HEURISTIC OPTIMIZATION OF SCHEDULING SCENARIOS FOR ACHIEVING STRATEGIC MINE PLANNING TARGETS

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ABSTRACT

An optimization process is described that can be systematically applied by mine planners to produce life-of-mine schedules aligned with their strategic targets, while maximizing the net present value of the mining operation. The software tool employed uses heuristics and an evolutionary algorithm to generate life-of-mine schedules of production and development activities. Generating such schedules is typically a very difficult task due to the large number of operational constraints that must be respected, and the vast number of alternative schedules; as a result the value of the mining operation can be compromised.

With an expansion at Newmont's Leeville mine in Nevada, the mine planners were given the task of producing feasible life-of-mine schedules with significantly increased production rates. Their initial efforts indicated that it would be a considerable challenge to generate such schedules in a timely manner. By systematically applying the proposed optimization process, the mine planners were able to generate optimized life-of-mine schedules with the desired production rate.

KEYWORDS

mine planning, schedule optimization , evolutionary algorithm, net present value

INTRODUCTION

Newmont Mining Corporation is a gold producer with a major presence in northern Nevada, where it owns approximately 2.5 million acres of land. One of these properties, the Leeville underground mining complex, shown in Figure 1, is the subject of this case study. The mine is accessed via a shaft, and consists of three major deposits in an area of mineralization called the Carlin Trend: West Leeville, Four Corners and Turf, at a depth of 1,400 to 2,100 feet. The primary mining methods are conventional long hole stoping, blind bench stoping, Avoca stoping, and up hole stoping. One of the main scheduling difficulties being carefully managed at Leeville is the provision of adequate ventilation for the dilution of contaminants in the active headings (Arya, Hartery, Danninger, Chik, Moorhead, Loup, & Smith, 2012; Arya & Terrillion, 2012).

Gold ounces and net present values (NPVs) presented in this paper have been altered for confidentiality.
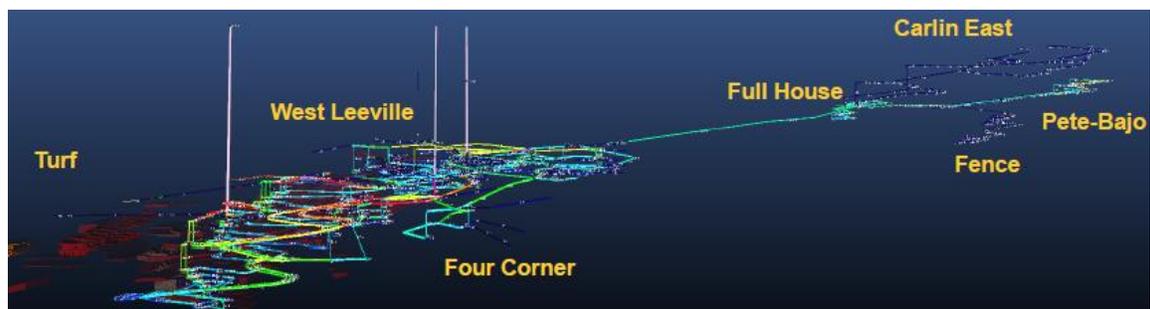

Figure 1 –Newmont's Leeville mining complex within the Carlin Trend (Ventilation management project at Leeville mining complex, 2013)

The stope and access layouts comprising the mine design are considered to be fixed for this study, and are provided as a set of discrete mining activities of fixed duration. Each mining activity has properties including gold grade, mine area, tons, and feet. An activity may have a scheduling constraint that specifies either a date before which it may not be excavated or an exact start time to be met. The case study project consists of 26,179 mining activities, 2,593 of which have constrained start days.

Constraints on the sequencing of mining activities, most often due to physical adjacencies, are represented by predecessor-successor links between pairs of activities. For this project, the associated precedence rule was finish-start in all cases; that is, the scheduled start time of the successor activity must be no earlier than the predecessor finish time plus the specified lag.

An activity may require one or more operational resources in order to proceed, and these resources may be constrained at the mine level. For this case study, constrained operational resources included hoisting weight, access development length, and paste fill weight. Additionally, there could not be two shaft development activities in progress at the same time, and there was a similar constraint on raise development activities. Ventilation constraints were specified as limits on the numbers of activities in progress on a given level at any one time.

The Schedule Optimization Tool, SOT, has been developed for optimizing the NPV of life-of-mine schedules (Fava, Millar, & Maybee, 2011). Every schedule generated by SOT adheres to all precedence constraints and operational resource constraints. A financial model specifies capital costs, operating costs, projected mineral prices, and a discount rate to be used in evaluating the NPV of each schedule. The optimization makes use of customized heuristics and an evolutionary algorithm.

The mining engineers at Leeville use SOT in their routine planning process. The automation enables them to generate updated life-of-mine plans quickly, while the optimization ensures good schedules, and an objective comparison of competing strategic options.

The mine planning problem has many inherently uncertain parameters, including mineral grades and prices. Saavedra Rosas (2009) describes a modified evolutionary solver for the explicit incorporation of uncertainty in mine planning and scheduling, known as the Genetic Optimizer for Stochastic Problems, or GOSP. Although this study treated all data as deterministic, it is recognized that GOSP could be applied to enhance the process, in order to generate robust schedules in the presence of uncertainty.

PROCESS FOR GENERATING AN OPTIMIZED LIFE-OF-MINE SCHEDULE

Gold Production Target

The first investigation was in relation to the gold production target, expressed in troy ounces per year. All capacities, whether intended as targets or constraints, are enforced at the level of granularity of a weekly period for this case study. As can be seen in Figure 1, the effect of this is that the gold production appears to be over-constrained in comparison to the specified annual target. This is the case because shortfalls may occur in any given week, but exceeding the target, although sometimes possible, is not permitted. The severity of this effect is directly related to the chosen level of granularity.

From the base target of 575,000 troy ounces per year, three increments and three decrements were utilized, resulting in the generation of seven scenarios. The step size was 25,000 troy ounces per year. This automatic flexing run performed a preliminary optimization for each of the seven resulting targets. Figure 2 shows the gold production in each year for each of the scenarios, and the corresponding NPVs. This analysis generated 13,000 schedules, and was completed in 9 hours.
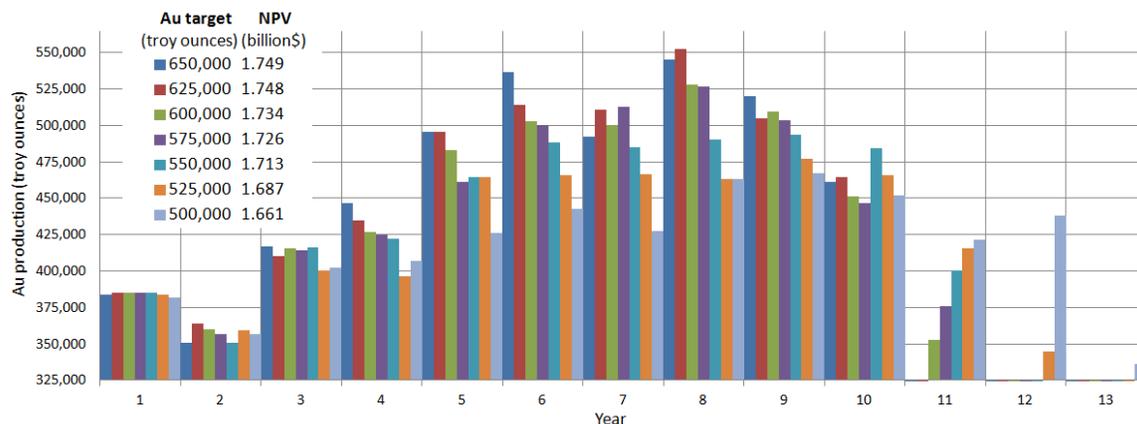
Figure 2 – Initial comparison of alternative targets for gold production

The mine planners selected the target of 575,000 troy ounces per year as the production schedule scenario to be carried forward for the case study, as it was considered likely that a smoothed gold production profile could be attained with this target through the subsequent optimization process.

Seeding Heuristics

SOT makes use of heuristics to bias the starting point of the search for high-NPV schedules. The selected heuristic effectively assigns priorities to individual stopes, which will be used to arbitrate the allocation of operational resources. The highest priority stopes are scheduled as early as permitted by constraints.

Eleven alternative seeding heuristics are listed in Table 1. When dealing with a mining project, it isn't known *a priori* which of these heuristics will lead to the best schedules. A flexing run is used to automatically apply each in turn, as well as the alternative of no seeding heuristic.

Table 1 – Preset Seeding Heuristics

Seeding Heuristic	Ranking Factor	Spatial Domain of Evaluation
1	highest mineral mass	activity
2	highest mineral grade	activity
3	least cost by mineral mass	activity
4	highest mineral mass	mine area
5	highest mineral grade	mine area
6	least development distance by mineral mass	mine area
7	least cost by mineral mass	mine area
8	highest mineral mass	activity and area
9	highest mineral grade	activity and area
10	least development distance by mineral mass	activity and area
11	least cost by mineral mass	activity and area

As shown in Figure 3, the 'highest mineral mass activity' heuristic was found to be the best for this mining project. This assessment was based on random samplings of 50 schedules for each heuristic, in view of both the average and the maximum NPVs of the resulting schedules, requiring a 2 hour run.
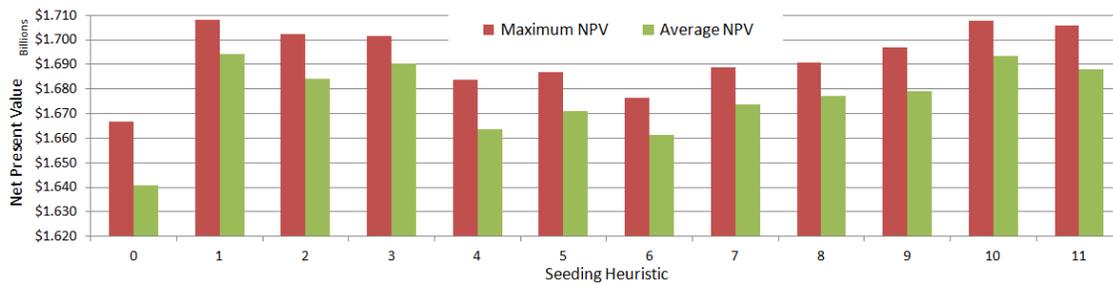
Figure 3 – Comparison of schedules produced with no seeding heuristic (shown as heuristic 0) and the 11 preset SOT seeding heuristics as listed in Table 1

Following the selection of the seeding heuristic, a second set of runs was completed to determine the degree to which this heuristic should be applied, with a range of 50% to 100% tested. When a seeding heuristic is applied 100%, the relative priorities of the stopes are set exactly, based on the selected property, such as mineral mass or mineral grade. By reducing the application of the seeding heuristic to, say, 80%, approximately 20% of the stope priorities will be randomly assigned. As shown in Figure 4, the highest-mineral-mass-activity heuristic performs best for this project when applied at 90%. For this analysis, 1,650 schedules were produced, requiring 3.2 hours.
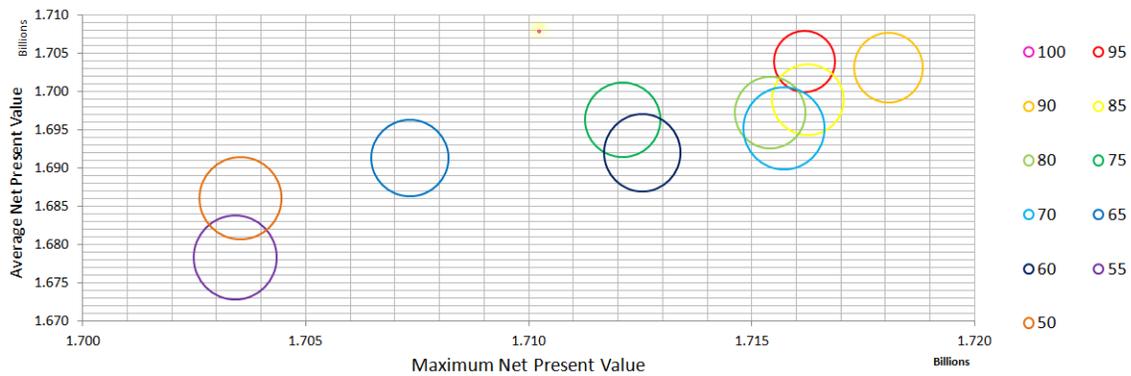

Figure 4 – Comparison of schedules produced with applications of the highest-mineral-mass-activity seeding heuristic ranging from 50% to 100%, showing the maximum NPV, average NPV, and (circle size) standard deviation

Evolutionary Learning

The evolutionary learning mechanism used by SOT is similar to a genetic algorithm (Goldberg, 1989), with mechanisms in place to ensure that all schedules generated are feasible. Here, feasibility means that a schedule adheres to all precedence and operational resource constraints.

The evolutionary algorithm generates a set of schedules; in this case, it generates a population of twenty schedules. Each schedule is then evaluated for its NPV. Of these twenty, the higher-NPV schedules tend to be selected more often, as specialized operations are applied in order to generate a new population of twenty schedules in the next iteration. This evolving of schedules continues as long as succeeding populations of schedules improve over those of past iterations. When there is no improvement in the NPV for, in this case, 10 successive iterations, the learning process has converged. For this case study, a schedule was considered to be improved over another only if its NPV was higher by at least $250,000. At convergence, the best schedules found are retained in the database, and a reset occurs, meaning that the learning process restarts with a new population, not based on any previous iteration. This

continues for the selected number of resets. The reset mechanism, which is just a repetition of the search from a new starting point, was implemented in light of the immense size of the search space, because the custom evolutionary algorithm performs a search which is, in a broad sense, local to the first population, unlike a conventional genetic algorithm.

The mine planner sets two parameters to specify how many of the highest-NPV schedules should be retained for review; for example, the 2 best schedules from each of the 5 best resets can be retained. A single reset may produce the 10 highest-NPV schedules overall, as occurred with reset 11 of Figure 5, and the best schedules from a given reset are likely to be very similar. These two parameters make it possible for the mine planner to have available for review a diverse set of the best schedules.

A seeding heuristic applied at an appropriate percentage can be used to bias the schedules generated in a manner that leads to higher-NPV schedules than the overall search space of feasible schedules. This is illustrated in Figures 3 and 4, which show the results of runs intended to assess statistical properties of the sets of schedules generated with alternative seeding heuristics and alternative percentage applications, respectively.

With the selected bias in place, namely, highest-mineral-mass-activity applied at 90%, the evolutionary algorithm was employed. It can be observed from Figure 5 that, even with a strong application of a heuristic seeding, there is a wide range of qualities of reset starting points. The learning algorithm assesses the initial population of a reset in comparison to previous resets of the learning run. The average or the maximum NPV of the initial population must be within a user-specified range of the corresponding NPVs of the previous initial populations that produced the best schedules of the run so far. If the initial population of the current reset does not meet these thresholds, the algorithm doesn't learn from that population, but immediately performs another reset. Typically, the threshold that a population must surpass in order to learn becomes more stringent as the run progresses.

The learning run shown in Figure 5 generated 8,240 schedules over 10.5 hours. The maximum NPV of $1.726 billion was found in iteration 180.
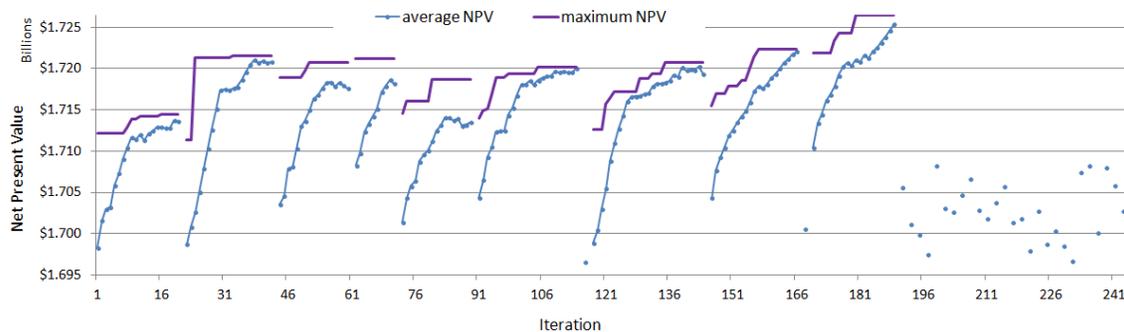

Figure 5 – A SOT learning run using the seeding heuristic of highest mineral mass, applied at 90%

Seeding based on a Prior Solution

The best schedule from the learning run of Figure 5 was used to generate a customized seeding heuristic, which was then applied in a succeeding learning run. This gives the custom-seeded learning run a consistently good starting point, as is shown in Figure 6. This type of a run focuses the search for high-NPV schedules on a narrower portion of the search space. The best schedule for this more focussed search was found in iteration 361, with an NPV of $1.734 billion. There were 31 resets, with 20,550 schedules produced over 16.6 hours. Ten resets did not have the learning algorithm applied to them because their initial populations did not meet the average-NPV threshold or the maximum-NPV threshold.
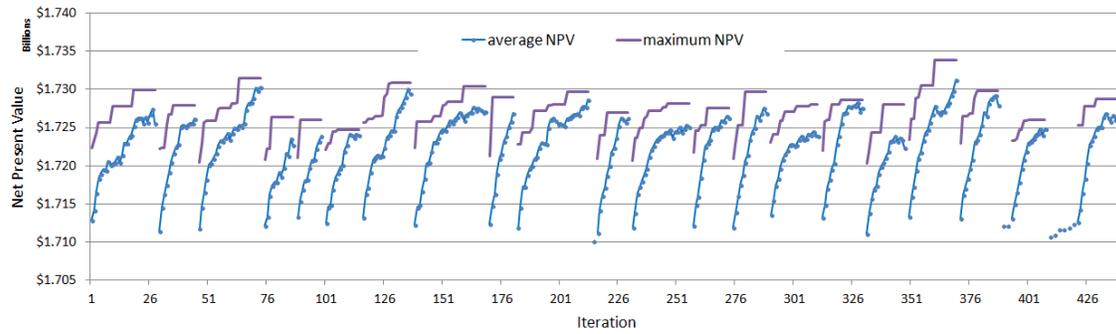
Figure 6 – A SOT learning run using a custom seeding heuristic obtained from a prior SOT solution

Slack Removal

The optimized schedules may have an undesirable characteristic; namely, in order to improve the NPV, an ore development activity may be scheduled far in advance of the stope it accesses. When desired, an algorithm can be employed to remove this type of slack from the schedule. For the resulting schedule, development activities will occur 'just-in-time', yet still allowing for any lag specified in the predecessor-successor linking. As activities are rescheduled, operational resources may be released in a way that allows some stoping activities to be scheduled earlier. Multiple passes of the algorithm are carried out, until all development is just-in-time and all stopes are scheduled as early as possible for the given constraints. The mine planner can choose how ore development activities should be scheduled in this case—whether as early as permitted in order to maximize early gold production or so as to remove slack from the schedule.

For this mining operation, with over 26,000 activities, slack removal takes just under an hour. The NPV of the schedule is increased from $1.734 billion to $1.779 billion by slack removal. Figure 7 shows the effect on the gold production achieved in each year of the mine life, and Figure 8 shows the corresponding ore production. A smoothed gold production profile was achieved for years 5 to 9, with a consistent ramp-up in years 1 to 4.
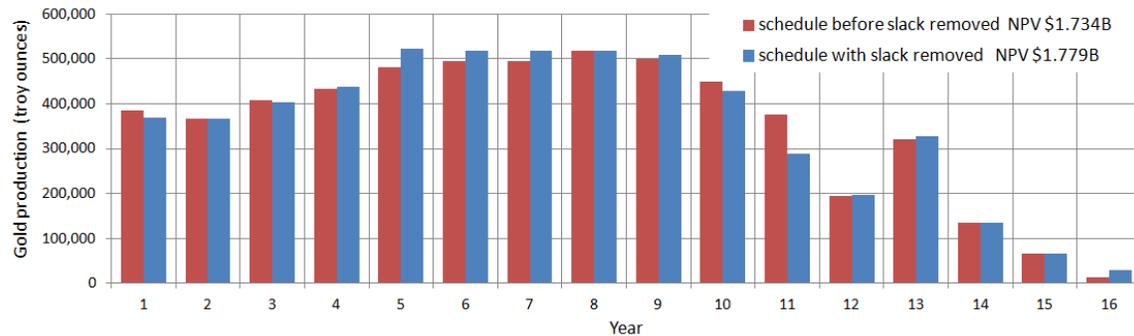

Figure 7 – Gold production profile of optimized schedule before and after slack removal
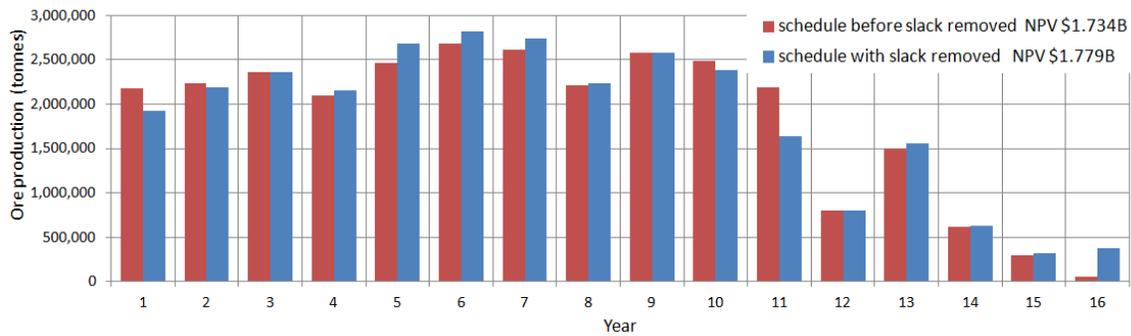
Figure 8 – Ore production profile of optimized schedule before and after slack removal

DISCUSSION

The benefits of automated scheduling and NPV optimization have been demonstrated by a case study employing the planned mining activities at Newmont's Leeville-Turf operation. Every schedule generated was feasible, and for a project with over 26,000 mining activities these were produced at the rate of about 17 per minute, with the exception of when the algorithm for removing slack was employed, in which case a single schedule was produced in just under one hour.

Based on a random sampling of 100 leveled schedules, the average NPV of a leveled schedule for this mining operation is $1.657 billion. We have described a systematic process for schedule optimization that was used to achieve an NPV of $1.779 billion, a difference of $122 million, or 7.4%. In addition, months of effort are replaced by automated runs occurring over a few days.

For most types of runs, significant optimization occurs in minutes, and the mine planner can monitor the progression of the run, to decide whether a one hour run is sufficient, or, such as in a case where the best possible NPV of a final scenario is sought, a run over many hours is warranted.

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