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State-of-the-art review of machine learning and optimization algorithms applications in environmental effects of blasting

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Abstract
The technological difficulties related with blasting operations have become increasingly significant. It is crucial to give due consideration to the evaluation of rock fragmentation and the threats posed by environmental effect of blasting (EEB). To address these challenges, numerous scholars have conducted extensive research employing various assessment techniques with the aim of mitigating risks and preventing the emergence of unfavorable EEB. The occurrence of EEB is prevalent during the excavation of hard rock, and it presents significant hazards to personnel safety, equipment integrity, and operational continuity. Therefore, conducting a systematic review of EEB is of utmost importance as it enables a comprehensive understanding of the contributing factors. Such an understanding plays a vital role in advancing EEB prediction and prevention methods. The careful selection of an appropriate EEB assessment method is a crucial aspect of blasting operations. However, there is a lack of comprehensive discussions on the applications of machine learning (ML) and optimization algorithms (OA) in addressing various EEB. Only a limited number of papers have briefly touched upon this topic. Therefore, the primary objective of this paper is to bridge this gap by conducting an analysis of global trends using CiteSpace and VOSviewer software from the year 2000 onwards. It comprehensively explores EEB classification and definition, encompassing air overpressure (AOp), ground vibration, dust, backbreak, flyrock, and rock fragmentation. Furthermore, the paper provides a compendium of the most recent ML and OA prediction techniques used to addresses EEB. Finally, the paper concludes by proposing future directions for exploring innovative approaches that combine data-driven ML techniques with knowledge-based or physics-based methods. Such integration has the potential to mitigate hazards during blasting operations and reduce the likelihood of unfavorable EEB occurrences.

Keywords Environmental effect of blasting · Machine learning · Optimization algorithms scientometric analysis · Air overpressure · Ground vibration · Dust · Backbreak · Flyrock · Rock fragmentation

Extended author information available on the last page of the article

1 Introduction

Rock fragmentation in mining involves the breakage of hard rock into appropriate sizes to facilitate downstream handling and processing. In spite of introduction of new technologies for breaking rock, blasting has currently remained most popular methodology for breaking rock (Yu et al. 2020a, b; Bayat et al. 2021; Abbaspour et al. 2018). The technique is also common in many underground space excavation projects for breaking hard rock, including the construction of diversion tunnels, underground mine, subways, and hydropower stations (Zou et al. 2021; Koopialipoor et al. 2019a; Ocak and Bilgin 2010; Singh et al. 2021).

The outcomes of a blasting event can significantly influence the entire mining operation, encompassing activities like waste/ore transportation and beneficiation (Ripley and Redmann 1995). Blasting carries substantial environmental, operational, and financial implications. Environmental effects of blasting (EEB), which a term defined as the intricate web of consequences stemming from explosive detonation in industrial settings, play a pivotal role in shaping the trajectory of blasting operations. (Murlidhar et al. 2020; Siskind and Stagg 1997) The comprehension and alleviation of these impacts stand as a top priority, not solely for the assurance of safety and effectiveness in blasting operations but also for the protection of the neighboring environment and communities. It is worth noting that only a fraction of the explosive energy utilized in blasting, around 25–30%, is effectively utilized for achieving the desired fragmentation, throw, and development of muck piles (Palamure 2016; Zhou et al. 2016, 2024). However, the transformation of excess energy results in undesired environmental effects, including dust/fumes, backbreak, ground vibration, airblast/air overpressure, and flyrock. Figure 1 illustrates the fundamental process and classification of environmental consequences associated with blasting.

The undesirable effects of blasting can escalate to the extent that they cause disturbance and pose risks to the safety, health, and well-being of individuals, as well as inflict damage to nearby structures and equipment (Dumakor-Dupey et al. 2021). Furthermore, blasting activities can have an impact on slope stability, geological structures, and groundwater.

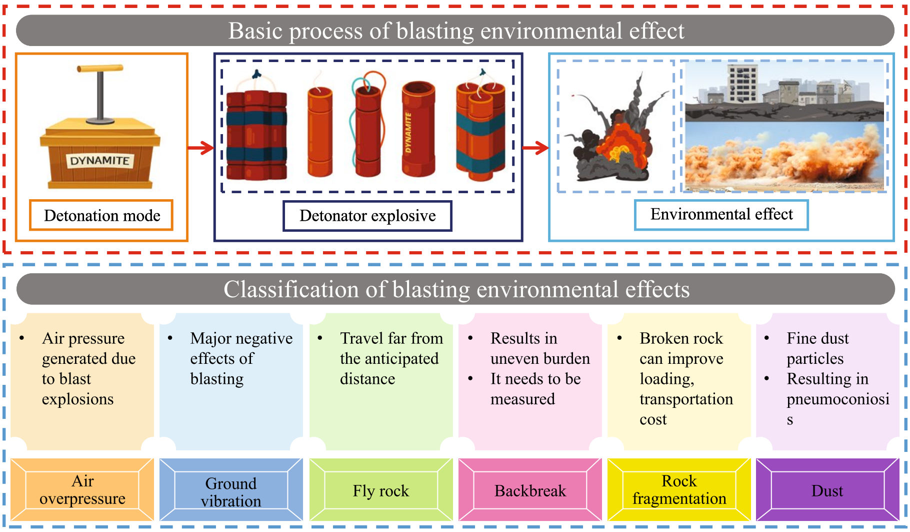

Fig. 1 The basic process and classification of blasting environmental effects

When soluble components from detonators and incompletely combusted explosives contaminate groundwater during blasting, it can give rise to various issues (Kernen 2010). The widening of fractures caused by the loss of lateral confinement can result in short-term turbidity as well as long-term alterations to existing wells (Birch et al. 2010). Moreover, the vibrations and AOp generated by blasting in proximity to cave sections can potentially compromise the structural integrity of the caves (Dumakor-Dupey et al. 2021). Several mining jurisdictions, including China, the United States, Brazil, Ghana, India, Turkey, and South Africa, have witnessed a significant number of complaints, with some escalating into protests against mining operations due to the impacts of EEB (Varris and Thorpe 2012; Bansah et al. 2016; Agrawal and Mishra 2020). These incidents highlight the importance of addressing the concerns and mitigating the adverse effects associated with blasting activities in order to foster sustainable excavation practices. Hence, it is of utmost importance to possess the capability to comprehensively summarize and visually assess EEB. This approach serves as a factual basis for conducting detailed investigations into the underlying mechanisms and classifications of EEB. Such an understanding is essential for developing effective strategies and measures to mitigate and manage the environmental impacts associated with blasting operations. By establishing a solid foundation of knowledge in this area, the civil engineering can work towards ensuring sustainable practices and minimizing the adverse effects on the environment.

The effective prediction and prevention of EEB present significant challenges due to their complex nature. The causes of EEB in blasting involve multiple factors, including the nonlinear behavior of blasting and the instability of explosives (Isaac et al. 2022). These challenges are inherent to the blasting environment. Hence, it becomes crucial to carefully consider the selection of prevention technologies based on the specific blasting conditions of the rock mass. Accurate prediction of the likelihood of various EEB events plays a pivotal role in choosing the appropriate preventive measures. Therefore, conducting a critical and up-to-date review of the available ML and OA for addressing EEB is essential prior to selecting a prevention technique. This comprehensive assessment will ensure that the most suitable ML and OA approaches are employed to effectively address the challenges associated with EEB.

The subsequent sections of this paper are organized as follows: Sect. 2 examines global collaborations, hotspots, and trends in various EEB by utilizing CiteSpace and VOSviewer (Chen 2006; Van Eck and Waltman 2017). Section 3 presents a summary of typical definitions of different EEB types and provides insights into their respective characteristics. Section 4 offers a comprehensive review of ML and OA methods for predicting EEB. Section 5 discusses the future directions of EEB research and outlines potential areas of exploration. Finally, in Sect. 6, comprehensive conclusions are drawn based on the extensive review conducted in this study.

2 Scientometric review on rock blasting

Over the past century, various technologies have been introduced for rock breaking, including surface miners, primary and secondary breakers, and tunnel boring machines (Mohamad et al. 2018; Bouzid and Bouaouadja 2000; Zhou et al. 2022). Despite the emergence of these new technologies, blasting has remained the most cost-effective method for rock breaking in mining, tunneling, and civil engineering projects (Jang and Topal 2013). The success of blasting largely depends on factors such as the properties of the rock mass, characteristics of the explosives used, blast design, and adherence to standard design procedures. These factors can be further classified as either favorable or unfavorable parameters (see Fig. 2). However, blasting is often accompanied by side effects or environmental issues, including fly rocks, seismic activity, air blast, and blast-induced ground vibration. These side effects have a negative impact on operations, leading to additional investments aimed at mitigating their effects and, most importantly, ensuring the safety of workers and the surrounding environment.

Numerous studies have been conducted to investigate EEB in order to enhance efficiency and applicability. These studies have focused on various aspects, including the prediction of backbreak (Zhou et al. 2021a; Dai et al. 2022), evaluation of blast-induced ground vibrations (Zhou et al. 2021b, 2021d; Gou et al. 2019), novel prediction of flyrock (Marto et al. 2014; Jahed Armaghani et al. 2016a, b; Zhou et al. 2020c), optimization of blast-induced air blast(Hajihassani et al. 2015a, b, c), prediction of air-overpressure (Hasanipanah et al. 2017a), prediction of rock fragmentation (Ebrahimi et al. 2016; Yu et al. 2021b; He et al. 2021; Fang et al. 2021), and minimization of blast-induced dust (Hosseini et al. 2022a, b, c, d). However, there is a limited number of papers that provide a systematic review

Fig. 2 The outcome of blasting

through bibliometric investigation to comprehensively examine the intellectual background of EEB. Additionally, there is a lack of systematic classification and organization of the knowledge pertaining to EEB into a state-of-the-art knowledge structure. This knowledge structure would enable the exploration of emerging sub-domains within EEB and facilitate the identification of current issues that require attention and further investigation. Given the increasing attention on EEB research among scholars, it is imperative to conduct a systematic analysis of the current state of this field. Such an analysis can help identify existing knowledge gaps and potential research directions.

To achieve this, a thorough literature review of the proposed research dimensions will be conducted using bibliometric analysis software, such as CiteSpace and VOSviewer (Li et al. 2020; Meng et al. 2020; Zhang et al. 2023a, b). These software applications are instrumental in conducting bibliometric analyses, providing valuable insights into the scholarly landscape. CiteSpace, a widely recognized bibliometric analysis tool, will facilitate the exploration of co-citation patterns among the selected articles, helping to identify seminal works and key research clusters in the field. It enables the detection of emerging trends and the evolution of research themes over time, offering a comprehensive view of the intellectual landscape (Li et al. 2020). In parallel, VOSviewer, another indispensable software tool, will assist in constructing bibliometric networks and visualizing bibliographic data. This includes generating co-authorship networks, co-occurrence maps of keywords, and bibliographic coupling networks, all of which contribute to a deeper understanding of the knowledge structure within the domain (Meng et al. 2020). The combined use of CiteSpace and VOSviewer offers a robust methodological framework for this study, allowing for a systematic and rigorous analysis of the literature. Through these tools, we aim to extract meaningful insights, uncover research trends, and identify influential countries and institutions, thereby enriching the scholarly discourse on the subject matter.

In this study, visualization software will be employed to perform a scientometric analysis of 530 English literature articles sourced from the Web of Science Core Collection (WOSCC) database. The literature search in WOSCC includes the following criteria: subject = [Prediction of and (blast-induced ground vibration or blast flyrock or blast backbreak or blast air overpressure or blast rock fragmentation or blast dust)], language restricted to English, the search date was June 6, 2023, and the time span was set from 2000 to 2023.

2.1 Global research analysis

To provide a quantitative representation of the spatial distribution of articles in the field of EEB, a co-country analysis is essential. Figure 3a showcases the leading countries that have made substantial contributions to EEB research. The top 10 countries with the highest number of publications are as follows: Iran (194 articles), China (138 articles), India (74 articles), Malaysia (57 articles), Vietnam (62 articles), Australia (41 articles), Turkey (29 articles), USA (29 articles), Russia (21 articles), and Korea (20 articles). These countries have been actively involved in research on EEB, particularly in the context of hard rock excavation, and have played a significant role in advancing the field. Additionally, these countries have produced innovative research outcomes, underscoring their dominant position in the domain of EEB. It is noteworthy to emphasize the contributions of Iran, China, India, Australia, USA, and Russia, as these countries play a pivotal role in shaping the field of EEB. China, as a developing country, has recognized the significance of disaster management and environmental protection, leading to extensive research on evaluating EEB over the past two decades. Zhou et al. (2021b) proposed an intelligent approach known as

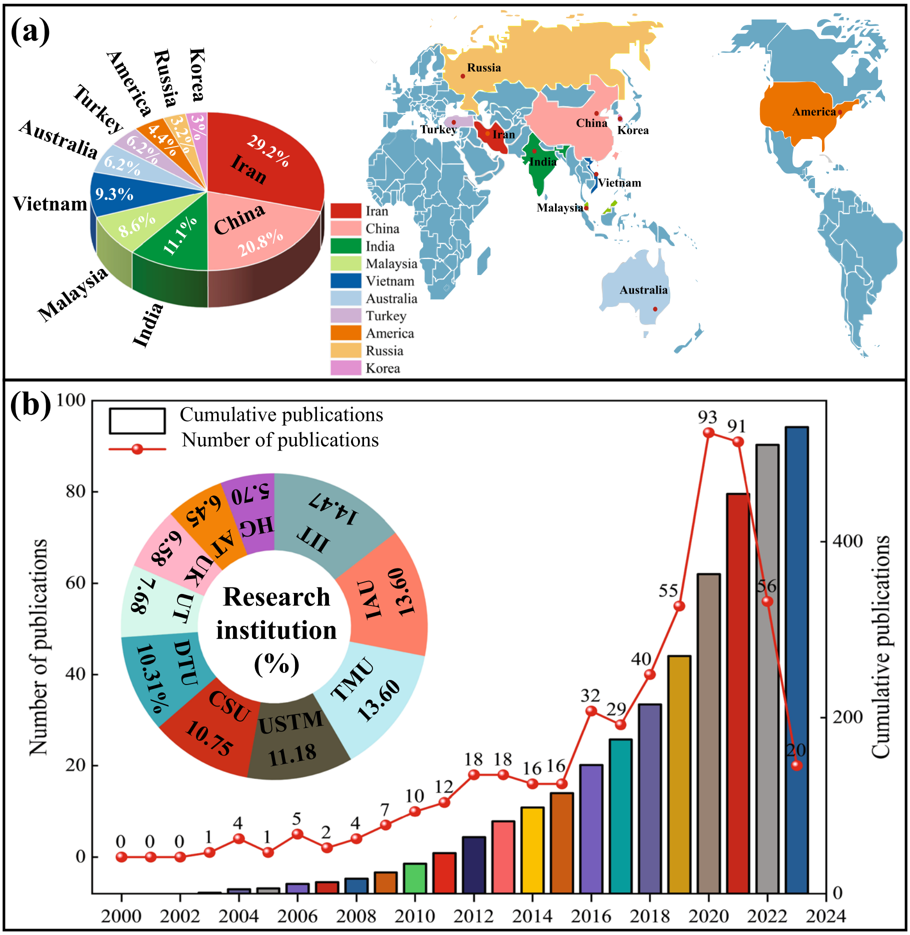

Fig. 3 **a** Research countries in the field of EEB and percentage of publications; **b** Issuing institutions and annual volume of documents. *IIT* (Indian Institute of Technology), *IAU* (Islamic Azad University), *TMU* (Tarbiat Modares University), *USTM* (University of Science and Technology Malaysia), *CSU* (Central South University), *DTU* (Duy Tan University), *UT* (University of Tehran), *UK* (University of Kashan), *AT* (AmilKabir University of Technology), *HG* (Hanoi University of Mining and Geology)

the Jaya-XGBoost (extreme gradient boosting) model, which combines the Jaya algorithm and high-efficiency XGBoost machine, to predict blast-induced ground vibrations. The research findings reveal that the Jaya-XGBoost model outperforms other machine learning models as well as traditional empirical models, demonstrating its superiority as a reliable prediction model. This study offers valuable insights to mining researchers and engineers who employ intelligent machine learning algorithms for the accurate forecasting of blast-induced ground vibrations. Another noteworthy study conducted by Dai et al. (2022) introduced a hybrid intelligence approach for the accurate prediction of backbreak in open pit blasting. This approach combined the random forest (RF) algorithm with particle swarm optimization (PSO) techniques. The primary objective of the study was to minimize the occurrence of undesired phenomena resulting from backbreak. By leveraging the strengths of RF and PSO, the proposed approach demonstrated improved accuracy in predicting backbreak, contributing to more effective management of open pit blasting operations and reducing associated adverse effects. Furthermore, Chen et al. (2021) conducted a study to explore the applicability of combining the firefly algorithm (FA), genetic algorithm (GA), and PSO with support vector regression (SVR) and artificial neural network (ANN) models for predicting blast-induced ground vibration. The researchers also introduced a modified version of the firefly algorithm, known as MFA, and combined it with the SVR model, forming the MFA-SVR model. To assess the feasibility of these proposed models, a case study was carried out in Johor, Malaysia. The findings of the study indicated that the MFA-SVR model exhibited significant capability in estimating ground vibration and demonstrated the ability to generalize to different scenarios. India and Australia have also significantly contributed to the field of EEB research over an extended period. Khandelwal and Singh (2009) developed an approach using ANN techniques to evaluate and predict blast-induced ground vibration and frequency by considering rock properties, blast design, and explosive parameters. To solve the drawbacks of backpropagation (BP)- ANN, Armaghani et al. (2014) suggested a novel method that combined the PSO algorithm with ANN. The flyrock distance and peak particle velocity (PPV) caused by blasting were simulated using this method. Trivedi et al. (2014) used ANN and multivariate regression analysis (MVRA) to predict the distance covered by flyrock resulting from blasting, aiming to improve the assessment of its impact.

Co-institution analysis plays a crucial role in identifying key research strengths within a specific field, while also offering a scientific assessment of the academic impact generated by these institutions. Figure 3b presents a comprehensive overview of the top 10 institutions based on their publication frequency. The Indian Institute of Technology emerges as the institution with the highest publication frequency, demonstrating its significant contribution to the field. It is closely followed by the Islamic Azad University and Tarbiat Modares University, which have also made notable contributions to EEB research. These higher education institutions, specializing in the mining industry, have emerged as prominent contributors within the field. In Vietnam, Duy Tan University stands out with 47 articles, indicating its growing influence in EEB research. The Hanoi University of Mining and Geology has also made a noteworthy impact with 26 articles. Additionally, internationally renowned scientific institutions like Central South University and the University of Science and Technology Malaysia have significantly contributed to the field, with 49 and 51 articles respectively. Of particular interest is the prominence of Iranian institutions, as evidenced by the presence of five Iranian institutions among the top 10 publishers in terms of institutional affiliation. This observation highlights the influential position and extensive attention given to EEB research within the Iranian academic community. Although advancements in internet technology have facilitated global communication, it is worth noting that institutional cooperation still tends to be predominantly driven by institutions and disciplines with similar interests. Consequently, interdisciplinary and cross-disciplinary collaboration remains relatively limited in the field.

2.2 Research hotspot analysis

Keywords hold great significance in summarizing and condensing the research content of an article, providing a concise representation of its main focus. Through the analysis of high-frequency keywords, researchers can identify prevailing and trending topics within the realm of EEB research. These frequently encountered keywords also serve as valuable indicators of research trends and areas of interest within the field.

2.2.1 Research on hot topics in EEB

This section provides an overview of the fundamental aspects of typical prediction techniques and their applications in EEB. This is accomplished through a concise introduction and the utilization of VOSviewer, a scientometric network construction and visualization tool (Batista et al. 2019; Dikshit et al. 2021). VOSviewer, developed by Van Eck and Waltman (2010) at Leiden University in the Netherlands, facilitates the identification of relationships among various entities by employing the concept of "co-occurrence clustering". This concept suggests that the simultaneous occurrence of two entities indicates their association. Correlations can vary in strength and direction, leading to the identification of different types of communities based on measures of relationship strength and direction. In this study, the analysis is divided into six cluster categories, each represented by a different color (see Fig. 4). Due to the extensive research areas encompassing the application of ML and OA in this paper, a detailed explanation of cluster development is omitted for the sake of brevity. The subsequent part of this section provides a concise introduction to the commonly employed ML algorithms in the context of EEB.

Figure 4 presents the VOSviewer plots representing the primary prediction methods of EEB. In Fig. 4a, the prediction of flyrock is depicted, wherein the VOSviewer software was employed to construct a keyword co-occurrence network for flyrock. Clusters are visually distinguished by different colors, namely Cluster 1 (red), Cluster 2 (blue), Cluster 3 (cyan), Cluster 4 (green), Cluster 5 (yellow), and Cluster 6 (purple). The co-occurrence map effectively identifies these six clusters, each reflecting distinct research frontiers within the flyrock prediction method. Within the network map, Cluster 1 occupies the central position and is primarily focused on the utilization of ANN. This is evident from the occurrence of terms such as "air," "mine," and "design." Additionally, other machine learning methods such as "particle swarm optimization," "gene expression programming," and "support vector machine" are also represented in this cluster. Furthermore, Cluster 1 considers external factors, as indicated by the co-occurrence of terms like "uniaxial compressive strength". On the left side of the network map, Cluster 2 places more emphasis on the application

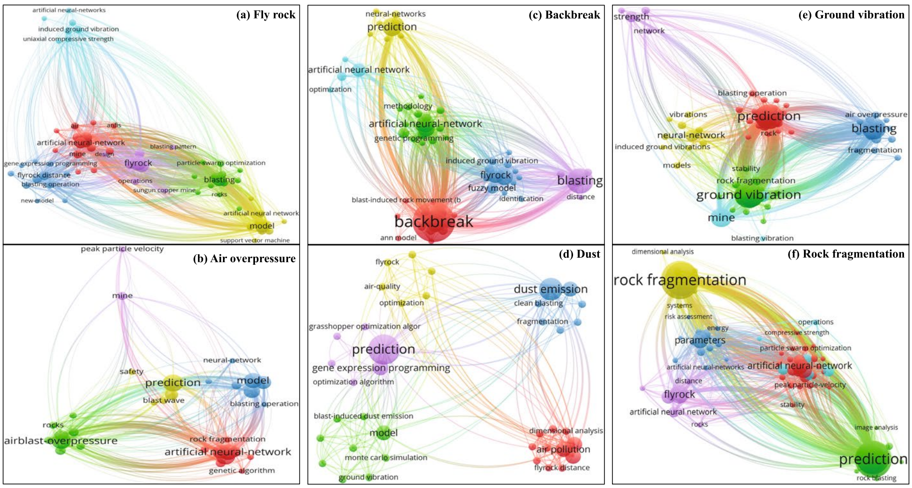

Fig. 4 VOSviewer plots for some main content of EEB. (Color figure online)

of ML and OA. This is evident from the presence of terms like "flyrock distance" and "blasting operation." By observing the size of the nodes and words, the proximity between two nodes, and the connections between keywords, we can deduce that ANN are widely employed in studying flyrock distance, blast-induced ground vibration, and mine design, among others. The occurrence of terms such as "new model" and "particle swarm optimization" demonstrates the influence of optimization algorithms within this research area. Furthermore, as depicted in Fig. 4a, Cluster 2 is generally associated with soil and rock properties, including "uniaxial compressive strength," "blasting pattern," "blasting operation," and "rocks."

Figure 4b–f display VOSviewer plots illustrating the applications of AOp, backbreak, dust, ground vibration, and rock fragmentation, respectively. The interpretation of these plots follows a similar pattern to that described for Fig. 4a. To maintain brevity, the detailed explanation of these plots is omitted here.

2.2.2 Research trend analysis

The keyword timeline view is shown in Fig. 5. It gives information about the temporal distribution of keywords and groups them into clusters for categorisation. Eight primary clusters are shown in the picture, and Table 1 contains more information. The machine learning, flyrock, peak particle velocity, measurement, blast vibration, operations, ground vibration, and rock fragmentation are the main hot themes discovered by analysis and summarization of the keywords inside each cluster.

In its early stages, EEB research primarily concentrated on investigating "rock fragmentation", "blast vibration", "bench blasting", "production blast", "energy", "environmental impacts", "classification problem", "fracture", "parameters" and "rock damage". Notably, experts employed "artificial neural networks", "support vector machines", "gene expression programming", "fuzzy inference system", "particle swarm optimization algorithm", "artificial bee colony", "imperialist competitive algorithm" and "numerical simulation" methods to optimize "blasting operation" by considering rock behavior parameters such as "peak particle velocity", "modulus", "brittle solids" and "uniaxial compressive strength". These approaches aimed to address issues related to "flyrock distance", "rock fragmentation","ari overpressure", "airblast" and "ground vibration" resulting from

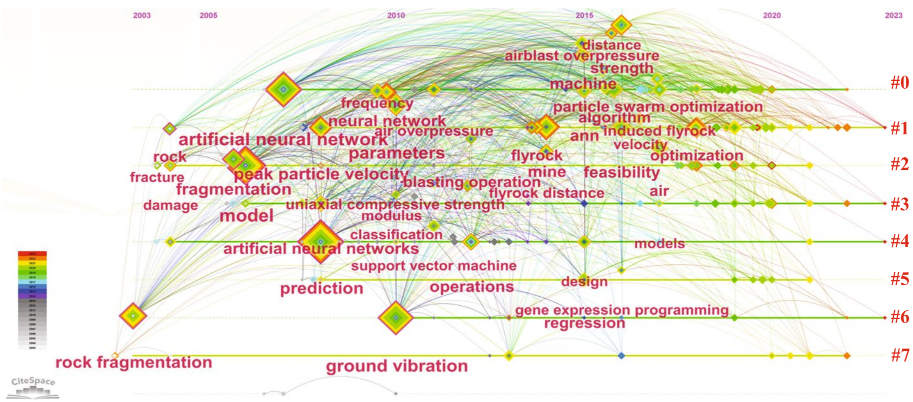

Fig. 5 CiteSpace plots for timeline chart of EEB keywords

Table 1 Keyword clustering for the blasting vibration

No	Cluster header	Main cluster
#0	Machine learning	Strength; hybrid model; imperialist competitive algorithm; computational intelligence; artificial neural network; optimization algorithms; artificial bee colony; optimization technique; particle algorithm; regression
#1	Flyrock	Random forest; flyrock distance; blasting environmental issue; Bayesian network; probabilistic prediction; blasting operation; open pit mines; adaptive neuro-fuzzy inference system; regression tree; risk assessment
#2	Peak particle velocity	Ground vibration; hybrid model; imperialist competitive algorithm; computational intelligence; production blast; peak particle velocity; genetic programming; opencast mines; vector machine technique; sensitivity analysis
#3	Measurement	Rock fragmentation; random forest; rock movement; decision tree; data analytics; ground vibration; fuzzy system; blasting operation; imperialistic competitive algorithm; particle size
#4	Blast vibration	Blast vibration; conventional vibration predictor equations; mean absolute error; artificial neural network; structural engineering; ground vibration; support vector regression; empirical equation; fuzzy c-means; artificial neural network
#5	Operations	Design; gene expression programming; ground vibration; Monte Carlo simulation; limestone mines; blasting cost; open pit mine; air overpressure; ensemble algorithm; gradient boosting machine; random forest
#6	Ground vibration	Ground vibration; peak particle velocity; rock blasting; open pit mine; machine learning; gene expression programming; Monte Carlo simulation; artificial neural network; equivalent distance; conventional equations
#7	Rock fragmentation	Rock fragmentation; artificial intelligence; meta-heuristic algorithm; mine blasting; hybrid model; image analysis; numerical simulation method; sieving analysis; artificial neural network; risk assessment

"blasting operations". Subsequently, the scope of EEB studies broadened as researchers adopted various soft computing techniques, including "machine learning", "hybrid models", "artificial intelligence", "Monte Carlo simulation", "optimization algorithms", "adaptive regression", "sieving analysis", "image analysis", "meta-heuristic algorithm" and "risk assessment" methodologies. These advancements were instrumental in advancing our comprehension of the environmental consequences associated with blasting activities and enabling the implementation of proactive measures.

3 Environmental effects of blasting

Blasting is a widely employed technique in mining, quarrying, and civil engineering projects, aiming to break down rock masses effectively (Dumakor-Dupey et al. 2021; Xie et al. 2021). In quarry projects, the primary goal of blasting is to achieve optimal productivity by attaining the desired fragmentation while ensuring safety measures, and simultaneously mitigating the detrimental effects of EEB (Fig. 6). These adverse effects comprise seismic activity, air blast, ground vibration, fly rock, backbreak, and noise. The severity of these effects increases when blasting operations are conducted in close proximity to residential buildings, factories, or offices, or when they are inadequately designed (Chen et al. 2015). Consequently, extensive research is conducted in the field of EEB to identify blast designs that optimize desired outcomes while minimizing undesired effects. Prior to conducting a state-of-the-art review on EEB prediction, it is crucial to establish a precise classification of EEB and gain a clear understanding of their definitions.

3.1 AOp or air blasting

One of the negative impacts connected to blasting operations is air blast, also known as air overpressure (AOp). It refers to the generation of large shock waves resulting from explosions, which are horizontally refracted by density variations in the atmosphere. These shock waves are produced by a variety of factors, such as the release of insufficiently contained gases, the direct release of energy from the surface, shock waves generated by large free faces, stemming column pulses during stemming ejection, and gas release pulses brought on by gases escaping through rock fractures (Bhatawdekar et al. 2021). Structures in close proximity to the blast zone can be affected by AOp, leading to the rattling of windows and roofing materials.

3.2 Blast-induced ground vibration

Among the negative effects of blasting, blast-induced ground vibration is a major worry for designers, planners, and environmentalists. Ground vibration has been the subject of much research, which has led to the creation of various methods intended to lessen its effects (Shahnazar et al. 2017; Bui et al. 2019a, b). The measurement of ground vibration is influenced by several key factors, including the quantity of explosive used, the distance between the monitoring point and the blast site, and the geomechanical properties of the rock mass (Zhang et al. 2021a, b). While the geomechanical properties of the rock are inherent and cannot be altered, researchers have devised empirical formulas to optimize a critical parameter—the quantity of explosive used in a given blast. This optimization seeks to achieve the lowest possible levels of ground vibration (Singh and Sastry 1986; Qiu et al. 2021).

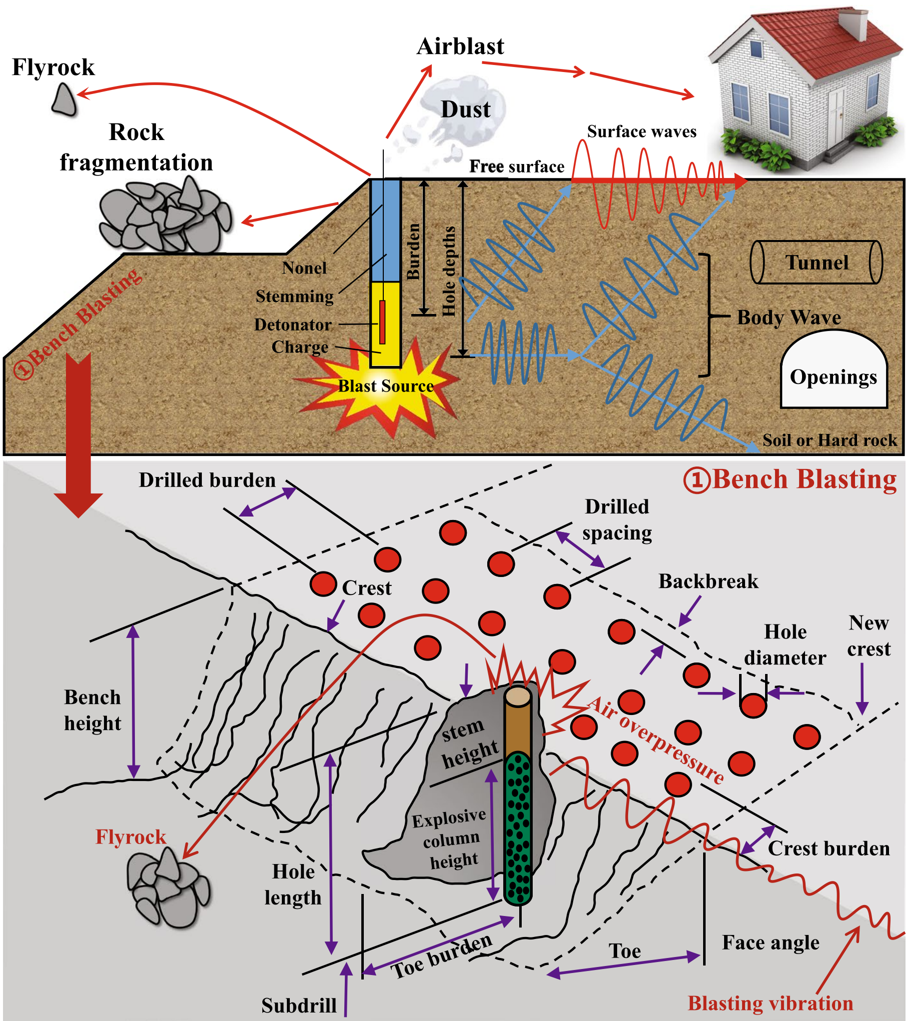

Fig. 6 The primary EEB classification and bench blasting effects

3.3 Flyrock

A severe threat to people and property in and around the blasting region is posed by flyrock, which is defined as the uncontrolled and excessive projectile of rock pieces during a blast that has the potential to travel distances beyond the targeted range (Raina et al. 2014). Accidents resulting from flyrock can range from minor incidents to fatal consequences (Fig. 7), making it a matter of great concern (Verkis 2011; Raina et al. 2014). Although flyrock accidents are not frequently reported (Davies 1995), they remain a substantial challenge to prediction. However, it is worth noting that instances of flyrock that do not cause any harm are more frequent and can be documented to improve the efficacy of current prediction algorithms.

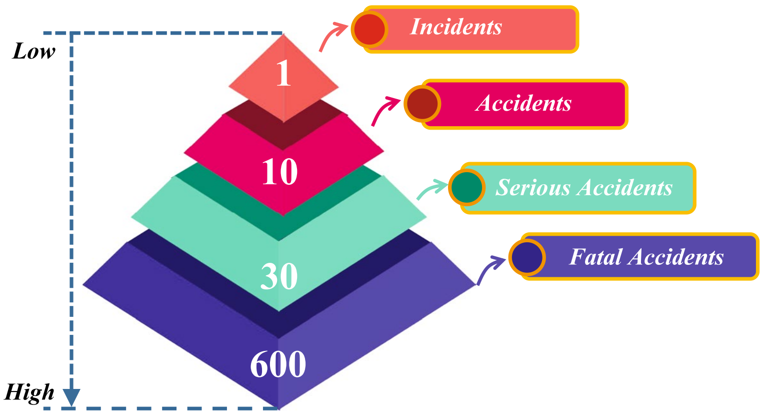

Fig. 7 The pyramid of safety incidents

3.4 Backbreak

According to Dai et al. (2022) backbreak is a phenomenon that develops after blasting operations in which rock fractures spread over the final row of blast holes. This phenomenon brings about various undesirable impacts, including an increase in the stripping ratio, potential damage to mining machinery, instability in mine walls, reduced drilling efficiency, and limitations on the overall slope angle (Monjezi and Dehghani 2008; Faramarzi et al. 2013; Monjezi et al. 2012; Sari et al. 2014). Consequently, the prediction of backbreak becomes a crucial step in achieving technically and financially effective results in blasting operations.

3.5 Rock fragmentation induced by blasting

In the mining and construction industries, blasting is a crucial tool for breaking apart rocks and destroying concrete. The standard method for fragmenting rocks using explosives entails a series of steps. Blastholes are first bored into the rock mass, and then explosives are placed inside these blastholes. The firing process is then started, which causes the explosives to detonate (Dumakor-Dupey et al. 2021). The rock mass is efficiently divided into smaller pieces because of the blasting operation (Hasanipanah et al. 2016a, b). The fragmentation process is influenced by various factors, including the blast design, characteristics of the rock mass, and the rapid release of energy during the blasting process (Zhou et al. 2021c; Rosales-Huamani et al. 2020).

3.6 Dust induced by blasting

Drilling and blasting operations in quarries have a tight relationship with dust production (Torno et al. 2011). Dust collectors are frequently included in drilling equipment to successfully reduce dust emissions into the atmosphere. However, depending on the climate in and around the blasting area, significant amounts of dust produced by blasting operations can have negative effects on the environment, human health, and various plant and animal species (Alvarado et al. 2015; Ghose 2002; Lal and Tripathy 2012; Roy et al. 2010). Unfortunately, it is difficult to lessen the negative effects of the dust that is released during blasting. Consequently, minimizing dust emissions should be prioritized as one of the objectives in optimizing blast design (Hosseini et al. 2021).

4 ML and OA methods to predict EEB

Given the intrinsic complexity of EEB, researchers often opt for soft computing methods to address design challenges and assessment issues in blasting operations, replacing cumbersome theoretical solutions. EEB problems are characterized by significant uncertainties and involve various factors that cannot be directly determined by engineers. Consequently, the popularity of Artificial intelligence (AI), ML, and deep learning (DL) methods has rapidly increased in this domain (Goh and Zhang 2014; Wang et al 2020). While AI, ML, and DL are interconnected, it is crucial to recognize their distinct concepts, as depicted in Fig. 8, which illustrates their differences and time progression (Dikshit et al 2021; Reichstein et al 2019). AI, as a field of research and development, focuses on designing and constructing machines capable of performing specific tasks without explicit instructions, with the ultimate goal of achieving human intelligence. ML serves as a pathway towards achieving AI, as it possesses the ability to identify inherent patterns within data and generate logical conclusions in the form of recommendations (van Natijne et al. 2020). OA algorithms play a vital role in ML, as they optimize the objective or loss function to develop the best-performing model. Figure 9 illustrates the primary categories of ML algorithms and the fundamental components of OA. DL, on the other hand, is a specific branch of ML that draws inspiration from the information processing mechanisms of the human brain. It aims to learn and represent the world as a hierarchical structure of nested concepts, eliminating the need for manual feature extraction (LeCun et al. 2015). To address the challenges in EEB, researchers employ a diverse range of ML, DL, and OA models, harnessing their capabilities in feature learning and expression. Therefore, conducting a comprehensive assessment of the existing literature on the application of ML, DL, and OA methodologies

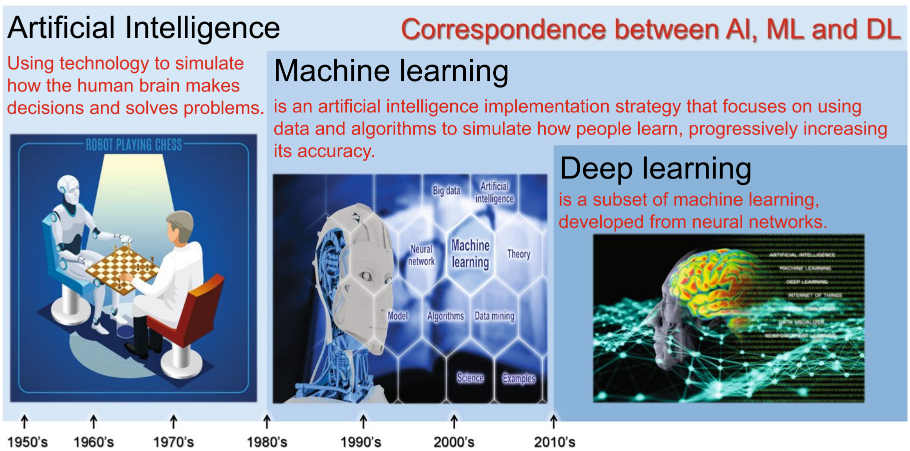

Fig. 8 The relationship and development of AI, ML and DL. (Image source: https://www.vcg.com/)

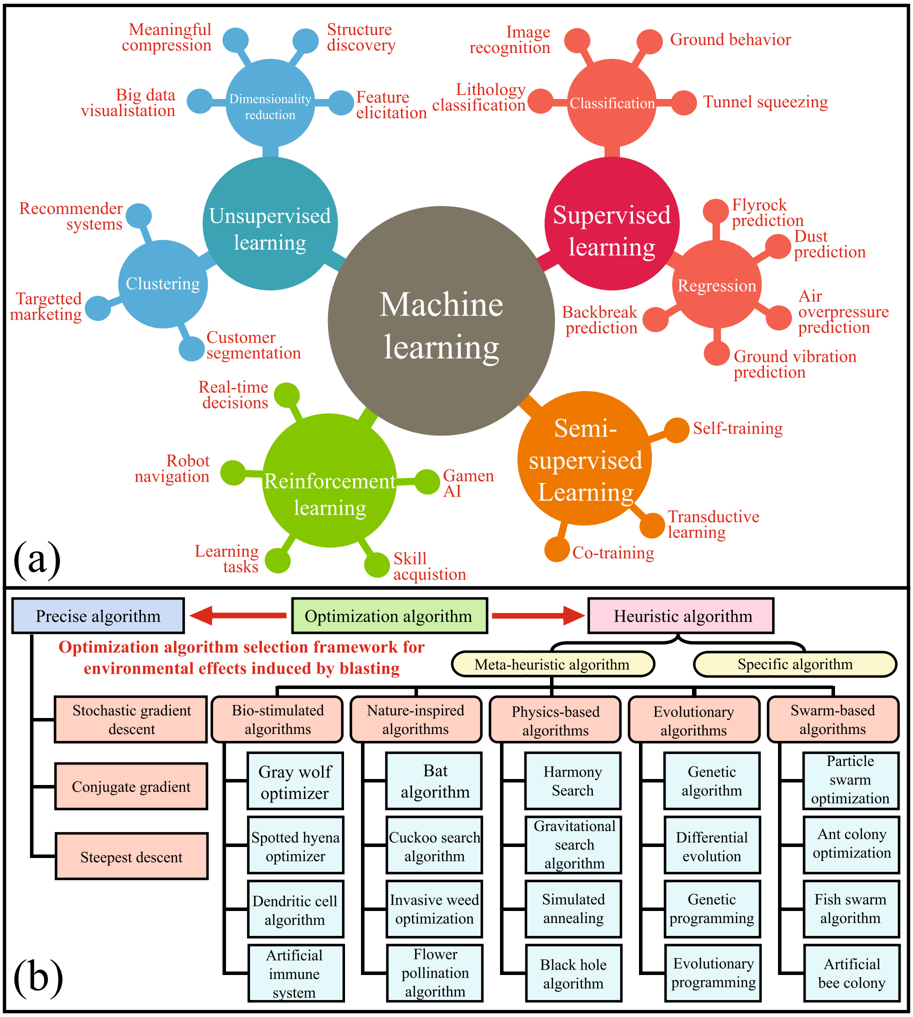

Fig. 9 The main classification of ML algorithms and the selection of OA algorithms. **a** Classification and application of ML algorithms; **b** The category of OA algorithms

becomes crucial for advancing EEB research. Such an assessment will provide a deeper understanding of how these approaches can contribute to the field of EEB and facilitate further advancements in this area of study.

4.1 Prediction of flyrock

When loose rock particles are suddenly and uncontrollably ejected or moved during blasting, they may migrate beyond of the authorized blasting zone(s) as a result of the explosive energy released (Guo et al. 2021; Abd Elwahab et al. 2023). Flyrock is one of the many hazards that can arise when blasting (Abd Elwahab et al. 2023; Han et al. 2020). It is essential to understand the mechanics driving blast-induced flyrock in order to properly reduce this risk (Ye et al. 2021; Li et al. 2023). Flyrock can arise by three different mechanisms, as shown in Fig. 10, according to Amini et al. (2012). These three methods are riffling, catering, and face bursting. Riffling happens when there isn't enough stemming material, which causes the blast gases to flow upward through the blast hole in the direction of least resistance. Stemming material and, occasionally, collar rock are ejected as a result of this. Catering occurs when gases escape through the stemming zone, which is normally found at the blasthole collar and may have been weakened by earlier explosions from the bench above. When explosive charges are placed close to important geological features or zones of weakness, face bursting occurs because the high-pressure gases can move forcefully through these weak places.

Flyrock poses a significant risk to nearby communities, as it has the potential to cause severe damage to properties and result in injuries and fatalities within the blast zone. Consequently, researchers have made considerable efforts to develop models aimed at predicting and mitigating flyrock incidents (Fig. 10). The equations proposed by Lundborg (1981) and Gupta (1980) have been utilized to estimate the distance that fly rocks can travel, thus establishing buffer and exclusion zones to safeguard workers, equipment, and surrounding areas. Nevertheless, because to their limited success in foretelling flyrock incidents within a 400-m throw radius, these techniques have failed to inspire researchers with confidence (Abd Elwahab et al. 2023). This deficiency is caused by sporadic mistakes made regarding the rock conditions and an inability to address the complexities inherent in the entire process. Statistical data is only applicable to certain locations where measurements have been made, which is another drawback of empirical approaches (Jamei et al. 2021). In recent times, ML and OA have emerged as valuable tools with a wide range of applications in flyrock prediction, as demonstrated in Table 2. To address the limitations of the BP-ANN approach, Armaghani et al. (2014) proposed a novel methodology that combines PSO with ANN. This innovative technique was employed to numerically simulate 44 datasets of flyrock distances obtained from three different granite quarry sites in Malaysia. Koopialipoor et al. (2019b) conducted a study aimed at predicting the occurrence of flying rocks

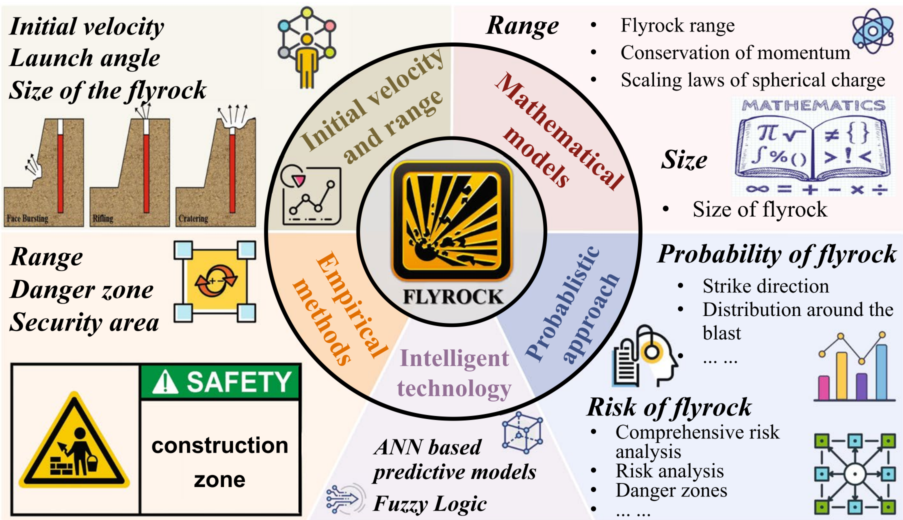

Fig. 10 Major methods of blast-induced flyrock prediction

Table 2 Prediction of blast-induced flyrock using ML and OA methods

References	Technique	Input	No. of dataset	Optimal result
Monjezi et al. (2010a)	ANN	HD, BS, ST, PF, SD, N, C, RD	250	$R^2 = 0.98$
Rezaei et al. (2011)	FIS	HD, S, B, ST, PF, SD, RD, C	490	$R^2 = 0.98$ RMSE = 1.98
Monjezi et al. (2011)	ANN	BS, c, D, AD, ST, SD, PF, SMR, BI	192	$R^2 = 0.97$
Monjezi et al. (2012)	ANN-GA	HD, S, B, ST, PF, SD, D, C, RMR	195	$R^2 = 0.978$
Amini et al. (2012)	SVM	HL, S, B, ST, PF, SD, D	245	$R^2 = 0.97$ RMSE = 4.5
Amini et al. (2012)	ANN	HL, S, B, ST, PF, SD, D	245	$R^2 = 0.92$ RMSE = 7.98
Tonnizam Mohamad et al. (2013)	ANN	HD, BS, ST, PF, C, D, N, RD, SD	39	$R^2 = 0.97$
Khandelwal and Monjezi (2013)	SVM	HL, S, B, ST, PF, SD	234	$R^2 = 0.95$
Monjezi et al. (2013)	ANN	HD, S, B, D, c, ST, SD, PF, RMR	310	$R^2 = 0.98$
Marto et al. (2014)	ICA-ANN, BP-ANN	RD, HD, BS, ST, PF, C, Rn	113	$R^2_{ICA\text{-}ANN} = 0.98$ $R^2_{BP\text{-}ANN} = 0.919$
Trivedi et al. (2014)	ANN	B, ST, qI, q, σ_c, RQD	95	$R^2 = 0.98$
Armaghani et al. (2014)	PSO-ANN	D, HD, c, S, B, ST, PF, RD, Sb, N	44	$R^2 = 0.94$
Ghasemi et al. (2014)	ANN, FIS	HL, S, B, ST, PF, C	230	$R^2_{ANN} = 0.939$ $R^2_{FIS} = 0.957$
Trivedi et al. (2015)	ANN, ANFIS	Q, qI, HD, B, S, ST, D, σ_c, RQD, v_0, deg	125	$R^2_{ANN} = 0.95$ $R^2_{ANFIS} = 0.98$
Armaghani et al. (2015a, b)	ANN, ANFIS	C, DI, BS, ST	166	$R^2_{ANN} = 0.834$ $R^2_{ANFIS} = 0.959$
Saghatforoush et al. (2016)	ANN	B, S, HL, ST, PF	97	$R^2 = 0.994$
Faradonbeh et al. (2016a, b)	GP	D, HD, BS, ST, C, PF	262	$R^2 = 0.908$
Yari et al. (2016)	BPNN	D, H, Sb, n, S, B, AN, DN, ST, PF, SD, T	334	$R^2 = 0.977$
Jahed Armaghani et al.(2016a, b)	ANN, ANFIS	C, PF	232	$R^2_{ANN} = 0.92$ $R^2_{ANFIS} = 0.98$
Bakhtavar et al. (2017)	H-DAFIS	B, ST, HL, S, N, C, T, PF, RMR	320	$R^2 = 0.976$

Table 2 (continued)

References	Technique	Input	No. of dataset	Optimal result
Hasanipanah et al. (2017c)	RT, MLR, PSO	HL, S, B, ST, PF, C	65	$R^2_{RT}=0.872$ $R^2_{MLR}=0.860$ $R^2_{PSO}=0.966$ $RMSE_{RT}=27.459$ $RMSE_{MLR}=29.053$
Koopialipoor et al.(2019b)	ICA-ANN, PSO-ANN, GA-ANN	S, B, ST, PF and RD	262	$R^2_{ICA\text{-}ANN}=0.958$ $R^2_{PSO\text{-}ANN}=0.044$ $R^2_{GA\text{-}ANN}=0.932$ $RMSE_{ICA\text{-}ANN}=0.045$ $RMSE_{PSO\text{-}ANN}=0.044$ $RMSE_{PSO\text{-}ANN}=0.058$
Faradonbeh et al. (2018)	GEP	D, S, B, ST, PF	76	$R^2=0.924$ $RMSE=29.956$
Rad et al. (2018)	LS-SVM, SVR	BS, H/B, Sb, ST, c, RD, PF	90	$R^2_{LS\text{-}SVM}=0.969$ $R^2_{SVR}=0.945$
Asl et al. (2018)	ANN	B, S, HL, SD, ST, C, PF, GSI	200	$R^2=0.93$ $RMSE=0.09$
Murthy et al. (2018)	ANN	B, S, HD, N, n, Tc, Fp	194	$R^2=0.9474$ $MSE=0.6584$
Lu et al. (2020)	ORELM, ELM, ANN, MR	S, B, T, PF, rock density	82	$R^2=0.955$ $RMSE=12.753$
Guo et al., (2021)	DNN-WOA, ANN	HD, C, B, S, ST, PF	240	$R^2=0.9781$ $RMSE=9.1119$
Nguyen et al. (2021)	WOA–SVM–L, WOA–SVM–P, WOA– SVM–RBF, WOA–SVM–HT, RF, GBM, ANN, CART	S, B, T, Wtotal, q	210	$R^2=0.977$ $RMSE=5.241$

Table 2 (continued)

References	Technique	Input	No. of dataset	Optimal result
Fattahi and Hasanipanah (2022)	ANFIS-GOA, ANFIS-CA	S, B, ST, PF, RD	80	$R^2 = 0.974$

HL hole length (m), *S* spacing (m), *B* burden (m), *ST* stemming (m), *PF* powder factor (kg/m3), *SD* specific drilling (m/m3), *C* maximum charge per delay (kg), *c* charge per delay (kg), *Tc* total explosive (kg), *Fp* firing pattern (diagonal (− 1)/V(1)), *Q* charge per hole (kg), *D* hole diameter (mm), *HD* hole depth (m), *RD* rock density (g/cm3), *BS* burden to spacing, *N* number of rows, *Rn* Schmidt hammer rebound number, *RMR* rock mass rating, *Sb* subdrilling (m/m3), *DI* distance from the blasting face (m), *RQD* rock quality designation (%), *qI* linear charge concentration (kg/m), *q* specific charge (kg/ton), *σc* unconfined compressive (Mpa), *H* bench height (m), *n* number of holes, *AN* ANFO (kg), *DN* dynamite (kg), *T* delay time (ms), *AD* average hole depth (m), *SMR* rock mass rating, *BI* blastability index, *v0* launching velocity (m/s), *deg* launching angle (degree), *H/B* stiffness factor, *H-DAFIS* hybrid dimensional analysis fuzzy inference system, *RT* regression tree, *MLR* multiple linear regression, *GP* genetic programming, *LS-SVM* least squares support vector machines, *SVR* support vector regression, *SVM* support vector machine, *PSO* particle swarm optimization, *GA* genetic algorithm, *ICA* imperialist competitive algorithm, *GEP* gene expression programming, *ANN* artificial neural network, *FIS* fuzzy inference system, *BP* back propagation, *ANFIS* adaptive neural fuzzy inference system, *GSI* geological strength index resulting from blasting operations, utilizing three hybrid intelligence systems: Imperialist Competitive Algorithm (ICA) -ANN, GA -ANN, and PSO -ANN. In this approach, the ANN model's weights and biases were adjusted using ICA, PSO, and GA. To achieve the objectives of the study, a comprehensive database consisting of 262 datasets was compiled. The training and testing Root Mean Squared Error (RMSE) values for the ICA-ANN, PSO-ANN, and GA-ANN prediction models were found to be 0.052, 0.045, and 0.057, respectively, and 0.045, 0.044, and 0.058, respectively. The results highlight the remarkable accuracy of the PSO-ANN model in effectively estimating the range of flying rocks generated by blasting operations. In a study conducted by Hasanipanah et al. (2017b), the effectiveness of Particle Swarm Optimization (PSO) was compared to Multiple Linear Regression (MLR) in developing a precise prediction equation for flying rocks. The researchers gathered data from 76 blasting events that took place in three quarries located in Malaysia, which allowed them to create a comprehensive database encompassing various controlled blasting parameters. The findings demonstrate that for the prediction of flying rocks, the suggested PSO equation outperforms the MLR equation.

Table 2 shows that controlled elements, such as blast design and geometry, continue to have a greater influence on flyrock distance forecasts than uncontrollable factors, such as geological and geotechnical conditions. Researchers have concentrated on particular input characteristics that have the most impact due to variances in mining sites. These characteristics have gotten a lot of attention, especially burden (B), stemming (ST), and spacing (S). Rock density (RD) has also been commonly utilized by researchers as input parameters (Nguyen et al. 2021; Tong and Ranganathan 2013; Pisner and Schnyer 2020; Zhou et al. 2020b). Some researchers have explored additional rock mass properties such as blastability index (BI), rock mass rating (RMR), and Schmidt hammer rebound number (Rn). In terms of explosives, powder factor (PF) and charge per delay (c) have been included to determine the extent of rock fragmentation and the intensity of the explosion, both of which directly correlate with flyrock occurrence. Blast hole depth (HD), blast hole diameter (D), and maximum charge per delay (C) have been underutilized in blast design parameters. The lack of attention given to D and HD raises questions regarding their neglect, despite their significant impact on the size of fly rocks, as mentioned earlier. C, though being the least used parameter, relates to the explosive energy released, and an increase in C results in an increase in flyrock distance. On the topic of uncontrollable parameters, geological and rock mechanical parameters have been minimally considered for prediction purposes, despite their potential influence on flyrock incidents, as observed in Table 1.

4.2 Prediction of AOp

Accurate prediction of air overpressure (AOp) resulting from blasting is crucial for mitigating its environmental impact and protecting nearby structures, as highlighted by Jahed Armaghani et al. (2016a). Previous studies (Singh et al. 2008; Hasanipanah et al. 2016b; Nguyen et al. 2020a; Amiri et al. 2016) have identified various influential factors on AOp generated by blasting, including B, S, ST, C, c, distance from the blast site, and type of explosive material. Among these factors, c and C have consistently shown the greatest influence on AOp, as supported by several studies (Verma and Singh 2013; Khandelwal and Kankar 2011; Singh and Verma 2010).

In the context of bench blasting conducted in opencast mines, Richards (2010) demonstrated that AOp propagates perpendicular to the bench face. However, accurately determining the intensity and nature of AOp remains a challenging and complex task. Blast design incorporates several critical variables that impact AOp, including B, S, ST, D, and HD. For instance, if the actual value of B is lower than the optimal value, the rock may not be fully fragmented, resulting in incomplete utilization of the explosive energy and the generation of highly intense AOp waves accompanied by noise. Insufficient ST allows explosive gases to escape into the atmosphere without adequate resistance, thereby increasing the risk of an explosion. Konya and Walter (1990) have suggested that modifying the ST material and increasing the length of ST can effectively control AOp.

The parameters employed by different researchers for the prediction of AOp due to blasting, together with their methods, input index, evaluation index, and amount of data, are shown in Table 3. C and the separation between the blast and the monitoring station were unavoidably employed by all researchers using ML and OA approaches as input parameters when predicting AOp. Multiple researchers have utilized ANN for predicting AOp resulting from blasting, including Mohamed (2011), Khandelwal and Singh (2005), Jahed Armaghani et al. (2015), Nguyen and Bui (2020), and Bui et al. (2020). Furthermore, various hybrid models combining ANN with optimization algorithms have been developed, such as PSO-ANN, GA-ANN, and ICA-ANN, as demonstrated by Tonnizam Mohamad et al. (2016), Jahed Armaghani et al. (2016a), and Hajihassani et al. (2015a, b, c). In addition to ANN, SVR have also been employed by some researchers for AOp prediction. The number of datasets utilized varied from 62 to 180. ANFIS models have also been utilized for AOp prediction by researchers like Jahed Armaghani et al. (2015) and Harandizadeh and Armaghani (2021). The number of datasets and corresponding R^2 values were reported as 128, 62, and 0.92, 0.62, respectively. Furthermore, researchers have developed hybrid models by combining ANFIS with various optimization algorithms, such as ANFIS-GA and ANFIS-PSO, as demonstrated by Harandizadeh and Armaghani (2021) and Ye et al. (2022). These hybrid models showed R^2 values ranging from 0.920 to 0.986.

4.3 Prediction of ground vibrations

As presented in Table 4, blast-induced vibrations represent a noteworthy environmental concern that has garnered considerable scientific interest. It is crucial to describe how blast vibrations are produced is of utmost importance in assessing their impact on the surrounding environment (Ding et al. 2020). Singh and Singh (2005) explained that during an explosive detonation within a borehole, the resulting gas from the explosion exerts a substantial dynamic pressure on the walls of the borehole. This pressure, in turn, transmits a strain wave to the adjacent rock mass encompassing the borehole. The strain wave carries a significant amount of strain energy, leading to various modes of fracture within the rock mass. These fractures include crushing, radial cracking, and reflection breakage, especially when a free face is present. These different fracture mechanisms contribute to the overall fragmentation and disintegration of the rock mass due to the blast-induced vibrations. As a result of the viscoelastic nature of rock, the elastic waves induced by the blast cause the individual rock particles to undergo oscillations (Zhou et al. 2020a; Zhang et al. 2020). These oscillations, occurring within the elastic zone, are commonly referred to as ground vibrations. The stress waves associated with these vibrations are known as Particle Peak Velocity (PPV) (Yu et al. 2022). These waves propagate outward in all directions from the borehole. However, due to the limited amount of energy they transfer to the rock mass, their energy diminishes exponentially as they travel farther away from the source (Yang and Hung 1997).

Table 3 Prediction of AOp using ML and OA methods

References	Technique	Input	No. of dataset	R^2
Khandelwal and Singh (2005)	ANN	C, D	56	0.96
Mohamed (2011)	ANN, FIS	C, D	162	0.92 (ANN)
				0.86 (FIS)
Khandelwal and Kankar (2011)	SVM	C, D	75	0.855
Mohamad et al. (2012a, b)	ANN	B, S, d, HD, ST, PF, N	38	0.93
Hajihassani et al. (2015a, b, c)	ANN-PSO	RQD, B, S, HD, ST, PF, C, N, D	62	0.86
Jahed Armaghani et al. (2015)	ANN-ANFIS, LMR	ST, B/S, PF, C, N, D	128	0.92 (ANN-ANFIS)
				0.855 (LMR)
Jahed Armaghani et al. (2016a)	ICA-ANN	C, D	70	0.83
Gao et al. (2019)	ANN, TLBM-ANN	RMR, C, D	85	0.91 (ANN)
				0.935 (TLBM-ANN)
Bui et al. (2019a)	Empirical, GLMNET	B, ST, C, PF, D	108	0.838 (Empirical)
				0.975 (GLMNET)
Nguyen and Bui (2019)	Empirical, ANN, RF, ANN-RF	B, S, ST, C, PF, D, VOD	114	0.429 (Empirical)
				0.966 (ANN)
				0.939 (RF)
				0.985 (ANN-RF)
Gao et al. (2020)	GMDH–GA	RMR, C, PF, D	84	0.988
Bui et al. (2020)	ANN, BART, BRT, SVR, GP, KNN	B, S, HD, d, PF, D	113	0.961 (ANN)
				0.945 (BART)
				0.898 (BRT)
				0.898 (SVR)
				0.949 (GP)
				0.89 (KNN)
Zhou et al. (2020a, b, c, d)	FS-FA	C, PF, D	86	0.977

Table 3 (continued)

References	Technique	Input	No. of dataset	R^2
Nguyen and Bui (2020)	Empirical, CART, KNN, ANN, BRR, SVR, GP	C, D, RH, AP, WS, WD, T	121	0.466 (Empirical) 0.949 (CART) 0.941 (KNN) 0.957 (ANN) 0.927 (BRR) 0.956 (SVR) 0.949 (GP)
Nguyen et al. (2020b)	ANN, BRNN, HYFIS	B, S, ST, H, N, C, PF, D, RH	146	0.961 (ANN) 0.936 (BRNN) 0.816 (HYFIS)
Nguyen et al. (2020c)	Empirical, RF, GBM	B, S, ST, H, N, C, PF, D, RH	146	0.871 (Empirical) 0.968 (RF) 0.97 (GBM)
Nguyen et al. (2020c)	IR, MLP, RF, M5-Rules	B, S, ST, C, PF, D	77	0.987 (IR) 0.99 (MLP) 0.978 (RF) 0.992 (M5-Rules)
Temeng et al. (2020)	BI-ENN, BPNN, SVM, GMDH, GenP, McKenzine	ST, NH, C, D	171	0.824 (BI-ENN) 0.8172 (BPNN) 0.8134 (SVM) 0.5878 (GMDH) 0.7196 (GenP) 0.7208 (McKenzine)
Ramesh Murlidhar et al. (2021)	GEP, M5', MLR	ST, JA, D	125	0.8621 (GEP) 0.7451 (M5') 0.7883 (MLR)

Table 3 (continued)

References	Technique	Input	No. of dataset	R^2
Ye et al. (2022)	ANFIS, ANFIS-GA, ANFIS-PSO, ANFIS-SFS	RQD, B, S, ST, NH, HD, C, PF, D	62	0.873 (ANFIS)
				0.935 (ANFIS-GA)
				0.965 (ANFIS-PSO)
				0.986 (ANFIS-SFS)
Hosseini et al. (2022a)	BPNN, GFFNN, BPCWNNs	B, S, K/B, ST, PF, C, D	90	0.944 (BPNN)
				0.957 (GFFNN)
				0.984 (BPCWNNs)
Zhang et al. (2022a, b)	RBF-2, MLP, RBF, GA-MLP, MARS, RF, SVM	B, S, D, ST, C, HD, PF	76	0.9735 (RBF-2)
				0.8893 (MLP)
				0.8988 (RBF)
				0.6599 (GA-MLP)
				0.9223 (MARS)
				0.8875 (RF)
				0.9065 (SVM)
Kazemi et al. (2023)	XGB-GWO, GEP, Empirical	B, S, D, NH, HD, PF	66	0.983 (XGB-GWO)
				0.989 (GEP)
				0.53 (Empirical)

RBF-2 a radial basis function network with an additional second hidden layer, *MLP* multilayer perceptron, GA-MLP MLP optimized by genetic algorithm, *SVM* support vector machine, *MARS* multi adaptive regression spline, *PSO* particle swarm optimization, *GWO* grey wolf optimization, *GEP* gene expression programming, *XGB* extreme gradient boosting algorithm, *ICA* imperialist competitive algorithm, *RF* random forest, *SVR* support vector regression, *BRR* Bayesian ridge regression, *GP* gaussian process, *BART* Bayesian additive regression trees, *BRT* boosted regression trees, *GMDH* group method of data handling, *KNN* hierachical K-means clustering and cubist algorithm, *BRNN* Bayesian regularized neural networks, *HYFIS* hybrid neural fuzzy inference system, *GBM* gradient boosting machine, *M5′* regression tree, *GeP* genetic programming, *SFS* stochastic fractal search algorithm, *FS* fuzzy system, *FA* firefy algorithm, *BI-ENN* brain-inspired emotional neural network, *BPNN* backpropagation neural network, *GenP* generalized predictor, *MF* McKenzie formula, *NAAS* National Association of Australian State, *BA* bat algorithm, *GLMNET* the lasso and elastic-net regularized generalized linear model, *LM* Levenberg–Marquardt algorithm, *B* burden, *S* spacing, *ST* stemming length, *HD* hole depth, *BS* burden spacing ratio, *RD* rock density, *RH* relative humidity, *AP* atmospheric pressure, *WS* wind speed, *WD* wind direction, *T* temperature, *RMR* rock mass rating, *VD* vertical monitoring distance from the blast face, *JA* joint aperture, *NH* number of holes, *HD* hole depth, *TLBO* teaching–learning-based optimization, *υ* Poison's ratio, *BI* blastability index, *Vp* p-wave velocity, *RQD* rock quality designation, *C* maximum charge per delay, *D* distance between monitoring point and blasting face, *PF* powder factor, *VOD* velocity of detonation, *N* number of rows, *SD* subdrilling, *LMR* linear multiple regression, *ANFIS* adaptive neuro-fuzzy inference system, *CART* classification and regression tree, *RBF* radius basis function, *K/B* stiffness ratio

Table 4 Prediction of ground vibrations using ML and OA methods

References	Technique	Input	No. of dataset	R^2
Singh et al. (2004)	ANN	B, BI, D, DI, E, HD, NH, S, ST, W	230	0.9829
Khandelwal and Singh (2006)	ANN	B, BI, D, DE, DI, E, HD, L, P, S, V P, VOD, W	150	0.9994
Khandelwal and Singh (2007)	ANN	D, W	150	Unreported
Iphar et al. (2008)	ANFIS	D, W	44	0.98
Khandelwal and Singh (2009)	ANN	B, BI, D, E, HD, P, S, V_P, VOD, W	154	0.9864
Khandelwal et al. (2010)	SVM	D, W	170	0.955
Monjezi et al. (2010b)	ANN	BS, D, DR, NH, UCS, W	269	0.954
Monjezi et al. (2011)	ANN	HD, ST, D, W	182	0.95
Khandelwal et al. (2011a)	ANN	D, W	130	0.92
Mohamed (2011)	ANN	D, W	162	0.94
Dehghani and Ataee-pour (2011)	ANN	B, D, DR, PF, S, N, NH, W, σ	116	0.775
Fisne et al. (2011)	FIS	D, W	33	0.92
Mohamad et al. (2012a)	ANN	D, W	12	0.9982
Mohammadnejad et al. (2012a)	SVM	D, W	26	0.944
Li et al. (2012)	SVM	D, W	32	0.89
Mohamadnejad et al. (2012b)	SVM	D, W	37	0.89
Singh et al. (2013)	ANFIS	BS, D, E, V_P, VOD, W	192	0.9986
Kumar et al. (2013)	GA	D, W	120	0.92
Ghasemi et al. (2013)	FIS	B, S, ST, N, W, D	120	0.95
Monjezi et al. (2013)	ANN	W, D, TC	20	0.93
Saadat et al. (2014)	ANN	D, HD, ST, W	69	0.9577
Armaghani et al. (2014)	ANN- PSO	B, D, HD, N, PF, S, SD, ST, W, ρ	44	0.9391
Xue and yang (2014)	ANN	B, BI, D, DE, DI, E, HD, L, P, S, V P, VOD, W	20	1
Hasanipanah et al. (2015)	SVM	D, W	80	0.957
Hajihassani et al. (2015a)	PSO-ANN	BS, W, HD, ST, SD, D, PF, RQD	88	0.89

Table 4 (continued)

References	Technique	Input	No. of dataset	R^2
Hajihassani et al. (2015b)	ICA-ANN	BS, ST, PF, W, D, V_p, E	95	0.98
Parida and Mishra (2015)	ANN	D, W	9	0.8981
Dindarloo (2015)	SVM	ρ, E, UCS, TS, J_s, B, S, HD/B, SC, ST, DR, D	100	0.99
Armaghani et al. (2015a)	ANFIS	D, W	109	0.97
Amiri et al. (2016)	ANN, KNN	D, W	75	0.8200(ANN) 0.8800(KNN)
Faradonbeh et al. (2016a, b)	GEP	BS, D, HD, PF, ST, W	102	0.914
Ghasemi et al. (2016a, b)	ANFIS-PSO, SVM	B, D, NH, S, ST, W	120	0.9570(ANFIS-PSO) 0.9240 (SVM)
Ghoraba et al. (2016)	ANN, ANFIS	D, W	115	0.9070(ANN); 0.9580(ANFIS)
Hasanipanah et al. (2017d)	PSO	D, W	80	0.9010(PSO-linear); 0.9380(PSO-power)
Monjezi et al. (2016)	GEP	D, W, WF	35	0.878
Faradonbeh and Monjezi (2017)	GEP	B, D, DI, HD, PF, S, ST, W	115	0.876
Hasanipanah et al. (2017e)	CART	D, W	86	0.95
Shahnazar et al. (2017)	ANFIS-PSO	D, W	81	0.984
Armaghani et al. (2018)	ICA	D, W	73	0.9300 (ICA—power) 0.9400 (ICA—quadratic)
Zhou et al. (2021b)	XGBoost, Jaya-XGBoost, RF, AdaBoost, ANN, Bagging	DI, HD, B, S, L, Q, BI, E, P, V_p, VOD, DE	150	0.9573 (Jaya-XGBoost) 0.9302 (XGBoost) 0.9147 (RF) 0.9044 (ANN) 0.8777 (AdaBoost) 0.9234 (Bagging)

Table 4 (continued)

References	Technique	Input	No. of dataset	R^2
Fissha et al. (2023)	BNN, RF, GBoosting, DT, KNN	MIC, D, SD, EV, BLI, BLA, MLI, MLA	100	0.94 (BNN)
				0.76 (RF)
				0.74 (GBoosting)
				0.70 (DT)
				0.67 (KNN)
Kumar et al. (2023)	GP	B, S, HD, ST, DE, D, PF, EF	40	0.8434
Guo et al. (2023)	PSO-LSSVM, LSSVM, GA-BP, BP	MECC, D, H, B, S, SD, PF	50	0.965 (PSO-LSSVM)
				0.887 (LSSVM)
				0.906 (GA-BP)
				0.878 (BP)
Tran et al. (2023)	BA-SVM, BA-KNN, BA-DTR, BA-ExTree, $\text{empirical}_{\text{USBM}}$, $\text{empirical}_{\text{Ambraseys}}$	B, S, ST, W, D	300	0.837 (BA-SVR)
				0.868 (BA-KNN)
				0.607 (BA-DTR)
				0.892 (BA-ExTree)
				0.760 ($\text{empirical}_{\text{USBM}}$)
				0.737 ($\text{empirical}_{\text{Ambraseys}}$)

ExTree extra trees, *BP* back propagation, *LSSVM* least-squares support vector machine, *GP* genetic programming, *BNN* bayesian neural network, *GBoosting* gradient boosting, *DTR* decision tree regressor, *BA* bagging regressor, *XGBoost* efficient extreme gradient boosting, *Jaya* Jaya algorithm, *ANFIS* Adaptive neuro-fuzzy inference system, *ANN* artificial neural network, *FIS* fuzzy inference system, *B* burden, *S* spacing, *MIC* maximum instantaneous charge, *SD* scaled distance, *EV* elevation, *BLI* blast longitudinal, *BLA* blast latitude, *MLI* measured longitudinal, *MLA* measured latitude, *BI* blastability index, *BS* burden to spacing ratio, *CART* classification and regression trees, *D* distance from the blasting face, *DE* density of explosive, *DI* hole diameter, *EF* Energy factor, *DR* delay per rows, *Q* explosive per hole, *E* Young modulus, *FIS* fuzzy inference system, *GA* genetic algorithm, *GEP* gene expression programming, *HD* hole depth, *ICA* imperialist competitive algorithm, *KNN* K-nearest neighbors, *L* charge length, *N* number of row, *NH* number of holes per delay, *P* Poisson's ratio, *PF* powder factor, *PSO* particle swarm optimization, *RQD* rock quality designation, *S* spacing, *SD* sub-drilling, *ST* stemming, *SVM* support vector machine, *TC* total charge, *UCS* unconfined compressive strength, V_p P-wave velocity, *VOD* velocity of detonation, *W* charge weight per delay, *WF* water factor, *TS* tensile strength, J_s joint spacing, *HD/B* hole depth-to-burden ratio, *SC* specific charge, σ point load index, ρ rock density, R^2coefficient of determination, *MECC* maximum explosive charge capacity, *H* negative elevation

The frequency and intensity of ground vibrations resulting from blasting operations are influenced by a complex interplay of various interconnected factors (Armaghani et al. 2014). According to Kumar et al. (2016), the geomechanical condition of the surrounding rock is the most crucial and widely applicable factor influencing ground vibrations resulting from blasting operations. Several factors contribute to this, including Rock Quality Designation (RQD), density, rock strength, geological strength index, and rock characteristics such as layering, rock type, slope of layers, unit weight, presence of rock discontinuities and joints, their orientation, soil-rock interface, and the presence of a water table. These factors collectively influence the frequency and intensity of ground vibrations induced by blasting. Geological discontinuities play a crucial role in the effectiveness of a blast and must be carefully considered during blast planning and engineering. The presence of such discontinuities significantly influences the transmission of blast vibrations (Singh and Sastry 1986). It is important to note that the distance between the monitoring equipment and the blast site also affects the measurement of ground vibrations. As the monitoring distance increases, the measured ground vibration tends to decrease due to the attenuation and dissipation of vibration energy. Therefore, the distance at which monitoring equipment is placed should be carefully considered to ensure accurate measurement of ground vibrations induced by blasting operations.

Regulatory constraints are imposed on blasting activities to mitigate the impact on structures, minimize the risk of seismic activity, and enhance blasting outcomes. These regulations impose limits on the vibration levels generated by blasting operations. To anticipate blast vibrations and ensure compliance with these regulations, various prediction models, including empirical, mathematical, and statistical approaches, have been employed However, these models often fall short of providing satisfactory forecasts due to their inherent limitations. In light of the exceptional capabilities of ML approaches, they have emerged as potential alternatives for predicting ground vibrations. Khandelwal and Singh, (2009) employed ANN technology to train and utilize 154 blast records from an open pit coal mine in India. The objective was to predict and compare PPV and frequency using ANN with other prediction techniques. To evaluate the performance of the ANN model, 20 new blast datasets were employed for testing and comparison against other prediction techniques. This approach allowed for the assessment of the accuracy and effectiveness of ANN in predicting PPV and frequency in the context of blasting operations. In the Siahbisheh project in Iran, Monjezi et al. (2011) utilized ANN to predict and forecast ground vibrations induced by explosions. This application of ANN aimed to accurately estimate and anticipate the impact of explosion-induced vibrations in the project area. By employing ANN technology, the study sought to enhance the understanding and management of ground vibrations resulting from blasting operations in the specific context of the Siahbisheh project in Iran. Zhou et al. (2021b) utilized a combination of the Jaya method and XGBoost to forecast PPV resulting from blast induced PPV. The Jaya-XGBoost model was specifically developed for this purpose. Through a comparative analysis with other ML models and conventional empirical models, the findings revealed that the proposed Jaya-XGBoost model exhibited the highest level of reliability and accuracy in predicting blast-induced PPV. This indicates that the Jaya-XGBoost model holds significant potential as a trustworthy forecasting tool for blast-induced PPV, surpassing other existing models in terms of performance and predictive capability.

Table 4 within this study presents an extensive compilation of primary research findings focused on ground vibrations induced by blasting, with insights drawn from the existing literature. Building upon the information provided in Table 4, it is apparent that ANN saw widespread utilization in the early 2000s and the early 2010s, encompassing diverse applications within the field. However, it is essential to emphasize that while all these studies utilized ANN, they each focus on distinct projects and target different application areas. Besides, it is observed that other ML methods, such as Fuzzy Inference Systems (FIS) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), were seen to be used less frequently than ANN over the time period between 2008 and 2013. However, as the mid-to-late twenty-first century approached, there was a resurgence of interest in this research domain. During this time, researchers initiated investigations into the application of hybrid models, which combine multiple techniques for improved predictive accuracy. Noteworthy contributions in this field include the seminal works by Zhou et al. (2021b), Armaghani et al. (2014), Hajihassani et al. (2015a), Hajihassani et al. (2015b), and Guo et al. (2023). These studies have significantly advanced the state of knowledge in ground vibration prediction, fostering substantial progress within the field.

4.4 Prediction of rock fragmentation

In surface mining operations, the primary objective of blasting is to separate the valuable ore from the surrounding rock mass. Achieving optimal fragmentation is the key outcome of any blasting operation, as it ensures that the resulting material is of an appropriate size for efficient loading, hauling, and subsequent processing activities (Hasanipanah et al. 2016a, b; Li et al. 2021). The quality of fragmentation plays a critical role in facilitating the smooth flow of operations downstream, leading to improved productivity and cost-effectiveness in mining processes.

In the field of rock fragmentation prediction, numerous scholars have developed theoretical and empirical models that rely on blast design parameters. Notably, Jia et al. (2022) are among the researchers who have contributed to this area. These models are designed to forecast the extent of rock fragmentation resulting from blasting operations. However, it's important to note that some of these models primarily focus on the BI often overlooking other critical rock mass parameters. While the BI plays a significant role in predicting fragmentation, it's essential to consider and incorporate other relevant rock mass characteristics to enhance the accuracy and reliability of fragmentation predictions (Yu et al. 2020a, 2021a). A more complete understanding of the fragmentation process can be attained by include a wider range of rock mass parameters in the models, which will enhance their prediction power in real-world mining settings. The blasting process is inherently nonlinear and complex, making it challenging to fully comprehend. The existing theoretical and empirical approaches to predict rock fragmentation have limitations as they rely on assumptions and consider only a limited number of influencing factors (Jia et al. 2022). To overcome these limitations, alternative techniques such as sieving or screening have been proposed. This method involves evaluating the size distribution of particles and fragments, providing a more comprehensive understanding of the fragmentation process. However, it is important to note that sieving or screening can be more expensive and time-consuming compared to traditional empirical methods (Bhatawdekar et al. 2021).

Indeed, ML applications offer significant potential for overcoming the challenges associated with blast prediction and improving blasting performance. ML techniques possess advanced processing capabilities and excel in regression and classification tasks, making them well-suited for addressing the complexities of blast-related data. To enhance the prediction and optimization of blasting performance, numerous researchers have developed ML and OA approaches. Notable studies by Koopialipoor et al. (2020), Shirani Faradonbeh et al. (2016), Jahed Armaghani and Azizi (2021), and Mohamad et al. (2019) are among the contributions in this area. These works investigate how to apply ML and OA methods to enhance the precision, effectiveness, and general performance of blasting operations.

Based on the information provided in Table 5, ANN were widely utilized in the early 2010s and the early 2020s for various applications in the field. However, it is noteworthy that the specific projects and applications of ANN varied from year to year. During the period from 2009 to 2016, other ML methods, such as FIS and Backpropagation Neural Networks (BPNN), were less frequently employed compared to ANN. In the late 2000s, there was a renewed interest in the topic, and researchers began to explore the use of hybrid/ensemble ML methods. These methods combine multiple OA and ML techniques to improve the accuracy and performance of predictions in blasting-related applications. The adoption of hybrid/ensemble ML methods indicates a continued effort to enhance the effectiveness and versatility of ML approaches in the field of blasting research. Ebrahimi et al. (2016) conducted a study at the Anguran mine in Iran, where they collected blasting parameters. They employed ANN to predict rock fragmentation and utilized the artificial bee swarm (ABC) technique to enhance the blasting mode parameters. It is discovered that ABC algorithm can optimize rock fragmentation with great precision when compared to Kuz-Ram empirical model. A new rock fragmentation prediction model was put forth by Hasanipanah et al. (2018) and is based on the integration of PSO and the adaptive neural fuzzy inference system (ANFIS). It is determined that the suggested PSO-ANFIS model is the best model after comparisons with SVR, ANFIS, and nonlinear multiple regression (MR) models. Based on statistical learning theory, Shi et al. (2012) predicted the mean particle size (X_{50}) arising from rock blast fragmentation in 90 different mine groups using the SVR regression approach. Results from SVR prediction were compared to those from ANN, MVRA, the conventional Kuznetsov approach, and observed X_{50} values. This approach yields admirable outcomes, and the support vector machine model's prediction accuracy is respectable.

According to Table 5, the most frequently employed variables in the field of blasting research were B, ST, and S, listed in descending order. These three parameters were consistently recognized as important factors in various blasting-related studies. B refers to the distance between adjacent blastholes, ST refers to the material placed at the top of the blasthole to confine the explosive gases, and S refers to the distance between blastholes. The prominence of B, ST, and S in blasting research indicates their crucial role in optimizing blasting operations and achieving desired outcomes. These parameters directly influence the distribution of explosive energy, fragmentation characteristics, and overall efficiency of the blasting process. Therefore, researchers frequently focus on studying and optimizing these variables to improve the performance and effectiveness of blasting operations. Another frequently employed input parameter in blasting research is D. D is essential to the fragmentation process along with the idea of the crushing zone around the hole and its connection with other blast design elements. The parameters "c" and "PF" are also crucial for increasing the energy of explosives to obtain increased fragmentation output since they are strongly related to fragment size, as shown in Table 5. Engineers can adjust the blasting process using these factors to generate the best possible fragmentation for operational goals and downstream processes. In addition to the parameters mentioned earlier, there are three additional interconnected characteristics that significantly influence fragmentation: HD, specific drilling (SD) and RD. Table 5 indicates that researchers have increasingly utilized ratios of blast design parameters instead of focusing on individual parameters alone. This approach allows for a reduction in the number of input factors while still capturing the important relationships between the parameters. The ratios HD/B, B/D, ST/B, S/B, and S/D have been particularly employed by researchers to predict blast fragmentation. By

Table 5 Prediction of rock blast fragmentation using ML and OA methods

References	Technique	Input	Output	No. of dataset	Performance
Monjezi et al. (2009)	FIS	B, S, ST, SD, PF, HD, RD, C	Fragmentation (%)	415	$R^2=0.96$
Monjezi et al. (2010c)	BPNN	BS, D, ST, TC, PF, N, MH, PI, TR	Fragmentation (cm)	132	$R^2=0.985$ RMSE = 0.995
Monjezi et al. (2010a)	ANN	D, HD, BS, ST, N, PF, RD, C	Fragmentation (%)	250	$R^2=0.98$
Kulatilake et al. (2010)	BPNN	S/B, HD/B, B/D, ST/B, PF, X_B, E	X_{50}, mean particle size (m)	91	$R^2=0.941$ RMSE = 0.009
Bahrami et al. (2011)	BPNN	D, AD, B, S, PF, SMR, BI, SD, ST, C	Fragmentation (%)	220	$R^2=0.97$ RMSE = 0.56
Kulatilake et al. (2012)	ANN	S/B, HD/B, B/D, ST/B, PF, X_B, E	X_{50}, mean particle size (m)	109	$R^2=0.94$
Shi et al. (2012)	SVM	S/B, H/B, B/D, ST/B, PF, E, X_B	X_{50}, mean particle size (m)	102	$R^2=0.962$ RMSE = 0.006
Sayadi et al. (2013)	ANN	B, S, HD, SD, SC	Fragmentation (m)	103	$R^2=0.85$
Enayatollahi et al. (2014)	ANN	HD, PF, SD, BS, S/B, WD, ST, C, N, RQD, T, B	Fragmentation (m)	70	$R^2=0.98$
Monjezi et al. (2014)	ANN	B, S, PF, N, D, C, ST, H	D_{20}, 20% passing size (cm)	135	$R^2=0.92$ RMSE = 1.4701
Monjezi et al. (2014)	ANN	B, S, PF, N, D, C, ST, H	D_{50}, 50% passing size (cm)	135	$R^2=0.941$ RMSE = 1.945
Monjezi et al. (2014)	ANN	B, S, PF, N, D, C, ST, H	D_{80}, 80% passing size (cm)	135	$R^2=0.95$ RMSE = 1.1041
Esmaeili et al. (2015)	SVM, ANFIS	DR, SC, ST, D, BI, S/B	Fragmentation (cm)	80	$R^2_{\ SVM}=0.83$ $R^2_{\ ANFIS}=0.89$
Shams et al. (2015)	FIS	B, S, D, Sch, J, PF, ST	D_{80}, 80% passing size (cm)	185	$R^2=0.922$ RMSE = 2.423
Ebrahim et al. (2016)	BPNN	B, S, ST, HD, PF	Fragmentation (cm)	34	$R^2=0.78$ RMSE = 2.76

Table 5 (continued)

References	Technique	Input	Output	No. of dataset	Performance
Ghaeini et al. (2017)	MI	UCS, P, RQD, JS, RD, SC, B, ST, S/D, JPO	D_{80}, 80% passing size	36	$R^2=0.81$ $RMSE=10.71$
Asl et al. (2018)	ANN	B, S, HL, SD, ST, C, PF, GSI	D_{80}, 80% passing size (cm)	200	$R^2=0.94$ $RMSE=0.1$
Dimitraki et al. (2019)	ANN	BI, PF, QB	X_{50}, mean particle size (cm)	100	$R^2=0.80$
Hasanipanah et al. (2018)	PSO-ANFIS, SVM, ANFIS	B, S, ST, SC, C	D_{80}, 80% passing size (cm)	72	$R^2_{PSO\text{-}ANFIS}=0.89$ $RMSE_{PSO\text{-}ANFIS}=1.31$ $R^2_{SVM}=0.83$ $RMSE_{SVM}=1.66$ $R^2_{ANFIS}=0.81$ $RMSE_{ANFIS}=1.78$
Gao et al. (2018)	GPR, SVM, ANFIS, PSO-ANFIS	B, S, ST, PF, C	D_{80}, 80% passing size (cm)	72	$R^2_{GPR}=0.948$ $R^2_{SVM}=0.83$ $R^2_{ANFIS}=0.81$ $R^2_{PSO\text{-}ANFIS}=0.89$
Li et al. (2021)	GA-SVR, PSO-SVR, SSA-SVR, GS-SVR, GWO-SVR	D, H, SD, B, S, ST, HD, Wd, S/B, ST/B, H/B, J/B, B/D, PF	Fragmentation (cm)	76	$R^2_{PSO\text{-}SVR}=0.8404$ $R^2_{GA\text{-}SVR}=0.8398$ $R^2_{SSA\text{-}SVR}=0.839$ $R^2_{GS\text{-}SVR}=0.8462$ $R^2_{GWO\text{-}SVR}=0.8392$
Hosseini et al. (2022b)	GEP, BPNN	n, HL, B, S, HA, ST, BRH, PF, C	D_{80}, 80% passing size (cm)	723	$R^2_{GEP}=0.981$ $R^2_{BPNN}=0.913$
Hosseini et al. (2022c)	RES	B, S/B, PF, MH, H/B, HIL, HDV, D, J/B, BI, IS, BHP, B/D	D_{80}, 80% passing size (cm)	64	$R^2=0.931$
Yari et al. (2023)	JSO-LightGBM,	B, S, PF, ST, HL, SD	D_{50}, 50% passing size (cm)	234	$R^2=0.996$

Table 5 (continued)

GWO grey wolf optimization, GS grid search, *LightGBM* light gradient-boosting machine, *JSO* Jellyfish search optimizer, *GA* genetic algorithm, *SSA* salp swarm algorithm, *RES* rock engineering system, *BPNN* back propagation neural network, *FIS* fuzzy inference system, *ANN* artificial neural network, *SVM* support vector machine, *ANFIS* adaptive network-based fuzzy inference system, *MI* mutual information, *GPR* Gaussian process regression, *PSO* particle swarm optimization, *HL* hole length (m), *BRH* blasted rock per hole (ton), *HD* hole depth (m), *S* spacing (m), *B* burden (m), *ST* stemming (m), *PF*, powder factor (kg/m^3), *n* number of holes, *SD* specific drilling (m/m^3), *C* charge per delay (kg/ms), *HA* hole slope, *D* hole diameter (mm), *RD* rock density (t/m^3), *BS* burden to spacing, *N* number of rows, *BI* blastability index, *TC* total charge-per-delay (kg/ms), *MH* maximum holes per delay, *PI* point load index (Mpa), *TR* delay between the rows (ms), *AD* average hole depth (m), *SMR* rock mass rating, X_B mean block size (m), *E* elastic modulus (Gpa), *BS* bench slope (degree), *WD* water depth (m), *RQD* rock quality designation (%), *T* tension strength (Mpa), *SC* specific charge (kg/m^3), *DR* ratio of total delays per number of rows, *S/B* spacing to burden ratio, *H/B* stiffness ratio, *UCS* uniaxial compressive strength (Mpa), *P* joint persistency (m), *Wd* verage width, *J* density of joint, *JS* joint spacing (m), *S/D* ratio of boreholes spacing to their diameters, *JPO* joint plane orientation, *H* bench height (m), *GSI* geological strength index, *QB* quantity of blasted rock pile in tons (tn), *Sch* Schmidt hammer rebound number, X_B in-situ block size (m), HIL hole inclination (deg), *HDV* hole deviation, *J* joint, *IS* initiation sequence, *BHP* blast holes pattern employing these ratios, researchers aim to capture the complex interplay between multiple blast design parameters and their impact on blast fragmentation. This approach allows for more efficient prediction models by reducing the number of input factors while still capturing the essential relationships and optimizing the blasting process.

4.5 Prediction of backbreak

Blasting operations have a significant influence on slope stability, primarily through the occurrence of backbreak. Backbreak refers to the displacement and fracturing of rock towards the blast area, leading to potential instability in the slopes. According to Bauer (1982), the inadequate control of backbreak in blasting operations would lead to the need for a reduction in the overall pit-slope angle. This reduction in slope angle, in turn, would have the consequence of increasing the stripping ratio. When backbreak is not adequately managed, the effectiveness of planned safety berms, which are designed to provide additional stability, would be compromised. Additionally, there would be a greater amount of loose face rock generated, further contributing to slope instability. The overall cost of manufacturing would significantly increase due to the detrimental effects of backbreak (Scoble et al. 1997). Multiple studies conducted by different researchers have investigated the variables that can potentially impact the severity of backbreak in blasting operations (Jenkins 1981; Konya and Walter 1991; Monjezi and Dehghani 2008). According to Konya (2003), backbreak tends to worsen when the ST (material placed on top of the explosive charge) and/or B (rock mass above the blasthole) increase. This suggests that controlling the ST and optimizing the B can play a crucial role in mitigating backbreak. Gates et al. (2005) identified two primary causes of backbreak. The first cause is an insufficient delay period between the initiation of successive blastholes. This insufficient delay does not allow sufficient time for the release of gases and energy from the previous blastholes, leading to increased backbreak. The second cause is an increase in the number of blasting rows, which can result in a larger excavation area and greater rock displacement, leading to more severe backbreak. These findings highlight the importance of considering variables such as ST, B, c, and S in order to effectively control and minimize backbreak during blasting operations.

To prevent backbreak in blasting operations, it is necessary to consider various factors, including the physicomechanical characteristics of the rock mass, the qualities of the explosives used, and the geometric aspects of the blasting pattern. In the past, empirical models for blast design were developed to meet essential requirements such as achieving adequate fragmentation, reducing backbreak, selecting a suitable muck pile profile, and minimizing oversize stones. However, these empirical models often lack an accurate and straightforward way to forecast backbreak, and they often only consider a subset of the crucial blasting parameters. Given the limitations of existing empirical methods, the use of mathematical techniques such as ML and OA may offer more comprehensive and effective solutions for backbreak prediction. The main findings of the study are displayed in Table 6. According to Esmaeili et al. (2014), traditional multiple regression statistical models and ANFIS and ANN applications for backbreak prediction were discussed. The findings demonstrate that in terms of forecasting backbreak, the designed ANFIS outperforms ANN and multiple regression. In an effort to anticipate backbreak in blasting operations at the Soungun Iron Mine in Iran, Khandelwal and Monjezi (2013) employed SVR method along with rock properties and blasting design factors. This study aimed to develop a predictive model that could effectively

Table 6 Prediction of backbreak using ML and OA methods

References	Technique	Input	No. of dataset	R^2
Bazzazi and Esmaeili (2012)	ANFIS	SB, H/B, d, ST, PF, RD, UCS, Nr, C L D, CPT	42	0.95
Sayadi et al. (2013)	BPNN, RBFNN	B, S, ST, H, PF, SD	103	0.871 (BPNN), 0.515 (RBFNN)
Khandelwal and Monjezi (2013)	SVM	B, S, ST, PF, HD, SD	234	0.987
Sari et al. (2014)	MVRA-LNBB	B, S, ST, PF, K	175	0.981
Esmaeili et al. (2015)	ANFIS, ANN	SB, H/B, ST, PF, RD, N_r, CLR	42	0.96 (ANFIS), 0.92 (ANN)
Ebrahimi et al. (2016)	ANN	B, S, ST, HD, PF	34	0.77
Faradonbeh et al. (2016a)	GP	B, S, ST, PF, H/B	175	0.976
Ghasemi et al. (2016a)	RF, ANFIS	B, S, ST, PF, K	175	0.971 (RF) 0.998 (ANFIS)
Ghasemi (2017)	GP, PSO-linear, PSO-quadratic	B, S, ST, PF, K	175	0.979 (GP) 0.973 (PSO-linear) 0.983 (PSO-quadratic)
Hasanipanah et al. (2017a)	PSO	B, S, ST, PF, RD	76	0.96
Hasanipanah et al. (2017f)	PSO-ANFIS	B, S, ST, PF	80	0.922
Eskandar et al. (2018)	PSO	B, S, ST, PF, RMR	84	0.96
Hasanipanah and Bakhshandeh Amnieh (2021)	GA, ICA	B, C, PF, SB, ST/B, i, VOD, d, d/B	62	0.934 (GA) 0.963 (ICA)
Kumar et al. (2021)	RF	SB, H/ST, ED, p-wav	140	0.979
Zhou et al. (2021a)	ELM, GRNN, RBF, SCA-RF, HHO-RF	B, S, ST, HD, PF, SD	234	0.95 (ELM) 0.965 (GRNN) 0.957 (RBF) 0.982 (SCA-RF) 0.981 (HHO-RF)
Yu et al. (2021a, b, c)	SVM, SVM-MFO, SVM-WOA	PF, B, SB, N_r, c, CPT, ST/B, UCS, W/B	85	0.844 (SVM) 0.985 (SVM-MFO) 0.974 (SVM-WOA)

Table 6 (continued)

References	Technique	Input	No. of dataset	R^2
Dai et al. (2022)	PSO-RF, SVM, GP, RF, ANN, CNN	SD, S, B, L, ST, PF	234	0.9507 (SVM) 0.9722 (GP) 0.9757 (RF) 0.9672 (ANN) 0.9277 (CNN) 0.9990 (PSO-RF)
Li et al. (2022)	ELM, ELM-PSO, ELM-FOA, ELM-WOA, ELM-LOA, ELM-SOA, ELM- SSA	SD, S, B, L, ST, PF	234	0.9671 (ELM) 0.9978 (ELM-PSO) 0.9760 (ELM-FOA) 0.9964 (ELM-WOA) 0.9981 (ELM-LOA) 0.9949 (ELM-SOA) 0.9971 (ELM-SSA)
Sharma et al. (2022)	MVRA, GP	SB, ST, PF, K	70	0.8167 (GP) 0.6305 (MVRA)

LMR linear multivariate regression analysis, *ANFIS* adaptive neuro-fuzzy inference system, *RBFNN* radial basis function neural network, *PLR* point load index (Mpa), BPNN back propagation neural network, *MVRA* multivariate regression analysis, *PSO* particle swarm optimization, *ANN* artificial neural network, *CNN* convolutional neural network, *RT* regression tree, *NLMR* nonlinear multivariate regression analysis, *GP* genetic programming, *LNBB* the natural logarithm of backbreak, *SCA* sine cosine algorithm, *HHO* Harris hawks optimizer, ELM extreme learning machine, *RBF* radial basis function, *GRNN* network and general regression neural network, *RF* random forest, *GA* genetic algorithm, *ICA* imperialist competitive algorithm, *SVM* support vector machine, *B* burden, *S* spacing, *ST* stemming length, *H* bench height, *HD* hole depth, *RD* rock density, *UCS* uniaxial compressive strength, *Nr* number of rows, *CLR* charge last row, *VOD* velocity of detonation, *PF* powder factor/specific charge, *SD* specific drilling, *SB* spacing to burden ratio, *H/B* stiffness ratio, *d* hole diameter, *ED* explosive density, *CPT* charge last row per total charge ratio, *K* geometric stiffness, *H/ST* bench height to stemming, *t* time delay, *C* maximum instantaneous charge, *PF* powder factor, *RMR* rock mass rating, *ST/B* stemming to burden ratio, *i* blasthole inclination, *B/d* burden to hole diameter ratio, *c* Charge per delay, *W/B* Water height to burden ratio, *L* hole length forecast the occurrence and severity of backbreak during blasting activities. Zhou et al. (2021a) conducted a study to determine the backbreak distance in blasting operations. They developed two hybrid prediction models based on RF algorithm, optimized using the harris hawks optimizer (HHO) and sine cosine algorithm (SCA). The fitness function employed in the optimization process was the root-mean-square error (RMSE). The findings of the study indicate that the SCA-RF model achieved a high coefficient of determination (R^2) value of 0.9829. This indicates that the model's performance met the engineering specifications for accurately predicting the backbreak distance in blasting operations.

4.6 Prediction of dust

Environmental and climate change initiatives are gaining increasing popularity among experts, as they recognize the importance of addressing environmental concerns (Bakhtavar et al. 2021a). Mining projects often raise significant environmental issues. In the case of surface mining, the discharge of dust resulting from blasting activities can have adverse effects on the environment and nearby residential areas. These effects are particularly concerning when a substantial amount of rock is blasted under unfavorable meteorological conditions, such as high wind speeds (Hosseini et al. 2021). Such environmentally damaging mining practices are contrary to the principles of climate-smart and green mining, and they can severely impact the sustainability of mining towns. It is essential to precisely predict the dispersion of dust emissions brought on by blasting operations to prevent potential issues. Accurate assessment enables proactive management and mitigation of the environmental effects brought on by these emissions.

The prediction of blast-induced dust emission distance has been a subject of numerous research efforts; however, there is a limited number of published statistical and empirical equations or models specifically focused on blast-induced dust in the mining sector (Roy et al. 2011; Sastry et al. 2015). In recent years, AI and ML solutions have emerged as potential approaches to studying dust emissions from mining operations. Table 7 in this study serves as a comprehensive compilation of primary research findings pertaining to dust emission in mining, derived from the existing literature. Below, we discuss the key findings and important variables as presented in Table 7.

According to Table 7, a summary of the most frequently utilized variables in the field of blasting research, arranged in descending order of their prevalence. Within the domain of explosive operations, certain key parameters, namely D, HL, WS, WD and T, exert significant influence on the dynamics of blast dust generation and dispersion. It is noteworthy that an increased D promotes enhanced fragmentation, resulting in a greater quantity of particulate matter being generated. In parallel, HL substantially contributes to the volume of displaced material, which is a critical factor in the generation of dust. WS plays a pivotal role in the dispersion of dust, as higher wind speeds lead to greater dispersion distances, thereby expanding the environmental impact of particulate matter. Conversely, lower WS values restrict dust propagation, causing it to settle in close proximity to the blast site. WD dictates the path along which dust disperses, influencing its impact on nearby communities and ecosystems. Additionally, T has a discernible effect on dust behavior, with temperature inversions potentially trapping dust at lower altitudes. A thorough understanding and precise management of these parameters are indispensable for effective control of blast dust within the context of explosive operations.

Table 7 Prediction of dust emissions using ML and OA methods

References	Technique	Input	Output	No. of dataset	Performance
Bakhtavar et al. (2021a)	GEP	D, HL, n, NH, ST, B, S, q, AH, T, WS, AP	DBIDEs	100	$R^2 = 0.8754$ $RMSE = 7.0181$
Bakhtavar et al. (2021b)	MLANN, FCM	D, HL, n, NH, ST, B, S, q, AH, T, WS	VHDBIDEs	100	$R^2 = 0.9267$
Hosseini et al. (2021)	MLP–DA, RBFNN–DA, MLP, RBF	D, HL, n, NH, ST, B, S, q, AH, T, WS, AP	Dh, Dv	100	R^2_{MLP-DA} (Dh) = 0.948 $RMSE_{MLP-DA}$ (Dh) = 4.029 R^2_{MLP-DA} (Dv) = 0.959 $RMSE_{MLP-DA}$ (Dv) = 3.897
Hosseini et al. (2022a, b, c, d)	GEP-GOA	D, HL, PF NH, ST, B, S, q, AH, T, WS, AP, WD	DBIDEs	100	$R^2 = 0.9145$
Hosseini et al. (2023)	RRES	P, UCS, NJ, AH, T, WS, AP, D, HL, n, NH, N, ST, B, S, PF, Sb	DBIDEs	45	$R^2 = 0.942$

MLANN Multi-layer artificial neural network, *DBIDEs* distribution of blast-induced dust emissions, *VHDBIDEs* vertical and horizontal distribution of blast-induced dust emissions, *Dh* horizontal distribution, *Dv* vertical distribution, *FCM* fuzzy cognitive map, *MLP* multi-layer perceptron, *ANN* artificial neural networks, *RBFNN* radial basis function neural networks, *DA* dimensional analysis, *GEP* gene expression programming, *GOA* grasshopper optimization algorithm, *RRES* reliability-based rock engineering system, *D* blast hole diameter, *HL* hole length, *n* number of holes, *NH* number of holes per delay, *ST* stemming, *B* burden, *S* spacing, *q* specific charge, *PF* powder factor, *AH* air humidity, *T* air temperature, *WS* wind speed, *WD* wind direction, *AP* atmospheric pressure, *P* porosity, *UCS* uniaxial compressive strength, *NJ* Number of major discontinuity sets, *N* Number of rows, *Sb* Subdrilling

5 Discussion and limitations

Mining operations encompass several facets, including mineral processing and environmental sustainability. One critical factor influencing these aspects is the environmental impact stemming from blasting activities. Inadequate execution of a blast can lead to adverse EEB consequences, such as flyrock, AOp, ground vibration, and backbreak. These repercussions give rise to significant concerns, ranging from community annoyance and structural damage to injuries and, in extreme cases, loss of life (Varris and Thorpe 2012; Bansah et al. 2016; Agrawal and Mishra 2020). Hence, the primary objective for every blasting engineer is to execute blasts while minimizing the occurrence of flyrock, dust, ground vibration, and AOp, all while achieving optimal detonation, ideal fragmentation, and limited backbreak. To identify the optimal blast design that maximizes desired outcomes while minimizing undesired ones, comprehensive studies on EEB become imperative.

AI, ML, OA, and DL technologies are rapidly gaining prominence in the industry. This is primarily in response to the inherent nonlinearity, unpredictability, and complexity of EEB issues, which involve various environmental factors. It is apparent from this short review that DL technology is more extensively utilized compared to ML and OA algorithms in addressing these challenges. For instance, at the initial stages of various EEB projects, researchers often employ ANN algorithms. However, despite the rapid development of DL theories, there are still certain shortcomings in DL algorithms. One notable issue is that, although numerous DL approaches can be applied to the same problem, the results may vary due to the distinct architectures of these DL methods. Furthermore, the uninterpretable nature of DL technology hinders engineers from extracting meaningful insights from the models, which, to some extent, slows down the progress of EEB research.

Various ML and OA methods have emerged as alternative approaches, driven by the limitations of DL in addressing diverse EEB projects. An essential aspect of employing ML and OA models for predicting and mitigating EEB revolves around the selection of input parameters. Nonetheless, this process is not devoid of challenges. One of the foremost challenges pertains to the transferability of models across different mining sites. Mining operations exhibit significant variations in geological conditions, rock properties, and blasting techniques. This raises a pivotal question: can models trained on data from one specific site be reliably applied to predict outcomes at another location? This challenge underscores the critical issue of generalization. A model that excels at one site may not readily adapt to another, highlighting the inherent limitations associated with the universal applicability of ML/OA models. Therefore, effective application of ML/OA models necessitates meticulous consideration of the parameters selected for model development. Moreover, even within a single mining site, the presence of spatial variability and anisotropic properties in geomaterials presents formidable challenges. The spatial variability in geological characteristics and rock properties is at the core of EEB prediction and demands thorough scrutiny. It underscores the fact that mining sites rarely exhibit uniform composition and behavior. These inherent variations can introduce unpredictability into model outcomes, especially when extrapolating beyond the boundaries of the training data. Consequently, a failure to account for spatial variability can yield models with predictions of limited reliability. It is imperative to acknowledge and address these uncertainties when deploying ML/OA models for EEB prediction. These models, while promising and accurate in specific contexts, necessitate meticulous consideration of site-specific conditions and the constraints they impose. The complications are further compounded by anisotropic properties. Geomaterials often manifest directional dependencies in their response to blasting operations. Grasping and incorporating these anisotropic behaviors into ML/OA models demand a nuanced comprehension of the materials involved. Overlooking anisotropy can lead to misleading predictions and hinder the efficacy of these models.

Another paramount consideration in the application of ML/OA models is the availability and quality of input parameters. The predictive power and accuracy of these models are intricately tied to the data they are trained on. Therefore, the process of selecting and characterizing input parameters necessitates meticulous attention. Different mining sites may present unique geological and geotechnical conditions, necessitating a tailored approach to parameter selection. The absence of essential parameters or the use of data of questionable quality can undermine the robustness of ML/OA models. To enhance the reliability of EEB prediction models, future research should concentrate on refining and expanding the range of input parameters. This includes incorporating a broader spectrum of geomechanical properties, geological features, and blast design parameters into the modeling process. Ensuring the availability and quality of these parameters is central to developing models that can be trusted for real-world applications.

In summary, the effective utilization of DL, ML and OA models for EEB prediction hinges upon a thorough comprehension of the parameters employed and their inherent constraints. By tackling these challenges head-on, researchers can propel the field of blast engineering forward, creating models that yield more precise predictions, improved management of environmental consequences, and ultimately, fostering sustainable mining practices.

6 Future directions

Understanding and mitigating the EEB of blasting operations is a crucial aspect of modern mining practices. As the mining industry continues to evolve, there is a growing need to explore innovative approaches that combine data-driven ML or DL techniques with knowledge-based or physics-based methods (Zhang and Phoon 2022). This integration can unlock new insights and pave the way for disruptive technologies that have the potential to revolutionize the field of blast engineering. In this section, we outline the future research directions for studying EEB, emphasizing the indispensable combination of data-driven models and physics-based approaches. Additionally, we present a potential working mechanism in Fig. 11, highlighting the possibilities for advancing these approaches.

6.1 Integration of data-driven and physics-based methods

To comprehensively investigate the environmental effects of blasting, it is imperative to leverage the strengths of both data-driven ML/DL models and physics-based approaches. Data-driven models have demonstrated remarkable success in handling large volumes of complex data, identifying patterns, and making predictions (Zhang et al. 2022a). By incorporating ML/DL techniques, researchers can analyze extensive datasets collected from various sources, including vibration records, ground displacement measurements, and particle velocity data. These models can identify correlations, establish predictive relationships, and classify different environmental impact scenarios based on specific blasting parameters.

Furthermore, the integration of data-driven ML/DL models with physics-based models enables a more comprehensive understanding of the blast-induced environmental effects.

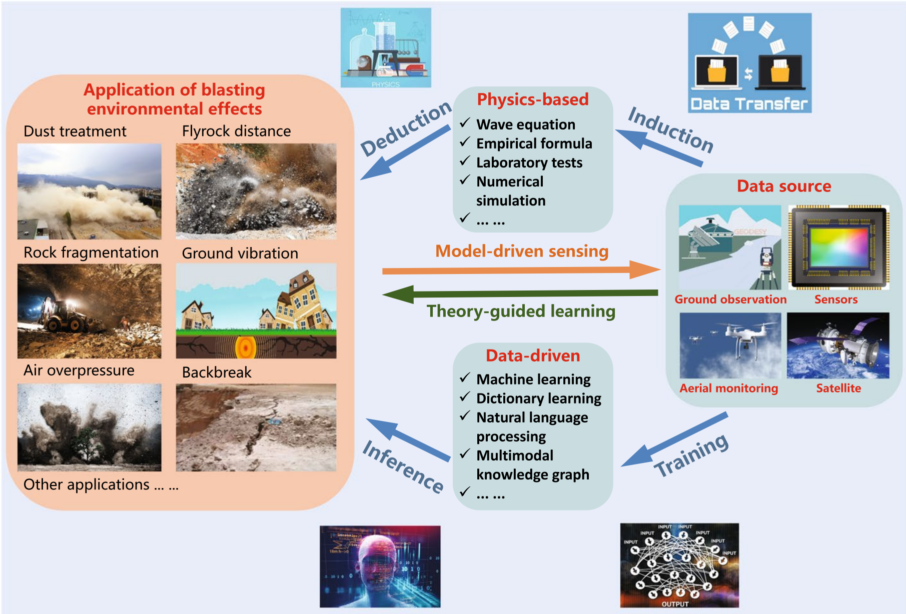

Fig. 11 The work mechanism of disruptive technologies

Physics-based models, rooted in fundamental principles, capture the underlying mechanisms governing blast-related phenomena (Zhang et al. 2021a). They provide insights into wave propagation, energy distribution, and ground response, allowing for a more detailed characterization of the environmental impact. The coupling of data-driven ML/DL models with physics-based models offers a powerful synergy, where data-driven models can complement physics-based models by learning patterns and improving predictions, while physics-based models provide the necessary physical understanding and guide the interpretation of data-driven results.

6.2 Development of disruptive technologies

The issues related to EEB encompass various aspects such as the prediction of flyrock distance, ground vibrations, AOp, rock fragmentation, and backbreak. These predictions are typically treated as numerical estimations. However, due to the spatial variability and anisotropic properties of geomaterials, there is significant uncertainty when quantifying their stiffness and strength. Consequently, the outcomes obtained through ML or DL approaches may not be deterministic in nature.

In this regard, the fusion of data-driven ML/DL models and physics-based models presents an opportunity to develop disruptive technologies in the field of blast engineering, and a possible working mechanism is provided in Fig. 11. By leveraging the strengths of both approaches, researchers can push the boundaries of knowledge and advance our ability to predict and mitigate EEB. These technologies hold the potential to revolutionize current practices and enhance the efficiency and sustainability of mining operations.

In conclusion, the future research directions for investigating EEB necessitate a combined approach, integrating data-driven ML/DL models with physics-based methods. This combination allows for a comprehensive understanding of the complex dynamics involved in blasting operations. Furthermore, the development of disruptive technologies through the coupling of these approaches can revolutionize the field, enabling more accurate predictions, better control of environmental impacts, and sustainable mining practices. By embracing the potential of data-driven and physics-based methods, researchers can unlock new frontiers in blast engineering, contributing to the advancement of rock mechanics and mining sciences.

6.3 Practice of integration technology case

The integration of data-driven ML/DL models with physics-based methods presents a promising avenue for mitigating EEB. This approach can be applied in various mining scenarios, and its potential benefits are profound. In this paper, we undertake a specific case study to elucidate the practical implementation and the consequential benefits of this integration in EEB prediction and mitigation.

In the scenario of controlling ground vibrations in quarry blasting, the implementation involves several critical steps. Firstly, a comprehensive dataset is meticulously curated, comprising historical blasting records, geological information, weather conditions, and real-time ground vibration measurements. Employing data-driven ML/DL models such as CNN or Recurrent Neural Networks (RNNs), historical data is dissected to unveil intricate patterns and correlations between blasting parameters (e.g., explosive type, charge size, distance to the blast) and ground vibration levels. The ML/DL models glean insights from this data and craft predictive models for ground vibrations. Concurrently, physics-based models are enlisted to simulate the propagation of blast waves and their interactions with geological formations. These models incorporate fundamental principles of wave mechanics and material properties, thereby offering comprehensive insights into the impact of various parameters on ground vibrations. The integration between data-driven models and physics-based models operates within a dynamic feedback loop, wherein data-driven models continually receive real-time vibration measurements, updating their predictions accordingly. Physics-based models validate these predictions by leveraging their profound understanding of the underlying physics. Any discrepancies trigger recalibrations within the data-driven models. A control system is then deployed, harnessing the integrated models to make real-time decisions during blasting operations. This system adjusts the blasting parameters in response to the predictions and the insights gleaned from physics-based assessments, ultimately minimizing ground vibrations.

The advantages stemming from this integrated approach are truly noteworthy. Firstly, it significantly enhances prediction accuracy, as the integration of data-driven models with physics-based models synergizes the ability to capture complex, non-linear relationships with a fundamental comprehension of wave propagation. Secondly, the real-time adaptability of this system is a pivotal strength, enabling it to adapt to changing conditions during blasting, thereby minimizing environmental impact. Furthermore, this approach effectively reduces the risk of excessive ground vibrations, a condition that could lead to structural damage and environmental harm, thereby ensuring that blasting operations always operate within safe limits. Emphasizing sustainability is paramount, as the reduction of EEB in mining operations not only mitigates environmental damage but also fosters positive community relations and regulatory compliance. Lastly, this integrated approach yields substantial cost savings by proactively preventing excessive EEB. This avoidance helps in mitigating potential damage claims, fines, and costly remediation efforts.

In conclusion, the integration of data-driven ML/DL models with physics-based methods in blasting operations holds the potential to revolutionize the field of blast engineering. Combining the strengths of both approaches enables more accurate predictions, better control of environmental impacts, and ultimately, more sustainable mining practices. This approach exemplifies the synergy between modern data-driven techniques and established physical principles, leading to a brighter future for the mining industry.

7 Conclusions

In this study, we have conducted a comprehensive literature review on EEB in blasting operations, specifically focusing on flyrock, AOp, ground vibrations, backbreak, dust and rock fragmentation. Various methods, including ML and OA, have been discussed in relation to the prediction and mitigation of these environmental effects. The integration of data-driven ML or DL techniques with physics-based approaches has emerged as a promising direction for future research in blast engineering.

Based on our analysis, it is evident that ML and OA methods have demonstrated considerable potential in predicting and managing EEB. These approaches have shown superior performance compared to traditional empirical models, enabling more accurate estimations of flyrock distance, AOp, ground vibrations, backbreak, dust and rock fragmentation. The utilization of ML/DL models allows for the analysis of large datasets, identification of complex patterns, and prediction of blast-induced environmental impacts. Combining these data-driven models with physics-based approaches enhances our understanding of the underlying mechanisms and provides a comprehensive perspective on EEB.

However, it is important to acknowledge certain limitations in the current state of research.

(1) First, despite the advancements in ML and OA techniques, there are still challenges in capturing the spatial variability and anisotropic properties of geomaterials, which can introduce uncertainties in predictions. Further research is needed to improve the accuracy and reliability of these models, considering the complex nature of rock mass behavior.
(2) Second, the predictive power of the developed models heavily relies on the availability and quality of input parameters. The selection and characterization of input variables require careful consideration, as different mining sites may exhibit unique geological and geotechnical conditions. Future studies should aim to refine and expand the range of input parameters, including geomechanical properties, geological features, and blast design parameters, to enhance the robustness of EEB prediction models.
(3) Third, the integration of data-driven ML/DL models with physics-based models opens new opportunities for disruptive technologies. However, there is a need for further research on the development of hybrid models that effectively combine these approaches. These models can leverage the strengths of data-driven models in handling complex data and identifying patterns while incorporating the physical understanding and guiding principles of physics-based models. This integration can lead to more accurate and comprehensive predictions of EEB.

In conclusion, the study of EEB in blasting operations is a complex and multi-faceted research area. ML, DL, and OA methods offer promising avenues for predicting and mitigating blast-induced environmental effects. The integration of data-driven models with physics-based approaches provides a comprehensive understanding of blast-related phenomena. Nonetheless, there are limitations in the current state of research that need to be addressed, such as capturing spatial variability, refining input parameters, and developing hybrid models. By addressing these challenges, future research can advance the field of blast engineering, leading to more accurate predictions, better control of environmental impacts, and sustainable mining practices.

Acknowledging the limitations and focusing on these areas of improvement, future studies can contribute to the development of disruptive technologies in blast engineering, enabling more effective and efficient blasting operations while minimizing environmental impacts. The advancements in EEB prediction models will play a vital role in achieving sustainable mining practices and ensuring the safety and well-being of communities surrounding mining sites.

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Declarations

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

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