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ENHANCED FRAGMENTATION ANALYSIS USING THE ROCK ENGINEERING SYSTEM APPROACH AND KUZ RAM MODEL FOR OPTIMIZING ROCK BLASTING

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ABSTRACT

Rock fragmentation is a key factor in blasting operations, as it significantly affects drilling and blasting costs, and the performance of downstream processes including loading, transportation, and crushing. Observations conducted at limestone quarry on the PT DAP jobsite indicated that the percentage of boulders produced ranged from 15.02% to 63.44%, with an average of 27.2%. Such variability in fragmentation size can hinder excavation efficiency and potentially disrupt production targets. Therefore, accurate prediction of rock fragmentation is crucial for optimizing blasting outcomes. This study evaluates the effectiveness of the Rock Engineering System (RES) model, which integrates 10 interacting parameters, in predicting blast-induced rock fragmentation. Twenty production blasting events were analyzed using field data, laboratory tests, and Split-Desktop software. The RES predictions were then statistically compared with actual field results and those obtained from the conventional Kuz-Ram model. The analysis revealed that the RES model achieved a coefficient of determination (R^2) of 0.94, indicating a strong correlation between predicted and actual fragmentation sizes. Additionally, the model demonstrated a Root Mean Square Error (RMSE) of 8.46, suggesting a low margin of prediction error. These results confirm that the RES model provides more accurate and reliable fragmentation predictions compared to the Kuz-Ram method. In conclusion, the RES model offers a more effective tool for predicting rock fragmentation in blasting operations, supporting improved planning and control of mining activities to enhance overall production efficiency.

1. Introduction

Effective rock fragmentation is critical to mining efficiency because it influences loading, hauling, and crushing performance, and optimal size distribution minimizes secondary

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breakage and improves productivity [12], [30]. Conversely, poor fragmentation—oversize or excessive fines—disrupts loading and elevates crushing energy and costs [30]. Loading and crushing performance are highly sensitive to fragment size; oversize can bypass or overload crushers, while too many fines reduce throughput [17], [29]. This underscores the need for accurate predictive models [15].

Traditional empirical models such as Kuz–Ram work well under certain conditions but often degrade under complex rock mass conditions or non-standard geometries [8], [20]. Kuz–Ram frequently overestimates fragment size because it under-represents rock mass heterogeneity (jointing, bedding, discontinuities) [1], [24], [26]. Recent advances improve precision using machine learning, image analysis, and statistical optimization to capture interactions between geology and blast design [4], [16].

A systems alternative is the Rock Engineering System (RES) by Hudson and Harrison (2000) [31], which integrates multiple interactive variables in a matrix to evaluate cause–effect relations. Studies report superior accuracy of RES-derived or RES-enhanced models, with lower errors and better alignment to observed results [28], [31]. Hybrid techniques combining RES principles with metaheuristics or neural networks further capture dynamic fragmentation behavior [5], [18]. Specific blast variables—e.g., initiation timing and borehole orientation relative to joint sets—materially influence outcomes [23], [6].

Inaccurate prediction increases oversize (costly secondary breakage, delays, equipment wear) [2], [19] and excessive fines (reduced crushing efficiency, energy waste) [32]. Hence, models must be tailored to site conditions and operational needs [12], [30], aligned with monitoring and drill/blast data streams [7], [9]. The RES addresses this by simulating wide-ranging parameter interactions; case studies show RES succeeding where empirical models underperform, clarifying the influence of burden, stemming, and hole diameter on fragmentation [3], [14]. Building on this, we apply RES to 20 production blasts at a limestone quarry, considering 10 key parameters, and evaluate accuracy via R2 and RMSE. We compare RES against measured outcomes and Kuz–Ram to highlight advantages and limitations.

2. Materials and Methods

In this study, ten key parameters (P1–P10) were carefully selected for integration into the RES model based on their recognized influence on blast fragmentation and their operational relevance at the quarry site. The selected parameters and their specific definitions are presented clearly in **Table 1** (Rock Engineering System Parameters), offering a structured overview that facilitates understanding and highlights their individual contributions to fragmentation outcomes.

Table 1 : Rock Engineering System Parameters

Effective Parameters in Fragmentation			
P1	Burden	P9	Blasthole inclination
P2	Maximum Instantaneous charge	P10	Blasthole deviation

P3	Powder Factor	P11	Hole diameter
P4	S/B ratio	P12	J/B ratio
P5	ST/B ratio	P13	Blast hole pattern
P6	Stiffness ratio	P14	Initiation sequence
P7	Number of rows	P15	Blastability index
P8	Time delay	P16	B/D ratio

The dataset used to calibrate and evaluate the RES model comprised data from twenty blasting events conducted at the limestone quarry site. On-site measurements and fragmentation analysis using Split-Desktop software provided critical insights into each blast. Moreover, essential rock mass properties—including uniaxial compressive strength (UCS), tensile strength, and geological discontinuities—were determined through laboratory experiments and detailed field surveys, as documented by [21] and [22]. This comprehensive and systematic data collection ensured that the RES model was calibrated and validated using robust and representative information, thereby enhancing the reliability and predictive accuracy of the study outcomes.

A critical component of the RES methodology involves constructing an interaction matrix to systematically capture and quantify the influences between all pairs of parameters. In this research, a 10×10 interaction matrix was developed, with each parameter (P1–P10) listed along both rows and columns. Every off-diagonal cell within this matrix was assigned numerical values ranging from 0 to 4, signifying the qualitative strength of the influence that one parameter has on another—where 0 indicates no interaction and 4 represents a very strong interaction. **Figure 1** (Matrix Interaction Box) visually illustrates the matrix structure, clarifying the relationships between parameters.

The numerical values in the matrix were determined using the Expert Semi-Quantitative (ESQ) approach, translating expert judgments systematically into quantifiable interactions. The sum of these values in each row and column enabled the calculation of "cause" and "effect" scores for each parameter. This facilitated the identification of parameters with the greatest influence on the overall system, highlighting interactions critical to predicting blast fragmentation outcomes accurately.

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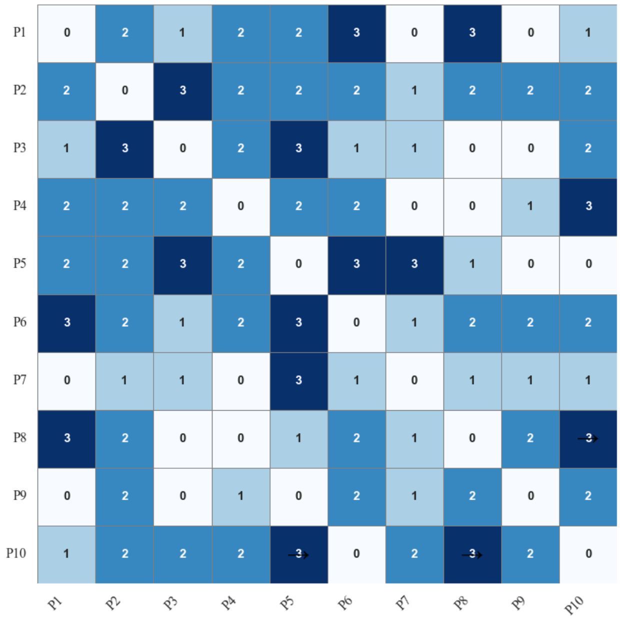

Figure 1. Matrix Interaction Box

3. Results and Discussion

Fragmentation analysis using the Split-Desktop software indicated a substantial occurrence of oversized fragments in the blasts. Out of the 20 blasting events analyzed, 14 produced boulders in quantities exceeding 20% of the total material, which is higher than the target allowance for oversized rock. This outcome underscores the impact of geometric inconsistencies; when burden and spacing diverge from the plan, they can cause uneven distribution of explosive energy and thus suboptimal breakage. As illustrated by the data summarized in **Figure 2**, the proportion of boulder-sized fragments across 20 blasting sessions ranged from as low as about 2.8% to as high as roughly 49%. This wide range aligns with the observations of Saka et al. (2024), who reported that even modest irregularities in burden or spacing can greatly influence energy distribution during a blast, leading either to over-fragmentation (excessive fines) or to insufficient breakage (too many boulders).

In addition to fragment size distribution, blast performance was evaluated using the X_{80} metric, which is the fragment size at which 80% of the blasted material is smaller (and 20% is larger). Figure 3 shows the X_{80} results for the blasts, revealing that in 16 out of 20 events, the X_{80} exceeded the target value of 80 cm. In the most extreme case, X_{80} reached approximately 120.3 cm. Such elevated X_{80} values clearly indicate that fragmentation was coarser than desired. In practical terms, this means that loading operations would be hindered, and the crushing circuit would face oversized material, necessitating additional secondary breakage. These findings are consistent with prior studies by [14] and [25], which noted that when fragmentation is suboptimal (with X_{80} larger than planned), mine operations suffer reduced efficiency due to the extra handling and breaking of large rocks.

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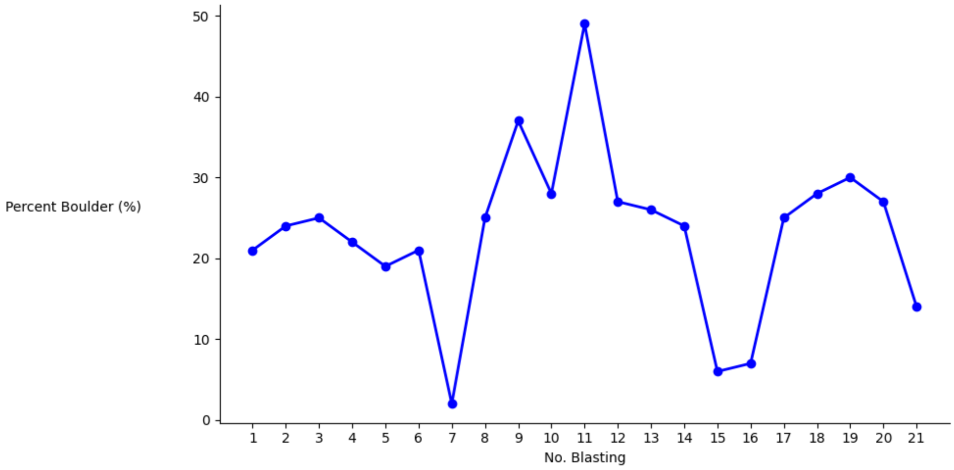

Figure 2. The Proportion of Boulder size fragments

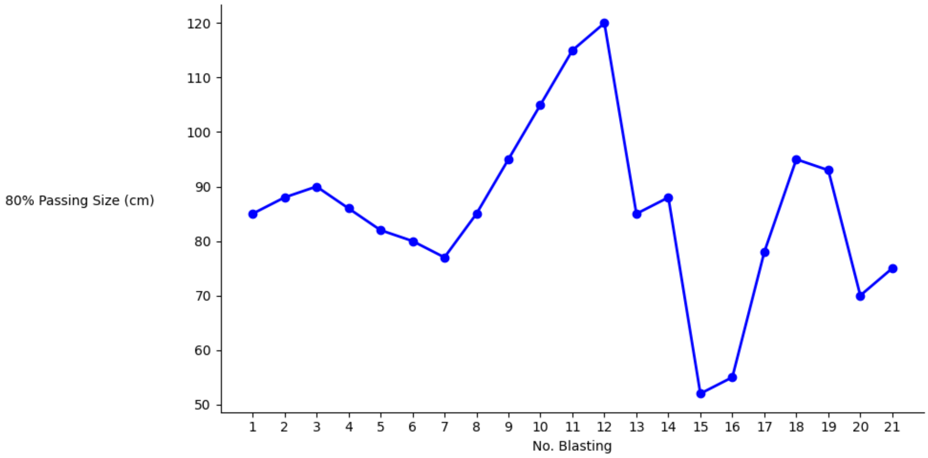

Figure 3. The Measure X_{80} boulder size

The Kuz-Ram model was used to predict fragmentation outcomes for the same series of blasts, and its predictions were then compared to the actual measured results. Across the board, the Kuz-Ram model overestimated the size of fragments produced. In other words, the predicted X_{80} values from Kuz-Ram were consistently higher than the X_{80} values determined from field measurements**. Table 2** summarizes this comparison, showing that for each blast event the model's forecast of X_{80} exceeded the observed value. This systematic over-prediction undermines confidence in the model's reliability for this site. A visual comparison in **Figure 4** of predicted vs. actual X_{80} further highlights the discrepancy: the data points deviate substantially from the ideal 1:1 agreement line, indicating that Kuz-Ram not only overestimates absolute fragment sizes but also fails to capture the true variability of fragmentation outcomes.

Table 2 : Summarize X80 Measurement and Kuz-Ram

No	X80 Measured(cm)	X80 Kuz-Ram (cm)	No	X80 Measure (cm)	X80 Kuz-Ram (cm)
1	82,7	88,19	11	90,64	101,11

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2	79,32	86,35	12	120,35	109,26
3	86,69	88,77	13	84,71	92,84
4	85,05	104,90	14	84,79	96,24
5	76,38	91,86	15	83,09	89,96
6	83,89	84,11	16	53,12	81,24
7	86,02	150,64	17	53,06	84,58
8	62,64	100,15	18	81,58	88,19
9	83,27	94,12	19	92,27	109,62
10	99,83	106,87	20	70,15	98,43

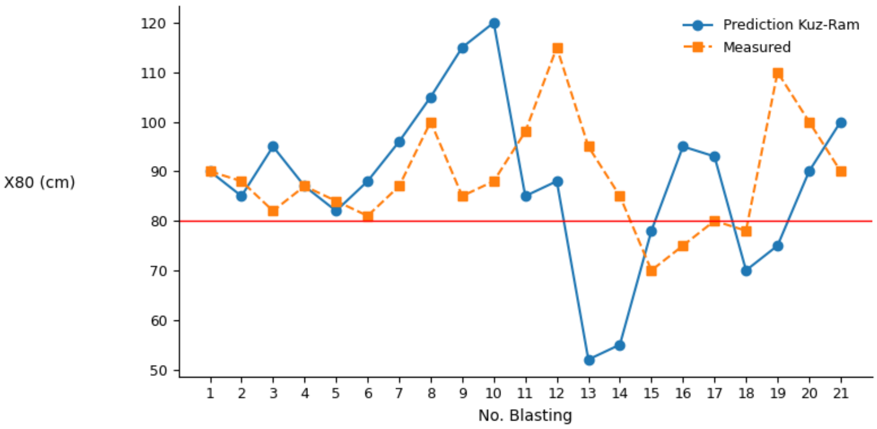

Figure 4. The Measured and predicted X80, Kuz-Ram based model.

Statistical analysis reinforces these observations. The coefficient of determination between the Kuz-Ram predictions and the actual X_{80} measurements was calculated to be $R^2 = 0.3146$ (as shown in **Figure 5**), suggesting a very weak correlation. Additionally, the Root Mean Square Error (RMSE) of the Kuz-Ram predictions was 22.22 (see **Table 3**), which is a large error relative to the target fragment size. An R^2 so low, coupled with such a high RMSE, quantitatively confirms that the Kuz-Ram model's performance in this context is poor.

Table 3 : RMSE Measured X80 and Kuz-Ram

No	X80 Measured (y)	X80 Kuz-Ram (y")	(y-y")	$(y-y")^2$
1	82,7	88,19	-5,49	30,14
2	79,32	86,35	-7,03	49,45
3	86,69	88,77	-2,08	4,34
4	85,05	104,90	-19,85	393,95
5	76,38	91,86	-15,48	239,76
6	83,89	84,11	-0,22	0,05
7	86,02	150,64	-64,62	4175,35

8	62,64	100,15	-37,51	1407,06
9	83,27	94,12	-10,85	117,70
10	99,83	106,87	-7,04	49,61
11	90,64	101,11	-10,47	109,54
12	120,35	109,26	11,09	122,94
13	84,71	92,84	-8,13	66,09
14	84,79	96,24	-11,45	131,08
15	83,09	89,96	-6,87	47,23
16	53,12	81,24	-28,12	790,73
17	53,06	84,58	-31,52	993,62
18	81,58	88,19	-6,61	43,69
19	92,27	109,62	-17,35	301,12
20	70,15	98,43	-28,28	799,99
Total				9873,43

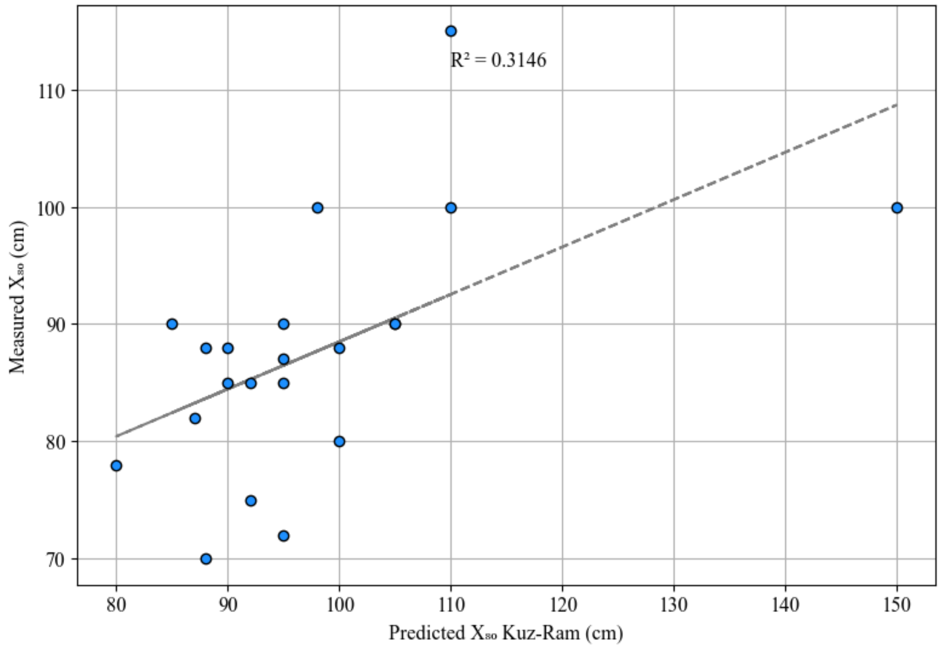

Figure 5. The Measured and predicted X80, Kuz-Ram based Model

These statistical outcomes reflect the limitations of the Kuz-Ram model when applied under heterogeneous conditions. A weak correlation and large prediction errors are expected if the model does not account for critical factors influencing fragmentation. This finding is in line with previous research indicating that Kuz-Ram's empirical formula can struggle in complex geological settings, as noted by [13], [15], and [17]. While the Kuz-Ram model remains popular for its simplicity and ease of use, its one-size-fits-all nature often means it cannot accommodate the variability found in real-world blasts. As a result, its accuracy may vary significantly depending on the context. For example, [27] and [3] have observed that Kuz-Ram tends to perform reasonably well in more homogeneous environments but becomes much less reliable at sites where rock properties or blast designs deviate from the norms on which the model was originally based.

In contrast to the Kuz-Ram results, the Rock Engineering System model demonstrated significantly better predictive performance for the quarry blasts. When we compared the RES-predicted X_{80} values to the actual measured values, we found a much stronger alignment. The statistical evaluation showed an R^2 of 0.9409, indicating a strong positive correlation between the RES predictions and the real outcomes. The RMSE for the RES model was 8.46, which is substantially lower than that of Kuz-Ram. These results imply that not only do RES predictions follow the general trend of the observed data, but the magnitude of errors is also much smaller. Indeed, as illustrated by **Figure 6** and **Figure 7**, the RES model's predicted fragmentation closely tracked the actual fragmentation measurements across the blasts, with the data points clustering nearer to the ideal agreement line.

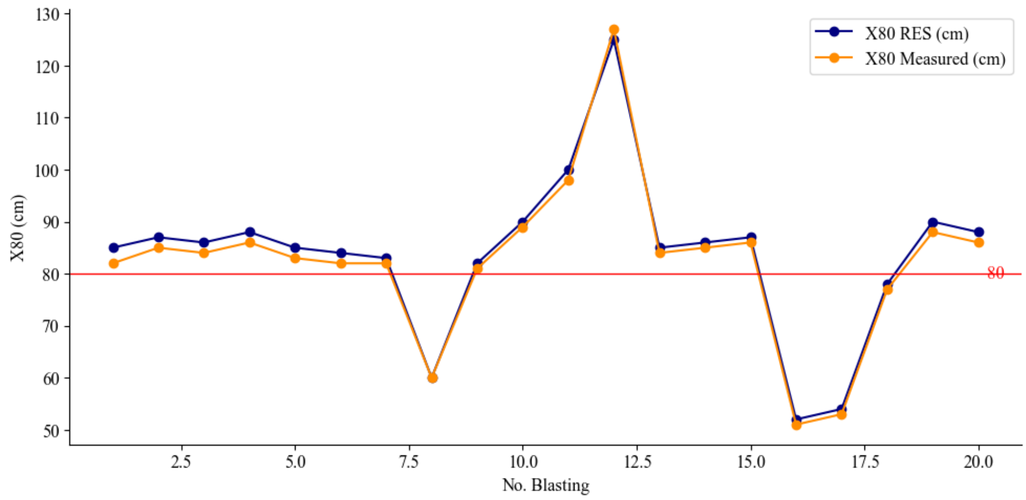

Figure 6.The Measured and X80 RES Prediction boulder size.

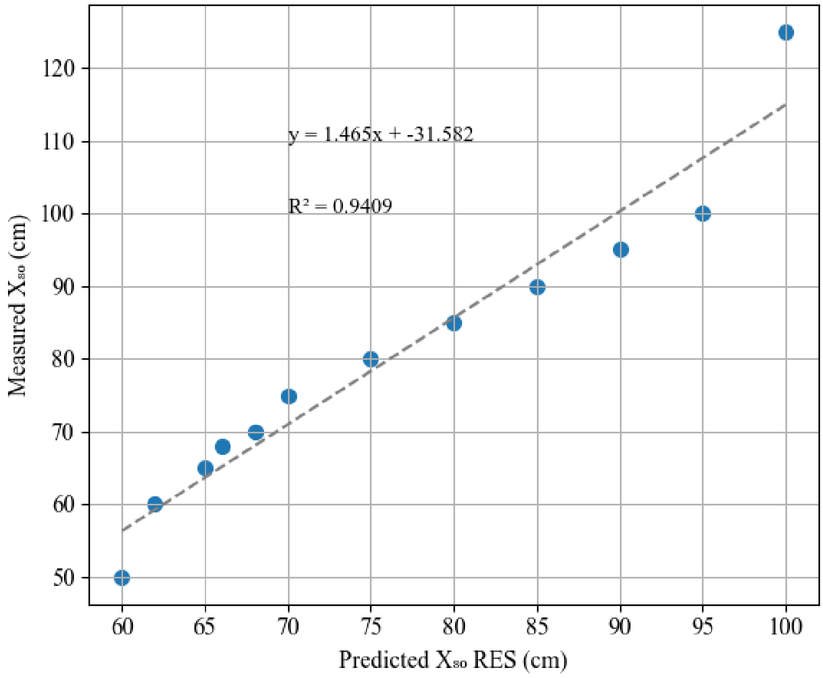

Figure 7. The Measured and Predicted X80, RES based model

The superior performance of the RES model can be attributed to its ability to incorporate a broad array of interactive factors into its predictions. Unlike the Kuz-Ram model, which uses a fixed empirical formula, the RES approach considers the combined influence of geotechnical conditions, blast design parameters, and operational factors. This holistic, systems-based perspective allows RES to capture the interdependencies that characterize real blasting processes ([15]; [29]). For example, RES can simultaneously account for how changing the spacing might alter the effect of rock joint spacing on fragmentation, or how delay timing interacts with the stiffness of the rock mass. By adapting to the specific context of each blast, the RES framework proves more flexible and context-sensitive. The markedly higher R^2 and lower error we obtained with RES in this study exemplify how an integrated model can better accommodate the nuances of a particular site, whereas an empirical model like Kuz-Ram might overlook those critical nuances.

The findings of this study reinforce the advantages of adopting the RES model. By simulating 20 blasting events and analyzing 10 influential parameters, the RES model was found to produce predictions that aligned more closely with actual field results. This was evidenced by a coefficient of determination (R2) of 0.94 and a Root Mean Square Error (RMSE) of 8.46, significantly outperforming the Kuz-Ram model, which exhibited an R2 of 0.314 and RMSE of 22.22. These results demonstrate that the RES model offers superior accuracy in predicting the X80 fragmentation size and provides a more reliable foundation for operational decision-making.

These findings also suggest that the RES model minimizes the inefficiencies typically associated with poor fragmentation outcomes. For example, oversized boulders necessitate secondary breakage, prolonging cycle times and increasing wear on loading equipment. Excessively fine fragments, on the other hand, reduce the efficiency of crushing and screening processes, increase energy consumption, and potentially lower ore recovery rates, as noted by [30] and [32]. By improving prediction accuracy, the RES model supports the optimization of blasting strategies, which in turn enhances productivity and reduces operational costs [3].

An additional strength of the RES model is its ability to provide insight into the causal relationships among parameters, thus improving engineers' understanding of how different variables interact during the blasting process. Variables such as burden, stemming ratio, powder factor, and initiation sequence all contribute differently to fragmentation outcomes, depending on the geological and structural characteristics of the rock mass. The causal matrix approach used in RES enables systematic evaluation of these interactions, ensuring that the most influential parameters are identified and prioritized [14].

However, the adoption of the RES model is not without limitations. One key challenge is its dependency on high-quality input data. Inaccurate or incomplete geological and operational data can lead to erroneous predictions, thereby reducing the model's reliability [3]. To mitigate this issue, comprehensive geological surveys and standardized data collection protocols should be implemented as a prerequisite to RES model application.

Another concern is the computational complexity of the model. The incorporation of numerous interactive parameters, while enhancing predictive accuracy, also increases the computational burden. This complexity may hinder real-time decision-making unless supported by advanced computing infrastructure or streamlined optimization algorithms [11]. To address this, the development of user-friendly software interfaces and the integration of machine learning techniques may help simplify the modeling process and reduce computational demand.

Additionally, parameter sensitivity presents a methodological challenge. Not all blasting environments respond similarly to changes in the same parameter. Therefore, site-specific sensitivity analysis is essential to identify which variables exert the greatest influence on fragmentation outcomes. Such an approach enables mining engineers to focus on accurately measuring and calibrating those key variables, thereby maximizing the model's utility [10].

Another practical challenge involves integrating the RES model with other digital tools used in mine planning and operations management. Differences in data formats, modeling assumptions, and user interfaces can impede seamless integration. To overcome this, the development of standardized data exchange protocols and modular software architecture is necessary. The use of the RES model also facilitates improvements in operational planning and strategic decision-making. By providing accurate predictions of fragmentation size, mining operations can design blasts that yield fragment distributions optimized for specific equipment and processing requirements. This directly reduces the need for reblasting and minimizes delays in loading and hauling [22]. Furthermore, better control over fragmentation size allows for the selection of appropriate crusher settings and screen configurations, thereby improving plant throughput and energy efficiency.

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A visual summary of the comparative predictive performance is presented in **Figure 8**, which displays the measured and predicted X80 values for both the Kuz-Ram and RES models. The graphical representation further confirms that the RES model exhibits closer alignment with actual field data, whereas the Kuz-Ram model consistently overpredicts fragmentation size. Supporting this observation, Table 4 summarizes the statistical outcomes, with the RES model achieving an R^2 of 0.66 and RMSE of 8.46, compared to the Kuz-Ram model's R^2 of 0.16 and RMSE of 22.22. These metrics underscore the superiority of RES in delivering accurate, reliable fragmentation predictions under complex geological conditions. Additionally, Figure 8 further illustrates the trend of measured versus predicted X80 values across both models, reinforcing the graphical evidence of the RES model's better alignment with actual outcomes. **Table 4** complements this analysis by presenting another layer of statistical comparison that reaffirms the higher predictive fidelity of the RES model in diverse blasting scenarios.

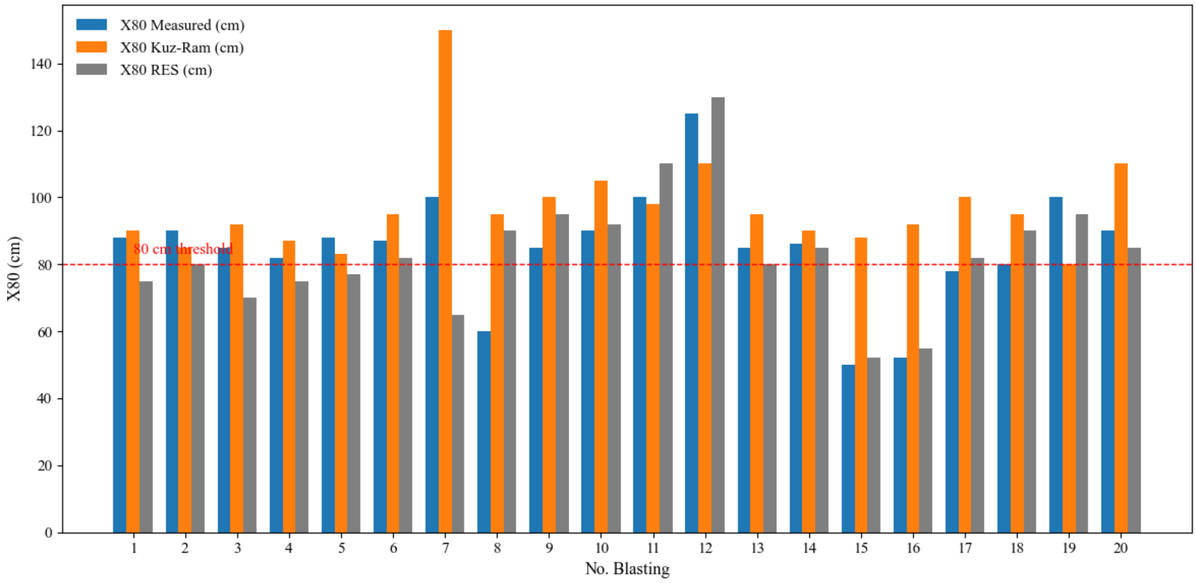

Figure 8. A Comparison between the measured and predicted X80 for Kuz-Ram and RES

Tabel 4 : Results of Statistical Analysis

Parameter	Kuz-Ram	RES
R^2	0,314	0,94
RMSE	22,22	8,46

4. Conclusions

In conclusion, this study systematically evaluated the effectiveness of the Rock Engineering System (RES) model against the conventional Kuz-Ram model for predicting blast fragmentation. The RES model demonstrated superior performance, achieving a coefficient of determination (R^2) of 0.94 and a Root Mean Square Error (RMSE) of 8.46. This significantly outperformed the Kuz-Ram model, which yielded an R^2 of 0.314 and an RMSE of 22.22, highlighting the RES model's enhanced accuracy in predicting X80 fragmentation size. These findings underscore the practical and theoretical advantages of the RES model, offering more reliable decision support over traditional approaches.

The primary contribution of this study lies in validating the RES model's capability to more accurately predict rock fragmentation by integrating a comprehensive set of interacting parameters, thereby accounting for geological and operational complexities that the Kuz-Ram model often overlooks. By minimizing inefficiencies associated with poor fragmentation, such as the need for secondary breakage and reduced crushing efficiency, the RES model supports optimized blasting strategies, leading to enhanced productivity and reduced operational costs.

However, the effectiveness of the RES model is contingent upon the availability of high-quality input data, adequate computational resources, and effective integration protocols. Future studies could explore the integration of machine learning techniques to further streamline the modeling process and reduce computational demand. Additionally, developing more user-friendly software interfaces and conducting site-specific sensitivity analyses to identify key influential variables could enhance the practical application of the RES model. As mining operations continue to prioritize efficiency, safety, and sustainability, the adoption of advanced modeling frameworks such as RES will become increasingly central to achieving these goals.

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Authors Contribution

Dedi Yulhendra (Conceptualization; Methodology; Data curation; Formal analysis; Writing – original draft; Visualization)

Mohd Hazizan Mohd Hashim (Supervision; Validation; Writing – review & editing)

Arya Alvito (Critically revised manuscript draft for intelectual content and oversaw the final approval for submission)

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