# Reconstruction time of a mine through reliability analysis and genetic algorithms

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## Synopsis

A mining system consists of many sub-systems such as drilling, blasting, loading, hauling, ventilation, hoisting and supporting. During mining operation, these sub-systems may experience various problems that stop the operation because of possible environmental, equipment and safety issues. In order to ensure delivery contracts in the required quality and safe mining medium, the operation should be, at least, performed in the specified reliability level of the system. If the system reliability decreases below the specified level, there will be safety and financial losses for the mining company. Therefore, the mine should be maintained by a reconstruction procedure to guarantee the operation continuity. Given that each sub-system has a different reliability function and maintenance cost, the determination of reconstruction time will be a complicated decision making problem. In this paper, the determination of reconstruction time is formulated as a nonlinear optimization problem and solved by genetic algorithms (GA). A case study was conducted to demonstrate the performance of the approach for an underground operation. The results showed that the approach could be used to determine the best action time.


Keywords: mining system; genetic algorithms; reconstruction time; reliability analysis

## Introduction

Each sub-system of mine production cycle will affect the availability of the production system. Many failures or disturbances occur in these sub-systems depending upon equipment type and properties, mining method, geological structure and rock characteristics. Possible problem sources of each sub-system are summarized shortly as follows:

- ➤ Drilling is the first process of the mining cycle and aims to open holes within rock masses. Drilling equipment features such as drill power, blow energy, rotary speed, thrust, rod design and fluid properties, and drilling patterns such as hole size, length and inclination will have influence on the system reliability.
- ➤ Blasting is a well-known rock fragmentation method performed in mining operations. In addition to rock properties and water conditions, other parameters affecting the reliability are explosives characteristics such as type, strength, detonation velocity, density, water resistance and detonation pressure.
- ➤ When the rock is fragmented, the materials are loaded to a transportation vehicle. In this sub-system, the properties of loading equipment, such as bucket capacity, travel speed, digging range and available power, are significant reliability parameters.
- ➤ Materials loaded are transported by haulage (horizontal) or hoisting (vertical). The performance is characterized by haul distance and properties of operation equipment.
- ➤ If there is no appropriate ventilation in an underground operation, the processes described above cannot be implemented. The availability parameters of process are determined by air quantity and speed, properties of ventilation equipment, size of openings and rock properties.
- ➤ Another vital sub-system is the support design, which is affected by opening sizes, support material, rock properties and types.

System reliability is defined by the reliabilities of sub-systems and the way sub-systems are configured. If the system reliability is below the acceptable reliability level, some environmental, financial and safety problems may take places. For instance, the operation may experience gas, dust and noise disturbances, subsidence in the ground, the collapse of mine walls, unsafe medium for personnel and delaying ore delivery. In order to avoid these problems, the mining company

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has to take action to prevent losses in an appropriate timing. The determination of maintenance time is a significant decision making problem. If you take action too early, it will be an unnecessary cost to the company. In other words, the company will prefer delaying this reconstruction as long as possible to maximize net present value of the venture. If the action timing is too late, unavoidable accidents, negative environmental impacts and financial losses will occur. In order to increase the system reliability via maintenance, the controllable variables described in the sub-systems should be improved. This improvement, of course, requires cost. Depending upon sub-system complexity, geological and geomechanical factors, and technological restrictions, improvability of each sub-system varies. The relative importance of each sub-system is determined by the feasibility concept[1] and is given as:

$$I_{R,i} = \frac{\partial R_s}{\partial R_i} \qquad [1]$$

where $I_{R,i}$ is the feasibility of item $i$ and, $R_s$ and $R_i$ are the reliabilities of system and item, respectively.

Because of the reasons given above, some sub-systems can be improved more cost-effectively. The level of improvability depends upon whether disturbance factors are controllable or uncontrollable. As the feasibility increases, the improvement to the cost of the system also increases. The reliability analysis concerns the determination of the probability density function (pdf) of the system, the calculation of failure rates, mean time to failure (MTTF) and mean time to repair it (MTTR), finding reliability importance of sub-systems, reliability allocation and the development of a risk measure. There are many researches on reliability in a mining context[2–9]. These researches mostly focus on the analysis of MTTF and MTTR. In the first stage of these researches, the system is defined and sub-systems are identified and coded. Then, data are analysed for verification of the identically and independently distributed (IID) assumption. A theoretical probability distribution is fitted to MTTF and MTTR data for sub-systems. Finally, reliability parameters of the system and each sub-system are estimated.

This research takes a further step in mining reliability analysis. Using the parameters of the distribution fitted to mining data, an optimization model is developed in such a way as to determine the best action time at minimum maintenance cost.

## Model

The objective is to find the optimum time of mine reconstruction in such a way as to minimize the total cost required to improve the system under the constraint of minimum acceptable system reliability. The problem is formulated as follows:

$$Minimize \sum_{i=1}^{S} \sum_{j=1}^{N} e^{\left[1-e^{-\left(\frac{t-\gamma_{ij}}{\beta_{ij}}\right)^{\alpha_{ij}}}\right]^{f_i}} \qquad [2]$$

$$R_{ij}(t) = e^{-\left(\frac{t-\gamma_{ij}}{\beta_{ij}}\right)^{\alpha_{ij}}} \qquad [3]$$

subject to

$$R_s(t) \le R_{req} \qquad [4]$$

$$R_s=(t)\begin{cases} \prod_{i=1}^{S} R_i & \text{for series sub-systems} \\ 1-\prod_{j=1}^{N}\left(1-R_j\right) & \text{for parallel sub-systems} \end{cases} \qquad [5]$$

$$0 \le R_{ij} \le 1 \quad \forall i \text{ and } j \qquad [6]$$

where

- $S$ the number of sub-systems
- $N$ the number of items in each sub-system
- $t$ maintenance time (decision variable, in years)
- $\alpha_{ij}$ shape parameter of item $j$ in sub-system $i$
- $\beta_{ij}$ scale parameter of item $j$ in sub-system $i$
- $\gamma_{ij}$ location parameter of item $j$ in sub-system $i$
- $R_{ij}(t)$ reliability of item $j$ of sub-system $i$ at time $t$
- $f_i$ feasibility of increasing reliability of sub-system $i$
- $R_s(t)$ the system reliability at time $t$
- $R_{req}$ minimum acceptable reliability

The following assumptions are made:

- The system involves s-independent sub-systems
- The system and its sub-systems can be expressed only in two states: failed or operational
- Only the failure properties of the sub-systems are considered
- The overall system cost is the summation of individual sub-system costs.

This objective function is valid for Weibull and exponential distribution, which are the most common distributions in reliability analysis. If the shape parameter, $\alpha_{ij}$, is equal to one, Weibull distribution is reduced to exponential distribution. The selection of exponential distribution refers to constant failure rate. However, the selection of the Weibull distribution refers to an increasing failure rate. The shape parameter gives a measure of evolution of failure rate. For other distributions, if required the objective function can be modified easily. This problem is a nonlinear problem and cannot be solved by standard commercial linear programming software. Therefore, metaheuristics such as GA are as an alternative solution approach.

## Optimization procedure

The problem is solved by the GA, which is a stochastic search algorithm that mimics the process of natural selection and genetics[10–15]. The GA has exhibited considerable achievement in yielding good solutions to many complex optimization problems. GA is especially useful for optimizing nonlinear models or large domain problems[16,17]. That is, when the objective functions are multi-model or the search space is irregular, highly robust algorithms are required so as to avoid trapping at local optima. The GA can reach the global optimum fairly. Furthermore, the GA does not require the specific mathematical analysis of an optimization problem.

The significant steps of GA are initialization process, objective (fitness) function evaluation, the selection process, crossover and mutation processes. The GA is an iterative algorithm that yields a pool of solutions at each iteration. Firstly, the pool of initial solutions is generated at random. A new pool of solutions is created by the genetic operators at each new iteration. Each solution is evaluated with an objective function. This process is repeated until the convergence is reached. The GA has been used for various mining problems such as production scheduling[18], the selection of process location[19] and the determination of production rates[20].

A solution is called a chromosome or string. The GA with an initial set of randomly generated chromosomes is called a population. The number of individuals in the population is called the population size. The objective function is known as the evaluation or fitness function. A new population is created by the selection process using some sampling mechanism. An iteration of the GA is called a generation. All chromosomes are updated by the reproduction, crossover and mutation operators in each new generation. The revised chromosomes are also called the offspring.

A simple algorithm of the GA consists of the following steps:

1. Initialize population size, crossover and mutation probabilities and rank-based evaluation parameters
2. Generate an initial population of strings
3. Evaluate the string according to the fitness function
4. Apply a set of genetic operators to generate a new population of strings
5. Select the chromosomes by roulette wheel
6. Go to Step 2 until the solution converges.

Binary or floating vector can be used as the representation structure in the GA. In this research a floating vector represents a real value of a decision variable as a chromosome because binary coding has received substantial criticism[21]. When the values of the decision variables are continuous, it is necessary to represent them by a floating vector. Furthermore, real-valued GA can ensure the values of decision variables to the full machine precision. The real valued GA also has the advantage of requiring less storage than the binary valued GA. As the number of bits in binary coding representation increases, the storage becomes important. The representation of the fitness function in real valued GA is also more accurate as a result.

The length of the vector of the floating number is the same as the solution vector. The chromosome $V=(x_1, x_2,\ldots,x_n)$ represents a solution $x = (x_1, x_2, \ldots, x_n)$ of the problem where $n$ is the dimension. In order to solve the problem by the GA, each solution is coded by a chromosome $V(x_1, x_2,\ldots,x_n)$. A pre-defined integer population-size, which is the number of chromosomes, is initiated at random. Until the pre-determined population size is reached, the feasible solutions are accepted as chromosomes in the population. Then the fitness value of each chromosome is calculated. The chromosomes are rearranged in ascending order on the basis of the fitness values.

Now the parameter, $a$, is initiated in the genetic system. The rank-based evaluation function is defined as follows:

$$E(V_i) = a(1-a)^{i-1} \quad i = 1,2,\ldots, population - size \quad [7]$$

When $i = 1$ represents the best individual, $i = population\text{-}size$ is the worst individual. The reproduction operator used herein is a biased roulette wheel, which is spun population-size times. A single chromosome is selected in each spin for a new population. The roulette wheel is a fitness-proportional selection. The probability of being selected is given by modifying Equation [7] to $P(V_i) = a(1\text{-}a)^{i\text{-}1}/[1\text{-}(1\text{-}a)^{population\text{-}size}]$.

This population is updated by the crossover and mutation operators. First of all, the crossover probability, $P_c$, is defined. $P_c$* *population-size* gives the expected value of the number of chromosomes undergoing the crossover process. In order to carry out this process, random numbers, $r_i$, are generated from interval [0, 1] in $i = 1$, *population-size*. If $r_i$ is smaller than $P_c$, $V_i$ is selected as a parent. The selected chromosomes are randomly grouped as pairs. If the number of selected chromosomes is odd, one of them is removed from the system. The crossover procedure is performed on each pair. Let the pair $(V_1, V_2)$ be subjected to the crossover operation. Firstly, a random number, $r$, is generated from the interval (0, 1). Then the crossover operator will yield two children $X$ and $Y$ as follows:

$$X = r * V1 + (1-r) * V2 \text{ and } Y = (1-r) * V1 + r * V2 \quad [8]$$

The feasibility of each child is checked. If so, the child is accepted.

The mutation operator is implemented on the new version of the population. Similar to the crossover operation, a mutation probability, $P_m$, is defined. $P_m$* *population-size* gives the expected value of the number of chromosomes undergoing the mutation operation. In this procedure a random number, $r_i$, is generated $i = 1$ to *population-size* from the interval [0, 1]. If $r_i$ is smaller than $P_m$, $V_i$ is selected as a parent for the mutation. A random direction, $d$, is generated. The selected parent will be mutated by $V + M^*d$ in this direction. If $V + M^*d$ is not feasible to the constraints, $M$ is set as a random number from interval [0, $M$] until it is feasible. If this procedure does not manage to find a feasible solution in a predetermined number of iterations, $M$ is set to zero.

Thus one generation is completed. The whole procedure is implemented up to the predetermined number of iterations. After finishing the program, the best solution is reported as the results yielding the best time to take action with a minimum cost. The best chromosome may not appear in the solution converged. Therefore, the best solution should be kept as from the beginning of procedure.

## Case study

The approach was demonstrated in a case study. The data were collected from the annual repair and maintenance reports of an underground mine operated in seven basic operations: hoisting, ventilation, drilling, blasting, loading, hauling and supporting (Figure 1). For each sub-system a theoretical distribution was fitted by EasyFit 4.0 and the corresponding distribution parameters were given (Figure 2–13). For all sub-systems, a Weibull distribution was fitted. Given that the reliability decreases with time, this is a rational assignment. The objective was to find the best maintenance time in such a way that the cost of increasing reliability was at a minimum. In the optimization procedure, a parameter indicating feasibility or relative importance of sub-systems with respect to the overall reliability of the system was initiated. As feasibility increased, the improvement of sub-system would be more costly (Figure 14). Data including

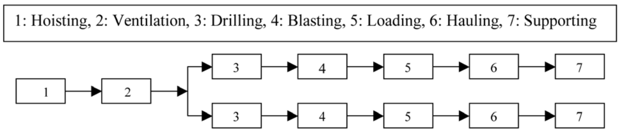


Figure 1—Illustration of the mining system

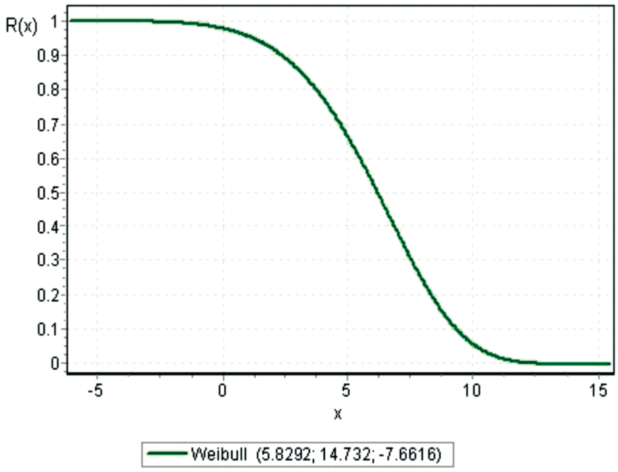


Figure 2—Reliability function for hoisting

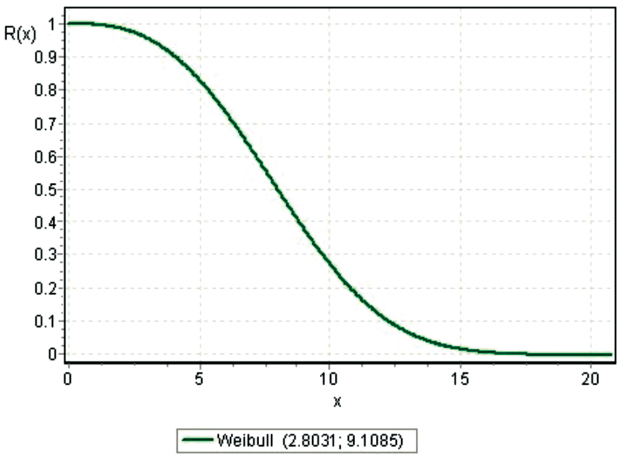


Figure 3—Reliability function for ventilation

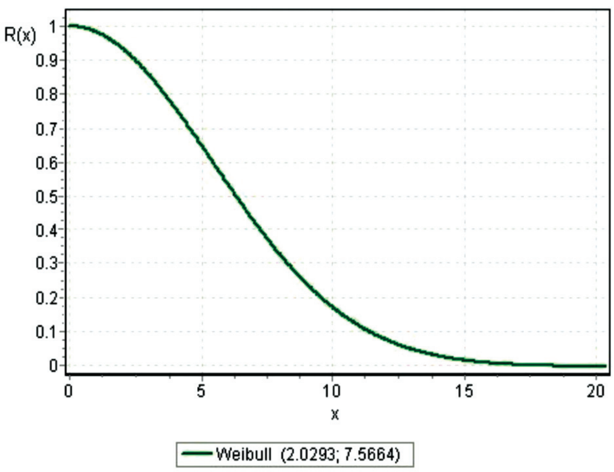


Figure 4—Reliability function for hauling 1

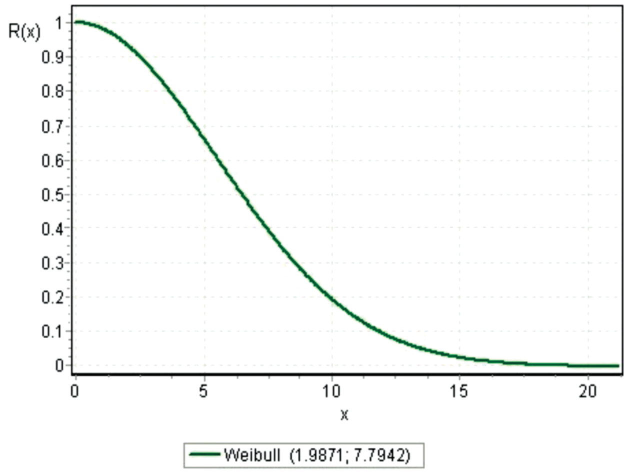


Figure 5—Reliability function for hauling 2

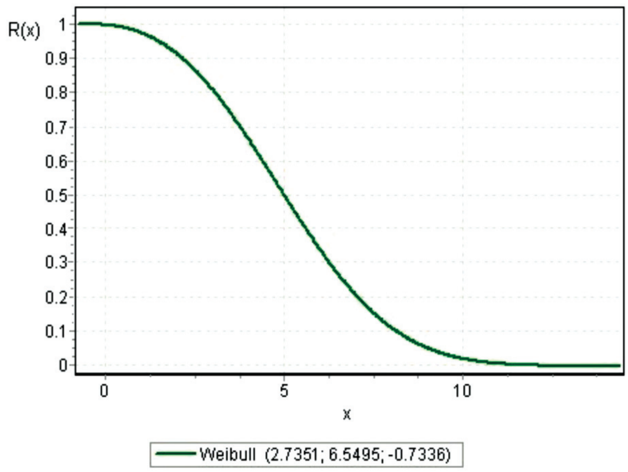


Figure 6—Reliability function for blasting 1

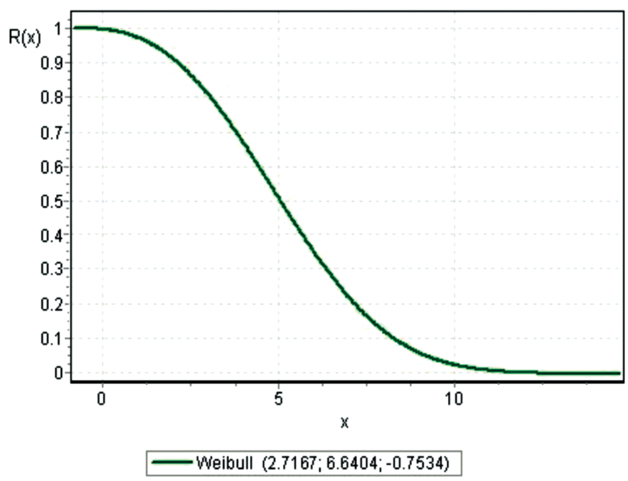


Figure 7—Reliability function for blasting 2

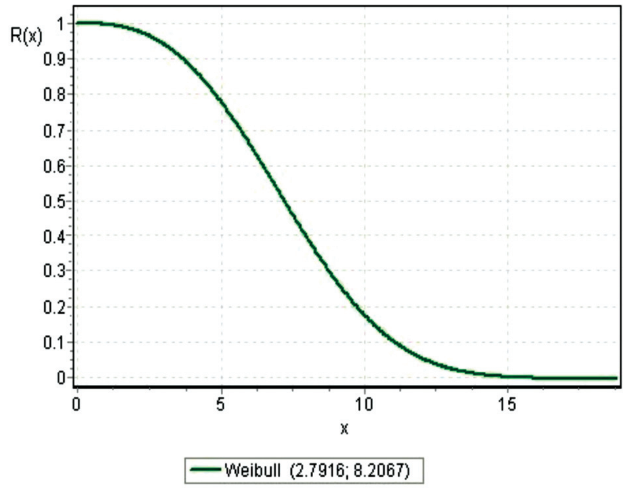


Figure 8—Reliability function for drilling 1

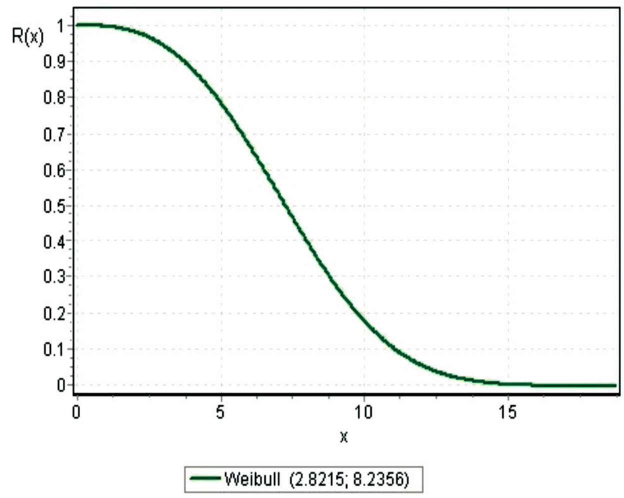


Figure 9—Reliability function for drilling 2

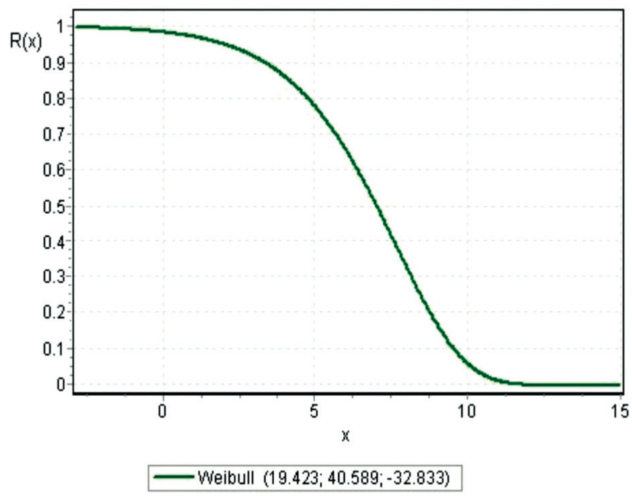


Figure 10—Reliability function for loading 1

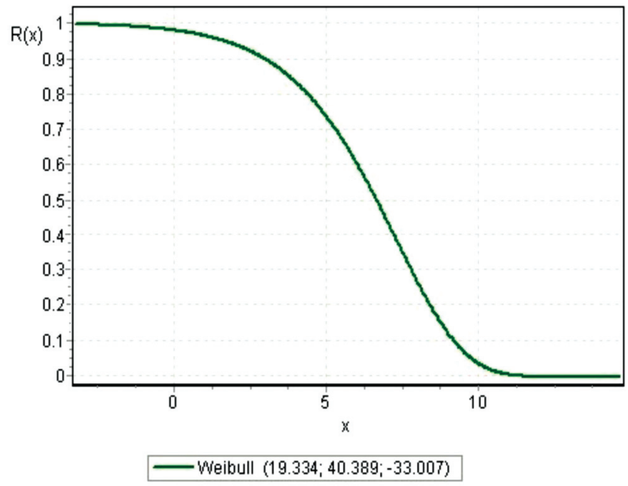


Figure 11—Reliability function for loading 2

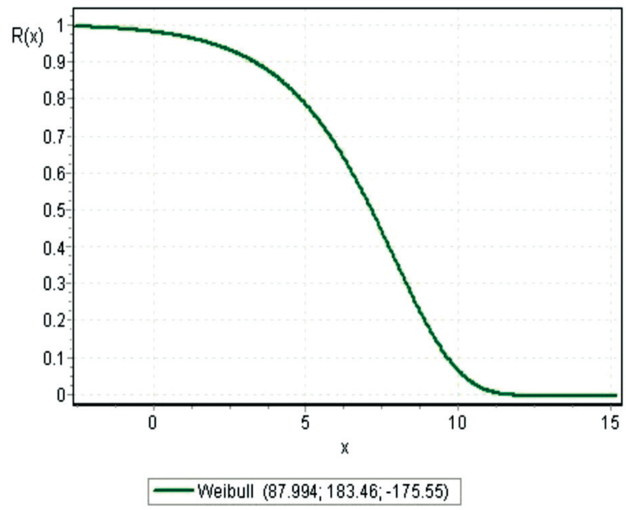


Figure 12—Reliability function for support 1

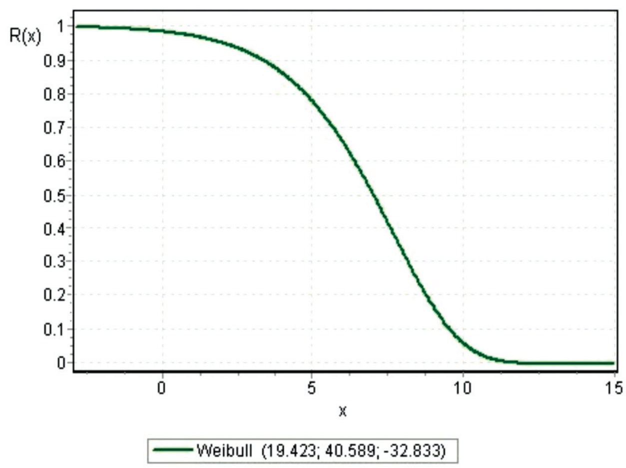


Figure 13—Reliability function for support 2



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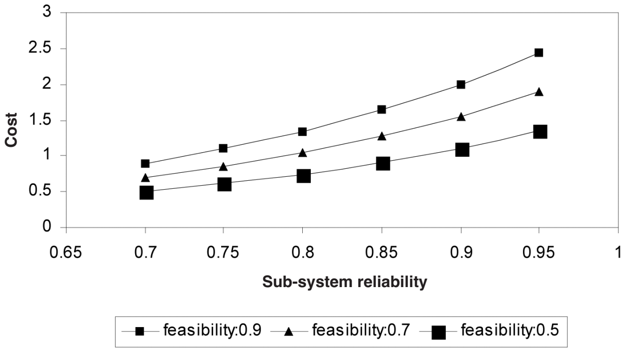


**Figure 14—Effect of feasibility on cost**

the distribution type and parameters, feasibilities and GA control parameters are given Table I. A computer program was written to implement the optimization procedure to solve by GA in FORTRAN.

There is no a clear rule for the selection of control parameters (the population size, parameter *a*, crossover and mutation probability). Therefore, the parameters were determined by an iterative approach. The fitness values versus the values of parameters are given in Figure 15. The population size, parameter *a*, crossover and mutation probabilities were selected as 25, 0.5, 0.25, 0.15 for 55%, respectively. It was observed that small population size led to the GA to quickly converge at a local optimum. On the other hand, large population size was prohibitively time consuming. With a high the parameter *a*, crossover and mutation probability converted the GA into a random search. With a low parameter *a*, crossover and mutation probability trapped at local optima. Figure 16 shows how the fitness value changes with the number of iterations. For all minimum acceptable reliabilities, the GA procedure started converging at about 3 000 iterations.

The procedure was repeated 3 000 times in approximately 10–15 minutes; the best solutions are given in Table II. For different specified system reliabilities, the evolution of optimal maintenance time is given in Figure 17. The cost of improvement will be higher in low reliabilities.

## Conclusions

In order to avoid important environmental, safety, quality and contractual losses, the mining production system should be, at least, operated at a minimum acceptable reliability level. When the reliability level decreases below a predefined level, the operation will be jeopardized. Therefore, the mine should be reconstructed to prevent possible problems. In this research, the optimal maintenance time is determined at minimum cost under the constraint of minimum acceptable reliability. This problem was formulated as a constrained optimization problem and solved by the GA. The results showed that the GA was a very powerful method to determine the maintenance time of a mine. The approach can be used easily for more complex systems.

*Table I*

**Parameter file**

| | |
|---|---|
| 25 | \number of chromosome |
| 3000 | \number of iterations |
| 12 | \number of subsystems |
| 2 | \number of series subsystems |
| 5 | \number of parallel subsystems |
| 3 | \number of parameters in weibull (alpha, beta, gama) |
| 1 | \number of subsystems in each series subsystem |
| 2 | \number of subsystems in each parallel subsystem |
| 5.8292 14.7320 -7.6616 | \weibull parameters for hoisting |
| 2.8031 9.1095 0.0 | \weibull parameters for ventilation |
| 2.0293 7.5664 0.0 | \weibull parameters for hauling in production face 1 |
| 1.9871 7.7942 0.0 | \weibull parameters for hauling in production face 2 |
| 2.7351 6.5495 -0.7336 | \weibull parameters for blasting in production face 1 |
| 2.7167 6.6404 -0.7534 | \weibull parameters for blasting in production face 2 |
| 2.7916 8.2067 0.0 | \weibull parameters for drilling in production face 1 |
| 2.8215 8.2356 0.0 | \weibull parameters for drilling in production face 2 |
| 19.4230 40.5890 -32.833 | \weibull parameters for loading in production face 1 |
| 19.3343 40.3890 -33.007 | \weibull parameters for loading in production face 2 |
| 87.9940 183.4600 -175.5500 | \weibull parameters for support in production face 1 |
| 19.4230 40.5890 -32.833 | \weibull parameters for support in production face 2 |
| 0.75 | \feasibility for hoisting |
| 0.50 | \feasibility for ventilation |
| 0.65 | \feasibility for hauling in production face 1 |
| 0.67 | \feasibility for hauling in production face 2 |
| 0.88 | \feasibility for blasting in production face 1 |
| 0.82 | \feasibility for blasting in production face 2 |
| 0.67 | \feasibility for drilling in production face 1 |
| 0.71 | \feasibility for drilling in production face 2 |
| 0.58 | \feasibility for loading in production face 1 |
| 0.51 | \feasibility for loading in production face 1 |
| 0.66 | \feasibility for support in production face 1 |
| 0.69 | \feasibility for support in production face 1 |
| 0.05 | \parameter (a-(1-a)i-1) |
| 0.25 | \crossover probability |
| 0.5 | \a large positive number required for rank-based evaluation |
| 0.15 | \mutation probability |
| 0.50 0.55 0.60 0.65 0.70 0.75 0.80 0.85 0.90 | \minimum acceptable reliability |
| 10 | \mine life |

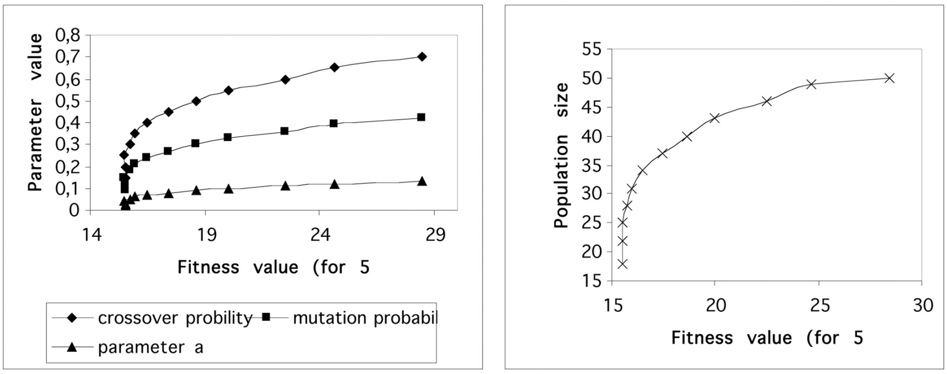


Figure 15—Evolution of fitness value with the control parameters

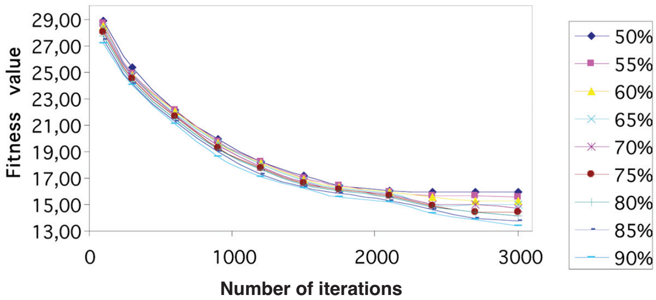


Figure 16—Evolution of fitness value with the number of iterations

*Table II*

**Sub-system reliabilities, cost and maintenance time for given minimum acceptable reliability**

| | 50% | 55% | 60% | 65% | 70% | 75% | 80% | 85% | 90% |
|---|---|---|---|---|---|---|---|---|---|
| Hoisting | 0.815 | 0.830 | 0.845 | 0.859 | 0.876 | 0.888 | 0.902 | 0.918 | 0.936 |
| Ventilation | 0.931 | 0.940 | 0.949 | 0.956 | 0.964 | 0.971 | 0.979 | 0.986 | 0.992 |
| Hauling 1 | 0.805 | 0.823 | 0.840 | 0.858 | 0.876 | 0.895 | 0.914 | 0.935 | 0.959 |
| Hauling 2 | 0.810 | 0.827 | 0.843 | 0.861 | 0.878 | 0.896 | 0.915 | 0.936 | 0.959 |
| Drilling 1 | 0.730 | 0.756 | 0.782 | 0.807 | 0.832 | 0.858 | 0.885 | 0.913 | 0.944 |
| Drilling 2 | 0.733 | 0.760 | 0.784 | 0.809 | 0.834 | 0.860 | 0.885 | 0.913 | 0.943 |
| Blasting 1 | 0.907 | 0.920 | 0.931 | 0.942 | 0.952 | 0.962 | 0.971 | 0.981 | 0.990 |
| Blasting 2 | 0.910 | 0.922 | 0.933 | 0.944 | 0.954 | 0.963 | 0.973 | 0.982 | 0.990 |
| Loading 1 | 0.887 | 0.897 | 0.906 | 0.915 | 0.924 | 0.932 | 0.941 | 0.950 | 0.960 |
| Loading 2 | 0.863 | 0.876 | 0.887 | 0.897 | 0.907 | 0.918 | 0.928 | 0.939 | 0.951 |
| Support 1 | 0.886 | 0.895 | 0.904 | 0.912 | 0.920 | 0.929 | 0.937 | 0.945 | 0.955 |
| Support 2 | 0.887 | 0.897 | 0.906 | 0.915 | 0.924 | 0.932 | 0.941 | 0.950 | 0.960 |
| Cost | 15.90 | 15.61 | 15.32 | 15.03 | 14.75 | 14.45 | 14.13 | 13.79 | 13.39 |
| Maintenance time | 3.56 | 3.38 | 3.19 | 2.99 | 2.79 | 2.56 | 2.30 | 1.98 | 1.57 |

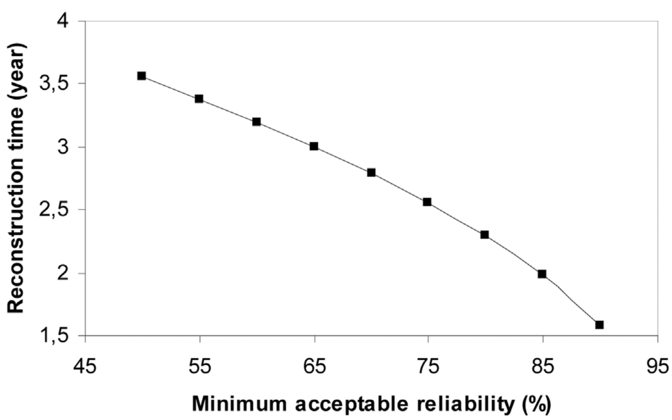


Figure 17—Evolution of maintenance time versus minimum acceptable reliability

## References


1. Mettas, A. Reliability allocation and optimization for complex system. http://www.reliasoft.org/pubs/2000rm_087.pdf 2000; 2000, 6 p., Accessed 28 January 2008
2. Kumar, U. and Huang, Y. Reliability analysis of a mine production system-A case study. *Proceedings of Annual Reliability and Maintainability Symposium*. 1999. pp. 167–172.
3. Louit, D.M. and Knights, P.F. Simulation of initiatives to improve mine maintenance, *Mining Technology* (Trans. IMM A) 2001, vol. 110, pp. 47–58.
4. Roy, S.K., Bhattacharyya, M.M., and Naikan, V.N.A. Maintainability and reliability analysis of a fleet of shovels. *Transactions of the Institution of Mining and Metallurgy, Section A- Mining Technology*, 2001. vol. 110, no. 2, pp. 163–171.
5. Vagenas, N. and Nuziaie, T. Genetic algorithms for reliability assessment of mining equipment. *Journal of Quality in Maintenance Engineering*, 2001, vol. 7, no. 4, pp. 302–311.
6. Hall, R.A. and Daneshmend, L.K. Reliability Modelling of Surface Mining Equipment: Data Gathering and Analysis Methodologies. *International Journal of Surface Mining, Reclamation and Environment,* 2003, vol. 17, no. 3, pp. 139–155.
7. Vagenas, N., Kazakidis, V., Scoble, M., and Espley, S. Applying a maintenance methodology for excavation reliability. *International Journal of Surface Mining, Reclamation and Environment,* 2003, vol. 17, no. 1, pp. 4–19.
8. Barabady, J. and Kumar, U. Reliability analysis of mining equipment: A case study of a crushing plant at Jajarm Bauxite Mine in Iran. *Reliability Engineering & System Safety*, 2008, vol. 93, no. 4, pp. 647–653.
9. Van Dyk, W. and Knobjes, B. Design for maintenance. *Journal of the South African Institue of Mining and Metallurgy*, 2006, vol. 106, no. 10, pp. 671–672.
10. Ansari, N. and Hou, N. *Computational intelligence for optimization*, Kluwer Academic Pub., 1997
11. Davis, L. *Handbook of genetic algorithms*. New York: V.N. Reinhold, 1991.
12. Haupt, R.L. and Haupt, S.E. *Practical genetic algorithms*. John Wiley & Sons, 1998.
13. Goldberg, D.E. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison Wesley Pub. Co., 1989.
14. Painton, L.A and Campbell, J.E. Genetic algorithms in optimization of system reliability, *IEEE Transactions on Reliability*, 1995, vol. 44, no. 2, pp. 172–178.
15. Reeves, C.R. Genetic algorithms. *Modern heuristic techniques for combinatorial problems*, 1993, Blackwell Pub. pp. 151–188.
16. Pham, D.T. and Karaboga, D. *Intelligent Optimization Techniques*, Springer, 2000.
17. Sivanandam, S.N. and Deepa, S.N. *Introduction to Genetic Algorithms*, Springer, 2008.
18. Denby, B. and Schofield, N. Open–Pit design and scheduling by use of genetic algorithms, *Transactions of the Institution of Mining and Metallurgy Section A- Mining Technology*, 1994, vol. 103, pp. A21–A26.
19. Kumral, M. Optimal location of a mine facility by genetic algorithms, *Transactions of the Institution of Mining and Metallurgy Section A- Mining Technology*, 2005, vol. 113, no. 2, pp. A83–A88.
20. Kumral, M. Genetic algorithms for optimization of a mine system under uncertainty, *Production Planning & Control*, 2004, vol. 15, no. 1, pp. 34–41.
21. Liu, B. *Uncertain Programming*. John Wiley and Sons Inc., 1999. ◆