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Artificial Neural Network Modeling as an Approach to Limestone Blast Production Rate Prediction: a Comparison of PI-BANN and MVR Models

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Abstract

Rock blast production rate (BPR) is one of the most crucial factors in the evaluation of mine project's performance. In order to improve the production of a limestone mine, the blast design parameters and image analysis results are used in this work to evaluate the BPR. Additionally, the effect of rock strength on BPR is determined using the blast result collected. In order to model BPR prediction using artificial neural networks (ANNs) and multivariate prediction techniques, a total of 219 datasets with 8 blasting influential parameters from limestone mine blasting in India are collected. To obtain a high-accuracy model, a new training process called the permutation important-based Bayesian (PI-BANN) training approach is proposed in this work. The developed models are validated with new 20 blast rounds, and evaluated with two model performance indices. The validation result shows that the two model results agree well with the BPR practical records. Additionally, compared to the MVR model, the proposed PI-BANN model in this work provides a more accurate result. Based on the controllable parameters, the two models can be used to predict BPR in a variety of rock excavation techniques. The study result reveals that rock strength variation affects both the blast outcome (BPR) and the quantity of explosives used in each blast round.

Abbreviations

AI = Artificial intelligence
ML = Machine learning
NN= Neural network
ANN = Artificial neural network
SVM = Support vector machine
GB = Gradient boosting
RF = Random forest
BPNN = Back-propagation neural network
MLR = Multiple linear regression

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1. Introduction

Nurhasan and Saputra define mining as the process of removing valuable minerals and other geological materials from the Earth for the human benefit [1]. The removal of these natural materials involved artificial fracturing with various techniques for a quick and easy recovery. These minerals exist in a hard rock mass that needs to be broken down in order to extract valuable materials for industrial applications. Blasting is one of the most used technologies for breaking large rock masses and reducing in-situ formation into smaller sizes to facilitate transportation and downstream processes [3]. Since the large rock mass cannot be transported from the mine site to the production plant without size reduction, blasting operations are therefore very important to facilitate further processing operations [3-5]. This concluded that the result of a blast operation has a significant impact on the mining operation's efficiency, and also affects the overall mining operation cost [2, 3]. Similar to this, the efficiency of other downstream processes like loading, transportation, and crushing is influenced by the blasting production rate [6]. A good blasting operation will require fewer production costs and procedures when taking into account the final product [7]. To increase the effectiveness of the loading operation and the liberation process during ore dressing, the blast fragment size must be sufficient for both the crusher and the loading equipment [8]. When the fragmented rocks have a proper size distribution during the blasting process, it will maximize the overall mine economics and lower the costs of downstream comminution such as crushing and grinding [3, 8, 9]. The question now remains on the way forward to identify the various factors contributing to blast result efficiency and impact on other operations. As mentioned by Bakhshandeh Amnieh *et al*., the blast result depends on both controllable (see Figure 1) and uncontrollable design factors [10]. According to Zhang *et al*., the result of blasting operations can be improved by optimizing the controllable parameters in the right proportion. Optimization of the adjustable parameters to complement the impact of constant factors such as rock geology had been attempted by several authors using both empirical and Machine Learning approaches [10, 11]. According to Amoako*et al*. and Singh and Singh, blast design geometry, explosive, and controllable variables dimensions are three different categories of blast design parameters that affect blasting production rate and operation cost [9,12]. These adjustable parameters within design control include drill hole diameter and depth in addition to charge length, spacing, load, and stemming height among others. Other than this, the uncontrollable factors affecting the blasting production results are also explained including the geological, hydrogeology condition, and geotechnical characteristics of the rock mass [13]. A crucial factor in the assessment of blast productivity has been identified as the estimation of blast fragmentation size [14]. A number of modeling techniques have been developed [17–22] that take both the controllable and uncontrollable parameters into account but less attention had been given to limestone mining production so far [15, 16]. Recently, there has been a significant increase in the use of machine learning (ML) algorithms in blasting operations to increase safety, and production rate despite a prediction gap existing in blast production rate. In addition to limiting production, the presence of large boulders in blasted muck piles raises the cost of basic hauling systems. The majority of the available empirical models and soft computing solutions used to improve blasting results are site- and deposit-specific and challenging for small-scale mining engineers and local miners to understand. Due to their inability to handle the internal complexity in blasting input parameters and lack of focus on limestone formation blasting, these empirical models were generally unsuccessful with limestone mines. This study aims to address the question of "How can the blast production rate in limestone mining be predicted using machine learning algorithms and developed multivariable empirical formula?"A permutation important-based artificial neural network has been adopted in this work for the development of a quantitative model using the blast results obtained from limestone blast production rate in order to address the aforementioned shortcomings of existing empirical models. The model gave sufficient training flexibility to the ANN algorithms through adopted transfer functions to permutate the predicted result to that of other training functions as the training proceeds. The same dataset was also used with multivariate regression (MVR) analysis techniques to create a comparative model as a way of assessing the PI-BANN model prediction performance. The case study mine explosive utilization rate, drilling operation rate, and rock strength property were also examined in the work.

2. Review of Artificial Neural Network techniques Application in Mining Field

As shown in Figure 1, the complexity of various blast design parameter has made the optimization of blast result through explosive quantity adjustment difficult. According to [23], a mining company can increase its rate of rock blast production to extract more material in a pre-determined amount of time through proper adjustment of well-known controllable parameters and explosive properties. This will actually help the mine management to complete the mine blasting process safely, more quickly, and effectively [24]. The development of empirical equations for the prediction of blast fragmentation using machine learning, multivariate approaches, linear equations, and other existing equations are some of the strategies many researchers have adopted to increase mine and quarry blast production rates. The application of the machine learning approach in solving engineering problems employs algorithms to systematically combine data [25].

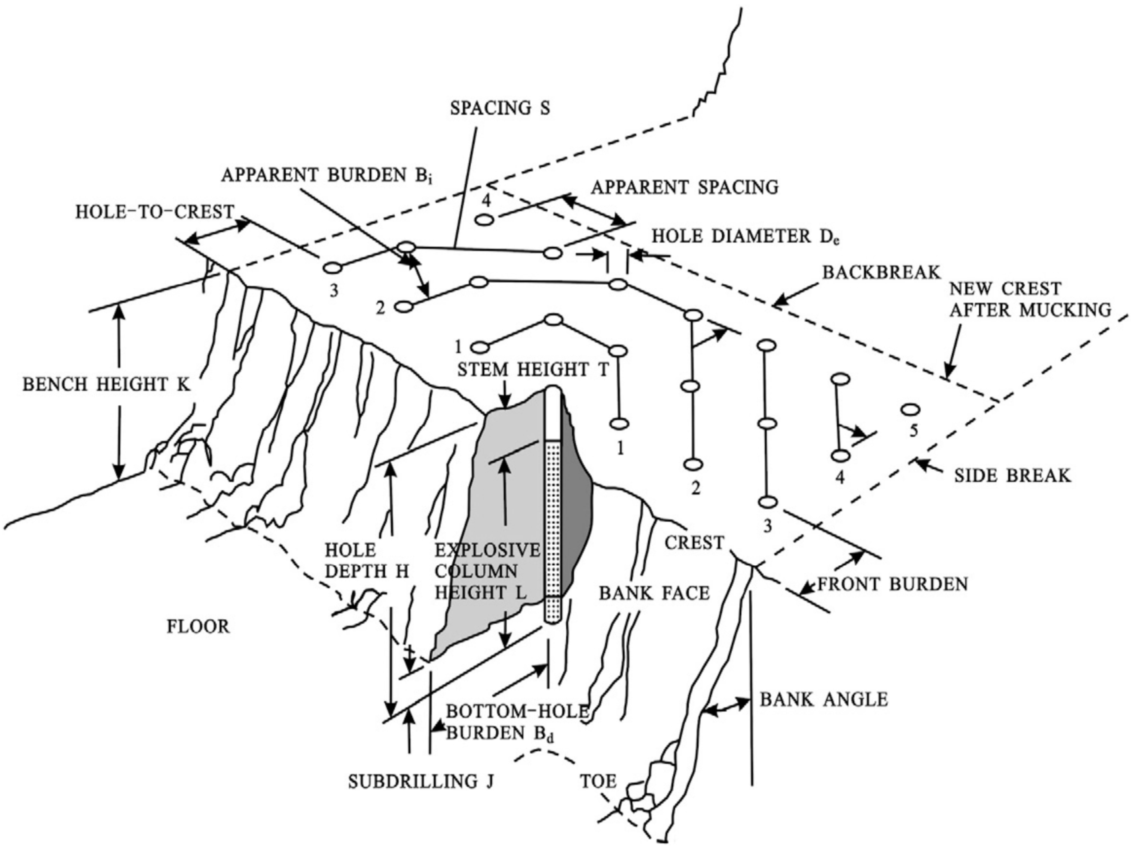


Figure 1. Blast design parameter terminology [17].

For example, artificial neural network modeling techniques tend to mimic human brain neuron working systems [26]. Similar to the neurons in the human biological nervous system, artificial neurons are computational units that depend on supplied memories to actualize general prediction behavior for a set of target predictions [27]. The input, hidden, and output layers, as shown in Figure 2, make up the structure of a typical ANN model. The basic artificial neural network processing units are connected to one another by a large number of weighted connections, which allows a direct communication between each neuron link [28].

Training neural networks had gotten several improvements in the past decade through the development of computer technology. This innovation supported the use of classical theory and machine learning to predict the distribution of rock blasting fragmentation has become more and more common [29]. According to Ouchterlony and Sanchidrián [30], a number of models have been taken into consideration over the years to evaluate and forecast blasting fragmentation.

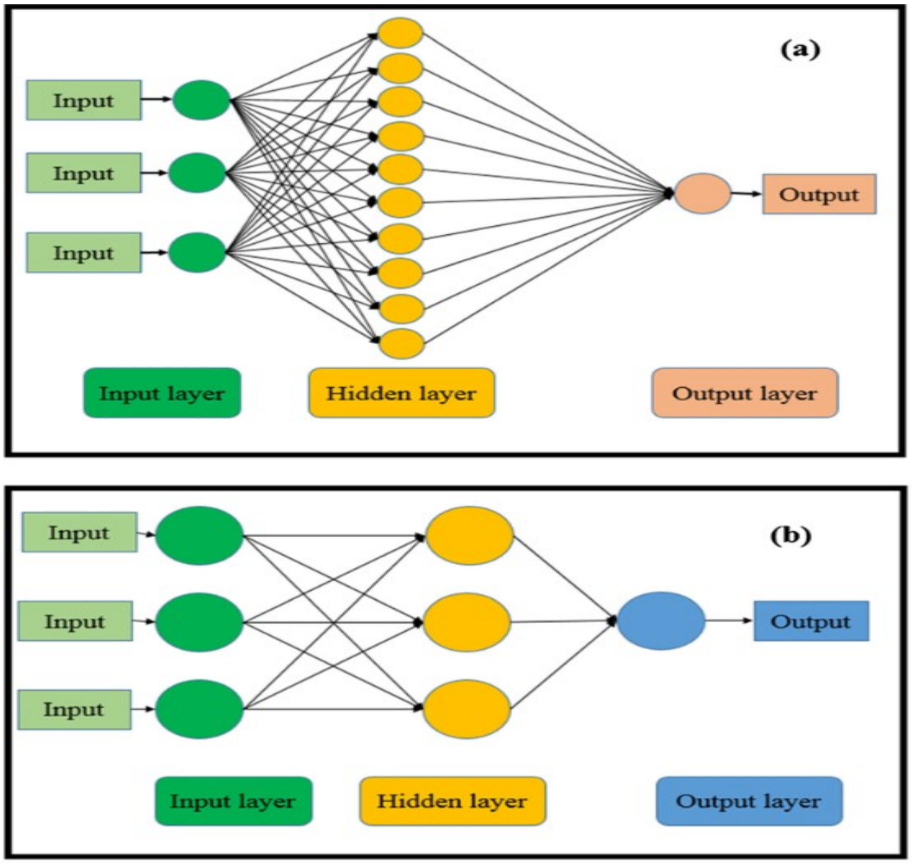


Figure2. Example of artificial neural network model with 3-input and 1-output diagram (a) feed forward neural network (b) radial basis network [39].

Models based on artificial intelligence (AI) are increasingly common among other types of models due to their excellent prediction outcomes for a number of pertinent factors [31]. Table 1 presents some past research works finding about blast fragmentation prediction using various soft computing techniques.

Table1. Recent works on fragmentation prediction using different soft computation techniques.

Input	Output	Technique	Performance	Source
B, S, ST, Q, MC	X_{80}	SVM	R^2= 0.83, RMSE = 1.66	Hasanipanah *et al.* [32]
B, S, ST, Q, MC	X_{80}	ANFIS	R^2= 0.81, RMSE = 1.78	Hasanipanah *et al.* [32]
B, S, ST, Q, MC	X_{80}	PSO-ANFIS	R^2= 0.89, RMSE = 1.31	Hasanipanah *et al.* [32]
D, T, PF, MC		(LMR), (ICA), (ANFIS), and ANN (ANN)	R= 95.6%, RSME= 5.04	Shakeri *et al.* [33]
B, S, ST, PF, MC	X_{80}	SVM	R^2= 0.83	Gao *et al.* [34]
B, S, ST, PF, MC	X_{80}	ANFIS	R^2= 0.81	Gao *et al.* [34]
B, S, ST, PF, MC	X_{80}	PSO-ANFIS	R^2= 0.89	Gao *et al.* [34]
B, S, ST, PF, MC	X_{80}	GPR	R^2= 0.94	Gao *et al.* [34]
MC, B, S, ST, PF, RMR	X_{80}	ICA	R^2= 0.947, RMSE = 1.23	Sayevand *et al.* [35]
B, S, ST, PF, MC	X_{80}	FFA-ANFIS	R^2= 0.98	Mojtahedi *et al.* [36]
Q, B, RMR, MC, ST,S	X_{80}	CSO	R^2= 0.985, RMSE = 0.847	Huang *et al.* [37]
PF, MC, S, ST, B, H	X_{100}	FFA-BGAM	R^2= 0.98, RMSE =1.213	Fang *et al.* [38]

Note: GPR-Gaussian process regression; CSO-Cat swarm optimization; BGAM-boosted generalized additive model; SVM-support vector machine; ICA-imperialist competitive algorithm; ANFIS-adaptive neuro-fuzzy inference system; PSO–ANFIS-the propose ANFIS; RMR-Rock mass rating; Xm-mean particle size (cm); X80-80% passing size (cm); X100-100% passing size (cm) ; S-spacing (m); B-burden (m); ST-stemming (m); PF-powder factor (kg/m^3); Q-specific charge (kg/m^3); MC-charge per delay (kg/ms); H-bench height (m);RMSE-Root mean square error; R^2-coefficient of determination.

Other research works including the prediction of based sediment using different scenarios by Afan *et al*. [39] and the prediction of tunneling-induced ground settlement with the small dataset by Liu *et al*.[40], and prediction of rock mass diggability index by Saeidi *et al*. [41] had shown the diverse application of machine learning application in mining operation improvement. Both [42] and [43] discussed the benefits and drawbacks of ANN in their studies. They noted that ANNs have the ability to handle non-linear data, quickly identify intricate correlations between dependent and independent variables, provide good fitting, and handle noisy data, among other advantages.

They indicated that some of the disadvantages of ANNs include overfitting, becoming stuck in a local optimum, being challenging to understand, and taking a long time to process for large neural networks. ANN as a machine learning technique had been used for mining operation optimization by several researchers in the past decade. In order to predict blast-induced vibration, BakhshandehAmnieh *et al*. used ANN and various linear regression models [10]. According to their research, ANNs' non-linear structure, high degree of flexibility, and low error made their prediction superior to other models and empirical relationships in terms of estimating PPV. When used for model development and for resolving engineering issues, ANN models deliver a good performance and simplicity [44]. ANNs have become more effective as powerful computing hardware has become more widely available. The speed and efficiency of ANNs, which need a lot of computational power to train and run, have significantly increased with the use of specialized hardware such as graphics processing units (GPUs) and tensor processing units (TPUs) [45].Another element is the development of original training techniques and algorithms. Back-propagation, gradient descent, and stochastic gradient descent are some of the more advanced methods for enhancing the training process that has been developed over time. These methods have increased the efficiency and precision of ANN learning, enhancing their capacity to carry out tasks like image recognition and natural language processing. The availability of large datasets and enhanced methods for data collection also contributed to the effectiveness of ANNs as a modeling tool. Due to the fact that ANNs require a large amount of data to learn patterns and make predictions, having access to high-quality datasets also enhanced their performance on a range of tasks. ANNs have generally become more efficient over time due to advancements in hardware, algorithms, and data [46]. Many researchers from around the world have concentrated on using ANN to optimize mining operations and safety as well as improve the performance of current models for the past ten years [28, 45–47]. The blast production rate is anticipated to be significantly impacted by the blast design parameters and blast particle size distribution [13]. With comparisons of the empirical models in the case study of small-scale dolomite quarries, studies like Taiwo [47] described the application of artificial neural networks for the improvement of small-scale dolomite mining in Nigeria. According to the [47] findings, the artificial neural network model gave accurate prediction as compared to the existing empirical models in terms of predicting the mean size of blast fragments. Sirjani *et al*. applied artificial neural networks (ANNs) and statistical models for predicting back-break, a type of ground failure that happens during blasting operations [48]. The burden, spacing, and explosive weight were just a few of the input variables that the authors used to create and train their ANN and statistical models. According to the study's findings, the ANN model was superior to the statistical models at predicting back breaks. The authors also talked about how using the ANN model in blasting operations might enhance safety and lower costs.

3. Field Study and Lab Work

3.1. Field study

In order to fulfill the aim of the research work, a field study at a limestone mine in the Indian state of Chattisgarh's BalodaBaazar district was carried out. From various benches levels in this mine, the blast design and result details including fragmentation images, of two hundred and nineteen (219) blast rounds were captured (3m, 9m, 8.3m, 9.3m, and 8.5m). The blast hole measured 114.3 mm in diameter. The blast hole had a length that varied from 3.0 to 10 meters. SME was used as the explosive and sensitized emulsion as the cast booster for all rounds, which were all drilled in a staggered pattern. By using a 17 and 42-millisecond shock tube system, the blasts were started instantly. In this mine, the following blast design parameters were measured: stemming length (m), blast hole diameter (mm), total explosive (kg), the charge per hole (kg), spacing (m), burden (m), and explosive parameters. For each blast round monitored while blasting in the bench face, the information gathered was used to calculate the powder factor. A suitable camera was used to capture images of the entire muck pile following blasting, which produced rock fragments. The powder factor (kg/m^3) and rock fragmentation particle size distribution of the entire muck pile were calculated using image processing software and blast data. Representative samples were taken from the case study mine for the strength property test using the method of "purposeful sampling" as described by Taiwo and Omotehinse [40]. Each blast round's powder factor was calculated using the general formula given by [47] and shown in Equation (1).

$$KS = \frac{We}{S \times B \times H} \tag{1}$$

where We is the explosive charge weight per hole in kg, B denotes the blast hole burden in m, S represent the drill hole spacing in m, and H is the drill hole length in m.

3.2. Rock strength and specific drilling rate

The uniaxial compressive strength of collected rock samples from each blast round was determined in accordance with the International Society of Rock Mechanics (ISRM) [49]. Each sample was prepared in accordance with the ISRM standard (length/diameter ratio of 2.5-3.0) and subjected to an increasing axial load until failure. Each specimen was loaded axially with spherical seating at a constant rate of stress to failure in 5-15 minutes ISRM [50]. During drilling, the specific drilling rate at the mine was also monitored using a stopwatch. Equation (2) was used to calculate the penetration rate per volume of rock intercepted by the drilling bit.

$$SDR = \frac{DHL}{DT} \tag{2}$$

where DHL is the drill hole length in m, DT is the drilling time in minutes, and SDR is the specific drilling rate in m/min.

3.2. Fragment size analysis using WipFrag software

The complete blast design parameters and explosive parameters were measured in the field prior to blasting the rock. After blasting, a suitable camera was used to capture scaled images of the entire muck pile. As described by Shehu *et al.*, evaluating blast fragmentation supports blast optimization and can be done using several techniques [51]. They also noted that the accuracy of fragmentation methods available varied depending on various factors [51]. The image analysis technique is one of the methods used for fragmentation analysis. This technique is an automated image-based granulometry system that uses digital image analysis of rock photographs and video tape images to determine grain size distributions, according to Maerz *et al*. [52]. To determine the boundaries of each individual fragment, the software employs powerful image analysis techniques [52]. Two different images were obtained from each blast round result (fresh blast picture and during loading). The 219 blast images collected from the case study were imported into the WipFrag software to generate each blast particle size distribution curve. Using both the automatic and manual editing tools, the images were delineated and analyzed. According to Maerz *et al*. [52], the delineated images were manually adjusted in order to obtain the fragmentation distribution curve. Figure 3 displays the blasts 1 and 2 muck piles along with the WipFrag software's analysis distribution curves.

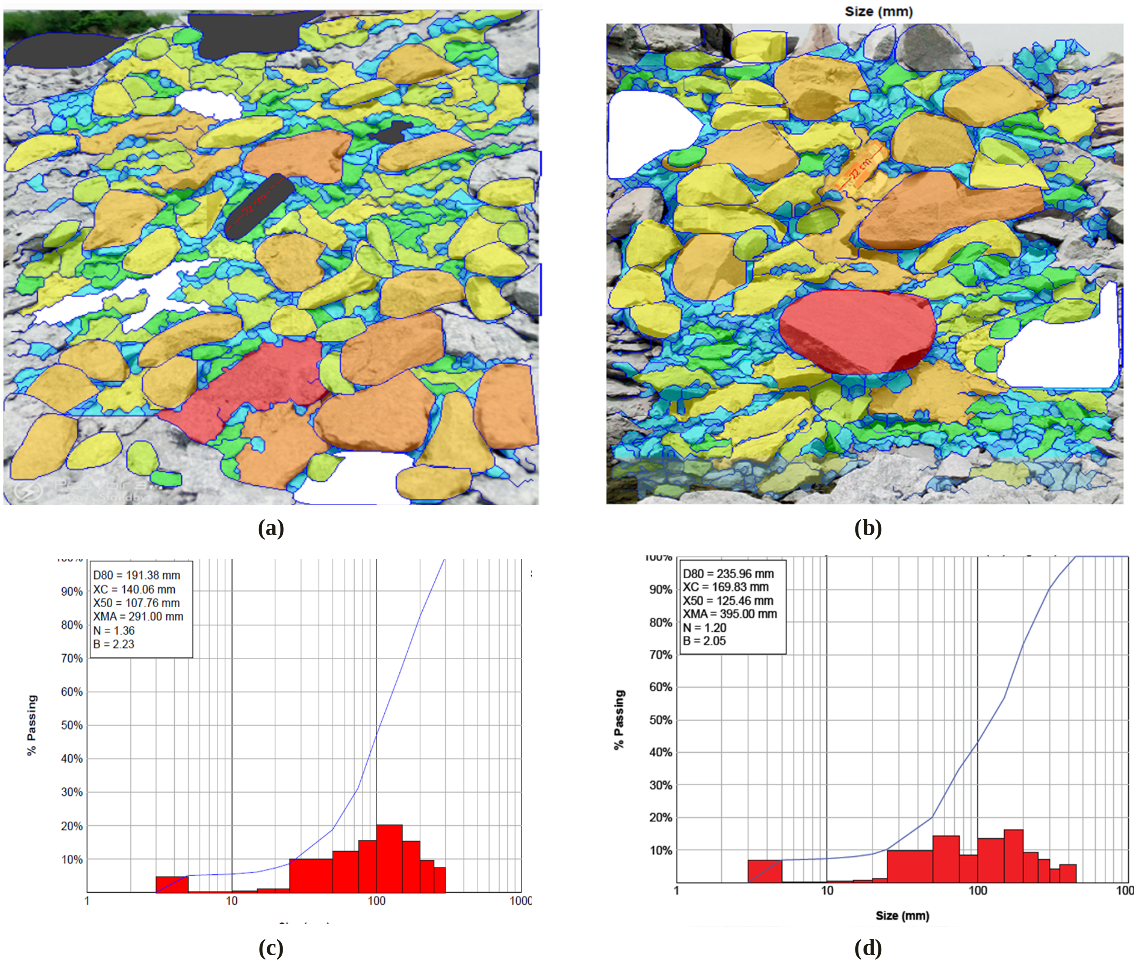


Figure3. Fragmentation analysis result from blasts 1 and 2; a & c show the processed blast image and the fragment distribution curve for blast 1, b&d show the processed blast image and the fragment distribution curve for blast 2.

3.3. Artificial neural network for predictions of blast productivity

The back-propagation BPNN technique was used to train the feedforward ANN for the prediction model proposed in this work. The error back-propagation technique was used in this study during the training iteration to help the network learn more about the relationship between the input and target datasets [53]. Additionally, Chen and Zeng noted that BPNN created a meaningful non-linear connection between input and output neurons through the use of iterative learning, and had the ability to predict dynamic non-linear behavior [54]. In this paper, we used two different transfer functions and permutation importance-based back-propagation neural network (PI-BPNN) algorithms to achieve optimal network training (trainbr and trainlm). Eight input variables including stiffness ratio, burden, spacing, bench height, number of holes, powder factor, stemming, and maximum instantaneous charge were used to predict the mine blasting operation's production rate. To assess the case study mine production rate, the primary crusher's opening size was used with the WipFrag analysis result to determine the percentage size efficient particle size in each blast round result. Based on the size of the crusher opening and the percentage passing size within the primary crusher inlet, the productivity of each blast round was calculated using the WipFrag analysis particle distribution curve. The rating scale for blast productivity ranged from 0% to 100%, with 0% to 35% denoting a poor blasting operation and greater than 35% denoting a superior one. The dataset (eight inputs and one target) was normalized to increase the model accuracy. The datasets were randomly split into three groups before being used to train the ANN model. The ANN model was trained using 80% of the datasets and validated and tested using 20% of the datasets. The MATLAB software was used to create the BPR proposed models. By combining the sigmoid functions for the input and output layers, the ANN model was created. Figure 4 depicts the modeling process used for the created ANN models. The training graphs and architecture information for one of the adopted training algorithms used during the creation of the proposed BPR ANN model are shown in Figure 5. Figure 5a displays the dataset Bayesian regularization algorithm training regression curves. The fitting line displays an 89.0% correlation for the test data for the first training stage, a 92.8% correlation for the combined dataset following optimal training, and a 90.0% correlation for the combined dataset. Many training architectures were taken into consideration in order to find the best performance model. The most accurate model for predicting blast productivity was found to be the 8-6-1 architectural structured neural model.

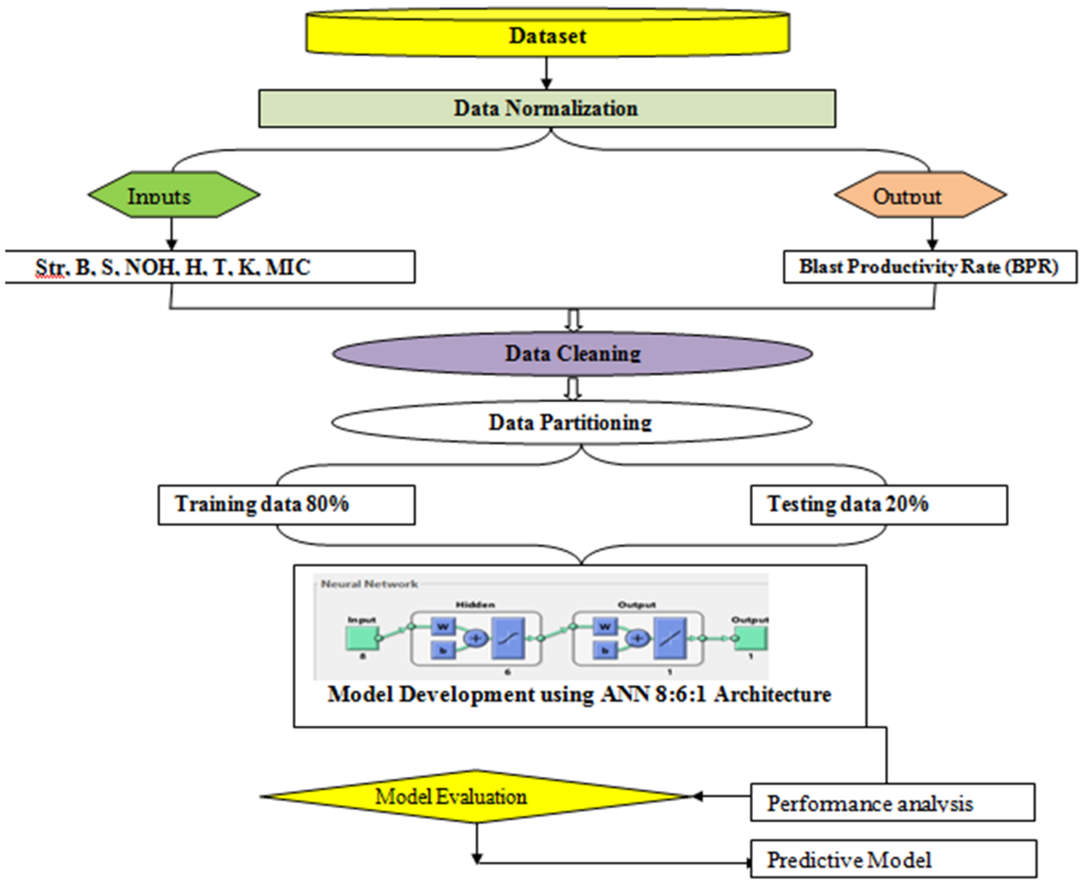
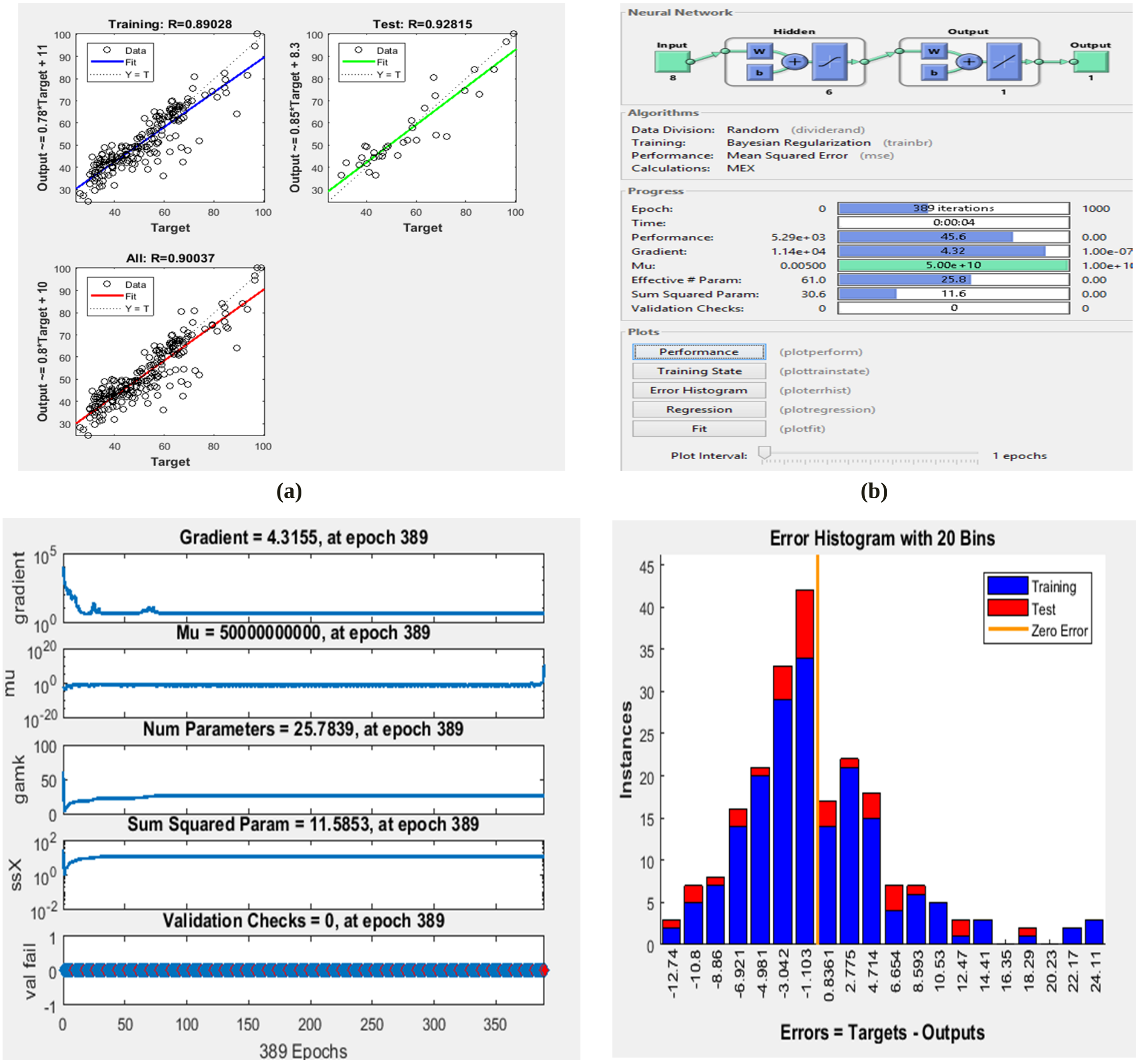


Figure 4. Designing process of ANN model proposed in this study.



(a) (b)

(c) (d)

Figure5. Performance and response of the dataset during the Bayesian regularization ANN modelling a. Training regression curve, b. Model Architecture, c. Training gradient performance, d. Error histogram of the model with 20 bins training property

3.4. Multivariate regression (MVR) for predictions of blast fragmentation efficiency

The MVR modeling approach has been used by several authors including [13], [55-57] to create equations that react to the influence of the dependent variable on the independent variable. The proposed MVR model in this work has one dependent variable and eight independent variables. The SPSS© program was used to develop the proposed blast production rate MVR model. The dependent and independent variable datasets were imported into the SPSS© program in order to perform the necessary modeling analysis, and the regression module tool was chosen from the regression analysis drawdown menu for the analysis.

3.5. Model prediction error determination

The prediction error analysis of the two proposed models (MVR and ANN) was evaluated using root means square deviation (RMSD) and mean bias (MB) Equations (3, 4).

$$\text{RMSD}=\sqrt{\frac{\sum_{i=1}^{N}(Pi-Ai)^{\wedge}2}{N}} \quad (3)$$

$$\text{MB}=\frac{1}{N}\sum_{i=1}^{N}(Pi-Ai) \quad (4)$$

where N indicates the number of datasets, A is the measured value, and P denotes the model predicted value, respectively.

4. Results and discussion

4.1. Rock strength and specific drilling rate

The strength of the case study limestone deposit was determined in accordance to ISRM. The statistic of the blast design parameter and uniaxial compressive strength are presented in Table 2.

The relationship between the blast production result and the rate at which explosives are used, as shown in Figure 6. The findings show that the blast production rate increases with the quantity of explosive charge used. The various results show the scattered responses for different explosive load weights for each blast round. This variation was noted to be caused by rock geology variation at different mine bench levels. Singh and Abdul's findings show a similar trend; their result revealed that productivity of blast results increased as the weight of the explosive detonated per delay increased in the same trend observed in this study [58]. Thornton *et al.* in their study explained such a relationship to be a result of an increase in the energy supply from excessive explosive charges [59].

Table 2. Statistics of the blast design parameter and rock strength.

	Spacing (m)	Burden (m)	Avg B.H(m)	Specific drilling (m/min)	PF	UCS (MPa)	Stemming (m)	Charge per delay	Blast productivity rate (%)
Min	2	2	3	0.15	1.82	64.18	1.7	5.68	26
Max	6.5	4	10	0.35	16.25	64.30	4	80.25	99.2

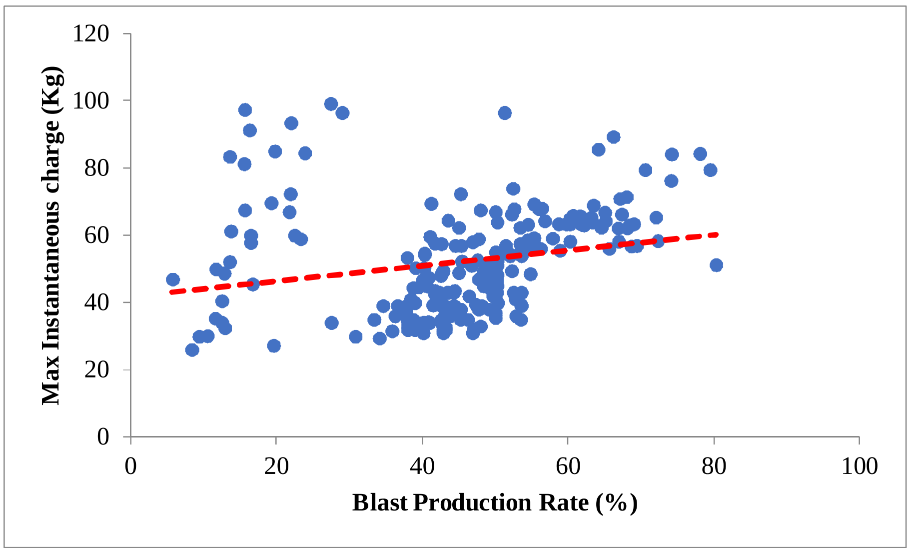


Figure 6. Relationship between blast production rate and the maximum instantaneous charge.

Three main strength descriptions are revealed for the case study formation when the rock's uniaxial compressive strength is compared with the explosive utilization rate. Depending on the blast round being observed, different explosive weight was used in the mine. Based on the uniaxial compressive strength test result conducted, the case study mine rock strength was classified into three major magnitudes 64.15MPa and 64.5MPa, respectively. Figure 7 shows that the explosive charge rate increases as rock strength increases [61, 62]. The explosive consumption rate was noted to increase continuously with high-strength rock benches as explained by Dotto *et al.* work [60]. Likewise, also, the drilling rate at the mine was found to be high for low-strength formations and low for high-strength formations, as shown in Figure 8. This Figure illustrates the specific drilling rate relationship with rock strength. The results of [63], which explain that the rock strength property has a significant impact on blast fragmentation, are supported by these findings.

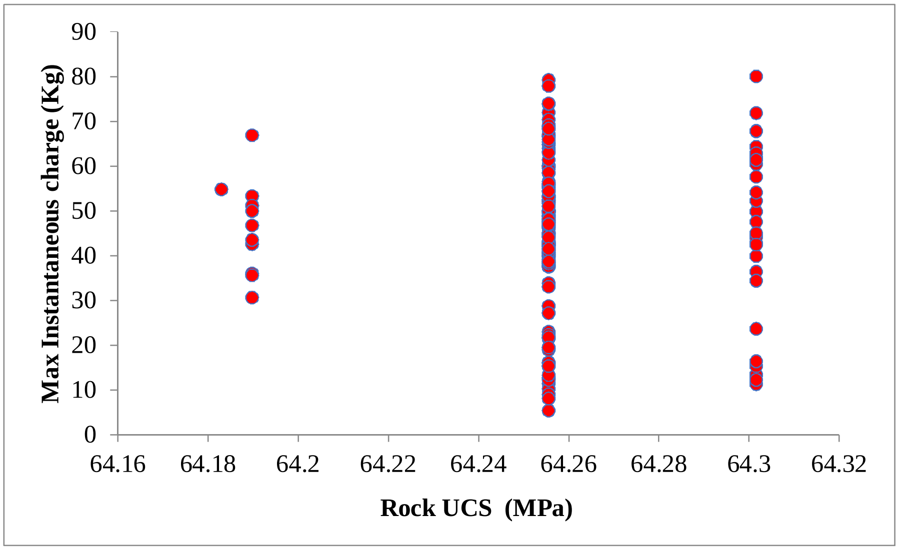


Figure 7. Relationship between rock USC and explosive utilization rate.

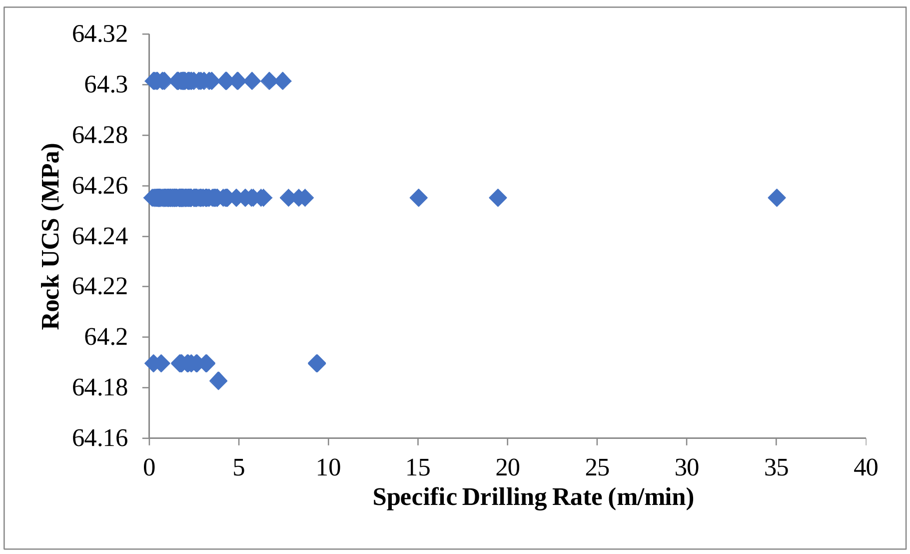


Figure8. Relationship between rock strength and drilling rate.

4.2. Propose developed ANN model

An 8-6-1 architecture and Bayesian regularization were both used for the development of the proposed blast production rate ANN model. The developed model was found to have 90.0% prediction accuracy at the training stage, as shown in Figure 9 after training with the back-propagation (BPNN) and permutation importance-based BPNN (PI-BPNN) algorithms, and 89.0% for the separate testing dataset (see Figure 10). Using the [47] approach, the best ANN model was extracted into useful mathematical equations to support model implementation. A short-code method was used to extract the weight and bias of the input layer, hidden layer, and output layer from the MATLAB optimum model, as shown in Table 3. The model's extracted mathematical expression is present in Equations (5–11).

$$BPR= 36.6\tanh(\sum_{i=1}^{4} Pi + 0.0910) + 62.6 \quad (5)$$

$$X_1=-0.091\tanh(0.023Str+0.026B-0.034S+0.044H+0.001N-0.052K+0.0258T+0.0194MIC-0.0082) \quad (6)$$

$$X_2=0.785\tanh(0.108Str-0.074B-0.177S+0.0448H+0.224N-1.316K+0.601T+0.527MIC+0.1481) \quad (7)$$

$$X_3=-0.9262\tanh(-0.169Str+0.5126B+0.650S+0.276H-0.4642N-1.1275K-0.045T+0.527MIC-0.3615) \quad (8)$$

$$X_4=-0.6806\tanh(0.074Str+0.162B+0.618S+0.231H+0.192N+0.159K+0.6311T+0.274MIC+0.1361) \quad (9)$$

$$X_5=0.929\tanh(-0.073Str-0.384B+0.621S-0.359H-0.1122N+0.523K-0.085T+0.203MIC-0.270) \quad (10)$$

$$X_6=0.766\tanh(-0.130Str+0.582B+0.1733S+0.1931H-0.453N-0.0548K+0.087T+0.3601MIC+0.4828) \quad (11)$$

where BRP is the blast production rate in %, Str is the stiffness ratio, B is the burden in m, S is the spacing length in m, H is the drill hole length in m, N is the number of hole blasted, K is the powder factor in Kg/m^3, T is the stemming length in m, and MIC is the maximum instantaneous charge in Kg.

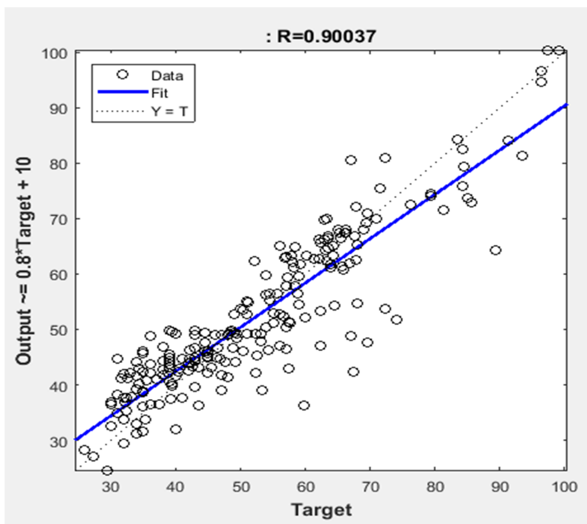


Figure 9. ANN model training regression curve.

Table 3. ANN optimum model weight and bias result.

Hidden layer Bias	**Input layer weight**							
	0.02317	0.02602	-0.03388	0.043943	0.000546	-0.05218	0.025791	0.019367
-0.00823	0.108444	-0.07363	-0.17711	0.04482	0.224339	-1.31645	0.600642	0.527133
0.148103	-0.16942	0.512632	0.650216	0.276471	-0.46423	1.12751	-0.04499	-0.36153
0.413182	0.074215	0.162439	0.618401	0.231364	0.192086	0.15913	0.631095	0.274035
0.136143	-0.07292	-0.38339	0.620613	-0.35956	-0.11219	0.522982	-0.08467	0.203193
-0.26954	-0.12964	0.581564	0.173314	0.193056	-0.45323	-0.05481	0.087053	0.360187
0.482841								
				Hidden layer weight				
Output layer bias		-0.09099	0.785298	-0.92623	-0.6806	0.92914	0.766091	
0.090987								

4.3. Propose developed MVR model

The network connection between the eight input variables was also modelled using multi-variant regression analysis, as shown in Equation (12).

$$Y(X) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (12)$$

Where β_0 is the intercept, β_1, β_2, … , β_n are the coefficients of the regression model, Y(x)is the predictive value, and x_1, x_2,…, x_n are the independent variables.

The proposed MVR model was developed from the analysis result present in Table 4. The coefficient of each parameter as determined by the MVR analysis was extracted into mathematical expression present in Equation (13).

$$BPR=41.534Str+11.33B-2.861S-18.55H+0.004N-3.469K+4.644T+0.649MIC+59.72 \quad (13)$$

where BRP is the blast production rate in %, Str is the stiffness ratio, B is the burden in m, S is the spacing length in m, H is the drill hole length in m, N is the number of hole blasted, K is the powder factor in Kg/m^3, T is the stemming length in m, and MIC is the maximum instantaneous charge in Kg.The developed MVR model evaluation summary is present in Table 5, the model as 74.9% coefficient of correlation and 7.97 standard error of estimation.

Table 4. MVR model coefficients as extracted from SPSS software.

Coefficients[a]						
Model		Unstandardized coefficients B	Unstandardized coefficients Std. error	Standardized coefficients Beta	T	Sig.
1	(Constant)	59.721	91.079		0.656	0.513
	Str	41.534	36.897	1.301	1.126	0.262
	B	11.330	30.662	0.139	0.370	0.712
	S	-2.861	1.392	-0.184	-2.055	0.041
	H	-18.549	12.246	-1.884	-1.515	0.131
	N	0.004	0.024	0.006	0.148	0.883
	K	-3.469	0.632	-.448	-5.493	0.000
	T	4.644	1.795	0.125	2.587	0.010
	MIC	0.649	0.129	0.631	5.025	0.000

a. Dependent variable: BPR

Table 5. Model performance evaluation summary.

Model summary				
Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.866[a]	0.749	0.740	7.97308

a. Predictors: (constant), MIC, N, B, T, K, S, Str, H

4.4. Model error analysis result

The actual field blast production rate results are shown in Figure 10 with the developed ANN and MVR models having coefficients of correlation (R^2) of 89.0% and 81.8%, respectively. Three types of estimation errors including root mean square deviation, the mean bias of the models, and the mean bias of the models were used to assess the performance of the suggested models. The findings of the error analysis conducted for this study are displayed in Table 6. MB and RMSD provide the apparent amount of error in the same unit as the physical quantity that each model calculates. The developed ANN and MVR models were evaluated with a new twenty dataset. The outcome demonstrates that ANN models are more accurate than MVR models in predicting BPR, which highlights ANN's superior prediction efficiency to MVR as also demonstrated in [64]. Although it has been used in a variety of ways, the application of ANN to blast improvement has only been soft computing without extraction of the mathematical equations [65, 66]. Among the two error analysis indices, the ANN model predicts the lowest blast production rate, while the MVR model predicts the highest (Figure 11).

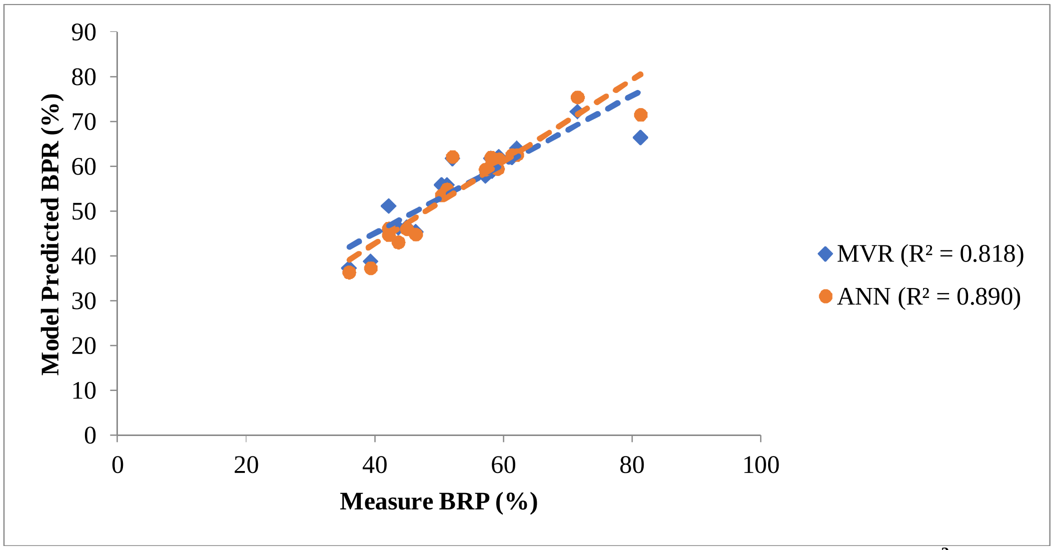


Figure 10. ANN and MVR Model Prediction accuracy evaluation result with R^2

Table 6. Model error analysis.

Models	RMSD	MB
ANN	3.99	1.67
MVR	5.09	2

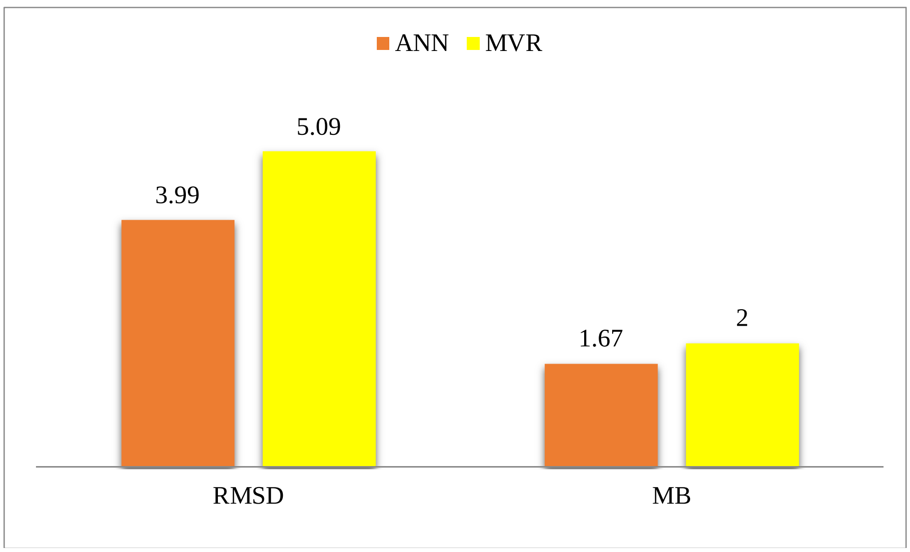


Figure11. Result of the proposed model error analysis.

5. Conclusions

The blasting production rate is the proportion of blasted material that can be fed directly into the primary crusher without further size reduction. By analyzing this trait, mine production can be increased, and blasting costs and overall production costs can be optimized. This work revealed a connection between production rate and the impact of rock strength properties on the use of explosives and drilling rate. The research's conclusions are outlined as follows:

1. The use of explosive in the mine varies depending on the rock strength as examined for all the blast rounds being monitored. The study revealed that blast rounds with 64.15 MPa and 64.5 MPa rock strengths required the highest explosive charge weight.
2. It was determined that for low strength formation, the mine-specific drilling rate was high, and for high strength formation, it was low.

3. In this study, two prediction models were created using ANN and MVR techniques to predict the blast production rate. The coefficient of correlation (R^2) indicates that the two models' prediction performance varies differently. The coefficient of correlation (R^2) for PI-BANN and MVR as checked with new 20 dataset after development are 89.0% and 81.8%, respectively.
4. RSMD and MB error analysis methods were used to assess the prediction error of the two models. The permutation importance-based back-propagation artificial neural network (PI-BANN) has the highest prediction accuracy, according to the error analysis.

The obtained results demonstrate that the proposed artificial neural network models are capable of an accurate prediction of blast production rate when compared to multivariate regression models. The suggested models are therefore suitable, and can be applied to pre-blast design painting. The models' performance demonstrated that the artificial intelligence method is a useful tool for raising the rate of blast production.

The authors' future work will focus on applying numerical modeling techniques such as universal discrete element continua (UDEC) and Fast Lagrangian Analysis of Continua (FLAC) in modeling the effect of geological properties on rock fragmentation and size separation. Moreover, the authors also plan to simulate slope stability using numerical modeling techniques by using fast Lagrangian analysis of continua.

Conflicts of interest

The authors declare no conflict of interest.

Availability of data and materials

The data used in the study are available from the corresponding author on reasonable request.

Ethical statement

Authors state that the research work was conducted according to ethical standards.

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مدل سازی شبکه عصبی مصنوعی به عنوان رویکردی برای پیش‌بینی نرخ تولید انفجار سنگ آهک: مقایسه مدل‌های PI-BANN و MVR

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چکیده:

نرخ تولید انفجار سنگ (BPR) یکی از مهمترین عوامل در ارزیابی عملکرد پروژه معدن است. به منظور بهبود تولید یک معدن سنگ آهک، پارامترهای طراحی انفجار و نتایج تجزیه و تحلیل تصویر در این کار برای ارزیابی BPR استفاده شده است. علاوه بر این، اثر مقاومت سنگ بر BPR با استفاده از نتیجه انفجار جمع‌آوری‌شده تعیین می‌شود. به منظور مدل‌سازی پیش‌بینی BPR با استفاده از شبکه‌های عصبی مصنوعی (ANN) و تکنیک‌های پیش‌بینی چند متغیره، در مجموع 219 مجموعه داده با 8 پارامتر تأثیرگذار انفجار از انفجار معدن سنگ آهک در هند جمع‌آوری شده‌اند. برای به دست آوردن یک مدل با دقت بالا، یک فرآیند آموزشی جدید به نام رویکرد آموزش بیزی مبتنی بر جایگشت مهم (PI-BANN) در این کار پیشنهاد شده است. مدل‌های توسعه یافته با 20 گلوله انفجار جدید تأیید شده و با دو شاخص عملکرد مدل ارزیابی می‌شوند. نتیجه اعتبار سنجی نشان می دهد که نتایج دو مدل به خوبی با سوابق عملی BPR مطابقت دارد. علاوه بر این، در مقایسه با مدل MVR، مدل PI-BANN پیشنهادی در این کار نتیجه دقیق تری را ارائه می دهد. بر اساس پارامترهای قابل کنترل، این دو مدل را می‌توان برای پیش‌بینی BPR در انواع تکنیک‌های حفاری سنگ مورد استفاده قرار داد. نتایج مطالعه نشان می‌دهد که تغییرات مقاومت سنگ هم بر نتیجه انفجار (BPR) و هم بر مقدار مواد منفجره مورد استفاده در هر دور انفجار تأثیر می‌گذارد.

کلمات کلیدی: خردایش سنگ، بهبود انفجار، شبکه عصبی مصنوعی مبتنی بر جایگشت، ارزیابی پیش‌بینی مدل، یادگیری ماشین.