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Simulated Learning Model for Mineable Reserves Evaluation

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During the lifetime of mining projects, the degree of knowledge of the deposit increases over time due to the continuous acquisition of additional data. The extra information is collected from different sources, including geologic mapping, production data, and infill drilling. With respect to the long term mine plan, the block model and the mining sequence are also updated, on a periodic basis. As the mining of the deposit progress, the block model becomes more accurate and uncertainty in ore production reduces, and the mining sequence becomes clearer. There has been extensive research on mine planning, but current techniques do not account for the evolution of the degree of knowledge of the deposit as an integral part of mine planning. Conventional paradigms assume that either that 1) the degree of knowledge of the deposit is static over time, or 2) there is access to perfect knowledge of the deposit. In this paper, a new paradigm for evaluating mineable reserves of surface mining projects is proposed. This new paradigm accounts for the dynamic behaviour of the degree of knowledge of the deposit in the design of the long term mine plan. During implementation, scenarios that characterize the dynamic nature of the mining of the deposit are simulated. Unlike conventional paradigms, where only the mining strategy is considered, the performance of the long-term mine plan in this new paradigm depends on both mining and data acquisition strategies. This feature provides a more realistic framework for evaluating mineable reserves than conventional paradigms. An example is presented to illustrate the implementation.

Introduction

In surface mining operations, the evaluation of mineable reserves consists of finding the mineable region of the deposit that results in the maximum profit of the mining project. The characteristics of the mineable reserves, including economic potential of the mining project and geometry of the mineable limits, are calculated during the design of the long term mine plan. The evaluation of mineable reserves involves many factors such as metal prices, mining and metallurgical technologies available, and local and international political environments. Geologic factors are represented by the block model of the deposit, which is built based on the current available geologic data, e.g., exploratory drilling campaign. Because of the complexity of the problem, many of these factors are assumed fixed (Hustrulid & Kuchta, 1995).

Due to the extensive lifetime of mining projects, the factors involved in the evaluation of mineable reserves are subject to variability as a function of time. In practice, the block model of the deposit is updated periodically to include extra information collected. This extra information is collected from different sources, including blasthole data, infill drilling data, geologic mapping, and rock mechanic studies (Erickson & Padgett, 2011). It is typically assumed that the block model is invariant throughout the lifetime of the mining project to simplify the long-term planning process.

Conventionally, the design of the long term mine plan consists of two steps 1) build the block model of the deposit, and 2) design the optimal mining sequence (Whittle & Whittle, 1999). Geostatistical techniques are typically implemented to construct the block model (Sinclair & Blackwell, 2002). The mining sequence is initially determined by optimization techniques (Alford, Brazil, & Lee, 2007). Extensive research has been conducted on mine sequencing algorithms that aim to maximize the net-present-value of the mining project. The proposed algorithms produce optimal results based on their respective conditions and assumptions.

In this paper, a new paradigm that accounts for the periodic updating of the block model of the deposit is proposed. The conventional static block model is replaced by a dynamic block model that updates periodically. The periodic updating of the mining sequence is considered as a computational learning process: in each period, the mining sequence adapts the newly acquired information from the previous period. The evaluation of mineable reserves is carried out based on a set of realizations of the mining of the deposit. Each realization is treated as a scenario of how the future geology of the deposit may reveal itself, subject to a specified future data acquisition strategy. The proposed paradigm is called a Simulated Learning Model (SLM) due to the consideration of the mining of the deposit as a computational learning process.

First, the existing paradigms for mine planning are summarized and previous research is discussed. Next, the event-based model that is used in the SLM paradigm to characterize the mining process of the deposit is presented. The following section compares the SLM paradigm to the conventional paradigms in terms of how uncertainty in the mining of the deposit is quantified. In the following two sections, the implementation aspects of the SLM paradigm and an example are discussed.

Background

Extensive research has been conducted for developing mine sequencing algorithms that aim to maximize the net-present-value of a mining project. Gaupp (2008) reviewed and classified the majority of available algorithms into two categories: 1) ultimate-pit based and 2) comprehensive based techniques. In the first category, the ultimate-pit is calculated first to outline mineable limits. In the second category, the mining sequence is calculated directly. Osanloo, Gholamnejad, and Karimi (2007) proposed a different classification. In general, these techniques produce optimal mining sequences with respect to the assumptions of the global environment in which the mine plan is designed. The global environment consists of the factors, including the anticipated geologic, economic, and political factors, involved in the evaluation of the mining project. With respect to the geologic factors, three paradigms based on type of block model built are typically implemented.

Paradigm 1 – Estimation

The geology of the deposit is characterized by a kriged estimate model. The mining of the deposit is defined by one mining sequence. This paradigm precedes early developments of geostatistics in publications by authors such as David (1977) and Journel and Huijbregts (1978). The main problem of this paradigm is the impact of the smoothing of the estimated model on the mining sequence. The kriging plan is often tuned to achieve reliable recoverable reserve predictions or to mitigate conditional bias (Isaaks, 2005). Since this paradigm relies on an estimated model, the value of the mining project is evaluated in expected terms with no consideration of uncertainty. This paradigm is widely implemented in practice due to its simplicity.

Paradigm 2 – Simulation A (Estimation Based)

This paradigm can be seen as an extension of paradigm 1. A set of simulated realizations of the deposit are built to evaluate the performance of the mining sequence, built based on paradigm 1. The realizations are processed through the single mining sequence to evaluate the uncertainty in ore production. This allows evaluating the mineable reserves in terms of uncertainty in operating metrics. The implementation of this paradigm has been presented by authors such as Dimitrakopoulos (1997) and Van Brunt and Rossi (1999).

Paradigm 3 – Simulation B

The geology of the deposit is characterized by a set of multiple realizations. One mining sequence is generated for each realization of the geology of the deposit. In this case, the project is directly evaluated in terms of operating metrics. This paradigm is not as widely implemented as paradigm 1 because the realizations of the geology of the deposit and mine sequence optimization runs are computationally, as each alternative must be processed individually (Dominy, Noppé, & Annels, 2002). Moreover, mining engineers would not know which alternative to follow.

The conventional paradigms discussed do not account for the periodical collection of data in future periods. The acquisition of additional data is an inherent part of the mining of the deposit and improves the accuracy of the mining sequence as the mining of the deposit progress. In geostatistics, the impact of uncertainty in the mining sequence has been discussed by many authors, including David (1977), Journel & Huijbregts (1978), and Chilés and Delfiner (1999). There are some works that consider the effect of the collection of the additional data on mine planning. Froyland, Menabde, Stone, and Hodson (2004) proposed the simulation of future infill drilling campaigns to assess the impact on the net-present-value of the mining project. Journel and Kyriakidis (2004) discussed the effect of future blasthole drilling data on the evaluation of mineable reserves. Isaaks (2005), proposed a methodology to account for the information effect in the block model of the deposit. Jewbali and Dimitrakopoulos (2009) discussed the impact of future blasthole drilling data in the design of a mining sequence. However, in these approaches, the time variable is not directly considered. The effect of the evolution of the DOKD, due to the continuous acquisition of additional data, on the performance of the mine plan is not accounted for.

Event-Based Model of the Mining Process

This model is used to approach the mining process in the SLM paradigm. In this model, the input parameters are grouped in two categories: 1) mining strategy and 2) data acquisition strategy. It will be referred to as SLM mining model. The mining strategy includes parameters involved in mine scheduling. The data acquisition strategy considers the parameters involved in acquiring additional data. The mining strategy is presented in the form of a mine sequencing algorithm that considers specific operating conditions to schedule mine production. Any of the different mine sequencing algorithms can be used as the mining strategy. The data acquisition strategy considers the collection of the additional data throughout the lifetime of the mining project. In practice, the additional data that contributes to the improvement of the degree of knowledge of the deposit (DOKD) is of many types and comes from different sources. In this paper, two sources are considered: 1) blasthole and 2) infill drilling data. The blasthole data is used primarily to fragment material in the scheduled regions during the mine operations. The infill drilling data is used mainly to improve the DOKD for medium-, long-term mine planning, and exploration purposes.

The lifetime of a mining project is divided in three stages: 1) pre-production, 2) production, and 3) post-production (Hustrulid & Kuchta, 1995). The evolution of the DOKD affects the mine plan in the last part of the pre-production stage in case infill campaigns are implemented. Throughout the production stage, the periods where material is extracted from the pit are considered. For example, in case that at the end of the production stage only material from stockpiles is sent to the respective processing plants, the corresponding periods are not considered. The post-production stage is not considered. For practicality, the lifetime of the mining project is considered as the time interval where the evolution of the DOKD affects the mining operations in the pit.

In the SLM mining model, the lifetime of the mining project is divided into periods (see Figure 1), which can be annual or semi-annual, depending on the company policies that dictates the frequency in which the mine plan is updated. The lifetime of the mining project is divided in a set of consecutive periods where a set of four events occur:

Event 1. Consolidation of existing data.
Event 2. Design of the mining sequence.
Event 3. Mining of the next scheduled region and acquisition of additional data.
Event 4. Reconciliation of the scheduled region.

Event 1 occurs at the beginning of the period. All the existing data is consolidated in one dataset. The DOKD at present time depends on the current consolidated dataset. As mining progress, the current dataset grows in size due to the continuous collection of additional data. The periodic growth of the current dataset results in the evolution of the DOKD. In Event 2, based on the current dataset, the block model of the deposit is built and the mining sequence is designed. In Event 3, the region targeted for extraction according to the current mining sequence is mined. In practice, to detail the mining of the targeted region, short- and medium-term plans are designed and implemented. Along with the mining of the targeted region, additional data from blastholes and infill drillholes are collected. Event 4 occurs at the end of the period and consists of reconciling the production of the current period.

In each period, the reconciliation compares planned versus executed values. Two types of metrics are considered: production and economic. In the case of the production metrics, due to the lack of perfect knowledge of the geology of the deposit, following strictly the mining sequence would result in a discrepancy between planned and executed production. The implementation of short- and medium-term mine plans details the mining of the current period and allows meeting the planned production target. The planned and executed production are considered similar. In the case of the economic metrics, the adjustment of the mining of the current period results in an increment of the planned mining cost. For example, if less ore is found non-scheduled regions are targeted for extraction by the short- and medium-term plans to compensate the production gap. In an opposite case, if more ore is found, the surplus has to be stored in stockpiles. Either way, the extra expenses incurred increase the planned mining cost. In the SLM mining model, the metric of economic performance is quantified in terms of the net-present-value. In the reconciliation, two types of net-cash-flow (NCF) are considered: 1) planned and 2) executed. The relationship between them is expressed as:

$$NCF_{ex}\left(D_i\right) = NCF_{pl} - AC\left(D_i\right), \tag{1}$$

where, D_i represents the dataset available at the beginning of the i-th period, NCF_{ex} and NCF_{pl} are the executed and planned of the i-th period, respectively, AC is the total extra cost incurred to adjust the mining of the i-th period.

The negative impact, in economic terms, due to not having access to perfect knowledge of the deposit is accounted for by the AC term. The executed NCF equals the planned NCF only when there is no need to adjust the mine plan of the current period, e.g., in the case of Paradigm 3, where it is assumed to have access to perfect knowledge of the geology of the deposit before designing the mining sequence.

At the end of the lifetime of the mining project, the mining sequence that is ultimately implemented consists of all the regions targeted for extraction in each period. This ultimate mining sequence will be referred to as operating mining sequence. The operating mining sequence results from the combined interaction between the mining and data acquisition strategies. Throughout the lifetime of the mining project, the data acquisition strategy improves the DOKD periodically, thus allowing the mining strategy to make more informed decisions.

Comparison of the SLM Mining Model to Conventional Paradigms

In the conventional paradigms, only the mining strategy is considered. The conventional paradigms are different in how they account for the DOKD throughout the lifetime of the mining project (see Figure 2). In the case of Paradigms 1 and 2, the DOKD of the initial dataset remains unaffected over time, as the acquisition of additional data throughout the lifetime of the mining project is not accounted for. In the case of Paradigm 3, it is assumed that perfect knowledge of the deposit is assumed accessible before designing the mine plan. Thus accounting for the acquisition of additional data would have no effect on reducing the production gap nor the adjustment cost. In terms of accounting for the evolution of the DOKD, Paradigms 1 and 2 are pessimistic, and Paradigm 3 is optimistic. The SLM paradigm is an intermediate scenario where the data acquisition strategy determines how the initial DOKD evolves throughout the lifetime of the mining project. The SLM paradigm presents a more realistic scenario since the dynamic nature of the mining of the deposit is accounted for.

Paradigms 1 and 2 can be considered as the baseline of the SLM paradigm because only the initial DOKD is considered. Unlike paradigm 3, in the SLM paradigm, in any case it is assumed achieving perfect knowledge of the deposit. Even if the whole deposit is acquired as additional data, the evolution of the DOKD starts to affect the design of the mining sequence from the second period onwards. The presence of uncertainty in the first period cannot be avoided. This sets the upper limit of the SLM paradigm. The evolution of the DOKD plays an important role in the performance of the mine plan, and thus, in the evaluation of mineable reserves. A little evolution of the DOKD may not have much impact on harnessing the full economic potential of the deposit. On the other hand, an aggressive evolution of the DOKD may be adverse, as the cost associated to the acquisition of additional data will tend to reduce the profit margin of the mining project.

Implementation Aspects

In the implementation of the SLM paradigm, the SLM mining model requires that the additional data, which is collected throughout the lifetime of the mining project, is accessible at the time of the evaluation of the mineable reserves. Since only the initial dataset is available, the evaluation of the mineable reserves is carried out by simulating the acquisition of the additional data. This approach is used in the evaluation of prediction models, where comprehensive simulation models are used when real information is not accessible (Conejo, Carrión, & Morales, 2010). In the SLM paradigm, geostatistical techniques are implemented to simulate the additional data. Different realizations result in multiple scenarios of how the deposit is mined (see Figure 3). Since the acquisition of additional data affects the mining of the deposit from the second period onwards, the mining of the first period is identical for all the scenarios generated.

Definition of the Mining Strategy

The mining strategy specifies how to proceed with the mining of the deposit based on a set of specified conditions. The mining strategy is specified in the form of a mine sequencing algorithm. Osanloo, Gholamnejad, and Karimi (2007) classified mine sequencing algorithms based on how they consider the block model in: 1) deterministic and 2) uncertainty-based. Since the reduction of production variability is important in the performance of the operating mining sequence, it is preferable to implement an uncertainty-based mine sequencing type algorithm.

Definition of the Data Acquisition Strategy

The data acquisition strategy consists of specifying how the collection of additional data is implemented. Since the blasthole source is primarily implemented to fragment material in the regions to mine, the infill drilling source is the only source of additional data that can be controlled. In this paper, three aspects of the acquisition of infill drilling data are considered: 1) objective, 2) quantity, and 3) timing. The objective aspect considers the goal of the data acquisition strategy. For example, the improvement in the accuracy of the mining sequence in the medium- or long-term. It may be preferable to dedicate part of the additional data acquisition plan to the medium-term production, as it has an immediate effect in the improvement of the performance of the operating mining sequence. The quantity aspect specifies the amount of data samples to collect from the drillholes in the infill drilling program. The objective and quantity aspects depend on the timing aspect, as infill campaigns are implemented in each period throughout the lifetime of the mining project. The objective and the quantity aspects are defined individually in each period for each of the infill drilling campaigns implemented throughout the lifetime of the mining project. Similar to the mining strategy, the data acquisition strategy is specified in the form of a data acquisition algorithm that sets the implementation of the infill drilling program, in terms of how, where, and when to place the infill drillholes throughout the lifetime of the mining project.

Simulation of the SLM realizations

The generation of the SLM realizations or scenarios of the mining of the deposit are based on the SLM mining model. Because of the huge number of factors and variables involved, the detailed reproduction of the SLM mining model is intractable. For practicality, some aspects are simplified and adapted during the implementation. The implementation of the SLM mining model is discussed as follows:

Event 1: Consolidation of Existing Information

This event consists of gathering all available information from exploratory, infill, and blasthole sources. The initial dataset consists of real available data that depends on the stage of the mining project. In case the mining project is about to start production, the initial dataset consists mainly of the exploratory drilling campaign. In case the mining project is already in the production stage, besides the exploratory drilling campaign, blasthole and infill drilling data are available. Throughout the lifetime of the mining project, the consolidated dataset grows in size, as simulated future collected dataset is included. There is one realization of the consolidated dataset for each realization of the mining of the deposit that is generated.

Event 2: Design of the Mining Sequence

This event starts with calculation of the block model of the deposit. Since the consolidated dataset consists of different of data of different types and scales, the modeling technique implemented should integrate diverse data. In mining, co-kriging is a popular technique that is able to integrate data from different sources. This technique is widely discussed by many authors such as Journel and Huijbregts (1978), Goovaerts (1997), and Chilés and Delfiner (1999).

The mining sequence is designed based on the block model of the deposit. A mining sequence algorithm that accounts for the operating conditions of the mining project is considered along with a specific set of operating parameters. The region of the group of blocks targeted for extraction serves as reference for outlining the operating design of the mining sequence. As in the case of the simulation paradigm, because of the difficulty of automating this process in the generation of a large number of scenarios of the mining of the deposit, the extraction sequence of the blocks is taken as the mining sequence.

Event 3: Mining of the Current Scheduled Region and Acquisition of Additional Data

The region targeted for extraction is mined from the block model. This is done by updating the current topography so that the blocks targeted are above the new topographic surface. The adjustment of the scheduled region by the short- and medium-term plans to meet the production requirements is skipped, as it is difficult to automate. The implication of skipping the adjustment of the targeted region is discussed in the next event.

The additional data is collected from the blasthole and infill drilling sources. In the case of the blasthole source, the additional data is collected from the mined region. The configuration of the blasthole samples is approached by using a regular grid pattern with operating dimensions that is positioned in each bench of the mined region. In the case of the infill drilling source, for practicality, the collar position of the drillholes can be approached either from the topographic surface before or after mining the current region. In practice, the collar positions are determined from the topographic surface that is updated as the targeted region is mined. Due to the scale of mining, the difference in the total drilling length is considered negligible. The geometric configuration and the number of infill drillholes to collect is defined in each period by the data acquisition algorithm and the specifications of the infill drilling program.

The data from the blasthole and infill drilling sources is obtained by simulating the sample values conditioned to the current consolidated dataset. As in the case of building the model of the deposit, because of the different data types and scales, the simulation technique should also be able to integrate diverse data. A suitable alternative is the implementation of co-simulation. In case the initial dataset only consists of the exploratory drilling campaign, the problem of inferring the joint statistics between the different data sources is a very difficult task (Journel & Kyriakidis, 2004). The scale and accuracy of the two sources are taken into consideration during the simulation of the additional data.

Event 4: Reconciliation of the Scheduled Region

At the end of the current period, the planned and the executed regions are compared. Since the adjustment of the targeted region by the short- and medium-term plans is skipped, these two regions are identical. In this context, Equation (1) is not valid. The adjustment cost, AC term, is approached based on the variability between the planned and executed production. Throughout the lifetime of the mining project, the executed production profile departs from the planned production profile, resulting in under- and over-production. In the case of over-production, the maximum capacity of the plant would restrict to processing. The surplus would be stored and processed in the following periods. In the case of under-production, the mine is not able to meet the production requirements. Either way, it is considered that the variability in the mine production has always a negative impact on the executed NCF with respect to the planned NCF. The AC term in equation (1) is approached by imposing penalties on the production variability.

The executed BCF is approached based on the production gap of the current period. or simplicity, the proposed approach considers the negative impact of the production gap on the executed NCF is independent in each period. Alternative approaches may consider the interaction between periods. For example, over-production in earlier periods may relieve the effect of under-production in latter periods. The proposed expression for calculating the executed NCF is:

$$NCF'_{ex}\left(D_i\right) = NCF_{pl} - AC'\left(D_i\right) \tag{2}$$

$$AC'\left(D_i\right) = \begin{cases} p_{ovp}\left(OT_{ex} - OT_{pl}\right) & \text{if } OT_{ex} \geq OT_{pl} \\ p_{unp}\left(OT_{pl} - OT_{ex}\right) & \text{if } OT_{ex} < OT_{pl} \end{cases},$$

where, NCF'_{ex} is the approached executed net cash flow, AC' is the approached adjustment cost, p_{ovp} and p_{unp} are assigned over- and under-production penalty factors, respectively, OT_{pl} is the planned ore production, and OT_{ex} is the executed ore production considering the long-term mining sequence is executed strictly without implementing short- nor medium-term plans. The production gap of the current period is expressed as the difference between the planned and executed ore production, $OT_{ex} - OT_{pl}$. The production gap can be calculated in different ways, ore tonnage, net-metal content, etc.

To calculate the referential executed production, at the end of the period, perfect knowledge of the mined region is considered accessible. The geology of the mined region is characterized by a realization conditioned to the current consolidated dataset and the newly collected additional data. The comparison between the executed and planned production values is made at block scale.

Example

A synthetic deposit is evaluated based on the conventional and the SLM paradigms. The implemented mining strategy consists of maintaining a constant production of 2500 MT of ore per period, throughout the lifetime of the mining project. For illustration purposes, no discount rate is used to calculate the profit of the mining project. The profit is calculated in terms of the sum-of-net-cash-flows (SNCF). The additional data considers the blasthole and infill drilling sources. For the infill drilling program, six infill drillholes per period is considered. The infill drillholes are positioned targeting the more uncertain regions, based on the kriging variance, close to the mined region. A sequential positioning is considered to implement the infill drilling campaigns.

The dimensions of the deposit are 400m x 240m x 160m east, north, and vertical, respectively. An initial topographic surface is used to outline the original state of the deposit before the mining takes place. The resolution of the block model is 100 x 60 x 40 with a block of 4 m x 4 m x 4 m. A constant block tonnage of 1 MT per block is used. When a block is intersected by the topographic surface, the tonnage is calculated based on the proportion of the block below the surface. The mining project is considered to be in the pre-production stage and the only available information is the initial exploratory drilling campaign that consists of twenty-eight drillholes placed over a regular grid pattern (Figure 4).

The evolution of the DOKD depends on the data acquisition strategy implemented. In Figure 5, a realization of the evolution of the DOKD is shown. Accounting for the evolution of the DOKD and its impact on the mining of the deposit is the core aspect of the SLM paradigm.

In each mining scenario that is generated, the simulated evolution of the DOKD accounts for the improvement of the accuracy of the mining sequence to mine the deposit. In Figure 6, the expected accuracy profiles, in terms of the mean-absolute-error (MAE) of ore production, of Paradigm 2 and the SLM paradigm is shown. As Paradigm 2 is the base case where only the initial data is considered, the difference between the two cases presents the effect of the additional data acquisition. The profile of production gap of the SLM paradigm depends on both the mining and data acquisition strategies, which is evaluated in the SLM framework.

In Figure 7, a case of the production gap of one realization of the SLM paradigm is shown. The production gap of the long-term mining sequence is used to approach the adjustment cost, which impacts directly on the planned and executed metrics. The executed SNCF is calculated as a function of the extracted material penalized by the production gap (equation 2).

In Figure 8, the mean and dispersion of the executed SNCF for the conventional and the SLM paradigms are presented. Paradigm 2 presents the lowest performance, as the difference between the planned and executed metrics do not improve. In the SLM paradigm, the progressive reduction of the production gap, throughout the lifetime of the mining project, helps to improve the executed SNCF of the mining project. Between the two cases, the SLM paradigm performs better than Paradigm 2. Paradigm 3 presents the best performance among all the paradigms evaluated. However, this evaluation is unrealistic as access to perfect knowledge of the deposit is a requirement.

In terms of the expected values of the executed SNCF, the conventional paradigms represented the lower and upper limits of the evaluation (see Figure 9). The SLM paradigm, depending on the data acquisition strategy implemented, will results in intermediate realistic scenarios.

In this section, the impact of implementing a specific data acquisition strategy in the evaluation of mineable reserves is presented. The unrealistic results of the conventional paradigms, underestimation and overestimation of the SNCF, are discussed and showed as inappropriate to assess the economic potential of the deposit.

Concluding Remarks

In this chapter, a new paradigm for evaluating mineable reserves named SLM paradigm is presented. In the SLM paradigm, the static behaviour of the model of the deposit and the mining sequence, considered in conventional paradigms, is replaced by a dynamic behaviour. The continuous adapting of the mining sequence due to the evolution of the DOKD is characterized as a computational learning process. The SLM paradigm provides a more realistic framework for evaluating mineable reserves than conventional paradigms.

Since only present data is accessible at the time of the evaluation of the mineable reserves, the acquisition of the additional data is simulated to overcome the problem that this data is not accessible until the end of the lifetime of the mining project. The simulation of the acquisition of the additional data helps to account for how the future geology of the deposit may reveal itself, subject to mining and data acquisition strategies. Each realization of the acquisition of the additional data results in an equally probable scenario of the mining of the deposit.

The implementation of the SLM paradigm is computationally more expensive than the implementation of the conventional paradigms. Most of the computational work corresponds to the updating of the block model of the deposit and the mining sequence. During the generation of each realization of the mining of the deposit, these two tasks are repeated periodically throughout the lifetime of the mining project.

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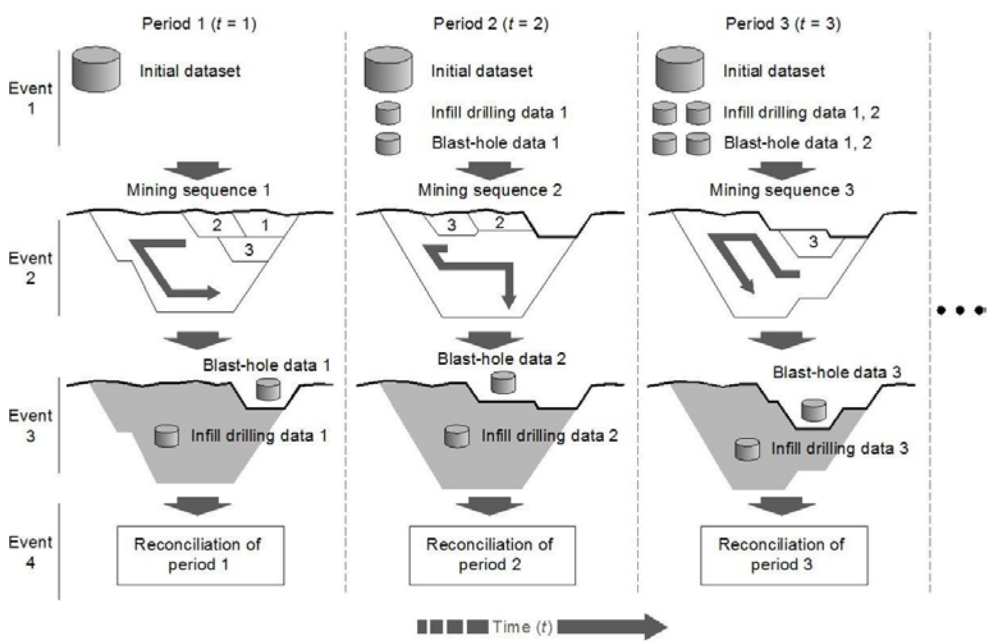

Figure 1: Sketch of the model of the mining process used in the SLM paradigm

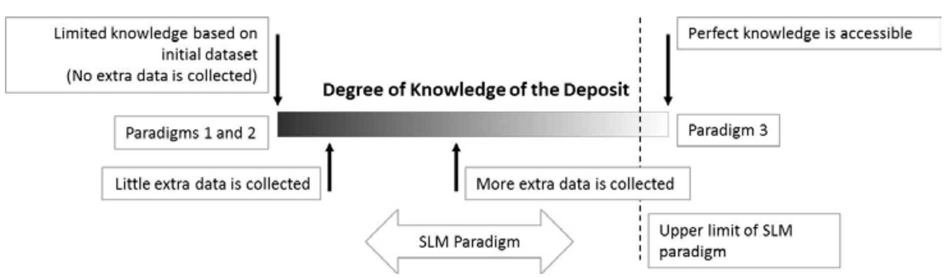

Figure 2: Schematic comparison of the SLM and conventional paradigms based on how they account for the DOKD

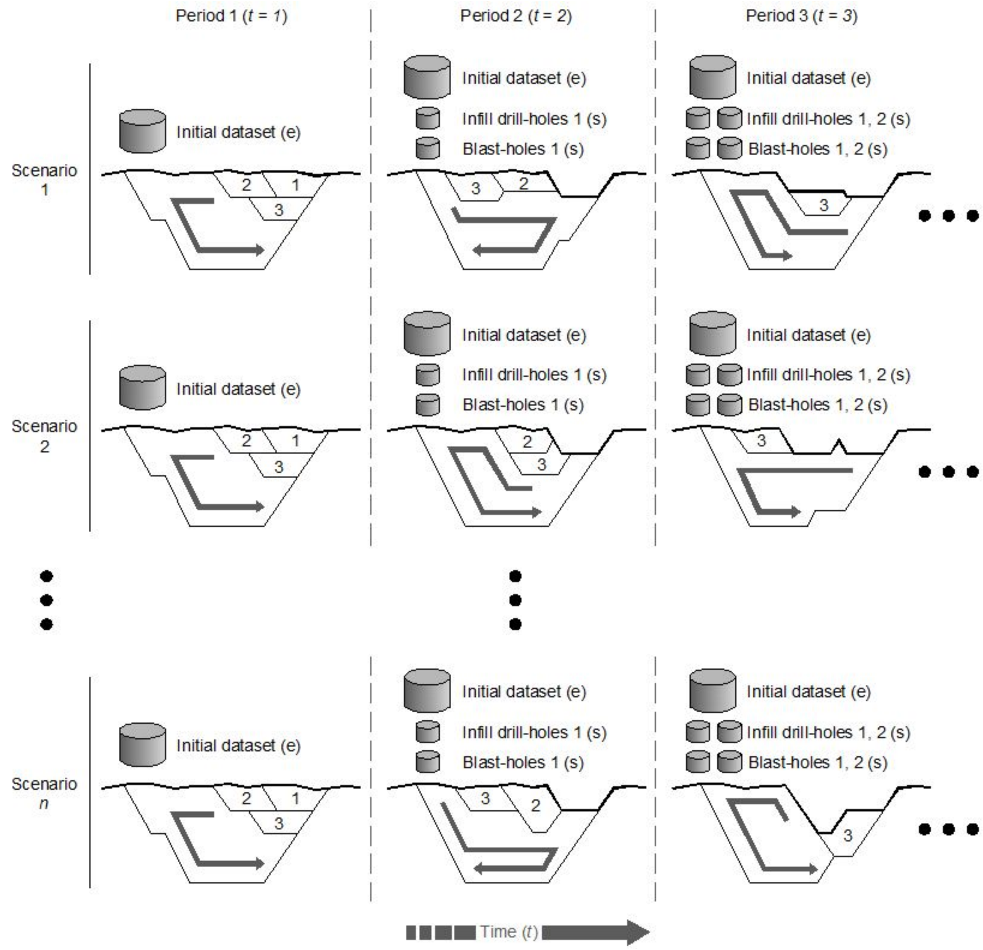

Figure 3: Sketch of the simulation model of the mining of the deposit

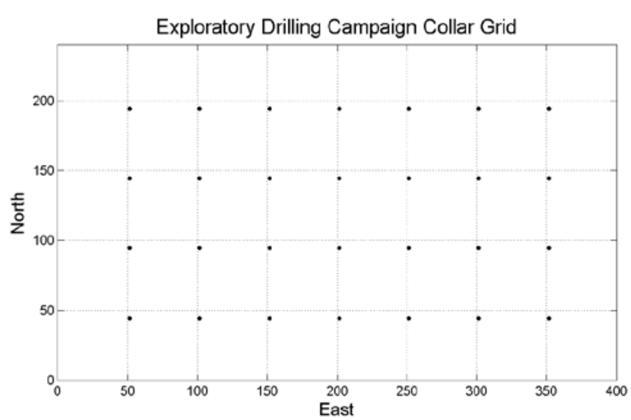

Figure 4: Position of drillholes of the initial exploratory drilling campaign

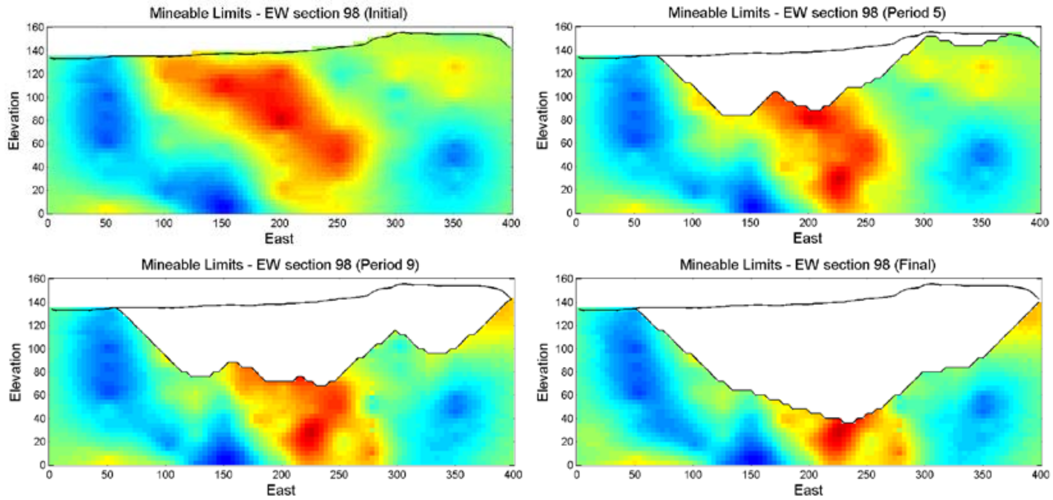

Figure 5: State of the block model of the deposit for the initial, 5th period, 9th period, and final period of SLM case with six infill drillholes per period

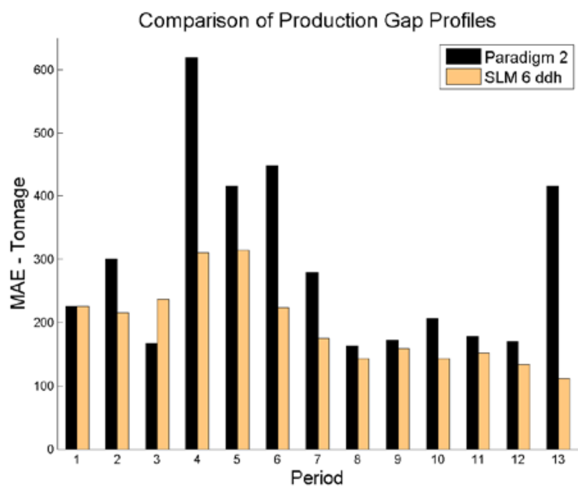

Figure 6: Impact of collection of additional data on the production gap

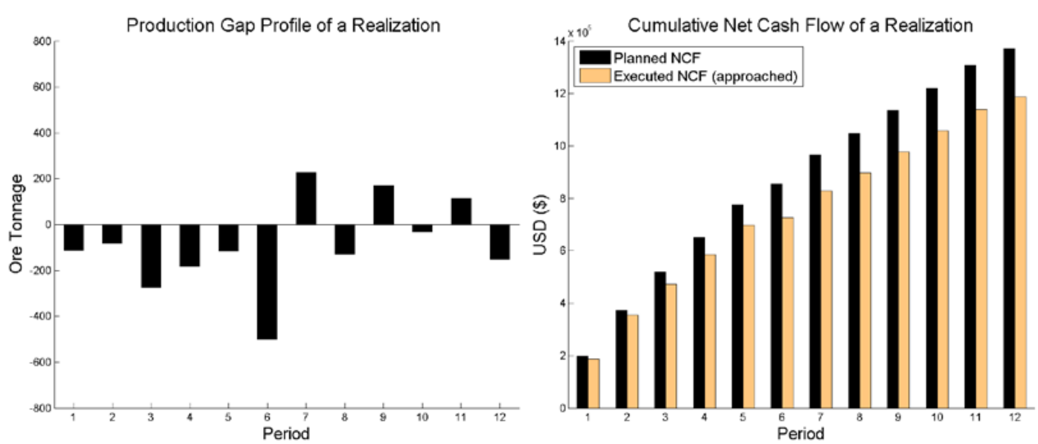

Figure 7: Impact of mining sequence production gap on the executed SNCF for a realization of a mining scenario

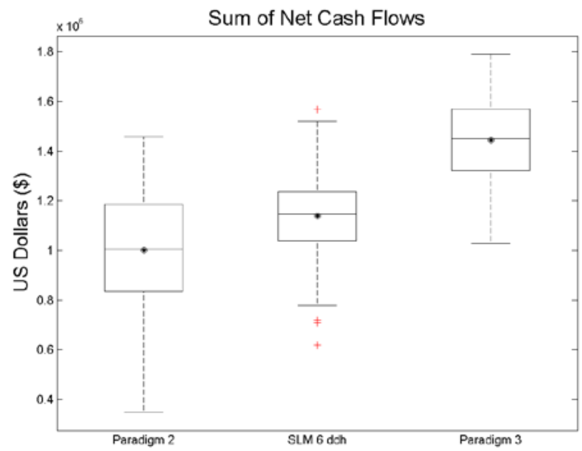

Figure 8: Variability of SNCF for conventional and the SLM paradigm

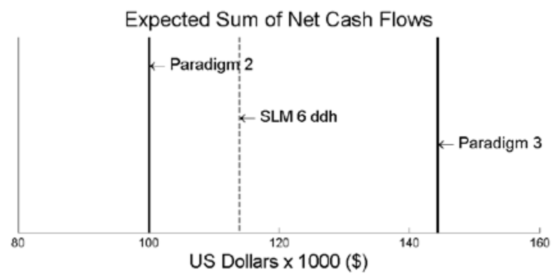

Figure 9: Comparison of executed SNCF values in expected value terms