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Article

Design of a Predictive model of a rock breakage by blasting using Artificial Neural Networks

Jimmy Aurelio Rosales-Huamani [1,*,‡], Robert Saenz Perez-Alvarado [1,‡], Uwe Rojas-Villanueva [1,‡] and Jose Luis Castillo-Sequera [2,‡]

1 Multidisciplinary Sensing and Universal Accessibility Group, National University of Engineering, Lima 15333, Peru; rpereza@uni.pe, urojasv@uni.edu.pe
2 Department of Computer Science, Higher Polytechnic School, University of Alcala, 28871. Alcalá de Henares, Spain; jluis.castillo@uah.es
* Correspondence: jrosales@uni.edu.pe; Tel.: +51-1-381-5639
‡ These authors contributed equally to this work.

Abstract: Over the years, various models have been developed in the stages of the mining process that have allowed predicting and enhancing results, but it is the breakage the variable that connects all the activities of the mining process from the point of view of costs (drilling, blasting, loading, hauling, crushing and grinding). To improve this process, we come up with an idea to develop a breakage prediction model; on the basis of the main variables involved in the drilling and blasting process. For this purpose, we design a computer model based on an Artificial Neuronal Networks (ANN), built by using the most representative variables that come into play with drilling and blasting, such as: the properties of the explosives, the geomechanical parameters of the rock mass, and the design parameters of drilling-blasting. For its experimentation and validation, we have taken the data from a copper mine as reference located in the north of Chile, because of we have the dataset of that ore deposit, which is valid and reliable to evaluate prediction problems based on ANN applied to copper mines. The ANN architecture was of the supervised type, feedforward, with 3 layers and 13 neurons in the only hidden layer, trained with the input data using a dataset with the previously mentioned variables, which then were compared with the breakage results. The model was feed backed in its learning process until it becomes perfected, and is a prediction option that can be used in future blasting of ore deposits with similar characteristics using the same representative variables. Therefore, this is a valid alternative for predicting rock breakage, given that it has been experimentally validated, and has achieved moderately reliable results, providing higher correlation coefficients than traditional models, and with the additional advantage that an ANN model provides, due to its ability to learn and recognize compiled dataset patterns. In this way, using this computer model we can obtain satisfactory results that allow us to predict breakage, providing an alternative for evaluating the costs that this entails.

Keywords: artificial neural networks; rock breakage; rock blasting

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1. Introduction

Currently, artificial intelligence is taking a greater role in the various processes of automation. Mining has not been elusive, having developed different models of Artificial Neural Networks (ANN) for prediction in the area of blasting. Within studies published on this subject, we can quote: In (Oraee and Asi), they mention that breakage of the rock after blasting is an important factor in the associated cost of the mine. In the work developed by the authors, they find that the breakage of the rock after blasting is estimated analytically using the neural networks, this study was carried out using the actual data collected from the Gol-e-Gohar iron mine in Iran [1]. In the work of (Kulatilake, Qiong,

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Hudaverdi and Kuzu) they developed a prediction model about rock fragmentation based on artificial neural networks, in order to predict the average size of the particles, resulting from fragmentation in rock blasting. In their work, the authors considered four learning algorithms to train neural network models. The authors concluded that the neural network model obtains greater accurate results than the empirical models [2].

However, the studies by (Shi, Zhou, Wu, Huang, and Wei) mention that, to solve the problems with regard to the inaccuracy in predicting the traditional method of assessing particle size distribution in blasting, Support Vector Machines (SVM) are used to predict the average particle size resulting from rock breakage in blasting. The prediction results using SVM were compared with those of ANN, concluding that the SVM method is quite accurate and provides a new way of predicting rock-blasting breakage [3]. Then in (Gao and Fu), they developed an ANN model to predict the distribution of rock breakage in a Tantalum-Niobium mine achieving satisfactory results, which favored the selection of blasting parameters and an improvement in production [4]. In studies conducted from a limonite quarry by (Sayadi, Monjezi, Talebu and Khandelwal), they compared the application of several Artificial Neural Networks with multivariate regression methods to develop a model for predicting rock breakage based on 103 shot records, concluding that artificial neural networks offer greater accuracy in predictions, these studies were conducted in Tehran, Iran [5]. Then in (Mohamad, Armaghani, Hajihassani, Faizi and Marto), they stated that rock blasting is the most common method of rock excavation in quarries and surface mines. Blasting has some environmental consequences, such as: soil shaking, air gust, dust, fumes and rock. One of the undesirable phenomena in the blasting operation is flyrock, which is a fragment of rock propelled by explosive energy beyond the area of the explosion. The prediction of the distance and size of the rocks thrown is a remarkable step in the reduction and control of blasting accidents in the operations, for this the authors used ANN to predict the distance and size of the rocks thrown in the blasting operations, the results obtained show that this technique is applicable for such prediction, this work was developed in a granite quarry located in Malaysia [6].

Independently (Saadat, Khandelwal and Monjezi) developed a model about Blasting of rocks-induced vibration prediction using artificial neural networks that were compared with empirical and multiple regression analysis models. From this, the authors have got better results of R^2 and Mean Square Error (MSE) using the artificial neural networks model. In their research, the authors used 69 records acquired from an iron mine at Go-e-Gohar, Iran [7]. In Malasya (Marto, Hajihassani, Jahed Armaghani, Tonnizam Mohamad, and Makhtar), developed a predictive model about Fly Rock originated because of blasting in an aggregate quarry. In their research, they applied a combination of Artificial Neural Networks and the Imperialist Competitive Algorithm (ICA-ANN) which was later compared with the empirical models, multiple regression analysis and backpropagation ANN. The prediction model proposed by the authors have got a R^2 higher than the other models [8]. The work of (Enayatollahi, Bazzazi and Asadi), compared 2 methods, using artificial neural networks and regression models in an investigation carried out in the Gol-e-Gohar iron mine, located in Iran. The authors conclude that the results obtained using artificial neural networks in the prediction of breakage resulting from blasting with respect to regression models are quite similar to those of reality [9]. Independently (Dheke, Pradhan, and Jade), they made a synthesis of all the studies carried out with ANN's to predict breakage and concluded that these models have distinct advantages such as flexibility, non-linearity, higher fault tolerance and adaptive learning over regression models [10].

At a gold mine, in Ghana (Tiile) developed an Artificial Neural Network using 180 rock-blasting records in order to predict the following parameters: airblast, blast-induced ground vibration and rock fragmentation. The model proposed by the authors have got the lower mean square error in comparison with the empirical and statistical models [11].

At the Midduk-Iran copper mine Iran (Taheri, Hasanipanah, Golzar and Majid) they proposed a hybrid model for the Blasting of rocks-caused vibration prediction. In their model, they combined the Artificial Neural Networks and the algorithm named Artificial Bee Colony (codename ABC-ANN).

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Artificial Bee Colony (ABC) was used as optimization algorithm to adjust the weights and bias of the artificial neural network, thereby achieving better performance than others models in terms of accuracy and generalization capacity [12]. This evolutionary optimization algorithm was inspired by the social behavior of groups of insects and animals such as swarms of bees, flocks of birds, and shoals of fish [13],[14]. Then in the publication of (Dhekne, Pradhan, Jade and Mishra), they developed an ANN model to estimate the number of resulting rocks from explosions in limestone quarries at one of Indian Province. In their work they taken as a database three hundred explosions carried out in 4 limestone quarries that have a similar geotechnical classification [15].

In a limonite quarry, in Malaysia (Murlidhar, Armaghani, Mohamad, and Changthan) a model hybrid were used based on Imperial Competitive Algorithm and Artificial Neural Network, in order to predict the breakage of rock through blasting, using as a input data diverse blasting parameters and characteristics of the rock mass. With the evaluation of the model mentioned before, the author conclude that the proposed model is quite efficient to estimate the breakage of rocks [16]. Then in Tajareh-Iran (Asl, Monjezi, Hamidi, Armaghani, 2018) developed a predictive model about Fly Rock and breakage of rock using an artificial neural networks model and the firefly algorithm. The authors have got a great performance on their model, obtaining satisfactory results of R^2 and mean square error (MSE) [17].

A study carried out in India by (Das, Sinha and Ganguly) developed a prediction of shaking model for blasting with ANN, taking 248 blast registration from three coal mines with different geological conditions, geomechanical characteristics, blast parameters as well as the distance between the blast point and the shaking monitoring station to predict the Peak Particle Velocity (PPV), obtaining more accurate results than other empirical models [18]. Finally, in (Lawal and Idris) developed a mathematical model based on Artificial Neural Networks in order to predict blast-induced vibrations at a mine in Turkey, taking 14 records to be testing. The authors have got better results of R^2 in comparison with the empirical models of Langefors-Kilhstrom and multiple regression analysis [19].

Based on all the above-mentioned studies, an Artificial Neural Networks (ANN) model of the multilayer perceptron type has been developed for the prediction of rock breakage using blasting. Taking the variables as data base involved in the drilling and blasting design, geomechanical properties of rock mass, explosives; which were the input data and the breakage results P_{80}, P_{50} y P_{20}, defined with 80%, 50% y 20% of the throughput size in the crusher within open pit mine, were used for the output data formation of a network. For its development, Python programming language was used for the design of ANN, also using the gradient descent algorithm. The main reason that led us to conduct this work is the necessity to prove the high level of reliability of ANN, as well as the application of artificial intelligence in the different processes of the mining business. In addition, we will verify the feasibility in the use of single hidden layer in the ANN design, as well as demonstrate the good performance of the model, on the basis of the parameters of rocks, drilling and blasting as data input, to predict P_{80}, P_{50} and P_{20} breakage sizes that in previous studies by different authors was not carried out.

The present work is divided up as follows, in section 2 the theoretical framework to be used, in section 3 we present the methodology to carry out the study, in section 4 we show collection of field data, in section 5 we explain the design and experimentation of the study, in section we show the experimental results obtained and finally in section 7 the conclusions obtained from the present study.

2. Theoretical frame

In rock blasting, rock breakage is one of the operations that requires a prior in-depth analysis. An adequate breakage has to take into account the variables to avoid inconveniences in the subsequent costs of loading, hauling, crushing and milling then it is important to know the variables that take a part in the drilling and blasting process, as well as the properties of the rock mass on which these activities are being performed, this are divided in 2 types of variables:

- Controllable variables: Explosives, Geometric blasting design and Startup sequences.

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- Uncontrollable variables: Geological and Geomechanical characteristics of the rock mass.

These variables are selected in a way that allow us to take advantage of the maximum energy of the explosive to obtain a breakage with which the performance of subsequent processes can be maximized, in other words if the distribution of breakage is controlled, will be obtained a significant improvement in the yields and costs of subsequent operations within the process chain. This is why, drilling and blasting are important in the process and its results such as breakage, Stack shape, bulking, dilution and microfracturing of the rock as they affect the efficiency of subsequent processes such as crushing and grinding, taking into account the environmental impacts that could lead to an adequate selection of breakage size, as can be seen in Figure 1.

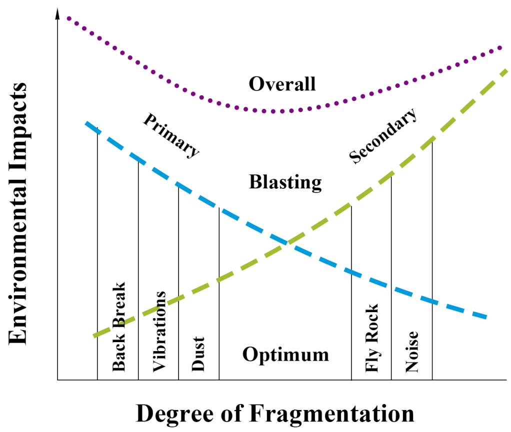

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Figure 1. Environmental Impacts vs Degree of Breakage [20]

In operations where mining is merely moving the ore from one to other place, these processes have allocated budgets and production, in such a its management carried out is aimed at maximizing production at minimum total cost of mining through the cost increase of breakage as shown in Figure 2.

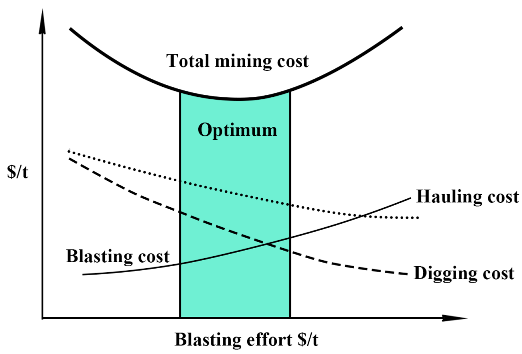

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Figure 2. Operating Costs versus Blasting Costs [21]

In most of mining operations it can be seen that the costs of crushing and grinding are relevant (40% to 60% of the total mine-grinding cost) so it is necessary to redistribute unit operations were they are more efficient and cheaper, such as after finding the most appropriate grain size distribution (through prediction models) commence optimizing of drilling and blasting designs so that the grain size distribution optimizes the performance of the subsequent rock treatment processes this could probably lead to increased drilling and blasting costs if necessary as shown in Figure 3.

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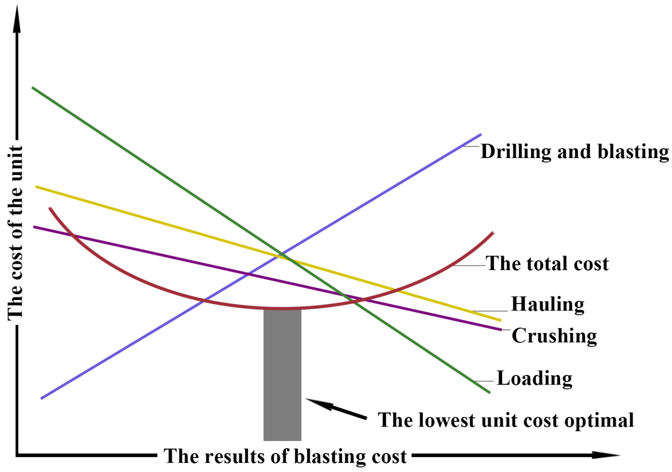

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Figure 3. Unit cost of operations vs blinding costs [22]

Exist empirical models that predict breakage taking into account these variables, such as the Kuz-Ram equation. Theoretically, Artificial Neural Networks (ANN) and Multiple Linear Regression could also be used to predict this breakage.

2.1. Kuz-Ram equation

Cunningham [23],[24] modified the Kuznetsov equation [25] in order to estimate the mean fragment size as well as used the Rosin-Rammler distribution [26] to describe the complete size distribution. The final equation developed by Cunningham is known as the Kuz-Ram model and is shown in the equation 1:

$$X_{50} = A\left(\frac{V_0}{Q_e}\right)^{0.8} Q_e^{\frac{1}{6}}\left(\frac{115}{E}\right)^{0.633} \tag{1}$$

Where:
X_{50}= percentage of passing fragments less than 50%.
A= Rock factor.
Q_e= explosive mass per drill.
E= Relative weight Strength of explosive
V_o/Q_e= volume per kg of explosive.

2.2. Use of the Artificial Neural Network (ANN)

ANNs are composed of many simple interconnected processing elements called neurons or nodes. Each node receives an input signal with information from other nodes or external stimuli, processes it locally through an activation or transfer function and generate an output signal that is sent to other nodes or external outputs as shown in Figure 4. Although a single neuron may seem extremely simple, the interconnection of several neurons that build a network is very powerful.

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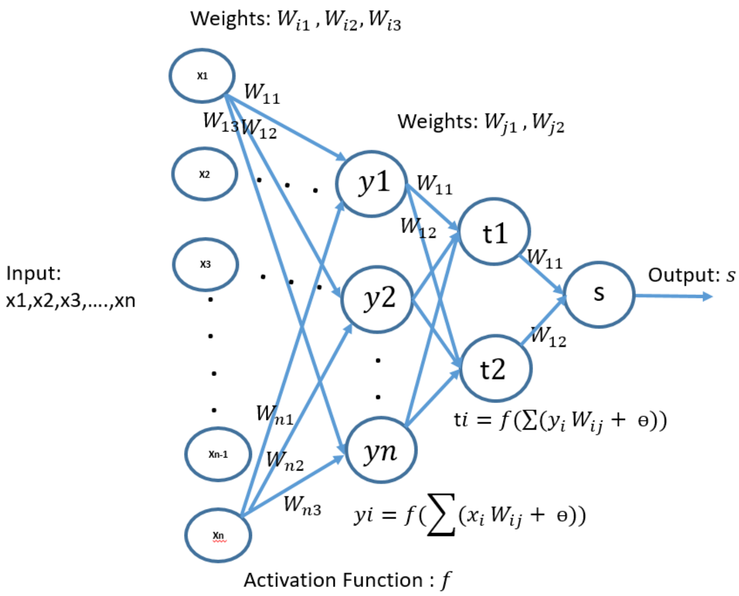

4.png

Figure 4. ANN model

The main advantage of ANN is its ability to incorporate non-linear effects and interactions between model variables, with no need a priori include them, as well as its ability to derive meaning from complicated or imprecise data. Recently, there has been a growing interest in obtaining adequate predictive models at mines. As far as the possible alternatives allows, artificial neural networks are increasing used. In this paper we will use the most common type of ANN trained with Multilayer Perceptron algorithms (MLP).

2.3. *Design of a Feedforward Neural Network (FNN) for the case study*

The correct design of an ANN typically consists on finding out the best configuration of the elements that make up its architecture. In our study, to determine the best architecture, we focus on the number of layers and the numbers of neurons in each layer, establishing the initial weights, the MLP transfer function, and considering previous studies to determine the best training algorithm for this kind of problem.

2.3.1. Number of layers

For this particular case of the mine problem, three layers have been considered as shown in the ANN design in Figure 7.

2.3.2. Number of Neurons in each Layer

The number of neurons per layer has been considered as in Figure 7 shown, that consist of 13 neurons in the hidden layer and one neuron in the exit layer.

2.3.3. Initialization of weight

At initialization, we use random weights that are small enough around the origin for the activation function to work in its linear regime.

2.3.4. Activation function of each layer

We use the sigmoid function, defined by the following expression, as the activation of each layer:

$$S_c = \frac{1}{1+e^{-cx}} \tag{2}$$

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Where:
Sc: Sigmoid function

2.3.5. Training algorithm

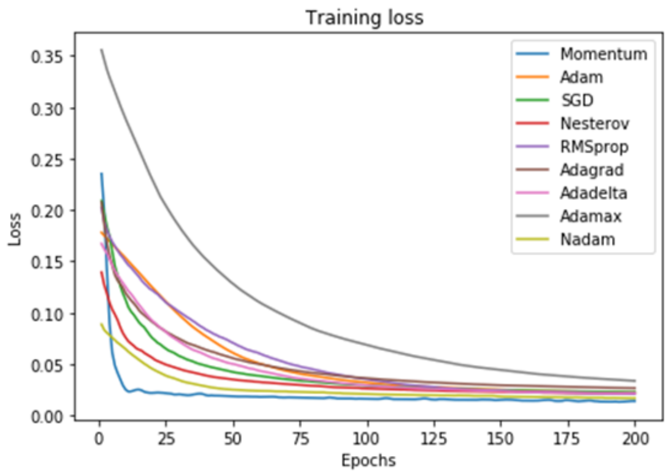
For the training and validation of the designed ANN, several descent algorithms were tested to find the convergence for optimal ANN. According to [27] he mentions that gradient descent algorithms are increasingly popular for performing the neural network optimization. In his study it mentions that there are several algorithms to optimize the gradient descent such as: Momentum, Nesterov, Adagrad, Adadelta, Adam, RMSprop, Adamax, and Nadam.

On that basis, with input data we have made several tests with the mentioned algorithms to find out which one is the most acceptable. The result is that the Momentum algorithm (blue curve) is the most acceptable for our case, as shown in Figure 5, reaching the global minimum with few cycles before the other algorithms.

The Momentum algorithm, which we use, updates its weights through the equation 3:

$$W_{t+1} = W_t - (\alpha W_{t-1} + \gamma \nabla f(W_t, X)) \tag{3}$$

Where:
W_t: Weights
α: usually 0.9
γ: learning rate
∇f: Gradient of the function f



5.PNG

Figure 5. Mean Square Error vs Training Cycles using Algorithm

2.4. Multiple Linear Regression

Multiple linear regression [28] allows the generation of a linear model in which the value of the dependent variable (Y) is determined from a set of independent variables called predictors $(X_1, X_2, X_3 \ldots)$. Multiple regression models can be used to predict the value of the dependent variable or to evaluate the influence that predictors have on it (the latter should be analyzed with caution so as not to misinterpret cause and effect). Multiple linear models follow equation 4:

$$Y_i = (\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni}) + e_i \tag{4}$$

Where:
β_0: is the ordinate in the origin, is the value of the dependent variable Y when all the predictors are zero.
β_i: is the average effect that the increase in one unit of the predictor variable Xi has on the dependent

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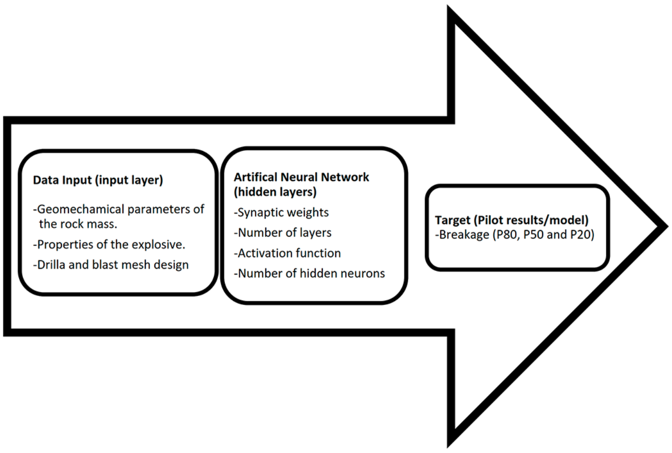
variable Y, holding all else constant. This are known as partial regression coefficients.
e_i: is the residual or error, the difference between the observed value and the one estimated by the model.

It is important to keep in mind that the magnitude of each partial regression coefficient depends on the units in which the predictor variable is measured apply, so its magnitude is not associated with the importance of each predictor. In order to determine what impact each variable has on the model, partial standardized coefficients are used, that are obtained through standardizing process (Subtracting the mean and dividing using the standard deviation) the predictor variables after adjusting the model. Based on the mentioned models and the available data, the study was carried out developing the multiple linear regression and ANN models, because of the data lacked the results predicted by the Kuz-Ram model. In the case of having the data from the Kuz-Ram model, the performance of ANN could be compared with the traditional method.

3. Methodology for the design of the ANN computer model

To achieve our proposal, the following methodology will be used, which consists of several parts and is shown in Figure 6. This methodology consisted in compiling the data from a study which contains the geomechanical parameters of the rock mass, properties of the explosive and design parameters of the drilling and blasting grid. The computer on which the ANN model was developed was in a Toshiba i7 laptop, 2.00 GH, 4GB RAM, Windows 10 operating system, with the Anaconda Navigator graphical user interface (GUI), in the Spyder development environment for Python version 3.6, Python libraries were used to obtain the design, then ANN was evaluated using various descending gradient algorithms [27] to obtain the optimal design and thus validate the results of P_{80}, P_{50} and P_{20} of the model with the actual values contained in the study data and with the statistical parameters obtained from the multiple linear regression model.



6.PNG

Figure 6. Methodology to carry out the proposal

4. Collection of field data

Drilling and blasting parameters, are taken from the study [29], which consists of 47 samples of blasting records made at a mine in northern Chile. These make up the following drilling and blasting parameters: burden (B), spacing (S), bench height (H), cue (T), drilling diameter (D), kilograms of charged explosive (Q), power factor (PF), and geotechnical ore units (Gus) which corresponds to a classification of the rock mass as a function of uni-axial compressive strength, fracture frequency, density, etc. It is worth mentioning that 37 samples were taken for the training of the network and 10 for the respective testing. The following training parameters are shown in Table 1:

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B(m)	S(m)	GU	Density (t/m^3)	Diameter (Inches)	Bench (m)	Overdrilling (m)	Stemming (m)	D. Expl (ton/m^3)	Kg. Expl	Powder Factor (kg/ton)	P_{80}	P_{50}	P_{20}
9.3	10.7	4	2.45	10.625	15	2	6.5	1.3	709	194	83.4	47.2	12.3
9.3	10.7	4	2.45	10.625	15	2	6.5	1.3	709	194	91.8	51	12.81
9.3	10.7	3	2.35	10.625	15	2	6.5	1.3	709	202	86.3	47.9	9.34
9.3	10.7	3	2.35	10.625	15	2	6.5	1.3	709	202	88.3	47.9	9.76
9.3	10.7	4	2.45	10.625	15	2	6.5	1.3	709	194	80.5	44.3	7.9
8	8	5	2.48	10.625	14	0	7	1.2	436	196	74.1	39.9	4.21
8.8	10.2	4	2.45	10.625	15	2	6	1.3	743	225	70.3	38.6	7.61
8.8	10.2	4	2.45	10.625	15	2	6	1.3	743	225	75.6	40.7	8.04
9	12	4	2.45	10.625	15	2	6	1.3	743	187	63.4	37.8	6.7
9	12	4	2.45	10.625	15	2	6	1.3	743	187	80.6	45.6	8.28
9	12	3	2.35	10.625	15	2	6	1.3	743	195	94.4	51.6	14.08
9	12	4	2.45	10.625	15	2	6	1.3	743	187	76.6	45.7	11.89
9	12	4	2.45	10.625	15	2	6	1.3	743	187	86	51	13.42
9	12	4	2.45	10.625	15	2	6	1.3	743	187	82.3	47.8	11.5
9	12	4	2.45	10.625	15	2	6	1.3	743	187	66.2	39.5	8.35
9	12	4	2.45	10.625	15	2	6	1.3	743	187	87.3	49.1	7.8
9	12	3	2.35	10.625	15	2	6	1.3	743	195	71.6	42.2	5.97
9	12	3	2.35	10.625	15	2	6	1.3	743	195	72.3	41.5	4.74
10	13	4	2.45	10.625	15	2	6	1.3	743	155	61.9	37.4	7.07
10	13	3	2.35	10.625	15	2	6	1.3	743	162	60.9	36.8	6.54
10	13	4	2.45	10.625	15	2	6	1.3	743	155	69.5	40.3	5.66
10	13	4	2.45	10.625	15	2	6	1.3	743	155	84	48.1	8.19
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	260.5	135.9	43.6
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	225.9	119.8	37.3
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	237.6	131.6	42.3
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	222.9	118.1	36.8
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	232.1	128.8	41.3
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	216.2	119	37.8
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	236.3	121.3	38.5
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	161	85.1	24.8
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	218.8	127.6	40.8
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	218.5	119.5	37.5
7	8	5	2.48	10.625	15	2	7.5	1.22	663	318	184.4	99.8	30.3
7	8	6	2.57	10.625	15	2	7.5	1.22	663	307	180	103.2	31.6
8.8	10.2	5	2.48	10.625	15	2	6	1.22	768	230	276.6	152.6	54.6
8.8	10.2	6	2.57	10.625	15	2	6	1.22	768	222	234.2	122.9	42.8
8.8	10.2	6	2.57	10.625	15	2	6	1.22	768	222	178.2	85.2	26.1
6	7	6	2.57	10.625	15	2	6	1.22	719	444	194.8	102.7	24.1
6	7	5	2.48	10.625	15	2	6.7	1.22	719	460	140.3	79.8	21.2
6	7	5	2.48	10.625	15	2	6.7	1.22	719	460	272.9	141.7	24.1
6	7	5	2.48	10.625	15	2	6.7	1.22	719	460	192.1	91.8	24.7
6	7	6	2.47	10.625	15	2	6.7	1.22	719	444	314.7	179.3	62.4
6	7	6	2.57	10.625	15	2	6.7	1.22	719	444	348	199	60.3
6	7	6	2.57	10.625	15	2	6.7	1.22	719	444	322.1	179.2	51.6
6	7	6	2.57	10.625	15	2	6.7	1.22	719	444	220.9	108.7	31.4
6	7	6	2.57	10.625	15	2	6.7	1.22	719	444	288.8	152.1	36.1
6	7	6	2.57	10.625	15	2	6.7	1.22	719	444	241.2	127.6	38.5

Table 1. Parameters used in ANN [29]

The variables burden, spacing, mineral geotechnical units, density, stemming, density of the explosive, kg of explosives, powder factor were taken as input variables as well as P_{80}, P_{50}, P_{20} as variables of output, since the diameter and bench parameters remain constant in data collection.

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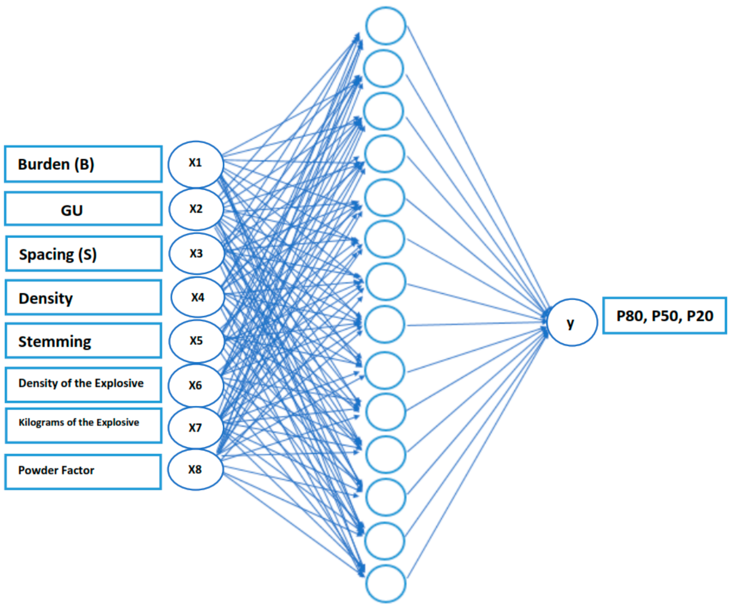
5. Design and Experimentation of ANN

Once the input data is obtained, such as geomechanical parameters of the rock, drilling and blasting design, explosives and the diameter of the breakage using blasting, we design the feed-forward neural network of the supervised type, considering the reliable and representative data avoiding the overfeeding of the ANN in order to achieve the desired learning. In the design of the architecture, we tested the number of layers and neurons that will make the ANN work properly for training using the data in Table1. Figure 7 shows the diagram of the ANN design with a hidden layer.



7.png

Figure 7. ANN Design

To determine the number of hidden layers we used the studies conducted by Cybenko [30] which show that any continuous function can be uniformly approximated by single-layer hidden neural network models. The number of hidden layers and neurons in each layer affect the capacity of the model for generalization, i.e., the accuracy in computing new examples [31]. Therefore, ANN in this work will only have a hidden layer as shown in Figure 7. The number of neurons in the hidden layer is determined based on 2 empirical formulas: Firstly Hecht-Nielsen [32], based on the theorem of Kolmogorov [33], suggests that 2n+1 (where "n" is the number of input parameters) should be used as the maximum number of neurons for a hidden layer of a backpropagation network. Therefore, if the number of input parameters is n= 8, the number of hidden neurons should be N$\leq$17. Finally, according to a second empirical formula of (Ge and Zu) [34], the number of neurons in the hidden layer must satisfy the following condition:

$$\sum_{i=0}^{n} C_N^i > K \tag{5}$$

Where:
$\sum_{i=0}^{n} C_N^i = \dfrac{N!}{i!(N-i)!} > K$
n: number of input parameters= 8
K: used dataset number= 47
N: number of hidden neurons to be determined
Resulting N>8. Therefore: 9$\leq$N$\leq$17.

These N values were used to determine the appropriate functioning of ANN, and to establish its architecture, which was evaluated for each N value, using two parameters; the root mean squared

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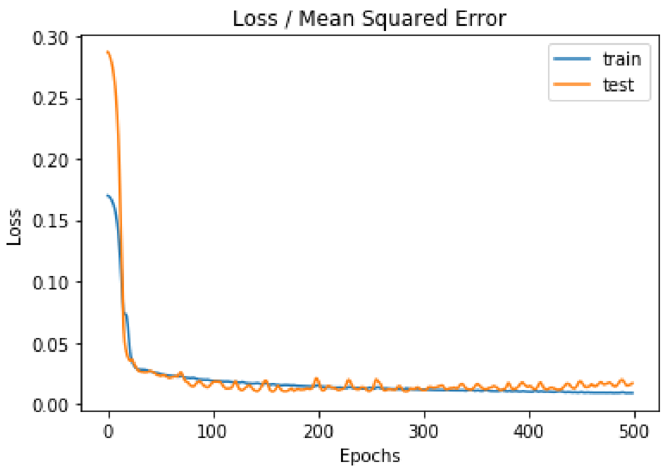
error and the correlation coefficient between predicted and actual values. Figure 6 shows the summary of the ANN design together with the input and output parameters to be obtained.

6. Experimental results and discussion

Once ANN architecture model has been designed, it is implemented, beginning with the training stage and then with the validation of the ANN. Therefore, with the values obtained previously, train then the ANN, minimizing the root mean squared error with the training data and the values of "n" (number of neurons in the hidden layer) using the Descending Gradient Algorithm over a number of 500 training cycles until the error is minimized. Figure 8 shows the root mean square error, which stabilizes as ANN training cycles increase, using the Descending Gradient Algorithm, for both training (blue curve) and testing data (orange curve).



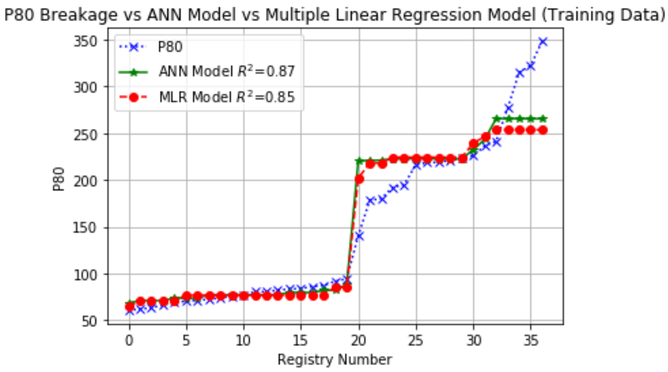
8.png

Figure 8. Root Mean Squared Error vs Number of cycles

Mean squared Error by Number of Simulations									
Number of Hidden Neurons	1	2	3	4	5	6	7	8	Average
10	0.013934	0.010181	0.010772	0.011604	0.013516	0.010188	0.009633	0.014887	0.011839
11	0.014779	0.010263	0.00894	0.0091	0.009728	0.010336	0.011956	0.0098	0.010613
12	0.011681	0.009246	0.009824	0.012855	0.010517	0.011888	0.008056	0.010981	0.010631
13	0.012474	0.011985	0.008593	0.008027	0.008891	0.008518	0.00879	0.00918	0.009557
14	0.009478	0.00777	0.012028	0.008874	0.012441	0.010617	0.010151	0.01007	0.010179
15	0.007212	0.008788	0.009467	0.012912	0.011154	0.00952	0.011585	0.010223	0.010108

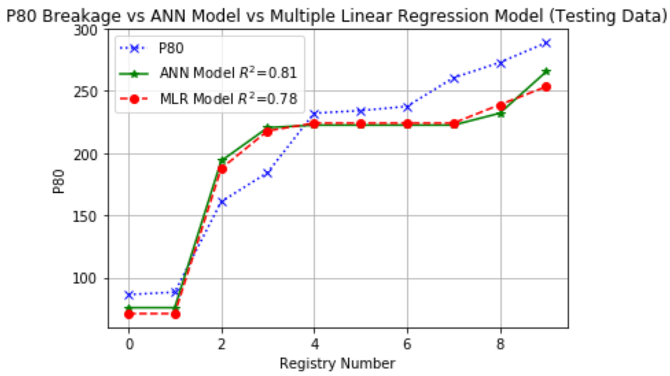
Table 2. Number of simulations vs. hidden neurons

Analyzing Figure 8, and Table 2 gained from ANN simulations, (which presents the root mean square error values for each number of neurons obtained during network training using 500 cycles), it is determined that with n=13 we get a lower root mean squared average error (0.009557). Therefore, we use n=13 in the ANN for the predictions of P_{80}, P_{50} and P_{20}. Then, we proceeded to compare them using training and testing data, and got the following results which we discuss on below:



9.png

Figure 9. P_{80} Breakage vs ANN Model vs Multiple Linear Regression Model (Training)



10.png

Figure 10. P80 Breakage, ANN model (testing)

Figures 9 and 10 show a comparison among the ANN and MLRM models of which, the ANN model depicts a greatest correlation according to $R^2 = 0.87$ and $R^2 = 0.81$ in training and testing respectively, as well as the other statistical parameters of the ANN model take values close to the real P_{80} according to Table 3.

	TRAINING			TESTING		
Statistical parameters	P_{80} (Real)	P_{80} (ANN)	P_{80} (MLRM)	P_{80} (Real)	P_{80} (ANN)	P_{80} (MLRM)
Correlation coefficient R^2		0.87	0.85		0.81	0.78
Mean (mm)	148.1	150.2	148.11	204.61	195.36	193.65
Standard deviation	85.82	80.8	78.98	68.86	61.99	63.27
Coefficient of variation	0.58	0.54	0.53	0.33	0.32	0.32

Table 3. Comparison table real P_{80}, ANN P_{80} and MLRM P_{80} (Training and testing)

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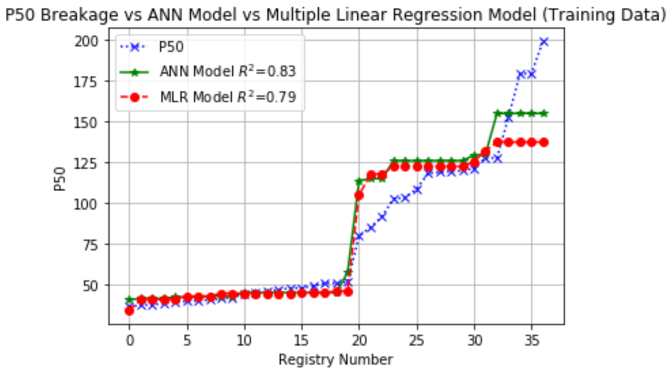
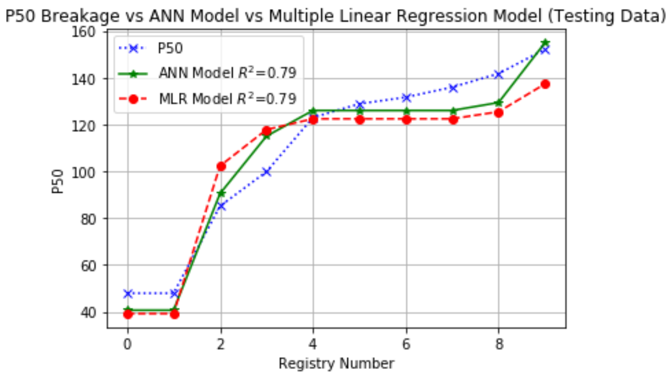


11.png

Figure 11. P_{50} Breakage vs ANN model vs Multiple Linear Regression Model (Training)



12.png

Figure 12. P_{50} Breakage, ANN and MLRM model (testing)

Figures 11 and 12 show a comparison among ANN and MLRM models of which the ANN model depicts a greatest correlation according to R^2 in training and other statistical parameters of the ANN model take values close to the real P_{50} according to Table 4.

	TRAINING			TESTING		
Statistical parameters	P_{50} (Real)	P_{50} (ANN)	P_{50} (MLRM)	P_{50} (Real)	P_{50} (ANN)	P_{50} (MLRM)
Correlation coefficient R^2		0.83	0.79		0.79	0.79
Mean (mm)	81.36	85.03	81.36	109.37	107.47	105.06
Standard deviation	46.53	45.34	41.59	35.87	36.56	33.91
Coefficient of variation	0.57	0.53	0.51	0.32	0.34	0.32

Table 4. Comparison of P_{50} real, P_{50} ANN and P_{50} MLRM (Training and testing)

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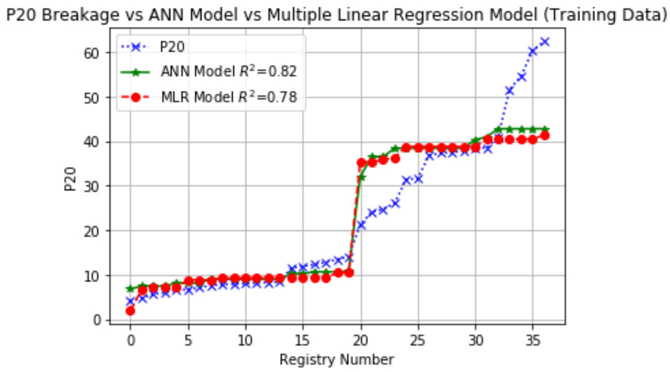
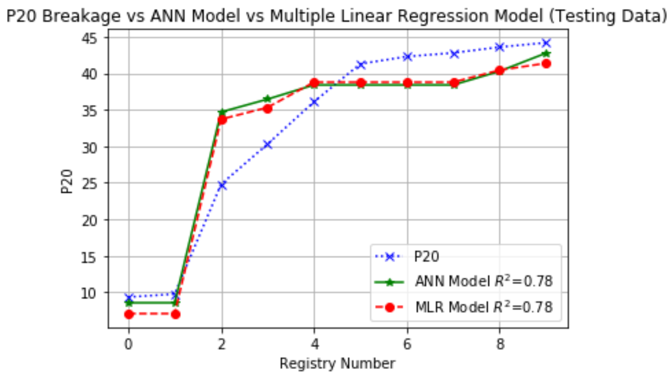


13.png

Figure 13. P_{20} Breakage, ANN and MLR model (Training)



14.png

Figure 14. P_{20} Breakage, ANN and MLR model (testing)

Figures 13 and 14 show a comparison among ANN and MLRM models of which the ANN model depicts a greatest correlation according to R^2 in training, while in testing a R^2 with similar values is shown, good results have been obtained for the prediction of P_{20} according to Table 5.

	TRAINING			TESTING		
Statistical parameters	P_{20} (Real)	P_{20} (ANN)	P_{20} (MLRM)	P_{20} (Real)	P_{20} (ANN)	P_{20} (MLRM)
Correlation coefficient R^2		0.82	0.78		0.78	0.78
Mean (mm)	22.38	22.93	22.38	32.45	32.49	32.01
Standard deviation	17.09	15.27	15.15	12.92	12.13	12.65
Coefficient of variation	0.76	0.66	0.67	0.39	0.37	0.39

Table 5. Comparison of P_{20} real, P_{20} ANN and P_{20} MLRM (Training and testing)

The values obtained from the correlation coefficient R^2 of each studied ANN model (P_{20}, P_{50} and P_{80}) are quite acceptable and the breakage can be controlled in such a way that performance and costs can be improved in the subsequent mining processes such as: loading, hauling, crushing and grinding.

7. Conclusions

On the basis of the results obtained from this study, we observe that using the proposed ANN model, we get a higher coefficient of correlation in the comparisons made with the training data, related to the models used with the testing data, this is mainly due to the sample size. In addition, it is observed that the correlation coefficients in the training models decrease in the comparisons of P_{80}, P_{50} and P_{20} (R^2= 0.87, 0.83 and 0.82), this is due to the fact that the main input variables are focused on the target of P_{80}, and they decrease the effect on the variables P_{50} and P_{20}.

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Therefore, the model obtained is an alternative to the one presented in the paper [29], and shows moderately reliable results. However, it is important to continue monitoring the blasting records to feed the site database and ensure greater representativeness of the parameters in order to that the model has a greater extended further than in its predictions, especially if working with various types of mines with other peculiarities.

In the present study, was considered several training algorithms according to [27], in order to evaluate its performances, the Momentum algorithm was selected because it reaches the global minimum and a marked stability in the root mean square error before the other algorithms.

Concerning to the linear models of the different variables P_{80}, P_{50} and P_{20} it is concluded that their results have a moderate linear adjustment, but it tends to decrease its accuracy when the data testing has a well-marked dispersion. However, the ANN model developed "learned from the data" to obtain a variability very similar to the real data under study.

In future study we expect to validate the ANN model with other real data from different mines and check its efficiency in prediction.

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Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
TLA	Three letter acronym
LD	linear dichroism

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Sample Availability: Samples of the compounds ...... are available from the authors.