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Comparative accuracy of Richard-Moore and Ghasemi models for Flyrock prediction in limestone blasting safety assessment

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ABSTRACT

This study aimed to compare the predictive accuracy of the Richard-Moore and Ghasemi models for limestone blasting and assess the adequacy of a 300 m equipment safety radius. Thirty blasting events at Bukit Karang Putih, PT Semen Padang, were evaluated using field-measured flyrock distances verified through GPS and ArcGIS. Model performance was assessed using RMSE and MAPE. The maximum observed flyrock distance was 210.74 m. The Ghasemi model achieved the lowest errors (RMSE 13.31 m; MAPE 6.81%), followed by Richard-Moore Face Burst (15.01 m; 8.03%). All observed and predicted distances remained below 300 m. The Ghasemi model provided more accurate site-specific predictions, while the existing safety radius accommodated the investigated events; however, broader validation across geological and operational conditions is required before wider application in mining contexts elsewhere.

Introduction

Blasting is a fundamental operation in open-pit mining because it facilitates rock fragmentation and directly influences the efficiency of subsequent loading, hauling, and processing activities. Despite these operational benefits, blasting can generate hazardous effects such as ground vibration, airblast, backbreak, overbreak, and flyrock. Among these effects, flyrock is particularly critical because fragmented rocks projected beyond the intended blasting zone can threaten personnel, damage equipment, and disrupt mining operations (Bhandari, 2021; International Society of Explosives Engineers [ISEE], 2020). This risk is particularly relevant in limestone mining, where variations in rock-mass structure and blasting configuration can produce substantial differences in fragmentation and rock displacement. Reliable prediction of flyrock distance is therefore essential for blast-design optimization, risk assessment, and the determination of appropriate operational safety boundaries (Monjezi et al., 2021; Jamei et al., 2021).

Flyrock generation is governed by interactions among blast geometry, explosive-energy distribution, and rock-mass characteristics. Parameters such as burden, spacing, stemming, blast-hole diameter, charge length, and powder factor can influence the confinement and release of explosive energy, while discontinuities, weathering, and rock strength may modify the direction and magnitude of rock displacement (Hasanipanah et al., 2022; Monjezi et al., 2021). Consequently, identical or similar blasting configurations may not necessarily generate comparable flyrock distances across different geological environments. This site dependency limits the direct transferability of empirical prediction models developed under specific mining conditions and highlights the importance of validating their predictions against actual field measurements before operational implementation (Jamei et al., 2021; Handayana et al., 2023).

Several empirical approaches have been proposed to estimate flyrock distance. The Richard and Moore model distinguishes flyrock according to face burst, cratering, and rifling mechanisms, reflecting different pathways through which explosive energy can eject rock fragments (Richard & Moore, 2005). In contrast, the Ebrahim Ghasemi model employs dimensional analysis to integrate relevant blasting parameters within a unified empirical prediction framework (Ghasemi et al., 2012). These differences in model formulation may lead to different predictive responses when applied to the same blasting conditions. More recently, artificial intelligence and machine-learning techniques have demonstrated considerable potential for modelling complex nonlinear relationships associated with flyrock generation (Hasanipanah et al., 2022; Koopialipoor et al., 2023). However, empirical models remain operationally relevant because of their simpler formulation, lower data requirements, and easier implementation in routine blasting practice (Handayana et al., 2023; Monjezi et al., 2021).

Previous investigations have emphasized that empirical flyrock models require field-based validation because prediction accuracy can vary considerably across mining environments (Jamei et al., 2021; Hasanipanah et al., 2022). Statistical error measures have consequently been employed to quantify agreement between predicted and observed flyrock distances, while comparative applications of the Richard and Moore and Ghasemi models have demonstrated that model performance is sensitive to site-specific blasting conditions (Handayana et al., 2023; Permatasari et al., 2024). Nevertheless, the existing evidence remains insufficient in two important respects. First, comparative validation of these empirical models under limestone-specific geological and operational conditions remains limited relative to broader surface-mining applications. Second, prediction accuracy has generally been treated as the primary endpoint, whereas its practical relationship with an established operational safety radius has received less attention (Permatasari et al., 2024). This creates a need for site-specific evaluation that integrates statistical prediction performance with its practical implications for blast-safety management.

This issue is relevant at Bukit Karang Putih, PT Semen Padang, where routine limestone blasting is conducted under an established 300 m equipment safety radius. Evaluating this boundary requires more than determining whether an empirical model produces relatively small prediction errors; it also requires examining whether observed and predicted flyrock distances remain within the operational safety limit under the investigated blasting conditions. Accordingly, the novelty of this study lies in integrating comparative validation of the Richard and Moore and Ebrahim Ghasemi models with a site-specific assessment of an existing equipment safety radius. This integrated approach connects statistical model performance with operational blast-safety requirements while recognizing that empirical model reliability remains dependent on local geological and blasting characteristics (Jamei et al., 2021; Hasanipanah et al., 2022).

Accordingly, this study aimed to compare the predictive accuracy of the Richard and Moore and Ebrahim Ghasemi models for flyrock generated by limestone blasting at Bukit Karang Putih, PT Semen Padang, and to assess the adequacy of the existing 300 m equipment safety radius under the investigated conditions. Model performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), allowing prediction errors to be examined in both absolute and relative terms. The analysis also considered the relationships between relevant blasting-geometry parameters and observed flyrock distances to support interpretation of site-specific flyrock behavior. Based on differences in model formulation, the study hypothesized that the two empirical approaches would exhibit different predictive performance when evaluated under equivalent field conditions (Jamei et al., 2021; Handayana et al., 2023; Permatasari et al., 2024).

Method

This study employed a quantitative case-study design to comparatively validate the Richard-Moore and Ebrahim Ghasemi empirical models under equivalent limestone-blasting conditions. The study was conducted at Bukit Karang Putih, PT Semen Padang, West Sumatra, Indonesia, during January–March 2026. Thirty blasting events were purposively selected because complete blasting-geometry records and measurable flyrock landing positions were available, with each event treated as one observational unit. The recorded parameters included burden, spacing, stemming, blast-hole depth, blast-hole diameter, charge length, burden face, and powder factor. Actual flyrock distance was defined as the horizontal distance from the blast location to the farthest identifiable flyrock landing position for each event. Blast coordinates and flyrock landing positions were recorded using the same GPS-based procedure and subsequently verified in ArcGIS. Identical measurement procedures were maintained across all events to ensure consistency and comparability of the field observations.

For each blasting event, the recorded parameters were entered into the corresponding empirical equations. The Richard-Moore approach was evaluated separately through its Face Burst, Cratering, and Rifling mechanisms, whereas the Ebrahim Ghasemi model generated flyrock predictions from its dimensional-analysis formulation. Each predicted distance was paired with the corresponding actual field measurement, ensuring that all prediction approaches were evaluated using identical observations. Predictive accuracy was quantified using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), where lower values indicated closer agreement between predicted and observed distances. RMSE represented prediction errors in distance units, whereas MAPE quantified relative prediction errors as percentages. Because the three Richard-Moore mechanisms represent distinct flyrock-generation processes, their prediction errors were reported separately rather than combined into a single Richard-Moore value. This procedure enabled direct comparison of prediction performance while preserving the mechanistic distinction among the empirical formulations.

Correlation analysis was performed to examine the associations between individual blasting parameters and actual flyrock distance. Correlation coefficients were interpreted as measures of association rather than causal effects, and statistical significance was assessed at $p < 0.05$. Model performance was primarily evaluated from RMSE and MAPE rather than statistical ranking alone. Operational safety was subsequently assessed by comparing the maximum observed and predicted flyrock distances with the existing 300 m equipment safety radius. The radius was considered to accommodate the investigated blasting events when all observed and predicted distances remained within this boundary; however, this criterion was interpreted as site- and period-specific evidence rather than proof of universal safety. The analysis was therefore restricted to the 30 blasting events observed during the study period and did not extrapolate model performance or safety-radius adequacy beyond the investigated geological and operational conditions.

Figure. 1. Maps IUP PT Semen Padang

Results and Discussions

The analysis of 30 limestone blasting events at Bukit Karang Putih, PT Semen Padang, demonstrated substantial variation in blasting geometry and flyrock response. The investigated blasting parameters included burden, spacing, stemming, blast-hole diameter, charge length, and powder factor. Burden ranged from 2.67 to 4.20 m with an average of 3.42 m, while spacing ranged from 2.68 to 5.20 m with an average of 4.01 m. Stemming ranged from 1.70 to 4.30 m with an average of 3.47 m, and the blast-hole diameter was relatively consistent, with an average of 0.1253 m. Charge length ranged from 2.50 to 7.27 m, while powder factor ranged from 0.18 to 0.49 kg/m³. These variations indicate that blasting design was adjusted to the operational and rock conditions encountered during individual blasting events.

Table 1. Descriptive statistics of blasting geometry parameters

Variabel	Satuan	Min	Maks	Rata-rata
Burden Awal	m	1	2,9	1,79
Burden	m	2,67	4,20	3,42
Spacing	m	2,68	5,20	4,01
Stemming	m	1,70	4,30	3,47
Diameter	m	0,1016	0,1270	0,1253
Charge Length	m	2,50	7,27	5,43
Powder Factor	kg/m³	0,18	0,49	0,30

The measured flyrock distances also varied considerably among the blasting events. The maximum actual flyrock distance was 210.74 m, while the average distance was approximately 92 m. The observed variation confirms that flyrock response differed among blasting events despite the generally comparable blasting configuration. This variation is important for model validation because prediction performance needs to be evaluated against the actual field response rather than inferred only from nominal blast-design parameters.

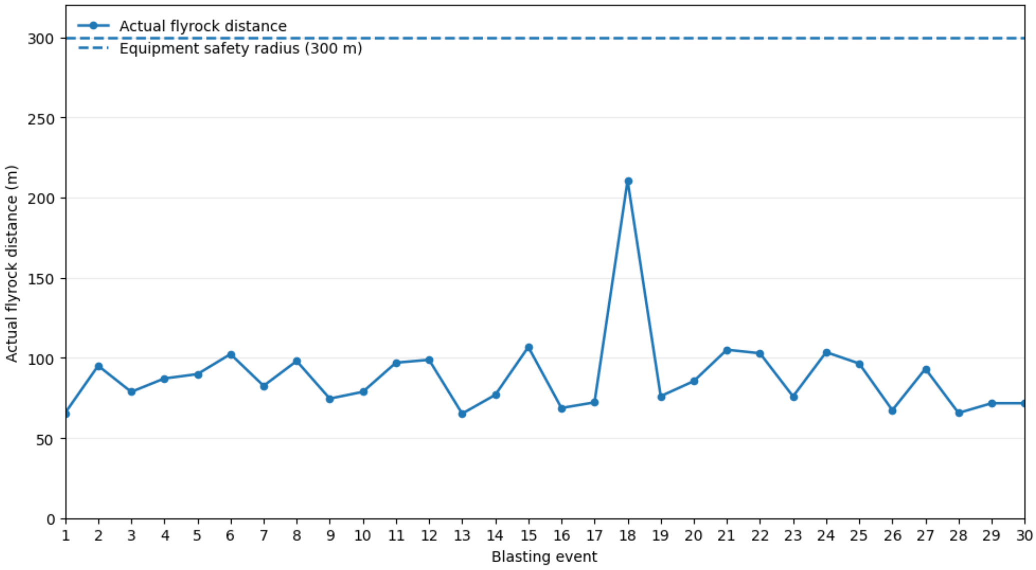

Figure 2. Distribution of Actual Flyrock Distance

The prediction results showed that both the Richard and Moore and Ebrahim Ghasemi models followed the general variation of the actual flyrock measurements, but their prediction errors differed. The Ebrahim Ghasemi model generally produced predictions closer to the observed field values, whereas the Richard and Moore model, particularly its cratering and rifling mechanisms, produced greater deviations. This difference is likely related to the formulation of the two models: Richard and Moore separates flyrock into specific mechanisms, while the Ghasemi model incorporates blasting parameters through a dimensional-analysis framework (Richard & Moore, 2005; Ghasemi et al., 2012). The result suggests that the model structure used by Ghasemi was more representative of the blasting conditions observed at the study site.

The quantitative accuracy assessment confirmed this difference. The Ebrahim Ghasemi model produced the lowest RMSE of 13.31 m and MAPE of 6.81%. The Richard and Moore Face Burst model produced an RMSE of 15.01 m and MAPE of 8.03%, whereas its Cratering and Rifling mechanisms resulted in substantially larger errors, with RMSE values of 41.17 and 68.69 m and MAPE values of 45.60% and 67.65%, respectively. Thus, the Ebrahim Ghasemi model provided the best overall agreement with the measured flyrock distances for the investigated limestone blasting conditions. The finding supports the importance of validating empirical models using actual field data before selecting a model for operational application (Jamei et al., 2021).

The lower error values of the Ebrahim Ghasemi model indicate better predictive performance under the observed conditions, but the difference between the two principal models should not be interpreted as evidence that one model is universally superior. Model performance is site-dependent and can be affected by geological conditions, blast geometry, and rock-mass characteristics. Previous studies have similarly emphasized that empirical flyrock models require local validation because the relationships between blast parameters and flyrock are not necessarily consistent across different mining environments (Hasanipanah et al., 2022; Monjezi et al., 2021).

Table 2. Accuracy assessment of flyrock prediction models

Metode	RMSE (m)	MAPE (%)	Ranking
Richard (Face Burst)	15,01	8,03	2
Richard (Cratering)	41,17	45,60	3
Richard (Rifling)	68,69	67,65	4
Ebrahim Ghasemi	13,31	6,81	1

The correlation analysis provided additional insight into which blasting parameters were most strongly associated with the observed flyrock distances. Burden Face showed the strongest relationship, with a correlation coefficient of 0.8427, indicating a very strong relationship in the investigated dataset. In contrast, burden, spacing, stemming, blast-hole depth, blast-hole diameter, powder column, and powder factor showed very low correlation coefficients, ranging from 0.0581 to 0.1940. This result indicates that the influence of blasting geometry on flyrock was not uniform and that Burden Face was the most prominent parameter in the present dataset.

Table 3. Correlation between blasting geometry parameters and actual flyrock distance

Blasting parameter	Correlation coefficient (r)	Relationship
Burden	0.0581	Very low
Spacing	0.1571	Very low
Stemming	0.0760	Very low
Blast-hole depth	0.0740	Very low
Blast-hole diameter	0.0797	Very low
Powder column	0.0730	Very low
Burden Face	0.8427	Very strong
Powder factor	0.1940	Very low

The strong relationship observed for Burden Face is consistent with the physical interpretation of face-burst flyrock. Burden determines the distance between the blast hole and the free face, and insufficient effective burden can facilitate excessive movement of broken material toward the free face. Stemming also contributes to gas confinement, while charge length and powder factor influence explosive-energy distribution. However, the very low correlations obtained for most other parameters indicate that their effects were not independently dominant within the range of conditions represented by the 30 blasting events. Therefore, the observed flyrock behavior should be understood as a combined response of blast geometry and site-specific rock conditions rather than as the effect of a single parameter. This interpretation is consistent with previous work emphasizing the complex relationship between blast design and flyrock generation (Ghasemi et al., 2012; Monjezi et al., 2021).

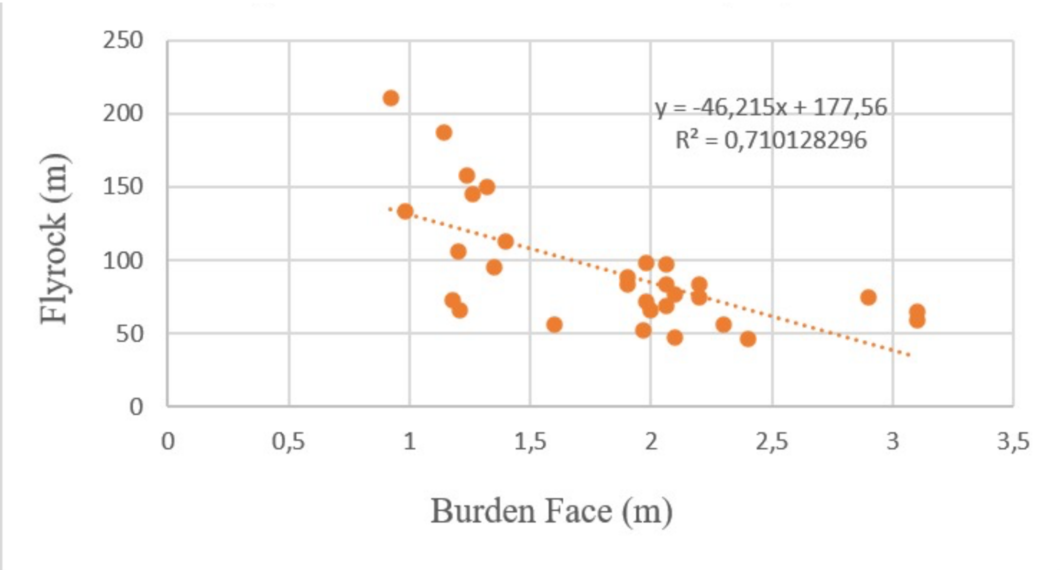

Figure 3. Relationship between Burden Face and Actual Flyrock Distance

The safety assessment demonstrated that all measured and predicted flyrock distances remained below the 300 m equipment safety radius established by PT Semen Padang. The maximum actual flyrock distance of 210.74 m therefore remained 89.26 m inside the prescribed safety boundary. The predicted results also remained below the same boundary. These findings indicate that the 300 m equipment safety radius was adequate for the blasting conditions represented by the 30 events analyzed during January–March 2026.

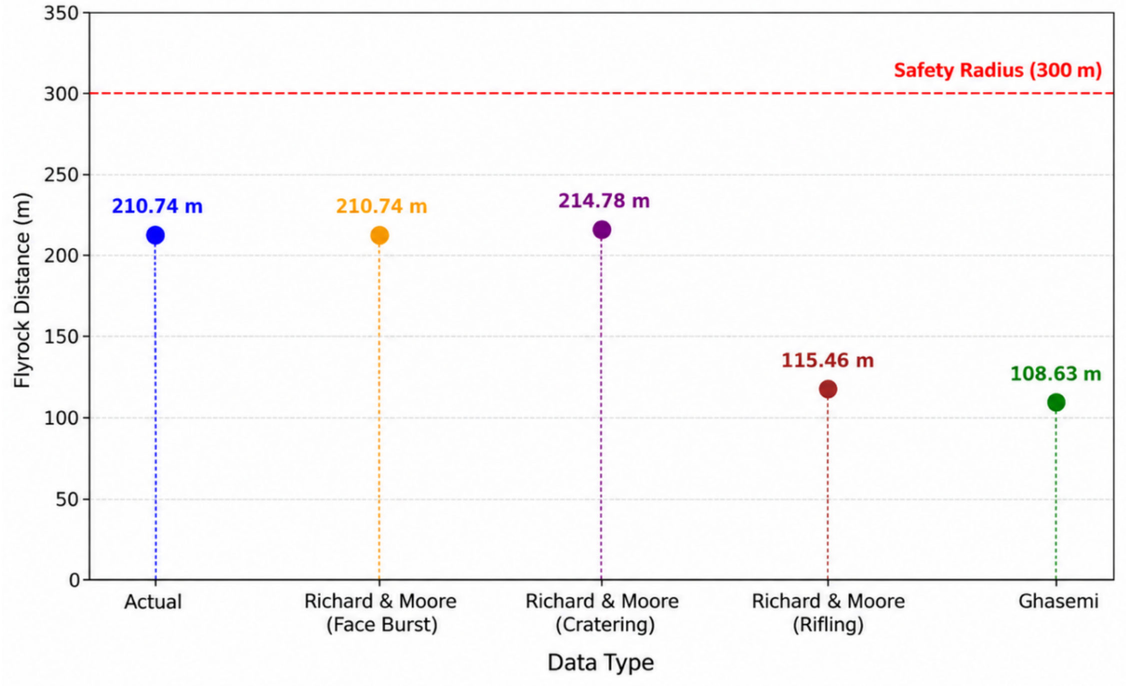

Figure 4. Safety Radius Assessment

From an operational perspective, the results indicate that model accuracy and safety-radius evaluation should be considered together. The Ebrahim Ghasemi model provided the lowest prediction error and therefore offers a more suitable predictive basis for evaluating blast conditions at the study site. Nevertheless, the adequacy of the 300 m safety radius cannot be interpreted solely from the accuracy of one predictive model. The radius assessment should continue to incorporate actual field observations, changes in blast geometry, and geological conditions in subsequent blasting operations. This is particularly important because geological discontinuities, weathering, and rock-mass heterogeneity may alter flyrock behavior even when nominal blast-design parameters remain similar.

The integrated findings answer the main research question by showing that the two empirical models did not provide identical predictive performance under the investigated limestone-blasting conditions. The Ebrahim Ghasemi model was the most accurate according to RMSE and MAPE, while Burden Face showed the strongest relationship with actual flyrock distance. Together, these results indicate that model selection should consider both statistical performance and the physical characteristics of the blasting environment (Babaeian et al., 2023; Bhatawdekar et al., 2021). The findings support previous evidence that local validation is necessary when applying empirical flyrock models in operational mining environments (Jamei et al., 2021; Hasanipanah et al., 2022).

Several limitations should be considered when interpreting these findings. The analysis was based on only 30 blasting events at a single limestone mining site over a three-month period. Consequently, the observed model performance cannot be assumed to represent other geological settings, rock-mass conditions, blast designs, or longer operational periods. In addition, the analysis focused on the available blasting-geometry variables and did not fully quantify other factors such as detailed discontinuity orientation, rock-mass strength, fragmentation characteristics, weather conditions, or spatial variations in geology. Future studies should therefore use larger datasets collected over longer periods, incorporate more detailed geological and geotechnical variables, and compare additional empirical and machine-learning models. Such studies could further determine whether the superior performance of the Ebrahim Ghasemi model remains consistent under different blasting conditions.

Overall, the results demonstrate that the Ebrahim Ghasemi model provided the strongest predictive performance for flyrock under the limestone-blasting conditions investigated at Bukit Karang Putih, while the 300 m equipment safety radius remained adequate for the observed events. The study advances operational flyrock assessment by linking statistical model evaluation, the dominant blasting parameter, and the practical safety boundary within a single site-specific analysis (Carpenter, 2025; Huang & Xue, 2022; Rouhani et al., 2026; Stojadinović et al., 2021).

The comparative evaluation demonstrates that empirical flyrock models respond differently even when they are applied to the same blasting events and field conditions. The Ebrahim Ghasemi model achieved the lowest prediction errors, with an RMSE of 13.31 m and MAPE of 6.81%, compared with 15.01 m and 8.03% for the Richard-Moore Face Burst mechanism. The substantially higher errors produced by the Cratering and Rifling mechanisms further indicate that the predictive suitability of an empirical formulation depends on whether its underlying mechanism adequately represents the dominant flyrock behavior at a particular site. The relatively low errors of the Ghasemi model suggest that its dimensional formulation captured the combined effects of the investigated blasting parameters more effectively under the limestone-blasting conditions of Bukit Karang Putih. This finding reinforces previous evidence that empirical flyrock models should be locally validated rather than transferred directly between mining environments without performance assessment (Pyra & Żołądek, 2025; Raina, 2023; Taiwo et al., 2023; Zangoei et al., 2022).

The differences among the Richard-Moore mechanisms provide an important physical interpretation of model performance. Face Burst produced considerably lower errors than Cratering and Rifling, suggesting that the conditions represented by the sampled blasts were more consistent with rock displacement toward the free face than with excessive vertical ejection or stemming-related projection. This interpretation is also compatible with the strong association observed between Burden Face and actual flyrock distance. Effective burden controls the resistance available to confine explosive energy toward the free face; consequently, variations in this parameter may substantially alter the trajectory and travel distance of fragmented rock. Nevertheless, the present results do not establish Burden Face as an independent causal determinant because flyrock generation results from interactions among blast geometry, explosive-energy distribution, and heterogeneous rock-mass conditions. The mechanism-specific performance of Richard-Moore should therefore be interpreted in conjunction with field characteristics rather than solely from statistical error values (Balakrishnan & Rai, 2021; Bhatawdekar et al., 2022; Wang et al., 2023; Zhang et al., 2025).

The correlation analysis further illustrates the complexity of flyrock generation. Burden Face exhibited a strong positive relationship with actual flyrock distance ($r = 0.8427$), whereas burden, spacing, stemming, blast-hole depth, blast-hole diameter, powder column, and powder factor showed comparatively weak individual relationships. These findings should not be interpreted as evidence that the latter variables are operationally unimportant. Their restricted ranges within the observed blasting designs, interactions with other parameters, and potential dependence on geological conditions may reduce their apparent bivariate relationships with flyrock distance. Flyrock is inherently a multivariable phenomenon in which individual blast-design parameters may exert nonlinear or interactive effects that cannot be adequately represented by simple correlation analysis. This complexity also explains the growing application of machine-learning approaches capable of modelling nonlinear interactions, although their advantages depend on sufficient data quantity, representativeness, and validation quality (Armaghani et al., 2020; Bhatawdekar et al., 2023; Ding et al., 2023; Sevelka, 2023).

From an operational perspective, the maximum observed flyrock distance of 210.74 m remained below the existing 300 m equipment safety radius, leaving a difference of 89.26 m between the maximum observation and the prescribed boundary. All model predictions also remained within this radius during the investigated period. These findings provide empirical support that the existing boundary accommodated the flyrock distances represented by the 30 observed blasting events. However, this result should not be interpreted as evidence that 300 m constitutes an universally adequate safety distance because extreme flyrock events may arise from geological discontinuities, abnormal confinement, deviations in blast execution, or combinations of conditions not represented in the present dataset. Consequently, prediction models should complement rather than replace field monitoring and blast-specific risk assessment. Operational safety decisions should continue to account for changes in blast geometry and rock-mass conditions, particularly when future blasts differ substantially from those used for model validation (Chen et al., 2024; Ding et al., 2025; Nayak et al., 2022; Yari et al., 2023).

The principal contribution of this study is therefore not merely the identification of the model with the lowest prediction error, but the integration of model validation, blasting-parameter relationships, and an operational safety boundary within a limestone-mining context. The findings indicate that the Ghasemi model can provide a useful site-specific predictive tool for the investigated conditions, while the performance differences among the Richard-Moore mechanisms demonstrate the importance of considering the physical mechanism represented by an empirical equation. Nevertheless, the evidence is based on 30 blasting events collected at a single site over a three-month period, limiting the statistical and geological domain within which the findings can be interpreted. Future validation should incorporate larger temporal datasets, detailed rock-mass and discontinuity characteristics, weather conditions, explosive properties, and independent validation samples. Comparisons with machine-learning approaches may subsequently determine whether more complex predictive methods provide meaningful improvements over locally validated empirical models for operational flyrock-risk management (Bhagat et al., 2021; Davarzani et al., 2022; Hasanipanah & Bakhshandeh Amnieh, 2020; Padmavathi et al., 2025).

Conclusions

The findings demonstrate that flyrock prediction performance is strongly influenced by the compatibility between an empirical model and the geological and blasting conditions of the site. Under the limestone-blasting conditions at Bukit Karang Putih, the Ebrahim Ghasemi model provided the most representative prediction performance, while Burden Face emerged as the most prominent blasting-geometry factor associated with actual flyrock behavior. The results also indicate that the existing equipment safety radius was adequate for the blasting conditions represented in the study period. The importance of this study lies in linking predictive-model evaluation with practical blast-safety management, rather than considering model accuracy independently from operational requirements. These findings support the use of site-validated predictive models as part of evidence-based blasting decisions and provide a practical basis for improving flyrock risk assessment at the study site. However, the conclusions are specific to the geological, operational, and blasting conditions represented by the available dataset and should not be generalized without further validation. Future research should incorporate larger datasets, longer observation periods, and additional geological and geotechnical variables to determine the robustness of the model performance under varying blasting conditions.

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