Multivariate statistics application in development of blast fragmentation charts for different rock formations in quarries

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Rock fragmentation is considered to be one of the most important aspects of quarrying because of its direct effect on the costs of drilling, which include blasting, loading, hauling and crushing. Thus, it is essential to consider fragmentation size in blasting design. Fragmentation depends on many variables, such as rock properties, geological structures, and blasting parameters. Although empirical models for the estimation of the size distribution of rock fragmentation have been developed by considering these parameters, no complete empirical prediction model for fragmentation exists since rock properties and geological structures vary from site to site. However, these models regard rock properties as constant. In this study, a step–wise multiple linear regression analysis has been carried out to determine the degree of dominance of various influencing parameters on fragmentation and to develop a fragmentation prediction model. The results showed that the rock mass properties, burden width and specific charge are the main parameters affecting fragmentation. The relations among those parameters were used to develop guideline charts to determine blast layouts for desired fragmentation on the basis of rock characteristics.

Key words: *Fragmentation, Multiple regression, UCS, image processing, rock formations*

Introduction

Quarries are a main source of aggregate for the construction work of infrastructures and housings. Blasting is one of the most important processes in a quarry since blasting affects the productivity and efficiency of quarrying, which is based mainly on the rock fragmentation. If rock fragmentation does not result in the desired size, production costs may be increased due to undesired secondary blasting and crushing. Mechanical crushing and grinding are particularly expensive operations at a mine, and considerable cost and throughput benefits can be obtained by breaking the rock through the effective use of explosives (Eloranto, 1997; Simangungsong, 2003). Therefore, blasting design should take rock fragmentation into account in order to cut down on costs. Over the years, many studies have tried to predict the fragmentation of rock from blasting (Cunningham, 1983, 1987; Morin and Ficarazzo, 2006; Zagreba, 2003).

It is a known fact that fragmentation is a function of three groups of parameters: rock mass properties, blast geometry, and explosive properties (Chatraborty et al., 2004; Koruc et al., 2002; Thorton et al., 2002). Among these parameters, rock mass properties are non-controllable but they should be known before blasting. The explosives used in mining operations are mainly bulk blasting agents (ANFO, Slurries, Emulsions), so in one sense, explosive properties might also be assumed to be non-controllable parameters. Then the only remaining controllable parameter is the blast geometry (burden, spacing, stemming, hole-diameter, and hole length). In addition to these parameters, the specific charge is also a controllable parameter since it is a function of blast geometry and specific gravity of explosive.

By analyzing the rock, fragmentation size after blasting, it is possible to design a blasting pattern for target fragmentation. In this study, rock fragmentation is analyzed from actual blasting in a quarry operation by using an image processing program; then a multiple linear regression analysis is performed to determine the effect of variables on fragmentation and to define a fragmentation prediction model.

Fragmentation assessment methods

In many cases fragmentation assessment that uses sophisticated image processing programs has replaced conventional methods, such as visual analysis, photography, photogrammetry, boulder count, and sieve analysis techniques (Chatraborty et al.,2004). Image processing includes image capturing of the muck pile, scaling the image, filtering the image, segmentation of the image, and measurement. Although this method allows rapid and accurate blast fragmentation size distribution assessments, many problems can be encountered while using image analysis programs. These problems are mainly as follows (Franklin et al., 1995; Kim et al., 2006; Ozkahraman, 2006):

1. these programs cannot take into account the interior rock: they can analyze only what is on the surface,

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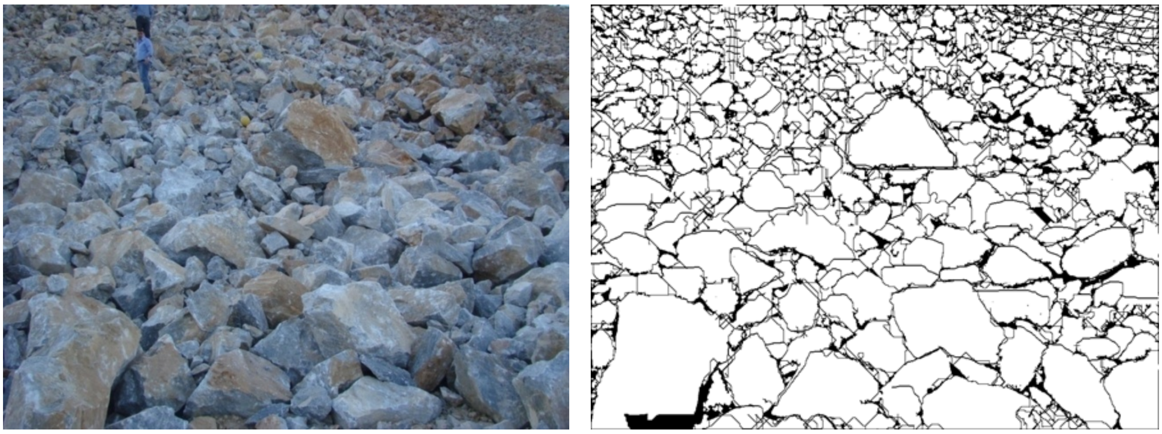
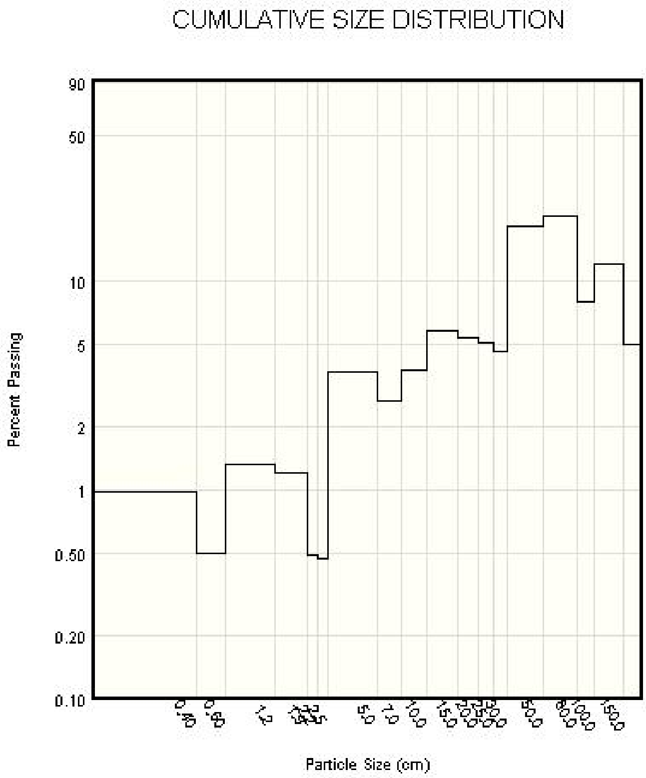
2. the analyzed particle size can be over-divided or combined. In other words, big boulders could be divided into smaller particles and smaller particles could be grouped into bigger particles,
3. fine particles can be underestimated, especially in a muckpile.

The best way to avoid these problems is to select the proper sampling strategies. Image processing programs provide better results if the thickness of the pile is small (Kim, 2006; Ozkahraman, 2006). Among the different image–processing programs, the following are the most commonly used: IPACS, TUPICS, FRAGSCAN, WIPFRAG and SPLIT (Cunningham, 1995; Dahlhielm, 1996; Haverman and Vogt, 1996; Liu and Tran, 1996; Maerz et al., 1996; Schleifer and Tessier ,1996).

In this study, digital image analysis using SPLIT 2.0 software was adopted for assessing the fragment size (P_{20}), (P_{50}), (P_{80}) and (P_{max}) from muck piles. The analysis technique includes steps like the image captures of a muckpile, uploading the images in the computer and analysis in the computer like scaling the image, filtering the image, edge detection, and conversion of 2D information to 3D. Fig. 1 shows a photograph of a muckpile together with two 220 mm ball images for scaling purposes. Fragmentation scaling is determined by the program.





size (mm)	%
2000.00	0.00
1500.00	4.96
1000.00	12.04
800.00	8.01
500.00	20.66
300.00	18.24
250.00	4.63
200.00	5.14
150.00	5.41
100.00	5.80
70.00	3.76
50.00	2.68
25.00	3.69
22.00	0.47
19.00	0.49
12.00	1.20
6.000	1.33
4.000	0.49
Pan	0.99
P20 Size (mm)	142.00
P50 Size (mm)	451.93
P80 Size (mm)	913.44
Top size (mm)	1890.31

SPLIT academic version

Fig. 1. The photo of Muckpile and SPLIT 2.0. results.

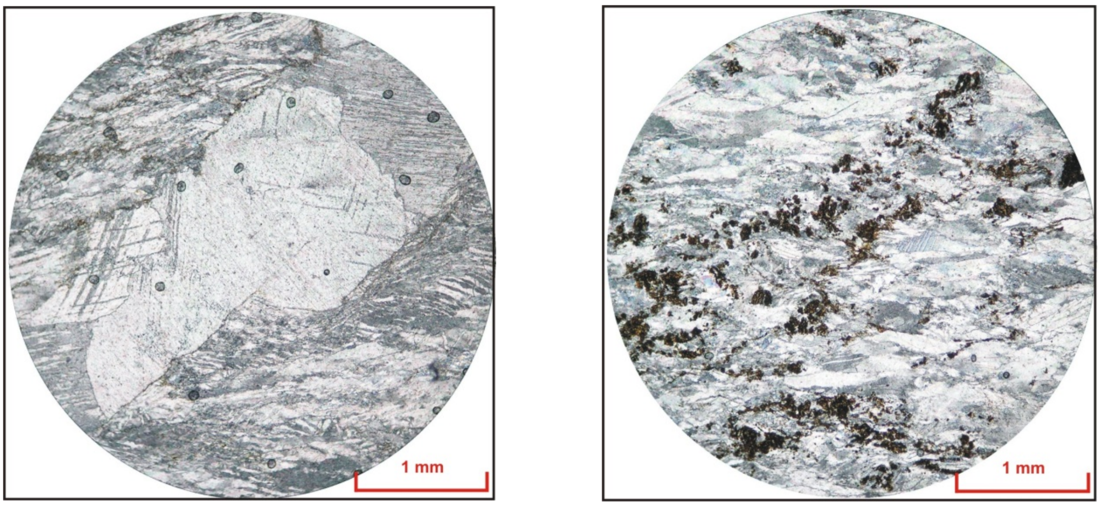
Field Investigation

The operation area was divided into 6 regions by visual observation on the basis of color and fissure since it is the easiest parameter to use for classifying various kinds of rocks. Then rock samples were collected from each region to determine the selected rock parameters, and the results are given in Tab. 1.

Tab. 1. Rock Properties.

		Regions						Unit
		R1	R2	R3	R4	R5	R6	
Uniaxial compressive strength (UCS)	Max	144	132	100	86	73	58	Mpa
	Min	110	102	87	71	60	37	
	Std Dev.	7.95	7.45	3.92	4.38	4.28	5.27	
	Average	131.19	117.00	93.92	79.10	66.07	45.25	
Density	Max	2.78	2.78	2.75	2.78	2.8	2.78	gr/cm^3
	Min	2.51	2.61	2.6	2.54	2.54	2.54	
	Std Dev.	0.07	0.04	0.05	0.08	0.10	0.07	
	Average	2.68	2.69	2.70	2.69	2.69	2.69	
Porosity	Max	0.33	0.38	0.38	0.39	0.38	0.39	%
	Min	0.25	0.27	0.28	0.26	0.29	0.33	
	Std Dev.	0.03	0.03	0.03	0.04	0.03	0.02	
	Average	0.29	0.31	0.33	0.34	0.35	0.37	
Water absorption by weight	Max	0.12	0.17	0.15	0.15	0.16	0.17	%
	Min	0.09	0.10	0.10	0.11	0.10	0.10	
	Std Dev.	0.01	0.02	0.02	0.01	0.02	0.02	
	Average	0.11	0.14	0.12	0.13	0.13	0.14	
Schmidt hardness	Average	52	49	45	42	40	37	L(ISRM)

As it can be seen in Tab. 1, the UCS (Uniaxial Compressive Strength)'s are different for each region with the highest average UCS of 131.19 Mpa for in region 1 and the lowest average UCS of 45.25 Mpa for in region 6. This situation indicates that the visual color-based classification is confirmed by the laboratory tests. In addition to the rock mechanic tests, microscopic views of rocks taken from each region have been prepared (Fig. 2). The microscopic views indicate that the calcite minerals are large for region 1, and they became smaller through region 6. The micro cracks are seen in the microscopic views of rocks taken from region 2 and then number of cracks increases from region 2 through region 6. In these cracks, clay, iron-oxide and manganese are seen. Therefore, the color of the rocks varies from region to region.



Microscopic view of region 1 *Microscopic view of region 6*

Fig. 2. Microscopic views of rocks taken from different region.

A total of 141 blasts were conducted in the quarry operation. Different rock mass properties, blast design parameters and blast results were observed in various rounds of blasting. The blast design parameters were different for each blasting mainly because of variations in the rock mass properties, the bench configurations, and the required production. The parameters of each blast round were recorded. The records and resulting fragmentation size distribution for each blast in region 1 are given in Table 2.

Tab. 2. Blast Parameters and Fragmentation Distribution for region 1.

Region	Hl	B	S	Cl	St	Qe.	p	q	P20	P50	P80	Top
			[m]			[kg/hole]	[m^3/hole]	[kg/m^3]		[mm]		
1	12	3	2,4	8,1	3,9	75	86	0,87	72,83	470,26	690,91	1407,29
	12	2,9	2,9	8,1	3,9	75	101	0,74	96,69	407,61	772,1	1399,03
	12	2,8	2,4	8,1	3,9	75	81	0,93	94,41	389,89	612,63	1103,01
	12	3	2,9	8,1	3,9	75	104	0,72	93,67	464,37	920,97	1816,93
	12	2,5	2,5	8,1	3,9	75	75	1,00	92,55	207,4	640,54	704,88
	12	3	2,7	8,1	3,9	75	97	0,77	79,2	485,34	710,23	1320,34
	14	2,5	3	10,8	3,2	100	105	0,95	64,77	206,05	471,99	777,58
	14	4	3,4	10,8	3,2	100	190	0,53	79,65	701,35	1369,61	2507,28
	9	2,9	2,5	4,9	4,1	50	65	0,77	70,64	410,44	924,27	1138,22
	9	3,1	2,5	4,9	4,1	50	70	0,72	58,22	554,72	1159,5	1479,91
	9	2,8	2,5	4,9	4,1	50	63	0,79	56,35	513,77	770,17	1295,34
	9	2,6	2,5	4,9	4,1	50	59	0,85	49,7	366,96	636,76	797,21
	9	3,5	2,5	4,9	4,1	50	79	0,63	198,54	650,49	1316,13	1656,97
	9	3,2	2,6	4,9	4,1	50	75	0,67	52,8	585	932,99	1588,25
	9	2,4	2,5	4,9	4,1	50	54	0,93	36,29	323,9	261,02	608,25
	9	2,1	2,6	4,9	4,1	50	49	1,02	45,85	101,12	166,65	289,55

Hl- hole length, B-Burden, S-Spacing, Cl-column length, St-stemming, Qe-explosive amount, p-production, q-specific charge

Data Analysis

Multiple linear regression (MLR) analysis is performed in order to assign relative importance to the independent variables, which may be interrelated. MLR analysis can be performed with the following:

a, Backward elimination: In this procedure, correlation starts with all the independent variables that are in the equation. The variables are checked one at a time, and the least significant is dropped from the model at each stage until the remaining variables in the equation provide a significant contribution to the prediction of the dependent variable.

b, Forward selection: In forward selection, the independent variable having the largest partial correlation is first selected, and its correlation is established with the dependent variable. Then variables are checked one at a time, and the most significant is added to the model at each stage. The procedure is terminated when all of the variables not in the equation have no significant effect on the dependent variable.

c, Stepwise regression: In this procedure, the regression equation is determined without any variables in the model. Variables are then checked one at a time using the partial correlation coefficient as a measure of importance in predicting the dependent variable. At each stage the variable with the highest significant partial correlation coefficient is added to the model. This procedure is continued until no further variables can be added or deleted from the model.

d, Simultaneous method: This method is called the "Enter Method" by the SPPS (Statistical Package for the Social Sciences) program. In this method, the user specifies the set of predictor variables for which the model is used. Then the success of the model for predicting the dependent variable is measured.

The simultaneous method is defined as the safest method to use, especially if there is no theoretical model (Brace et al., 2003). Therefore, the simultaneous method is used in this study.

In the first test, the degrees of influence of the UCS, the burden, spacing, and specific charge on the fragmentation size (P_{80}) were determined using the Enter Method of MLR. The steps of the test were as follows:

Systematic differences among the fragmentation sizes of the six regions were controlled with dummy variables (d2, d3, d4, d5, d6). A dummy variable is often used in regression models to distinguish different treatment groups, such as locations having a different UCS. The dummy variables given in Tab. 3 will enable us to use a single regression equation to represent regional differences. For example, d2 is one for 66.07 MPa, and zero for all other strengths. It is expected that P80 will increase with UCS.

Tab. 3. Regional Intercept Dummy Variables.

Uniaxial Compressive Strength [Mpa]	**Dummy Variables**				
	d2	**d3**	**d4**	**d5**	**d6**
45.25	0	0	0	0	0
66.07	1	0	0	0	0
79.1	0	1	0	0	0
93.92	0	0	1	0	0
117	0	0	0	1	0
131	0	0	0	0	1

Tab. 4. Summary of Multiple Regression Analysis.

a) Model Summary

Model	R	R Square[b]	Adjusted R Square	Std. Error of the Estimate
1	.991[a]	.983	.982	84.72839

a. Predictors: d6, d5, d4, d3, d2, S, B, q

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

b) ANOVA[c,d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.410E7	8	6762511.354	941.998	.000[a]
	Residual	947614.747	132	7178.900		
	Total	5.505E7	140			

a. Predictors: d6, d5, d4, d3, d2, S, B, q

b. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

c. Dependent Variable: p80

d. Linear Regression through the Origin

c) Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	B	277.384	18.004	1.373	15.407	.000
	S	-11.146	24.095	-.058	-.463	.644
	q	-836.768	72.547	-.879	-11.534	.000
	d2	196.659	24.275	.116	8.101	.000
	d3	291.177	25.986	.171	11.205	.000
	d4	386.813	26.664	.271	14.507	.000
	d5	512.376	31.379	.324	16.329	.000
	d5	673.095	40.921	.363	16.449	.000

The results of the MLR are given in Tab. 4. The following can also be interpreted from Tab. 4:

- The equation of the model is as follows(Tab. 4c):

$$P80 = 277.384 \times B - 11.146 \times S - 836.768 \times q + 196.659 \times d1 + 291.177 \times d2$$
$$+ 386.813 \times d3 + 512.376 \times d4 + 673.095 \times d5$$

- The ability of the model equation to fit the actual data as indicated by the adjusted R square is 0.982. It means that the correlation of this regression relationship is very high (Tab. 4a).

- The "F" value for the model and the coefficients of the independent variables, with the exception of "Spacing," are significant at the 1 % level of significance (Tab. 4b). The signs of the variables are consistent with the expectations (the signs associated with all regression coefficients are in accord with a priori expectations).
- The regional intercept dummy variables are significantly different from zero, which suggests that the categorization of location by uniaxial compressive strength is one of the key explanators of fragmentation size differentials. As the UCSs increase, the intercept of the model increases.

In Table 4c, the high value for the standardized Beta coefficient indicates that the specific charge in this predictor variable has a large effect on the dependent variable. The t and sig(p) values give a rough indication of the impact of each variable. Big t values and small p values indicate that a variable has a large impact on the criterion variable. The results indicate that "spacing" has no impact on the fragmentation size, as it can be seen that t=-4.63 and p=0.644 for "spacing." Because of this, another regression model excluding "spacing" and given in Table 5, was tried.

Tab. 5. Summary of Multiple Regression Analysis (excluding "spacing").

a) Model Summary

Model	R	R Square[b]	Adjusted R Square	Std. Error of the Estimate
1	.991[a]	.983	.982	84.47765

a. Predictors: d5, d4, d3, d2, d1, B, q

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

b) ANOVA[c,d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.410E7	7	7728364.953	1082.939	.000[a]
	Residual	949150.904	133	7136.473		
	Total	5.505E7	140			

a. Predictors: d5, d4, d3, d2, d1, dilkal, bpmm

b. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

c. Dependent Variable: p80

d. Linear Regression through the Origin

c) Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	B	269.864	7.715	1.336	34.978	.000
	q	-863.169	44.653	-.907	-19.331	.000
	d1	195.561	24.087	.115	8.119	.000
	d2	294.929	24.615	.173	11.982	.000
	d3	392.524	23.564	.275	16.658	.000
	d4	519.780	26.911	.329	19.315	.000
	d5	686.091	29.665	.370	23.128	.000

a. Dependent Variable: p80

b. Linear Regression through the Origin

The new regression model can be interpreted as follows:

- The equation for the model is as follows:

$$P80 = 269.864 \times B - 863.169 \times q + 195.561 \times d1 + 294.929 \times d2$$
$$+ 392.524 \times d3 + 519.780 \times d4 + 686.091 \times d5$$

- For different UCS values, the predictor equations are given in Table 6.

Tab. 6. Predictor equations for each region.

Region	UCS [MPa]	Models
R1	45.25	$P80 = 269.864 \times B - 863.169 \times q$
R2	66.07	$P80 = 195.561 + 269.864 \times B - 863.169 \times q$
R3	79.01	$P80 = 294.929 + 269.864 \times B - 863.169 \times q$
R4	93.92	$P80 = 392.524 + 269.864 \times B - 863.169 \times q$
R5	117	$P80 = 519.780 + 269.864 \times B - 863.169 \times q$
R6	131	$P80 = 686.091 + 269.864 \times B - 863.169 \times q$

- The adjusted determination coefficient is 0.982, which means that the derived model satisfactorily explain the relation between the fragmentation size and the involved variables.
- The p-value for the F-test statistic is less than 0.01, providing strong evidence against the null hypothesis which states that the coefficients of the predictors are equal to zero.
- Each coefficient of the predictors has the expected sign and all are significantly different from zero at the 1 % level.

Development of guideline charts

The MLR analysis indicated that the critical parameters for fragmentation size are the UCS of the rock, burden, and specific charge, as given in Tab. 5. Among those parameters, UCS is the uncontrollable parameter, and it varies within the quarry. The equations given in Tab. 6 define the relation among fragment size, burden, specific charge, and the UCS of rock. Based on these relations, blasting design charts were developed to determine the size of the controllable parameters for obtaining the desired fragmentation size in different areas of the quarry. The charts, having been developed for different UCSs, are given in Fig. 3 - 5. The charts provide specific charge recommendations on the basis of the desired fragmentation and the given burden. By using these charts, a planning engineer can easily determine the specific charge needed for the known area of a quarry in order to get the desired fragmentation size.

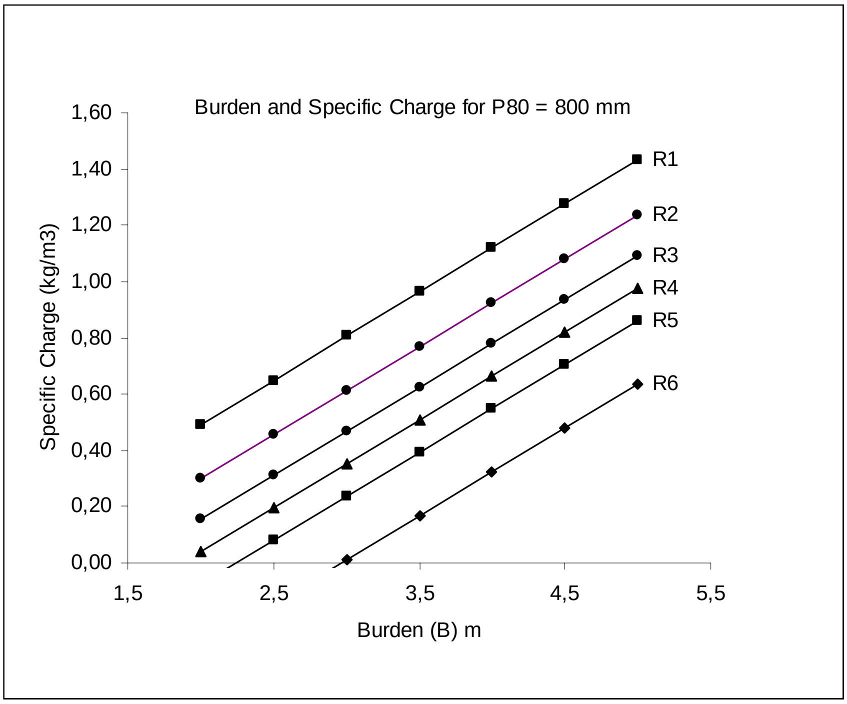


Fig. 3. Type I Chart (P80=800 mm).

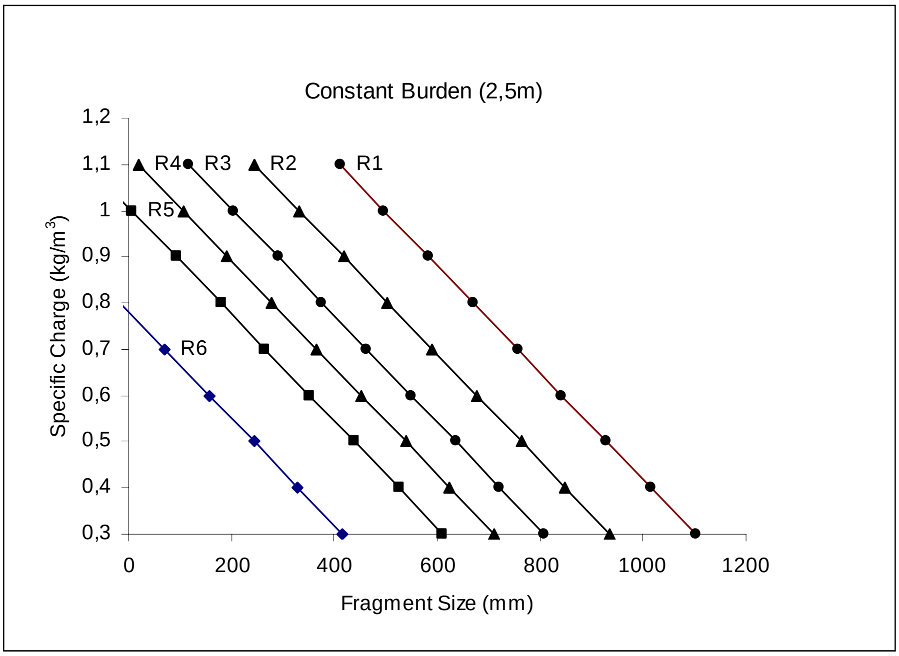


Fig. 4. Type II Chart (Burden width = 2,5 m).

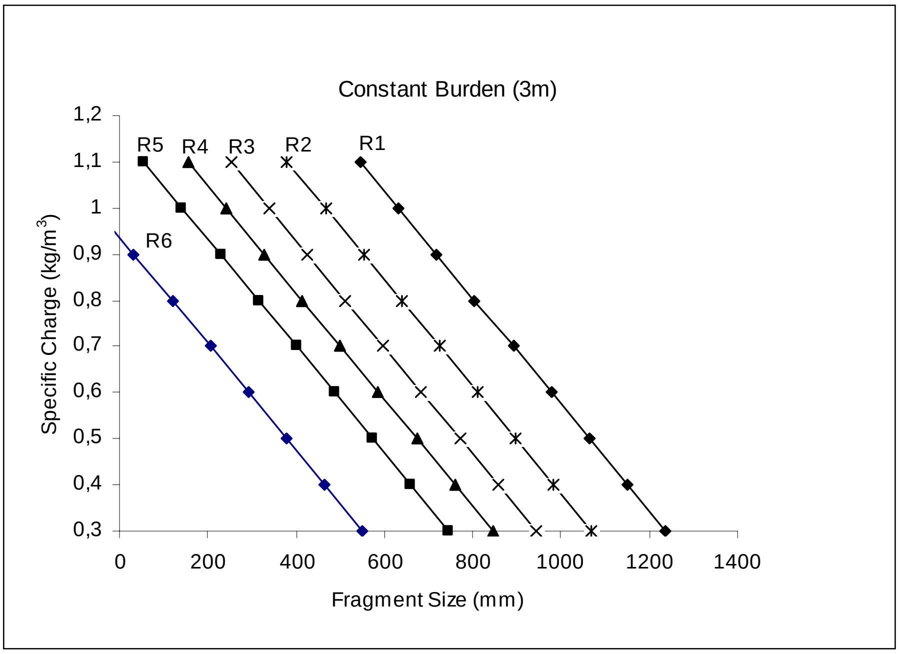


Fig. 5. Type II Chart(Burden width = 3 m).

Conclusions

The desired fragmentation in quarry blasting is defined by the end use of the product. The task of fragmentation assessment has been quite easy and fast with the advent of digital image processing techniques using various software packages. Precise guidelines are yet to be evolved to predict or control fragmentation size in various kinds of formations. An MLR analysis was carried out, keeping the observed 80 percentile (P80) fragment size as a dependent variable and various parameters such as UCS, burden, spacing, and specific charge as independent variables. The UCS, burden, and specific charge were found to be the most dominant variables, and the prediction models were developed on the basis of these parameters. The specific charge is a function of explosive density, hole-diameter, stemming, burden and spacing. Among these parameters, explosive density and hole-diameter are not easy to change.

So in order to change the specific charge, the stemming, burden, and/or spacing should be changed. On the basis of developed prediction models, different blasting guideline charts have been drawn to determine the specific charge for the desired fragmentation size. The prediction models and charts, which are site-specific, provide the planning engineer with a tool to design better blasting for the desired resulting fragmentation size in a given part of the quarry. These charts were developed by using different software (SPLIT 2.0., SPPS and MS EXCEL), and similar studies can be carried out for different quarries in order to develop site-specific charts. Hence, the study can be further expanded to consider more independent variables in order to obtain more precise guidelines to define a specific charge for a desired fragmentation size.

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