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Review

Breaking new ground: Opportunities and challenges in tunnel boring machine operations with integrated management systems and artificial intelligence

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ABSTRACT

Advances in tunnel boring machines (TBM) have leveraged applied artificial intelligence to promote sustainable and automatic tunneling construction. This paper highlights the significance of AI-based management subsystems for automatic TBM operations and presents recent key contributions in the field by identifying three key parallel subsystems: modeling, monitoring, and control. Moreover, each subsystem is evaluated from the standpoint of practical implications. In this context, specific challenges are identified, suggesting research paths that include integrated management systems, and encouraging further investigations into TBM automation by integrating the existing management subsystems from an operational perspective.

1. Introduction

Over the past century, a shift in the industrial revolution, combined with precipitous population growth, has intensified urbanization. Efforts are required to satisfy and ensure the demand for different urban services, including usable and potable water, safe public spaces, health services, efficient energy supply, food production, and effective means of transportation [1–3]. Moreover, with the growth of cities, road, and underground transportation development have become crucial to access while saving time. As a result, the field has positively impacted economic growth and social development [4].

Road infrastructures generally consist of bridges, highways, interchanges, roads, roundabouts, and tunnels. Tunneling has played a crucial role in transport development as it reduces cost, distance, and negative environmental consequences [5]. For instance, underground transportation has rapidly developed. It is preferred over other transportation means because it can reduce traffic congestion and alleviate vehicle exhaust pollution [6]. Accordingly, approximately 2.86 million people commute daily via subway in megacities such as Seoul. Meanwhile, the annual number of passengers averages between 2 and 11 million commuters per station, with 344 train stations and an underground coverage of >49% [7,8].

Moreover, tunneling has been utilized for various purposes, including water conveyance megaprojects for municipal water supply, industrial processes, irrigation, and even hydroelectric plant operation, thus allowing clean energy production [9]. Other tunnel services include sewage, pedestrian and bike access, and mining operations. In this context, the tunnel boring machine (TBM) has been preeminent in large-scale tunneling development as it is considered safe, efficient, environmentally friendly, and cost-effective; it can also maintain the stability of the surrounding rock mass [10]. Nevertheless, the effectiveness of the TBM operation is strongly sensitive to degradation by external factors, including uncertain geological conditions, groundwater flows, rock bursts, and high-stress ground [11].

Generally, overcoming problems during TBM-guided operation involves generating an immediate response by adjusting parameters under the guidance of the operator’s experience. However, this may lead to excessive wear and abrasion of the cutters, degradation of tunneling efficiency, and machine blockage, negatively impacting additional project costs and delays [12]. In addition, significant parts of the TBM, such as the disc cutters, are particularly affected by poor tunneling performance and depend heavily on parameters such as cutter head (CHD) torque and thrust force. Similarly, TBM monitoring involves other issues, including detecting abnormal events, such as mud cake formation, and predicting cutter wear [13–15]. Therefore, proper and real-time management of TBM operations is required, which gives room

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for novel intelligent techniques to facilitate the integration of computational methodologies. Notably, this is becoming a hot topic among the tunneling research community.

The trend toward digitalization and automation has facilitated advances in informatics in different domains, shifting from traditional operations to smart management that utilizes various technologies that enable automation, digitalization, and autonomous decision-making. These technologies have paved the way for the fourth industrial revolution or Industry 4.0, including the Internet of Things (IoT), big data, cloud computing, building information modeling (BIM), machine learning (ML), artificial intelligence (AI), deep learning (DL), and additive manufacturing (AM) [16,17]. In addition, data democratization and constant data collection have facilitated unprecedented access to various datasets in the industrial, chemical, energetic, and construction domains [18].

Among AI technologies, ML techniques differ from traditional programming, allowing computers to learn from historical datasets [19]. These methodologies have been widely exploited in the field of TBM-based tunneling, with two important trends being recognized: (1) *modeling of external factors and effects*, such as ground and rock mass ahead classification, vibration and collapse prediction tasks [20–22], and (2) *TBM operation management*, involving prediction and optimization of TBM parameters, fault diagnosis, lining crack detection, monitoring of cutter conditions, and prediction of TBM performance and energy consumption [23]. The first identified path involves vital tasks for making decisions on future TBM operations based on external factors and evaluating the consequences in the urban environment and construction operation safety. In contrast, the second path exploits several ML algorithms for the autonomous management of the TBM operation.

The major applications of ML in TBM operation include the following:

1. *Predicting* operating parameters involves considering the effects of external factors, namely geological conditions, utilizing several regression methodologies ranging from statistical to neural analysis or physics-informed neural networks [24,25]. Moreover, operation performance is modeled via sequential digesting neural networks as long short-term memory (LSTM) or gated recurrent units (GRU), and memory cells are added to the recurrent neural networks (RNN) [25]. In this context, explaining different effects from independent to predicted variables has become necessary for assessing the various impacts on the desired operational performance. Accordingly, causal explanations and even the novel tool for explainable AI, Shapley Additive Explanations (SHAP), have been added to the analysis [26]. Furthermore, the life of the component has also been estimated via neural methods; for instance, the disc cutter life of the TBM [15].
2. *Fault diagnosis and detection* are mostly applied to the predictive maintenance of equipment components to ensure safe and efficient TBM operation. In this case, ML algorithms based on feature learning and generative models are widely utilized as they map normal conditions of a historical dataset in a latent space, thus learning the intrinsic behavior of the process. Meanwhile, an abnormal situation can be easily detected, identified, and reconciled in an operational context [27]. For example, autoencoders (AEs), a nonlinear variation of principal component analysis (PCA), have been utilized to detect CHD clogging conditions or faulty sensors for roller states on TBM main bearings [13]. On the other hand, generative adversarial networks (GAN) can be employed to detect tunnel-lining cracks through image analysis [28].
3. *Parameter optimization and control* focus on selecting optimal parameters to achieve a sustainable balance in the TBM operation. Metaheuristic algorithms, such as particle swarm optimization (PSO) and genetic algorithm (GA), play a pivotal role in determining optimal parameters in a real-time schema [29,30]. Advanced techniques include the development of intelligent policy adoption from a reinforcement learning (RL) trade-off and feeding an agent with performance measures (rewards), based on which proper control actions are generated [31].

The current industrial shift has focused on replacing operators' experiences with the AI decision-maker; however, these applications have been performed individually rather than holistically, decreasing algorithm efficiency. Therefore, integrating AI-based management subsystems is a novel alternative to autonomous TBM operation. This paper reviews ML and DL applications for autonomous and smart TBM operations and discusses subsystem integration opportunities and challenges. The review is divided into five main segments.

The integrated management system (IMS) concept, its divisions, and novel AI-based methodologies are introduced first. Through IMS subsystems, previous TBM autonomous operation research is summarized. AI-driven modeling, predictive models, and TBM operational implications are covered in the second segment. The third segment introduces AI-driven monitoring models for TBM operation and component safety and abnormal condition diagnosis. The fourth segment covers AI-driven control and optimization methods. The final section discusses the challenges of using ML/DL in an online and real-time schema and integrating methodologies for holistic and autonomous TBM operation. Furthermore, several opportunities are discussed as cutting-edge ML algorithms, combined with the widely available dataset from the TBM, for the development of sustainable practices in autonomous AI-guided operations.

2. Artificial intelligence-guided integrated management systems and implications for TBM operation

IMSs have been defined as the integration of parallel subsystems that, conducted separately, may result in effort duplication. Moreover, this type of management can be applied to different areas of execution within an organization, thus ensuring quality, safety, and high productivity [32]. Recent research has focused on implementing IMS in different domains; for instance, wastewater treatment plants, air quality, and chemical processes [33–35]. Furthermore, data streams have facilitated the training of ML models in a black-box form that neglects chemical reactions and physical interactions. This has followed the advent of ML algorithms and the installation of multiple sensors and data loggers and several soft-computing tasks for modeling/predicting, classifying, and learning features from historical data. To establish rational explanations, this review classifies the IMS into three main subsystems: *modeling, monitoring, and control*, which are described as follows:

- *Modeling:* Generates estimations for different variables involved within the operation or environment, including future estimations, that is, forecasting
- *Monitoring:* Employs the estimated information from the modeling subsystem to discriminate the conditions of a process
- *Control:* Utilizes the estimated values from the modeling subsystem, generating a control schema for identifying manipulated variables that need to be regulated when controlling a desired variable within certain conditions

AI methodologies and subsystems can be coupled to manage any environment properly. Fig. 1 illustrates the abovementioned subsystems coupled with several broadly studied AI-based algorithms required to perform the IMS tasks. The development of artificial neural networks (ANN) has predominantly guided the modeling subsystem for predicting interest variables. Other structures have been established by observing different needs according to data properties [36,37]. For instance, RNN has been utilized for the management of time-dependent variables or sequential data; memory-gated variations that include memory and

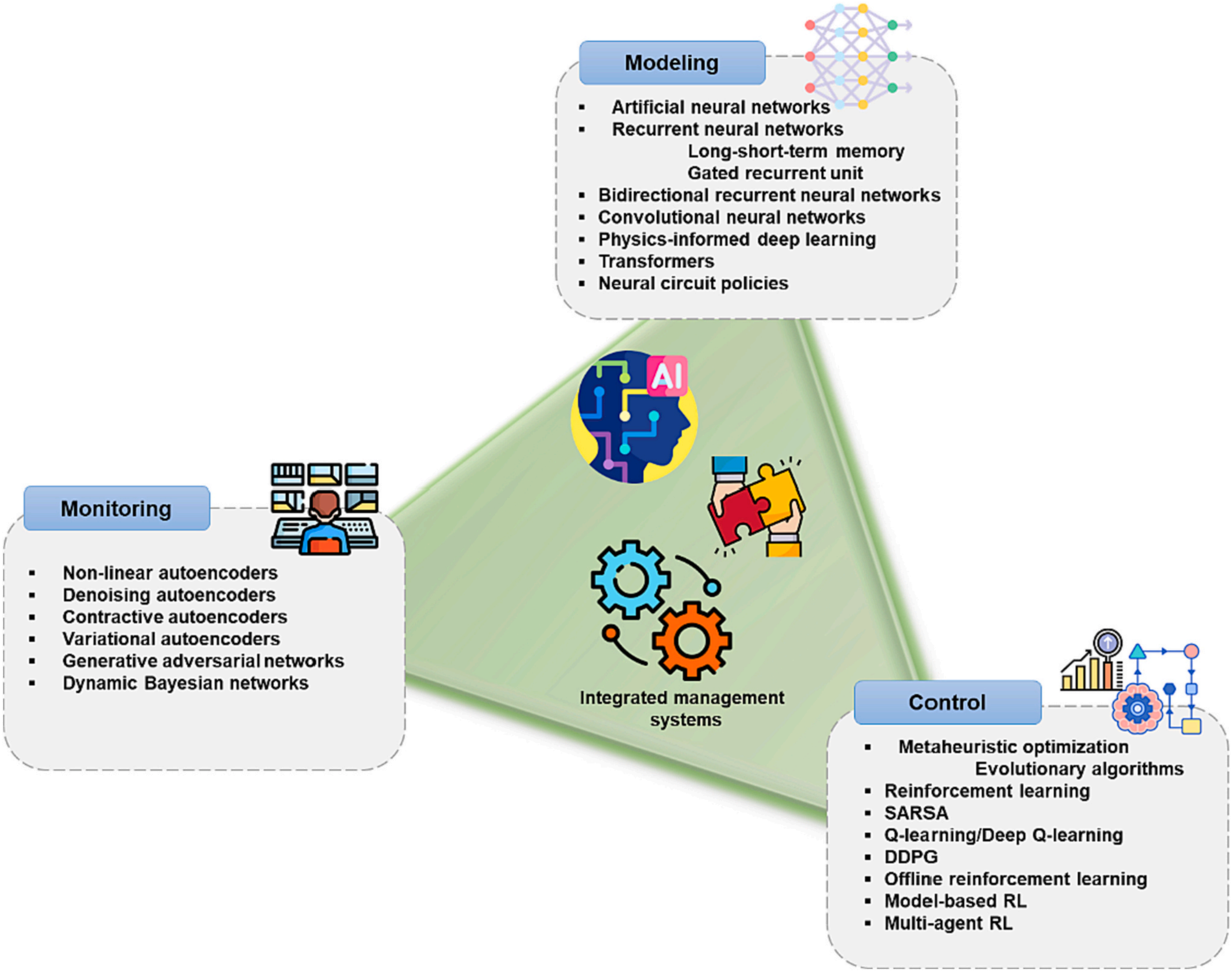


Fig. 1. Current trend in AI algorithms on different subsystems of IMS.

forget gates for retaining relevant information of the data while avoiding gradient deploys, like LSTM and GRU; and networks with added liquidity as neural circuit policies [38–40]. Conversely, images can be digested by convolutional neural networks (CNN), whereas new trends aim to incorporate physical knowledge of the process within neural networks [24,41].

For monitoring, on the other hand, the branch framework is utilized for fault detection and diagnosis, heavily relying on learning intrinsic representation of the data through projecting to a latent space, which may be low dimensional; the PCA method, one of the most popular for this task, utilizes linear transformations of the data [42]. However, process data is known to be nonlinear and time-dependent, opening the possibility of applying nonlinear transformations for these projections. Nonlinear AEs with their variants, namely denoising autoencoders (DAEs) and contractive autoencoders (CAEs) can overcome this disadvantage [27,43–45]. Other methods include an adversarial framework to detect whether process data is subject to normal conditions as well as probabilistic feature extraction, including variational autoencoders (VAEs) and dynamic Bayesian networks (DBNs), which can also address temporal data dependencies [46–51].

Finally, AI-based control tasks predominated following the introduction of metaheuristics algorithms for optimization, including PSO, GA, and numerous nature-inspired algorithms [52,53]. In addition, the RL schema for control has been weighted against optimal control and has yielded advantages. RL involves interaction in which an agent decides actions in a certain environment, and algorithms such as Q-learning and DQN have been strongly utilized in complex environments [54,55]. New research on RL has facilitated the usage of continuous actions as in the deep deterministic policy gradient (DDPG). For complex environments where the collection of many experiences is costly and hazardous, offline RL (Offline-RL) has been proposed to conduct the agent–environment trade-off using only static datasets [56,57]. Advanced variations of RL include the utilization of multiple agents interacting in a shared environment, whereas model-based RL employs a known model of the environment to maximize rewards [58,59].

The intersection between the AI-guided IMS and the TBM operation yields safe and sustainable automation, exploiting the available operational data during tunneling. Fig. 2(a) depicts the author keywords co-occurrences for articles published from 2017 to 2023, retrieved on October 2023, exported from the Scopus database with a search strategy that considers topics such as: “TUNNEL BORING MACHINE” AND (“MACHINE LEARNING” OR “DEEP LEARNING” OR “PARAMETER OPTIMIZATION” OR “REINFORCEMENT LEARNING” OR “ARTIFICIAL INTELLIGENCE” OR “NEURAL NETWORKS” OR “AUTOENCODERS” OR “MONITORING” OR “PREDICTIVE MAINTENANCE” OR “CUTTER WEAR” OR “FAULT DIAGNOSIS”); extracting titles, abstracts, and keywords of the articles; and retrieving a total 307 publications after filtering.

The depicted network is generated with VOSviewer software [60]. Notably, the node size indicates the frequency of the occurrence of a keyword in the literature, whereas the density of the link signifies how frequently the pairing occurs within the literature. Noticeably, TBM had

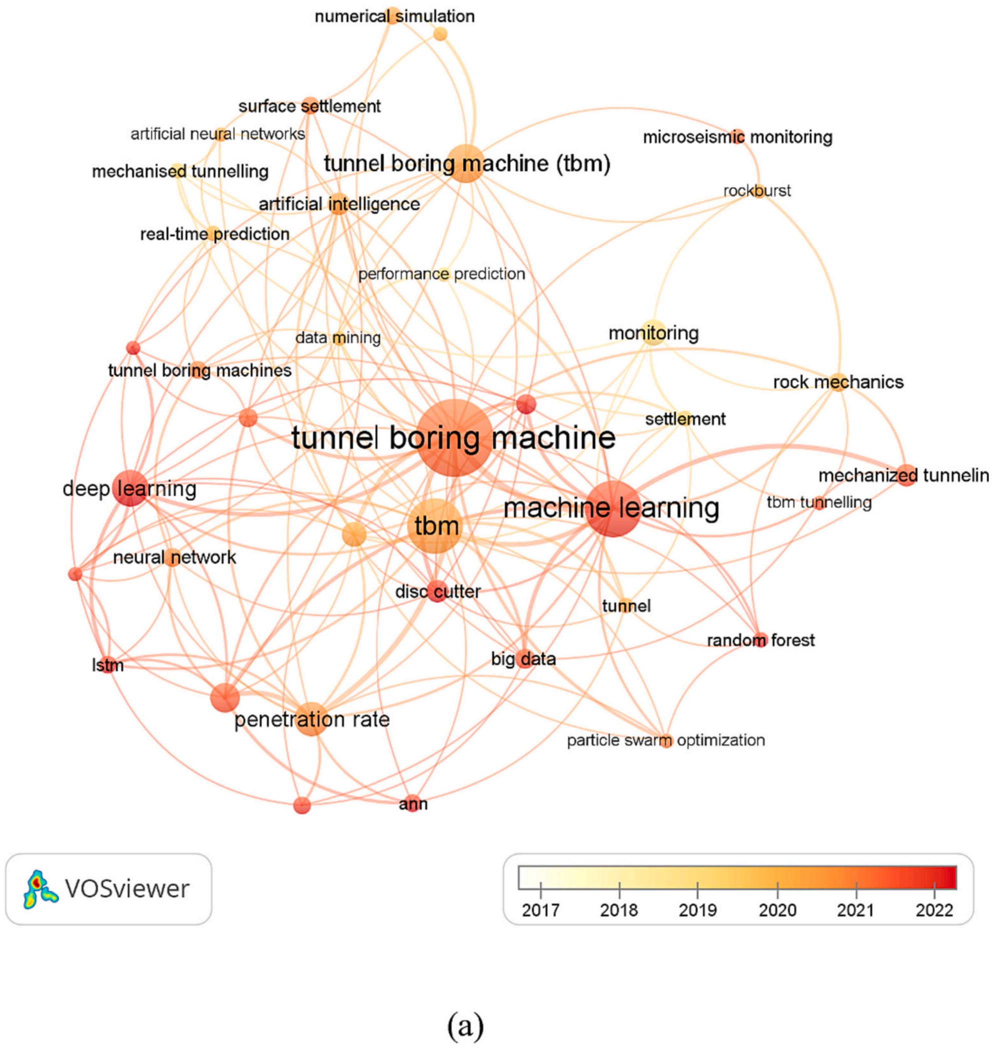


Fig. 2. Trend of studies regarding the intersection of TBM and AI assessed by (a) keywords co-occurrences network between 2017 and 2023, (b) tendency of published studies over the years, and (b) proportion of documents according to subject areas .

been latent in the research community in relation to other parameters, including penetration rate, disc cutter wear, and operational parameters. Meanwhile, regarding new investigations, the trend is inclined toward incorporating DL and ML methodologies, as depicted in Fig. 2(b), evidences an increasing tendency over the years on the published documents regarding these investigations. On the other hand, Fig. 2(c) illustrates the proportions of subject areas of these studies, occupying the Engineering and Earth and Planetary Sciences as the most related study areas.

3. TBM data collection, assimilation, and relevant features

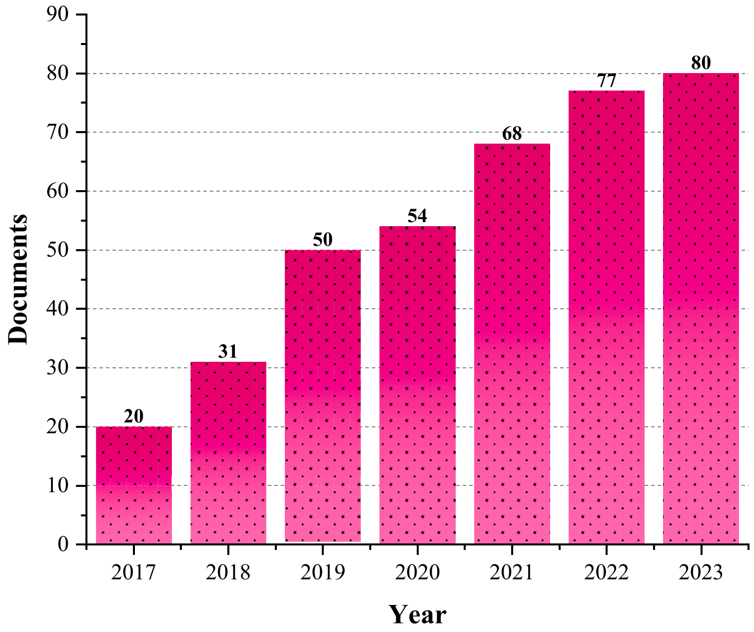
During the operation of TBMs, a multitude of measurements are obtained from different devices and sensors, characterizing the results of this collection as a big-data type of data frame. Big data possesses the characteristics of volume, variety, velocity, veracity, and value; furthermore, despite the fact that great data volume implies providing more details regarding the operation, it becomes more challenging to process [61].

Several TBM projects report a multitude of measurements during the excavation. For instance, the database for the Yinsong water diversion project in Jilin, China, counts approximately 199 parameters per second, accounting for a total of 120 GB of data [62]. The Yinchuo project, located in Inner Mongolia, comprises two main water diversion tunnels collecting approximately 401 parameters. On the other hand, the T308 MRT tunnel construction project in Singapore has measurements of 767 features during excavation [26]. Therefore, in general, TBM excavation projects can measure thousands to millions of observations that need to be assimilated and processed for posterior usage [63]. The measurements during the TBM operation are typically organized in “rings,” referred to as discrete sections or cycles of the tunnel excavation.

AI-based models work as data-intensive entities, requiring sufficient amounts of data or observations to work efficiently, denominating these models as “*data-hungry*” [64]. Furthermore, the performance of these models relies mostly on the types of data fed into them. The TBM tunneling parameters have certain characteristics representing advantages, including [29,52,65]:

- *Real-time*: Tunneling parameters instantly feedback the change in geological conditions an equipment response.
- *Spatiality*: The geological conditions affect the TBM parameters.
- *Constraint pluralism*: The TBM operation considers multiple aspects for its efficiency, considering risk, energetic efficiency, and other factors constituting a complex constraint relationship.

Considering the abovementioned characteristics, most studies



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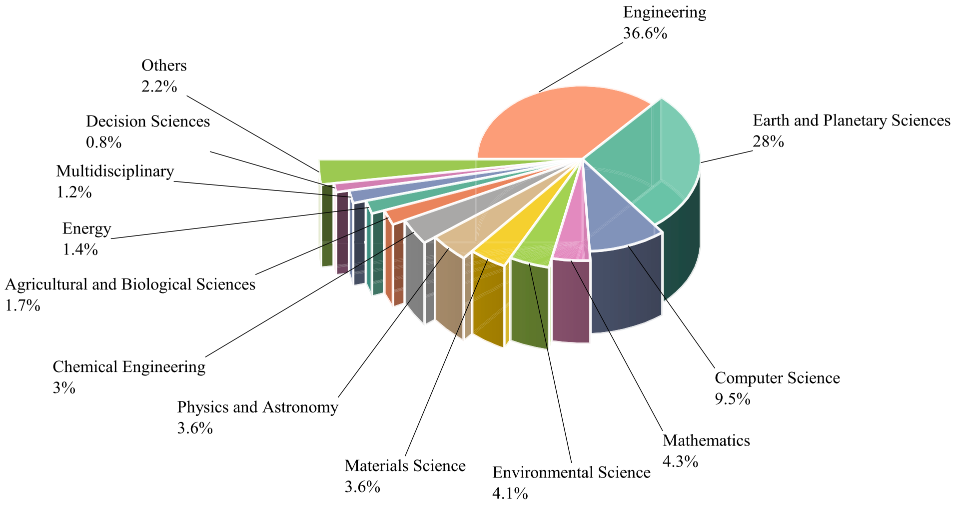


(c)

Fig. 2. (*continued*).

integrating AI into a management system for the TBM operation often consider relevant the operational and geological features that directly affect the equipment response and downtimes due to maintenance [66]. The operational and geological features interplay in the excavation process of the TBM. For instance, the hardness of the geological material influences increased CHD torque, while the abrasiveness of the geological materials plays an important role in the cutter elements wear. In addition, on a resistant geological environment, (i.e., cohesive rock-masses), demands more thrust force to advance. For these reasons, the performance, and operational parameters are closely related to the geological environment being excavated. Table 1 presents a summary of relevant variables divided into operational and geological features utilized in AI-based TBM management studies with their respective description.

4. AI-based modeling of major applications on TBM operations

ML algorithms are advantageous for their data-intensive behavior.

Table 1
Description of relevant operational and geological variables utilized in AI-based TBM management frameworks.

Variable category	Description
Operational variables	
Penetration rate	The ratio of excavation distance to excavation time during the construction stage
Cutterhead thrust force	Axial force applied to the cutter head, directed along the longitudinal axis of the TBM
Cutterhead torque	Rotational force applied to the cutter head assembly
Cutterhead rotation speed	Rotational movement of the cutter head
Foam injection ratio	The ratio of foam injected into the cutter head to in situ volume of soil being excavated
Articulation displacement	Jack system activation for curved excavations
Articulation deviation	Measurement of deviations from the desired alignment caused by the cutter head movement (Horizontal or vertical)
Earth pressure	The force exerted by the surrounding geological material on the tunnel face
Geological variables	
Uniaxial compressive strength	The maximum compressive stress of rock or soil can withstand when subjected to a uniaxial (unconfined) compression test
Brazilian tensile strength	Tensile strength of rocks subjected to diametral tensile load
Young modulus	Material property of the excavated rock mass describing how it deforms in response to a load
Cohesion	Property that characterizes the internal strength within the rock mass
Friction angle	The ability of the rock mass to resist sliding along internal planes or surfaces when subjected to shear stress

They can digest a multitude of data instances to generate and train black-box models for predicting a desired parameter; they use different input parameters while neglecting existing interactions. The application of these methodologies relies on shifts between the operator's experience and smart and real-time decision-making. Various datasets can be generated and collected in the present industrial scenarios, including time series, sound, images, and videos [18].

4.1. Artificial neural networks and neural variations

As ML has been in constant evolution and research, the baseline, considered as the ANN structure, has also been modified to meet the requirements for managing new data types, starting from the simple feedforward neural networks or multilayer perceptrons (MLPs) (Fig. 3 (a)). These mainly comprise three sets of layers: 1) the input layer, in which where the input variables of the models should be fed—the number of neurons is defined by the number of independent variables existing in the dataset; 2) hidden layers, which take input from previous layers and computes a weighted operation defined as $w_i x_i$ and a bias term (b) addition after which, the transition is propagated through an activation function that is commonly nonlinear, such as ReLU, Sigmoid, tanh, SoftMax, among others; and 3) the output layer, which stores the estimated values for the dependent variables—the neuron number in this layer is given by the number of dependent variables [67].

After defining the neural network architecture, historical data is used for training. A loss function, such as MAE and MSE for regression tasks or binary cross-entropy for classification tasks, compares the output actual values, or real values in the dataset, to the predicted values, or estimated values from the neural network model. The loss function is minimized by backpropagation optimization. The calculated loss is backpropagated to help adjust weight based on a gradient compared to the error. Gradient descent, Adam, and Adadelta are popular optimizers. In an epoch, this process is repeated as many times as the user set. A model with reliable results from new input data is the result [68].

The FFN model is mostly utilized for independent variables; however, data characteristics of industrial processes are mostly time-dependent and nonlinear. Therefore, further investigation was devoted to developing neural architectures to digest time-series and sequential data, such as sound and natural language, considering RNN. In contrast, data with 2 and 3 dimensions can be digested using CNN [41,69–72]. Fig. 3(b) illustrates the taxonomy of an RNN, where a node Z_t receives the current X_t and hidden state of the hidden layer in the previous state h_{t-1} as the input; when considered thus, as an ANN with loops (recurrent operations), the information can long persist. The feedforward structure can be described as copies of the same network in a passing message schema. Despite the capability of RNNs for modeling sequential data, problems related to exploiting gradients make it challenging to learn; therefore, adding memory cells has been broadly utilized, including in LSTM and GRU [73].

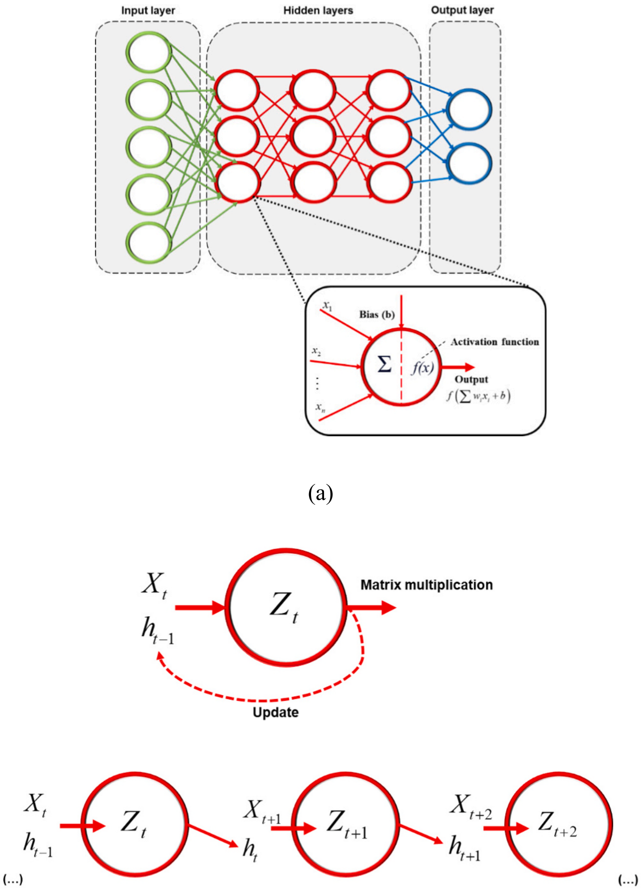
Fig. 3(c) depicts the memory structure for the LSTM (left) and GRU (right), which can separate the cell into memory compartments or gates [74]. The LSTM cell consists of an input gate (i_t), output gate (o_t), forget gate (f_t), and a candidate value ($\tilde{c}_t$). Here, the forget gate computes how much of the previous memory needs to be removed from the cell state [75,76]. On the other hand, the GRU cell contains only two gates: the update gate (z) and the reset gate (r). The first incorporates the input and output gates analogical to the LSTM because it decides how much data must be propagated from the previous storage. Conversely, the reset gate is applied to the previous state, integrating the new input with the stored information. In this context, the number of GRU model parameters is considerably fewer and computationally simpler than those of the LSTM [77–79].

CNN is a unique type of ANN that processes data using a grid-like topology. These models have mostly been exploited for computer vision applications [80]. Fig. 3(d) illustrates the structure of a simple CNN, which incorporates convolutional, pooling, and fully connected layers. The convolutional layers extract features from the input images; then, the pooling layers subsample the feature maps; the output of these layers is then flattened and propagated through fully connected layers to generate a prediction. CNN variations exist, such as ResNet and AlexNet [21,41]. Other algorithms include graphical structural information, which the neural networks can digest using GNNs [81].

4.2. AI-based modeling applications in TBM operation, challenges, and opportunities

Variations of ANN, RNN, and even CNN have been extensively employed for different purposes in TBM operation; specifically, operational parameters have mostly been estimated through a trained neural model; these parameters include cutter-head torque, advance rate, thrust force, and articulation deviations. Moreover, certain parameters are regarded as the TBM performance, including forecasting cutter wear conditions, penetration rate, and energy consumption. AI-based modeling can be viewed as a regression or classification task. For the planning phase of the TBM operations, AI-based simulations allow obtaining beforehand value knowledge including the duration, estimating downtimes and delays, projecting a realistic tunneling performance; this approach can be extended to construction phases in which real-time data measurement and training model warns the operators about short-term TBM performances to tackle possible drawbacks during this phase [82].

Fig. 4 depicts the three main phases of generating AI-based regression or classification prediction models [83]. A multivariable dataset is first selected and pretreated to define the variables of interest as independent (predictors) or dependent (predicted). Then, outliers and missing data points are filtered out, and the dataset is split into training and testing sets for modeling and validation. After recognizing the data type, the ML algorithm is selected according to the problem, followed by model training and hyperparameter selection to accurately model the dependent variable after optimization. In the third phase, model performance evaluation, the model fidelity is assessed using several metrics and environmental implications are assessed.



(a)

(b)

Fig. 3. Neural networks architectures, including (a) feedforward neural networks with a single neuron taxonomy, (b) recurrent neural networks architecture and feedforward propagation, (c) recurrent neural networks memory gates LSTM (left) and GRU (right), and (d) structure of convolutional neural network.

The numerical evaluation can be conducted using different evaluation metrics, which determine how well the predictive model estimates the interest variable, and comparing actual values (y) with predicted values ($\hat{y}$): n represents the number of samples. For the classification task, the results are expressed by true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The governing equations are presented in Table 2 and described as Eqs. (1)–(6).

Recent research on AI-based modeling applications from 2017 to 2023 is summarized in Table 3. With the aid of decision tools incorporated into soft models, TBM operations can be carried out successfully. These models establish a connection between a variety of input sources, including TBM-related parameters, CHD rotational speed, CHD torque, CHD power, torque, thrust, bentonite flow rate, horizontal and vertical deviations, and displacements. The geology of the region and the condition of the rock, as measured by uniaxial compressive strength, Brazilian tensile strength, rock quality designation (RQD), and the locations and directions of rock fractures, are external factors.

The outputs, however, are generated by finding optimal backpropagation-based weights that yield a feasible relationship among the given input variables. Among the interest variables to predict, the relevance of CHD torque and thrust forces is prominent due to the high interest in replacing the operator decision-making based on experience in incorporating smart and automatic tools. Moreover, operational deviations and resulting parameters, such as penetration and advance rates, have been well addressed. In contrast, parameters such as energy consumption and the cutter wear life prediction have not been sufficiently studied.

Soft-computing techniques face several real-world application challenges. Applying other methods can open up new research paths and unlock AI development and real-world applications. AI modeling in TBM operations aims to select parameters autonomously instead of relying on human decisions, but when removing human skills from the analysis, extra information should be provided that is understandable and accessible to humans. Explainable AI (XAI) models are clear and transparent, especially for applications where AI-based decisions have substantial consequences.

The Shapley additive explanations (SHAP), a game theoretic methodology, has been broadly applied to achieve model interpretability in the trained AI models by assigning an importance value to each feature for a given prediction [85]. Another technique is the local interpretable model-agnostic explanations (LIME), which works by approximating the decision boundary of an ML model locally around a specific instance or sample and then identifying the most relevant prediction features [98]. Finally, several fields have applied XAI for adding interpretations, including determining input impacts on the predicted values: the corresponding framework is illustrated in Fig. 5(a) [99].

In the TBM operations, Wang, Zhang, and Fu (2023) incorporated XAI and causality for modeling tunneling performance and concluded that the thrust force is sensitive to TBM-related variables, whereas soil pressure is more sensitive to temporal-dependent data points [26]. Fu, Wu, Ponnarasu, and Zhang (2023) suggested that a hybrid DL model can estimate TBM articulation and tail deviations by utilizing GCN-LSTM

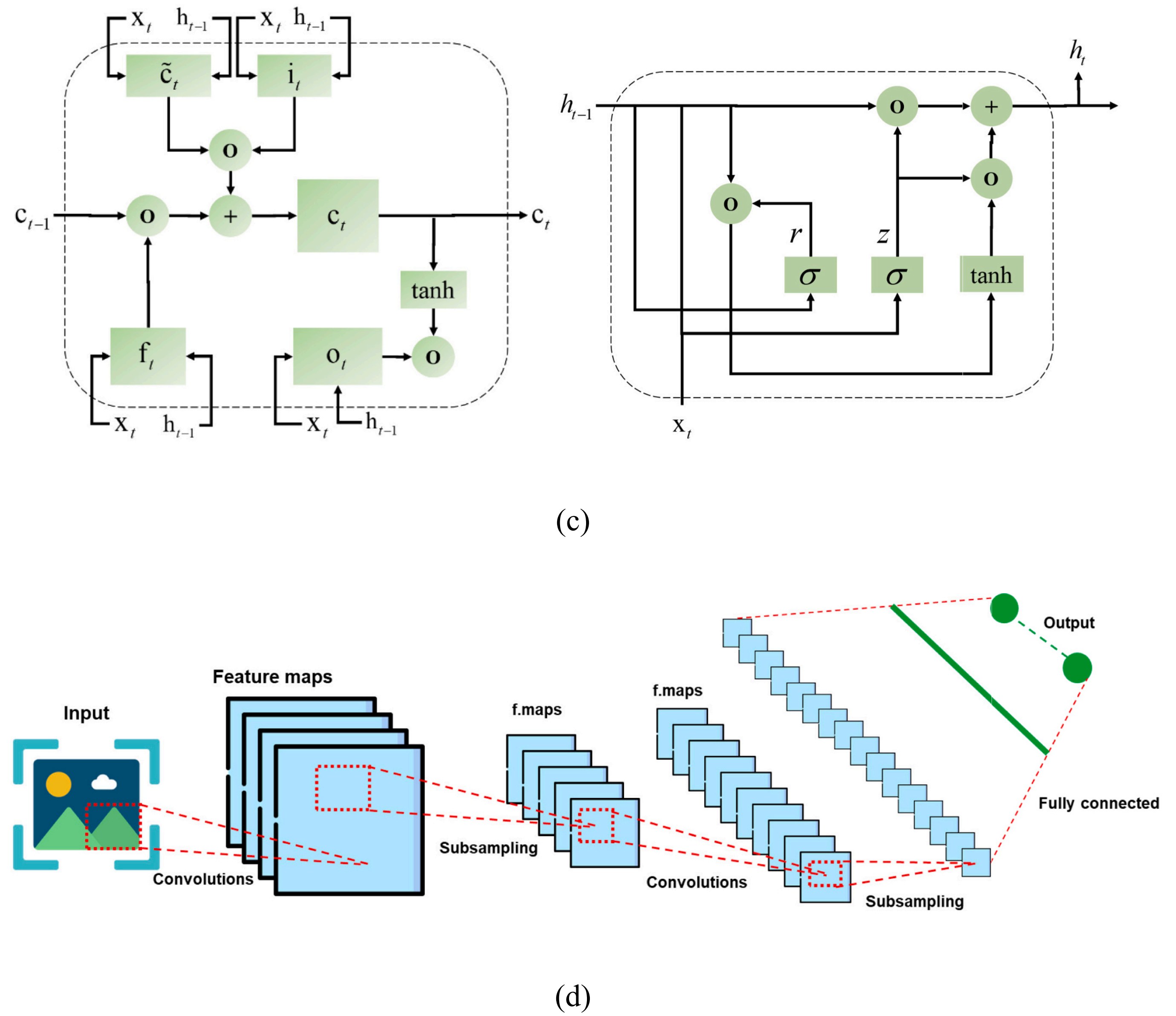


Fig. 3. (*continued*).

and SHAP to determine crucial contributing factors. This analysis revealed that historical deviations contributed the most to current deviations, whereas present adjustments only influence future deviations [85]. These studies have demonstrated the beneficial interpretable capabilities of XAI for real-world problems; nonetheless, the potential of these methodologies in other aspects of the TBM operation remains unexplored. For instance, values with practical and economic significance for TBM operation on the disc cutter life and wearing are produced, which are especially dependent on the CDH working process [15]. Novel methodologies related to machine vision are powerful tools for TBM operations, they provide real-time visual information enhancing efficiency, safety and decision-making on the excavation process; for instance, major applications include geological characterization, identifying different lithologies during excavation, cutter head monitoring to provide information related to cutters condition, alignment tracking for real-time adjustments, and tunnel face inspection to identify cracks, structural problems, and fractures [100].

Numerous models have been introduced to predict the lifespan of disc cutters under different operating conditions, and adjustment factors have also been estimated [101,102]. However, the unpredictability of geological conditions, including changes in rock and soil types, the presence of fault zones, and groundwater inflows, introduces significant uncertainties for TBM operations. Although adding these conditions as predictor variables add significance to the model, they are not controllable factors. Therefore, alternative strategies must be considered to prolong the lifespan of the disc cutter life while maintaining effective tunneling rates. One possible alternative is to employ XAI techniques to determine the major factors affecting disc cutter failure among the controllable variables, such as CHD torque and thrust forces. By adjusting these parameters accordingly, the optimal usage of the disc cutter can be ensured, and the risk of premature failure reduced.

Another challenge involves in the wide variety of tunneling environment conditions and differences in TBM models. For instance, Moosazadeh et al. (2023) assessed the effects of mixed ground and groundwater presence on the maintainability, reliability, and cutterhead life, evidencing great contrast between grounds, increasing the maintainability times and equipment life reduction by 42% for saturated ground [66]. The AI-based models presented in the literature could estimate operating parameters; however, model training is conducted in specific conditions utilizing data from certain distributions, such as rock

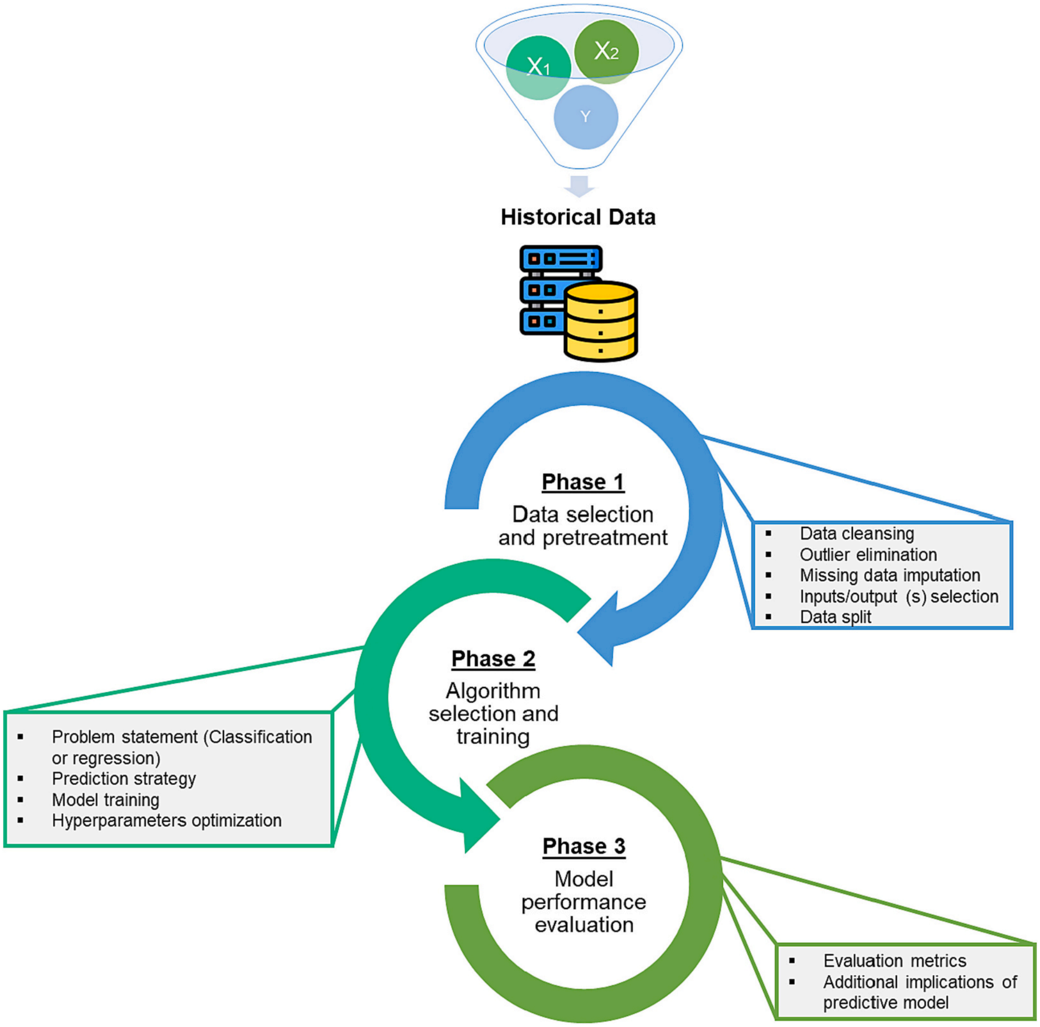


Fig. 4. AI-based modeling procedure phases.

Table 2
Evaluation metrics for AI-based modeling including regression and classification tasks.

Evaluation metric	Modeling task	Equation	No.
Mean absolute error	Regression	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	(1)
Coefficient of determination		$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - \overline{y})^2}$	(2)
Mean squared error		$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	(3)
Root mean squared error		$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	(4)
Mean average percentage error		$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{\hat{y}_i}\right\rvert \times 100$	(5)
Accuracy	Classification	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	(6)

mass conditions, geology, TBM model, and project scope, for each investigation. Nonetheless, these models can be considered local because they may not be helpful under varying conditions, inhibiting their generalizability when managing data from different domains. Additionally, research for determining general models to be replicated in different domains in response to the need for a new ML paradigm: transfer learning (TL), is lacking [10].

TL involves a different method of training a learning model; it relies on the fundamental human ability to transfer previous knowledge to solve different but related tasks. Computationally, TL methods transfer knowledge from different source domains to the target domains [103]. TL is composed of domain and learning tasks for source and target domains. A domain is represented as $D = \{X, P(X)\}$, where $X = \{x_1, x_2, \ldots, x_n\}$ is the n-dimensional feature space, whereas $P(X)$ is the marginal probability distribution of X. On the other hand, the tasks are explained as $T = \{Y, P(Y \mid X)\}$, where Y represents the targets, and $P(Y \mid X)$ is the conditional probability of Y given X. The source domain (D_s) and learning task (T_s) and the target domain (D_T) and learning task (T_T) are considered. The transfer mechanism learns the target conditional probability distribution $P(Y_T \mid X_T)$ by utilizing the information from the domain and tasks; the following framework is depicted in Fig. 5(b). This can be done with pre-trained models, domain adaptation, multitask learning, progressive neural networks, and cross-lingual TL algorithms [104].

AI-based modeling methods for TBM operation use source domains to represent models trained with a specific data distribution on a current project's inherent conditions. In contrast, target domains are new environments where source knowledge must be learned. Because TL computing uses pre-trained models, it reduces training data, improving efficiency over traditional ML on TBM operation modeling. It also

Table 3
Recent AI-based modeling applications for different variables involved in TBM operation.

Algorithm	Data type	Input variables	Output variable (s)	Error measurement	Ref.
Causal explainable GRU	Time-series	Penetration, CHD torque, CHD rotation per minute, CHD power, thrust speed average, Scanner much volume, Foam fill rate, Bentonite flow rate, thrust cylinders (right, down, left, top), Articulation displacement (A, B, C, D), Horizontal deviation (articulation, tail), Vertical deviation (articulation, tail)	Thrust force Soil pressure	$0.9140 < R^2 < 0.9184$	[26]
Multichannel decoupled deep neural network	Multi-feature	CHD speed, tunneling speed, geological type (one-hot encoding)	Torque Thrust	MSE (Torque) = 0.030 ± 5.83e-5 Accuracy (Torque) = 91.49 ± 0.24 MSE (Thrust) = 0.0005 ± 3.54e-6 Accuracy (Thrust) = 95.24 ± 0.24	[84]
Graph convolutional networks coupled with LSTM	Multi-feature	Thrust force, penetration, CHD torque, CHD rotational speed, Earth pressure at the left and right chamber, thrust cylinders four positions, articulation displacement	Articulation horizontal deviation Articulation vertical deviation Tail horizontal deviation Tail vertical deviation	Average $R^2 = 0.941$; 4.52% < improvement <19.52% Average RMSE = 1.445; 24.15% < improvement <49.66% Average MAE = 1.009; 11.63% < improvement <56.81%	[85]
Convolutional neural networks	Big data	Random CHD rotation speed, penetration rate, CHD torque, and CHD thrust of the loading phase The mean value of CHD rotation speed and penetration rate of boring phase	Mean values of CHD torque and CHD thrust of the stable phase	CHD torque; $R^2 = 0.81$, MAPE = 10.09% CHD thrust; $R^2 = 0.81$, MAPE = 6.32%	[86]
Long-short-term memory enhanced with grey wolf optimization	Multi-feature	Uniaxial compressive strength, Brazilian tensile strength, Peak slope index, Distance between planes of weakness, Rock fracture class, Angle between the plane of weakness, and TBM-driven direction	Penetration rate	$R^2 = 0.9795$ RMSE = 0.004	[87]
Extreme learning machine with particle swarm optimization	Multi-feature	Rock quality designation, Uniaxial compressive strength, Rock mass rating, Brazilian tensile strength, Thrust force per cutter, Revolution per minute	Advance rate	$0.96 < R^2 < 0.97$ 0.12 < RMSE <0.15	[88]
CNN-BiLSTM-Attention	Big data	CHD rotation speed, thrust, torque, penetration rate, chamber earth pressure	Advance rate	RMSE = 1.657 MAE = 1.044 $R^2 = 0.955$	[89]
Attention-based graph convolutional networks	Multi-feature	Net stroke per ring, Thrust force, CHD torque, CHD RPM, Screw RPM, Average chamber pressure, Average soil pressure	Penetration rate Energy consumption	Penetration rate: RMSE = 4.178, MAE = 2.967, MAPE = 15.48% Energy consumption: RMSE = 4313.7, MAE = 2422.8, MAPE = 15.17%	[90]
Bi-LSTM	Multi-feature	CHD rotational velocity, CHD power, CHD pressure, Penetration rate, Total thrust force, Advance rate, Sum of motor current, Sum of motor torque, Sum of motor power, Rock mass field penetration index	CHD torque	59 < MAE < 609, 6.51% < MAPE <42.63%, $0.18 < R^2 < 0.98$	[91]
Imperialist competitive algorithm with artificial neural networks	Multi-feature	Thrust, Revolutions per minute, Uniaxial compressive strength, Brazilian tensile strength, Distance between planes of weakness, Rock quality designation	Penetration rate	$R^2 = 0.887$, MSE = 0.0645	[92]
LSTM-CNN	Multi-feature by transformation	Single acceleration amplitude	Cutter wear status: Normal, Uniform-wear, Angled-wear	Accuracy = 87.6%	[93]
Spatio-temporal LSTM	Multi-feature	Thrust force, CHD torque, CHD rotational speed, Earth pressure at left and right chamber	Penetration rate	Average MAE = 1.319 Average RMSE = 2.003 $R^2 = 0.8866$	[94]
Gaussian process regression	Multi-feature	Specific energy, Quartz content, Excavation depth, Thrust force, Cutter rotation speed, Penetration rate, Screw rate, Grouting pressure, Soil pressure	Disc cutter life	RMSE = 107.4 MAPE = 4.02% $R^2 = 0.885$	[15]
LSTM-MLP with adaptive genetic algorithm	Multi-feature	Boot pressure, propulsive pressure, propulsive force, CHD power, CHD torque, control pump pressure, CHD speed, penetration, and propulsive speed	CHD torque	MAE = 184.85 RMSE = 211.18 MAPE = 8.19%	[95]
Polynomial regression –based decision tree guided ensemble regression models	Multi-feature	Advance rate, cutterhead torque, and cutterhead thrust	Earth pressure of the chamber	$R^2 > 0.88$ for the ensemble regression models with different number of trees	[96]
Causal-temporal graphic convolutional network	Multi-feature	Penetration rate, CHD rotational speed, Soil pressure in front, Earth pressure in middle chamber, Screw conveyor rotational speed, Screw conveyor torque, pressure in screw conveyor	CHD torque, Thrust force	CHD torque: RMSE = 64.53, MAE = 40.90, $R^2 = 0.902$ Thrust force: RMSE = 1168.59, MAE = 635.76, $R^2 = 0.838$	[97]

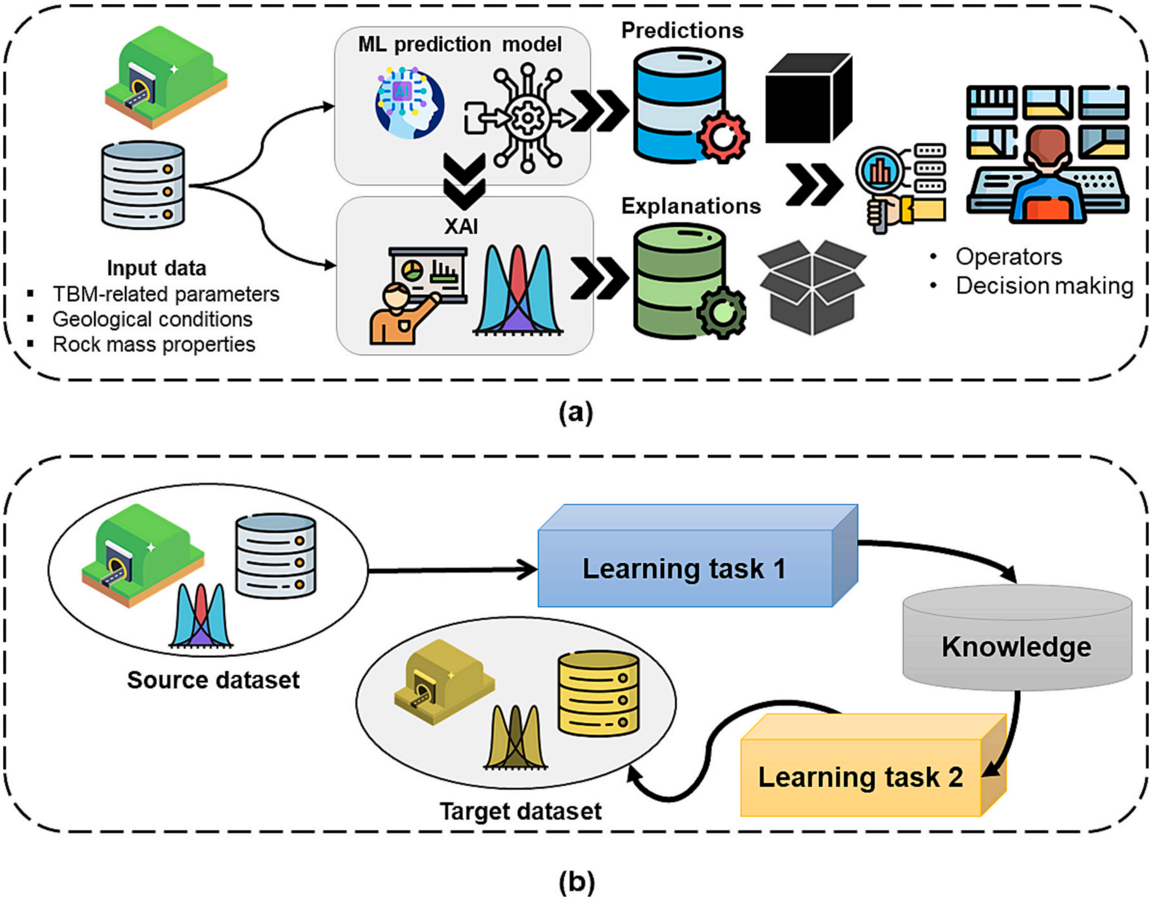


Fig. 5. Challenges and opportunities in AI-based modeling corresponding to (a) XAI techniques implementation and (b) TL shift for different sources dataset.

improves generalization and reduces overfitting by letting models learn more generalized features from pre-trained models. Because pre-trained models can be fine-tuned with small amounts of data, TL is more data-efficient and meets TBM operations' data collection challenges.

4.3. Neural-based feature representation for process monitoring: autoencoders and generative models

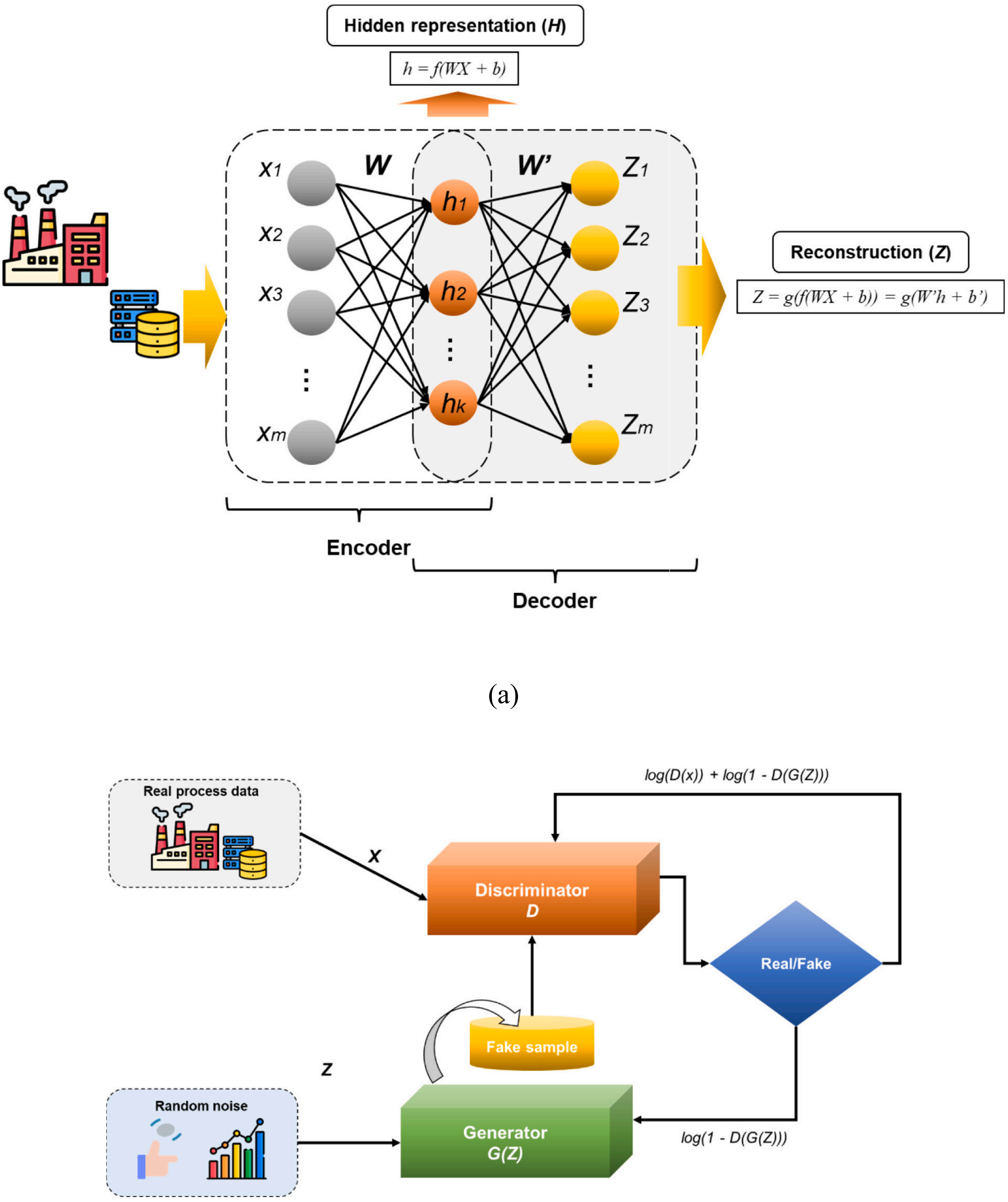
Over the past decades, the industrial scale has grown rapidly, with ensuring reliability while enhancing process safety emerging as top priorities. Accordingly, novel process monitoring methodologies, including fault diagnosis and detection, have been investigated to ensure product quality and process safety. Process monitoring in the industrial context can be divided into two main parts: (1) Model-guided approaches that utilize mathematical representations for modeling plants, balances, and existing interactions of the plant or system and (2) data-based approaches based on historical process data utilizing statistical methods [105].

Certain difficulties in model-guided approaches for process monitoring emerge due to system complexities associated with the numerous factors and disturbances that need to be considered. On the contrary, data-based approaches neglect the interactions within the plant and rely on the intrinsic relationships and properties in the historical dataset, thus achieving numerous advantages over model-based approaches. Therefore, various methods have been studied and suggested, including unsupervised multivariate statistical approaches, such as PCA, which is a benchmark for this field and a starting point for novel and adaptive methods, including independent component analysis (ICA), Fisher discriminant analysis (FDA), and partial least squares (PLS), with dynamic variations as dynamic PCA, kernel-added PCA (KPCA), and dynamic ICA [27,106–108].

Process monitoring using data-based models compares process behavior to the desired or normal model. Monitoring the deviation between current and modeled normal process behaviors can detect process faults. The normal process behavior is extracted from historical industrial data and projected into feature representations, where statistics can be constructed. For instance, the PCA linearly transforms high-dimensional industrial data into principal components projected in a low-dimensional subspace, preserving its characteristics. Variable correlations are removed [109].

The PCA-based process monitoring is explained as follows: Let the multivariate process data $X\in\mathbb{R}^{n\times m}$, where n is the number of samples and m is the number of variables, be decomposed into two subspaces namely the principal component subspace X', that is a linear combination of X, and the residual subspace (E). The original dataset can be explained as $X = X'W^T = \sum_{i=1}^{m} x'_i w_i^T$, where W is the loading matrix. On the other hand, considering the selected principal components (r) to retain, X can be rewritten as $\widehat{X} = X'_r W_r^T = \sum_{i=1}^{r} x'_i w_i^T + E$. The residual subspace is constructed from the difference between the original matrix and the reconstructed matrix as $E = X - \widehat{X} = XW_{m-r}W_{m-r}^T = X'_{m-r}W_{m-r}^T$.

The development of neural networks evidenced that the complexity of industrial processes cannot be modeled by utilizing only linear transformations; characteristics such as time dependency and nonlinearity can be addressed using AE, a neural variation of the PCA. These structures consist of two main parts, the encoder and decoder, as depicted in Fig. 6(a). Analogically, the AE projects the input $X\in\mathbb{R}^{n\times m}$ to a hidden representation $H\in\mathbb{R}^{k}$ via an activation function $f(\bullet)$, generally a nonlinear function; then $h = f(Wx + b)$. The hidden representation encapsulates a rich subspace that is then mapped to output Z using the decoder as determined by $g(h)$. Here, Z is the reconstruction resulting



(a)

(b)

Fig. 6. Illustration of the general structures of (a) autoencoders and (b) generative adversarial networks.

from forcing the AE to choose the best and richest compressed representation to reconstruct the given inputs. The parameters (φ) of this neural structure, including $\varphi = \{W, b, W', b'\}$, are determined by backpropagation optimization of the objective function $S(\varphi)$, as explained in Eq. (7).

$$S_{AE}(\varphi) = \sum L(x, g(f(x))) \tag{7}$$

Here, L represents the reconstruction error that can be selected as any loss function in a neural network.

Since this structure was introduced, several AE variations have been suggested to improve the performance. For instance, the DAEs is robust because the AE is fed a contaminated input; therefore, the noisy data are forced to eliminate the noise and recover the original data [110]. Furthermore, probabilistic variations, namely VAEs, combine Bayesian inference to obtain a nonlinear feature space, where the encoder and decoder are probabilistic [111]. Finally, numerous structures have been introduced based on combining LSTM, CNN, or even advanced neural networks for real-world applications, and they have achieved excellent performance compared to typical feature learning methods [13,112,113].

AE structures have been categorized as powerful tools for generative modeling. This is because the hidden representation of the AE encapsulates the characteristics of the historical/process data in normal conditions, allowing the model to decode and generate new datasets that conform to these characteristics [114]. Likewise, within generative models, adversarial learning, specifically generative adversarial networks (GAN), has gained popularity. It uses two neural networks, namely a generator (G) and a discriminator (D), as depicted in Fig. 6(b) [115,116]. The generator network takes a random sample and generates fake data samples, whereas the discriminator network distinguishes between the real and fake data samples. Then, the generator network aims to generate fake data samples that are indistinguishable from the real ones, while the discriminator network aims to identify the fake samples correctly.

These networks are trained simultaneously; D is trained to maximize the probability of assigning the correct label to real samples and fake samples from G. Meanwhile, G is trained to minimize $\log(1 - D(G(Z)))$, where $D(\bullet)$ represents the probability of the generated samples belonging to the real sample space.

4.4. AI-based monitoring applications in TBM operation, challenges, and opportunities

Monitoring and generative frameworks for neural approaches applied to industrial settings and in the TBM operation share a similar process, as depicted in Fig. 7. Here, the multivariate dataset is projected into a comprehensible space utilized for comparison or reproduction. Different monitoring studies are compiled in Table 4, encapsulating different objectives for the TBM operation and intersection with smart monitoring. Nonetheless, feature extraction methods such as AE and generative models have not been as widely exploited in comparison to AI-based modeling applications summarized in section 3.2. Three main objectives pertaining to monitoring frameworks have been identified: generative modeling, fault diagnosis, and anomaly detection.

For instance, generative modeling is mainly utilized to generate synthetic TBM data. Unterlass et al. (2022) suggested the Wasserstein GAN for generating synthetic datasets for TBM operation. These are usually restricted to the general public, limiting technology development, including ML algorithms and additional methodologies [117]. Therefore, democratizing synthetic data with distributions that imitate the intrinsic relationships of original datasets represents an outstanding opportunity. Furthermore, a synthetic dataset is untraceable, thus avoiding legal issues, and it can realistically be used for developing advanced soft-computing techniques.

CNNs have been proposed for monitoring the vibration on TBM main bearings through three-axial data collection for fault diagnosis applications; this method reveals the neural model to be adaptive as it can be utilized under different conditions at the rotational speed [118]. Signal processing has been applied within the same scope; for instance, the

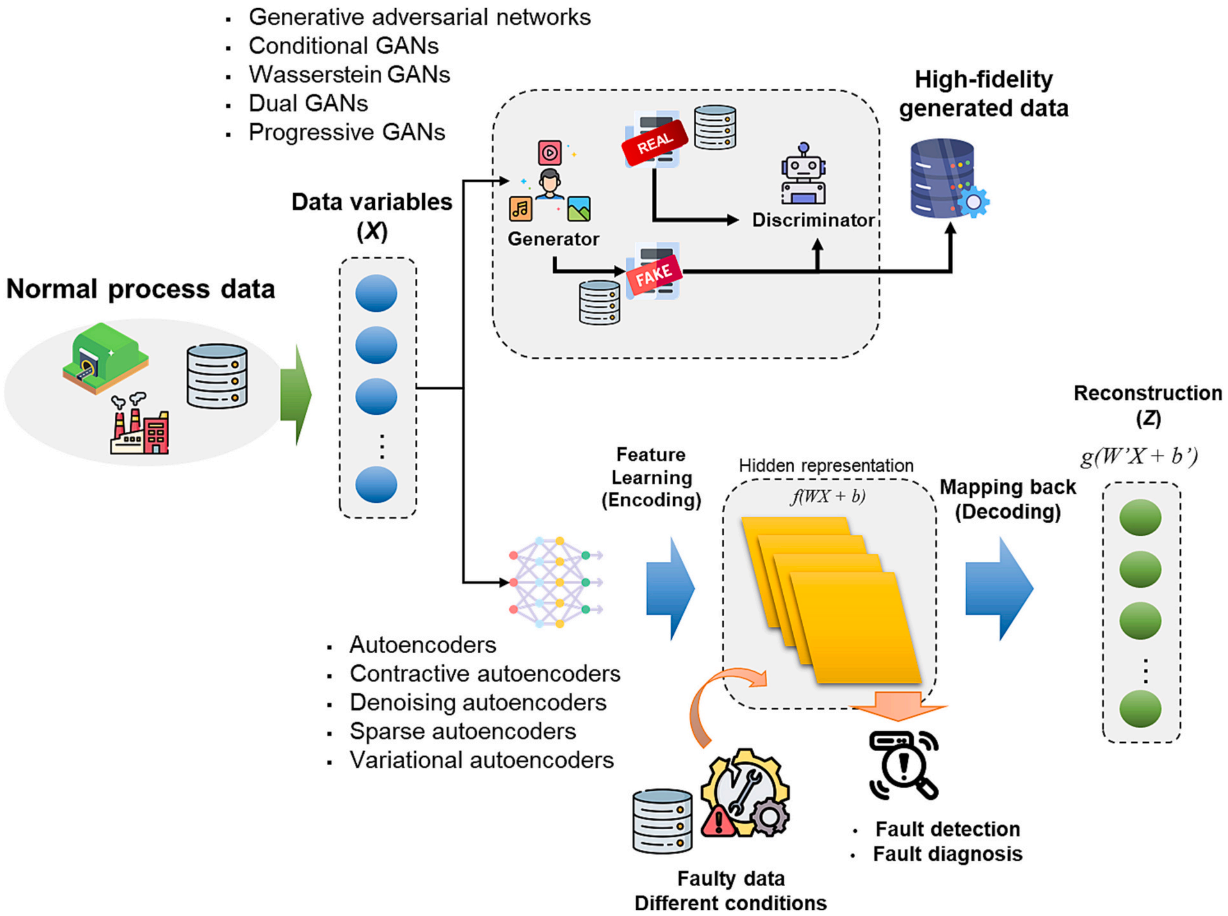


Fig. 7. Monitoring frameworks for TBM operation in for high-fidelity data generation via adversarial learning, anomaly detection, and fault diagnosis through feature extraction algorithms.

Table 4
Recent AI-based monitoring applications for different variables involved in TBM operation.

Algorithm	Task	Data description	Research objectives	Remarks	Ref.
Wasserstein Generative Adversarial Networks	Generative modeling	TBM operational data	To generate synthetic TBM data utilizing real data from a European tunnel construction site for public and legal utilization	Errors in dissimilarity between real and synthetic with MAPE 1.034% - 1.084%	[117]
LSTM-autoencoder and transformer detection method	Anomaly detection and outlier removal	Historical TBM data and working state	To detect the cutter head clogging status of TBM via transformers while removing outliers utilizing an LSTM-based autoencoder	Detection of clogging status with an accuracy of 98.85%	[13]
Two-stream CNN with multichannel detrending inputs	Fault diagnosis	Three-axis vibration signals	To monitor the vibration of TBM main bearings under different conditions of rotational speed	Accuracy at low speed is 95.52%	[118]
Empirical mode decomposition	Fault diagnosis	Tri-axial acceleration on the barrel of the gripper cylinder	To establish a fault diagnosis method guided by EMD for identifying the characteristics of the gripper cylinder during the TBM operation	Successfully indicated characteristics of complex vibrations from the TBM operation	[121]
Hilbert transform and complex demodulation	Fault diagnosis	Normal forces acting on the edge of cutting disc and rock	To extract intrinsic relationships of the features for identifying damages in cutting discs of TBM	Disc cutter defects were successfully identified	[122]

empirical mode decomposition decomposes a signal into intrinsic mode functions (IMFs), capturing the oscillatory components of the signals without requiring any prior knowledge of the signal [119]. Additionally, the Hilbert transform method transforms a signal in the time domain to a frequency domain, extracting the envelope of the signal [120]. These methods decompose three axial vibrations and normal forces to identify the characteristics of the gripper cylinder during TBM operation and damage to the cutting discs. Moreover, recurrent AEs, such as LSTM, have been introduced for anomaly detection models within the TBM operation to identify clogging conditions in the cutter head. This type of AE is unique because it digests the time series, incorporating the temporal dependencies in the process.

Despite advances in AI, TBM monitoring techniques have not been studied in depth to exploit feature extraction. These techniques generally provide a representation that allows the computation of statistics for a more tractable quantification of the abnormal and normal states of the studied processes. In this context, an opportunity from the gap in the research is the application of the sensor validation framework. This framework has been widely studied and applied in industrial settings, including indoor air quality networks, wastewater treatment plants, and construction [43,123–125].

The sensor validation framework is not limited to managing anomalies in sensor networks; the detection, identification, and diagnosis features can also be utilized to detect changes in process conditions, e.g., geological changes, burst occurrences, and groundwater infiltration. This framework is illustrated in Fig. 8, and consists of three main parts. First, fault detection is performed to determine whether a fault in the sensor network or an abnormal event has occurred. For this, the normal conditions of the sensor network or multivariate process information are utilized to generate control statistics; when new information from the process is obtained, whether the measurements exceed these limits is analyzed to categorize the same as a fault or abnormal event.

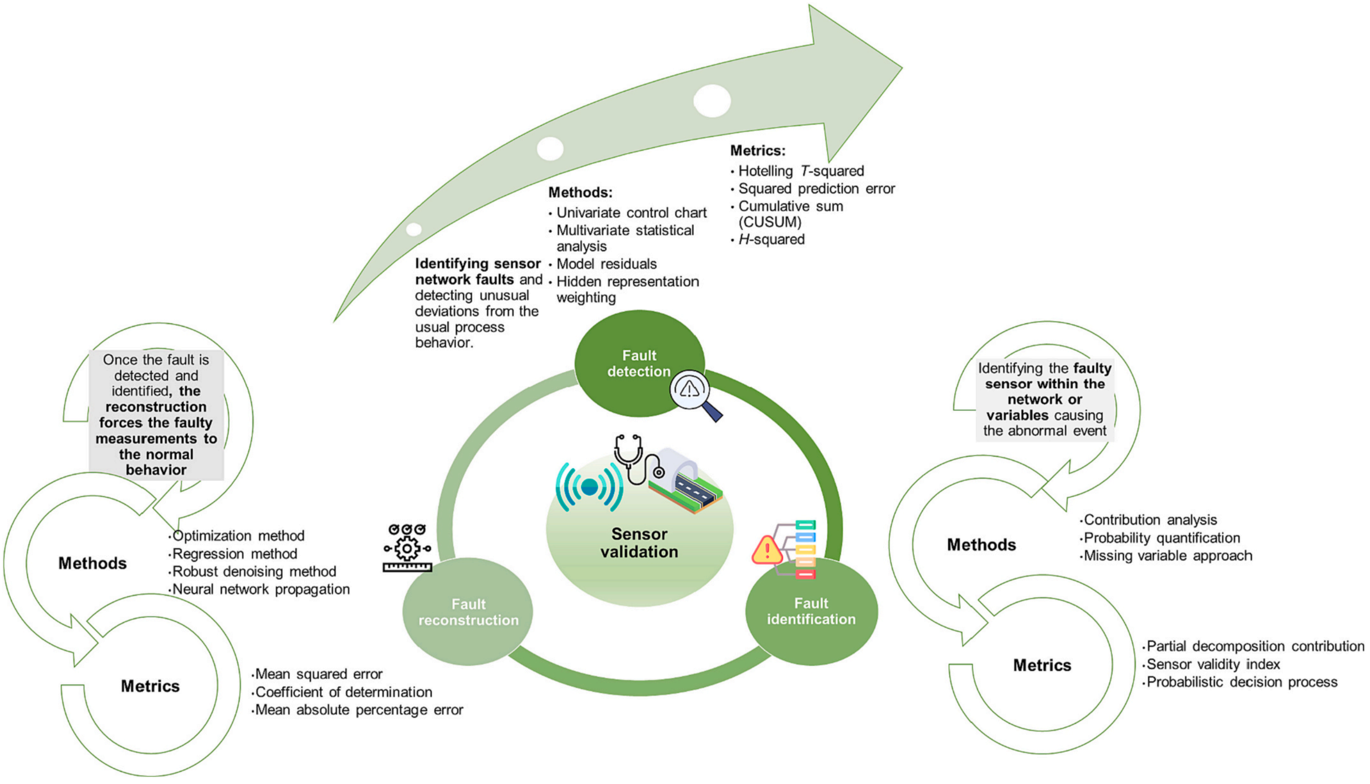


Fig. 8. Sensor validation framework divided into fault detection, identification, and reconstruction.

Second, fault identification is conducted when a fault is detected to determine which sensor is responsible for the faulty state. This can be achieved through contribution analysis or probabilistic approaches. Regarding TBM operation, this can be useful for determining the variable responsible for an abnormal state or whether the advance encounters some difficulties. This can also be extended to fault diagnosis, in which the changes and their related events during the TBM operation can be characterized and attributed to the relevant events that can be further recognized in an online schema.

Finally, fault reconstruction modifies faulty conditions to normal. The literature focuses on optimization, regression, and neural network propagation. Reconstruction is an inherent AE task for neural networks, but statistical approaches require iterative and denoising algorithms. In hostile environments like the TBM, where sensors fail and provide inaccurate data, this task is crucial for sensor network sanity.

In conclusion, feature extraction has not been widely utilized in TBM operations, but it may pave the way for the execution of new maintenance tasks. TBMs are complex and costly, making them susceptible to delays and additional expenses in the event of a breakdown. Thus, early fault detection can reduce downtime and breakdowns. Since these methods train with the same data source, geology and TBM type affect system conditions. Consequently, the TL schema can be utilized to translate abnormal events into other environments utilizing data from other environments. This enables precise fault detection and identification, which facilitates the tunneling project.

4.5. Optimal control, metaheuristics, and reinforcement learning control

Control systems aim to regulate a process toward the desired operating conditions, thus increasing profitability while maintaining efficiency [126]. However, in general, every control system defines an objective guided by a conflict; for instance, in TBM operation, different performance metrics such as advance speed, penetration rate (PR), and specific energy can be obtained, which contradicts the energy consumption. Therefore, multiobjective optimization problems are required to strike sustainable balances between the conflicting variables measured by a cost function.

Several control techniques have been intensely studied, including optimal control, metaheuristics, and reinforcement learning control. Optimal control refers to determining control inputs, i.e., setpoints or parameters, to minimize the cost function and satisfy the constraints set. This control schema assumes that the dynamics of the system are known. The control procedure is then defined as an optimization problem that can be solved either numerically or analytically through dynamic programming (DP) and model predictive control (MPC) [127,128]. However, generating a model that imitates the actual behavior and dynamics has become a major issue due to the complexity and disturbances within. Therefore, data-driven and neural approaches have been proposed to improve the accuracy of process definitions.

Metaheuristics have also been introduced into control problems, serving as optimization methods for finding optimal or near-optimal solutions to complex problems. These methods have been widely applied to large problem spaces and local optima problems. These models work iteratively, exploring the solution space while assessing the improvement in candidate solutions and forming a set of potential solutions that are then evaluated according to the fitness as they continue exploring. Finally, the algorithm ends when the ending criteria are met, or a satisfactory solution is found. These algorithms are mostly nature-inspired, including the genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO), which are utilized in several engineering fields [129–131].

Reinforcement learning, on the other hand, is an adaptive control technique that learns optimal control policies through a trade-off game between the agent and the environment. The RL process is depicted in Fig. 9, in which the agent learns from feedback received from the environment. The loop follows the Markov decision process (MDP) and utilizes a sequential decision-making process. It consists of the environment states (S), actions (A), and rewards (R). First, the agent generates an action that is performed in the environment; then, it is evaluated through a reward function and modeling future behavior, becoming the feedback for the agent to learn. Accordingly, the agent needs many interactions to ensure an optimal policy (π) [132,133].

The MDP develops π, mapping the actions to states for maximizing the expected return (J) resulting from the summation of the expected rewards, as explained in Eq. (8)

$$J_t \triangleq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots = \sum_{i=0}^{\infty} \gamma^i R_{t+i+1} \tag{8}$$

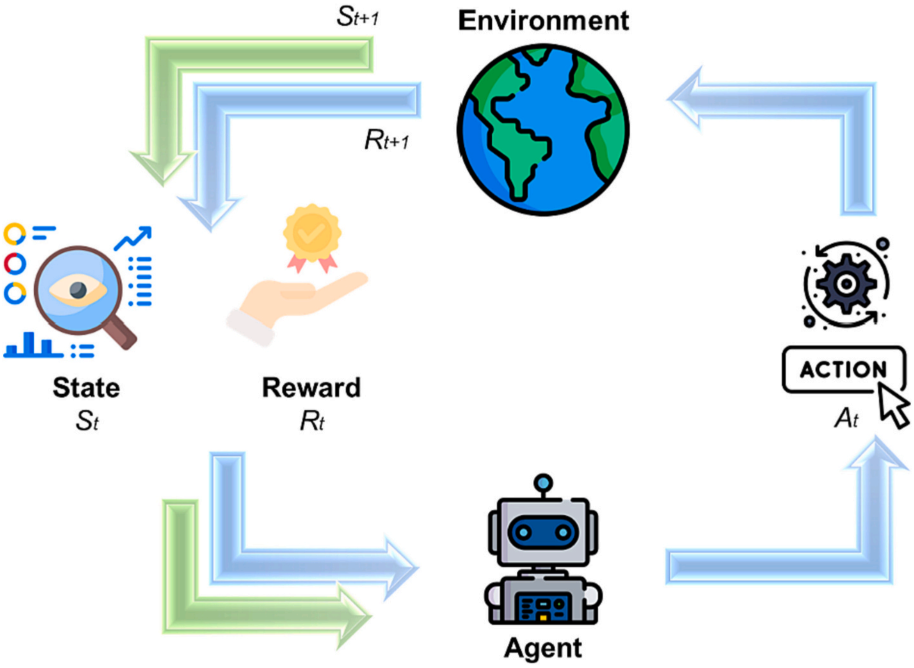


Fig. 9. Flowchart of the RL control system.

Here, γ represents a discount rate used due to the importance of immediate rewards rather than future rewards with $\gamma \in [0,1]$. The value of a state under a given policy is defined as V_π, whereas an action in that state under a given policy is q_π.

$$V_\pi \triangleq \mathbb{E}_\pi\left[\sum_{i=0}^{\infty}\gamma^i R_{t+i+1}|S_t = s\right], for\ s \in S \tag{9}$$

$$q_\pi(s,a) \triangleq \mathbb{E}_\pi[J_t S_t = s, A_t = a] = \mathbb{E}_\pi\left[\sum_{i=0}^{\infty}\gamma^i R_{t+i+1}|S_t = s, A_t = a\right] \tag{10}$$

The training consists of running multiple iterations for searching the optimal policy to maximize the rewards. In a particular environment, for the states or observations at time t (S_t), the agent generates or selects an action (A_t) to perform; the state is then updated (S_{t+1}) together with the reward (R_{t+1}), which are fed back to the agent for policy modification before the next action (A_{t+1}). In this context, the agents within the RL control system become optimization tools that capture complex and nonlinear patterns; several methods have been introduced to produce the best policy given MDP, such as dynamic programming, Monte Carlo, the temporal difference (TD), policy gradient, and actor–critic methods.

4.6. *AI-based control applications in TBM operation, challenges, and opportunities*

TBM effectiveness generally relies on the operator's experience, which varies according to the skill level, jeopardizing tunneling efficiency. Therefore, several automatic control systems have been proposed to ensure efficient operation by optimizing parameters such as the cutter head torque, thrust force, advance speed, and rotational speed of

Table 5

Recent AI-based control methodologies for the TBM operation and structural design.

Algorithm	Observation space	Action space	Performance and rewarding	Remarks	Ref.
Deep deterministic policy gradient	Cutterhead rotational speed* Advance speed* Groundwater total pressure Soil cohesion Internal friction angle	Rotational speed controller Advance speed controller	Increasing the advance rate and reducing the energy consumption	The proposed system increased the average excavation speed by 17.33% and the advance/energy consumption rate by 9.91%	[31]
Proximal policy optimization	Binary vector of cutter lives	Selection of cutters to change	Rate of functional cutters and total cutters Time for cutter head inspection and replacement	The proposed system optimized the policies for cutter changing to maximize the number of functional cutters while decreasing the maintenance efforts	[134]
Light gradient boosting machine (LightGBM) and particle swarm optimization (PSO)	Advance rate* Cutterhead rotational speed Penetration rate Mean and variance field penetration index Mean and variance torque penetration index	Thrust force Cutterhead torque	Maximizing the advance rate via penetration rate and the cutter head rotational speed	A just-in-time control strategy increased the advance rate by 23.7%	[29]
Quantum particle swarm optimization (QPSO)	Cutterhead thrust Cutterhead torque Cutterhead power Penetration Penetration rate* Rock mass class	Penetration depth Cutterhead rotation speeds	The optimization defines the balance between the penetration rate and the rock-breaking specific energy	The proposed method increased the TBM penetration rate ranging from 13.71% - 14.85% while reducing the rock-breaking specific energy by 9.18% and 9.41%	[135]
Grey wolf optimizer generalized regression neural network (GWO-GRNN) and nondominated sorting genetic algorithm (NSGA-II)	Advance speed* Ground settlement* Total thrust force Rotation speed of cutter head Cutterhead torque Grout amount Grout pressure Geological conditions	Total thrust force Rotation speed of cutter head Cutterhead torque Grout amount Grout pressure	Maximizing advance speed while minimizing the ground settlement	After parameter optimization, the advance rate was increased while the ground settlement was decreased with respect to non-optimized operations	[136]
Self-adaptive multipopulation genetic algorithm	Cutter tip width* Edge angle* Edge radius* Rock-breaking capability of disc cutter Energy consumption of rock breaking Load-bearing capability of cutter bearing Wear life of cutter ring Wear uniformity of cutter ring	Cutter tip width* Edge angle* Edge radius*	Rock-breaking capability of disc cutter Energy consumption of rock breaking Load-bearing capability of cutter bearing Wear life of cutter ring Wear uniformity of cutter ring	Rock breaking capability, wear life, and wear uniformity is improved by 28.1%, 9.4%, and 9.8%, while energy consumption and load-bearing capability decreased by 2.8% and 3.3% for tuff. For granite, the rock-breaking capability, energy consumption, load-bearing capability, and wear uniformity increased by 13.7%, 5.7%, 12.9%, and 22.1%, while the performance of wear life deteriorated by 2.6%.	[137]

[*] Controlled variables.

the cutter head. Notably, a conflict is defined as the objective function, for instance, advance rate and energy consumption.

Table 5 presents studies on AI-based control for automatizing TBM operation and structural design. The description includes the implemented algorithm, observation space, action space, conflicting objectives considering performance or reward, and the main results. According to recent studies, control frameworks are also useful for determining optimal times for cutter changes and structural design for the TBM cutter rings. Moreover, the main task has been optimizing tunneling parameters under different conditions.

The leading research on operation control involves the use of metaheuristics techniques, considering a multiobjective or many-objective problem. For instance, the trade-off typically consists of maximizing advance rate while minimizing specific rock-breaking energy consumption and grout settlement. The implemented algorithms include particle swarm optimization (PSO), as proposed by Li et al. (2023), introducing a just-in-time (JIT) framework that soft models the tunneling loads from rock-machine mapping models and an optimization model considering the excavation efficiency and construction safety that can increase the advance rate by 23.7% [29]. The operational strategy proposed in this study consists of JIT for real-time and adaptive management, satisfying the particular characteristics of the TBM tunneling parameters, including the variant geological conditions, while maintaining the risk under control.

In addition to the real-time setting of these control systems, these strategies can manage multiple objectives while manipulating multiple variables. For instance, the nonsorted genetic algorithm (NSGA-II) has also been introduced in the control strategy, as proposed by Liu, Li, and Liu (2022), where the objectives are the maximization of advance speed, indicating the efficiency of the construction while minimizing the ground settlement that corresponds to environmental disruption. The manipulated variables comprise thrust force, rotation speed and torque of cutter head, grout amount, and pressure [136]. Moreover, structural parameters for designing TBM disc cutters have been evaluated as many-objective problems, as introduced by Lin, Xia, and Wu (2019) via a self-adaptive multi-population genetic algorithm; here, a total of five objectives are formulated, including aspects related to the wear life and uniformity, rock-breaking capability, energy consumption, and load bearing capability [137].

Evidently, the RL framework has not been thoroughly exploited. Nevertheless, two ways of implementing this control strategy exist; for instance, the most recent implementation of this framework was in the study of Zhang et al. (2022), who proposed a DDPG-based control system for manipulating the rotational and advance speed to optimize the trade-off between energy consumption and advance rate; an increase in excavation speed and lower energy consumption in difficult grounds was reported [31]. In addition, the authors report that the proposed method has a significant advantage over a human operator who requires months of training in contrast to the RL agent, whose training only takes hours.

Moreover, the RL framework has been utilized to find optimal timing for cutter changes, as Erharter and Hansen (2022) proposed, using a proximal policy optimization agent to determine the cutters to be replaced via multiaction selection. The decision conforms to a monitoring environment for each cutter that utilizes information such as theoretical durability, distance from the cutter position to its head center, and the rolling distance of each cutter within a rotation. The agent is rewarded according to the time and effort required to change the cutters and the number of cutters in a functional state [134]. This study provided a realistic environment and relevant reward function; however, deploying realistic environments is challenging and a latent problem due to the complexity and TBM component failure associated with tunneling.

For instance, Erharter et al. (2021) proposed an RL-based tunneling process strategy in which the agent is a virtual geotechnician, thereby simplifying the reward setting to penalization of face instabilities [138]. The authors recognized that a more realistic environment provides a more robust decision-making process that addresses aspects such as geological conditions, groundwater, in-situ stress, excavation geometry, and even tunnel cross-sectional analyses via 2D and 3D finite element analysis (FEM); however, FEM is computationally expensive. In this context, RL frameworks are known to be data-hungry, as the online training of the agents requires a large number of interactions to converge to an optimal policy. Furthermore, in practical terms, modeling the entire TBM tunneling process is complex, and obtaining data from direct interaction with the tunneling environment is not feasible due to the hazardous conditions this is associated with. However, this presents an opportunity; for instance, during the normal tunneling process, many sensors can collect different information, such as TBM actions and environment interactions. This information can be further processed to provide optimal policies via static datasets using offline reinforcement learning (ORL) [139].

Unlike conventional RL control strategies, the ORL framework relies on historical static datasets from the transitions within the interactions. For the TBM-based excavation process, these interactions can be collected from log data; the variables include advance rate, torque, thrust, cutter head rotation speed, soil and rock parameters, and groundwater pressure. A buffer can then be initialized from this experience, and the agent can be trained using off-policy algorithms. Moreover, the agent learns by approximating a high-dimensional function but extrapolating beyond the data domain, which can be corrected through constraining [140,141]. Given the risks and costs associated with online interactions of the TBM operation, the shift to ORL can be considered for further policy exploration and experimentation, as illustrated in Fig. 10 (a). Recently studied algorithms for ORL include the policy in the latent action space (PLAS), implicit Q-learning, conservative Q-learning, and behavior cloning [140–142].

Another research opportunity within the control strategies of the TBM operation is replacing single agents that receive rewards based on performance. Instead, the training could be expanded to multiple agents, that is, multiagent reinforcement learning (MARL), in which multiple agents learn and cooperate to achieve a common goal; this is useful when objectives generate specific rewards, and other agents' actions are considered [58,143,144]. For instance, agents can receive a reward based on the action performance depending on the advance rate, specific energy consumption, machine attitude changes, or ground settlement by varying different actuators to maximize the total reward. Algorithms related to MARL have been proposed, including QMIX and G2ANet [144–146]. On the other hand, the agents that could be present for the TBM operation are presented in Fig. 10(b), with their objectives being as follows:

1. *The machine agent*: To optimize the TBM parameters, including torque, speed, and thrust, for maximizing excavation speed while decreasing energy consumption, considering stability issues and excessive cutter wear occurrence
2. *The conveyor agent*: To optimize the conveyor system parameters, including capacity, loading strategies, and speed, for maximizing transportation efficiency while decreasing downtimes.
3. *A monitoring agent*: To analyze the excavation process data for detecting anomalies to provide feedback to other agents for action adjustment.

4.7. Practical implications and future research on AI-based TBM management

This review has identified the subsystems for TBM management from recent AI. Three main paths are presented and evaluated across different management aspects and objectives, namely, modeling, monitoring, and control. Nevertheless, these subsystems working in parallel multiply efforts but neglect some management considerations. Therefore, the IMS concept is suggested for achieving sustainability in a pluralist

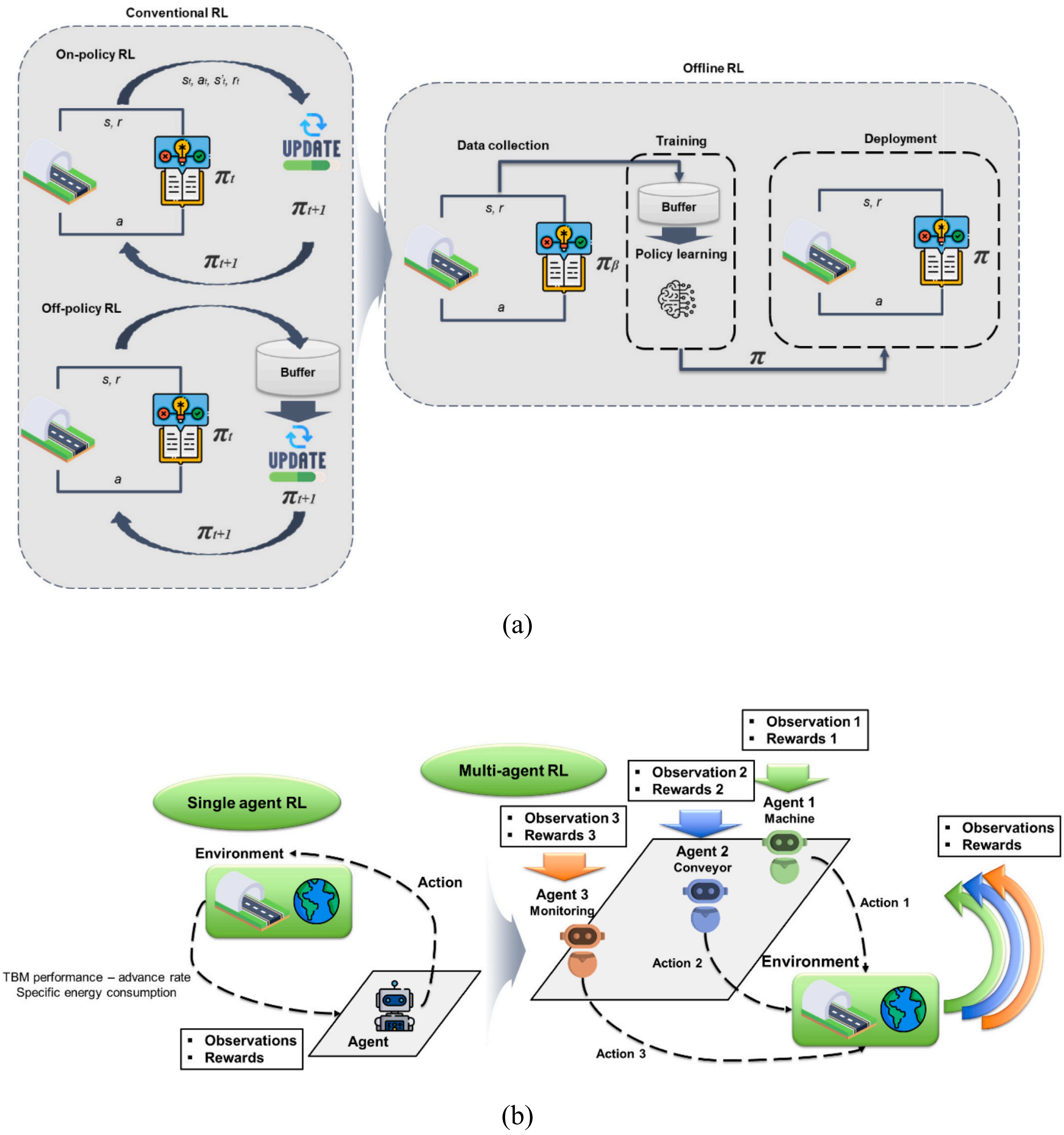


Fig. 10. Illustrations of (a) conventional and offline RL, and (b) single and multi-agent RL control strategies.

environment such as the TBM. Moreover, it improves communication and coordination to achieve a common goal and appropriately manage risks.

The literature should be used to establish subsystem interconnections and future research directions for practical purposes. The objectives, challenges, and research opportunities are depicted in Fig. 11. The objective is to summarize the interconnections between each subsystem and determine how they can complement one another, particularly the control subsystem, for operational efficiency. The modeling subsystem faces complex processes and uncertainties in the TBM working environment that are difficult to represent mathematically. Modeling based on AI has made mathematical representations into black-box models. For coupling RL-based control strategies, a feedback system between the agent and the environment in which the agent acts is suggested. In contrast, the agent is rewarded for choosing optimal policies by the environment. As in an online control framework, this allows for a real-time model for accurate TBM responses. For training RL agents, high-fidelity responses are required.

On the other hand, the monitoring subsystem is crucial to any industrial process because it detects anomalies and failures to ensure product quality. Implementing AI-based sensor validation frameworks to ensure sensor network sanity or identify TBM operation changes was

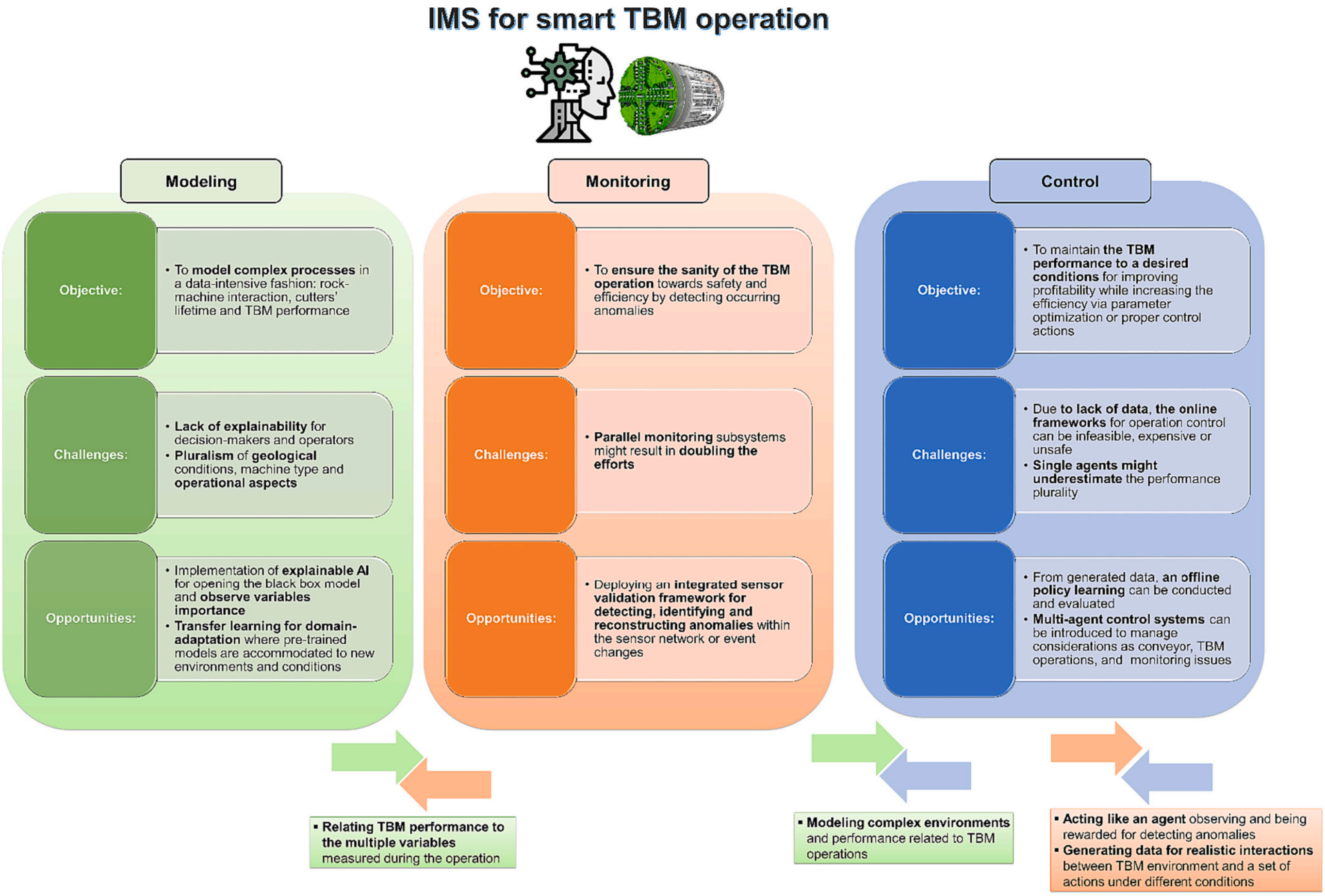


Fig. 11. IMS assessment of the existing interconnections for smart TBM operation.

identified as a research opportunity. RL agents can use a monitoring module to define anomaly detection rewards. The generative models mostly used for monitoring tasks can also be used for data generation, which is important for creating synthetic data generation models that realistically resemble TBM operational data patterns that are difficult to obtain due to conflicting factors. Many generated TBM operational datasets help train RL algorithms without privacy issues and advance autonomous TBM operation research.

Despite the fact that the integration of intelligent frameworks into TBM operations has yielded solutions, the application of these frameworks carries significant computational cost implications. As integrated AI systems have not been fully implemented in the field, it is difficult to provide precise computational cost-based metrics. Nonetheless, this review contains significant ramifications that require special consideration because they have multiple effects. In this context, it is necessary to develop AI-based management strategies for TBM operations that balance the multiple effects of computational costs with operational, acquisition, and environmental costs. Several computational cost repercussions are detailed below:

- *Data volume and AI model complexity*: The plural measurements at different time resolutions comprising operational, sensor, and geological data represent substantial computational resources for pre-processing, feature engineering, and model training. Moreover, selecting AI models has a direct effect on computational power and memory; therefore, this complexity should be balanced with the availability of resources.
- *Real-time processing*: Given the excavation operability, maintaining real-time management is pivotal; therefore, low-latency processing in real-time demands cloud-based solutions with low-latency capabilities.
- *Hardware infrastructure*: In general, the training of DL models has been aided with high-performance Graphics Processing Units (GPUs) or Tensor Processing Units (TPUs); however, this comprises substantial acquisition and operational expenses.
- *Energy consumption*: Depending on the selected AI model, training and running these models consume a significant amount of energy, representing operational and environmental costs; therefore, it is necessary to explore efficient and alternative structures to mitigate these costs.

Recent research has sought to automate TBM operations and transfer decision-making to machines using artificial intelligence. To accelerate progress and reduce energy consumption, however, these methods must be integrated for sustainability and proper management. Diverse subsystems were evaluated to propose new research directions. Consideration was given to AI-based modeling, XAI, and transfer learning in order to explain black boxes and learn across the diverse conditions of TBM operations. Additionally, AI-based monitoring employs the sensor validation framework to detect, identify, and reconstruct abnormal measurements in a TBM sensor network or for event detection. Lastly, AI-based control frameworks employ RL, which enables new approaches such as ORL to discover optimal policies without online experimentation. Multiple agents are incorporated into an automatic framework to coordinate their actions and achieve a sustainable TBM operation.

5. Conclusions

This paper summarizes contributions from recent studies on the broad AI applications related to TBM operations, in which three main paths are recognized: modeling, monitoring, and control. First, each subsystem is evaluated and contrasted, given the practical implications of the TBM. Then, different challenges are identified, elucidating novel research paths toward automation of TBM operation and sustainability. Thereafter, several AI methods are suggested for addressing the explainability challenges, including XAI and TL, to tackle pluralism while explaining the impacts of existing TBM variables and generating black box models. Moreover, sensor validation frameworks within the monitoring tasks are suggested for integrating anomaly detection, identification, and reconstruction. Finally, the RL strategy is evaluated for TBM control, revealing that ORL algorithms can learn optimal policies for proper TBM management by utilizing static datasets. Meanwhile, the multiagent RL framework considers additional objectives via agents to achieve a common goal.

The IMS concept is suggested for further research paths to manage the parallelism by reducing efforts and redundancy, including the utilization of AI-based models for generating realistic responses in an online RL control scheme; on the other hand, the monitoring module can be integrated into the control schema as an additional agent for considering the sanity of sensor networks or changes in operational aspects. Additionally, including generative modeling for TBM synthetic dataset generation, democratizing the data, and allowing further investigations encourage the research community toward tunnel development and automatic TBM operation from an integrated operational point of view.

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.

Data availability

Data will be made available on request.

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