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MINIMISING BACKBREAK AT THE DEWAN CEMENT LIMESTONE QUARRY USING AN ARTIFICIAL NEURAL NETWORK

MINIMALIZACJA ZASIĘGU KRUSZENIA ZŁOŻA POZA OBSZAREM PRAC STRZAŁOWYCH W KAMIENIOŁOMIE WYDOBYWAJĄCYM WAPIEŃ DO PRODUKCJI CEMENTU W DEEWAN, PRZY WYKORZYSTANIU SZTUCZNYCH SIECI NEURONOWYCH

Backbreak, defined as excessive breakage behind the last row of blastholes in blasting operations at a quarry, causes destabilisation of rock slopes, improper fragmentation, minimises drilling efficiency. In this paper an artificial neural network (ANN) is applied to predict backbreak, using 12 input parameters representing various controllable factors, such as the characteristics of explosives and geometrical blast design, at the Dewan Cement limestone quarry in Hattar, Pakistan. This ANN was trained with several model architectures. The 12-2-1 ANN model was selected as the simplest model yielding the best result, with a reported correlation coefficient of 0.98 and 0.97 in the training and validation phases, respectively. Sensitivity analysis of the model suggested that backbreak can be reduced most effectively by reducing powder factor, blasthole inclination, and burden. Field tests were subsequently carried out in which these sensitive parameters were varied accordingly; as a result, backbreak was controlled and reduced from 8 m to less than a metre. The resulting reduction in powder factor (kg of explosives used per m^3 of blasted material) also reduced blasting costs.

Keywords: Neural Network, backbreak, sensitivity analysis, modeling, blast design, quarry

Kruszenie części złoża poza obszarem prowadzonych prac strzałowych oznacza nadmierne pękanie skał poza ostatnim rzędem otworów strzałowych w trakcie prac w kamieniołomach i prowadzi do destabilizacji górotworu poprzez zmianę nachylenia warstw skalnych, powoduje niepotrzebną fragmentację skał i obniża efektywność prac wiertniczych. W pracy tej wykorzystano sztuczną sieć neuronową (ANN) do przewidywania zasięgu kruszenia dalszej części złoża przy wykorzystaniu 12 parametrów wejściowych. Parametry te opisują różne zmienne czynniki, np. charakterystyka materiału wybuchowego czy przyjęty plan prac strzałowych w kamieniołomie Deewan w regionie Hattar w Pakistanie. Prowadzono proces uczenia sieci dla różnej architektury modelu, wybrano model 12-2-1 ANN, jako

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model najprostszy, zapewniający najlepszy wynik a współczynniki korelacji uzyskane dla fazy uczenia i walidacji wyniosły odpowiednio 0.98 i 0.97. Przeprowadzona analiza wrażliwości modelu wykazała że zasięg kruszenia dalszych części złoża obniżyć można poprzez zmianę parametrów ładunku strzelniczego, zmianę nachylenia otworów strzałowych oraz zmianę przybitki. Badania terenowe w czasie których ulegały zmianie wartości wyżej wymienionych wrażliwych parametrów wykazały, że zasięg kruszenia złoża poza obszarem prac strzałowych ograniczono z uprzednich 8 m do wielkości poniżej jednego metra. Obniżenie współczynnika charakteryzującego ładunek (kg zastosowanego materiału wybuchowego przypadający na 1 m^3 rozkruszonego materiału skalnego) pozwoliło także na obniżenie kosztów prac strzałowych.

Słowa kluczowe: sieci neuronowe, zasięg kruszenia, analiza wrażliwości, modelowanie, projektowanie robót strzałowych, kamieniołom

1. Introduction

Drilling and blasting costs, which account for a quarter of total operational costs, may contain half of these costs due to certain adverse factors such as backbreak, toe, boulders, etc. (Oraee & Asi, 2006). Failure to properly design blasting procedures at the final pit walls can cost many millions of dollars in additional waste removal (Workman, 1992). Backbreak, or rock breakage beyond the bounds of the last row in bench blasting (Olofsson, 1990), generally leads to pit wall angles smaller than those required, and may require costly artificial support techniques (Workman, 1992). It causes instability of rock slopes (Ashby, 1981), minimum drilling efficiency, and improper fragmentation (Monjezi & Dehghani, 2008). Wyllie & Mah (2004) suggested controlled blasting techniques such as cushion blasting, line drilling, and pre-shearing in order to minimise backbreak. These techniques are generally expensive and time-consuming (Workman, 1992), and therefore cheaper and efficient ways for controlling backbreak need to be devised. Various studies have been carried out to identify the key blast design parameters influencing backbreak. Modelling backbreak requires robust and adaptable models to derive an optimal blast design (Monjezi & Dehghani, 2008). Empirical methods and traditional modelling techniques such as multivariate regression fail to derive the cause of backbreak in cases where it is affected by numerous parameters nonlinearly. Artificial intelligence has been diversely applied in earth sciences recently, using fuzzy logic (Demicco & Klir, 2004; Muhammad & Glass, 2011), neural networks (Bonaventura et al., 2017; Chatterjee et al., 2010; Izadi et al., 2017; Rogiers et al., 2012; Roslin & Esterle, 2016; Muhammad et al., 2014), and neuro-fuzzy modelling techniques (Cherkassky et al., 2006; Kar et al., 2014; Valdés & Bonham-Carter, 2006; Yegireddi & Uday Bhaskar, 2009; Yurdakul et al., 2014; Zoveidavianpoor et al., 2013). Recently, several researchers have solved backbreak problems through applying neural networks (Jang & Topal, 2013; Monjezi & Dehghani, 2008; Monjezi et al., 2013; Saadat et al., 2014; Sayadi et al., 2013; Ebrahimi et al., 2016), neuro-fuzzy techniques (Ghasemi et al., 2016), stochastic optimisation (Sari et al., 2013), and machine learning techniques (Khandelwal & Monjezi, 2012; Mohammadnejad et al., 2013). The findings differed according to rock type, as the characteristics of explosives and geometry of blast design are different in different conditions.

In this paper, a prediction model based on an artificial neural network (ANN) was developed to predict the backbreak phenomenon at the Dewan Cement limestone quarry in Hattar, Pakistan. Two additional parameters (i.e. blasthole inclination and number of free faces) were included in the development of the ANN-based backbreak prediction model. The most sensitive input parameters were identified and modified appropriately in order to minimise backbreak.

In the next section, a brief overview of previous backbreak models is presented; subsequently, a case study is presented, followed by sensitivity analysis, results and discussion, and a final conclusion section.

2. Modelling the backbreak phenomenon

The input variables for backbreak are classified as follows: geometrical, concerned with the spatial design and orientation of the blastholes; explosive-dependent, concerning the intensity and mode of use of explosives; operational, concerning controlling factors during blasting, e.g. delays; and uncontrollable, such as geology and rock type. Previously, researchers considered burden, spacing, hole depth, and stemming as input variables for evaluating backbreak (Sayadi et al., 2013; Mohammadnejad et al., 2013; Monjezi et al., 2013; Monjezi & Dehghani, 2008; Khandelwal & Monjezi, 2012; Monjezi et al., 2010; Sari et al., 2013). Certain additional parameters such as drillhole height, specific charge (Sayadi et al., 2013), specific drilling (Sayadi et al., 2013; Mohammadnejad et al., 2013; Monjezi et al., 2013), number of rows (Faramarzi et al., 2012; Monjezi et al., 2013), powder factor (Faramarzi et al., 2012; Monjezi et al., 2013; Sari et al., 2013), delay per metre (Monjezi et al., 2013), charge per delay (Monjezi et al., 2010), rock density (Monjezi et al., 2013; Monjezi et al., 2010), geometric stiffness (Sari et al., 2013), and rock factor (Monjezi et al., 2013) have also been included as inputs for developing backbreak models. In most cases, the backbreak phenomenon is nonlinear; therefore, artificial intelligence has been preferred to multivariate regression in the development of backbreak prediction and control models. An artificial neural network (ANN) is a type of supervised learning technique emulating the human nervous system. It consists of a layered set of nodes whereby each node has a weighted connection to a set of nodes in subsequent layers (Hopfield, 1984). The weights are optimised by supervising minimisation of errors between the predicted and actual outputs. Minimisation of error, i.e. 'learning', in adapting to known outputs is done through techniques such as backpropagation, developed in the 1980s. The adaptability of the models is due to a nonlinear function in each node. Once the network is trained, i.e. when the error of outputs is minimised to an acceptable level, it can be used to predict the outputs for any given values of inputs. Currently the ANN technique is one of the most logical practices for solving composite problems (Khandelwal et al., 2004). The theoretical background of the technique is explained clearly in the literature (Tadeusiewicz, 2015; Mehrotra et al., 1997; Muhammad et al., 2014). Some studies resulted merely in a prediction model for backbreak phenomenon (Khandelwal & Monjezi, 2012; Mohammadnejad et al., 2013), without explicit identification of the controlling variables that minimise backbreak. Others identified different combinations of sensitive parameters from the model for different situations. Some researchers have reported that increased backbreak is due to increases in stemming, burden (Sayadi et al., 2013), stiffness ratio, and improper delay timing (Gates et al., 2005). Monjezi & Dehghani (2008) observed that the most important parameters concerning the backbreak phenomenon are the ratios of stemming to burden and last-row charge to total charge, powder factor, total charge per delay, and the number of rows in a blasting round. Rock factor, number of rows (Monjezi et al., 2014), stemming length, hole depth, burden, and hole spacing (Monjezi et al., 2010) are other sensitive parameters related to controlling backbreak. Konya and Walter (1991) reported that the reasons for backbreak include excessive stemming (i.e. more than 0.7 of burden) on hard rock benches, excessive burden in stiff benches, and improper delay times (i.e. between 4-6 milliseconds of delay between back holes).

3. Case study: the Dewan Cement quarry in Hattar, Pakistan

The Dewan Cement limestone quarry in Hattar is located at 35º50′38.61″N, 72º52′15.04″E, 4.5 km from the crusher of the plant, in the province of Khyber Pakhtunkhwa, Pakistan. Due to inappropriate blasting patterns, backbreak was a major problem, reaching up to 8 m. Consequently, the working bench is cut off, necessitating excessive drilling, blasting, and dozing in order to bring the bench to an operational condition, which leads in turn to an increase in the overall cost of mining. When the blast was designed, the diameter of the blastholes was set to 104 mm and the explosive charge divided into three portions: bottom charge, column charge, and stemming portion. A high explosive such as Tovex/Wabox was used as the bottom charge, ANFO as a column charge, and drill cuttings as stemming material. The explosive cartridge used was 75 mm in diameter and 500 mm in length. The stemming of the shot holes was set to 0.7 times the burden in accordance with Konya & Walter (1991). Data was collected by varying design parameters between the limits shown in Table 1. A list of detailed parameters is given in Table 2. Input parameters such as burden and spacing are established parameters of importance for backbreak. They are included in the model, albeit with subtle variations in order to investigate their effect in combination with other variables. Data was recorded for 40 different blast designs, represented by 12 input variables and the corresponding output, i.e. backbreak. All of the variables were normalised via range transformation to values between 0 and 1.

TABLE 1

General blast design parameters at the Dewan Cement limestone quarry

Parameter	Description
Height of the bench	6-18 m
Burden	3-3.5 m
Spacing	3.5-4.5 m
High explosive (by volume)	10-30%
ANFO (by volume)	70-90%
Delay per row	50-100 milliseconds
Hole-to-hole delay	25-75 milliseconds

3.1. Multivariate linear regression

The linear regression coefficients shown in Table 2 were derived using the least squares method. The predicted values were back-transformed to original values and compared with the actual values. Multiple linear regression showed a poor fit at the extreme ends (where higher and lower backbreak values were recorded); accordingly, the reported correlation between predicted and measured backbreak was 0.45. Thus a reliable method such as ANN was required to model the nonlinear complex relationship between the input and output variables.

TABLE 2

Input variables for modelling the output (Q: backbreak) and coefficients of input variables obtained from multiple linear regression

No.	Parameter	Linear regression coefficients	
1	A; burden (m)	Corresponding regression coefficients of the input variables	6.075808
2	B; spacing (m)		–1.81371
3	D; hole depth (m)		–0.27086
4	E; blasthole inclination to horizontal		0.641112
5	F; high-explosive percentage		0.536875
6	G; ANFO percentage		1.954375
7	H; stemming (m)		–0.01341
8	K; powder factor		0.665464
9	L; delay per row (milliseconds)		–0.04076
10	M; hole-to-hole delay (milliseconds)		0.041225
11	N; no. of rows		0.075211
12	O; no. of free faces		–0.25939
Output variable: Q; backbreak		Regression constant	–3.14

TABLE 3

Correlation between actual vs predicted following training and validation phases using different ANN architectures

Model Architecture	Training R^2	Validation R^2
12-2-1	0.98	0.97
12-3-1	0.97	0.96
12-4-1	0.98	0.95
12-5-1	0.98	0.93
12-6-1	0.98	0.97
12-7-1	0.98	0.92

3.2. Training and validation of ANN model for predicting backbreak

A three-layered ANN was developed in MATLAB. The input layer contained 12 neurons and a bias node and the output layer comprised a single output neuron for backbreak. Various architectures were trained by varying the number of nodes in the hidden layer. The best model architecture with a minimum sum of squared error (SSE) and the highest correlation (R^2) was retained for further analysis. Various model architectures and their correlation for training and validation data of the output variables are shown in Table 3. Among these, the 12-2-1 network architecture was the simplest, with greater correlation (in equal measure) in the training and validation phases. Graphic comparisons of predicted and measured outputs in the training phase using the 12-2-1 ANN architecture are shown in Fig. 2. Fig. 3 shows a plot of actual against predicted values of backbreak from the validation phase.

4. Sensitivity analysis

To analyse the sensitivity of backbreak to input parameters, a sensitivity analysis was carried out using the trained neural network model. The relative strength of effects (RSE) values were calculated for each input ranging from –1 to 1 (Monjezi et al., 2010). RSE is a type of parameter utilised to predict the relative significance of input factors compared to output units (Monjezi & Dehghani, 2008).

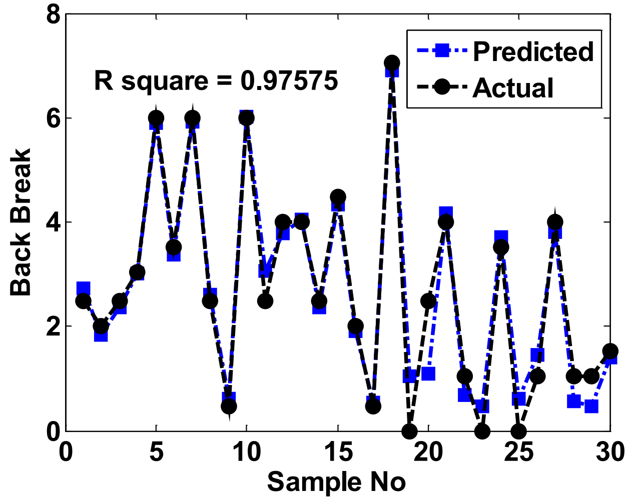

Fig. 2. Measured and predicted backbreak from the 12-2-1 ANN model during training

The larger the absolute value of RSE, the greater the effect of the corresponding input on the output. The RSE values plotted against the input variables are shown in Fig. 4. Factors with higher absolute RSE values (i.e. greater than 0.5 or less than –0.5) were identified as the most sensitive positive and negative factors in controlling backbreak. The overtraining of some ANN architectures (12-3-1, 12-5-1, and 12-7-1) is reflected by divergent RSE values of burden (A), spacing (B), and, to some degree, of high explosive (F) and ANFO (G). However, all seven models yielded the same consistent RSE values for certain input variables. Depth of hole (D), stemming (H), delay/row (L), h-h delay (M), and number of rows (N) were declared insensitive variables, while inclination (E), powder factor (K), and number of free faces (O) were unanimously declared the most sensitive variables by all six ANN architectures in this study.

5. Results and discussion

The 12-2-1 architecture proved to be the best model for this case, with minimum error (highest correlation) in both the training and validation stages, and was therefore retained to assess the sensitivity of the backbreak. Sensitivity analysis suggested that by decreasing burden (A), inclination (E), powder factor (K), and number of free faces (O) with positively strong RSE

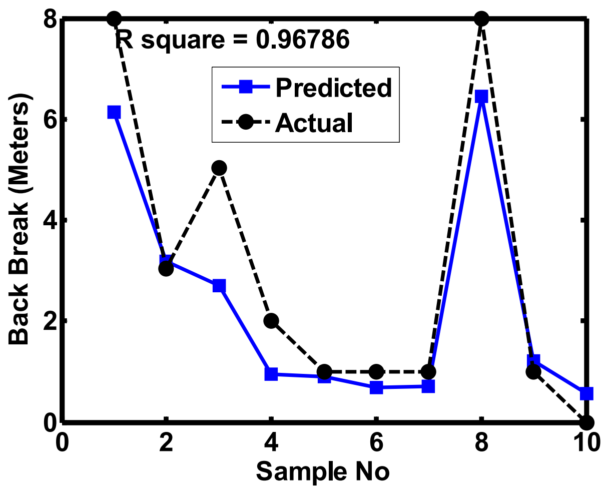

Fig. 3. Actual vs predicted backbreak in the validation phase using 12-2-1 ANN

values a decrease in backbreak has to occur. Similarly backbreak will also decrease with increased values of O: the number of free faces with negatively strong RSE values (i.e. less than –0.5). Since the number of free faces is an uncontrollable factor, while an increase in the quantity of high explosives could have an adverse effect on cost, these factors were ignored.

Row-to-row delay and number of rows showed no effect on backbreak, possibly because the number of rows in this case was less than or equal to two. Several new blasting designs were formulated based on this information. The sensitive parameters were varied accordingly and 12 geometrical blast patterns (Annex C) were devised to minimise backbreak. Blasthole inclination

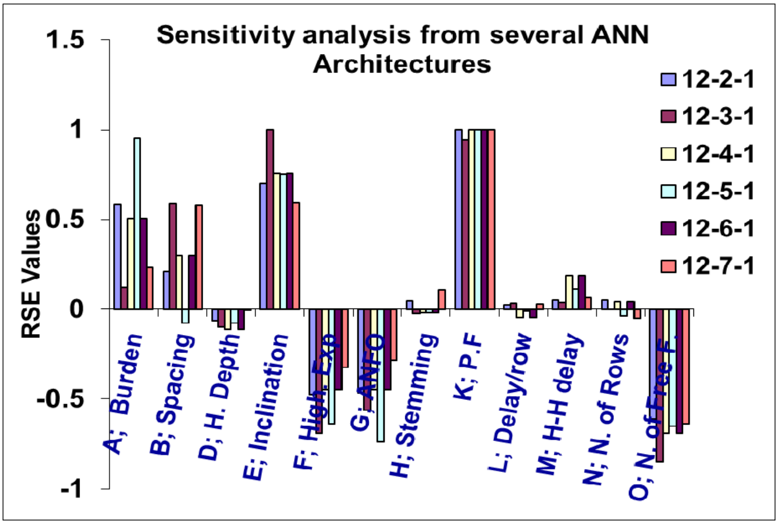

Fig. 4. Relative strength effects (RSEs) of variables on backbreak

played a major role, one that has been ignored in previous models, in controlling backbreak at the Dewan Cement limestone quarry. The correlation of the ANN model was higher (0.98 and 0.97) than that of the support vector machine (SVM) model presented by Mohammadnejad et al. (2013). The importance of blasthole inclination is supported by other empirical studies (Bhalchandra, 2011; Smith et al., 2001) for reducing backbreak. Geological features, such as sedimentary layering in the quarry, were constant; therefore, geological properties such as bedding angle were not included. However, where required, geology such as the layering of limestone beds and their orientations may be incorporated in the model to make it more robust. Backbreak was reduced from 8 to 0.5 m by: 1) reducing the blast-hole inclination from 85º to 75º; 2) reducing the burden to obtain a spacing-to-burden ratio of 1.5 as opposed to the previous ratio of 1.32. The powder factor was reduced from 0.62 to 0.55 kg/m^3; as a consequence, the cost per ton was also reduced from Pakistani Rs. 24/ton to Rs. 18/ton, which increased the yield of blasted material from 5 to 6 tons/kg of explosive.

6. Conclusions

To summarise, a 12-2-1 ANN prediction model for backbreak outperformed linear regression in modelling the backbreak phenomenon. The network was trained using 30 blast case patterns and validated by 10 blast cases from the Dewan Cement quarry in Hattar, Pakistan. The model showed a correlation of 0.98 for training data and 0.97 for validation data. Sensitivity analysis showed that the most sensitive geometrical parameters for controlling backbreak phenomenon are, in decreasing order: powder factor, blasthole inclination, and burden. It was concluded that by reducing the blasthole inclination from 85º to 75º and maintaining the burden at 2/3 of spacing, backbreak was reduced from 8 to 0.5 m.

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Annex A: Training data from the Dewan Cement limestone quarry

Burden	Spacing	Hole depth (m)	Blasthole Inclination	High explosive %	ANFO%	Stemming (m)	Powder factor	Delay per row	Hole-to-hole delay	No. of rows	No. of free faces	Backbreak (m)
1	2	3	4	5	6	7	8	9	10	11	12	13
3.00	4.00	16.16	85.00	25.99	74.01	2.90	1.21	0.00	25.00	1.00	1.00	2.5
3.00	4.00	16.16	85.00	29.41	70.59	2.90	1.14	0.00	25.00	1.00	1.00	2.0
3.00	4.00	16.16	85.00	20.00	80.00	2.90	1.31	0.00	25.00	1.00	2.00	2.5
3.00	4.00	12.80	80.00	20.00	80.00	3.00	1.33	75.00	50.00	3.00	3.00	3.0
3.00	4.00	16.16	85.00	21.82	78.18	2.90	1.35	50.00	25.00	3.00	1.00	6.0
3.00	4.00	16.16	85.00	18.92	81.08	2.80	1.37	0.00	50.00	1.00	3.00	3.5
3.50	4.50	16.16	85.00	12.50	87.50	2.90	1.27	0.00	25.00	1.00	1.00	6.0
3.00	4.00	9.45	75.00	11.11	88.89	2.90	1.36	0.00	50.00	1.00	1.00	2.5
2.50	3.50	12.80	80.00	25.00	75.00	2.30	1.29	0.00	25.00	1.00	2.00	0.5
3.50	4.50	16.16	85.00	10.60	89.40	2.90	1.24	50.00	50.00	3.00	1.00	6.0
3.00	4.00	12.80	80.00	12.00	88.00	2.40	1.36	50.00	25.00	2.00	2.00	2.5
3.00	4.00	12.80	80.00	13.04	86.96	2.10	1.33	50.00	25.00	2.00	1.00	4.0

1	2	3	4	5	6	7	8	9	10	11	12	13
3.00	4.00	16.16	85.00	17.81	82.19	2.80	1.26	100.00	50.00	2.00	1.00	4.0
3.00	4.00	9.45	75.00	9.58	90.42	2.20	1.34	50.00	25.00	2.00	3.00	2.5
3.00	4.00	12.80	80.00	12.50	87.50	2.50	1.36	50.00	25.00	2.00	1.00	4.5
3.00	4.00	12.80	80.00	12.79	87.21	2.50	1.33	0.00	25.00	1.00	2.00	2.0
3.00	4.00	9.45	75.00	17.36	82.64	2.50	1.24	0.00	25.00	1.00	2.00	0.5
3.00	4.00	16.16	85.00	13.49	86.51	2.50	1.40	0.00	25.00	1.00	1.00	7.0
3.00	4.00	9.45	75.00	17.24	82.76	2.20	1.25	0.00	75.00	1.00	2.00	0.0
3.00	4.00	9.45	75.00	14.90	85.10	2.20	1.29	0.00	50.00	1.00	2.00	2.5
3.00	4.00	12.80	80.00	14.53	85.47	2.20	1.35	0.00	25.00	1.00	1.00	4.0
3.00	4.00	9.45	75.00	16.71	83.29	2.20	1.27	0.00	25.00	1.00	2.00	1.0
3.00	4.00	9.45	75.00	23.78	76.22	2.20	1.23	0.00	25.00	1.00	2.00	0.0
3.00	4.00	12.80	80.00	16.94	83.06	2.50	1.35	50.00	25.00	2.00	1.00	3.5
3.00	4.00	9.45	75.00	17.72	82.28	2.20	1.25	50.00	25.00	3.00	2.00	0.0
3.00	4.00	12.80	80.00	13.79	86.21	2.50	1.30	0.00	25.00	1.00	2.00	1.0
3.00	4.00	12.80	80.00	16.60	83.40	2.50	1.31	100.00	50.00	2.00	1.00	4.0
3.00	3.50	6.09	70.00	26.02	73.98	2.50	1.30	50.00	25.00	2.00	2.00	1.0
3.00	4.00	6.09	70.00	20.00	80.00	2.70	1.24	0.00	25.00	1.00	1.00	1.0
3.00	4.00	9.45	75.00	15.29	84.71	2.10	1.28	0.00	75.00	1.00	2.00	1.5
3.00	4.00	16.16	85.00	16.67	83.33	2.90	1.38	0.00	25.00	1.00	1.00	8.0
3.50	4.50	12.80	80.00	21.51	78.49	3.00	1.21	100.00	50.00	2.00	1.00	3.0
3.00	4.00	12.80	80.00	14.29	85.71	2.70	1.36	50.00	25.00	2.00	2.00	5.0
3.00	4.00	9.45	75.00	14.29	85.71	2.10	1.27	50.00	25.00	2.00	2.00	2.0
3.00	4.00	12.80	80.00	14.44	85.56	2.50	1.22	50.00	25.00	2.00	2.00	1.0
3.00	4.00	9.45	75.00	18.10	81.90	2.20	1.24	0.00	50.00	1.00	2.00	1.0
3.00	4.00	9.45	75.00	16.73	83.27	2.20	1.27	0.00	25.00	1.00	2.00	1.0
3.50	4.00	16.16	85.00	13.39	86.61	3.00	1.32	0.00	75.00	1.00	1.00	8.0
3.00	4.00	12.80	80.00	14.46	85.54	2.50	1.28	0.00	25.00	1.00	2.00	1.0
3.00	3.50	6.09	70.00	15.57	84.43	2.50	1.28	50.00	25.00	2.00	2.00	0.0

Annex B: Validation data from the Dewan Cement limestone quarry

Burden (m)	Spacing (m)	Hole depth (m)	Blasthole Inclination	High explosive %	ANFO%	Stemming (m)	Powder factor	Delay per row	Hole-to-hole delay	No. of rows	No. of free faces	Backbreak(m)
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
3	4.0	13	85	17	83	2.9	0.8	0	25	1	1	8.0
4	4.5	10	80	21	79	3.0	0.5	100	50	2	1	3.0
3	4.0	10	80	14	86	2.7	0.7	50	25	2	2	5.0
3	4.0	9	80	15	85	2.5	0.5	50	25	2	2	1.0
3	4.0	10	75	14	86	2.1	0.6	50	25	2	2	2.0

1	2	3	4	5	6	7	8	9	10	11	12	13
3	4.0	10	75	18	82	2.2	0.5	0	50	1	2	1.0
3	4.0	10	75	17	83	2.2	0.6	0	25	1	2	1.0
4	4.0	13	85	13	87	3.0	0.7	0	75	1	1	8.0
3	4.0	16	80	15	85	2.5	0.6	0	25	1	2	1.0
3	3.5	8	70	16	84	2.5	0.6	50	25	2	2	0.0

Annex C: Post-sensitivity analysis of blast design

Burden (m)	Spacing (m)	Hole depth (m)	Blasthole Inclination	High explosive %	ANFO%	Stemming (m)	Powder factor	Delay per row	Hole-to- hole delay	No. of rows	No. of free faces	Backbreak (m)
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
3	4.5	10	75	8	92	2.0	0.6	50	50	1	3	1.0
3	4.5	7	75	15	85	2.2	0.5	75	25	2	1	0.5
3	4.5	16	75	13	87	2.2	0.6	50	25	1	2	1.0
3	4.5	10	80	17	83	2.1	0.6	75	25	1	2	1.0
3	4.5	10	75	12	88	2.2	0.5	50	25	1	2	0.5
3	4.5	7	75	14	86	2.1	0.5	50	25	1	3	0.0
3	4.5	10	75	14	86	2.8	0.5	75	50	2	2	1.0
3	4.5	13	75	14	86	2.5	0.6	50	25	1	3	0.0
3	4.5	16	75	11	89	2.4	0.6	50	25	1	2	1.0
3	4.5	10	75	15	85	2.3	0.5	75	50	1	3	0.0
3	4.5	13	75	12	88	2.3	0.5	75	25	1	3	0.0
3	4.5	10	75	13	87	2.3	0.6	50	25	1	2	0.5