTM-autoencoder. These deep learning techniques have shown significant potential in improving the accuracy of construction fault detection.

Additionally, research has been conducted on key components of shield machines, such as disc-cutters (Kui et al., 2016; Ren et al., 2018; Elbaz et al., 2021; Mahmoodzadeh et al., 2021a; Zhou et al., 2023), main bearings (Zhang et al., 2012b; Fu et al., 2022b), and hydraulic systems (Li et al., 2017a). These studies contribute valuable insights into prognostics and health management intelligence for shield machines. It is important to note that most existing fault detection methods are data-driven, and addressing the weak generalization ability and poor interpretability of these methods remains a challenge.

In 2017, the State Key Laboratory of Shield Machine and Boring Technology in China successfully implemented a shield machine construction big data application platform, as depicted in Fig. 5. This platform has been adopted by over 220 shield and TBM projects from more than 30 construction companies across China, as well as ongoing projects in countries such as Israel, Singapore, and Malaysia, etc. It has collected a vast array of engineering information, including geological maps, tunneling parameters, segment attitude, earth subsidence, and more, comprising over 1000 types of data. The total accumulated data has now reached an impressive 200 TB. The platform offers several essential functionalities, including intelligent monitoring, comprehensive analysis, collaborative management, and intelligent application. Users can access real-time operational information and historical data of shields and TBMs through a mobile application. Additionally, the platform provides services like risk alerts, equipment management, comprehensive analysis, decision support, and technical consultations tailored to the specific needs of relevant entities. Furthermore, shield manufacturing companies such as the China Railway Engineering Equipment Group and the China Railway Construction Heavy Industry Group have also successfully established their own shield construction big data platforms. These big data platforms and services lay a solid foundation for conducting analysis on big data and achieving shield machine fleet construction intelligence. In addition, construction management related works, such as tunneling time planning (Vargas et al., 2014), cost estimation and management (Guan et al., 2014; Mahmoodzadeh and Zare, 2016; Mahmoodzadeh et al., 2021b), provide valuable insights in this field.

The current research status in the field of operation intelligence of shield machines will be discussed in detail in Section 3. In summary, significant advances have been made in the field of intelligent shield machines. However, it is important to acknowledge that the development of intelligent shield machines is still in its early stages. The existing research has achieved only a limited level of autonomy, implying a relatively low degree of intelligence. There is still tremendous potential for the future development of intelligent shield machines. As technology continues to progress and research expands, we can expect significant advances in terms of autonomy and intelligence. With further innovation and refinement, intelligent shield machines have the potential to revolutionize the construction industry by enhancing efficiency, accuracy, and safety.

3 State-of-the-art of smart operation

Operation intelligence, also known as smart operation, aims to replace or assist human operators in basic operation and control tasks of shield machines such as pressure balancing, excavation, and steering. Smart operation is the core of completing tunneling tasks in response to geological uncertainties. Therefore, researching key technologies for smart operation is of significant importance among all aspects of shield machine intelligence.

3.1 Intelligent pressure balance control on the excavation face

Pressure balance control on the excavation face is a crucial technology for ensuring the safety of shield machine construction. This is because pressure balance control has a direct impact on surface subsidence. Unbalanced pressure on the excavation face can result in severe damage to buildings on the surface and pose a threat to personnel. When the ambient soil and water pressure exceeds the pressure in the shield excavation chamber, surface collapse accidents can occur. Conversely, when the ambient soil and water pressure is less than the sealing chamber pressure, surface uplift (for EPB shields) or slurry blowout through the surface (for SPB shields) accidents may occur. Manual pressure balance control on the excavation face is considered not reliable or effective enough. Therefore, researchers have been working on automating the process of pressure balance control to

Fig. 6 Ø2.5m multi-purpose test rig for slurry shield machine: (a) overview of the test rig, (b) slurry processing, (c) hydraulic system for loading, (d) hydraulic system for driving

replace manual operation.

Kuwahara et al. (1988) developed a fuzzy controller to automate earth chamber pressure control for EPB shields by imitating skilled driver operations. Yeh (1997) used a BP neural network to automatically control earth chamber pressure and the simulation results show that the system is a feasible one. Liu et al. (2011) established a least-squares support vector machine prediction model for setting the pressure of the excavation chamber, which outperformed the BP neural network through simulation comparison. Li et al. (2009a) controlled the EPB pressure by optimizing the angular velocity of the screw conveyor. Yang et al. (2009) established a theoretical model of excavation chamber pressure through theoretical analysis and developed a thrust system and screw conveyor electro-hydraulic control system using proportional integral derivative (PID) controllers. The system's performance was validated under constant reference input on a test rig. Xie et al. (2016) developed an adaptive robust controller for the thrust hydraulic system to realize instantaneous regulation of the excavation chamber pressure. Shao and Lan (2014) proposed a method for evaluating the stability of the excavation face based on the normal vector angle of the center of the pressure field of the excavation chamber. Based on this, they adopted a particle swarm algorithm to develop a solution method for the optimal screw conveyor speed to ensure the stability of the excavation face. Liu and Zhang (2018) developed a least squares support vector machine model-based multiple-variable predictive control strategy to control the screw conveyor speed and advance speed simultaneously. To further address the problem of synchronous optimization control of multiple subsystems of the shield machine, they also proposed an adaptive dynamic programming-based method (Liu et al., 2020) to control the excavation chamber pressure.

For SPB shields, several studies have focused on the stability mechanism and condition of the excavation face under different geological conditions. Li et al. (2009b) investigated the face stability of a large slurry shield-driven tunnel in soft clay. Lu et al. (2021) proposed a centrifugal model test to study the face failure model and limit support pressure of slurry shield tunnels in mixed ground. Jin et al. (2022) conducted geotechnical analysis on the face stability of the slurry shield machine in water-bearing ground. Related works can be found in the references (Zhang et al., 2018; Ling et al., 2021; Shang et al., 2023). In terms of intelligent control, Song (2011) proposed a fuzzy logic-based pressure balance control scheme that uses a fuzzy PID controller to achieve constant value control for air chamber pressure and a feed-forward PID controller to control the slurry feeding flow. However, this system can only achieve semi-automatic control of the SPB process as the supporting pressure still needs to be set manually. Zhou et al. (2013) developed an empirical engineering model for the maximum and minimum setting values of the air chamber pressure and proposed a predictive control system using an Elman neural network model to replace the manual setting of the air chamber pressure value. Li and Gong (2019) proposed a predictive control scheme for slurry pressure balance using a diagonal recurrent neural network and evolved particle swarm optimization. Wang et al. (2021) used a LSTM neural network to predict the slurry pressure in the excavation chamber with instantaneous tunneling parameters and the geological data. In addition to indirect-type slurry shields, Li et al. (2015) established a pressure balance dynamic model for the direct-type shield machine and proposed a predictive function controller.

These works have made significant contributions in the area of intelligent supporting pressure balance control for shield machines. However, the level of autonomy achieved by these methods is not yet satisfactory. For both EPB and SPB shield machines, pressure control in the excavation chamber is a multi-input process that requires the coordination of multiple subsystems. Most existing research can only achieve partial automation of one subsystem, while manual operation of other subsystems is still required. This limits the degree of autonomy that can be achieved. Furthermore, little is known about the coupling mechanism of multiple systems for pressure balance on the excavation face. To address these issues, our research team proposed a cyber-physical-system-based hierarchical autonomous supporting pressure balance control scheme for SPB shields (Zhang et al., 2020). In this work, the mechanism of multi-system coupling interactions in the SPB process is revealed by establishing a state space model and conducting a singular value decomposition analysis. The control system is divided into two layers: the coordination layer and the execution layer. The coordination layer is responsible for decision-making at the upper level, while the execution layer handles the closed-loop control of the actuator at the lower level. The system is capable of autonomously and simultaneously controlling the inflow and outflow rates of the slurry pumps as well as the pressure in the air chamber, without the need for human intervention. By analyzing field big data and comparing the system's performance with that of the human operator, it was demonstrated that the accuracy of SPB control improved by 64.76%. To further validate the performance of the system, we have built a Ø2.5m multi-purpose test rig for slurry shield machine, as shown in Fig. 6. The test rig comprises several subsystems, including a load simulation system, a simulated shield system, a slurry circulation system, a slurry processing system, hydraulic systems, and an electric control system. This setup enables various experimental tests such as pressure balance control, slurry circulation, slurry separation, and electro-hydraulic control. The experiments are currently underway, and we anticipate that this technology will be applied in actual shield tunneling construction in the near future.

3.2 Intelligent decision-making and performance optimization

Excavation is the primary task of shield machines. Dealing with changes in complex geological environments, making intelligent decisions regarding operational parameters of the subsystems, and optimizing shield tunneling performance are key issues for shield operation intelligence.

Current research on intelligent decision-making and performance optimization of shield operational parameters can be broadly classified into two main groups: supervised machine learning-based methods and optimization-based methods. The first group uses supervised machine learning or deep learning techniques to determine the operational parameters under various working conditions. Extensive studies have been conducted to predict key performance metrics of shield tunneling, including advance rate (Elbaz et al., 2019; Mokhtari et al., 2020; Wang et al., 2020; Lin et al., 2021; Fu et al., 2022a; Lin et al., 2023b), thrust force (Hasanpour et al., 2018; Kong et al., 2022; Lin et al., 2022), cutter-head torque (Hong et al., 2021; Qin et al., 2021; Shi et al., 2021), energy consumption (Zhang et al., 2012a; Elbaz et al., 2022; Zhou et al., 2022), and face pressure (Bai et al., 2021), among others. Additionally, Zhou et al. (2018) proposed a novel approach to assess the geological risk level by employing a complex network modeling methodology, which introduces a fresh perspective to the field. Shahrour and Zhang (2021) proposed some recommendations for the efficient application of soft computing methods in TBM performance prediction with a focus on the selection of the soft computing technique, input parameters, and optimal soft computing architecture.

While supervised machine learning-based methods aim to replicate human operation by analyzing construction field data, there is limited discussion of how the predicted information can be effectively used to enhance decision-making and control of the shield operational parameters for performance improvement. One significant limitation of these methods is their inherent dependence upon a sufficient accumulation of data. This makes them unsuitable for the initial stages of tunnel construction. Another notable drawback is their reliance on supervised labels, as they essentially learn from the experiences of human operators. Although these methods can approach human performance, surpassing it proves challenging. Furthermore, these methods encounter the same challenge as other supervised learning approaches, namely limited generalization capabilities. Despite these limitations, using supervised learning for accurate prediction of shield performance metrics still holds significant potential for the detection of shield anomalies, modeling of the shield-environment interaction, and intelligent control of the shield operational parameters, etc.

To further improve tunneling performance, the second group of research involves optimization methods. Xu et al. (2022) used the energy entropy method to identify the optimal disc cutter spacing. Through experimental investigation, Zhang et al. (2021b) recommended the optimal cutting tool alloy hardness interval for dense fine silty sand ground. Wang et al. (2018a) developed a multidisciplinary optimization method based on reliability to determine the major structural and operational parameters of the TBM. Sun et al. (2018) employed a collaborative optimization architecture to find the optimal design parameters of a hard rock TBM that minimize the construction period. Lin et al. (2023a) proposed a robust optimization method supported by an interactive and explainable AI system to optimize the layout of newly constructed tunnels. These works provided valuable insights into optimizing tunneling performance, particularly during the TBM design phase.

Once the design parameters are determined, the tunneling performance of a shield machine depends on the selection of operational parameters for different geological conditions. Faramarzi et al. (2020) employed the discrete element method to analyze the optimal cutterhead torque and thrust force. Zhang et al. (2012a) optimized the energy consumption of shield machines using a combined mechanical and regression analysis. These studies primarily focus on the single-objective optimization of shield tunneling performance. However, as a complex engineering system, the tunneling performance of a shield machine often involves multiple conflicting optimization objectives. To address the multi-objective optimization problem in shield tunneling, scholars have conducted extensive research. Wang et al. (2023) proposed an improved loss function-based artificial neural network combined with quantum particle swarm optimization to increase the penetration rate and, simultaneously, reduce the rock-breaking specific energy. In recent years, the nondominated sorting genetic algorithm (NSGA-II) has been introduced to solve the multi-objective shield performance optimization problem and obtain decision-making solutions. In NSGA-II-based methods, machine learning models are frequently used to predict objective performances. For instance, Liu et al. (2022) selected advance rate and surface settlement as objectives and combined a grey wolf optimizer-generalized regression neural network model with the NSGA-II algorithm to obtain optimal operational parameters. These parameters include total thrust force, rotational speed of the cutterhead, torque of the cutterhead, grout amount, and pressure. Feng et al. (2022) integrated a support vector machine model with the NSGA-II algorithm to optimize surface settlement and cutter wear.

However, these methods are based on static optimization, which can only optimize immediate performance metrics under specific conditions. They are difficult to adapt to changing geological conditions in real-time or to optimize long-term performance. In terms of completing an overall tunneling project, the long-term comprehensive tunneling performance holds greater significance than immediate performance. For instance, the cumulative energy consumption and average tunneling speed over a specific period provide a more accurate reflection of the shield tunneling performance compared to the energy consumption and tunneling speed at a particular moment. To address these issues, deep reinforcement learning (DRL) has received increasing attention from researchers. Elbaz et al. (2023) integrated the deep-Q learning algorithm and particle swarm optimization to predict thrust force and torque. Zhang et al. (2022) proposed an autonomous optimal excavation method based on DRL, where a DRL agent determines the optimal operating action sequence trajectory for a shield machine. This approach not only has the potential to replace human operation but has also proven effective in improving long-term comprehensive excavation performance.

3.3 Intelligent attitude control and trajectory correction

The quality of tunnel construction is directly impacted by the amount of deviation of the shield excavation axis from the designed tunnel axis. Misalignment of shield excavation axis is a challenging problem and is due to uneven geological load, shield center deviation, segment assembly errors, and improper selection of operational parameters. The complexity of geological loads and the shield's characteristics, such as large inertia, non-linearity, and time-delay, make it difficult to correct trajectory deviation. Manual control is limited by human experience and perception, leading to lag and difficulty in correcting deviation. Severe serpentine motions are a common phenomenon for shield machines. The current method for trajectory correction is based on deviation information provided by the laser guidance system, and human operators adjust pressure levels in the thrust cylinder groups to correct the trajectory. However, this system has a low autonomy level since human operators have full control. To overcome the shortcomings of human operation and improve the accuracy of the shield excavation trajectory, researchers have conducted numerous studies on intelligent control of shield attitude and trajectory correction.

The shield thrust system operates as a parallel mechanism. Shield attitude control and trajectory correction encompass various elements, including trajectory planning at the upper-level, actuator control at the lower-level, as well as the underlying forward and inverse kinematics and dynamics. Literature in this field can be structured and organized based on these perspectives.

Kuwahara et al. (1988) attempted to replace manual operation with fuzzy control to control the shield attitude, with industrial trials also being conducted. Guo et al. (2012) developed a trajectory correction decision method based on support vector data description. Huang et al. (2022) combined the grid method with multi-layer perception to control the tunneling posture of the shield machine. These studies mainly focused on the upper-level decision-making, with no consideration given to the control and execution errors of the thrust cylinders at the lower level.

In terms of lower-level actuator control, Yue et al. (2011; 2012) established a shield load model based on theoretical analysis and the load observer method and developed a sliding mode robust controller for thrust force of cylinder groups to improve the disturbance rejection capability of the actuators. Wang et al. (2018b) established constraint equations of the thrust mechanism workspace and proposed two types of automatic control systems for attitude and trajectory tracking. These studies mainly focused on the robust control of the thrust cylinder at the lower level to accurately execute the upper-level correction commands as much as possible under the disturbance of the environmental load.

Autonomous control requires equal attention to both upper-level planning and lower-level actuator execution. Ineffective correction commands at the upper level can hinder effective deviation correction, even with precise lower-level execution. Similarly, large execution errors at the lower level can prevent satisfactory correction, even with accurate upper-level commands. To address this, some researchers have begun to combine upper-level decision-making with lower-level control. For example, Xie et al. (2012) developed an automatic trajectory tracking control system for shield machines by combining deviation correction trajectory planning with thrust cylinder control.

Research on the theoretical model of geological loads for shield machines is usually conducted in the fields of civil engineering and mechanics, while studies on attitude control are carried out in the disciplines of mechanical engineering and control. However, it should be noted that the accuracy of shield attitude regulation is determined by a combination of load, actuation control, and deviation correction parameter planning. Despite this, due to the complexity of geological loads and disciplinary barriers, it has been a significant challenge for the industry to establish accurate shield-environment dynamic interaction models, and that hinders the development of intelligent control of shield attitude and trajectory deviation correction. Recently, with the advances in artificial intelligence, machine learning, and especially deep learning, new opportunities have emerged for establishing accurate mappings from operating and geological parameters to trajectory deviations. For instance, Zhou et al. (2019) developed a shield machine attitude hybrid deep learning prediction model based on convolutional neural network and recurrent neural network. Shen et al. (2022) incorporated a wavelet transform into the LSTM to achieve real-time prediction of shield moving trajectory during tunneling. Xiao et al. (2021) compared the performance of various artificial intelligence methods on the prediction of shield machine attitude. It can be observed that an attitude prediction model can be used in both the upper-level decision-making and shield-environment dynamic interaction modeling. A shield-environment dynamic interaction model can be considered as a sub-set of the upper-level decision-making methods.

Previous studies have covered various aspects of intelligent control technology for shield machine attitude and trajectory correction, including upper-level decision-making, lower-level actuator control, and shield-environment dynamic interaction models, which have the potential to achieve autonomous control. Meanwhile, it should also be noticed that most of the existing research is theoretical and simulation-based and lacks experimental verification and industrial application.

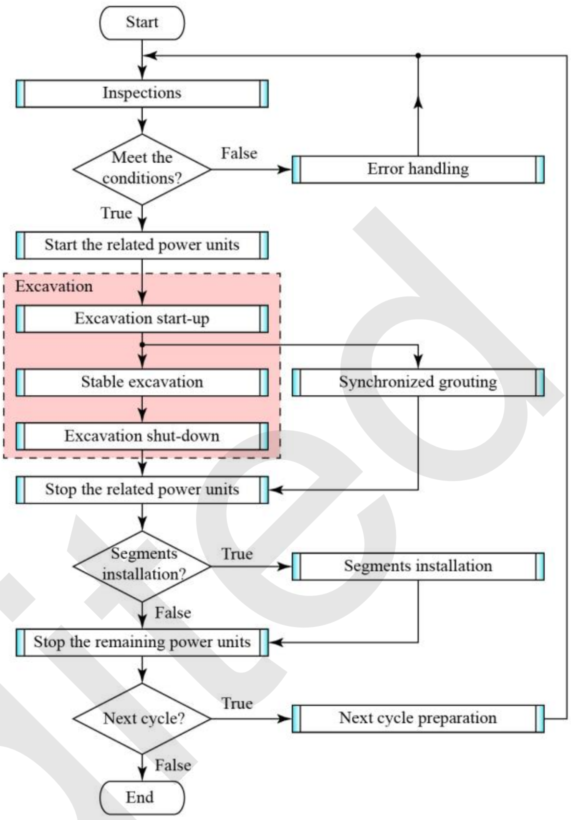


Fig. 7 The overall tunneling process flow of a shield machine

4 Autonomous operation framework

From the preceding sections, it is evident that autonomous operation is the development direction and long-term goal of smart operation of shield machines. To date, an overall technical framework for the autonomous operation of shield machines has not yet been established. The lack of a technical framework leads to fragmentation of research activities, making it difficult to form a full-featured smart operation system. The architecture design of an autonomous operation system can be divided into stand-alone level and shield machine fleet level, which will be discussed in detail in this section.

The stand-alone level autonomous operation architecture is suitable for implementing autonomous operation on a single shield machine. Shield machines are large and complex systems that follow specific sequences or flow of execution during their operations, similar to a factory assembly line. The overall tunneling process flow of a shield machine mainly consists of inspections, starting the power unit, ex-

Table 1 Inspection items for EPB shield machines before start-up

No.	Inspection items	No.	Inspection items
1	Extension water pipes and cables connections are normal	8	Oil level of the grease injection system is normal
2	Power supply is normal	9	Foaming agent level is normal
3	Circulating water pressure is normal	10	Grouting system is ready
4	Filters are normal	11	Back-up track is normal
5	Belt conveyor is normal	12	Muck removal system is ready
6	Air compressor is operating normally	13	Operation panel is normal
7	Tank oil level is normal	14	Guidance system is functioning

cavation, synchronized grouting, segment assembly, stopping the power unit, and preparing for the next cycle, as shown in Fig. 7. The boxes with double vertical line borders in Fig. 7 represent sub-processes, signifying that they possess distinct execution flows of their own. While the tunneling process flow is depicted in the form of a program flowchart in Fig. 7, it is crucial to recognize that in present engineering practice, these process flows are only partially automated. The operator's role remains vital in controlling the execution flow throughout the process. Additionally, integrating smart operation technology into shield machines should be considered alongside the relevant process flows to maximize the potential of the existing technological foundation. Through a detailed analysis of each process and its sub-processes, it is possible to identify the areas where smart operation technology can be applied to optimize the shield machine's performance.

The tunneling process of a shield machine begins with the "inspections" subroutine, as depicted in Fig. 7. After the inspection procedure, the flow of execution proceeds to a decision block to determine if all boot conditions for the shield machine have been met. If not, the flow of execution goes to the "Error handling" subroutine, which handles the error and returns to the "Inspections" subroutine to check the boot conditions again. If all boot conditions are met, the flow of execution proceeds to the "Start the related power units" subroutine to start the power units sequentially. The excavation process follows, which requires the most significant level of intelligence and is marked in red in Fig. 7. Considering its complexity, the excavation process can be further divided into three sub-processes: excavation start-up, stable excavation, and excavation shut-down. After the excavation process is started up, the flow of execution proceeds to stable excavation and synchronized grouting simultaneously. After the excavation process is shut down, the related power units are stopped by the corresponding subroutine. If the segment assembly process is confirmed, the flow of execution enters the "segments assembly" subroutine. Otherwise, the flow of execution enters the "stop the remaining power units" subroutine. If the excavation of the next cycle is confirmed, the flow of execution enters the next cycle preparation subroutine, and then returns to the inspection subroutine. Otherwise, the tunneling process is ended.

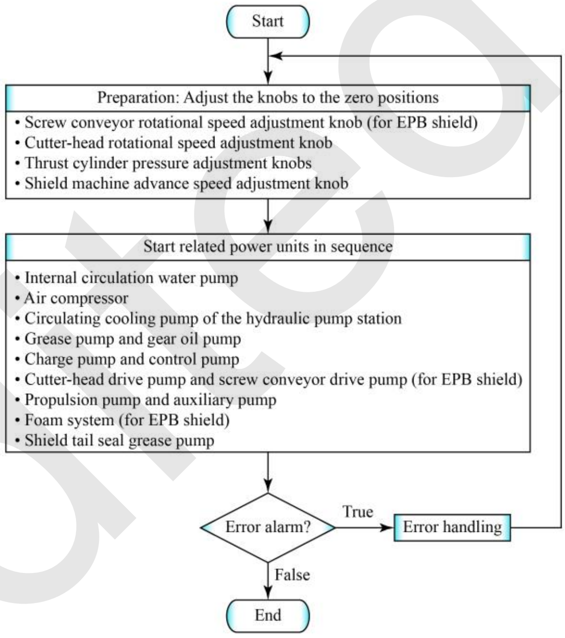


Fig. 8 Flowchart of the "start the related power units" subroutine

Table 1 illustrates the inspection items required for EPB shield machines prior to start-up. Some inspection items can be easily automated, while others require further innovation for automated inspections. For example, computer vision-based methods (Hamledari et al., 2017; Da Costa et al., 2020; Dong and Catbas, 2020) can be used to inspect the state of the belt conveyor, while mobile robots (Yu et al., 2007; Lu et al., 2017; Sutter et al., 2018) can aid in inspecting the extension water pipes and cable connections.

The flowchart in Fig. 8 shows the process of

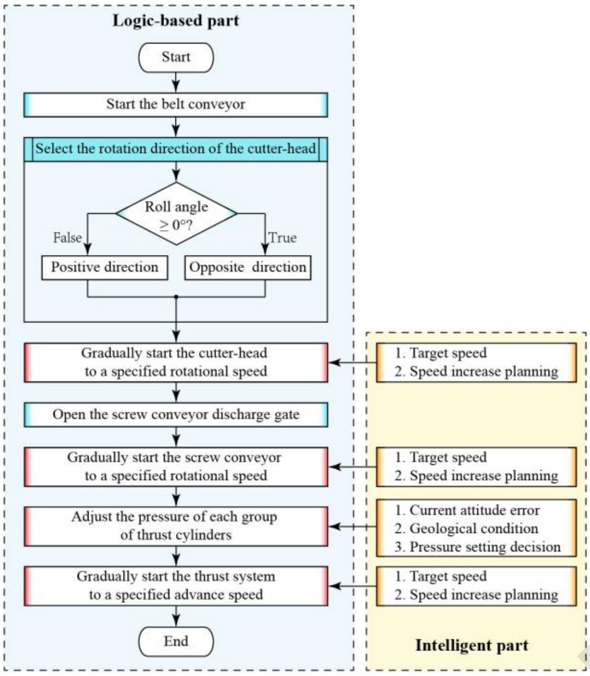


Fig. 9 Excavation start-up routine of the EPB shield machine

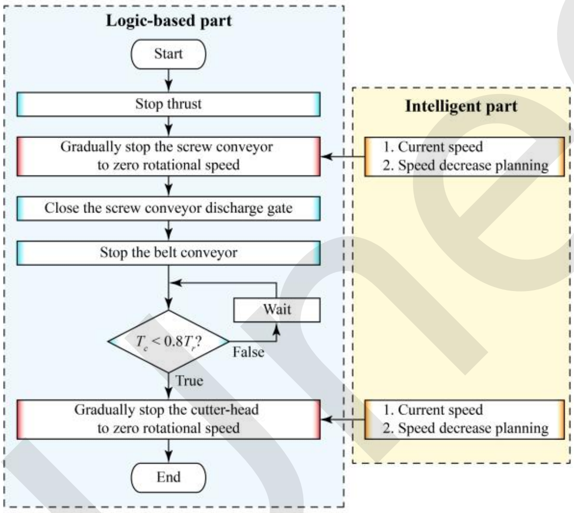


Fig. 10 Excavation shut-down routine of the EPB shield machine

starting the related power units. It can be observed that this process does not require much human intervention and can be easily fully automated by using programmable logic controllers (PLCs). The operation of the conventional "excavation start-up" sub-process is completed using a combination of process logic and intelligence, as depicted in Fig. 9. The blue shaded area in Fig.9 represents the logic-based process followed by the human operator. While the yellow marked area represents intelligent

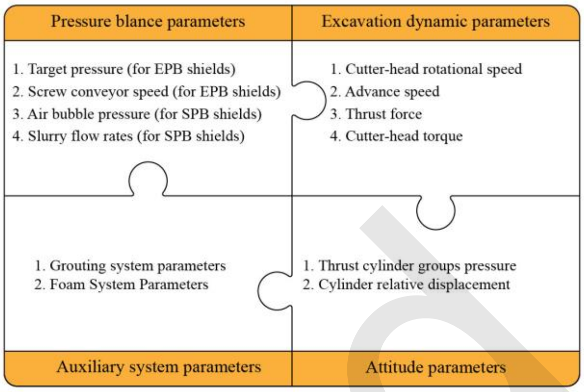


Fig. 11 Four groups of parameters involved in the stable excavation operation

modules to realize automated smart operation. It can be expected that the execution sequence and adjustment of digital quantities can be easily automated. By contrast, processes that require decision-making or continuous adjustment of analog quantities require intelligence, as outlined in the boxes with red borders. These tasks are completed by human operators in current engineering practice, and they can be automated using intelligent modules. At the beginning of the excavation start-up phase, the cutter-head rotational speed, screw conveyor rotational speed, and advance speed are all zero. The excavation start process requires gradually increasing these speeds to reach their respective target values. By providing the corresponding target speed and speed increase planning, the intelligent start operation of the cutter-head, screw conveyor, and thrust system can be achieved. The target speed can be obtained using machine learning, statistics from historical construction field data, or human experience. Once the initial and target speed values are known, various planning strategies, such as third-order and fifth-order polynomial trajectory planning methods, can be used to plan the speed increase trajectory. Adjusting the pressure of each group of thrust cylinders is a more complex process, involving guiding and deviation correction strategies. However, this process can also be automated by providing the current deviation and geological data and making decisions on the pressure level and relative displacement of the thrust cylinder groups, as described in Section 3.3. The flowchart for the "excavation shut-down" sub-process is illustrated in Fig. 10. The excavation shut-down process requires gradually reducing the speed of the screw conveyor and cutter-head rotation until they reach zero. Thus, it

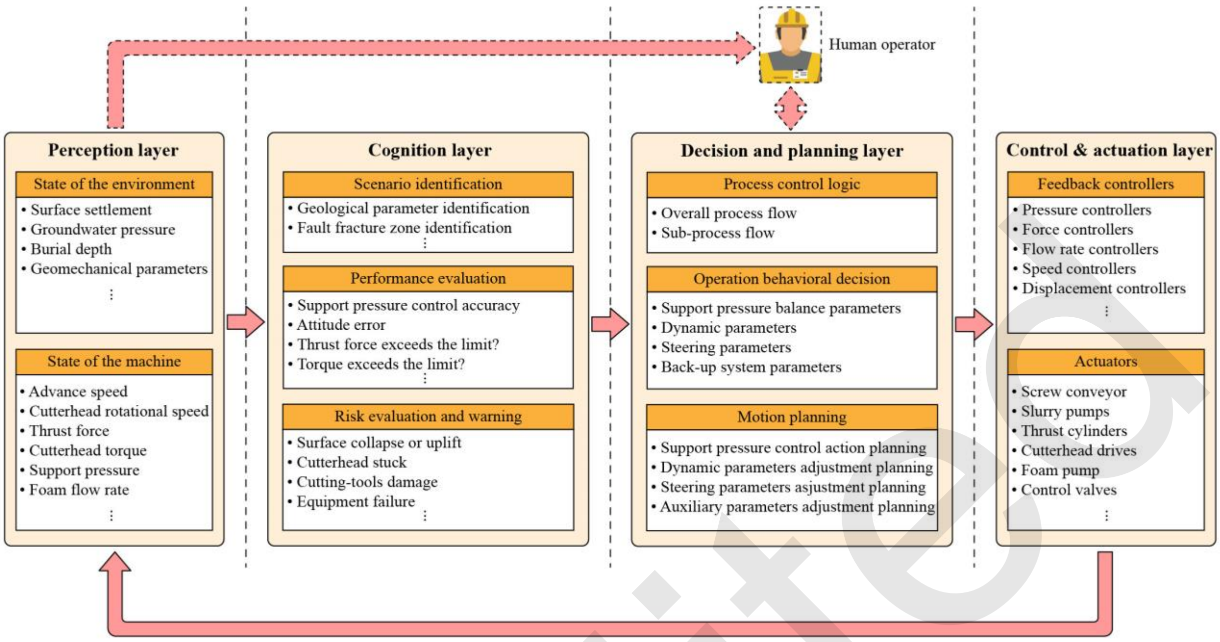


Fig. 12 Stand-alone-level autonomous operation architecture

can be automated using similar methods as the excavation start-up process.

The stable excavation process involves a significant amount of decision-making and continuous adjustment of analog quantities, with very few fixed reference operating procedures. Therefore, the stable excavation process requires a significant amount of intelligence. It is the most challenging part of smart operation. In current engineering practice, the stable excavation process still relies on manual operation. Through analyzing the operation process of a shield operator, the stable excavation operation can be broken down into the adjustment of four groups of parameters. These four groups of parameters are coupled to each other, and they include face support pressure balance parameters, excavation dynamic parameters, attitude parameters, and auxiliary system parameters, as shown in Fig. 11. Specifically, when it comes to EPB shield machines, the pressure balance parameters primarily consist of the target earth pressure and screw conveyor speed. On the other hand, for SPB shield machines, the pressure balance parameters mainly involve the air chamber pressure and the slurry flow rates. Excavation dynamic parameters mainly encompass cutter-head rotational speed, advance speed, thrust force, and cutter-head torque. The attitude parameters primarily involve the pressure of thrust cylinder groups and the relative displacement of the cylinders. Lastly, the auxiliary system parameters mainly comprise the parameters of the grouting and foam systems. These four groups of parameters can be individually set by different intelligent modules.

The processes related to “stop power units” can be readily automated using PLCs. On the other hand, the tasks involving “segment installation” and “next cycle preparation” are typically not shield machine operator dependent. However, automating them requires a substantial level of equipment and component intelligence, as described in Section 2.

Based on the analysis conducted, we propose a system architecture for the autonomous operation of intelligent shield machines at the stand-alone level. As illustrated in Fig. 12, the system architecture consists of four subsystems: the perception layer, the cognitive layer, the decision and planning layer, and the control and actuation layer. The perception layer serves as the foundation of the autonomous operation system and is responsible for gathering information about the shield machine and the geological environment using various sensors and measurement technologies. The information obtained includes the shield machine's advance speed, cutterhead rotational speed, thrust force, cutterhead torque, and support pressure, as well as the state of the environment, such as surface settlement, geological category, pressure of the ground and water, burial depth, and geomechanical parameters.

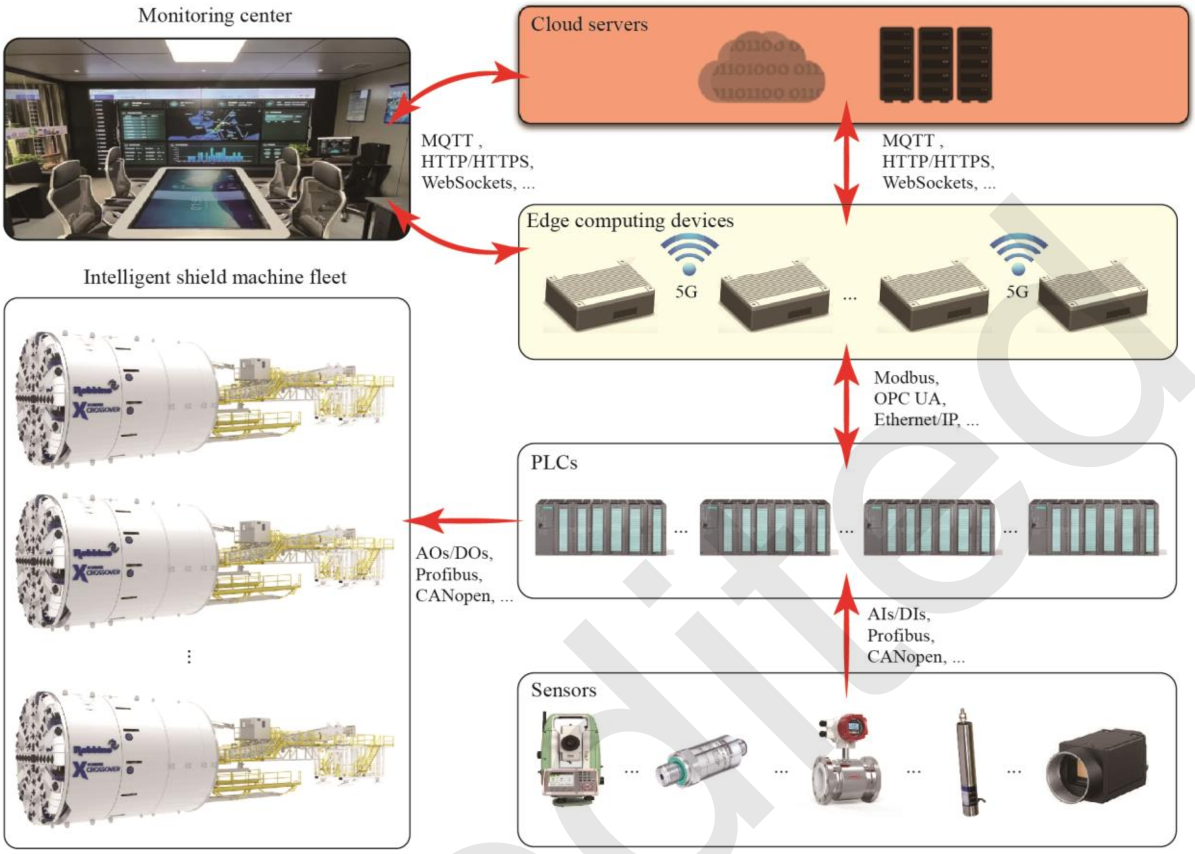


Fig. 13 Shield machine fleet level autonomous operation architecture

The cognitive layer processes the information gathered by the perception layer and uses it to form a comprehensive understanding of the current tunneling situation. This layer consists of three modules: scenario identification, performance evaluation, and risk evaluation and warning. The scenario identification module identifies geological parameters and high-risk special geology to form a basic judgment on the excavation strategy. The performance evaluation module evaluates the current excavation performance, which serves as the basis for forming the operation behavioral decision. The risk evaluation and warning module assesses various risks, such as surface collapse or uplift, cutterhead stuck, and cutting-tool damage, and modifies the operation parameters accordingly.

The decision and planning layer is the key system of the autonomous operation system, and it is responsible for making operation behavioral decisions. This layer comprises three modules: process control logic, operation behavioral decision, and motion planning. The process control logic module determines which step of the current operation is in the overall and sub-process flow and keeps all operations within the process logic. The operation behavioral decision module determines reasonable behavior of the four main groups of operation parameters of the shield machine according to the information transmitted by the cognitive layer. The motion planning module plans smooth change trajectories of the operation parameters based on the operation behavior commands and the current perception information and sends them to the control layer for execution.

Finally, the control and actuation layer accurately executes the operation instructions of the decision and planning layer. This layer is divided into feedback controllers and actuators modules. The feedback controllers module converts the trajectories of the operation parameters generated by the motion planning module into specific instructions that each actuator can execute. These instructions are sent to each actuator of the actuators module through the output ports of the PLC to complete the excavation of the shield. By using feedback closed-loop control in the feedback controllers module, the system can overcome the influence of disturbances and obtain expected operation parameter values more accurately.

The red arrows in Fig. 12 represent the direction of information flow. Starting from the perception layer, passing through the cognition layer, decision and planning layer, and control and actuation layer, and finally returning to the perception layer. This closed loop of information represents fully autonomous excavation. The red arrows with dashed boundaries in Fig. 12 represent optional directions of information flow. This flow direction begins from the perception layer to the human operator, then to the decision layer, forming a loop that represents human-assisted operation. By developing the diverse intelligent modules within each layer illustrated in Fig. 12, a comprehensive autonomous operation system for a stand-alone shield machine can be established.

For shield machine fleet level, we propose a coordinated "cloud-edge-device" autonomous operation architecture, as shown in Fig. 13. In this architecture, the cloud severs are responsible for tasks like model training and updating, data storage and analysis, and shield machine fleet coordination control and scheduling. The edge computing devices handle the deployment of the stand-alone level autonomous operation system and realize information exchange between shield machines. The device side consists of PLCs, sensors, and the intelligent shield machine fleet, which are tasked with completing tunneling operations, information acquisition and transmission functions. Lastly, a monitoring center can be employed to manage and monitor the tunneling process of the intelligent shield machine fleet. The communication protocols between various components are also depicted in Fig. 13. It's important to emphasize that, based on the specific requirements of the application and the hardware in use, these communication protocols may vary. Moreover, it's essential to acknowledge that the available communication protocols may not be distinct; generally, multiple options exist to achieve a particular technical objective.

5 Challenges and recommendations

While intelligent shield machine technology and its smart operation have seen rapid advancements, there are still several persistent challenges. Addressing these issues will significantly enhance the acceptance of intelligent shield machines and contribute to their broader adoption. Thus, we recommend conducting research in the following aspects.

(1) Robust shield-environment interaction model with strong generalization capability

The construction process of shield machines has been extensively studied by various disciplines such as civil engineering, mechanical engineering, and control engineering. Each discipline uses its own modeling approaches but, depending on the requirements of their respective analyses, these models often focus on specific factors while overlooking others. For instance, in analyzing ground deformation caused by shield tunneling, civil engineering simplifies the characteristics of cutter-head movement. On the other hand, mechanical engineering simplifies the geological load when examining the structure of the cutter-head or shield tunneling trajectory. Meanwhile, control engineering simplifies the geological disturbance and concentrates solely on the dynamic characteristics of the subsystem under study while analyzing and designing closed-loop controllers for each subsystem. Although these models and methods have proven applicable in their respective fields, they fail to accurately reflect the dynamic characteristics of shield-environment interaction and the complex coupling effects between subsystems. Consequently, they may not fully capture the intricacies of shield-environment interaction in practical scenarios. Recently, machine learning and deep learning have been widely utilized in shield-environment interaction modeling. However, these algorithms suffer from inherent flaws, limiting their generalization capabilities and thereby restricting their application to different excavation stages and tunnels. To enhance operational performance, it is crucial to develop a robust shield-environment interaction model with strong generalization capability. Additionally, a multi-system coupling mechanism with high-precision quantitative expression is essential to comprehensively understand the interplay between different subsystems and to improve overall tunneling processes. Furthermore, quantifying and managing the uncertainties involved in the model is also a crucial aspect of future research.

(2) Automatic actuator controller design and tuning technology

Highly autonomous intelligent control systems typically adopt a layered structure, with the precision and accuracy of lower-level actuators playing a crucial role in determining the overall task completion results. Shield tunneling involves various types of actuators, such as those used for pressure balance control in SPB shield machines, including slurry feeding pumps, slurry draining pumps, and air chamber pressure control valves. Similarly, EPB shield machines use actuators like screw conveyors for pressure balance control, while cutter-head drive systems utilize pump-controlled or valve-controlled hydraulic motors or electric motors. The thrust system, on the other hand, relies on valve-controlled hydraulic cylinders. As the autonomy level of shield machines increases, it becomes essential for each actuator to be equipped with a separately designed closed-loop feedback controller to enhance execution accuracy and disturbance rejection capabilities. However, designing the closed-loop feedback control system for each actuator involves multiple iterative cycles of modeling, design, simulation, and adjustment, making the process complex and time-consuming. Additionally, due to the intricate interaction between the machine and its environment, theoretical modeling of many processes proves challenging, and the coupling mechanisms of multiple systems remain unclear. Moreover, even if different shields utilize the same type of actuators, variations in geological conditions and shield diameters lead to significant differences in actuator controller structure and parameters. Consequently, controller designs cannot be easily reused, presenting a substantial challenge in actuator controller design and parameter tuning.

(3) Intelligent shield machine operating system platform

As outlined in Section 2.1, shield machine intelligence encompasses several crucial aspects, such as environmental state perception intelligence, equipment and component intelligence, operation intelligence, prognostics and health management intelligence, and shield machine fleet construction intelligence. Each of these aspects involves a series of distinct sub-tasks that require collaborative execution. They face various uncertainties and have diverse requirements for sampling and execution speed. Consequently, constructing a comprehensive intelligent shield tunneling system independently presents a significant challenge for both individuals and research teams. To tackle this challenge, the development of a universal and open intelligent shield machine operating system platform becomes imperative. Such a platform would facilitate communication and collaboration among different sub-tasks, allowing diverse teams to develop intelligent shield tunneling functionalities and seamlessly integrate them. This approach is crucial as it will substantially expedite the advancement of intelligent shield machine technology.

(4) Experimental and engineering verification

Safety, reliability, and robustness are critical considerations that must be effectively addressed during the development of next-generation intelligent shield technologies. They are the primary obstacles that hinder the progress of intelligent shield technologies, preventing them from transitioning from research prototypes to commercial applications. Due to the substantial cost associated with shield construction and the potential risks involved, conducting direct industrial test validations of new technologies poses significant challenges. This is especially true for smart operation technologies, which require careful validation before implementation. As a result, scaled model experiments play a vital role in the study and development of smart operation technologies for shield tunneling. However, shield tunneling entails the complex interaction of multiple systems, including the cutter-head, support pressure balance control, thrust system, and the surrounding rock environment. To design an effective scaled model, comprehensive simulations must account for the individual roles and loads of each system, as well as establish a mapping relationship between field construction data and prototype test data. Widespread adoption of intelligent shield machines may depend on public acceptance and trust in the technology. Negative perceptions or concerns about automation in construction could impact adoption rates. Moreover, tunnel projects often require approvals and permits from government authorities. The deployment of advanced intelligent shield machines may, therefore, require the establishment of additional standards for validating, inspecting, and using these machines effectively.

6 Conclusions

In this study, a systematic review of intelligent shield machine technology is conducted, with a particular emphasis on its smart operation. The fundamental issues of the intelligent shield machine, including its definition, meaning, contents, and development mode are addressed. An autonomous operation framework is proposed, encompassing both stand-alone and shield machine fleet levels. Additionally, challenges are identified, and recommendations are provided, to facilitate the achievement of autonomous operation.

The development of intelligent shield machines follows an evolutionary path from conventional shields, gradually achieving autonomous tunneling by integrating intelligent modules. As technology advances and innovation accelerates, this exciting field holds the key to transforming conventional TBMs into cutting-edge TBRs. While this technology is in its early stages, all aspects of shield intelligence have made rapid strides. It's worth noting that the widespread adoption of intelligent shield machines may hinge on public acceptance and trust in the technology. Negative perceptions or concerns about automation in construction could potentially affect adoption rates. There remains a substantial amount of research to be undertaken, particularly concerning shield-environment interaction models with strong generalization capabilities, automatic actuator controller design and tuning, intelligent shield machine operating system platforms, as well as experimental and engineering validation.

The future of intelligent shield machines is filled with promise, offering vast potential and opportunities. The incorporation of automation, artificial intelligence, and advanced sensing capabilities will undoubtedly revolutionize tunnel construction, enhancing efficiency, safety, and environmental sustainability. We encourage relevant research teams to dedicate themselves to the promising field of intelligent shield machines, conducting collaborative research, and unleashing of the full potential of intelligent shield machines.

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Author contributions

Yakun ZHANG and Guofang GONG designed the research. Yakun ZHANG wrote the first draft of the manuscript. Jianbin LI and Liujie JING reviewed this work and contributed via discussion. Huayong YANG revised and edited the final version.

Conflict of interest

Yakun ZHANG, Guofang GONG, Huayong YANG, Jianbin LI, and Liujie JING declare that they have no conflict of interest.

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中文概要

题　目：智能盾构机及其智能操控技术的发展现状与展望

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目　的：近年来智能盾构技术的发展体现出盾构机正在由传统的隧道掘进机转变为隧道掘进机器人的趋势。这一转变旨在解决传统盾构机行业在施工环境和人工操控方面所面临的挑战。本文的旨在梳

理智能盾构技术的发展现状，分析智能盾构的关键基础问题，推动智能盾构及其智能操控的技术进步。

创新点： 1. 提出了智能盾构的定义，分析了智能盾构的含义、内容和发展模式；2. 从盾构单机作业和盾构机群施工两个层面提出了盾构自主操控技术框架。

方　法： 1. 通过系统的文献分析，梳理了智能盾构的技术发展现状，提出了智能盾构的定义，分析了智能盾构的含义、内容和发展模式（图 2）；2. 通过分析盾构掘进过程各环节的操作流程，从盾构单机作业和盾构机群施工两个层面提出了盾构自主操控技术框架（图 12、13）；3. 针对智能盾构及其自主操控技术发展中所面临的挑战，给出了未来研究中需重点关注的问题建议。

结　论： 1. 智能盾构的发展应采用在传统盾构的基础上集成相应智能模块的方式逐渐演进；2. 盾构掘进操控中涉及到的离散数字量调控采用 PLC 逻辑控制比较容易实现自动化，而需要决策和连续调节的模拟量调控则需要相应的智能化模块；3. 智能盾构技术发展迅速，潜力巨大，在强泛化能力的盾构－环境交互模型、执行器控制器自动设计与整定、智能操控平台、试验与工程验证等方面仍面临挑战。

关键词： 智能盾构; 隧道掘进机; 智能隧道掘进机器人; 自动驾驶; 自主控制; 盾构机; TBM; 智能 TBM