



A Review of Artificial Intelligence Applications in Mining and Geological Engineering

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Abstract. Artificial intelligence (AI) is well-known as a robust technique that can support and improve the quality of human life. In the mining industry, applications of AI changed the sciences and technologies, as well as the performance of the mining industry, especially in mining and geological engineering. Smart mines were introduced and widely applied around the world with advanced technologies based on the applications of AI. This paper aims to provide a comprehensive view of AI applications in mining and geological engineering, as well as the ideas for studies in the future. The paper focuses on the published papers of AI applications in rock mechanics, mining method selection, mining equipment, drilling-blasting, slope stability, environmental issues, and relevant geological engineering. The advantages and disadvantages of AI applications in mining and geological engineering will be analyzed and discussed in detail.

Keywords: Mining industry · Geo-engineering · Artificial intelligence · Machine learning · The fourth industrial revolution

1 Introduction

“Mining is not everything, but without mining, everything is nothing.” Max Planck - a famous English philosopher, said that. It has affirmed the vital role of the mining industry in the world. It is considered as an essential key and has a significant impact on many other industries. Indeed, large industries such as aviation, automobile manufacturing, mechanics, energy, electronics, to name a few, are all supplied with raw-fuel by-products of the mining industry [1–5]. With the significant demand for raw materials from other industries, advanced mining technologies also need to be applied to improve mining efficiency and minimize negative impacts on the surrounding environment. Of those, artificial intelligence (AI) is considered as a robust tool for mining problems [6]. In fact,

mining activities and geological engineering are taken into account as important issues and attract much attention from scholars as well as engineers. The problems related to the environment are phrased as impacts induced by mining activities [7].

In actuality, mining and geological engineering is a combination of underlying sciences, and they are not that simple. The primary objective of mining and geological engineering is natural resources, rock, soil, groundwater, surface water, and most of them are uncertainty factors [8–11]. Surveying, exploration and geological mapping for mines have encountered many difficulties and inaccuracies due to these uncertainty factors. Therefore, managers of mines are often faced with many complex decision-making problems without certainties [12, 13]. They can cause severe damage to people and property as well as significantly affect the production efficiency of the mine if not properly assessed. Issues related to working efficiency and optimal planning for mining are also inherently unsatisfied by investors [14]. That led to a series of changes to the improvement and optimization of mine design [15, 16]. In open-pit mines, the dangers of blasting operations are always of great concern to engineers and scientists. Blast-induced ground vibration, air over-pressure, fly-rock, back-break, dust, and toxic are always the challenges of engineers and researchers in the effort of reduction of blast-induced issues [17–19]. Many mines were forced to close due to the adverse effects of blasting. Besides, natural hazards are also considered a rival of engineers and managers. Research efforts to ensure the stability of benches and slopes are non-stop due to the influence of many uncertainty factors, as well as impacts from blasting and earthquakes [20–22].

For underground mines, similar difficulties have also been mentioned. Besides, due to the effect of mine pressure, heterogeneous rock environment and blast-induced ground vibration, as well as earthquakes, can lead to the collapse of the underground mines [23, 24]. Toxic gases, such as methane, CO, SO₂, are also potential dangers of fire and suffocation in underground mines [25–27].

In recent years, AI is considered a powerful tool capable of solving practical problems related to mining and geo-engineering. This paper aims to provide a review of AI applications in mining and geological engineering, discussion of these AI applications, as well as the chances for future in the mining industry.

2 Applications of Artificial Intelligence in Mining and Geological Engineering

2.1 Rock Mechanics

Rock mechanics is one of the indispensable fields in mining engineering. It is considered as a foundation to choose methods of mining, drilling, blasting, or assessing slope stability. However, it is an uncertainty problem and very hard to evaluate precisely. Currently, many soft computing techniques have been introduced to analyze and evaluate the uncertainty of rock mass (Fig. 1), and their performance has been significantly enhanced [28]. Herein, the FLAC3D is numerical modeling software for geotechnical analyses of soil, constructs, groundwater, rock, and ground support. It can analyze or design many engineering problems, research and testing, the factor of safety prediction, and the back-analysis of failure. Whereas the 3DEC is a three-dimensional numerical modeling code

for advanced geotechnical analysis, and its features are similar to the FLAC3D. Unlike the FLAC3D or 3DEC software, the PFC3D can be customized and applied to an extensive range of numerical investigations. It has been successfully applied for geoscience investigation, such as brittle rock fracturing, hydraulic fracturing, slope stability, soil-tool interactions, cave mining. And bulk material flow/mixing. On another side, the RS³ software is a 3D finite element analysis program for tunnel and support design, modeling slopes, foundation design, embankments, surface and underground excavations, groundwater seepage, consolidation, and more. Similar to the RS³, but the Examine2D is a 2-dimensional plane strain boundary element program for the elastic stress analysis of underground excavations. Phase2 software was also designed for similar purposes, but it is an extremely versatile 2D elastoplastic finite element stress analysis program. Whereas, the RESOBLOCK software was designed to investigate the stability of excavations and the impact of different rock bolting patterns. However, these techniques are often time-consuming and expensive.

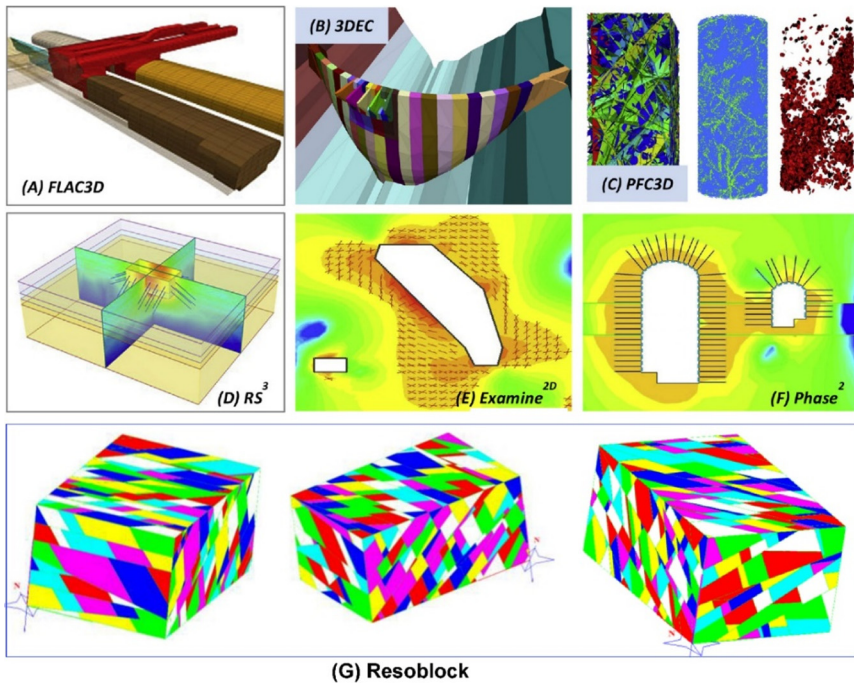


Fig. 1. Some applications of numerical analyses for rock mass [6, 29].

In recent years, AI has been studied and widely applied in evaluating and predicting rock mechanics-related problems. Along with the soft computing techniques for numerical simulation, as mentioned above, AI is taken into account as a robust tool to predict/estimate/forecast the rock mechanics and rock engineering. It can overcome the drawbacks of the numerical analysis methods with low cost and save time. Sonmez, Gokceoglu, Nefeslioglu, and Kayabasi [30] applied an artificial neural network (ANN)

to estimate rock modulus in intact rocks. Accordingly, the modulus ratio ranges of intact rock (E_i) are extensive, and they are even overlapped, as illustrated in Fig. 2. Therefore, the use of average values of E_i may be too rough since the uncertainty of rock mass. To overcome this drawback, Sonmez, Gokceoglu, Nefeslioglu and Kayabasi [30] used ANN with the uniaxial compressive strength and unit weight to estimate E_i with high reliability (i.e., correlation coefficient $R = 0.82$).

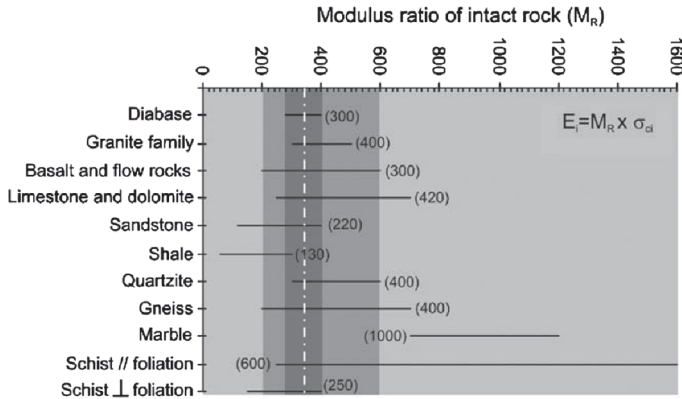


Fig. 2. The modulus ratio ranges of intact rock (with different intact rocks) [30].

In another study, Ocak and Seker [31] also developed an ANN model to predict the elastic modulus of intact rocks. A promising result was introduced in their study with a root-mean-squared error (RMSE) of 0.191 and R of 0.926. It should be noted that the uniaxial compressive strength and unit weight was also used to predict E_i as those previous study of Sonmez, Gokceoglu, Nefeslioglu, and Kayabasi [30]. Herein, core samples were collected and analyzed for the data collection (Fig. 3).

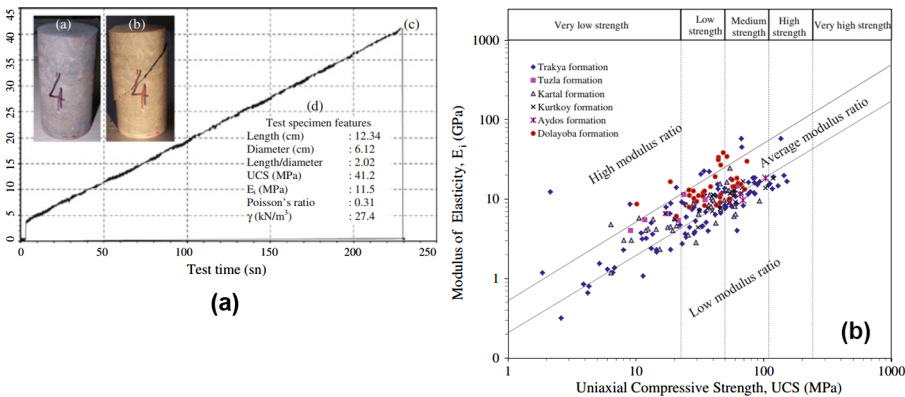


Fig. 3. Data collection and analysis [31]. (a) The specimen tests and loading period-stress; (b) Distribution of the dataset

Majdi and Beiki [32] also applied ANN to predict the deformation modulus of rock masses. However, the genetic algorithm (GA) was also applied to optimize the ANN model aiming to obtain better performance. The flowchart of the GA-ANN model for predicting the deformation modulus of rock masses is shown in Fig. 4. In another study, Rukhaiyar and Samadhiya [33] applied ANN to predict the strength of intact sandstone. Unlike the previous studies, Rukhaiyar and Samadhiya [33] used three input parameters, such as uniaxial compressive strength, intermediate, and principal stresses. One hundred ninety-two samples were collected from available databases of previous studies; however, the performance of the ANN was very high (i.e., $RMSE = 10.73$, $R^2 = 0.97$). This result showed the insights of AI (i.e., ANN) in rock mechanics and rock engineering. Similarly, Rashidi, Hajipour and Asadi [34] also applied ANN to predict the strength of intact limestone with a promising result. Based on the literature review, it is clear that ANN is a reliable method to estimate/predict/forecast the rock mechanics, as well as effectiveness supporting in rock engineering.

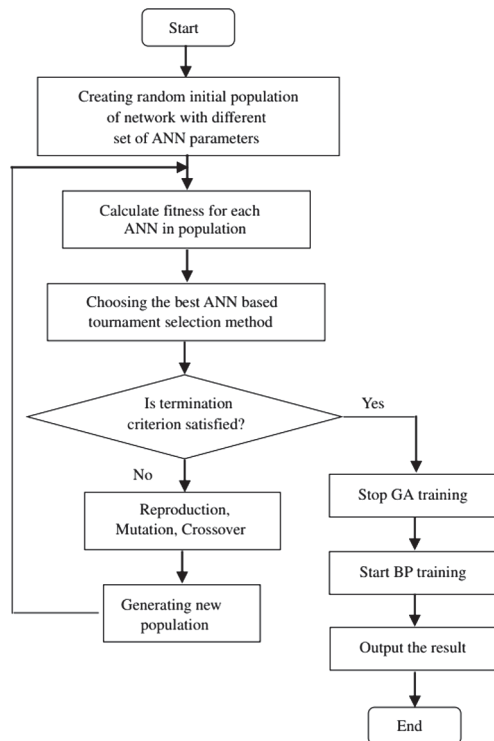


Fig. 4. Flowchart of the GA-ANN model.

On another side of rock mechanics, rockburst is taken into account as one of the critical behaviors of rock mass in deep openings. In this regard, AI techniques have also been applied to evaluate, classify, and predict the ability of rockburst, as well as the intensity of it. Indeed, Dong, Li, and Kang [35] classified rockburst using the

Random Forest (RF) algorithm. Their classification results showed that RF was a good algorithm in classifying the intensity of rockburst. Zhou, Yun, Deng, Li and Liu [36] also applied various AI techniques, such as RF, Bayes, K-nearest neighbors (KNN), and cloud model (CM), for classification of rockburst intensity. Finally, they found that the CM technique can predict rockburst better than those of the other models. In another study, Faradonbeh and Taheri [37] also applied three AI techniques, i.e., emotional neural network (ENN), decision tree C4.5, and gene expression programming (GEP), for predicting the intensity of rockburst with a promising result. Zhou, Koopialipoor, Li, and Armaghani [38] considered and developed a novel hybrid AI model based on ANN and artificial bee colony (ABC) optimization algorithm for predicting rockburst, called ABC-ANN. They claimed that the ABC-ANN model can predict rock burst with high accuracy. Figure 5 illustrates the vertical stress distribution around a workface and the accuracy of the AI techniques used for predicting rock burst.

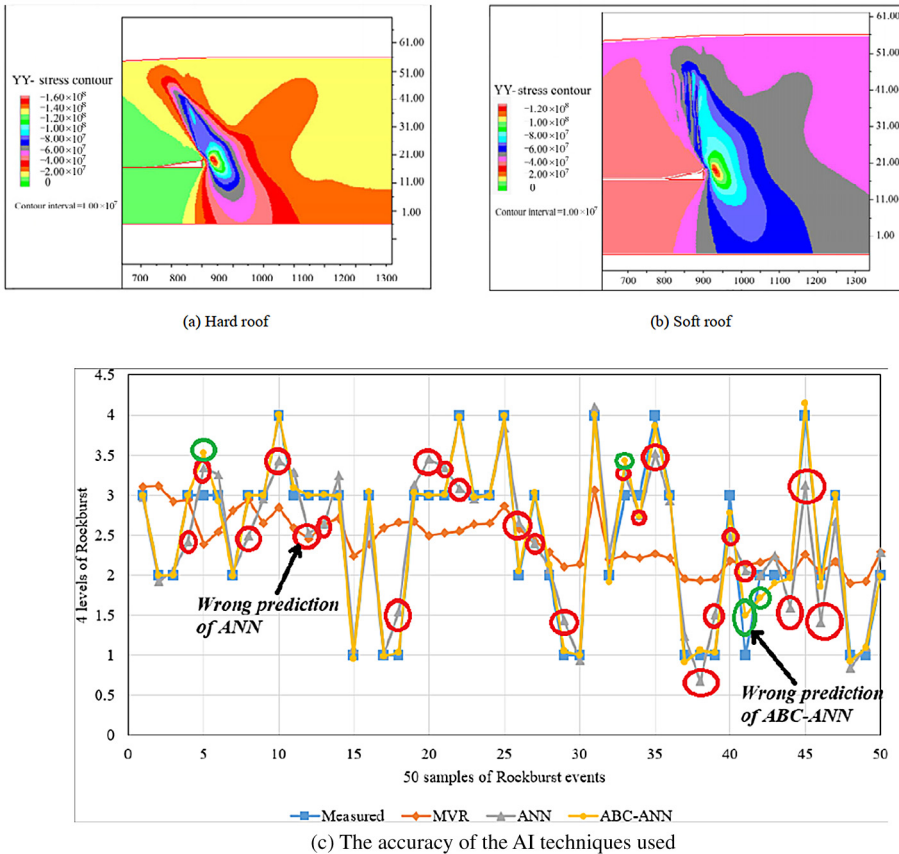


Fig. 5. Illustration of vertical stress distribution around a workface and the accuracy of the AI techniques used for predicting rockburst [38, 39].

2.2 Mining Method Selection

Mining method selection is one of the most stages of mining. It decides economic, technical, and environmental efficiency. Mining method selection is taken into account as a problem with multiple decision making, as mentioned in Fig. 6. In fact, some mines use only one mining method. However, some of the mines with more complex conditions require the use of a combination of different mining methods. Therefore, choosing the optimal mining method is a challenge for engineers and researchers.

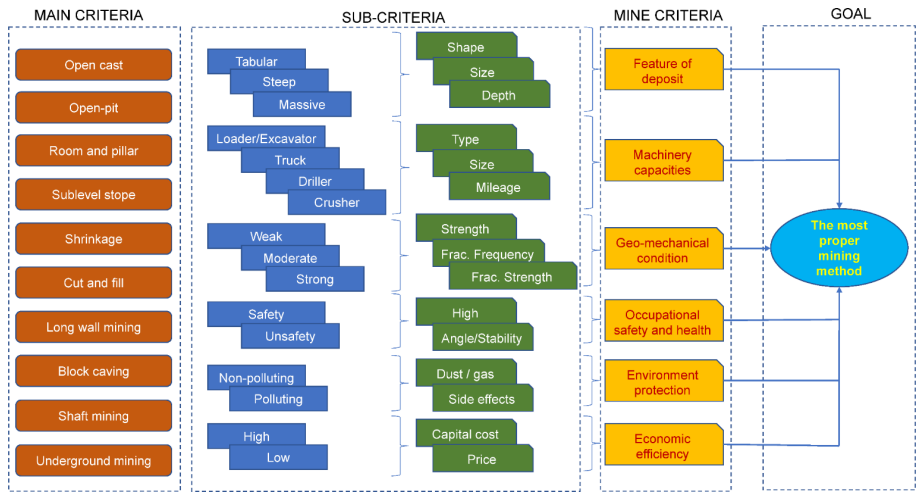


Fig. 6. Framework of mining method selection based on criteria.

To solve these above problems, AI has been studied and introduced as a useful tool in decision making and mining method selection early. Indeed, Yun and Huang [40] applied the theory of fuzzy set to select the optimal mining method for an underground mine. Three stages were applied for this aim, including initial selection, technical and economic evaluation, as well as the final decision.

In another work, mining method selection was also defined as the most critical point in practical engineering. It was recommended as a significant effect on productivity, safety, and economics. Therefore, Guray, Celebi, Atalay, and Pasamehmetoglu [41] proposed an AI model for mining method selection based on 13 different expert systems. This system can support engineers as much as possible to select a suitable mining method with the highest efficiency. Naghadehi, Mikaeil, and Ataei [42] also successfully applied the fuzzy analytic hierarchy process (FAHP) model for mining method selection in an underground bauxite mine of Iran. This model is based on the practical and majority criterial to make a decision. Another approach for mining method selection was also proposed by Azadeh, Osanloo, and Ataei [43] based on an enhanced method of the Nicholas technique [44]. Accordingly, a similar model (i.e., AHP) was applied for this task. However, fuzzy trapezoidal factors were also used to model the mining method. Furthermore, an algorithm with two steps (e.g., hierarchical technical–operational model

(HTOM) and hierarchical economic model (HEM)) was proposed in their study for selecting the suitable mining method. Considering the mechanization criteria, Özfiat [45] proposed a fuzzy model for mining method selection with a promising result. Taking into account other criteria (i.e., geological and geometrical characteristics), Dehghani, Siami, and Haghi [46] applied the grey and Tomada de Decisão Interativa Multicritério (TODIM) methods for mining method selection. Their results showed that the approaches applied are better than the previous methods. Fu, Wu, Liao, and Herrera [47] showed that hesitant fuzzy linguistic gained and lost dominance score is a robust technique to select the suitable mining method (HFL-GLDS). The framework of this method is shown in Fig. 7. In a new study, Liang, Zhao, and Hong [48] proposed the MULTIMOORA model for mining method selection. This model combined three methods, including stepwise weight assessment ratio analysis (SWARA), Heronian mean (HM) operators, and a combination of SWARA and HM, to making a final decision.

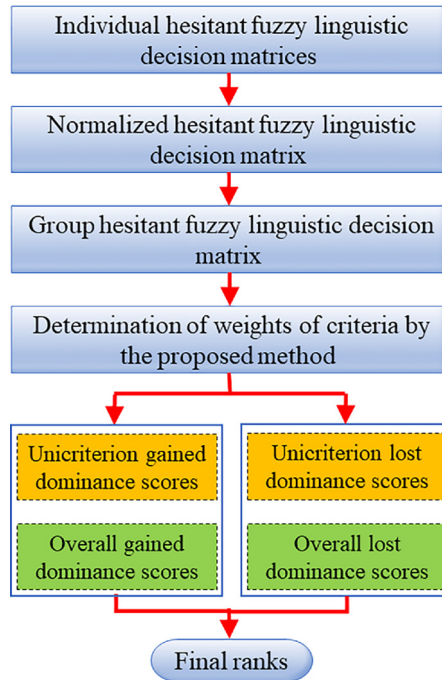


Fig. 7. Framework of the HFL-GLDS technique for mining method selection [47].

2.3 Mining Equipment Selection

In mining, equipment is indispensable for mining activities, such as drilling, blasting, loading/unloading, transporting, dumping, crushing, to name a few. However, the selection of proper mining equipment is not easy. Different types of equipment with different attributes have a complicated relationship and significantly affect the productivity of

mines [49]. Also, the selection of inappropriate mining equipment can significantly affect the economic efficiency of mines [50], even affect the surrounding environment [51]. There are two approaches to select mining equipment, including traditional and AI methods. As recommended by previous researchers, AI methods often provide better performance than traditional methods, and they should be used to select the optimal mining equipment [52, 53]. In this study, we focus on some AI techniques for mining equipment selection as a review for the feature of AI, as well as future studies. The concept of mining equipment selection using AI techniques is described in Fig. 8.

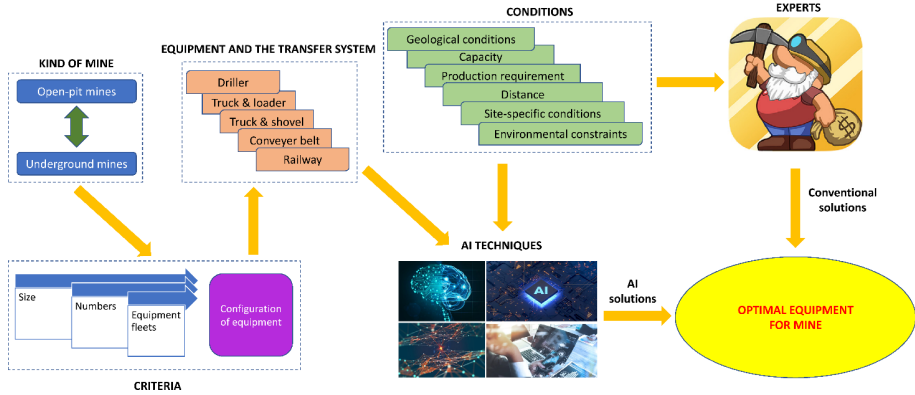


Fig. 8. The concept of mining equipment selection.

A review of the literature shows that AI techniques have been successfully applied in the selection of mining equipment. Indeed, genetic algorithms were applied to assess the feasibility as well as the compatible mining equipment [54]. Başçetin, Öztaş, and Kanlı [55] also reviewed computer software (e.g., EQS) based on an AI technique (i.e., fuzzy set theory) for selecting mining equipment. It was then introduced as a useful tool for multiple attribute decision-making, as well as mining equipment selection. In another study, Bazzazi and Karimi [56] used a fuzzy system to decide for mining equipment selection in an open-pit mine, i.e., loading-haulage. The AHP and entropy methods were combined and applied to calculate the weights of attributes. Finally, an optimal loading-haulage was selected and introduced for an open-pit mine of Iran with high reliability. In another study, AGHAJANI BAZZAZI, Osanloo, and Karimi [57] studied and proposed a new fuzzy system to select mining equipment based on three main common factors (i.e., critical, objective, and subjective factors). In this way, time consumption has significantly reduced. Based on the advances in computer science, Ahmad and Mondal [58] also developed an AI system for mining equipment selection with a combination of AHP and mixed-integer non-linear programming (MILP). This system includes two stages, calculating relative weights and finding allocations of each spare-part. Their results showed that the mining equipment with optimal parameters would be better than those of ranking. Based on machine learning algorithms and AI techniques, Samatamba, Zhang, and Besa [59] proposed an optimization algorithm for evaluating and optimizing the effectiveness of mining equipment. Sensitive inputs of the life cycle and overall

equipment effectiveness were taken into account and analyzed. Eventually, the effectiveness of mining equipment (e.g., drill rigs, loaders, dump trucks) was optimized aiming to improve the production of the mine.

2.4 Drilling-Blasting

Drilling-blasting is an essential operation for rock fragmentation or rock movement in mining, especially in open-pit mines [60, 61]. According to scientists, the effectiveness of rock fragmentation is high, depending on the drilling and blasting parameters [62, 63]. Low effectiveness of rock fragmentation can cause significant effects on the economic, environmental, and other operations (e.g., loading/unloading, transporting, crushing). Hence, to optimize the effectiveness of drilling-blasting operations, AI techniques have also been studied and applied as state-of-the-art tools with high performance.

Regarding drilling operation—a high-cost operation in open-pit mines, the performance, as well as the parameters of drilling operations, are primary concerns of engineers. Akin and Karpuz [64] applied an artificial neural network (ANN) to estimate the drilling parameters in shallow carbonates and sandstones formations. Their results were then compared with conventional methods. Finally, the ANN model was introduced as a satisfactory model for this aim. In another study, Bhatnagar and Khandelwal [65] used ANN and multivariate regression analysis (MVRA) methods to evaluate drilling performance. The results with an R^2 of 0.985 and MAE of 0.355 of the ANN model revealed that it is a robust AI technique for predicting drilling performance. Drilling troubles were also predicted by Lind and Kabirova [66] using ANN. The researchers found that ANN was a state-of-the-art method for predicting the drilling troubles (Fig. 9).

Fattahi and Bazdar [67] proposed various ANN-based models for predicting the drilling rate in open-pit mines. Accordingly, ANN and optimization algorithms (i.e., firefly algorithm (FA), simulated annealing algorithm (SAA), shuffled frog leaping algorithm (SFLA), an invasive weed optimization algorithm (IWO)) were combined for the aim of drilling rate prediction. Drilling parameters, as well as rock mass properties, were taken into account as the influent parameters for predicting the drilling rate. Finally, their results revealed that the SAA-ANN model provided better accuracy than those of the other models. AI techniques have also been taken into account to predict the penetration rate of driller in open-pit mine by Al-AbdulJabbar, Elkatatny, Mahmoud, and Abdulraheem [68]. The fact that the penetration of rate was improved 22% compared with the conventional methods in their study. Sabah, Talebkeikhah, Wood, Khosravanian, Ane-mangely, and Younesi [69] also applied several AI models to estimate the drilling rate, including ANN, support vector regression (SVR), and ANN-PSO (particle swarm optimization). A superior accuracy was demonstrated on the ANN-PSO model in predicting the drilling rate in their study. However, its performance is rivaled by the SVR model. It is clear that both ANN-PSO and SVR are robust AI techniques for this aim. In a recent study, Liao, Khandelwal, Yang, Koopialipoor and Murlidhar [70] developed a novel hybrid AI model for predicting the drilling rate based on the artificial bee colony (ABC) optimization algorithm and ANN (i.e., ABC-ANN). They claimed that the effectiveness of drilling parameters could be improved using the proposed ABC-ANN model.

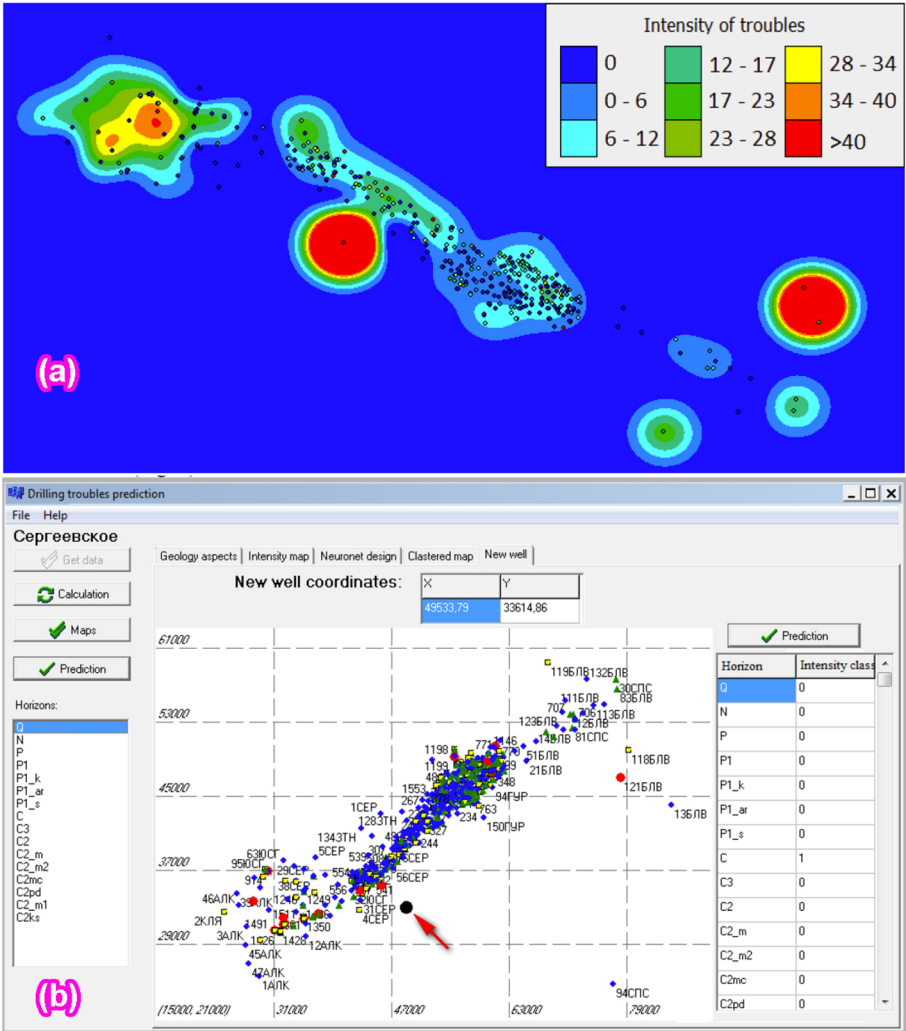


Fig. 9. Drilling points and the trouble predictions of new well using ANN [66]. (a) Clustered oilfield map; (b) Prediction of a new well

Regarding blasting operations in mining, many studies successfully applied AI techniques for optimizing blasting parameters and predicting blast-induced issues. Some applications of AI in blasting operations, as well as their performances, are listed in Table 1.

From Table 1, it is clear that AI techniques have been successfully applied in blasting operations. Of those, blast-induced ground vibration was taken into account as the most concern of the researchers since its side effects on the surrounding environment [103–107]. Based on these AI techniques, blast patterns have been designed and optimized to reduce the side effects of blasting operations [108]. Nevertheless, a review of the literature shows that most of the published studies focused on predicting/estimating the problems induced by blasting only, as illustrated in Fig. 10, and the optimization problems have not been appropriately handled.

Table 1. Applications of AI techniques in blasting and their performances

Reference	Blasting issues					AI techniques	Performances
	Ground vibration	Air over-pressure	Fly-rock	Rock Fragmentation	Back-break		
Khandelwal and Singh [71]	✓	–	–	–	–	ANN	$R^2 = 0.986$; MAE = 0.196
Monjezi, Ahmadi, Sheikhan, Bahrami and Salimi [72]	✓	–	–	–	–	MLP, GRNN	RMSE = 0.031
Monjezi, Ghafurikalajahi and Bahrami [73]	✓	–	–	–	–	ANN	$R^2 = 0.927$; RMSE = 0.071
Nguyen, Bui, Bui and Mai [74]	–	✓	–	–	–	MLP, BRNN, HYFIS	$R^2 = 0.961$; RMSE = 2.319
Hajihassani, Armaghani, Monjezi, Mohamad and Marto [75]	✓	✓	–	–	–	PSO-ANN	$R^2 = 0.890$; MSE = 0.038
Nguyen and Bui [76]	–	✓	–	–	–	RF-ANN	$R^2 = 0.985$; RMSE = 0.847
Marto, Hajihassani, Jahed Armaghani, Tonnizam Mohamad and Makhtar [77]	–	–	✓	–	–	ICA-ANN	$R^2 = 0.981$; RMSE = 6.582
Trivedi, Singh and Raina [78]	–	–	✓	–	–	ANN	$R^2 = 0.983$; RMSE = 0.990
Nguyen, Bui, Tran, Le and Do [79]	✓	–	–	–	–	ANN	$R^2 = 0.964$; RMSE = 0.738
Amiri, Amnieh, Hasanipanah and Khanli [80]	✓	✓	–	–	–	ANN-KNN	$R^2 = 0.950$; RMSE = 1.700
Saadat, Khandelwal and Monjezi [81]	✓	–	–	–	–	MLP	$R^2 = 0.957$; MSE = 0.000722
Hasanipanah, Monjezi, Shahnazar, Armaghani and Farazmand [82]	✓	–	–	–	–	SVM	$R^2 = 0.957$; RMSE = 0.340

(continued)

Table 1. (continued)

Reference	Blasting issues					AI techniques	Performances
	Ground vibration	Air over-pressure	Fly-rock	Rock Fragmentation	Back-break		
Trivedi, Singh and Gupta [83]	–	–	✓	–	–	ANN, ANFIS	$R^2 = 0.980$; RMSE = 1.170
Armaghani, Hajihassani, Marto, Faradonbeh and Mohamad [84]	–	✓	–	–	–	ICA-ANN	$R^2 = 0.984$
Nguyen, Drebenstedt, Bui and Bui [85]	✓	–	–	–	–	HKM-ANN	$R^2 = 0.983$; RMSE = 0.554
Dindarloo [86]	✓	–	–	–	–	GP	$R^2 = 0.970$; RMSE = 4.700
Hasanipناه, Faradonbeh, Amnieh, Armaghani and Monjezi [87]	✓	–	–	–	–	CART	$R^2 = 0.950$; RMSE = 0.170
Zhang, Nguyen, Bui, Tran, Nguyen, Bui and Moayedi [88]	✓	–	–	–	–	PSO-XGBoost	$R^2 = 0.968$; RMSE = 0.583
Monjezi, Baghestani, Faradonbeh, Saghand and Armaghani [89]	✓	–	–	–	–	GEP	$R^2 = 0.878$; RMSE = 3.470
Hasanipناه, Faradonbeh, Armaghani, Amnieh and Khandelwal [90]	–	–	✓	–	–	RT	$R^2 = 0.872$; RMSE = 27.459
Hasanipناه, Shahnazar, Arab, Golzar and Amiri [91]	–	–	–	–	✓	PSO-ANFIS	$R^2 = 0.922$; RMSE = 0.130
Armaghani, Hajihassani, Sohaei, Mohamad, Marto, Motagbedi and Moghaddam [92]	–	✓	–	–	–	ANFIS	$R^2 = 0.971$; RMSE = 2.329
Nguyen, Bui, Bui and Cuong [93]	✓	–	–	–	–	XGBoost	$R^2 = 0.952$; RMSE = 1.742
Arthur, Temeng and Ziggah [94]	✓	–	–	–	–	GPR	$R = 0.834$; RMSE = 0.157
Nguyen [95]	✓	–	–	–	–	SVM	$R^2 = 0.924$; RMSE = 0.396
Faradonbeh, Armaghani, Amnieh and Mohamad [96]	–	–	✓	–	–	GEP, FFA	$R^2 = 0.924$; RMSE = 29.956
Hasanipناه, Amnieh, Arab and Zamzam [97]	–	–	–	✓	–	PSO-ANFIS	$R^2 = 0.890$; RMSE = 1.310

(continued)

Table 1. (continued)

Reference	Blasting issues					AI techniques	Performances
	Ground vibration	Air over-pressure	Fly-rock	Rock Fragmentation	Back-break		
Gao, Karbasi, Hasanipanah, Zhang and Guo [98]	–	–	–	✓	–	GPR	$R^2 = 0.948$; RMSE = 2.010
Asl, Monjezi, Hamidi and Armaghani [99]	–	–	✓	✓	–	FFA-ANN	$R^2 = 0.940$; RMSE = 0.100
Mojtahedi, Ebtehaj, Hasanipanah, Bonakdari and Amnieh [100]	–	–	–	✓	–	FFA-ANFIS	$R^2 = 0.980$; RMSE = 0.520
Zhang, Bui, Trung, Nguyen and Bui [101]	–	–	–	✓	–	ACO-BRT	$R^2 = 0.962$; RMSE = 1.643
Zhou, Li, Arslan, Hasanipanah and Amnieh [102]	–	–	–	✓	–	FFA-ANFIS, GA-ANFIS	$R^2 = 0.989$; RMSE = 0.974

Note: MLP (Multiple layers perceptron); GRNN (General regression neural network); BRNN (Bayesian regression neural network); HYFIS (Hybrid fuzzy inference system); PSO (Particle swarm optimization); RF (Random forest); ICA (Imperialist competitive algorithm); KNN (K-nearest neighbors); SVM (Support vector machine); ANFIS (Adaptive neuro-fuzzy inference system); HKM (Hierarchical K-means clustering); GP (Genetic programming); CART (Classification and regression tree); XGBoost (extreme gradient boosting machine); GEP (Gene expression programming); RT (Regression tree); GPR (Gaussian process regression); FFA (Firefly algorithm); ACO (Ant colony optimization); BRT (Boosted regression tree); GA (Genetic algorithm).

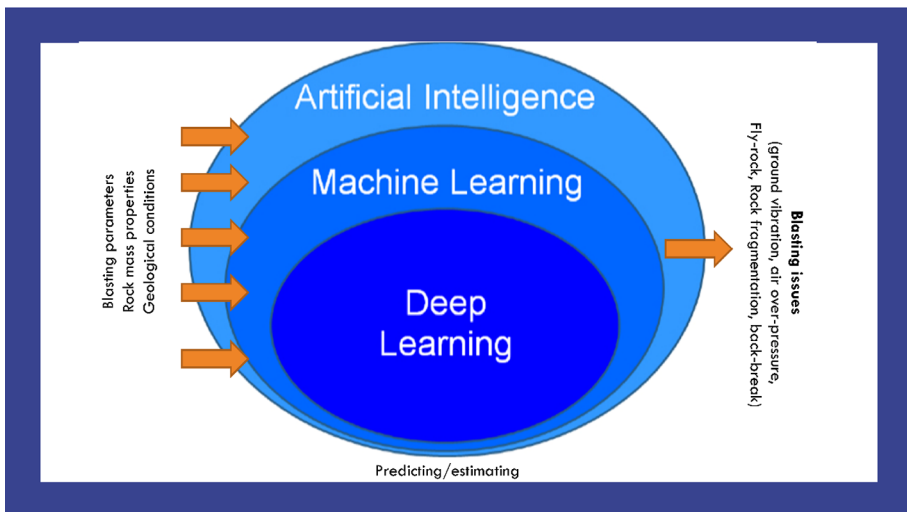


Fig. 10. Framework of AI techniques for blasting issues in mining.

2.5 Slope Stability

As one of the critical problems in open-pit mines, slope stability is necessary to be evaluated and predicted carefully and precisely. Similar to the side effects of blasting operations, instability of slope in open-pit mines can make serious effects, even fatal to humans. It disrupts the production and severely affects the economy of mines [109], especially deep open-pit mines [110]. In actual, there are many methods to evaluate the stability of slope in open-pit mines, such as Kinematic [111], 2D and 3D Finite Element Analysis (FEM) [112–114], elastoplastic finite elements [115, 116], limit equilibrium and strength reduction methods [117], upper bound approach [118], numerical manifold [119], Monte Carlo [120], to name a few. Of those, most of them are the numerical and simulation methods, as illustrated in Fig. 11.

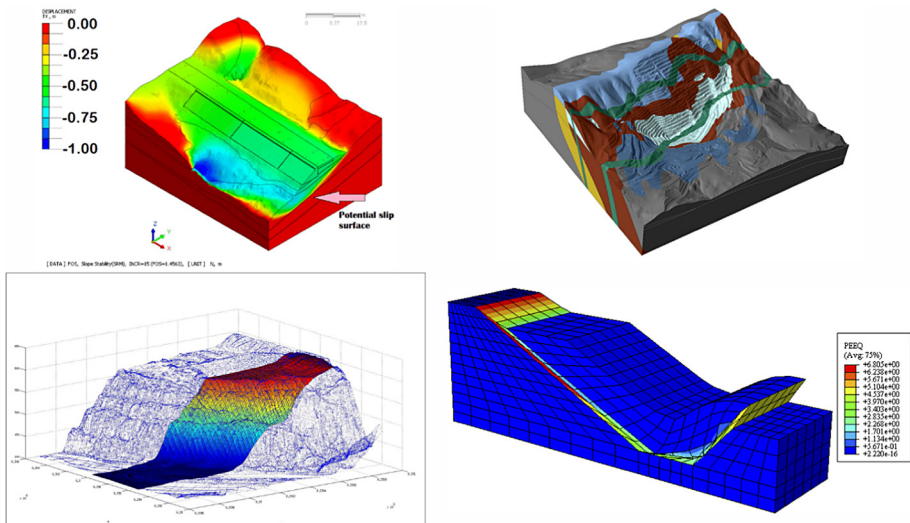


Fig. 11. Some evaluations of slope stability based on the 3D FEM technique.

In recent years, AI techniques have also been successfully applied in evaluating and predicting slope stability [121–123]. Indeed, grey systems and ANN have been applied to predict slope stability by Lu and Rosenbaum [124]. They were introduced as a robust tool to predict the movement of the ground in the future with high reliability based on geotechnical properties. Other scholars also conducted similar studies based on ANN for predicting slope stability with a promising result [125–128]. In another study, Kang, Li, and Ma [129] also applied the artificial bee colony (ABC) algorithm to analyze the slope stability. Hoang and Pham [130] also proposed another hybrid AI model to assess slope stability based on the FFA and the Least Squares Support Vector Classification (LS-SVC). The accuracy was then improved by roughly 4% compared with the conventional methods. Based on the optimization algorithms, Luo, Bui, Nguyen, and Moayedi [131] developed a novel hybrid model for predicting slope stability under the combination of the PSO algorithm and the Cubist algorithm (CA), i.e., PSO-CA model.

Koopialipoor, Armaghani, Hedayat, Marto, and Gordan [132] developed various hybrid AI models for a similar purpose, including PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN models. Finally, the PSO-ANN model was found as the best model in their study for predicting slope stability. Similar studies can be found in the following papers with similar approaches [133–139].

For predicting slope stability using AI techniques, there are two approaches based on the classification and regression problems. For the classification approach, the datasets are often the cases in actual and the history datasets are collected based on the phenomena (i.e., stability or instability). For the regression approach, the AI models were developed based on the analysis results from numerical models or software. Normally, the safety of factor (SOF) is used as the criteria to evaluate the stability of the slopes or benches [140], and it can be modeled and extracted from 2D or 3D finite element analysis. According to Zhou, Cheuk, and Tham [141], the slopes and benches are stable with the $SOF > 1$. However, Sakellariou and Ferentinou [127] recommended that the SOF should be more than 1.2 to ensure the stability of the slopes. Figure 12 illustrates the approaches (i.e.,

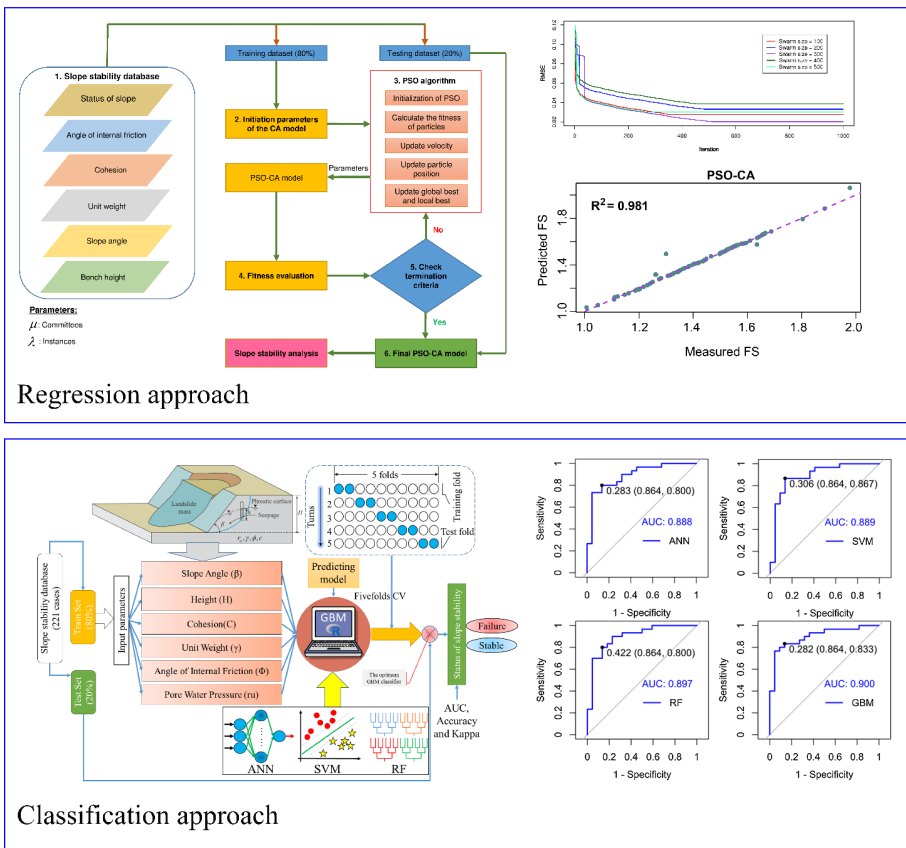


Fig. 12. Two AI approaches in evaluating slope stability (i.e., classification and regression) [131, 142].

classification and regression) for predicting slope stability, as well as the framework and model assessment methods of these approaches.

2.6 Environmental Issues

Regarding environmental issues in mining, they are taken into account as significant concerns of managers, as well as residential areas [143]. Nowadays, environmental issues are more carefully considered in terms of economic efficiency for sustainable development in mining [144–146]. Many countries have closed down open-pit mines because of their massive impact on the environment, especially soil, water, air, and ecosystems [147–149]. The environmental impacts of mining activities seriously have a significant effect on human health, even cause fatal if affected for a long time. Therefore, to overcome these drawbacks, AI techniques have been successfully applied in many fields, as well as smart mines. The concept of AI techniques for environmental issues in mining is presented in Fig. 13.

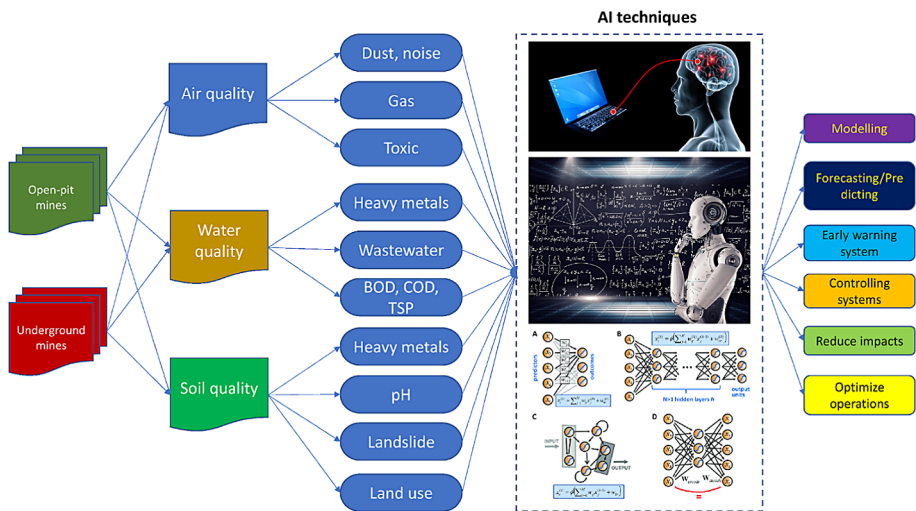


Fig. 13. Concept of AI techniques for environmental issues in mining.

In underground mines, methane emissions were modeled and predicted by ANN with a promising result [150]. It was considered as a foundation for ventilation in underground mines aiming to reduce gas and toxic, as well as the risk of fire in underground mines. Another similar study was also conducted to predict methane emissions in longwall using ANN [151]. Coal dust and methane explosions were also warned as the most critical factors in underground coal mines [152]. Therefore, the strategies for removing dust were proposed using AI techniques [153–155]. Also, strategies for ventilation in underground mines using AI techniques have been proposed and applied as well. Karacan [156] developed an ANN model for predicting and optimizing ventilation air in underground mines. Hua and Liangshan [157], ZHANG, and DOU [158] also used ANN to assess and control the ventilation system for underground mines with high performance.

In open-pit/open-cast mines, environmental impacts include not only air quality but also water and soil quality. Concerning air quality in open-pit mines, dust, gas, toxic, even radiation, are those of the severe impacts on the air environment. Unmanned aerial vehicle (UAV) was used to monitor dust in operations in open-pit mines (e.g., blasting, transporting, crushing, to name a few) [159–162]. Subsequently, hazardous mining-induced were assessed and mapped/predicted by AI techniques based on the datasets collected from UAV [163, 164]. In another study, Patra, Gautam, Majumdar, and Kumar [165] predicted dust concentration in open-cast mine using ANN with high reliability. Bui, Lee, Nguyen, Bui, Long, Le, Nguyen, Nguyen, and Moayedi [166] also proposed a novel AI technique based on the Support Vector Machine for regression problems (SVR) and the Particle Swarm Optimization (PSO) algorithm (i.e., PSO-SVR) to estimate PM10 concentration from drilling operations in open-pit mines with high accuracy. Then, an integrated life cycle inventory and ANN model were established to manage air pollution in the open-pit mine [167]. Nagesha, Kumar, and Singh [168] used ANN to predict PM10 and PM2.5 in open-cast mining operations with high accuracy and reliability.

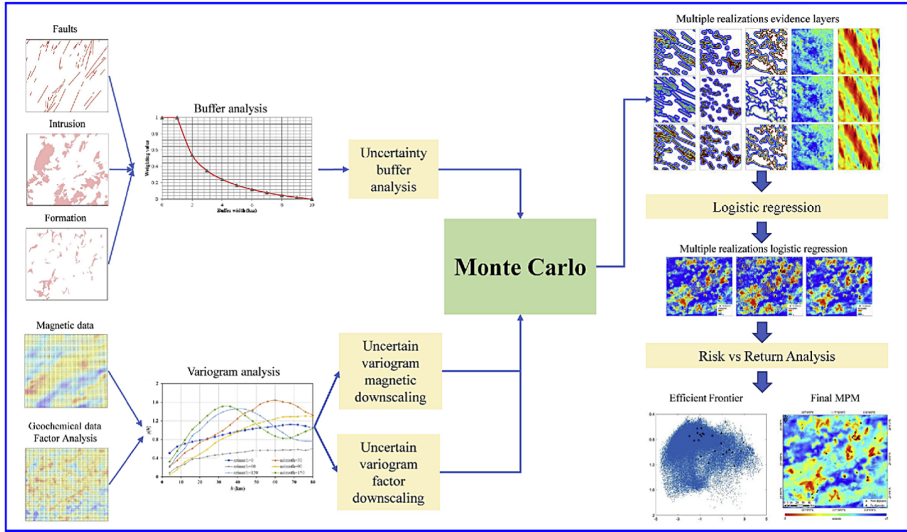
For water pollution, wastewater is considered as a big concern of mining companies, especially metal or mining. It can make dangerous for ecology as well as the health of humans [169, 170]. In recent years, many techniques have been proposed to treat wastewater in mining industries. For example, nanofiltration technology has been applied to treat mining wastewater with high performance [171]. The low-cost absorption techniques for removing heavy metals were also studied and applied in the treatment of mining wastewater [172–175]. Then, AI techniques have been used to estimate or predict the efficiency of heavy metals absorption [176–180]. They were evaluated as successful in predicting, as well as assessing the efficiency of heavy metals absorption with high accuracy.

Similar to water pollution, heavy metals can also appear in the soils of mining industries, and it became a severe problem in many countries around the world [181–184]. Although heavy metals can occur in natural soils; however, they were found in industrial, residential, agricultural, and mining areas as well with high contributions [182]. Of those, mining is considered as the most significant sources of heavy metals in soil [185–188]. To improve the quality of soils in mine sites, many techniques were applied, especially heavy metals uptake techniques [189–193]. Subsequently, AI techniques have been applied to predict and optimize the reduction of heavy metals in soils [194–197]. Also, intelligence models were applied to estimate the number of heavy metals in soils with high accuracy, for example, ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR) [198]. Generally, AI techniques are taken into account as useful techniques in the management and improvement of soil pollution in the mining industry.

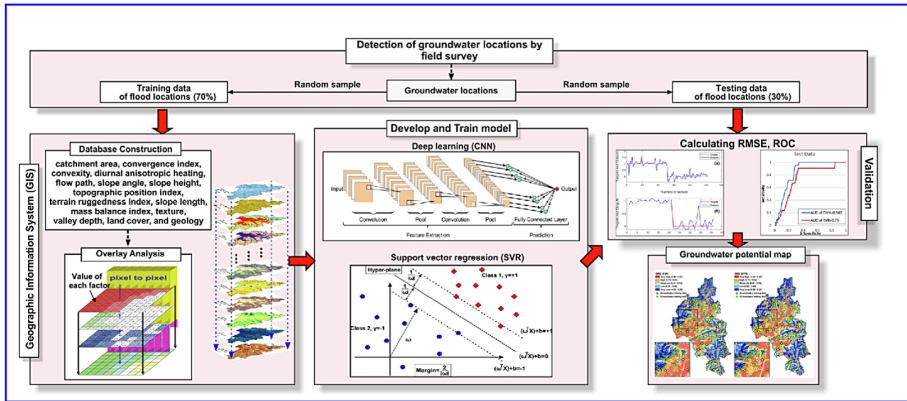
2.7 Mineral and Groundwater Potential Mapping

In geological engineering, AI techniques have also been widely applied in many areas, such as mineral potential mapping, estimating the components of minerals, landslide susceptibility map, modeling groundwater, to name a few. Of those, mineral and groundwater potential mapping is the most effective application of AI techniques with high

reliability. An example of mineral and groundwater mapping using AI techniques is shown in Fig. 14.



(a)



(b)

Fig. 14. Framework of AI models for mineral and groundwater potential mapping (a) Mineral potential mapping [199]; (b) Groundwater potential mapping [200]

In this regard, AI techniques were combined with Geographic Information Systems (GIS) to determine the locations of minerals as well as their components and contents. Spatial data and geo-informatics, remote sensing, properties of the rock mass, geological conditions, to name a few, were used as the input variables for modeling and establishing mineral and groundwater potential maps. Accordingly, Porwal, Carranza, and Hale [201] applied a fuzzy system to predict potentially mineralized zones. Their results confirmed

that AI techniques are good candidates to construct mineral and groundwater potential maps. A similar study was also conducted by Porwal, Carranza, and Hale [202] using a radial basis functional link net (RBFLN) with a promising result. In another study, a variety of AI techniques, such as ANN, wavelet neural network (WNN), and SVM, were also developed and used for predicting Cu mineralization [203]. Chen and Wu [204] developed an extreme learning machine (ELM) model for mapping polymetallic prospectively with an accuracy of 82%. Also, many other similar studies were conducted for mineral potential mapping using AI techniques. The studies mainly use different AI models to create mineral maps and compare them as well as evaluate their performance.

For groundwater mapping, many AI techniques are also developed and applied with high accuracy. Naghibi, Pourghasemi, and Dixon [205] used a boosted regression tree (BRT), RF, and CART models to produce groundwater spring potential maps. Their results showed that the BRT model provided the highest accuracy in the groundwater potential mapping with an accuracy of 81%. Naghibi, Ahmadi, and Daneshi [206] also applied SVM, RF, and RFGA Genetic Algorithm) to assess groundwater potential by spring locations. The accuracy of the RFGA model obtained 85.6% for potential groundwater mapping. Nhu, Rahmati, Falah, Shojaei, Al-Ansari, Shahabi, Shirzadi, Górski, Nguyen, and Ahmad [207] developed a novel AI system based on bivariate, and multivariate models to establish groundwater spring potential maps with accuracy was up to 85%. Through several above studies, it is clear that AI techniques can be used for potential groundwater mapping with high performance and accuracy. They can explain the relationship between uncertainty factors very well and providing outstanding results.

3 Discussion

From the above reviews, it can be seen that AI techniques have been widely applied in mining and geological engineering with greatly improved efficiency. AI applications have leveraged the power of rock mechanics as powerful tools to simulate and predict rock components and stresses. Nowadays, one can simulate the rock mass and its properties with high accuracy using AI techniques [208–210]. This technology is considered as the foundation for designing, developing, and optimizing other technologies related to rock mechanics, such as rock fragmentation, design tunnels, and underground mines, assessment of landslide and slope stability, to name a few. However, some drawbacks of AI techniques have also been shown in previous studies. The accuracy of AI techniques is highly dependent on data collection and analyses [74, 211]. The problems related to over-fitting and under-fitting are big concerns of developers in AI technology [212–214]. Besides, some other aspects of rock mechanics have not been studied and applied using AI techniques to predict and optimize, or the ability to apply has not satisfied scientists. Indeed, AI models for predicting/forecasting and optimizing rockfall seem to be very rare, and the accuracy is lowly [215]. For cracks in the rock, this is an essential parameter in assessing the properties of the rock mechanics as well as predicting the stability of the slopes and other works-related. However, previous researches just only stopped at simulating the fracture system of rock mass without prediction and evaluation by AI techniques. As for the rockburst phenomenon, the accuracy of the AI methods was just over 65% and had not satisfied scientists. Meanwhile, rock mechanics and uncertainty factors play an essential role in the classification and prediction of rockburst intensity.

Concerning mining method selection, even though the concept was shown in Fig. 6 and many researchers have successfully applied AI in this field. Nevertheless, previous and current studies have not been thoroughly combined with the criteria (i.e., main criteria, sub-criteria, and mine criteria) to select the most proper mining method. To solve this problem, a detailed database with high precision of criteria, as well as operations in mining, is necessary. Also, they should be combined with AI techniques in mine planning, as well as optimization of mine planning and boundaries [216–218] to select the most proper mining method.

For mining equipment selection, although the reviews showed that AI techniques had been successfully applied in this field. However, previous and current studies just only focused on the pairs of equipment related to loading and transporting, e.g., loading-haulage, truck-shovel. Whereas, many types of equipment can be used in mining, as mentioned in Fig. 7, and they have a significant effect on the productivity of mines. Thus, researches on the mining equipment selection with various types of equipment (e.g., driller, truck, shovel, conveyer, railway) using AI techniques is challenging for engineers and researchers. Remarkable, mining equipment selection and optimization using AI techniques are taken into account as a useful solution for hybrid mines (combining open-pit and underground mine sites) aiming to increase productivity, decrease costs, and reduce the impacts on the surrounding environment.

For drilling-blasting operations, it can be seen that AI technologies are pretty complete. They provided AI models that can predict blast-induced ground vibration, air over-pressure, fly-rock, rock fragmentation, and back-break with high accuracy. However, the geological conditions-related parameters still seem to be a hard problem with scientists in predicting blasting issues since the uncertainty factors of the rock environment. Besides, the development of novel AI models for blasting issues is still necessary to contribute to the knowledge of AI, and providing novel AI models that can predict blasting issues in many areas with high accuracy.

Similar to drilling-blasting operations in mining, applications of AI in evaluating and predicting slope stability has met the demands of the assessment and forecast of slope stability with high accuracy. However, novel AI models and technologies using satellite image, UAV combined with AI models to evaluate and predict slope stability is necessary for the future. Also, the combination of GIS with AI techniques in drilling-blasting operations is a potential solution for other studies in the future aiming to improve the accuracy of drilling-blasting operations, as well as their impacts on the surrounding environment.

The problems related to the environment in mining were also investigated, evaluated, and forecasted by AI models, as reviewed above. However, AI models for predicting/forecasting air quality in mines (i.e., open-pit and underground mines) seem not to be conducted. Air quality controlling systems for mining using the Internet of Things (IoT) and AI techniques have not also been proposed. These systems are considered as an essential problem in assessing and forecasting air quality of mines. It is an important criterion to reduce the negative impacts on the surrounding air environment and human health. Soil environment has not been paid much attention in addition to heavy metal pollution. AI models for evaluating and predicting the concentration of heavy metals

in the soil, as well as the effectiveness of soil heavy metal handling systems are imperfect. Therefore, future research should focus on analyzing and forecasting heavy metal pollution and the ability to treat them with heavy metals uptake systems based on AI techniques. Water environment issues also need more attention and in-depth study. AI techniques in assessing, analyzing, and forecasting the quality of wastewater, as well as the quality of water after being treated in mines, are necessary to ensure the impacts of wastewater in mines on the surrounding environment are minimal.

Concerning AI applications in geological engineering, scientists have been very successful in using them for mineral and groundwater potential mapping, as reviewed above. The accuracy of AI techniques was demonstrated to be higher than traditional methods. Also, combining GIS and AI models have increased the accuracy of AI models not only in terms of mineral/groundwater content but also in terms of spatial and location accuracy, as well as their distribution positions. However, researches on the development of novel AI models for geological engineering is still needed in the future, especially new AI applications for geological engineering in deep-sea mining, prediction of composition and content of minerals, groundwater, to name a few.

4 Conclusion

In this paper, applications of AI in mining and geological engineering were reviewed. Their advantages and disadvantages were mentioned and discussed in this paper. Furthermore, the potential solutions, as well as future research, have been indicated as well. This paper showed that AI techniques had been widely applied with high performance in the mining industry. The ANN-based and hybrid AI models are state-of-the-art techniques with high accuracy that is the goal of researchers in recent years. Besides, precise data and information are the indispensable requirement of AI techniques. It decides the accuracy and reliability of AI models in practical engineering. However, engineers and researchers often have difficulty in this regard due to uncertainties and impreciseness previously described. Therefore, data needs to be accurately collected with high reliability to improve the accuracy of AI models in mining and geological engineering. In general, AI techniques are advanced techniques that play a large role in mining and geological engineering. They should be used in practical engineering to improve the performance, as well as minimize impacts on the surrounding environment.

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