Refining Infill Drilling with Geologic Features

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Infill drilling campaigns are designed based on many different criteria, such as reduction of the global variance, improvement in the delineation of ore materials, reduction of uncertainty in the short term plan, etc. The design of infill campaigns is a longstanding problem that is not usually solved from the perspective of the impact on the revenue of a mine plan. In this paper, a sequential stochastic methodology to calculate the drilling locations of infill campaigns is presented. The proposed methodology is able to combine different criteria in the design of the infill campaign, including the effect on the revenue of the mine plan. The details of the implementation of the proposed approach are discussed in the paper. For illustration purposes, an example of the implementation on an artificial 3D deposit is presented.

Introduction

The optimal design of drilling campaigns is a problem that has been widely discussed by many researchers (Drew, 1979), (Miller Jr., 1991), (Shieh, Chu, & Jang, 2005), etc. In mining, the design of exploratory or infill drilling campaigns are based on different objectives, e.g., minimizing the global estimation variance, improvement of the delineation of economic regions, etc. (Aspie & Barnes, 1990). This paper focuses on the design of infill campaigns. An optimal infill drilling campaign is defined as the one that maximizes the improvement of the geologic knowledge of the deposit to minimize the production gap while reducing the drilling cost. The evaluation of the impact of different infill campaigns on the profit margin of a mining project has been discussed by (Cuba & Deutsch, 2011).

In this paper, a methodology to design infill campaigns is presented. The proposed methodology can be adapted to different objectives, e.g., minimizing the global and local variability of the project revenue, minimizing the geometric variability of the ultimate pit or next mining sequences, etc. The proposed methodology consists of a sequential selection of the locations of each infill drill-hole. The candidate infill drill-holes are simulated and the set of realizations is used to evaluate the impact in the specified objective functions. The proposed approach can be implemented as part of the simulated learning model (SLM) paradigm (Cuba, Boisvert, & Deutsch, 2010) to account for the discount effect due to drilling at different time periods. The details of the implementation are discussed in the next section and an example based on a 3D deposit is presented in the following section.

Stochastic sequential evaluation of infill drill-holes

The proposed approach consists of a stochastic evaluation of the candidate infill drill-holes that can be drilled over the deposit. Due to the large number of candidate locations, a searching algorithm is implemented to reduce the computation time, which consists of identifying potential regions in the deposit. The search algorithm is initialized by searching over a coarse drilling pattern over the deposit, and as potential regions are identified, the drilling pattern is reduced in those regions to increment the accuracy of the search. An important part of the evaluation is the definition of the metrics of performance. The infill drill-holes can be targeted based on their effect on: the dispersion of the total revenues of the ultimate pit, the dispersion of the total amount of ore material within the ultimate pit, the geometric variability in the position of the following next sequence, the geometric variability of the ultimate pit, etc.

For each location in the initial drilling pattern, the sampled values of each of the infill drill-holes are simulated conditioned to the existing data. An ultimate pit and its corresponding mining sequence is calculated for each realization of the infill drill-hole candidate and the existing data. The simulated infill drill-holes can be ranked according to the targeting criteria. For example, in the case of the reduction of the variability of the revenue criteria, the drilling location that results in the maximum variance of the ultimate pit revenues is targeted. An infill drill-hole at the targeted location will confirm the set of geologic features in the sampled region thus eliminating the major source of revenue variability in the deposit. To improve the accuracy in the selection of the infill drilling location, a denser drilling pattern is drilled around the more variable regions. To add more infill drill-holes to the drilling campaign, the previous simulated infill drill-holes are kept as part of the available information and the searching process is repeated again.

The proposed approach samples the different variability fields depending on the targeting criteria. The searching algorithm reduces the computation time to find the optimal targeting locations. During the evaluation of the infill locations two or more criteria can be considered by weighting the importance of the criteria in the ranking of the locations.

Example

The example consists of an existing exploratory campaign of 15 drill-holes sampled over a regular grid pattern of 75 x 75 m. The dimension of the deposit is 400 x 240 x 160 m^3. The initial grid search covers the deposit over a 50 x 50 m regular grid pattern (see Figure 1). The search grid fairly covers the unsampled locations left by the existing campaign. In this example, the target drilling location is calculated based on two criteria: 1) reduction of the variability of the total ore material mined and 2) reduction of the variability of the total revenue of the ultimate pit. The evaluation of the candidate locations is done by simulating 10 realizations per location.

For the case of reducing the variability of the ore material mined, the standard deviation of the total ore content within the ultimate pit is used as a metric of performance. At each search grid location, the standard deviation of the ore content within the ultimate pits affected by the infill drill-hole realizations is used. The variability at the existing data location is set to zero, since drilling at a sampled location will have no effect in the geometric variability of the ultimate pit. Based on the standard deviations of the total ore content at the locations of the search grid, an interpolated map is generated to identify the more sensitive regions (see Figure 2 - left). The regions of high values are identified as candidate regions. If necessary, the search grid can be refined to improve the accuracy of the map. The same process is repeated for the case of reducing the variability ultimate pit revenue. The interpolated map shows the more sensitive regions for positioning an infill drill hole based on the ultimate pit revenue criteria (see Figure 2 - right).

From the two maps in Figure 2, the targeted locations for positioning the infill drill-hole are calculated at the maximum value in the map. By drilling at these locations, the regions of high variability in each respective criterion are reduced. In Figure 3, the targeted locations with respect to the ore content and ultimate pit revenue are presented. If additional drilling is required, the process is repeated while keeping the simulated infill drill-hole at the targeted location as part of the existing dataset.

Conclusions

The proposed approach is a sequential methodology that can be used to evaluate the sensitivity of the mining sequence based on different criteria. The goal of designing an infill drilling campaign is to reduce the variability of the metric of performance of the criteria evaluated. In the proposed methodology, many criteria can be combined in the decision of positioning an infill drill-hole by weighting the metrics according to their respective importance in the decision.

Although the implementation is computationally expensive, the algorithm can be implemented in parallel. Modern computers are able to handle many computational processes at the same time. A parallel implementation reduces significantly the computation time of the implementation.

The proposed methodology can be implemented as part of the SLM to evaluate infill campaigns from the perspective of reducing the variability in the dispersion of the planned regions within periods. The SLM paradigm allows that the proposed infill campaigns can be evaluated as a function of time.

Bibliography

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Figures

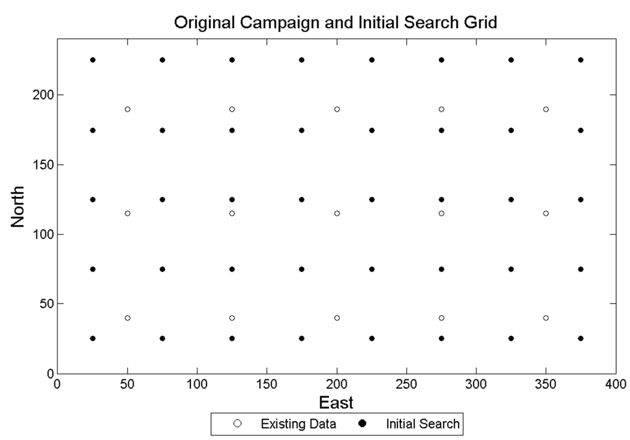

Figure 1: Drilling grid of existing drill-holes (empty dots) and initial search grid (black dots)

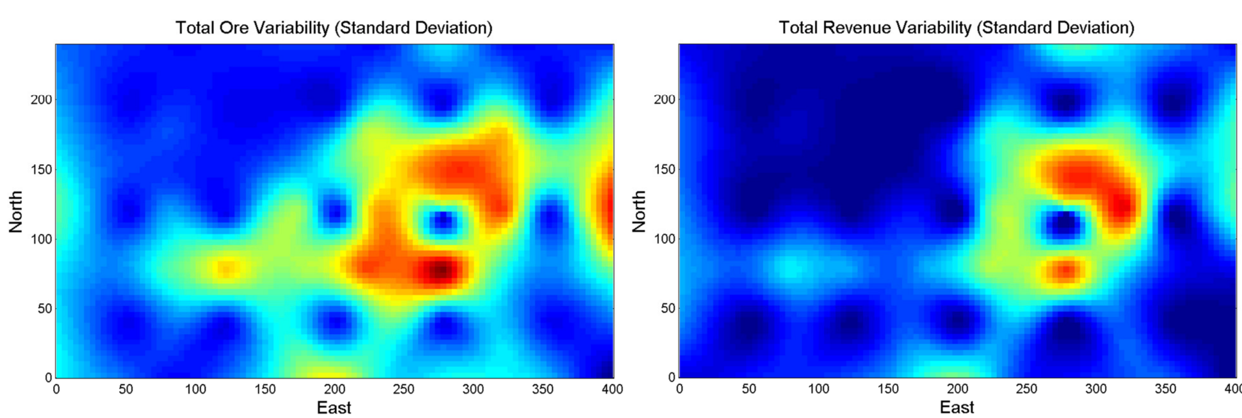

Figure 2: Map of total ore variability (left) and total revenue variability (right) within the ultimate pit

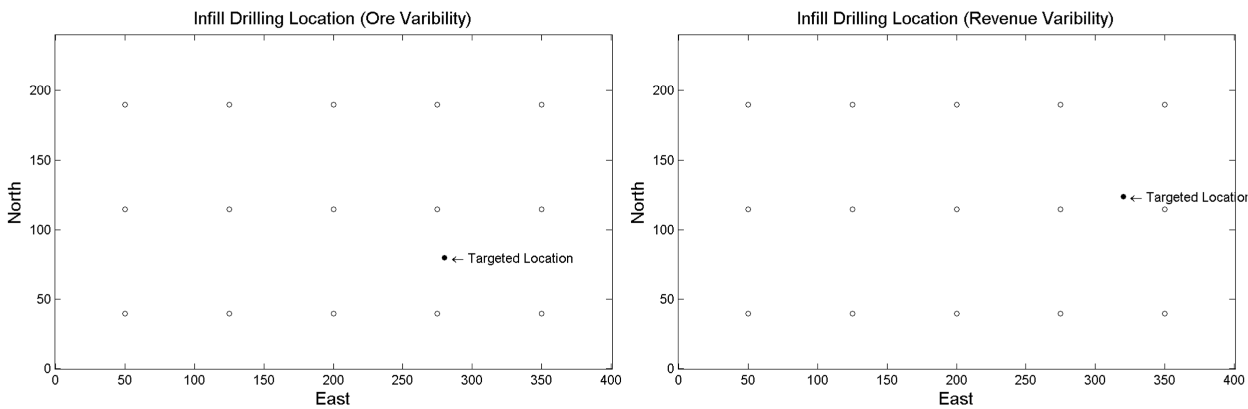

Figure 3: Targeted infill drilling location based on reducing ore variability (left) and based on reducing ultimate pit revenue variability (right)