Stochastic Long-Term Production Scheduling of Iron Ore Deposits: Integrating Joint Multi-element Geological Uncertainty and Ore Quality Control

Jorg Benndorf and Roussos Dimitrakopoulos

Abstract Meeting production targets in terms of ore quantity and quality is critical for a successful mining operation. In situ grade variability and uncertainty about the spatial distribution of ore and quality parameter cause both deviations from production targets and general financial deficits. A stochastic integer programming formulation (SIP) is developed herein to integrate geological uncertainty described by sets of equally possible scenarios of the unknown orebody. The SIP formulation accounts not only for discounted cashflows and deviations from production targets, discounts geological risk, while accounting for practical mining. Application at an iron ore deposit in Western Australia shows the ability of the approach to control risk of deviating from production targets over time. Comparison shows that the stochastically generated mine plan exhibits less risk in deviating from quality targets that the traditional mine planning approach based on a single interpolated orebody model.

Keywords Stochastic integer programming · Mine scheduling · Joint-simulation · Iron ore

Introduction

Long-term mine planning and production scheduling aim to define the "best" mine plan subject to the constraints imposed by physical and geological conditions, policies and the operational mining approach. The term "best" is defined by management objectives. These typically include maximising the monetary value of the mining project as well as meeting customer expectations and guaranteeing a safe operation. The expectations of customers are defined largely in terms of ore AQ1

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tonnage and ore quality characteristics to be delivered. In the case of multi-element deposits, ore quality characteristics are defined by multiple inter-correlated elements. For example, in iron ore deposits, the elements iron (Fe), phosphorus (P), silica (SiO_2), alumina (Al_2O_3) and loss of ignition (LOI) are critical for ore quality. Additionally, in many cases ore is produced out of multiple pits with different ore characteristics. The goal of any global, long-term mine planning approach is to send the most homogeneous ore blend out of multiple pits, meeting customer specifications, while guaranteeing optimal pit development and maximizing the utilization of available mineral resources. In practice, however, when implementing a mine plan, differences frequently occur between the produced ore quantity and quality characteristics. It is well recognized that uncertainty in the description of the spatial distribution of grades of various pertinent elements in the orebody as well as their in situ variability are major contributors to these differences. AQ2

Traditional approaches to mine planning optimization are based on a single estimated model of the orebody that is unable to account for in situ variability and uncertainty associated with the description of the orebody (David 1977, 1988). Contrary to estimation techniques, a different set of techniques provide a tool to address shortcomings of estimation methods, termed conditional simulation (Goovaerts 1997; Chiles and Delfiner 1999; Dimitrakopoulos 2007). Based on drill-hole data and their statistical properties, conditional simulations generate several equally probable models (or scenarios) of a deposit, each reproducing available data and information, statistics and spatial continuity, that is, the in situ variability of the data. The difference between the equally probably scenarios are a quantitative measure/description of uncertainty. The subsequent integration of this grade uncertainty and local variability into mine planning optimization allows for the understanding and control of geological risk. This in turn aims to decrease project risk and increase profitability.

The detrimental effects to mine planning optimization from ignoring in situ grade variability and uncertainty in the description of orebodies are well documented (Ravenscroft 1992; Dowd 1997; Dimitrakopoulos et al. 2002, and others). For example, Dimitrakopoulos et al. (2002) show the danger of relying on estimated (average type) orebody models when optimizing. In their example, net present value (NPV) assessment of the conventionally generated life-of-mine schedule using simulated scenarios of the orebody shows the most likely NPV to be materialized standing at 25% lower than forecasted. The substantially positive contribution of accounting for grade uncertainty through multiple simulated scenarios and new stochastic optimization approaches is also well documented. Godoy and Dimitrakopoulos (2004) show a long-term production scheduling approach based on simulated annealing applied to a gold mine to result in a 28% increase of project value compared to the conventional approach. Leite and Dimitrakopoulos (2007) show the same order of improvement using this approach at a copper deposit. A more general and flexible long-term production scheduling method that allows the control of geological risk between production periods in terms of magnitude and variability is based on stochastic integer programming or SIP (Birge and Louveaux 1997), and it is documented in Ramazan and Dimitrakopoulos (2008). An application of the SIP formulation to the long-term production scheduling of a single-element deposit demonstrates its effectiveness and advantages in terms of additional project value and associated risk management even for a relatively short life of mine.

This paper contributes a mine planning optimization approach that addresses joint multi-element grade uncertainty, as common in many mineral deposits, such as iron ore. More specifically, the stochastic integer programming approach of Ramazan and Dimitrakopoulos (2008) is expanded to (a) multi-element deposits, and (b) includes new mineability constraints to facilitate accessibility and equipment size constraints. In addition, the formulation developed herein is exhaustively tested in an application at an open pit iron ore mine in Western Australia, and within the context of multi-pit production planning. Testing includes the ability of the SIP to control the risk of deviating from production targets in terms of ore quality characteristics. In the next sections, the stochastic mathematical programming formulation is first presented. The application and testing of the formulation are presented, along with a comparison between the SIP and a traditional approach based on one estimated orebody model. Discussion and conclusions follow.

Stochastic Production Scheduling

Global optimization of long-term production scheduling addresses issues of optimal sequencing considering multiple pits, multiple elements, blending issues, stockpiling options and alternative processing or product options (Whittle 2007). The task of long-term production scheduling in a multi-pit operation can be divided into two stages. The first stage is a multi-pit scheduling approach, which defines ultimate pit outlines as well as proportions and element qualities, where each pit and period contribute to the global target in order to optimize the global asset. In the second stage the physical extraction sequence of blocks in each single pit is defined as constraints to production rates and targeted element grades implied by the multi-pit scheduling approach. This contribution concentrates on the long-term scheduling of a single pit; multi-pit scheduling approaches have already been successfully implemented, e.g. BLASOR, developed in BHP Billiton's Technology group (Stone et al. 2007).

The goal of long-term production scheduling under grade uncertainty of single pits is to define a physical extraction sequence of blocks over periods so as to meet multiple goals. These goals include (a) best mine development and best use of available mineral resources for a maximization of the monetary value of the asset, (b) control of risk of deviating from production targets, and (c) guarantees of a safe operation. In this context, controlling the risk of deviating from production targets is a major contribution and involves controlling probabilities and magnitudes of deviations from production targets, as well as fluctuation of produced grades over periods. The underlying geological uncertainty is captured by a set of conditionally simulated orebody models. Generally, production targets may be in terms of

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Chapter No.: 12 Date: 13-10-2017 Time: 9:07 am Page: 4/18

produced ore and waste tonnes and grades of different elements. Constraints are in terms of practicality of the schedule guaranteeing equipment accessibility, mining capacity, processing capacity, geotechnical aspects as well as blending requirements.

Stochastic Formulation for Long-Term Production Scheduling

A general formulation for long-term production scheduling under geological uncertainty for multi-element deposits based on SIP is presented next. It is based on the single element formulation in Ramazan and Dimitrakopoulos (2008). The objective function and relevant constraints are explained in detail.

Objective Function

The SIP objective function, presented here for scheduling multi-element single deposits, combines several goals. It aims to generate a production schedule that optimizes the economic pit development considering constraints imposed by the global multi-pit approach, while minimising deviations from production targets in terms of tonnages and ore-quality as well as minimising costs of non-smooth mining. Equation (1) presents the three parts of the objective function,

$$\begin{aligned} \text{Maximise} \quad & \sum_{t=1}^{P}\sum_{i=1}^{N} c_i^t \cdot x_i^t \\ & -\sum_{s=1}^{S}\sum_{t=1}^{P}\sum_{r=1}^{R}\left({}^{s}qu_r^t \cdot yu_r^t + {}^{s}ql_r^t \cdot yl_r^t\right) \\ & -\sum_{t=1}^{P}\sum_{j=1}^{K}\left(c_{SM} \cdot Y1_j^t\right) \end{aligned} \qquad (1)$$

where P is the number of periods, N denotes the total number of blocks to schedule, S represents the number of simulated orebody models used to capture geological uncertainty, R is the number of targets including grade targets for different elements and ore tonnage targets; c_i^t represents the economic contribution of block number i when mined in period t and is a representation of the expected economic value over all values of block i at time t derived from each realisation s $E\{(\mathrm{NPV})_i^t\}$; x_i^t is a variable representing the percentage of block i mined in period t; if an x_i^t variable is defined as binary (0 or 1), it is assigned 1 if block i is mined in period t and assigned 0 if not; ${}^{s}qu_r^t$ is the upper deviation from production target r at time t considering orebody model s, yu_r^t is the unit cost of ${}^{s}qu_r^t$ to penalise excess production; ${}^{s}ql_r^t$ is the lower deviation from production target r at time t considering orebody model s, yl_r^t is the unit cost of ${}^{s}ql_r^t$ to penalise a deficit in production. $Y1_j^t$ is the number of surrounding blocks, which are not mined in the period t or earlier when mining block j. Surrounding blocks are those, which are no more than 3 blocks apart in each direction (Fig. 1). The costs c_{SM} are penalties associated with $Y1_j^t$. Note that this penalty only applies to a subset K of all blocks N. To avoid overlapping, only every third block in each direction is considered to be the central block j.

The first part of the objective function is used for maximising the discounted economic value in the context of the global optimization. Note the global multi-pit approach accounts for interactions between different pits and aims to maximise usage of resources and global value. The first part in Eq. (1) maximises the local NPV of the single pit under consideration aiming to define an optimal mine development constricted by the global plan. It accounts for profit-defining aspects, such as stripping ratio. The discounted economic block value is calculated as expected value from each realisation. The second part of the objective function handles the deviations from production targets imposed by the multi-pit scheduling approach for each simulated orebody model s including grades of all elements and ore tonnage. By optimising over S possible scenarios, captured through multiple equally probable orebody models, this part of the objective function aims to control uncertainty and variability of the produced grades and ore tonnage. The magnitude of grade variability in the generated schedule is controlled for each element e considered and time period t by penalties associated with deviations ${}^{s}ql_r^t$ and ${}^{s}qu_r^t$. Note that deviations for each target and period yu_r^t and yl_r^t are calculated by the corresponding constraints, which are the grade constraint and the ore tonnage constraint. Part three of the objective function controls smooth mining by penalising not mining adjacent blocks in same period, the central block j is scheduled, or earlier (Fig. 1). $Y1_j^t$ represents hereby the percentage of the 8 directly adjacent blocks and the 25 blocks that are two block-widths distant, which have not been mined in the same period as block j. Deviations of smooth mining for each considered block j and period t $Y1_j^t$ are calculated in the smooth mining constraint. The priorities of the three competing parts in the objective function are controlled by the magnitude of corresponding cost parameters for each part relative to each other. The mine planner has to adjust these parameters so to define the best schedule that

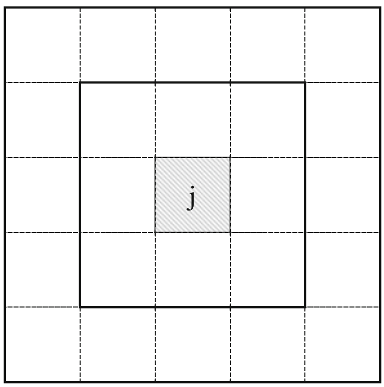

Fig. 1 Inner and outer window around block j in smooth mining constraint (after Dimitrakopoulos and Ramazan 2004)

compromises his objectives, for example the level of risk the planner is willing to accept.

Constraints

The reserve constraint ensures that each block i is only being mined once over all periods P and is given by

$$\sum_{t=1}^{p} x_i^t = 1 \quad (2)$$

By setting the sum of binary variables of one block over all periods equal to one, the block must be mined during the life of the mine.

All overlaying blocks m_i must be mined before mining a given block i. This can be implemented using cone templates representing the required wall slopes. One possible formulation is given through

$$m_i \cdot x_i^t - \sum_{l=1}^{m_i} \sum_{r=1}^{t} x_l^r \leq 0 \quad (3)$$

where l is the counter for the m_i overlaying blocks.

Grade deviations ${}^{s}qu_r^t$ from the upper bound and ${}^{s}ql_r^t$ from the lower bound for each element, period t and simulated orebody model s are defined by grade constraints given in Eqs. (4a) and (4b).

$$\sum_{i=1}^{n} (g_{si}^e - G_{max}^e) \cdot O_i \cdot x_i^t - {}^{s}qu_r^t = 0 \quad (4a)$$

$$\sum_{i=1}^{n} (g_{si}^e - G_{min}^e) \cdot O_i \cdot x_i^t + {}^{s}ql_r^t = 0 \quad (4b)$$

where g_{si}^e is the grade for element e of block i considering orebody model s, G_{min}^e and G_{max}^e are the targeted minimum and maximum average grades of element e of the ore material to be processed in a period t, O_i is the ore tonnage inside block i.

Ore tonnage deviations ${}^{s}qu_r^t$ from the upper bound and ${}^{s}ql_r^t$ from the lower bound of the target at each period t are defined by

$$\sum_{i=1}^{n} (O_i \cdot x_i^t) - qu_r^t = PC_{max} \quad (5a)$$

$$\sum_{i=1}^{n} (O_i \cdot x_i^t) + ql_r^t = PC_{min} \quad (5b)$$

where PC_{min} and PC_{max} are the targeted minimum and maximum ore tonnage to be mined limited by the processing capacity.

The absolute tonnage of handled material, ore and waste, at period t is modelled through constraint

$$\sum_{i=1}^{n} (O_i + W_i) \cdot x_i^t \le MC_{max} \tag{6}$$

where W_i is the waste tonnage inside block i and MC_{max} denotes the maximum mining capacity.

A practical mining requirement is equipment access and mobility realised through smooth mining patterns, which determine a feasible mining sequence. The percentage deviations related to smooth mining as introduced in the objective function ($Y1_j^t$) are calculated through a smooth mining constraint,

$$-\sum_{k=1}^{nb1} 2 \cdot x_k^t - \sum_{k=1}^{nb2} 1 \cdot x_k^t + (nb1 \cdot 2 + nb2 \cdot 1) \cdot x_j^t - Y1_j^t \le 0 \tag{7}$$

Here, nb1 is the number of blocks directly adjacent (inner window) to block j to mine and nb2 is the number of blocks which are two block-width distant to block j (outer window) as illustrated in Fig. 1. Note that blocks in the inner window are penalised twice as much as blocks in the outer window. This setup indicates that it is more desirable to mine blocks in the inner window together with block j than blocks in the outer window. If possible, blocks in the outer window are mined together with block j; however, the solver has enough flexibility to mine those blocks in other periods.

Controlling Risk Over Time for Different Objectives

As presented in the previous section, penalties associated with deviating from production targets introduced in the objective function aim to control risk of deviation for each element. These penalties can be defined in different magnitudes for each element and period. This enables the mine planner to control the risk for each element over time. The ability to control the risk over time is a concept introduced by Dimitrakopoulos and Ramazan (2004) using a geological risk discount rate. This discount rate is directly applied to penalties and thus controls the risk distribution between periods. A high geological discount rate indicates that the SIP formulation herein is emphasised to generate a schedule that is less risky in early periods than in later periods. This may be useful when the operation aims to mine less risky parts of the deposits in early periods and more uncertain parts in later periods. As mining progresses, more information about those uncertain parts will become available in form of operational exploration. A geological discount rate of 0% generates schedules that are expected to exhibit a similar level of risk in all periods. The difference between penalties applied to upper deviations and lower deviations defines the priority of upper and lower deviations from targets. For example, it may be more important in an operation to keep the deficit in production as low as possible while excess production may not be of importance.

Production Scheduling Under Uncertainty: An Application at Yandi Central 1 Iron Ore Deposit, WA

Next, mine production scheduling under multi-element grade uncertainty is applied to the Yandi Central 1 iron ore deposit in Western Australia. The first part describes the Yandi Central 1 deposit focusing on geology, mining operation and current production scheduling practice. The problem specification and description of input data are discussed subsequently, in particular the process of incorporating the stochastic production scheduling approach of a single deposit into the global multi-pit scheduling problem. The input in terms of simulated ore body models is presented as well as the operational, economical and risk controlling parameters. Following, the practical approach of scheduling Yandi Central 1 is detailed, including the practical implementation of the scheduling formulation and the manual mine design to convert results to a practical schedule. A comparison between schedules generated using a stochastic formulation to those using a deterministic formulation considering one estimated ore body model is found at the end of this section and demonstrates the benefit of the stochastic approach.

Yandi Operation and Current Production Scheduling Practice

The Yandi Central 1 deposit is part of the larger Yandi channel iron deposits (CID), which occurs alongside the Marillana–Yandicoognica Creek system about 120 km northwest of Newman, Western Australia. This deposit is part of the Yandi joint venture operation, which includes multiple pits. The fundamental objective of this complex operation is the achievement of customer defined on-grade shipments at lowest costs by optimally blending from different pits with a diverse range of resource grades. Critical geochemical parameters when evaluating the deposit are iron content (Fe), silica content (SiO_2), alumina content (Al_2O_3), phosphorus content (P) and the water and organic content measured as loss on ignition (LOI), as they influence the physical and chemical properties of the product and the performance of the beneficiation process.

For the global multi-pit optimization of the Yandi joint venture operation, BHP Billiton’s Technology group developed a scheduling-algorithm, termed BLASOR (Stone et al. 2004). Among other details BLASOR assigns targets in terms of AQ3 produced ore tonnes and grades for each period to each pit as contributing to the global target. Although BLASOR, as used here, accounts for multiple elements, the approach is based on a single estimated orebody model and does not incorporate local uncertainty and in situ variability.

Problem Specifications and Input for Scheduling

The in situ variability and the incomplete knowledge of the spatial distribution of the elements in the orebody are most critical for meeting customer specifications. In order to incorporate in situ variability and uncertainty of geochemical parameters in mine production scheduling, techniques for optimization under uncertainty can be employed. The application of stochastic mine production scheduling to Yandi Central 1 is based on stochastically simulated orebody models generated using the computationally joint direct block simulation approach (Boucher and Dimitrakopoulos 2008). Operational, economic and risk defining parameters are explained in subsequent sections in more detail.

Stochastic Orebody Models at Yandi Central 1

The basis for mine production scheduling under geological uncertainty is a series of simulated orebody models of the deposit. For this case study, 20 simulated orebody models of the main ore zone (MOZ) are used, generated by Boucher (2003). This joint-simulation of the five considered elements Fe, P, SiO_2, Al_2O_3 and LOI guarantees the local reproduction of cross-correlation between the elements. Note that Fe is strongly correlated with the elements SiO_2 and Al_2O_3. Each of the resulting orebody models contains 3049 blocks in total. Block dimensions are 25 m by 25 m by 12 m, representing typical mining units. Each block contains the attributes total tonnage, ore tonnage as well as total content of each element Fe, P, SiO_2, Al_2O_3 and LOI. As an example, a map of the spatial distribution of Fe grades in the orebody model is presented in Fig. 2 for the case of simulated realisation number five.

Operational Parameters

Operational parameters, including ore production and required qualities are defined by the global multi-pit scheduling approach undertaken by BLASOR. BHP Billiton Iron Ore provided scheduling results defining the contribution of Yandi Central 1 to the global target for the following five years referred to as periods. For confidentiality reasons, BLASOR results are scaled (Table 1).

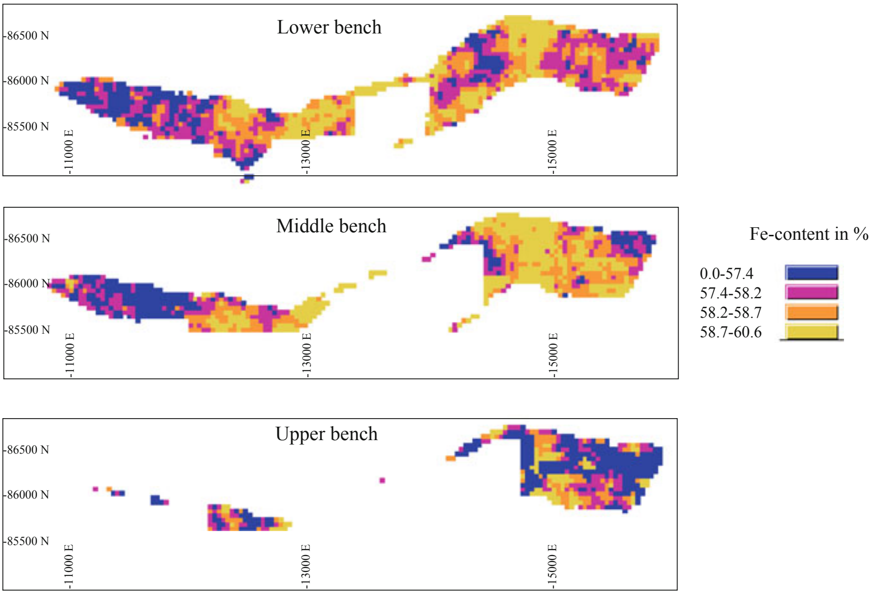

Fig. 2 Spatial distribution of Fe-grades in realisation number five for the lower, middle and upper bench

Table 1 Ore tonnage and grade constraints for scheduling Yandi Central 1

BLASOR scheduling results of Yandi Central 1 for first periods						
Period No	Ore tonnage (wt)	Fe (%)	P (%)	SiO2 (%)	Al_2O_3 (%)	LOI (%)
1	14,000,000	57.1–59.4	0.032–0.038	4.6–5.2	0.90–1.05	9.5–11.0
2	10,000,000	57.1–59.4	0.032–0.038	4.6–5.2	0.90–1.05	9.5–11.0
3	10,000,000	57.1–59.4	0.032–0.038	4.6–5.2	0.90–1.05	9.5–11.0
4	9,000,000	57.1–59.4	0.032–0.038	4.6–5.2	0.90–1.05	9.5–11.0
5	7,200,000	57.1–59.4	0.032–0.038	4.6–5.2	0.90–1.05	9.5–11.0

Note Ore/Waste cut-off grade is Fe $\geq$ 56%

Ideally, shipping grades are to be delivered with nearly zero variability. Since this is unlikely, the industry sets target bands limited by an upper and lower bound. Grades should not fall outside this band. Table 1 summarises initial ore tonnage and grade limits. The differentiation between ore and waste prior to the optimization is realised through an Fe grade cut-off of 0.56%. Further, it is assumed that the operation is flexible enough to account for different ore and waste production rates

Table 2 Economical parameters for long-term production scheduling of the Yandi Central 1 iron ore operation

Parameter	Costs/Price
Price per ton recovered metal	\$30
Mining costs per ton	\$5
Processing costs per ton	\$5
Economical discount rate	10%
Geological discount rate	10%

between periods. For this reason, the maximum mining capacity, including ore and waste production, was set to 20,000,000 t, which is about 5,000,000 t more than the maximum rate. Due to the flat geometry of the deposit, one slope region is sufficient to characterise the geotechnical constraints. The general slope angle is set at 45°.

Economical and Risk-Controlling Parameters

Table 2 presents the economic parameters, including price, mining and processing costs and discount rates. Mining costs include blasting, extraction and transportation costs; processing costs account for crushing, conveying and stockpiling. Two discount rates are identified, the economical discount rate and the geological discount rate. The economical discount rate discounts cash flows over periods, while the geological discount rate controls the risk of producing grades that fall outside the limits over the periods. Recovery is 100%.

The stochastic scheduling approach applied in this case study is concerned with the risk of not meeting production targets of produced element-grades. Penalties for deviating from production targets are set initially to 1\$/unit of deviation.

The Practical Scheduling Approach

Initial Run and Practical Mine Design

The upper part of Fig. 3 shows results of an initial run using above specified parameters. The extraction sequence appears smooth and feasible, however there are few blocks scheduled surrounded by blocks scheduled in different periods. To generate a practical mining schedule that guarantees minimum mining width and equipment accessibility, results of the stochastic formulation are refined using manual mine design and haul road construction. These standard tools are available in commonly used mine scheduling software packages. In this study open pit design from Earthworks Datamine is used (Datamine manual 2002). The schedule generated by the formulation can be used as a guideline to construct polygons for each

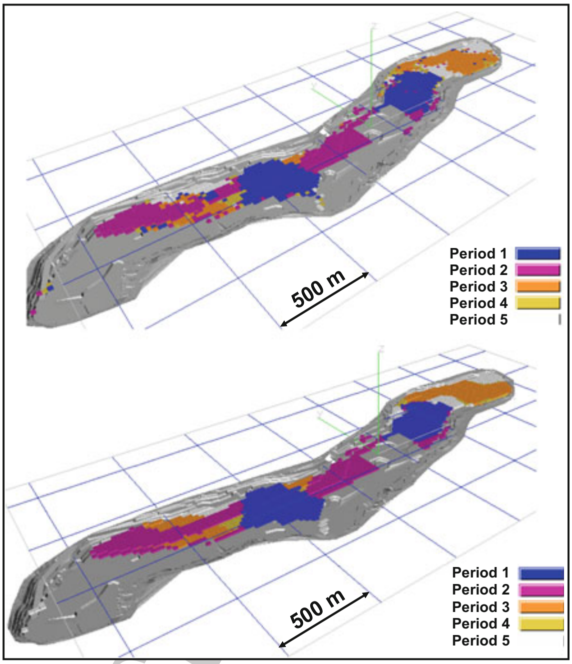

Fig. 3 Stochastic schedule in ultimate pit—before (upper part) and after (lower part) smoothing using manual design

period and bench. These polygons, in combination with haul roads and ramps, define the pit design for each period and provide a mineable production schedule. Parameters used in this designing process are a 12 m bench height, 45° slope angle and a 5 m berm between two toe and crest string, a road width of 25 m and a 8% ramp incline. The lower part of Fig. 3 shows a south-east isometric view of the resulting smooth schedule. Benndorf (2005) demonstrated that this type of smoothing has no significant impact on the results, which means that the smoothed schedule is still near to optimal.

Evaluating Results

In addition to produced ore and waste tonnage, results are evaluated in terms of risk profiles of produced grades per period, in particular for Fe, SiO_2, Al_2O_3, P and LOI (Fig. 4). For each period the grades are shown considering each simulated orebody realisation, which represent possible scenarios based on information available. The spread of the different realisations provide an indication about uncertainty in produced grades per period when extracting the deposit according to the generated schedule. Analyzing the risk profiles of Fe, P and LOI results concludes that there is no risk of deviating from production targets. SiO_2 and Al_2O_3 appear to be more

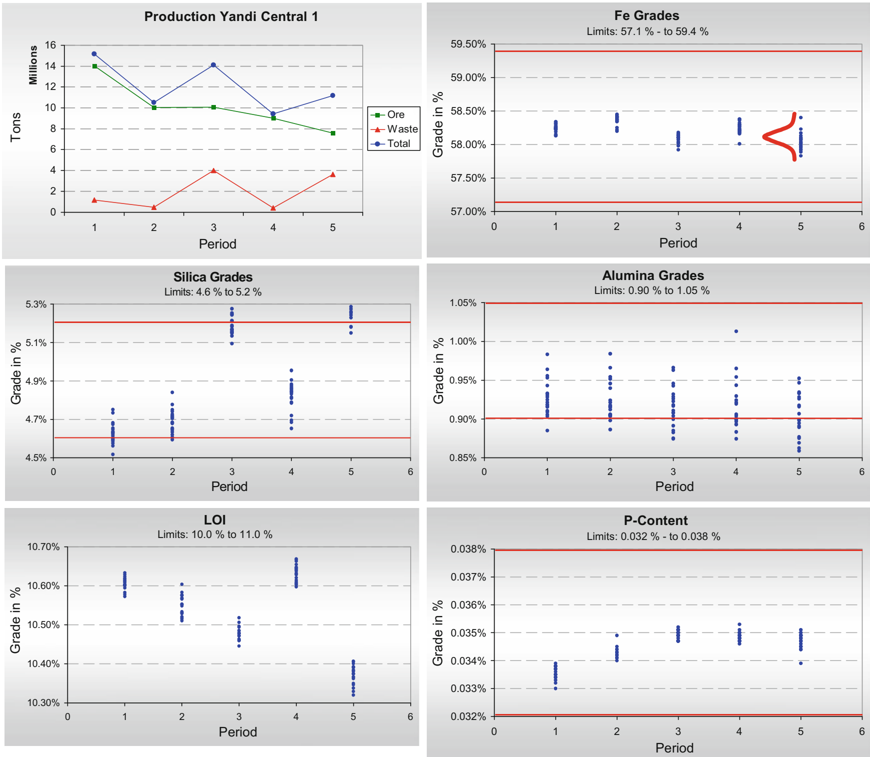

Fig. 4 Results of stochastic scheduling in terms of ore and waste tonnages and risk profiles for Fe, SiO_2, Al_2O_3, P and LOI

critical in meeting production targets. For example, four out of twenty simulated orebody models for SiO_2 indicate a deviation from the lower target in period one. Thus, there exists a 20% chance of not meeting production targets for SiO_2 in period one.

The Ability to Control Risk

A major contribution of the presented scheduling formulation is the ability to control risk of deviating from production targets considering different quality parameters. As experienced in the initial run, SiO_2 and Al_2O_3 appear most critical in meeting targets. To investigate the ability to decrease risk, three different schedules were generated applying different penalties to both critical elements. The three schedules were generated using low (1$ per unit deviation per ton), medium (10$ per unit deviation per ton) and high penalties (100$ per unit deviation).

Layout: T1_Standard | Book ID: 457301_3_En | Book ISBN: 978-3-319-69319-4
Chapter No.: 12 | Date: 13-10-2017 | Time: 9:07 am | Page: 14/18

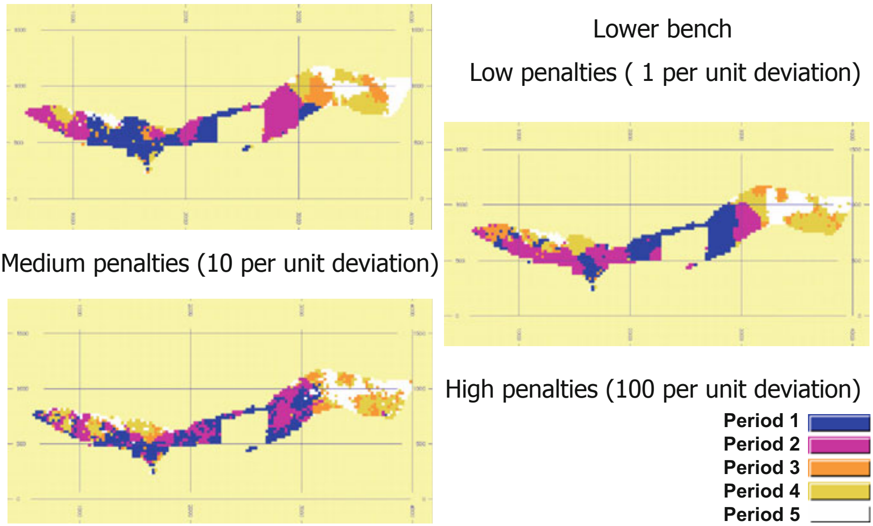

Fig. 5 Different extraction schedules depending on the magnitude of penalties for the lower bench

Figure 5 shows the extraction sequence of the lower bench for each schedule. In the case of each schedule, the deposit would be extracted in a different sequence. The dispersion of the schedules increases with the magnitude of the penalties. In the case of low penalties, the extraction sequence is smooth. Although medium penalties generate a more dispersed schedule, it is still smooth enough to be converted to a feasible schedule using manual mine design. High penalties generate a very dispersed schedule, which could hardly be efficiently realised. The dispersion is an expression of a higher selectivity, necessary in order to produce a homogeneous product in a tight quality band. Figure 6 shows the risk profiles for SiO_2 and Al_2O_3 for the three generated schedules. In case of SiO_2, the effect of increasing penalties already becomes obvious in the case of medium value penalties. Compared to the low penalty case, the fluctuation of grades between periods decreases significantly and there exists only a slight probability of deviating from targets in period 2, 3 and 4. Higher penalties improve the result only marginally. In the case of Al_2O_3, a decrease in probability of deviating from targets is recognizable with higher penalties, however, there still exists a certain amount of risk. This is an expression of a high in situ variability and uncertainty of the element, which cannot be avoided by blending in the pit. A solution here, to decrease the risk, could be to blend the ore with ore from different mines, where Al_2O_3 is less variable and uncertain.

Generally, this evaluation of the scheduling formulation demonstrates that less risk of deviation comes with a cost of higher selectivity, which is caused by the two competing objectives in the objective function: minimize risk of deviating from production targets and generate a smooth schedule.

Layout: T1_Standard | Book ID: 457301_3_En | Book ISBN: 978-3-319-69319-4
Chapter No.: 12 | Date: 13-10-2017 Time: 9:07 am | Page: 15/18

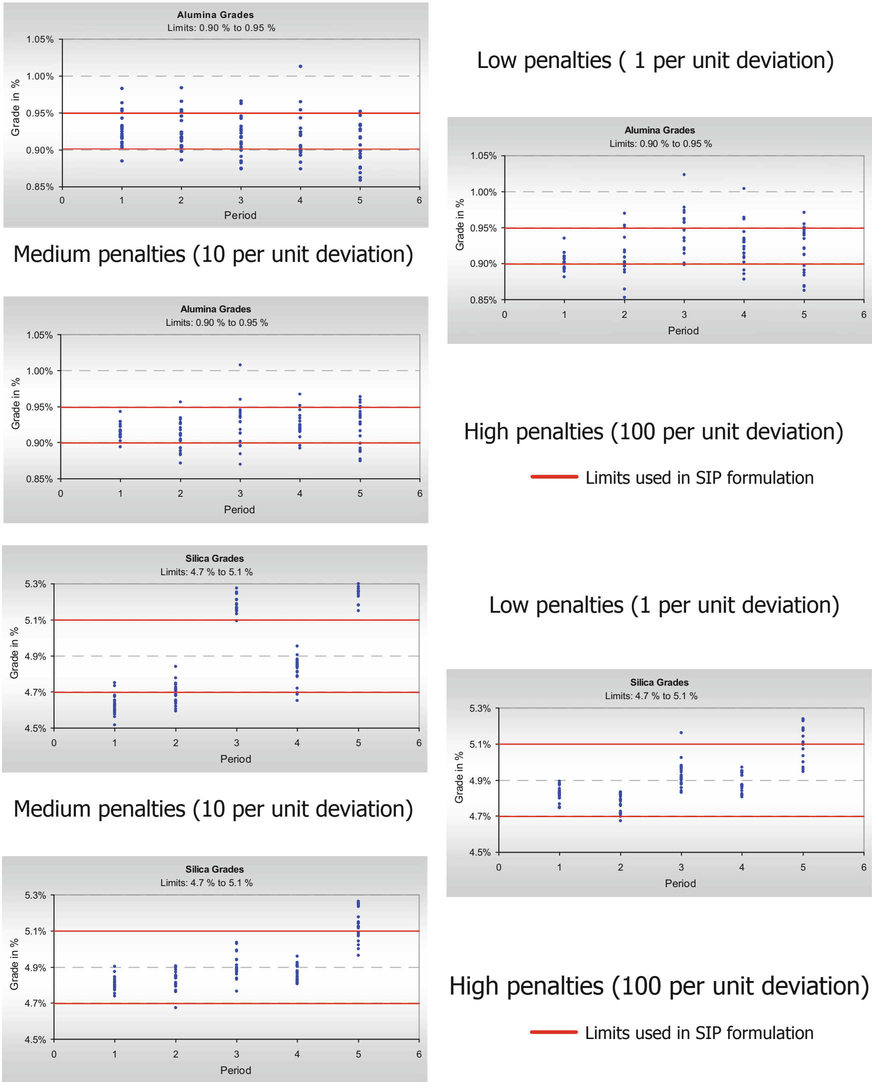

Fig. 6 Risk profiles for produced grades (alumina and silica) depending on penalties

Comparison to Traditional Production Scheduling Approaches

To demonstrate the benefit, stochastic modelling generates compared to an average-type based scheduling formulation, two production schedules are compared; one generated using 20 simulated orebody models referred to as the stochastic schedule and the second schedule is generated using a single

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Chapter No.: 12 Date: 13-10-2017 Time: 9:07 am Page: 16/18

average-type orebody model referred to as E-type model. The E-type orebody model is calculated by averaging block values of the 20 simulated orebodies for each element. The same scheduling formulation with parameters comparable to the stochastic approach generates the E-type schedule. Figure 7 shows the extraction sequence for the stochastic schedule and the E-type schedule for the lower bench. Both schedules show a relatively smooth sequence, which can be practically realised after manual open pit mine design. Figure 8 presents risk profiles for the critical elements SiO_2 or Al_2O_3 of both schedules. From the risk profiles presented in Fig. 8, it is evident that the E-type based schedule is not able to account for geological uncertainty. Although the mean values of the element grades produced

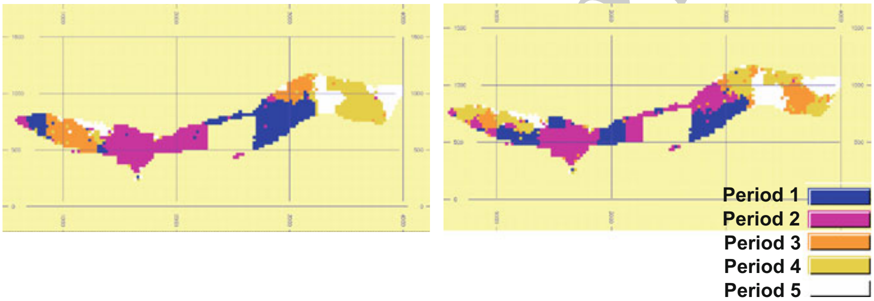

Fig. 7 Extraction sequence for the stochastic schedule (left) and the E-type based schedule (right)

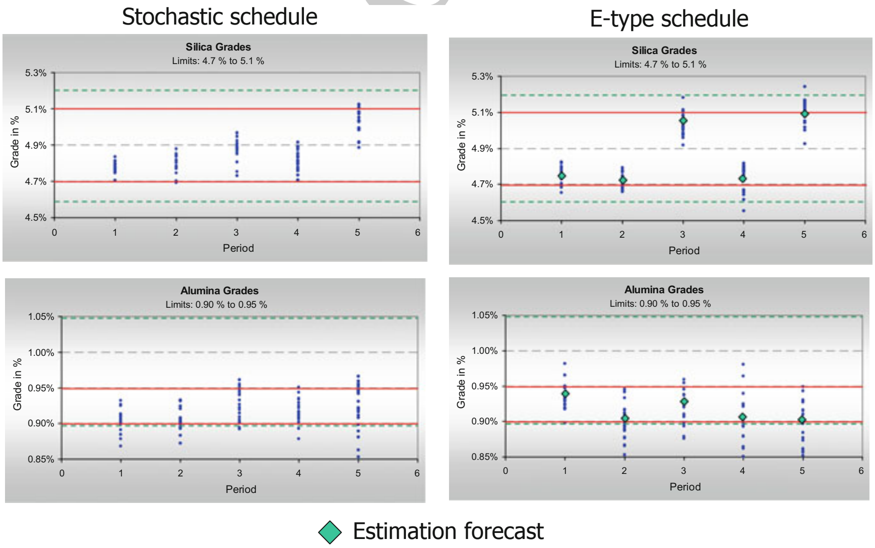

Fig. 8 Risk profiles for produced grades (silica and alumina) for the stochastic schedule (left) and the E-type based schedule (right)

in a period are inside the production targets, considerable deviations from upper and lower production limits for SiO_2 or Al_2O_3 are visible. In the stochastic schedule SiO_2 deviates only slightly in periods two and five with a probability of 5 and 20% respectively. The E-type schedule shows SiO_2 deviations from targets in each period with an average probability of 30%. The probabilities of deviating from upper and lower limits are almost twice as high for the E-type schedule compared to the stochastic based schedule, especially for Al_2O_3.

Conclusions

A new stochastic integer programming based mine production scheduling approach, which considers jointly multi-element geological uncertainty, is presented and successfully applied to production scheduling at the Yandi Central 1 deposit, WA. It is demonstrated that the SIP formulation presented, can be implemented as part of a multi-pit scheduling approach. In this application, results from BLASOR, a multi-pit scheduling optimization approach, are used to define the contribution of the Yandi Central 1 deposit, Western Australia, to the global target per period in terms of desired grades of elements and ore tonnages.

Results demonstrate the ability of the stochastic approach to control risk of deviating from production targets for critical quality defining elements. A comparison between the stochastically generated production schedule and a schedule generated using one estimated orebody model illustrated the benefit, stochastic models can generate. The stochastic schedule shows a higher probability in meeting production targets, which decreases overall project risk and can increase project value.

References

Benndorf J (2005) Efficient sequential simulation methods with implications on long-term production scheduling. Unpublished M.Phil thesis, The University of Queensland, Brisbane, p 225

Birge JR, Louveaux F (1997) Introduction to stochastic programming. Springer, New York, p 421

Boucher A (2003) Conditional joint simulation of random fields on block support. Unpublished M. Phil thesis, University of Queensland, Brisbane, p 168

Boucher A, Dimitrakopoulos R (2008) Block-support simulation of multiple correlated variables. Mathematical Geosciences (in press)

Chiles JP, Delfiner P (1999) Geostatistics, modeling spatial uncertainty. Wiley, New York, p 695

Datamine Manual (2002) Datamine-guide graphical mining software reference manual

David M (1977) Geostatistical ore reserve estimation. Elsevier, Amsterdam, p 364

David M (1988) Handbook of applied advanced geostatistical ore reserve estimation. Elsevier, Amsterdam, p 216

Dimitrakopoulos R (2007) Risk analysis in ore reserves and mine planning: conditional simulation concepts and applications for the mining industry. AusIMM-McGill 2007 Professional Development Seminar Series, p 385

Dimitrakopoulos R, Farrelly C, Godoy M (2002) Moving forward from traditional optimization: grade uncertainty and risk effects in open pit design. Trans Inst Min Metall Sect A 111:A82–A87

Dimitrakopoulos R, Ramazan S (2004) Uncertainty based production scheduling in open pit mining. SME Trans 316:106–112

Dowd PA (1997) Risk in minerals projects: analysis, perception and management. Trans Inst Min Metall Sect A 106:A9–A18

Godoy MC, Dimitrakopoulos R (2004) Managing risk and waste mining in long-term production scheduling. SME Trans 316:43–50

Goovaerts P (1997) Geostatistics for natural resources evaluation. Oxford University Press, New York, p 483

Leite A, Dimitrakopoulos R (2007) A stochastic optimization model for open pit mine planning: application and risk analysis at a copper deposit. IMM Trans Min Technol 116(3):109–118

Ramazan S, Dimitrakopoulos R (2004) Recent applications of operations research in open pit mining. SME Trans 316:73–78 AQ4

Ramazan S, Dimitrakopoulos R (2008) Production scheduling with uncertain supply: a new solution to the open pit mining problem. Eur J Oper Res (Submitted)

Ravenscroft PJ (1992) Risk analysis for mine scheduling by conditional simulation. Trans Inst Min Metall Sect A 101:A104–A108

Stone P, Froyland G, Menabde M, Law B, Pasyar R, Monkhouse P (2007) Blasor-blended iron ore mine planning optimization at Yandi. In: Orebody modelling and strategic mine planning: uncertainty and risk management models. The Australian Institute of Mining and Metallurgy, Spectrum Series 14, 2nd edn. pp 133–136

Whittle G (2007) Global asset optimization. In: Orebody modelling and strategic mine planning: uncertainty and risk management models. The Australian Institute of Mining and Metallurgy, Spectrum Series 14, 2nd edn, pp 331–336

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