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Improvement of Blast-induced Fragmentation Using Artificial Neural Network and BlastFrag© Optimizer Software

Izboljšanje učinka vpliva miniranja na fragmentacijo z uporabo umetne nevtronske mreže in napredne programske opreme

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Abstract in English

The Golden Girl dolomite quarry was selected by the authors to develop predictive artificial neural network (ANN) models and software for optimization of blast fragment size distribution. Blast images from the quarry were analysed using WipFrag©. Seven controllable and two uncontrollable blast parameters, and WipFrag© image analysis results for fifty blasts were used to train ANN models. The reliability of the established models was tested, and the Bayesian regularization algorithm with the architecture of 9-8-3 was found to be superlative. The superlative model was compared with the modified Kuz-Ram model and found to be accurate. The optimum ANN models were translated into mathematical formulas and used to develop user-friendly software called BlastFrag optimizer. The software was validated with R^2 greater than 80% for all models and was found suitable for predicting blast fragment size distribution. The optimized result revealed that percentages for oversize and mean-size fragments were reduced from 68.4% and 418 mm to 27.83% and 101.6 mm, respectively, and undersize fragments increased from 50% to 72.17%.

Keywords: blasting, muck-pile, fragment size, ANN model, Bayesian regularization

Abstract in Povzetek

V članku je predstavljen razvoj napovednega modela z uporabo umetne nevronske mreže ANN (ang. Artificial Neural Network) in programske opreme za optimizacijo porazdelitve velikosti fragmentacije miniranja na primeru kamnoloma dolomita. Slike iz miniranja v kamnolomu so bile analizirane z uporabo programske opreme WipFrag©. Za usposabljanje modela ANN je bilo uporabljenih sedem nadzorovanih in dva nenadzorovana parametra miniranja ter slikovna analiza WipFrag© za 50 odstrelov. Preizkušena je bila zanesljivost modelov. Izkazalo se je, da je bajezijski algoritem z arhitekturo 9-8-3 superlativen. Superlativni model je bil primerjan z modificiranim modelom Kuz-Ram, ki je bil natančen. Optimalni modeli ANN so bili prevedeni v matematične formule in uporabljeni za razvoj uporabniku prijazne programske opreme, imenovane BlastFrag optimizer. Razvita programska oprema je bila potrjena z R^2 večjim od 80 % za vse modele. Ugotovljeno je bilo, da je primerna za napovedovanje porazdelitve velikosti fragmentacije miniranja. Optimizirani rezultat je pokazal, da se je odstotek s preveliko in povprečno velikostjo delcev zmanjšal iz 68,4 % oziroma 418 mm na 27,83 % oziroma 101,6 mm ter odstotek s premajhno velikostjo delcev zvišal s 50 % na 72,17 %.

Ključnebesede: miniranje, odstreljen material, velikost fragmentacije, ANN model, bajezijska regularizacija

Introduction

The profitability of a blasting operation depends on the ability of the mining engineer to produce a fragment size distribution as close as possible to the optimal range for downstream operations. In practical terms, *oversize* is defined as size ranges greater than the crusher's gape and that therefore require secondary breakage before further handling. In hard rock mining strategies, drilling and blasting are the most broadly utilized techniques for fragmenting the rock in preparation for transportation and stock-piling [1]. Sang and Katsuhiko [1] defined an optimal blast as that which yields the predetermined fracture size dispersion by means that are compatible with safety ecological, and financial guidelines. An ineffectively initiated rock blast would most likely end in useless fracture and may create dangerous impacts like fly rocks, ground vibration, air impact, and back break [2]. The presence of boulders in the blasted muck causes problems in production, and additionally increases the expense of hauling. Everything considered, the expense and effectiveness of mucking, stacking, and comminution (crushing and granulating) operations will be profoundly impacted by the outcome of the blasting operation. A few fragmentation-estimating techniques are available [3], some of which incorporate oversized rock count techniques, sieving, visual investigation, and scoop stacking rate as well as picture examination strategies [1, 4–6]. The research reported here uses WipFrag as an example of a picture examination strategy for the investigation of blasting operations. The drilling and blasting activities have huge significance in the productivity of mining operations. The high degree of automation and coordination that define the nature of the production framework embraced in the mining industry require precise planning so that all units work dependably to achieve the projected production targets [7].

Although some efforts have been made to further develop insightful, experimental, and soft computing approaches that would positively impact results [2, 8–9], less consideration has been given to small-scale and artisanal miners whose blast operations depend on the use of pneumatic, hand-held jackhammer drill holes. It is important that more consideration be given to limited, small-scale mine blast design because the generation of oversized fragments during blasting affects the economy and efficiency of the downstream tasks. This can be achieved by using available fragmentation prediction software and models to anticipate the fragment size distribution resulting from a particular set of blasting parameters. However, the cost of buying the available software packages is too high for local mining industries. Therefore, this research was initiated in order to develop a blasting optimization software application that could predict the percentage of oversized, undersized, and mean particle size resulting from a blast.

Materials and Methods

In order to develop the models, blasting data that include controllable and uncontrollable factors related to different blasts were used to cover a wide range of values for the following parameters: burden (B), spacing (S), hole depth (H), drill hole diameter (D), stemming length (T), powder factor (K), uniaxial compressive strength (U), rock density (M), and charge weight (W). A total of 50 blasting operations were monitored in Golden Girl Quarry (10 blasts from Gate axis, 5 blasts from Zack axis, 5 blasts from S.K axis, 21 blasts from Timothy axis, 5 blasts from akakagbe axis, 4 blasts from golden building axis). The quarry is located at the Akoko Edo local government area, Edo state, Nigeria as shown in Figure 1. Blast images were analysed with WipFrag© software. Intact rock samples were collected from blasts using the grab-sampling method. The samples were tested for uniaxial compressive strength and density according to The International Society for Rock Mechanics (ISRM) methods[10]. A database of WipFrag analyses and blast parameters obtained from the monitored blasts is presented in Tables 1 through 3, which will enable general application of the proposed model The data set was trained and validated using ANN and a modified Kuz-Ram model. The generated models were used to develop the BlastFrag optimizer software, which was adopted for the optimization of the Golden Girl Quarry blasting operation.

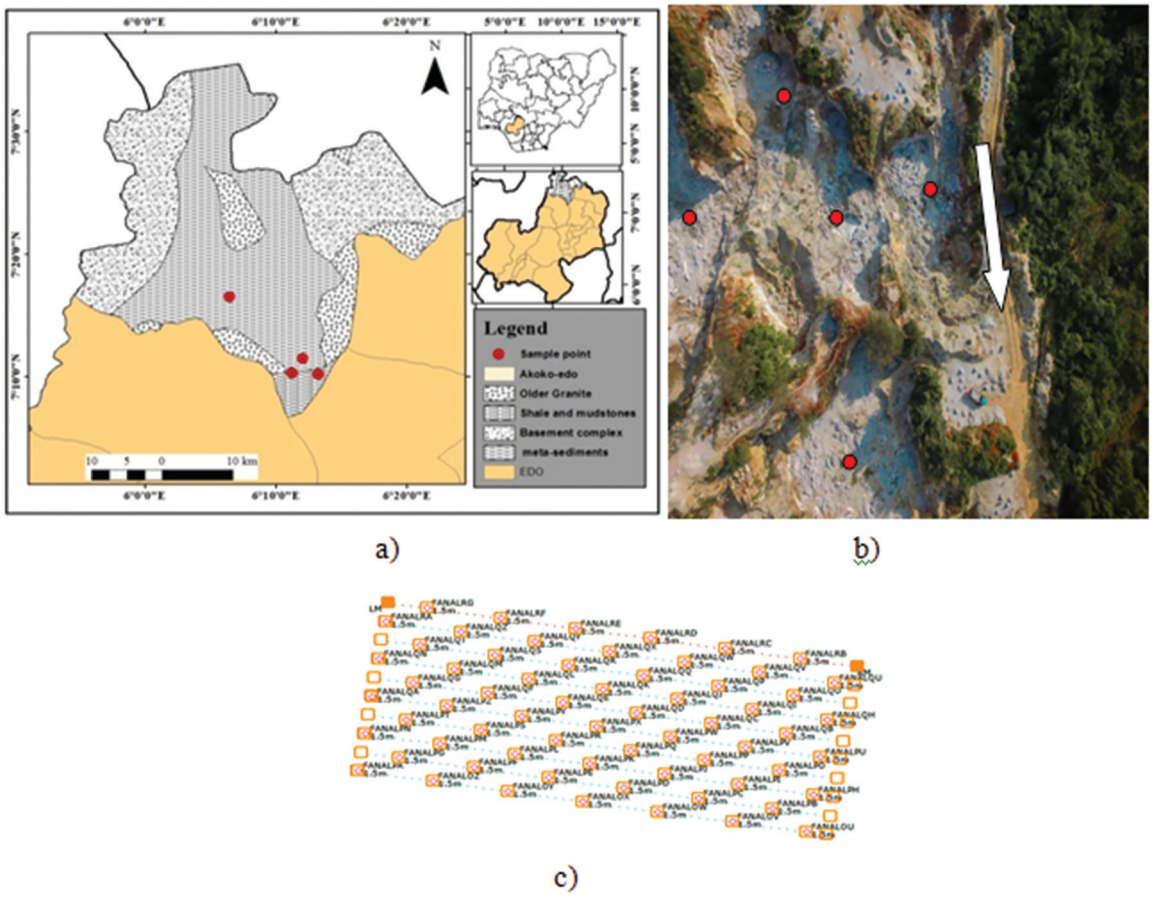


Figure 1: *a) Geological map of Akoko Edo, showing case study area. b) Quarry face showing the sampling points marked with red circles. c) Quarry scheme of the drilling patterns.*

Table 1: *Explosive data and information about the quarry*

Parameter	Pit 1	Pit 2	Pit 3	Pit 4	Pit 5	Pit 6
Charge length (m)	0.65-0.7	0.67-0.76	0.6-0.76	0.6-0.7	0.6-0.78	0.6-0.8
Type of explosive	Dynogel	Dynogel	Dynogel	Dynogel	Dynogel	Dynogel
Density of ANFO (kg/m^3)	820	820	820	820	820	820
Density of explosive (kg/m^3)	1190	1190	1190	1190	1190	1190
Powder factor (kg/m^3)	0.8-0.0.9	0.0.7-0.8	0.5-0.6	0.5-0.86	0.6-1.0	0.7-0.85
RWS	1.45	1.45	1.45	1.45	1.45	1.45
VOD (m/s)	5250	5250	5250	5250	5250	5250
Explosive strength	1.45	1.45	1.45	1.45	1.45	1.45

Rock properties

The rock properties were determined in the laboratory following the method suggested by ISRM [11] and conform to ISRM standards [10].

Fragmentation analysis

In the mining industry, accurate fragmentation measurement can be used to evaluate the behaviour and efficiency of explosive energy

Table 2: *Blast design parameters for the quarry*

Parameter	Pit 1	Pit 2	Pit 3	Pit 4	Pit 5	Pit 6
Burden (m)	0.7	0.82	0.85	0.85	0.7	0.85
Spacing (m)	0.85	0.96	1.10	1.1	1.0	1.1
Hole depth (m)	1.25	1.3	1.35	1.3	1.35	1.35
Drill pattern	staggered	Staggered	staggered	staggered	staggered	square
Hole diameter (m)	0.04	0.04	0.04	0.04	0.04	0.04
Drill hole depth (m)	1.25	1.3	1.35	1.3	1.35	1.3
Stemming (m)	0.65	0.7	0.66	0.66	0.7	0.6
Drilling accuracy	0.054	0.054	0.054	0.054	0.054	0.054
Charge length (m)	0.65-0.7	0.67-0.76	0.6-0.76	0.6-0.7	0.6-0.78	0.6-0.8
Charge weight (kg)	0.96-1.02	0.80-0.95	0.9-1.14	0.8-0.85	0.6-0.8	0.65-0.85
Crusher gap (m)	0.28	0.28	0.28	0.28	0.28	0.28

Table 3: *Summary of the rock characterization of Golden Girl Quarry*

Parameter	Pit 1	Pit 2	Pit 3	Pit 4	Pit 5	Pit 6
Uniaxial compressive strength (MPa)	173.75	178.75	171.25	167.75	168.75	186.25
Joint spacing (m)	0.76	0.26	0.64	0.20	0.32	0.28
Dip direction (^{0})	298	312	260	034	312	064
Dip angle (^{0})	58	30	74	42	48	78
Rock density (kg/m^3)	2804	2790	2886	2760	2860	2800
Young modulus (GPa)	60	75	75	68.5	60	75

released during charge detonation for rock blasting. Maerz and Germain [12] established that fragmentation analysis can be used along with in situ block size to evaluate the productivity of blasting and the accuracy of blasting simulations. It can be used to reduce downstream production costs and to improve the mine production rate [13].

WipFrag system

WipFrag is a picture examination framework for sizing materials, for example, blasted or crushed stone heaps; it has likewise been found to be appropriate for assessing the molecular transport of ammonium nitrate prills, glass dabs, and zinc concentrate for an accurate fixation measurements. WipFrag estimates 2-D net and reproduces 3-D dispersion utilizing the standard of geometric likelihood [14]. Maerz [15] established that WipFrag is a state-of-the-art, image-based granviometry system designed primarily for high-contrast graytone images, despite the fact that it can also evaluate hued prints. Pictures are uploaded to the software, which changes the picture into a parallel picture comprising a net of square diagrams as displayed in Figure 2b. Fifty blast images were collected using after-blast image capturing with a scaling object in place (0.5 m by 0.5 m, white helmet and 1 m by 1 m frame as shown in Figure 2a. Maerz et al. [16] established three analysis methods using WipFrag, including basic, calibrated, and zoom merge methods. The zoom merge method was recommended by Maertz et al. [16] as accurate and was used in this paper for blast image analysis.

The WipFrag analysis as shown in Figure 2c was performed for each blast using the case study primary jaw crusher gape size as the base limit to calculate the percentages of undersized and oversized fragments with "undersized" defined as fragments that pass through the gape and "oversized" being fragments that are retained without passing through the gape.

Artificial neural network model development

Artificial neural networks (ANNs) are systems modelled on the human brain that attempt to simulate the functioning of the human cerebrum and sensory system. Simpson [17] defined ANNs as computational models inspired by natural neural organization that are used to assess large amounts of information with complex interactions, that is, structured as networks rather than as linear interactions. Construction of an ANN has three major components: transfer function, network design, and learning law [17]. Kosko [18] explains that ANNs are created from calculations based on natural standards. Execution of the ANN network model relies upon the neuron connections and network's architecture [19], which can be designed with neurons connected in multiple ways. The adoption of the feed-forward approach was suggested by Shahin et al. [20] to solve extremely nonlinear dependent parameters that are not involved in the input variables. The multilayer perception (MLP) neural network is a well-recognized feed-forward ANN [8, 17, 21]. The neuron connection technique has several nodes in three layers (the input layer, the hidden layer, the output layer) all connected by weights and bias as shown in Figure 3.

Training of the network was trained using Levenberg-Marquardt back-propagation and

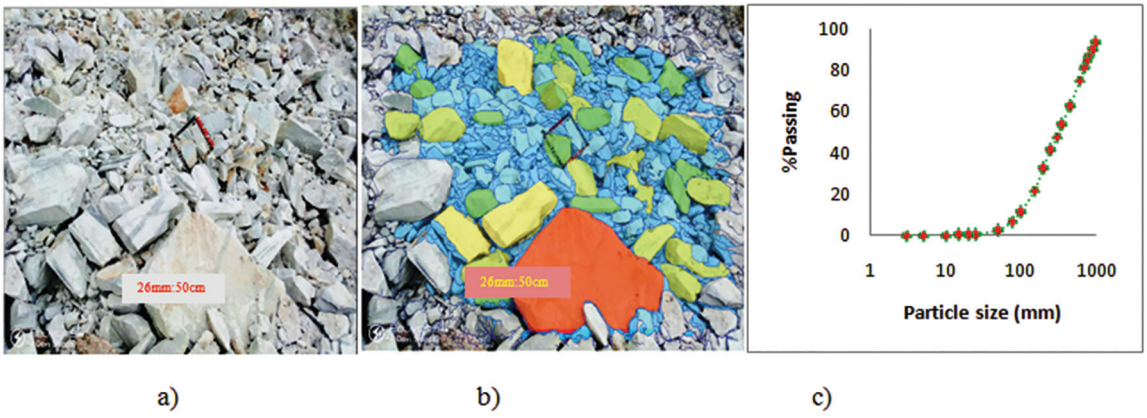


Figure 2: *a) Blast image with 1 m by 1 m scaling frame and image scale, b) Delineated image with scale, and c) WipFrag result particle size distribution curve.*

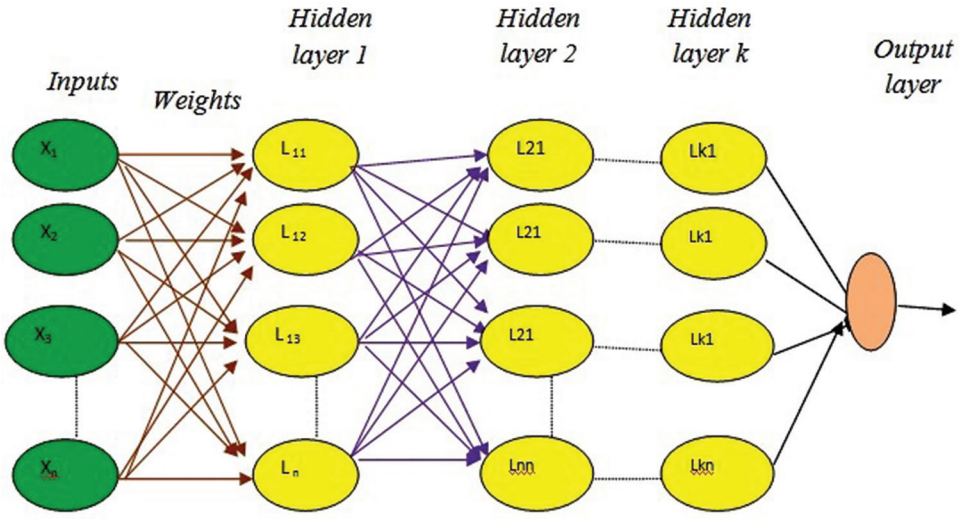


Figure 3: *ANN connection network structure.*

Table 4: *Input parameters and their symbols*

Parameter	Symbol	Range	Parameter	Symbol	Range
UCs	U	160–186.25Mpa	% oversize	Q	23.3%–70%
Density	M	2800–2886 kg/m^3	% undersize	Y	32%–72.1%
Spacing	S	0.8–1.1 m	Mean size (mm)	V	220%-–480 mm
Hole depth	D	1.25–1.35 m			
Stemming length	T	0.6–0.7 m			
Hole diameter	H	0.04 m			
Powder factor	K	0.6–1.0 kg/m^3			
Charge weight	W	0.6–0.96 kg			
Burden	B	0.7–0.85 m			

the Bayesian regularization algorithm. The Levenberg-Marquardt back-propagation algorithm ordinarily takes more memory yet less time. Training ends when speculation stops improving, as demonstrated by an increase in the mean square error of the approval tests. The Bayesian regularization algorithm ordinarily takes additional time but can result in good generalization for troublesome, small, or boisterous, datasets. Training ends as indicated by versatile weight minimization (regularization). Equation (1) shows the general form of the principle of operation of the ANN model as noted by Lawal et al. [22].

$$p_j = f_{sig/purlin}\left\{ b_0 + \sum_{k=1}^{n}\left[f_{sig}\left(b_{nk} + \sum_{i=1}^{m} w_{ik}\,\Gamma_i \right)^{wk\times\ldots} \right] \right\} \quad (1)$$

where, n is the number of neurons in the hidden layer; b_{nk} is the bias in the k^{th} neuron of the hidden layer; b_0 is the bias in the output layer; w_k is the weight of connection between the k^{th} of the hidden layer and the single output neuron; w_{ik} is the weight of connection between the i^{th} input parameter and the hidden layer; Γ_i is the input variable i; p_j is the output variable; and f_{purlin} and f_{sig} are the linear and nonlinear transfer functions, respectively.

The datasets required for the ANN training in this research were extracted from fifty blast operations traversing six distinctive selected pits at the Golden Girl Quarry situated at Akoko, Edo State, Nigeria. Nine input and three output parameters were utilized for the ANN training. The proposed ANN models were created on MATLAB© version R2017a utilizing Bayesian regularization and the Levenberg-Marquardt back-propagation training algorithm. Eight different ANN models were used for the prediction of percentage of oversize, undersize, and mean-size fragments. The input data considered for the research are presented in Table 4 and are made up of those parameters that are generally sensitive to the output. Nine input variables representing U, M, S, D, T, H, K, M, and B were utilized in each model. A three-layer Bayesian regularization algorithm—defined by nine input layers, eight neurons, and three output layers—was selected for building the proposed ANN models. A three-layer neural network was used to predict rock percentage oversize blast materials and percentage undersize blast materials because of its ability to accommodate large amounts of input data and its capabilities for solving vastly complex problems.

Results and Discussion

ANN models for the prediction of blast fragmentation size distribution

According to the training performance for different ANN network architectures and training algorithms, the Bayesian algorithm takes more time in data training as compared to the Levenberg-Marquardt algorithm. In order to determine the optimal ANN network architecture, mean square error (MSE), root mean square error (RMSE), maximum relative error

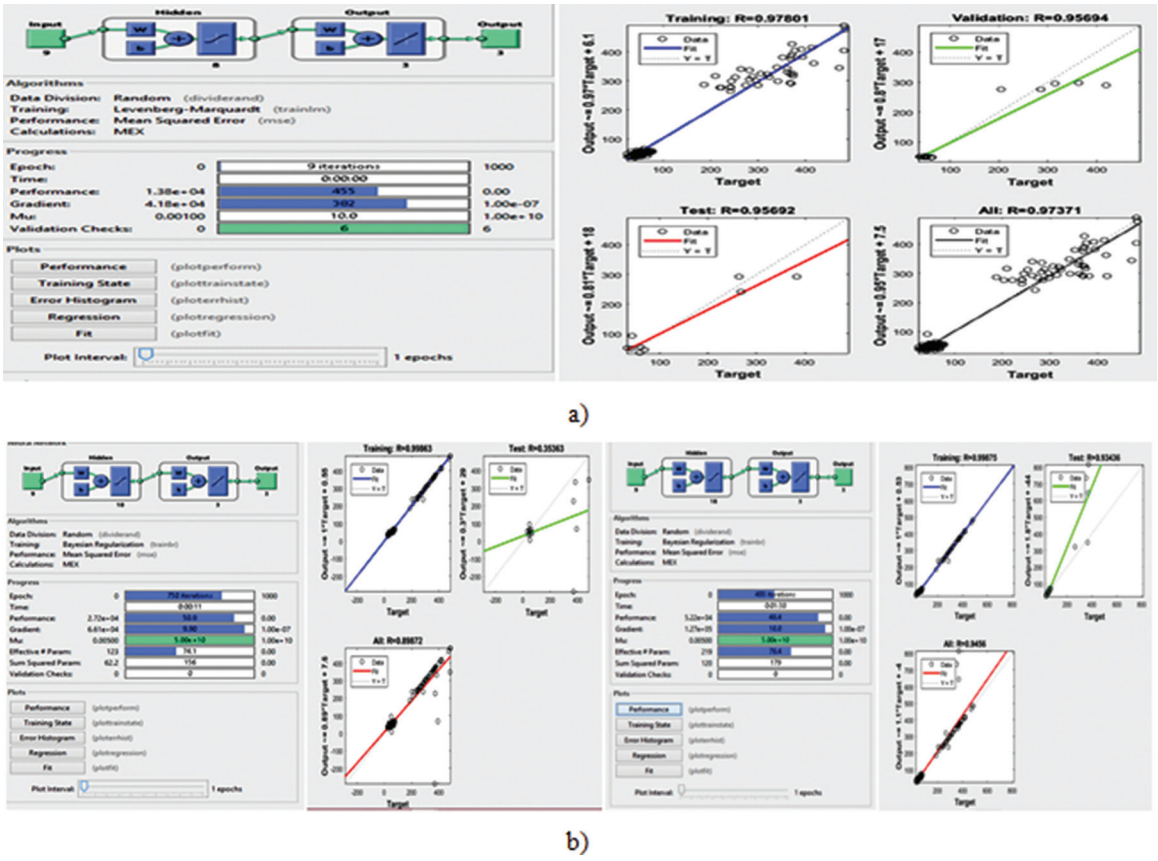


Figure 4: *a) Levenberg-Marquardt models architecture and network regression curves, b) Bayesian regularization algorithm models architecture and network regression curves.*

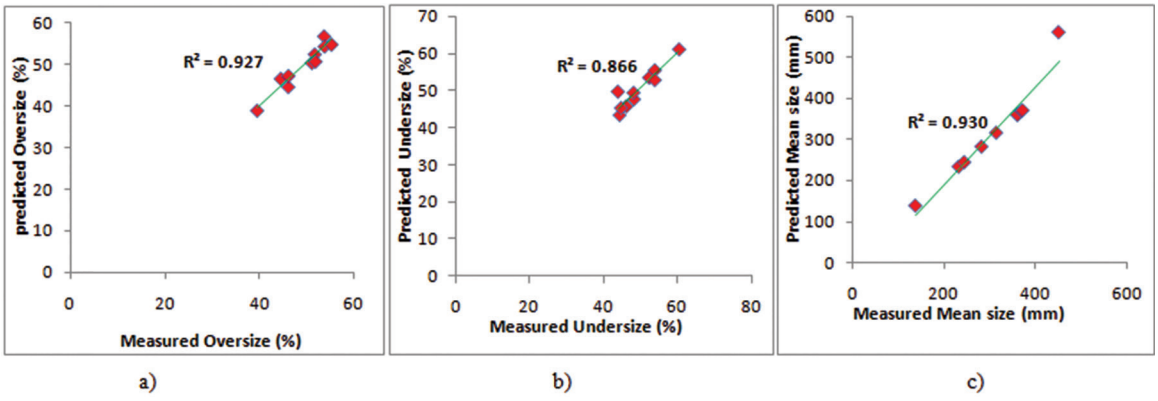


Figure 5: *Relationship between predicted and measured a) percent oversize; b) percent undersize; c) mean size using ANN.*

(MRE), and determination coefficient (R^2) were determined as described by the literature [23–25] for the various models.

The various algorithm performances were analysed using statistical tools, and the trained ANN regularization algorithm models made predictions with the highest accuracy. Figure 4 shows that the R-value for the model training, validation, and test is above 90%. Therefore, the proposed ANN model can successfully predict the blast fragmentation percentage for oversize, undersize, and mean-size fragments. The optimum models were validated with ten datasets. Figure 5 shows the model validation

results, the correlation between predicted and measured outputs for the three outputs (percentage oversize, percentage undersize, and the mean size) provided a high coefficient of determination (R^2) of between 87% and 93%, making the proposed models suitable for the prediction of blast fragmentation size percentages.

The proposed models were transformed into mathematical expressions through the weights and biases based on the ANN general equations presented in Equation (1) in order to enable the easy application of the proposed ANN models for the prediction of blast fragment particle size distribution. The mathematical models obtained for percentages of oversize, undersize, and mean size are presented in Equations (2-4). The proposed model equations were used to develop a software application called the BlastFrag optimizer.

The software requires that the user input the nine input parameters; it then predicts the possible output for the given data and optimizes the supply data using the basting rule of thumb using the Langford blasting formula. Figure 6 shows the software user display interface, the programming code of the software. The predictions obtained directly as outputs from the ANN models and those from the BlastFrag optimizer software were compared to validate the mathematically transformed ANN as shown in Figure 7. It was found that the coefficient of determination for the software is 100%, indicating that the proposed equations are replicates of their respective ANN models.

$$Q = 11.55\tanh\left(\sum_{i=1}^{8} Xi - 0.1603\right) + 45.415 \quad (2)$$

Where;

X_1 = -1.264[tanh(-0.9371+0.5511U+ 0.2418M-1.6908S+3.2295H+1.2932T- 0.92D-1.6066B+……+1.3196W+1.601K)]

X_2 = 1.1026[tanh(0.1053+0.9892U+ 0.5419M+1.3026S-0.5298H- 1.3373T+ 0.6678D-1.0059B+…… .2.5979W+0.4762K)

X_3 = 1.73[tanh(-2.214+0.4549U-0.3531M+ 1.0911S+1.9649H+2.7928T-0.8829D- 0.1656B+…….+0.4334W+0.8929K)]

X_4 = -1.9205[tanh(-0.511-1.1043U- 1.2781M-4.1108S-1.8184H- 1.6006T.0,5101D+2.2472B+...- 1.0147W+1.3332K)]

X_5 = -1.1692[tanh(0.8712-0.5419U+ 0.1954M+3.0582S-1.1224H- 0.0046T+0.1026D-0.8198B+.....- 1.3481W-1.368]

X_6 = -1.5332[tanh(-0.6763+0.204U-1.5771M+ 0.3394S+1.4095H-1.9506T-1.17056D- 1.9912B+...-0.8562W+0.4285K)]

X_7 = -1.2113[tanh(0.407+1.2402U+0.1091M+ 0.8108S-0.1397H+0.1418T+0.1424D- 0.6376B+...+1.3727W-0.2674K)]

X_8 = -1.1239[tanh (0.2348+3.5206U +0.338M+ 2.3944S+2.102H+1.0452T+0.0895D+3.43 36B....+1.5461W-1.6191K)]

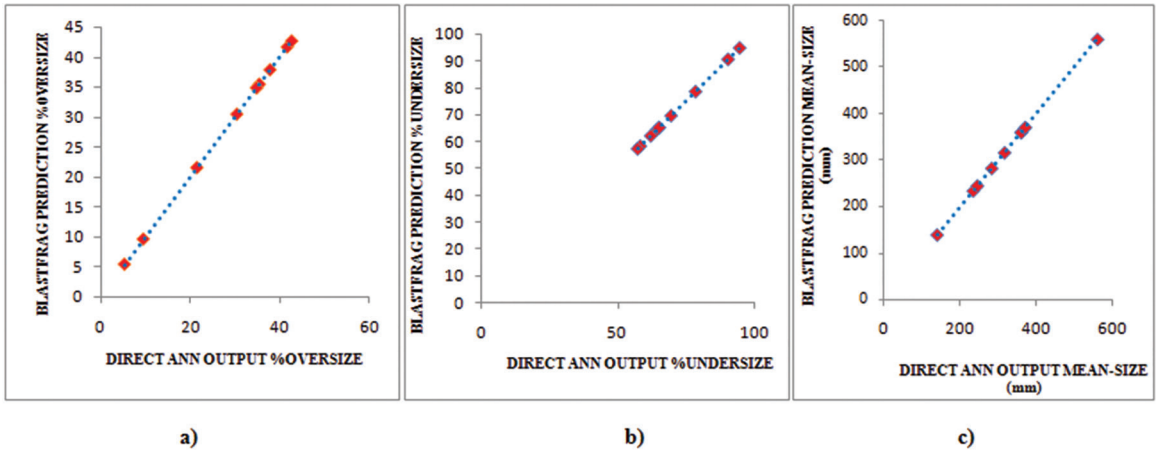


Figure 6: *Comparison of the ANN simulation input with the software (a) %oversize; (b) %undersize; (c) mean size.*

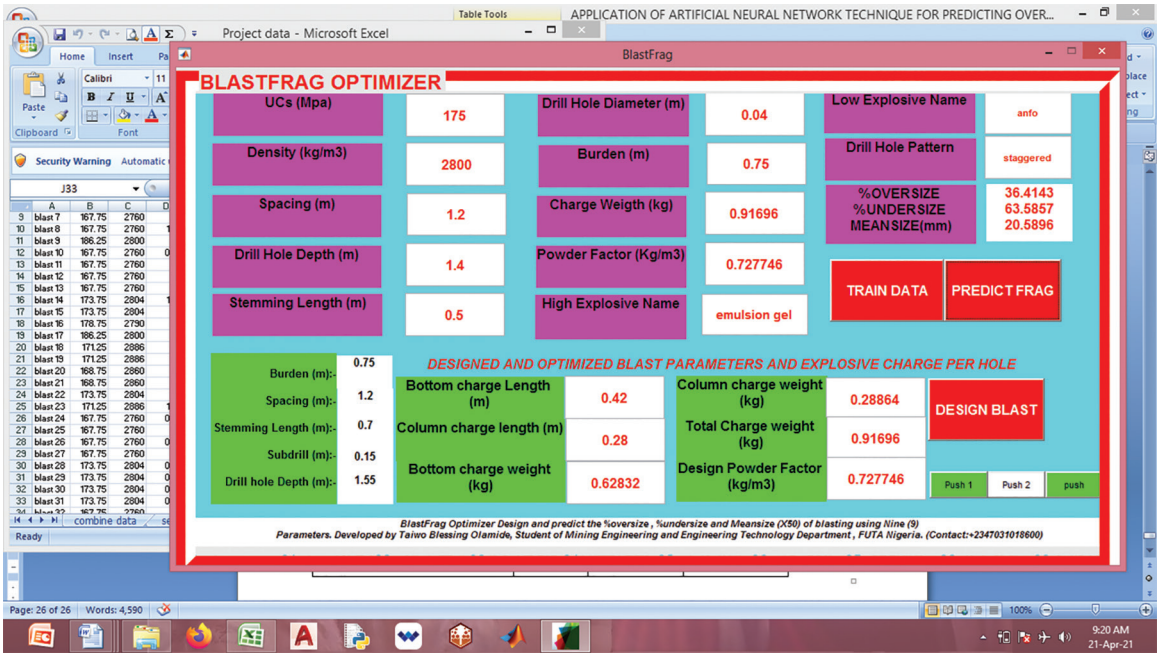


Figure 7: *BlastFrag optimizer user interface.*

$$Y = 23.105\tanh\left(\sum_{i=1}^{8} Xi + 0.1603\right) + 69.52 \quad (3)$$

Where;

X_1 = 1.264[tanh(-0.9371+0.5511U+0.2418M-1.6908S+3.2295H+1.2932T-0.92D-1.6066B+.....+1.3196W+1.601K)]

X_2 = -1.1026[tanh(0.1053+0.9892U+0.5419M+1.3026S-0.5298H-1.3373T+0.6678D-1.0059B+.....-2.5979W+0.4762K)]

X_3 = -1.73[tanh(-2.214+0.4549U-0.3531M+1.0911S+1.9649H+2.7928T-0.8829D-0.1656B+.....+0.4334W+0.8929K)]

X_4 = 1.9205[tanh(-0.511-1.1043U-1.2781M-4.1108S-1.8184H-1.6006T.0,5101D+2.2472B+.....-1.0147W+1.3332K)]

X_5 = 1.1692[tanh(0.8712-0.5419U+0.1954M+3.05825S-1.1224H-0.0046T+0.1026D-0.8198B+...-1.3481W-1.3658K)]

X_6 = 1.5332[tanh(-0.6763+0.204U-1.5771M+0.3394S+1.4095H-1.9506T-1.17056D-1.9912B+...-0.8562W+0.4285K)]

X_7 = 1.2113[tanh(0.407+1.2402U+0.1091M+0.8108S-0.1397H+0.1418T+0.1424D-0.6376B+.....+1.3727W-0.2674K)]

X_8 = 1.1239[tanh (0.2348+3.5206U 0.338M+2.3944S+2.102H+1.0452T+0.0895D+3.4336B+1.5461W-1.6191K)]

$$V = 148.205\tanh\left(\sum_{i=1}^{8} Xi - 0.1654\right) + 171.515 \quad (4)$$

Where;

X_1 = -2.7975[tanh(-0.9371+0.5511U+0.2418M-1.6908S+3.2295H+1.2932T-0.92D-1.6066B..+1.3196W+1.601K)

X_2 = -0.1986[tanh(0.1053+0.9892U+0.5419M+1.3026S-0.5298H-1.3373T+0.6678D-1.0059B+.....-2.5979W+0.4762]

X_3 = 2.6124[tanh(-2.214+0.4549U-0.3531M+1.0911S+1.9649H+2.7928T-0.8829D-0.1656B+....+0.4334W+ 0.8929K)]

X_4 = -2.3725[tanh(-0.511-1.1043U-1.2781M-4.1108S-1.8184H-1.6006T.0,5101D+2.2472B+.....-1.0147W+1.3332K)]

X_5 = -3.1791[tanh(0.8712-0.5419U+0.1954M+3.05825S-1.1224H-0.0046T+0.1026D-0.8198B+....-1.3481W-1.3658K)]

X_6 = -2.9608[tanh(-0.6763+0.204U-1.5771M+0.3394S+1.4095H-1.9506T-1.17056D-1.9912B+...-0.8562W+0.4285K)]

X_7 = 1.297[tanh(0.407+1.2402U+0.1091M+0.8108S-0.1397H+0.1418T+0.1424D-0.6376B+.....+1.3727W-0.2674K)]

X_8 = -2.6255[tanh (0.2348+3.5206U+0.338M+2.3944S+2.102H+1.0452T+0.0895D+3.4336B+.....+1.5461W-1.6191K)]

Where, U is the UCS in MPa; M is the rock density in kg/m^3; S is the spacing in m; H is the drill hole depth; T is the stemming length in m; D is the hole diameter in m; K is the powder factor in kg/m^3; W is the charge weight in kg; B is the burden in m; Q is the %oversize material; Y is the %undersize material; and V is the mean size of the blast muck pile.

Modified KUZ-RAM model

The Kuz-Ram model predicts fragmentation from blasting in terms of mass percentage of fragments passing; according to Choudhary and Gupta, [26] the following assumptions, drawn from explosive energy utilization, can be made: finer fragmentation is generated from higher explosive energy; weak rocks and smaller blast-hole diameters produce more regular fragmentation sizing as a result of uniform distribution of explosives in the rock mass; small burdens and a greater spacing-to-burden ratio produces a high percentage of oversize materials. The modified Kuz-Ram model is similar to the original Kuz-Ram model, but the Kuznetsov equation is modified by an additional factor of 0.073, which is included in the formula for the prediction of the mean fragment size [27]. The reason for adding the additional factor is that joint aperture is considered an effective parameter. The uniformity index of the Kuz-Ram model is also replaced by a modified uniformity index, which is based on the original uniformity index equation proposed by Cunningham and a blast ability index (BI). Table 5 compares the optimum ANN model as we have developed it with the modified Kuz-Ram model, the ANN model predicted outputs were compared with those of the modified Kuz-Ram and found to be more accurate than the modified Kuz-Ram model with the root mean square error (RMSE) relatively lower relatively compared to those of the modified Kuz-Ram model for the same parameters. Also, the coefficient of determination (R^2) for the parameters in the ANN model is closer to unity compared to those of the modified Kuz-Ram. Hence, the ANN model predicts output with suitable accuracy compared to the modified Kuz-Ram model. Percentage oversize prediction by the ANN model as seen in Table 6 is the best with an R^2 of 0.927. The modified Kua-Ram model also predicted mean size (X_{50}) better than it did for percentage oversize and undersize even though the Kuz-Ram model is not as accurate as that predicted by the ANN models that we have developed.

Table 6: *Computed RMSE and R^2 for comparing ANN and modified KUZ-RAM models*

Models	Blasting Parameters	R^2	RMSE
ANN model	Oversize (%)	0.927	1.09
	Undersize (%)	0.866	1.14
	Mean-size (mm)	0.930	3.46
Modified Kuz-Ram model	Oversize (%)	0.111	4.48
	Undersize (%)	0.073	4.58
	Mean-size (mm)	0.157	14.03

Blasting parameters and production optimization with BlastFrag

Table 7 shows the blast outputs and cost per hole blast statistics before and after optimization. An increase in the percentage of undersized fragments and a decrease in the percentage of oversized fragments is an indication of enormous improvement following simulation of the input blast parameters using BlastFrag software prior to blasting. The productivity and charge cost per drill hole were improved by 45.2% and 5%, respectively. There was also a 45.17% gain in productivity as illustrated in Table 7.

Conclusions

This paper reports on an attempt to improve blast preplanning design using the artificial neural network technique. The following conclusions have been drawn:

1. ANN prediction models were developed using seven controllable parameters obtained from fifty monitored blasts and two uncontrollable rock properties determined in the laboratory following the standard procedures suggested by Gheibie et al. [27]. The rock properties conform to ISRM standards [10] for six dolomite pits.

Table 7: *Blasting output statistics and cost per hole blast*

Blast parameters	Blast before ANN model design	Blast with BlastFrag model design
Diameter (mm)	0.04	0.04
Burden (m)	0.7	0.8
Spacing (m)	1.1	1.2
Drill hole length (m)	1.3	1.4
Rock average specific gravity	2.8	2.8
Production per hole blasted (Tonnes)	2.59	3.76
Percent oversize	68.4%	27.83%
Percent undersize	50%	72.17%
Mean size (mm)	418.0	101.6
Profit from blast per hole (Naira)	10,360	15,040
Cost per hole charge (Naira)	1000	950

2. Fifty data sets with seven input parameters and three outputs were trained with ANN using the Levenberg-Marquardt and Bayesian-Regularization Training Algorithms.
3. Error analyses were performed to further compare the performance of the ANN models generated from the Levenberg-Marquardt and the Bayesian-regularization training algorithms adopted for this study. Indices of RMSE, R^2, and MRE are calculated for predicted outputs and compared with the real outputs. It was found that the performance of the Bayesian regularization training algorithm model had maximum accuracy and minimum error compared to the Levenberg-Marquardt training algorithm model.
4. The prediction models that have been developed have strong prediction accuracy and can be used to determine fragmentation size distribution in a dolomite quarry. The models we have developed were deployed in BlastFrag optimizer software for user-friendly implementation.
5. The newly developed software was compared with the modified Kuz-Ram model for predicting the percentage of fragments passing, percentage of fragments that were undersize, and the mean fragment size of dolomite blast results. For all the blasting results investigated, the BlastFrag optimizer showed a higher coefficient determination than the modified Kuz-Ram model. The performance of the proposed models can be used for field blast design for the dolomite quarry.

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