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A genetic algorithms approach for grade control planning in a bauxite deposit

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ABSTRACT: This study investigated genetic algorithms for an optimization of grade control planning in a bauxite deposit. The objective of the study is to minimize the month wise grade deviations of the two quality characteristics namely Al_2O_3% (Alumina) and SiO_2% (Silica) from their quality specifications over two years time period. For this purpose, a selected area of the deposit was chosen for grade control planning. The management of the mine was particularly interested in meeting the quality norms of Alumina and Silica for the specific time period by extracting the materials from the studied area of the deposit. Using the genetic algorithms approach, a grade control plan was generated which avoided large combinatorial problem of other conventional algorithms like the dynamic programming. Further, the genetic algorithms also provided a large number of sub-optimal grade control plans in quick time period, one of which could be most suitable to the mine management on a given practical situation. Using this approach five best grade control plans were generated, and their properties were thoroughly analyzed in this paper.

1 INTRODUCTION

The design and scheduling of an open pit mine operations poses a perennial challenge to the mining industry. An effective open pit design and production scheduling has paramount importance in surface mining operations. The effect of pit design and scheduling has major consequences to a mine management in mine investment decisions, design and planning, mine operations such as grade control, mine automation and production. Open pit production scheduling is the development of an extraction sequence of mining blocks leading from the initial condition of the deposit to the ultimate pit limit. The aim of planning a mining sequence is to decide which parts of a deposit and waste to mine in which time period so that several requirements can be satisfied simultaneously including grade control. The difficulty of working out the best mining sequence arises due to the very large number of possible combinations of mining blocks that may be extracted during a particular planning period.

Several attempts have been made to address the scheduling problems effectively. A simplified approach that was practiced to generate a production-scheduling plan is the trial and error method with the use of interactive graphics (Franklin 1985, Holding & Stokes 1990). Although the technique is simple and generally accepted; however, it is not possible to consider and analyze every combination in a short time. Therefore, they were refined more scientifically to meet the requirements of a schedule. In this regard, operations research (O.R.) techniques were applied to production scheduling problems for choosing the best mining sequence. Among the various O.R. techniques, the linear programming has received the great attention of the mining engineers in open pit production scheduling. As early as 1967, a short-range open pit scheduling model was formulated and solved using the linear programming methodologies by Kim (1967). However, a major restriction of utilising this technique is that the number of constraints must be kept small. The complexity of multilevel open pit mining, especially the precedence constraints, can lead to a very large linear programming model that can be expensive to solve in the most practical cases. The goal programming is another operations research technique developed for meeting the multi-objective goal criteria in production scheduling (Chanda 1990, Smith & Tao 1994). The integer programming is also used for production planning. However, it is a less frequently used technique in open pit scheduling, because of the complexity of the solution algorithms. A special group of the integer programming model is the 0–1 integer programming, where each variable is allowed to take values of only 0 or 1. The solution time of a 0–1 integer programming model tends to increase exponentially with the number of variables (Fytas et al. 1993). However, above operations research techniques are mostly applied to the short range production planning designed to address the scheduling problem in presence of several mining constraints. Subsequently, several researchers also attempted to develop optimal scheduling algorithms based on the dynamic programming (Elbrond et al. 1997, Lizotte & Elbrond 1982, Roman 1973, Dowd 1976, Yun & Yegulalp 1982), the graph theory and the concept of ranked positional weighting (Gershon 1987) in long range production scheduling. Any attempt to generate production scheduling using the dynamic programming requires an exhaustive search, and results in a huge number of combinatorial alternatives. As for example, a small block model consisting of $20 \times 20 \times 20$ matrix (8000) blocks that is to be scheduled over ten time periods requires as many as billions of permutations. Even after such a huge computation, the generated solutions may not be feasible because of practical mining constraints. In a real deposit, the number of blocks could be so high that it might create a massive search space, which would be beyond the capabilities of present computer technology.

This paper investigated the genetic algorithms for solving a real time practically feasible production schedule with particular reference to the grade control planning. The idea behind the use of the genetic algorithms is that using this procedure an optimal block sequence for grade control can be generated quickly after examining only a small fraction of search space. Hence it can eliminate the large combinatorial problem that arises out from the dynamic programming approach.

2 GENETIC ALGORITHMS FOR GRADE CONTROL PLANNING

The genetic algorithms (GA) are becoming very popular in many scientific domains including mining. The genetic algorithms are search procedures that are based on the mechanics of the genetics and the natural selection (Goldberg 2000). These procedures converge quickly to the optimal solutions after examining only a small fraction of the search space and have been successfully applied to complex optimization problems in engineering. The algorithms combine an artificial survival of the fittest approach with genetic processes such as reproduction, cross-over and mutation to produce better solution from iteration to iteration and consequently reach an optimal solution. A brief overview of operations of the genetic algorithms for block sequencing problem is illustrated in Figure 1. The process in this study involves for

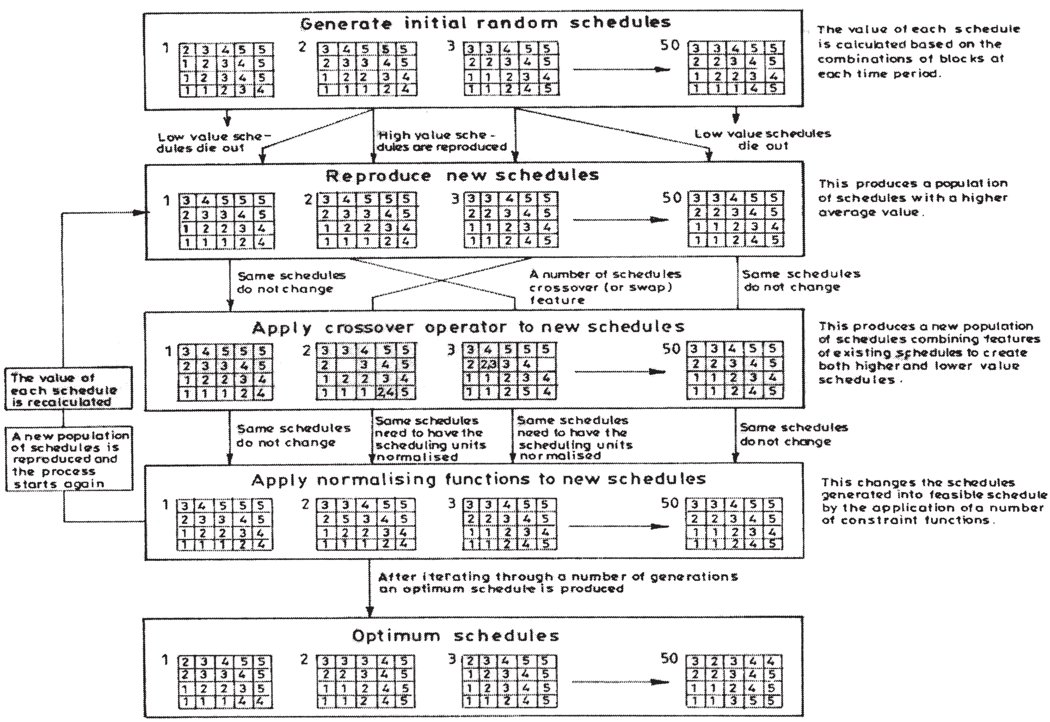

Figure 1. Genetic search for generating optimal schedules.

scheduling of an extraction sequence of mining blocks for optimal grade control. The following operations are performed for generating extraction schedule using genetic algorithms.

2.1 *Generation of random schedules*

The GA process starts with the generation of a population of feasible random schedules. The size of the population is one of the controllable parameters in the system, which is carefully chosen in order to achieve increased efficiency of the genetic algorithms. In the present study individual schedules are generated by the random selection of mining blocks in such a way that individual schedules honor the precedence constraints.

2.2 *Assessment of the schedules*

A fitness value is calculated for each of the schedules in the population. Depending upon the objective function, the fitness values of the individual schedules are assessed. The objective function for this study is selected as the cumulative grade deviations from the target ore grade specifications for the entire schedule period.

2.3 *Reproduction of schedules*

During the reproduction phase individual schedules either survive to the next generation or are removed. With the use of a probabilistic technique, a new generation is created in which schedules from the previous generation with better fitness values have a greater chance of surviving than those with inferior fitness values. It is in this phase that the survival of the fittest approach is employed. Indeed, it is possible to generate multiple copies of a highly fit schedule into the next generation. The reproductive phase is critical in that it must ensure that sufficient genetic diversity is maintained from generation to generation. It must also ensure that convergence to an optimum result is sufficiently rapid by allowing good schedules to reproduce faster than bad schedules.

2.4 *Crossover of schedules*

During crossover selected schedules are randomly combined in pairs on a probabilistic basis. In general, 70% of the schedules are crossed over, and 30% remains unaffected. Each schedule in a selected pair is then modified by the crossing over of certain features in the schedule. Crossover will result in the crossed pair having modified schedule characteristics. Some of the modified schedules will have superior fitness values, improving their chances of survival into future generations, whereas some will have inferior fitness values, reducing their chances of survival.

2.5 *Mutation of schedules*

Mutation is also performed on a probabilistic basis. As a result, very few cells in the schedule are modified in a random manner. This helps to maintain genetic diversity and prevents the system from converging to a false local optimum solution. Thus, the genetic algorithms provide a global optimal solution.

2.6 *Normalization (feasibility) of schedules*

Both crossover and mutation cause the resulting schedules to violate scheduling constraints and after each such operation the generated schedules are normalized to turn into the feasible schedules. For example, the precedence constraints are violated during mutation and cross-over. Using normalization operation the schedules are modified in small margin to generate feasible solutions.

All the above steps for producing of an optimal solution are illustrated through a simple example shown in Figure 2. Figure 2 clearly demonstrates the step by step mechanisms of the genetic algorithms to reach an optimal schedule. The procedure begins with the generation of an initial population of random schedules. The figure reveals that an initial population of five strings is selected, and each string consists of five genes. The value of each gene represents the grade deviation at the particular time period, which is coded

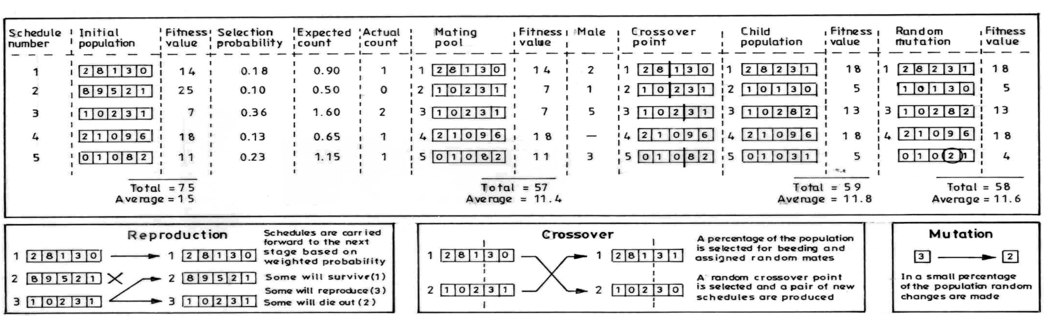

Figure 2. An example for the use of genetic algorithms in production scheduling.

into a string as real value inside a small box. The cumulative grade deviation of each schedule is attributed as the fitness value of the string. A new generation starts with reproduction. The mating pool for the next generation is created by selecting strings randomly from the population on the basis of weightings derived from the fitness values. In Figure 2, strings 1, 4 and 5 are copied once in the mating pool, and string 3 is copied twice, whereas string 2 is not copied. In an active pool, crossover proceeds in two steps: at first some of the strings are mated randomly, after which mated strings crossover at a random site. In Figure 2, random choice of mates has resulted in a mating of string 1 with string 2 and of string 3 with string 5. String 4 has not mated. The last operator, mutation, is performed on gene by gene basis. There is a very low probability of mutation from generation to generation. In Figure 2, one gene (circled) has undergone mutation and changed the value from 3 to 2.

Following reproduction, crossover and mutation the new population is generated, and the fitness values are recalculated. The results of this single phase of generation reveal that the average grade deviation (fitness value) of the final population is reduced.

3 CASE STUDY

The study was conducted in a bauxite deposit. The deposit extends over an area of about 16 square kilometers. For the operational conveniences, the deposit has been divided into north, central and south blocks. The central block has been divided into two sectors namely, sector I and sector II. The present study was conducted in the sector II of the central block. The central block of the deposit is an integrated part of the lateritic profile, and is derived by the insitu chemical weathering of khondalite in tropical surroundings. At the mine, the lateritic bauxite profile is in the form of a flat or gently undulating At places, it is interspersed with outcrops of the unleached/partially leached parent rock.

The average thickness of the ore body varies from 12 to 14 m. The quality control practitioners at the mine hardly follow any scientific rule for the extraction of the mine blocks. However, they felt the urgent need of meeting their quality specifications according to the customer needs. Therefore, they identified an area which could be optimally extracted to meet their desired quality goal over the two years time period. In this context, the genetic algorithms approach was investigated to provide them an optimal scheduling plan for the grade control practices.

Prior to generate a schedule plan, a geostatistical ore block model for the study area applying ordinary kriging technique was developed using 179 exploratory borehole data collected from the mine. The proposed model was derived based on the two quality characteristics, Al_2O_3% and SiO_2%. Hence, grade model was prepared based on estimated block grades of Al_2O_3% and SiO_2% of size $70 \times 10\,m^2$. In the model, there are 98 blocks which can be extracted for the period of two years with four blocks in a month. The aim is to derive a schedule which will minimize the month wise grade deviations for the two years period. In general, the spatial distribution of the bauxite ore reveals that grade variations among the mining blocks are not so high. It suggests that differences among the schedules' properties will be small.

A computer program was developed in C to generate an optimal schedule using the genetic algorithms. The process starts with the generation of a set of feasible random schedules that satisfy the precedence constraint; that is a block can be extracted only if any of the surrounding blocks is already extracted. Remember that this is a flat deposit with an average thickness of 12–14 meters. Therefore, the material is extracted in a single lift or some times in double lifts. In case of double lifts, lower portion of ore body is immediately extracted after the upper portion of the ore body gets removed.

3.1 *Grade control schedule with genetic algorithms*

Therefore, it is assumed that entire material of a mining block could be extracted in a single time period. Scheduling of the deposit was made over the 24 months time intervals with the objective of meeting the quality specifications of SiO_2% and Al_2O_3% at each month period. The quality norms are specified as 42.5 ± 2% for Al_2O_3%, and 3.0% for SiO_2%. Therefore, the fitness function of the schedules is chosen in such a way that absolute grade deviations from the quality specifications are minimized at each time period which in turn minimizes the absolute cumulative grade deviation over the whole time period.

To start with the process, 50 random schedules were generated, as if each schedule represents a genetic string or chromosome. Since the schedule was prepared for 24 months, the length of the genetic string was 24 genes. Each gene of a chromosome (schedule) takes the value of month-wise grade deviations from the target quality specifications. The fitness value of each schedule was assessed by the cumulative grade deviation, which was derived by summing up month-wise grade deviations (coded into a gene) over the 24 months time period. Depending upon the fitness value of a schedule, it was selected in the next phase for reproduction of the new schedules. The selection was based on a probabilistic technique called the stochastic remainder selection without replacement (Goldberg 2000) where schedules with lower fitness values were given higher priority for selection (since the optimal problem here is the minimization of cumulative grade deviation). After the selection of the schedules, they were paired up randomly to exchange their properties to generate new schedules via crossover operation. In crossover operation, a crossover point is selected at random over the string length. Initially double point crossover operation was attempted; however, due to its increased rate of constraint violations single point crossover operation was retained. Also, the crossover operation was performed according to the probability 0.7 that a crossover operation should take place. During crossover operation, new schedules received properties from both the parent schedules according to the position of the crossover point. In the event of no crossover operation, the child schedules received the values of parent schedules. The mutation occasionally took place according to probability of mutation p_m, 0.001. During mutation a gene arbitrarily changed its value. After the new schedules were created, they were ready to generate a next set of schedules. This process continued after iteration to iteration and finally process was stopped at a final stage when the solution quality did not get improved for 200 iterations more after reaching the final stage.

3.2 *Result and discussion*

The genetic algorithms were run for a number of trials. The result presented here is the outcome of one of the good trials. In this trial, analysis of the initially set of 50 random schedules revealed that the average fitness value of the schedules was 36.62, and that of the fittest and the worst schedules were 32.39 and 40.72 respectively. After running the program for 36 generations, the best set of schedules was obtained, and the values of average fitness, the fittest and the worst schedules were 34.64, 28.50 and 39.52 respectively. The properties of the five best schedules were studied along with a manual schedule. Figures 3 and 4 present the month-wise grade variations of the variables Al_2O_3% and SiO_2% over the two years period according to the six schedules.

From Figure 3, it is revealed that the fluctuations of Al_2O_3% for the schedules 2 and 3 are although consistent, there occur some occasional peak values which render the schedule to incur higher fitness value than the schedules 1, 4 and 5. On the other hand, the fluctuations of Al_2O_3% for the manual schedule is relatively erratic than the genetic algorithms based schedules. Figure 4 indicates that variation of SiO_2% is more or less identical for all the schedules except the manual schedule, where some peak values occur occasionally. Figures 5 and 6 present the grade deviations of the variables Al_2O_3% and SiO_2% from the specified grades of 42.5% of Alumina and 3.0% of Silica. Figure 5 shows that the grade deviation of Al_2O_3% is maximum for the manual schedule; in contrast other schedules show more or less identical pattern. Further, it is indicated from Figure 6 that grade deviations of SiO_2% over the whole time period are negative for all the schedules (below the 3% level). Figure 7 presents the cumulative grade deviation of both the variables Al_2O_3% and SiO_2% for the six schedules. It is revealed that the cumulative grade deviation is minimum for the schedule 5. On the other hand, the schedules 1, 2, 3 and 4 assume more or less identical pattern. For the manual schedule, the grade deviation curve runs above the other schedules, which indicates that the grade deviation of the manual schedule attains maximum value. Figure 8 presents the extraction sequence for one of those five genetic algorithms based schedule.

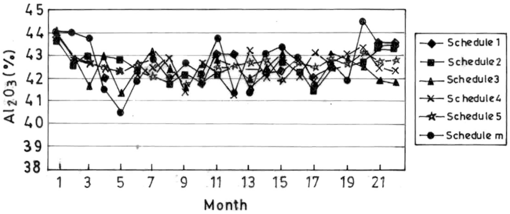

Figure 3. Month-wise grade fluctuation of Al_2O_3% according to six different schedules.

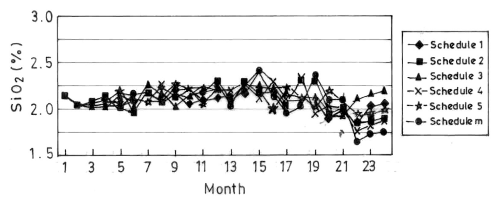

Figure 4. Month-wise grade fluctuation of SiO_2% according to six different schedules.

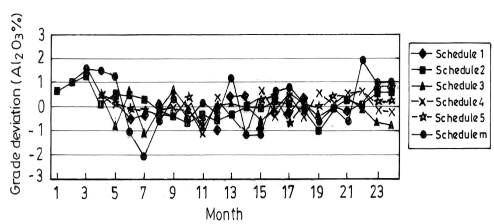

Figure 5. Month-wise grade deviation of Al_2O_3% according to six different schedules.

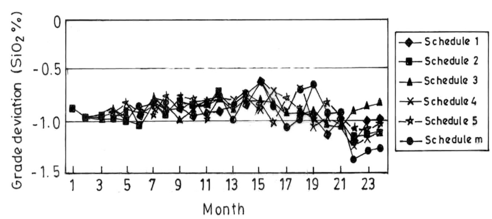

Figure 6. Month-wise grade deviation of SiO_2% according to six different schedules.

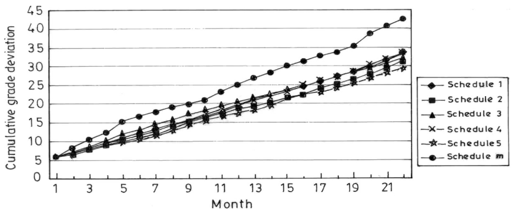

Figure 7. Cumulative grade deviation of the six different schedules.

20134.13 N

22	22	22	23	24	24	25
20	20	21	23	23	20	22
19	18	17	21	17	19	21
19	18	16	14	15	17	19
20	14	13	13	14	15	18
11	9	10	12	15	16	17
10	8	11	12	12	23	16
10	7	8	24	11	13	14
7	6	6	9	10	11	25
3	4	5	9	12	16	15
2	24	4	5	6	9	13
1	2	3	5	7	8	18
1	2	3	4	5	21	8
1	1	2	3	4	6	7

19994.13 N

18803.84E 19293.84E

#Number indicates the time of extraction

Figure 8. Extraction sequence of the schedule 1.

At this point the mine management will be able to decide the practical feasibility for the application of the various optimal schedules produced from the genetic algorithms by analyzing their general characteristics. By studying the various characteristic features of the schedules, the management might be able to decide the practical feasibility of application of a particular schedule for their grade control operations.

4 SUMMARY AND CONCLUSION

It is often stated that the optimal schedules generated by elegant mathematical techniques become infeasible when they are turned into real applications that violate many operational constraints. It is also argued that mine production scheduling is best carried out by a team of experienced engineers who are able to ensure that only feasible schedules are developed. There is a need to address these problems properly. An application of the artificial intelligence technique namely the genetic algorithms offers the potential for a pragmatic approach to the solution of generating practical feasible schedules. Applying iterative procedures and searching a fraction of search space using the genetic algorithms, one can discard poor alternatives and retain good ones. The good alternatives are gradually modified and finally reach towards a number of near optimal solutions. In this study, applicability of the genetic algorithms has been investigated for production scheduling in a bauxite mine for grade control purpose. The main aim for this case study was to generate a schedule which can minimize grade deviations from their quality specifications over time. A number of random schedules were generated which were gradually modified to achieve better solutions after a good number of iterations. Finally, the five best schedules are presented and their characteristics were studied. Now, it is left to the mine management to decide over which schedule will be the best suitable for their practical application. Although, the initial results of the study are quite encouraging, however, it is based on only a basic technical constraint namely, precedence constraints. Further investigation is required to incorporate other practical operational constraints to generate more practically feasible schedules.

REFERENCES

Chanda, E.C.K. 1990. An application of goal programming to production planning in the crushed stone industry. International Journal of Surface Mining, Reclamation and Environment 4: 125–129.

Dowd, P. 1976. Application of dynamic and stochastic programming to optimize cutoff grades and production rates. Transactions of Institute of Mining and Metallurgy, Section A 85: A22–31.

Elbrond, J., Dubois, J. & Daoust, G. 1977. Rate of production and cutoff Grade-a program for teaching and experimentation. Proceedings of 15th International Symposium on Application of Computers and Operations Research in the Mineral Industry, Brisbane, Australia: 13–19.

Franklin, P.J. 1985. Computer aided short term mine planning. CIM Bulletin 78(879): 49–52.

Fytas, K., Pelley, C. & Calder, P. 1987. Optimization of short and long range production scheduling. CIM Bulletin 80(904): 55–61.

Gershon, M. 1987. Heuristic approaches for mine planning and production scheduling. International journal of Mining and Geological Engineering 5: 1–13.

Goldberg, D.E. 2000. Genetic algorithms in search, optimization, and machine learning. Don Mills, Ontario: Addison-Wesley Publishing Company, Inc.

Holding, S.W. & Stokes, M.A. 1990. Mine activity and resource scheduling with the use of three dimensional component modeling. Transactions of Institute of Mining and Metallurgy, Section A. 99:A53.

Kim, Y.C. 1967. Mathematical programming analysis of mine planning problems. Ph.D.Thesis. The Pennsylvania State University, University Park, PA.

Lizotte, Y. & Elbrond, J. 1982. Choice of mine mill capacities and production scheduling using open ended dynamic programming. CIM Bulletin 75(839): 154–163.

Roman, R.J. 1973. The use of dynamic programming for determining mine mill production scheduling. Proceedings of 10th International Symposium on Application of Computer Methods in the Mineral Industry, Johannesburg, South Africa: 165–169.

Smith, M.L. & Tao, W.Y. 1994. Mine production scheduling for optimization of plant recovery in surface phosphate operations. International Journal of Surface Mining 9: 41–46.

Yun, Q. & Yegulalp, T. 1982. Optimum scheduling of over burden removal in open pit mines. CIM Bulletin 75: 22–31.