Journal of Mining and Environment (JME) Vol. 16, No. 4, 2025, 1195-1219

Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

Optimization of Fragmentation and Operational Costs of Drilling and Blasting using Hybrid Machine Learning Models in an Open-Pit Mine in Peru

Marco Antonio Cotrina-Teatino[1]*, Jairo Jhonatan Marquina-Araujo[1], Jose Nestor Mamani-Quispe[2], Solio Marino Arango-Retamozo[1], Johnny Henrry Ccatamayo-Barrios[3], Joe Alexis Gonzalez-Vasquez[4], Teofilo Donaires-Flores[2], Maxgabriel Alexis Calla-Huayapa[5]

1. Department of Mining Engineering, Faculty of Engineering, National University of Trujillo, Trujillo, Peru
2. Faculty of Chemical Engineering, National University of the Altiplano of Puno, Puno, Peru
3. Department of Mining Engineering, Universidad Nacional San Cristobal de Huamanga, Ayacucho, Peru
4. Department of Industrial Engineering, Faculty of Engineering, National University of Trujillo, Trujillo, Peru
5. Faculty of Industrial Process Engineering, National University of Juliaca, Juliaca, Peru

Article Info

Received 15 September 2024

Received in Revised form 14 March 2025

Accepted 29 March 2025

Published online 29 March 2025

DOI: 10.22044/jme.2025.15049.2873

Keywords

Fragmentation

Hybrid models

Machine learning

Particle swarm optimization

Cost of extraction

Abstract

Mining plays a crucial role in the economy of many countries, contributing significantly to GDP, employment, and industrial development. However, optimizing drilling and blasting operations remains a key challenge in open-pit mining due to its direct impact on operational costs and rock fragmentation efficiency. This work aims to optimize fragmentation (X50) and drilling and blasting costs using hybrid machine learning models, an innovative approach that improves predictive accuracy and economic feasibility. Six models were developed: Artificial Neural Networks (ANNs), Decision Trees (DT), Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Support Vector Regression (SVR), optimized using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The dataset, comprising 100 blasts, was split into 70% for training and 30% for testing. The SVR+PSO model achieved the highest accuracy for fragmentation prediction, with an RMSE of 0.27, MAE of 0.21, and R2 of 0.92. The RF+GA model was most effective for cost prediction, with an RMSE of 414.58, MAE of 354.14, and R2 of 0.99. Optimization scenarios were implemented by reducing burden (4.3 m to 3.8 m) and spacing (5.0 m to 4.5 m), achieving a 5.7% reduction in X50 (17.6 cm to 16.6 cm) and a 9.5% cost decrease (63,000 USD to 57,000 USD per blast). Predictions for 30 future blasts using the RF + GA model estimated a total cost of 1.7 MUSD, averaging 55,180 USD per blast. These findings confirm the effectiveness of machine learning in cost optimization and improving blasting efficiency, presenting a robust data-driven approach to optimizing mining operations.

1. Introduction

The mining process begins with blasting, where the distribution of rock plays role in determining the quality and quantity of final products. proper control of blasting to achieve an optimal size distribution can significantly enhance the profitability of a mine or plant [1]. Currently, drilling and blasting are considered the most efficient and cost-effective methods for material removal and ore extraction in open-pit mines. Rock fragmentation is key to assessing the economic viability of a mining project [1–4]. An appropriate blast design is essential for achieving the desired fragmentation results [5, 6]. According to Adamson et al. [7], an accurate evaluation of fragmentation is crucial to optimizing the design variables of explosives and blasts, which can lead to a significant reduction in operational costs. Additionally, previous studies by Marton et al., Monjezi et al., and Shim et al. [8–10] have shown that fragmentation size directly impacts drilling,

Corresponding author: mcotrinat@unitru.edu.pe (M.A. Cotrina-Teatino)

secondary blasting, loading, handling, and milling costs.

According to Hustrulid [11], the unit operations in the mine-to-mill sub-system such as drilling, blasting, loading, and hauling, are directly related to the average fragment size, which requires meticulous optimization. The variables affecting fragment size generated by blasting can be grouped into three categories: (1) controllable variables, such as blast geometry; (2) partially controllable variables such as explosive properties; and (3) uncontrollable variables such as rock mass properties [12, 13]. Parameters influencing rock fragmentation include borehole diameter, charge, spacing, burden, stemming, and delay timing [14]. Various empirical models have been developed to predict fragmentation such s the Kuznetsov model and the Rosin-Rammler formula [15]. Cunningham [16] introduced a new model to predict fragment size, while Hjelmberg's model [17] considers both rock mass type and blast pattern to calculate the average size. The Kuz-Ram model is widely used in the industry to predict the size distribution of fragmentation after blasting [18], although none of these models incorporates all relevant parameters.

In the recent years, various researchers in mining engineering have adopted advanced approaches to predict fragmentation, with one of the most prominent being the use of Artificial Neural Networks (ANNs), which can solve complex problems with high accuracy and minimal error margin. This is due to the ability of ANNs to manage non-linear relationships between input and output variables [19–23]. The average fragment size (X_{50}) refers to the sieve size through which 50% of the fragmented material passes [4]. Recently, the use of Machine Learning (ML) techniques to optimize drilling and blasting design has increased, ranging from heuristic methods to hybrid approaches. Recent studies show that the application of ML can significantly reduce operational costs, as demonstrated by Bakhtavar et al. [24], who reported a 23% reduction in blasting costs. Other studies by Bayat et al. [25] and [26] recorded decreases of 89% and 88%, respectively, in delay costs by optimizing blast patterns using ML, while Rezaeineshat et al. [22] noted a 57% reduction in these costs. These advancements highlight the effectiveness of ML models in improving profitability and operational efficiency.

According to the literature, Sharma et al. [4] predicted rock fragmentation in an open-pit coal mine, where the optimal method was the Random Forest Algorithm (RFA) with an R^2 of 0.94 based on 100 blasting events. Zhao et al. [27] developed a rock fragmentation prediction model using hybrid models optimized with the Bayesian Optimization Algorithm (BOA), utilizing a total of 102 data sets, where the best-performing model was XGBoost-BOA with an R^2 of 0.96. Similarly, Amoako et al. [28] used a hybrid approach combining ANNs and Support Vector Regression (SVR) to predict rock fragmentation, with ANNs achieving the best model with an R^2 of 0.87. In the research by Vergara et al. [29], a predictive model was generated to estimate rock fragmentation size using the Adaptive Neuro-Fuzzy Inference System (ANFIS) in combination with Particle Swarm Optimization (PSO) across 92 blasting events, yielding a model with an R^2 of 0.85. Hasanipanah et al. [30] proposed a new model to forecast rock fragmentation using an ANFIS system combined with PSO, which was compared with Support Vector Machines (SVMs) and Multiple Regression (MR). The model achieved an R^2 of 0.89, based on 72 blasting events. Esmaeili et al. [31] employed two soft computing models, Support Vector Machines (SVM) and ANFIS, and compared them with the Kuz-Ram method across 80 blasts in an iron ore mine in Iran. They found that the ANFIS model had an R^2 of 0.89. Fang et al. [32] proposed a new soft computing model for rock fragmentation modeling with high accuracy, based on an Enhanced Generalized Additive Model (BGAM) and a FireFly Algorithm (FFA), termed FFA-BGAM. Likewise, Shams et al. [33] developed a predictive model to forecast rock fragmentation using a Fuzzy Inference System (FIS) at the Sarcheshmeh copper mine in Iran. Hasanipanah et al. [34] evaluated the risks associated with rock fragmentation and its prediction at the Sarcheshmeh copper mine, proposing the Rock Engineering Systems (RES) technique based on 52 blasting events. Finally, Gebretsadik et al. [35] implemented machine learning and deep learning algorithms to predict fragmentation grades (in percentage) in open-pit mining, using models such as Random Forest Regression, Support Vector Regression, and XGBoost.

Yari et al. [36] predicted rock fragmentation using a novel ensemble technique, specifically the Light Gradient Boosting Machine (LightGBM) and the Jellyfish Search Optimizer (JSO). Sri Chandrahas et al. [37] evaluated XGBoost, K-Nearest Neighbor, and Random Forest algorithms to simultaneously predict rock fragmentation and induced ground vibration. Bahrami et al. [38] implemented an ANNs method to develop a model for predicting rock fragmentation due to blasting in an iron ore mine. Al-Bakri et al. [39] applied ANNs for the prediction and optimization of explosion-induced impacts. Monjezi et al. [14] predicted rock fragmentation at the Sarcheshmeh copper mine by developing a model using ANNs. Ebrahimi et al. [40] in their research, considering the robustness of artificial intelligence methods, applied an ANNs to predict fragmentation and breakage, also using an Artificial Bee Colony (ABC) algorithm to optimize blasting pattern parameters. Li et al. [41] adopted Support Vector Regression (SVR) techniques as basic prediction tools and implemented five optimization algorithms: Grid Search (GS), Gray Wolf Optimization (GWO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Salp Swarm Algorithm (SSA), to enhance prediction performance and optimize hyperparameters. Hekmat et al. [42] predicted rock fragmentation based on a modified Kuz-Ram model. Similarly, Moomivand et al. [43] developed a new empirical fragmentation model using rock mass properties, blast hole parameters, and dust factor. Chandr et al. [44] in their study selected the Customized XGBoost Algorithm (CXGBA) and the improved Genetic XGBoost Algorithm (IGXGBA) to create an empirical formula for simultaneously predicting the average fragmentation size (MFS) and Peak Particle Velocity (PPV) using geo-explosion parameter datasets. Furthermore, Taji et al. [45] considered seven blast outcomes including fragmentation degree, muck pile, overbreak, boulders, floor and toe conditions, environmental considerations, and ignition failures to develop a rational and cost-effective blast operation optimization. Raj et al. [46] used machine learning models, including Decision Tree Regressor, Random Forest Regressor, Support Vector Regressor, and Extreme Gradient Boosting (XGBoost) Regressor, to predict blast results, specifically the average fragmentation size. Finally, Kahraman et al. [47] created a hybrid AI model and voting system to improve the robustness of the blasting prediction model for the blast tip volume, with eight models, including Hybrid 6, which combines LightGBM, Gradient Boosting Machines (GBM), Decision Trees (DT), Extra Trees (ET), Random Forests (RF), CatBoost, CART, AdaBoost, and XGBoost.

Regarding drilling and blasting costs, Gm Mj et al. [48] studied current cost trends associated with drilling and blasting operations in an open-pit mine in Ghana, and developed geometric parameters for drilling and blasting that were cost-effective for the mine. Similarly, Munagala et al. [49] applied machine learning to reduce overall blasting costs by 23% and decrease explosive usage by 89% compared to traditional models. Fattahi et al. [50] presented a blasting cost prediction model using data from six Iranian limestone mines, employing optimization algorithms such as Firefly (FF) and Gray Wolf Optimization (GWO). Bastami et al. [51] predicted blasting costs in limestone mines using a Genetic Expression Programming (GEP) model and ANNs, as well as Linear Multi-variable Regression (LMR) and Non-Linear Multi-variable Regression (NLMR). Additionally, Bakhshandeh et al. [52] applied simulated annealing to optimize blasting costs considering the overpressure constraints in open-pit gypsum mines in Baghak. Guo et al. [53] used blasting fragmentation as a prediction indicator and proposed a hybrid intelligent model based on multiple parameters, employing a Least Squares Support Vector Machine (LSSVM) optimized with a Genetic Algorithm (GA) for prediction. They compared the performance of GA-LSSVM with LSSVM optimized using Time-Rate Optimization (RIME-LSSVM) and Particle Swarm Optimization (PSO-LSSVM), resulting in a reduction of the operational chain cost by 139,400 CNY, generating an annual saving of 1,672,800 CNY. Hryhoriev et al. [54] emphasized a multi-factorial model to predict rock crushing quality, incorporating rock mass features, explosives, and specific costs using linear regression analysis. Fattahi and Ghaedi [55] employed the Rock Engineering Systems (RES) method to construct a complex, nonlinear model for predicting blasting costs, considering uncertainties in geotechnical parameters. Given the inherent uncertainty in the parameters that affect blasting costs, intelligent methods, due to their ability to handle these uncertainties, present a promising alternative to traditional approaches, offering high-accuracy blasting cost estimates with a low margin of error [30, 56–59].

Hosseini et al. [60] indicate that production costs significantly increase, while productivity decreases. They also note that massive rock fragmentation and high-intensity ground vibration are symptoms of inadequate blasting. Gebretsadik et al. [61] improved rock fragmentation evaluation in mining blasts using machine learning models, identifying that factors affecting fragmentation include rock mass characteristics, blast geometry, and explosive properties. They applied Random Forest (RF), Support Vector Regression (SVR), XGBoost, and a deep learning model (Neural Network Regression) to optimize fragmentation prediction. Dotto and Pourrahimian [62] analyzed the effects of rock mass and explosive properties on blast outcomes through numerical simulation using case studied data. Likewise, Gao et al. [63] conducted large-scale blasting experiments to investigate the influence of rock properties and blasting parameters on the post-blast fragment size distribution and fines content. They found that by controlling the crushing zone size and adjusting explosive performance, it is possible to reduce the fines content. Sayadi et al. [64] compared various artificial neural networks for the simultaneous prediction of fragmentation and rock throw, including Backpropagation Neural Networks (BPNN) and Radial Basis Function Neural Networks (RBFNN). The parameters used in the fragmentation (X_{50}) and drilling and blasting cost predictions across different studies are shown in Table 1 and Table 2.

Table 1. Rock fragmentation predicting using machine learning techniques.

Technique	Inputs variables	R^2	Source	Number of blasts used
RFA	E/B, L_d/B, S/L_d, $R_{n(L)}$	0.94	Sharma et al. [4]	100
XGBoost-BOA	E/B, L_d/B, B/d, S/B, q, TB, EM	0.96	Zhao et al. [27]	102
ANNs	E/B, L_d/B, B/d, S/B, q, TB, EM	0.87	Amoako et al. [28]	102
ANFIS-PSO	B, B/E, S_p, q	0.85	Vergara et al. [29]	92
PSO-ANFIS	q, S, E, B, Q	0.89	Hasanipanah et al. [30]	72
ANFIS	q, S, n, d, E/B, BI	0.89	Esmaeli et al. [31]	80
FFA-BGAM	Q, q, E, S, B	0.98	Fang et al. [32]	136
FIS	B, E, d, $R_{n(L)}$, f_i, q, L_s	0.92	Shams et al. [33]	150
RES	B, Q, q, E/B, S/B, L_d/B, Ib, d, B/d	0.86	Hasanipanah et al. [34]	52
RF	n, E, B, BI, q	0.94	Gebretsadik et al. [35]	219
LightGBM	S, E	0.99	Yari et al. [36]	-
XGboost	E/B, Qe, Ib, f_i	0.91	Sri Chandrahas et al. [37]	152
ANNs	d, L_d, B, E, q, BI, B_s, S, Te	0.97	Bahrami et al. [38]	220
ANNs	L_d, B, E, S, q, Qe	0.92	Al-Bakri et al. [39]	230
FIS	B, E, L_d, B_s, S, Q, ρ_r, q	0.96	Monjezi et al. [9]	415
ANNs	B, E, S, B_s, q, L_d, BI, d, Q	0.98	Monjezi et al. [14]	250
ANNs	d, L_d, B/E, S, n, Q, ρ_r, q	0.99	Monjezi et al. [65]	-
ANNs	B, E, S, L_d, q	0.78	Ebrahimi et al. [40]	152
SVR	d, L_d, F_i, E, B, L_d/B, B/d, E/B, UCS, q	0.84	Li et al. [41]	176
Kuz-ram	Te, Vo, B, E, B_h	0.80	Hekmat et al. [42]	20
Q, q S_{ANFO}	d, Q, q, S_{ANFO}, BI	0.87	Moomivand et al. [43]	42
IGXGBA	J_n, A_J, A_{hj}, UCS, l_d, Qe	0.97	Chandr et al. [44]	152

Table 2. Prediction of total operational costs for drilling and blasting using machine learning techniques.

Technique	Inputs variables	R^2	Source	Number of blasts used
Traditional	$B, S, d, A_b, S_{drill}, l_s, C_P$	-	Gm Mj et al. [48]	NA
Machine learning	Controlables e incontrolables	-	Munagala et al. [49]	
BC Prediction model with firefly (FF) and gray wolf (GWO) optimization	d, S_{ANFO}, $S_{drill}, UCS, q, n, S, G_e, l_s, l_d, G_e, E_d$	0.96	Fattahi et al. [50]	146
GEP (Genetic Expression Programming)	S_{ANFO}, $n, l_d, d, B, S, l_s, S_{drill}, R_h, UCS, X50$	0.93	Bastami et al. [51]	146
ANNs		0.95		
SA (Simulated Annealing)	d, S, Q, l_s	-	Bakhshandeh et al. [52]	70

where, B is the burden (unit: m), E is the spacing (unit: m), d is the drill diameter (unit: m), S is the stemming length (unit: m), l_d is the drill length (unit: m), q is the specific charge (unit: kg/m^3), b_s is the specific drilling (unit: m/m^3), Q is the maximum charge (unit: kg/m^3), ρ_r is the rock density (unit: kg/m^3), B/S is the burden/spacing ratio, n is the number of drill holes, BI is the volatility index, f_i is the joint density (unit: m^{-1}), $R_{n(L)}$ is the number of rebounds of the Schmidt hammer, $ANFIS$ stands for Adaptive Neuro-Fuzzy Inference System, RFA stands for random forest algorithm, E/B is the spacing/burden ratio, l_d/B is the drill length/burden ratio, S/l_d is the stemming length/drill length ratio, BOA stands for Bayesian Optimization Algorithm, B/d is the burden/drill diameter ratio, S/B is the stemming length/burden ratio, TB is the in-situ block size, EM is the elastic modulus, S_p is the overdrilling, PSO stands for Particle Swarm Optimization, FFA stands for Firefly Algorithm, $BGAM$ stands for boosted generalized additive Model, FIS stands for Fuzzy Inference System, RES tands for Rock Engineering System, Ib is the drill inclination, $LightGBM$ stands for Light Gradient Boosting Machine, Qe is the total explosive (unit: kg), UCS is the uniaxial compressive strength, V_o is the volume removed (unit: m^3), B_h is the bench width (unit:m), S_{ANFO} is the relative weight strength of ANFO, J_n is the number of joints, A_J is the joint angle, A_{hj} is the horizontal joint width, A_b is the bench height, S_{drill} subdrilling, C_P is the drilling cost, G_e is the specific gravity, E_d is electric detonators, R_h is rock hardness, and X_{50} is the fragmentation size.

Table 1 and Table 2 show that most computational techniques used to predict the average fragment size of rocks (X_{50}) primarily focus on blast design variables, overlooking the significant impact that rock mass properties have on X_{50}. A comprehensive review of the literature reveals that studies employing hybrid machine learning models to predict fragmentation in open-pit mines are limited. Additionally, previous works have considered a small number of influential parameters, resulting in less robust prediction models. Therefore, this study incorporates hybrid models that have not been previously implemented, along with their optimizers GA and PSO. It also includes a wide range of drilling, blasting, cost, and geomechanical parameters to predict and optimize both fragmentation and drilling and blasting costs. This research is important because it addresses a critical gap in current literature. By incorporating hybrid models and optimizers like GA and PSO, along with a wide range of parameters, this study aims to significantly improve the ability to predict and optimize both fragmentation and drilling and blasting costs. This is crucial for improving mining efficiency, reducing costs, and enhancing the overall profitability of mining operations. The innovative use of these techniques, combined with geomechanical data, allows for more robust, reliable, and accurate predictions, benefiting both the mining industry and the academic field of mining engineering.

What is novel in this study is the combination of advanced machine learning techniques and the inclusion of a broader range of operational parameters, which allows for a more comprehensive and accurate prediction of fragmentation and operational costs. The use of these innovative methods, particularly hybrid models optimized with GA and PSO, represents a significant step forward in optimizing the mining process, especially in open-pit operations where fragmentation and cost efficiency are key factors for profitability. In this study, data from 100 blasts conducted in northern Peru, 10 km from the city of Huamachuco, were collected for this study. The region is primarily characterized by two types of alteration: Massive Silica (SM) and Granular Silica (SG). These alterations significantly influence the blasting outcomes and are crucial for understanding the dynamics of rock fragmentation and the associated operational costs. These collected data are integral to predicting both the average fragment size (X_{50}) and the costs related to drilling and blasting operations. The primary objective of this research is to optimize the average rock fragmentation (X_{50}) and drilling and blasting costs using hybrid machine learning models. These models include Artificial Neural Networks with Genetic Algorithms (ANNs + GA), Decision Trees with Genetic Algorithms (DT + GA), Random Forests with Genetic Algorithms (RF + GA), Extreme Gradient Boosting with Genetic Algorithms (XGBoost+GA), Artificial Neural Networks optimized with Particle Swarm Optimization (ANNs+PSO), and Support Vector Machines optimized with Particle Swarm Optimization (SVR+PSO). Additionally, future predictions of total drilling and blasting costs for 30 blasts are generated using the best predictive model. The paper is structured as follows: Section 2 presents the materials and methods, Section 3 discusses the results, and Section 4 concludes the research.

2. Materials and Methods

2.1. Studied area

The study area is in an open pit mine in northern Peru, approximately 10 km from the city of Huamachuco. This region is characterized by diverse geology and significant mineral alterations that influence blasting operations. Specifically, two predominant alteration types are highlighted: Massive Silica (SM) and Granular Silica (SG), which exhibit variable geomechanical properties that significantly affect rock fragmentation during blasting.

The Massive Silica (SM) alteration is associated with a Uniaxial Compressive Strength (UCS) of 0.2 MPa and is characterized by a granular and vuggy structure, which can lead to unpredictable fragmentation patterns due to its variability. In contrast, the Granular Silica (SG) alteration, with a UCS of a 0.1 MPa, has a granular texture primarily composed of gray silica and iron oxides. This alteration results in different fragmentation behavior and energy absorption compared to SM.

Geomechanical parameters, such as uniaxial compressive strength (UCS), rock density and the structural characteristics of the alterations, play a crucial role in optimizing blast designs and fragmentation efficiency. These factors must be carefully considered when designing blasts to ensure adequate fragmentation and reduce the associated drilling and blasting costs. Figure 1 presents a map of the study area, showing the geographical location of mine.

2.2. Database analysis

Table 3 provides specific details on the blasting practices implemented in the mine, which were carefully optimized to address the geological conditions of these alterations.

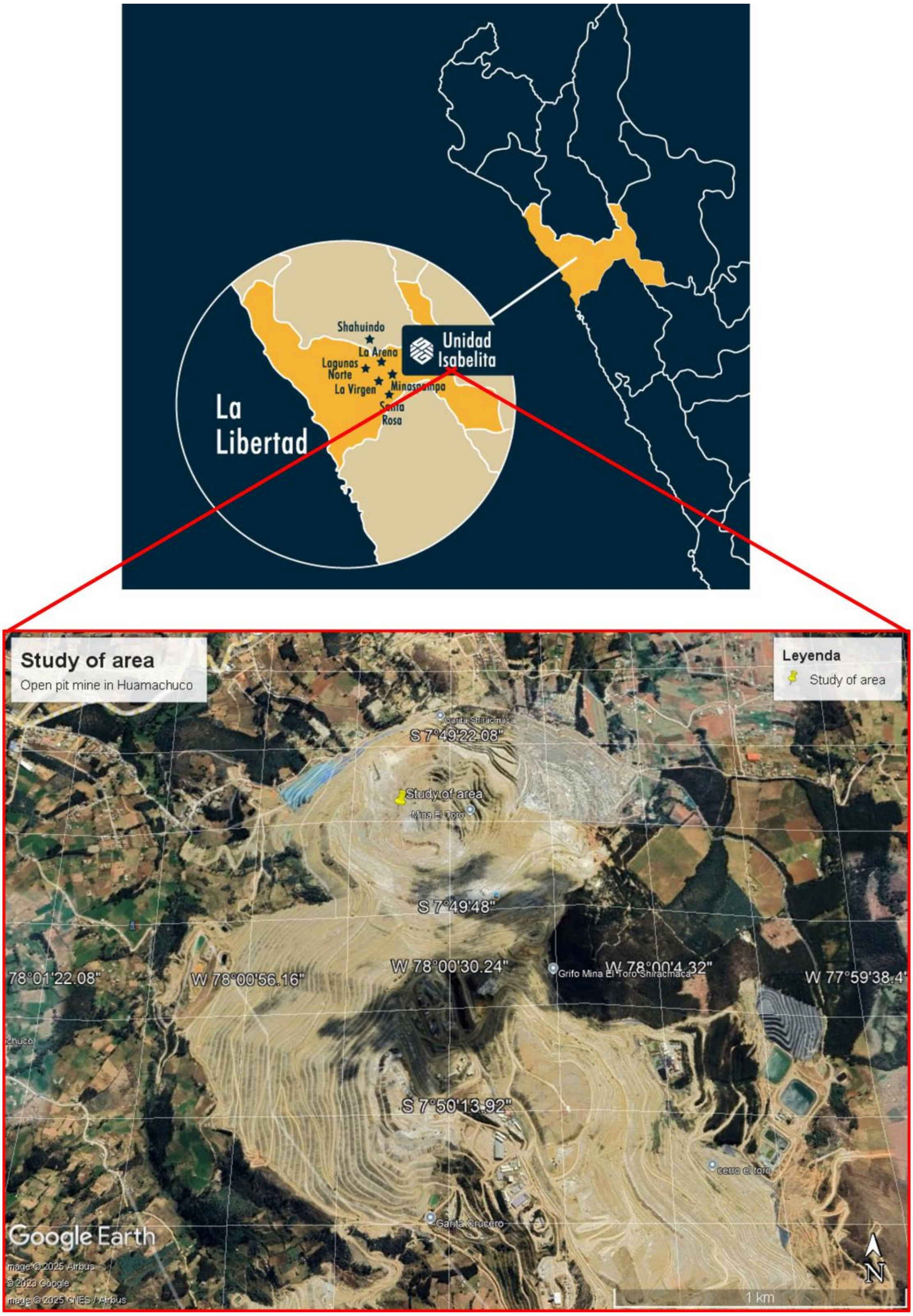

Figure 1. Map of the studied area.

Table 3. Operational details of blasting in the open-pit mine.

Variable	Value
Burden (m)	3.60-4.30
Spacing (m)	4.50-5.00
Bench height (m)	7.10-7.90
Drill diameter (cm)	17.00
Powder factor (kg/m^3)	0.44-0.60
Total explosive per drill hole (kg)	167.72-190.22
Blasted material (t)	27609.66-44930.27
Stemming (m)	1.50-2.90
Average drill length (m)	8.10-8.90

This study utilizes a dataset consisting of 100 blasting records, each containing two sets of input parameters: one for predicting rock fragmentation and the other for predicting drilling and blasting costs. To predict the fragmentation (X_{50}), a total of 13 input parameters were considered. These variables include uniaxial compressive strength (UCS), rock density influence (RDI), joint spacing (E_j), hardness factor (H_f), burden (B), spacing (E), amount of explosives (QE), Powder Factor (FP), and several ratios such as spacing to burden ratio (E/B), drill length to burden ratio (LH/B), burden to drill diameter ratio (B/D), bench height to burden ratio (AB/B), and stemming-to-burden ratio (S/B). These parameters were selected due to their known influence on the fragmentation process and the expected variations they cause in blast outcomes. For predicting drilling and blasting costs ($Cost_{TotalP\&V}$), a separate set of 8 input parameters was used. These include: number of drill holes (TP), total explosives quantity (QTE), and various cost factors such as ANFO cost per blast ($Cost_{ANFO}$), detonator cost per blast ($Cost_{Detonador}$), exanel cost per blast ($Cost_{Exanel}$), booster cost per blast ($Cost_{Booster}$), explosive cost per blast $\left(Cost_{blasting}\right)$, and drilling cost per blast $\left(\mathrm{Cost}_{\mathrm{drilling}}\right)$. These variables were chosen as they directly contribute to the operational costs involved in the drilling and blasting operations (see Table 4).

Table 4. Statistical summary of data collected from the open-pit mine.

Category	Parameter	Variables	Symbol	Min	Max	Mean
Input	Rock mass	Uniaxial Compressive Strength	UCS	0.10	0.20	0.15
		Joint Spacing	E_j	7.25	10.25	8.75
		Hardness Factor	H_f	90.00	135.00	112.50
		Density Influence	RDI	13.80	29.00	21.24
	Drilling	Burden	B	3.60	4.30	3.95
		Spacing	E	4.50	5.00	4.75
		Number of Drill Holes	TP	90.00	118.00	106.39
	Blasting	Explosives Quantity	QE	167.72	190.22	176.99
		Powder Factor	FP	0.44	0.60	0.51
		Total Explosives	QTE	15530.34	21945.04	18821.64
		Spacing to Burden Ratio	E/B	1.16	1.25	1.21
		Drill Length to Burden Ratio	LH/B	1.88	2.47	2.20
		Burden to Drill Diameter Ratio	B/D	21.18	25.29	23.24
		Bench Height to Burden Ratio	AB/B	1.65	2.19	1.95
		Stemming to Burden Ratio	S/B	0.35	0.81	0.49
	Operational costs	ANFO Cost per Blast	$Cost_{ANFO}$	10715.94	15142.08	12986.93
		Detonator Cost per Blast	$Cost_{Detonator}$	1159.65	1520.42	1370.83
		Exanel Cost per Blast	$Cost_{Exanel}$	102.15	133.93	120.75
		Booster Cost per Blast	$Cost_{Booster}$	428.40	561.68	506.42
		Total Blasting Explosive Cost	$Cost_{blasting}$	12520.93	17488.50	15120.63
		Drilling Cost per Blast	$Cost_{drilling}$	33947.52	46061.60	40255.98
Output		Average Fragment Size	X_{50}	15.26	18.34	16.8
		Total Drilling and Blasting Cost	$Cost_{TotalP\&V}$	46468.45	63483.46	55376.61

The correlation matrix shows the relationships between the parameters used in the predictions, grouped into four categories: geomechanical (A), drilling (B), blasting (C), and drilling and blasting costs (D). In the geomechanical group, X_{50} has strong correlations with UCS, RDI, and HF, indicating their significant influence on fragmentation. In the drilling parameters, spacing and drill length show moderate correlations with X_{50}. For the blasting parameters, the amount of explosives and drill-hole geometry strongly correlate with both fragmentation and drilling and blasting costs. Lastly, drilling and blasting cost parameters are highly interrelated, reflecting their direct impact on drilling and blasting costs (see Figure 1).

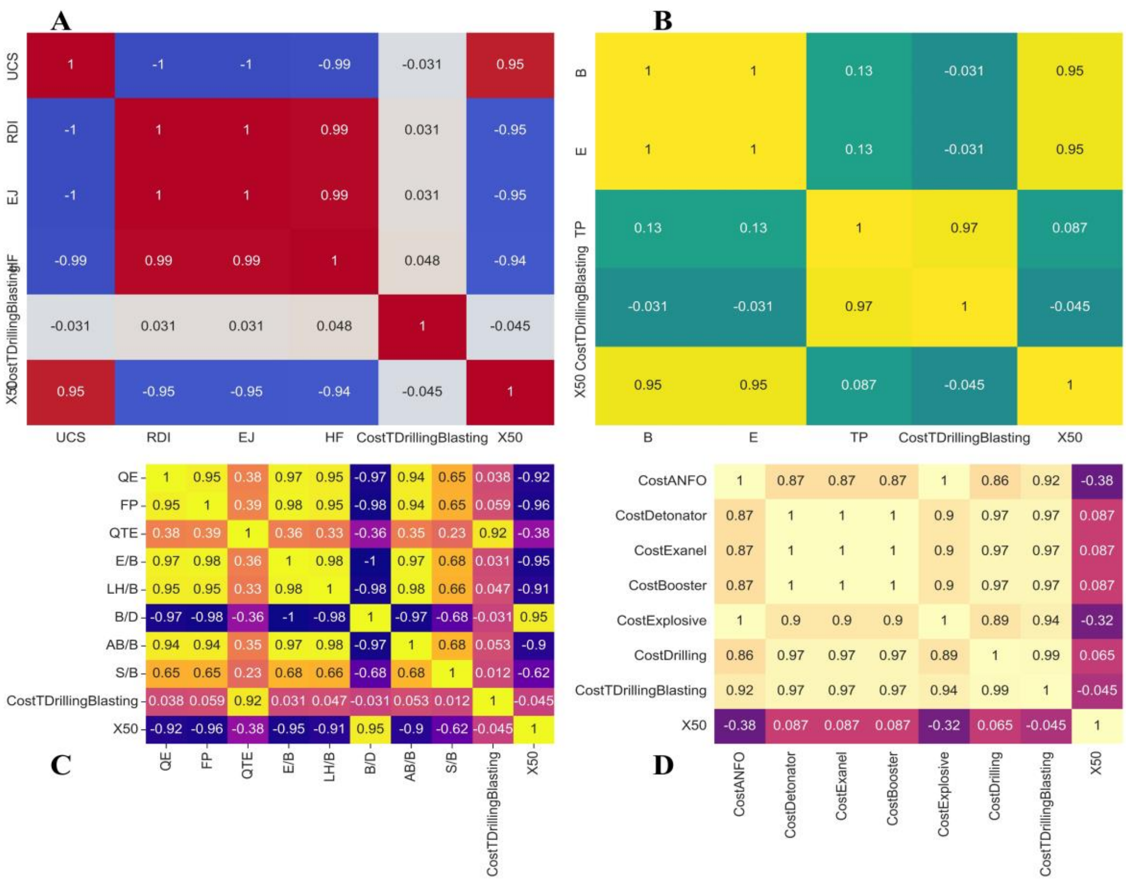

Figure 2. Correlation matrix of parameters used in the predictions: A: Geomechanical and/or rock mass parameters. B: Drilling parameters. C: Blasting parameters. D: Drilling and blasting costs.

2.3. Pre-processing and hyperparameter tuning

Six distinct models were developed to predict rock fragmentation and the total operational costs of drilling and blasting. These models included artificial neural networks, random forests, decision trees, and extreme gradient boosting, adjusted through genetic algorithms. Additionally, neural networks and support vector machines for regression were optimized using particle swarm optimization. The acquired data were randomly divided into training and set sets. The dataset underwent various preprocessing stages, such as normalization and scaling within a range of 0 to 1, followed by data partitioning. Subsequently, 70% of the normalized data was used for model training, while the remaining 30% was used for testing. The predictive performance of the models was evaluated using metrics such as the coefficient of determination (R^2), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) [4, 66, 67] . The formulas used for these evaluations are as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(A_i - P_i)^2}{\sum_{i=1}^{N}(A_i - -A)^2} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - A_i)^2}{N}} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(P_i - A_i) \tag{3}$$

where P_i and A_i are the predicted and actual values of X_{50}, respectively.

2.3.1. Artificial neural network with genetic algorithm (ANNs + GA)

Artificial neural networks are computational models inspired by the human brain, designed to recognize patterns and make predictions [68]. They consist of layers of interconnected nodes that transform input data, and their basic function is mathematically represented as $y = f(WX + b)$, where W represents the weights, X the input, b the bias, and f the activation function. ANNs are trained using algorithms such as gradient descent, and their key hyperparameters include the number of layers, neurons, and the learning rate [69, 70]. Genetic Algorithms (GA), inspired by natural evolution, optimize these hyperparameters by exploring large search spaces. AGA adjusts parameters such as the number of layers and neurons, and its process includes selection, crossover, and mutation of solutions, represented as $child = \alpha * parent_1 + (1 - \alpha) * parent_2$. The combination of ANNs + GA enhances the network's predictive ability by optimizing tasks such as fragmentation and cost prediction in mining [71]. Table 5 specifies the final hyperparameter values selected by the Genetic Algorithm for the prediction of fragmentation (X_{50}) and drilling and blasting costs. For fragmentation, the final learning rate was 0.04, with a batch size of 11 and 56 epochs. For costs, the learning rate was 1.80, with a batch size of 76, and the number of epochs was 76.

Table 5. Hyperparameters used in ANNs + AG.

Hyperparameter	Value (X_{50})	Hyperparameter	Value (Cost)
Learning rate	0.04	Learning rate	1.80
Batch size	15	Batch size	76
Number of epochs	56	Number of epochs	76
Neurons per layer	64 y 32	Neurons per layer	10 y 5
Activation function	ReLU	Activation function	ReLU
Loss function	MSE	Loss function	MSE
Optimization algorithm	Adam	Optimization algorithm	Adam
Selection algorithm	3	Selection algorithm	3
Crossover algorithm	0.5	Crossover algorithm	0.5
Mutation algorithm	0.2	Mutation algorithm	0.2

2.3.2. Random forest with genetic algorithm (RF + GA)

The Random Forest (RF) algorithm is an ensemble learning method that builds multiple decision trees and uses majority voting for classification or averaging for regression. Its formula for a prediction is $\hat{y} = \sum_{t=1}^{T} f_t(x)$, where T is the number of trees and $f_t(x)$ is the prediction of tree t. The key hyperparameters include the number of trees ($n_{estimators}$), the maximum depth (max_depth), and the minimum number of samples to split a node ($min\_samples\_split$) [72–74]. The Genetic Algorithm (GA) is used to optimize these hyperparameters by searching for the best configuration through iterations of selection, crossover, and mutation. This hybrid RF-GA approach improves model performance, particularly useful for predicting fragmentation and costs in mining by efficiently handling the complexity of geological data [75]. The final optimized values for fragmentation prediction include 71.36 estimators, a maximum depth of 15.00, and 20.52 minimum samples for splitting. For cost prediction, the final values include 90.00 estimators, the same maximum depth of 15, and 3 minimum samples for splitting. For both fragmentation and cost prediction, the same selection (value 3), crossover (value 0.5), and mutation (value 0.2) algorithms were used, ensuring consistency in the optimization approach employed (see Table 6).

Table 6. Hyperparameters used in RF+AG.

Hyperparameter	Value (X_{50})	Hyperparameter	Value (Costs)
Number of estimators	71.36	Number of estimators	90.0
Maximum depth	15.0	Maximum **d**epth	15
Minimum samples for split	20.52	Minimum samples for split	3
Selection algorithm	3	Selection algorithm	3
Crossover algorithm	0.5	Crossover algorithm	0.5
Mutation algorithm	0.2	Mutation algorithm	0.2

2.3.3. Decision tree with Genetic Algorithm (DT + GA)

The Decision Tree (DT) is a predictive model that uses rules derived from data to make predictions, where each node represents a feature, each branch a decision rule, and each leaf an outcome. The key hyperparameters include the maximum depth (max_depth), the minimum number of samples to split a node ($min_{samples_{split}}$) and the criterion for splitting quality (entropy or Gini index). Mathematically, entropy is defined as $H(X) = -\sum_{i=1}^{n} p_i \log{(p_i)}$, where p_i is the probability of class i. The hybrid DT-GA model optimizes these hyperparameters by selecting, crossing, and mutating configurations to maximize the tree's accuracy in tasks such as predicting fragmentation and costs in mining, enhancing its robustness against geological data variability [76, 77]. For fragmentation prediction, a maximum depth of 0.52 and a minimum of 13.26 samples for splitting were selected, while for cost prediction, a learning rate of 7.09 and a batch size of 15.74 were established (see Table 7).

2.3.4. XGBoost with Genetic Algorithm (XGBoost + GA)

XGBoost is a machine learning algorithm based on decision trees that uses boosting to improve accuracy in classification and regression tasks. Its key hyperparameters include the learning rate ($learning_{rate}$), the number of trees ($n_{estimators}$), the maximum depth (max_$depth$) and regularization terms ($\lambda\ and\ \alpha$) to prevent overfitting. Mathematically, the prediction is represented as $\hat{y}_i = \sum_{k=1}^{K} w_k h_k(x_i)$, where w_k re the weights and h_k are the individual trees [37, 78]. The Genetic Algorithm (GA) is used to optimize the XGBoost hyperparameters, adjusting configurations to maximize accuracy and minimize error in tasks such as fragmentation and cost prediction. This hybrid approach combines the efficiency of XGBoost with the exploration capabilities of GA, resulting in a robust and efficient model [37]. For fragmentation prediction, a maximum depth of 4.38 and a minimum of 12.70 samples per split were selected, while for cost prediction, a final learning rate of 0.08 and a batch size of 9.29 were established. The optimized hyperparameters include a learning rate of 0.05 for fragmentation and 0.08 for costs, with 385.07 estimators for fragmentation and 165.43 for costs. Additionally, the Gamma values were adjusted to 0.04 for fragmentation and 2.24 for costs, and the minimum child weight was set to 12.70 for fragmentation and 4.40 for costs (see Table 8).

Table 7. Hyperparameters used in DT + AG.

Hyperparameter	Value (X_{50})		Value (Costs)
Maximum depth	0.52	Maximum depth	7.09
Minimum simples for division	13.26	Minimum simples for division	15.74
Selection algorithm	3	Selection algorithm	3
Crossover algorithm	0.5	Crossover algorithm	0.5
Mutation algorithm	0.2	Mutation algorithm	0.2

Table 8. Hyperparameters used in XGBoost+AG

Hyperparameter	Value (X_{50})	Hyperparameter	Value (Costs)
Maximum depth	4.38	Maximum depth	9.29
Learning rate	0.05	Learning rate	0.08
Number of estimators	385.07	Number of estimators	165.43
Gamma	0.04	Gamma	2.24
Minimum child weight	12.70	Minimum child weight	4.40
Selection algorithm	3	Selection algorithm	3
Crossover algorithm	0.5	Crossover algorithm	0.5
Mutation algorithm	0.2	Mutation algorithm	0.2

2.3.5. Support vector regression with particle swarm optimization (SVR + PSO)

Support Vector Regression (SVR) is a machine learning technique that extends Support Vector Machines (SVM) to regression problems, aiming to predict values with the greatest simplicity possible within a tolerable margin of error defined by the ∈ parameter. The key hyperparameters include the regularization parameter C, which controls the penalty for errors, and ∈ which defines the width of the tolerance margin. Mathematically, SVR optimizes the following function:

$$min\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \max\left(0, |y_i - f(x_i)| - \epsilon\right) \quad (4)$$

where w re the model weights, C is the regularization term, y_i are the actual values, and, y $f(x_i)$ are the model predictions. Particle Swarm Optimization (PSO) is used to adjust the hyperparameters C, ∈ and the kernel parameter γ in an RBF kernel. PSO guides the hyperparameter configuration towards the best possible solution, optimizing SVR accuracy in complex and nonlinear tasks such as fragmentation and cost prediction in mining [79]. This SVR-PSO approach is ideal for scenarios with noisy data and nonlinear relationships between variables, maximizing accuracy through continuous parameter optimization [80, 81]. For fragmentation prediction, the final optimized values were C = 1000.00, epsilon of 0.01, and gamma of 0.0001, while for cost prediction, the optimized values were C = 1000.0, epsilon of 0.34, and gamma of 0.20, with lower and upper bounds of [0.1, 0.001, 0.0001] and [1000, 1, 1], respectively (see Table 9).

Table 9. Hyperparameters used in SVR+PSO.

Hyperparameter	Value (X_{50})	Hyperparameter	Value (Costs)
C (Regularization)	1000.00	C (Regularization)	1000.00
Epsilon	0.01	Epsilon	0.34
Gamma	0.0001	Gamma	0.20
Lower limit	[0.1, 0.001, 0.0001]	Lower limit	[0.1, 0.001, 0.0001]
Upper limit	[1000, 1, 1]	Upper limit	[1000, 1, 1]
Swarm size	10	Swarm size	10
Maximum of iterations	10	Maximum of iterations	10

2.3.6. Artificial neural network with particle swarm optimization (ANNs + PSO)

The hybrid ANNs-PSO model combines ANNs with Particle Swarm Optimization (PSO) to enhance prediction accuracy by tuning hyperparameters such as the number of neurons, layers, and learning rate. In this approach, PSO optimizes these parameters, allowing the ANNs to dynamically adjust to minimize errors in tasks like rock fragmentation prediction in mining. This model is robust and precise, capable of adapting to variability in geological and operational data. A simple analogy is to imagine explorers (PSO) searching for treasure (the optimal configuration), adjusting their direction based on clues (hyperparameters) to get closer to the goal (maximum prediction accuracy) [82–84]. For fragmentation prediction, a learning rate of 0.03, a batch size of 10, and 90 epochs with 64 and 32 neurons in the hidden layers were used. For cost prediction, the learning rate was 0.1, the batch size was 10, and 100 epochs were used with 10 and 5 neurons in the hidden layers. The lower and upper bounds for PSO parameters were set at [0.001, 10, 10] and [0.1, 100, 100], respectively, with a swarm size of 10 and a maximum of 10 iterations for both cases (see Table 10).

Table 10. Hyperparameters used in ANNs + PSO.

Hyperparameter	Value (X_{50})	Hyperparameter	Value (Costs)
Learning rate	0.03	Learning rate	0.1
Batch size	10	Batch size	10
Number of epochs	90	Number of epochs	100
Neurons per layer	64 y 32	Neurons per layer	10 y 5
Lower limit	[0.001, 10, 10]	Lower limit	[0.01, 10, 10]
Upper limit	[0.1, 100, 100]	Upper limit	[0.1, 100, 100]
Swarm size	10	Swarm size	10
Maximum of iterations	10	Maximum of iterations	10

2.4. Simulation and optimization scenarios

To improve the predictive accuracy of the models and evaluate their practical applicability in real mining operations, a series of simulation and optimization scenarios were developed. These scenarios aimed to analyze how different drilling and blasting configurations influence rock fragmentation (X_{50}) and total operational costs [85–87]. The methodology for these simulations follows a structured approach:

Pessimistic scenario: Represents suboptimal blasting conditions, where excessive burden and spacing result in coarser fragmentation and higher operational costs due to inefficient energy distribution. Realistic scenario: Simulates current operational conditions in the mine, ensuring that predicted fragmentation and costs remain within historically recorded ranges. Optimistic scenario: Implements optimized blast design parameters, such as reduced burden and spacing, to achieve finer fragmentation and lower drilling and blasting costs while maintaining operational efficiency.

Once the most influential parameters were identified, an iterative optimization process was conducted to enhance both fragmentation quality and cost efficiency. The optimal scenario was determined by minimizing costs while ensuring the desired fragmentation size, achieving a balance between operational effectiveness and economic feasibility.

Subsequently, the best-performing model was used to forecast future drilling and blasting costs over 30 upcoming blasts, providing valuable insights for strategic mine planning and cost optimization.

3. Results and Discussion

Six hybrid models were used to predict fragmentation and optimize drilling and blasting costs in an open-pit mine, with an 80% confidence limit

3.1. Artificial neural network with genetic algorithm (ANNs + GA)

Figure 3 shows the training and validation loss in the prediction of fragmentation and total operational costs for drilling and blasting. For fragmentation, the training loss drops sharply from around 140 to nearly 0 in less than 15 epochs, stabilizing at values close to 0. The validation loss shows a similar pattern, starting at around 42 and also stabilizing near 0. This indicates that the model has effectively learned without overfitting. In terms of total operational costs for drilling and blasting, the training loss quickly decreases from an initial value higher than $3x10^9$, stabilizing near 0 after 30 epochs, indicating effective model fitting. The validation loss follows a similar pattern, confirming that the model does not overfit and is able to generalize well for cost prediction. Figure 4 shows the predicted fragmentation points, which closely align with the actual values, with a coefficient of determination (R^2) of 0.81 for the training set and 0.74 for the test set, indicating high accuracy in explaining between 74% and 81% of the variability in the fragmentation data. Additionally, the data points align closely to the equality line, with an R^2 of 0.99 for the training set and 0.98 for the test set in predicting the total operational cost of drilling and blasting.

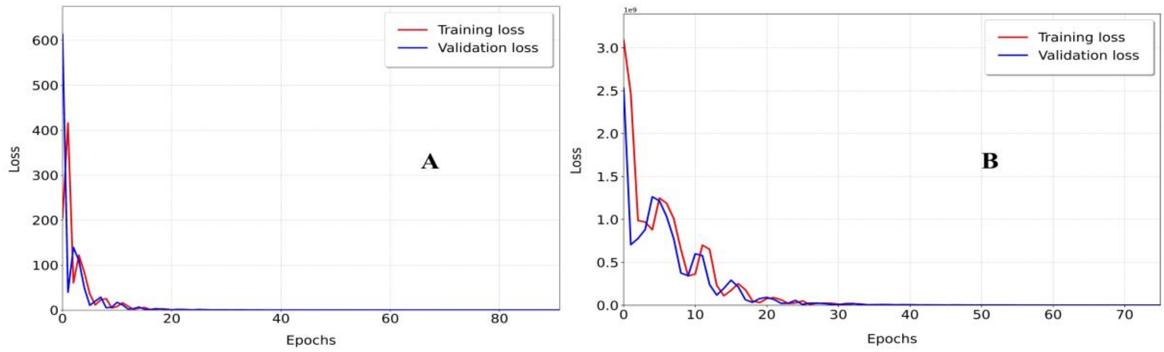

Figure 3. Training and validation loss graphs. A: Training and validation loss in fragmentation prediction. B: Training and validation loss in total operational cost prediction for drilling and blasting.

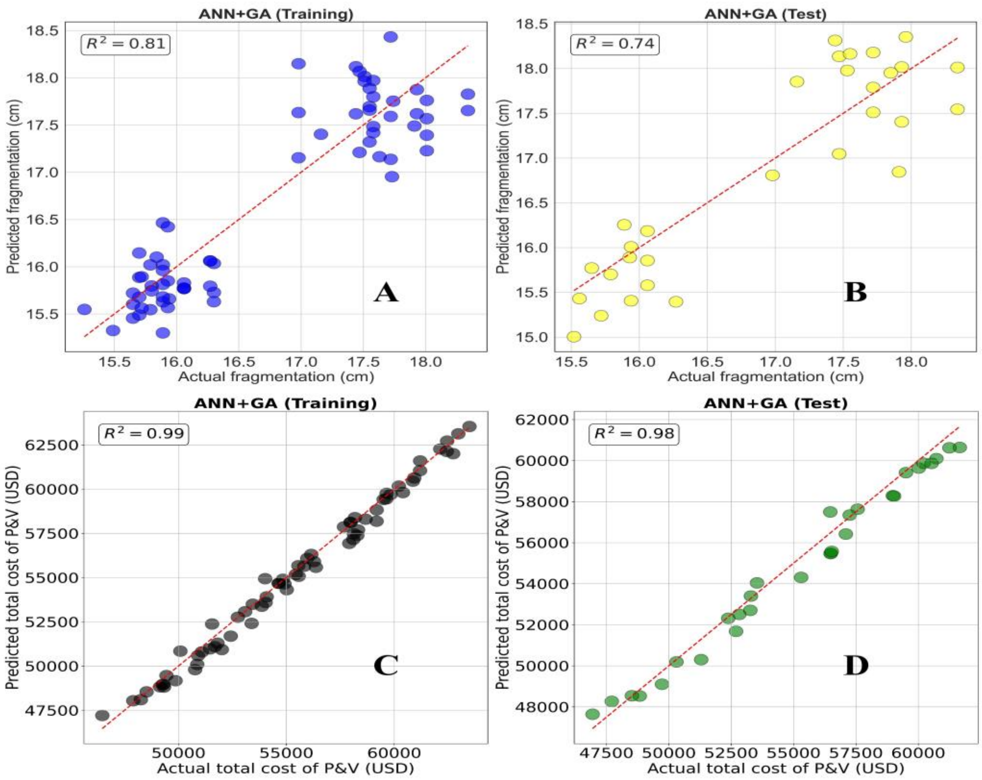

Figure 4. Comparison of actual vs. predicted values using ANNs + GA. A: Fragmentation training set. B: Fragmentation test set. C: Training set for total operational costs of drilling and blasting. D: Test set for total operational costs of drilling and blasting.

3.2. Decision tree with genetic algorithm (DT + GA)

Figure 5 shows a high correlation between actual and predicted fragmentation, with an R^2 of 0.91 for the training set and 0.90 for the test set in fragmentation prediction. Additionally, there is a close alignment between actual and predicted costs, with an R^2 of 0.99 for the training set and 0.95 for the test set in predicting total costs for drilling and blasting.

3.3. Random Forest with Genetic Algorithm (RF + GA)

In Figure 6 there is a high degree of alignment between actual and predicted fragmentation, with an R^2 of 0.94 for the training set and 0.91 for the test set. The data points near the equality line indicate that the RF+GA model predicts fragmentation with high accuracy, explaining between 91% and 94% of the variability in both sets. Additionally, the data points align almost perfectly with the equality line in cost prediction, with an R^2 of 1.00 for the training set and 0.99 for the test set.

The most important variable for predicting fragmentation is E, with an importance score of 0.202, followed by the B/D with 0.153, and Hf with 0.105, indicating their significant influence on the fragmentation process. In terms of costs, the most relevant variable is drilling cost with an importance of 0.779, followed by explosive cost with 0.07, suggesting that these are the main factors influencing total drilling and blasting costs (see Figure 7).

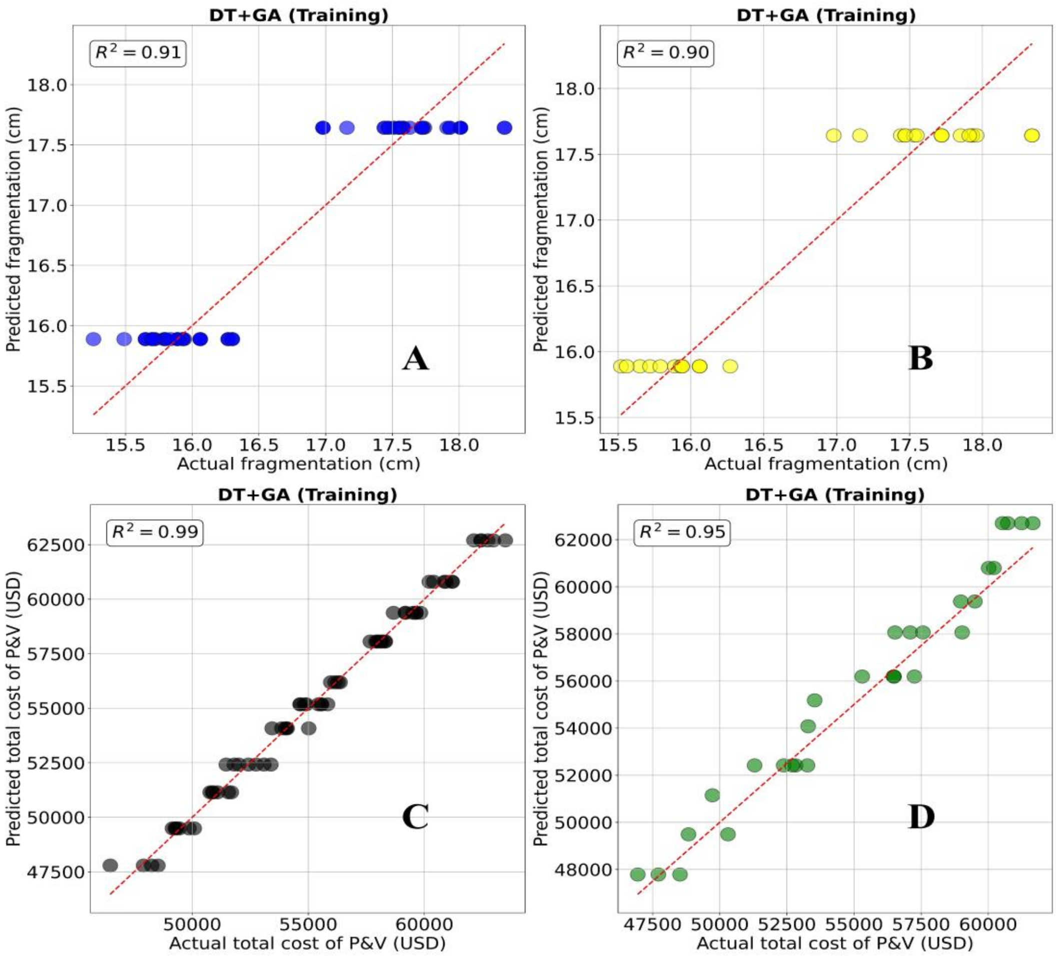

Figure 5. Comparison of actual vs. predicted values using DT+GA. A: Fragmentation training set. B: Fragmentation test set. C: Training set for total operational costs of drilling and blasting. D: Test set for total operational costs of drilling and blasting.

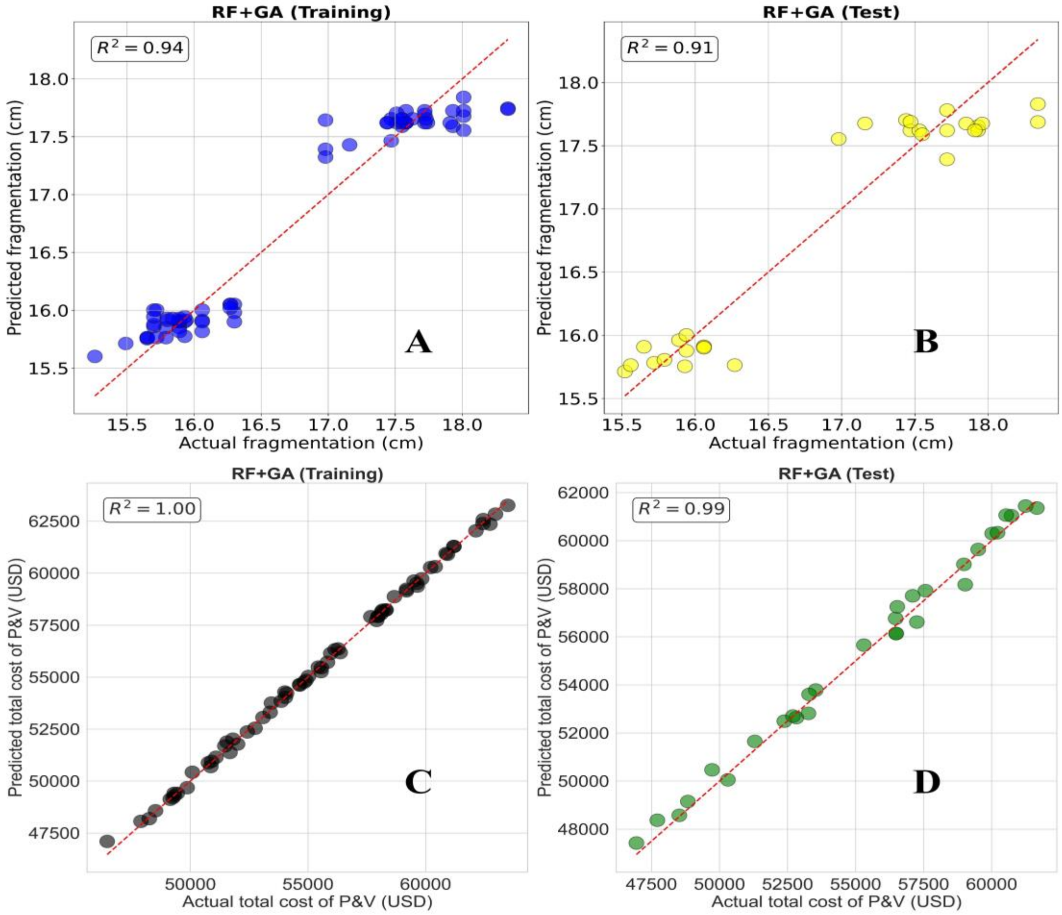

Figure 6. Comparison of actual vs. predicted values using RF + GA. A: Fragmentation training set. B: Fragmentation test set. C: Training set for total operational costs of drilling and blasting. D: Test set for total operational costs of drilling and blasting.

3.4. XGBoost with genetic algorithm (XGBoost + GA)

The predicted fragmentation values closely match the actual values, achieving an R^2 of 0.96 for the training set and 0.91 for the test set, demonstrating the high accuracy of the XGBoost+GA model. Likewise, the predicted drilling and blasting costs show an almost perfect alignment with the actual values, with an R^2 of 1.00 for the training set and 0.99 for the test set, confirming the model's reliability in accurately estimating total drilling and blasting costs (see Figure 8).

3.5. Artificial neural network with particle swarm optimization (ANNs + PSO)

The loss decreases significantly for both the training and validation sets during the first 10 epochs, before stabilizing at very low values, indicating good convergence without overfitting. In terms of costs, both curves begin at high values (greater than 3×10^9) and stabilize near zero by epoch 30 (see Figure 9).

The predicted fragmentation values closely match the actual values, achieving an R^2 of 0.82 for both the training and test sets, demonstrating the good predictive capability of the ANNs+PSO model. Similarly, the predicted drilling and blasting costs align closely with the actual values, with an R^2 of 0.97 for the training set and 0.96 for the test set, confirming the model's reliability in cost estimation (see Figure 10).

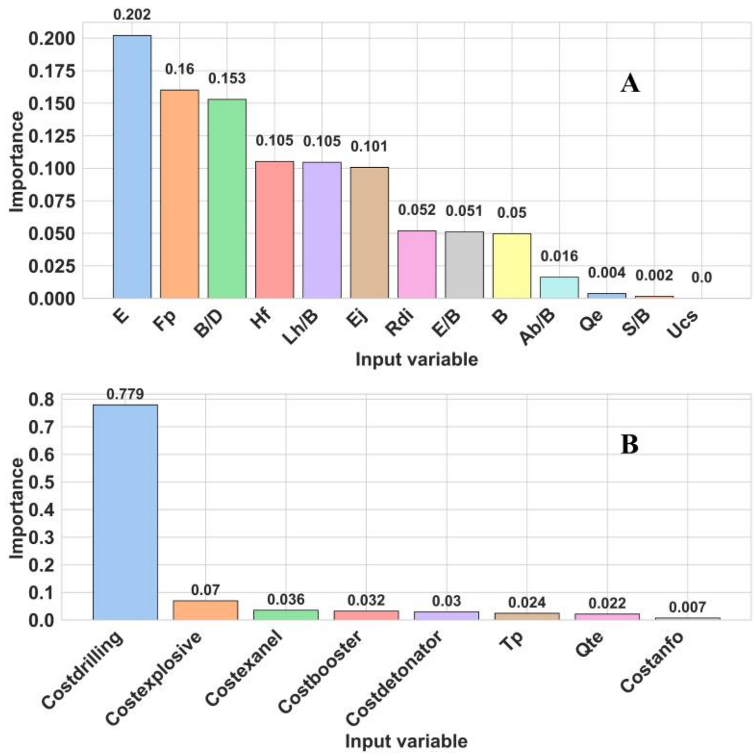

Figure 7. Importance of input variables in predictions. A: Importance in fragmentation predictions. B: Importance in total operational cost predictions for drilling and blasting.

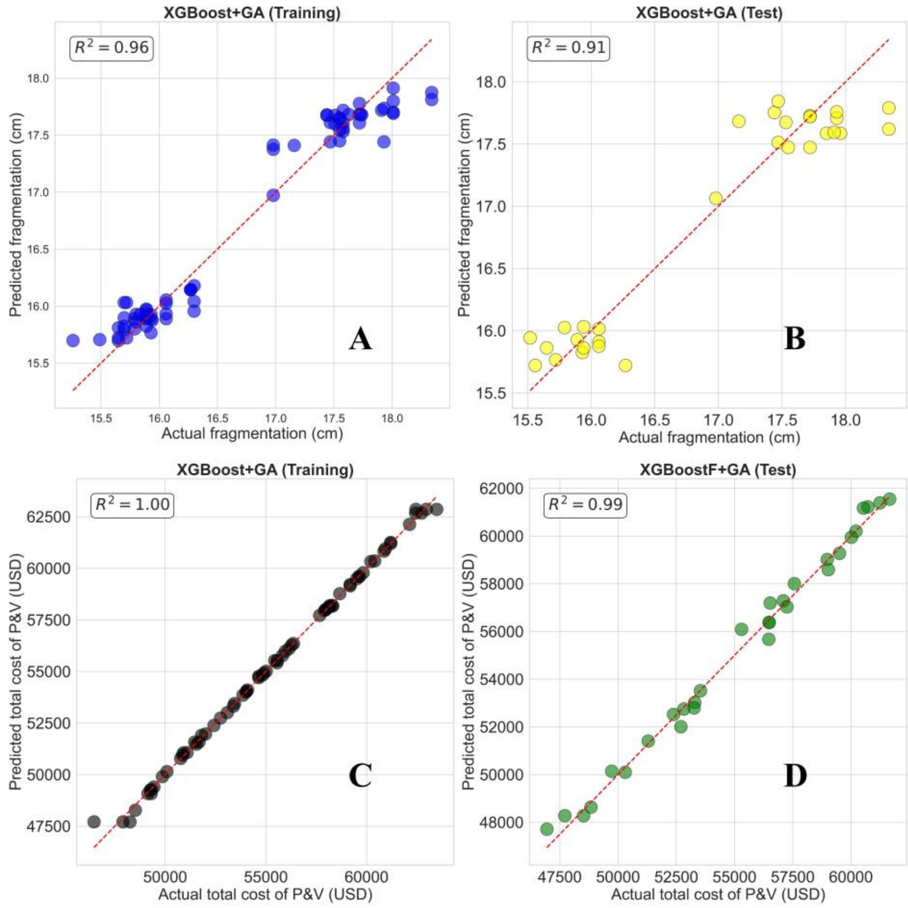

Figure 8. Comparison of actual vs. predicted values using XGBoost + GA. A: Fragmentation training set. B: Fragmentation test set. C: Training set for total operational costs of drilling and blasting. D: Test set for total operational costs of drilling and blasting.

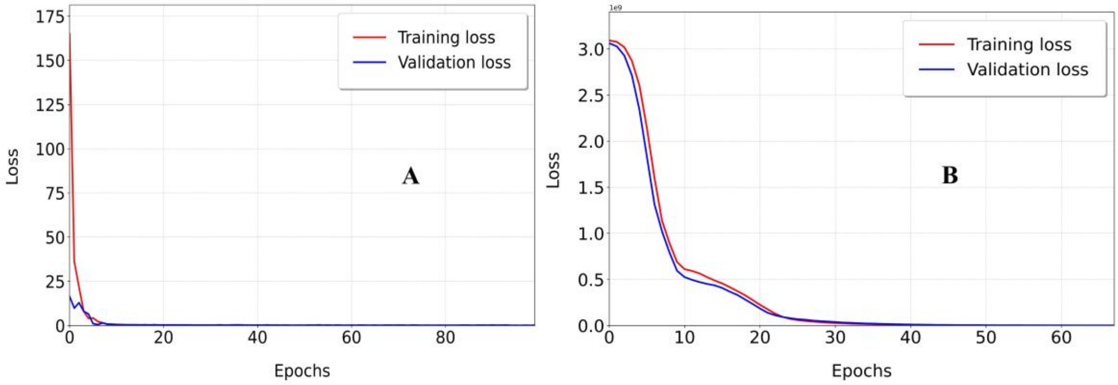

Figure 9. Training and validation loss graphs with ANNs + PSO prediction. A: Training and validation loss in fragmentation prediction. B: Training and validation loss in total operational cost prediction for drilling and blasting.

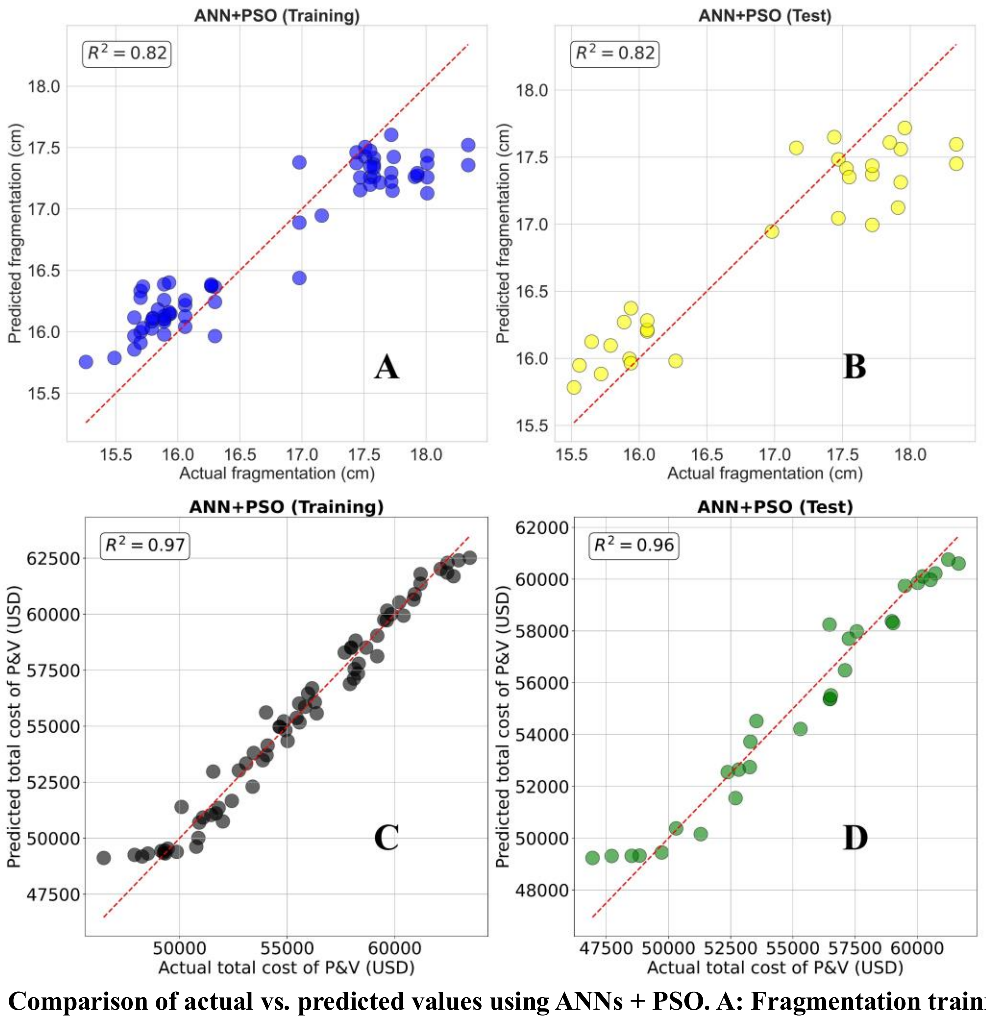

Figure 10. Comparison of actual vs. predicted values using ANNs + PSO. A: Fragmentation training set. B: Fragmentation test set. C: Training set for total operational costs of drilling and blasting. D: Test set for total operational costs of drilling and blasting.

A high correlation is observed between actual and predicted fragmentation, with an R^2 of 0.93 for the training set and 0.92 for the test set. The data points align consistently with the equality line, confirming the accuracy of the SVR+PSO model in predicting fragmentation. Figure 11 illustrates these results, showing that the predicted costs also closely match the actual values, with an R^2 of 0.97 for the training set and 0.98 for the test set. This indicates that the model is highly precise in estimating total drilling and blasting costs.

3.6. Evaluation metrics for predictions using hybrid models

The SVR + PSO model achieved the best performance in fragmentation prediction, with an RMSE of 0.27, an MAE of 0.21, and an R^2 of 0.92 on the test set, demonstrating high accuracy. The XGBoost+GA model followed closely, with an RMSE of 0.29, an MAE of 0.22, and an R^2 of 0.91. Similarly, the RF+GA model performed well, also achieving an RMSE of 0.29 and an R^2 of 0.91. On the training set, the best-performing models were XGBoost+GA, both with an RMSE of 0.19 and an R^2 of 0.96, indicating their strong generalization capability. The ANNs+PSO model, although it produced reasonable results, lagged behind with an RMSE of 0.40 and an R^2 of 0.82 on the test set (see Table 11). The results obtained in this study are comparable to previous research. Zhao et al. [88], using hybrid models such as GBoost-BOA, achieved an R^2 of 0.96 in fragmentation prediction, slightly higher than the R^2 of 0.92 obtained by the SVR + PSO model in this study. Similarly, Gebretsadik et al. [89] employed Random Forest Regression (RFR), reaching an R^2 of 0.94, a value close to the R^2 of 0.91 obtained with our RF + GA model.

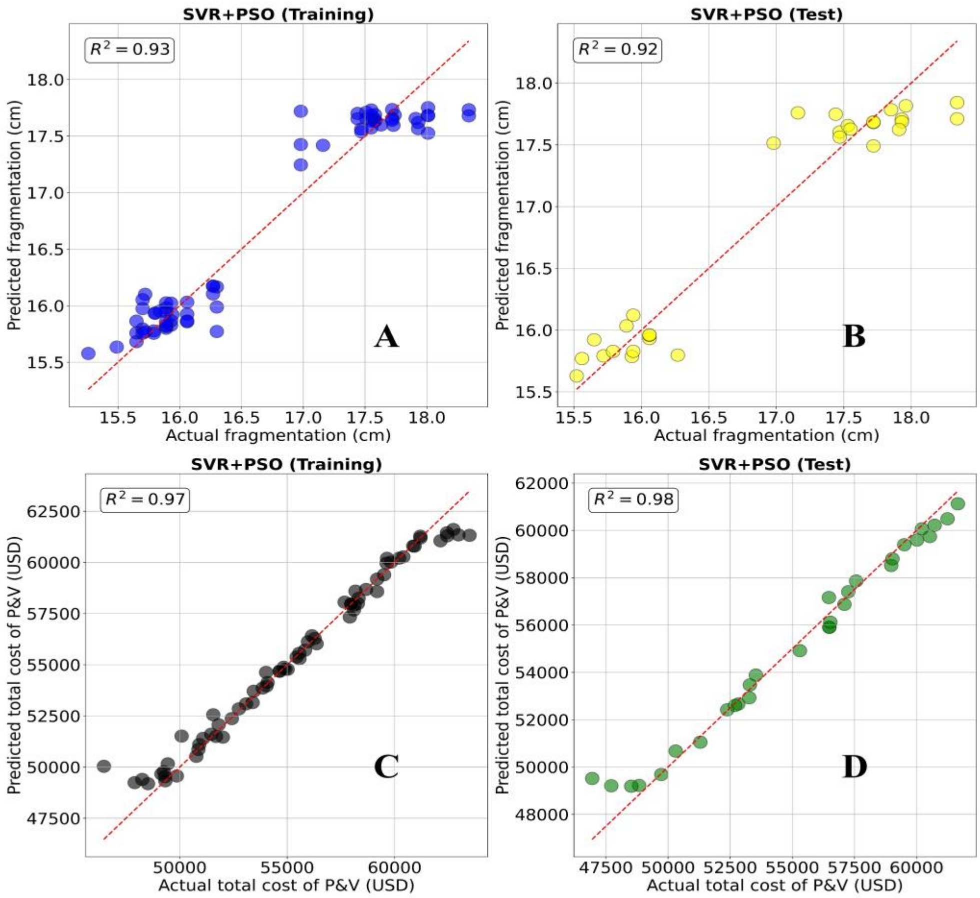

Figure 11. Comparison of actual vs. predicted values using SVR + PSO. A: Fragmentation training set. B: Fragmentation test set. C: Training set for total operational costs of drilling and blasting. D: Test set for total operational costs of drilling and blasting.

Table 11. Fragmentation prediction evaluation metrics using machine learning models.

Metrics	ANNs + GA	RF + GA	DT + GA	XGBoost + GA	SVR + PSO	ANNs + PSO
Test						
RMSE	0.49	0.29	0.30	0.29	0.27	0.40
MAE	0.40	0.23	0.24	0.22	0.21	0.33
R^2	0.74	0.91	0.90	0.91	0.92	0.82
Training						
RMSE	0.40	0.23	0.28	0.19	0.24	0.39
MAE	0.32	0.17	0.21	0.14	0.18	0.33
R^2	0.81	0.94	0.91	0.96	0.93	0.82

The RF + GA model achieved the best performance in predicting drilling and blasting costs, with an RMSE of 414.58, an MAE of 354.14, and an R^2 of 0.99 on the test set. The XGBoost+GA model also performed well, with an RMSE of 420.80, an MAE of 368.83, and an R^2 of 0.99. Although the SVR + PSO model had a higher RMSE of 679.10, it still maintained a strong predictive capability with an R^2 of 0.98. On the training set, RF + GA and XGBoost + GA once again stood out, achieving RMSE values of 168.05 and 201.29, respectively, along with an R^2 of 1.00, demonstrating excellent generalization capability. While the ANNs+GA model also obtained a high R^2 of 0.99, its RMSE of 501.89 indicates a higher margin of error compared to the top-performing models (see Table 12).

Table 12. Drilling and blasting cost prediction evaluation metrics using machine learning models.

Metric	ANNs + GA	RF + GA	DT + GA	XGBoost + GA	SVR + PSO	ANNs + PSO
Test						
RMSE	659.89	414.58	990.41	420.80	679.10	901.88
MAE	563.93	354.14	832.06	368.83	474.50	738.28
R^2	0.98	0.99	0.95	0.99	0.98	0.96
Training						
RMSE	501.89	168.05	432.94	201.29	716.36	715.93
MAE	397.36	127.30	341.98	130.69	416.06	549.41
R^2	0.99	1.00	0.99	1.00	0.97	0.97

The predicted values in the test set closely align with the actual values for both fragmentation prediction and total drilling and blasting costs. In fragmentation prediction (Part A), most points predicted by different models are positioned near the equality line (dashed line), with the SVR+PSO model showing the most consistent alignment, demonstrating superior accuracy. Figure 12 illustrates this comparison, where in total drilling and blasting cost prediction (Part B), the RF + GA and XGBoost + GA models exhibit the highest accuracy, closely matching the actual cost values.

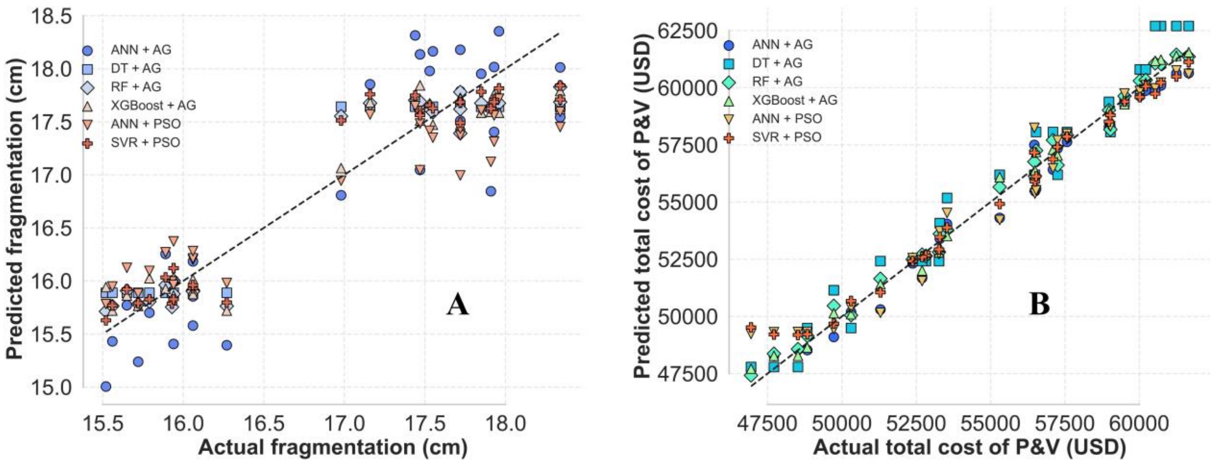

Figure 12. Comparison of actual vs. predicted values in the test set. A: Fragmentation prediction comparison. B: Total operational cost prediction comparison for drilling and blasting.

3.7. Optimization of fragmentation and drilling and blasting operational costs

The optimization of rock fragmentation size (X_{50}) and drilling and blasting costs is analyzed under three different scenarios: pessimistic, real, and optimistic. In the pessimistic scenario, fragmentation size remains around 17.6 cm, while in the real scenario, it fluctuates between 17.0 cm and 17.4 cm. In the optimistic scenario, fragmentation is further reduced to a range of 16.6 cm to 17.0 cm, representing a 5.7% decrease compared to the pessimistic scenario. This finer fragmentation is achieved by adjusting the burden to 3.8 m and the spacing to 4.5 m, improving overall fragmentation efficiency. Figure 13 illustrates these results, highlighting the impact of optimized parameters on X_{50} reduction. Meanwhile, Figure 14 presents the optimization of drilling and blasting costs, where in the pessimistic scenario, costs remain around 63,000 USD. In the real scenario, they vary between 59,000 and 60,000 USD, while in the optimistic scenario, costs are further reduced to a range of 57,000 to 58,000 USD, achieving a 9.5% reduction compared to the pessimistic case.

The comparison between AI-predicted results and real mining data from Peruvian open-pit operations. Cardenas et al. [90] and Churra [91] demonstrates a high level of accuracy in fragmentation prediction and a relatively small deviation in cost estimation. The predicted rock fragmentation (X_{50}) of 16.80 cm closely aligns with the actual mining fragmentation of 17.907 cm, with only a 6.18% deviation, confirming the reliability of AI models in fragmentation forecasting. Similarly, the predicted drilling and blasting costs (58,000 USD) are 7.84% lower than the actual mining cost of 62,937.03 USD, indicating that while machine learning effectively models costs, operational and logistical factors not included in the dataset may influence real expenditures. These minor discrepancies suggest that AI models are highly applicable to real mining conditions, with potential refinements needed in cost estimation by incorporating additional financial and logistical variables (see Table 13). Despite these differences, the findings validate that AI can serve as a reliable tool for optimizing rock fragmentation and cost forecasting, enabling data-driven decision-making that enhances efficiency, cost-effectiveness, and operational predictability in mining processes.

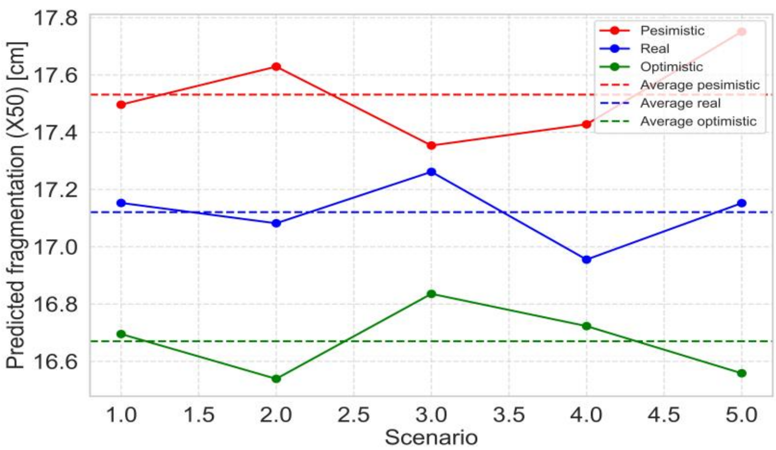

Figure 13. Rock fragmentation size optimization scenarios.

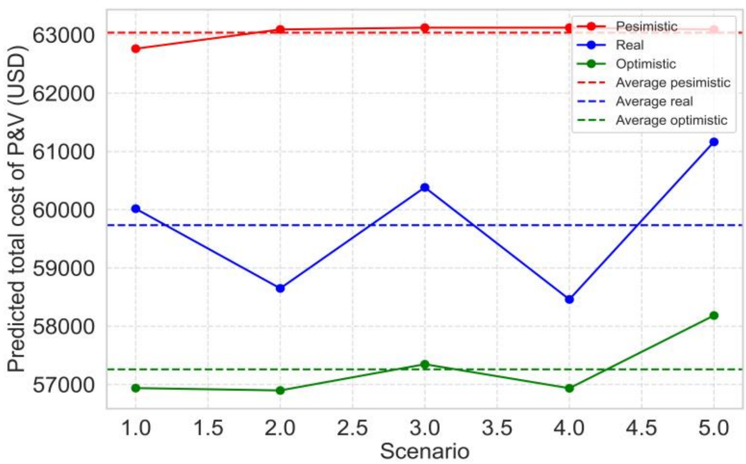

Figure 14. Optimization scenario for total operational costs of drilling and blasting.

Table 13. Validation of machine learning predictions against real mining data in Peru.

Metric	This study	Real mining data [90, 91]	Deviation from real data (%)
Rock fragmentation (cm)	16.80	17.907	6.18
Drilling and blasting costs (USD)	58,000.00	62,937.03	7.84

3.8. Prediction of future total operational costs for drilling and blasting

The prediction of total operational costs for drilling and blasting over 30 future blasts using the RF+GA model demonstrates a strong correlation between predicted and historical costs, where the predicted values (red line) follow a similar trend to historical data (blue line), reinforcing the model's high predictive capacity. The estimated costs range between 50,306 USD and 59,574 USD, remaining within historically observed margins, while the average cost per blast is 55,180.37 USD, leading to a total accumulated cost of 1.7 MUSD for the 30 projected blasts (see Table 14). These findings align with international studies, such as Zhao et al. [88], who applied hybrid predictive models to estimate blasting costs and achieved stable and reliable forecasts. Figure 15 illustrates this trend, further validating the model's capability to accurately predict cost variations, demonstrating its potential as a reliable tool for economic forecasting in mining operations.

Table 14. Predicted drilling and blasting costs for the 30 future blasts.

N° blasting	Predicted cost (USD)	N° blasting	Predicted cost (USD)
1	55,005.23	16	59,506.55
2	57,384.43	17	56,191.85
3	50,898.03	18	50,306.59
4	52,274.83	19	57,458.21
5	54,499.95	20	54,044.92
6	54,551.70	21	57,031.42
7	54,533.11	22	53,499.66
8	52,715.26	23	57,727.46
9	59,574.21	24	56,987.80
10	53,918.04	25	53,540.49
11	55,373.87	26	52,213.21
12	58,651.57	27	54,843.00
13	53,657.34	28	57,220.08
14	55,751.38	29	54,473.15
15	57,231.50	30	54,346.26
Total (USD)			1,655,411.10
Average (USD)			55,180.37

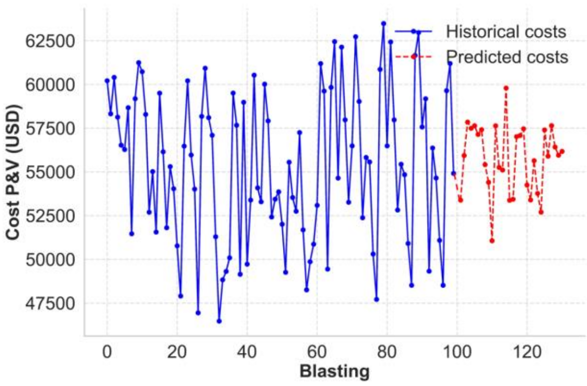

Figure 15. Prediction of total operational costs for drilling and blasting over 30 future blasts using RF + GA.

4. Conclusions

In this work, drilling and blasting parameters and costs in an open-pit mine were optimized using hybrid predictive models, with the SVR + PSO model showing the highest efficacy for fragmentation prediction, achieving an RMSE of 0.27, an MAE of 0.20, and an R^2 of 0.92. For predicting the total operational costs of drilling and blasting, the best model was RF+GA, with an RMSE of 398.87, an MAE of 336.01, and an R^2 of 0.99. Three scenarios pessimistic, real, and optimistic were considered in the predictions. In the optimistic scenario, the fragment size was reduced to 16.6 cm by adjusting key parameters, such as the burden and spacing, to 3.8 m and 4.5 m, respectively. The total operational costs were optimized to an average of 57,000 USD per blast.

The exploratory data analysis identified key factors influencing fragmentation, with the burden-to-drill diameter ratio (r = 0.96) and uniaxial compressive strength (r = 0.95) being the most significant. In terms of costs, the number of drill holes and the cost of explosives (r = 0.92 and r = 0.94, respectively) showed a strong correlation with total costs. This approach allowed for the prediction and projection of future costs for 30 blasts using the RF + GA hybrid model, resulting in a total cost of 1.655 MUSD and an average of 55,180.37 USD per blast.

The limitations of this work include the exclusion of additional geotechnical variables such as soil moisture, rock anisotropy, and rock mass density, which could improve prediction accuracy. The models could benefit from incorporating these variables in future studies. It is also recommended to conduct tests in different geological and operational settings, as well as to explore other hybrid optimization algorithms, to achieve more robust and generalizable optimization in mining operations.

References

[1]. Michaux, S., Djordjevic, N. (2005). Influence of explosive energy on the strength of the rock fragments and SAG mill throughput. *Miner Eng*, *18* (4), 439-448.

[2]. Choudhary, BS., Agrawal, A., Arora, R. (2021). Stemming material and Inter-row delay timing effect on blast results in limestone mines. *Sadhana - Academy Proceedings in Engineering Sciences*, *46* (23).

[3]. Khandelwal, M., Saadat, M. (2015). A Dimensional Analysis Approach to Study Blast-Induced Ground Vibration. *Rock Mech Rock Eng*, *48,* 727-735.

[4]. Sharma, M., Choudhary, BS., Raina, AK., Khandelwal, M., Rukhiyar, S. (2024). Prediction of rock fragmentation in a fiery seam of an open-pit coal mine in India. *Journal of Rock Mechanics and Geotechnical Engineering, 16* (8), 2879-2893.

[5]. Choudhary, BS., Rai, P. (2013). Stemming plug and its effect on fragmentation and muckpile shape parameters. *Int J Min Miner Eng*, *4* (4), 296-311.

[6]. Rai, P., Yang, HS., Choudhary, BS. (2012). Formation of slot cut for creating free face in solid limestone bench: A case study. *Powder Technol, 228*, 327-333.

[7]. Adamson, WR., Scherpenisse, CR., Diaz, JC. (1999). The use of blast monitoring/modelling technology for the optimisation of development blasting. *AusIMM Proceedings 306.*

[8]. Marton, A., Crookes, R. (2001). A case study in optimising fragmentation. *AusIMM Proceedings 306*.

[9]. Monjezi, M., Rezaei, M., Yazdian Varjani, A. (2009). Prediction of rock fragmentation due to blasting in Gol-E-Gohar iron mine using fuzzy logic. *International Journal of Rock Mechanics and Mining Sciences*, *46* (8), 1273-1280.

[10]. Shim, HJ., Ryu, DW., Chung, SK., Synn, JH., Song, JJ. (2009). Optimized blasting design for large-scale quarrying based on a 3-D spatial distribution of rock factor. *International Journal of Rock Mechanics and Mining Sciences*, *46* (2), 326-332.

[11]. Hustrulid, W. (1999). Blasting principles for open pit mining: Volume 1 - General design concepts. *General Design Concept 1*.

[12]. Sharma, M., Choudhary, BS., Kumar, H., Agrawal, H. (2021). Optimization of Delay Sequencing in Multi-Row Blast using Single Hole Blast Concepts. *Journal of The Institution of Engineers (India): Series D*, *102*, 453-460.

[13]. Zhu, Z., Mohanty, B., Xie, H. (2007). Numerical investigation of blasting-induced crack initiation and propagation in rocks. *International Journal of Rock Mechanics and Mining Sciences*, *44* (3), 412-424.

[14]. Monjezi, M., Bahrami, A., Yazdian Varjani, A. (2010). Simultaneous prediction of fragmentation and flyrock in blasting operation using artificial neural networks. *International Journal of Rock Mechanics and Mining Sciences*, *47* (3), 476-480.

[15]. Kuznetsov, VM. (1973). The mean diameter of the fragments formed by blasting rock. *Soviet Mining Science*, *9*, 144-148.

[16]. Cunningham, C. (1983) The Kuz-Ram model for prediction of fragmentation from blasting. *Proceedings of the 1st International Symposium on Rock Fragmentation by Blasting.*

[17]. Hjelmberg, H. (1983). Some ideas on how to improve calculations of the fragment size distribution in bench blasting. *In: Proceedings of the 1st international symposium on rock fragmentation by blasting*.

[18]. Gheibie, S., Aghababaei, H., Hoseinie, SH., Pourrahimian, Y. (2009). Modified Kuz-Ram fragmentation model and its use at the Sungun Copper Mine. *International Journal of Rock Mechanics and Mining Sciences*, *46* (6), 967-973.

[19]. Khandelwal, M., Mahdiyar, A., Armaghani, DJ., Singh, TN., Fahimifar, A., Faradonbeh, RS. (2017). An expert system based on hybrid ICA-ANN technique to estimate macerals contents of Indian coals. *Environ Earth Sci*, *76* (399).

[20]. Khandelwal, M., Armaghani, DJ. (2016). Prediction of Drillability of Rocks with Strength Properties Using a Hybrid GA-ANN Technique. *Geotechnical and Geological Engineering*, *34*, 605-620.

[21]. Rahul., Khandelwal, M., Rai, R., Shrivastva, BK. (2015). Evaluation of dump slope stability of a coal mine using artificial neural network. *Geomechanics and Geophysics for Geo-Energy and Geo-Resources*, *1,* 69-77.

[22]. Rezaeineshat, A., Monjezi, M., Mehrdanesh, A., Khandelwal, M. (2020). Optimization of blasting design in open pit limestone mines with the aim of reducing ground vibration using robust techniques. *Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 6* (40).

[23]. Srivastava, A., Choudhary, BS., Sharma, M. (2021). A Comparative Study of Machine Learning Methods for Prediction of Blast-Induced Ground Vibration. *Journal of Mining and Environment*, *12* (3), 667-677.

[24]. Bakhtavar, E., Sadiq, R., Hewage, K. (2021). Optimization of Blasting-Associated Costs in Surface Mines Using Risk-based Probabilistic Integer Programming and Firefly Algorithm. *Natural Resources Research*, *30*, 4789-4806.

[25]. Bayat, P., Monjezi, M., Mehrdanesh, A., Khandelwal, M. (2022). Blasting pattern optimization using gene expression programming and grasshopper optimization algorithm to minimise blast-induced ground vibrations. *Eng Comput, 38*, 3341-3350.

[26]. Bayat, P., Monjezi, M., Rezakhah, M., Armaghani, DJ. (2020). Artificial Neural Network and Firefly Algorithm for Estimation and Minimization of Ground Vibration Induced by Blasting in a Mine. *Natural Resources Research*, *29*, 4121-4132.

[27]. Zhao, J., Li, D., Zhou, J., Armaghani, DJ., Zhou, A. (2024). Performance evaluation of rock fragmentation prediction based on RF-BOA, AdaBoost-BOA, GBoost-BOA, and ERT-BOA hybrid models. *Deep Underground Science and Engineering*, *4* (1), 3-17.

[28]. Amoako, R., Jha, A., Zhong, S. (2022). Rock Fragmentation Prediction Using an Artificial Neural Network and Support Vector Regression Hybrid Approach. *Mining, 2* (2), 233-247.

[29]. Vergara, B., Torres, M., Aramburu, V., Raymundo, C. (2021). Predictive Model of Rock Fragmentation Using the Neuro-Fuzzy Inference System (ANFIS) and Particle Swarm Optimization (PSO) to Estimate Fragmentation Size in Open Pit Mining. *Lecture Notes in Networks and Systems*, 124-131.

[30]. Hasanipanah, M., Amnieh, HB., Arab, H., Zamzam, MS. (2018). Feasibility of PSO–ANFIS model to estimate rock fragmentation produced by mine blasting. *Neural Comput Appl*, *30*, 1015-1024.

[31]. Esmaeili, M., Salimi, A., Drebenstedt, C., Abbaszadeh, M., Aghajani Bazzazi, A. (2015). Application of PCA, SVR, and ANFIS for modeling of rock fragmentation. *Arabian Journal of Geosciences*, *8,* 6881-6893.

[32]. Fang, Q., Nguyen, H., Bui, XN., Nguyen-Thoi, T., Zhou, J. (2021). Modeling of rock fragmentation by firefly optimization algorithm and boosted generalized additive model. *Neural Comput Appl*, *33*, 3503-3519.

[33]. Shams, S., Monjezi, M., Majd, VJ., Armaghani, DJ. (2015). Application of fuzzy inference system for prediction of rock fragmentation induced by blasting. *Arabian Journal of Geosciences, 8,* 10819-10832.

[34]. Hasanipanah, M., Jahed Armaghani, D., Monjezi, M., Shams, S. (2016). Risk assessment and prediction of rock fragmentation produced by blasting operation: a rock engineering system. *Environ Earth Sci*, *75* (808).

[35]. Gebretsadik, A., Kumar, R., Fissha, Y., Kide, Y., Okada, N., Ikeda, H., Mishra, AK., Armaghani, DJ., Ohtomo, Y., Kawamura, Y. (2024). Enhancing rock fragmentation assessment in mine blasting through machine learning algorithms: a practical approach. *Discover Applied Sciences*, *6* (223).

[36]. Yari, M., He, B., Armaghani, DJ., Abbasi, P., Mohamad, ET. (2023). A novel ensemble machine learning model to predict mine blasting–induced rock fragmentation. *Bulletin of Engineering Geology and the Environment*, *82* (187).

[37]. Sri Chandrahas, N., Choudhary, BS., Vishnu Teja, M., Venkataramayya, MS., Krishna Prasad, NSR. (2022). XG Boost Algorithm to Simultaneous Prediction of Rock Fragmentation and Induced Ground Vibration Using Unique Blast Data. *Applied Sciences (Switzerland), 12* (10), 5269.

[38]. Bahrami, A., Monjezi, M., Goshtasbi, K., Ghazvinian, A. (2011). Prediction of rock fragmentation due to blasting using artificial neural network. *Eng Comput*, *27*, 177-181.

[39]. Al-Bakri, AY., Sazid, M. (2021). Application of Artificial Neural Network (ANN) for Prediction and Optimization of Blast-Induced Impacts. *Mining, 1* (3), 315-334.

[40]. Ebrahimi, E., Monjezi, M., Khalesi, MR., Armaghani, DJ. (2016). Prediction and optimization of back-break and rock fragmentation using an artificial neural network and a bee colony algorithm. *Bulletin of Engineering Geology and the Environment*, *75*, 27-36.

[41]. Li, E., Yang, F., Ren, M., Zhang, X., Zhou, J., Khandelwal, M. (2021). Prediction of blasting mean fragment size using support vector regression combined with five optimization algorithms. *Journal of Rock Mechanics and Geotechnical Engineering*, *13* (6), 1380-1397.

[42]. Hekmat, A., Munoz, S., Gomez, R. (2019). Prediction of Rock Fragmentation Based on a Modified Kuz-Ram Model. *Proceedings of the 27th International Symposium on Mine Planning and Equipment Selection - MPES 2018*, 69-79.

[43]. Moomivand, H., Vandyousefi, H. (2020). Development of a new empirical fragmentation model using rock mass properties, blasthole parameters, and powder factor. *Arabian Journal of Geosciences*, *13* (1173).

[44]. Chandr, S., Singh, B., Venkataramayya, M., Fissha, Y. (2023). An inventive approach for simultaneous prediction of mean fragmentation size and peak particle velocity using futuristic datasets through improved techniques of genetic XG Boost algorithm. *Mining, Metallurgy & Exploration*, *41*, 2391-2405.

[45]. Taji, M., Ataei, M., Goshtasbi, K., Osanloo, M. (2013). ODM: A new approach for open pit mine blasting evaluation. *JVC/Journal of Vibration and Control*, *19* (11).

[46] Raj, AK., Choudhary, BS., Deressa, GW. (2024). Prediction of Rock Fragmentation for Surface Mine Blasting Through Machine Learning Techniques. *Journal of The Institution of Engineers (India): Series D.*

[47]. Kahraman, E., Hosseini, S., Taiwo, BO., Fissha, Y., Jebutu, VA., Akinlabi, AA., Adachi, T. (2024). Fostering sustainable mining practices in rock blasting: Assessment of blast toe volume prediction using comparative analysis of hybrid ensemble machine learning techniques. *Journal of Safety and Sustainability*, *1*, 75–88

[48]. Afum, B., Temeng, V. (2015). Reducing Drill and Blast Cost through Blast Optimisation-A Case Study. *Conference: 3rd UMaT Biennial International Mining and Mineral Conference*.

[49]. Munagala, V., Thudumu, S., Logothetis, I., Bhandari, S., Vasa, R., Mouzakis, K. (2024). A comprehensive survey on machine learning applications for drilling and blasting in surface mining. *Machine Learning with Applications*, *15*, 100517.

[50]. Fattahi, H., Ghaedi, H., Armaghani, DJ. (2024). Enhancing blasting efficiency: A smart predictive model for cost optimization and risk reduction. *Resources Policy*, *97,* 105261.

[51]. Bastami, R., Aghajani Bazzazi, A., Shoormasti, HH., Ahangari, K. (2020). Prediction of Blasting Cost in Limestone Mines Using Gene Expression Programming Model and Artificial Neural Networks. *Journal of Mining and Environment*, *11* (1), 281-300.

[52]. Bakhshandeh Amnieh, H., Bidgoli, MH., Mokhtari, H., Bazzazi, AA. (2019). Application of simulated annealing for optimization of blasting costs due to air overpressure constraints in open-pit mines. *Journal of Mining and Environment*, *10* (4), 903-916.

[53]. Guo, J., Zhao, Z., Zhao, P., Chen, J. (2024). Prediction and Optimization of Open-Pit Mine Blasting Based on Intelligent Algorithms. *Applied Sciences*, *14,* 5609.

[54]. Hryhoriev, Y., Lutsenko, S., Shvets, Y., Kuttybayev, A., Mukhamedyarova, N. (2024). Predictive calculation of blasting quality as a tool for estimation of production cost and investment attractiveness of a mineral deposit development. *IOP Conf Ser Earth Environ Sci, 1415*, 012027.

[55]. Fattahi, H., Ghaedi, H. (2024). Optimizing mining economics: Predicting blasting costs in limestone mines using the RES-based method. *International Journal of Mining and Geo-Engineering, 58,* 181-190.

[56]. Álvarez-Vigil, AE., González-Nicieza, C., López Gayarre, F., Álvarez-Fernández, MI. (2012). Predicting blasting propagation velocity and vibration frequency using artificial neural networks. *International Journal of Rock Mechanics and Mining Sciences*, *55,* 108-116.

[57]. Dehghani, H. (2018). Forecasting copper price using gene expression programming. *Journal of Mining & Environment*, *9.*

[58]. Nguyen, H., Bui, XN., Tran, QH., Le, TQ., Do, NH., Hoa, LTT. (2019). Evaluating and predicting blast-induced ground vibration in open-cast mine using ANN: a case study in Vietnam. *SN Appl Sci*, *1* (125).

[59]. Yu, Z., Shi, X., Miao, X., Zhou, J., Khandelwal, M., Chen, X., Qiu, Y. (2021). Intelligent modeling of blast-induced rock movement prediction using dimensional analysis and optimized artificial neural network technique. *International Journal of Rock Mechanics and Mining Sciences*, *143*, 104794.

[60]. Hosseini, M., Khandelwal, M., Lotfi, R., Eslahi, M. (2023). Sensitivity analysis on blast design parameters to improve bench blasting outcomes using the Taguchi method. *Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 9* (9).

[61]. Gebretsadik, A., Kumar, R., Fissha, Y., Kide, Y., Okada, N., Ikeda, H., Mishra, AK., Armaghani, DJ., Ohtomo, Y., Kawamura, Y. (2024). Enhancing rock fragmentation assessment in mine blasting through machine learning algorithms: a practical approach. *Discover Applied Sciences*, *6*, 223.

[62]. Dotto, MS., Pourrahimian, Y. (2024). The Influence of Explosive and Rock Mass Properties on Blast Damage in a Single-Hole Blasting. *Mining*, *4* (1), 168-188.

[63]. Gao, P., Pan, C., Zong, Q., Dong, C. (2023). Rock fragmentation size distribution control in blasting: a case study of blasting mining in Changjiu Shenshan limestone mine. *Front Mater*, *10.*

[64]. Sayadi, A., Monjezi, M., Talebi, N., Khandelwal, M. (2013). A comparative study on the application of various artificial neural networks to simultaneous prediction of rock fragmentation and backbreak. *Journal of Rock Mechanics and Geotechnical Engineering, 5* (4), 318-324.

[65]. Monjezi, M., Amiri, H., Farrokhi, A., Goshtasbi, K. (2010). Prediction of rock fragmentation due to blasting in Sarcheshmeh copper mine using artificial neural networks. *Geotechnical and Geological Engineering*, *28,* 423-430.

[66]. Marquina, J., Cotrina, T., Mamani, J., Noriega, E., Vega, J., Cruz, J. (2024). Copper Ore Grade Prediction using Machine Learning Techniques in a Copper Deposit. *Journal of Mining and Environment*, *15* (3), 1011–1027.

[67]. Nabavi, Z., Mirzehi, M., Dehghani, H., Ashtari, P. (2023). A Hybrid Model for Back-Break Prediction using XGBoost Machine learning and Metaheuristic Algorithms in Chadormalu Iron Mine. *Journal of Mining and Environment*, *14* (2), 689-712.

[68]. Cotrina, M., Marquina, J., Mamani, J., Arango, S., Gonzalez, J., Ccatamayo, J., Noriega, E. (2024). Predictive model using machine learning to determine fuel consumption in CAT-777F mining equipment. *Int J Min Miner Eng*, *15*, 147–160.

[69]. Taiwo, BO., Gebretsadik, A., Fissha, Y., Kide, Y., Li, E., Haile, K., Oni, OA. (2023). Artificial Neural Network Modeling as an Approach to Limestone Blast Production Rate Prediction: a Comparison of PI-BANN and MVR Models. *Journal of Mining and Environment*, *14* (2), 375-388.

[70]. Fathi, M., Alimoradi, A., Ahooi, HH. (2021). Optimizing Extreme Learning Machine Algorithm using Particle Swarm Optimization to Estimate Iron Ore Grade. *Journal of Mining and Environment*, *12* (2), 397-411.

[71]. Ataei, M., Sereshki, F. (2017). Improved prediction of blast-induced vibrations in limestone mines using Genetic Algorithm. *Journal of Mining and Environment*, *8* (2), 291-304.

[72]. Parikh, R., Wilson, B., Marrah, L., Su, Z., Saha, S., Kumar, P., Huang, F., Dutta, A. (2022). tRForest: a novel random forest-based algorithm for tRNA-derived fragment target prediction. *NAR Genom Bioinform*, *4* (2).

[73]. Nunes, E., Groenner, B., Godinho, S., Ussi, C., Phin, D., Rezende, L. (2022). Variable selection for estimating individual tree height using genetic algorithm and random forest. *For Ecol Manage*, *504*, 119828.

[74]. Silva, R., Padovani, K., Góes, F., Alves, R. (2019). A random forest classifier for prokaryotes gene

prediction. *Proceedings - 2019 Brazilian Conference on Intelligent Systems, BRACIS 2019*.

[75]. Rezaei, M., Asadizadeh, M. (2020). Predicting Unconfined Compressive Strength of Intact Rock Using New Hybrid Intelligent Models. *Journal of Mining and Environment*, *11* (1), 231-246.

[76]. Rodríguez-Mazahua, N., Rodríguez-Mazahua, L., López-Chau, A., Alor-Hernández, G., Machorro-Cano, I. (2022). Decision-Tree-Based Horizontal Fragmentation Method for Data Warehouses. *Applied Sciences (Switzerland), 12* (21), 10942.

[77]. Estrada-Gil, JK., Fernández-López, JC., Hernández-Lemus, E., Silva-Zolezzi, I., Hidalgo-Miranda, A., Jiménez-Sánchez, G., Vallejo-Clemente, EE. (2007). GPDTI: A genetic programming decision tree induction method to find epistatic effects in common complex diseases. *Bioinformatics*, *23* (13), 167-174.

[78]. Tao, H., Habib, M., Aljarah, I., Faris, H., Afan, HA., Yaseen, ZM. (2021). An intelligent evolutionary extreme gradient boosting algorithm development for modeling scour depths under submerged weir. *Inf Sci, 570,* 172-184.

[79]. Sayevand, K., Arab, H. (2019). A fresh view on particle swarm optimization to develop a precise model for predicting rock fragmentation. *Engineering Computations (Swansea, Wales)*, *36* (2), 533-550.

[80]. Nikakhtar, L., Zare, S., Mirzaei, H. (2023). Performance Comparison of Particle Swarm Optimization and Genetic Algorithm for Back-analysis of Soil Layer Geotechnical Parameters. *Journal of Mining and Environment, 14* (1), 217-232.

[81]. Anemangely, M., Ramezanzadeh, A., Tokhmechi, B. (2017). Determination of constant coefficients of Bourgoyne and Young drilling rate model using a novel evolutionary algorithm. *Journal of Mining and Environment, 8* (4), 693-702.

[82]. Hajihassani, M., Jahed Armaghani, D., Sohaei, H., Tonnizam Mohamad, E., Marto, A. (2014). Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Applied Acoustics, 80,* 57-67.

[83]. Lazzús, JA. (2013). Neural network-particle swarm modeling to predict thermal properties. *Math Comput Model*, *57* (9-10), 2408-2418.

[84]. Zhu, B., Huang, J., Chen, Y., Chen, Z. (2012). Dynamic packet fragmentation based on particle swarm optimised prediction. *International Journal of Wireless and Mobile Computing, 5* (4), 386-393.

[85]. Yu, J., Liu, X., Wang, L., Wu, H. (2022). Optimization and Simulation of Monitoring Technology of Blasting Rock Movement Trajectory Based on the Improved SVM Algorithm. *Math Probl Eng*, *2022* (1), 4825212.

[86]. Abbaspour, H., Drebenstedt, C., Badroddin, M., Maghaminik, A. (2018). Optimized design of drilling and blasting operations in open pit mines under technical and economic uncertainties by system dynamic modelling. *Int J Min Sci Technol*, *28* (6), 839-848.

[87]. Yussupov, K., Myrzakhmetov, S., Aben, K., Nehrii, S., Nehrii, T. (2021). Optimization of the drilling-and-blasting process to improve fragmentation by creating of a preliminary stress in a block. *E3S Web of Conferences, 280*, 08015.

[88]. Zhao, J., Li, D., Zhou, J., Armaghani, DJ., Zhou, A. (2024). Performance evaluation of rock fragmentation prediction based on RF-BOA, AdaBoost-BOA, GBoost-BOA, and ERT-BOA hybrid models. *Deep Underground Science and Engineering, 4* (1), 3-17.

[89]. Gebretsadik, A., Kumar, R., Fissha, Y., Kide, Y., Okada, N., Ikeda, H., Mishra, AK., Armaghani, DJ., Ohtomo, Y., Kawamura, Y. (2024). Enhancing rock fragmentation assessment in mine blasting through machine learning algorithms: a practical approach. *Discover Applied Sciences,* 6, 223.

[90]. Cárdenas, J., Huerta, G., Salas, J. (2022). Mejora de fragmentación a través de la aplicación de carga explosiva en el taco para la reducción de sobre tamaños en roca de alta dureza. *Instituto de Ingenieros de Minas del Peru.*

[91]. Churra, O. (2023). Reducción de los costos de servicios auxiliares e incidentes por caída de rocas utilizando la voladura controlada en la mina Toquepala - SPCC. *Tesis de ingeniero de minas, Universidad Nacional del Altiplano.*

بهینه‌سازی خردایش و هزینه‌های عملیاتی حفاری و انفجار با استفاده از مدل‌های یادگیری ماشین ترکیبی در یک معدن روباز در پرو

مارکو آنتونیو کوترینا-تئاتینو[1*]، جایرو جوناتان مارکوینا-آرائوخو[1]، خوزه نستور مامانی-کویسپه[2]، سولیو مارینو آرانگو-رتاموزو[1]، جانی هنری کاتامایو-باریوس[3]، جو الکسیس گونزالس-واسکوئز[4]، تئوفیلو دونرس-فلورس[2]، مکس گابریل الکسیس کالا-هوایاپا[5]

۱. گروه مهندسی معدن، دانشکده مهندسی، دانشگاه ملی تروخیو، تروخیو، پرو

۲ .دانشکده مهندسی شیمی، دانشگاه ملی آلتیپلانو پونو، پونو، پرو

۳ .گروه مهندسی معدن، دانشگاه ملی سن کریستوبال د هوامانگا، آیاکوچو، پرو

۴ .گروه مهندسی صنایع، دانشکده مهندسی، دانشگاه ملی تروخیو، تروخیو، پرو

۵. دانشکده مهندسی فرآیندهای صنعتی، دانشگاه ملی جولیاکا، جولیاکا، پرو

ارسال ۲۰۲۴/۰۹/۱۵، پذیرش ۲۰۲۵/۰۳/۲۹

* نویسنده مسئول مکاتبات: mcotrinat@unitru.edu.pe

چکیده:

معدن نقش حیاتی در اقتصاد بسیاری از کشورها ایفا می‌کند و به طور قابل توجهی به تولید ناخالص داخلی، اشتغال و توسعه صنعتی کمک می‌کند. با این حال، بهینه‌سازی عملیات حفاری و انفجار به دلیل تأثیر مستقیم آن بر هزینه‌های عملیاتی و راندمان خردایش سنگ، همچنان یک چالش کلیدی در معدنکاری روباز است. هدف این کار بهینه‌سازی خردایش (X50) و هزینه‌های حفاری و انفجار با استفاده از مدل‌های یادگیری ماشین ترکیبی است، رویکردی نوآورانه که دقت پیش‌بینی و امکان‌سنجی اقتصادی را بهبود می‌بخشد. شش مدل توسعه داده شد: شبکه‌های عصبی مصنوعی (ANNs)، درخت‌های تصمیم‌گیری (DT)، تقویت گرادیان شدید (XGBoost)، جنگل تصادفی (RF) و رگرسیون بردار پشتیبان (SVR)، که با استفاده از الگوریتم ژنتیک (GA) و بهینه‌سازی ازدحام ذرات (PSO) بهینه‌سازی شده‌اند. مجموعه داده‌ها، شامل ۱۰۰ انفجار، به ۷۰٪ برای آموزش و ۳۰٪ برای آزمایش تقسیم شد. مدل SVR+PSO با RMSE برابر با ۰.۲۷، MAE برابر با ۰.۲۱ و R2 برابر با ۰.۹۲، بالاترین دقت را برای پیش‌بینی خردایش به دست آورد. مدل RF+GA با RMSE برابر با ۴۱۴.۵۸، MAE برابر با ۳۵۴.۱۴ و R2 برابر با ۰.۹۹، بیشترین اثربخشی را در پیش‌بینی هزینه داشت. سناریوهای بهینه‌سازی با کاهش بار (۴.۳ متر به ۳.۸ متر) و فاصله (۵.۰ متر به ۴.۵ متر) اجرا شدند و به کاهش ۵.۷ درصدی در X50 (۱۷.۶ سانتی‌متر به ۱۶.۶ سانتی‌متر) و کاهش ۹.۵ درصدی هزینه (۶۳۰۰۰ دلار آمریکا به ۵۷۰۰۰ دلار آمریکا به ازای هر انفجار) دست یافتند. پیش‌بینی‌ها برای ۳۰ انفجار آینده با استفاده از مدل RF+GA، هزینه کل ۱.۷ میلیون دلار آمریکا را تخمین زد که به طور متوسط ۵۵۱۸۰ دلار آمریکا به ازای هر انفجار است. این یافته‌ها اثربخشی یادگیری ماشین را در بهینه‌سازی هزینه و بهبود راندمان انفجار تأیید می‌کند و یک رویکرد قوی مبتنی بر داده برای بهینه‌سازی عملیات معدن ارائه می‌دهد.

کلمات کلیدی: خردایش، مدل‌های ترکیبی، یادگیری ماشین، بهینه‌سازی ازدحام ذرات، هزینه استخراج.