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Application of simulated annealing for optimization of blasting costs due to air overpressure constraints in open-pit mines

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Abstract
Estimating the costs of blasting operations is an important parameter in open-pit mining. Blasting and rock fragmentation depend on two groups of variables. The first group consists of mass properties, which are uncontrollable, and the second one is the drill-and-blast design parameters, which can be controlled and optimized. The design parameters include burden, spacing, hole length, hole diameter, sub-drilling, charge weight, charge length, stemming length, and charge density. Blasting costs vary depending on the size of these parameters. Moreover, blasting brings about some undesirable results such as air overpressure, fly rock, back-break, and ground vibration. This paper proposes a mathematical model for estimating the costs of blasting operations in the Baghak gypsum mine. The cost of blasting operations in the objective function is divided into three parts: drilling costs, costs of blasting system, and costs of blasting labours. The decision variables used to minimize the costs include burden, spacing, hole diameter, stemming length, charge density, and charge weight. Constraints of the model include the boundary and operational limitations. Air overpressure in the mine is also anticipated as one of the model constraints. The non-linear model obtained with consideration of constraints is optimized by simulated annealing (SA). After optimizing the model by SA, the best values for the decision variables are determined. The value obtained for the cost was obtained to be equal to 2259 $ per 7700 tons for the desired block, which is less than the blasting costs in the Baghak gypsum mine.

1. Introduction

Drilling and blasting are the major unit operations in open-pit mining. In spite of all the efforts made to introduce mechanization in open-pit mines, blasting continues to dominate the production procedure in those mines. Currently, explosives make about 5% of the direct cost of production, and if the aggregate cost of drilling and blasting is taken together, this may go as high as 30% of the direct cost of production.

Drilling and blasting are the most fundamental and sensitive parameters affecting the economy and life of the mine. Drilling and blasting costs in any project can be as high as 25% of the total production cost. Proper adoption of drilling and blasting methods can significantly contribute to profitability, and thus optimization of these parameters is essential. Performing an optimal blast entails reducing the total cost of rock fragmentation, improving the efficiency of drilling operations, loading, haulage, and processing operations. Blasting and rock fragmentation depend on two groups of variables. One group has mass properties that are uncontrollable, and the other includes blasting design parameters that can be controlled and optimized. All the relevant parameters should be considered when designing a blast. The controllable parameters that should be considered are hole diameter, burden, spacing,

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stemming, sub-drilling, hole length, charge length, charge weight, and delay time.

In blasting, whenever an explosive is detonated, transient airblast pressure waves are generated, and these transitory phenomena last for a few seconds [1]. Only a fraction of explosive energy (20–30%) is used in the actual breakage and displacement of the rock mass. The rest of the energy is wasted, causing undesirable effects like ground vibrations, AOp, flyrocks, noises, back-breaks, and over-breaks [2]. AOp is an undesirable by-product of blasting that is directly related to some parameters such as blast design, weather, and terrain conditions. AOp is produced by a large shock wave from the explosion point into the free surface. Consequently, AOp is a shock wave, which is refracted horizontally by density variations in the atmosphere. An audible high frequency sound and a sub-audible low-frequency sound are two atmospheric pressure waves of AOp [3]. The minimum sound frequency that is detectable by human ear is 20 Hz, and sound frequencies lower than that are unhearable. However, there is a possibility to get a concussion with sound waves above 20 Hz. According to Kuzu *et al.* [4], AOp is known in terms of sound, which is measured in Pascals (Pa) and Decibels (dB). When AOp wave energy exceeds the atmospheric pressure (194.1 dB), the surrounding structures may be affected with some damage [5]. The average level and higher spectral frequencies in AOp tend to be higher due to explosions, whilst the amplitude of AOp decreases by 6 dB for every doubling of the distance between the blast and the recipient [6]. Based on the differences between the source spectra and the propagation conditions, the range of attenuation becomes smaller, i.e. -3.1 to -10 dB. An AOp level of the structural damage possibility is 180 dB, glass break is 130–150 dB, and window vibration is 110–130 dB. Therefore, many attempts have been made to keep AOp below 110 dB in critical areas where the public is concerned [4, 7, 8]. In general, AOp waves are produced from four main sources in blasting operations [9-11]:

1- Air pressure pulse (APP): displacement of the rock at bench face as the blast progresses.

2- Rock pressure pulse (RPP): induced by ground vibration.

3- Gas release pulse (GRP): escape of gases through rock fractures.

4- Stemming release pulse (SRP): escape of gases from the blast-hole when the stemming is ejected.

It is a well-established fact that different parameters can cause AOp. These parameters are categorized into two main groups: blast design parameters and rock mass properties [12-14]. Blast design or controllable parameters such as specific charge, charge weight per delay, burden, spacing, time delay interval, sub-drilling, stiffness ratio, and type of explosive material can be changed by engineers, whereas rock mass properties cannot be changed by them.

Very few research works have been conducted on the optimization of blasting and the related costs. All investigations in the area of prediction and optimization of blasting and its parameters include burden, spacing, hole diameter, hole length, stemming length, sub-drilling, powder factor, explosive type, charge length, and charge weight, and the blasting results include fragmentation, fill factor, back-break, flyrock, ground vibration, air over-pressure, and various mining issues such as the production rate, cut-off grade, equipment, and production planning. Regression analysis, empirical models, and artificial intelligence methods have been applied in previous studies. Jimeno *et al.* provided the basic equation for calculating the cost of each drilling meter based on the direct and indirect costs. Direct costs include maintenance, personnel, energy, grease, oil, bit, etc., and indirect costs include depreciation, insurance, taxes, etc. [15]. Eloranta obtained a connection between the cost of mineral haulage and the costs of drilling and blasting process on the basis of spesific charge and fragmentation [16]. In an article entitled "Optimum Blasting: Is it minimum cost per broken rock or maximum value per broken rock?", Kanchibotla studied the maximum profitability, costs, and optimum blasting in a gold mine and an open-pit coal mine based on computer simulations and field studies [17]. Awuah-Offei *et al.* forecasted the truck and shovel requirements using the SIMAN simulation [18]. Tangchawal used the threshold limit of damage and the probability method for vibration prediction and optimization [19]. Singh *et al.* made an attempt to predict ground vibration using an Artificial Neural Network(ANN) and multivariate analysis incorporating a large number of parameters that affect ground vibration [20]. Tawadrous used an ANN on blast design [21]. Bascetin and Nieto described the determination of a cut-off grade strategy based on Lane algorithm, adding an optimization factor based on the generalized reduced gradient (GRG) algorithm to maximize the project NPV [22]. Monjezi and Dehghan used the ANN technique to determine the near-optimum blasting pattern so that back-break is reduced [23]. Rajpot explored the effect of fragmentation specifications on blasting costs, and presented a model for investigating the impact of the hole diameter on the blasting requirements to achieve the fragmentation of d80 and calculating the blasting design parameters for dimensions of 75-350 millimeters [24]. Kuzu *et al.* used the operational and geological parameters in assessing blast induced airblast-overpressure in quarries [25]. Bakhshandeh Amnieh *et al.* investigated the potentials of ANN in the prediction of ground vibrations due to blasting in open-pit mines [26]. Khandelwal and Kankar made an attempt to predict the blast-induced air-overpressure (AOp) by support vector machine (SVM) using maximum charge per delay and distance from blast-face to monitor AOp station [27]. Usman and Muhammed analyzed the application of the PCA hybrid analysis based on the information and 31 blasting parameters obtained from a cement mine in northern Pakistan, and these parameters were used as a model for predicting the blasting costs [28]. Kulatilake *et al.* used the neural network model and multivariate regression analysis for the prediction of mean particle size in rock blast fragmentation [29]. Khandelwal and Monjezi tried to predict back-break in blasting operations of Soungun iron mine, Iran, incorporating rock properties and blast design parameters using the support vector machine (SVM) [30]. In an article, Anon obtained the cost of drilling and blasting in the North Park copper and gold mines in Australia through optimization of the blasting design and use of the Uni Tronic™ electrical blasting system, and succeeded in providing a better fragmentation with a lower specific charge [31]. Trivedi *et al.* predicted the distance covered by the flyrock induced by blasting using ANN and multi-variate regression analysis (MVRA) for a better assessment [32]. Afum and Temeng, in a paper, reduced the cost of drilling and blasting operations in an open-pit gold mine in Ghana in three pits through blasting optimization and the use of the Kuz-Ram model, and ultimately obtained the average fragmentation of 25 up to 56 cm [33]. Adebayo and Mutandwa studied the correlation among blast-hole deviation, size of rock fragments, and cost of fragmentation, and in their work, they used ANFO, heavy ANFO, and emulsion in hole with a diameter of 191 to 311 mm, and the results obtained showed that an increase in hole deviation led to an increase in the average size of the rock fragments, and the cost of drilling and blasting increased as well [34]. Jahed *et al.* presented the neuro-fuzzy inference system (ANFIS) and ANN models for the prediction of blast-induced air-overpressure (AOp) in quarry blasting sites [35]. Ghasemi *et al.* used the regression tree (RT) analysis and adaptive neuro-fuzzy inference system (ANFIS) for the assessment of back-break in open-pit mines [36]. Yari *et al.* developed an evaluation system for selection of the most suitable pattern among the previously performed patterns to provide an efficient production [37]. In a study, Ghanizadeh *et al.* collected the data from three copper mines in Iran to obtain a function of the hole diameter, bench height, uniaxial compressive strength, and joint set orientation, calculating the blasting cost per cubic meter as a linear model using the kamfar software and statistical methods [38]. Miranda *et al.* wrote an article on the numerical methods to find the minimum blasting cost compared to the traditional and experimental methods. Their model was based on the development of the blasting pattern with the automatic adjustment of the burden, spacing, stemming, sub-drilling, and number of holes in order to guarantee the production demand in terms of the blasting volume [39]. As it can be seen, few studies have looked at the blasting costs in mines. In addition, in articles written in the field of blasting cost study, the number of blasting design parameters used is very limited. In this research work, a mathematical model for estimating the blasting cost is not provided, and relationships are presented through regression and prediction by different methods.

Meta-heuristic methods are another set of methods used in optimization problems. Hajihassani *et al.* presented a new approach based on the hybrid ANN and particle swarm optimization (PSO) algorithm to predict AOp in quarry blasting [40]. Khan and Niemann-Delius provided production plans of open-pit mines using the PSO algorithm [41, 42]. Setin and Dowd Stenin focused on the optimization of multiple cut-off grades by genetic algorithm (GA) and compared the results obtained with those of the dynamic search and network searching methods. By maximizing the net peresent value, they set a cut-off grade for a block of three minerals [43]. Using GA, Ruiseco *et al.* investigated optimization of the waste-ore range as part of the mining operations [44]. Hasanipanah *et al.* used PSO to predict ground vibration caused by blasting [45]. Soleymani and Sattarvand focused on optimizing long-term production plans in open-pit mines [46]. Bahrami *et al.* designed hybrid models to predict groundwater inflow to an advancing open-pit mine and the hydraulic head (HH) in observation wells at different distances from the center of the pit during its advance. Hybrid methods coupling ANN with GA methods (ANN–GA) and simulated annealing (SA) methods (ANN–SA) were utilized [47]. Saghatforoush *et al.* used an ANN and the ant colony optimization (ACO) to solve the problem of flyrock and back-break in the Delkan iron mine [48]. Taheri *et al.* proposed a hybrid model for predicting blast-produced ground vibration in Miduk copper mine, Iran, using a combination of the ANN and the artificial bee colony (ABC) (codename, ABC-ANN) [49]. Ghasemi presented the application of PSO technique to estimate the back-break induced by bench blasting based on the major controllable blasting parameters [50].

One of the most important issues in mining operations is paying attention to the operation costs, which include drilling, blasting, loading, haulage, crushing, and processing. The cost of blasting operations can be reduced by optimizing the design parameters of blasting. Although optimization and cost reduction are the primary purposes of mining operations, few mines have actually achieved this end. There are two types of costs. One is the cost of the blasting operations including the cost of explosives, drilling, etc., and the other is the cost of the post-blasting operations including the cost of loading, haulage, crushing, milling, etc. It is also necessary to pay attention to the unwanted results of the blasting such as the air blast. This paper defines a relationship between the design parameters of blasting and the air blast by regression, and examines the blasting costs including the cost of drill-hole, cost of the blasting system, and mining labors' costs. A relationship between the design parameters of blasting and blasting costs due to air blast constraint is also determined in order to minimize the costs.

2. Mathematical modeling of costs

2.1. Objective function definition

Blasting operations in mines have different kinds of costs that can be taken into consideration in economic debates and thus increase profits to mines. Blasting operations can be divided into several sections, each with its own costs. One section involves the drilling of blast holes, which requires equipment for drilling with the corresponding costs. The next section is the cost of the blasting system. Depending on the type of blasting system used and its use for blasting the target block, the cost of blasting will vary. The third part of the costs of the blasting operations is the blasting labor costs. Depending on the number of labor used to blast, the cost will vary. The decision variables in the objective function are to minimize costs such as burden, spacing, hole diameter, stemming length, charge density, and charge weight.

The cost of hole drilling is determined by Eq. 1.

$$F_1 = n \times H \times C_1 \tag{1}$$

where F_1 is the cost of drill-hole ($), n is the total number of holes, H is the depth of hole (m), and C_1 is the cost of a drilling meter in inch ($) [51]. The following relations are also used:

$$n = n_1 \times n_2 \tag{2}$$

$$n_1 = \frac{L+D}{D+S} - 1 \tag{3}$$

$$n_2 = \frac{W+D}{D+B} - 1 \tag{4}$$

$$H = L_1 + T \tag{5}$$

$$L_1 = \frac{m}{\rho \times \frac{\pi D^2}{4}} \tag{6}$$

where n_1 is the number of holes in the row, n_2 is the number of holes in the vertical row, L is the length of the block (m), D is the diameter of the hole (m), S is the spacing (m), W is the width of the block (m), B is the burden (m), L_1 is the length of charge (m), T is the length of stemming (m), m is charge weight (kg), and ρ is the charge density (kg/m^3). Equations 2 to 6 are expansions of the relations in Lopez's book [51]. By putting Eqs. 3 and 4 in Eq. 2, and Eq. 6 in Eq. 5, and Eqs. 2 and 5 in Eq. 1, Eq. 7 is obtained:

$$F_1 = \left(\frac{L+D}{D+S} - 1\right)\left(\frac{W+D}{D+B} - 1\right)\left(\frac{4m}{\rho \times \pi \times D^2} + T\right) \times C_1 \times \frac{D}{0.0254} \tag{7}$$

A value of 0.0254 is used to convert inches to meters. Because of the more advantages and fewer disadvantages of the NONEL system compared to the other systems, as well as the use of this system in most mines, the NONEL system is considered as a system used in block blasting. Thus the cost of the blasting system includes two parts: the NONEL system and the hole charge costs, which are determined by Eq. 8:

$$F_2 = \left[\left((H+1+S)(n_1-1) + (H+1)\right) \times n_2 + (n_2-1) \times B\right] \times C_2 + \frac{\pi D^2}{4} \times (H-T) \times \rho \times n \times C_3 \tag{8}$$

where F_2 is the cost of the blasting system ($), C_2 is the cost of the NONEL per meter ($), and C_3 is

the cost of the charge per kilogram ($). By putting Eqs. 2, 3, and 4 in Eq. 8, Eq. 9 is obtained.
The costs of the blasting labors are comprised of three parts: labors required for blast hole charging, labors required for stemming, and labors required for the NONEL system costs, and are determined by Eqs. 10, 11, and 12, respectively:

$$F_2 = \begin{bmatrix} \left((H+1+S)\left(\frac{L+D}{D+S}-2\right) + (H+1) \right) \times \left(\frac{W+D}{D+B} - 1 \right) \\ + \left(\frac{W+D}{D+B} - 2 \right) \times B \end{bmatrix} \times C_2 + \frac{\pi D^2}{4} \times (H-T) \times \rho \times \left(\frac{L+D}{D+S} - 1 \right)\left(\frac{W+D}{D+B} - 1 \right) \times C_3 \quad (9)$$

$$K_1 = \frac{\pi D^2}{4} \times (H-T) \times \left(\frac{L+D}{D+S} - 1 \right)\left(\frac{W+D}{D+B} - 1 \right) \times \frac{C_4}{A_1} \quad (10)$$

$$K_2 = \frac{\pi D^2}{4} \times T \times \left(\frac{L+D}{D+S} - 1 \right)\left(\frac{W+D}{D+B} - 1 \right) \times \frac{C_4}{A_2} \quad (11)$$

$$K_3 = \begin{bmatrix} \left((H+1+S)\left(\frac{L+D}{D+S}-2\right) + (H+1) \right) \times \left(\frac{W+D}{D+B} - 1 \right) + \\ \left(\frac{W+D}{D+B} - 2 \right) \times B \end{bmatrix} \times \frac{C_4}{A_3} \quad (12)$$

where K_1 is the cost of the labor required for blast hole charging ($), K_2 is the cost of the labor required for stemming ($), K_3 is the cost of the labor required for the NONEL system ($), C_4 is the cost of the labor per hour ($), A_1 is the volume of the charge that a labor puts in the blast hole (m^3) in an hour, A_2 is the volume of the stemming that a labor puts in the blast hole (m^3) in an hour, and A_3 is the length of the NONEL system that a labor could charge in the blast hole (m) in an hour. Therefore, the blasting costs can be obtained from the combination of Eqs. 10, 11, and 12, which yields Eq. 13, where F_3 is the cost of the labors required for blasting ($). The objective function that, according to the parameters of blasting design, i.e. the decision variables, minimizes the costs of blasting operations, is determined by combining Eqs. 7, 9, 13, and 14.

3. Optimization methods for non-linear problems

Optimization methods for multivariate, non-linear programming problems fall naturally into three classes, which are: direct search methods, gradient methods, and intelligent optimization methods. Direct search methods require only the evaluation of the objective function. The use of partial derivatives of the objective function is not required. These methods are iterative: start with an initial guess of the solution and then proceed by generating a sequence of new estimates, each of which represents an improvement over the previous ones.

These optimization methods attempt to reduce the uncertainty space of the solution to the objective function by examining points near the estimated solution. The test points determine the direction of search in which the maximum is expected to lie. Random search method, Grid search method, uni-variate search technique, simplex search technique, pattern search method (Powell's method or Hooke and Jeeve's method), Rosenbrock's method of rotating coordinates, and alternating variable method are some of these methods [52, 53]. In gradient methods, the evaluation of the first and possible higher order derivatives of the objective function is required in addition to the objective function. These methods are useful in finding the optimum solution of continuous and differentiable functions. Steepest descent method, conjugate gradient method (Fletcher-Reeves), Newton's method, and variable metric method (Davidon-Fletcher-Powell) are examples of these methods [52, 53].
In the recent years, several researchers have taken an interest in the use of intelligent optimization methods to solve non-linear programming problems. These techniques have the ability to solve difficult problems and have become popular in many scientific domains. Genetic algorithm, Tabu search, and simulated annealing are some instances of such methods. Intelligent optimization methods can explore the search space better than the direct search methods for a given number of function evaluations, and are more likely to find the true global optimum.

$$F_3 = \frac{\pi D^2}{4} \times (H - T) \times \left(\frac{L+D}{D+S} - 1\right)\left(\frac{W+D}{D+B} - 1\right) \times \frac{C_4}{A_1} + \frac{\pi D^2}{4} \times T \times \left(\frac{L+D}{D+S} - 1\right)\left(\frac{W+D}{D+B} - 1\right) \times \frac{C_4}{A_2} \left[\begin{array}{l} \left((H+1+S)\left(\frac{L+D}{D+S} - 2\right) + (H+1)\right) \times \left(\frac{W+D}{D+B} - 1\right) \\ + \left(\frac{W+D}{D+B} - 2\right) \times B \end{array}\right] \times \frac{C_4}{A_3} \tag{13}$$

$$\begin{aligned} \min cost &= F_1 + F_2 + F_3 \\ &= \left(\frac{L+D}{D+S} - 1\right)\left(\frac{W+D}{D+B} - 1\right)\left(\frac{4m}{\rho \times \pi \times D^2} + T\right) \times C_1 \times \frac{D}{0.0254} \\ &+ \left[\begin{array}{l} \left((H+1+S)\left(\frac{L+D}{D+S} - 2\right) + (H+1)\right) \times \left(\frac{W+D}{D+B} - 1\right) \\ + \left(\frac{W+D}{D+B} - 2\right) \times B \end{array}\right] \times C_2 \\ &+ \frac{\pi D^2}{4} \times (H - T) \times \rho \times \left(\frac{L+D}{D+S} - 1\right)\left(\frac{W+D}{D+B} - 1\right) \times C_3 \\ &+ \frac{\pi D^2}{4} \times (H - T) \times \left(\frac{L+D}{D+S} - 1\right)\left(\frac{W+D}{D+B} - 1\right) \times \frac{C_4}{A_1} \\ &+ \frac{\pi D^2}{4} \times T \times \left(\frac{L+D}{D+S} - 1\right)\left(\frac{W+D}{D+B} - 1\right) \times \frac{C_4}{A_2} \\ &+ \left[\begin{array}{l} \left((H+1+S)\left(\frac{L+D}{D+S} - 2\right) + (H+1)\right) \times \left(\frac{W+D}{D+B} - 1\right) \\ + \left(\frac{W+D}{D+B} - 2\right) \times B \end{array}\right] \times \frac{C_4}{A_3} \end{aligned} \tag{14}$$

3.1. Simulated annealing

The simulated annealing (SA) algorithm is a simple, effective, and meta-heuristic optimization algorithm for the solution of NP optimization problems. Similar to most meta-heuristic algorithms, it has been established by modeling and simulating one of the nature's laws or phenomena. It has been presented based on substituting physical elements in the process of physical annealing (system state, state variation energy, temperature, and freezing state) with the elements of the optimization problem (possible solution, cost, neighborhood solution, controlling parameter, and heuristic solution) [54]. This algorithm consists of two basic mechanisms: 1) producing the substitute, and 2) an acceptance rule [55]. SA is a generic probabilistic approach for finding an approximation to the global optimum of a given objective function Φ [56-57]. From a previous solution S_i, another solution S_{i+1} is achieved through a random perturbation of one of the variables in S_i. The acceptance of S_{i+1} as a feasible solution is determined by the Metropolis criterion:

$$P_c(S_i \to S_{i+1}) = \begin{cases} 1 & if \;\; \Phi(S_{i+1}) \le \Phi(S_i) \\ \exp\left(\frac{\Phi(S_{i+1}) - \Phi(S_i)}{T}\right) & if \;\; \Phi(S_{i+1}) \le \Phi(S_i) \end{cases} \tag{15}$$

where T denotes a positive control parameter (also referred to as the annealing temperature). If S_{i+1} is accepted, a new solution S_{i+2} is derived from S_{i+1}, and the probability P_c ($S_{i+1} \to S_{i+2}$) is calculated with a similar criterion. Many iterations are run at every temperature, and then the temperature, is gradually reduced. In the preliminary steps, very high temperatures are adjusted so that worse solutions can be more probable to accept. With the gradual decrease in temperature, there is a less probability for the worse solution to be accepted in the final steps; therefore, the algorithm converges on a near-optimal solution. The flow-chart algorithm is given in Figure 1. To run the simulated annealing algorithm, it is necessary that, first, such annealing parameters as the annealing function, the temperature updating function, and the initial temperature be specified. The annealing function is either “Boltzmann” or “fast”, and the temperature updating function is selected from among exponential, logarithmic, and linear functions. The initial temperature can be defined both as a number or a function. Simulated annealing is one of the meta-heuristic methods that has been used to find the optimal solution of such different mining problems as optimally locating the additional drillholes [58], and controlling and guiding exploration and extraction operations [59]. Xia *et al.* also used simulated annealing and genetic algorithm for the optimal control of cobalt crust seabed mining parameters [60]. Luo *et al.* used a hybrid genetic and simulated annealing algorithm for the optimization of the seismic processing phase-shift plus finite-difference migration operator [61]. Tan *et al.* used the two algorithms of simulated annealing and Monte Carlo to search for the critical failure surfaces of the slope [62]. Soltani-mohammadi and Bakhshandeh Amnieh used simulated annealing to investigate ground vibration and calculate the permissible charge weight for blasting operations [63]. Soltani-mohammadi and Hezarkhani proposed a mathematical model to find the optimal location of additional drillholes where the information gathered from drillholes has the highest possible value. Due to the combinatorial nature of this model, a simulated annealing-based algorithm was used for its solution [64]. Soltani-mohammadi *et al.* tried to define the objective function with the aim of considering local variability in boundary uncertainty assessment by the application of combined variance. Thus in order to verify the applicability of the proposed objective function, it was used to locate the additional boreholes in the Esfordi phosphate mine through the implementation of metaheuristic optimization methods such as simulated annealing and particle swarm optimization [65]. Kurma optimized ore-waste discrimination and block sequencing through simulated annealing [66]. Safa et al. tested the applicability and efficiency of minimizing combined variance as the objective function of the additional sampling, adopted it in a salt marsh (east of Iran) on the basis of a simulated annealing-based algorithm [67], and proved this function to be efficient and applicable. Research on the application of simulated annealing algorithms shows that this algorithm has been used in various mining issues but there are no specific studies that discuss blasting costs as their main concern.

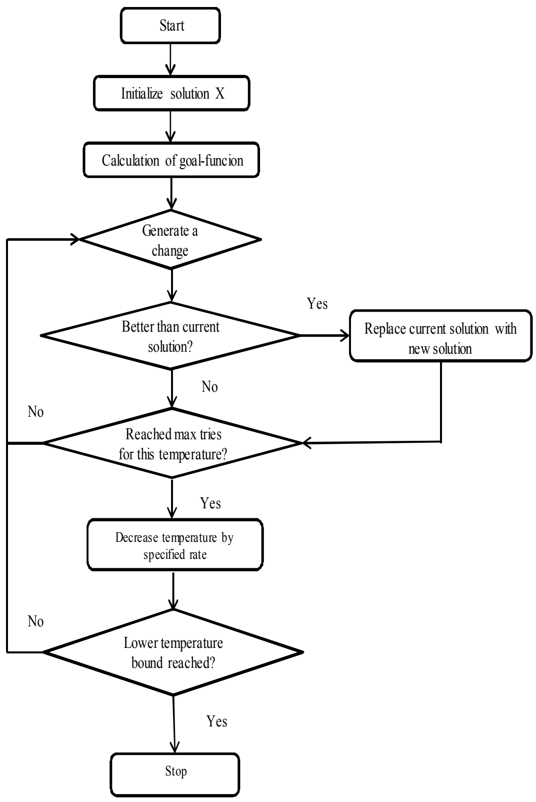

Figure 1. Simulated annealing algorithm.

4. Case study

Baghak gypsum mine is located 130 km northeast of Isfahan on the 30th km of the old Kashan-Natanz road. Geographically, the mine is located at a latitude of 33˚50′13″N and a longitude of 51˚37′36″E in the south of Kashan. The location of the Baghak gypsum mine is shown in Figure 2. The production capacity of this mine is 150000 tons per year. Blasting is carried out 9 to 10 times per month, depending on the weather conditions. In this case study, ammonium nitrate and fuel oil (ANFO) and the non-electric (NONEL) were used as the main explosive and initiation materials, respectively. The blast-holes were stemmed using fine gravels. During data collection, 70 blasting operations were investigated and the parameters of hole depth, charge weight, burden, spacing, stemming length, charge density, and distance from the blast-face were measured. The variations in the blasting design parameters are shown in Table 1.

Different patterns are used for blasting in mines. However, little attention is paid to the costs in choosing these patterns. In the Baghak gypsum mine, the decision variables, taken into account to minimize the cost of blasting operations, include burden, spacing, hole diameter, charge weight, charge density, and stemming length. Since the blasting operations in the Baghak gypsum mine are conducted close to the residential areas, AOp is an important blasting environmental impact in this mine. The nearest building to the mentioned quarry site is about 320 m far. By conducting the blasting operations in the Baghak gypsum mine, AOp sometimes causes damage to the surrounding residential areas, especially the buildings' windows. Therefore, AOp is a significant problem in this mine. In each blast, AOp was recorded using a VibraZEB seismograph. The AOp values were monitored using linear L type microphones connected to the AOp channels. A range of AOp values from 93 dB to 129 dB can be recorded by VibraZEB. The microphones have an operating frequency response from 2 to 250 Hz, which is adequate for measuring AOp accurately in the frequency range critical for structures and human hearing. All AOp values were recorded in front of the bench. Considering the location of the nearest building, the distance between the monitoring point and the blast-face was set in the range of 160–690 m.

The values for the parameters in the objective function for the Baghak gypsum mine are given in Table 2. Using ANFO for hole charge and NONEL system for blasting, costs of C_1, C_2, C_3, and C_4 were taken from the Baghak gypsum mine, and values of A_1, A_2, and A_3 were measured in the same mine. The length and width of the desired block, hole length, and rock density were 35, 10, and 11 m (considering 1 m of sub-drilling), and 2200 kg/m^3, respectively.

Table 1. Variations in the decision variables.

Decision variables	Symbol	Min	Max	Average	Standard deviation
Hole diameter [mm]	D	76	152	114	10
Spacing [m]	S	2.5	4.1	3.3	0.5
Burden [m]	B	1.4	3.2	2.3	0.5
Charge weight [kg per hole]	m	37	106	71.5	10
Charge density [kg/m^3]	ρ	730	900	815	10
Stemming length [m]	T	1.3	3	2.15	0.5

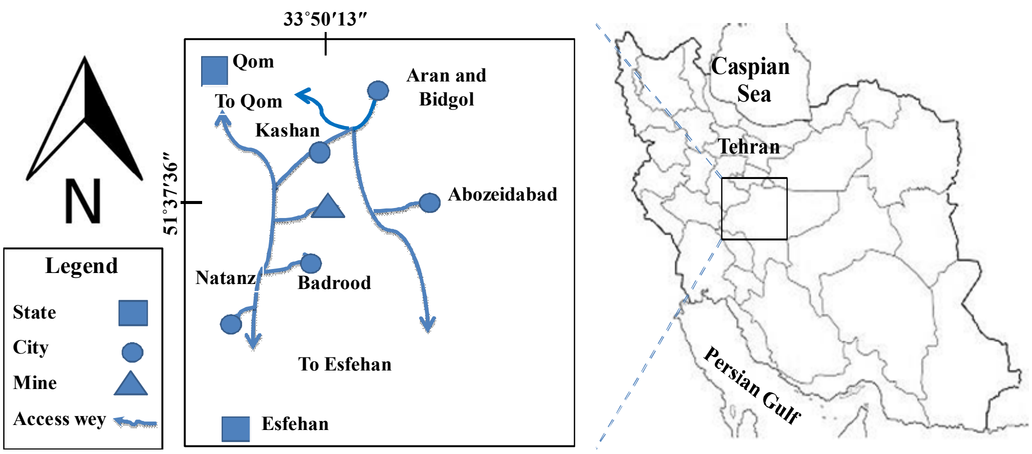

Figure 2. Location of Baghak gypsum mine.

Table 2. Values of the parameters in the subject function.

Parameters	C1	C2	C3	C4	A1	A2	A3
Value	0.54 [$/in.m]	0.135 [$]	0.6 [$]	3.2 [$]	14.2 [m^3/h]	0.106[m^3/h]	1980 [m/h]

4.1. Constraint of AOp

After collecting data and measuring the amount of air overpressure in the Baghak gypsum mine, a mathematical relation for air blast was determined according to Eq. 16. In this regard, by regression, the air overpressure is expressed in terms of hole length, stemming length, burden, spacing, charge weight, charge density, distance from the blast-face and hole diameter.

$$Aop = -0.002H^{1.811} + 0.003T^{4.991} - 0.004B^{5.267} + 0.003S^{3.919} + 0.052m^{1.085} + 0.012\rho^{0.67} - 0.252D^{0.793} + 0.119d^{1.041} + 119.111 \tag{16}$$

where AOp is the air overpressure (dB), H is the hole length (m), T is the stemming length (m), B is the burden (m), S is the spacing (m), m is the charge weight (kg), ρ is the charge density (kg/m^3), D is the distance from the blast-face (m), and d is the hole diameter (mm). As already mentioned, the air overpressure near the building should be less than 110 dB. Therefore, Eq. 16 is smaller than /equal to this number and is expressed as the most important constraint in modeling, which is presented in Eq. 17.

$$-0.002H^{1.811} + 0.003T^{4.991} - 0.004B^{5.267} + 0.003S^{3.919} + 0.052m^{1.085} + 0.012\rho^{0.67} - 0.252D^{0.793} + 0.119d^{1.041} + 119.111 \le 110 \tag{17}$$

4.2. Constraints

The constraints for the intended objective function are as follow:

$$24D + 24S + DS - 126D - 126B - BD \le 0 \tag{18}$$

$$\pi \times D^2 \times \rho \times T - 4m < 0 \tag{19}$$

$$8\pi \times \rho \times D^2 - 4m < 0 \tag{20}$$

$$4m - 14\pi \times \rho \times D^2 < 0 \tag{21}$$

$$T + \frac{4}{\pi} \times m \times \rho^{-1} \times D^{-2} - H = 0 \tag{22}$$

$$B - S \le 0 \tag{23}$$

$$D - B < 0 \tag{24}$$

$$D - S < 0 \tag{25}$$

$$0.15 \le D \le 0.2 \tag{26}$$

$$6 \le S \le 8 \tag{27}$$

$$5 \le B \le 7 \tag{28}$$

$$140 \le m \le 340 \tag{29}$$

$$800 \le \rho \le 900 \tag{30}$$

$$5 \le T \le 7 \tag{31}$$

$$D, S, B, m, \rho, T \ge 0 \tag{32}$$

$$-0.002 \times 10^{1.811} + 0.003T^{4.991} - 0.004B^{5.267} + 0.003S^{3.919} + 0.052m^{1.085} + 0.012\rho^{0.67} - 0.252 \times 320^{0.793} + 0.119d^{1.041} + 119.111 \le 110 \tag{33}$$

Eq. 18 shows that the number of holes in the vertical row is smaller than/equal to the number of holes in the row. Eq. 19 shows that the stemming length is smaller than the charge length. Eqs. 20 and 21 represent the interval of variations of charge length in the hole. Eq. 22 shows that the sum of the stemming length and the charge length must be equal to the hole length. Eq. 23 indicates that the burden is smaller than/equal to the spacing, and Eqs. 24 and 25 show that the hole diameter is smaller than the burden and spacing [51]. Boundary constraints are explained in Eqs. 26 to 32. Eq. 33 is a constraint of AOp in the mine. The distance from the nearest building to the mine and the hole length are 320 and 10 m, respectively. By placing these numbers in Eq. 17, this constraint is expressed as Eq. 33.

4.3. Application of simulated annealing for optimization

The concept of simulated annealing is based on a strong analogy between the physical annealing process of solids and the problem of solving large combinatorial optimization problems [52]. In a physical multiparticle system, 'annealing' is a thermal process for obtaining the lowest energy state of a solid in a heat bath. The process mainly comprises the following two steps [52]: step 1) increasing the heat bath temperature to a maximum value at which the solid melts, step 2) carefully reducing the temperature of the heat bath until the particles arrange themselves in the ground state of the solid.

In the simulated annealing method, the following two equivalences between a physical system and an optimization problem are assumed [52, 53] (i) states (arrangements of particles) of a physical system are equivalent to solutions of an optimization problem; (ii) the energy of a physical system is equivalent to a cost function of an optimization problem.

Using this optimization method, the purpose is to find the optimized values for the decision variables D, S, B, m, ρ, and T due to the important constraint of air blast and then the optimized formula as the mine cost. In order to apply the SA optimization method, the MATLAB program was used in this work.the SA parameters were determined by performing a simulated annealing of 20 times compared with the lowest cost. For example, one of the most important cases in the simulated annealing algorithm is the initial temperature value. This parameter is taken into consideration for determining the local optimal solution. Numbers 20, 50, 70, 100, 120, 150, 200, 250, 300, 400, and 500 are considered for solving the model. An algorithm was run 20 times for each number, and the results obtained were presented in Figure 3. The objective function's minimum was set to 150 at the initial temperature. After optimization with SA, the optimized average values obtained for the decision variables after 10 times of running the program are as follow: D = 119 mm, S = 3 m, B = 2.5 m, m = 63.8 kg, ρ = 730 kg/m^3, T = 2.2 m, and the min cost was equal to 2259 $ per 7700 tons. The values for the decision variables and the objective function as well as the standard deviation of the measured values are shown in Table 3. There were certain bits for hole drilling in the mine. Therefore, the nearest diameter of the hole drilling was 115 mm. The independent variables of number of holes in a row (n_1), number of holes in the vertical row (n_2), and the charge length (L_1) were equal to 10.25, 2.89, and 7.8 m, respectively. n_1 and n_2 cannot be decimal numbers. thus the resulting numbers were rounded up. The values of n_1 and n_2 were equal to 11 and 3, respectively.the fitness value chart is presented in Figure 4. This chart is one of the runs taken by the MATLAB software that stops at iteration 8647. Since the solutions obtained from the meta-heuristic methods are local optimal, the modeling was performed by the GAMS 3.0 software. The result is 2210 $ for the cost. This value differs from the simulated annealing algorithm with less than 2.2% and is very close to the optimal value.

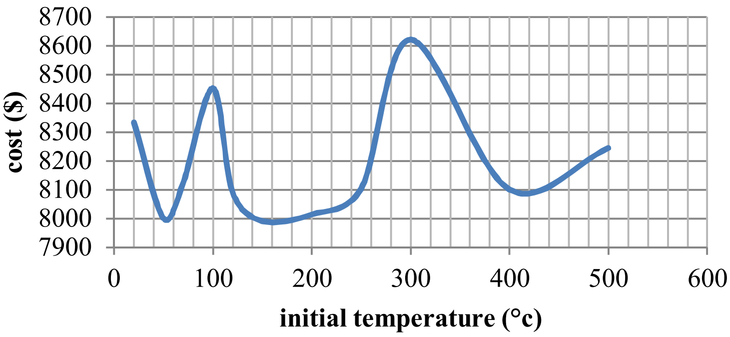

Figure 3. Objective function changes with respect to the initial temperature variations in the simulated annealing algorithm.

Table 3. Determined value of decision variables by simulated annealing algorithm.

Decision variables	X_1(m)	X_2(m)	X_3(m)	X_4(kg)	X_5(kg/m^3)	X_6(m)	Cost ($)
Average data	119	3	2.5	63.8	730	2.2	2259
Standard deviation	0.0015	0.0067	0	3.122	6.87	0.122	34.8

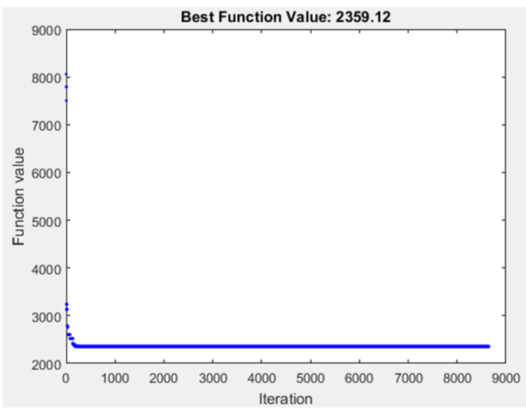

Figure 4. Best fitnes of values.

5. Results and conclusions

Blasting operations play a significant role in mining costs. Blasting operations are made up of a number of different sections, namely drill-hole, blasting system, and blasting labors, each with its own costs. Blasting operations depend on blasting design parameters including burden, spacing, hole diameter, hole length, stemming length, charge length, charge weight, sub-drilling, and delay time. By changing these parameters, the cost of blasting will also change. In addition, with the changes in these parameters, the results of blasting operations such as air blast, fly rock, ground vibration, and back break change and, if not addressed, may damage the mine and its surrounding buildings. Establishing a relationship between the blasting parameters and the costs of the three sections of drill-hole, the blasting system and the blasting labors can be an important step in controlling the cost of blasting. In this paper, the general aim was to propose the minimum cost of blasting operations for the Baghak gypsum mine due to the air overpressure phenomenon. A mathematical model was presented, taking into account the blasting design parameters and the cost of blasting operations. Decision variables for optimization of blasting cost are burden, spacing, hole diameter, stemming length, charge density, and charge weight. Also a mathematical relation for air overpressure and blasting design parameters was determined by regression. After measuring the required data and parameters, using the simulated annealing (SA) optimization method, the mathematical model was optimized due to its constraints and decision variables and the minimum cost was obtained. The most important constraint in this model was the air overpressure phenomenon. SA parameters were determined by performing a simulated annealing of 20 times compared with the lowest cost. After optimizing with the SA, the optimized average values obtained for decision variables after 10 times of running the program are as follow: D = 119 mm, S = 3 m, B = 2.5 m, m = 63.8 kg, ρ = 730 kg/m^3, T = 2.2 m, and the minimum cost was equal to 2259 $ per 7700 tons, which is less than the costs of blasting patterns in the mine. The standard deviations of the decision variables indicate that the values obtained are close to each other at each running of the algorithm. By running the model through the GAMS 3.0 software, the cost value of 2210 $ was determind. Therefore, the result obtained by the SA algorithm is less than 2.2% different from the result of the GAMS 3.0 software. In other words, the optimal local value is very close to the optimal value. The blasting block parameters in the mine included: D = 0.076 m, S = 2.5 m, B = 1.5 m, m = 50 kg, ρ = 800 kg/m^3, T = 1.5 m, and the cost was equal to 2974 $ per 7700 tons. The results obtained show that by applying the model in the mine, the cost of blasting operations can be improved by about 24%. Considering the phenomenon of air overpressure, the damage to the nearest building to the mine can be prevented. The major shortcoming was optimizing the pattern without considering the desired fragmentation and attention to the blasting consequences such as flyrock and vibration was not an applicable approach. Then independent variables of the number of holes in the row, the number of holes in the vertical row, and the charge length were determined.

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بهینه‌سازی هزینه‌های انفجار توسط الگوریتم تبرید شبیه‌سازی‌شده با در نظر گرفتن محدودیت انفجار هوا در معادن روباز

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چکیده:

تخمین هزینه عملیات انفجار یکی از پارامترهای مهم عملیات معدنکاری است. انفجار و خردشدگی سنگ به دو گروه از متغیرها وابسته است. گروه اول خواص توده سنگ بوده که غیر قابل کنترل می‌باشند و گروه دوم پارامترهای طراحی انفجار بوده که قابل کنترل و بهینه‌سازی می‌باشند. پارامترهای طراحی شامل بارسنگ، فاصله‌داری، طول چال، قطر چال، اضافه‌حفاری، وزن خرج، طول خرج، طول گل‌گذاری و چگالی خرج می‌باشند. هزینه انفجار با توجه به اندازه این پارامترها متغیر است. علاوه بر این انفجار شامل پدیده‌های ناخواسته مانند انفجار هوا، پرتاب سنگ، عقب‌زدگی و لرزش زمین است. در این پژوهش، یک مدل ریاضی برای تخمین هزینه عملیات انفجار در معدن گچ باغک ارائه می‌شود. هزینه عملیات انفجار در تابع هدف به سه بخش هزینه حفاری، هزینه سیستم انفجار و هزینه پرسنل انفجار تقسیم می‌شود. متغیرهای تصمیم مورد استفاده برای کمینه کردن هزینه شامل بارسنگ، فاصله‌داری، قطر چال، طول گل‌گذاری، وزن خرج و چگالی خرج است. محدودیت‌های مدل شامل محدودیت‌های مرزی و عملیاتی است. انفجار هوا در معدن به عنوان یکی از محدودیت‌های مدل پیش‌بینی شده است. مدل غیرخطی به دست آمده با توجه به محدودیت‌های مدل توسط الگوریتم تبرید شبیه‌سازی شده بهینه می‌شود. بعد از بهینه‌سازی مدل توسط الگوریتم، مقادیر بهینه متغیرهای تصمیم تعیین می‌شوند. مقدار تعیین شده برای هزینه انفجار برابر ۲۲۵۹ دلار به ازای ۷۷۰۰ تن بلوک مورد نظر بوده که این مقدار از هزینه به دست آمده در معدن کمتر است.

کلمات کلیدی: هزینه، عملیات انفجار، انفجار هوا، بهینه‌سازی، تبرید شبیه‌سازی شده.