Production Estimate in Selective Underground Mining by Simulations

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ABSTRACT

Generally, mine planning is undertaken towards the development of production plans using fixed parameters, which provide little flexibility for changing production plans in case of unplanned events. Therefore, it is important to introduce variables during the planning process which would allow the mine planning to have a better alignment with real mining conditions and would allow to decrease the operational uncertainty towards the development of a more agile production plan.

Among the variables that affect the geomechanical planning process are, for example, stope stability and overbreak, for which a correct quantification can mean the success of a plan or a major deviation from it, which would prevent achieving the production targets. As these events occur with variability, it is necessary to carry out studies to better understand these conditions and how they are influenced by various factors.

To incorporate different operational variables and geomechanical factors, such as over-excavation or stability factors, within the uncertainty model, a methodology is being developed to assess the variability of a mining plan in selective underground mines for short to medium terms.

In this paper, the development of a new methodology is described; this methodology enables gathering of information associated with short term planning towards refining the medium-term production plans.

The methodology is being developed using tools currently available at the DELPHOS Mine Planning Laboratory, DSIM and UDESS, which simulate various scenarios and scheduling activities, which will, subsequently, add value to the mine planning process.

INTRODUCTION

Mine planning is a discipline within Mine Engineering which main objective is the maximization of value for the different stakeholders. It is therefore natural for mine planners to model the production and value of a project in terms of different parameters or decisions, which are then optimized to obtain the best possible value. The range of techniques to do so is big and may go from the manual evaluation of a few scenarios to the utilization of advanced techniques from operations research and optimization (for example, mixed integer programming) in order to model the production of mine operations and use them to derive best-value plans.

In order to perform such optimizations, the planning process needs to be fed with lots of data, for example operational data that involves the performance of equipment. These performance indicators are obtained from nominal equipment productivity parameters which are adjusted using operational multipliers like mechanical availability, operational losses, etc. The main goal is to have the most accurate data in order to obtain a meaningful plan.

A problem with this static approach is that it does not account for the variability of different tasks, the evolution of the layout over time, interference between different pieces of equipment is complex to estimate. A more fundamental problem with this is that, indeed, the actual values of these parameters depend on the long-term plan. For example, the transportation capacity of a mine depends on the relative transportation distances and therefore is not a constant.

One tool that is commonly used precisely to address the issues described above is discrete-event simulation (DES), which allows to understand the behavior of the system, from the modelling of the different agents, the tasks their perform and their interaction in a dynamic setting. While this kind of approach indeed can be used to solve many of the complexities described before, it is hard being used for long-term optimization, mainly because of the computational difficulties of doing so and the fact that simulation (and optimization) software are very adapted to specific tasks and it is then difficult to combine them.

Indeed, optimization and simulation are complementary techniques that combined can provide high value plans that are also robust in terms of operational uncertainty, for example. The natural way to combine these techniques is illustrated in Figure 1, where the output of an optimization model (that is the plan) is simulated to obtain the overall performance as well as specific KPI for key equipment and conversely, these data enters as new parameters in order to compute a new plan. In the case of this paper, the plan will consist of the production and preparation activities for an underground mine, and the simulation will estimate equipment (LHDs, Jumbos, Simbas, etc.) for different stages in the life of the mine, so they can be fed back to the planning process.

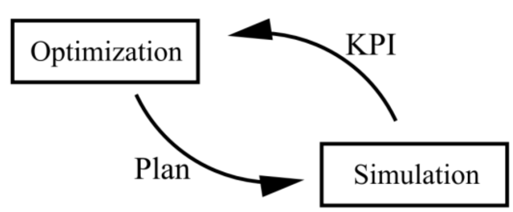

Figure 1 - Interaction between Optimization model and Simulation

The iterative process has to be started from an initial plan that can be obtained from an optimization process or not, that is then simulated to estimate equipment productivity. The new parameters are then fed to the optimization process to update the plan accordingly, and so on.

Unfortunately, implementing this methodology can be very difficult to implement, because optimization solvers (like Gurobi®, CPLEX®, etc.) and simulation software (Arena®, ProModel®, etc.) are specialized to their specific task and possess limited capabilities to interact with other software in an efficient way. Because of this, we have developed optimization and simulations models for mine planning that allow this kind of integration by means of scripting. The models (which are also available as software tools named UDESS and DSIM for optimization and simulation, respectively) are described now.

Optimization Model

The optimization model that we use is a general scheduling that takes as input: (a) activities (or tasks), their lengths and operational resource requirements, (b) the logical precedences between these activities, and (c) the net profit of performing such activities. The model computes the schedule of activities that complies with precedence and resource availability, but such that the maximum value (or minimum cost) is obtained. This model has been successfully tested in scheduling of production and preparation for panel caving in the deterministic [7], and under operational uncertainly [1], scheduling of projects under price uncertainty [6]. It has also been used in an interactive way like the one described in Figure 1, but using other models like material flow in a caving mine [2], seismic risk [3], and dilution in a cut and fill [8].

Simulation Model

Contrarily to commercial solutions, the simulation model is specifically oriented to material handling in open pit mines, as well as production and preparation in underground mining. It implements: (a) a set of functions and that allow to easily define a layout and modelling of movement of equipment, (b) several agents (trucks, shovels, LHDs, etc.) that can be used as is or extended to model more complex situations, and (c) reports specially tailored to mine operations (cycle times, production, etc.)

Mainly it has been used mostly in open pit mine, for example to study the variability of production due to operational and geometallurgical uncertainty [4] as well as to simulate autonomous hauling systems [5].

As mentioned before, in this paper we will mainly focus on the arrow going from "Simulation" to "Optimization" (Figure 1), but indicate how we plan to close the iterative step using the optimization model.

METHODOLOGY

In this article we aim to compare the deviations in estimations considering a deterministic approach (based on means) to the results obtained from simulation. The methodology for this will be to:

1. Define an application case with realistic layout and equipment.
2. Estimate production for the layout based on a deterministic approach.
3. Split the sources of uncertainty into ones modelled by simulation and others.
4. Define different cases to simulate in the mine and estimate production for these cases.
5. Compare the results with the deterministic approach. In particular, to indicate what are the planning decisions that would change with regards to the deterministic case.

MODELLING

For the sake of this work, we will consider the following decomposition of time for the equipment, based on ASARCO approach:

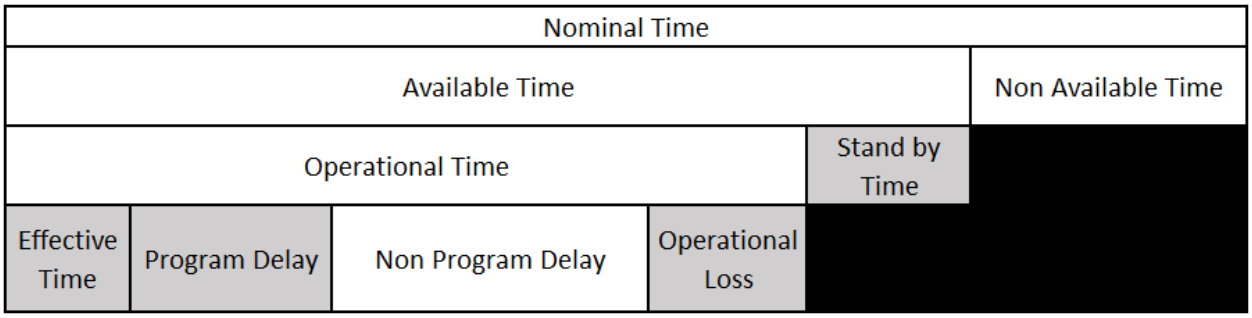

Figure 2. ASARCO Table

We will consider the activities of (a) Drilling in development front, (b) Explosive loading, (c) Blasting, (d) Muck movement and (e) Front fortification. The models will consider the layout that includes the moving paths of equipment as well as the following relevant elements: drawpoints, ore passes, and development fronts. The equipment considered in this version of the model are the drilling equipment (Jumbo and Simba), development and production LHDs and the truck with explosive. Each equipment type will have different values in the terms of KPI. We will consider variability on each of these parameters. (See Table 1. Equipment in Simulation Model

Each box in Figure 2 represents a period length. For the deterministic model, we will use operational factor for all of them as follows: Non available Time=4.8h (20%), Stand by Time: 3.3h (13%). Operational Loss: 1.4min (<1%), Non Programmed Delays 30min (2%), Programmed Delay: 6h (25%). Conversely, for the simulation model will use the same values, except for the greyed boxed which are an output of the model.

EXAMPLE OF APPLICATION

Mine layout considers 21 stopes, but only 9 are operating (the others are extracted in later periods). The stopes are distributed in 3 levels, each has 3 available stopes and 6 development fronts. For this setting, we will consider the following equipment: 4 LHDs (1 for production at each level and 1 for muck movement), 2 Simbas per level, 1 Jumbo for the whole mine sector and 2 explosive trucks, 1 for production and 1 for production and development.

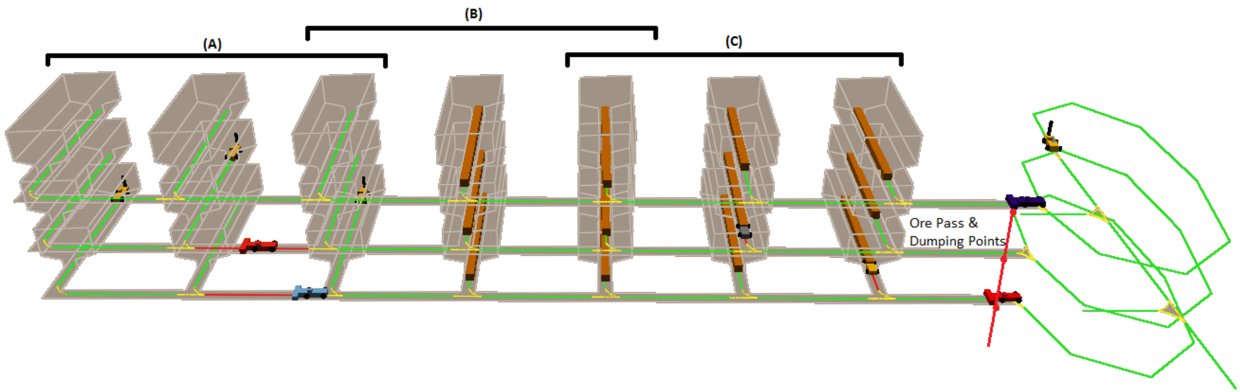

Figure 3. Mine Layout consisting of 3 levels with 7 stopes each. Dumping points are circled with red on the right side.

The relevant distances are (a) Ramp between levels: 232 [m], (b) Access Road (section): 50 [m], (c) Productivity Road(section): 70 [m] and (d) Broken Ore per Ring: 2,400[t].

Production Estimation Using a Deterministic Approach

A deterministic approach for estimating the production will consider average distance, i.e., central stopes at area "B" in Figure 3. These stopes are at a distance of 270 meters from the dumping points, which yields a cycle time of 3.1[min] for LHD and an estimated production of 2,786 [t/day] per LHD, or 8,358 [t/day] for the mine. On the other hand, the Simbas require 12 hours to prepare one 2,400 [t] ring, plus 3 hours for setting up the machine and then prepare it to move, plus 5 hours for shift changes and meal times. As a result, 2 Simbas can prepare an equivalent of 4,068 [t/day], therefore we need to add a second Simba per level, so the LHD will be the operational limiting. (Notice that, for the distance considered, 1 Simba cannot prepare enough material for 1 LHD).

Production Estimation Using Simulations

Table 1 summarizes the parameters used in the simulation model. U(a,b) represents a uniform distribution with given limits. We run 3 different sets of simulations, each correponding to production concentrated in areas "A", "B" and "C" (see Figure 3).

Table 1. Equipment in Simulation Model

Equipment	Type	Modelled Properties
LHD	Production/Development	Capacity: 12 + U(-1.5,1.5) [ton] Movement Speed: Direct 20 [km/h], Reverse 10 [km/hr] Load Time: 15 + U(-2,12) [s] Dump Time: 15 + U(-2,12)[s]

Simba	Production	Drilling Time: 15 + U(-0.5,0.5) [hr] Movement Speed: 10 [km/hr]
Jumbo	Development	Drilling Time: 2 + U(0,1) [hr] Movement Speed: 10 [km/hr]
Truck with Explosive	Production	Work Time: 2 + U(-0.5,0.5) [hr]

As Table 2 shows, the simulated material movement in case "B" is very similar in simulation and deterministic approach(2,785.9 [ton/day]), and this difference reach almost 10 [ton/day], but in the other hand, the other experiment shows a bigger difference, showing over than 500 [ton/day] per LHD. This result is for the layout of the example application, so this difference will be larger in a more realistic setting.

Table 2. Simulated results and comparison to deterministic case ([t] for LHD).

	Case A	**Case B**	**Case C**
Movement Material (without factors)[t/day]	2,835.7	3,546.1	4,240.1
Stand By Time [hr]	2.8	3.3	5.6
Operational Loss [min]	0.8	1.4	1.4
Operational Delay [hr]	5.9	5.9	5.9
Movement Material (with factors)[t/day]	2,221.3	2,777.8	3,321.4

The simulation replicas show that there's interaction between equipment and can even be quantified, but the example does not show a significant decrease in productivity expected, mainly because the fleet only interact in a few ways.

The Stand by Time grows if the travel distance is lower, and in the case 3 reach almost 6 hours. This value could be smaller if there are more stopes available in the mine, or increase the broken ore rate in the system. This is very relevant, because it means that the bottleneck is in the Simba equipment, something that does not follow from the deterministic analysis. This may have a very important impact in terms of selecting the optimal combination of fleets, for example in a more heterogeneous setting.

This result is a first step and it is necessary to apply many improvements within the model, for example activities related to Non Operational Delay (Fuel Load) or the Available Factor.

CONCLUSION

The production estimate using simulations reveals that the use of averages in the deterministic case hides the variability that exists in the process itself which is due to changes in cycle times. The conventional method is very accurate in the mid problem, but it's not a good approach if you don't consider the extreme values of the layout.

Simulation allows quantification of operational losses that are taking place in an underground mine, but there must be a better definition of the equipment that are in operation and that loss will be influential in the outcome, along with a greater amount operational restrictions within the system.

Considering these simulated productivity indexes can impact the decisions of requirements, for example, for the fleet as the layout evolves. We expect that, extending the simulation to different parts of the lifetime of the mine can help providing better approximates for the long-term planning and, as presented in the introduction, being able to iterate in the planning construction will imply to generate more robust plans and a tighter estimation of equipment needs, as well as a better production estimate.

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