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Improvement of Small-Scale Dolomite Blasting Productivity: Comparison of Existing Empirical Models with Image Analysis Software and Artificial Neural Network Models

Blessing Olamide Taiwo

Department of Mining Engineering, Federal University of Technology, Akure, Nigeria

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Abstract

Assessment of blast results is a significant approach for the improvement of mining operations. The different procedures for investigating rock fragmentation have their limitations, causing different variation prediction errors. Thus every technique is site-explicit, and applicable for a few explicit purposes. This work evaluates the existing empirical blast fragmentation model predictions in the case study of small-scale dolomite quarries. An attempt is made to compare the prediction accuracy of the modified Kuz-Ram model, Lawal 2021 model, and Kuznetsov-Cunningham-Ouchterlony (KCO) model with the WipFrag© analysis result and proposed artificial neural network (ANN) models. The prediction error analysis of the current models and that of the new proposed ANN models is evaluated using the three model assessment indices. The assessment indices uncover that the KCO model when compared to the modified Kuz-Ram model has the least error for most blast round percentage passing size predicted. However, the proposed artificial neural network models show high prediction exactness in predicting blast fragment mean size than the existing empirical models. Therefore, the proposed ANN models can be used to improve the productivity of small-scale dolomite blasting operation results for practical purposes.

1. Introduction

The mining operation activities are well-known to take place in large- and small-scale capacities depending on the working operation strength. Steven has noted that Africa has gained more ground in small-scale mining activities as most activities in the continent are practiced in rural areas by local miners with limited training, financial capacity, and mining types of equipment [1]. Small-scale mines have a great affinity to contribute significantly to national socio-economic development including poverty alleviation role through employment provision, contributing to national incomes, and contributing to state revenues. Small-scale miners also lack professionalism with limited mining engineers and expertise. Blasting operations in small-scale mines and quarries are done haphazardly with different consequences to the environment, the surroundings, and even distant communities and to the miners themselves. Jug *et al*. have indicated that making blast activity profitable is one of the approaches to limiting extra expense increment on downstream operations like mucking, loading, pulverizing, and processing [2]. Kulatilake *et al*. have also stated that when blasting operation results give undesired fragmentation, it affects mine operation efficiency and delays in materials handling [3]. Dinis *et al*. have explained further that 15% to 20% of open-pit mine operation expenses are represented by drilling and blasting operation costs [4]. Small-scale mine blasting operation improvement using model implementation is important in light of the fact that is critical for profitability and safety production maximization [5-7]. According to Mutinda *et al*. the rock fragmentation model is a fundamental tool in blasting operation for design and parameter simulation [8]. Various attempts

Corresponding author: taiwoblessing199@gmail.com (B. Olamide Taiwo).

had been made to develop several prediction models for blast particle size distribution including the use of artificial intelligence algorithms and soft computing approaches [9]. Moreover, the development of fragmentation models provides innovative solutions to blasting problems such as the improvement of mine to mill fragmentation products [9, 10]. Many authors' works have revealed that the activities in large-scale mines differ in size, nature, and utilization of equipment compared with small-scale mining industries. Most large-scope mine blasting activity includes the use of equipment capable of drilling long and big diameter holes to accommodate a large volume of explosives unlike small-scale mining companies with a handheld pneumatic jackhammer. Small-scale mining activities had made high commitments to the national economy in the past in spite of less research work zeroing in on its improvement [1]. The fragmentation of rock mass in small-scale mines using explosive provides an important solution to the run-off-mine productivity but limited understanding of the effect of blast design controllable parameter on the blast result have been given little attention from the researchers. Improving blast activity in a small diameter drill hole is important to enhance the operation result. Therefore, a rapid and reliable technique is required for assessing the blast results that can be justified with existing traditional methods for high prediction efficiency. This research work is necessitated by the need to evaluate the existing empirical fragmentation models on small-scale mine blasting operations and compare them with modern models. The study objectives are to determine the prediction performance of the Modified Kuz-Ram model, Kuznetsov-Cunningham-Ouchterlony (KCO) model, and Lawal [11] model for small diameter drill hole marble blast mean fragment size using selected quarries in southwest Nigeria as a case study. The second section of the study develops a proposed artificial neural network model for predicting blast means fragmentation size prediction, which is finally compared with the existing models.

2. Mine blast fragment size model review

The availability of various developed models for the prediction of blast fragmentation size distribution has been noted by Babaeian *et al.* [12]. These models can be categorized into the empirical and mechanistic base on the prediction result nature [13]. According to Franklin *et al.* on blast fragmentation, the empirical models are identified as those estimation models that accommodate the blast design parameters such as burden, spacing, and powder factors with different units for the prediction of blast fragmentation results [14]. The mechanistic models adopt basically two approaches in blast fragmentation prediction. The model evaluates blast productivity from the perspective of the explosive energy distribution during blast detonation through either fundamental principles of physics or the dynamic of explosive wave and gas energy utilization. Ouchterlony and Sanchidrián have indicated that this blast fragmentation model technique requires a large number of numerical techniques, which makes its prediction process require intense iteration and unnecessarily long computation times [13]. The high complexity of the dataset required for mechanistic models limited its application in mine sites. Mutinda *et al.* have noted that the blast fragmentation empirical model requires the collection of historical and experimental field blast information, which is subjected to scientific fitting and computational articulation approaches [8]. The adoption of empirical models back dates to the 1970 model developed by da Gama [15] for the prediction of blast fragmentation size adoption explosive energy, rock characteristics, and charge needed as the predicting variables. Figure 1 presents the chronological development of the empirical models for blast fragmentation improvement. The two well-identified blast fragmentation prediction models are Kuznetsov-Cunningham-Ouchterlony (KCO) and Modified Kuz-Ram models MKM. The two models were developed and put into use by Cunningham in 2005 [8, 13, and 16] to reduce the number of oversize materials delivered during blasting, and illuminate the mine administrator regarding the reasonable blast properties that are probably going to bring about the ideal fragment size. [17] has mentioned that, apart from these well-known models, other newer techniques for examining blast fragments have been recently proposed such as artificial neural networks (ANNs) models [9,18] and multivariate regression (MVR) [19].

2. Materials and methodology

Improvement of mining blast operation results has taken different approaches including the adoption of models proposed by several authors from different 1900s till date [13]. One major limitation of the empirical model is the site limitation and operation-specific constraint. A successful blast operation always requires a safe and profitable technique to minimize explosive energy loss to blast environmental challenges. Fifty-six (56) blasting operations resulting from six pits belonging to different local miners at Fanalou dolomite quarry in Atte and Ikpeshi, Akoko Edo, Nigeria were used in this work. Figure 2 shows the mine blast design pattern. The descriptive statistics of the blast charge design parameter for the blast rounds captured for this study are presented in Table 1.

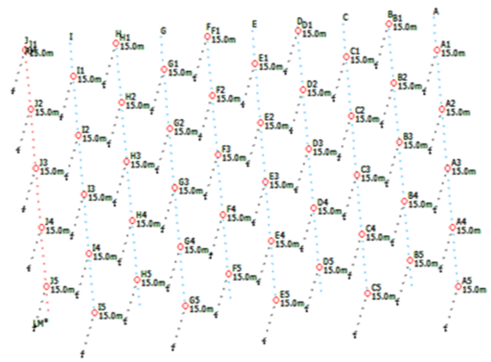
Table 1. Descriptive statistics of blast charge design parameter datasets.

	D(m)	B/De	B (m)	S(m)	PF (kg/m^3)	Explosive load weight (kg)	CCL (m)	BCL (m)	Blast mean size (mm)
Max	0.04	30	1.2	1.3	1.80	1.06	0.38	0.46	483.2
Min	0.04	15	0.6	0.7	0.44	0.51	0.12	0.22	122.62
Average	0.04	20.86	0.83	1.06	0.77	0.85	0.22	0.42	328.64
Variance	-	6.910	0.011	0.013	0.039	0.01	0.005	0.01	5660.21
Standard deviation	-	2.63	0.11	0.12	0.20	0.10	0.077	0.083	75.23

CCL= Length of ammonium nitrate fuel oil charge, Lexp= Bottom charge length (primary charge)

The blast images captured from the mine were analyzed with the Wipfrag software to measure the blast fragment size distribution. Fifty-six images were captured in accordance with [35]. Fifty of the images were used for the proposed ANN model development, and six were used for the existing empirical model evaluation. The image analysis software was used to determine the size distribution curve of the blast images captured from the mine blast rounds. Maerz described an image analysis software package such as WipFrag software that uses a grayscale technique as a state of art image-based gravimetry image processing package [35]. To predict the blast fragmentation size distribution in this study using the existing empirical models, six blast rounds were monitored, and the blast design parameters, explosive properties, and rock properties were measured (please see Figure 3). In the case study mine, the mine working bench height was 1.5 m and about 22.5 m in depth. The drilling operation is performed by pneumatic Jackhammer in conjunction with 8.6 bar diesel air compressor. The mined rock mass rating was evaluated using the Bieniawski RMR rating, the formation has a rough surface, no separation, unweathered wall rock surface, no infilling, and persistence length of 1-3 m [36].

Figure 1. Early fragmentation empirical models for blast fragmentation prediction.



a. Blast design

Figure2. Case study mine blast design pattern.

The rock comprises massive dolomitic marble with RMR 65 according to Bieniawski rock mass classification. The packaged emulsion gel explosive and ANFO are used in the mine for their basting operation. The company makes use of a staggered drilling pattern as shown in Figure 2. The blasts are initiated by a non-electric solacord having 6800m/s VOD detonate instantaneously under the No.6 detonator. The density and UCS of the dolomite rock sample are 2800 kg/m^3 and 44.39 MPa, respectively, as tested according to [37, 38] standard.

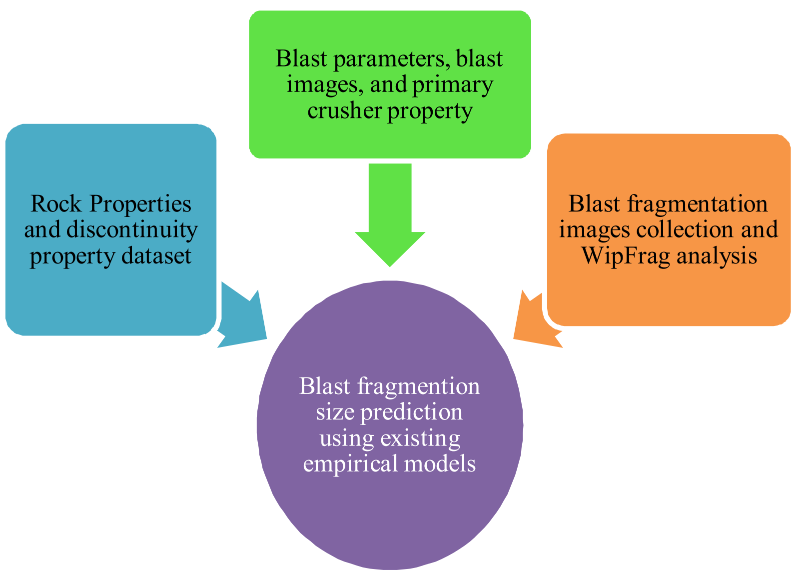


Figure3. A flow chart of empirical modeling work.

2.1. Application of existing empirical fragmentation modelsin blasting

2.1.1. Kuznetsov-Cunningham-Ouchterlony (KCO) model

The Swebrec work provides a replacement equation for the Rosin-Rammler general equation adopted in the Kuz-Ram model; the Swebrec result is shown in Equation (1) (also see Figure1). Swebric function includes three parameters: the mean size of the material size (X_{50}) going through the essential crusher gape, (X_{Max}) denotes the maximum block size, and b indicated curve undulation parameter similar to and depending on the uniformity index of the Kuz- Ram model [6, 39].

$$P(x) = \frac{1}{1+\left[\frac{In\left(\frac{Xmax}{X}\right)}{In\left(\frac{Xmax}{X50}\right)}\right]^{b}} \quad (1)$$

where P(x) denotes the percentage fraction of fragments passing sieve size X, and b signifies the curve undulation parameter. X_{Max} is the maximum blast fragment size (considered as the S or B length).

$$B=\left[2In2\left(In\left(\frac{Xmax}{X50}\right)\right)\right]n \quad (2)$$

where n is the uniformity index calculated using Equation (3)

$$n = [2.2 - 14\left(\frac{B}{D}\right)]\ [0.5\ (1 + \left(\frac{S}{B}\right)]^{0.5}\ [1 - \left(\frac{W}{B}\right)] \times [\mathrm{abs}\left(\frac{BCL-CCL}{L}\right) + 0.1]^{0.1}[\left(\frac{L}{H}\right)] \quad (3)$$

where B denotes the burden (m), S depicts the spacing (m), D indicates the hole diameter (mm), W denotes the standard deviation of drilling accuracy (m), BCL means the bottom charge length (m), CCL means the column charge length (m), L depict the total length of the drilled hole (m), and H means the bench height (m). Eq. 4 shows the general Kuznetsov equation.

$$X_{50} = AK^{-0.8} \times Q^{1/6} \left(\frac{115}{REE}\right)^{19/20} \quad (4)$$

where A is the rock factor calculated using Equation (5), Q is that the mass of explosive been utilized in kg, K is that the powder factor (specific charge) in kg/m^3, and REE is that the relative effective energy of the explosive; this is often derived by dividing absolutely the weight strength of the explosive in use by absolutely the weight strength of ANFO and multiply by 100%.

$$A=0.06(RMD+RDI+HF) \quad (5)$$

where HF indicates the hardness factor, and RMD is the rock mass description. When rock is powdery and friable RMD is equal to 10, when joints are vertical RMD is assigned the same value as JF; when the rock mass is massive, RMD is 50. JF is the joint factor, calculated using Equation (6):

$$JF = (JCF \times JPS) + JPA \quad (6)$$

where JCF depicts the joint condition factor to which 1 is assigned for tight joints, 1.5 for relaxed joints, and 2 for gouge-filled joints, JPS denotes the vertical joint plane spacing; [8] indicated that JPS is 10 when $Sj < 0.1$ m, 20 if Sj is assigned value between 0.1 and 0.3 m, 50 if Sj is an assigned value between 0.3 and 0.95 $\sqrt{BS}$, and 80 if $Sj > \sqrt{BS}$. JPA represents the joint plane angle; Mutinda *et al*. have noted that the value of JPA when the joints dip out-of-face is assigned value 20, when striking perpendicular to the face, JPA value is assigned value 30, and when the joints dip into the face it assigned value 40. RDI depicts the rock density influence in kg/m^3, defined by Equation (6) [8].

$$RDI = (25 \times \vartheta) - 50 \quad (7)$$

where ϑ denotes the rock density in kg/m^3.

In order to predict the blast fragmentation size distribution of small-scale mine employing KCO model, the rock parameter, explosive property, and blast design parameters presented in Table 2 into Equation 1-7.

2.1.2. Modified Kuz-Ram model

The Modified Kuz-Ram (MKM) model is an improved version of the first Kuz-Ram model with adjusted values of 0.073 introduced to the mean size equation of the initial Kuz-Ram model [6]. The uniformity index of the Kuz-Ram model was also modified. The modified Kuz-Ram model as compared with the ordinary Kuz-Ram model has a better prediction of fine materials. The Cunningham's uniformity index Equation 3 remains unchanged for the modified Kuz-Ram model. Rosin-Rammler's equation for percentage passing is determined using Equation (7). Faramarz *et al*. have also noted that Equation (7) is important in characterizing the muck pile size distribution [40].

$$R_x = [-0.693(\frac{X}{Xm})^n] \quad (7)$$

$$X_m = 0.073BI(\frac{Vo}{Qe})^{0.8} \times Q_e^{1/6} (\frac{SANFO}{115})^{-19/30} \quad (8)$$

$$n` = 1.88 \times n \times BI^{-0.12} \quad (9)$$

$$BI = 0.5(RMD+ JPS+ JPA+ RDI + HF) \quad (10)$$

Where X_m denotes the mean fragment size, cm; BI depict the blastability index, Vo means the volume of rock broken by one blast hole, m^3, Qe represents the mass of explosive in each hole, kg; S_{ANFO} denotes the relative weight strength of the explosive to ANFO, n means the uniformity index, n` represents the modified uniformity index and RMD, JPS, JPA, RDI, and HF have the same meanings as defined in Equations (5-6)

The volume of the rock broken by one blast hole V_o (m^3) can be found by Equation (11).

$$V_o = B \times S \times H \quad (11)$$

In order to predict blast fragmentation size distribution of small scale mine employing modified Kuz-Ram model, the rock parameter, explosive property and blast design parameters presented in Table 1-2 into Equation 7-11.

Table 2. Dolomite rock characteristics and model parameters.

Blast No.	RDI	RMD	JPS	JPO	HF	BI	Vo	Qe	n'	N
Pit 1	20	50	20	10	34	67	0.8911	0.86	1.98	1.74
Pit 2	19.75	50	20	10	34	66.875	0.8645	0.72	2.05	2.01
Pit 3	19	50	20	10	34	66.5	0.945	0.51	2.52	1.81
Pit 4	20.1	50	20	10	34	67.05	1.056	0.87	2.15	2.16
Pit 5	20.1	50	20	10	34	67.05	1.04	0.956	2.15	1.9
Pit 6	20.1	50	20	10	34	67.05	1.016	0.89	2.22	1.85

2.1.3. Lawal2021 new modified Kuz-Ram model

The drilling and blasting design parameters obtained from the Limestone quarry data from [41] and iron ore mine data from [42] were used by Lawal [11] to modify the Kuz-Ram model. This research work modified the prediction of the fragment size by the Kuz-Ram model using the results of the image analysis and the least square method of error minimization present in Equation 12. The modification introduced a new land coefficient of the rock factor of 0.03739 contrary to one proposed by Lilly [24]. The newly proposed model has an overall percentage error difference between the proposed model and the actual value to be about 3.5%, while having 65% accuracy to the Kuz-Ram model [11]. Equation 13 presents the original Kuz-Ram model, and Equation 14 presents Lawal [11] modified Kuz-Ram model.

$$F_o=\sum_{i=1}^{n}(Xo-Xn)^2 \quad (12)$$

where F_o is the objective function of the least square method of error minimization, X_o is the actual results, and X_n the new model prediction result.

$$X_{50}=0.06(RMD+JF+RDI+HF)K^{-0.8}\times Q^{1/6}\left(\frac{115}{ANFO}\right)^{19/30} \quad (13)$$

$$X^{new}=0.03739\left[(RMD+JF+RDI+HF)K^{-0.8}\times Q^{1/6}\left(\frac{115}{ANFO}\right)^{19/30}\right] \quad (14)$$

In order to predict the blast fragmentation size distribution of small scale mine employing Lawal[11] modified Kuz-Ram model, the rock parameter, explosive property and blast design parameters presented in Table 1-2 into Equation 14.

2.2. Application of artificial neural network approach in predicting blast fragmentation

The artificial neural network (ANN) modeling technique learns from the data samples presented to the system; it adopts this data to adjust their weights in an attempt to capture the relationship between the historical set of the model inputs and the corresponding outputs. Fifty-six input and output data used in this study was extracted from the blast records of the Fanalou Company Nigeria limited located in Edo state, Nigeria. The model flow sheet is presented in Figure 4.

The ANN model proposed in this work was trained with 40 datasets, validated with 5 datasets, and tested with 5 datasets. The model was trained using a MATLAB-based ANN tool. The model with a 6-6-1 (6-input 6-neurons 1-output) architecture structure trained with the Levenberg-Marquardt algorithm was found to be optimum (Figure 5c). The training performance, regression curve, and architecture structure is presented in Figure 5 (a-b). The bias and weight of the optimum ANN model are substituted into Equation 15 to obtain the applicable mathematical equations present in Equation 16. The extracted Equation 16 was compared with the existing model using new six blasting datasets.

$$p_j=f_{sig/purlin}\left\{b_0+\sum_{k=1}^{n}\left[f\,sig\left(\mathrm{bnk}+\sum_{i=1}^{m}\mathrm{wik}\Gamma\mathrm{i}\right)wk\times\ldots\right]\right\} \quad (15)$$

where b_0 is the bias in the output layer, w_k is the weight of the connection between the k^{th} of the hidden layer and the single output neuron, n is the number of neurons in the hidden layer, b_{nk} is the bias in the k^{th} neuron of the hidden layer, w_{ik} is the weight of the 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 non-linear transfer functions, respectively.

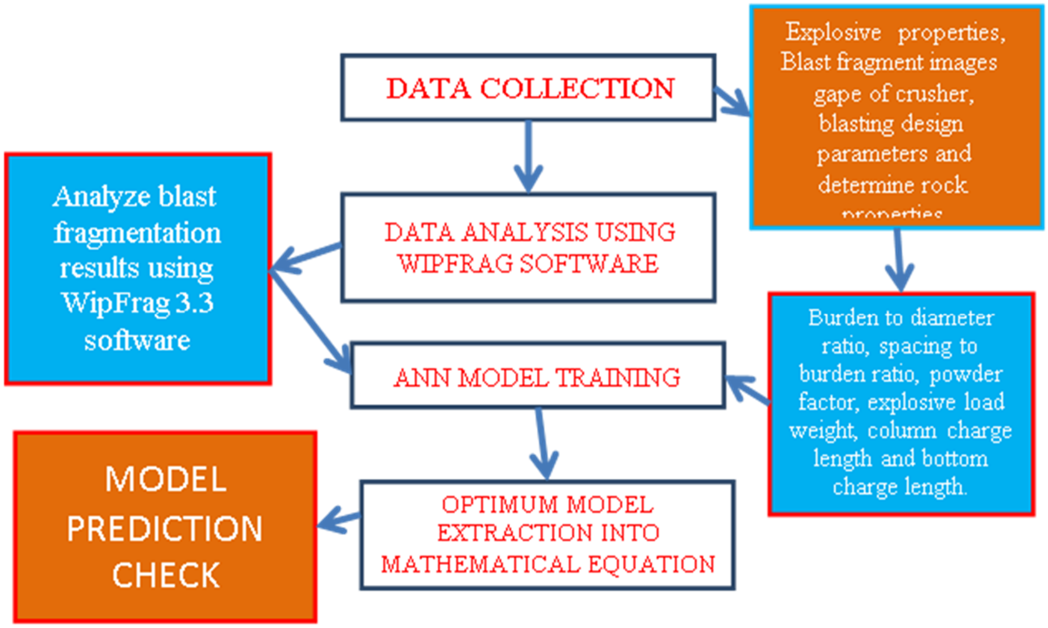
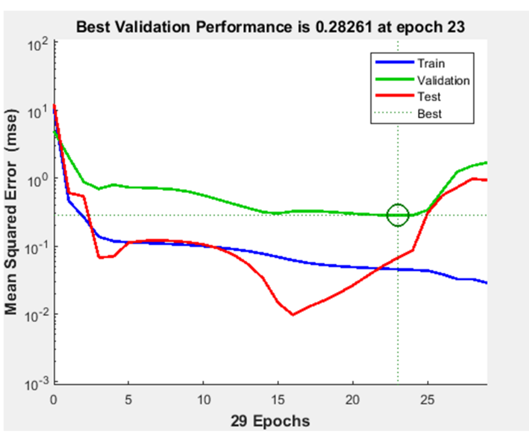
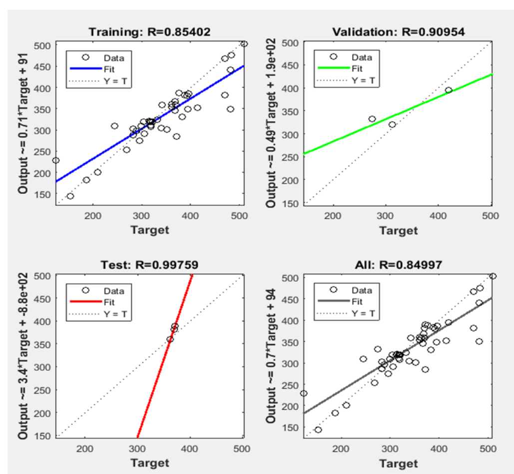


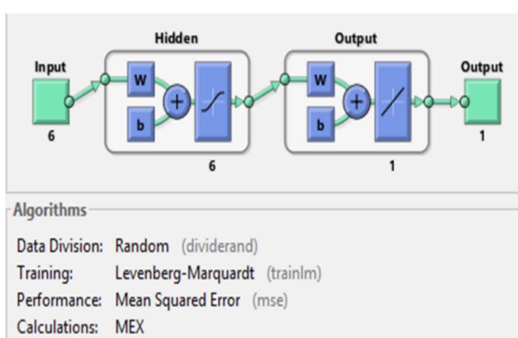
Figure 4. A flowchart of ANN model development.



(a)



(b)



(c)

Figure 5. ANN training performance (a), optimum model regression curve (b), and ANN model architecture (c).

$$X_{50}=193.1\text{Tanh}\left(\sum_{1}^{6} Ki-1.33081\right)+315.81 \tag{16}$$

$K1=0.071833\text{Tanh}\,(-3.34025B/De-0.5345S/B+2.0561PF+0.0549ECW+0.3870CCL-0.6659BCL-1.9479)$

$K2=1.37751\text{Tanh}\,(-2.2095B/De-1.9309S/B+0.1790PF+0.7189ECW+0.2432CCL-0.6573BCL+0.7358)$

$K3=1.5086\text{Tanh}\,(0.0669B/De-1.2418S/B-3.1964PF+1.5283ECW-0.3934CCL+2.4292BCL+0.4609)$

$K4=1.5086\text{Tanh}\,(-1.5693B/De+2.6793S/B+1.1071PF+0.0415ECW-0.0257CCL-1.7074BCL-0.7962)$

$K5=-1.6021\text{Tanh}\,(-0.3537B/De+0.1709S/B+0.8585PF-1.2947ECW-0.1624CCL-1.6767BCL-2.4068)$

$K6=1.9552\text{Tanh}\,(0.5520B/De-5.1015S/B-0.6960PF-0.6825ECW+2.7092CCL+0.2510BCL+0.8187)$

where B/De is the burden to diameter ratio, S/B is the spacing to burden ratio, PF is the powder factor in kg/m^3, ECW is the explosive charge weight in kg, CCL is the drill column charge length in m, BCL drill bottom charge length in m, and X_{50} is the blast fragment mean size.

3. Results and discussion

3.1. Wipfrag analysis and model size distribution result

Figure 6 presents the size distribution curve result from the image analysis software. The result from the Wipfrag analysis indicated that the mine blast result had poor to moderate fragmentation with uniformity index (n) ranging from 1.11 to 1.67 [23].

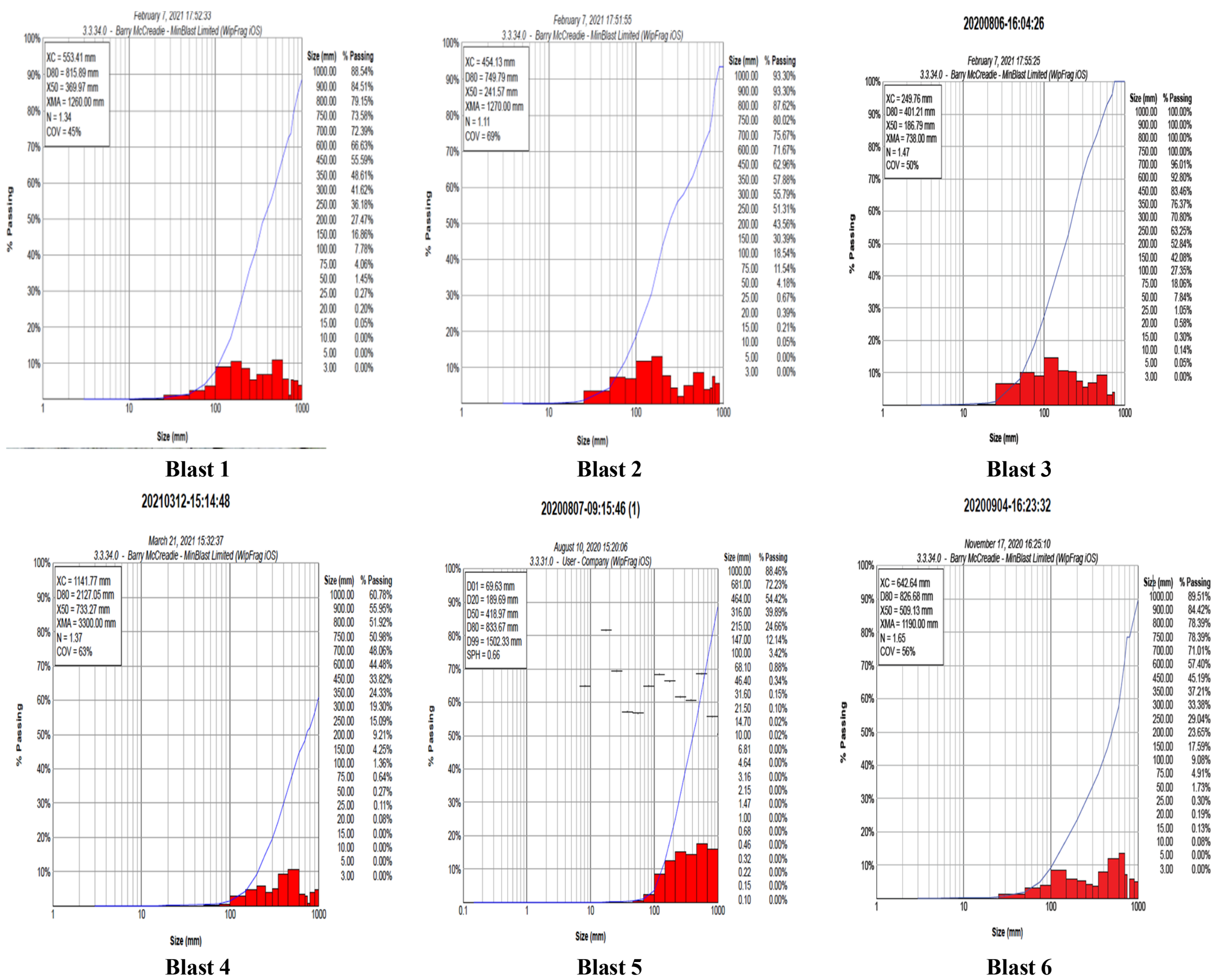


Figure 6.WipFrag analysis result for blast images.

Figure 7 presents the predicted particle size distribution for interpolation of the two existing empirical models obtained using Equation 1 and Equation 7 with the result from the image analysis software. The curve interpolation result shows that the existing models have poor prediction performance for the six blast rounds. The company's primary crusher gape size was identified to be 350mm, materials bigger than this size is considered to be a boulder, those within the size range are considered to be the optimum size, and those smaller to be the undersize materials. The two models underestimated fine materials in most blast rounds, as shown in Figure 7(a-f).

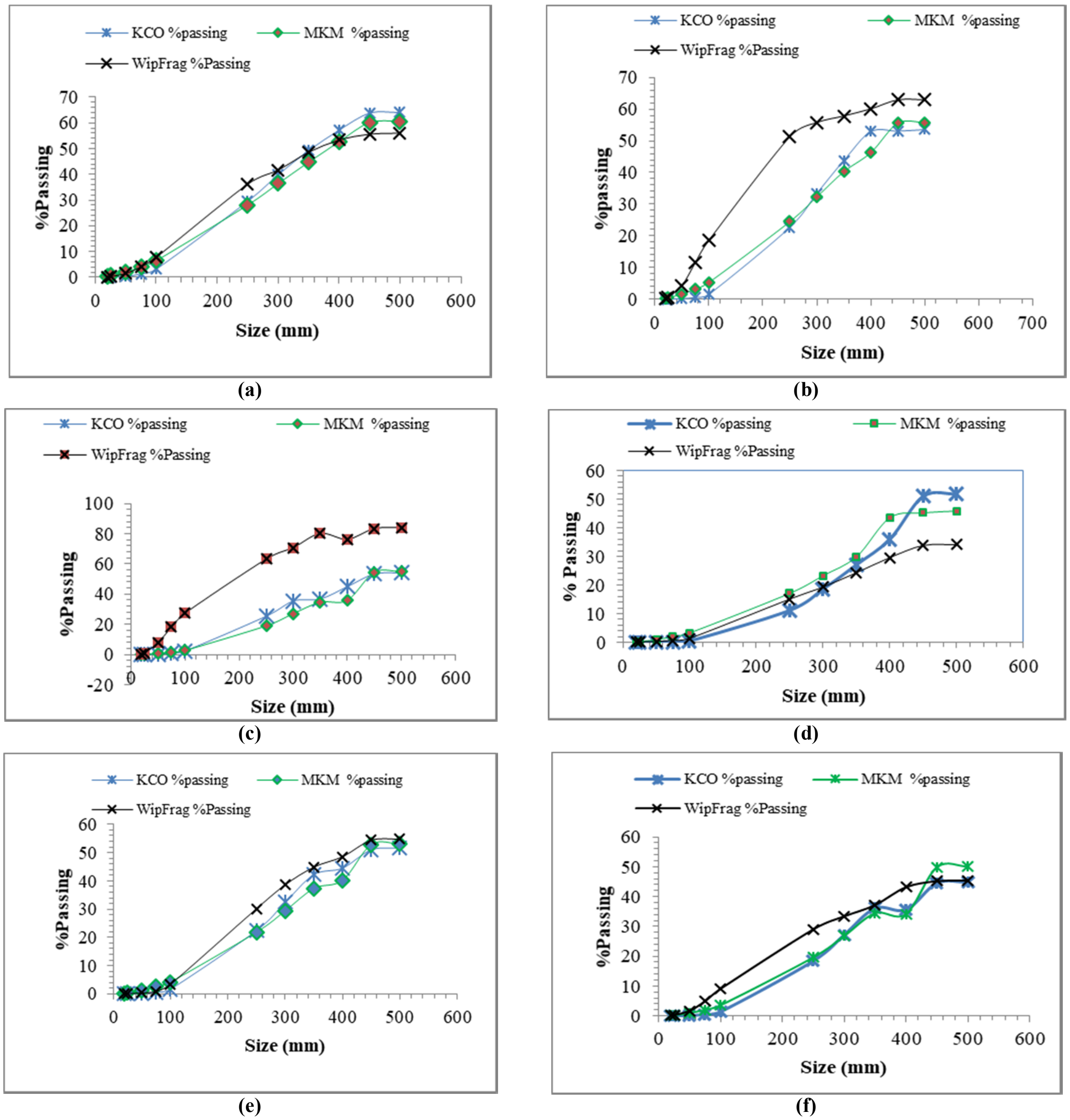


Figure 7. Relationship between predicted and actual %passing for (a) blast 1, (b) blast 2, (c) blast 3, (d) blast 4, (e) blast 5, and (f) blast 6.

3.2. Model comparative analysis

The prediction performance comparison of the newly proposed ANN model and the existing fragmentation models was done with new six blast rounds. The prediction result from the models was presented in Figure 8 and Table 3. The prediction correlation coefficient (R^2) of the modified Kuz-Ram, KCO and the Lawal [11] models are 0.79, 0.86, and 0.82, respectively, while the correlation coefficient of the newly proposed ANN models is 0.98. Table 3 shows the prediction result of the existing and newly proposed models.

Table 3. Prediction result of existing and new proposed models.

Blasts ID	Actual Wipfrag X_{50} (mm)	MKM X_{50} (mm)	KCO X_{50} (mm)	Lawal[11] X_{50} (mm)	ANN X_{50} (mm)
BT1	396.58	382.702	354.6163	196.0161	385.9566
BT2	387.89	426.85	381.7574	218.6283	382.6537
BT3	469.88	498.24	478.0767	255.1935	467.5579
BT4	392.14	430.65	393.7873	220.5746	379.6081
BT5	418.97	467.7022	435.423	239.5524	394.3984
BT6	509	517.5695	493.7069	265.0939	502.6328

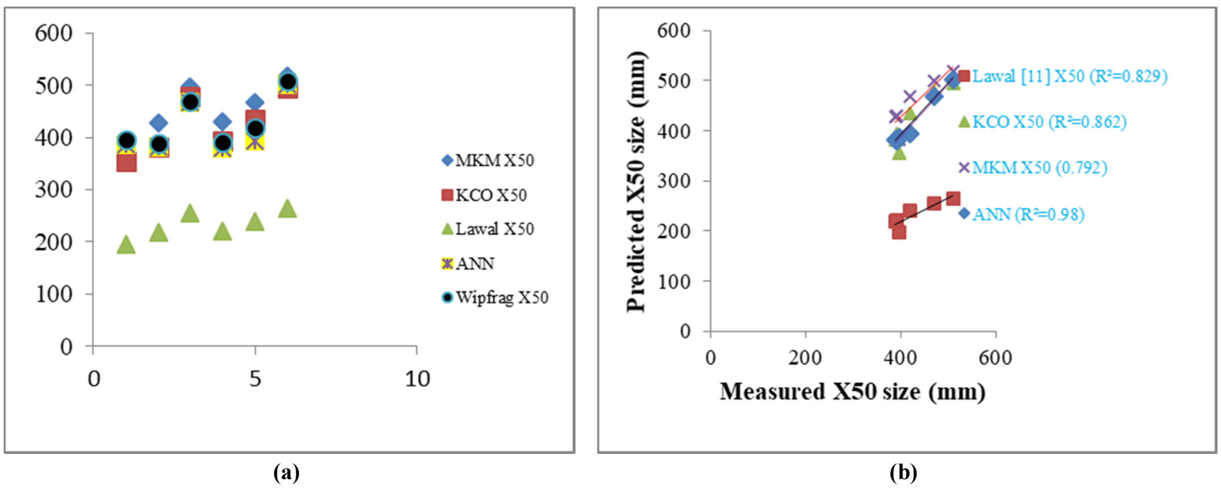


Figure 8. Comparison between new proposed model and existing models (a) model prediction relationship with measured mean size, (b) model prediction performance evaluation using least square error analysis correlation coefficient.

The Lawal [11] model underestimated the blast mean size with a 45.7% deviation from the Wipfrag measured values, as presented in Figure 8a. The modified Kuz-Ram model overestimated the actual blast mean size with a 5.9% deviation from the Wipfrag measured values. The least-square error correlation coefficient of the proposed ANN models was revealed in Figure 8b to be 0.98, which is closer to unity. Based on this comparison, the ANN models were revealed to predict the blast means size better than the existing models with a lower coefficient of correlation.

4. Model error analysis

To accurately evaluate the existing models' prediction error, four model error assessment indices were used to assess the model predicted values. The error analysis indices used are Root mean square error (RMSE), the goodness of fit (R^2), mean absolute error (MAE), and value account for (VAF).

RMSE is an applied statistical index that shows the fitted standard deviation of the variation between two values obtained from different models; it is calculated using Equation (17).

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(Ai-Pi)^2}{N}} \quad (17)$$

The goodness of fit (correlation coefficient R^2) Equation 18 was adopted in this work to examine the model fitness and prediction correlation strength.

$$R^2 = [1-\frac{\sum_{i=1}^{N}(Pi-Ai)^2}{\sum_{i=1}^{N}(Pi-Me)^2}] \quad (18)$$

MAE is a widely adopted model error analysis indicator that expresses the mean absolute error of model predicted values. It also gives close reflection of the exact predictive value relationship with the actual value. MAE is calculated using Equation (19).

$$\text{MAE}=\frac{1}{N}\sum_{i=1}^{N}/Ai-Pi/ \quad (19)$$

where P_i indicates the predicted value, and A_i indicates the actual value.

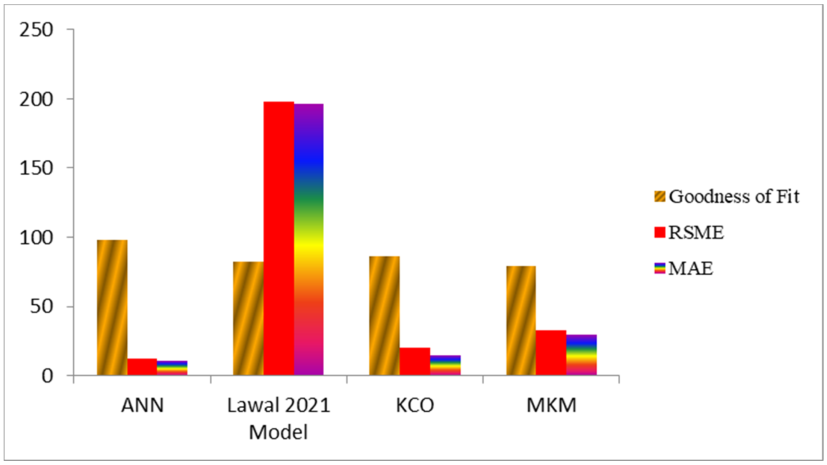


Figure 9. Model error analysis comparison result.

The predicted values from the existing models that form the new proposed artificial neural network models and also the actual mean size measure by the Wipfrag software were substituted into Equations 17-19 to determine RSME, R^2, and MAE in this work. Figure 9 presents the error analysis result of the existing and proposed models. The results displayed in Figure 9 affirm that the ANN models predict the blast fragmentation mean size with lower RMSE, and MAE, and with a high goodness of fit in all the six blast rounds.

5. Conclusions

In the small-scale mining industry, the operations are carried out based on little professionalism due to the availability of cheap and sophisticated innovation and technology. Blast operation optimization using local existing blast design ideas is one of the great challenges faced by small-scale mines. As a result of the limitation to advance software and technology, artisanal and small-scale mine blasting engineers decide to make use of the traditional approach to design and predict blast operation results.

In this work, the author proposed an artificial neural network technique for the prediction of small-scale dolomite blast mean size. The prediction accuracy of three existing empirical models was also evaluated and compared with the proposed model. The ANN techniques employed in this work were collected from the blast operation carried out in six pits in Fanalou quarry at Akoko Edo Nigeria. Six independent variables and six neuron architectures were used to mimic the predicted blast mean size database.

The proposed model shows a higher prediction performance in estimating small diameter dolomite blast mean size than KCO, modified Kuz-Ram, and Lawal 2021 models.

It was obtained that the KCO model had RSME =19.89, MAE=14.95, the goodness of fit of 86.20, the modified Ku-Ram model has RSME =32.778, MAE=29.50, the goodness of fit of 79.20, the Lawal [11] model RSME =198.36, MAE=196.57, the goodness of fit of 82.60, and the proposed ANN models have RSME =12.56, MAE=10.28, the goodness of fit of 98.0. Other artificial intelligence (AI) modeling techniques like Adaptive Neuro-Fuzzy Inference System (ANFIS) and others are recommended to improve blast mean size prediction. However, the performance of the ANN proposed model is satisfactory, and can be used for practical purposes.

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بهبود بهره‌وری انفجار دولومیت در مقیاس کوچک: مقایسه مدل‌های تجربی موجود با نرم افزار تحلیل تصویر و مدل‌های شبکه عصبی مصنوعی

بِلسینگ اولامید تایو*

گروه مهندسی معدن، دانشگاه فناوری فدرال، آکوره، نیجریه

ارسال ۲۰۲۲/۰۳/۲۳، پذیرش ۲۰۲۲/۰۸/۲۲

* نویسنده مسئول مکاتبات: taiwoblessing199@gmail.com

چکیده:

ارزیابی نتایج انفجار یک رویکرد مهم برای بهبود عملیات معدنکاری است. روش‌های مختلف بررسی خردایش سنگ، محدودیت‌های خود را دارند که موجب بروز خطاهای مختلف پیش‌بینی می‌شوند. بنابراین هر روشی برای یک سایت معدنی چند هدف مشخص قابل استفاده است. این کار مداهای تجربی پیش‌بینی خردایش سنگ را در مقیاس کوچک برای مطالعه موردی معادن دولومیت ارزیابی می‌کند. دقت پیش‌بینی مدل اصلاح‌شده Kuz-Ram، مدل Lawal 2021، و مدل Kuznetsov-Cunningham-Ouchterlony (KCO) با نتایج تحلیل ©WipFrag و مدل‌های شبکه عصبی مصنوعی (ANN) مقایسه شده است. با استفاده از سه شاخص ارزیابی مدل به تحلیل و مقایسه‌ی خطای پیش‌بینی مدل‌های فعلی و مدل‌های ANN پیشنهادی جدید پرداخته شد. شاخص‌های ارزیابی نشان می‌دهند که مدل KCO در مقایسه با مدل اصلاح‌شده Kuz-Ram کمترین خطا را برای پیش‌بینی درصد ابعاد خردایش ناشی از انفجار دارد. با این حال، مدل‌های شبکه عصبی مصنوعی پیشنهادی دقت پیش‌بینی بالایی را در پیش‌بینی میانگین ابعاد خردایش ناشی از انفجار نسبت به مدل‌های تجربی موجود نشان می‌دهند. بنابراین، مدل‌های ANN پیشنهادی می‌توانند برای بهبود بهره‌وری نتایج عملیات انفجار دولومیت در مقیاس کوچک برای اهداف کاربردی مورد استفاده قرار گیرند.

کلمات کلیدی: استخراج در مقیاس کوچک، انفجار، مدل‌های خردایش ناشی از انفجار، شبکه عصبی مصنوعی، بهینه سازی انفجار.