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Prediction of Blast-Induced Backbreak Using Burden, Spacing, Powder Factor, And Geometric Stiffness

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ABSTRACT: Back break, defined as rock fracturing that extends beyond the last row of blastholes into the intended final wall or the next bench, is a persistent problem in open-pit mining and quarrying that compromises slope stability, increases dilution, and raises downstream costs. This study develops an empirical multiple linear regression (MLR) model to predict backbreak from five commonly logged blast design parameters: burden, spacing, stemming length, powder factor, and a geometric stiffness ratio, following the variable framework established in prior backbreak-prediction studies [3], [5]. A dataset of 36 field blast records was compiled, and predictor collinearity, model significance, and residual behaviour were assessed using standard regression diagnostics. A reduced four-variable model (burden, spacing, powder factor, and geometric stiffness) explained 97.6% of the variance in the observed dataset (in-sample $R^2 = 0.976$, adjusted $R^2 = 0.972$, $F(4,31) = 310.1$, $p < 0.001$), with a root-mean-square error of 0.35 m and mean absolute percentage error of 9.4%; six-fold cross-validation produced a mean out-of-fold R^2 of 0.84, indicating somewhat weaker but still reasonable performance on held-out data. Burden and powder factor were the strongest positive predictors, while spacing exerted a negative, moderating effect, consistent with established blast mechanics. The results support the use of routinely collected design parameters for practical, low-cost backbreak forecasting and pre-blast design adjustment, while highlighting multicollinearity among burden-related variables as a limitation warranting cautious interpretation of individual coefficients.

KEYWORDS: backbreak; blast design; burden; powder factor; multiple linear regression; rock fragmentation; open-pit mining

I. INTRODUCTION

Backbreak is defined as the unintended fracturing and displacement of rock behind the last row of blastholes in a bench blast, beyond the design excavation limit. It is one of the most common and costly undesirable outcomes of open-pit and quarry blasting operations, contributing to loss of wall stability, increased scaling and rehabilitation costs, dilution of ore at the pit boundary, hazards to personnel and equipment operating near unstable crests, and difficulty maintaining planned bench geometry for subsequent blast rows [1], [10]. Because backbreak originates from the interaction of explosive energy with the rock mass and the geometric layout of the blast, it is influenced jointly by rock mass properties (which are difficult and costly to characterise at every blast) and by design parameters that are set, logged, and controlled by the blasting engineer on every round [4].

Among the controllable design parameters, burden (the distance from a blasthole to the nearest free face), spacing (the distance between adjacent holes in a row), stemming length (the inert material placed in the collar of the hole above the explosive column), and powder factor (the mass of explosive used per unit volume of rock, kg/m³) are the most routinely recorded. A geometric stiffness ratio broadly, bench height relative to burden is often used as a secondary indicator of how well confined the blast column is relative to the free face; low stiffness (short, wide benches relative to burden) has repeatedly been linked to poorer fragmentation control and greater risk of overbreak or backbreak [3], [9].

Empirical and statistical modelling of blast outcomes fragmentation, flyrock, ground vibration, and backbreak has a long history in rock engineering because first-principles models require rock mass inputs (in-situ block size, joint spacing and orientation, intact rock strength) that are rarely measured on a per-blast basis, whereas design parameters are captured for every round as a matter of course. Early work applied neural networks to backbreak prediction at case-study mines [1], [3], and subsequent studies compared regression against support vector machines [2], adaptive neuro-fuzzy systems and regression together [5], genetic programming [7], and rule- or risk-based indices [4], [6], [8]. Multiple linear regression (MLR) remains a widely used and interpretable baseline against which more complex machine-learning approaches are typically compared in this literature, because its coefficients can be related directly back to blast mechanics and because it requires comparatively little data to fit reliably; several of these studies report MLR as a weaker but still informative benchmark relative to ANN or ANFIS models built on the same data [2], [5].

The objective of this study is to develop and evaluate an MLR model that predicts backbreak from burden, spacing, stemming, powder factor, and geometric stiffness using a compiled dataset of 36 blast records, to identify which of these parameters are the strongest statistical drivers of backbreak, and to assess the practical reliability of the resulting model through residual diagnostics and cross-validation.

II. MATERIALS AND METHODS

A. Dataset

A dataset of 36 individual bench blast records was compiled, each comprising five design/input variables burden (m), spacing (m), stemming length (m), powder factor (kg/m³), and a geometric stiffness ratio (dimensionless) and the corresponding measured backbreak (m) recorded behind the last row of holes. This set of five predictors follows the variable framework used by Esmaeili et al. [5] in their regression, ANN, and ANFIS comparison for open-pit backbreak, and is consistent with the parameters identified as most influential across the wider backbreak literature [1], [3], [9]. The geometric stiffness ratio is defined as bench height divided by burden,

GS = H / B

where H is the bench height (m) and B is the burden (m); values in the present dataset range from 2.4 to 4.5. The full dataset is reproduced in the Appendix (Table V). Table I summarises the descriptive statistics of all variables.

TABLE I. DESCRIPTIVE STATISTICS OF THE BLAST DESIGN PARAMETERS AND MEASURED BACKBREAK (N = 36)

Statistic	Burden (m)	Spacing (m)	Stemming (m)	Powder Factor (kg/m³)	Geom. Stiffness	Backbreak (m)
Minimum	2	3	1.8	0.15	2.4	1
Maximum	5	6	4.5	1.05	4.5	10
Mean	3.64	4.8	3.68	0.45	3.18	4.03
Std. deviation	0.71	0.58	0.67	0.23	0.48	2.27
Coeff. of variation (%)	19.6	12.1	18.3	50.4	15	56.4

Backbreak ranged from 1.0 to 10.0 m (mean 4.03 m, SD 2.27 m), reflecting a broad spread of blast conditions from small, tightly controlled rounds to larger, heavily loaded blasts. Powder factor and backbreak showed the highest relative variability (coefficient of variation of 50.4% and 56.4% respectively), consistent with these being the parameters most actively adjusted by the operator between blasts and most sensitive to overall blast severity.

B. Statistical Analysis

Pearson correlation coefficients were first computed between all pairs of variables to characterise pairwise linear association and to flag potential multicollinearity among predictors prior to regression. An initial multiple linear regression model was then fitted with all five predictors (burden, spacing, stemming, powder factor, geometric stiffness) using ordinary least squares (OLS):

Backbreak = β0 + β1(Burden) + β2(Spacing) + β3(Stemming) + β4(Powder Factor) + β5(Geometric Stiffness) + ε (1)

Variance inflation factors (VIF) were computed for each predictor to quantify multicollinearity. Backward elimination was then applied, removing the least significant predictor (highest p-value) provided its removal did not materially reduce adjusted R², to obtain a more parsimonious model. Model adequacy was assessed via the coefficient of determination (R²), adjusted R², the overall F-test, individual predictor t-tests, the Shapiro–Wilk test for normality of residuals, a residuals-versus-fitted plot for homoscedasticity, and a normal Q–Q plot. Predictive performance was quantified using the root-mean-square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) on the fitted data, and generalisation was estimated using a single six-fold cross-validation (random shuffled partitioning into six folds, each held out once). All analyses were performed in Python 3 using the statsmodels and scikit-learn libraries.

III. RESULTS

A. Correlation Analysis

Table II and Fig. 1 present the Pearson correlation matrix. Backbreak correlated most strongly with powder factor (r = 0.950) and burden (r = 0.941), followed by stemming (r = 0.862), spacing (r = 0.741), and, more weakly and negatively, geometric stiffness (r = -0.417). The predictors themselves were also strongly intercorrelated most notably burden with stemming (r = 0.934) and burden with powder factor (r = 0.903) reflecting standard blast design practice in which burden, spacing, and stemming are scaled together (typically as ratios of hole diameter) and powder factor rises together with burden as more rock is broken per hole (see Fig. 2).

TABLE II. PEARSON CORRELATION MATRIX OF BLAST DESIGN PARAMETERS AND BACKBREAK

	Burden	Spacing	Stemming	Powder Factor	Geom. Stiffness	Backbreak
Burden	1.000	0.885	0.934	0.903	-0.625	0.941
Spacing	0.885	1.000	0.840	0.740	-0.601	0.741
Stemming	0.934	0.840	1.000	0.797	-0.623	0.862
Powder Factor	0.903	0.740	0.797	1.000	-0.416	0.950
Geom. Stiffness	-0.625	-0.601	-0.623	-0.416	1.000	-0.417
Backbreak	0.941	0.741	0.862	0.950	-0.417	1.000

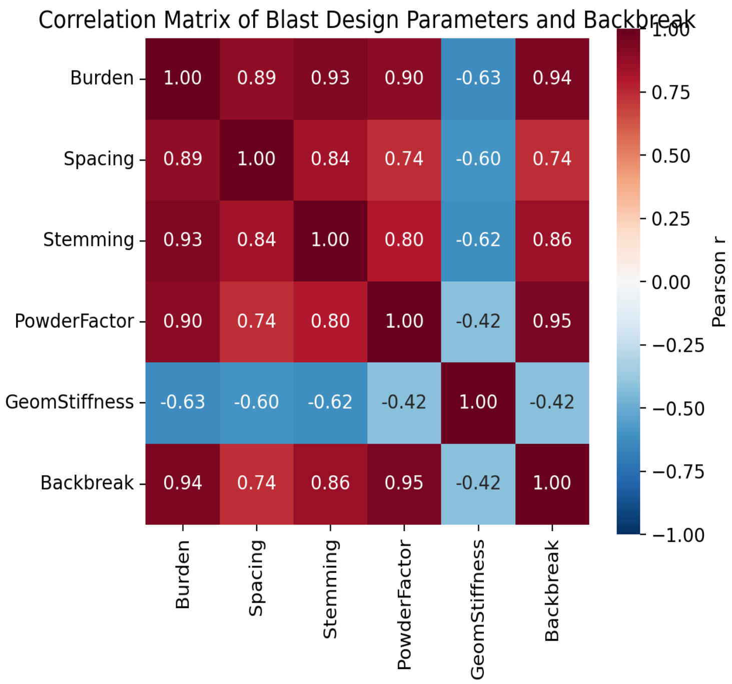

Fig. 1. Correlation heat map of blast design parameters and backbreak.

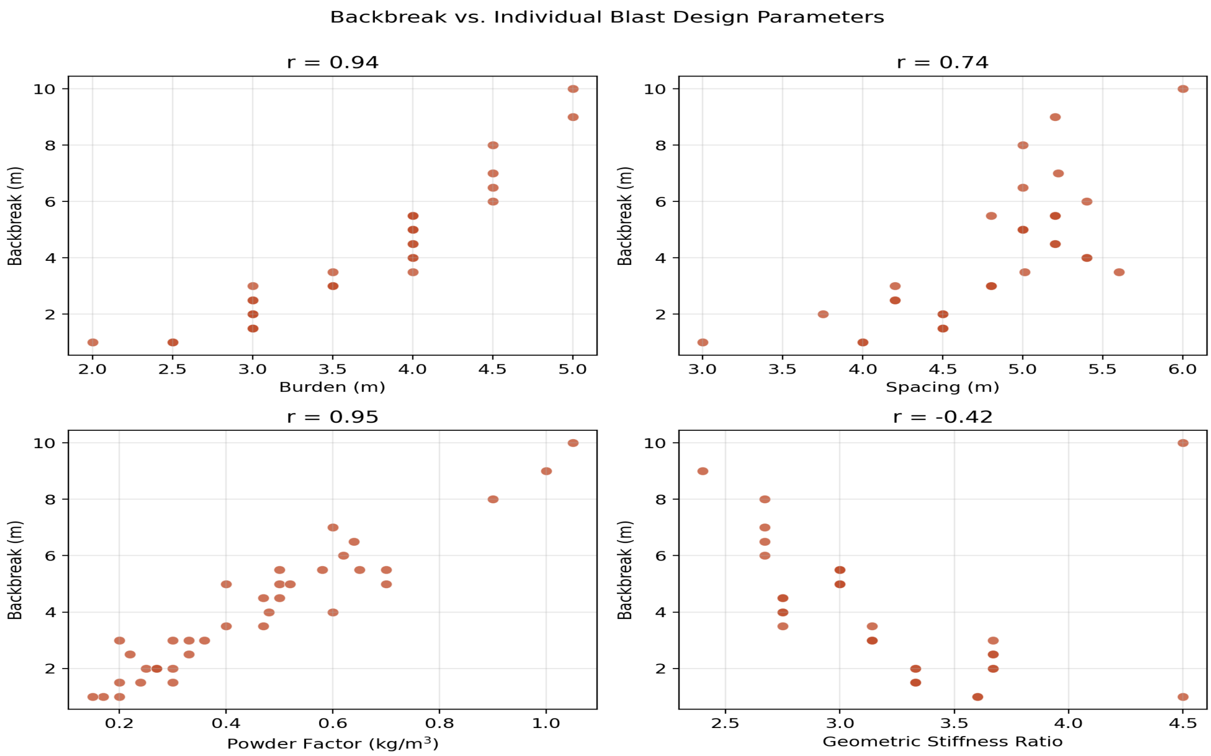

Fig. 2. Backbreak versus individual blast design parameters: burden, spacing, powder factor, and geometric stiffness.

B. Regression Model

The full five-predictor model explained 97.6% of the variance in backbreak ($R^2 = 0.976$, adjusted $R^2 = 0.972$, $F(5,30) = 244.7$, $p < 0.001$). Stemming was not statistically significant in the presence of the other predictors ($p = 0.460$), consistent with its high correlation with burden (VIF = 28.3 for burden in the full model), and was removed by backward elimination. The reduced four-predictor model burden, spacing, powder factor, and geometric stiffness retained essentially the same explanatory power ($R^2 = 0.976$, adjusted $R^2 = 0.972$, $F(4,31) = 310.1$, $p < 0.001$) while improving parsimony and reducing the Akaike Information Criterion (AIC) from 37.8 to 36.5. All four remaining predictors were statistically significant at the 0.1% level (Table III).

TABLE III. ORDINARY LEAST SQUARES REGRESSION COEFFICIENTS FOR THE REDUCED MODEL (DEPENDENT VARIABLE: BACKBREAK, M)

Predictor	Coefficient	Std. Error	t-value	p-value	95% CI
Constant	-6.719	1.274	-5.275	<0.001	[-9.32, -4.12]
Burden (m)	3.417	0.361	9.455	<0.001	[2.68, 4.15]
Spacing (m)	-1.211	0.247	-4.896	<0.001	[-1.72, -0.71]
Powder Factor (kg/m^3)	2.849	0.753	3.784	0.001	[1.31, 4.38]
Geometric Stiffness	0.889	0.191	4.658	<0.001	[0.50, 1.28]

The fitted model is:

Backbreak = -6.719 + 3.417(Burden) - 1.211(Spacing) + 2.849(Powder Factor) + 0.889(Geometric Stiffness) **(2)**

Burden and powder factor were the strongest positive predictors of backbreak: holding other variables constant, each additional metre of burden was associated with a 3.42 m increase in predicted backbreak, and each additional kg/m^3 of powder factor was associated with a 2.85 m increase. Spacing had a significant negative coefficient (-1.21 m per metre of spacing), indicating that, for a given burden, wider spacing is associated with reduced backbreak plausibly because it reduces hole-to-hole confinement and relative charge concentration along the row. The positive coefficient on geometric stiffness (0.89) at first appears counter to its negative simple correlation with backbreak (-0.417); this sign reversal is a classic multicollinearity effect, arising because geometric stiffness is confounded with burden in the raw data, and its partial effect once burden is held constant should be interpreted cautiously rather than taken as evidence of a genuine positive causal effect.

Table IV reports variance inflation factors for the reduced model. Burden retained a high VIF (16.4), reflecting its geometric coupling with the other design variables; spacing, powder factor, and geometric stiffness had more moderate VIFs (2.1–7.3). This level of multicollinearity is common in blast design datasets, where burden, spacing, and stemming are conventionally set as fixed ratios of hole diameter rather than varied independently, and it constrains the precision and causal interpretation of individual coefficients, even though the reduced model retained strong predictive performance within the present dataset.

TABLE IV. VARIANCE INFLATION FACTORS (VIF) FOR THE REDUCED MODEL PREDICTORS

Predictor	**VIF**
Burden	16.38
Spacing	5.10
Powder Factor	7.34
Geometric Stiffness	2.05

C. Model Diagnostics and Validation

Residuals from the reduced model were approximately normally distributed (Shapiro–Wilk statistic = 0.979, $p = 0.710$), and the residuals-versus-fitted plot (Fig. 4a) showed no systematic pattern or evidence of heteroscedasticity across the range of predicted values. The normal Q–Q plot (Fig. 4b) showed close adherence to the reference line, with no substantial departures at either tail. The Durbin–Watson statistic (1.57) indicated no strong autocorrelation in the residuals, as illustrated in Fig. 3.

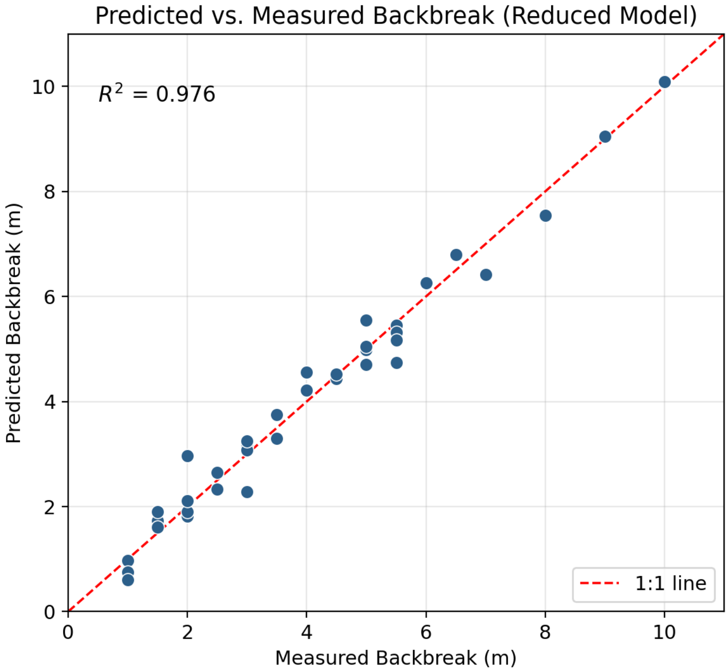

Fig. 3. Predicted versus measured backbreak for the reduced regression model.

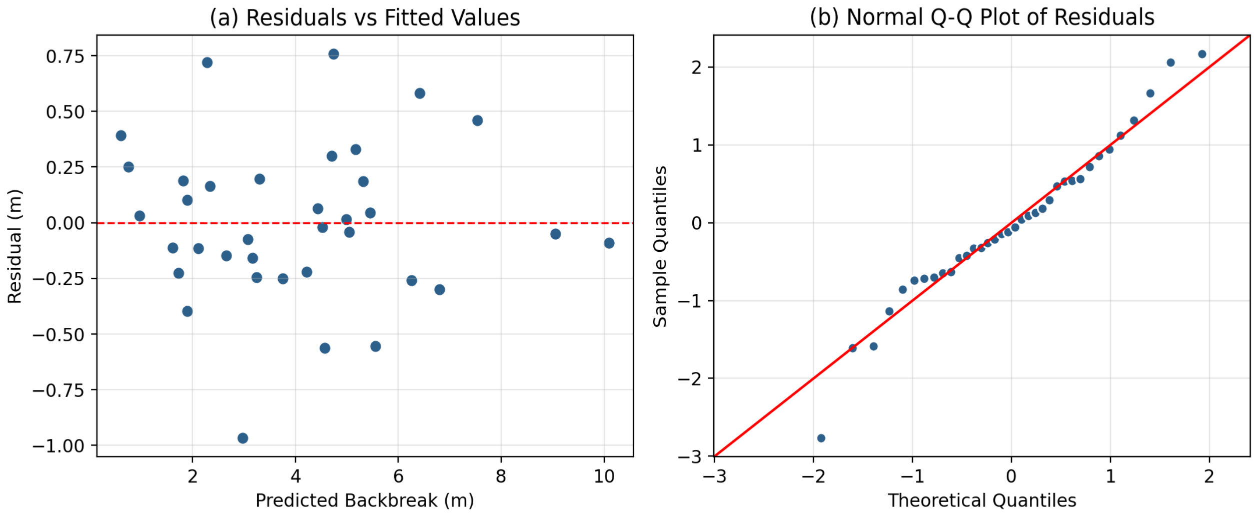

Fig. 4. (a) Residuals plotted against fitted values; (b) normal Q–Q plot of residuals.

The reduced model achieved a root-mean-square error of 0.35 m, a mean absolute error of 0.27 m, and a mean absolute percentage error of 9.4% on the fitted data a strong fit given that measured backbreak spans an order of magnitude (1–10 m). To assess generalisation beyond the fitted sample, a single six-fold cross-validation (shuffled random partitioning, each fold held out once) was performed: the mean out-of-fold R^2 was 0.84 (SD 0.19) and the mean out-of-fold RMSE was 0.49 m (SD 0.20 m). The reduction in R^2 from the in-sample value (0.976) to the cross-validated value (0.84), together with the relatively high standard deviation across folds, is expected given the modest sample size (n = 36) split across six folds of roughly six observations each, and indicates that while the model generalises reasonably, its performance on genuinely new blast conditions should be expected to be somewhat weaker than the in-sample fit statistics suggest.

IV. DISCUSSION

The results confirm that backbreak in this dataset is strongly and jointly determined by burden, powder factor, spacing, and (in a partial, confounded sense) geometric stiffness, with these four routinely logged parameters together accounting for the great majority of variance in observed backbreak. This is broadly consistent with blast mechanics: burden and powder factor jointly govern the effective specific energy delivered to the rock ahead of and behind the last row of holes, and both were the strongest positive predictors here, matching the intuitive and widely reported finding that over-burdened, heavily loaded blasts produce larger backbreak because insufficient burden relative to charge energy allows fracturing to propagate past the intended excavation line.

The negative partial coefficient on spacing suggests that, for a fixed burden, increasing hole spacing helps contain backbreak, which is plausible if wider spacing reduces the cumulative confinement and stress superposition between adjacent holes along the last row. However, because burden, spacing, and stemming are highly correlated in the underlying dataset, the magnitude and even the sign of individual coefficients most visibly the positive sign on geometric stiffness, despite its negative simple correlation with backbreak should be interpreted as partial, model-conditional effects rather than as isolated causal relationships. Multicollinearity does not undermine the model's usefulness for prediction, but it does limit how confidently any single coefficient can be used to justify a specific design change without also considering the correlated adjustments practitioners would normally make to burden and stemming at the same time.

From a practical standpoint, the model's accuracy (RMSE of 0.35 m in-sample, approximately 0.5 m under cross-validation) is precise enough to be useful for pre-blast screening: a blast engineer could use the fitted equation, together with the burden, spacing, powder factor, and stiffness ratio planned for an upcoming round, to flag designs likely to produce backbreak in excess of a site-specific tolerance before the round is fired, and adjust burden or powder factor accordingly. This is of particular value on sites where backbreak has direct safety implications for crest stability or where it threatens to undercut planned final-wall geometry.

The fit obtained here ($R^2 = 0.976$) compares favourably with multiple-regression baselines reported elsewhere in the backbreak literature, where linear regression has generally underperformed paired non-linear models fitted to the same data: Khandelwal and Monjezi [2] reported a markedly lower coefficient of determination for multivariate regression than for their support vector machine model at the Soungun iron mine, and Monjezi et al. [3] likewise found conventional regression to trail an artificial neural network at the Chadormalu iron mine. The comparatively strong linear fit obtained in the present dataset may reflect a narrower, more internally consistent range of blast conditions than in those larger, multi-site datasets, again pointing to sample diversity as a key factor governing how much a linear model can capture.

Several limitations should be noted. First, the sample size ($n = 36$) is modest for a five-variable regression, and although diagnostics showed no evidence of poor fit, the wide standard deviation in cross-validated R^2 across folds (SD = 0.19) indicates the model's generalisation error is itself uncertain and would benefit from a larger, more geologically diverse dataset, of the scale used in comparable studies (for example, 175 blasts in [7]). Second, the model omits explicit rock mass parameters (joint spacing, rock quality designation, intact strength, in-situ block size) that are known from the wider blasting literature to influence backbreak independently of design geometry [4], [6]; to the extent that rock mass conditions were relatively uniform across the blasts compiled here, or covary with the design parameters used, the present model implicitly captures some rock mass effects, but this cannot be verified without site/geology metadata, which was not available in the source data. Third, the pronounced multicollinearity among burden, spacing, stemming, and powder factor means the model is best used as a joint predictive tool rather than as a basis for isolating the marginal effect of changing a single design variable; ridge regression, partial least squares, or a design-of-experiments approach explicitly varying one parameter at a time would be needed to separate these effects more cleanly. Future work should extend the dataset across a wider range of sites and rock types, incorporate rock mass classification indices where available, and compare the present linear model against the non-linear approaches that have outperformed regression elsewhere in this literature artificial neural networks [1], [3], [9], support vector machines [2], adaptive neuro-fuzzy systems [5], and genetic programming [7] to establish whether the relationship between design parameters and backbreak is adequately captured by a linear form across the full range of practical blast conditions.

V. CONCLUSION

A multiple linear regression model relating backbreak to burden, spacing, powder factor, and geometric stiffness was developed and evaluated using 36 field blast records. The reduced four-predictor model explained 97.6% of the variance in the observed dataset (adjusted $R^2 = 0.972$), with all coefficients significant at $p < 0.01$, residuals consistent with normality and homoscedasticity, and a cross-validated R^2 of 0.84. Burden and powder factor were identified as the strongest positive predictors of backbreak, with spacing acting as a significant moderating factor, consistent with established blast mechanics; strong multicollinearity among the design variables, however, means individual coefficients should be interpreted as joint, model-conditional effects rather than independent causal contributions. The model offers a practical, low-cost tool for pre-blast backbreak screening using parameters that are already routinely recorded on most blasting operations, while underscoring the value of larger, geologically annotated datasets, independent external validation, and non-linear modelling approaches for future refinement.

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TABLE V. FULL DATASET OF 36 BLAST RECORDS USED IN THE ANALYSIS (APPENDIX)

1	4	5.4	4	0.6	2.75	4
2	4	5.2	4	0.47	2.75	4.5
3	3	3.75	3.2	0.25	3.67	2
4	4	5.4	4	0.48	2.75	4
5	4	4.8	4.1	0.58	3	5.5
6	4	5	4.1	0.7	3	5
7	3	4.5	3	0.27	3.33	2
8	3	4.5	3	0.3	3.33	2
9	3.5	4.8	3.6	0.33	3.14	3
10	2	3	1.8	0.17	4.5	1
11	3.5	4.8	3.8	0.3	3.14	3
12	3.5	4.8	3.8	0.36	3.14	3
13	3	4.5	2.8	0.24	3.33	1.5
14	3	4.5	3.2	0.27	3.67	2
15	3	4.5	2.9	0.2	3.33	1.5
16	4	5	4.1	0.5	3	5
17	4	5	4.1	0.4	3	5
18	4	5.6	4	0.4	2.75	3.5
19	4	5	4.1	0.52	3	5
20	4	5.2	4	0.5	2.75	4.5
21	4.5	5.4	4.3	0.62	2.67	6
22	3.5	5.01	3.8	0.47	3.14	3.5
23	3	4.2	3.6	0.33	3.67	2.5

24	2.5	4	2.3	0.2	3.6	1
25	3	4.5	2.8	0.3	3.33	1.5
26	5	5.2	4.5	1	2.4	9
27	2.5	4	2.4	0.15	3.6	1
28	4	5.2	4.1	0.5	3	5.5
29	4	5.2	4.1	0.7	3	5.5
30	4	5.2	4.1	0.65	3	5.5
31	4.5	5	4.3	0.64	2.67	6.5
32	3	4.2	3.6	0.22	3.67	2.5
33	4.5	5.22	4.3	0.6	2.67	7
34	4.5	5	4.5	0.9	2.67	8
35	3	4.2	3.6	0.2	3.67	3
36	5	6	4.5	1.05	4.5	10