An Approach to Reliability Allocation Problem in a Mining System

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ABSTRACT: Throughout the design of a mine system, the reliability of system should be assessed. When the estimated reliability is inadequate, how to satisfy a reliability target is significant problem. Selection of a mine production design requires maximizing system reliability. The minimum required reliability for each sub-system of a mine system should be estimated so as to accomplish a system reliability objective with minimum cost. A minimum reliability should be allocated to each sub-system with regard to the cost of increasing reliability. The objective is to develop a mine production design that will achieve the desired reliability while performing all sub-system functions at a minimum cost. This requires a balancing act of determining how to allocate reliability to the sub-systems in the system. In this research, the problem is solved by genetic algorithms (GA).

1 INTRODUCTION

A mining system contains sub-systems such as drilling, blasting, loading, hauling and hoisting. In order to ensure pre-defined system reliability, the minimum required reliability for each component should be estimated. The problem is to seek a trade-off between cost of increasing reliability and satisfactory reliability to guarantee safety and customer orders. There are many researches on the reliability in mining context (Kumar and Huang, 1993, Roy *et. al,* 2001, Venegas *etat.* 2003 and Hall *et. ai,* 2003). These researches focused on the analysis of mean time to failure (MTTF) and mean time to repair it (MTTR). In the first stage of these researches, the system is defined and sub-systems are identified and coded. Then, data are analyzed 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 system and each sub-system are estimated. This paper takes previous researches a step further by determining optimal reliability allocation for each sub-system such a way as to reach predefined system reliability.

In order to improve the system, the parameters described in five sub-systems should be improved. This mprovement, of course, requires cost. Depending upon sub-system complexity, geological and geomechanical factors, and technological restrictions, im$_T$ provability of each sub-system varies to each other. Relative importance of each sub-system is determined by feasibility concept (Mettas, 2000). Because of the reasons given above, some sub-system can improved more costly (Figure 1).

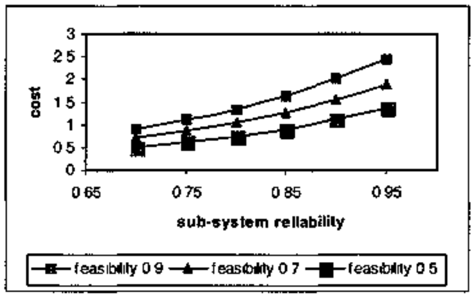

Figure 1. Effect of feasibility on cost

2 GENETIC ALGORITHMS

The problem is solved by the GA, which is a stochastic search algorithm that mimics the process of natural selection and genetics (Goldberg 1989, Reeves 1993, Davis 1991, Haupt & Haupt 1998). The GA has exhibited considerable achievement in yielding good solution to many complex optimization problems 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 optimization problem 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 new iteration Each solution is evaluated with an objective function This process is repeated until the convergence is reached

A solution is called a chromosome or string The GA with an initial set of randomly generated chromosomes called a population The number of individuals m 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 m each new generation The revised chromosomes are also called the offspring

Simple algorithm of the GA consists of the following steps

1 Generate an initial population of strings
2 Evaluate the string according to the fitness function
3 Apply a set of genetic operators to generate a new population of strings
4 Go Step 2 until a solution converges

3 PROBLEM DESCRIPTION

Binary or floating vector can be used as the representation structure m the GA In this research a floating vector represents a real value of a decision variable as a chromosome because binar> coding has received substantial criticism (Liu 1998) 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 floating number is 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

do i=l, population-size
$chr_i = x_j = (r_n * (xupp_j - xlow_j)) + xlow_j \quad (j = 1, nvar)$
enddo

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

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

When $i = 1$ represents the best individual, i = *population-size* is the worst individual The reproduction operator used herein is a biased roulette wheel, which is spun *population-size* time A single chromosome is selected in each spinning for a new population The roulette wheel is a fitness-proportional selection The selection process is as follows

1 The cumulative probability q_i is calculated for each chromosome

$$q = \begin{cases} q_0 = 0 & if\ i = 0 \\ q_i = \sum_{j=1}^{i} E(V_j) & if\ i = 1, \ldots, population-size \end{cases}$$

2 A random number r is drawn m $(0, q_{population\text{-}size})$
3 The chromosome V_i is selected such that $q_{i-1} < r \le q_i$
4 The second and third steps are repeated *population-size* time

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 number of chromosomes undergoing on the crossover process In order to carry out this process, random numbers, r_i, are generated from interval [0, 1] in ; = 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 ıs removed from the system. The crossover procedure is performed on each pair Let the pair *(Vj, 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

$$X = r^*V1 + (1-r)^*V2 \text{ and } Y = (1-r)^*V1+r^*V2 \quad (2)$$

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

The mutation operator is implemented on new version of population Similar to the crossover operation, a mutation probability, *P,„,* is defined *P,„* * *population-size* gives the expected value of number of chromosomes undergoing the mutation operation In this procedure a random number, *r„* is generated *i=l* to *population-size* from the interval [0, 1] If *r,* smaller than P_m *V,* is selected as a parent for the mutation A random direction, *d,* is generated m 31[3] The selected parent will be mutated by V + *M*d* in this direction A proper large number, *M,* is also initiated m this section

If *V + M*d* is not feasible to the constraints, M ıs set as a random number from interval *[0, M]* until it is feasible If this procedure does not manage to find a feasible solution m a pre-determıned number of iterations, *M* ıs set to zero

Thus one generation is completed All procedure is implemented up to the pre-determıned number of iterations After finishing the program, the best solution is reported as the results yielding the minimum cost of increasing system reliability

4 APPLICATION

The problem is expressed as minimization of cost of per cent increasing reliability m such a way as to meet minimum reliability requirement

$$\pi_i = Min \sum_{i=1}^{jvar} e^{\left[f \frac{R(t)-R_{min}(t)}{R_{max}(t)-R_{min}(t)} \right]} \quad (3)$$

Subject to

$$\prod_{i=1}^{jvar} R_i(t) \geq R_s(t) \quad (4)$$

$$R_{i\,min}(t) \leq R_i(t) \leq R_{i\,max}(t) \qquad ; = 1, \quad ,;var \quad (5)$$

$$R_i(t) \geq 0 \quad \forall_i \quad (6)$$

Where *jvar* is the number of decision variables attributed to the reliabilities, *R,(ı* jıs reliability estimation of sub-system ; at time *t*, $R_s(t)$ is the required system reliability at time *t*, $R_{,imK}(t)$ is maximum attamable reliability of sub-system (at time /, $Ä_{(mm}(0$ is reliability estimation of sub-system (at time *t, f,* is feasibility of increasing reliability of sub-system *ı* The objective shows exponential behaviour The objective contains three parameters / is the feasibility of increasing a sub-system reliability and varies between 0 and 1 As/ approaches to 1, the improvement of system reliability is more difficult and expensive

The technique was demonstrated on a hypothetical data Mining system comprises seven basic operations (sub-systrms) such as drilling, blasting, loading, hauling, hoisting, ventilation and draining Maximum available reliabilities and feasibilities were estimated from old data and experiences These data is given in Table 1

Table 1 GA parameters and reliability data

30	\number of chromosome
200	\number of iterations
7	\number of subsystems in each face
0 68 0 92 0 80	\min-max reliabilities and feasibility (1)
0 78 0 95 0 75	\mm-max reliabilities and feasibility (2)
0 74 0 97 0 30	\mm-max reliabilities and feasibility (3)
0 67 0 94 0 60	\rmn-max reliabilities and feasibility (4)
0 78 0 93 0 80	\mm-max reliabilities and feasibility (5)
0 88 0 95 0 50	\mm-max reliabilities and feasibility (6)
0 91 0 99 0 90	\mm-max reliabilities and feasibility (7)
0 05	\parameter (a-(1 -a)i-1)
0 30	\crossover probability
0 5	\a large positive number
0 15	\mutation probability
0 50	\required reliability

in order to solve the problem with the GA, a computer program was written There is no clear rule for the selection of control parameters (the population size, parameter *a,* crossover and mutation probability) Therefore, the parameters were determined by the experimentation 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 High the parameter *a,* crossover and mutation probability caused to convert the GA into a random search Low the parameter *a,* crossover and mutation probability caused to tiap at local optima The procedure was repeated 300 times in approximately 15 minutes, the best solutions were given in Table 2

Table 2 Optimal results

Cost	8 783957
Sub-system 1	0 8848201
Sub-system 2	0 9005929
Sub-system 3	0 9672122
Sub-system4	0 9255640
Sub-system 5	0 8447140
Sub-system 6	0 9023753
Sub-system 7	0 9267560
System reliability	0 5039344

5 CONCLUSIONS

In order to avoid important safety, quality and contractual losses, a mining production system should be operated m pre-defined reliability In this research, the minimum required reliability of each sub-system was estimated to achieve the required system reliability with minimum cost This allocation problem was formulated as a constrained optimization problem and solved by the GA The results showed that the GA was very powerful method for the reliability allocation problem As long as the equation of system reliability is derived, the approach can be used to solve problem

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