Equipment Specific Optimum Blast-Design Using Genetic Algorithm

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Abstract: Design of blasting parameters plays an important role in the optimization of mining cost as well as cost of subsequent processing of ore. Drilling and handling costs are the major mining cost. This work presents an indirect optimization model for mining cost, through optimization of blasting parameters for a particular set of drilling and loading equipment.

Index Terms: Blast design, Crossover, Economic, Fragmentation, Genetic Algorithm, Mutation, Optimization, and Population.

1. Introduction

The increasing demand of the opencast mining due to enhanced demand for coal and minerals has led to use of the huge amount of explosive for blasting particularly in India. It is an established fact that when an explosive is detonated in a blast-hole only a fraction of the explosive energy is utilized in breaking the rock and the rest is lost producing ground vibration, noise and generation of fly-rock, etc. Hence there is a great demand for optimizing the blast design [1]. In fact efficient and effective blast design is the key to economic sustainability of a surface mining project. The efficiency of blasting operations can be evaluated in many ways depending on the purposes. In mining operations, it depends on mineralized or sterile zone. In mineralized zone the aim is to produce a particular fragment size suitable for ore handling and processing. In sterile zone, required fragments size is dictated by handling and disposal issues only [2]. Despite significant developments have achieved in explosive technology, but much progress has not been observed in effective utilisation of explosive energy mainly due to the complex nature of the problem. Monitoring of the blasted muck handling operations is a widely used technique for evaluation of blasting efficiency. Handling of muck is primarily governed by fragmentation. An example is the DIGMATE system developed by McDonnel Douglas Electronics, Co. which evaluates the productive performance of a dragline in coal mining operations [3]. Blasting also causes ground vibration, produces noise and generates fly rock. When the ground vibration passes through the surface structures, it induces vibration in these structures also. These induced vibrations may produce a resonance in the structures if its frequency matches with the natural frequency of the structures. This leads to the damage of the structures. Frequency and peak particle velocity (PPV) are most commonly used parameters for assessment of ground vibration [1].Therefore the optimum blast design should result effective fragmentation for efficient operation of the blasted muck handling equipment, efficient utilization of explosive energy, control of associated hazards like ground vibration, noise and fly rock generation. Morin and Ficarazzo 2006 [4] have used Monte Carlo simulation as a tool to predict fragmentation in blasting based on the Kuz-Ram model. A plethora of studies has been reported on the efficient blast design with little importance on the drilling and blasted muck handling equipment. But sometimes it happens that the mining organizations have to use a particular set of these equipment shifted from another closed down unit, procured before the blast design is finalised, interested to use certain models due to added advantages. Therefore, blast design not only has to be efficient, but also has to be effective for this equipment set. In this paper a Genetic Algorithm (GA) based model has been used to optimize the blast design process. The proposed model takes into account the explosive parameters, rock parameters, blast-hole parameters for efficient and effective blast fragmentation suitable for handling the blasted muck and delimiting the blasting hazards like, ground vibration, noise, and fly rock.

2. A Brief Review of Genetic Algorithm

Genetic algorithms (GAs) are search techniques based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a randomized information exchange to form a search algorithm with some of the innovative flair of human search. In every generation, a new set of artificial creatures is created using bits and pieces of the fittest of the old; an occasional new part is tried for good measure. They efficiently exploit information to speculate on new search points with an expected improved performance [5].GA is different from traditional optimization and search procedure in the following ways:

1. GAs work with a coding of parameter set, not the parameter themselves.
2. GAs search from a population of points, not a single point.
3. GAs use objective function information, not derivatives or other auxiliary knowledge.
4. GAs use probabilistic transition rule, not deterministic rules.

A simple Genetic Algorithm that yields good results in many practical problems is composed of three operations:

1. Selection
2. Crossover
3. Mutation

3. A Prelude to Blasting in Surface Mines

3.1 Rock fragmentation

Based on his studies in Quebee-Cartier iron open pit mine, Mackenzie 1966 [6] presented his classical conceptual curves showing the cost variability of different unit operations in mining(Drilling, Blasting, Loading, Hauling, Crushing) with the degree of fragmentation, measured in terms of specific surface m^2/t area and mean fragment size[7]. Mackenzie's objective was to determine the cost curve based on the mean fragmentation size. He showed that loading, hauling and crushing cost decreased with increasing rock fragmentation while drilling and blasting cost increased with increasing rock fragmentation. The summation of cost resulted in an inverted cost curve with a minimum fragmentation cost and thus the optimum fragmentation size [6]. This concept of optimum fragmentation that minimizes the entire cost of mining operation is critical for optimizing a drilling and blasting program. Mechanical crushing and grinding are expensive operations at a mine site and therefore considerable cost and throughput benefits can be obtained by breaking the rock using explosives effectively.[8],[9],[10]. Prediction of the degree of fragmentation of a blast design offers significant advantages. It provides muck with a desirable size distribution and specifications. Knowing the size distribution for a particular blast and rock-mass conditions, the mining company can adapt the blast design if suitable or take into account that are not meeting the required specification. Such advantage can also be used for selecting material handling equipment, crushers and conveyor systems. The factors that have been identified as of importance for fragmentation process grouped into three categories:

1. Explosive parameter
2. Charge loading parameter
3. Rock parameter

The main attributes of explosive parameters are density, detonation velocity, detonation impedance, gas volume and available energy. The relative ability of different explosives to transmit their pressure to stress a given rock is a function of their detonation impedances and is defined as the product of density and detonation velocity of the explosive. Detonation velocity can be understood as the velocity with which shock waves propagate through the blast hole. Charge loading parameters include the diameter, length of charge, stemming, type of initiation and point of initiation. Theoretical studies show that changing the diameter, length and point of initiation for the charge of given explosive can produce larger differences in the peak strain in the rock than using an explosive with a considerably different detonation pressure. To reduce the environmental impacts and maintain the desirable fragment sizes, air-decking is also tried and applied. Air-decking, basically, is an empty space in a blast hole. It could be located at the bottom, middle or top of the charge column. Rock parameters that influence the action of explosives and fragmentation are density, strain wave propagation velocity, characteristic impedance, energy absorption, compressive strength, tensile strength, variability of rock and structure. The characteristic impedance of the rock i.e., the product of density of rock and the velocity of the shock waves in the rock plays an important role. The susceptibility of rock to tensile failure by stress pulse reflection is indicated by blast-ability coefficient of rock which is defined as the ratio of compressive strength to tensile strength. Increased water content seems to reduce the energy absorption and thus makes breakage easier. In situ stress fields may cause preferred direction of breakage in rock. Blasting pattern should be designed to take advantage of rock structure such as by planning free faces parallel rather than perpendicular to marked vertical joint planes or in rocks with well-developed bedding plane, by keeping the free face perpendicular rather than parallel to the direction of dip. Kuznetsov1973 [11] formulated a semi-empirical equation based on field investigation and a review of published data that relates the mean fragment size to the mass of explosive, the volume blasted and the rock strength. This equation expresses the mean fragment size and the applied blast energy per unit volume of rock (powder factor) as a function of rock type i.e.

$$X_m = A * \left(\frac{V_0}{Q_T}\right)^{0.8} * Q_T^{\frac{1}{6}} \ldots\ldots\ldots \quad (1)$$

Where, X_m = mean fragment size (cm).

A =Rock factor.

V_0 = Rock volume (m^3) broken per blast-hole = Burden × Spacing ×Bench Height.

Q_T = mass (kg) of TNT containing the energy equivalent to the explosive charge in each blast-hole.

Rock factor $(A)$is also called as blast-ability index. Blast-ability is defined as how easy it is to explore a rock mass under specified blast design. Rock factor (A) depends on Rock Mass Description (RMD), Joint Factor (JF), Rock Density Index (RDI) and Hardness Factor (HF). The expression of rock factor can be given by the expression as given below.

$$A = 0.06 * (\mathrm{RMD} + \mathrm{JF} + \mathrm{RDI} + \mathrm{HF}) \quad \ldots \quad \ldots \quad \ldots \quad (2)$$

Cunningham 1983 [12] and later Lilly 1986 [13] have presented methodologies for evaluating the rock factor(A) based on the Geo-mechanical properties of rock to be blasted. The value of rock factor is basically calculated from geological data such as in-situ block size, joint spacing, joint orientation, rock specific gravity, Young's modulus and unconfined compressive strength. It varies from 8-12. For very soft rock it can be 8, for medium hard rock can be 10 and for a very hard rock it could be 12. Cunningham 1983 [12] shows how the basic equation (1) can be modified to treat various types of explosives relative to the performance of ANFO (ammonium nitrate–fuel oil, the most common bulk mining explosive) mixtures with the use of following equations:

$$Q_T = Q_e \frac{S_{ANFO}}{115} \quad \ldots \quad \ldots \quad \ldots \quad (3)$$

Where Q_e= mass of explosive being used (Kg).

S_{ANFO}= Relative weight strength of the explosive relative to ANFO.

The equation can also be stated as a function of the specific charge K (Kg of explosive/m^3 of rock) using

$$\frac{V_0}{Q_e} = \frac{1}{K} \quad \ldots \quad \ldots \quad \ldots \quad (4)$$

Equations (3) and (4) can be used to rewrite equation (1) for calculating the mean fragmentation size $X_m$for a given powder factor as

$$X_m = A * (K^{-0.8}) * {Q_e}^{1/6} * \left(\frac{115}{S_{ANFO}}\right)^{19/30} \quad \dots \quad \dots \quad \dots \quad (5)$$

3.2 Prediction of Blast-induced vibration level

A number of researchers [14], [15] have studied blast-induced vibration to formulate and predict the damage level on an empirical basis. Interactions between the vibrations and propagating media give rise to several types of waves, including direct compression waves and shear body waves, refracted body waves, both horizontally and vertically polarized surface waves. As a practical way, analysis of damage to structures does not require knowledge of what happens between the source and the receiver or of the type of wave. Many years of experience have shown that the PPV values from blast-induced vibrations for cylindrical explosive geometry (cylindrical charge: length (L) to diameter (D) ratio greater than 6:1) are related to the scale distance (SD). One of the most widely used PPV predictors established by USBM is given below.

$$PPV = H_s(SD)^{-\beta} = H_s * \left(\frac{R}{\sqrt{Q_e}}\right)^{-\beta} \quad \dots \quad \dots \quad \dots \quad (6)$$

Where,

PPV= peak particle velocity (mm/s or in/s) at a distance of R (m).

H_s&β = site factors.

SD=scaled distance for cylindrical charge (m/kg$^{0.5}$ or ft/lb$^{0.5}$) =$\frac{R}{\sqrt{Q_e}}$where R is the distance from the blast-hole.

4. Blast Design Optimization using Genetic Algorithm

Application of GA to optimize blasting provides a set blast-design parameters that results efficient and effective fragmentation for a particular combination of drilling and loading equipment. The first step in the optimization of blast-design using GA is the formulation of fitness function and the list of boundary restrictions.

4.1 Formulation of fitness function for blast design problem

In GA, survival of a solution is judged by its fitness value calculated from the formulated fitness function. As the degree of fragmentation is in the primary focus in blast design, formulation of fitness function using the concept of mean fragmented size is logical. The Optimum blast design aims to blast the rock to a fragment size so that the contractor may carry out the process of mucking the material at a minimum possible time with the given size of excavator when blast holes are drilled by the existing drill machine (s).Therefore excavators load the blasted materials onto the dumper in the minimum number of scoops. Hence there is a need to maximize the number of blasted rock fragments by the excavator per scoop. Here we assume that the proposed blast design is ideal and the rock breaks into fragments of nearly of uniform size. Thus, assuming a swell factor of 0.74, and fill factor of 0.95, the fitness function as well as the objective function is as follows:

$$\text{Maximixe} \quad N = \frac{\mathrm{V_b}*0.74*0.95}{\left\{\frac{4}{3}*\pi*\left(\frac{\mathrm{X_m}}{2}\right)^3\right\}} \dots \quad \dots \quad \dots \quad (7)$$

Where

V_b= Bucket capacity of the excavator (m^3)

X_m= mean fragment diameter (m)

N= number of fragments per scoop.

Also,

$$Q_T = Q_e * \frac{S}{2.72*10^6} \quad \dots \quad \dots \quad \dots \quad (8)$$

Where

S = Absolute weight strength of the explosive being used (j/kg) and $2.72 * 10^6$J/kg is the absolute weight strength of TNT.

Now,

$$Q_e = \pi * \left(\frac{D}{2}\right)^2 * (H + J - T) * d \quad \dots \quad \dots \quad \dots \quad (9)$$

Where,

D =Borehole diameter (m)

H = Bench Height (m)

J = sub-grade drilling (m)

T = stemming (m)

d = density of explosive (kg/m^3)

Using equations (1, 8& 9), the objective function equation (8) can be modified as:

$$N = \frac{V_{b*}0.74 * 0.95}{\frac{4}{3} * \pi * 0.332 * A^3} * \left\{\frac{D^{3.8} * (H + J - T)^{1.9} * d^{1.9}}{\left(B * S_p * H\right)^{2.4} * S^{-1.9}}\right\}$$
$$= K * \left\{\frac{D^{3.8} * (H + J - T)^{1.9} * d^{1.9}}{\left(B * S_p * H\right)^{2.4} * S^{-1.9}}\right\} \dots (10)$$

Where, k is a constant for a set of rock parameters and loading equipment. Equation (10) shows that the fitness function has a set of variables, namely: Burden (B), Spacing (S_p), Bench Height (H), Sub-grade drilling (J), Stemming (T), Weight strength of explosive (S), Density of explosive (d), Borehole Diameter (D), and Bucket capacity (V_b). A particular set of excavator and drill machine, Bucket capacity (V_b)and Borehole Diameter (D) are fixed. Developed methodology has been used for popular excavators' models of 3.8 m^3, 4.5 m^3, 5.0 m^3, 8.3 m^3, 10.0

m^3, 16.5 m^3 and 20.0 m^3 bucket capacity and drilling machines with blast-hole diameters 63mm, 75mm, 115mm, 150mm, 229mm and 250mm. For a 16.5 m^3 excavator the equation becomes

$$N = 5738.5819 * \frac{D^{3.8} * (H+J-T)^{1.9} * d^{1.9}}{(B*Sp*H)^{2.4} * S^{1.9}} \quad \dots \quad \dots \quad \dots \quad (11)$$

4.2 Boundary restriction to the blast design problem

Boundary restrictions for the feasible solution sets help to achieve faster convergence to search heuristic algorithm like GA. For a blast design problem the limitations are the usual range of variables, i.e. Burden (0.616 m ≤ B ≤10.9 m), Spacing (7.084 m ≤ S_p ≤12.53 m), Bench Height (15 m ≤ H ≤18.3 m), Sub-grade drilling (0.616 m ≤ J ≤6.45 m), Stemming (3.08 m ≤ T ≤14.17 m), Weight strength of explosive (1.6j/kg≤ S ≤2.4j/kg), Density of explosive (1.3$g/cm^3 \leq d$ ≤1.9g/cm^3) and PPV (≤ 10mm/s).For the minimization of ground vibration one can directly use the following expression derived from equations (6 &9), i.e.,

$$PPV = \frac{H_s * R^{-\beta}}{\pi^{\frac{-\beta}{2}} * \left(\frac{D}{2}\right)^{-\beta} * (H+J-T)^{\frac{-\beta}{2}} * d^{\frac{-\beta}{2}}} \dots \quad \dots \quad \dots \quad (12)$$

For standard values of $H_s = 1200, \beta = 1.6 \; and \; R = 200 \; m$equation (12) reduces to

$$PPV = 0.00248579 * \frac{1}{\left(\left(\frac{D}{2}\right)^2 * (H+J-T) * d\right)^{-0.8}} \dots \quad \dots \quad \dots \quad (13)$$

5. Result and Discussion

GA proves to be an effective tool in designing blast round for opencast mines. Proposed GA based blast design model gives the most favourable values of design parameters like burden, spacing, sub-grade drilling, stemming and absolute weight strength of explosives for a particular hole-diameter which is controlled by the used drilling equipment. Output parameter values are in close agreement with those obtained from other well established empirical methods. The proposed model was run on Matlab-2009 for the computation of all the parameters. For the most common excavator (16.5 m^3) and drill machine (115 m) the fitness function with the set of constraints are as follows.

$$Maximize, \; N = 5738.5819 * \frac{D^{3.8} * (H+J-T)^{1.9} * d^{1.9}}{(B*S_p*H)^{2.4} * S^{-1.9}} \dots\dots \quad \dots \quad (14)$$

Subjects to constraints

$$PPV = 0.00248579 * \frac{1}{\left(\left(\frac{D}{2}\right)^2 * (H+J-T) * d\right)^{-0.8}} \leq 10$$

100≤ $D \leq$ 445
15≤ H ≤18.3
0.616≤ J ≤6.45
3.08≤ T ≤14.17
1.3≤ d ≤1.9
0.616≤ B ≤10.9
7.084≤ Sp ≤12.53
1.6≤ S ≤2.4

Taking D=115mm

$$Maximize, \; N = 3.885584675 * \frac{10^{11} * (H+J-T)^{1.9} * d^{1.9}}{(B*Sp*H)^{2.4} * S^{-1.9}} \dots\dots\dots \; (15)$$

Subjects to constraints

$$1.625297955 * \frac{1}{((H+J-T)*d)^{-0.8}} \leq 10$$

15≤ H ≤18.3
0.616≤ J ≤6.45
3.08≤ T ≤14.17
1.3≤ d ≤1.9
0.616≤ B ≤10.9
7.084≤ Sp ≤12.53
1.6≤ S ≤2.4

Genetic algorithms work with a coding of variables and need design space to be converted into genetic space. As GA uses a set of points at a time from a population in contrast to the single point approach by traditional optimization methods, therefore, it generates a population of points at the end of the iteration. The best set of point in the population reaches the optimal solution. At each step, GA selects individuals at random from the current population to be parents and uses them to reproduce the children for the next generation. Over successive generations, the population evolves toward an optimal solution. The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

1. Selection rules select the individuals, called parents that contribute to the population in the next generation.
2. Crossover rules combine two parents to form children for the next generation.
3. Mutation rules apply random changes to individual parents to form children

As discussed above we have to deal with the population of points rather than a single point called as population size. More the population size better would be the accuracy of results. So in our case we have taken the population size-1000. There are a number of selection strategies such as Roulette-wheel selection, Tournament selection, Rank selection, stochastic uniform selection, etc. In this model, selection rule used is stochastic uniform selection. Stochastic uniform lays out a line in which each parent corresponds to a section of the line of length proportional to its expectation. The algorithm moves along the line in steps of equal size, one step for each parent. At each step, the algorithm allocates a parent from the section it lands on. The first step is a uniform random number less than the step size. Stochastic uniform lays out a line in which each parent corresponds to a section of the line of length proportional to its expectation. The algorithm moves along the line in steps of equal size, one step for each parent. At each step, the algorithm allocates a parent from the section it lands on. The first step is a uniform random number less than the step size. Crossover combines two individuals, or parents, to form a new individual, or child, for the next generation. After the completion of the selection phase, then the crossover operator comes into play its role. Crossover operator is a recombination operator and selects a pair of two individual strings for mating, then a cross-site is selected at random along the string length and the position values are swapped between two strings following the cross-site. There exist many types of crossover operations in genetic algorithms such as single-site crossover, Two-point crossover, multipoint crossover etc. In our work scattered crossover is used for obtaining results. Scattering creates a random binary vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child. In GA the term crossover rate is usually defined as the ratio of the number of pairs to be crossed to some fixed population. Typically varies from 0.5 to 1 and here it is assumed as 0.8. After cross over, the strings are subjected to mutation. Mutation of a bit involves flipping it, changing 0 to 1 and vice versa with a very small mutation probability. The Mutation rate is the probability of mutation which is used to calculate the number of bits to be muted. The probability varies from0.001 to 0.5. Taking equation (14) as the fitness function, the proposed model was run on Matlab-2009, setting population size 1000, population type-double vector, Uniform-selection, Scattered-crossover and Mutation constraints dependent. After three iterations, the obtained output gives the blast design parameters that are as follows:

$$H = 15m$$
$$J = 0.622m$$
$$T = 8.518m$$
$$d = 1.353g/cm^3$$
$$B = 0.616m$$
$$Sp = 7.084m$$
$$S = 1.6j/kg$$

Figure 1 shows the best function value of each generation with the number of iterations. Here the program terminates after 3 iterations and the fitness value at the end of the iteration is shown in the figure 3 that clearly shows that the fitness value increases after first iteration and after that it remains almost constant and the program terminates after iteration 3.

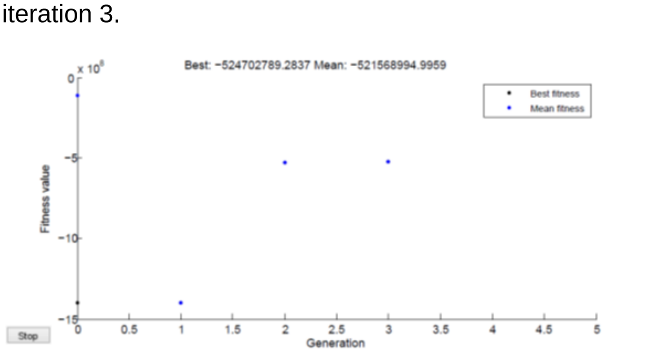

Fig:-1: *Change of Best-fitness value with generation*

6. Conclusion

The efficacy of the proposed model primarily depends on the selection of the fitness function. Judicial selection of the fitness function translates to excellent blast design. As GA is basically a mathematical tool which operates on the fitness values of the selected strings which are obtained by mathematical manipulations on the various variables. So there are chances that the obtained solution may not be a practical one. This problem can be eliminated with the prior knowledge of the parameter values and imposing restriction so that they may be corrected at initial stage and hence take the benefit of the tools through quick optimization process.

7. References

[1] Khandelwal, Manoj and Singh, T.N., 'Prediction of blast induced ground vibration and frequency in opencast mines', Journal of sound and vibration, 2006, 289, 711-725.

[2] Hudson J.A, Comprehensive rock engineering 4; Pergamon; Oxford, 1993, 15-18.

[3] Williamson S., Mackenzie C. and O' Laughlin H., 'Electrical shovel performance as a measure of blasting efficiency', Trans 1st Int. symp. Rock Fragmentation Blasting 2, 1993, 625-635.

[4] Mario A. Morin and Francesco Ficarazzo, 'Monte Carlo Simulation as a tool to predict blasting fragmentation based on Kuz-Ram model', Computers and Geosciences 2006, Vol.32, Issue3, 352-359.

[5] Goldberg, David E., 'Genetic Algorithm in search, optimization and machine learning'; 1987, Pearson Education (P) Ltd., Singapore.

[6] Mckenzie, A.S., 'Cost of Explosives-do you evaluate it properly? ', Mining Congress Journal, 1996, 52, (5), 32-41.

[7] Chakraborty, A.K. and Jethwa, J. L., 'Feasibility of air-deck blasting in various rock mass conditions – A case study', Proceedings of the fifth international symposium on rock fragmentation by blasting – FRAGBLAST-5, 1996, 343-348.

[8] Eloranta, J., 1997:'The efficiency of blasting versus crushing and grinding', The Journal of Explosives Engineering, 1997, 12–14.

[9] Simangunsong, G.M., et al., 'Optimization of blasting fragmentation base on optimized comminution', Proceedings Annual Meeting, Japan Explosives Society, 2003, Tokyo.

[10] Katsabanis, P.D., et al., 'Blasting effects on the grindability of rocks', Proceedings of the International Society of Explosives Engineers 30th Annual General Conference, 2004, New Orleans, LO.

[11] Kuznetsov, V.M., 'The mean diameter of the fragments formed by blasting rock', Sov Min Science, 1973, 9,144-148.

[12] Cunningham, C. V. B., 'The Kuz-Ram model for prediction of fragmentation from blasting', Proceedings of the First International Symposium on Rock Fragmentation by Blasting, 1983, 439-454, Lulea, Sweden.

[13] Lilly, P.A., 'An empirical method of assessing rock mass blastability', Proceedings of Large Open pit Planning Conference, 1986, 89-92, Parkville.

[14] Kuzu, Cengiz, 'The importance of site-specific characters in prediction models for blast-induced ground vibrations', Soil Dynamics and Earthquake Engineering, 2008, 28, (5), 405-414.

[15] Singh, R.D, 'Principles and Practices of Modern Coal Mining'; 1997, New Age International (P) Ltd., New Delhi.