Prediction of fly-rock during boulder blasting on infrastructure slopes using CART technique

Narayan Kumar Bhagat, Aditya Rana, Arvind K. Mishra, Madan M. Singh, Atul Singh and Pradeep K. Singh

CSIR – Central Institute of Mining and Fuel Research, Dhanbad, Jharkhand, India; Indian Institute of Technology (Indian School of Mines), Dhanbad, Jharkhand, India

ABSTRACT
Boulder blasting is a different process from conventional bench blasting. Fly-rock produced in boulder blasting is a major safety concern due to the presence of 360° free-face which may result into excessive throw of the fragments radially up to 900 m distance causing accidents. Many researchers have attempted to predict the fly-rock using empirical and soft computing tools in bench blasting. But, there is paucity of literature to predict the extent of fly-rock in boulder blasting. Machine learning techniques are frequently used in bench blasting to predict ground vibrations, air overpressure, fly-rocks, but it has been rarely used in boulder blasting. In this study, an attempt has been made to use Classification and Regression Trees (CART) technique to predict the fly-rock distance in boulder blasting. Multiple linear regression (MLR) technique has been used to compare the results obtained by the CART technique. Sixty-one boulder blasting events were monitored while excavating the accident-prone slope areas of Konkan Railways. The performance of the developed models using both the techniques has been evaluated using the coefficients of determination ($R^2$) and root-mean-square error (RMSE) values. The results indicate that CART model ($R^2 = 0.9555$ and RMSE = 1.141) provides better output than MLR model. This paper suggests the use of CART technique in boulder blasting, which will be useful in execution at sensitive locations to predict and control the fly-rock distance.

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CONTACT Narayan Kumar Bhagat  narayan_bhagat@yahoo.co.in

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1. Introduction

Wyllie (1991) reported that a cut-slope created 20–30 years back should be stabilized considering poor construction practices and continuous degradation due to weathering. Rockfall or landslide along railways or highways in the hilly terrain is a frequent phenomenon. In one of the scientific study, Mignelli et al. (2014) reported that the rock slopes situated aside many kilometres of roads are prone to rockfalls and need proper mitigation. Similar rockfall problems are also frequently observed along hundreds of kilometres of slopes aside railways and roadways in India which have caused several accidents and traffic delays (Mid Day News 2014; Ansari et al. 2015; Deccan Chronicle News 2019). Also, lots of rock excavations are in progress for upgrading infrastructures in the vicinity of existing railways and roadways. The rock excavation especially where isolated boulders are found in the slope mass need, safe removal considering the safety of railway tracks, overhead electric lines, signal posts, roadways and residential structures.

Available techniques such as mechanical breaking (rock-breaker, impact hammer, drop ball, high-pressure water-jet), chemical breaking and blasting with explosives (pop shooting, plaster shooting) are being used to fragment oversized boulders (Dick et al. 1983; Kristin and Maras 1994; Murray et al. 1994; Jimeno et al. 1995). In mechanical breaking technique, the transportation of rock-breaker in remote locations are not feasible. Further, it is also difficult to use machineries with limited manoeuvrable space thereby creating chances of dislodgement of the unstable slope. In chemical breaking technique, the use of chemicals for fragmentation of boulders in a large scale is very difficult. The untimely dislodgement of fragments towards the tracks, roads, etc. may also cause accidents. However, blasting with explosives to break the boulders is often used in hilly terrain where the use of other techniques are not feasible (Sawmliana et al. 2018; Deccan Chronicle News 2019; Bhagat et al. 2020b).

During the process of boulder breaking by explosives and blasting, the possibility of uncontrolled fly-rocks is very high due to the presence of multiple free faces. A layout of the bench and boulder blasting is illustrated in Figure 1. Factors affecting the generation of fly-rock in bench blasting are broadly categorized into controllable and uncontrollable groups (Bhandari, 1997; Bajpayee et al. 2004; Khandelwal and Monjezi 2013). In controllable group, some influencing parameters are borehole diameter and depth, sub-grade drilling, inclination of a borehole, burden, spacing, number of rows, explosive quantity per hole and per delay, liner charge concentration, deck-charging, specific charge, total charge, delay in between holes and explosive properties (strength, density, detonation velocity, wrapped or unwrapped form) (Bhandari, 1997; Khandelwal and Monjezi 2013; Trivedi et al. 2014; Armaghani et al. 2020). The uncontrollable parameters group consist of rock mass strength (compressive and tensile strength, density of rockmass) and geological properties (dip, strike, joint-spacing, soft layer in intermixed strata, rock quality designation, rock mass rating and weathering grade) (Fletcher and D’Andrea 1986; Bajpayee et al. 2004; Han et al. 2020). Parameters affecting the generation of fly-rock in boulder blasting are mainly controllable except the strength and density of rock mass.

The mechanics of fly-rock generation can be explained by mainly three theories (i.e. face burst, cratering and rifling) (Bhandari, 1997; Ghasemi et al. 2012;
Zhou et al. 2019). Inadequate burden and soft geological formation lead to face burst (Little and Blair 2010; Armaghani et al. 2016) whereas, low stemming to burden or hole diameter ratio and incompetent stemming material are responsible for cratering and rifling respectively (Lundborg et al. 1975; Hasanipanah et al. 2018). Further, cratering and rifling can generate fly-rock in any direction whereas, face burst can generate in free face direction only (Armaghani et al. 2016). In the case of boulder blasting, the direction of face burst is undefined due to uneven burden and multiple free faces.

Figure 1. Typical layout of bench blasting (a), and boulder blasting (b).
| Researchers                      | Input parameters used                                                                 | Empirical relation                                                                 | Limitations/FLY-rock range                                                                 |
|---------------------------------|----------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------|
| Lundborg et al. (1975)          | (Ø in inches), (FD in meters), Fragment size thrown (FT in meters)                     | \( FD = 260 \times \frac{\varnothing}{\varnothing^2} \) \( FT = 0.1 \times \varnothing^3 \) | For 34 mm Ø hole, BD-317 m and FT-0.135 m                                                |
| Lundborg (1981)                  | (Ø in inches), (SC in kg/m³)                                                            | \( FD = 143 \times \frac{\varnothing}{(SC - 0.2)} \)                              | For bench blasting. Usually, SC < 0.2 kg/m³                                                |
| Gupta et al. (1988)              | ST/B                                                                                    | \( FD = \left[ \frac{111.2}{1.3} \right]^\frac{1}{2} \)                            | For bench blasting only. Developed for large diameter holes (102 mm)                      |
| Richard and Moore (2005)         | \( k = \) rock constant and for hard rock it is 27,                                     | \( FD = k^2 \times \left[ \frac{\sqrt{m}}{ST} \right]^{2.6} \)                  | For ST/B ratio = 0.55, FD = 61 m                                                          |
| Richard and Moore (2005)         | \( g = \) gravitational constant (9.8 m/s²), m = Linear charge concentration (kg/m)   | \( FD = k^2 \times \left[ \frac{\sqrt{m}}{ST} \right]^{2.6} \)                  | For ST/B ratio = 1.88, FD = 26 m                                                          |
| Richard and Moore (2005)         | and B = Burden (m), ST = Stemming length (m), \( \theta = \) drillhole angle.           | \( FD = k^2 \times \left[ \frac{\sqrt{m}}{ST} \right]^{2.6} \times \sin 20\theta \) | For bench blasting only. Developed for large diameter holes (102 mm)                      |
| McKenzie (2009)                  | (Ø in mm), shape factor (Fs = 1.1 and 1.3) and confinement state,                       | \( FD = 11 \times SDBm^{-2.167} \times \left( \frac{\varnothing}{2} \right)^{0.667} \) | Mainly suitable for crater blasting                                                      |
| Ghasemi et al. (2012)            | B, S, ST, HD, Ø, SC and CPH                                                             | \( FD = 6946.547 \left[ B^{-0.796} S^{0.783} S^{1.994} T^{1.649} HD^{1.766} \frac{SC}{CPH}^{-1.465} \right] \) | For bench blasting only. For bench blasting using 115 and 165 mm Ø holes, FD was in between 20 and 56 m |
| Trivedi et al. (2014)             | CPH, HD, Linear charge concentration (q), SC, B, Unconfined compressive strength (\( \sigma_c \)), ST, RQD | \( FD = \frac{10^{6.1} \varnothing^{1.2} \sigma_c^{0.8} CPH^{0.8}}{B^{0.3} \varnothing^{0.2} SC^{0.8} \sigma_c^{0.8}} \), | For bench blasting using 115 and 165 mm Ø holes, FD was in between 20 and 56 m            |
| Hasanipanah et al. (2017)         | HD, S, B, ST, SC and MCPD                                                               | \( FD = (-90.62 \times HD) + (7.76 \times S) - (4.31 \times B) + (53.99 \times ST) + (0.62 \times SC) + (8.38 \times MCPD) + 5.23 \) | For bench blasting only. For bench blasting using 115 and 165 mm Ø holes, FD was in between 20 and 56 m |
Empirical formulae primarily developed for bench blasting to predict fly-rock distance are given in Table 1 and some of them may be implemented in boulder blasting as well. Lundborg (1981) developed a formula based on hole diameter and specific charge to predict fly-rock and throw (Table 1). This formula requires a specific charge of more than 0.2 kg/m³ for prediction, whereas in boulder blasting, the specific charge is normally lower than this threshold value. Formula developed by Gupta et al. (1988) uses stemming to burden ratio only (Table 1). Richard and Moore (2005) have also developed formulae for estimation of fly-rock due to the face burst, cratering and stemming ejection using 102 mm borehole diameter (Table 1). The aforesaid formulae use limited parameters and their predictions are also not so significant. Other formulae shown in Table 1 cannot be used in boulder blasting as they need at least one parameter which is not related to boulder blasting.

The review of blasting parameters influencing fly-rock generation reveals that the controllable parameters like sub-grade drilling, spacing, number of rows, delay between holes and row, maximum charge per delay and uncontrollable geological parameters do not play any major role in boulder blasting. Further, in many cases of boulder blasting, single or multiple holes blasting is conducted instantaneously. Hence, empirical formulae and soft computing tools developed for predicting fly-rock in bench blasting cannot be used directly in boulder blasting. Borehole diameter, density of rock, volume of the boulder, hole depth, burden, specific drilling density, number of holes, charge per hole, stemming length, total charge and specific charge are the major parameters which affect fly-rock generation in boulder blasting. It is also clear from the literature review that the large hole diameters are having higher probability of fly-rock to a greater distance (Mishra and Rout 2012; Mohamad et al. 2012; Koopialipoor et al. 2019). Due to the occurrence of frequent accidents in Indian mines, the Directorate General of Mine Safety (DGMS) have prohibited the use of large hole diameters in boulder blasting to prevent the chances of accidents (Kumar 2020). DGMS have recommended only 32 mm hole diameter with small quantity of explosive (DGMS (Tech) Circular No. 14 of 2020). The quantification of explosive for proper boulder breakage is a significant factor to avoid any fly-rock and hence; it needs careful attention while designing boulder blasting. Mishra and Rout (2012) reported an accident due to fly-rocks at 550 m distance while blasting a boulder having the dimension of 3 m × 1.5 m × 1.6 m. Two holes of 45 mm diameter and depths of 1.5 m each were drilled in the boulder and charged with 1.56 kg of explosive per hole. The specific charge used for breaking the boulder was 0.43 kg/m³. Various studies suggest that a specific charge of 0.08–0.15 kg/m³ is required for breaking the open lying boulders whereas for a partially buried boulder, 0.15–0.2 kg/m³ is optimum (Jimeno et al. 1995; Heinio 1999). Jimeno et al. (1995) also added that the specific charge of 0.2 kg/m³ or more will be required to get any throw during the bench blasting. Bhagat et al. (2020a) also reported that the specific charge values of 0.04–0.1 kg/m³ was sufficient to break the rock in small blast geometry without causing throw. The possibility and extent of fly-rock with these specific charges are not revealed in the above studies.

Many researchers have used different soft computing tools in their research work to predict the fly-rock distance in bench blasting. But, in case of boulder blasting, not
| Researchers          | Input parameters used                                                                 | Soft computing techniques with performance indices                                                                 | Limitations/ Fly-rock range                                                                 |
|----------------------|----------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------|
| Mohamad et al. (2012) | Ø, HD, B, ST, hole angle, charge length, CPH, SC                                       | ANN, No of dataset used= 16, $R^2 = 0.92$                                                                          | For 89 mm Ø holes in boulder blasting, FD range =160 to 240 m.                           |
| Monjezi et al. (2012) | HD, S, B, ST, SC, SD, Ø, MCPD, RMR                                                    | ANN-GA, No of dataset used = 195, $R^2 = 0.89$                                                                      | For bench blasting only                                                                  |
| Trivedi et al. (2014) | CPH, HD, Linear charge concentration ($q$), SC, B, Unconfined compressive strength ($\sigma_c$), ST, RQD | $FD = \frac{10^6 \times q \times S \times \sigma_c^{0.14}}{\gamma \times \rho D^2}$. No of dataset = 125, MVRA ($R^2$)=0.815, RMSE-3.1, ANN ($R^2$) = 0.983, RMSE-0.99 | For bench blasting using 115 and 165 mm Ø holes, FD was in between 20 and 56 m          |
| Armaghani et al. (2016) | HD, S, B, ST, SC, MCPD, Ø, N, D, SD                                                   | ANN-PSO, No of dataset used= 44, $R^2 = 0.94$                                                                        | For bench blasting only                                                                  |
| Armaghani et al. (2016) | MCPD, SC                                                                              | ANN, ANFIS, No of dataset used = 232, ANN ($R^2$) = 0.92 ANFIS ($R^2$) = 0.98                                      | For bench blasting only                                                                  |
| Armaghani et al. (2016) | HD, S, B, ST, SC, MCPD and RMR                                                       | MLR, Monte Carlo Simulation                                                                                       | For bench blasting only                                                                  |
| Hasanipanah et al. (2017) | HD, S, B, ST, SC and MCPD                                                            | $FD = (-90.62 \times HD) - (7.76 \times S) - (4.31 \times B) + (53.99 \times ST) + (0.62 \times SC) + (8.38 \times MCPD) + 5.23$ | No of dataset = 65, MLR ($R^2$)=0.855, RMSE-23.25                                             |
| Zhou et al. 2019      |                                                                                       | ANN model with architecture of 6 9 14 9 1                                                                           | For bench blasting only                                                                  |
| Koopialipoor et al. 2019 | Ø, HD, B/S ratio, ST, SC, MCPD,                                                       | No of dataset = 262, ICA-ANN ($R^2$)=0.958, RMSE-0.045, GA-ANN ($R^2$) = 0.959, RMSE-0.044, PSO-ANN ($R^2$) = 0.932, RMSE-0.058 | For bench blasting                                                                       |
| Lu et al. (2020)      | B, S, ST, SC, D                                                                       | ANN, ELM, ORELM, No. of datasets: 82, ANN ($R^2$) = 0.912, ELM ($R^2$) = 0.955, ORELM ($R^2$) = 0.958            | For bench blasting only                                                                  |
| Armaghani et al. (2020) |                                                                                       | SVR-GWO                                                                                                            | For bench blasting only                                                                  |
| Li et al. 2021        |                                                                                       | Combination of Fuzzy Delphi Method and ANN-based Models                                                             | For bench blasting only                                                                  |
much studies have been conducted by the researchers throughout the globe. However, Mohamad et al. (2012) have conducted a study of sixteen boulder blasting in mines using soft computing tool. They developed an ANN model using eight input parameters (specific charge, charge length, stemming, hole diameter, hole depth, burden, hole angle and explosive per hole) and found that specific charge, charge length, stemming are the most significant and relevant parameters. The coefficient of correlation in ANN method was 0.92. In the study diameter of drill holes were 89 mm whereas the distance of predicted fly-rock ranged between 160 and 240 m. A brief summary with selected input parameters, soft computing tools and limitations have been presented in Table 2 which reveals that there is no readily available tool that can limit the extent of fly-rock within 20 m in bench or boulder blasting. Further, there is a lack of research works which have utilized the empirical models and soft-computing techniques for predicting the fly-rock during boulder blasting with higher level of accuracy.

Hasanipanah et al. (2017) presented prediction of fly-rock in bench blasting at Ulu Tiram quarry Malaysia using regression tree method and compared the results with multiple linear regression (MLR) (Table 2). They suggested that the regression tree is a simple method compared to a complicated technique like ANN in terms of classification, recognition, and estimation. They also displayed that regression tree can forecast better than ANN and conventional statistical methods. Rana et al. (2020) reported that the decision tree-based Classification and Regression Trees (CART) model can be effectively used to control blasting nuisance such as ground vibration. Further, Murlidhar et al. (2021) defined decision tree as a ‘white box’ technique that develop direct graphical structures to explain the relationship between variables more easily than other machine learning methods. They recommended the use of decision tree technique for the problems having numerous variables acting reciprocally and in a nonlinear manner. Further, MLR has also been used by many researchers for the prediction of blasting nuisances in rock blasting (Armaghani et al. 2016; Hudaverdi and Akyildiz 2019). Both the techniques are very powerful and have wide applicability with versatility.

In this paper, an attempt has been made to predict fly-rock distance in boulder blasting using the decision tree-based CART technique which is easy to implement in field by practicing engineers. The input parameters were varied in multiple steps to identify the most influencing parameters to predict the fly-rock distance using statistical tests and sensitivity analysis. Three models of MLR (consisting of three different sets of inputs) have been developed and their performance indicators have been compared with the corresponding three CART models. The performance indices of three CART models have been ranked and their sensitivity analysis has also been carried out to select the best CART model. Sixty-one experiments were carried out at infrastructure slope sites of the Konkan Railway Corporation (KRC) in India to develop the models. The outcome of this study has provided a handy and practical tool to predict the fly-rock distance in many similar cases of unstable slope conditions. The developed model can also be used to resolve similar problems of fly-rock at mining and civil construction sites as well as for delineating the safety distances while conducting boulder blasting.
2. Site descriptions

The 741 km long KRC route passing through the Western Ghats of India (from Roha near Mumbai, Maharashtra to Thokur, Karnataka) is divided into two sections (Ratnagiri and Karwar). The tracks of KRC were laid in between 1993 and 1997 by excavating the upland region of Deccan Volcanic Provinces, which is considered a vulnerable region for landslide and rockfall. There are 564 rock and soil-mixed boulder cuttings (cumulative length – 226.71 km) along the railway route. The dimension after excavating the rock mass of cuttings varies from 10 to 50 m in height, and 50–1000 m in length with slope angles varying between sub-verticals to verticats. The slope mass of cuttings mainly consists of Basalt, Breccia overlaid by lateritic soil or soil-mixed boulders in the Ratnagiri section. Two sets of vertical joints striking NW-SE, NE-SW and horizontal joints are commonly found. In addition to the above, random joints as well as natural and blast-induced fractures are also visible in most cuttings. A red bole soft layer (300–1000 mm thick) is sandwiched between two basaltic formations throughout the cuttings at Ratnagiri section, thereby allowing water percolation during the Indian monsoon. This soft layer is also known as a potential spot for slope failure or rockfall. Granite and Granitoide rocks are common in the Karwar section. Kinematic analysis of geological discontinuities of the slope under investigation before flattening revealed the higher probability of wedge, planar and toppling failures (Bhagat et al. 2020a). KRC observed more than 949 cases of rockfall and soil slippage including few train accidents between 1998 and 2011 (Garg et al. 2013). The heavy precipitation during southwest monsoon (more than 3000 mm annual precipitation), differential weathering due to soft and hard strata are some of the main cause for rockfall and slope failures.

Different sensitive structures (railway track, optical fibre cable, high tension transmission line and signal posts) were located within 2–5 m distance of slopes and in some cases, public residential structures were also located within 50 m distance.

3. Parameters influencing fly-rock and design of boulder blasting

Bhandari (1997) has explained the methodology of boulder blasting. He stated that the depth of hole to break the boulder should be in the range of 0.25–0.5 times the thickness of the boulder. He also suggested that hole should be stemmed properly and burden should not be too low in any direction otherwise results would be poor breakage. Further, in case of large sized boulders, spacing of holes should be 0.5–0.9 times the thickness of the boulder with drilling density in the range of 0.2–1.0 m/m³ and specific charge varying between 0.1 and 0.3 kg/m³. The detailed review of different parameters influencing boulder blasting clearly indicated that the geological aspects and blast design parameters for boulder blasting are completely different from bench blasting. In bench blasting, the geological parameters, delay between the holes, scattering in delays, undercut and misfire plays important role apart from the established blast design parameters. However, in boulder blasting, no delay is required between the holes. The geological parameters also do not play much role in boulder blasting except for the strength of rock and its density. The density of the rockmass plays a significant role in flying of fragments. The lighter fragments may travel a long
distance due to attainment of momentum during blasting operations (Lundborg 1981). Based on the review of research works (Table 1) and other available parameters on boulder blasting to predict the fly-rock distance, values of eleven pertinent parameters such as hole depth (HD in m), burden (B in m), specific drilling density (SD, in m/m³), number of holes (NH), charge per hole (CPH in kg), stemming (ST in m), stemming to burden ratio (ST/B), total charge (TC in kg), specific charge (SC, kg/m³), the volume of the boulder (V, m³) and density of rock (D in kg/m³) were recorded for 61 blasting events at KRC cutting sites. The variations in the diameter of boreholes were not considered due to the detrimental effects of large borehole diameter and were kept as 34 mm diameter during the trials.

4. Methodology used in data collection

Boreholes were drilled in the centre of boulders and depths of borehole were kept between 1/4 and 3/4 of the height of boulder. The directions of blast-holes were kept vertical for restricting the fly-rock and extent of throw. The emulsion cartridge explosives of 25 mm diameter were used to charge the 34 mm diameter boreholes. The velocity of detonation of explosive was 4000 ± 200 m/s and density was 1150 ± 50 kg/m³. Detonating cord (D-cord, 10 g/m of PETN) and electric detonators were used to initiate the explosives within borehole. Drill cuttings were used as stemming material. The different input parameters of boulder blasting were carefully recorded during the trial blasts. The estimation of boulder’s size was carried out using levelling staff and measuring tape. Fly-rock distances in vertical and horizontal directions were measured using a high-speed camera (250 frames per second). The recorded videos were further analyzed with Kinovea-0.8.15 software to estimate the distance of fragments thrown (fragment size > 5 cm) by pre-calibrating the boulder size in software (Figure 2). The fly-rock distances were also measured and verified manually using a
measuring tape. The extent of fragments thrown and cracks developed during the experiment are shown in Figure 3. Flow-chart elaborating the study and model development is depicted in Figure 4.

5. Statistical analysis of compiled dataset

Statistical analysis is a process to draw inferences from the collected data samples. Prior to application of any advanced method for data analysis, mainly two types of statistical analysis viz. descriptive and inference are carried out to understand the data, identify the trends, locate the anomalies and visualize the raw data. Descriptive statistics delivers a data summary in the form of minimum, maximum, mean,
median, mode, standard deviations and other information of a data sample. Hence, it enables us to present the data in a more logically with simplicity. Whereas, inferential statistics is carried out to study the data even further by making a hypothesis leading to rational decisions about the reality of the effects observed.

Ghasemi and Zahediasl (2012) reported that in general any advanced analysis methods like correlation, multiple regression, t-tests and analysis of variance (namely parametric tests) are carried out by considering, data following normal distribution. They further reported that if the sample size is greater than 30 or 40, the violation of normality assumption will not cause any major problem. With this assumption, we can use parametric procedures even if data are not normal. Moreover, for visual inspection of data distribution to judge the distribution readily, researchers are often using boxplot, frequency distribution, probability-probability plot and quantile-quantile plot to check the normality and locate outliers. To display boxplots of sixty-one dataset consisting of eleven input and one output parameters, XLSTAT (Version-
2021.2.1) software has been used (Figure 5). The boxplots revealed that some parameters are having outliers which are atypical events but they were used in the analysis. Further, the correlation matrix of all the 61 datasets has been established between the inputs and output (Table 3). The established correlation coefficients clearly indicates that there is negative correlation of fly-rock distance with rock density ($-0.41$) and burden ($-0.27$). However, the correlation is positive ($>0.27$) with specific charge, total charge, charge per hole, specific drilling density, number of holes and volume of rock. Rest other parameters such as hole depth, stemming to burden ratio and stemming length are having lower correlation coefficient values ($<\pm0.17$).

6. Prediction of fly-rock distance

Two types of predictive models, i.e. MLR and CART, have been developed to predict fly-rock distance. As discussed in the previous sections, eleven input parameters have been used to estimate the fly-rock distance. Forty-nine datasets (80% of total datasets) have been randomly selected to train the models whereas the remaining 12 datasets (20%) were selected to test the model’s performance and ability (Faradonbeh et al. 2016).

6.1. MLR

The MLR model has been widely used by many researchers in mining for predicting the blasting-induced nuisances (Tables 1 and 2). The dependent variable and one or more independent variables can be correlated using MLR. This technique is based on minimizing the end differences between predicted and measured output values. An MLR model, in terms of the independent variables, can be represented as:

$$Y = \{a_0 + a_1x_1 + \cdots + a_ix_i + e\}$$  \hspace{1cm} (1)

where ‘Y’ is the predicted variable, ‘$a_0$’ is intercept, ‘$a_i$’ ($i = 1, 2, \ldots, n$) are the coefficients up to $i$th input parameter, ‘$x_i$’ ($i = 1, 2, \ldots, n$) are input parameters up to $i$th term and ‘$e$’ is the error associated with the prediction.
To develop the MLR model with highly influencing inputs, the different combinations of eleven inputs were examined in multiple steps (Himanshu et al. 2018) considering the results of boxplots and correlation. For testing the significance of models analysis of variance, $F$-test, Shapiro–Wilk test, $R^2$, root-mean-square error (RSME) have been considered (Table 4). The significance value of calculated $F$-test of each model is lower than 0.05, indicating null hypothesis of no linear relationship amongst selected inputs and output, is rejected (Hudaverdi and Akyildiz 2019). Further, normality test of the residuals of a MLR models using Shapiro–Wilk test as suggested by Ghasemi and Zahediasl (2012) has also been performed. The computed p-value lower than the significance level $= 0.05$ is taken to reject the null hypothesis (i.e. the residuals follow a normal distribution) and vice versa to accept the alternative hypothesis. The computed $P$-value obtained from Shapiro–Wilk test of developed MLR models is greater than significance value of 0.05, thus, indicating that one cannot reject the Null hypothesis for the developed models. Hence, all the three sets of inputs of developed MLR models follow normal distribution and can be used to predict the fly-rock distance. A higher value of $R^2$ of each model which is more than 90% for training dataset indicates higher predicting probability (Armaghani et al. 2016). Therefore, all the three developed models with varying sets of inputs can be further used for the development of predictive models for MLR and CART tools.

Based on the statistical information depicted in Table 4, model 2 exhibited overall higher performance indices compared to other MLR models. Hence, model 2 has been selected as predictive model. Statistical information of training and testing dataset of selected model are given in Table 5. The more statistical details such as regression coefficients, standard error, $t$-value and p-value of inputs of developed model 2 are given in Table 6. The predictor equation of the MLR model 2 is indicated in Equation (2).

$$FD = 47.31 + (-0.019 \times D) + (-4.154 \times B) + (2.149 \times ST/B) + (-40.899 \times CPH) + (184.066 \times SC)$$

(2)

where $D$ in kg/m$^3$, $B$, ST in m, SD, in m/m$^3$, CPH in kg and SC in kg/m$^3$, respectively.
Table 4. Detail of inputs, analysis of variances, F-test, Shapiro–Wilk test, $R^2$ and RMSE of training and testing dataset of three MLR models.

| MLR model no. | Input parameters | Source       | DF  | Sum of squares | Mean squares | F     | Pr > F | P-value | alpha | $R^2$ | RMSE | $R^2$ | RMSE |
|---------------|------------------|--------------|-----|----------------|--------------|-------|--------|---------|-------|-------|------|-------|------|
| 1             | V, D, B, SD, ST/B, CPH, TC, SC | Model  | 9   | 916.715        | 101.857      | 53.204| <0.0001| 0.113   | 0.05  | 0.925 | 1.524| 0.758 | 6.322|
|               |                  | Error       | 39  | 74.664         | 1.914        |       |        |         |       |       |      |       |      |
|               |                  | Corrected total | 48  | 991.379        |              |       |        |         |       |       |      |       |      |
| 2             | D, SD, ST/B, CPH | Model  | 5   | 903.526        | 180.705      | 88.447| <0.0001| 0.374   | 0.05  | 0.911 | 1.793| 0.7938| 4.868|
|               |                  | Error       | 43  | 87.853         | 2.043        |       |        |         |       |       |      |       |      |
|               |                  | Corrected total | 48  | 991.379        |              |       |        |         |       |       |      |       |      |
| 3             | D, SD, CPH, SC   | Model 2     | 4   | 895.644        | 223.911      | 102.909| <0.0001| 0.579   | 0.05  | 0.903 | 1.888| 0.7932| 4.69 |
|               |                  | Error       | 44  | 95.736         | 2.176        |       |        |         |       |       |      |       |      |
|               |                  | Corrected total | 48  | 991.379        |              |       |        |         |       |       |      |       |      |
The relationship between predicted and actual fly-rock distance for training and testing dataset using the predictive MLR model 2 on 1:1 slope line is shown in Figure 6. Here, the $R^2$ for training and testing dataset are 0.9114 and 0.7938 as well as RMSE for training and testing dataset are 1.7932 and 4.4868 respectively.

### 6.2. CART technique

The most common technique of classification and prediction is the decision tree. The technique of CART was initially proposed by Breiman et al. (1984) and is one of the
most preferred decision tree algorithms. The decision tree is an inverted graphical tree representing the regression results (Figure 7). The most influencing parameter is placed on the top ‘root node’ with its probable values. The root node further branches into interior nodes using specific tests. Further, the data split into leaf nodes according to the tests. The ‘test’ compares the predicted value to a predefined constant using ‘if and then’ condition for splitting. A stopping criterion is used for terminating tree development. The value of the dependent variable can be forecasted using a single node or with a combination of nodes. Nevertheless, the data can be classified simultaneously by analysing the superiority of nodes.

The XLSTAT software (version 2021.2.1) has been used to develop the CART model to predict fly-rock distance. The same forty-nine training dataset and sets of inputs, used for developing the three MLR models have been used again to develop three CART models. Each set of inputs have been used to calibrate the CART model and the same twelve dataset has been used to test the performance capability of the model. Three main parameters that needed to be tuned are minimum parent size, minimum son size, and maximum tree depth. The minimum parent size and maximum tree depth were varied between 2 to 30 whereas, a minimum number of son size was fixed at 2 for obtaining at least two instances representing the fly-rock distance at the leaf node. The complexity parameter was fixed at 0.0001. A grid search method was performed by varying the minimum parent size and maximum tree depth to get the optimal tree. A mean-square-error statistical index has been used to enable the performance of each grown tree. Three different CART models have been developed with different tree depths and parent size from each set (Table 7). The performance indices of training and testing dataset of developed CART models 2 and 3 exhibit higher accuracy level with equal overall ranking. Hence, both models can be used as predictive model. However, application of CART model 2 seems to have

Figure 7. Architecture of the regression tree model.
Table 7. Result of CART models and their ranking.

| CART model no. | Input parameters      | Max. tree depth | Parent size | CART result | Ranking | RMSE | Total rank |
|----------------|-----------------------|-----------------|-------------|-------------|---------|------|------------|
| 1              | V, D, B, SD, ST/B, CPH, TC, SC | 6               | 11          | 0.9157      | 1       | 1.706| 1.669      | 4                     |
| 2              | D, SD, ST/B, CPH, SC  | 5               | 5           | 0.9290      | 3       | 1.436| 1.141      | 10                    |
| 3              | D, SD, CPH, SC        | 5               | 3           | 0.9288      | 2       | 1.440| 1.056      | 10                    |
better option as it uses an additional parameter, i.e. ST/B ratio. This ratio is vital in predicting the fly-rock distance as reported by Gupta et al. (1988). Figure 8 depicts the best CART model’s tree structure obtained from Model 2 of which ‘if and then’ rule is constructed. The ’if and then’ rule obtained from the said decision tree is given in Table 8. Further, Table 8 reveal that nodes 3, 8, 11, 20, 21 and 36–39 are leaf nodes and there is no additional information left to create new nodes. The application of this developed CART model is easy to predict the fly-rock distance of boulder subjected to blast. For example, at node 39, the predicted fly-rock distance is 0.9 m in 6.1% of cases if, a charge per hole is greater than 0.056 kg, specific charge is varying between 0.03 and 0.056 kg/m$^3$ and density of rock is greater than 2632.5 kg/m$^3$. The relevant outcomes of the CART model are discussed in results and discussion section.

7. Sensitivity analysis of the proposed CART model

Sensitivity analysis has been carried out to know each input parameter’s relative influences, on the prediction of fly-rock results obtained by the CART model. This analysis helped in finding each input parameter contribution in the CART modelling process. For this purpose, a relevancy factor (RF) has been calculated for each of five input parameters using Equation (3) (Murlidhar et al. 2021).

$$RF = \frac{\sum_{i=1}^{n} (I_i - \bar{I}_k)(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (I_i - \bar{I}_k)^2 \sum_{i=1}^{n} (P_i - \bar{P})^2}}$$ (3)
Table 8. Constructed 'if-then rules' for predicting fly-rock distance.

| Nodes | FD (prediction) | Rules |
|-------|-----------------|-------|
| Node 1 | 4.00 | If $SC \leq 0.109$ then $FD = 0$ in 93.9% of cases |
| Node 2 | 3.06 | If $SC > 0.109$ then $FD = 0$ in 6.1% of cases |
| Node 3 | 18.4 | If $SC \leq 0.109$ and $SC \leq 0.056$ then $FD = 0$ in 77.6% of cases |
| Node 4 | 2.18 | If $SC > 0.109$ and $SC > 0.056$ then $FD = 0$ in 16.3% of cases |
| Node 5 | 7.23 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D \leq 2632.5$ then $FD = 0$ in 6.1% of cases |
| Node 8 | 5.33 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ then $FD = 0$ in 71.4% of cases |
| Node 9 | 1.91 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ then $FD = 0$ in 12.2% of cases |
| Node 10 | 7.88 | If $SC \leq 0.109$ and $SC > 0.056$ and $D \leq 2655$ then $FD = 0$ in 4.1% of cases |
| Node 11 | 5.25 | If $SC \leq 0.109$ and $SC > 0.056$ and $D > 2655$ then $FD = 0$ in 4.1% of cases |
| Node 18 | 0.97 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ and $SC \leq 0.030$ then $FD = 0$ in 30.6% of cases |
| Node 19 | 2.61 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ and $SC > 0.030$ then $FD = 0$ in 40.8% of cases |
| Node 20 | 6.50 | If $SC \leq 0.109$ and $SC > 0.056$ and $D \leq 2655$ and $CPH \leq 0.0515$ then $FD = 0$ in 6.1% of cases |
| Node 21 | 9.27 | If $SC \leq 0.109$ and $SC > 0.056$ and $D > 2655$ and $CPH > 0.051$ then $FD = 0$ in 6.1% of cases |
| Node 36 | 0.78 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ and $SC \leq 0.030$ and $ST/B \leq 1.13$ then $FD = 0$ in 24.5% of cases |
| Node 37 | 1.73 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ and $SC \leq 0.030$ and $ST/B > 1.13$ then $FD = 0$ in 6.1% of cases |
| Node 38 | 2.91 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ and $SC > 0.030$ and $CPH \leq 0.056$ then $FD = 0$ in 34.7% of cases |
| Node 39 | 0.90 | If $SC \leq 0.109$ and $SC \leq 0.056$ and $D > 2632.5$ and $SC > 0.030$ and $CPH > 0.056$ then $FD = 0$ in 6.1% of cases |
where $I_{i,k}$ and $I_k$ represent, the $i$th and mean values of the $k$th input variable for $n$ data samples respectively and $P_i$ and $P$ show the $i$th and mean values of the predicted FD for $n$ data samples respectively. Higher RF value shows that the input has higher impact on the prediction of the output value. The RF values for the inputs of the CART models 2 and 3 are shown in Figure 9. From the figure it is clear that the most influential parameters for fly-rock distance assessment is the specific charge for model 2. This result is in agreement with the previous researches carried out by various researchers (Mohamad et al. 2012; Armaghani et al. 2014). The effect of rock density on fly-rock is negative which implies that the denser rock would cover less distance (Lundborg 1981). Further, specific drill density is rarely used in prediction of fly-rock in bench blasting but has a significant role in boulder blasting. It is also reported by Bhandari (1997). The charge per hole is having greater influences on fly-rock distance and an increase in the explosive quantity per hole would create more fly-rocks (Mishra and Rout 2012). The stemming to burden ratio is established fact which greatly influences the fly-rocks scattering (Gupta et al. 1988). Aforesaid facts have also been experienced by the authors during the trail blasts.

8. Results and discussion

Empirical formulae developed for mostly predicting fly-rock in bench blasting, are not applicable for boulder blasting (Table 1). Further, review of past research also indicates that there is lack of proper soft computing techniques which can be directly used in the fly-rock assessment in boulder blasting (Table 2). It is also difficult to trace which model would be the best for considering the field applicability. In several instances, various soft computing tools have been successfully used in solving mining and geotechnical problems. Therefore, the benefits of the prevailing soft computing techniques such as CART and MLR have been used in this study for prediction of fly-rocks in boulder blasting. The different blast design parameters of sixty-one boulder blasting were collected and analyzed statistically. The dataset for training and
testing have been selected randomly and divided into 80 and 20% ratio respectively. Initially, boxplots, analysis of variances, $F$-test, Shapiro–Wilk test and multiple regressions have been used to decide the group of most influencing inputs to develop models. The best MLR model 2 was developed using five inputs (D, SD, ST/B, CPH and SC) having high performance indices ($R^2 = 0.9114$ for training and $R^2 = 0.7938$ for testing). Hence, Equation (2) can be used as handy formula to predict fly-rock in boulder blasting.

The same training and testing dataset of three MLR models have also been used to develop the three CART model. The best CART model from each group of data has been obtained through varying the parent size and maximum tree depth. The $R^2$ and RMSE have been used to evaluate the performance of the best model. The performance indices of CART model 2 and model 3 gave higher accuracy and their overall ranking are also equal (Table 7). This shows that any of models, either 2 or 3, can be used as predictive model. Further, model 2 is having an addition input parameter, i.e. ST/B, which is known for its detrimental effect on fly-rock and inclusion of this parameter would strengthen the model. Nevertheless, in relevancy factor analysis of developed CART models 2 and 3, model 2 showed slightly better results apart from additional relevancy factor (0.384) of ST/B ratio (Figure 9). Hence, CART model 2 has been selected as predictive model. The relationship between measured and predicted fly-rock distances for the CART model 2 is shown in Figure 10. The performance indices of testing datasets of superior MLR model 2 ($R^2 = 0.7932$, RMSE = 4.868) and the best CART Model 2 ($R^2 = 0.9555$, RMSE = 1.141) clearly indicate that CART model 2 is superior to MLR model for predicting the fly-rock distances. The comparison between measured and predicted fly-rock distances by CART model 2 and MLR model 2 is illustrated in Figure 11. This figure also clearly indicates the prediction by CART model 2 is very closer to the actual fly-rock distance. The results of sensitivity analysis also show that the relevancies of used input parameters in prediction of fly-rock distance are following the established research findings.
9. Limitations and future scope of work

The prediction of fly-rock distance in boulder blasting is very important to define safety zone for the protection of nearby structures from unwanted incidents. For this, it requires a clear understanding of the subject and complete checks on unforeseen parameters (experience of the blasting crew, inferior quality of explosive and accessories). Incorporation of all these parameters in any predictive model is not feasible; however, an attempt should be made to perform the operation easier with utmost safety. The empirical MLR equation and CART model developed in the study are limited for boulder blasting using a 34 mm diameter borehole. Further, this study does not address dynamic strength property of rockmass as well as fragmentation analysis. Hence, in future to have better results these parameters can be incorporated in the model using hybrid intelligence techniques.

10. Conclusions

The concern of uncontrolled fly-rock is the foremost hurdle in boulder blasting. Literature reviews on boulder blasting revealed a need for suitable technique to mitigate the problem of boulder handling along railways and roadways situated in hilly areas. The developed technique can be further implemented at open-pit mines and civil construction projects. The paper describes the soft computing approach in the form of CART and MLR models for mitigating fly-rock during boulder blasting. For the accurate and precise prediction of fly-rock distance, sixty-one boulder blasting were conducted along the Indian KRC railway route and associated eleven input parameters were recorded. Statistical analyses have been carried out to evaluate the fitness of dataset. For the development of models using CART and MLR techniques, out of 61 datasets, 49 were used to train the models and 12 for testing the models. Multiple regressions and relevant statistical tests have been carried out to select three sets of input parameters for developing three MLR and three CART models for comparison. Sensitivity analysis has been carried out to find the relevancy of selected
inputs in model predictability. The CART model 2 and MLR model 2 were found as the best models, each consisting of five inputs (i.e. rock density, specific drill density, charge per hole, stemming to burden ratio and specific charge). The $R^2$ and RMSE values of testing dataset of CART model 2 are 0.9555 and 1.141 whereas for the MLR model, they are 0.7938 and 4.868 respectively. Therefore, the CART model 2 is proved to be the better model compared to MLR for predicting fly-rock distance. The relevancy factor analysis of inputs of the best model revealed that the most contributing parameters of boulder blasting in chronological order are specific charge (0.935), specific drill density (0.847), charge per hole (0.583), stemming to burden ratio (0.383) and rock density (−0.243). CART model 2 showed promising results in the study and has great potential to predict the fly-rock for deciding the safety zone, protecting the railways, roadways and other structures situated in the proximity of boulders to be fragmented.

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**Data availability statement**

The datasets generated during and/or analyzed during the current study is available in the name NKBhagat_Data repository (http://dx.doi.org/10.17632/rpxf6svm69).

**References**

Ansari MK, Ahmed M, Singh TN, Rajesh, Ghalayani I. 2015. Rainfall, a major cause for rock-fall hazard along the roadways, highways and railways on hilly terrains in India. Proceedings of the Engineering Geology for Society and Territory. Vol. 1. Cham: Springer. p. 457–460.

Armaghani DJ, Hajijhassani M, Mohamad ET, Marto A, Noorani SA. 2014. Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. Arab J Geosci. 7(12):5383–5396.
Armaghani DJ, Koopialipoor M, Bahri M, Hasanipanah M, Tahir MM. 2020. A SVR-GWO technique to minimize flyrock distance resulting from blasting. Bull Eng Geol Environ. 79: 4369–4385.

Armaghani DJ, Mahdiyar A, Hasanipanah M, Faradonbeh RS, Khandelwal M, Amnieh HB. 2016. Risk assessment and prediction of flyrock distance by combined multiple regression analysis and Monte Carlo simulation of quarry blasting. Rock Mech Rock Eng. 49(9): 3631–3641.

Armaghani DJ, Mohamad ET, Hajihassani M, Abad SA, Marto A, Moghaddam MR. 2016. Evaluation and prediction of flyrock resulting from blasting operations using empirical and computational methods. Eng Comput. 32(1):109–121.

Bajpayee TS, Rehak TR, Mowrey GL, Ingram DK. 2004. Blasting injuries in surface mining with emphasis on flyrock and blast area security. J Saf Res. 35(1):47–57.

Bhagat NK, Mishra AK, Singh MM, Rana A, Singh PK. 2020a. Innovative directional controlled blasting technique for excavation of unstable slopes along a busy transportation route: a case study of Konkan Railway in India. Min Metall Explor. 37(3):833–850.

Bhagat NK, Mishra AK, Singh MM, Rana A, Tewari S, Singh PK. 2020b. Blasting technique for stabilizing accident prone slope for sustainable railway route. Curr Sci. 118(6):901–909.

Bhandari S. 1997. Engineering rock blasting operations. A.A. Balkema: Rotterdam, Netherlands p. 388.

Breiman L, Friedman J, Olshen R, Stone C. 1984. Classification and regression trees. Wadsworth Int Group. 37(15):237–251.

Deccan Chronicle News. 2019. Boulder-slip hits B’luru-M’luru rail traffic, rain lashes Ghats. [accessed 2020 July 27]. https://www.deccanchronicle.com/nation/current-affairs/210719/boulder-slip-hits-bluru-mluru-rail-traffic-rain-lashes-ghats.html.

Dick RA, Fletcher LR, D’Andrea DV. 1983. Explosives and blasting procedures manual. US Department of the Interior, Bureau of Mines. No. 8925.

Faradonbeh RS, Armaghani DJ, Abd Majid MZ, Tahir MM, Muralidhar BR, Monjezi M, Wong HM. 2016. Prediction of ground vibration due to quarry blasting based on gene expression programming: a new model for peak particle velocity prediction. Int J Environ Sci Technol. 13(6):1453–1464.

Fletcher LR, D’Andrea DV. 1986. Control of flyrock in blasting. Proceedings of 12th Conference on Explosives and Blasting Technique, Atlanta, Georgia. p. 167–177.

Garg A, Naswa P, Shukla PR. 2013. Impact assessment and management framework for infrastructure assets: a case study of Konkan railways. [accessed 2020 July 27]. http://re.indiambientportal.org.in/reports-documents/impact-assessment-and-management-framework-infrastructure-assets-case-study-konkan#sthash.lpw22WBt.Dpuf.

Ghaseemi A, Zahediasl S. 2012. Normality tests for statistical analysis: a guide for non-statisticians. J Endocrinol Metab. 10(2):486–489.

Ghaseemi E, Sari M, Ataei M. 2012. Development of an empirical model for predicting the effects of controllable blasting parameters on flyrock distance in surface mines. Int J Rock Mech Min Sci. 52:163–170.

Gupta RN, Bagchi A, Singh B. 1988. Optimising drilling and blasting parameters to improve blasting efficiency. New Delhi: CBIP. Rock Mechanics in India, Status Report. p. 185–206.

Han H, Armaghani DJ, Tarinejad R, Zhou J, Tahir MM. 2020. Random forest and Bayesian network techniques for probabilistic prediction of flyrock induced by blasting in quarry sites. Nat Resour Res. 29(2):655–667.

Hasanipanah M, Armaghani DJ, Amnieh HB, Koopialipoor M, Arab H. 2018. A risk-based technique to analyze flyrock results through rock engineering system. Geotech Geol Eng. 36(4):2247–2260.

Hasanipanah M, Faradonbeh RS, Amnieh HB, Armaghani DJ, Monjezi M. 2017. Forecasting blast-induced ground vibration developing a CART model. Eng Comput. 33(2):307–316.

Hasanipanah M, Faradonbeh RS, Armaghani DJ, Amnieh HB, Khandelwal M. 2017. Development of a precise model for prediction of blast-induced flyrock using regression tree technique. Environ Earth Sci. 76(1):27.
Himanshu VK, Roy MP, Mishra AK, Paswan RK, Panda D, Singh PK. 2018. Multivariate statistical analysis approach for prediction of blast-induced ground vibration. Arab J Geosci. 11(16):1–11.

Hudaverdi T, Akyildiz O. 2019. A new classification approach for prediction of flyrock throw in surface mines. Bull Eng Geol Environ. 78(1):177–187.

Jimeno EL, Jimino CL, Carcedo FJA. 1995. Drilling and blasting of rocks. Rotterdam: A.A. Balkema.

Khandelwal M, Monjezi M. 2013. Prediction of flyrock in open pit blasting operation using machine learning method. International Journal of Mining Science and Technology. 23(3): 313–316.

Koopialipoor M, Fallah A, Armaghan DJ, Azizi A, Mohamad ET. 2019. Three hybrid intelligent models in estimating flyrock distance resulting from blasting. Eng Comput. 35(1): 243–256.

Kristin S, Maras M. 1994. Secondary rock breaking by use of impactors. In: Z. Rakowski (Eds.), Geomechanics 93-Strata Mechanics/Numerical Methods/Water Jet Cutting. Routledge, Oxfordshire, England, UK. p. 441–444.

Kumar P. 2020. Precautions against premature blast of site mixed emulsion (SME) site mixed slurry (SMS) explosive. DGMS (Tech) Circular No. 14 of 2020.

Li D, Koopialipoor M, Armaghan DJ. 2021. A combination of fuzzy Delphi method and ANN-based models to investigate factors of flyrock induced by mine blasting. Nat Resour Res. 30(2):1905–1924.

Little TN, Blair DP. 2010. Mechanistic Monte Carlo models for analysis of flyrock risk. Rock Fragm Blast. 9:641–647.

Lu X, Hasanipanah M, Brindhadevi K, Amnieh HB, Khalafi S. 2020. ORELM: a novel machine learning approach for prediction of flyrock in mine blasting. Nat Resour Res. 29(2):641–654.

Lundborg N. 1981. The probability of flyrock. SveDeFo, Stockholm.

Lundborg N, Persson A, Ladegaard-Pedersen A, Holmberg R. 1975. Keeping the lid on flyrock in open-pit blasting. Eng Min J. 176:95–100.

McKenzie CK. 2009. Flyrock range and fragment size prediction. Proceedings of the 35th Annual Conference on Explosives and Blasting Technique. Vol. 2. International Society of Explosives Engineers.

Mid Day News. 2014. Over 500 tonnes of food grain lie on tracks as train derails. [accessed 2020 May 15]. https://www.mid-day.com/articles/over-500-tonnes-of-food-grain-lie-on-tracks-as-train-derails/15553178.

Mignelli C, Peila D, Lo Russo S, Ratto SM, Broccoliato M. 2014. Analysis of rockfall risk on mountainside roads: evaluation of the effect of protection devices. Nat Hazards. 73(1):23–35.

Mishra AK, Rout M. 2012. Flyrocks—detection and mitigation at construction site in blasting operation. World Environ. 1(1):1–5.

Mohamad ET, Armaghan DJ, Noorani SA, Saad R, Alvi SV, Abad NK. 2012. Prediction of flyrock in boulder blasting using artificial neural network. Electron J Geotech Eng. 17: 2585–2595.

Monjezi M, Khoshalan HA, Varjani AY. 2012. Prediction of flyrock and backbreak in open pit blasting operation: a neuro-genetic approach. Arab J Geosci. 15(3):441–448.

Monjezi M, Mehrdanesh A, Malek A, Khandelwal M. 2013. Evaluation of effect of blast design parameters on flyrock using artificial neural networks. Neural Comput Appl. 23(2):349–356.

Murlidhar BR, Bejarbaneeh BY, Armaghan DJ, Mohammed AS, Mohamad ET. 2021. Application of tree-based predictive models to forecast air overpressure induced by mine blasting. Nat Resour Res. 30(2):1865–1887.

Murray C, Courtley S, Howlett PF. 1994. Developments in rock-breaking techniques. Tunnelling Underground Space Technol. 9(2):225–231.

Rana A, Bhagat NK, Jadaun GP, Rukhairyar S, Pain A, Singh PK. 2020. Predicting blast-induced ground vibrations in some Indian tunnels: a comparison of decision tree, artificial neural network and multivariate regression methods. Min Metall Explor. 37(4):1039–1053.
Richard AB, Moore AJ. 2005. Golden pike cut back fly rock control and calibration of a predictive model. Terrock Consulting Engineers Report, Kalgoorlie Consolidated Gold Mines, 37.

Sawmliana C, Singh PK, Roy MK, Singh RK, Himanshu VK. 2018. Safe dismantling of unstable boulder using controlled blasting in the historical Town of Gaya, India. Proceedings of the 12th International Symposium on Rock Fragmentation by Blasting, Lulea, Sweden. p. 417–427.

Trivedi R, Singh TN, Raina AK. 2014. Prediction of blast-induced flyrock in Indian limestone mines using neural networks. J Rock Mech Geotech Eng. 6(5):447–454.

Wyllie D. 1991. Rock slope stabilization and protection measures. Proceedings of the 34th Ann. M. AEG, Chicago, IL. p. 41–64.

Zhou J, Koopialipoor M, Murlidhar BR, Fatemi SA, Tahir MM, Armaghani DJ, Li C. 2019. Use of intelligent methods to design effective pattern parameters of mine blasting to minimize flyrock distance. Nat Resour Res. 29:625–639.