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Stochastic long-term production scheduling of the LabMag iron ore deposit in Labrador, Canada

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Abstract: A long-term production schedule for the LabMag iron ore deposit in northern Québec, Canada is derived using stochastic integer programming. The optimization formulation maximizes the schedule's net present value, while simultaneously managing the risk of deviations in production tonnages and qualities by considering stochastic simulations of the orebody instead of a single deterministic model. The formulation also smooths and minimizes haul truck requirements and ensures that as mining progresses, space is created within the mined out pit for the return of waste material.

Key Words: Open pit mine design, production scheduling, stochastic integer programming (SIP), iron ore.

1 Introduction

The LabMag iron ore deposit is part of the Millennium Iron Range, a 210 kilometer belt of taconite in northern Québec and Labrador, Canada. Taconite is a sedimentary rock in which the iron minerals are interlayered with quartz, chert, or carbonate and the iron content is commonly present as finely dispersed magnetite between 20–35% Fe. Although the majority of steel production is supported by iron ore sourced from high-grade hematite deposits (typically around 60% Fe), the long-term growing demand for steel has led to higher raw material prices that allow for comparatively lower grade magnetite deposits (typically 20–35% Fe) to also be developed. LabMag has significant economic potential: it contains 3.7 billion tonnes of measured resources at an average total iron content of 29.8% and a low average silica of 2.1%. However, the capital expenditure needed to build this project is estimated at over 5 billion dollars (SNC-Lavalin 2014), which necessitates careful evaluation of all sources of risk. Resource estimation is one of the main sources of risk in a mining project since knowledge of the orebody is primarily based on drilling, which is often sparse because it is expensive. If the expected ore tonnages and qualities are not obtained when mining, the project cash flows are directly affected. The expected quantities and qualities of ore and waste are defined by the mine production schedule, which specifies the sequence of extraction and is dependent on the resource estimation. The goal of mine production scheduling is thus to maximize the expected profit (while also meeting all production targets and constraints) by creating an extraction schedule that is robust in the face of geological risk and has the highest chance possible of actually being realized.

Conventional mine planning optimization methods are based on a single deterministic orebody model and can yield misleading results because they do not account for the likely deviation from the model in reality (Ravenscroft 1992, Dowd 1997, Dimitrakopoulos et al. 2002, Godoy and Dimitrakopoulos 2004). In order to consider the geological risk of an orebody, a set of different scenarios can be created that are all equally probable representations of the orebody, and which all reproduce the orebody's spatial variability (Goovaerts 1997). Such geostatistical simulations can be used to quantify the various elements of risk associated with a mining project: operating costs, capital costs, royalties, commodity price, taxation, tonnage, and grade (Dowd 1997, Godoy and Dimitrakopoulos 2011). Previous studies (Albor Consuegra and Dimitrakopoulos 2009) have shown that a set of 10-15 orebody simulations captures the variability of a deposit since the results converge when more are added. Geological uncertainty can then be managed by directly incorporating stochastic simulations with the mine scheduling framework.

Dimitrakopoulos and Ramazan (2004) introduce a framework that considers grade uncertainty in a mixed integer programming (MIP) formulation that produces a schedule with ore grades within a selected range of probability. The concept of geological risk discounting (GRD) is introduced, which is akin to financial discounting and generates schedules with less geological risk in the earlier periods. Another approach is presented and applied at the Fimiston gold mine in Western Australia that uses a simulated annealing algorithm (Godoy 2002, Godoy and Dimitrakopoulos 2004). This approach perturbs an initial schedule with an optimized net present value (NPV) based on a single orebody model by swapping blocks between different periods in order to reduce geological risk to the schedule. Using this approach, the study achieved a 28% higher expected NPV than a conventional schedule and also had a greater probability of meeting production targets. Variants of this approach were applied to copper deposits where improvements to the NPV of 10% (Albor Consuegra and Dimitrakopoulos 2009) and 26% (Leite and Dimitrakopoulos 2007) were also seen relative to conventional schedules. In each of these studies, when the optimization was not constrained to the conventional ultimate pit limits, a larger pit limit was found to contain more metal and generate an even higher NPV. A more flexible method for long-term production scheduling is based on stochastic integer programming (SIP) (Birge and Louveaux 1997), a type of mathematical programming and modelling that considers multiple equally probable scenarios and generates the optimal result for a set of defined objectives within the feasible solution space bounded by a set of constraints. SIP for mine scheduling is introduced in Ramazan and Dimitrakopoulos (2004, 2008). Their formulation maximizes the NPV while minimizing deviations from production targets using a different penalty for each target. Leite and Dimitrakopoulos (2014) apply the same formulation at a copper deposit and produce a risk-robust NPV 29% higher than that of a conventional schedule. Benndorf and Dimitrakopoulos (2013) applies a SIP formulation at an iron ore deposit with a formulation that integrates joint multi-element geological uncertainty. Additional considerations are easily incorporated into the modeling framework: two other relevant studies use SIP to optimize the NPV while simultaneously optimizing the cut-off grades (Menabde et al. 2007) and incorporating simulated future grade control data at a gold deposit (Jewbali 2006). Boland et al. (2008) demonstrate stochastic formulations for mine production scheduling with endogenous uncertainty, in which decisions made in later time periods can depend on observations of the geological properties of the material mined in earlier periods, and most recently they characterize the minimal sufficient constraints for such formulations so that solving them is more efficient (Boland et al. 2014).

In this study, an SIP formulation similar to Benndorf and Dimitrakopoulos (2013) is presented to control the risk profiles of the mine production in terms of four underlying metallurgical properties: the head iron (FeH), Davis Tube (Schulz 1964) weight recovery (DTWR), the product concentrate iron (FeC) and silica (SiC) grades. Additional consideration is given to truck haulage requirements and tailings management. The formulation seeks to minimize haulage costs by considering a truck haulage operating cost that varies with distance of the mined material from the processing plant. The optimization decides dynamically to which of two destinations to send each block: the waste dump or the process plant. Constraints are also included to smooth the annual haul truck fleet requirements in order to avoid purchases that lead to under-utilized equipment. The formulation in this study also seeks to maximize the space available for in-pit tailings disposal. The LabMag tailings (roughly two thirds of the mined ore) can be returned to the mined out pit in order to reduce the environmental footprint. LabMag is a stratigraphic deposit and its layers come to the surface at a low dip of only six degrees, which makes it amenable to this type of tailings management strategy.

In the following sections, an SIP formulation for long-term production scheduling with equipment and tailings management is presented. The case study at LabMag follows, and the scheduling results are compared to conventionally scheduled results. Finally, the results are discussed and conclusions follow.

2 SIP Formulation

The following objective function is defined as the maximisation of the NPV minus various penalty terms that control the geological risk profile, minimize fleet requirements, and promote mining adjacent blocks in the same period in order to generate a practical schedule.

2.1 Notation

The constant and variable factors used in the SIP model are defined below:

- P: Number of periods
- N: Number of blocks in the orebody model
- D: Number of destinations
- S Number of simulations
- Q: Number of metallurgical qualities
- $V_{i,d,s}$: Value of block i in simulation s going to destination d in time period t
- $TH_{d,t}$: Total truck hours in period t for destination d

Small differences in tonnage (and thus truck hours) can be expected due to variations in the lithology and thus the density but are ignored here for simplicity.

- C_t^{TH}: Operating Cost ($/hour) for trucking, discounted by period t
- $b_{i,d,t}$: Binary variable with a value 1 if block i is mined in period t and sent to destination d; and 0 otherwise.
- Pen^{conc}: The penalty per tonne deviation ($/t concentrate) from the target concentrate production in each period; constant
- Pen^{q}: The penalty per tonne of quality content ($/t quality q) in each period above or below the associated upper or lower limits respectively; constant

- $\overline{dev}_t^{conc}$: Concentrate tonnes in excess of the upper limit
- $\underline{dev}_t^{conc}$ Concentrate tonnes less than the lower limit
- $\overline{dev}_t^{q}$: Tonnes of metal or mineral q in excess of the upper limit, where $q = 1, \ldots, Q$ considered qualities
- $\underline{dev}_t^{q}$: Tonnes of metal or mineral q less than the lower limit
- $c_t = \frac{1}{(1+r)^{t-1}}$: A function for discounting profits and costs with the discounting factor r according to the period t when the block is mined
- $g_t = \frac{1}{(1+GRD)^{t-1}}$: A function for discounting geological risk with the discounting factor GRD according to the period t when the block is mined

2.2 Mining block economic block value

The undiscounted value for each block is defined as:

$$V_{i,d,s} = \begin{cases} NR_{i,s} - CONC_{i,s} * PCost \ - ROM_{i,s} * OCost \ - W_{i,s} * WCost, & d = 1 \\ -(ROM_{i,s} + W_{i,s}) * WCost, & d = 0 \end{cases} \tag{1}$$

given that

$$CONC_{i,s} = ROM_{i,s} * eWR_{i,s} \tag{2}$$

where for block i and simulation s, $NR_{i,s}$ represents the net revenue, $OCost$ and $WCost$ the mining cost of ore and waste respectively (excluding truck haulage, which is penalized directly in the objective), $PCost$ the processing cost (considers crushing, concentration, filtration, pelletization, transportation, administration, etc.), ROM the run-of-mine tonnage from the iron-bearing lithologies, W the tonnage from waste rock, and eWR the effective weight recovery (considers ideal Davis Tube Weight Recovery as well as plant efficiency parameters).

Note that by having trucking costs in the objective function as opposed to the block value, it is possible to consider trucking costs for a block that vary depending on the period that block is scheduled to be mined. In future research, if mobile crushers are considered rather than a fixed plant location, the haulage cost could also be dependent on the variable distance to the crusher.

2.3 Objective function

The objective function of the SIP model is constructed as the maximization of a profit function, defined as the total expected net present value minus penalties for deviations from planned production targets and penalties for not mining the blocks adjacent to a mined block (Benndorf and Dimitrakopoulos 2013).

Maximize Obj =

$$\sum_{t=1}^{P}\sum_{i=1}^{N}\frac{1}{S}\sum_{d=1}^{D}\sum_{s=1}^{S} c_t V_{i,d,s} b_{i,d,t} \tag{3a}$$

$$-\sum_{t=1}^{P}\sum_{i=1}^{N}\sum_{d}^{D} b_{i,d,t} c_t TH_{d,t} C_t^{TH} \tag{3b}$$

$$-g^t \sum_{t=1}^{P}\sum_{s=1}^{S} [Pen^{conc}\left(\overline{dev}_{st}^{conc} + \underline{dev}_{st}^{conc}\right) + \sum_{q=1}^{Q} Pen^q \left(\overline{dev}_{st}^{q} + \underline{dev}_{st}^{q}\right) \tag{3c}$$

$$-\sum_{t=1}^{P}\sum_{i=1}^{N} Pen^{smooth} dev^{smooth} \tag{3d}$$

This objective function includes four distinct terms. The term (3a) is the primary term and represents the net present value of all blocks mined in the optimization. The term (3b) represents the trucking operating cost, which is minimized. The term (3c) acts to penalize deviations from target concentrate tonnes, and the target silica grade and weight recovery (see the next section for more details). The variables for the deviations are determined by the optimization process, based on the corresponding constraints that are set. The term (3d) is a penalty for not mining adjacent blocks. It is desirable to mine blocks in groups in order to generate a practical schedule. There is a trade-off between the penalty terms, and it is the relative size of the penalties that determine this trade-off.

2.4 Constraints

2.4.1 Reserve constraints

Reserve constraints ensure a block cannot be mined more than once:

$$\sum_{d=1}^{D}\sum_{t=1}^{P} b_{i,d,t} \leq 1 \qquad \forall i, i = 1, \ldots, N \tag{4}$$

Slope and sequencing constraints

Each block can only be mined if the blocks above are mined in the same or an earlier period in order to maintain the maximum geotechnical slope angle in all directions. In order to accommodate in-pit tailings disposal as mentioned in the introduction, each block was set to be mined only if the block to the south-west (cross-dip, towards where the deposit daylights at surface) is mined in the same or an earlier period.

For each i, where $j \in$ {predecessors blocks of block i}

$$\sum_{d=1}^{D} (b_{i,d,t} - \sum_{k=1}^{t} b_{j,d,k}\ ) \leq 0 \tag{5}$$

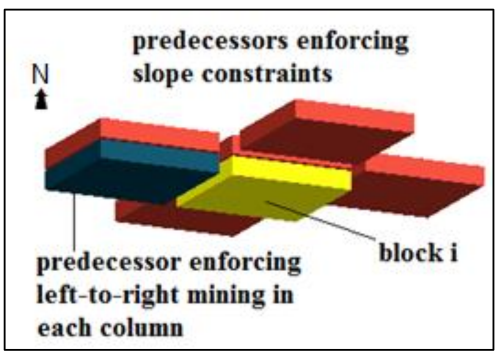

Figure 1: Predecessor blocks for slope and sequencing constraints.

2.4.2 Haulage capacity constraints

The objective function has a term that seeks to minimize truck operating costs by minimizing haul distances. This term competes with the need to meet blending constraints, so it is possible to obtain a schedule that has a given number of trucks in one year that then decreases in the subsequent year. This effectively means a truck is purchased and then left unused, or that an extra truck must be leased. It is more desirable to have the number of trucks only be an increasing function, where more trucks are bought as they are needed, and then fully used in subsequent periods. To allow for small numerical deviations, here the number of trucks required in a given period must be more than the previous period (with leeway of half the available working hours of one truck). That is to say the total number of truck hours (ore, stockpile, waste) required in a given period cannot be less than the previous period's truck hours minus half of one truck's working hours for a year.

$$\sum_{i=1}^{N}\sum_{d=1}^{D} H_d b_{i,d,t} - \sum_{i=1}^{N}\sum_{d=1}^{D} H_d b_{i,d,(t-1)} \geq -\frac{1}{2} \textit{Total working hours available for one truck in one period} \tag{6}$$

where $t = 2, ..., P$; H_d is the total time (hours) required for transportation of a block to destination d (the cycle time for one truck is on the order of minutes, but since each block can contain approximately half a million tonnes, many truck cycles are needed).

Processing capacity constraints

The total tonnage of concentrate produced is penalized if in excess or less than the target product tonnage for that period.

For each $t = 1, \ldots, p$; and each $s = 1, \ldots, S$ ($d = 1$ for grade/tonnage constraints, since there are no target waste amounts)

$$\text{Upper bound} \quad \sum_{i=1}^{N} CONC_{i,s} b_{i,d,t} - \overline{dev}_{st}^{conc} \leq Conc_t^{target} \tag{7}$$

$$\text{Lower bound} \quad \sum_{i=1}^{N} CONC_{i,s} b_{i,d,t} + \underline{dev}_{st}^{conc} \geq Conc_t^{target} \tag{8}$$

where $Conc_t^{target}$ is the target quantity (tonnes) of concentrate that is to be produced in period t.

2.4.3 Quality constraints

For each period, the average grade or value of each metallurgical quality has to be less than or equal to a maximum value and greater than or equal to a minimum value.

For each $t = 1, \ldots, P$; and $q = 1, \ldots, Q$

$$\text{Upper bound} \quad \sum_{i=1}^{N} tonnes_{i,s} grade_{i,s,q} b_{i,d,t} - \overline{dev}_{s,t}^{q} \leq \sum_{i=1}^{N} tonnes_{i,s} grade_{q,t}^{max} b_i^{dt} \tag{9}$$

$$\text{Lower bound} \quad \sum_{i=1}^{N} tonnes_{i,s} grade_{i,s,q} b_{i,d,t} + \underline{dev}_{s,t}^{q} \geq \sum_{i=1}^{N} tonnes_{i,s} grade_{q,t}^{min} b_i^{dt} \tag{10}$$

where $tonnes_{i,s}$ is the tonnage of ore or concentrate used to weight each quality; $grade_{i,s,q}$ is the value of quality q for block i, simulation s; $grade_{q,t}^{max}$ is the maximum value or grade of quality q allowed in period t (constant); $grade_{q,t}^{min}$ is the minimum concentrate product grade allowed in period t (constant).

2.4.4 Equipment access & mobility constraints

Without specific constraints for smooth mining, the optimization may tend to schedule isolated blocks rather than blocks that are grouped together. Conceptually, the way each mobility constraint operates for a given block i is to sum the binary variables for the surrounding blocks and to penalize the amount of surrounding blocks that are not mined in the same time period as block i. This introduces a cost-element to not mining adjacent blocks, which is balanced with a factor for the relative importance of this constraint to the other goals.

For every time period t and block j (every 3rd in each direction):

$$\frac{W * O_j * b_{j,t}}{O_j} - \sum_{k=1}^{W} \frac{O_k * b_{k,t}}{O_k} - Y_{j,t} \leq 0 \tag{11}$$

or:

$$W * b_{j,t} - \sum_{k=1}^{W} b_{k,t} - Y_{j,t} \leq 0 \tag{12}$$

where W is the total number of blocks in the window excluding the central block; k is an index to the W blocks in the window; $Y_{j,t}$ is the smoothing deviation for block j, time period t.

The $Y_{j,t}$ variables are included in the objective function, which will tend to minimize these values. Combined with these constraints, they will be forced to exactly the difference in number of surrounding blocks versus the number of surrounding blocks that are mined in the same period (i.e. the deviations). The objective function then penalizes these amounts in order to promote mining the blocks grouped together. Note that this is a simplification of the formulation in (Dimitrakopoulos and Ramazan 2004), where the actual tonnages are used rather than just the number of blocks since some blocks could have only a small tonnage. However, in the case of relatively large blocks of consistent tonnage, as in taconite iron ore deposits, the different in formulations would not have a large impact.

3 Application at LabMag iron ore deposit

The formulation in the previous section is applied at the LabMag taconite iron ore deposit in northern Labrador, Canada in order to create a mine production schedule that considers multi-element grade uncertainty as well as equipment and tailings requirements.

3.1 Stochastic orebody models at LabMag

Mine production scheduling here considers geological variability by using ten stochastic conditional simulations. Each realization consists of a joint simulation of the seven correlated layer thicknesses as well as the joint simulation of four correlated ore characteristics in each layer. Each model consists of 13,400 blocks (100m × 100m × 15m). Since all ore lithologies are processed in the plant in the same manner, scheduling considers the average qualities of all layers in each block.

The two primary waste-types for the LabMag deposit are overburden (OB) and Menihek Shale (MS). The OB overlies the entire deposit and is minimal (the underlying rock is commonly exposed at surface). The MS layer is present on the north-east side of the deposit, overlying the iron layers and dipping parallel to them at approximately 6 degrees (see Figure 2).

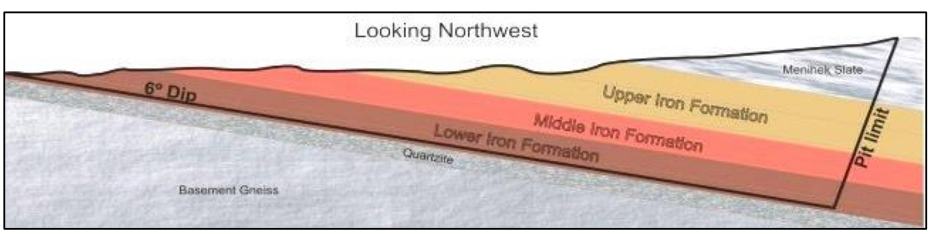

Figure 2: Typical cross-section.

3.2 Implementation

The SIP model described above was implemented in Visual C++ using the ILOG CPLEX API. The initial attempts to solve the full orebody model for all 10 periods proved to be unsolvable in a reasonable amount of time (the optimization had made little progress after several days, running on a 64-bit Dell Precision M6500 Intel I7 quad-core @ 1.73 GHz and 16 GB of RAM). The initial 13,400 blocks considered are the blocks contained within the ultimate pit derived using the nested Lerchs-Grossman algorithm. Since only the first ten years are scheduled within the optimization and the LabMag ultimate pit contains more than twenty-five years of ore at the planned capacity, the precise pit limit need not be discussed further here. To reduce the number of blocks, a new pit was designed that takes as many blocks as possible but avoided the MS waste layer. Since the optimization targets the first 10 years and tries to minimize trucking hours as well as unnecessary waste, it was evident that the optimization would avoid the MS region of the deposit anyway. This brought the number of blocks down to 8,411. The optimization is broken down into four sub-optimizations (see Figure 3) each set to stop once there was less than 1% gap between the solution and the optimal solution.

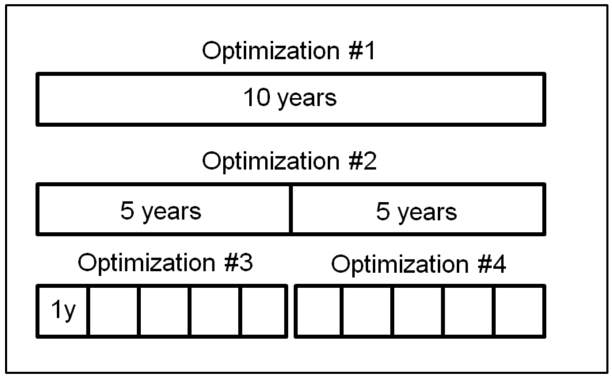

Figure 3: Schematic representation of four-stage schedule optimization.

Table 1 shows the annual targets for the concentrate production, with a ramp-up of the process plant. Table 2 shows the DTWR and SiC targets that are used in the optimization along with the various penalties. The process plant is designed for 27% DTWR, but an range around this target that the plant can still handle is permitted to allow the optimization to select the most economic material when also considering haul cycle times and the other constraints. The silica range is selected to be within the plant tolerance levels. The average silica of the single period (10 year) optimization is 2.2%, so this became the new target for subsequent optimizations because a consistent silica blend is desired across all periods. The DTWR range is kept the same to allow for scheduling higher DTWR material whenever possible. Scheduling higher DTWR has a trade-off with haul distance however, because most of the higher grade DTWR material is located in the north end of the deposit, which is further from the crusher.

Deviations from the targets are penalized in the objective function, and it is the relative magnitude and not the exact values of the penalties that control how they are balanced in the objective function. The highest weight penalty is given to the concentrate tonnage, with a slightly higher penalty for shortages than

Table 1: Annual concentrate production targets.

Year	1	2	3–10
Production level	60%	85%	100%
Target concentrate	13.2	18.7	22.0

Table 2: Grade targets and penalties.

Optimization		#1	#2	#3	#4
DTWR	Max %	29			
	Min %	23			
SiC	Max %	2.5	2.2	2.2	2.2
	Min %	1.8	2.2	2.2	2.2
Concentrate tonnage	Excess Penalty \$/t	800M			
	Shortage Penalty \$/t	1000M			
SiC	Penalty on % above max	100M			
	Penalty on % below min	100M			
DTWR	Penalty on % above max	1M			
	Penalty on % below min	1M			
Smoothing	Penalty per block	1000			

excess tonnage. Due to the discrete nature of the blocks being scheduled, an even tonnage equal to the target is unlikely, and this promotes scheduled tonnages slightly higher than the target rather than slightly lower. The value is determined by increasing it until the expected scheduled concentrate tonnages meet the targets. The other quality penalties are then set relative to the concentrate tonnage deviations penalty. The second highest weighting is given to silica deviations to enforce a consistent blend. The third and fourth highest weightings are given to DTWR deviations and non-smooth mining. The penalty for non-smooth mining is determined last. As discussed in Benndorf and Dimitrakopoulos (2013), high penalties for tonnage and quality deviations relative to non-smooth mining penalties tend to yield schedules with more dispersion of the scheduled blocks. The non-smooth mining penalty here are determined by setting it to zero initially, and then slowly increasing it until the number of scattered blocks in each period are few enough that a feasible schedule could be manually designed without too much difficulty.

3.3 Results

The results of the optimization are shown in Figure 4 and provide the optimal period in which to mine each block, and whether to send the block for processing or to the waste dump. An interesting result is that the only blocks sent to the waste dump are located at the surface of the deposit and contain mostly OB, and/or MS waste, which means that all scheduled material within the 7 iron-bearing units is sent to the plant. Had ore blocks with a low DTWR been sent to the dump, this would have promoted the concept of stockpiling ore with a low weight recovery. However, this is not the case. Given the cost of mining and low DTWR economic break-even cut-off, the only reason to stockpile ore would be to restrict the silica levels. In the optimized schedule, the silica levels are managed without the need for such a restriction.

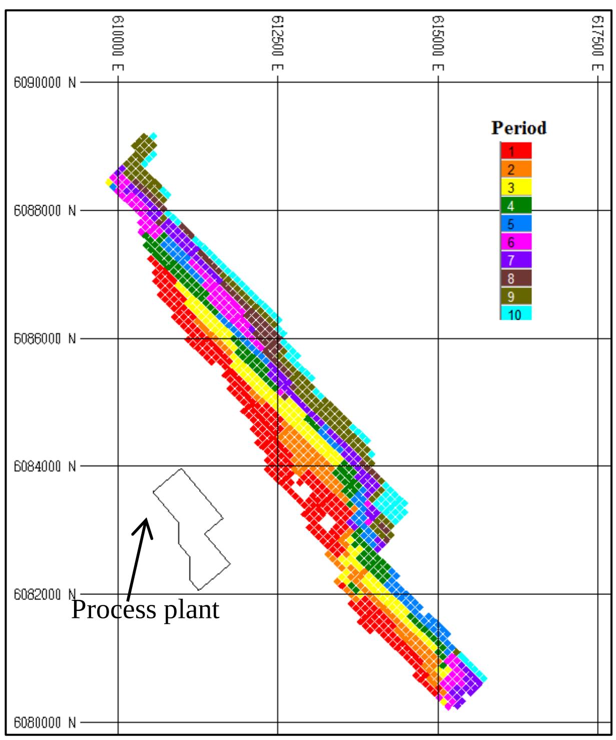

Figure 4: Blocks colored by period in the stochastic optimization schedule.

A practical mining schedule (Figure 5) was designed based on the block-scale optimization. The optimization considers the first 10 years, and an additional 15 years were scheduled manually to allow for full comparison against a previous deterministic schedule. The pit designs use a 15 m bench height, 45 degree slope angle for the pit sides and hanging wall, and the pit bottom follows the natural inclination of the orebody at approximately 6 degrees (10.5%). Although this slope is not optimal for the haul trucks, various

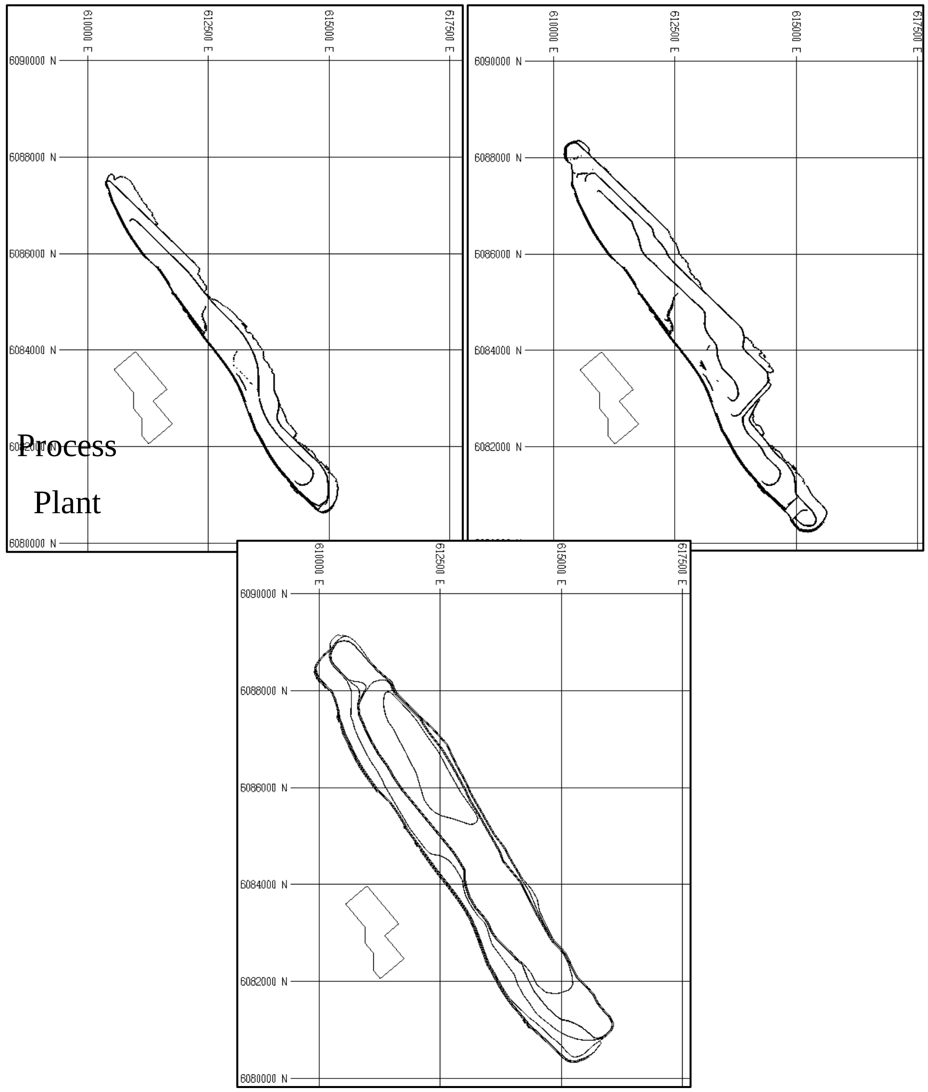

Figure 5: End of period mine designs based on the stochastic optimization schedule (Year 5, 10, 25).

truck manufacturers were consulted and they agreed that it is manageable. Catch berms of 9.5 m with a face angle of 70 degrees were included for additional safety considerations. Since the orebody daylights at surface, the ultimate pit does not require the design of a permanent access ramp to the pit bottom. The benches will be mined flat and the pit access will be developed along the floor as the pit wall advances towards the East.

A previous conventional design is shown in Figure 6. For this schedule, the pit is divided into 8 slots that are roughly 1,000 m wide at surface. There is an opening slot, 4 slots on the North side and 3 slots on the South side. The slots are mined from West to East (to the full-width extent of the defined resources) and developed down to the final pit floor. Once a slot is completely mined out additional coarse tailings can be placed in the pit.

The evolution of the pit in the stochastic optimization schedule (Figure 5) is along the full length of the deposit, progressively deepening perpendicular to the strike. This means that compared to the deterministic schedule, shorter haul times are required in earlier periods and less trucks since the trucks can travel at near top-speed (30-35 km/h on a straight-away), whereas on an incline of 8% with 2-3% rolling resistance, they are limited to 15 km/h or less. Another advantage of mining along the length of the deposit is that the grades vary primarily along the strike: higher DTWR material is found to the north, but with higher SiC as well.

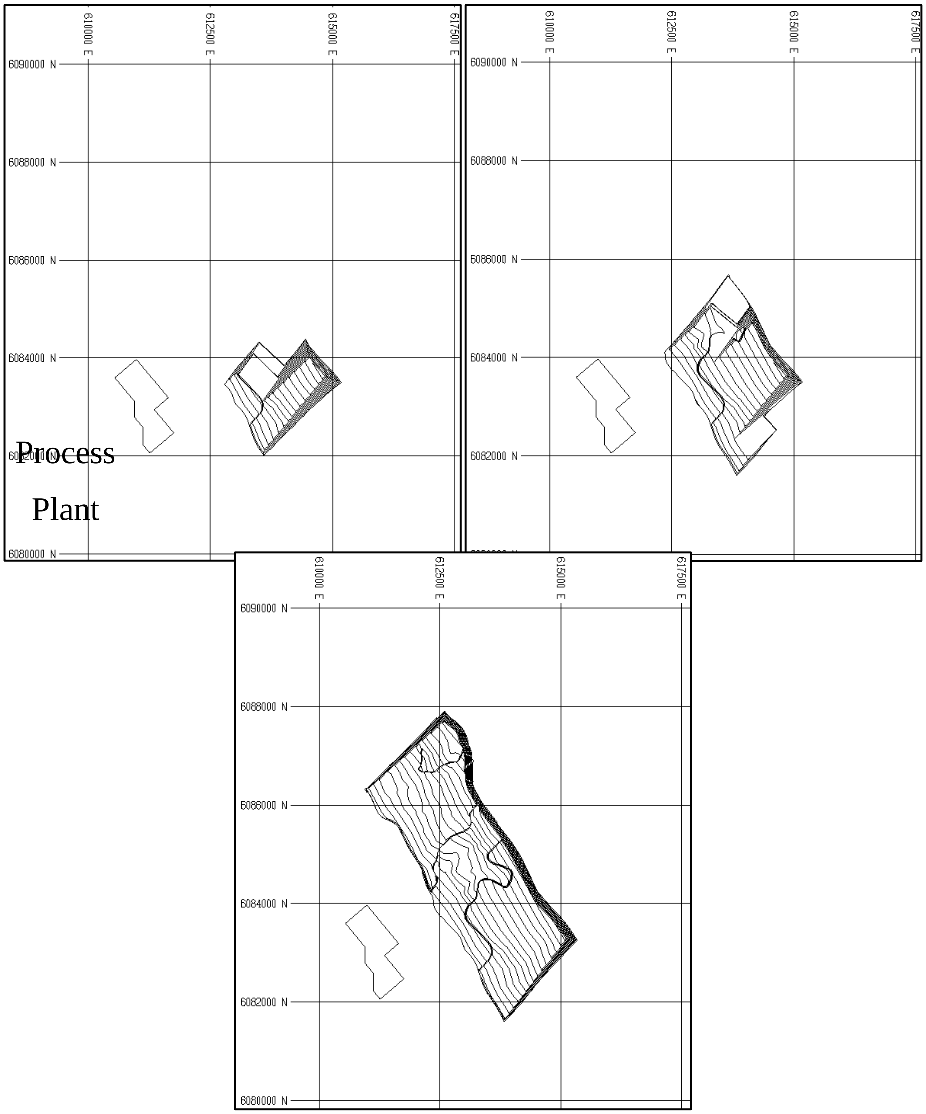

Figure 6: End of period mine designs based on the deterministic schedule (Year 5, 10, 15).

Having open faces along the full length of the deposit allows for more flexibility during operations to achieve the necessary blend.

Figure 7 shows that the truck productivity of the optimized schedule is at its maximum in the earlier periods, and steadily declines with each period as the pit is deepened and the cycle times increase. For the deterministic schedule, the productivity moves up and down as each full-width slot is mined. The optimized schedule ensures higher productivity in earlier periods and thus lower corresponding operating costs.

In Figure 8 to Figure 13, the previous results from the conventionally derived schedule based on a deterministic geological model are contrasted with the results from the stochastic optimization schedule. Besides showing the tonnages and qualities of each schedule, the risk profiles of each are also shown. The red bars shown correspond to the P10 and P90 values, which show an 80% confidence interval within which to expect the true value. The dotted blue lines show the expected value, which is the mean of the values from each simulation. The dotted black lines represent the evaluation of each push-back using the deterministic model. Any differences between the confidence levels derived using the simulations and the values derived using the deterministic model demonstrate where relying on the deterministic model can be misleading.

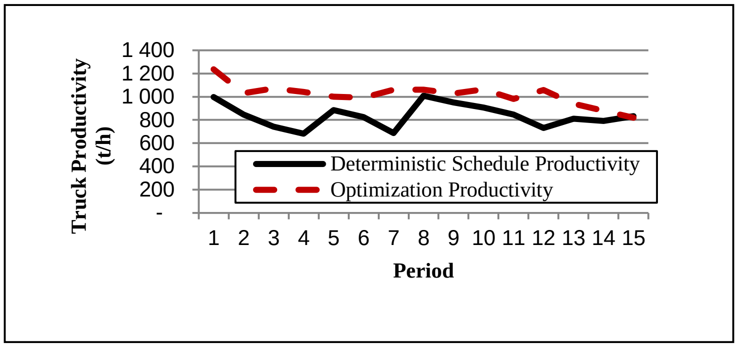

Figure 7: Truck productivity for the conventional and optimized schedules.

3.3.1 Risk management in the stochastic optimization schedule

The analysis in this section pertains exclusively to the lower charts in Figure 8 to Figure 13, which show the results from the optimized schedule. Figure 8 shows that the predicted annual ROM ore tonnes (with ramp-up of 60% and 85% target product tonnage in years 1–2 respectively) will be achieved with little risk. Although the ROM varies up to 10 million tonnes year-to-year, with peaks in years 5 and 7 in particular, this is not problematic in and of itself: achieving the target concentrate tonnages is the primary scheduling goal, which depends on the DTWR and FeC as well as the ROM tonnage. Another concern could be that these fluctuations indicate fluctuations in fleet requirements, but the fleet requirements depend not only on the ROM tonnes, but the haul distance and the waste tonnages as well. The deterministic model systematically

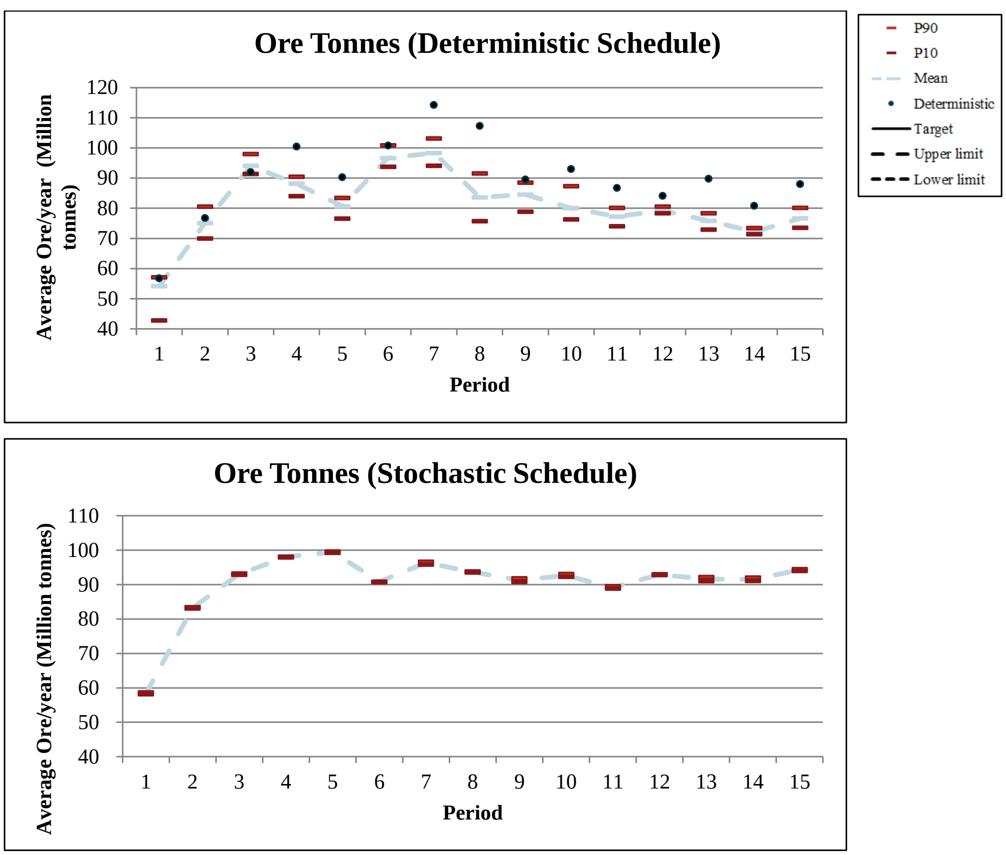

Figure 8: ROM ore tonnes in deterministic schedule (above) and stochastic schedule (below).

over-estimates the quantity of concentrate tonnes. The is due to differences in the head iron (FeH) in the simulations compared to the FeH in the deterministic model. The densities of each lithology are dependent (and calculated using regressions) on the FeH in each layer as determined in a previous study on density (Milord 2012). The fact that the deterministic model predicts slightly higher ROM tonnages per period indicates that the averaged FeH values of the deterministic model result in overestimation of the tonnages.

Figure 9 shows that the predicted annual concentrate tonnes will meet the target of 22 mtpy in all years with a high degree of probability. Although the ROM tonnes fluctuate annually, this is balanced by the DTWR (i.e. a year with less ROM has a greater average weight recovery) and/or by a greater FeC. Even though there may be variability in the individual qualities for a given period, their combined interplay results in low variability in concentrate tonnes. This non-intuitive result highlights the necessity of the SIP formulation for managing the variability of all four qualities. Furthermore, when evaluating the stochastic schedule with the deterministic model, we see 1-2 million tonnes more per year than the mean of the simulations. In general, the deterministic model over-estimates the DTWR by 1-2%, which has a significant impact on the expected concentrate tonnage.

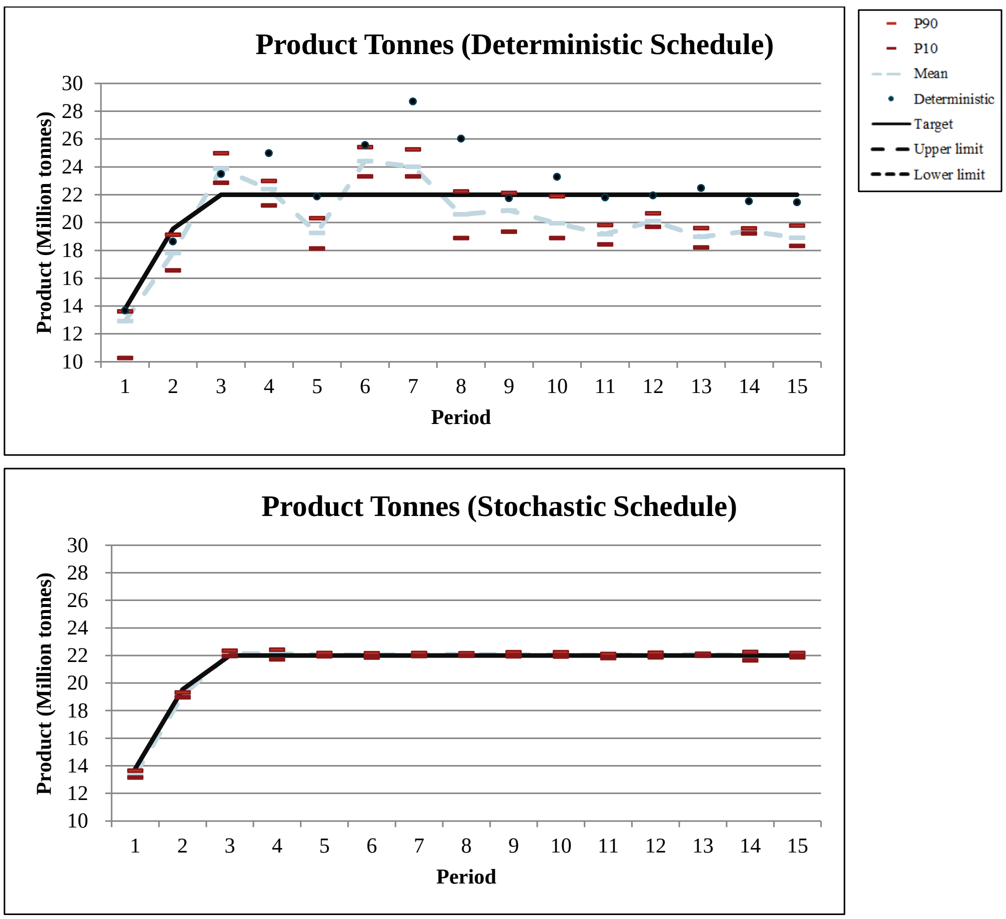

Figure 9: Product tonnes in deterministic schedule (above) and stochastic schedule (below).

The annual waste tonnages are shown in Figure 10. The optimization was performed on a pit that purposely excluded the MS, so little MS was expected. There is some very small amount of MS due to variations in the surfaces between the various simulations. The waste in the schedule consists mostly of OB only and is low in all years. The overlying OB is very thin, so fluctuations of the amounts of OB within each simulation were relatively small and so the risk profiles for the waste here are relatively low. The very low amount of waste mining was intended, and is a crucial component to minimizing costs in the first 10 years.

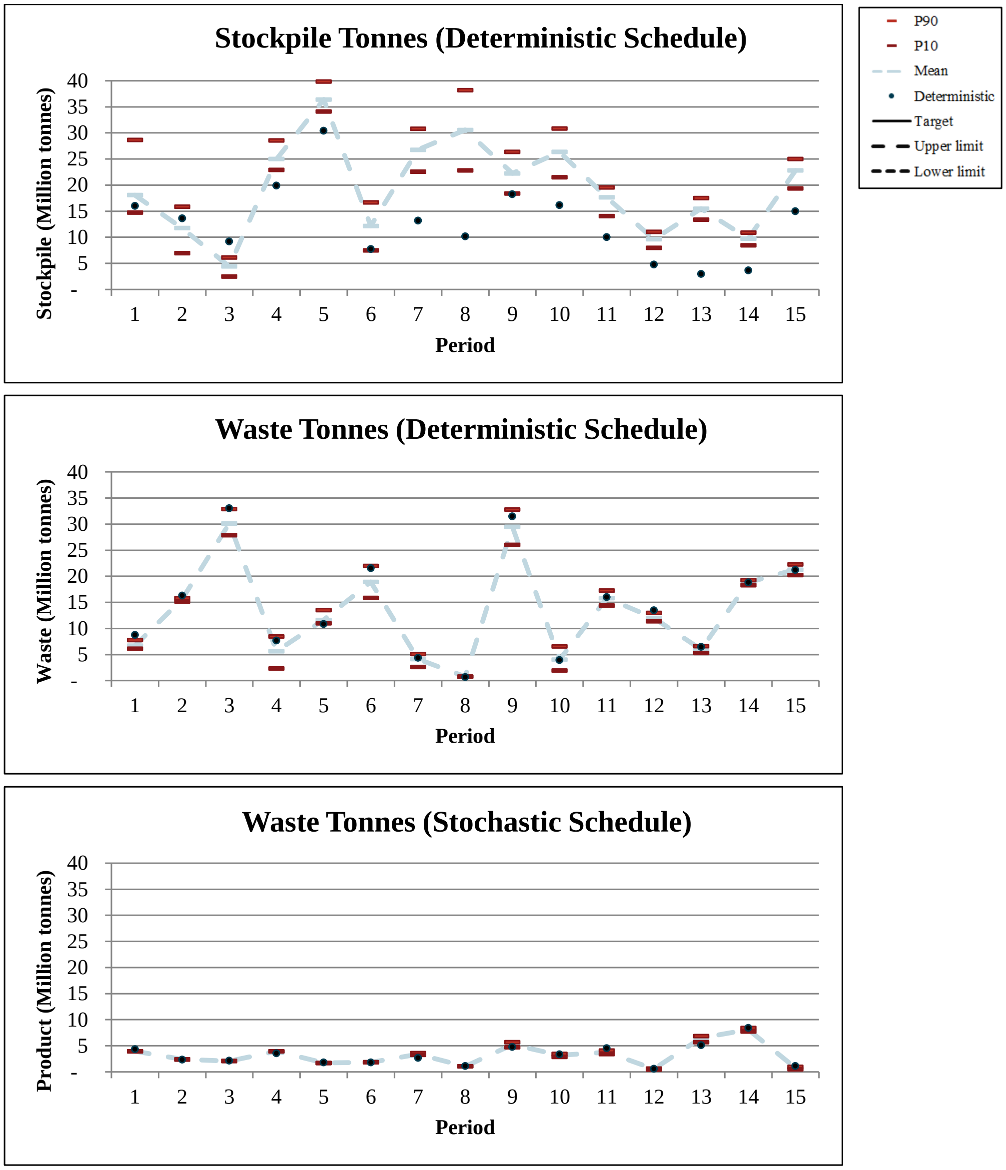

Figure 10: Stockpile and waste tonnes in the deterministic schedule (above 2) and waste tonnes in the stochastic schedule (below).

The annual DTWR values (Figure 11) vary by only 0.4% on average. An interesting result was that the DTWR was not higher in earlier periods as expected. This was expected because a greater weight recovery means less ore must be mined to produce the same tonnage of concentrate, which means lower costs. This result can be explained by the benefit of a higher DTWR compared to a higher cost of mining at depth. The optimization seeks the greatest profit, so lower DTWR ore can be mined as long as the benefit of mining nearer to the surface offsets the benefit of any potential material with a higher DTWR. However, this may be an artificial result: processing costs and plant efficiencies are variable with respect to feed material, yet they are assumed fixed in this study. With the inclusion of more detailed variable processing costs and efficiencies, it is likely that higher DTWR material would be scheduled in earlier periods before the process plant is fully commissioned and operating consistently.

Figure 12 shows that the FeC varies very little year to year, although its slight variation does have an impact on the concentrate tonnes. The annual SiC values (Figure 13) are all less than the maximum specified silica of 2.5%, and is relatively constant around a mean of 2.2%.

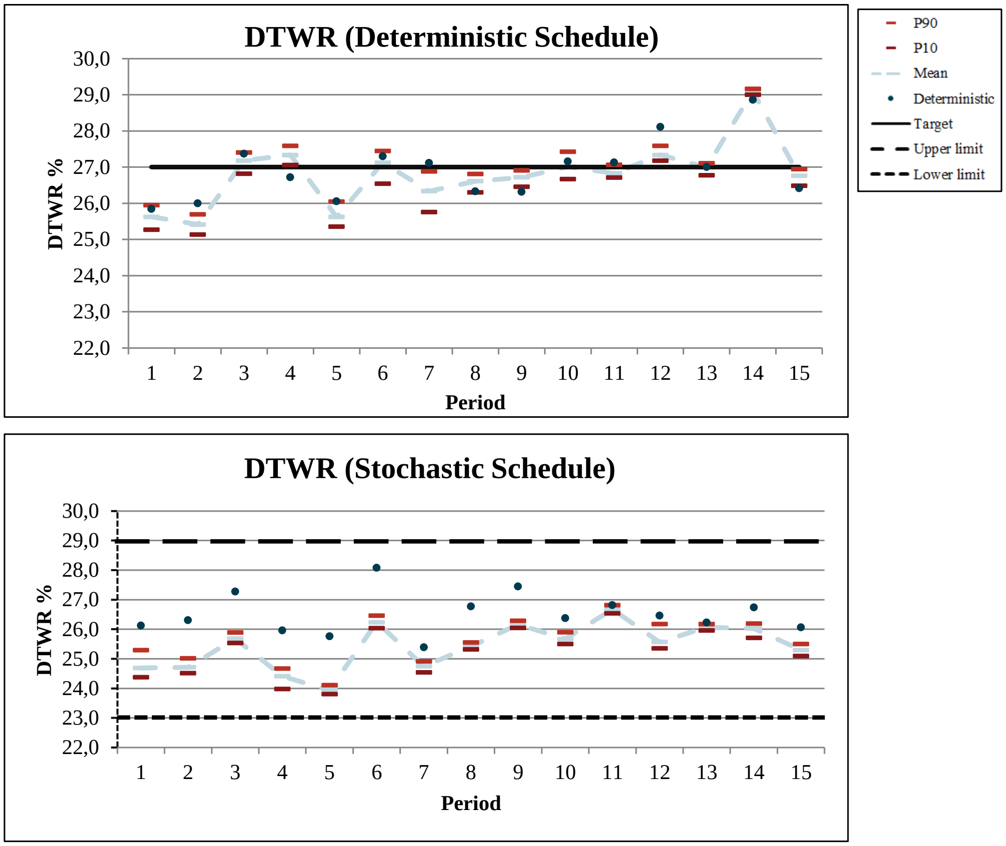

Figure 11: DTWR of ore in deterministic schedule (above) and stochastic schedule (below).

3.3.2 Schedule comparison

The stochastic optimization schedule is now compared to the conventionally derived deterministic schedule to demonstrate the benefit of stochastic modeling.

The reduction in the risk of tonnage deviation is seen immediately in comparing the two schedules in Figure 8 to Figure 10. The 80% confidence range in the stochastic schedule for ROM ore, concentrate tonnes, and waste tonnes is significantly less than that of the pre-existing deterministic schedule. In addition to a reduced range of tonnage variation, the expected product tonnage is centered precisely around the target values. This is not the case for the deterministic schedule, which potentially has both shortfalls and excesses of product tonnes. Although more tonnes need to be mined in the stochastic schedule in order to meet the product targets, it is important to note this is due to the trade-off with haulage costs: the net profit is in fact larger because the location of the material mined is nearer to both the surface and to the process plant.

Compared to the stochastic optimization schedule, Figure 10 shows that the deterministic schedule mines a significant amount of MS waste as well as additional ore that is stockpiled instead of being sent to the plant. These two materials account for a large difference in equipment requirements, which translates to higher costs than those for the stochastic schedule.

Less variation is expected in the DTWR of the optimized schedule compared to that of the deterministic schedule, although not for all periods. As previously explained, this relates to the interplay of DTWR, FeC, and FeH in determining the concentrate tonnes. Although the deterministic schedule had a target of 27% DTWR, this target was often not met. The stochastic schedule did not have a target DTWR, only hard upper and lower bounds, which are met for all periods.

The silica (SiC) range for each year in the stochastic schedule can be seen to fall within the specified upper and lower limits of 2.5% and 1.8% respectively, hovering around the target of 2.2% and demonstrating the

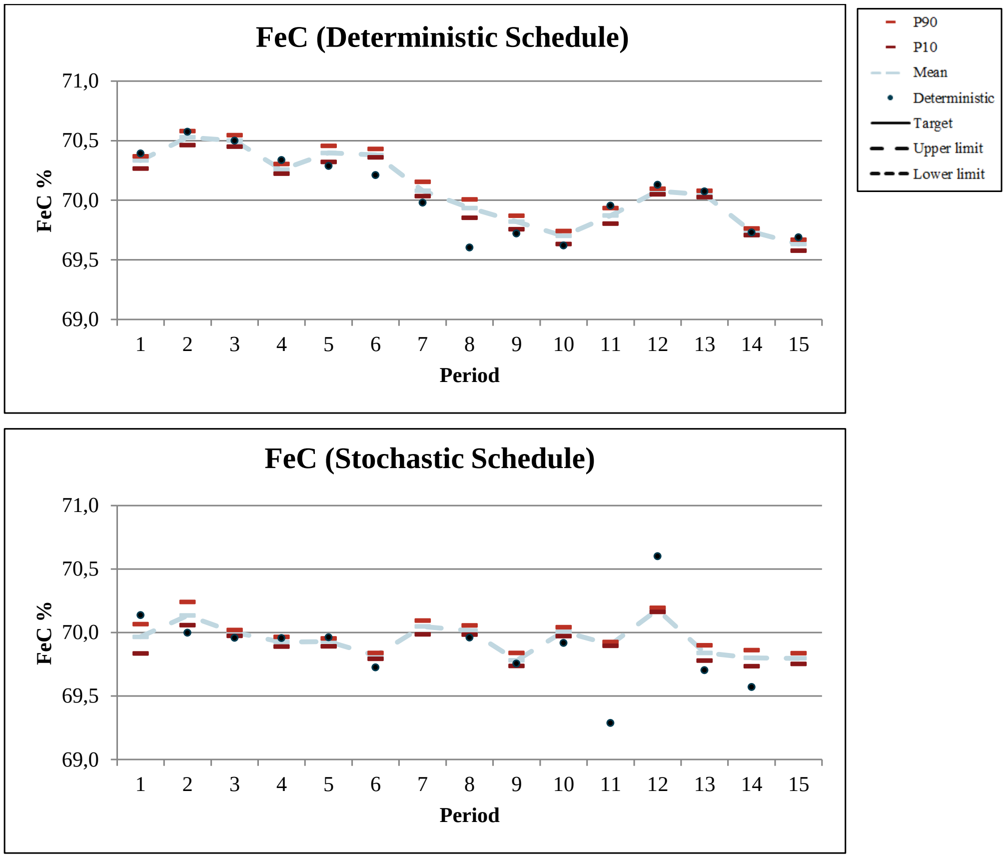

Figure 12: FeC of ore in deterministic schedule (above) and stochastic schedule (below).

ability of the stochastic modeling to reduce risk of not meeting targets. Some values are slightly higher than the target, and this occurs because the weighting of the silica constraints (Eq. 9 and 10) are lower than the weighting of the concentrate tonnage constraints (Eq. 7 and 8). This also explains why there is no significant reduction in the range of variability of SiC from the range in the deterministic schedule. Note that the deterministic schedule had no hard upper and lower limits: it just had a target of 2.1% silica. However, the deterministic schedule silica varies considerably from this target, with much lower values in earlier periods, and much higher values in later periods.

Figure 14 shows the previous truck and cable shovel fleet along with the required equipment based on the schedule in this study. Equipment calculations take into account a variety of factors including mechanical availability, utilization, job efficiency, operating delays, payload, spot times, dump times, load times, and cycle times. The new maximum number of trucks required over the 10 year period is 20 trucks, as opposed to the previous 35 trucks. Less trucks are needed because the haul cycle times are shorter, so the trucks are more productive. In addition, there is less waste mining (almost no mining of the waste MS layer), which also contributes to the reduced number of equipment. The necessary cable shovels was reduced by one, which is significant because each cable shovel costs almost four times as much as one truck. Figure 14 shows a comparison between the fleet requirements of the two schedules for haul trucks and the primary cable shovels. The change in fleet requirements reduces the capital cost requirements by 23.7% and a corresponding reduction in the operating costs by 26.2%.

The impact of these cost reductions and the reduction of geological variability can be seen together in a comparison of discounted cash flows for both schedules (Figure 15). Compared to the deterministic schedule, the optimized schedule has an expected NPV that is +16.9%. The 80% confidence range is 2.5%, ranging from a P10 value for the NPV of +15.6 to a P90 value of +18.1% of the deterministic schedule.

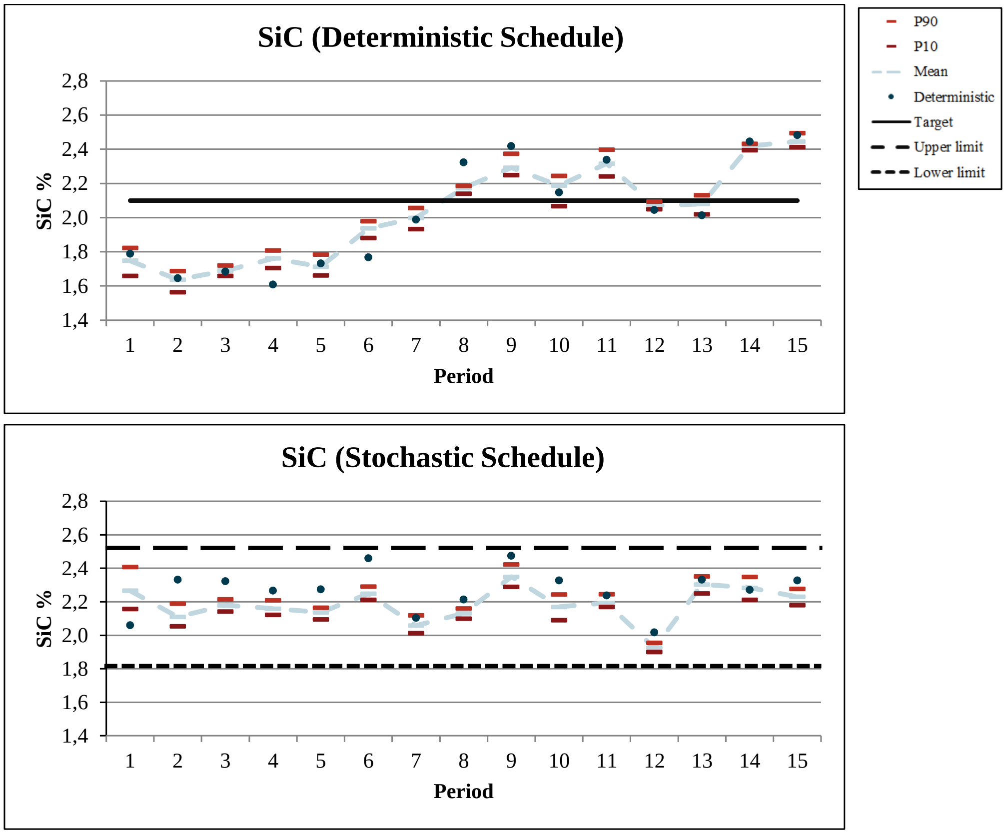

Figure 13: SiC of ore in deterministic schedule (above) and stochastic schedule (below).

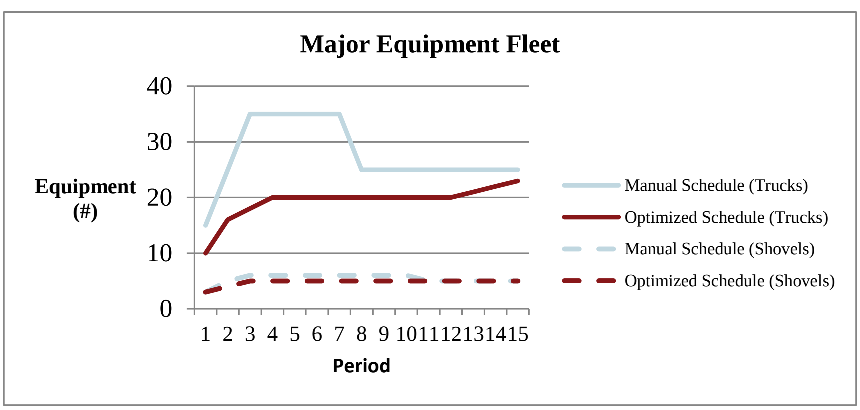

Figure 14: Major equipment fleet comparison between that of the current optimization study and that of a conventional production schedule.

4 Conclusions

A feasible mining schedule was derived for the LabMag iron ore deposit using a SIP formulation that minimizes the risk of deviation of concentrate tonnages and product silica grades from their targets. The optimized schedule also yielded an expected NPV 16.9% higher than that of a conventional schedule and has a higher chance of being realized due to the reduced risk in concentrate tonnages. These benefits are obtained because stochastic scheduling uses multiple simulations to assess the risk of different block groupings, which is ignored by conventional scheduling based on a single estimated orebody model. The SIP framework used here also

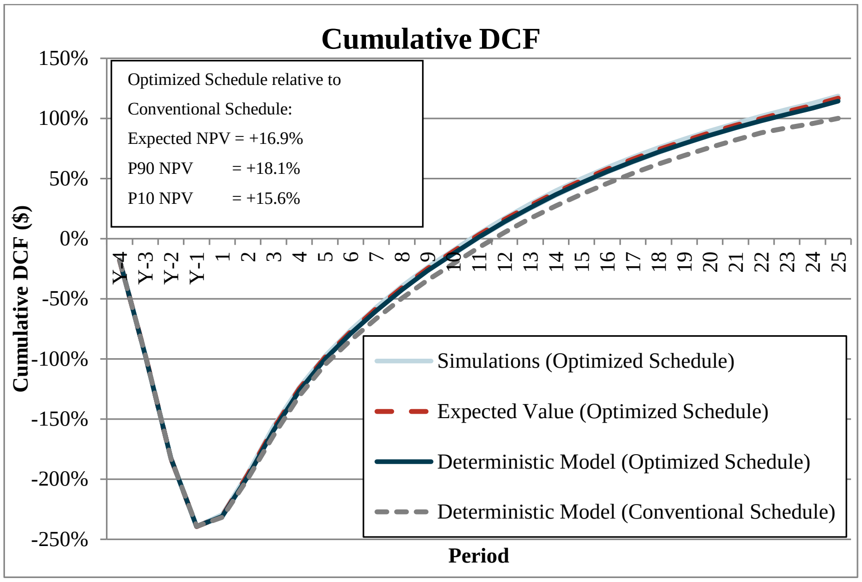

Figure 15: Cumulative DCF of optimized schedule relative to that of a conventional schedule.

allows for easily balancing multiple goals simultaneously, which is otherwise a challenging task. An even higher NPV could potentially be achieved if the optimization used a block selectivity closer to that of the equipment selectivity, as there would be greater flexibility in the combinations of blocks for scheduling purposes.

The presented scheduled formulation accounts for haulage distances by minimizing trucking costs while also ensuring a smooth truck fleet with no sudden jumps or drops in requirements. In comparison to the first ten years of the previous life-of-mine schedule, the proposed schedule reduces the required number of trucks by 15 (previous total of 35 trucks) to 20 total trucks and the required number of shovels by 1 to 5 shovels total. This has a corresponding impact of 23.7% reduction in capital costs, and 26.2% reduction in operating costs over the first 10 years. The proposed schedule mines the orebody in a progressively deepening fashion, maintaining a larger working area at any given time, rather than mining a slot that reaches the full depth of the deposit. This also permits the eventual disposal of dry tailings and waste inside the pit in order to reduce the environmental footprint.

References

Albor Consuegra, F., and R. Dimitrakopoulos. Stochastic mine design optimization based on simulated annealing: Pit limits, production schedules, multiple orebody scenarios and sensitivity analysis. IMM Transactions, Mining Technology, 118(2), 2009, 80–91.

Benndorf, J., and R. Dimitrakopoulos. Stochastic long-term production scheduling of iron ore deposits: Integrating joint multi-element geological uncertainty. Journal of Mining Science, 49(1), 2013, 68–81.

Birge, J.R., and F. Louveaux. Introduction to Stochastic Programming. Springer series in operations research, New York, 1997.

Boland, N., I. Dumitrescu, and G. Froyland. A multistage stochastic programming approach to open pit mine production scheduling with uncertain geology. Optimizaton Online. 2008. http://www.optimization-online.org/DB_FILE/2008/10/2123.pdf (accessed April 10, 2014).

Boland, N., I. Dumitrescu, G. Froyland, and T. Kalinowski. Minimum cardinality non-anticipativity constraint sets for multistage stochastic programming with endogenous observation of uncertainty. University of New South Wales, School of Mathematics and Statistics. 2014. http://web.maths.unsw.edu.au/~froyland/Non-anticip_Gen_Matroid_v6.pdf (accessed April 10, 2014).

Dimitrakopoulos, R., and S. Ramazan. Stochastic integer programming for optimizing long term production schedules of open pit mines: Methods, application and value of stochastic solutions. Mining Technology, 117(4), 2008, 155–167.

Dimitrakopoulos, R., and S. Ramazan. Uncertainty based production scheduling in open pit mining. SME Transactions, Society for Mining, Metallurgy, and Exploration, 316, 2004, 106–112.

Dimitrakopoulos, R., C. Farrelly, and M.C. Godoy. Moving forward from traditional optimisation: Grade uncertainty and risk effects in open pit mine design. Mining Technology, 111(1), 2002, 82–88.

Dowd, P.A. Risk in minerals projects: Analysis, perception and management. Transactions of the IMM, Section A: Mining Technology, 106, 1997, 9–18.

Godoy, M. The effective management of geological risk in long-term production scheduling of open pit mines. PhD Thesis, University of Queensland, Brisbane, Queensland, Australia, 2002.

Godoy, M., and R. Dimitrakopoulos. A risk quantification framework for strategic risk management in mine design: method and application at a gold mine. Journal of Mining Science, 84(2), 2011, 235–246.

Godoy, M., and R. Dimitrakopoulos. Managing risk and waste mining in long-term production scheduling. SME Transactions, 316, 2004, 43–50.

Goovaerts, P. Geostatistics for natural resources evaluation. Oxford University Press, New York, 1997.

Jewbali, A. Modelling geological uncertainty for stochastic short-term production scheduling in open pit metal mines. PhD Thesis, Queensland: School of Engineering , University of Queensland, 2006.

Leite, A., and R. Dimitrakopoulos. A stochastic optimisation model for open pit mine planning: application and risk analysis at a copper deposit. Mining Technology, 116(3), 2007, 109–116.

Leite, A., and R. Dimitrakopoulos. Production scheduling under metal uncertainty: Application of stochastic mathematical programming at an open pit copper mine and comparison to conventional scheduling. Journal of Mining Science and Technology, 24, 2014, (in press).

Menabde, M., G. Froyland, P. Stone, and G. Yeates. Mining schedule optimization for conditionally simulated orebodies. In Orebody Modelling and Strategic Mine Planning: Uncertainty and risk management models, 379–384. AusIMM Spectrum Series 14, 2nd ed., 2007.

Milord, I. Densité relative de LabMag et KéMag. Table jamésienne de concertation minire, Chibougamau, 2012.

Ravenscroft, P. J. Risk analysis for mine scheduling by conditional simulation. Transactions of the Institute of Mining and Metallurgy, Section A (Mining Technology), 1992, 104–108.

Schulz, N.F. Determination of the magnetic separation characteristics with the Davis Magnetic Tube. SME-AIME Transactions, 229, 1964, 211–216.

SNC-Lavalin. Technical report on the feasibility study of the LabMag iron ore deposit, Labrador, Canada. Montréal, 2014.