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Hybrid objective function applied to optimize infill sampling location

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ABSTRACT

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Different moments of the exploration of mineralized bodies demand that sampling infill be made, those new samples have the objective of furthering knowledge about mineralized rock grade distribution. Usually, drillholes collars are located by geologists with experience and knowledge about the domain under analysis. Other methodologies can be applied to help the decision of where to locate the drillholes, for example, optimization of the infill drillhole location. Optimization is a method to assess the best parametrization to solve a problem, in the case of the infill location the problem depends on what the new samples are made for. Some research utilizes the kriging variance to guide the location of the new samples but has a limitation in assessing the sample distribution uncertainty. Another method that can be applied to locate the infill samples is simulation variance, which is dependent on the sample value. The application of a compost objective function to optimize the infill location is tested. This compost function considers both models kriged and simulated to search for the optimal infill drillhole configuration, therefore, considering both the sample spatial distribution and uncertainty. This method is compared with the objective function that uses either the kriged or simulated data directly to assess the competence of the compost one. Another test considers the influence of the values associated with the samples while searching for the optimum location of drillholes. Those tests have proven that the use of the simulation alone fared better in locating the infill samples in synthetic data than the compost or the kriging-dependent objective function. Both objective functions that utilize direct models, either kriged or simulated, fared better in different distributions. Considering the values associated with the samples, the median fares better than the other 3 values, mean, P10, and P90 of the simulated block distribution. Regarding the methodology of the search is important to notice that optimizing the direction of the drillhole tends to have a better response regarding the objective function but more tests should be made. The optimized infill location tends to further the representativity of the original sampling after the drillholes are done, therefore it can help assess portions of the domain with higher uncertainty that should be considered when the infill location decision is being made.

Terms: **Infill, Optimization, Kriging, Simulation, Objective function, Uncertainty, Modeling.**

1 – **INTRODUCTION**

Infill sampling is necessary for all phases of the mining enterprise. Higher uncertainty of the mining profitability, while in the initial research, demands for the best and more reliable data to decrease it. The location of infill samples is usually dependent on the research demand, being either the region with higher grade and/or higher uncertainty. The decision as to where to locate infilled samples is made by a geologist or mining engineer that knows the data and genetic history of the mineralization. This approach is subjective but effective, despite that an objective approach is necessary to guide the location that considers the needs of the research and the original information disposed of in the research. One approach to contemplate possible infill location sites are made utilizing computational optimization. Different methods of how to optimize the infill were proposed, with many utilizing the estimation uncertainty to guide the model to locate new samples. Besides, the mining project phase is also considered, in the initial stages the focus is on the uncertainty of the data, and while exploiting the mine operational aspects are focused on increasing efficiency.

Several studies were made considering the kriging variance as a guide to locate infill sampling. Examples of those studies are: Szidarovszky (1983); Gershon (1987); Groenigen *et alli* (1999); Delmelle & Goovaerts (2009); Wilde (2009); Soltani *et alli* (2011); Mohammadi *et alli* (2012); Silva & Boisvert (2013); Soltani & Hezarkhani (2013); Dutaut & Marcotte (2020). Those works differ from each other by the optimization algorithm utilized or the application of the kriging variance as the objective function, that can be considered alone, be averaged in the domain, weighted, with the estimated value, and others. However, there is a limitation if the kriging variance is utilized to assess uncertainty, as its value is homoscedastic, considering only the distance and spatial configuration of the samples that were used to estimate the node. This limitation does not mean the application of the kriging variance is useless, once it can point out regions of the domain that are sub-sampled, what must be considered while locating infill drillholes. This limitation arises from the need to consider different approaches while using kriging variance, such as using weights, adding other values to the objective function, or using a completely different model to derive the objective function.

Another approach is infill optimization based on different methodologies, as examples: Boucher, Dimitrakopoulos, and Vargas-Guzman (2004); Boucher, Dimitrakopoulos & Vargas-Guzman (2005); Al-Mudhafer (2013); Martínez-Vargas (2017);

Dirkx & Dimitrakopoulos (2018). Their research is based on simulated models of the data, or the objective function considers other aspects, such as profitability, misclassification, and other relevant factors that should be considered when infilling samples. The important factor to decide the approach, the algorithm, or the objective function, is the purpose of the infill location search.

Two papers compose the bulk of this thesis, one using a compost approach, combining estimated and simulated models to derive an uncertainty factor of the original data that represents local and global uncertainty in a single function. Utilizing kriging variance and simulated model uncertainty, this function represents subsampled portions of the domain while indicating regions with higher local variability. Another distinction is the time frame of the application, in this thesis, the focus is given to the initial stage of the mineral prospect when the uncertainty of the enterprise is higher. To obtain the best information as possible, with high reliability, is extremely important to indicate and further the knowledge regarding the mineralized body spatial distribution, so the focus is to warranty that infill will provide higher representativity as possible. In that way, this work will present the compost objective function and compare it to the approach of the single objective function to assess the competence of each in locating the infill regarding the population data. Another test considers the effect of the value associated with the samples while optimizing the infill location. This method tests 4 possible values that can be utilized as the new sampled value to assess the effects while optimizing. The last test considers the optimization that varies the drillhole direction while searching for the optimum infill location. All analyses were held in synthetic data created by Takafuji (2015) and Takafuji *et al.* (2017) and a real data set on a mine site. The synthetic data is preferred to assess the competence of the methodology proposed as the population distribution is available allowing comparisons with the optimized infilled samples. While the real data demonstrates the application in more complex domains than the synthetic data.

2 – CONCLUSIONS

The optimization of infill location by the methodologies presented is functional. The SBV minimization is the best at furthering the representativity of the synthetic data while the KBV fared better with the Capanema Mine information. This is probably related to the type of distribution each of those bodies has, the synthetic being a high variability, positive skewness

copper ore, and the Capanema iron ore that has a smaller variability, with negative skewness. More tests must be made to check if a distribution with lower variability can be better infilled with the KBV minimization than the others, with the help of synthetic data with the populational value at hand. The compost objective function, which considers the kriged and simulated models to locate the infill fared worse regarding population representativity than the direct functions under the same constraints.

The use of different values associated with the samples while searching for the optimum infill location demonstrates that the median fared better compared to the other values, for the synthetic data. Meanwhile, the P90 systematically fared worse in all comparisons made. The mean as sample value is functional but tends to show more chaotic results, with a higher uncertainty of better representing the populational distribution than the median. Optimization that variates the direction of the drillholes tends to better minimize the objective function, as more data could be found if different directions are made. But further tests must be made to assess the competence of the direction variation while locating infill.

The optimization methods proposed are functional in furthering the representativity regarding the population, but this does not mean that should be used alone. The consideration of different information must be taken while the infill is located. One point of contempt to the methods presented is the economic factor of making new drillholes, i.e., the cost of the new information compensates when considering the profitability that said information returns. This and other information, such as geological information of the ore body, tonnage of ore, and others, should be considered with the methods proposed to better assess the locations that would return the information of more interest to the mining. Therefore, this work proves that the proposed methods are competent in at least helping find the portions of the domain that would provide more representation to the population, and less uncertainty, while the infill location is considered.

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