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# Development of an empirical model for predicting the effects of controllable blasting parameters on flyrock distance in surface mines

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ABSTRACT

Prediction of flyrock distance has a remarkable role in reduction and control of blasting accident in surface mines. In this paper, at first a new empirical equation for predicting flyrock distance was developed using dimensional analysis. The equation extended based on controllable blasting parameters that compiled from 150 blasting events in Sungun copper mine, Iran. Then, flyrock phenomenon is simulated using this equation and Monte Carlo (MC) method. Results showed that MC is a good means for modeling and assessing the variability of blasting parameters. Finally, sensitivity analysis was conducted to analyze the effects of the controllable blasting parameters on flyrock distance. Based on correlation sensitivity, the most effective parameters were powder factor, stemming and burden. Finally, it should be noted that the proposed flyrock equation and obtained results are site-specific; it should be used only in the Sungun copper mine, and it should not be used directly in other surface mines.



## 1. Introduction

Blasting is a primary means of extracting minerals and ores at surface mining operations. The main purpose of blasting operations is rock fragmentation and requires a large amount of explosives. The explosives release a large amount of energy during explosion, which only 20–30% of it is utilized for breaking and displacement of rocks and the rest of it is wasted in the form of environmental side impacts [1]. Flyrock is one of these environmental impacts that is defined as the rock propelled beyond the blast area by the force of an explosion [2]. The flyrock of these rock fragments beyond the allowable limits leads to facility and structure damages [3]. Also, main reason of many fatal and non-fatal blasting accidents in surface mining is excessive flyrock beyond the protected blast zone [4–8]. According to Fig. 1, flyrock can result from three key mechanisms which are explained briefly in the following [5,9,10]:

*Face burst* occurs when explosive charges intersect or are in close proximity to major geological structures or zones of weakness. The high-pressure gases of the explosives jet along the weakness zones (paths of low resistance) and generate noise, airblast, and flyrock. In these circumstances, burden conditions usually control flyrock distances in front of the face.

*Cratering* occurs when the ratio of stemming height to blasthole diameter is too small or the collar rock is weak. In this situation, flyrock can be projected in any direction from a crater at the hole collar.

*Rifling* occurs when stemming material is inefficient or is absent. Blast gases can stream up the blasthole along the path of least resistance resulting in stemming ejection and sometimes ejection of the collar rock as harmful flyrock.

During recent years, various approaches have been developed for flyrock analysis in surface mines that can be divided into two categories. One approach is the mechanistic modeling in which the physics mechanisms are clearly identified [10–14]. The other approach is the empirical approach, which involves no details of physics mechanisms and the results in an empirical equation are obtained by some "best statistical" analysis of measured flyrock range data [3,15,16]. There are advantages and disadvantages of both approaches. The advantage of mechanistic models is that they include universal mechanisms such as trajectory shape, air drag, rock bounce etc., which are not site dependent. The disadvantage of these models is that in order to calculate the flyrock range, they require inputs such as launch angle, launch velocity and fragment mass, which are difficult to obtain, and are site dependent to some degree. The advantage of empirical models is that they directly give the flyrock range via a single and simple equation. The main disadvantage of empirical models is that they are site dependent, simply because the statistical fits are only done for the site-measured range of data. Of course there

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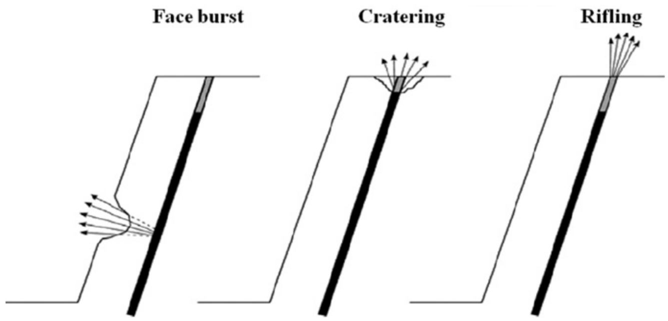


**Fig. 1.** Schematic illustration of flyrock mechanisms.

are also models that have an element of both mechanistic and empirical [9]. Nowadays, application of artificial intelligence techniques such as artificial neural network and fuzzy logic is increasing in this field [17–20].

Additional studies on flyrock phenomena can be found in [5,8,21–29]. Based on these studies, flyrock occurrence and intensity is influenced by controllable and uncontrollable parameters. Controllable parameters can be changed by the blasting pattern, while uncontrollable parameters are natural and cannot be changed. The main controllable parameters causing flyrock are insufficient burden, improper delay timing, inadequate stemming, inaccurate drilling, and unwarranted powder factor. Whereas, poor geological and geotechnical conditions specially existence of loose rock in the upper part of the blast hole are considered to be the uncontrollable parameters affecting flyrock.

The detrimental effects of flyrock are unavoidable and cannot be completely eliminated, but certainly can be minimized up to a permissible level to avoid damage. One of the effective approaches to control and prevent flyrock accidents is prediction of flyrock range and effects of blasting parameters on it. This enables mining engineers and contractors to locate the workers and equipments in a safe area and distance so hazards due to flyrock can be minimized. For this purpose, various empirical models were developed for prediction of flyrock distance that most of them are based on blasthole diameters and specific charge [3,11,13,30]. These methods do not include all effective parameters on flyrock, consequently they have very low predictive capacity. On the other hand, accurate prediction of flyrock is very difficult because of uncertainty in blasting parameters. In order to overcome these shortcomings, in this paper a stochastic model for prediction of flyrock distance in surface mines is developed. This model takes into account the uncertainty arising from variability in blasting parameters and uses Monte Carlo (MC) method for stochastic analysis. It is clear that for performing MC simulation an empirical equation is necessary, so at first this equation is established using dimensional analysis. This equation is developed based on the most effective controllable blasting parameters on flyrock, which were collected from blasting operations in Sungun copper mine located in the northwest region of Iran. Then, to analyze the effect of each controllable parameter on flyrock range, sensitivity analysis is conducted.

## 2. Case study: Sungun copper mine

### 2.1. Mine description

Sungun Copper Mine is one of Iranian porphyry copper mines, which is located in a mountainous area approximately 125 km northeast of Tabriz town in East Azarbaijan province in the northwest part of Iran, between 46° 43° E longitudes and 38° 42° N latitudes (Fig. 2). This mine is at 2000 m above sea level. The geology of Sungun porphyry deposit is very complicated and various rock types can be found. The mineralization in this deposit occurs in the Cenozoic Sahand–Bazman orogenic belt [19,31]. The main minerals of the deposit are chalcopyrite, pyrite, chalcocite, cuprite, malachite, covellite. Other minerals such as molybdenite, gold and silver are seen in the deposit. Therefore, copper is considered the main product of the mine, whereas molybdenum is a by-product. The geological reserve of the deposit is approximately 796 Mt, whereas the proved reserve is approximately 410 Mt with an average grade of 0.67%. The ore is extracted by open pit mining employing three drilling machines, five hydraulic shovels, twelve trucks with a capacity of 150 t each, and various supporting equipments during production operation. According to the mine plan, the final open-pit depth is considered to be 725 m starting from level of 2350 m to level of 1625 m (as the final minable bottom level). The height and slope of working benches are 12.5 m and 68°, respectively. The angle of overall slope is 37°. The width and slope of ramp are 30 m and 5°, respectively. The age of mine has been estimated about 32 years and overall stripping ratio (W/O) is 1.7. The geotechnical studies show that the major fault systems of the area have WW–SE, N–S and ENE–WSW strikes. In the mine area the overall rock mass is extremely broken and fractured and the geomechanical characteristics of rock mass are uniform throughout the mine and rock mass rating (RMR) is about 40.

**Fig. 2.** Sungun copper mine.

In this mine, blasting operation is performed for rock excavation. ANFO is used as the main explosive material and detonating cord is applied for initiation. Pattern geometry is staggered and drilling cuttings are used as stemming material.

### 2.2. Data collection

In this paper, for developing flyrock distance equation and determining the effects of controllable parameters of blasting patterns on flyrock distance, a database including all of controllable blasting parameters was compiled from 150 blasting operations in ore zone of Sungun copper mine. For collecting this database, burden, spacing, stemming, blasthole length, blasthole diameter, powder factor and mean charge per blasthole were gathered as controllable parameters, and the maximum flyrock distance was measured as a favorable parameter in each blasting round. In each blasting pattern, burden, spacing, stemming, blasthole length and blasthole diameter were measured by a tape meter. The amount of mean charge per blasthole was recorded for each blast by controlling the charge of blasthole. Powder factor was obtained by division of mean charge per blasthole on blast volume (burden × spacing × blasthole length) [32]. In order to measure the flyrock, all mechanisms were considered but, based on field observations the maximum flyrock distance was due to face burst mechanism in first blast row. Then, the maximum horizontal distance between original face and landed fragments was considered as flyrock distance and was measured using a hand-held GPS (global

**Table 1**
Basic descriptive statistics of the parameters collected from Sungun copper mine.

| Parameters | Unit | Symbol | Min. | Mean | Max. | Std. dev. |
|---|---|---|---|---|---|---|
| Burden | m | $B$ | 2.5 | 4.17 | 5 | 0.41 |
| Spacing | m | $S$ | 3 | 4.89 | 6 | 0.54 |
| Stemming | m | $S_t$ | 2 | 3.85 | 4.5 | 0.34 |
| Blasthole length | m | $H$ | 8 | 11.82 | 16 | 1.82 |
| Blasthole diameter | m | $D$ | 0.089 | 0.134 | 0.152 | 0.010 |
| Powder factor | Kg/m$^3$ | $P$ | 0.15 | 0.4 | 1.12 | 0.12 |
| Mean charge per blasthole | Kg | $Q$ | 50 | 89.41 | 139.17 | 16.25 |
| Flyrock distance | m | $F_d$ | 30 | 68.23 | 95 | 14.20 |

positioning system). It is worth mentioning that only the fragments which had the capacity to damage, injury or fatality were considered and based on past experiences in Sungun copper mine these fragments have the approximate diameter of 10 cm and smaller landed fragments were neglected. The basic descriptive statistics of this database are summarized in Table 1.

## 3. Development of a flyrock predictive model

### 3.1. Flyrock equation

In this section, an equation for the prediction of flyrock distance is developed using dimensional analysis. The dimensional analysis can be defined as a research method to deduce more information about a certain phenomenon relying on the postulate that any phenomenon can be described through a dimensionally homogeneous equation. In other words, dimensional analysis is a technique for restructuring the original dimensional variables of a problem into a set of dimensionless products using the constraints imposed upon them by their dimensions [33,34]. In this section, an equation for the prediction of flyrock distance is developed using dimensional analysis. Flyrock is assumed to be a function of the controllable blasting parameters as below:

$$F_d = f(B, S, S_t, H, D, P, Q) \tag{1}$$

Now, in order to specify the relationship among the independent and dependent variables of the problem Eq. (1) can be transformed into

$$f(F_d, B, S, S_t, H, D, P, Q) = 0. \tag{2}$$

In dimensional analysis, it is necessary to select a unit system. There are totally two main systems: mass and force systems. In mass system, three units are regarded, namely, mass ($M$), length ($L$), and time ($T$), whereas force system includes force ($F$), L, and T. Here, the mass system has been chosen because M, L and T are the fundamental units. Accordingly, dimensions of each variable can be defined as follows: $[F_d]=\mathrm{L}$, $[B]=\mathrm{L}$, $[S]=\mathrm{L}$, $[S_t]=\mathrm{L}$, $[H]=\mathrm{L}$, $[D]=\mathrm{L}$, $[P]=\mathrm{ML}^{-3}$ and $[Q]=\mathrm{M}$.

The fundamental theorem of dimensional analysis indicates that the total number of dimensionless parameters ($\pi$ terms) that can be formed from a list of physical quantities (variables) is $n-m$, where $n$ is the total number of physical quantities and $m$ the total number of fundamental dimensions occurring in them. In this paper, $n$ is equal to eight and $m$ is two (M and L), so the total number of dimensionless parameters is six. If $P$ and $Q$ are selected as repeating variables so $[P/Q]$ has dimensions of $\mathrm{L}^{-3}$, and hence $[P/Q]^{1/3}$ has the dimension of $\mathrm{L}^{-1}$. Therefore, all dimensionless parameters are as follows: $\pi_1=F_d(P/Q)^{1/3}$, $\pi_2=B(P/Q)^{1/3}$, $\pi_3=S(P/Q)^{1/3}$, $\pi_4=S_t(P/Q)^{1/3}$, $\pi_5=H(P/Q)^{1/3}$ and $\pi_6=D(P/Q)^{1/3}$. Now, Eq. (2) transformed into the following based on obtained results for dimensionless parameters:

$$f\,[F_d(P/Q)^{1/3}, B(P/Q)^{1/3}, S(P/Q)^{1/3}, S_t(P/Q)^{1/3}, H(P/Q)^{1/3}, D(P/Q)^{1/3}] = 0 \tag{3}$$

The relationship among the dimensionless products can be linear or non-linear. Linear and non-linear equations are written as follows:

$$F_d(P/Q)^{1/3} = a_1 + b_1\,[B(P/Q)^{1/3}] + c_1[S(P/Q)^{1/3}] + d_1[S_t(P/Q)^{1/3}] + e_1\,[H(P/Q)^{1/3}] + f_1\,[D(P/Q)^{1/3}] \tag{4}$$

$$Ln\,[F_d(P/Q)^{1/3}] = a_2 + b_2\ln\,[B(P/Q)^{1/3}] + c_2\ln\,[S(P/Q)^{1/3}] + d_2\ln\,[S_t(P/Q)^{1/3}] + e_2\ln\,[H(P/Q)^{1/3}] + f_2\ln\,[D(P/Q)^{1/3}] \tag{5}$$

By the help of multiple regression analysis of the collected data from blasting operation in the Sungun copper mine, unknown coefficients of Eqs. (4) and (5) can be determined. By the comparison between correlation coefficient ($R^2$) of the both linear and nonlinear equations, it was concluded that the nonlinear equation is more suitable. The unknown coefficients were calculated by SPSS 16.0 [35] to be $a_2$=8.846, $b_2$=−0.796, $c_2$=0.783, $d_2$=1.994, $e_2$=1.649, and $f_2$=1.766. Finally, Eq. (5) can be simplified as below, which is the most proper empirical equation for determination of flyrock distance throughout Sungun copper mine:

$$F_d = 6946.547\,[B^{-0.796}S^{0.783}S_t^{1.994}H^{1.649}D^{1.766}\,(P/Q)^{1.465}] \tag{6}$$

### 3.2. Performance of flyrock equation

The coefficient of determination between the measured and predicted values of flyrock distance is a good indicator to check the prediction performance of the equation. Fig. 3 shows the relationships between measured and predicted flyrock distance, with good coefficient of determination. According this figure, the determination coefficient of presented flyrock equation is 83.38%.

Furthermore, variance account for (VAF) (Eq. (7)) and root mean square error (RMSE) (Eq. (8)) indices were calculated to assess the prediction capacity performance of the equation [36]:

$$VAF = \left[1 - \frac{\mathrm{var}(A_i - P_i)}{\mathrm{var}(A_i)}\right]100 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2} \tag{8}$$

where $A_i$ and $P_i$ are the measured (actual) and predicted values, respectively, and $N$ is the number of samples.

If the VAF is 100 and RMSE is 0, then the equation will be excellent. The VAF and the RMSE indices for proposed flyrock equation were obtained 83.38% and 6.09, respectively, which show that this equation can provide a good prediction for flyrock distance.

## 4. Stochastic modeling approach for prediction of flyrock range

### 4.1. Background

The most common sampling technique used in stochastic analysis is the Monte Carlo (MC) method. MC method allows the variability and/or uncertainty of the available data to be adequately taken into account. The frequency histograms and/or the density functions that best describe the data distribution are used as input. In a MC simulation, a random value is selected for

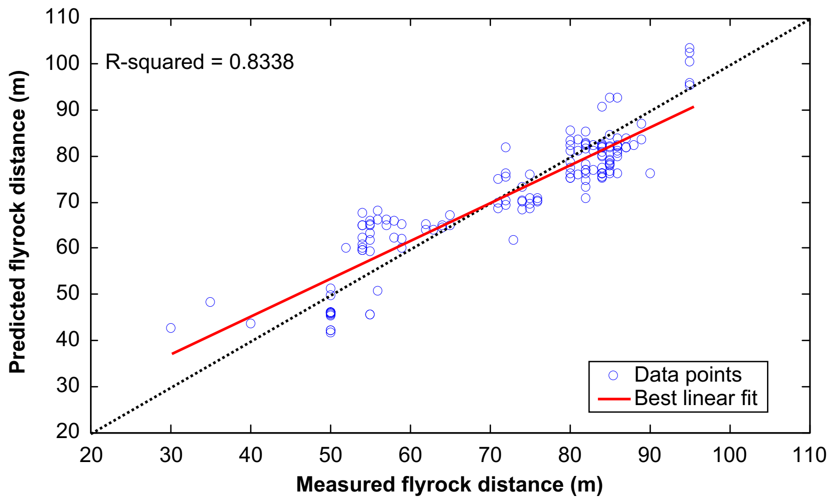


**Fig. 3.** Relationship between measured and predicted flyrock distance.

each of the inputs, based on the range of estimates. The model is calculated based on this random value. The result of the model is recorded, and the process is repeated many times. A typical MC simulation calculates the model hundreds or thousands of times, each time using different randomly-selected values. When the simulation is complete, a large number of results are obtained from the model, each based on random input values. These results are used to describe the likelihood, or probability, of reaching various results in the model.

If the value taken on by one variable has no influence upon the value assumed by another variable, then these variables are said to be independent in MC models. Independence of random variables greatly simplifies the representation and analysis of uncertainty, and often independence is assumed even where it is not really true. A complete probabilistic treatment of dependent random variables requires joint probability distributions, which for two variables may be depicted as a surface. Simple descriptors suffice in place of full probability distributions for many applications; the descriptors for covariance and correlation coefficient indicate the degree of dependence among the variables.

Recently, MC has been successfully applied to many real world problems especially in modeling complex systems in the science and engineering field especially mining, rock mechanics and engineering geological. For example, MC methods were used in porous media flow and transport problems for ground water contamination and remediation studies. Huang et al. [37] applied MC methods to study groundwater flow and solute transport in heterogeneous, dual-porosity media and compared the results with analytical models. Lu and Zhang [38] demonstrated the development of an important sampling method to solve complicated problems with MC and applied it to fluid transport problems in aquifers. You et al. [39] used MC for modeling of uncertainty in a tunneling project in order to determine of support pattern. Morin and Ficarazzo [40] used stochastic techniques and MC simulations to predict fragmentation of rock during blasting. They have shown that the results produced by the simulator were comparable with the data obtained from a quarry, and that the use of MC extended the understanding of the factors affecting blast fragmentation. Little and Blair [10] applied MC for analysis of flyrock risk. Sari [41] and Sari et al. [42] demonstrated the use of MC simulations to evaluate the strength and deformability of rock masses by including the uncertainties of the intact rock strength and discontinuity parameters. They concluded that the MC method provided a viable means for assessing the variability of rock mass properties. Ghasemi et al. [43] used MC for quantifying the uncertainty of coal pillar safety factor. Karacan and Luxbacher [44] described a practical approach for implementing stochastic determination of gob gas ventholes (GGV) production performances and for generalizing the prediction capability of deterministic models. They indicated that this approach was a promising method of representing the variability in GGV performances and to improve the limited and site-specific character of the deterministic models.

**Table 2**
Probability distribution functions of input variables used in MC simulation.

| Input variable | Function |
|---|---|
| *B* | Discrete ({2.5,3,4,4.5,5}, {0.007,0.06,0.66,0.26,0.013}) |
| *S* | Discrete ({3,3.5,4,4.5,5,5.5,6}, {0.02,0.027,0.033,0.16,0.52,0.233,0.007}) |
| $S_t$ | Logistic (4.05788, 0.15848) |
| *H* | Triangular (6.8371, 13, 16.0791) |
| *D* | Discrete ({0.09,0.1,0.11,0.13,0.14,0.15}, {0.02,0.007,0.013,0.3,0.647,0.013}) |
| *P* | Loglogistic (0.043997, 0.33764, 6.8696) |
| Q | Normal (90.537, 17.523) |

### 4.2. Monte Carlo simulation

In the Section 3, an empirical model (Eq. 6) estimating flyrock distance was built using the dimensional analysis. In this section, this model is used to simulate flyrock danger and determine the most influential input variables on the flyrock range. In the stochastic model, burden, spacing and blasthole diameter are assumed as discrete probability distributions since these inputs take only very few realizations and it is not possible to define them as continuous probability distributions (*CPD*). However, stemming length, blasthole length, powder factor, and mean charge per blasthole were represented with suitable *CPD* functions based on the available data (Table 2). Fig. 4 shows all of the input variables used in the stochastic model and their frequency histograms.

@RISK software [45] was used as the MC simulator in this work. This program provides utilization of MC functions and random distributions as MS-Excel™ add-in features and creates spreadsheet models that employ MC simulations. This software allows for a basic data fitting by the use of Maximum Likelihood Estimators to estimate the distribution parameters (i.e. to determine the parameters that maximize the likelihood of the sample data). Furthermore, the goodness of the data fit is performed by

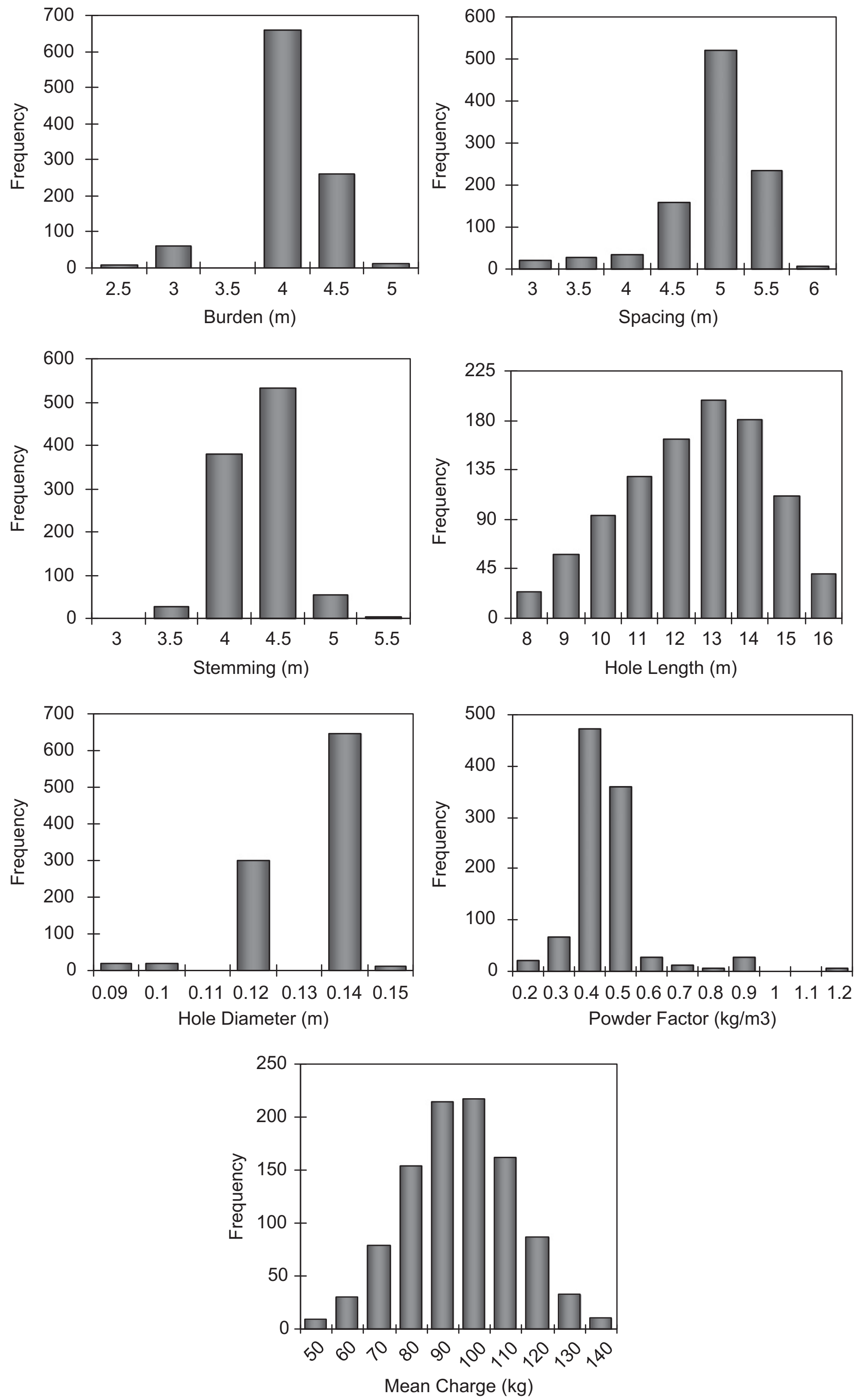


**Fig. 4.** Frequency histograms of input parameters used in MC simulations.

Chi-squared [χ2] statistics, determining the sum of differences between the observed and expected sample outcomes. For the model, 5000 iterations are performed with Latin hypercube sampling to closely resemble the resulting probability distribution. This means that every run of the simulation yields 5000 different possible combinations of input variables, which are sampled randomly from the defined distributions. In the Monte Carlo analysis, the Latin hypercube sampling may be viewed as a stratified sampling scheme designed to ensure that the upper or lower ends of the distributions are used in the analysis, and requires fewer simulation runs to produce the same level of precision with complex models.

To develop an improved method of MC simulation of flyrock range in the study, it is important to take into consideration the relationships between input parameters. As can be seen in Table 3, some significant relationships between input parameters present. It is known that burden, spacing, stemming, blasthole diameter, and blasthole length are closely related and the

**Table 3**
Spearman's rho correlation coefficients between input variables.

| | *B* | *S* | $S_t$ | *H* | *D* | *P* | *Q* |
|---|---|---|---|---|---|---|---|
| *B* | 1 | | | | | | |
| *S* | 0.83 | 1 | | | | | |
| $S_t$ | 0.45 | 0.33 | 1 | | | | |
| *H* | 0 | 0 | 0 | 1 | | | |
| *D* | 0.33 | 0.56 | 0.40 | −0.38 | 1 | | |
| *P* | −0.65 | −0.56 | 0 | 0 | 0 | 1 | |
| *Q* | 0 | 0 | 0 | 0.54 | 0 | 0.4 | 1 |

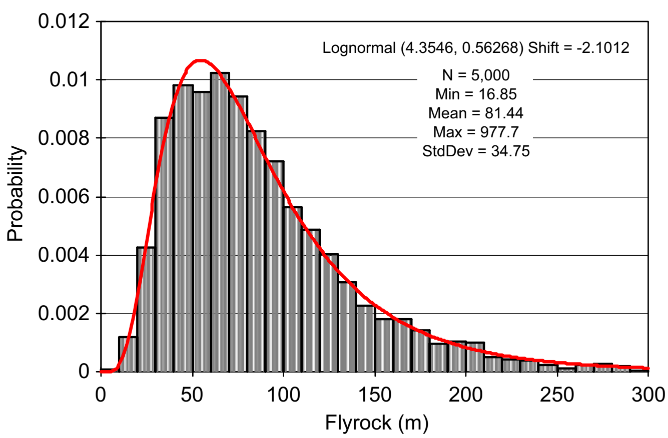


**Fig. 5.** Resulting flyrock distance distribution model obtained from MC simulation.

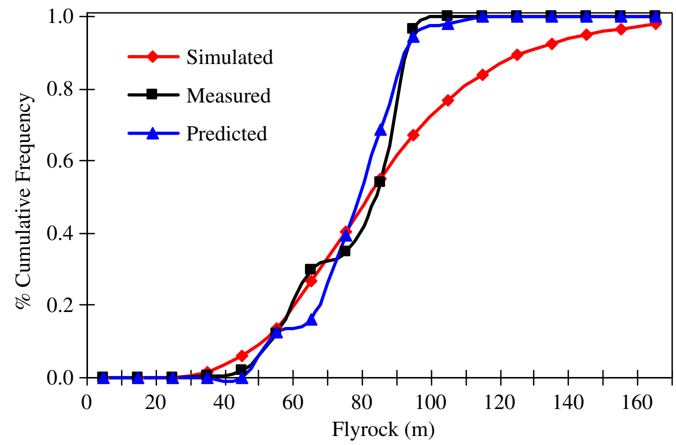


**Fig. 6.** Comparison of measured, predicted and simulated flyrock distance cumulative frequencies.

**Table 4**
Corresponding values of input variables w.r.t. the specified flyrock values obtained from the simulation results.

| | $F_d$ | *B* | *S* | $S_t$ | *H* | *D* | *P* | *Q* |
|---|---|---|---|---|---|---|---|---|
| Maximum | 977.7 | 2.5 | 3.0 | 3.9 | 13.3 | 0.13 | 2.98 | 125.5 |
| Minimum | 16.9 | 4.0 | 3.5 | 3.1 | 13.1 | 0.09 | 0.34 | 87.7 |
| Mean | 81.4 | 4.1 | 4.9 | 4.1 | 12.0 | 0.14 | 0.39 | 90.5 |
| 1% | 232.6 | 3.6 | 4.6 | 4.4 | 12.4 | 0.14 | 0.70 | 91.8 |
| 99% | 23.4 | 4.1 | 4.5 | 3.6 | 11.6 | 0.11 | 0.31 | 90.7 |

common formulas usually calculate one of them as a function of the others. Therefore, these correlations should be taken into account in simulation modeling if one wants to obtain meaningful combinations during sampling of inputs rather than doing a completely random sampling. Significant rank order correlations (Spearman's rho) between input parameters are included in the MC model by incorporating these relationships via a correlation matrix in the program.

In the stochastic estimation of flyrock distance, the following steps are taken into consideration:

i. The data for controllable blasting parameters was compiled from the blasting patterns of Sungun open-pit copper mine.
ii. Distribution functions, which represent both the probability and range of values that would be expected in the blasting patterns, were defined for each of the controllable blasting parameters.
iii. The stochastic assessment of flyrock distance was accomplished using the discrete and continuous probability distributions from the previous step as inputs for each parameter in Eq. (6).
iv. 5000 MC simulations were executed to obtain a statistical representation of the flyrock risk in the spreadsheet model.

Fig. 5 presents resulting flyrock distribution model obtained from MC simulations and summary statistics. Fig. 6 compares the measured, predicted and simulated flyrock distance cumulative frequencies. The type of best fitting model to flyrock is found to be lognormal distribution with a mean of 4.35 and standard deviation of 0.56. Average flyrock distance is simulated as 81.44 m with a standard deviation of 34.75 m. Minimum and maximum flyrock ranges are computed as 16.85 m and 977.7 m, respectively. It is clear from the results that the model predicts an extensive range of flyrock. Even, there is a risk for the Sungun copper mine from a rock fragment, which can be thrown almost 1 km away with a possibility of 1/5000. The probability for a flyrock range exceeding 300 m is only 0.0094. This distance plus some safety factor can be used to estimate the safe distance for flyrock in this mine. Table 4 indicates corresponding values of input variables w.r.t. the specified flyrock values obtained from the simulation results. For the maximum flyrock case, powder factor, charge per blasthole, and blasthole length take the highest values, while burden and spacing take the smallest values. On the other hand, for the minimum flyrock case, significant differences are observed between the blasthole diameter, powder factor, and charge per blasthole.

### 4.3. Sensitivity analysis

@RISK software performs two different sensitivity analyses: regression sensitivity and correlation sensitivity. In regression sensitivity, a multiple regression analysis using stepwise selection criteria is performed by variation of one input parameter across the possible range while other input parameters are kept constant on their mean values. Basically, when running a sensitivity analysis, @RISK program runs a regression where each iteration represents an observation. Same procedure is repeated for all input parameters to find most influential parameters on flyrock phenomenon. Consequently, sensitivity analysis was conducted to identify the effects of contributing parameters on flyrock range. The dependent variable is the output cell (flyrock) and the independent variables are each "random" @RISK function defined for each input variables in the spreadsheet model.

In correlation sensitivity, however, the program finds the rank order correlations from the simulated results of input and output variables. The rank order correlation value returned by @RISK can vary between −1 and +1. Rank order correlation calculates the relationship between two data sets by comparing the rank of each value in a data set. To calculate rank, the data is ordered from lowest to highest and assigned numbers (the ranks) that correspond to their position in the order. This method is preferable to linear correlation when we do not necessarily know the probability distribution functions from which the data were drawn.

In statistics, standardized coefficients or beta coefficients can be defined as the estimates resulting from an analysis performed on variables that have been standardized so they have variances of 1. This is usually done to answer the question of which of the independent variables has a greater effect on the dependent variable in a multiple regression analysis, when the variables are measured in different units of measurement. Before fitting the multiple regression equation, all variables (independent and dependent) can be standardized by subtracting the mean value and dividing by the standard deviation. The coefficients listed in the @RISK sensitivity report are normalized regression coefficients associated with each input. A regression value of 0 indicates that there is no significant relationship between the input and the output, while a regression value of $+1$ or $-1$ indicates a $+1$ or $-1$ standard deviation change in the output for a 1 standard deviation change in the input.

Table 5 shows the regression sensitivity ranking results of flyrock equation (Eq. 6). Here, the $+0.93$ coefficient for powder factor is the standardized, or beta weight coefficient of powder factor in this regression. According to standardized $b$ coefficients, powder factor is the most influential parameter on the flyrock range. One unit increase in the standard deviation of the powder factor increases the standard deviation of the flyrock range by 0.93. The next most effective parameter on flyrock is the mean charge per blasthole. One unit increase in standard deviation of charge per blasthole decreases standard deviation of flyrock range by 0.71. The least effective parameter on the flyrock is the burden according to regression sensitivity analysis. One unit increase in standard deviation of burden decreases standard deviation of the flyrock range only 0.18.

When ranking by the correlation coefficients are considered in Table 5, the most effective three parameters on the flyrock range are the powder factor, stemming and burden, respectively. The least effective parameters on the flyrock range are the spacing and mean charge per blasthole, respectively. The obtained ranks for parameters in regression are not compatible with intuition whereas in correlation they are more reasonable based on engineering judgments and past experiences. There should be a multicollinearity effect on the regression analysis. Multicollinearity occurs when independent variables in a model are correlated to each other as well as to the output. Unfortunately, reducing the impact of multicollinearity is a complicated problem to deal with, but it may be considered to remove the variable that causes the multicollinearity from the sensitivity analysis.

In a different study, Rezai et al. [17] developed a fuzzy model to predict flyrock distance on the data collected from an open-pit iron mine. They performed a sensitivity analysis to determine the most effective parameters on the flyrock using the cosine amplitude method (CAM). The sensitivity analysis revealed that the most effective parameters on the flyrock were the powder factor and stemming length whereas the least effective was the rock density. Aghajani-Bazzazi et al. [15] reported flyrock distances for fifteen blasts at Esfordi phosphate mine with blast design parameters. They analyzed the influence of burden, stemming length and powder factor, whereas they did not include variation due to blasthole length or blasthole diameter. Linear, exponential, power and polynomial regression methods were compared in their research. Based on the results, an empirical formula was developed to predict the flyrock distance and powder factor was the major factor contributing to flyrock range.

**Table 5**
Sensitivity ranking of input variables according to regression and correlation analysis.

| Name of the variable | Stepwise regression | Correlation coefficient |
|---|---|---|
| Powder factor ($P$) | $+0.93$ (1) | $+0.53$ (1) |
| Stemming ($S_t$) | $+0.31$ (4) | $+0.42$ (2) |
| Burden ($B$) | $-0.18$ (7) | $-0.30$ (3) |
| Blasthole length ($H$) | $+0.63$ (3) | $+0.22$ (4) |
| Blasthole diameter ($D$) | $+0.25$ (5) | $+0.22$ (5) |
| Spacing ($S$) | $+0.24$ (6) | $+0.13$ (6) |
| Charge per blasthole ($Q$) | $-0.71$ (2) | $-0.02$ (7) |

The values in the bracket () shows the ranking.

## 5. Discussion and conclusions

Flyrock can be a serious hazard associated with blasting. Many surface blasting accidents involving injury result from excessive flyrock beyond the protected blast zone. Numerous cases of equipment damage at the mine, quarry or construction site have resulted from flyrock. Therefore, exact and accurate prediction of flyrock will be a significant measure for eliminating related problems. Flyrock prediction is a complex issue in mining industry because at first many parameters influence flyrock phenomenon that can be divided generally into two categories; controllable and uncontrollable parameters. Second, most of these parameters accompany with uncertainty due to variability in blasting parameters. The aim of this study was to predict flyrock distance and effects of controllable blasting parameters on it using stochastic modeling. In this study, for prediction of flyrock distance an empirical equation and MC method were used. Flyrock empirical equation was developed based on collected data from blasting events in Sungun copper mine by dimensional analysis. This model is constituted of major controllable blasting parameters, such as burden, spacing, stemming, blasthole length, blasthole diameter, powder factor, and mean charge per blasthole. Also, sensitivity analysis was conducted for the determination of the effects of controllable blasting parameters on flyrock distance. The results of the presented study can be explained as follows:

1. For flyrock empirical equation, coefficient of determination ($R^2$), VAF and RMSE indices were obtained as 83.38%, 83.38% and 6.09, respectively, so this equation can sufficiently predict flyrock distance with acceptable accuracy.
2. It is important to note that the validity of the proposed equation is limited by the data range and sample types, which are used to derive the equation. Therefore, it is strongly recommended that it is not assumed to be applicable to all surface mines. Similar equations can also be developed in other surface mines, which employ a similar mining method to those reported in this study in order to predict flyrock distance.
3. A comparison between simulation results and measured values of flyrock in the field, indicates that the MC simulation can predict flyrock distance relatively well. The real mean flyrock is 72.43 m while the predicted value is 81.44 m.
4. In this paper, the sensitivity analysis was performed employing two methods: regression sensitivity and correlation sensitivity. The obtained results from these methods were different but, the powder factor was the first parameter in controlling flyrock in both methods. Based on regression sensitivity the most effective parameters were powder factor, mean charge per blasthole and blasthole length whereas based correlation sensitivity these parameters are powder factor, stemming and burden. The observed differences between two methods are due to multicollinearity effect. It is worth mentioning that the obtained ranks for parameters in correlation sensitivity are

more reasonable based on engineering judgments and past literatures.

5. Based on sensitivity analysis, stemming length, spacing, blasthole length, blasthole diameter and powder factor have a direct relationship with flyrock distance while burden and mean charge per blasthole have an indirect relationship. It means that increase in stemming length, spacing, blasthole length, blasthole diameter and powder factor cause more flyrock distance, while increase in amounts of burden and mean charge per blasthole leads to decrease in flyrock distance. It can be simply understood that the indirect relationship between mean charge per blasthole and flyrock distance is not in accordance with intuition. It is obvious that an increase in mean charge per blasthole leads to an increase in flyrock distance. The main reason of this contradiction is due to the approach of developing flyrock equation. It is clear that the necessity of equation in dimensional analysis is identical dimensions in both sides of equation. Since, in proposed flyrock equation the dimension in left-hand side of equation is L, the dimension of right-hand side should be the same. Among controllable blasting parameters; burden, spacing, stemming, blasthole length and blasthole diameter have the dimensions of length ($L$), and two other parameters, powder factor and mean charge per blasthole have the dimensions of $M/L^3$ and M, respectively. Thus, in order to equalize the dimension of both sides the ratio of $P/Q$ was used, which has the dimension of L. This means that in order to develop the flyrock equation by dimensional analysis based on collected data in Sungun copper mine, the $Q$ has indirect relationship with flyrock inevitably. Consequently, this indirect relationship is observed in results of sensitivity analysis.

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