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Optimizing Mining Economics: Predicting Blasting Costs in Limestone Mines Using the RES-Based Method

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ABSTRACT

The mining process involves several sequential stages, including drilling, blasting, loading, transportation, and mineral processing. Among these stages, blasting costs (BC) exhibit greater sensitivity compared to others. Inadequate blasting practices can lead to additional drilling, increased explosive consumption, and environmental consequences such as ground vibrations. The variability in blasting patterns and ore rock hardness results in variations in BC. Consequently, there is a need for a method that can establish a relationship between design, geotechnical parameters, and blasting costs while accounting for uncertainties in input parameters. In this study, the rock engineering system method (RES) was employed to construct a complex and non-linear model for predicting blasting costs, considering uncertainties in geotechnical parameters. Data from six limestone mines in Iran were utilized, incorporating 146 data points. The input parameters used for creating this relationship included hole diameter, burden, emulsion, hole number, hole length, spacing, stemming, sub-drilling, rock hardness, ANFO, number of electric detonators, unia-xial compressive strength, and specific gravity. The model was built using 80% of the data (117 data points) to establish the RES-based method, with the remaining 20% (29 data points) dedicated to evaluating and validating the model. To assess its performance, the RES-based method was compared to other statistical regression techniques, utilizing statistical indicators such as root mean square error (RMSE), mean square error (MSE), and coefficient of determination (R2). The results demonstrated that the RES-based method significantly outperformed other statistical approaches with impressive accuracy, as indicated by MSE=0.00608, RMSE=0.078, and R2=0.9518 in predicting explosion costs. Therefore, the model developed through this method can be effectively applied in mining and rock mechanics projects, providing a high level of accuracy.

Keywords: *Blasting costs, RES-based method, Mining economy, Limestone mines, Predicting blasting costs.*

1. Introduction

Blasting operations have become the predominant method for large-scale production in both surface and underground mining today. Hence, optimizing these operations offers a promising avenue for enhancing profitability and reducing production costs in mines. The primary objective of drilling and blasting in both surface and underground mining is to achieve proper rock fragmentation. Carrying out efficient drilling and blasting operations marks the initial step toward achieving the desired crushed rock dimensions required for feed supply to processing plants. Rock fragmentation resulting from blasting significantly impacts the overall economic performance of the mine in various ways (Singh & Singh, 2005). Conducting successful blasts reduces rock crushing costs, enhances the efficiency of drilling, loading, and hauling operations, minimizes additional drilling and backbreak, mitigates ground vibration, minimizes throw, and improves post-extraction drilling operations. Therefore, optimizing and meticulously designing this stage not only minimizes mining costs but also enhances subsequent stages of the production process, bolsters safety measures, and ultimately maximizes production value (Latham, Van Meulen, & Dupray, 2006; Lowery, Kemeny, & Girdner, 2001; Qu, Hao, Chen, Li, & Bian, 2002; Rezaei, Monjezi, & Varjani, 2011). To attain these objectives, it is crucial to identify the factors influencing blasting and drilling processes. Determining the factors influencing blasting and drilling operations (input parameters) is the initial stage for executing effective blasting. Subsequently, the optimal blast pattern is designed based on these factors. Generally, the factors influencing blast pattern design can be categorized as uncontrollable and controllable parameters. Uncontrollable parameters are inherent environmental factors that dictate the design for better results. These factors include geomechanical conditions of the mining area, such as rock strength, joints, faults, as well as weather conditions like humidity, temperature, and atmospheric precipitation. On the other hand, controllable parameters are subject to modification, and their proper and principled design leads to optimized blasting. Examples of controllable parameters include geometric parameters of the drilling pattern, hole diameter, hole distance and depth, physical properties of explosives, explosive quantity, and delay time (Monjezi, Rezaei, & Varjani, 2009). Despite extensive research efforts, no reliable theoretical relationships have been established to date for the blast pattern design based on design and geomechanical parameters. In many cases, the blast pattern design is carried out using traditional approaches and personnel experience. Numerous studies have been conducted to develop scientific and reliable methods for the optimizing blast design, resulting in cost reduction. These studies encompass numerical modelling (Abbaspour, Drebenstedt, Badroddin, & Maghaminik, 2018; Esen, La Rosa, Dance, Valery, & Jankovic, 2007; Kanchibotla, 2003; Leng, Fan, Gao, & Hu, 2020; Miranda, Leite, & Frank, 2019; Nielsen, 1987; Pomasoncco-Najarro et al., 2022; Zhu, 2009),

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regression and statistical methods (AFENI, 2009; Akande & Lawal, 2013; Antipas Thadei Safari & Karim Rajabu, 2011; Ghanizadeh Zarghami, Shahriar, Goshtasbi, & Akbari, 2018; Nikkhah, Vakylabad, Hassanzadeh, Niedoba, & Surowiak, 2022), as well as analytical and experimental models (Lyashenko, Vorob'ev, Nebohin, & Vorob'ev, 2018; Roy, Paswan, Sarim, & Kumar, 2017; S. Wang et al., 2019; H.-S. Yang & Rai, 2011; R. Yang, Kavetsky, & McKenzie, 1989). Although these methods yield reasonably accurate results, they face limitations. Numerical models, for instance, accept only one value for input parameters and require separate calculations for each value, making it challenging to achieve a comprehensive and unified analysis for multiple points. Analytical models often create simplified mathematical relationships between blast conditions and outcomes, neglecting certain factors and assumptions, thereby reducing model accuracy. Regression methods, on the other hand, suffer from reduced accuracy due to input parameter uncertainty and a large number of variables. Furthermore, empirical equations derived from individual experiences in specific projects cannot be universally applied to different cases. Consequently, with advancements in technology and artificial intelligence, smart algorithms have been employed to design blast algorithms and predict results. These methods offer the advantage of considering uncertainties in input parameters and handling extensive datasets with high accuracy (Asl, Monjezi, Hamidi, & Armaghani, 2018; Bakhshandeh Amnieh, Hakimiyan Bidgoli, Mokhtari, & Aghajani Bazzazi, 2019; Bakhtavar, Sadiq, & Hewage, 2021; de Miguel-García, Martín-Chinea, & Gómez-González, 2021; Dehghani & Ataee-Pour, 2011; Hasanipanah, Amnieh, Arab, & Zamzam, 2018; Jang & Topal, 2013; Kulatilake, Qiong, Hudaverdi, & Kuzu, 2010; Kumar, Mishra, & Choudhary, 2021; Ozdemir & Kumral, 2019; Sadeghi, Monjezi, & Jahed Armaghani, 2020; Silva, Amaya, & Basso, 2017; M. Wang, Shi, Zhou, & Qiu, 2018; Yu et al., 2021; J. Zhou et al., 2021). In this context, the focus of this paper lies in the utilization of the RES approach. This method accounts for uncertainties in input parameters while remaining simple, avoiding lengthy and tedious coding processes, cost-effective, and time-efficient. Moreover, it enables simultaneous analysis of multiple variables impacting blasting costs. Extensive research has been conducted in the field of RES, covering topics such as vulnerability and risk assessment following the Songun copper mine explosion (Faramarzi, Ebrahimi Farsangi, & Mansouri, 2013), evaluation of coal mine methane gas drainage potential (Ghanbari, Ataei, Sereshki, & Saffari, 2018), estimation of maximum ground surface settlement resulting from tunneling using the earth pressure balance shield tunneling (TMB-EPB) (Fattahi & Babanouri, 2018), safety factor calculation and risk analysis for circular failure (Fattahi, 2017), forecasting rock throw and fragmentation danger resulting from explosions in the Sarcheshme copper mine (Hasanipanah, Jahed Armaghani, Monjezi, & Shams, 2016), prediction and estimation of rock mass deformation modulus (Fattahi & Moradi, 2018), injection techniques to improve the condition of rock mass in underground tunnels, dams, and foundations (Saeidi, Azadmehr, & Torabi, 2014), measurement and prediction of the penetration rate of the TBM drilling machine in underground spaces (Fattahi & Moradi, 2017), creation of maps to calculate landslide occurrence in Sallekular, situated in the Jama River Gorge (Meten, Bhandary, & Yatabe, 2015), prediction of fire hazard in coal mine strata (Saffari, Sereshki, Ataei, & Ghanbari, 2013), quantitative analysis of gas and explosion risk in coal mines (Q. Zhou, Herrera, & Hidalgo, 2019), estimation of explosion and rock mass fragmentation for mines in Chile and Canada (Azadmehr, Jalali, & Pourrahimian, 2019), the blast-induced peak ppaper velocity estimation method (Adesida, 2023), estimation of advance speed and penetration of the TBM in underground structures (Frough & Torabi, 2013), prediction of land surface settlement and damage to surface structures caused by underground tunnel excavation (Mohammadi & Azad, 2021).

From the studies conducted in the field of rock engineering, it becomes evident that the parameters influencing the model's output are remarkably intricate. Geotechnical parameter values differ significantly from one point to another, making it impractical to attain the desired results through conventional and traditional methods. In response, this article introduces a novel approach - the rock engineering system method, or RES - to establish a new relationship capable of considering all parameter values at any given point. This application of the RES method to the context of blasting costs in limestone mines represents an innovative and pragmatic study. To date, no studies have employed this method to build complex, non-linear relationships while addressing the uncertainties in geological parameter values, setting it apart from earlier research. Another distinct advantage of this method, in contrast to studies focused on explosion costs, is its adaptability and the flexibility of the relationships it establishes. In essence, if the relationship created proves applicable in all scenarios with similar geological and geotechnical conditions, it can be a valuable asset. However, in situations involving different geological conditions or variations in input parameters, this research provides a framework for updating the established relationship with minimal time and exceptional accuracy to form new relationships tailored to specific geological conditions. This study distinguishes itself from prior research on blasting costs by demonstrating that the utilization of the RES method can offer engineers and practitioners in the field of rock engineering the most cost-effective and time-efficient means of developing highly accurate functional equations.

In this paper, to account for input parameters uncertainties, data from 146 data points in six limestone mines in Iran were utilized. Subsequently, the RES method was employed to model blasting costs, considering 13 influential factors that significantly impact the evaluation of blasting cost performance in mines. Statistical indicators, including MSE, R^2, and RMSE were used to assess the effectiveness of the RES technique in modelling the nonlinear and complex system.

2. Database used in this study

This study utilizes two databases to model and evaluate the RES method. Specifically, data from six limestone mines in Iran have been utilized. Table 1 provides the characteristics of these six mines, and their geographical locations within Iran are illustrated in Figure 1.

Table 1. The characteristics of six limestone mines in Iran (Bastami, Aghajani Bazzazi, Hamidian Shoormasti, & Ahangari, 2020).

No.	Name of the mine	Annual extraction capacity (tons)	Definite storage	Nearest city to mine
1	Moslem Abad	300000	7000000	Hamedan
2	Sepahan Mobarakeh	600000	13500000	Esfahan
3	Abelou	4000000	89340000	Neka
4	Barkhordar1	160000	1600000	Nurabad
5	Tang Fani	100000	900000	Pol Dokhtar
6	Tajareh	150000	4300000	Khorramabad

To ensure the use of real data, the BC of these six mines were collected from 2011 to 2018. The data was subsequently updated based on the cost increase that occurred in January 2019, serving as the foundation for this paper. Based on the collected data, the blasting company's salary accounts for 8.5% of the total cost, while personnel, transport, consumption monitoring, escort, and container costs contribute to 16.8% of the expenses. Additionally, the cost of secondary fragmentation and adverse effects of blasting represents 11.8%, and the cost of purchasing explosives comprises 62.9% of each blast's total cost (Bastami et al., 2020).

The fly rock was measured using Total Station mapping cameras and laser meters. Rock crushing in six limestone mines was assessed using the Split Desktop 4 software and the image analysis method. Random imaging was conducted, considering dimensional variations and utilizing two scales at the top and bottom of the explosive coupe. In one of the mentioned mines, Figure 2 depicts the sequential stages of image analysis utilizing the Split Desktop software (Bastami et al., 2020).

Overall, a total of 146 data samples, comprising geomechanical and design parameters, were utilized in the analysis of six limestone mines in Iran. The input parameters include hole diameter (D), burden (B), emolite (EM), hole number (N), hole length (H), spacing (S), stemming

(T), sub-drilling (J), rock hardness (HA), ANFO (AN), the number of electric detonators (Det), uniaxial compressive strength (σ_c). and specific gravity (γ_r). The blasting cost serves as the output or prediction in this research. Table 2 presents some of the input parameters along with the measured BC (Bastami et al., 2020).

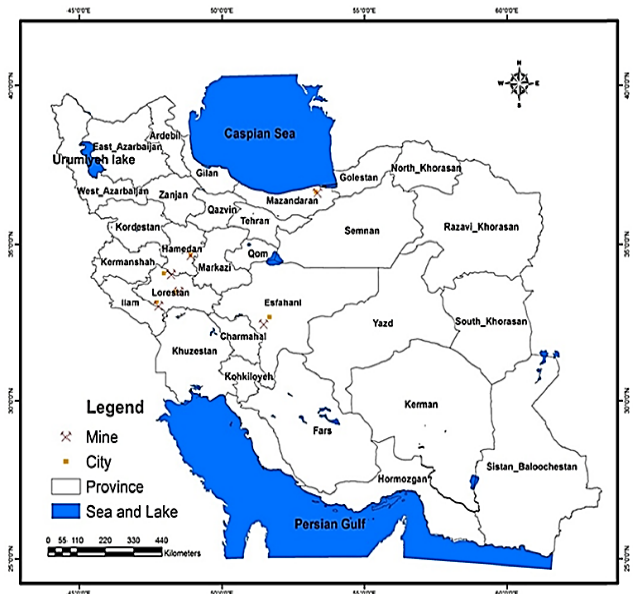

Figure 1. The geographical location of limestone mines on the map of Iran (Bastami et al., 2020).

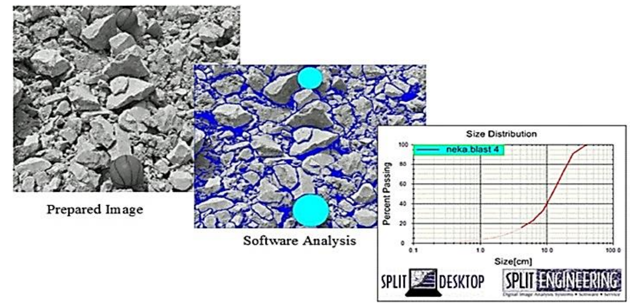

Figure 2. The steps of using the Split Desktop software in one of six limestone mines in Iran (Bastami et al., 2020).

Table 3 provides a statistical summary of the input and output data, including minimum, maximum, average, mode, median, range, and standard deviation values. It offers an overview of the dataset used in the analysis.

To gain a better understanding of the statistical parameters presented in Table 3, a box diagram depicting the input and output parameters can be generated using statistical software such as the SPSS, as shown in Figure 3.

3. Rock Engineering Systems

The RES method, initially proposed by Hudson (1992), is a robust tool for modelling and identifying crucial parameters as well as interaction mechanisms in rock engineering projects. It allows for the simultaneous analysis of relationships between various factors,

Table 2 The part of input and output data for modelling (Bastami et al., 2020).

No.	Inputs													Output
	AN (Kg)	Det	EM (Kg)	N	H (m)	D (mm)	B (m)	S (m)	T (m)	J (m)	γ_r (ton/m^3)	HA (Mhos)	σ_c (Kg/cm^3)	BC (Rials/ton)
1	5500	270	260	270	6.3	76	1.8	2.1	0.9	0.5	2.7	3.5	671	18239
2	9300	490	500	436	6.8	76	1.8	2.2	0.9	0.5	2.7	3.5	671	15486
3	10000	650	500	404	8	76	1.7	2	0.9	0.5	2.7	3.5	671	18110
4	4300	230	280	215	6	76	1.7	2	1	0.5	2.7	3.5	671	23481
5	6200	590	320	500	4	76	1.8	2	1.1	0.5	2.7	3.5	671	20946

Table 3. The statistical description of the input and output dataset.

Type	Parameters	Minimum	Maximum	Mean	Mode	Median	Range	Std. Deviation
Input	AN (Kg)	1020	12400	8551.3014	10000	9700	11380	2598.48504
	Det	45	650	347.8288	400	343	605	122.43328
	EM (Kg)	40	600	295.4041	300	300	560	115.37469
	N	29	553	271.4863	190	242.5	524	136.60864
	H (m)	4	20.40	9.5253	9	9	16.4	3.21751
	D (mm)	76	100	82.9315	76	76	24	8.21828
	B (m)	1.70	3.5	2.3603	3	2.3	1.8	0.52986
	S (m)	1.90	4	2.7966	3.5	2.6	2.1	0.61391
	T (m)	0.9	3.6	1.8329	2.5	1.8	2.7	0.55263
	J (m)	0.2	1.5	0.8247	0.5	0.6	1.3	0.41582
	γ_r (ton/m^3)	2.60	2.7	2.6665	2.7	2.7	0.1	0.03961
	HA (Mhos)	3	3.5	3.2705	3.3	3.3	0.5	0.16153
	σ_c (Kg/cm^3)	530	671	600.5616	620	620	141	49.94935
Output	BC (Rials/ton)	7157	23481	13467.924	8887	13587	16324	3994.76247

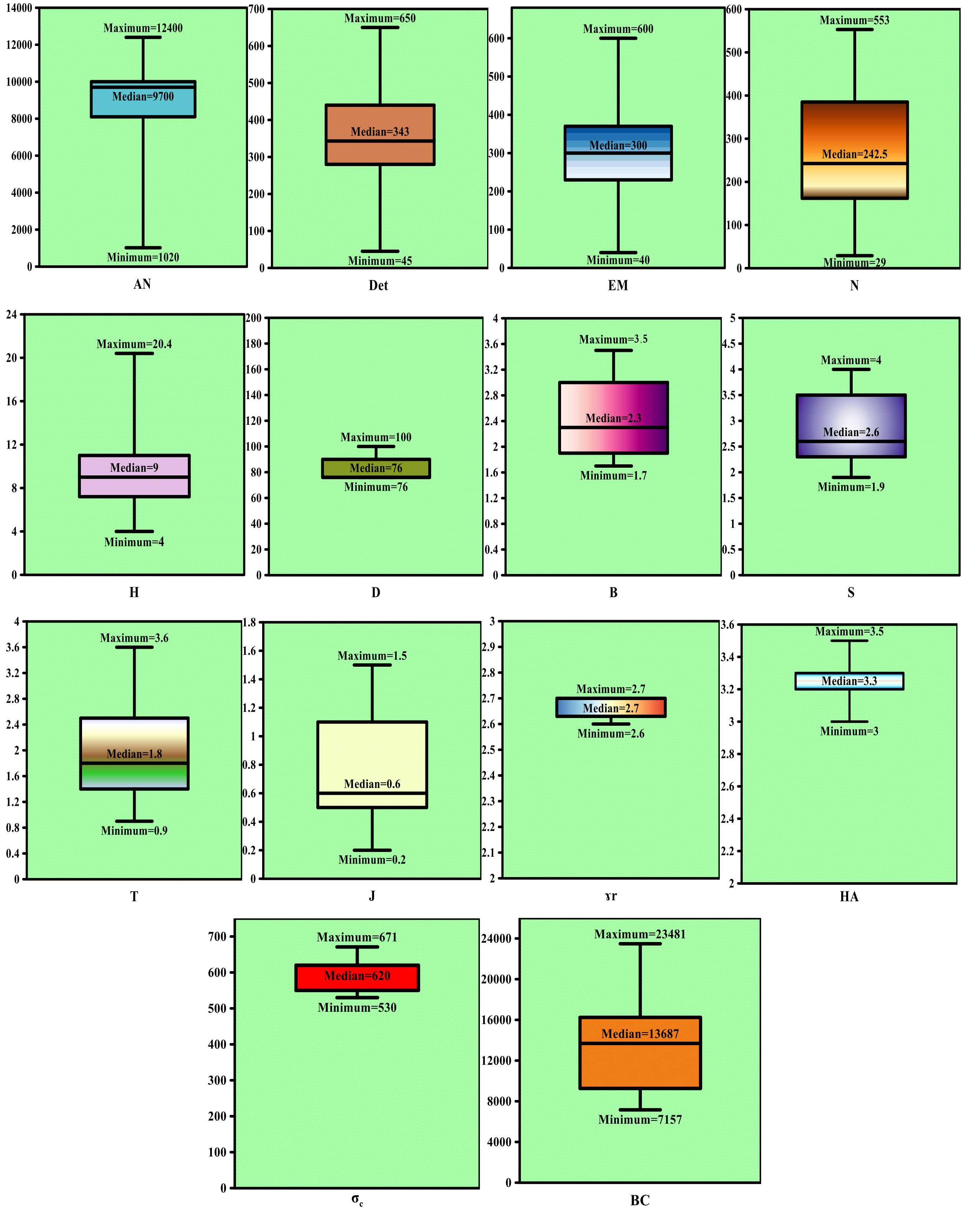

Figure 3. The box diagram of input and output parameters from Table 3.

including rock mass properties, construction, and structural elements, while considering their interactions. Conventional methods may not suffice when dealing with complex rock engineering projects characterized by numerous complexities and interactions. In such cases, the RES approach becomes indispensable as it enables the comprehensive consideration of all relevant parameters and their interactions. The key components of the RES method include identifying critical parameters, effective pathways, feedback loops, and evaluating appropriate engineering techniques through the use of an interaction matrix. This matrix serves as a fundamental element in the RES and presents the interconnections among the influential parameters in a rock engineering project. The input parameters or primary factors are placed along the major diagonal of the matrix, as depicted in Figure 4, while the interactions between these factors are represented outside the main diagonal (Andriani & Parise, 2017; Shad, Sereshki, Ataei, & Karamoozian, 2018). To determine the interactions and parameter influences, specific numerical codes are assigned, and the results can be derived through computations on the rows and columns. Figure 4 illustrates the clockwise interaction between parameters, where parameter B impacts parameter A in the lower-left quadrant and parameter A impacts B in the upper-right quadrant.

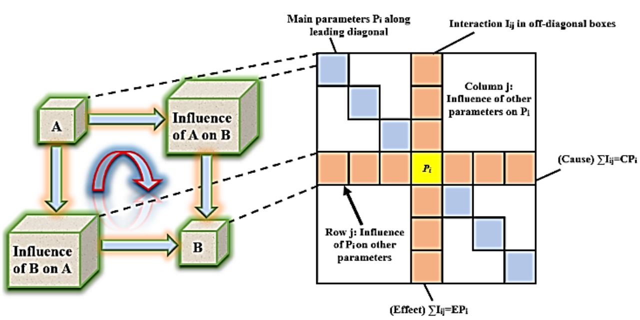

Figure 4. How the interaction matrix works in the RES-based method (Hudson, 1992)

To evaluate the parameters' impact on the system, the interaction matrix needs to be coded. Hudson has provided five coding methods for the interaction matrix, including the explicit method, probabilistic expert semi-quantitative (PESQ) method, continuous quantitative coding (CQC) (Lu & Latham, 1994), binary method, and expert semi-quantitative (ESQ) method. Among these, the ESQ method is commonly used due to its simplicity and high accuracy. In this method, an expert or a group of experts, based on field research, engineering judgments, relevant documentation, expert experience, and potentially theoretical and numerical analyses or other research findings, assign(s) numerical values ranging from 0 to 4 to indicate the strength of interaction between parameters. A coding value of 4 indicates a strong interaction, while 0 denotes no interaction between the matrix parameters. Table 4 presents the coding values and the intensity of interaction between parameters according to the ESQ method.

Table 4. The expert semi-quantitative (ESQ) method (Hudson, 1992).

Code number	Concept
4	Intense interaction
3	High interaction
2	Moderate interaction
1	Low interaction
0	No interaction

Once the interaction matrix is coded, a cause-effect diagram can be constructed. As shown in Fig. 4, the sum of row values in the interaction matrix represents the "cause" or the effect of a parameter on the system, while the sum of column values represents the "effect" or the impact of the system on the parameter. These cause and effect values, denoted as C and E, respectively, are plotted on a coordinate axis to create a cause-effect diagram. The interaction state of each factor is determined based on its position in the space defined by the coordinates C and E. A factor with a higher numerical value for the sum of cause and effect values (C+E) indicates a stronger interaction with the overall system. Conversely, the degree of dominance of a factor over the system decreases as the subtraction of cause and effect values (C-E) increases. To construct a cause-effect diagram for each parameter, the cause and effect values are summed. Equation (1) is employed to obtain the weight (a_i) of parameter i using the percentage value of (C+E) (Benardos & Kaliampakos, 2004).

$$a_i = \frac{(C_i+E_i)}{(\sum_{i=1}^{n} C_i+\sum_{i=1}^{n} E_i)} \times 100 \qquad (1)$$

To analyze the collapse risk of loose regions in underground structures excavated using the TBM, Enardos and Kaliampakos [60] proposed the vulnerability index (VI). This index, calculated using Equation (2), enables the assessment of vulnerability based on the weights (a_i) obtained from Equation (1), the maximum parameter value (Q_{max}), and the value of each parameter (Q_i). The VI serves as an indicator of project risk, with higher values indicating increased risk, as outlined in Table 5. In this research, the VI is utilized for predicting blasting costs.

$$VI = 100 - \sum_{i=1} a_i \frac{Q_i}{Q_{max}} \qquad (2)$$

Table 5. The classification of the VI ((Benardos & Kaliampakos, 2004)).

Risk description	Low-medium	Medium-high	High-very high
VI	0-33	33-66	66-100
Category	I	II	III

3.1. parameters affecting blasting cost

The parameters that affect blasting costs, required for constructing the BC model using the RES approach, are listed in Table 6.

Table 6. The input variables used to build the RES-based model.

P_n	Parameter	Symbol
P_1	ANFO	AN (Kg)
P_2	Number of electric detonators	Det
P_3	Emolite	EM (Kg)
P_4	Hole number	N
P_5	Hole length	H (m)
P_6	Hole diameter	D (mm)
P_7	Burden	B (m)
P_8	Spacing	S (m)
P_9	Stemming	T (m)
P_{10}	Sub-drilling	J (m)
P_{11}	Specific gravity	γ_r (ton/m^3)
P_{12}	Rock hardness	HA (Mhos)
P_{13}	Uniaxial compressive strength	σ_c (Kg/cm^3)

3.2. Interaction matrix

To establish the RES-based BC model, a 13*13 interaction matrix was completed using the ESQ approach. 13 key parameters influencing BC were identified, and experts and engineers in the field of rock mechanics and geotechnical engineering completed questionnaires to code the interaction matrix. Table 7 presents the coding of the interaction matrix for the BCbased on expert opinions.

The cause and effect values of each parameter are then used to create a cause-effect diagram, represented in Figure 5. The diagram indicates the dominant parameters in the lower right corner and the parameters influenced by the system in the upper left corner. Parameters 2, 4, and 5 (the number of electric detonators, hole number, and hole length) are completely influenced by the system, whereas parameters 10, 11, and 13 (sub-drilling, specific gravity, and uniaxial compressive strength) have the most significant effect on the system. Table 8 provides the weight (a_i), effect (E), cause (C), interactive intensity (C+E) and dominance (C-E) for each parameter.

Table 7. The effect of input parameters on each other in the interaction matrix.

P_1	2	0	0	0	2	4	1	2	4	0	0	0
3	P_2	0	0	0	2	0	0	0	0	0	0	0
0	1	P_3	0	0	0	1	0	0	0	0	0	0
0	0	0	P_4	0	0	0	0	0	0	0	0	0
0	0	0	0	P_5	0	0	1	0	0	0	0	0
3	0	0	0	0	P_6	3	0	0	0	0	0	0
4	0	1	0	0	3	P_7	1	0	4	0	0	0
4	0	0	0	0	0	4	P_8	0	4	1	0	0
3	0	0	0	0	0	1	0	P_9	4	4	0	0
4	4	0	0	1	4	4	4	4	P_{10}	4	4	0
4	4	3	1	1	4	4	4	4	4	P_{11}	3	4
0	1	1	3	1	0	1	0	0	1	4	P_{12}	4
0	3	1	2	3	0	0	0	0	4	4	3	P_{13}

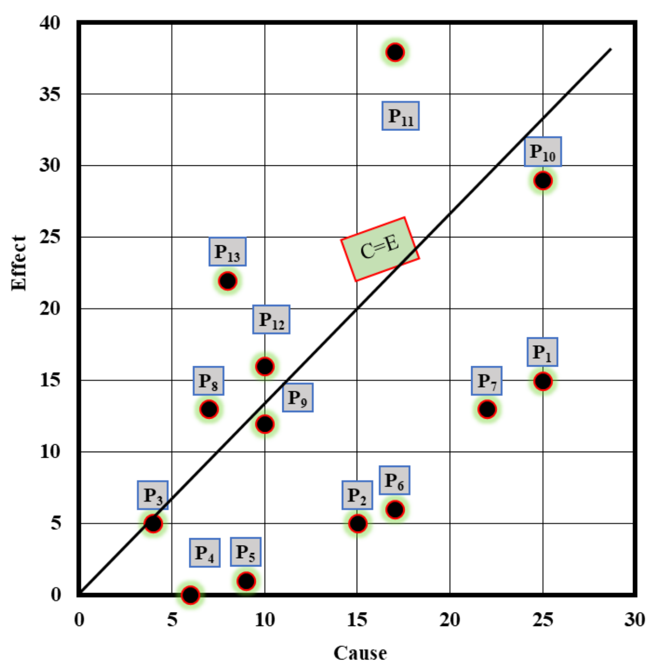

Figure 5. The Cause-Effect Plot for principal parameters of the BC.

Table 8. Weighting of the key variables BC.

Main factor	C	E	C-E	C+E	a_i(%)
AN (Kg)	15	25	-10	40	11.4286
Det	5	15	-10	20	5.71429
EM (Kg)	5	4	1	9	2.57143
N	0	6	-6	6	1.71429
H (m)	1	9	-8	10	2.85714
D (mm)	6	17	-11	23	6.57143
B (m)	13	22	-9	35	10
S (m)	13	7	6	20	5.71429
T (m)	12	10	2	22	6.28571
J (m)	29	25	4	54	15.4286
γ_r (ton/m³)	38	17	21	55	15.7143
HA (Mhos)	16	10	6	26	7.42857
σ_c (Kg/cm³)	22	8	14	30	8.57143
Total	175	175	0	352	100

The values of C+E are obtained for each parameter individually, and their representation on a coordinate axis allows the visualization of interaction intensity. Parameters with greater interaction intensity have a more pronounced impact on the system, where even slight changes in these parameters can lead to significant system changes. Figure 6 displays the C+E values for the principal parameters of the BC.

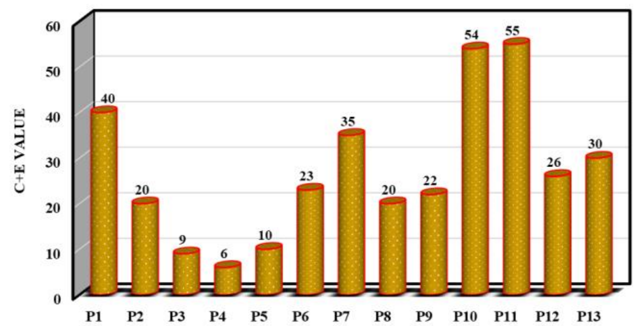

Figure 6. The C+E values for principal parameters of the BC.

3.3. Rating of parameters

To rank the factors influencing blasting costs, specialists and engineers in the field of rock engineering provided ratings from 0 to 4, representing five classes. A rank of 0 indicates the worst or most unfavorable condition, while a rank of 4 indicates the best or most favorable state. Table 9 presents the suggested ratings and ranges for parameters affecting the prediction of blasting costs.

Table 9. The suggested ratings and ranges.

NO.	Parameters	Values and Ratings					
1	AN (Kg)	Value	>11000	8000-11000	6000-8000	4000-6000	4000>
		Rating	0	1	2	3	4
2	Det	Value	0-44	44-250	250-400	400-531	>531
		Rating	0	1	2	3	4
3	EM (Kg)	Value	0-80	80-170	170-380	380-500	500<
		Rating	0	1	2	3	4
4	N	Value	0-100	100-200	200-330	330-400	400<
		Rating	0	1	2	3	4
5	H (m)	Value	>12	10-12	8-10	6-8	6>
		Rating	0	1	2	3	4
6	D (mm)	Value	>170	150-170	120-150	100-120	100>
		Rating	0	1	2	3	4
7	B (m)	Value	>3.1	2.7-3.1	2.5-2.7	1.8-2.5	1.8>
		Rating	0	1	2	3	4
8	S (m)	Value	>3.8	3.1-3.8	2.7-3.1	2.2-2.7	2.2>
		Rating	0	1	2	3	4
9	T (m)	Value	>3.1	2.5-3.1	2-2.5	1-2	1>
		Rating	0	1	2	3	4
10	J (m)	Value	>1.1	0.6-1.1	0.5-0.6	0.4-0.5	0.4>
		Rating	0	1	2	3	4
11	γ_r (ton/m³)	Value	0-2.5	2.5-2.63	2.63-2.65	2.65-2.7	>2.7
		Rating	0	1	2	3	4
12	HA (Mhos)	Value	0-2.5	2.5-3	3-3.2	3.2-3.5	>3.5
		Rating	0	1	2	3	4
13	σ_c (Kg/cm³)	Value	0-531	531-539	539-621	621-671	>671
		Rating	0	1	2	3	4

3.4. Risk analysis and Performance evaluation of blasting cost

For risk analysis and performance evaluation of blasting costs, 146 data points were utilized in this study. Among these, 117 data points were used to calculate the VI and establish a relationship using the RES-based technique, while the remaining 29 data points were employed to evaluate the established relationship. Table 10 illustrates an example computation of the VI for dataset number 1. Figure 7 displays the variations of the VI for the 117 data points, indicating an average VI of 43.83, which suggests the presence of medium-high risk in the second risk group.

Table 10. The values, ratings and vulnerability indices for dataset number 1.

Parameters	Value or description	Value rating (Q_i)	Weighting (% a_i)	VI
AN (Kg)	5500	4	11.4286	23.8571
Det	270	2	5.71429	
EM (Kg)	260	2	2.57143	
N	270	2	1.71429	
H (m)	6.3	3	2.85714	
D (mm)	76	4	6.57143	
B (m)	1.8	3	10	
S (m)	2.1	4	5.71429	
T (m)	0.9	4	6.28571	
J (m)	0.5	2	15.4286	
γ_r (ton/m^3)	2.7	3	15.7143	
HA (Mhos)	3.5	3	7.42857	
σ_c (Kg/cm^3)	671	3	8.57143	

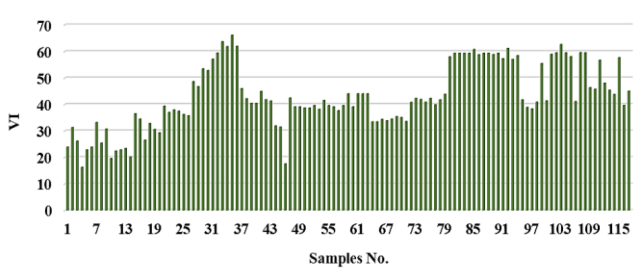

Figure 7. The VI for the sample of data points.

To predict the BC using the RES-based method with high accuracy (R^2= 0.8953) was performed, as depicted in Figure 8. The developed equation (Eq. 3) can be used as the basis for predicting the BC in the training stage.

$$BC = 0.9276VI^2 - 390.48VI + 28748 \quad (3)$$

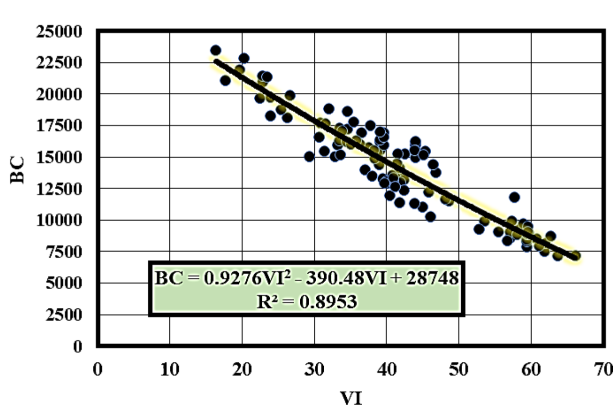

Figure 8. BC–VI prediction model.

4. Results and evaluation of model performance

To assess the performance of the built model, 29 data points were used for both verification and evaluation. Table 11 presents a comparison between the predicted and actual values of blasting costs.

Table 11. The comparison of the values obtained from the built and measured model of the BC.

NO.	VI	Measured BC	Predicted BC (RES Model)
1	25.213	18948	19492.47535
2	25.639	19165	19346.17872
3	22.514	21131	20426.84402
4	36.506	15804	15729.44124
5	32.884	14828	16910.68011
6	29.545	16557	18020.82438
7	35.298	16514	16120.48305
8	66.548	7233	6870.261103
9	60.44	10466	8535.810771
10	62.5	8271	7966.4375

The accuracy of the built model was evaluated using three statistical indices: MSE, RMSE, and R^2. The lower the MSE and RMSE values, and the closer the R^2 value to 1, the higher the accuracy of the model. Equations (4), (5), and (6) define these evaluation criteria.

$$\text{MSE}=\frac{1}{n}\sum_{k=1}^{n}(t_k-\hat{t}_k)^2 \quad (4)$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{k=1}^{n}(t_k-\hat{t}_k)^2} \quad (5)$$

$$R^2=1-\frac{\sum_{k=1}^{n}(t_k-\hat{t}_k)^2}{\sum_{k=1}^{n}t_k^2-\frac{\sum_{i=1}^{n}t^2}{n}} \quad (6)$$

In the above equations, '*n*' represents the number of samples, t_k represents the actual amount, and $A = \hat{t}_k$ represents the predicted value for the kth observation. The statistical indices MSE, RMSE, and R^2 for the built model were calculated as 0.00608, 0.078, and 0.9518, respectively, based on the evaluation criteria. These results indicate high accuracy of the model, with the error being close to zero and the accuracy close to one. Therefore, the developed model using the RES-based method can accurately predict the BC in different projects. Figure 9 illustrates the accuracy of the predicted values (RES) compared to the actual values using the R^2 statistical index.

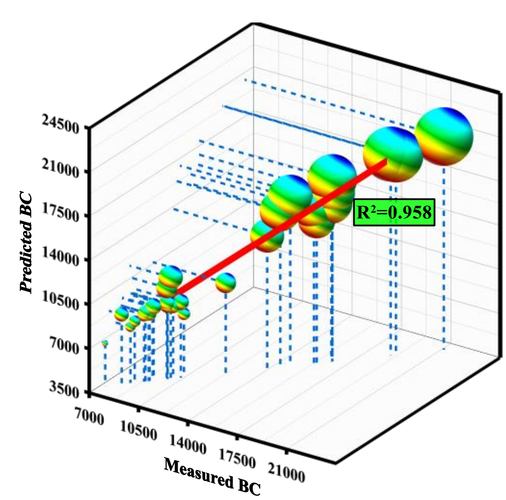

Figure 9. The accuracy of the prediction model BC using R2.

To further understand this, Figure 10 presents a comparison between the values obtained using the RES-based method and the actual values. If the graph of the predicted values deviates significantly from the actual values, the model cannot be used effectively for prediction. However, in this case, the predicted values closely align with the actual values, as the graphs overlap each other. This demonstrates the high accuracy of the model. Considering the incorporation of uncertainty in the developed model, the relationship established using the RES method can be applied to predict the BC in other mining projects as well (case studies).

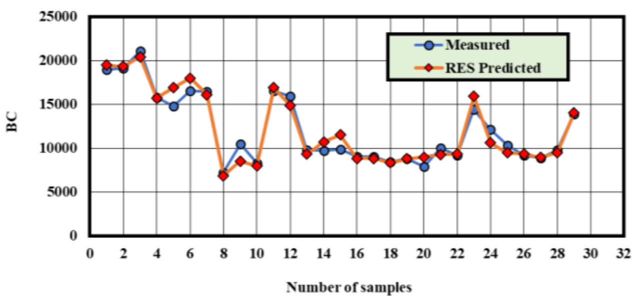

Figure 10. The comparison of Predicted and Measured BC for the RES-based Model.

5. Discussion

The process of mining involves various steps, including drilling, blasting, loading, transportation, and mineral processing. Among these steps, blasting is particularly sensitive as it can significantly impact mining costs. Improper blasting techniques can result in additional drilling, increased consumption of explosives, and environmental damage. Therefore, optimizing BC is crucial for the economic viability of mining operations. In this study, the researchers focused on predicting BC in limestone mines using the RES-based method. The RES-based method takes into account the uncertainties and complexities associated with rock parameters, providing a more accurate estimation of blasting costs. By establishing a relationship between design, geotechnical parameters, and blasting costs, the RES-based method offers a valuable tool for mining engineers and rock mechanics specialists. The blasting cost model was built using data collected from six limestone mines in Iran, resulting in a total of 146 data points. A wide range of input parameters was considered, including D, B, EM, N, H, S, T, J, HA, AN, Det, σ_c. and γ_r. The dataset was divided into two parts: 80% of the data (117 data points) were used to construct the RES-based model, while the remaining 20% (29 data points) were used for model evaluation and validation.

The performance of the RES-based model was assessed using statistical indices, including MSE, RMSE, and R^2. The results demonstrated that the RES-based method achieved high accuracy in predicting blasting costs, with MSE = 0.00608, RMSE = 0.078, and R^2= 0.9518. These findings indicate the potential of the RES-based method to overcome the limitations of traditional approaches and improve blast cost estimation accuracy. The implications of this study are significant for professionals working in mining and geotechnical operations. The accurate prediction of BC can lead to improvements in design, extraction, and production processes, resulting in cost and time savings for mining operations. Additionally, it can help mitigate environmental issues associated with inefficient blasting practices and enhance overall productivity. The RES-based method offers valuable insights and aids decision-making processes, enabling engineers to make informed judgments regarding BC in all mining projects. By considering uncertainties, avoiding simplifications, and incorporating critical elements, the RES approach provides a powerful tool for addressing rock behavior problems in mining and geotechnical operations.

6. Conclusions

The RES-based method presented in this study offers an effective solution for predicting BC in mining applications. Its accuracy, ability to overcome challenges, and potential to enhance productivity and efficiency in mining and geotechnical operations make it a valuable tool for the fields of mining engineering and rock mechanics. By employing the RES approach, mining professionals can optimize blasting cost estimation and make informed decisions to improve mining economics.

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