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# ESTIMATION OF AIR OVERPRESSURE USING BAT ALGORITHM

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**Abstract:** Air overpressure (*AOp*) is an undesirable phenomenon in blasting operations. Due to high potential to cause damage to nearby structures and to cause injuries, to personnel or animals, *AOp* is one of the most dangerous adverse effect of blasting. For controlling and decreasing the effect of this phenomenon, it is necessary to predict it. Because of multiplicity of effective parameters and complexity of interactions among these parameters, empirical methods may not be fully appropriate for AOp estimation. The scope of this study is to predict *AOp* induced by blasting through a novel approach based on the bat algorithm. For this purpose, the parameters of 62 blasting operations were accurately recorded and *AOp* were measured for each operation. In the next stage, a new empirical predictor was developed to predict *AOp*. The results clearly showed the superiority of the proposed bat algorithm model in comparison with the empirical approaches.

***Keywords***: *metaheuristic, bat algorithm, air overpressure, blasting*

## 1. INTRODUCTION

The main purpose of blasting operations in open pit mines is to crush rock to desirable fragmentation and cast it in such way to form a pile of blasted rock suitable for further loading and hauling. Although, this operation is the most favorable method for crushing the rocks in open pit mines, but blasting operations are causing side effects such as fly rock, dust, ground vibrations and air-blast (Raina et al. 2004). Table 1, shows

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the distribution of the energy of the explosion and its related phenomena. As it is considered from Table 1, the main part of this energy is converted to the ground vibration and air overpressure (*AOp*).

Table 1. Energy consumption in blasting operation (Jimeno et al. 1995)

| Type of phenomenon | Energy consumption [%] |
|---|---|
| Fly rock | 1 |
| Back break | 4 |
| Air blast | 38 |
| Ground vibration | 40 |
| Fragmentation | 17 |

In blasting, whenever an explosive is detonated transient air blast pressure waves are generated (Wharton et al. 2000) and these transitory phenomena last for a second or so. Unlike blast induced ground vibrations, air blast impacts the house through the roof, walls and windows of the structures and rarely can cause damage in quarrying. But this can be confused with the effects of ground vibrations. Therefore, air blast is an annoyance problem in quarrying, but may result in confrontation between the quarry management and those affected (Konya and Walter, 2000; Roy, 2005).

Sometimes, airblast is called as “blast noise”. But, the term “blast noise” is misleading. The main difference between air blast and noise is that, air blast is the pressure wave that is associated with the detonation of an explosive charge, whereas noise is the audible and infrasonic part of the spectrum: from 20 Hz to 20 KHz. Air blast are the low frequency air vibrations with values that are usually under 20 Hz.

Energy below 20 Hz is inaudible, however, it can be sensed in the form of concussion. The sound and concussion together are known as air blast-overpressure (*AOp*) which is measured in terms of Pascal (Pa) or decibels (dB) over the required frequency range. As its name implies, air blast-overpressure is a measure of the transient pressure changes. These low-intensity pulsating pressure changes, above and below ambient atmospheric pressure, are manifested in the form of acoustical waves traveling through the air. When calculating maximum overpressure values, the absolute value of the greatest pressure change is used – regardless of whether it is positive or negative change. The frequency of the blast overpressure determined by measuring, how many up-and-down pressure changes occur in one second of time. According to Wiss and Linehan (1978), the main causes of this phenomenon are the following:

– Ground vibration brought on by an explosion (Rock pressure pulse).
– Escape of gases from the blasthole when the stemming is ejected (stemming release pulse).
– Escape of gases through the fractures created in the rock mass face (Gas release pulse).

– Detonation of the initiating cord in the open air.
– Displacement of the rock at bench face as the blast progress (Air pressure pulse).
– Collision between the projected fragments (Fig. 1).

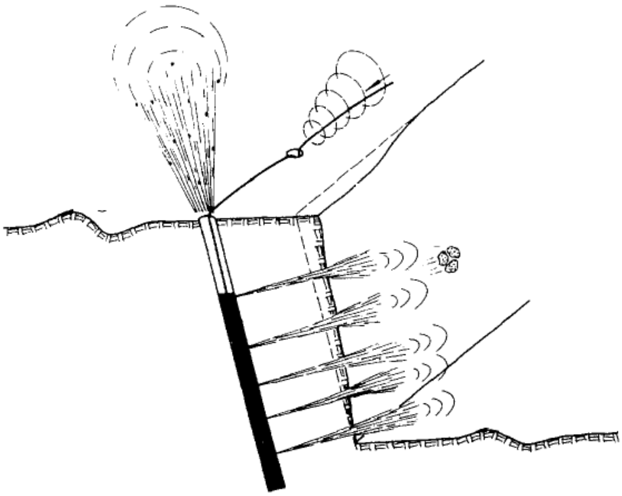


Fig. 1. Air blast fronts in blasting (Jimeno et al. 1995)

There are many influential factors on *AOp*. The effective parameters of blast induced *AOp* is directly related to parameters such as maximum charge per delay, detonator accuracy, burden and spacing, stemming, direction of initiation and charge depth. Furthermore, *AOp* is influenced by other parameters such as atmospheric conditions, overcharging, weak strata and conditions arise from secondary blasting (Bhandari 1997; Siskind et al. 1980; Littlen and Murrary, 1996; Loose et al. 2003). However, *AOp* induced by blasting is not easy to predict as the same blast design can produce different results in different cases.

Based on influential parameters on *AOp*, many attempts have been done to establish correlations for *AOp* prediction. According to National Association of Australian State (NAAS) (Wu, Hao, 2005), *AOp* from confined blasthole charges can be estimated from following empirical formula:

$$P = \frac{140\sqrt[3]{\frac{E}{200}}}{d}, \tag{1}$$

where: $P$ is overpressure in kPa, $E$ is mass of charge in kg, and $d$ is distance from center of blasthole in meter. McKenzine (1990) suggested an equation to describe the decay of overpressure as follows:

$$dB = 165 - 24\log\left(\frac{D}{W^{1/2}}\right), \tag{2}$$

in which, *dB* is the decibel reading with a linear of flat weighting, *D* is distance in meter, and *W* is the maximum charge weight per delay in kg.

In the absence of monitoring, the use of cube-root scaled distance factor (*SD*) is another method to predict *AOp*. A relationship between the distance and the explosive charge weight per delay is used through the *SD* values. *SD* is formulated as below:

$$SD = DW^{-0.33}, \tag{3}$$

where *D* denotes the distance to the explosive charge in meter and *W* is the explosive charge weight in kg and *SD* is the scaled distance factor.

The establishment of a relationship between *AOp* and *SD* values is possible if sufficient data is available. A site-specific *AOp* attenuation formula can be developed when statistical analysis techniques are applied to the representative *AOp* data (White, Franfield,1993; Rosenthal and Morlock, 1987; Cengiz, 2008). The form of the prediction equation is given as follow:

$$AOp = H(SD)^{-\beta}, \tag{4}$$

in which, *AOp* is measured in Pa or *dB*, *H* and $\beta$ are the site factors. *SD* calculated by Eq. (3) is widely used in surface blasting to predict *AOp* (Hajihassani et al. 2014).

With regard to the fact that the number of effective parameters on the *AOp* is too high and the interactions are too complicated, empirical methods may not be fully suitable for estimating this phenomenon. Currently, new techniques such as artificial neural networks (ANNs), particle swam optimization (PSO), genetic algorithm (GA), and differential evaluation (DE) are frequently applied (Dehghani, Ataee-pour 2011; Hajihassani et al. 2014; Dehghani and Shafaghi, 2017; Saghatforoush et al. 2016).

Kuzu et al. (2009) established a new empirical relationship between *AOp* and two parameters (distance between blast face and monitoring point and weight of explosive materials) which are the most important variables on *AOp*. Hajihassani et al. (2014) presented a PSO-based ANN model for predicting the *AOp*. Results of this research show that the presented model can estimate *AOp* with correlation coefficient of 94%. Segarra et al. (2010) provided a new *AOp* predictive equation based on monitoring data in two quarries with 32% accuracy. Their proposed model was validated using five new blasting data with 22.6% accuracy. Numerical models including both free air and rock material properties were programmed and linked to Autodyn2D by Wu and Hao (2005) for simulation ground shock and airblast pressures generated from surface explosions. They concluded that numerical results give a very good prediction of airblast pressures in the free air. Rodriguez et al. (2007) developed semi-empirical model for prediction of the air wave pressure outside a tunnel due to blasting work. Their method was tested with several cases and it was proved that it can be used under different conditions. Rodriguez et al. (2010) demonstrated that how natural or artificial barriers can be affected in results of the air wave propagation induced by blasting outside the tunnel. They proposed the phonometric curve and iso-attenuation curves to represent the phenomenon and suggested charge–distance curve for solving the problem. Mahdiyar et al. (2018) for predicting *AOp*, used multiple linear regression (MLR) and Monte Carlo simulation techniques. The obtained results indicated that distance from the blast face and maximum charge per delay were the most effective variables in the calculation of AOp. Gao et al. (2019) proposed a new hybrid of group method of data handling (GMDH) and genetic algorithm (GA) for predicting *AOp*. For this purpose, they considered four input parameters: maximum charge per delay, distance between the blasting point and monitoring station, powder factor and rock mass rating. Zhou et al. (2019) proposed a new data-driven model in the prediction of *AOp* using a hybrid model of fuzzy system (FS) and firefly algorithm (FA). Bui et al. (2019) for predicting *AOp*, applied and compared seven artificial intelligence (AI) techniques such as random forest, support vector regression, Gaussian process, Bayesian additive regression trees, boosted regression trees, *k*-nearest neighbors, and artificial neural network (ANN). This study demonstrated that AI techniques are excellent for predicting blast-induced AOp in open-pit mines.

For solving the problems of the traditional estimation formula and based on the high performance of the meta heuristic methods, in this research bat algorithm was used for predicting the *AOp*. For achieving this aim, at the first step, a mathematical equation was determined and then using the bat algorithm, the coefficients of the mentioned equation will be optimized.

## 2. BAT ALGORITHM

Bat algorithm (BA) is a heuristic algorithm proposed by Yang in 2010. It is based on the echolocation capability of micro bats guiding them on their foraging behavior.

### 2.1. ECHOLOCATION CAPABILITY OF BATS

Most bat species use a type of sonar called as echolocation to communicate, recognize different types of insects, sense distance to their prey and move without hitting to any obstacle even incomplete darkness. All animals including bats, which use echolocation capability, emit some pulses. These pulses contain frequencies ranging from high pitch (>200 kHz) to low pitch (~10 kHz). Pulses, upon hitting the objects or the prey that are around a bat, form echoes. The bat listens to the echo and then analyzes and evaluates codes in these echoes (Fenton 2004). The echolocation characteristics are idealized within the framework of the following rules by benefiting such features of bats:

– All bats use echolocation to sense distance, and they also “know” the difference between food/prey and background barriers in some magical way.
– Bats fly randomly with velocity $v_1$ at position $x_i$ with a frequency $f_{\min}$, varying wavelength and loudness $A_0$ to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0.1]$, depending on the proximity of their target.
– Although the loudness can vary in many ways, it is assumed that the loudness varies from a large (positive) $A_0$ to a minimum constant value $A_{\min}$.

## 2.2. THE STRUCTURE OF BAT ALGORITHM

(a) Initialization of bat population. The search space is assumed as a region that contains many prey sources on it. The algorithm tends to find the high or optimum quality food in the search space. Because locations of food sources are not known, initial population is randomly generated from real-valued vectors with dimension $d$ and number $N$, by taking into account lowerand upper boundaries. Then, quality of food sources locatedwithin the population are evaluated.

$$x_{ij} = x_{\min} + \varphi(x_{\max} - x_{\min}), \tag{5}$$

where $i$ = 1, 2, ..., $N$, $j$ = 1, 2, ..., $d$, $x_{\max}$ and $x_{\min}$ are upper and lower boundaries for dimension $j$, respectively. $\varphi$ is a randomly generated value ranging from 0 to 1.

(b) Generation of frequency, velocity and new solutions. Evaluated fitness values of all bats influence their movements. Bats fly with velocity $v_i$ which is affected by a randomly predefined frequency $f$. Finally, they locate their new position $x_i$ in the search space.

$$f_i = f_{\min} + \beta(f_{\max} - f_{\min}), \tag{6}$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_*) f_i, \tag{7}$$

$$x_i^t = x_i^{t-1} + v_i^t, \tag{8}$$

where $f_i$ is a frequency value belonging to the $i$-th bat, $f_{\min}$ and $f_{\max}$ are minimum and maximum frequency values, respectively, $\beta$ indicates a randomly generated value, $x_*$ is the obtained global best location (solution) after comparison of all solutions among $N$ bats so far and $v_i^t$ implies the velocity of the $i$-th bat at $t$-th time step.

(c) Local search capability of the algorithm. In order to improve local search capability of the algorithm, Yang has created a structure in order that the bat can improve the solution near the obtained one.

$$x_{\text{new}} = x_{\text{old}} + \varepsilon \bar{A}^t \tag{9}$$

where $x_{\text{old}}$ is a high quality solution chosen by some mechanism (e.g., roulette wheel), $\bar{A}^t$ is average loudness value of all bats at $t$-th time step and $\varepsilon$ is a randomly generated value ranging from −1 to 1.

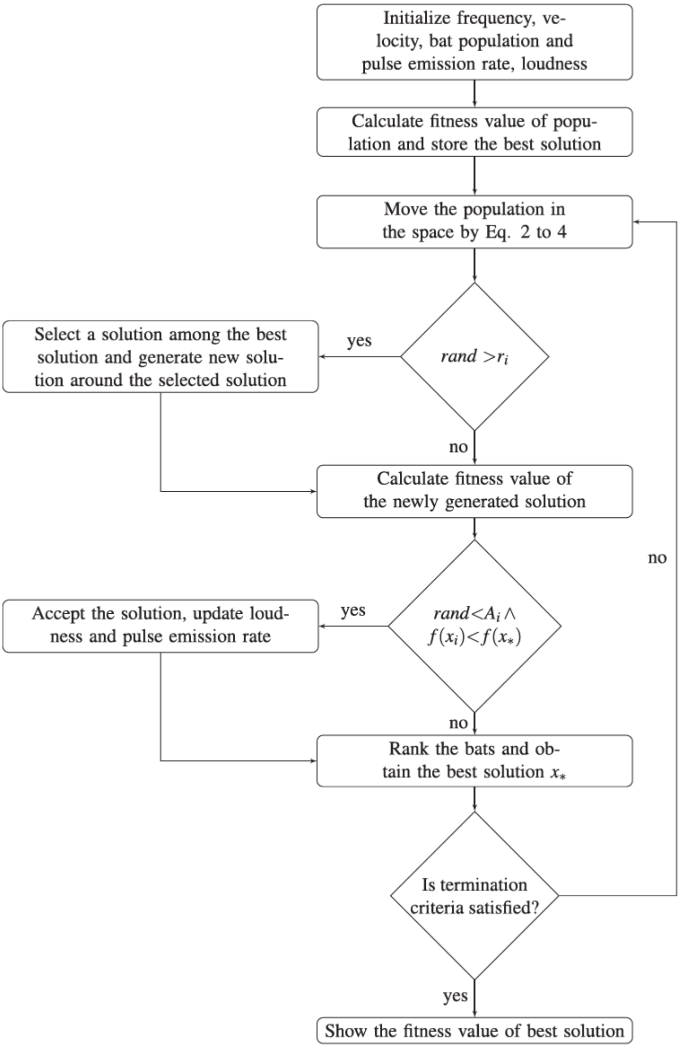



Fig. 2. Flowchart of bat algorithm

(d) Loudness and pulse emission rate. The loudness $A$ and pulse emission rate $r$ are updated as a bat gets closer to its target, namely its prey. Loudness $A$ is decreased while pulse emission rate $r$ is increased with respect to Eqs. (10) and (11), respectively.

$$A_i^{t+1} = \alpha A_i^t \,, \tag{10}$$

$$r_i^{t+1} = r_i^0 (1 - e^{\gamma t}) \tag{11}$$

where $\gamma$ and $\alpha$ are constraints, $r_i^0$ is the initial pulse emission rate value of the *i*-th bat. Flow chart of the algorithm is given in Fig. 2.

## 3. CASE STUDY

In this paper, a total of 62 blasting operations had been investigated from four granite quarry sites in Malaysia (Hajihassani et al., 2014). These sites are located near Johor city, the capital of the Johor State. Granite quarry in the mentioned sites are blasted using 75, 89, and 115 mm diameter blastholes and ANFO with NONEL was used as the main explosive material. Fine gravels were used as the stemming material. During data collection, blasting parameters such as burden, spacing, stemming length, hole depth and powder factor, were measured. The blast face angle was fixed during the investigation. *AOp* was monitored in each blasting operation using a linear *L* type microphones connected to the *AOp* channels of recording units manufactured by VibraZEB. This instrument records *AOp* values ranging from 88 dB up to 148 dB. The microphones have an operating frequency response from 2 to 250 Hz, which is adequate to measure accurately overpressures in the frequency range critical for structures and human hearing. All *AOp* measurements have been carried out in front of the quarry bench, in the same elevation and approximately perpendicular to it. Also, geological discontinuities play a vital role in *AOp* phenomena. If there is any geological discontinuity, explosive gases escape from the blastholes which lead to high magnitude of *AOp*. It should be mentioned that the distance of monitoring point from the

Table 2. The range of the blasting design parameters

| Type of data | Parameter | Symbol | Unit | Min. | Mean | Max. | Standard deviation |
|---|---|---|---|---|---|---|---|
| Input | Hole length | L | M | 10 | 15.15 | 25 | 3.9 |
| | Powder factor | PF | $kg/m^3$ | 0.34 | 0.52 | 0.76 | 0.11 |
| | Max. charge per delay | Q | Kg | 60 | 88.15 | 171 | 26.95 |
| | Stemming length | St | M | 1.7 | 2.09 | 3 | 0.27 |
| | Burden | B | M | 1.5 | 2.37 | 3.2 | 0.48 |
| | Spacing | S | M | 2.65 | 3.32 | 4 | 0.42 |
| | Number of holes | N | - | 12 | 40 | 89 | 14.2 |
| | Distance | D | M | 300 | 498.39 | 600 | 143.14 |
| Output | Air-Over pressure | AOp | dB | 89.1 | 105.1 | 126.3 | 10.03 |

blasting face was 300 and 600 m in different sites. As already mentioned, the weather condition is an influential parameter on *AOp* induced by blasting. Since the weather conditions in the case studies blasting sites were approximately similar, this parameter was omitted from the investigated parameters. The range of the blasting design parameters is shown in Table 2.

## 4. BAT ALGORITHM MODEL

After testing the various regression function in SPSS, it is concluded that the cubic function present better result than other prediction function. Also, in order to evaluation the presented model, two equation based on the distance were developed. Therefore, for finding the best equation for estimating the *AOp*, a cubic equation was developed as below:

$$\begin{aligned} AOp = {} & a_1 + a_2(L) + a_3(L^2) + a_4(L^3) + a_5(PF) + a_6(PF^2) + a_7(PF^3) + a_8(Q) + a_9(Q^2) \\ & + a_{10}(Q^3) + a_{11}(St) + a_{12}(St^2) + a_{13}(ST^3) + a_{14}(B) + a_{15}(B^2) + a_{16}(B^3) \\ & + a_{17}(S) + a_{18}(S^2) + a_{19}(S^3) + a_{20}(N) + a_{21}(N^2) + a_{22}(N^3). \end{aligned} \tag{12}$$

Based on Eq. 12 the influence of suggested important parameters on *AOp* is investigated using bat algorithm. In bat procedure the purpose is to optimize the following objective function:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(O_i - T_i\right)^2}{N}}\ , \tag{13}$$

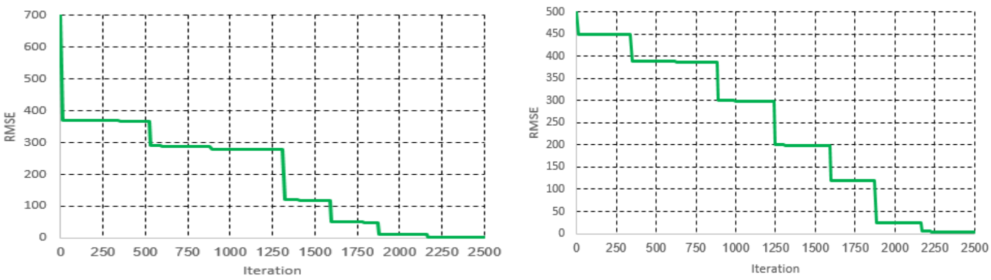
where $O_i$ and $T_i$ represent predicted and measured *AOp*, respectively and $N$ is the total number of predicted and measured data sets. *RMSE* is known as root mean square error. The bat model is implemented in MATLAB software. In bat algorithm, the number of unknowns ($n$) is 25 and the population size ($NP$) was taken as 35. The Loudness, Pulse rate and number of iteration were selected 0.85, 0.5 and 40000, respectively. Also, for preparing the equation 90 percent of the dataset were used. The rest of data were used for validation. *RMSE* for the *AOp* at distance 300 and 600 were determined 0.7 and 4.8, respectively. The reduction in *RMSE* during bat algorithm implementation process is illustrated in Fig. 3.

Using bat algorithm, a new empirical formula was prepared, which the coefficients of this equation can be rewrite as below:

$$\begin{aligned}AOp_{300} &= 213.2+30.3(l)-1.2(L^2)+0.01(L^2)+546.8(PF)-1448.8(PF^2)\\&+1203.6(PF^3)-14.1(Q)+0.2(Q^2)-0.001(Q^3)-4.1(St)+3.2(St^2)\\&-91.9(B)+15.5(B^2)+79.9(S)-11.7(S^2)+0.3(N)+0.001(N^2),\end{aligned} \tag{14}$$

$$\begin{aligned}AOp_{600} &= -2408.4+12.0(L)-0.8(L^2)+0.02(L^3)+1296.3(PF)-2582.4(PF^2)\\&+1620.4(PF^3)-1.3(Q)+0.01(Q^2)-530.4(St)+264.3(St^2)-43.6(St^3)\\&+121.7(B)-53.5(B^2)+7.7(B^3)+2287.6(S)-674.3(S^2)+65.6(S^3)\\&-1.3(N)+0.04(N^2),\end{aligned} \tag{15}$$

where, $AOp_{300}$ and $AOp_{600}$ are the measured $AOp$ at distance of 300 and 600 meters, respectively. The coefficient of correlation for training data is shown in Fig. 4.




(a) $AOp_{300}$ (b) $AOp_{600}$

Fig. 3. *RMSE* vs. iteration during bat algorithm implementation process

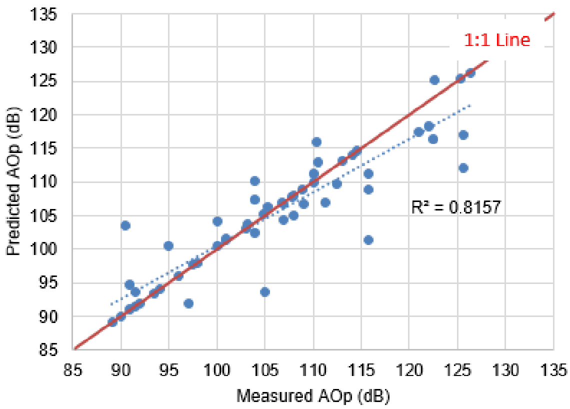



Fig. 4. Correlation of coefficient of bat algorithm prediction model

## 5. DISCUSSION

### 5.1. VALIDATION

For validating the determined formulas, at first, 10 percent of datasets were selected randomly. In the next step, the results of determined formulas were compared with the conventional equations. The result of comparison is shown in Table 3. For this purpose, models were compared using the root mean square of error (RMSE), mean absolute error (Ea), mean relative error (Er) and value account for (VAF) indexes. The coefficients of Eq. 4 are calculated as $H = 414.19$ and $\beta = -0.286$ for this mine using regression method.

$$E_a = |O_i - T_i| \tag{16}$$

$$E_r = \left( \frac{|O_i - T_i|}{O_i} \right) \times 100 \tag{17}$$

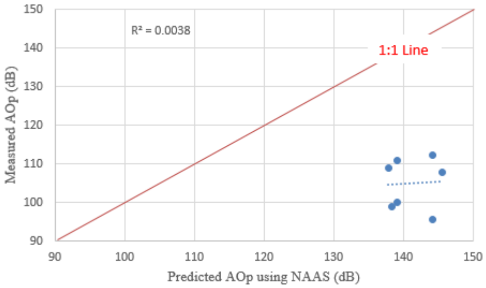
$$VAF = \left[ 1 - \frac{\operatorname{var}(O_i - T_i)}{\operatorname{var}(T_i)} \right] \times 100 \tag{18}$$

Table 3. Comparison between presented equation and the conventional equations

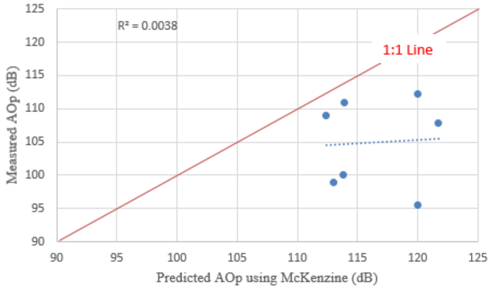
| | $R^2$ [%] | *RMSE* | $E_a$ [m] | $E_r$ [%] | *VAF* [%] |
|---|---|---|---|---|---|
| NAAS (Wu, Hao 2005) | 0.38 | 36.86 | 36.25 | 35.01 | –18.56 |
| McKenzine (1990) | 0.38 | 13.39 | 11.43 | 11.28 | –28.15 |
| USBM (Siskind et al. 1980) | 0.43 | 13.26 | 10.57 | 10.13 | –305.89 |
| PSO-ANN (Hajihassani et al. 2014) | 72.19 | 3.57 | 3.53 | 3.39 | 66.42 |
| Bat algorithm | 82.28 | 2.94 | 2.09 | 1.94 | 81.84 |

Figure 6 shows the correlation coefficient of the prediction models. Figure 5 revealed that results of bat algorithm are more accurate as compared to PSO-ANN and conventional models. The presented method is location sensitive and it is not a final solution at any other mine.

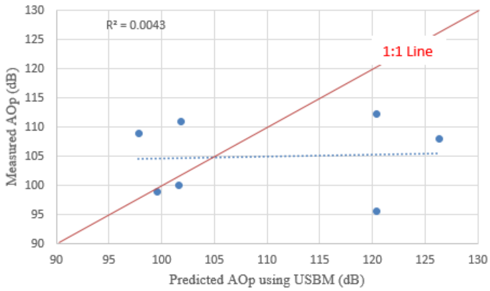
As it is shown in Fig. 6, NAAS equation overestimates the *AOp*. PSO-ANN and bat algorithm estimate the *AOp* more accurate than other models. It means that the meta-heuristic models can predict the blasting consequences with high performance.



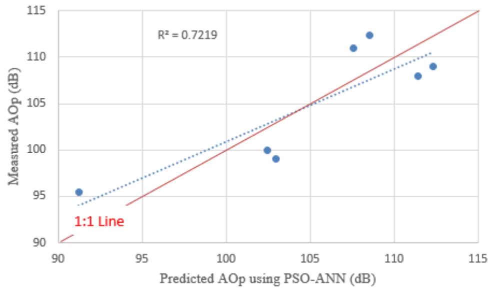

(a) NAAS



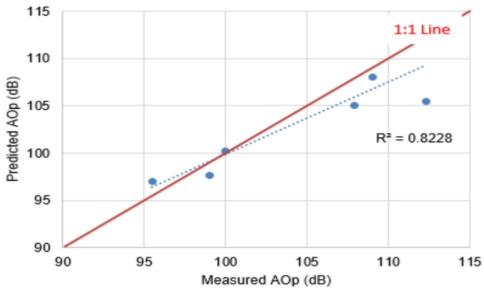

(b) McKenzine




(c) USBM




(d) PSO-ANN




(e) Bat algorithm

Fig. 5. Correlation coefficient of *AOp* prediction models

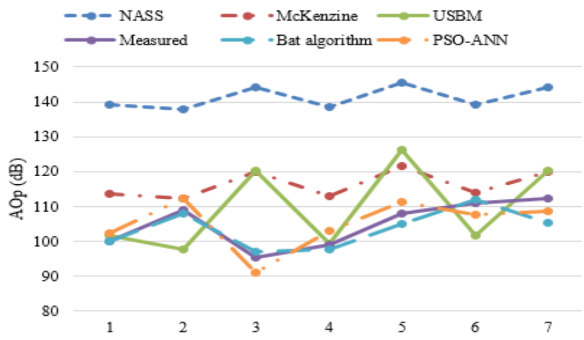



Fig. 6. Comparison between prediction models

5.2. SENSITIVITY ANALYSIS

A useful concept has been proposed to identify the significance of each "cause" factor (input) on the "effect" factors (outputs). This enables us to hierarchically recognize the most sensitive factors affecting *AOp*. For achieving this aim, Two types of sensitivity analysis i.e. tornado and spider graphs were conducted. In tornado sensitivity analysis, the ranges of correlations are between –1 and +1 (Armaghani et al. 2016b). Figure 7 shows tornado analysis for *AOp*. As it is shown in this figure, distance to blasting point, maximum charge per delay and powder factor are the most effective parameters on *AOp*. Also, burden have the least effect in this regard.

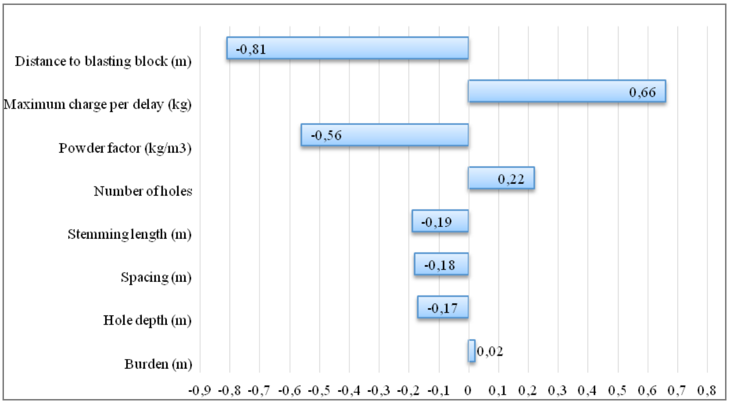



Fig. 7. Tornado analysis

Spider analysis of the AOp is shown in Fig. 8. As it is mentioned in this figure, changing in "maximum charge per delay" has the most effect on AOP. It is obvious that unlike the distance to blasting point, with increasing the amount of charge in each delay, AOp increases dramatically.

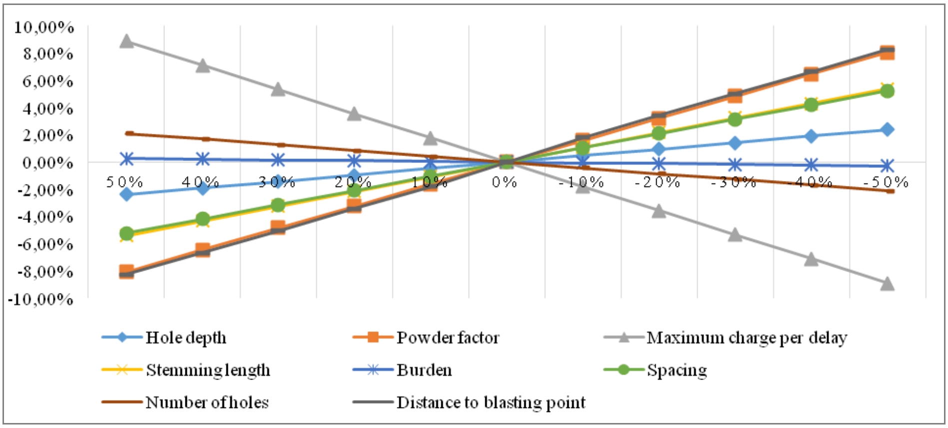



Fig. 8. Spider analysis

### 5.3. IMPACT OF INITIATION SYSTEM ON AOP

Initiation system is one of the most important parameter, which can cause the *AOp*. Using the detonating cord can produce high frequency and hence audible energy within the air overpressure spectrum. For solving this problem, detonating cord should be used as sparingly as possible, and any exposed lengths covered with as much material as possible (At least use 150 mm thick cover of sand or drill cutting to cover trunkline detonating cord). Because just a few feet of exposed cord can lead to significant amounts of audible energy and, hence, high air overpressure levels. On the other hand, exploding the detonation cord may damage the stemming and cause air blast. Using NONEL shock tube or electric systems instead of detonating cord is the another solution. These systems can reduce the wave superposition by increasing delay time among shots. Beside the above mentioned points, it is necessary to avoid blasting in cloudy weather, carry out blasting at midday and avoid blasting when strong winds are blowing towards the residence.

## 6. CONCLUSION

In this paper, in order to prediction of *AOp* phenomenon in blasting operation in open pit mines, application of various methods, i.e., bat algorithm, PSO-ANN model and conventional models were investigated. The following results were obtained:

– On the basis of the acquired results, the present study concludes that bat algorithm is a robust and versatile technique to improve the efficiency of blasting in open pit mines by controlling the undesirable phenomenon.

- Based on the blasting design parameters, a new mathematical equation was presented for calculating the *AOp*. The correlation coefficient and RMSE of the equation obtained were 83% and 2.94, respectively. The presented equation is location sensitive and it can use as a guidance for other open pit mines.
- The proposed mathematical model has been compared by available conventional AOp predictors and yields excellent blast results.
- The conventional methods, usually, overestimate the *AOp,* while, the metaheuristic models can estimate this phenomenon with more accuracy.
- Based on the sensitivity analysis, it was concluded that the most important parameters on the *AOp* phenomenon are the distance to blasting point, maximum charge per delay, powder factor.
- As the initiation system and climate conditions have a very important impact on *AOp,* it is recommended to investigate their effect on *AOp* in future studies.

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