Ants Colonies to solve a Micro Mine Planning Problem

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Abstract

In this paper we introduce an algorithm for solving a micro copper mine planning problem. In the last 10 years this real-world problem has been tackled using linear integer programming. The model has 90,000 constraints and 15,000 variables. In order to obtain a solution in a reasonable time, the model was simplified and solved using CPLEX. The problem model simplification relaxs many important constraints like geological and physicals. We propose an algorithm based in ants colonies ideas which takes into account this kind of constraints and it is able to find best quality solutions.

1 Introduction

Chile is the world's largest copper producer and the profit obtained by the copper extraction has an important role in the country economy. For that, it is very important to reduce the extraction costs and to improve mine extraction planning. This problem belongs to the class of combinatorial optimization problems. In the last 10 years, this real-world problem has been tackled using linear integer programming. Because any software was able to solve the complete model, it was simplified relaxing some geological and physical constraints. The simplified model was solved using CPLEX. Because of the success obtained solving complex problems like timetabling problem, [4], [2], scheduling [1], vehicle routing problem [3], travel salesman problem [5] and real-world applications [6], [7], [9], [8] using genetic algorithms, tabu search, simulated annealing, local search techniques, ant colonies, metaheuristics and hybrid algorithms, we have been motivated to tackle our problem by these techniques. Now, we propose an

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algorithm based on ants colonies which takes into account all the constraints. The planning of this paper is the follow: In section two we define our real-world problem, in section three we present the linear integer programming model simplified, in section four we introduce our algorithm. In section five we present the results obtained using real data and random generated mine planning problems. Finally, in the last sections we present the conclusions and the future issues.

2 Problem Definition

In a mine we can identify sections, blocks and cells. A mine is composed by a set of sections. A section is a portion of the working area of a mine. Each section is divided in big blocks, and the blocks are composed by cells. Our real-world problem is one section of a copper mine which is composed by m blocks. The goal is to define the optimal extraction planning. The optimal value is related to the cost and to the present value of the extraction benefit. The problem has many types of constraints, like accesability, geologicals, capacity and economicals.

Accesability:

- Inside a block we must extract the first cell to be able to extract the second one, and the second one in order to have the third and so on.
- In order to have access to a block, we must pay an habilitation cost. This cost is only charged to the first cell of the block

Economicals

- The benefit is calculated using an benefit present value with a discount rate of 10%

Geological:

- The biggest type of constraints is called "subsidence constraint". Mine subsidence is movement of the ground surface as a result of the collapse or failure of underground mine workings. This kind of constraints establishs a physical relation between blocks. The extraction of a block defines an upper cone. The extraction of the blocks belonging to this cone is not allowed because of physical laws. In other words the blocks in the cone will be inhabilated for ever.

Capacity

- We are able to extract a maximum of k cells by year.

The optimization is for a 20 years planning.

3 Model

In this section we present the linear programming model solved using CPLEX.

Goal : Maximize NPV (Net Present Value)

Variables:

$$z_{i,t} = \begin{cases} 1 & \text{if block } i \text{ is exploited in } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$h_{j,t} = \begin{cases} 1 & \text{if blocks group } j \text{ is habilitated in } t \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Objectif Function

$$NPV = \sum_{i,t} r^t U_i z_{i,t} - \sum_{j,t} r^t C_j h_{j,t} \tag{3}$$

where r is the discount rate, U_i is the benefit of the block i, C_j is the habilitation cost of the blocks group j.

Constraints

- Consistency

$$\sum_t z_{i,t} \leq 1, \forall i \tag{4}$$

$$\sum_t h_{j,t} \leq 1, \forall j \tag{5}$$

Remark 3.1 *The blocks are exploited only once, the habilitation is made only once*

- Accesibility

$$z_{i,t} \leq \sum_{s \leq t} h_{j(i),t}, \forall i, \forall t \tag{6}$$

Remark 3.2 *The habilitation is before exploitation*

- Subsidence

$$z_{i,t} + z_{i',s} \leq 1, \forall i, \forall t, \forall i' \in I(i), \forall s \geq t \tag{7}$$

Remark 3.3 *The exploitation of block i produces an inhabilitation of the blocks belongs to its upper cone*

- Capacity

$$\sum_t z_{i,t} \leq C, \forall t \tag{8}$$

The most important assumption of this model is that when we decide to exploit the block i, we must extract all of its cells, and the capacity is given by block and not by cell. We can distinguish two types of problems: The first one is known as a Macro problem, that is the blocks planning extractions. The second one is a Micro sequence problem, where we suppose a block composed by cells and the best extraction policy could be to extract only some cells of the block and not to extract the whole block. In this paper, we concentrate our attention on the Micro planning problem. CPLEX was not able to solve the complete model that includes all of these considerations. This is our motivation to introduce an algorithm that is able to manage all the constraints involved. In the next section, we present our approach begining by the definition of the representation and its evaluation function.

4 Algorithm

4.1 Evaluation Function

In our approach the representation gives the planning extractions by block. The evaluation function includes the hardest physical constraints. Because of when a block is exploited other blocks became inhabilitated for ever, we have included an opportunity cost related to the impossibility of obtain the benefit of the inhabilitated blocks.
Thus, the algorithm searchs not only the block with the higgest profit, else the block with its gain justifies to inhabilitate the other ones. This is shown in figure 1. Considering the black ones as the richest ones. If we decide to extract the black block in the bottom of the mine, its extraction will inhabilitate the other ones, between the blocks inhabilitated there are some with a good profit value.

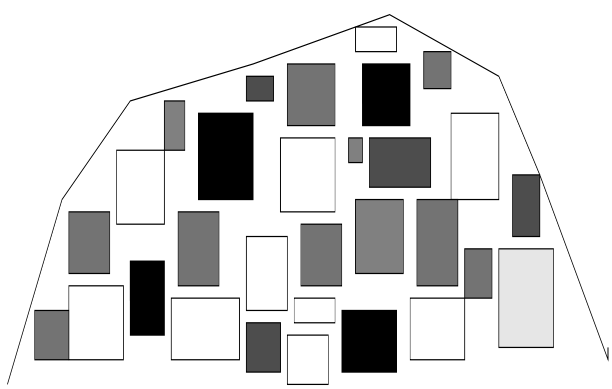

Figure 1: Mine with different kinds of blocks

4.2 Algorithm Structure

We introduces an Ants colonies based algorithm which generates moves to obtain pre-solutions that satisfy all the constraints. Thus, the move is defined such as the algorithm obtains only feasible solutions. The most important constraints are the subsidency constraints. At the beginning, the algorithm selects randomly one cell of one block. This cell will be extracted. Thus, as a consequence of its extraction the algorithm inhabilitates the other blocks which are in the upper cone of this block.
The blocks inhabilitated will be added in a Tabu List for ever. The next blocks feasible to be extracted will be the blocks that are not in the Tabu List, that means the blocks that satisfy the subsidency constraints. Each block belonging to the Allowed-List is evaluated taking into account its gain, the habilitation cost, the extraction cost and the opportunity cost. The opportunity cost is calculated using the gain of the blocks that will not be able to be exploited in the following extractions. Figure 2 shows the algorithm.

```
Begin /* Heurístic ACS for Mine Extraction*/
i=1
For each cycle t
Select randomly a position block for each ant k
While i<max-blocks do
        if U(0,1) < ρ0
              Extract cell with the biggest probability value P_ij^k
        else Choose randomly the cell to be extracted
        Modify the Tabu List
        Modify the extraction sequence
        Modify pheromone
        i++
endfor
end
```

Figure 2: ACS heuristic for Micro Mine Planning Problem

The transition rule, i.e. the probability P_{ij}^k that the ant k extracts the cell j right after cell i is:

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}(t)[\eta_{ij}]^\beta}{\sum_{h \in J_i^{k(t)}} \tau_{ih}(t)[\eta_{ih}]^\beta} & \text{si } j \in J_i^k \\ 0 & \text{e.o.c.} \end{cases} \tag{9}$$

Where β is a parameter to control the pheromone intensity with the ant visibility. $\tau_{ij}(t)$ is the pheromone intensity, $\eta_{ij}(t)$ is the ant visibility and J_i^k

the cells allowed to be extracted from the cell i, which are not in the Tabu List. The pheromone level is locally modified using:

$$\tau_{ij}(t) = (1-\rho)\tau_{ij}(t-1) + \rho\tau_0 \tag{10}$$

and globally by:

$$\tau_{ij}(t) = (1-\rho)\tau_{ij}(t-1) + \rho\frac{Q}{L^+} \tag{11}$$

where ρ is the evaporation coefficient, L^+ is the gain of the best found current extraction sequence. The visibility in this model depends directly of the evaluation function of the cell to be extracted.

5 Results

We have considered for our tests real world data. We have also generated randomly some instances of a mine considering various configurations of blocks gain. For that, we take into account the following:

- A hard configuration: When the mine has many blocks with the same gain and not concentrated
- A normal configuration: When the mine has blocks that the algorithm can identify as the better ones to be extracted
- An easy configuration: When a mine has blocks with very different gains and the identification of the better ones is obvious.

5.1 Parameters

In order to test our algorithm we have used only normal and hard configurations. We have generated randomly 10 different mine configurations $a_1, a_2, .., a_{10}$. We use tunning to find the best parameters. The values used was:

- $\beta \in \{1, 3, 5, 7\}$
- $Q \in\in \{50, 100, 150\}$
- $\rho \in \{0.5, 0.8, 0.9\}$
- $r_0 \in \{0.8, 0.9, 0.95\}$
- $r \in \{1, 1.5, 2, 2.5, 3, 3.5\}$

We have tested 648 runs of the algorithm for each problem using various parameters. The number of ants is the number of blocks to be extracted, i.e. 80. The number of cycles equal to 200.
We have obtained the best results using $(r, \beta, Q, \rho, r_0) = (1.5, 1.0, 150, 0.5, 0.8)$, that means that the pheromone visibility and the intensity have the same importance value. The exploration has more importance than exploitation.

The figure 3 shows for the real problem the values obtained.

Problem	Real					
	r	β	Q	ρ	r_0	Value
Best	1.5	1.0	150.0	0.5	0.95	31.42
200+	1.5	3.0	150.0	0.5	0.8	17.4130
200−	2.5	1.0	50.0	0.8	0.8	−7.1556

Figure 3: Benchmarks with different parameters for the real problem

We identify by 200+ the 200 better results, and with 200− the worse 200 results.

6 Discussion

We have obtained better results applying an Ants Colonies based technique than the linear programming relaxed model. Nevertheless, in order of being exact in the interpretation of the results, our algorithm uses a metaheuristic technique, thus is not able to obtain the optimal value and its performance depends strongly of the random number generator.

7 Conclusions

We have introduced an Ants Colonies algorithm for solving a micro-mine planning problem. We shown that this kind of technique could be a good alternative to solve real world problems for which traditional techniques are not able to solve it. The biggest problem is that we are not sure that it is the optimal value. On the other hand, the algorithm found a better optimal value for our real world problem. We have also studied the behaviour of the algorithm solving other kind of mine configurations, with more levels than the real one, and with some instances hardest than the real one. The algorithm shows be better using $(r, \beta, Q, \rho, r_0) = (1.5, 1.0, 150, 0.5, 0.8)$ as parameters. Now, we are going towards to solve the Microsequence mine planning problem using other metaheuristics.

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