Open Pit Strategic Mine Planning with Automatic Phase Generation

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ABSTRACT

A strategic mine plan is a fundamental part of any mining operation. It must provide a realistic and operative extraction and processing schedule, and yield the highest value for the business. For open pit mines, the problem can be modelled as a set of blocks representing the deposit, for each of which we need to decide if it is going to be mined, if so, when and where it will be sent (process, stock or dump). This problem can be proven to be of NP-Hard complexity. The traditional approach used by mining engineers to tackle this complexity is to separate the problem into more tractable components, solving each separately. The first step is to use the Lerchs-Grossman (LG) algorithm to obtain the final pit limit, as well as a set of optimised pit shells (nested pits), using different input prices. Then, using this input, operational phases are designed. Third, the set of phases can be used as an input for a phase-bench style optimisation, usually using a mathematical programming-based algorithm.

There are, however, several problems with this approach. First, dividing the problem into simpler parts has the consequence that any compromises made at early stages limit the potential value left for the following steps. Second, LG is a static algorithm, with no concept of the time-value of money, capacity limits, opportunity costs, etc. Phase design is essentially a manual step, for which nested pits provide insufficient information in practice, and therefore the quality of the result in terms of potential net present value (NPV) depends strongly on the experience and expertise of the designer. This means that key input data such as commodity prices, different processes capacities and mine movement limits, are considered only at scheduling, when there is little room for optimisation. This sequential approach limits the potential value in each step, where a simplified problem is addressed, instead of addressing the real, and more complex problem, which is dynamic and should be solved as a whole.

We present in this paper an algorithm, and its commercial software implementation, that addresses the dynamic problem as a whole, simultaneously and automatically creating a high-value strategic mine plan that adheres to basic operational constraints, determining dynamic cut-off grades and delivering a set of phases which can serve as a much stronger guide than nested pits for the final design. We discuss some of the key elements of the algorithm and propose a new methodology for strategic mine planning, where phase design dynamically responds to mining strategy definition. Results using different mining and operational parameters on a fictitious copper deposit are used as a demonstrative example.

INTRODUCTION

Strategic mine planning is the process that defines the potential value of extracting a mineral deposit for commercial exploitation and, at the same time, it determines how the extraction should proceed to materialise this value proposition. It is of utmost importance that the process successfully accomplishes both goals simultaneously: it must reach the highest possible net present value (NPV) out of investing in the endeavour and, at the same time, provide a realistic high-level plan for each year of the operation's lifetime. If the high-level plan cannot be transformed into
more detailed mid-level and short-term plans, for their actual execution, then the value proposition is invalid.

For open pit mines, the most important decisions that have to be made in the process of strategic mine planning include the following:

- define the ultimate pit
- determine the kind of processing plants that are going to be installed
- select which parts of the deposit are going to feed these plants
- define the mining and processing rates
- determine what is going to be mined, stockpiled and reclaimed each year
- determine the life of the mine.

These decisions can be made by defining a mathematical model that represents the mine and solving the planning problem for this model. In this mathematical model, the deposit is discretised into a set of blocks (the block model), each block characterised by a set of properties, such as location, density, grade, rock type, etc. The problem to be solved then is to decide which blocks to mine each year and how to process them. The decision is constrained by certain mining and processing restrictions, and geotechnical constraints that determine which blocks have to be extracted before each block is available. This mathematical problem, also called open pit mine production scheduling problem (OPMPS), has been shown by Gleixner (2008) to be of NP-Hard complexity. This means that there is no known procedure that can generate a solution to the problem in polynomial time. In concrete terms this implies an optimal solution may not be found in practice for large size instances of the problem.

Beyond the mathematical model, the real-life problem requires solutions that can be implemented in actual mines. Therefore, the acceptance criteria for any practical solution involves validating its operational feasibility. The blocks mined must have a certain continuity from one period to the next, and the costs and logistics of operating mining assets such as shovels and trucks have to be considered. Additionally, the extracted blocks must be chosen in a way such that can be spatially grouped into cohesive, multiperiod, well-formed volumes called phases or pushbacks. Only a given number of phases can co-exist in a given time, and they must comply with certain geometric, mining and economic restrictions. If the solution obtained for the mathematical problem cannot be translated into a spatial extraction in the form of operational phases, then it is not a solution to the real-life problem.

The strategic planning of open pit mines has been a subject of much work and research, both in the academic community as well as in the mining industry, but there is currently no tool or methodology to solve the real problem considering all the restrictions and conditions previously described. Treated as an academic problem, there are several approaches that have been proposed to derive a solution. Some of them can be found in the reviews done by Gholamnejad, Karimi and Osanloo, Gholamnejad and Karimi (2008) and later by Newman et al (2010). Some of these proposed methodologies are more complete than others, in the sense that they take into account more aspects of the problem. However, a common factor of all generic academic approaches is that the problem is analysed as an optimisation exercise, which, although it is a very interesting scientific exercise, it provides solutions that tend to be of little use to the mining industry. The main reason for this lack of applicability in a real context is that when the problem is solved as an optimisation exercise, it does not consider the operational feasibility requirement described above. The mining industry, on the other side, has traditionally opted for decomposing the problem into more manageable parts, and has developed tools and methodologies to solve each part. This is a result of not having a more complete or holistic methodology to address the problem as a whole. As will be explained later, this approach has provided good enough solutions so far, but it is far from the best approach. A somewhat remarkable exception in the industry may be BHP Billiton, which has developed an in-house software called Blasor to greatly improve the quality of information that goes into phase design, as shown by Stone et al (2007).

In this paper we present an algorithm and its software implementation that solves the block scheduling problem, reaching a schedule of high NPV, while simultaneously generating a set of coarse extraction phases, in which the volumes extracted each period are cohesive and follow basic operational constraints. The phases formed are coarse in the sense that they are well-formed groups of continuous blocks, with no consideration of ramps, roads, accesses, etc and therefore, the resulting set of phases does not aim to replace phase design, but should serve as a strong guide for that process. More importantly, through this new algorithm and software we propose a departure from the common way of approaching strategic mine planning, in which phase design is moved further down the chain, in order to make the design fit the chosen mining strategy, instead of just fitting the mining strategy to the chosen design.

TRADITIONAL STRATEGIC MINE PLANNING PROCESS AND ITS IMPROVEMENT OPPORTUNITIES

The traditional long-term mine planning process can be thought of as a divide-and-conquer strategy, where the complexity of the problem is tackled by separating it into subproblems, each simpler and easier to solve, hoping that, when the different solutions are joined together, the overall solution will be good enough for the initial problem. Some of the subproblems can be optimised, and there are several good algorithms and commercially available tools that do a very good job at this. But other parts are still a mostly manual process, and their results depend heavily on the experience and expertise of the professionals involved.

This approach is, by definition, giving up the potential value and practicality of a solution that could be achieved by a more holistic methodology. Besides this limitation, the approach has been used successfully in the industry for many years.

Stages of traditional strategic mine planning

For the purposes of this paper we have identified four progressive stages in the strategic mine planning process. Different companies’ processes may have more or less clearly defined stages, but these basic stages are usually present. The stages starting with a given block model representation of the deposit and appropriate costs and recovery models.

These stages are performed sequentially, but there should be an iterative process overall of these stages in order to reach a complete solution.

Ultimate pit limit and optimal pit shells

The first step is to decide what part of the deposit is going to be mined. The basic mathematical problem to solve is the following: given a set of blocks, a price for each commodity, and fixed cut-off grades or a cost and revenue value model, decide which blocks are going to be extracted and where they are going to be sent. This is known as the ultimate pit limit (UPL) problem. It is a relaxation of the basic scheduling
Problem, simplifying it by not considering time or capacity restrictions, assuming that the extraction is instantaneous and plants can process any amount of blocks. The UPL problem can be optimally solved with the algorithm presented by Lerchs and Grossman (1965) or with more recent network-based algorithms such as pseudoflow or push-relabel for the maximum flow problem by Hochbaum and Chen (2000), all of which deliver solutions in reasonable time, even for large mines (given the current size of block models).

The solution of the UPL problem can be used to delimit the area to be mined. It is also usually solved with different prices, or revenue factors that multiply the expected long-term price, in order to obtain a series of pit shells to provide guidance as to which should be the sequence of extraction. This series is sometimes referred to as nested pits, since increasing prices guarantees that each pit is contained in the next one. With the information provided by tonnage-grade curves of the different pit shells, some initial definitions for mining and processing rates can be made.

It is important to remark that the problem addressed by the Lerchs-Grossman (LG) algorithm is static, since it relates to a single instant in time, while the strategic mine planning problem is dynamic, because it relates to many time periods. Assuming continuity from the first to the final pit shell, is a creative construct to add dynamism to the solution, but nothing can be said of its quality in this new domain. Somrit and Dagdelen (2013) provide evidence that this sequence can be improved with an algorithm that considers time value of money. Furthermore, if multiple products and processes are competing for the mineral resources and/or there are important blending constraints, there is reason to believe the extraction sequence could be greatly improved.

**Phase design**

Using the series of nested pits as a guide, big volumes of extraction are selected and designed with the aid of computer aided design (CAD) software. There are several tools to help in this process, but the selection, design and generation of these volumes is essentially a manual task performed by an expert. The experience of the team of professionals involved in this process is key in order to provide a good design. Since the pit shells and their tonnage-grade curves are almost the only reference to abide by, if they provide volumes that can be easily modified to become operational phases, the process can be simple and different professionals may arrive at similar results. If, on the contrary, the pit shells aren’t well-formed or are too large, then the resulting design and its quality can become very variable.

The main pitfall, and a major problem with approach, is that it can be extremely difficult to judge what is good design in terms that are not completely operational, since the performance of the design in terms of a scheduled mine plan can’t be known until the scheduling has been done. Phase design can be a tedious and time-consuming process, and, therefore, it is often left out of the iteration cycle, with an unknown effect on the final plan.

**Phase-bench scheduling**

Once phase design is complete, an extraction and processing schedule can be determined. Usually the time of extraction of each bench of each phase (phase-bench or panel) is chosen using an optimisation software tool. The traditional approach is to aggregate block model information into tonnage-grade curves for each panel, or sectors in a panel, which are fed into a mixed integer linear programming algorithm that provides optimal extraction tonnages from each phase on each period, as well as optimal selection of material destinations, which can be processing plants, stockpiles or waste dumps. Including variable cut-off grade and stockpiling optimisation in this state is also very common.

Different scenarios are produced and analyzed. For projects, this leads to a decision about the final processing plants that are going to be installed, and the mining and processing rates that should be used, along with an estimate for NPV. For ongoing operations, changes in mining configuration are evaluated in order to take advantage of opportunities presented by new conditions or information.

Even though optimisation software can deliver optimal results, it is important to keep in mind that the set of designed phases is a fundamental component of the problem model solved. The obvious problem with this approach is that potential value could be missed because solutions are limited to operate within the existing design, whereas a variation of it could yield significant improvements. Furthermore, this problem may not affect all configurations equally. A possible effect of this could be that the chosen set of processing plants is not the best for the deposit, but merely the best for the given design. The non-obvious problem is that there is no straightforward method to determine if (and how) the design is the bottleneck for any particular configuration on a given planning exercise.

Another problem may arise, related to aggregating block information into units such as panels or sectors within panels, where a long-term mine plan may be extremely difficult or even impossible to transform into a mid- or short-term plan. This could happen if the materials and tonnage reported by the long-term optimisation tool can’t be physically found in the deposit, and are simply a product of averaging data from different locations in the same bench-phase.

**Evaluation and risk analysis**

Once a mining sequence and schedule are completed, a financial analysis may be performed, in many cases, by different teams of professionals. This analysis considers the required investments and other contingent information to reach a final evaluation of each of the proposed plans. In some companies, this process also includes risks assessments and options analysis, which considers uncertainty sources such as commodity market prices, geological information or variability in equipment performance and availability.

The result of these evaluations should be contrasted with the initial costs models used for obtaining pit shells. If differences are significant enough, then the pits shells should be updated and the complete process started over.

**METHODOLOGY**

With the motivation to address the problems identified above, we have developed an algorithm that generates an extraction and processing schedule and a set of associated phases of extraction at the same time, instead of requiring a design as an input. This algorithm is implemented in a commercial software application called DeepMine. In this paper we present the key elements of how the algorithm works and how it dynamically shapes the set of phases as the mine plan is created. This work further develops the algorithm described by Echeverria et al (2013).

The basic inputs of this algorithm are the block model, a mining configuration (set of processes, capacities, blending constraints, etc), a set of nested pits (including one to be used as an upper limit on the final pit), commodity market price information, and some specific operational parameters.
that will be described in the next section. The basic outputs of the algorithm are a strategic mine plan for the life of the mine, and the set of blocks to be extracted each year, grouped in coarse phases, that comprises that plan. The generated phases are considered coarse in the sense that they do not account for ramps, roads, accesses or other short-term logistic considerations, and should not be taken as a definitive design, but as a starting point for the final phase design. The key value of this methodology is that the phase proposal will be regenerated as a response to any changes in the input configurations for the mine plan, which can be related to the quantity and characteristics of the process considered, their capacities, the mining capacity, blending restrictions, commodity market prices, etc. Because of this feature, it is possible to postpone actual phase design until after the mining strategy has been largely defined. This transforms phase design into a refinement process of a conscious strategic decision, overcoming the issues exposed in the previous section.

Solution space reduction and phase generation

Our algorithm uses an approximate dynamic programming approach to create and explore several development possibilities for the mine. The basic methodology then, is to create many possible states in which the mine might be at a particular period, based on the many ways to select which blocks to mine in that period. Then, for each of these possible states, develop a number of possible new states, and so forth. After a great number of possible paths have been explored, the path that leads to the highest NPV can be selected.

Since the raw number of combinations of how to select which blocks to mine in a given period is too large for any attempt of solution in reasonable time, two important strategies are used to reduce the solution space, while guiding the solution.

First, in order to comply with operational constraints and the requirement of having to translate the results to phases or pushbacks, blocks will only be extracted in cohesive volumes. There are a maximum number of such volumes, or active phases, which can be extracted each period, given by the number of shovels and other mining machinery required to do so. There are also constraints for the dimensions of these volumes, such as the maximum length, maximum sinking rate and minimum width. All of these parameters can be used to restrict the kind of volumes that can be extracted. A key feature of these volumes is that they are not predefined. They must be formed dynamically, responding to all variables of the problem, considering past extractions and future consequences of each path analysed. We call these volumes extraction zones.

Another technique used to restrict the solution space is to use the results from the LG algorithm to guide exploration. First, only blocks within the ultimate pit are extractable. This is a reasonable assumption to make without losing generality of the solution, since the ultimate pit problem is unconstrained by time and process capacities, it establishes an upper limit for the solution of the more general problem. The algorithm also uses intermediate pits as temporary bounds for pushbacks as a way to guide the solution into the final pit. This approach reduces the space of solutions that can be found and affects the shapes of resulting phases since, as will be explained below, the boundary of the extracted volumes can be restrained by the pit. Although intermediate pits are used in the algorithm, the way in which their information is considered allows for solutions that are much more flexible than just assuming phases will follow pit exact boundaries, as is the case with optimisations that use pit shells in place of phases to do bench scheduling.

As represented in Figure 1, the algorithm uses a combination of heuristics and clustering methods to find several possible locations for an extraction zone. Some possible zones may be limited by the boundary of the current LG pit shell, while others might be only limited by width and length parameters. Using these alternative extractions for each period, the algorithm can then create many different states for the mine, depending on which zone or combination of zones is chosen to be mined. Depending on the available mining capacity, not all zones might be fully mined.

Typically two forms can emerge, an extraction zone that will form a pit, by excavating the current topography, and another that will expand an existing pit, enlarging it towards the final LG pit shell, forming a pushback. For this second kind of extraction zones, the group of LG nested pits is used to snap zones to the limit of one pit shell, automatically chosen in order to make the forming pushback comply with the minimum width restriction. A zone that was extracted in one period might be target for continuing exploitation the immediately following period. In this case, a new zone is generated that continues the extraction, going deeper in the mine along the geometry defined by the original zone. This enables zones to form phases over time. As is the case with individual zones, phases are an emerging phenomenon of the algorithm, which can be controlled through the modification of parameters, but they are not predefined.

The criteria that decides when to continue generating new zones on a particular location is a combination of parameters including the current NPV of the forming phase and the specified minimum and maximum phase tonnage settings. Whenever a phase is finished, a new phase may start elsewhere, since the equipment is considered now free for use. See Figure 2 for a reference of how phases are formed from a group of continuing extraction zones.

Expansion tree of possible solutions and choosing the best one

Using the mechanism explained above, it is possible to form a tree of possible states for the mine each year, where only operationally feasible states are generated. Starting from several ways in which the first phase could be started, each would provide an alternative state for the mine after the first year of operation. In turn, each of these states can produce many different configurations for the second year and so forth. This tree can be constructed for a number of years or until the final pit is completely mined.

Each state or node in this tree would represent a different topography at the end of the period. And a group of blocks extracted that are contained in the set of extraction zones chosen for that particular node. For all these blocks a destination must be chosen from the set of processing plants, stockpiles and waste dumps. Each newly generated state will optimise the destination chosen for each extracted block, taking into consideration processing capacities, existing stockpiles and blending constraints. As a result, the solution will also report the minimal grade of each commodity that was sent on each period to each processing plant, which would match the dynamic cut-off grade in basic cost configurations. Each state stores these and many other associated metrics like accumulated NPV, cash flow, refined metal produced, amount of ore sent to each processing plant, etc.

Eventually, and especially for large block models (tens of millions of blocks), computer resources will not be enough to keep the resulting tree of states and its continuing growth. Therefore, at a certain point, it will have to be pruned, based on actual NPV, predicted future NPV and some other metrics.
After pruning, only the most promising states are kept for further exploration. The tree then grows again until another pruning is required or the maximum life-of-mine (LOM) is reached. When the maximum LOM is reached, the tree is explored to find the state that delivers the highest NPV (see Figure 3). The path that leads from the initial mine site topography to the node of maximum NPV will be then the chosen strategic mine plan. This plan will comprise a yearly...
extraction and processing schedule which is organised in phases generated by the aggregation of individual extractions that are continuous for a few years.

An advantage of this approach is that the number of alternatives created in the expansion tree can be controlled. Therefore, there can be a manageable trade-off between runtime and the quality of the solution. This is exploited in the software DeepMine, where the user can select among three distinct settings: quick, balanced and deep. This allows for quick exploration exercises, capable of giving a high NPV solution in minutes even for the largest block models, or for a more refined search, which can take several hours, but yield an increase of up to 15 per cent in NPV.

**CASE STUDY**

**Testing the algorithm with different operational parameters**

As a demonstrative example, a fictitious copper and molybdenum deposit named Cobra was used to test the algorithm. Mining and processing parameters were adapted from a similar real-life deposit, and include a main concentrator plan and a secondary low-grade oxides process. A set of 16 nested pits were generated, using a variable copper price from US$0.5/lb to US$2.0/lb, and a fixed price for molybdenum of US$13/lb. The final pit contains 2428 Mt of material, of which 1362 Mt is considered ore. Figure 4 shows the obtained set of nested pits shown in different colours in DeepMine’s visualisation. As can usually occur with real mines, the obtained pit shells are concentric and the first one is too big to be a phase by itself. In this case, as in many others, it is not obvious how to translate this set of nested pits into operational phases.

The resulting extraction sequence generated after running the algorithm can be seen in Figure 5 where each generated phase is presented in a different colour. The associated mine plan operates the mine and plant at full capacity and has negative cash flows only for the initial prestripping years. The algorithm was then run with the same mining and economic parameters, but with a different setting for the maximum length for the generated phases. The effects on the derived sequence can be seen in Figure 6. Again, the new plan uses all available mine capacity and keeps the plant working at full capacity and presents healthy cash flows. These parameter changes can potentially impact any aspect of the mine plan, beyond its obvious impact in the generated set of phases. In the same way, a change such as adding a new processing plant, changing their capacities, or even changing commodity market prices can also have an effect in the generated set of phases, beyond the changes in the mine plan. Figure 7 shows the results of increasing mine capacity in 20 per cent. Again, both the sequence and the mine plan adapt to the operating conditions. As the algorithm searches for the best possible mine plan and associated set of phases, in terms of the highest NPV, based on the given mining or operational parameters, the big change seen in the set of phases in this case is due to the fact that the new set is able to provide a better NPV.
CONCLUSIONS

There are several opportunities to improve how strategic mine planning is performed. In the traditional process, early design decisions may compromise the final value proposition of the plan. Furthermore, the current process does not have a straightforward method to detect and correct the limitations of early designs. Mining companies using the traditional process can only rely on the intuition of experienced professionals to be able to overcome the inherent limitations of using a sequential approach, with manual intermediate steps, to solve a highly complex problem with many open variables.

In this paper we present a new algorithm that can simultaneously generate a strategic mine plan and its related set of phases. This algorithm is implemented in version 2.0 of the strategic mine planning software DeepMine. With this algorithm, the opportunity is introduced to incorporate changes in phase design directly into the definition of a mining strategy, without the need for an initial process of manual phase design, avoiding making early compromises with an unknown effect. This algorithm could increase the value of new and ongoing mining operations, by helping improve the quality of results of strategic mine planning processes and allowing strategic mine planning engineers to quickly adapt to changing conditions and to take full advantage of existing opportunities.

REFERENCES


