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Evaluating the efficiency of the genetic algorithm in designing the ultimate pit limit of open-pit mines

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ABSTRACT

The large-scale open-pit mine production planning problem is an NP-hard issue. That is, it cannot be solved in a reasonable computational time. To solve this problem, various methods, including metaheuristic methods, have been proposed to reduce the computation time. One of these methods is the genetic algorithm (GA) which can provide near-optimal solutions to the problem in a shorter time. This paper aims to evaluate the efficiency of the GA technique based on the pit values and computational times compared with other methods of designing the ultimate pit limit (UPL). In other words, in addition to GA evaluation in UPL design, other proposed methods for UPL design are also compared. Determining the UPL of an open-pit mine is the first step in production planning. UPL solver selects blocks whose total economic value is maximum while meeting the slope constraints. In this regard, various methods have been proposed, which can be classified into three general categories: Operational Research (OR), heuristic, and metaheuristic. The GA, categorized as a metaheuristic method, Linear Programming (LP) model as an OR method, and Floating Cone (FC) algorithm as a heuristic method, have been employed to determine the UPL of open-pit mines. Since the LP method provides the exact answer, consider the basics. Then the results of GA were validated based on the results of LP and compared with the results of FC. This paper used the Marvin mine block model with characteristics of 53271 blocks and eight levels as a case study. Comparing the UPL value's three ways revealed that the LP model received the highest value by comparing the value obtained from GA and the FC algorithm's lowest value. However, the GA provided the results in a shorter time than LP, which is more critical in large-scale production planning problems. By performing the sensitivity analysis in the GA on the two parameters, crossover and mutation probability, the GA's UPL value was modified to 20940. Its UPL value is only 8% less than LP's UPL value.

Keywords: *Floating cone algorithm, Genetic algorithm, Linear programming model, Sensitivity analysis, Ultimate pit limit*

1. Introduction

Planning an open-pit mine includes determining open-pit mines' UPL and production schedule. The UPL is designed to select the waste dump location, surface facilities, extractable reserves, and the amount of waste removal. The UPL is also called the economic area of the mine where the outside mining is no longer economical. This area is determined based on the economic block model. The economic block model of the deposit is prepared by considering its economic parameters. Accordingly, in the UPL design methods, a group of blocks that maximize a selected parameter such as profit, metal content, or net present value is considered for determining the UPL[1, 2].

UPL design methods can be divided into heuristics, metaheuristic techniques, and operational research (OR) methods. In 1965, Pana introduced the Floating Cone Algorithm (FC), as a heuristic method, for determining the UPL. This algorithm cannot provide an accurate answer or a mathematical guarantee to provide an optimal solution because it depends on the direction of the search and does not have a mathematical base[1]. The OR methods include the Linear Programming (LP) model, dynamic programming, graph theory, and network flow theory[3]. Lerchs-Grossmann, in 1965, developed graph theory that converts the economic block model of the deposit into a directional diagram. In a directional diagram, each vertex represents blocks, and each arc represents the interdependence of the blocks. The direction of arcs from one end to the other shows the priority of extracting the second block to the first block, and the weights are obtained from the economic values of the blocks. This algorithm assumes that the UPL problem is equal to finding the maximum weight of the weighted directional graph. Zhao and Kim tried to improve the Lerchs-Grossmann algorithm by considering the arcs defined in the ore-waste interfaces[1, 4]. Johnson, in 1968, used network flow theory to solve the UPL optimization problem. In this network, two hypothetical blocks, Source Node, and Sink Node are created at the bottom and top of the block model. Each block is considered a node, and arcs connect all the blocks in the block model. After networking, operational research methods can solve the maximum flow problem[5]. Also, Underwood and Tolwinski 1998 determined the UPL using a network flow algorithm[6]. These algorithms arrive at a real optimal solution because using a mathematical model to solve the problem of open-pit mine UPL. However, the LP method in block models with many blocks responds over a long time due to many decision variables. Therefore, to design the UPL of Large block models, methods that quickly return near-optimal solutions are often necessary. Metaheuristic methods are easily adaptable to optimization problems in open-pit mines and provide suitable solutions rapidly[8 ,7].

In recent years, metaheuristic algorithms have been used to solve complex real-life problems from different fields, such as the large-scale open-pit mine production planning problem. Most metaheuristic algorithms are inspired by the biological evolution process, swarm

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behavior, and physics law[9]. Metaheuristic methods include neural networks, particle swarm optimization, genetic algorithms (GA), tabu search (TS), simulated annealing (SA), and ant colony optimization (ACO)[10 ,7 ,1]. Accordingly, researchers, including Denby and Schofield (1994 and 1998), simultaneously used GA to solve open-pit mine planning [2]. Shishvan and Sattarvand proposed a new metaheuristic method based on ACO to solve the problem of open-pit mining planning[11]. Kumral and Dowd also used SA to solve an open pit mine planning problem[12]. Khan et al. used a particle swarm optimization algorithm to solve the problem of long-term open-pit production planning[13].

The large-scale open-pit mine production planning problem is an NP-hard issue. That is, it cannot be solved in a reasonable computational time. Among the existing methods, the GA, based on the correct definition of its parameters (such as population size, crossover probability, mutation probability, and fitness function), offers a near-optimal solution at a sufficient time in open pit planning problems[14]. In this paper, to evaluate the efficiency of the GA technique based on pit values and computational times, the GA has been used to determine the UPL of the Marvin test mine[15]. Sensitivity analysis was performed to achieve the maximum UPL value obtained from the GA. The UPL value results of the GA were compared with the LP model and the FC algorithm values to validate the capability of the GA.

Background:

As mentioned, the LP model, GA, and FC are used to design the UPL of open-pit mines. Based on the economic block model of the deposit and slope constraints, the LP model designs the UPL. The total value of the blocks in the UPL must be the highest possible. Equations 1 and 2 show this mathematically[15, 16].

$$Max \sum_{i=1}^{N} x_i v_i \tag{1}$$

$$subject\ to: \ x_i \leq x_j \quad i = 1,2,\cdots,N \quad \forall j \in P_i \tag{2}$$

$$x_i \in \{0,1\}$$

$$v_i = R \times SP \times Gr_i - (MC + PC) \tag{3}$$

Where v_i represents the economic value of block i, and N is the total number of blocks in the block model. R is the ore recovery percent. SP is the selling price of ore per ton. MC is the mining cost per ton, and PC is the processing cost per ton. Gr is the ore grade in block i. x_i is a binary variable for block i. if a block is within the UPL, its value is one; otherwise, it is zero. j is the precedence block of block i, which means it must be extracted before block i, provided that the slope constraint is met. P_i is a set of blocks located in the extraction cone of block i. For this reason, an upward cone with a slope of 45 degrees is created for each block. The cone's vertex should be in the Geometric center of that block. Then all the blocks whose Geometric centers are inside this cone are placed in theP_i (figure 1). As the size of the block model (the number of blocks) increases, so does the number of variables and decision constraints.

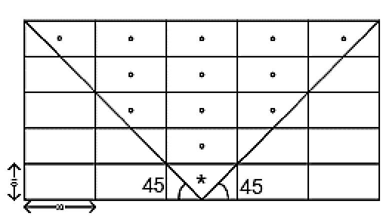

Figure 1: A set of blocks in the extraction cone of a block[17].

The following method for designing UPL is the FC algorithm that Pana introduced in 1965. This algorithm first designed an upward cone for ore blocks based on the desired slope angle. Then the value of all the blocks in the cone is added together. If the result is a positive value, all the blocks inside the cone are removed. Otherwise, it is ignored. In this case, other ore blocks are searched, and cones are formed. This process continues until there are no more ore search blocks left. The results of this algorithm depend on the direction of the investigated model. This algorithm cannot provide an accurate answer or a mathematical guarantee of an optimal solution[1]. The Final algorithm for designing the UPL is GA. John Holland introduced the GA in the early 1970s. This algorithm is a search technique used to find accurate or approximate solutions to optimization problems. A GA is a class of evolutionary algorithms that use evolutionary biology-inspired processes such as inheritance, mutation, selection, and crossover[18].

The GA begins the search with random solutions called populations. A chromosome represents a random solution, and a chromosome comprises several components called genes. Some of these chromosomes are randomly paired to produce offspring. The viability of solutions for future generations depends on their quality (fitness value)[19]. Then, a method such as the roulette wheel was used to select a new population based on the calculated fitness values for each chromosome[20]. After creating a new population, the crossover probability combines selected chromosomes to produce new solutions, while the mutation probability provides possible diversity in the population. Using the crossover probability alone to create a child causes the genetic algorithm to get stuck in the local optimal. The mutation probability was used to reduce this problem by proving the difference between new children and parents and encouraging diversity. The process of evolution was repeated until the final condition for obtaining the chromosome with the highest fitness value was met; this is known as termination criteria[19, 21]. Since the GA is a flexible method, the results can be improved by changing its parameters. In other words, by performing sensitivity analysis on a number of its parameters, the UPL presented by the GA is checked, and the best value is selected[22, 23]. Figure 1 shows the applying steps of the GA.

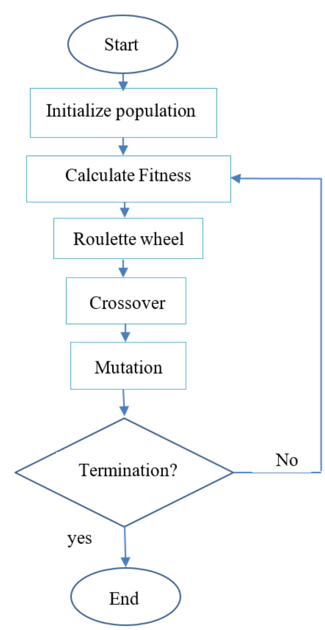

Figure 2. The applying steps of the GA.

2. Methodology

This paper aims to determine the UPL of the Marvin test mine, one of the instances of the MineLib library[15]. The Marvin block model has 53271 blocks in 8 levels, and the size of each block is 30*30*30 meters. First, applying the GA to this model needs to define the chromosome. Chromosome length equals the number of columns (the blocks in the same X and Y direction and different levels on top of each other in the block model) with at least a positive block in the economic block model. For example, figure 3 shows a 2D block model with five columns with positive blocks. Accordingly, the number of states per chromosome gene equals the number of positive blocks in the corresponding column. The fitness function for this problem is the value of the corresponding pit of a chromosome. Each gene of a chromosome corresponding block in the block model is indicated, and the extraction cone is constructed; the combination of the extraction cones indicates the pit limit. The total

value of the blocks located in the identified pit is the chromosome's fitness. Then the value of the parameters related to the GA must be selected correctly, which is done using sensitivity analysis to achieve the maximum value of UPL(Fitness).

1	2	3	4	5	6	7
-1	+1	+1	-1	-1	-1	-1
-1	-1	-1	-1	+2	+1	-1
-1	-1	+2	-1	+3	-1	-1
-1	-1	-1	+1	-1	-1	-1

Figure 3: The number of columns with at least a positive block.

As mentioned before, using sensitivity analysis, the best deals are got for the parameters of the GA, namely crossover and mutation, obtained when the maximum UPL value is received. One simplest and most common approach to using sensitivity analysis is changing one factor at a time to see what effect this produces on the output. That appears to be a logical approach as any change observed in the result will unambiguously be due to the single parameter change. Furthermore, one can keep all other parameters fixed to their central or baseline values by changing one parameter simultaneously. That increases the comparability of the results (all 'effects' are computed regarding the same central point in space) and minimizes the chances of computer program crashes, more likely when several input factors are changed simultaneously[24]. Then, by drawing a convergence plot, the sensitivity analysis results are checked to determine whether the results converge to constant values. The convergence plot is drawn based on the best fitness value of each iteration, and this iteration continues until the algorithm reaches the best fitness value. In other words, the repetition is done until the fitness value is no longer improved. The maximum UPL value is then determined based on the maximum convergence value. Also, based on the maximum UPL value, the best crossovers and mutations are determined. This paper changed crossovers and mutations between [0.03,0.7] and [0.05,0.15]. Also, in this paper, the chromosome numbers of the initial population were considered 40, and the termination criterion was considered 300.

3. Results and discussion

As described in the previous section, the LP, the FC, and the GA were applied to the Marvin block model to obtain the UPL. The numerical study was implemented on the Intel (R) Core i7computer (3.4 GHz CPU) with 16 gigabytes of RAM running under Windows 7.

In GA, by performing sensitivity analysis on a number of its parameters, the UPL presented by the GA was checked, and the best value was selected. In this article, each time, one of the two parameters of crossover probability and mutation probability was changed randomly by keeping the number of population and termination constant. Table 1 shows the numerical results of the sensitivity analysis.

Table 1: Sensitivity Analysis based on Crossover and Mutation probability changed.

	Crossover	Mutation	UPL value ($)	Ore block Num.	Waste block Num.	UPL block Num.
Run 1	0.1	0.01	18127	4738	12034	16772
Run 2	0.15	0.01	18583	4682	12091	16773
Run 3	0.2	0.01	19271	4739	12307	17046
Run 4	0.3	0.01	16697	4730	11659	16389
Run 5	0.4	0.01	19748	4774	12471	17245
Run 6	0.5	0.01	17219	4686	11736	16422
Run 7	0.6	0.01	17309	4702	11776	16478
Run 8	0.7	0.01	20940	4784	12789	17573
Run 9	0.03	0.05	18053	4599	11859	16458
Run 10	0.03	0.1	17149	4689	11714	16403
Run 11	0.03	0.15	20145	4786	12573	17359

By changing the crossover probability to 0.7, the maximum UPL value was equal to 20940. Changing the mutation probability to 0.15 allowed the maximum UPL value to 20145. After drawing the convergence plot for the sensitivity analysis results shown in Figure 4, an examination of the graph shows that the crossover and the mutation associated with Run5 provided the maximum value for the UPL.

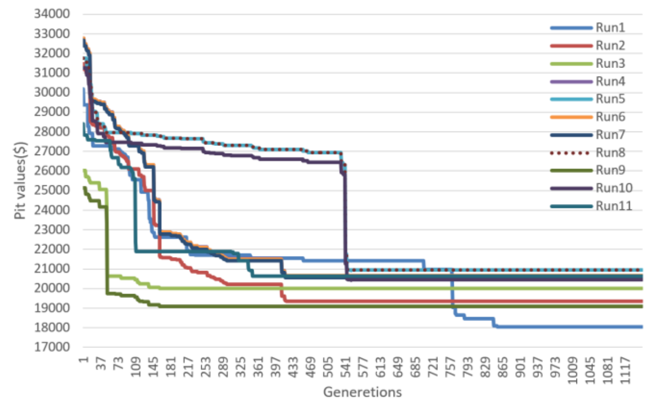

Figure 4: The convergence plot of sensitivity analysis.

As a result, when the crossover and the mutation probability are 0.7 and 0.01, the UPL value is the highest. Table 3 shows the UPL specifications obtained from UPL design methods based on the UPL value, the number of waste, and ore blocks within the UPL.

Table 2: UPL from LP, GA, and FC.

Description	UPL values($)	Ore blocks numbers	Waste blocks numbers	UPL blocks numbers	Run time(s)
LP	22786	4312	818	5130	95.4
GA	20940	4784	12789	17573	4.1
FC	12747	2789	1901	4690	2.3

According to Table 2, the UPL value obtained from the FC algorithm has the lowest value. Comparing the LP model and GA, although the value of the UPL in the LP model is higher than in the GA, run time in GA is less than in LP, which means that GA is faster than LP, which is more critical in large-scale production planning problems.

4. Conclusion

This paper aims to evaluate the efficiency of the GA technique based on the pit values and computational times compared with other methods of designing the UPL. In other words, in addition to GA evaluation in UPL design, other proposed methods for UPL design are also compared. The GA offers a suitable solution based on the correct definition of GA parameters (such as population size, crossover probability, mutation probability, and fitness function). The UPL obtained from the GA was compared with the UPL obtained from the LP to evaluate the GA. All three methods were applied to the block model of the Marvin mine. Comparing the GA and other methods revealed that the LP model received the highest UPL value. The UPL value obtained from each mentioned method and the FC algorithm got the lowest values. However, compared to LP, the GA provided the results in a shorter time, which is more critical in large-scale production planning problems. By performing the sensitivity analysis in the GA on the two parameters, crossover and mutation probability, when the crossover and the mutation probability were 0.7 and 0.01, the GA's UPL value is modified, and its UPL value is only 8% less than LP's UPL value.

Nevertheless, the UPL value of FC is 44% less than that of LP. Unlike the FC algorithm, GA is not dependent on search direction. By performing sensitivity analysis, the best values for the parameters related to the GA were determined to provide the best response by this algorithm.

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