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Investigation of rock blast fragmentation based on specific explosive energy and in-situ block size

Hossein Inanloo Arabi Shad [a, *], Farhang Sereshki [a], Mohammad Ataei [a], Mohammad Karamoozian [a]

[a] *Faculty of Mining, Petroleum and Geophysics, Shahrood University of Technology, Shahrood, Iran*

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ABSTRACT

In order to control and optimize a mining operation, it is important to assess the fragmentation caused by blasting and subsequent crushing and grinding stages. Prediction of the mean size of a fragmented rock through the rock mass characteristics, the blasting geometry, the technical parameters and the explosive properties is an important challenge for the blasting engineers. Some of the effective parameters on rock fragmentation have been investigated in several empirical models. A model for fragmentation in bench blasting was developed using the effective parameters on the existing empirical models to propose a simple applicable model for predicting the X_{50} value. The proposed model was calibrated by nonlinear fits to 35 bench blasts in different sites from the Sungun copper mine, the Akdaglar quarry, the and Mrica quarry. In order to validate the proposed model, the results were compared to the data obtained from six blast sites in the Chadormalu iron ore mine and the Porgera gold mine. The results indicated a small variance in X_{50}, which was calculated by the proposed model through the image processing approach. The Comparison of the powers between the proposed and the Kuz-Ram models showed that the specific explosive energy and the powder factor are almost the same. The advantage of the proposed model over the Kuz-Ram model is the specific explosive energy, since this parameter includes the powder factor and the weight strength of an explosive. In addition, a sensitivity analysis was conducted based on the artificial neural network. The results showed that the burden and the specific explosive energy were the most effective parameters in the proposed model.

Keywords : *Effective parameter, Empirical models, Open pit mines, Rock fragmentation*

1. Introduction

Rock blasting is the most commonly used method for rock breakage in mining. Controling the blast fragmentation after blasting is always an important subject for the mining industry. Blasting has a significant impact on downstream processes of mining such as the mucking productivity through the rock diggability, the excavator efficiency, the oversize problems and secondary blasting, the crusher throughput and the energy consumption, the plant efficiency, yield, and recovery. Moreover, many investigations has indicated that blasting influences the overall cost of a mining operation. Blasting has been proven to be the most energy-efficient stage in the comminution process. Optimizing the fragmentation by blasting can achieve an energy efficiency between 15% and 30%, in contrast to grinding in which the efficiency is approximately 2%. Over the past decades, the optimization of the whole mining system has been taken into account from drilling to grinding or even the subsequent steps. The so called "mine to mill optimization" concept defines the system and its subsystems, determines the objective(s) of the system, searches the different solutions and alternatives to reach the objective(s), and finally, evaluates and chooses the best existing alternative. Therefore, prediction of rock fragmentation in open-pit mines is one of the important keys in the mine to mill optimization [1, 2, 3, 4, 5, 6, 7, 8, 9]. Several studies have been conducted on blastability and prediction of fragmentation. The parameters that determine fragmentation by blasting is divided into four groups: (a) Blast design parameters; (b) explosive parameters; (c) rock mass structure parameters; and (d) intact rock and discontinuity physical and mechanical properties. Since a large number of parameters influence the blast fragmentation, it is obvious that the fragmentation process is extremely complex and thus it is an extremely challenging task to develop the models to predict the blast fragmentation. In such states, empirical approaches are used incorporating case history data (from either full-scale blasting in one or more than one production sites, or from small experimental scale shots) along with statistically based procedures in developing the prediction equations. Generally, multivariate regression analysis are used to develop the fragmentation prediction models. Each model uses different blasting plans and rock mass parameters. The empirical models should be seen as rough indications of how the effective parameters may contribute to rock fragmentation. In order to generalize these models as general engineering models, they should be tested on different rock types rather than only one. This can be conducted by proposing some parameters to be fitted to the actual rock fragmentation parameters [10, 11, 12, 13, 14]. The purpose model in this research is to consider such effective parameters to propose a simpler model for predicting the mean fragment size of a bench blasting based on available accurate parameters. The mean fragment size (X_{50}) is an indicator for the fragment size distribution of muckpiles. When the mean fragment size of the muckpile is determined, the fragment size distribution of the muckpile can be calculated using the size distribution curves.

2. Review of blast fragmentation models

Kuznetsov [15] proposed a blasting formula between mean fragment size and specific charge. Cunningham [16, 17] developed a new model

* Corresponding author Tel: +989124756725, Fax: +982332395509, *E-mail address:* h.inanloo@shahroodut.ac.ir (H. Inanloo Arabi Shad).

to predict the rock fragmentation based on the Kuznetsov model and the Rosin–Rammler's formula. Further, Hjelmberg [18] developed the SveDeFo model based on including the rock mass type and the blast pattern for prediction of the mean fragment size. Otterness et al. [19] performed an extensive study to correlate the shot design parameters to fragmentation. Kou and Rustan [20] proposed an empirical model to predict the mean fragment size. Lownds [21] used the distribution of explosives energy to predict the fragmentation by blasting. Aler et al. [22] evaluated the blasting efficiency through a comparison between the block size of the rock mass resulting from existing fractures and the fragmentation size distribution resulting from blasting. In addition, they carried out a research work to predict the blast fragmentation through multivariate analysis procedures.

The crushed zone model (CZM) [23] and the two-component model (TCM) [24] are two empirical models of the extended Kuz-Ram models to improve the prediction of fine particles. In the CZM model, the fragments size distribution in the fine and coarse regions is modeled by two separate functions. These two functions are based on the well-established Rosin-Rammler distribution. Tensile fracturing produces the coarse part, and the Kuz-Ram model predicts the size distribution of this part. Compressive fracturing in the crushed zone, for which the Rosin-Rammler function gets a different value of n and XC, produces the fine part. In the TCM model, two Rosin-Rammler functions are used to predict the run of the mine size distribution. The sum of the two distribution functions, multiplied by the respective fraction of the total mass, represents the fragment size distribution of the entire mass of fragmented rock. TCM is a five-parameter model that two of the parameters are related to the coarse fraction, one is related to the fines fraction, and the other two are related to the fine part of the distribution. Morin and Ficarazzo [7] applied the Monte Carlo simulation as a tool for prediction of fragmentation based on the Kuz–Ram model. In 2010, Ouchterlony proposed a new fragment size distribution function [23]. Also, Gheibie et al. [25], [26] tried to enhance the fragmentation prediction through modifying the Kuznetsov and Kuz–Ram models. Monjezi et al. [27] developed a fuzzy logic model for prediction of rock fragmentation by blasting. Kulatilake et al. [28] presented a piece of work, predicting the mean particle size in rock blast fragmentation using neural networks. Also, Monjezi et al. [29] used neural networks to predict the rock blasting fragmentation. Chakraborty et al. and Hudaverdi et al. [30], [31] applied multivariate analytical procedures to predict the rock fragmentation by blasting. Faramarzi et al., [32] presented a new model for prediction of rock fragmentation by blasting based on the basic concepts of the rock engineering systems (RES).

Akbari et al. [33] investigated the influence of rock mass properties, blast design parameters and explosive properties on blast fragmentation. They stated that increasing the spacing, persistence, opening, roughness, waviness of discontinuities, and Vp and the uniaxial compressive strength (UCS) of intact rock as well as increasing the discontinuities angle with the bench face of the blasting block will increase the size distribution of the blasted rocks.

3. Methods and Materials

A total of 35 datasets were used in this research that are presented in Table 1. All blasting tests in the Sungun copper mine were collected by the authors and are listed in the table with a *Sun* abbreviation. The Sungun copper mine is located 120 km of the Tabriz City in northwestern Iran, and it hosts about 740 million tons of copper ore. In this mine, multiple images were captured from different locations of the muckpile after each blast. The images were analyzed separately and the results were combined. Discontinuity properties of the rock and the apparent in-situ block size of the benches were measured through surveying the joint parameters.

The blasts shown by symbol 'Akd' were performed at the Akdaglar quarry by Hüdaverdi et al. [34]. The Akdaglar quarry is located in northern Istanbul, Turkey. The research was conducted to investigate the application of heavy ANFO explosives in quarries. The quarry's rock is sandstone. The production capacity of the quarry is 5000 ton/day. In the Akdaglar quarry, Wipjoint and Wipfrag image processing software was applied on each blast and gathered the block size distributions before and after the blasts.

The blasts shown by symbol 'Mr' were obtained from the research of Ouchterlony et al. [35] performed in the Mrica quarry in Indonesia. The research was part of SveDeFo's investigations on the fragmentation prediction models.

Generally, the blast design parameters and the rock mass parameters are considered together to create a mean fragment size prediction model. Most of the existing models that are used to predict the rock fragmentation consider the intact rock and rock mass properties on one side with the other side being the intact mean fragment size along with the associated energy. Three theories are concerned with the required energy for fragmentation. However, Bond's theory is generally recognized to be the best model for describing blasting operations compared to the others [36]. Kuznetsov showed that the mean fragment size of a muckpile is a function of powder factor and the geological structure. He suggested that, for a particular rock type, the mean fragment size is related to the quantity of used explosives [15, 16]. Based on the researches by Ouchterlony and Cunnigham, the joint spacing, the specific gravity of rock and the specific charge are highly correlated with rock fragmentation [37-38, 39, 40, 41]. Also, the contribution of the specific charge is seen to be higher in the proposed model by Chung & Katsabanis rather than the Kuz-Ram model [42]. Another important parameter on fragmentation is the in-situ block size. The in-situ block size plays a major role in creating the mean fragment size of a muckpile. Kim and Kemeny developed a model for rock fragmentation in which they demonstrated the in-situ block size to be the most effective parameter on fragmentation [8].

The proposed equation (Eq. 1) has the intact rock and the rock mass properties on one side with the other side being the specific explosives energy and the mean fragment size.

$$X_i \times \rho_r = Se \times F \quad (1)$$

Where X_i is the average apparent in-situ block size (meter), ρ_r is the specific gravity of the rock (g/cm^3), Se is the specific explosive energy (Kcal/t), and F is the mean fragment size (cm). One may rearrange the above equation to obtain a better-arranged equation as below:

$$F = a \times (Se/\rho_r)^b \times X_i^c \quad (2)$$

In this study, SPSS V.16 software was used for statistical and regression analyses. The values of a, b and c coefficients were 579.354, -0.822 and -0.137, respectively, with the corresponding determination coefficient being R^2=0.470.

The burden parameter is one of the most important and critical variables in designing the blast pattern in open pit mines to which other blasting variables are associated. Its value depends upon the blast hole diameter, rock characteristics, and the type of utilized explosives [12, 43]. In the Kou-Rustan and SveDeFo models, spacing and burden have the highest weights [35, 20]. Therefore, we introduced a spacing to burden ratio and burden into the above equation.

$$F = a \times (Se/\rho_r)^{b} \times X_i^c \times (S/B)^d \times (B)^e \quad (3)$$

Where a, b, c, d, and e are 73.533, -0.548, 0.266, 1.089 and 0.735, respectively, with the determination coefficient being R^2=0.750. The associated determination coefficient with the Eq. 3 is seen to be increased by 0.280 compared to that of the Eq. 2; this shows the influences of spacing and burden on the fragmentation process.

Bench height is another effective parameter on rock fragmentation. The higher bench height leads to the higher rock column in front of the blasthole. By increasing the height of rock column, its strength decreases. Therefore, the rock column should be better broken in such conditions [12, 43]. As an effective parameter, this parameter is also included into the Kou-Rustan and Chung–Katsabanis models. To further increase the accuracy of the model, one may introduce the expression (H/B) into Eq. 3.

$$F = a \times (Se/\rho_r)^{b} \times X_i^c \times (S/B)^{d} \times (B)^e \times (H/B)^{f} \quad (4)$$

Where a, b, c, d, e and f coefficients are 78.654, -0.556, 0.266, 1.090, 0.772 and -0.017, respectively, with the determination coefficient being R^2=0.750. It was observed that the determination coefficient did not change. As it can be seen from Table 1, the minimum and maximum values of the H/B ratio are 2.5 and 6 respectively. Exponentiation of these numbers by -0.017 is 0.97 and 0.98, respectively, which are close to 1, since H/B tends to be eliminated.

The specific gravity of explosive is another effective parameter on rock fragmentation. With increasing this parameter, the detonation velocity and strength of explosive will increase as well, which lead to further rock fragmentation. Explosives generate two types of energy: gas and shock waves [12], the ratio of them is related to the specific gravity of explosive. In the next step, this parameter was introduced into Eq. 3.

$$F = a \times (Se)^{b} \times X_i^{c} \times (S/B)^{d} \times (B)^{e} \times (\rho_e/\rho_r)^{f} \qquad (5)$$

Table 1. data collected to develop the fragmentation model.

Mine Name	B (m)	S (m)	D (mm)	H (m)	ρ_r (g/cm^3)	ρ_e (g/cm^3)	Se (kcal/t)	X_i (m)	F (cm)
Sun	4.5	5.5	140	12.5	2.3	0.9	145.39	0.4	22
Sun	4.5	5.5	140	12.5	2.4	0.9	139.33	0.4	22
Sun	4.5	5.5	140	12.5	2,3	0.9	145.39	0.4	24
Sun	4.5	5.5	140	12.5	2.4	0.9	139.33	0.5	24
Sun	4.5	5.5	140	12.5	2.4	0.9	139.33	0.4	25.5
Sun	4.5	5.5	140	12.5	2.43	0.9	137.61	0.5	26.5
Sun	4.5	5.5	140	12.5	2.5	0.9	133.76	0.8	27
Sun	4.5	5.5	140	12.5	2.49	0.9	134.33	0.8	28.5
Sun	4.5	5.5	140	12.5	2.6	0.9	128.62	0.8	29
Sun	4.5	5.5	140	12.5	2.65	0.9	126.19	1.2	32
Sun	3.5	4,9	140	12.5	2.51	0.9	161.27	1	30
Sun	1,2	3.3	76	12.5	2.51	0.9	94.66	0.8	30
Sun	4	5	140	12.5	2.48	0.9	127.74	0.9	35
Sun	4	5	140	12.5	2.51	0.9	122.71	0.9	33
Sun	4	5	140	12.5	2.7	0.9	123.85	1.2	42
Akd	2.2	2.5	89	7	2.7	0.8	224.89	0.93	16.45
Akd	2.2	2.5	89	7	2.7	0.8	224.89	1.15	17.25
Akd	2	2.5	89	6.5	2.7	0.8	231.41	1.32	21.12
Akd	2.2	2.7	89	5.5	2.7	0.8	185.78	1.26	17.37
Akd	2.2	2.5	89	7	2.7	1.27	204.44	2.01	19.65
Akd	2.5	2.8	89	7	2.7	1.27	160.00	1.24	15.17
Akd	2	2.5	89	7	2.7	1.27	222.22	1.13	14.43
Akd	2.2	2.7	89	5.5	2.7	1.27	168.89	1.86	12.71
Mr	2.5	3	76	15	2.5	0.98	168.09	1.67	17
Mr	2.5	3	76	15	2.5	0.99	174.46	1.67	17
Mr	2.5	3	76	10	2.5	1.06	189.59	1.03	17.5
Mr	2.5	3	76	15	2.5	0.98	167.93	1.67	12.5
Mr	2.5	3	76	15	2.5	1.15	173.22	1.67	6.5
Mr	2.5	3	76	15	2.5	1.30	136.42	1.67	12.5
Mr	2.5	3.5	76	10	2.5	1.39	96	1.03	19
Mr	2.5	3.5	76	10	2.5	1.27	114.24	1.03	16
Mr	2.5	3.5	76	15	2.5	1.39	115.20	1.67	15
Mr	2.4	3	76	10	2.5	1.21	158.52	1.03	20
Mr	3	3.5	76	10	2.5	1.23	128.17	1.03	16.5
Mr	3	3.5	76	10	2.5	1.25	104.96	1.03	20.5

Where a, b, c, d, e and f coefficients are 160.603, -0.701, 0.260, 0.748, 0.596 and 0.750, respectively, with the determination coefficient being R^2=0.799. Based on these coefficients, the equation is modified as below:

$$F = 160.63 \times (Se)^{-0.701} \times X_i^{0.260} \times (S/B)^{0.748} \times (B)^{0.596} \times (\rho_e/\rho_r)^{0.750} \qquad (6)$$

In order to consider the effect of the borehole diameter on fragmentation, and to compare it with the burden value, the expression (S/B) was substituted by (S/D) where D is expressed in meter.

$$F = a \times (Se)^{b} \times X_i^{c} \times (S/D)^{d} \times (B)^{e} \times (\rho_e/\rho_r)^{f} \qquad (7)$$

Where a, b, c, d, e and f coefficients are 49.279, -0.883, 0.138, 0.569, 0.363 and 0.205, respectively, with the determination coefficient being R^2=0.712. It was observed that the determination coefficient was decreased, since S/D tends to be eliminated, hence one may have a final form as that represented by Eq. 6.

In order to assess the statistical significance of Eq. 6, a regression analysis was conducted on the observed and model-predicted values. The multiple correlation coefficient (R) is the linear correlation between the observed and predicted values of the dependent variable. Its large value (close to 1) demonstrates a strong relation. The coefficient of determination R^2, is the squared value of the multiple correlation coefficient and is the most popular criterion used to judge the model fit. R^2 is the percent of the variance in the dependent variable and is explained collectively by all of the independent variables. An R^2 value close to one, as well, indicates the significance of regression. For example, the regression model explains the R^2 value given in Table 2 showing 80% of the variation in the mean particle size (X_{50}). The residuals are the difference between the observed and the model-predicted values. The residuals are diagnostic of the soundness of the model and the residual analysis is a key part of judging its quality. The F test was applied to test the significance of the regression model. If the significance value of the F statistic was less than 0.05, meaning that the variation explained by the model was not incidental [44]. Table 2 shows a significance value of very close to zero based on the F value. It indicates the significance of the developed regression equation. All these values indicate that the regression is important and strong for Eq. 6.

Table 2. Regression analysis obtained for Eq. 6.

R	R^2	Adjusted R^2	Standard error	Observations
0.894	0.799	0.793	0.034	35

Analysis of variance (ANOVA)					
	df	Sum of squares	Mean square	F	Significance F
Regression	1	0.157	0.157	131.035	0.000
Residual	33	0.039	0.001		
Total	34	0.196			

The exponent of the specific explosive energy is negative for Eq. 6. The increase of the specific explosive energy results in the decrease of the mean particle size. In addition, the exponents associated with other expressions are positive. The increase of these expressions result in the increase of the mean particle size.

4. Discussion

4.1. Validation of model

In order to validate the proposed model, six blasts were studied in the

Chadormalu iron ore mine (Table 3). The mine is located 180 km northeastern of Yazd in Central Iran. This mine contains 400 million tons of iron, of which 330 million tons is the mineable reserves. In this mine, multiple images were captured from different locations of the muckpile after each blast. The images were separately analyzed using the Goldsize program and the results were combined. The image processing steps for a blast at The Chadormalu iron ore mine and the corresponding muckpile distribution curve are shown in Figs. 1 and 2. Discontinuity properties of the rock and the apparent in-situ block size of the benches were measured through surveying the joint parameters. The proposed model was further verified using a blast performed in the Porgera gold mine [45]. Furthermore, in this mine, image analysis was used to estimate the size distribution of the mine run. The predicted values of X_{50} by the proposed model were in a good agreement with the measured X_{50} (Table 4). As it can be seen from Table 4, the proposed model succeeded to improve the accuracy of X_{50} predictions by 10%, on average.

Fig. 1. Image processing for a blast, the Chadormalu iron ore mine.

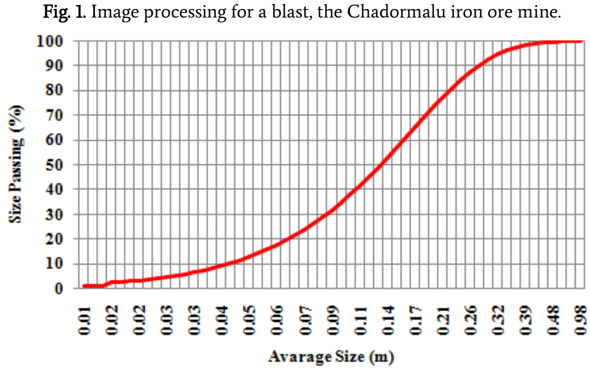

Fig. 2. Distribution curve for a blast, the Chadormalu iron ore mine.

Table 3. Data collected from the Chadormalu iron deposit and the Porgera gold mines.

Mine Name	B (m)	S (m)	D (mm)	H (m)	ρ_r (g/cm^3)	ρ_e (g/cm^3)	Se (kcal/t)	X_I (m)
Chad	3	3.5	165	10	4.5	0.9	297	0.5
Chad	3	3.5	165	10	4.5	0.9	325	0.5
Chad	3	3.5	165	10	4.5	0.9	327	0.5
Chad	3	3.5	165	10	4.5	1.15	430	0.5
Chad	3	3.5	165	10	4.5	1.15	430	0.5
Chad	3	3.55	165	10	4.5	0.9	284	0.3
Por	5.3	6.3	200	10	2.7	1.25	195	0.55
had	3	3.5	165	10	4.5	0.9	297	0.5

Table 4. Comparison of results of image processing and the proposed model.

Mine	Chad	Chad	Chad	Chad	Chad	Chad	Por
Measured (cm)	17.53	16.86	16.13	12	12.35	12.55	15
Predicted (cm)	17.85	16.78	16.71	11.46	11.46	16.16	18.62
Difference (%)	1.83	0.48	3.60	4.5	7.2	28.77	24.13

A sensitivity analysis was carried out to determine the effectiveness of each parameter in Eq. 6. The sensitivity analysis was performed using the artificial neural network method. The artificial neural network method employed the criterion proposed by Yang and Zhang [46] and was also used by Monjezi and Dehghani [47]. According to this technique, the relative strength of effects (RSE) can be calculated using the neural network trained by the back propagation algorithm with a given sample set. Using the RSE, the most important factors in the model performance can be recognized, hierarchically [46]. For a given input, larger absolute values of RSE mean the greater effect on the corresponding output. RSE is a dynamic parameter that changes with the variance of input factors (Fig. 3). It was observed that the burden and the specific explosive energy were the most effective parameters in the Eq. 6.

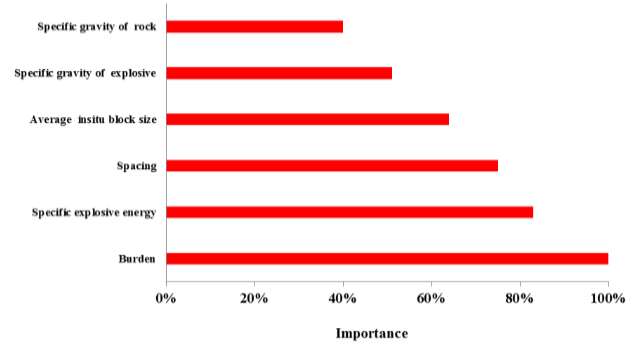

Fig. 3. The importance of parameters in Eq. 8.

4.2. Comparison between the proposed and the Kuz-Ram models

A popular blasting fragmentation prediction model is the Kuz-Ram empirical fragmentation model which has been used widely by many researchers and engineers [15, 48]. The original equation developed by Kuzentsov [15] and Cunningham [19, 20] modified the Kuznetsov's equation to estimate the mean fragment size and used the Rosin–Rammler distribution to describe the entire size distribution. The uniformity exponent of the Rosin–Rammler distribution was estimated as a function of the blast design parameters. The final equation suggested by Cunningham, known as the Kuz–Ram model can be given as follows:

$$X_m = A \times (K)^{-0.8} \times Q_e^{0.167} \times (115/S_{ANFO})^{0.633} \quad (7)$$

Where X_m is the mean fragment size (cm), A is the rock factor, K is the powder factor (kg of explosives/m^3), Q_e is the mass of explosive per blast hole (kg), S_{ANFO} is the relative weight strength of explosive (ANFO=100).

The rock factor "A" in Kuznetsov's equation was estimated incorporating the blastability Index (BI) of Lilly [49].

$$A = 0.06(RMD+JPS+JPO+RDI+HF) \quad (8)$$

Where RMD is the rock mass description (powdery or friable=10, blocky=20 and massive=50), JPS is the joint plane spacing (close<0.1 m=10, 0.1 – 1.0=20, >1.0=50), JPO is the joint plane orientation (horizontal=10, dip out face=20, strike normal to face=30, dip into face=40), RDI is the rock density influence equal to 25d–50 where d is the density and HF is the hardness factor equal to E/3, if the modulus of elasticity (E) is <50 GPa; HF=UCS/5, if E is >50 GPa, where UCS is the uniaxial compressive strength.

Comparing the power of the proposed and the Kuz-Ram models shows that the specific explosive energy and the powder factor as the energy part of these models are almost the same. The specific explosive energy in the proposed model includes the powder factor and the weight strength of explosive in the Kuz-Ram model. In addition, the burden parameter as the critical parameter in the fragmentation is considered in the proposed model.

As such, the predicted mean fragmentation size was compared to the Kuz-Ram model using the actual data obtained from the Chadormalu iron ore mine (Fig. 2 and Table 5). The results suggested that the proposed model has successfully improved the accuracy of the predictions by 11.37 %, on average.

Table 5. Comparison of the mean fragment size of image processing, the proposed and the Kuz-Ram models in the Chadormalu iron ore mine.

Mine	Chad	Chad	Chad	Chad	Chad	Chad
Measured (cm)	17.53	16.86	16.13	12	12.35	12.55
Predicted (cm)	17.85	16.78	16.71	11.46	11.46	16.16
Kuz-Ram	20.40	18.08	17.59	13.91	13.91	19.24

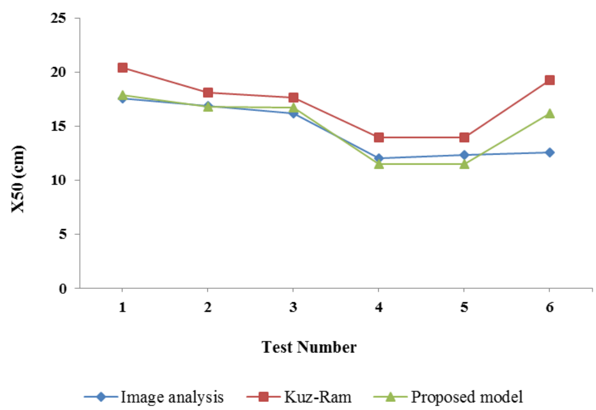

Fig. 4. Comparison of the mean fragment size of image processing, the proposed and the Kuz-Ram models in the Chadormalu iron ore mines.

Fig. 4 shows that the predicted data by the proposed and the Kuz-Ram models are parallel. This may show that the models have the same base.

5. Conclusion

A new well-applicable model for fragmentation by blasting was developed based on the investigation of the effective parameters in various empirical models. The proposed model was calibrated by nonlinear fits to 35 bench blasts in different sites from the Sungun copper mine, the Akdaglar quarry, and the Mrica quarry. The results were in a good agreement with the actual data collected from the Chadormalu iron deposit and the Porgera gold mine that were employed as the validation cases. The Comparison of the powers between the proposed and the Kuz-Ram models showed that the specific explosive energy and the powder factor are almost the same. Moreover, a comparison was carried out between the results of the Kuz-Ram model and those of the proposed model, in terms of X_{50} estimations. The results showed that the proposed model successfully improved the accuracy of X_{50} predictions by 11.37%, on average. In addition, the sensitivity analysis based on the artificial neural network showed that the burden and specific explosive energy were the most effective parameters in the proposed model. The advantage of the proposed model over the Kuz-Ram model is its specific explosive energy, because this parameter includes the powder factor and the weight strength of explosive.

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