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Evaluation of Surface Mining Exploratory Drilling Strategies

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During the lifetime of a mining project, infill drilling campaigns are conducted to gain information on the characteristics of the deposit. Due to the periodic updating of information, the mining sequence of the project reduces the gap between planning and production, thus reducing extra costs to adjust the planned production to plant requirements. The reduction of the production gap is proportional to the amount of information sampled in the infill campaigns. However, the reduction in the production gap is reached at the cost of increasing the infill drilling cost. An effective infill drilling plan balances the reduction of extra costs due to production gap versus the implementation costs. The design of an optimal infill drilling plan is an important part of mining design. Conventional paradigms to calculate mining sequences, estimation and simulation, do not account properly for the effect of infill drilling campaigns. The simulated learning model paradigm accounts for the evolution of uncertainty due to periodic data collection. In this paper, a stochastic framework based on the simulated learning model paradigm is proposed to evaluate the effect of different infill drilling plans in the profit of mining projects. An artificial example is used to illustrate the discussion.

Introduction

During the lifetime of a mining project, infill drilling campaigns are one of the main source of information for updating the model of the deposit, along with blast-hole information. The importance of the model the model of the deposit is to reduce the gap between the planned production and the executed production in the short and medium term. Production gaps result in additional operating costs to adjust production to plant requirements. Infill drilling campaigns are planned based on different objectives, e.g., minimizing global estimation variance, improvement in the delineation of economic regions (Aspie & Barnes, 1990). The configuration of drilling plans has been discussed by many authors such as (Drew, 1979), (Miller Jr., 1991), (Shieh, Chu, & Jang, 2005).

The main factor that controls the amount of information sampled by infill drilling campaigns is the infill drilling budget. Conventional mine planning paradigms, estimation and simulation, consider the infill drilling cost as part of the capital cost of the project. In the case of the estimation paradigm, the profit of the project is calculated by subtracting the capital cost from mining sequence revenue, and in the case of the simulation paradigm, the simulated profits are calculated by subtracting the capital cost from each of the simulated revenues. Despite evaluating different infill drilling plans of different costs, the effect that they have is the reduction of the profit margin as the drilling cost increases. In this context, cheaper infill drilling plans help to increase the profit margin of the mining project. Conventional paradigms do not account for the improvement in the mine design and reduction in grade uncertainty due to infill drilling.

Froyland, et al. (2004) proposed a methodology to value, in economic terms, additional infill drilling information. The authors calculated the value of infill drilling information (VOIDI) as the difference in performance of a mine plan in terms of the net present value (NPV), under perfect and present knowledge scenarios. The simulation and estimation paradigms were implemented to account for the perfect and different present knowledge scenarios, respectively. The authors concluded that infill drilling campaigns which costs are larger than VOIDI are not feasible. In this approach, the increment in the executed revenue of mining sequences due to additional information is accounted for. However, one limitating with this approach is that infill campaigns are assumed to be drilled once and not periodically throughout the lifetime of the project.

To account for the evolution of uncertainty over time due to periodic implementation of infill campaigns, a methodology based on the simulated learning paradigm (SLM) is implemented. Three scenarios are considered: 1) perfect knowledge, 2) periodic updating due to implementation of infill campaigns, and 3) no-updating. The perfect knowledge scenario is implemented with the simulation paradigm, the SLM paradigm accounts for the periodic evolution of uncertainty, and the estimation paradigm accounts for the base case where no infill drilling campaign is drilled. In this stochastic framework, several infill drilling plans can be evaluated in terms of their effect on the revenue and profit of the project.

The framework used to evaluate the mining sequences is discussed in the next section, where three scenarios are described. The stochastic evaluation of mining sequences in perfect knowledge, periodic evolution of uncertainty, and no infill drilling influence is discussed. The effect of infill drilling in the mining sequence is discussed in the next section. Finally, the methodology to implement the proposed approach and the interpretation of the results is discussed. An artificially generated initial exploratory campaign is used to set an example in the evaluation of different infill drilling plans. In each section the results of the example are used to illustrate the discussion of the presented sections.

Evaluation of performance of mine plans

In economic terms, the performance of a mine plan is measured based on the profit that it generates from mining a mineral deposit. The profit of the mining project is calculated based on two components: 1) revenue, and 2) cost. The revenue component consists of the sum of the periodic cash-flows throughout the planned lifetime of the project. The cost component is calculated as the investment necessary to make the mining process to operate. This component is also referred to as capital cost, and is included at the last stages of the ultimate pit selection (Hustrulid & Kuchta, 1998). Profit is expressed as:

$$P = R - C \,, \tag{1}$$

where, P is the profit of the mine plan, R is the revenue of the mining sequence, and C is the capital cost of the mine plan. The operating costs are included in the revenue component, which is the sum of the cash flows of the project.

During the mine planning process, pit optimization and pit sequencing techniques are implemented to maximize the revenue of the project. The performance of a mining sequence is measured based on the revenue they generate. In this paper, three cases are set for evaluating the performance of a mining sequence:

- **Ideal**: In the ideal case, the real geology of the deposit is accessible. This allows for an optimal mine plan of the project.
- **Expected**: In the expected case, the real geology of the deposit is not accessible but only a limited portion of information from drilling. The mining sequence of the project is designed based on a model of the deposit, which is built based on the information available, usually the existing exploratory drilling campaign.
- **Operative**: In the operative case, the real geology of the deposit is not accessible at the time of the design of the mine plan but afterwards. The mining sequence is designed as in the expected case, based on a model of the deposit, and evaluated based on the real geology mined. Since reality is accessible in the mined regions, it allows calculating the operative performance of the mining sequence.

The ideal case is impossible, since the real geology of the deposit is never accessible. Even after mining a deposit, the regions outside the final pit are still unknown. The expected and the operative cases occur in practice. In the expected case, the performance of the mining sequence is measured based on the model of the deposit. In the operative case, after executing the mine plan, the performance of the mining sequence is calculated by matching the mining sequence versus the real geologic conditions of the mined regions in the deposit. In mining, the effect of the difference in the prediction of estimated models versus reality has been widely discussed by many authors and is usually referred to as the information effect, e.g., (Journel & Huijbregts, 1978), (Chilés & Delfiner, 1999), (Isaaks, 2005). The words: ideal, expected, and operative will be used to identify the performance elements of the mining sequence in each case, respectively.

The ideal mine plan results in the maximum revenue that can be obtained from mining a deposit. The operative performance of an expected mine plan is proportional to the degree of knowledge of the deposit. As more drilling is accessible, the model of the deposit usually becomes more accurate, thus reducing the gap between the ideal revenue and the operative revenue. The expected revenue is only optimal for the model of the deposit, but not directly for the deposit. The revenue gap can be expressed as:

$$G_R = R_I - R_O \,, \ \forall \ R_I \geq R_O \,, \tag{2}$$

where, G_R is the revenue gap, R_I is the maximum ideal revenue, and R_O is the operative revenue.

For illustration, consider an initial exploratory campaign of 15 drill-holes and the real geology of a deposit. The model of the deposit is built based on the available exploratory campaign. The mining sequences based on reality versus the mining sequence based on an estimated model are compared in terms of scheduled materials (see Figure 1). In the case of the mining sequence based on reality, or the ideal mining sequence, there is no gap between the planned and executed configuration of the materials in the deposit (see Figure 1 - left). In the case of the mining sequence based on the estimated model, or estimated mining sequence, the configuration of materials planned and mined throughout the lifetime of the project are different (see Figure 1 - right). In practice, within periods, mine plans are modified to satisfy plant conditions, thus incurring in additional cost to fix the operational variability. In the case of the estimated mining sequence, depending on the configuration of the ore bodies in the estimated model, it is possible to obtain larger expected revenues than of the ideal mining sequence. However, these expected revenues are based on models of the deposit not in reality. In Figure 2, the ideal revenue is compared versus the operative and expected revenues. For this example, the revenue gap is 39% of the ideal revenue of the deposit, and is due to the uncertainty in the estimated model of the deposit.

Stochastic Evaluation of Mining Sequences

In practice, reality is not available to calculate the operative performance of mine plans. A stochastic approach is implemented to calculate the revenue gap in expected value terms. Simulated models can be built to generate a set of equally probable alternate reality scenarios of a deposit. As in the previous example, where a realization of the deposit was used to calculate one revenue gap scenario, a set of realizations of the revenue gaps can be simulated from a set of realizations of the deposit. Leave-one-out techniques are used to evaluate stochastic models by comparing the model outcomes versus real information of the phenomenon modelled.

For illustration purposes, an example based on the exploratory campaign of 15 drill-holes is presented. A simulated model of 25 realizations is used to characterize 25 alternate realities of the deposit. The model of the deposit is estimated based on the available drilling campaign. The performance of the estimated mining sequence is compared against the 25 ideal cases. The histogram of the proportions of the operational revenues with respect to the ideal revenues is presented in Figure 3 - left. The average difference from the ideal case is 49.3%. In Figure 3 - right, the operative versus ideal revenues are compared. The deviation of the cloud of revenues with respect to the 45 degree line is due to the limited information from the deposit.

Effect of infill drilling on the mine plan

The reduction of the revenue gap is proportional to the accuracy of the model of the deposit. The spatial configuration of the samples and the amount of samples in the exploratory drilling campaign define the degree of accuracy of the model. Different configurations of new drill-holes approach the current operative revenue to the ideal revenue differently. The contribution of the additional drill-holes to the current revenue can be expressed as:

$$G_R = R_I - \left(R_O + DR\right) \tag{3}$$

where, DR is the increment of revenue due to additional drilling. The increment of the revenue DR depends on 1) the strategy adopted to position new drill-holes, and 2) the number of drill-holes to be added. By evaluating one drilling strategy, the increment in DR depends on the number of drill-holes added. However, incrementing the operative revenue of the project by adding more drill-holes to the exploratory campaign does not necessarily guarantee the improvement of the profit of the mine plan. An increment of exploratory drill-holes tends to reduce revenue gap at the cost of increasing the capital cost. The effect of adding extra drill-holes on the profit of the mine plan (1) can be expressed as:

$$P_O' = \left(R_O + DR\right) - \left(C_O + DC\right), \tag{4}$$

where, P_O' is the operative profit of the mine plan affected by the additional drilling, and DC is the cost of the extra drill-holes. For simplicity, DR and DC will be referred to as drilling extra revenue and drilling extra cost, respectively. By combining (1) and (4), the profit influenced by the additional drilling can be expressed as:

$$P_O' = P_O + DR - DC\,. \tag{5}$$

In order to justify additional exploratory drill-holes, the increment in the capital cost DR should be smaller than the increment in the operative revenue of the mine plan DC, that is, $DC<DR$. Otherwise, the increment in the exploratory campaign will reduce the operative profit of the mine plan, which ultimately is the measure of performance of the mining project. In Figure 4, the effect of additional drilling is presented graphically. In Figure 4 - left, DR and DC curves are plotted as a function of the number of additional drill-holes. The region in between these two curves represents the feasible region where additional drilling will increase the profit of the project. Out of this region, the effect of adding extra drill-holes will tend to reduce the profit margin of the mine plan. The optimal extra drilling strategy that maximizes the profit of the project is found by maximizing the difference between DR and DC. In Figure 4 - right, the drilling extra revenue is expressed in terms of the revenue gap (3). The point where the two curves intersect, G_R and DC, can be used as an indicative of the optimal configuration of drill-

holes in the current strategy, which will result in the maximum increment in the profit of the project. The proposed framework can be used to evaluate different drilling strategies in order to maximize the profit of the project.

The profit gap is defined as the difference between the optimal profit of the deposit and the current operative profit. The profit gap will be also referred to as the cost due to uncertainty, since it is the margin of profit lost due to the incomplete knowledge of the deposit. The optimal profit is calculated by finding the optimal strategy of collection of extra information that balances the drilling revenue and drilling cost. It can be expressed as:

$$G_P = P_{MX} - P_O, \; \forall \; P_{MX} \geq P_O,$$

where, G_P is the profit gap or cost due to uncertainty and P_{MX} is the optimal profit of the project. The reduction of the profit gap is not entirely related to the revenue gap, since the profit gap accounts for the entire mine plan, while the revenue gap only for the mining sequence.

During the evaluation of a mine plan by implementing conventional paradigms, the extra drilling cost is properly included in the capital cost, and has no real influence on the mining sequence. In the case of the simulation paradigm, in each of the mining sequences generated perfect knowledge of the deposit is assumed, hence evaluating additional drilling has no effect in the profit of the project. The cost that corresponds to additional drilling is assumed constant, and is subtracted from each of the revenues of the mining sequences. In the proposed model to evaluate mining sequences, due to the assumption of perfect knowledge of the deposit, the simulation paradigm is implemented to calculate the ideal mining sequences. In the case of the estimation paradigm, the mining sequence accounts for uncertainty and its performance in terms of revenue can be estimated. However, evaluating the addition of extra drill-holes to the existing exploratory campaign is not realistic.

In practice, the addition of extra exploratory drill-holes is made in the form of infill drilling campaigns, which are drilled periodically following an infill drilling plan. The infill drilling plan is part of the global mine plan of the project, as well as the scheduling of mining equipment, the configuration of waste dump areas, etc. Since the infill drilling campaigns are implemented periodically, the effect on the performance of the mining sequence, drilling revenue and drilling cost, is discounted periodically along with the project revenue. In terms of uncertainty, the improvement of accuracy of the model is affected from the period in which the infill campaign is drilled. The evaluation of a single generic infill drilling campaign to account for the additional collection information is not realistic. In this context, the estimation paradigm represents a case where the periodic drilling of infill campaigns does not occur, that is, the state of uncertainty remains static over time. To account for the period collection of information thorughout the lifetime of the project, the effects of infill drilling strategies are evaluating by implementing the SLM paradigm, which is a framework that is used to evaluate the economic potential of a deposit under different data collection scenarios (Cuba, Boisvert, & Deutsch, 2010). The SLM paradigm accounts for the evolution of uncertainty in the model of a deposit over time, and its effects in the performance of the mine plan.

In the proposed approach, the SLM paradigm is used to evaluate different infill drilling plans in the stochastic model used to evaluate the estimated mining sequence in the previous section. The infill drill-holes sample the deposit from the corresponding simulated models that represent the alternate realities. Infill drilling campaigns are evaluated in terms of the targeting strategy and the number of infill drill-holes drilled in each period. The targeting strategy defines the location and geometric configuration of the infill drill-holes on the current surface of the deposit. The number of infill drill-holes in each period is defined based on the infill drilling budget of the project. Based on a targeting strategy, different configurations of the number of infill-drill holes per period can be evaluated. For example, an infill drilling plan that consists of two drill-holes per period will have a different effect than an infill drilling plan of ten drill-holes per period. A variable configuration of the number of infill drill-holes per period can be also used.

For illustration purpose, the effect of improving the accuracy of the model due to the sampling of infill drilling campaigns is presented and discussed in three cases: 1) estimation paradigm, 2) SLM paradigm with six infill drill-holes per period, and 3) SLM paradigm with fifty infill drill-holes per period. The SLM paradigm is implemented as a continuation of the example presented previously. In the estimation paradigm, the accuracy of the mining sequence under performs the required mine production (see Figure 5 - left). In global terms, the mining sequence reaches the planned ore production in 80.53% (see Figure 5 - right). In the case of the SLM mining sequence with six drill-holes, the accuracy by period (see Figure 6 - left) is less variable from the second period on.

This is because the first infill campaign is drilled at the beginning of the second period, for this reason the variability of the first period is similar, both for the estimated and for the SLM mining sequence. The reduction of variability is periodic as the periods continue, because the following periods are being supported by the accumulated infill information up to date. The global accuracy rises up to 84.73% (see Figure 6 - right). The comparison in global terms is not straightforward because the SLM paradigm accounts for uncertainty in the lifetime of the project. In the case of the SLM mining sequence with fifty infill drill-holes, the reduction of the variability in the accuracy of the mining sequence is significant compared to the previous two cases (see Figure 7 - left), due to the large infill campaign implemented. The periodic variability in the accuracy drops rapidly from the second period on. In global terms the variability increases drastically to 90.77% (see Figure 6 - right). Much of this variability comes from the variability of the first period. Since the variability of the accuracy of the first period cannot be changed, it will affect the variability of the global accuracy of the mining sequences in every scenario of the infill drilling campaigns.

The periodic variability of a mining sequence results in extra cost because additional work has to be done to satisfy the plant requirements. In case of having a sub-production of ore, the mining sequence has to adjust in the short term schedule to fill the ore production gap. In case of having an over-production of ore, the extra material has to be stored in additional stocks, which increases the transportation cost. In both cases, the additional cost is charged to the operational cost of each period, thus reducing the operative revenue of the mining sequence.

The improvement in the accuracy of the model leads to an increment of the operative revenue of the mining sequence. The estimated mining sequence is the base case that is free of any influence of infill drilling campaigns. In Figure 8, for an infill drilling plan of four drill-holes per period, a comparison of the proportional operative revenues versus the ideal revenues is presented. The influence of this infill drilling plan can be seen by comparing the behaviour of these revenues versus the base case (see Figure 3). Notice the proportional operative revenues tend to approach to the ideal revenues. In Figure 9, the effect of a large infill drilling campaign that consists of fifty drill-holes per period is presented. Due to the large increment of additional drilling, the operational revenues approach much closer to the ideal revenue than in the infill campaign of four drill-holes per period.

The effect of improving the operative revenue of the mining sequences for different number of infill drill-holes is presented in Figure 10. The proportional operative revenues of the base case are compared to different configurations of the number of infill drill-holes per period. As the amount of extra information sampled by the infill campaigns grow, the revenues of the mining sequence approaches to the ideal revenue. The variability of the proportional revenues also decreases proportionally to the amount of information sampled (see Figure 10 - left). For evaluation purpose, the effect of the infill drilling plans is measured in average terms (see Figure 10 - right).

The increment of the operative revenue of the mining sequence is at the cost of implementing the infill drilling plan. The profit of the mine plan is maximized by maximizing the difference between the infill revenue and the infill cost (5). In Figure 11, the increment in the profit of the mine plan as a function of the drilling revenue and drilling cost for the example deposit is presented. The area of the profit curve (1) above the base case represents the feasible region where the infill drilling increases the profit of the mine plan. Beyond fifteen drill-holes per period, despite the increment in the accuracy of the model and in the revenue of the mining sequence, the profit margin tends to reduce due to the drilling cost. From another perspective, the revenue gap can be interpreted as the money that is lost because the uncertainty in the deposit. By combining the drilling cost and the revenue gap cost into a global net cost, the maximum profit of the mine plan is found when global cost is minimized (see Figure 12), that is, when the referential drilling cost intersect with the revenue gap. Notice the region between the global net cost and the ideal revenue is similar to the region of the drilling revenue and drilling cost. The global revenue grows up to very large number as more infill drill-holes are drilled, while the revenue gap will never reach zero because of the variability of the first period (see Figure 5, Figure 6, and Figure 7).

Methodology

The implementation of the stochastic model to evaluate infill drilling plans is presented as a workflow. The steps presented can deal with only one targeting strategy. The variable that is evaluated is the scale of the information sampled from the deposit. The steps are:

1. Generate a set of realizations of the deposit conditioned to the existing information. Each realization of the deposit represents an equally probable alternate reality of the deposit and is the base line for comparing the different states of accuracy during the updating of information.

2. Upscale the realizations of the deposit and calculate a mining sequence of each of them. The mining sequences will provide the set of ideal revenues of the project. The ideal revenues are the base line to calculate the revenue gaps of the different configurations of the infill drilling plan. These revenues represent the maximum revenue that can be obtained from executing a mining sequence.
3. Built an estimated model of the deposit conditioned to the existing information. The performance in terms of revenue of the mining sequence based on this model represented the base case or minimum revenue case for a mining sequence.
4. Set the range of the scale of infill sampling information for the current infill drilling plan evaluated. In the case of the exampled presented, the range was set from 1 to 6, 10, 15, 20, 30, and 50 constant infill drill-holes per period. Variable configurations can be also evaluated, such as a decreasing or increasing number of drill-holes per period.
5. Implement the SLM paradigm to calculate the mining sequence and the operative revenue for each infill drilling configuration. In the implementation of the SLM paradigm, the infill drill-holes sample from the corresponding realizations of each scenario.
6. Calculate the proportional drilling revenue curve in average terms. For evaluation purpose, the proportions of the SLM revenues with respect to the ideal revenue are calculated. This allows comparing the SLM revenue against one referential value of the ideal case.
7. Calculate proportional infill drilling plan cost for each configuration of number of infill drill-holes evaluated. As well as the SLM revenues, the infill drilling costs are calculated in terms of the proportion of the ideal revenue.
8. Search for the configuration of the infill drilling plan that results in the maximum increment in the profit of the project. This can be done in two ways: 1) finding the infill drilling configuration that results in the maximum difference between infill revenue and infill cost (see Figure 11), or 2) finding the minimum global net cost (see Figure 12).

The effect of different infill drilling plans can be evaluated by comparing their profit or global cost curves. These curves are calculated for each different drilling plan. Among all the drilling plans evaluated, the infill drilling plan that results in the maximum profit increment or minimum global net cost is selected as the best infill drilling candidate for the project.

Conclusions

In this paper, a methodology to quantify numerically the effect of infill drilling campaigns in the performance of a mine plan is proposed. For each infill drilling plan evaluated, the configuration of data selection that results in the maximum increment in the profit of a mine plan is calculated. The selection criterion for picking the best infill drilling campaign is set to find the maximum increment in the profit of the mine plan.

The proposed methodology relies on the implementation of the SLM paradigm to account for the periodic evolution of uncertainty in the deposit. The SLM realizations are generated for each alternate realities of the simulation paradigm. The estimated paradigm represents the base case where the mining sequence is not influenced by any infill drilling plan. The effect of each infill drilling campaign on the mining sequence is an increment in the operative revenue with respect to the estimated mining sequence.

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Figures

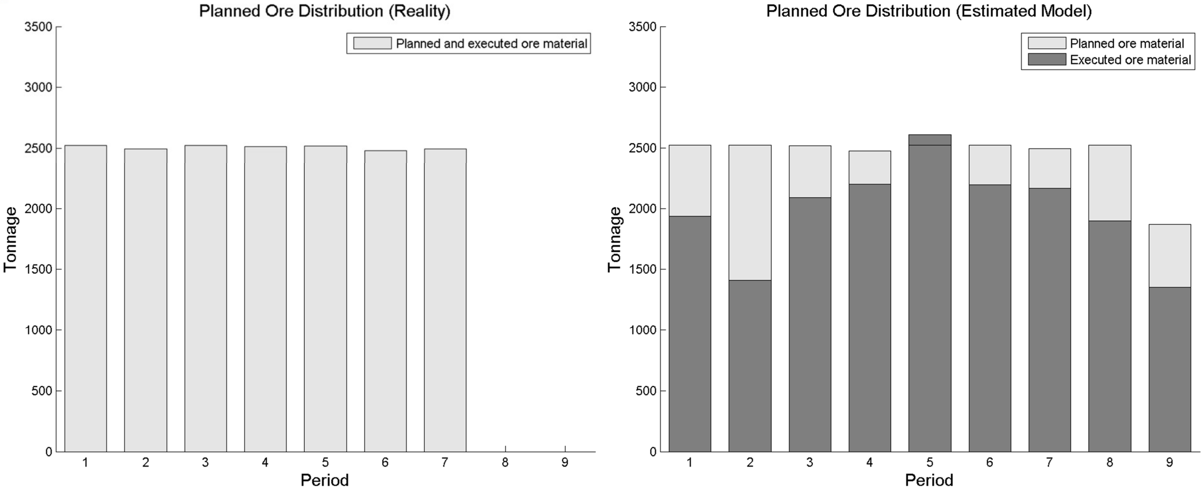

Figure 1: Distribution of ore material by period of a mine plan based on reality (left) and on estimated model (right)

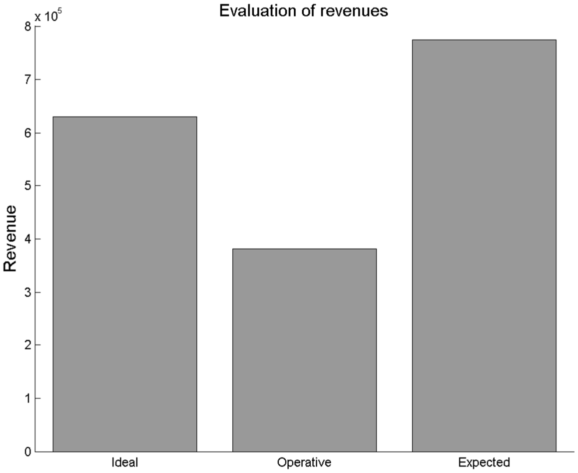

Figure 2: Comparison of ideal, operative, and expected revenue of a deposit

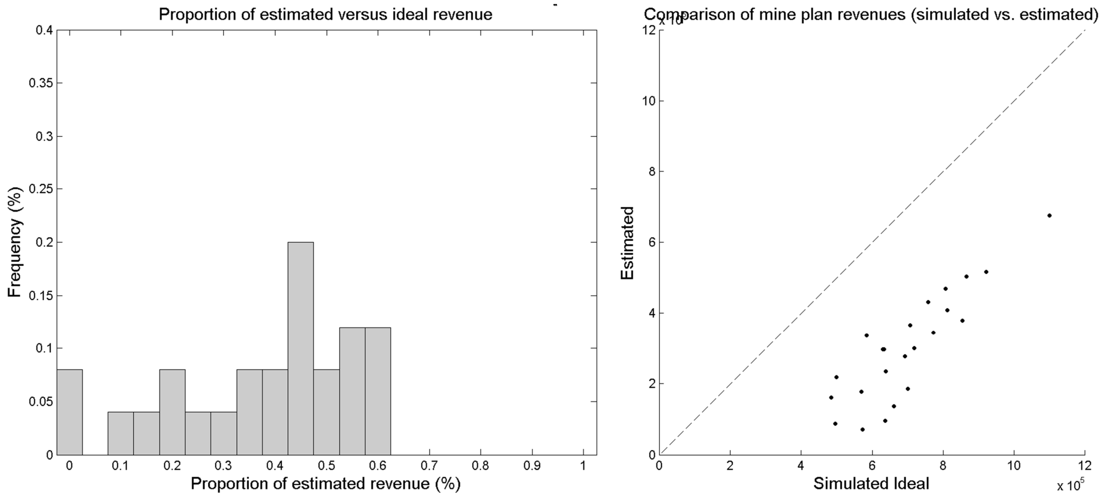

Figure 3: Histogram of proportions of estimated revenue with respect to the ideal case (left), and scatter plot of ideal versus operative revenues of estimated model (right)

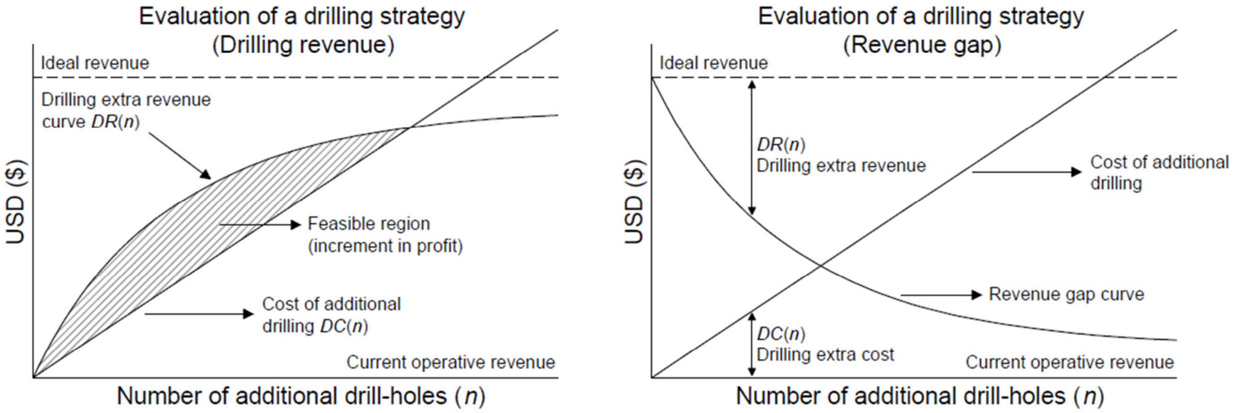

Figure 4: Sketch of the effect of additional drilling on the profit of a mine plan in terms of drilling revenue (left) and revenue gap (right)

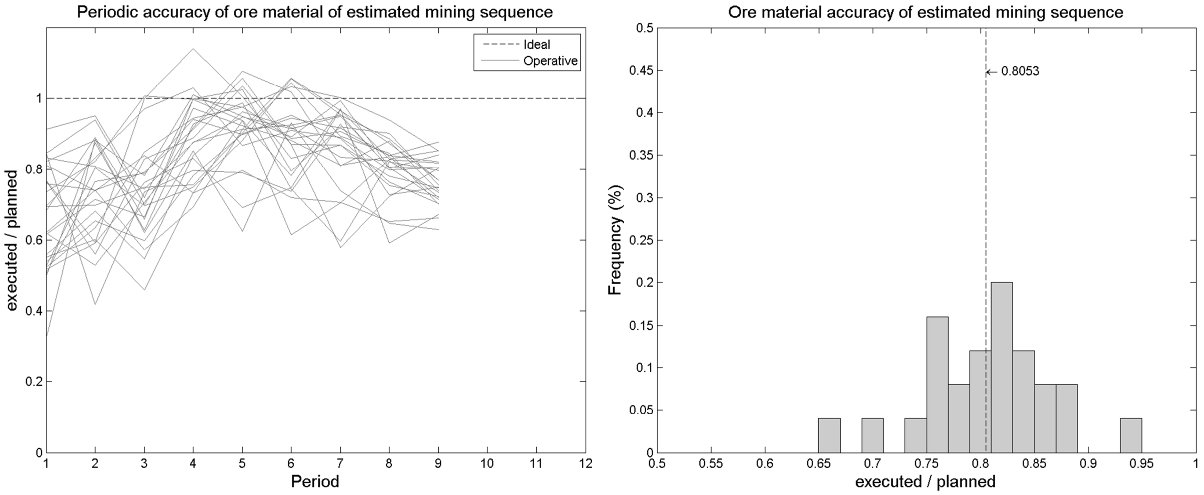

Figure 5: Accuracy in ore prediction of estimated mining sequence by period (left) and global (right) per realization

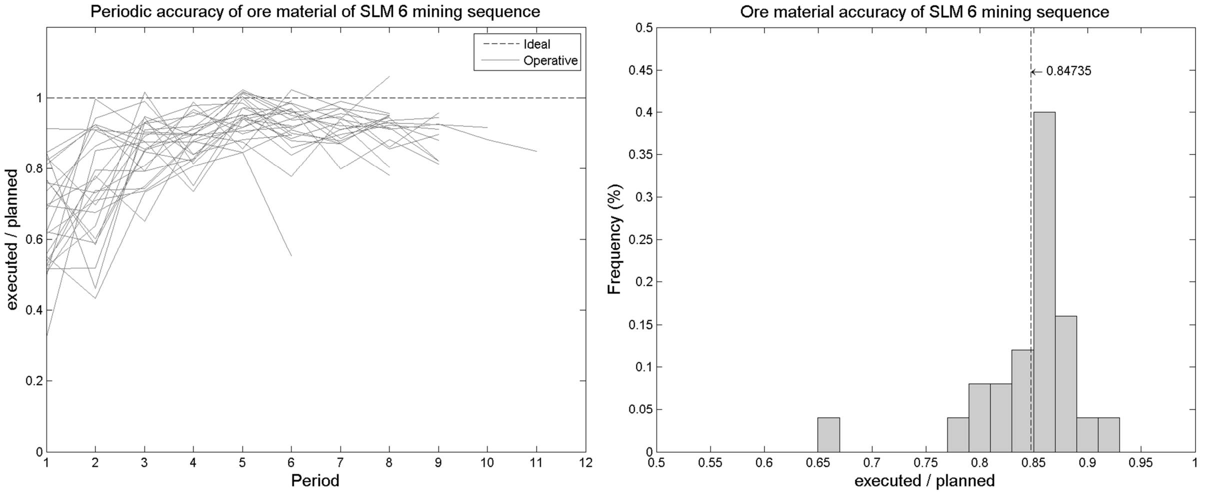

Figure 6: Accuracy in ore prediction of SLM mining sequence with six infill drill-holes by period (left) and global (right) per realization

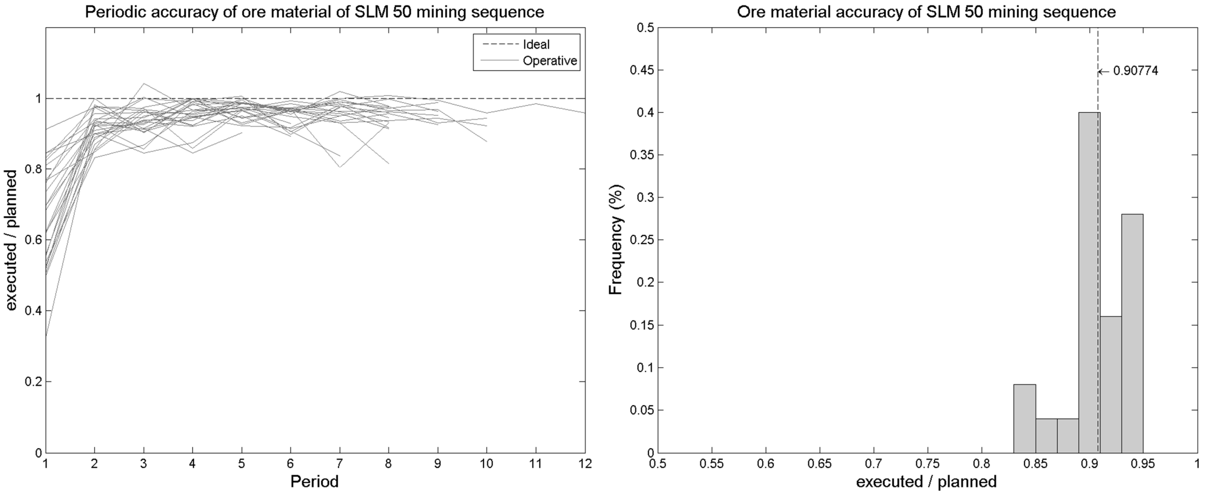

Figure 7: Accuracy in ore prediction of SLM mining sequence with fifty infill drill-holes by period (left) and global (right) per realization

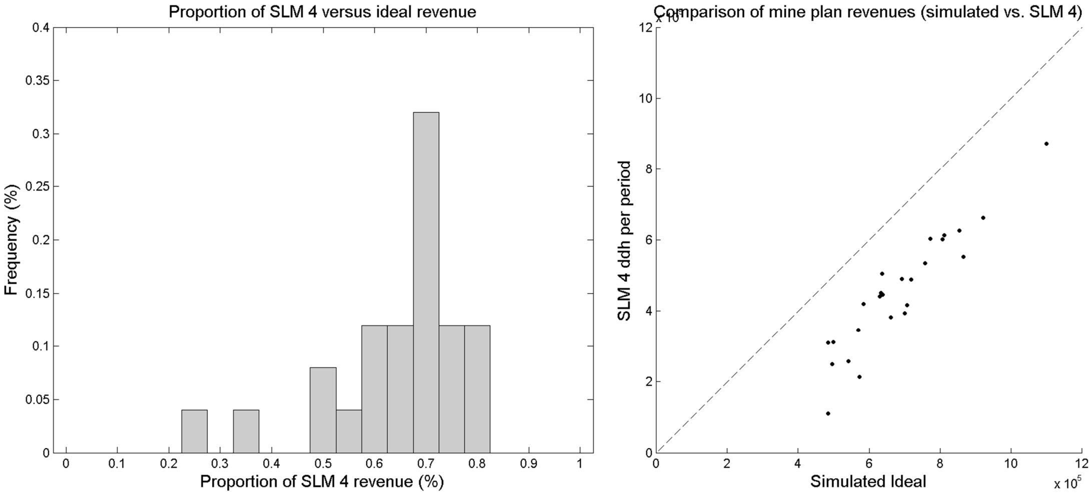

Figure 8: Histogram of operative proportional revenue (left) and scatter plot of ideal revenue versus operative revenue (right) of SLM mining sequence with four infill drill-holes

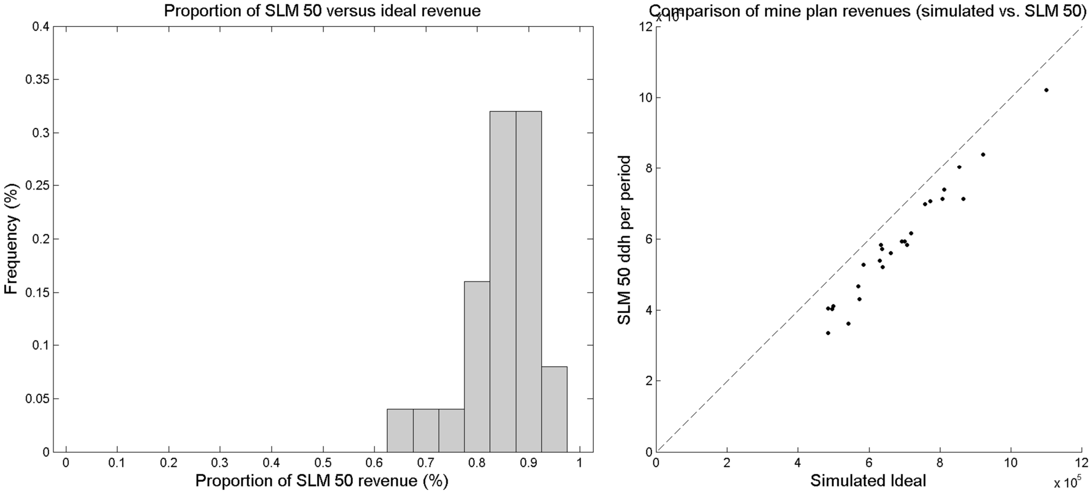

Figure 9: Histogram of operative proportional revenue (left) and scatter plot of ideal revenue versus operative revenue (right) of SLM mining sequence with fifty infill drill-holes

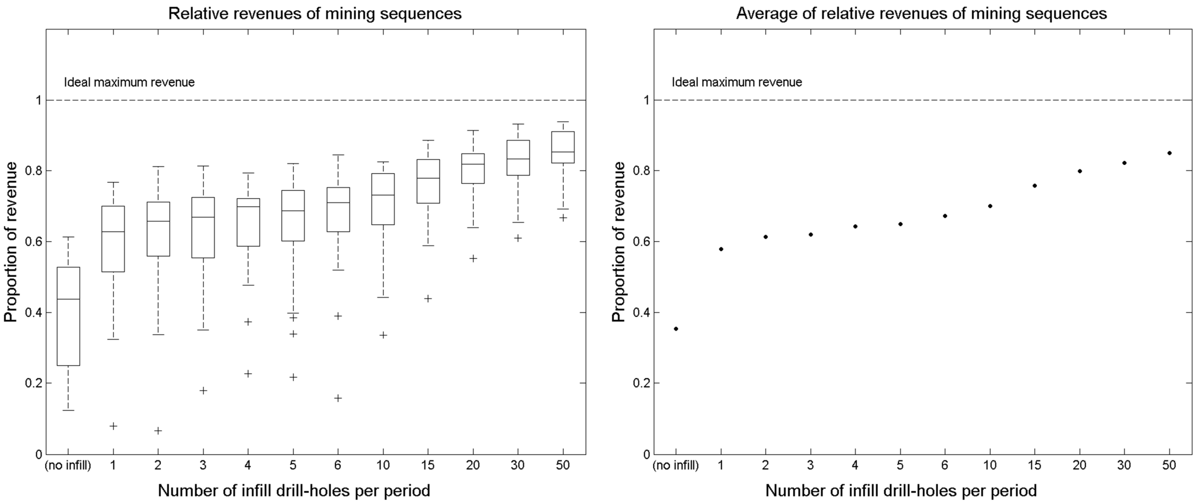

Figure 10: Effect of number of infill drill-holes per period in the operative revenue of mine sequences

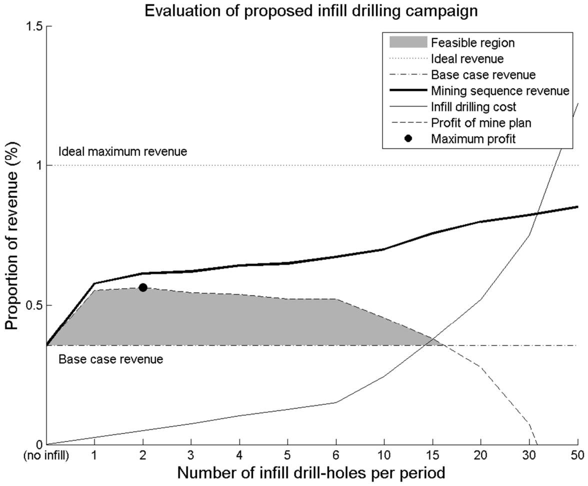

Figure 11: Evaluation of infill drilling plans in terms of profit increment

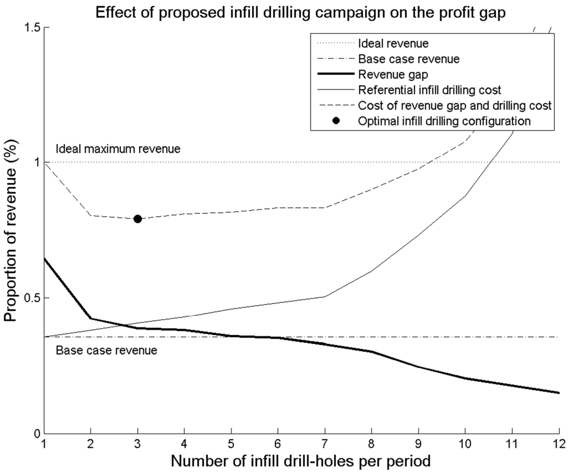

Figure 12: Evaluation of infill drilling plans in terms of net total cost