Capital Decisions as Part of Strategic Scheduling Process

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ABSTRACT

Mining businesses work by looking at long term opportunities to make an economic gain from a resource. An investment decision in a mine is based upon a time frame of generally 10 or more years. Economic modelling, forecasting, research and business planning goes on to support that investment decision, and a huge amount of money is spent to realise a new mine.

Strategic schedules often do not incorporate the capital investments as part of the optimisation models. From a strategic point of view, an important aspect is to analyse different mill capacities, different truck configurations or even different infrastructure, particularly from a multi-deposit point of view.

The ability to simultaneously optimise strategic capital decisions as well as multiple mining policies (cutoff grade, mill capacities, trucks, stockpiles, etc.) across multiple mine sites greatly reduces the iterative process involved in globally optimising a business.

This paper presents a global optimisation approach utilising a customised memetic algorithm. A memetic algorithm can be thought of as a synergy of evolutionary and classical optimisation techniques.

Keywords

Strategic capital decisions, investments, optimisation.

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INTRODUCTION

Mining businesses work by looking at long term opportunities to make an economic gain from a resource. An investment decision in a mine is based upon a time frame of generally 10 or more years. Economic modelling, forecasting, research and business planning goes on to support that investment decision, and a huge amount of money is spent to realise a new mine. The objectives at that stage are to achieve the planned business outcomes and meet the expectations of investors or bankers and JV partners.

Of course, it is not all that simple and probably very soon after mining starts, new information is learned, assumptions are adjusted, surprises happen and expectations are adjusted (up or down). A mining operation is an extremely complex environment and the impact of a very large number of variables combines to cause those investment assumptions to look less and less accurate over time as mining proceeds.

Typical strategic schedule models usually do not include important capital expenditure features such as capacity decay or expiration, precedence over time (rail before plant) or mutually exclusive option sets (choices of plant size). By not including these features, a strategic mine scheduling model for a capital-sensitive operation is unable to be optimised to deliver maximum value. (L Blackwell, 2014).

The ability to simultaneously optimise strategic capital decisions as well as multiple mining policies (cut-off grade, mill capacities, trucks, stockpiles, etc.) across multiple mine sites greatly reduces the iterative process involved in optimising a business and unlocks value.

Evolutionary algorithm (EA) is an umbrella term used to describe population-based stochastic direct search algorithms that in some sense mimic natural evolution. (Bartz-Beielstein et al, 2014).

In general, any abstract task to be accomplished can be thought of as solving a problem, which, in turn, can be perceived as a search through space of potential solutions. Since usually we are after “the best" solution, we can view this task as an optimisation process. For small spaces, classical exhaustive methods usually suffice; for larger spaces special artificial intelligence techniques must be employed. (Zbigniew Michalewicz).

METHODOLOGY

The problem under discussion is the simultaneous optimisation of extraction sequence and cut-off grade for single/multiple elements in the face of multiple processing streams and multiple mines under some capital decisions which can make the project go ahead or abort.

The implementation requires single/multiple block model(s) with the following assumptions:

- Development of an ultimate pit limit or pushback or some portion inside the ultimate pit limit that can be mined, processed and refined in several years.
- Capacities constraints (i.e. mining, processing, refining capacities and others).
- Economic models (i.e. operating costs and metal price).
- Proper stage design is optional but preferred. The impact of proper stage designs on cut-off grade optimisation cannot be stressed enough.
- The ore reserves inside the pit limit or pushback in terms of mineral grade and tonnage distribution. A grade tonnage distribution is calculated for each phase-bench-lithologies combination.

The objective function of cut-off grade optimisation modelling is maximisation of NPV in the presence of capacity constraints (mine, mill, market and stockpiles), operational constraints (sinking rate, bench turnover, accumulation constraints, blending etc.), multiple processing streams and extraction sequences.

It can be represented mathematically as follows:

$$Max\ NPV = \sum_{n=1}^{N} \frac{P_n}{(1+d)^n} - \sum_{n=1}^{N} I_o - C_{c_m}$$

Equation 1

Where:

d= Discount rate (%)

Pn = Total Profit per processes ($)

Io = Capital Decisions - Investments ($)

C_{c_m} = Closure cost per pit ($)

N = number of periods.

$$I_o = Ti + PPi + In + Dc$$

Equation 2

Where:

Ti = Truck Investment

PPi = Processing Plant Investment

In = Infrastructure Investment

Dc = Dynamic Capital.

$$Pn = (P_{process\ 1} + P_{process\ 2} + \cdots + P_{process\ n}) - fT$$

Equation 3

Where:

$P_{process\ n}$ = Profit at process n

f = fixed cost per year ($/year)

T = length of period considered, usually a year.

$$P_{process_n} = (Pr - Sc) * \bar{g}_n * y_n * Q_{c_n} - m * Q_{m_n} - c * Q_{c_n} - r * Q_{r_n} - rc * Q_{m_n}$$

Equation 4

Where:

Pr: Price ($/unit of product)

Sc = Selling cost ($/unit of product)

$\bar{g}_n$ = average grade of material presented at process n

y_n = recovery at process n

m = Mining Cost ($/ton)

rc = Rehabilitation cost ($/ton)

c = Processing cost ($/ore ton)

r = rehandling cost ($/ore ton)

f = fixed cost per year ($/year)

T = length of period considered, usually a year

Q_{c_n}= Quantity of ore presented at process n

Q_{m_n}= Quantity of material mined

Q_{r_n}= Quantity of ore reclaimed presented at process n.

Algorithm

The algorithm consists of three evolutionary and one classical optimisation algorithm (Figure 1). These include:

- The core or master evolutionary algorithm
- Local search evolutionary algorithm
- Capital Decision Search (combination of integer programming and evolutionary algorithm)

The main responsibilities for each algorithm include:

- Master
  - o Exploring cut-off grade search space
  - o Exploring stockpile cut-off grade search space
  - o Exploring extraction sequence search space
  - o Responsible for optimal reclaim strategy from stockpiles

- Local Search
  - o Exploring the immediate neighbourhood of process and stockpile cut-off space for a given extraction sequence, in other words during the local search the extraction sequence is fixed

- Capital Decisions Search
  - o Responsible for optimising different capital policies
    - § Integer Programming
      - · Optimise the composition of the truck fleet required across the life of mine
    - § Evolutionary algorithm
      - · Highly customise genetic algorithm responsible for optimising processing capacity
      - · Highly customise genetic algorithm responsible for optimising infrastructure

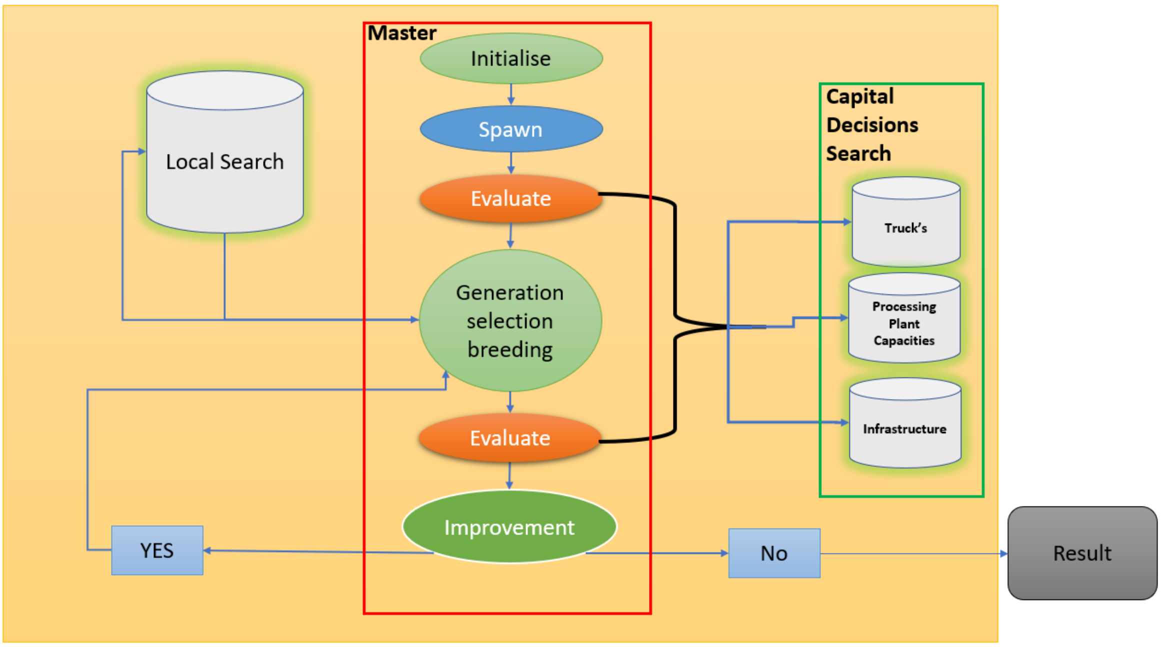

Figure 1: Algorithm

This new framework provides the ability to analyse multiple capital policies during the optimisation thereby reducing the iterative nature of the process.

Evolutionary algorithms are understood as population based stochastic direct search algorithms that in some sense mimic natural evolution. Points in the search space are considered as individuals (solution candidates), which form a population. Their fitness value is a number, indicating their quality w.r.t. the problem at hand. Besides initialisation and termination as necessary constituents of every algorithm, EAs can consist of three important factors: a set of search operators (usually implemented as 'recombination' and 'mutation'), an imposed control flow, and a representation that maps adequate variables to implementable solution candidates (the so-called 'genotype-phenotype mapping'). (Bartz-Beielstein et al, 2014).

The importance of this model is that the capital decisions are evaluated as part of the net present value during the optimisation. This will allow the decisions to be evaluated at the right time in order to maximise the net present value.

RESULTS AND DISCUSSION

This algorithm was proved in a typical open pit project. The dataset contains 3 pushbacks and it has a mine life of 16 years. The above approach should give a good indication of the timing of various investments in order to maximise the project NPV.

We will evaluate three different scenarios, trucks, processing capacity and infrastructure.

First Scenario: Analysing Truck Policy

Here we will evaluate the optimal composition and timing of the truck fleet. We are considering two different truck types. The main parameters considered are shown in the table below:

Truck Type	Purchase Cost ($)	Life (years)	Capacity (tonnes)
Truck A	$5,500,000	5	300
Truck B	$3,500,000	4	90

Table 1: Truck Policy - Parameters

From Figure 2 below, it can be seen that six new trucks of Type A are purchased in year 1. One truck of Type B is purchased in year 5. Furthermore, at the end of year 5, all the trucks of Type A are retired. Therefore, in year 6, five new trucks of Type A are purchased. In year 10, two new trucks of Type B are purchased and three new trucks of Type A during year 11. In year 14 all trucks of Type B are retired. Finally, a single truck of Type A is purchased in year 16.

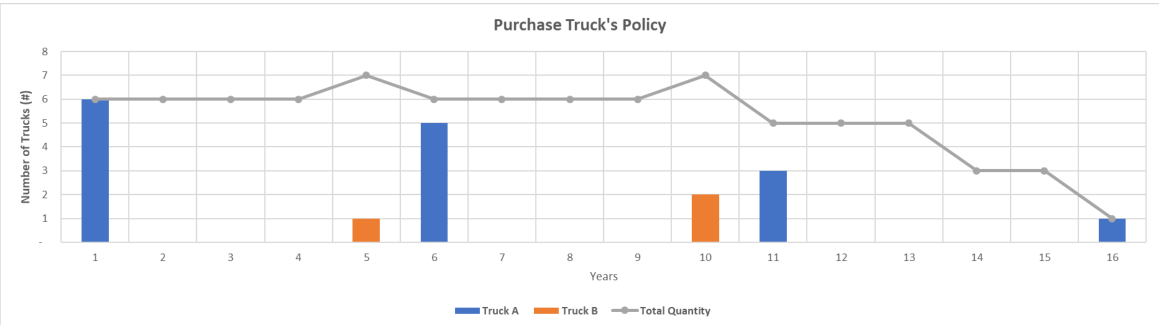

Figure 2: Purchase Truck Policy

Second Scenario: Analysing Optimum Processing Capacity

In this example we will optimise the policy for processing capacity. Here, three different processing capacities will be evaluated.

It is important to note that the scale of economics is considered here. Larger capacities are usually associated with lower unit costs. This needs to be part of the optimisation in order to provide the optimum processing capacity.

Processing Type	Incremental Purchase Cost ($)	Processing Cost Escalation ($/ton)	Processing Capacity (t/y)
Processing A	20,000,000	1.5	2,000,000
Processing B	10,000,000	1.0	3,000,000
Processing C	15,000,000	0.5	4,500,000

Table 2: Process Capacity Policy - Parameters

In this case the results are shown in the image below:

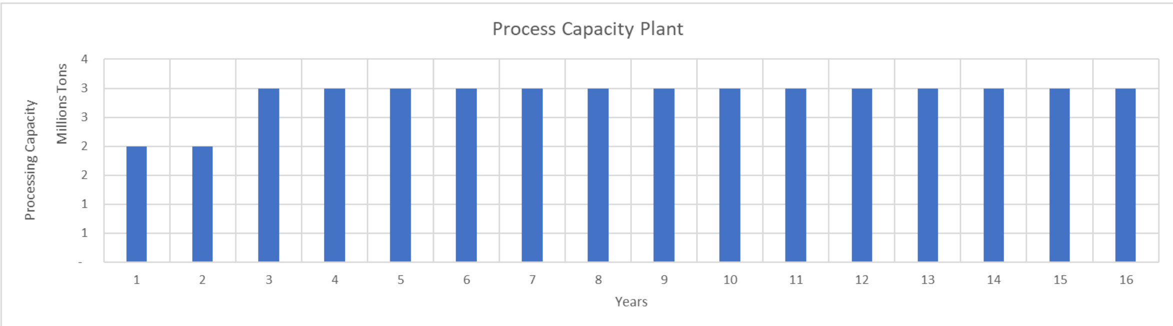

Figure 3: Process Capacity Plant (tons/year).

Here, the optimal policy started with a plant capacity of 2,000,000 tons per year and after year 2 increases by one million tons to 3,000,000 tons.

Third Scenario: Evaluate the best infrastructure

Here we will evaluate the order in which infrastructure are being brought online. For this example, we have three different sites (i.e. A, B and C) with two port capacities (i.e. Port A and Port B) and the investment associated with each option can be shown in the following image:

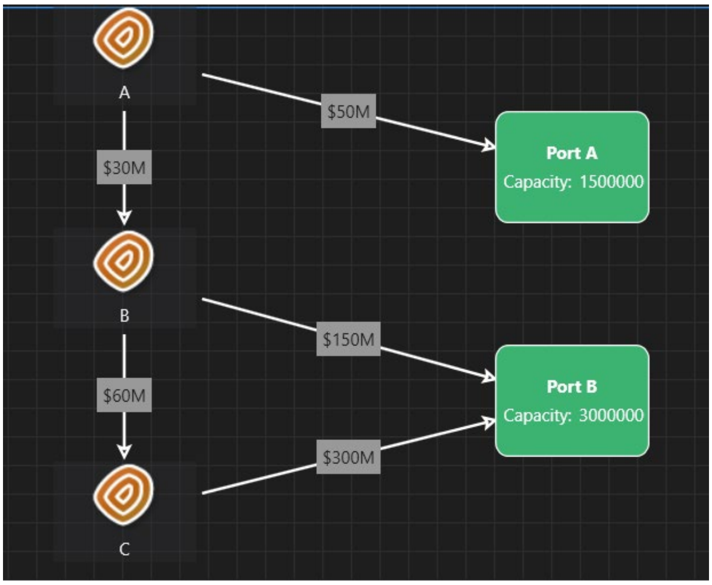

Figure 4: Infrastructure Setup

The results from an infrastructure point of view are as follows:

- Pit B to Port B online in period 1.
- Pit C to Port B online in period 1.
- Pit A to Pit B online in period 18.

Since the timing of installing infrastructure is considering during the scheduling the result is a more robust and global optimised net present value (i.e. NPV).

CONCLUSION

The memetic algorithm allows for the efficient global optimisation of multiple policies such as:

- Extraction sequence
- Multiple cut-off grade policies
- Stockpile policies
- Various capital decision policies such as equipment, plant capacity and infrastructure

The use of evolutionary algorithms provides a flexible and powerful framework to solve complex, non-linear problems in an efficient way without making any assumptions of the fitness landscape. They have many advantages, particularly around their ease of implementation, easily incorporating surrogate models and other optimisation techniques.

Finally, as always, the result from any technique is only as good as the model on which it is operating.

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