-RESEARCH PAPER-

International Journal of Mining and Geo-Engineering

IJMGE

IJMGE 56-1 (2022) 25-32

DOI: 10.22059/IJMGE.2021.310930.594870

Powder factor prediction in blasting operation using rock geo-mechanical properties and geometric parameters

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Article History:

Received: 05 October 2020.

Revised: 14 January 2021.

Accepted: 04 June 2021.

ABSTRACT

Prediction of powder factor is a major activity while preparing drilling and blasting operation, as the total production cost depends on it. It is a major input parameter in blast design as it influences the efficiency of subsequent operations in mining. Generally, effective parameters that influence powder factor can be divided into three namely, rock mass, geometric and explosive parameters. In this study, the rock mass properties and geometric parameters were studied based on the ratio of the mass of explosive and blast design. The main objective of this study is the application of a rock engineering system (RES) to calculate the powder factor index (Pfi) based on predominant rock mass properties and geometric parameters. This approach was applied to a database of twenty-four blast sites comprising of rock mass rating, blastability index, porosity, specific gravity, uniaxial compressive strength, burden, the ratio of spacing to burden, ratio of drilled-hole depth to burden, drilled-hole diameter, and ratio of the burden to drilled-hole diameter. The relationship between these parameters and how each of them influences the powder factor was studied and used to predict the powder factor index. The result shows that rock mass rating, blastability index, porosity, specific gravity, uniaxial compressive strength, and drilled-hole diameter affect powder factor. It also shows that Pfi is a robust technique for generating an improved line of fit and predicting more dependable and accurate valuation of powder factor with the coefficient of determination (R^2) of 0.86, and root means square error (RMSE) of 0.023 when compared with the traditional multivariable regression method.

Keywords: *Blasting, Burden, Powder factor index, Rock engineering system, Rock mass rating*

1. Introduction

Optimization of a mining operation to achieve desirable muck pile size distribution is a trending research area [1]. This is because drilling and blasting account for between 10 to 35% of overall operation cost [2] and the efficiency of subsequent operation depend on the size distribution of muck pile achieved after blasting [3-5]. The total production cost depends on suitable blast design and appropriate explosive selection. Powder factor and burden depend on the drilled-hole diameter and had been identified as important parameters in blast design [6-7] as the prediction and optimization of blasting conditions hang on them. Also, the powder factor has a vital influence on blast results, that is, fragmentation [8], and its appropriate prediction is an important research goal [7]. Estimation of the Powder factor was usually done through trial-by-error blasting which makes some researchers refer to blasting as an art rather than science [9-11], but researchers had set out the basis for the selection of powder factor and burden to make the activity more scientific. Powder factor is a measure of explosive for a given volume of material to be blasted [12-13] and its accurate prediction will reduce the cost incurred during the trial by error and secondary blasting [5]. The optimal powder factor for the minimal overall cost was defined as the powder factor required for optimum fragmentation, throw and ground vibration [11]. Blast design is meant to achieve desirable fragmentation economically with a high level of safety, if rock mass properties, explosive characteristics, and blast geometry are considered appropriately [14]. Rock mass properties are not within the control of blasters and engineers, thus, they are called uncontrollable parameters, whilst explosives can be selected based on their characteristics and blast geometry can be determined depending on rock mass properties are to referred as controllable properties [15-20].

Many methods had been used by researchers to estimate powder factor but the most popular ones had been linked to blast geometry and equivalent weight strength of explosives used [12] without consideration for rock mass properties and explosive characteristics. In this method, it was assumed that irrespective of explosive types and properties, an equal weight of different explosives, will produce the same impact when detonated. Many methods for the prediction of powder factor using rock mass properties and blast design parameters include but are not limited to comminution theory and work index [9], artificial neural network [21-22], multivariable regression analysis [23], and bond work index [6]. The complexity of the relationships between factors that determine suitable powder factors has made all the developing relationships and empirical equations insufficiently useful for all rock types and conditions. This has necessitated the development of a new approach to the prediction of powder factors.

However, the use of the Rock Engineering System (RES) model proposed by Hudson [24] has demonstrated to be a multi-task and robust approach for unraveling complex engineering problems like powder factor. Many researchers had applied the RES model in various engineering fields especially in rock mechanics, solving the problem associated with heterogeneity and the anisotropy nature of rock masses. RES model had been used for rock mass classification [25], investigate the effects of an earthquake in the stability of natural slope [26], prediction of fragmentation where intrinsic rock properties are

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relatively constant [27], hazard assessment of rockfall [28], the study of failure susceptibility zoning [29], prediction of tunnel boring machine downtimes [30], categorization of coal spontaneous combustion in coal regions [31], risk assessment owning to out-of-seam dilution(OSD) in longwall faces [32], flyrock risk assessment and distance prediction [33], studying of the caving probability of rock mass in block caving mines [34], landslide susceptibility mapping [35], prediction of overbreak in tunnel driven in hard rocks [36-37] and slope stability monitoring [38]. Recently, Rock Engineering System had been used for muck pile size distribution prediction and it has yielded good results and its accuracy has surpassed some of the models previously used for fragmentation prediction [19, 36 & 39] because it can relate many parameters measurable and descriptive. Thus, this study will be predicting powder factor using rock geomechanical properties and geometric parameters with the aid of the RES model and evaluating powder factor risk index with parameters from the twenty-four selected blast locations whilst multivariable analysis will be used to develop a regression model for comparison and evaluation of results.

2. The rock engineering system (RES)

The rock engineering system is a powerful engineering tool for characterizing the effective parameters in rock engineering problems [24 & 25]. The interaction matrix device is the key element in the RES approach. This matrix is used for characterizing the principal parameters and the interaction mechanisms in RES. In structuring the interaction matrix, the principal parameters influencing the system are located along the main diagonal of the matrix, whilst the intensity of the relationship of the parameters, which is assigned with coded values are located in the perpendicular positions. Figures 1 and 2 describe an interaction structure for two parameters and a general concept of coding the interaction structure respectively.

The expert semi-quantitative (ESQ) logic of assigning code to the relationship between parameters in the interaction matrix as described by Hudson [24], is an important and useful process in structuring the system. By this method, the interaction between every two factors is quantified using number 0 (no interaction), 1 (weak interaction), 2 (medium interaction), 3 (strong interaction) and 4 (critical interaction) [24 & 36]. Other methods used for coding the matrix are 0-1 binary and continuous quantitative coding (CQC) [24, 30, 40-42] as well as probabilistic expert semi-quantitative (PESQ) and expert method [31]. Also, a general view of the coding of the interaction matrix is shown in Figure 1. The codes on the row of pi are the influence of pi on all other parameters in the system whilst codes on the column through pi are the effects of other parameters on Pi. In principle, there is no limit to the number of parameters that may be included in an interaction matrix.

Thereafter the coding of the interaction matrix by inserting corresponding value to each perpendicular cell of the structure, the measure of how each parameter influences the system is named cause (Ci), and the effect of the system on each parameter is called effect (Ei). Cause (C) is the addition of all the coding values for each row in the interaction matrix while effect (E) is the addition of all the coding values for each column (Equations 1 and 2). That is, the impact of an individual parameter on the system and the effect of the system on each parameter is called C and E respectively (Figure 4). The cause-effect diagram is formed by (Ci Ei) coordinate values plotted in cause and effect space. The diagonal line is the plot when causes and effects are of the same value and it represents the locus point in which all parameters have equal dominance and subordination. The dominance parameters, that is those with a cause greater than effect, are on the right-hand side of the diagonal line in the plot whilst the subordinate parameters, that is, those parameters with cause less than effect, are on the left-hand side of the diagonal line.

With such a plot, it is, subsequently, conceivable to identify which parameter assumes a significant function in affecting the system. Also, the sum and subtraction of the C and E values, (C + E, C - E) are called interactive intensity and dominance, respectively and it is an indicator of the parameter significance in the system. The parameter weighting factor (ai) is formulated with Equation 3 using the percentage value of C + E [24-25, 43-44].

$$C_{pi} = \sum_{j=1}^{n} I_{ij} \tag{1}$$

$$E_{pj} = \sum_{i=1}^{n} I_{ij} \tag{2}$$

$$\alpha_i = \frac{(C_i + E_i)}{(\sum_i C_i + \sum_i E_i)} \times 100 \tag{3}$$

where C_i is the cause of the ith parameter, E_i is the effect of the ith parameter.

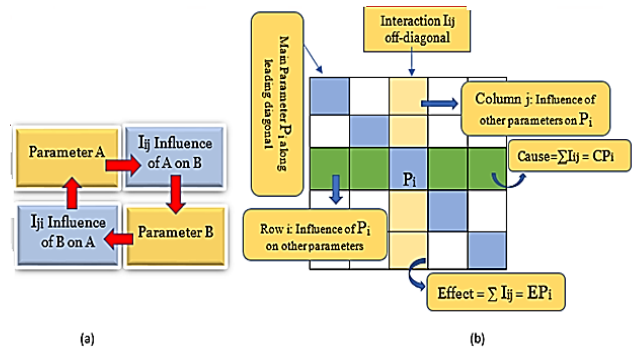

Figure. 1. The principle of the interaction matrix in RES, (a) two parameters (b) unlimited parameters [24 & 37].

3. Research Methodology

3.1. Case study

To achieve the specific objective of this study, data was collected from twenty-four blasting sites in southern Nigeria, which were involved in aggregates production. The physiographical study of the research locations falls within the Precambrian assemblage of igneous and metamorphic underlying stratifying rocks of southwestern Nigeria. The rocks that made up the basement, notwithstanding dissimilarities on lithological descriptions, are classified loosely into three groups namely, the migmatite-gneiss complex, the schist orogens, and the unified African granites [45] Elueze, 2000). The schist belts in made up of low-grade metasediments and metabasic rocks that developed in a sequence of distinctly N-S gravitating synformal trenches folded into the crystalline migmatite-gneiss complex ranges from 2.0 to 3.0 Ga [46-47] and it is the oldest and most present rock type in the basement, resulting from several tectonothermal activities that have assembled rocks of diverse origins. The older granites show the most pervasive tectonic fabric indicating igneous reactivation resulting from the Pan-African activities [48]. The older granite is majorly a fine-medium grained to coarse porphyritic rock whose composition is in between tonalite to granodiorite to granite syenite [49]. The selected blasting sites used ammonium nitrate granules mixed with fuel oil (ANFO) and dynamite cartridges for column and priming charge respectively. The blasting engineers are well experienced and had over the time used trial by error method to arrive at a suitable powder factor for each of the sites. The appropriate evaluation of a specific charge also known as powder factor influences the overall economics of mining operations. Therefore, the evaluation of the risk level induced by the powder factor is an essential area of study. Thus, in this study, rock properties that were thought to influence powder factors were carefully assessed following standard procedures suggested by the International Society of Rock Mechanics (ISRM). Also, blast geometry parameters were measured on the field for each of the selected locations whilst powder factor for each of the blasts was estimated.

3.2. RES application to powder factor

As stated earlier, rock mass and geometric parameters affecting powder factors were identified. The Rock engineering system approach was used to model the interaction of rock mass properties and blast geometric parameters for powder factor prediction. In order to get this done, 108 blasts were monitored in twenty-four selected blast sites and ten principal parameters that influence powder factor were evaluated. The influence of these parameters on powder factor was carefully studied to develop an appropriate interaction matrix used for the development of a rock engineering system.

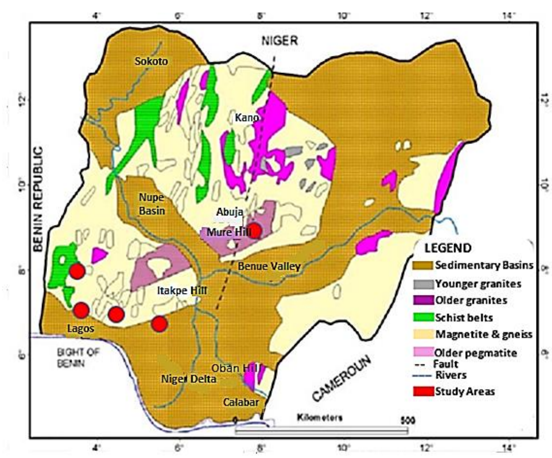

Figure. 2. Geological Map of Nigeria Showing the study areas

3.2.1 Parameters for PF prediction

In this paper, ten (10) parameters that can influence powder factors were identified and used for the prediction using the rock engineering system model. The parameters are those associated with rock properties and blast geometry. For rock properties, rock mass rating (RMR), blastability index (BI), porosity (n), specific gravity (G_S), and uniaxial compressive strength (UCS) were selected, whilst for the blast geometric parameters, burden (B), spacing to burden ratio (S/B), the ratio of hole depth to burden (H/B), hole diameter (D) and the ratio of the burden to hole diameter (B/D) were considered. These parameters were numbered as presented in Table 1 for identification on the RES interaction matrix table. The description of the datasets used for this study is shown in Table 2.

Table 1: Parameters for Rock Fragmentation Prediction

Parameter	Parameter no	Parameter	Parameter no
Rock mass rating (RMR)	P1	Burden (B)	P6
Blastability index (BI)	P2	Spacing/burden (S/B)	P7
Porosity (n)	P3	Hole depth/burden (H/B)	P8
Specific gravity (G_S)	P4	Hole diameter (D)	P9
UCS	P5	Burden/ Hole diameter (B/D)	P10

Table 2: Description of the parameters used in the modelling

No.	Parameter	Unit	Symbol	Min	Max
1	Rock mass rating	-	RMR	49	72
2	Blastability index	-	BI	41	85
3	Porosity	%	n	0.8	2.8
4	Specific gravity	-	G_S	2.42	3.2
5	Uniaxial Compressive strength	MPa	UCS	82.2	140.25
6	Burden	m	B	1.1	3
7	Spacing to burden	-	S/B	1	1.4
8	Hole depth to Burden	-	H/B	1.3	7
9	Hole diameter	mm	D	25.4	101.6
10	Burden to hole diameter	-	B/D	22.47	59.06
11	Powder factor	k/m³	PF	0.54	0.76

3.2.2 Rating of parameters

Rating of the parameter's values was done upon their classification/categorization and influence on PF. For instance, for a certain parameter that has five classes, the classes will be rated 0 to 4. Zero represents the worst scenario of influence of such parameter on PF while 4 connotes the best. That is, zero means poor effect or unfavourable condition on PF, and 4 implies the most favourable condition on powder factor. The rating of the individual parameter used in this work can be seen in Table 3. The ratings of parameters were proposed based on the judgments of five veterans in the field of rock blasting and excavation and also on the outputs of other researchers [12, 36, 39, [50 & 51]. This means that if the highest value for a certain parameter enhances rock fragmentation, the higher the measured value of such parameter, the higher the rating that will be assigned. Consequently, if the highest value of a parameter resists fragmentation, the higher the measured value the lower the rating value.

Table 3: Proposed ratings for parameters effective in powder factor

Parameter	Value/description and rating					
RMR	Value	<20	20 – 40	41 – 60	61 – 80	81 – 100
	Rating	4	3	2	1	0
BI	Value	0–20	21–40	41–60	61–80	81–100
	Rating	0	1	2	3	4
n	Value	<1.5	1.5 – 2.5	2.5 – 3.5	>3.5	
	Rating	3	2	1	0	
G_S	Value	<2	2 – 2.5	2.5 – 3	>3	
	Rating	0	1	2	3	
UCS (MPa)	Value	<25	25 – 50	51 – 100	101 – 250	>250
	Rating	0	1	2	3	4
B (m)	Value	<1	1-1.5	1.5-2	2-3	>3
	Rating	4	3	2	1	0
S/B	Value	<1	1–2	2–3	3–4	>4
	Rating	4	3	2	1	0
(H/B)	Value	<1	1–2	2–3	3–4	>4
	Rating	4	3	2	1	0
D (mm)	Value	<100	100 – 150	150 – 200	200 – 250	>250
	Rating	0	1	2	3	4
B/D	Value	<20	20–40	>40		
	Rating	0	1	2		

3.2.3 Interaction matrix

The interaction matrix for parameters affecting the powder factor was established and presented in Table 4. The ten principal parameters to be used for powder factor prediction were arranged along with the main diagonal cells of the matrix table whilst the effect of each parameter on another was allocated to the corresponding off-diagonal cells. The coding values were assigned to all off-diagonal cells using the ESQ method. The value for each of the parameters was considered based on the recommendation of 5 experts in the field of blasting and rock fragmentation. The intensity rating for the individual parameter in the interaction matrix is the addition of the coded values for cause and effect (C+E), that is row and column and it was used as a pointer to the parameter's significance on the RES structure. The degree of dominance of each parameter in the interaction matrix is the difference in their cause and effect (C-E). The intensity of all the parameters used for the predictive model is shown in Figure 3. The percentage of the intensity was used to calculate the weighty factor of each parameter using Equation 3 and presented in Table 5. To understand the role of each parameter in the system, the coordinate values of each parameter were plotted in cause and effect space to form the C-E plot for the effective parameters for powder factor evaluation as shown in Figure 3. It can be seen from the C-E plot that rock mass rating, blastability index, porosity, specific gravity, uniaxial compressive strength, and drilled-hole diameter affects the system. That is, they are dominant in the system whilst burden, spacing to the burden, hole depth to the burden, and burden to drilled-hole diameter, are affected by the system. This means that they are the subordinate in the system. Figure 4 shows the interaction intensity of parameters in the system. The histogram shows that little changes in blastability index, uniaxial compressive strength, burden, and hole depth to burden ratio will have a great influence on the system behaviour.

Table 4: Interaction matrix for parameters affecting PF

P1	3	0	0	0	3	2	0	0	2
3	P2	0	0	2	3	2	2	1	3
2	2	P3	2	3	2	1	1	0	1
0	1	0	P4	3	2	1	1	0	2
2	2	0	0	P5	3	2	2	0	2
0	0	0	0	0	P6	2	2	0	0
0	0	0	0	0	0	P7	0	0	0
0	0	0	0	0	2	3	P8	2	1
0	0	0	0	0	3	1	2	P9	2
0	0	0	0	0	3	0	2	0	P10

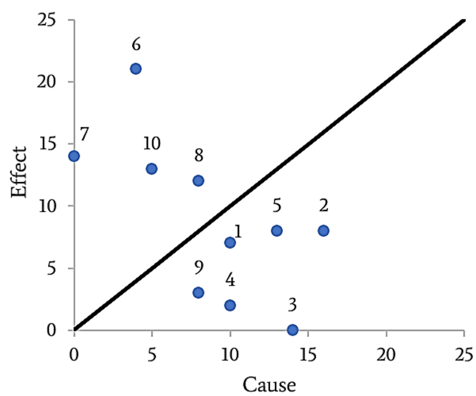

Figure. 3. E-C Plot for principal parameters of PF

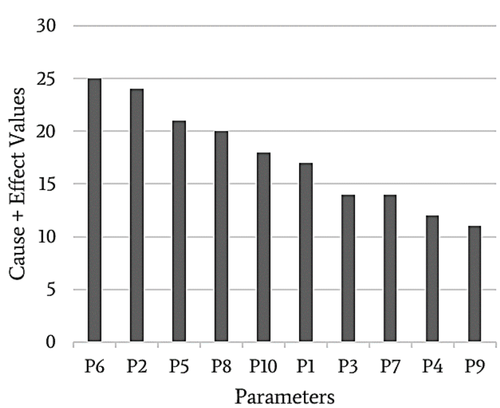

Figure. 4. Interaction intensity for the parameters

3.3. Prediction of PF using RES model

Bernados and Kaliampakos [43], Faramarzi et al. [36], and Hasanipanah et al. [39] used RES based approach to estimate the vulnerability index (VI) of rock fragmentation using Eqn. 4

$$VI = 100 - \sum_{i=1} \alpha_i \frac{Q_i}{Q_{max}} \tag{4}$$

where α_i, Q_i and Q_{max} are the weight factor, the value (rating), and the maximum value assigned for the ith parameter (normalization factor) influencing fragmentation respectively. The maximum value assigned for VI is 100 indicating the worst rock fragmentation whilst the minimum value is 0 which also indicates the best case for rock fragmentation point of view. That is, the highest value of the index indicates the highest degree of vulnerability. A similar approach was adopted in this study for the assessment of powder factor risk level. The parameter powder factor index (Pfi) is calculated in this study using Equation 5.

$$Pfi = 100 - \sum_{i=1} \alpha_i \frac{Q_i}{Q_{max}} \tag{5}$$

Table 5: The weighting of the principal parameters of powder factor

Code	Parameters	C	E	C + E	C – E	α_i (%)
P1	Rock mass rating (RMR)	10	7	17	3	9.66
P2	Blastability index (BI)	16	8	24	8	13.64
P3	Porosity (n)	14	0	14	14	7.95
P4	Specific gravity (G_S)	10	2	12	8	6.82
P5	Uniaxial compressive strength (UCS)	13	8	21	5	11.93
P6	Burden (B)	4	21	25	-17	14.21
P7	Spacing/ Burden (S/B)	0	14	14	-14	7.95
P8	Hole depth/ Burden (H/B)	8	12	20	-4	11.36
P9	Hole diameter (D)	8	3	11	5	6.25
P10	Burden/hole diameter (B/D)	5	13	18	-8	10.23
Sum		**88**	**88**	**176**	**0**	**100**

where α_i, Q_i and Q_{max} are the weight factor, the value (rating), and the maximum value assigned for an ith parameter (normalization factor) influencing powder factor respectively. The maximum value assigned for Pfi is 100 indicating the most unfavourable case whilst the minimum value is 0 indicate the most favourable case for the powder factor viewpoint. The classification of the risk level, that is powder factor risk index (Pfi) is partitioned into three key groups of 0 to 33 33 to 66, and 66 to 100 with diverse severity of the controlled scale of 0-100 [43]. In the first class (0-33), a small-scale problem in the design of blast may be experienced but it is not significant to the overall cost of drilling and blasting operations. In the second class (33-66), a slight problem may be experienced in blast design but it impacts the cost of drilling and blasting may be monitored. In the third class (66-100), the blast design may turn out to be highly problematic resulting in poor fragmentation and additional cost for secondary blasting. The value of Pfi determined for each selected site for this study is presented in Table 6. Finally, linear regression was developed for the relationship between Pfi and the actual powder factor (Table 7) for estimating the powder factor as presented in Equation 6.

$$PF = 1.2019 - 0.0106Pfi \tag{6}$$

where *pfi* is the powder factor index and PF is the powder factor in kg/m^3. As shown in Figure 5, the coefficient of correlation (R^2) is 0.86, indicating a good relationship. Furthermore, Figure 6 shows a good agreement between the measured and predicted values of the powder factor.

3.4. Comparing RES and regression predictive model

Multivariable regression analysis of the ten parameters used in RES the model was done to predict powder factor. In doing this, a version of SPSS software was used for the regression analysis. The values of the identified ten parameters namely, rock mass rating (RMR), blastability index (BI), porosity (n), specific gravity (G_S), uniaxial compressive strength (UCS), burden (B), spacing to burden ratio (S/B), the ratio of hole depth to burden (H/B), hole diameter (D) and the burden to hole diameter ratio (B/D) were computed as independent variables whilst burden was computed as the dependent variable. The regression model is presented in Equation 7. The analysis of variance of the regression model shows that the significant factor is 0.016 whilst the coefficient of determination is 0.74.

Table 6: Powder factor index (Pfi) developed for the selected blast sites

Site	RMR	BI	n	G_S	UCS	B	S/B	H/B	D	B/D	Pfi
1	1	2	3	2	3	1	3	0	0	1	54.7
2	1	2	2	2	3	2	3	0	0	1	53.8
3	1	2	3	1	3	1	3	0	1	1	55.4
4	1	2	3	2	3	1	3	0	0	1	54.7
5	1	2	2	1	2	1	3	1	1	1	58.2
6	2	2	3	3	3	2	3	0	0	1	52.7
7	2	1	1	2	2	1	3	0	1	1	62.4
8	1	2	1	1	2	1	3	0	0	1	65.2
9	2	2	2	2	2	2	2	2	0	1	50.7
10	2	2	2	1	2	1	3	0	0	1	60.2
11	1	2	2	2	3	1	3	0	0	1	57.3
12	0	2	3	3	3	2	3	0	0	1	51.3
13	0	2	3	2	3	1	3	0	0	1	57.1
14	2	3	2	2	2	2	3	0	0	1	50.9
15	2	1	2	2	3	1	3	0	0	1	58.3
16	2	2	3	1	2	3	3	1	0	2	42.5
17	1	2	1	1	2	3	3	0	0	2	53.0
18	1	2	2	3	3	1	3	0	0	1	55.1
19	1	1	1	1	2	3	3	3	0	2	47.9
20	2	1	1	1	2	3	3	3	0	2	45.5
21	1	4	2	2	3	2	3	1	0	1	44.1
22	1	2	2	2	2	1	3	0	1	1	58.8
23	1	2	1	1	2	1	3	1	1	1	60.8
24	1	2	2	2	3	1	3	0	0	1	57.3
Q_{max}	4	4	3	3	4	4	4	4	4	2	
α_i	9.66	13.64	7.95	6.82	11.93	14.21	7.95	11.36	6.25	10.23	100

Table 7: PF and their corresponding Pfi

Site	PF	Pfi	Site	PF	Pfi	Site	PF	Pfi
1	0.62	54.7	9	0.68	50.7	17	0.67	53.0
2	0.66	53.8	10	0.57	60.2	18	0.57	55.1
3	0.60	55.4	11	0.60	57.3	19	0.72	47.9
4	0.59	54.7	12	0.62	51.3	20	0.74	45.5
5	0.60	58.2	13	0.59	57.1	21	0.75	44.1
6	0.64	52.7	14	0.65	50.9	22	0.59	58.8
7	0.54	62.4	15	0.60	58.3	23	0.60	60.8
8	0.54	65.2	16	0.76	42.5	24	0.55	57.3

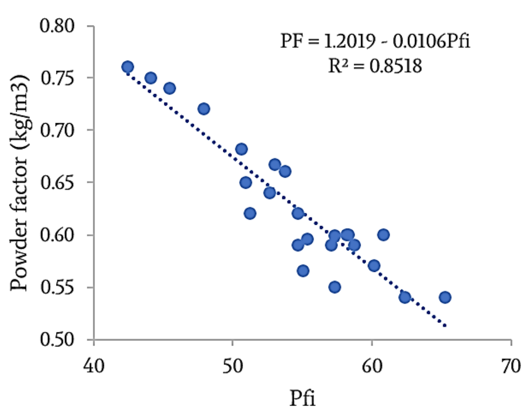

Figure. 5. PF predictive model using Pfi

Accuracy of the developed models and their goodness of fit were then assessed by statistical measures like mean absolute deviation (MAD), root mean square error (RMSE), and mean absolute percentage error (MAPE). RMSE gives the mean error weighted according to the square of the error. However, it cannot indicate the direction of the deviation but give greater weight to large errors than a small error on the average. This makes it apt to use when large errors are undesirable but not suitable for errors of small samples. Contrarily, the accuracy factor shows the deviation between model predictions and observed datasets. Hypothetically, a predictive model is said to be outstanding when RMSE is 0, R^2 is 1, MAD is 0 and MAPE is 0%. The formula for calculating RMSE, MAD, and MAPE are presented in Equations 8 -10 respectively.

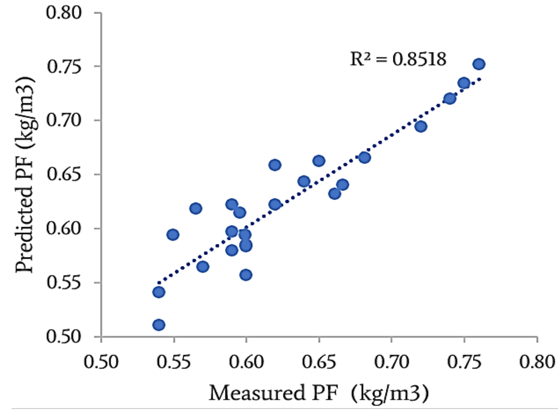

Figure 6. Measured and predicted PF

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{i\,(meas)} - X_{i\,(pred)}\right)^2} \quad (8)$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|X_{i\,(meas)} - X_{i\,(pred)}\right| \quad (9)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_{i\,(meas)} - X_{i\,(pred)}}{X_{i\,(meas)}}\right| \quad (10)$$

where $X_{i\ (meas)}$ and $X_{i\ (predi)}$ are measured and predicted variables respectively, whilst n is the number of observations. Comparison of the RES and regression models using the statistical analysis as shown in Table 8. It can be seen from the table that the RES model has the ability to predict the powder factor more accurately than the regression model. Figure. 7 shows the comparison between actual measured and predicted powder factor using RES and regression models.

It can be seen from the figure that the values predicted using RES are more adaptable to real data.

Table 8: Comparing RES and regression model

Model	R²	RMSE	MAD	MAPE (%)
RES	0.85	0.024	0.019	1.85
Regression	0.74	0.032	0.026	4.19

$$PF = 0.60 - 0.02n - 0.05G_s + 0.002RMR + 0.001BI - 0.0003UCS - 0.16B + 0.029\frac{S}{B} - 0.002\frac{H}{B} + 0.003D + 0.005\frac{B}{D} \quad (7)$$

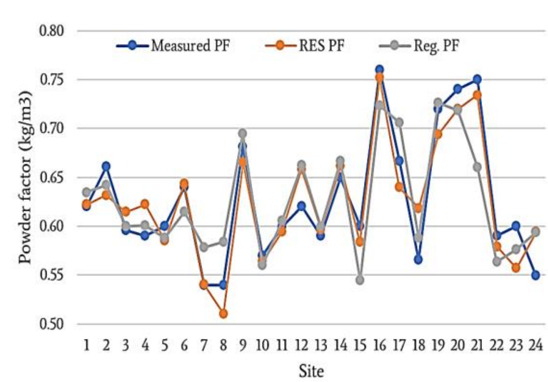

Figure 7. Comparison of measured PF with RES and regression predicted PF

4. Discussion

Data were gathered from 24 blast sites to examine the influence of rock geomechanical properties and blast geometric parameters on powder factor using rock engineering system methods. The results of this research show that the evaluation of the relationship between each parameter considered to influence powder factor through an interaction matrix was a key component in estimating powder factor. The interaction matrix methods had proved to be reliable in evaluating the interactivity of many parameters. Moreover, the results have shown that the qualitative parameters identified could be used easily to estimate optimum powder factor with the aid of the RES method.

In the cause-effect diagram and the histogram of interactive intensity, it was shown that rock mass rating, blastability index, porosity, specific gravity, uniaxial compressive strength, and drilled-hole diameter are the dominant parameters in the system. That is, they have more effect on the system with porosity having the most effect. On the other hand, burden, the ratio of spacing to the burden, the ratio of drilled-hole depth to the burden, and the ratio of the burden to drilled-hole diameter are dominant parameters in the system. The ratio of spacing to the burden is the most affected parameter in the system. The histogram of the interaction intensity shows that blastability index, uniaxial compressive strength, burden, and the ratio of drilled-hole diameter to burden have the highest interaction within the system with the burden being the most sensitive parameter in the system. Hole diameter, specific gravity, the ratio of spacing to the burden, and porosity have the lowest interaction within the system. However, the slope of the histogram shows an averagely gradual descent to the right, therefore, it will be impossible to say only a few parameters are vital to the definition of the system interactivity or that other parameters do not have influence in the system. Thus, all ten parameters combined to influence powder factor and were used for the computation of powder factor index values.

The powder factor index was calculated using the values of the weighty factor, the maximum rating assigned to each parameter, and the actual rating of the parameters based on their quantitative values. The slope of the relationship between the powder factor index and the actual measured powder factor shows that the index reduces with the powder factor. This means that the risk of poor blast design increases with low powder factor and the result of poor blast design is inappropriate rock fragmentation. This observation is in accordance with that of other researchers who found that fragmentation risk increases with fragment size [36 & 39] The correlation of the risk assessment values and the powder factor was used to model the predictive relationship for powder factor using the rock engineering system. The coefficient of determination of the model is 0.86 which indicates a very strong degree of association. The result was compared with that of the regression model and it indicates that the RES model is a better predictor of powder factor. The most important contribution of this result is that with the RES model, the relationship between rock mass properties can actually be used to determine appropriate blast design for the overall economy of drilling and blasting operations. This model is a substituted alternative for the trial-by-error blast.

5. Conclusion

The RES model presented in this study has shown that drilling and blasting is a science and not art has earlier said by some researchers. The RES is an expert-based system that can accommodate many input parameters and the accuracy of the system depend on the experience of the user on how each parameter relates with another. The RES system was used to develop a predictive model for powder factor and rock geomechanical parameters such as rock mass rating, blastability index, specific gravity, porosity, and uniaxial compressive strength affected the system. In addition to the geomechanical properties, the drilled-hole diameter is the only geometric parameter that affects the system. As it is known that other geometric parameters depend on drilled-hole diameter, the results show that a good relationship was established between geomechanical properties and geometric parameters in this study. The study has also proved that the RES model is a better predictor of powder factor when compared with the conventional multivariable regression model with a coefficient of determination (R^2) value of 0.86 and 0.74 respectively. Also, the analysis of model error shows that RES has limited predictive error than the regression analysis with root mean square error (RMSE) and mean absolute percentage error (MAPE) of 0.024 and 1.85% for RES and 0.032 and 4.19% for the regression model.

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