

APPLICATIONS OF CONDITIONAL SIMULATIONS TO RESOURCE CLASSIFICATION SCHEMES

Mario E. Rossi
GeoSystems International
479 Cascadita Terrace
Milpitas, CA, 95035
USA
1-408-956-1395
mrossi@geosysint.com

Jorge Camacho V.
Minera Michilla S.A.
Sucre 220, Of. 606
Antofagasta
Chile
56-55-627-521
jcamacho@michilla.cl

ABSTRACT

Geostatistical conditional simulations are becoming increasingly popular as tools that provide models of uncertainty at different stages of a mining project. They have been used as grade control tools in daily operations, to assess the uncertainty of minable reserves at the project's feasibility stage, and to assess mineralization potential in certain settings. Other applications include assessment of recoverable reserves, resource and reserve classification, and drill hole spacing optimization studies. All large-scale applications of conditional simulations intend to benefit from the "correct" (or "accurate") characterization of uncertainty, adequately describing the variability observed from the data and its impact on the final objective.

The objective of this paper is to compare the ad-hoc "uncertainty model" provided by a traditional classification scheme with the probability intervals resulting from a conditional simulation model. It is argued that the uncertainty model derived from the use of classification schemes is of little practical use to the mining company or operation. The paper emphasizes differences in uncertainty based on the size of the mining unit considered and the extraction method, and local geological differences. Most importantly, it discusses confidence intervals for these mining units, as compared to the relative precision envisioned by a typical classification scheme.

The application described in this paper is taken from a medium-sized Cu open and underground mine in northern Chile, and it demonstrates the impact of several variables on the resulting conditional simulation models. It also compares a more "traditional" resource classification scheme applied, and the wide difference in local confidence intervals for each mining unit.

INTRODUCTION

Geostatistical conditional simulations is a set of tools that were developed for characterizing and modeling the variability of the regionalized variable of interest, thus providing uncertainty models for these variables. These uncertainty models are, for example, quantitative models of possible deviations from expected tonnages and grades, and so they allow for specific and useful risk assessments, which will vary with the general objectives of the work. In this paper, the emphasis is risk assessments of predicted tonnages and grades within a mine plan, and its impact on cash flows.

The conditional simulations required to derive these uncertainty models can be obtained using a number of available techniques, generally classified as parametric or non-parametric, Gaussian or Indicator-based, etc. The reader is referred to the references for further details about conditional simulations, such as Goovaerts (1997).

The objective of this paper is to contrast the differences between the more traditional form of uncertainty models, through the use of resource classification schemes, and the use of geostatistical models of uncertainty. This is particularly relevant given the recent push within Canada and elsewhere to provide solid guidelines for Resource Classification, and third-party understanding and use of resource statements published by mining companies, both from the regulatory viewpoint and the investor's viewpoint.

There are several aspects of Resource Classification schemes that should be emphasized to better understand this paper:

1. A Resource Classification Scheme is generally intended to provide some measure of the degree of confidence in the resource statements (in the terminology used in this paper, and "uncertainty model"). The same can be said about the geostatistical conditional simulation models.
2. Internally, mining companies can take a very different view of the classification of resources used, and this can vary widely among different levels of management, and different technical groups within the company (geologists, mine planners, and metallurgists).

Despite the new and old guidelines in place that may contribute to give the appearance of objectivity to the whole process, the fact is that very few "qualified persons" would independently agree on the same resource classification scheme for a given mining property. In addition, management's perception is likely to be different, and classically, simplistic. Finally, technical personnel will generally disagree among themselves about the significance of the Resource Classification scheme used, and how to inject the different levels of confidence into the mine plan and projected cash flow.

This general confusion and lack of understanding of the significance and meaning of resource classification schemes ("traditional" uncertainty models) can be improved by using a geostatistical model of uncertainty. Without implying that these models are "objective" (by definition, an objective model does not exist!), a more detailed description of the predicted uncertainty for each particular block, phase, zone, or geologic region of the deposit allows for a better understanding and use of the classification scheme implemented.

In addition, questions such as "how different is measured from indicated?", or "does measured mean 0% error?", or "how different is measured in Zone A compared to Zone B?", can have a quantitative answer, as provided by the conditional simulation model. These ideas are better argued through a real-life case study. This paper presents the work done at Minera Michilla S.A., a medium-sized oxide Cu deposit near the Pacific coast, approximately 100km north of Antofagasta, in northern Chile.

THE LINCE-ESTEFANIA MINE

As mentioned before, the Lince-Estefanía mine is located within the district of the same name, some 120km to the north of Antofagasta, near the paved Highway 1. The mine is currently operated by Minera Michilla S.A., producing about 50,000 tons of cathod Cu per year from both an open pit (Lince, using a 10m bench height) and an underground mine (Estefanía, mostly cut-and-fill with 5m lifts). The mine is located approximately at 900m above sea level. Minera Michilla is a subsidiary of Anaconda Chile, which is also part owner of Los Pelambres, and is currently constructing a new mine called El Tesoro, both in Chile. Figure 1 shows the location of the district in northern Chile.



Figure 1: Location Map of the Michilla District and Mines.

The district geology shows a very significant strato-volcanic sequence, called La Negra Formation, regionally dipping 30° to the NW, and composed of a series of andesites and volcanic breccias of different characteristics. The andesites vary from aphanitic to porphyritic, intermixed with the volcanic breccias. Mineralization is hosted in this

volcanic séquence, where breccias are more favorable hosts. For more detailed descriptions, the reader is referred to Ferraris and Di Biase (1978).

The resulting mineralized bodies (“mantos”) are ellipsoidal in shape, of variable dimension and grades, and generally concordant with stratification. It is difficult to predict the existence and the size of each manto, as well as its grade distribution. Generally, the mantos are small, 4 to 5m thick, with length and widths of up to 40 or 50m, and many being less than 25m. Mineralization is mostly Atacamite, with some Chrysocolla (“green” oxides), as well as mixed and sulphide Cu mineralization at depth (chalcosite, covelite, chalcopyrite, bornite, etc.). Grades within the mantos are typically 1 to 5% Total Cu, with up to 10% Cu. The cathod plant receives a head grade of 1.6% Cu. Global resources at this stage are, at a 0.5% Cu cutoff, roughly 63 Million tons with a 1.44% TCu grade, and a 0.86% Soluble Cu grade (SCu). This is distributed in various zones and at different depths, and includes all drill-indicated resources to date. The main subzones within the deposit are separated into amenable to open pit (Lince), or underground (Estefanía). In addition, within the open pit mine there are several zones, grouped as Lince, D4 Zone, and Hilary; within the underground mine, zones are delimited by mining extraction sequence, and are named using letters and numbers, such as A1, B2, D3, and so forth. There are at least 17 areas of interest within the open pit and underground mines. Resources are classified following the AusIMM standards (JORC code), as adopted by Anaconda Chile, and result in about 21% of the total resources being classified as measured, 64% classified as indicated, and the rest classified as inferred.

In early 2000 an infill drilling campaign was completed, and the existing drillhole database updated. The geologic model was updated, and a new resource block model was obtained. The grade model was obtained through a multiple indicator kriging model. Following the completion of the Resource Model and its classification into Measured, Indicated, and Inferred, a conditional simulation model was implemented to assess uncertainty and risk. This conditional simulation model was also based on indicator kriging techniques, so that both models would be based on similar Random Function models.

After selecting some of the key sectors and phases for the upcoming 5 years of extraction (both from the open pit mine and for the underground mine), the conditional simulation model was reblocked and assigned to the same blocks used in the Resource Model. This allows for a direct comparison between the two models, and to assign an uncertainty model to the predicted grade. Figure 2 is a schematic representation of the general work flow at Minera Michilla.

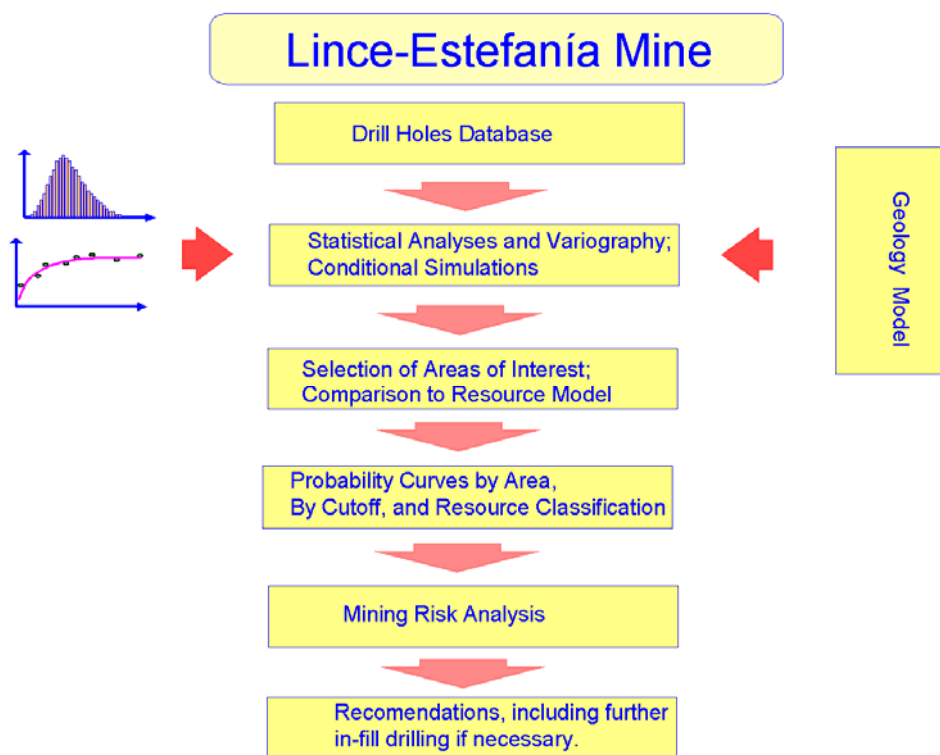


Figure 2: Schematic Work Flow, Lince-Estefanía.

CONDITIONAL SIMULATION MODEL FOR LINCE-ESTEFANÍA

The conditional simulation technique used at Lince-Estefanía is called Sequential Indicator Simulation (SIS, Alabert, 1986). The use of SIS is consistent with the use of multiple indicator techniques for obtaining resource estimates.

The geologic model used at Michilla includes the definition of a mineralized envelope, defined at 0.1% TCu. The purpose of the mineralized envelope is to define the volume within which mineralization can exist; outside this volume, there is no mineralization. In this sense, this is a geochemical-type boundary, whose purpose is to avoid overestimation of the kriging process into barren areas. This is necessary because mineralized bodies can abruptly end due to a post-mineral fault, or without any obvious reasons.

In addition, there are 3 major “geologic units” defined (in fact, lithological groupings), which are used to constrain the resource estimates; the more important units are the volcanic breccias (generally mineralized), andesites (could be mineralized, but generally barren or poorly mineralized mantos), and intrusives (including tectonic breccias), which are mostly barren, but could occasionally present significant mineralization.

In the estimation and simulation process, 5m down-the-hole composites were used, and tagged according to the interpreted geologic units. The composite length was chosen because it is representative of the selectivity of the operation. Even though the nominal bench height is 10m, the open pit could select partial benches if deemed necessary.

The SIS technique requires, as does the multiple indicator kriging (MIK) used to estimate resources, the definition of indicator thresholds in order to discretize the original grade distribution. The definition of these indicators was identical for the estimation and the simulation models, and included the following indicator classes: from 0.0 to 0.19% TCu; from 0.2 to 0.49% TCu; from 0.5 to 0.79% TCu; from 0.8 to 0.99% TCu; from 1.0 to 1.19% TCu; from 1.2 to 1.49% TCu; from 1.5 to 1.99% TCu; from 2.0 to 2.99% TCu; from 3.0 to 4.99% TCu; from 5.0 to 6.99% TCu; from 7.0 to 9.99% TCu; and greater than 10.0% TCu.

Indicator Variograms for TCu and by Geologic Unit.

The indicator method requires that an indicator variogram model be obtained for each of the 11 thresholds defined above. In addition, there should be one set of indicator models per Geologic Unit considered, and per subzone or area in the deposit. So there are 33 indicator variogram models required per subzone of the deposit. In addition, 3 major zones were defined for the purpose of variogram modeling (Lince, D4+Hilary, and Estefanía), resulting in a total of 99 variogram models for the resource estimation and conditional simulation model. These variograms are not shown here for the sake of brevity.

There are a few observations that should be made with respect to these variogram models.

- The variogram models used for the resource estimation are the same than those required for the conditional simulation work. This is, this part of the work (as all other required statistical work) is only done once, and used for both the resource estimation and the conditional simulation models.
- As expected, the variogram models for lower indicator thresholds (waste or low grade) are more continuous than the higher grade thresholds.
- As the indicator thresholds are increased, the overall spatial correlation decreases, evidenced, for example, with nugget effects increases. This corresponds to the intuitive notion that higher grade mineralization has less spatial correlation than the more pervasive, lower grade mineralization.
- There can be differences in anisotropy angles and ranges for different grade ranges, as is the case for Lince-Estefanía. This can be explained by different geologic controls affecting parts of the grade distribution differently, for example with a specific set of structures controlling the higher grade mineralization. Therefore, there are different grade populations superimposed within the deposit, and modeling different anisotropies for different grade ranges is entirely appropriate assuming they correspond to different mineralization events.

As mentioned before, the deposit was separated into three major sectors: Lince (present open pit mine, above 500m elevation), D4/Hilary (future open pit expansion, above 500m elevation), and Estefanía (underground, below 500m elevation). The conditional simulation model was obtained on a 5x5x5m grid, and the volume modeled is such that it results in a simulation model with more than *40 million* nodes. Although not every node receives in the end a simulated value, the model is obtained for the complete grid, including the restriction that at least one 5m composite be in the neighborhood of the node before the simulated value can be obtained. After the simulated model is obtained, it is restricted to the areas where the 0.1% TCu mineralized envelope exists, as mentioned above. Although it not by far the largest simulation ever obtained by this autor, the reader can begin to appreciate the logistics involved in handling one of these models.

Conditional Simulation Models.

The final simulation model obtained for the Lince-Estefanía is based on a two-stage simulation. First, a simulated geologic model was obtained, by simulating the variable presence or absence of each of the Geologic Units used (Volcanic Breccias, Andesites, or Intrusives). The output from this stage is a model representing the probability that each Geologic Unit exists at a given node.

The purpose of this first stage is to inject the relationship between grade and each Geologic Unit. For example, a node with a high probability of being a volcanic breccia is more likely to have better grades than one with a high probability of being an andesite. This relationship between Geologic Unit and grade is input into the grade simulation as prior distributions of possible Cu grades for each node simulated. The original statistics of the 5m composites are used to derive these models for each area within the deposit. For example, for Lince, the 5m composites tagged as volcanic breccias have 57% of the values less than 0.2% TCu. For 5m composites tagged as andesites, this number is 64%, while for 5m composites tagged as intrusives it is 71%. Also, there is a 10% probability that the 5m composites tagged as volcanic breccias have a grade greater than 3%, while this percentage is 3.2% and 2.8% for andesites and intrusives, respectively. This information is compiled for each threshold used, and in geostatistical jargon is called “soft” (or fuzzy) information, used in the form of prior probability distributions.

The second phase in obtaining the the final simulated model is to use the prior distributions as well as the 5m composites themselves. There are several important simulation parameters that need to be defined, such as:

- The search ellipsoid applied an octant search, with a nominal 25m search radius, with anisotropic ranges corresponding to the same orientation of the median indicator variogram.
- A minimum of 2 composites were required to simulate a node, using a maximum of 10 composites and 10 previously simulated nodes.

These and other parameters are adapted to the characteristics of each area simulated within the deposit. Therefore, each simulation model reflects the different geologic characteristics of each subzone of the deposit, through the use of different indicator variogram models, and simulation parameters.

After obtaining the simulation models, several checks are required in order to ensure that the simulated values obtained have the expected characteristics. It is important, for example, to verify that the distribution of the simulated values is similar to the distribution of the original 5m composites, in average grade, variability, etc. Figure 3 shows a quantile-quantile graph of the 5m composites vs the simulated nodes for the Lince area. If the points approximately align on the 45° degree line, then the composites and the simulated values have similar distributions. Other statistical checks include histograms, and variogram model reproduction. It should be emphasized that the simulated values should reproduce the original composite distribution (it is not a block model in the traditional sense of the word), and thus all composite statistics. See, for example, Goovaerts (1997) for a more detailed discussion on conditional simulations.

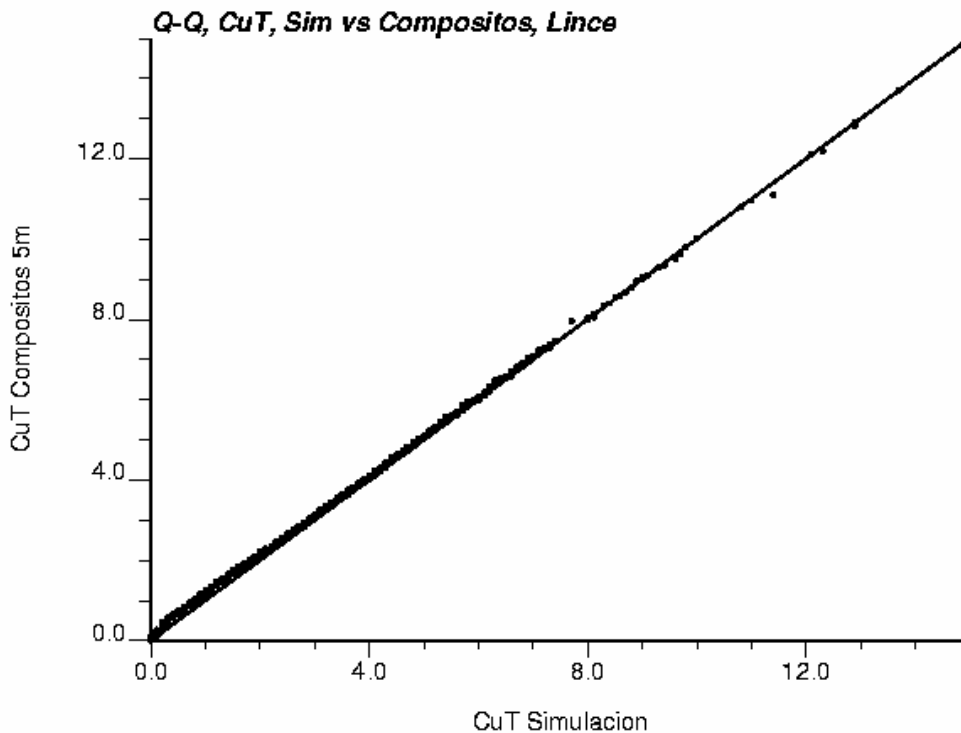


Figure 3: Comparison for TCu, Simulated Values vs 5m Composites, Lince.

It is also important to check that the simulation model represents well the spatial distribution of grade, much like it is done for kriged resource models. Simple visual inspection of sections and plans of the output simulation model should show whether the

composite grades and its patterns of grade distributions are reproduced as expected. Figure 4 shows a plan view (Bench 690 elevation) for the Lince area, Simulation No. 1.

There are several aspects that need to be taken into account when checking a simulation:

1. There are several TCu values for each node (in this case, 10 TCu values). These 10 values represent a probability curve of possible values for that particular point in the deposit, and depending on which specific value of the model is looked at, it may appear that it “underestimates” or “overestimates” the local grade.
2. The simulation will not necessarily honor the grades of the composites to the degree that a kriged block model is expected to. Although the simulation will result in the same composite grade if it falls at the same location of a simulated node, the simulated value may deviate (even significantly, on occasions) from the closest composite, due to the random aspects of the process. On average, and taking the probability curve as a whole (the complete set of simulated values for the node), the simulation should reflect the grade distribution in its vicinity.

It should be noted that the simulation models are more difficult to understand, and therefore to validate, due to some of the random aspects of the technique, and to differences with the more traditional resource block models usually obtained.

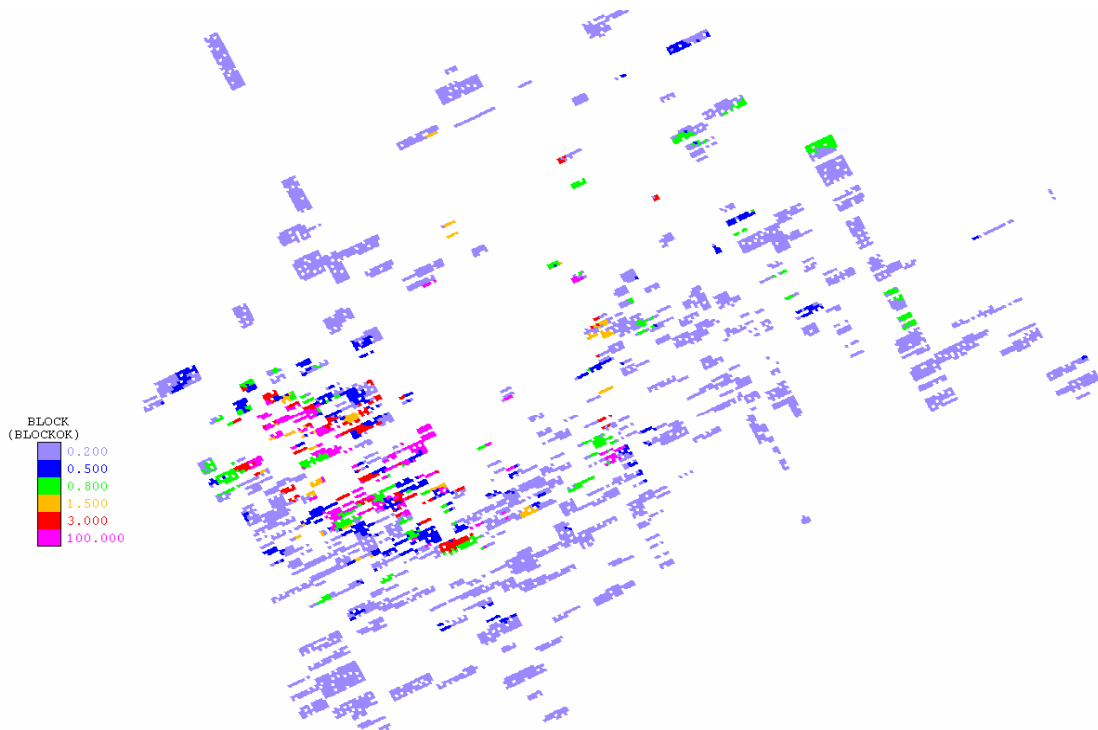


Figure 4: Bench 690, Simulation No. 1, Lince.

PROBABILITY INTERVALS BY AREA

After adequately checking the simulation, the models were reblocked and assigned to the same blocks of the resource models, in order to develop the uncertainty models for the resource estimates by areas.

The original resource block model has variable block sizes, from a nominal 6.25x5x5m down to 3.125x2.5x2.5m (or 2x2x2 subcelling), to allow for better definition of the geologic contacts. Each of these subcells have a TCu grade and also a classification code (measured, indicated, or inferred).

The blocks of the resource model and the simulated nodes were averaged (reblocked) to a 10x10x10m block size for the open pit areas (Lince, D4, and Hilary), and to 10x10x5m for the underground mine (Estefanía). Recall that each block of the resource model has a classification code (measured, indicated, or inferred) which was assigned to the reblocked models using the majority volume rule.

The block model was split into 17 subzones within the deposits, corresponding to different production areas (current or planned for production within the next few years). For each of these subzones, the block model average was obtained, as well as the average from the 10 simulations, as well as the averages of each of the 10 simulated values for each block within the subzone. Note that the definition of these subzones within the deposit correspond to tonnages and grades planned to be extracted according to an existing schedule. In this sense, the uncertainty model described by the set of 10 simulated values for each area is used as part of the mining risk assessment (and the risk on the predicted cash flow), and also in comparing with the traditional resource classification scheme.

In this paper only 4 sectors are presented, two open pit areas and two underground areas corresponding to a medium term planning horizon. The areas are the D4 area, and Mining Phase 7 of the Lince pit (open pit), and the A1 and D1/D2 areas combined (underground). It is convenient that each of these sectors be represented in the computer with a three-dimensional solid, such that these solids can be used to select the blocks of interest and calculate volumes. The 3-D solids are typically produced by the mine planning group, such that the resource and simulation (uncertainty) models can be processed.

There are several options available to both process the information and perform the mining risk analysis, and to present the model of uncertainty (conditional simulation model). In this paper, and for simplicity, only the following information is presented:

- Average of the area (Sector) according to the Resource Block Model (“Prom. MB” on the graphs).
- Average of the area (Sector) according to the simulated values (“Prom. Sims” on the graphs).
- Lower Probability Limit, defined as the relative difference between the average of the 10 simulated values that represent the 15th percentile of the distribution of

possible values for each block, and the Block Model estimated value (“Lim. Inf.” on the graphs).

- Upper Probability Limit, defined as the relative difference between the average of the 10 simulated values that represent the 85th percentile of the distribution of possible values for each block, and the Block Model estimated value (“Lim. Sup.” on the graphs).

The results are presented for four different cutoff grades: 0% TCu (or global), 0.5% TCu, 1.0% TCu, and 1.2% TCu. The results are expressed in % TCu, and the Upper and Lower Probability Limits are expressed with respect to the Block Model Average. This is called here the 70th percentile Probability Interval. Using a degree of statistical license, this probability interval can be directly associated with the more traditional “confidence interval”. In addition, for each area (Sector), the results are presented by Resource Classification categories (measured and indicated), in addition to total resources (which includes inferred as well as the previous two). Figures 5 through 8 present these results.

The results were obtained using volume-weighting for each Sector and Model; in other words, the metal content for each cutoff and classification category were first obtained (assuming a constant density), and from that the grades presented in Figures 5 through 8 derived.

ANALYSIS OF RESULTS AND CONCLUSIONS

In addition to specific conclusions for each sector described below, the following are some of the more important general observations and conclusions:

1. The average grade of the simulations do not generally agree with the average grade as obtained from the block model for most sectors. This is a consequence of the differences in the dilution incorporated into each model; note how the averages at a 0% cutoff are much more similar. This is an important contributor (also known as recoverable reserves, see for example Rossi and Alvarado, 1998) to the overall uncertainty, and it is dependent on the local geology and the geostatistical models used.
2. The simulation model results in probability intervals that are not symmetric with respect to the expected value. The traditional “±” does not apply. This is because the TCu grades do not follow a Gaussian model, nor do the expected errors. There is no real reason why the probability of error on one side of the expected value has to be identical to the probability of error of the opposite side.
3. It is entirely possible that the expected value (according to the Block Model) fall entirely outside the probability limits defined; this can happen because the simulation model is obtained independently of the estimation model (even if applying the same Random Function), and because cutoff grades are used (conditional statistics).
4. The probability intervals are different for each cutoff grade analyzed. It is also different from Measured to Indicated to Inferred resources (not shown here). In general, higher cutoff grades result in wider probability intervals (higher uncertainty)

and risk, as expected), and the same can be said for the difference between measured, indicated, and inferred resources. Clearly, the key in this analysis is the behavior of the predicted grade-tonnage curve for each sector.

5. The measured, indicated, and inferred classes are not very useful when analyzing uncertainty and risk within local areas. The reason is that the resource classification scheme is usually developed on a global basis, and is in itself a global statement of uncertainty, and thus only appropriate for long-term risk. As this study shows, it is not appropriate to use the same scheme for local risk assessment (by mine planners, for example). That is, a certain area or block can be classified as measured within the long-term context, but on a month to month basis be only indicated or inferred.
6. The individual classification categories show significant variability, even within the same class, for different sectors. For example, the measured resources for Phase 7 Expansion (for the 0.5% TCu cutoff) show that the 70% probability interval is within 23% of the Block Model, while the same “measured” resources for Sector A1 is within 26% of the block model grade. What is measured in one area (maybe with probability intervals in the order of 20%) may significantly different probability intervals in another area, with significant probability intervals. This is due to local geologic differences, additional complexities of the mineralization controls, and local differences in drill hole coverage.

More sector-specific comments are as follows:

- **Sector Phase 7 (Lince, Figures 5(a) to 5(c)):** the simulation model predicts that the block model is conservative (i.e., there is upside potential) for cutoffs below 0.5%TCu, while the opposite is true for 1%TCu cutoff and above. This is true for each classification category considered, although more so for indicated and inferred resources. Since the actual cutoff used is around 0.7%TCu, the conclusion is that the block model is approximately unbiased, according to the simulation model. Measured are within 23% of the predicted Block Model grade, while indicated resources are within 30% of the expected grade.
- **Sector D4 (Open Pit, Figures 6(a) to 6(c)):** the simulation model predicts for all cutoffs that the block model is conservative, although clearly not as much for the higher cutoffs. There is a clear difference in the width of the upper and lower limits between the measured and the indicated categories (Figures 6(a) and 6(b)), and more so with respect to the inferred resources.
- **Sector D1/D2 (Underground, Figures 7(a) to 7(c)):** For this area, the cutoff grade to be considered is the higher 1.0%TCu (and in recent times, 1.2%TCu). Therefore, the conclusion is opposite from the previous two sectors. In addition, most of the resources in the area are classified as indicated. The probability intervals for these indicated resources at the 1.0%TCu cutoff is -17%/+5%, meaning that the true grade can be up to 17% lower and 5% higher than the predicted grade.
- **Sector A1 (Underground, Figures 8(a) to 8(c)):** In this area the simulation model predicts a lower average grade for both measured and indicated resources. Note that the average grades are higher than in the sectors shown, and also that most of the resources in this area are indicated. The overall variability in this

area is similar to the variabilities observed in other higher-grade areas of the deposit.

As it can be inferred from the brief análisis above, the amount of information that can be derived from a simulation model is significantly larger than what has been presented here. As a consequence of risk analysis similar to what has been presented here (but more detailed), infill drilling campaigns, mine call factors, and other planning and scheduling measures are taken to reduce the risk of not achieving the predicted cash flow.

In addition, technical personnel and management have a tool to better understand the consequences of the resource classification schemes, and their significance. None of this detailed analysis is possible with the traditional resource classification scheme alone.

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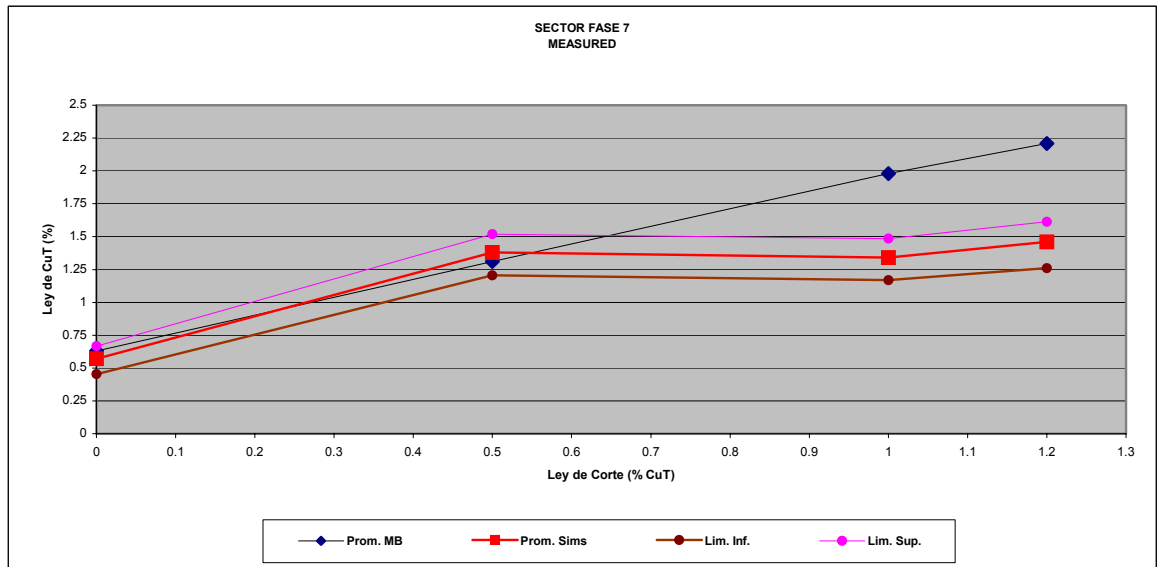


Figure 5(a): Measured Resources (Proven Reserves), Sector Phase 7 (Open Pit).

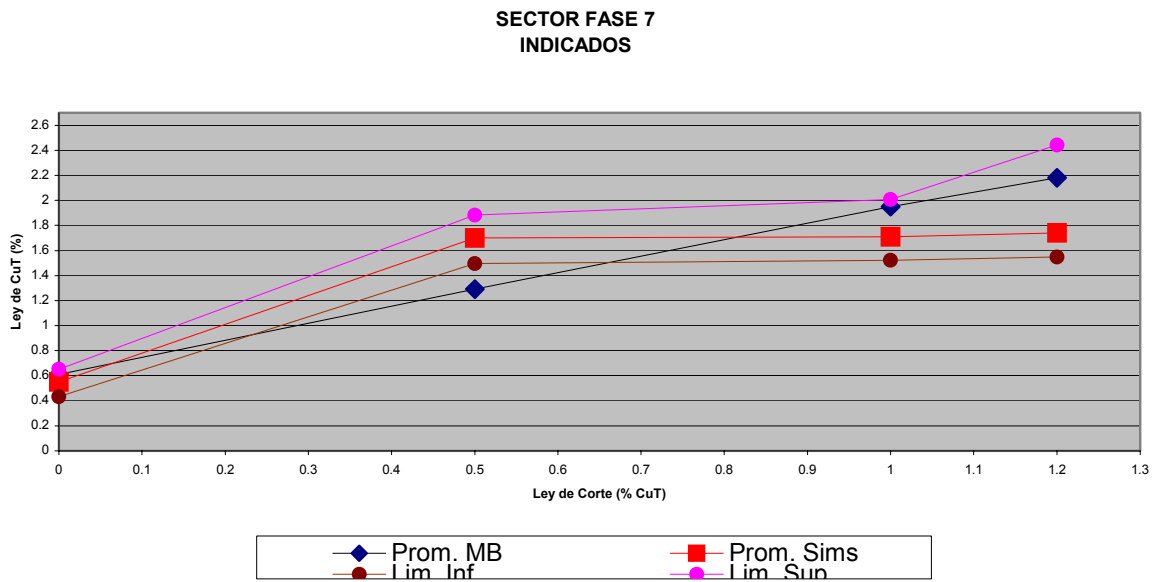


Figure 5(b): Indicated Resources (Probable Reserves), Sector Phase 7 (Open Pit).

SECTOR FASE 7
INFERIDOS

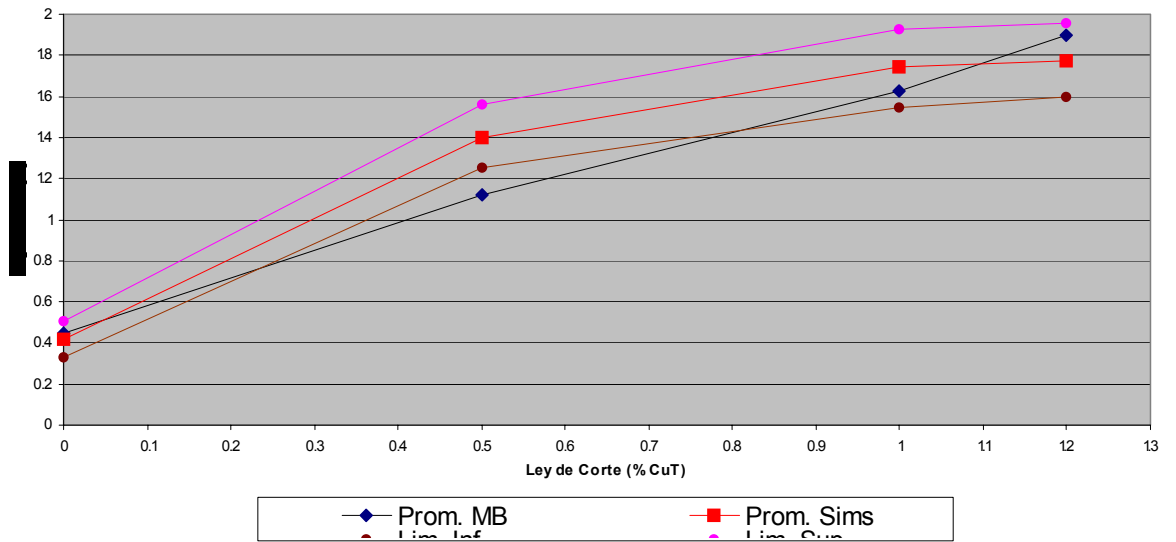


Figure 5(c): Inferred Resources, Sector Phase 7 (Open Pit).

SECTOR FASE 7
RESERVAS TOTALES

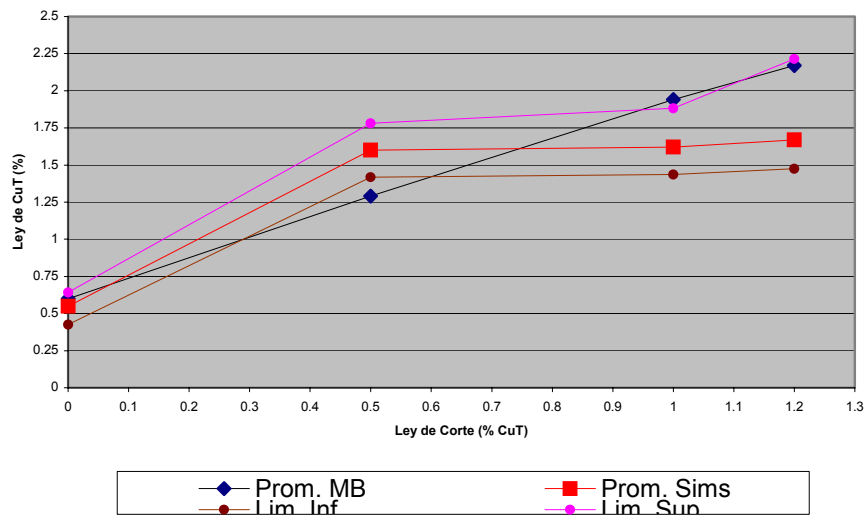


Figura 5(d): Total Resources, Sector Phase 7 (Open Pit).

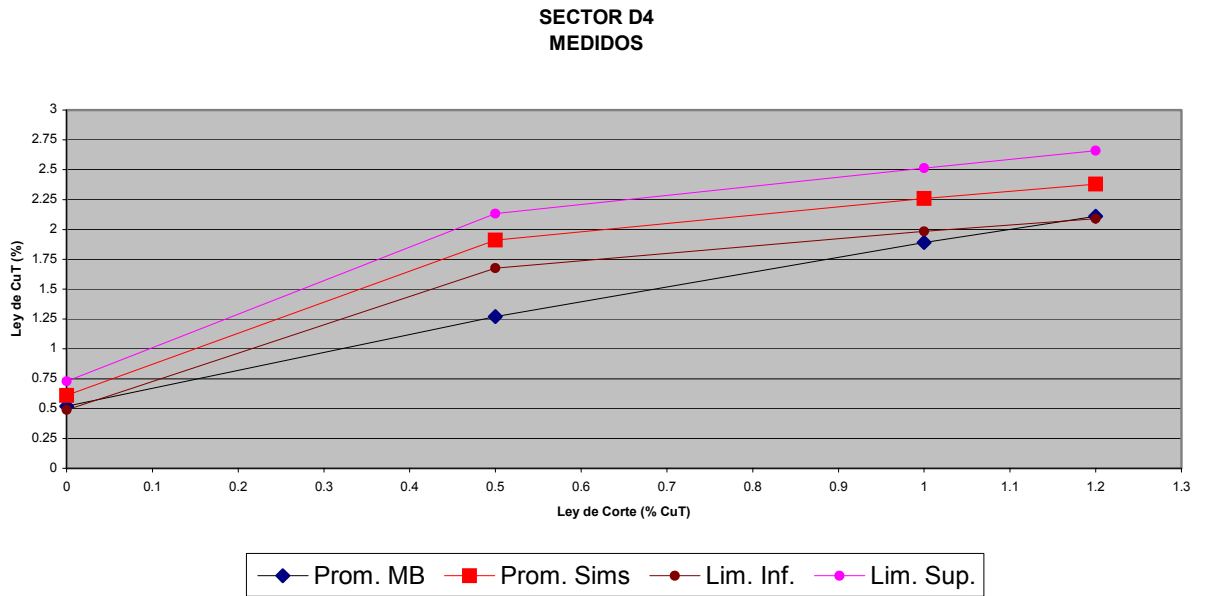


Figure 6(a): Measured Resources (Proven Reserves), Sector D4 (Open Pit).

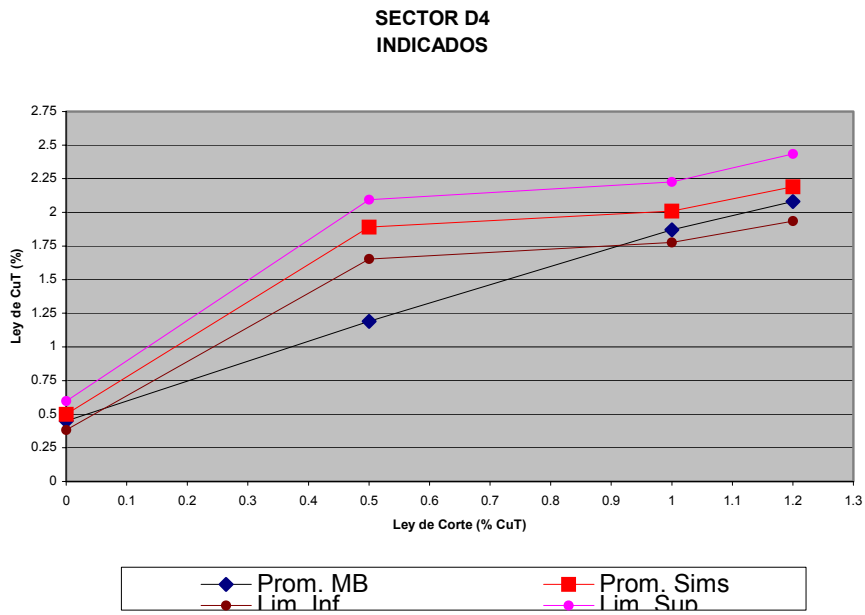


Figure 6(b): Indicated Resources (Probable Reserves), Sector D4 (Open Pit).

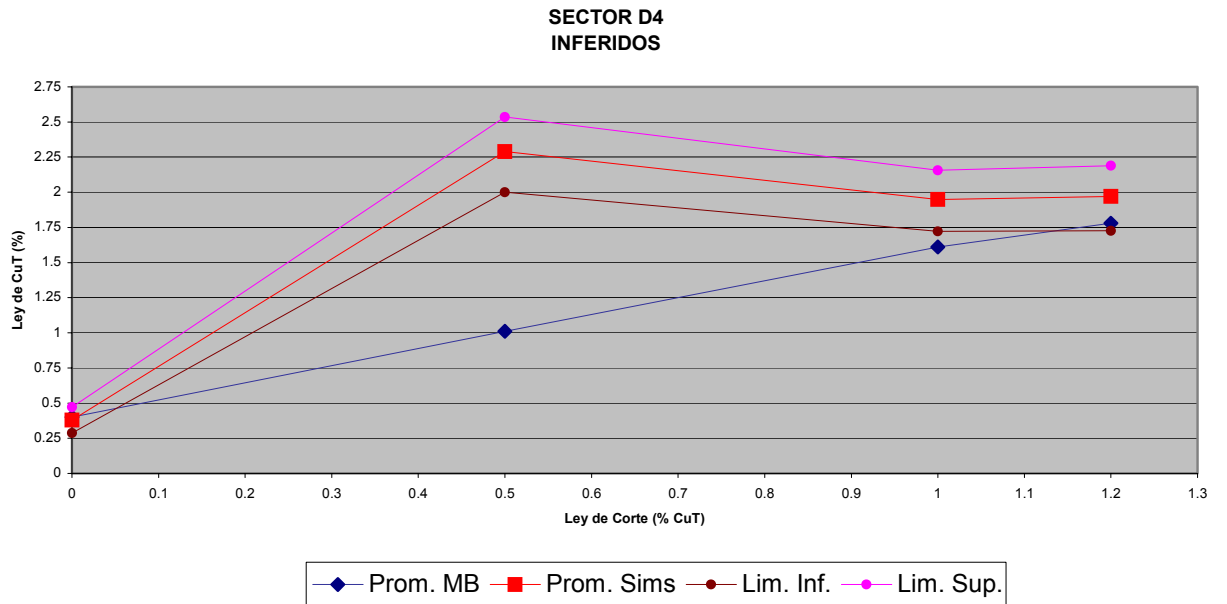


Figure 6(c): Inferred Resources, Sector D4 (Open Pit).

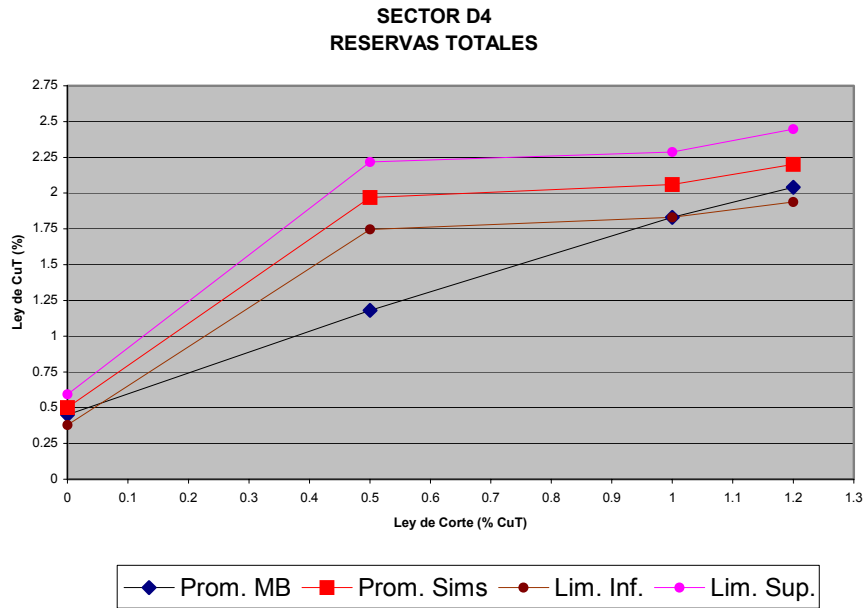


Figure 6(d): Total Resources, Sector D4 (Open Pit).

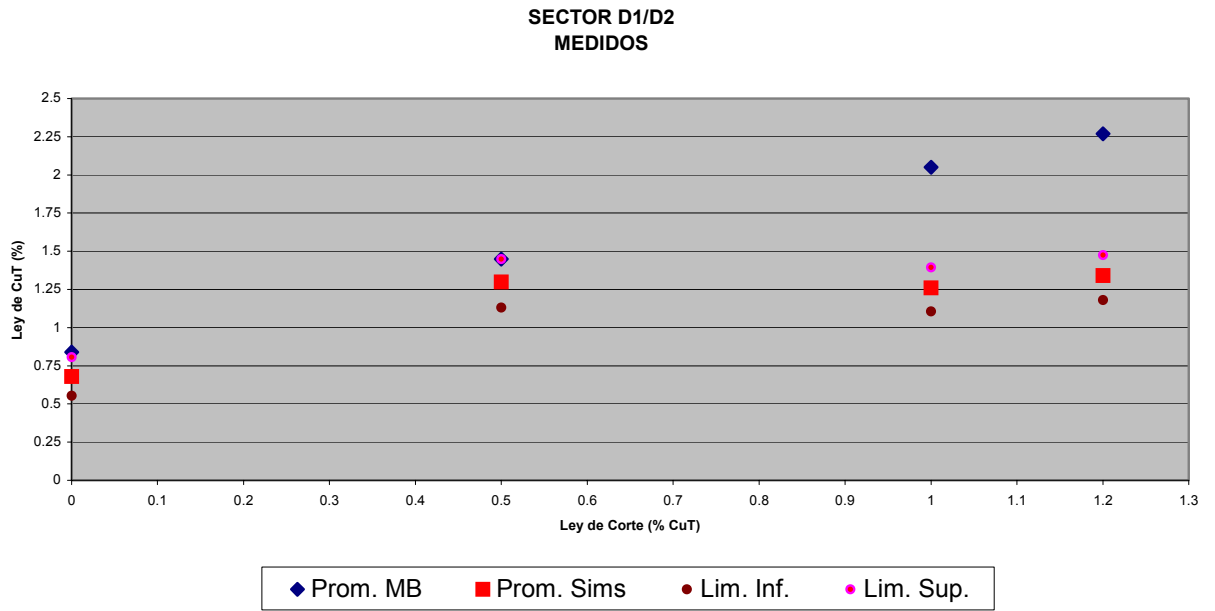


Figure 7(a): Measured Resources (Proven Reserves), Sector D1/D2 (Cut and Fill).

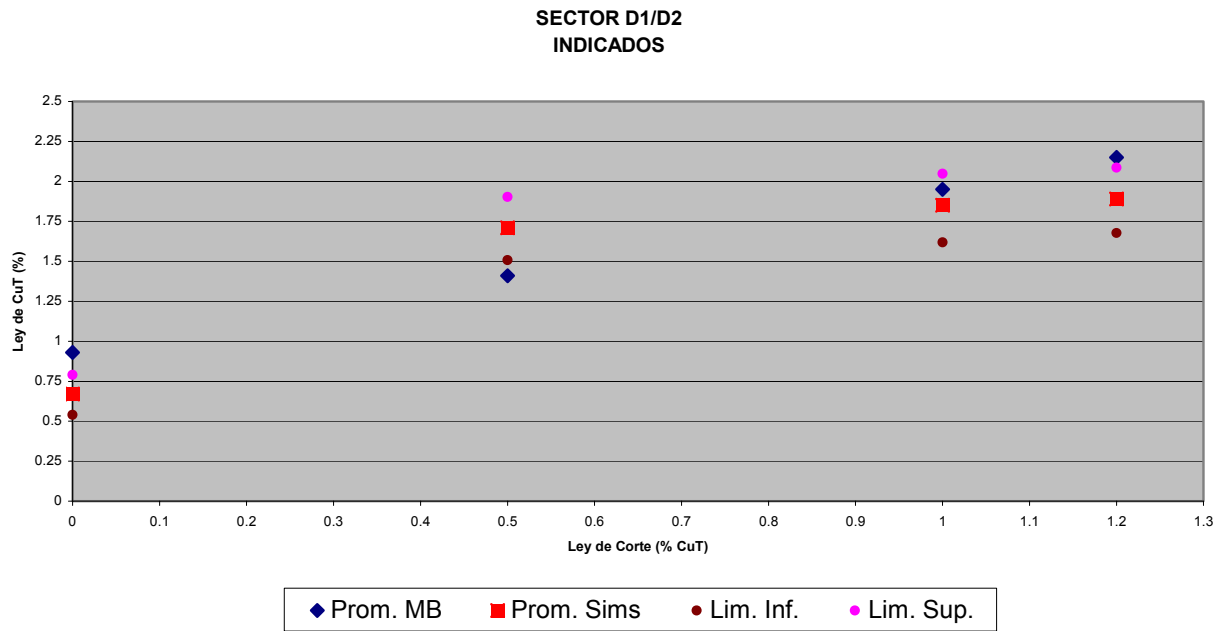


Figure 7(b): Indicated Resources (Probable Reserves), Sector D1/D2 (Cut and Fill).

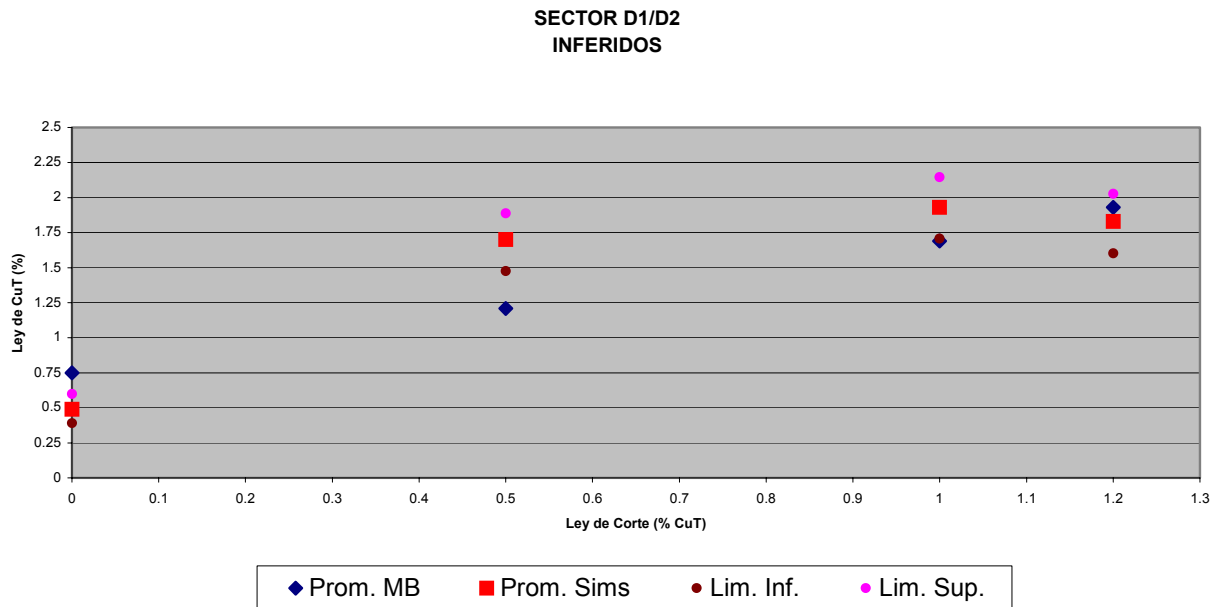


Figure 7(c): Inferred Resources, Sector D1/D2 (Cut and Fill).

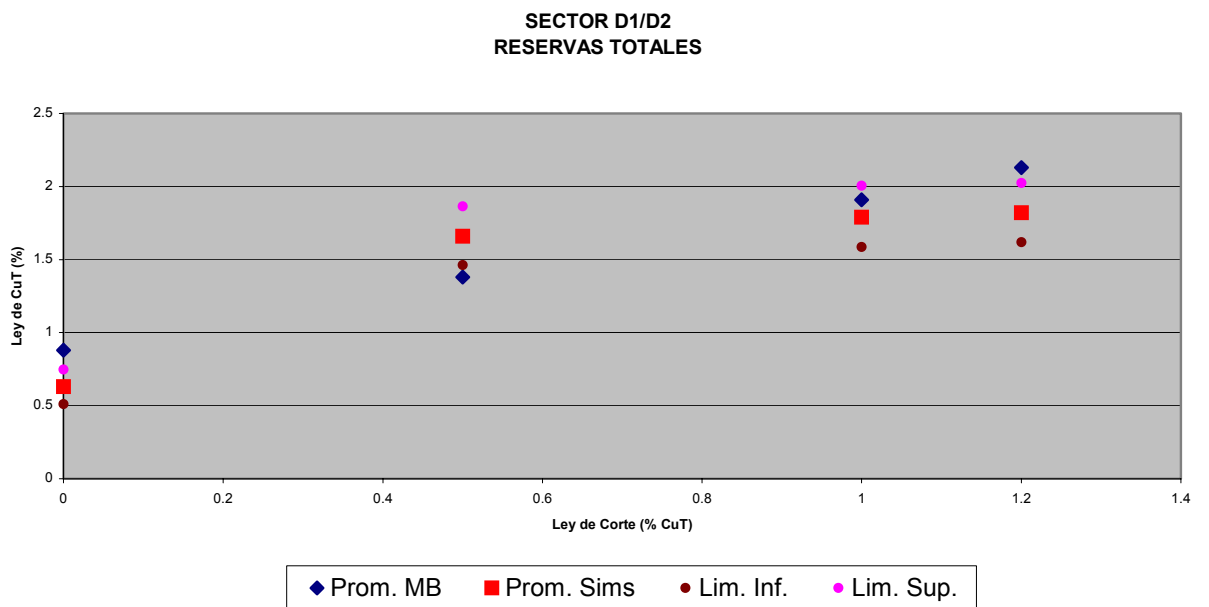


Figura 7(d): Total Resources, Sector D1/D2 (Cut and Fill).

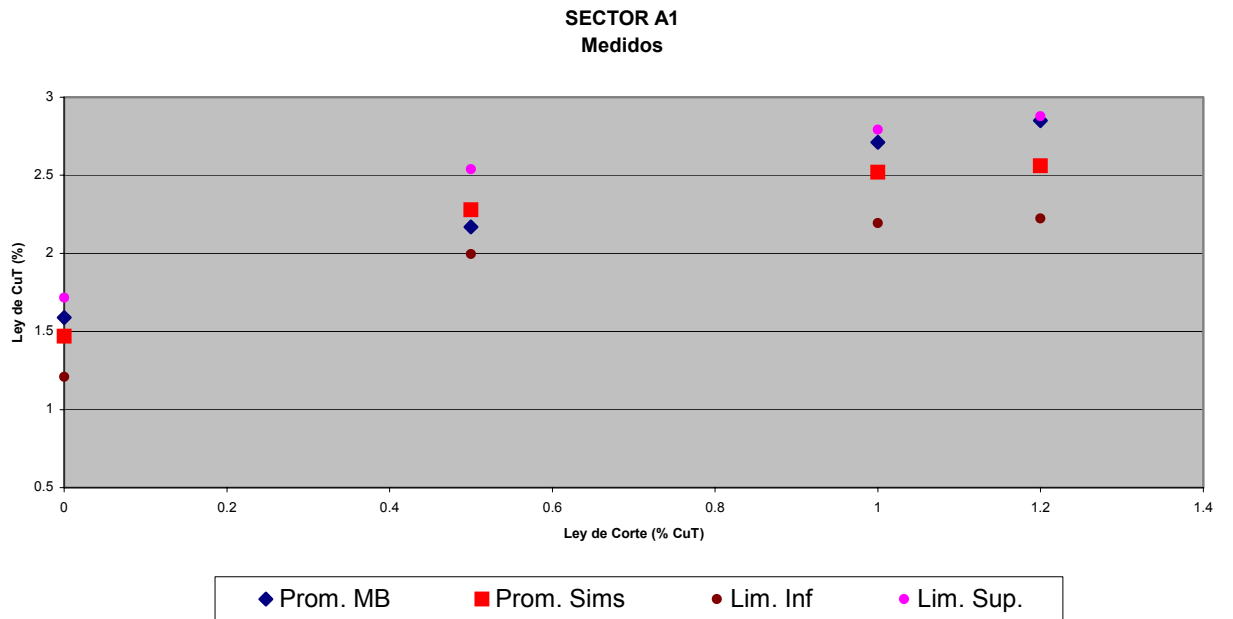


Figure 8(a): Measured Resources (Proven Reserves), Sector A1 (Cut and Fill).

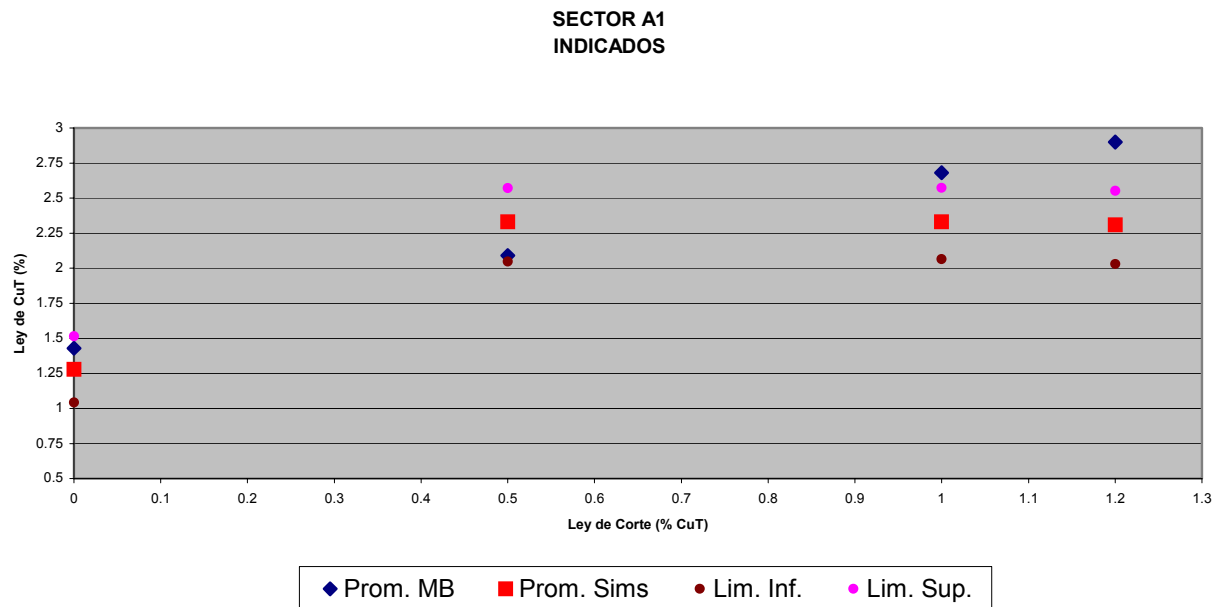


Figure 8(b): Indicated Resources (Probable Reserves), Sector A1 (Cut and Fill).

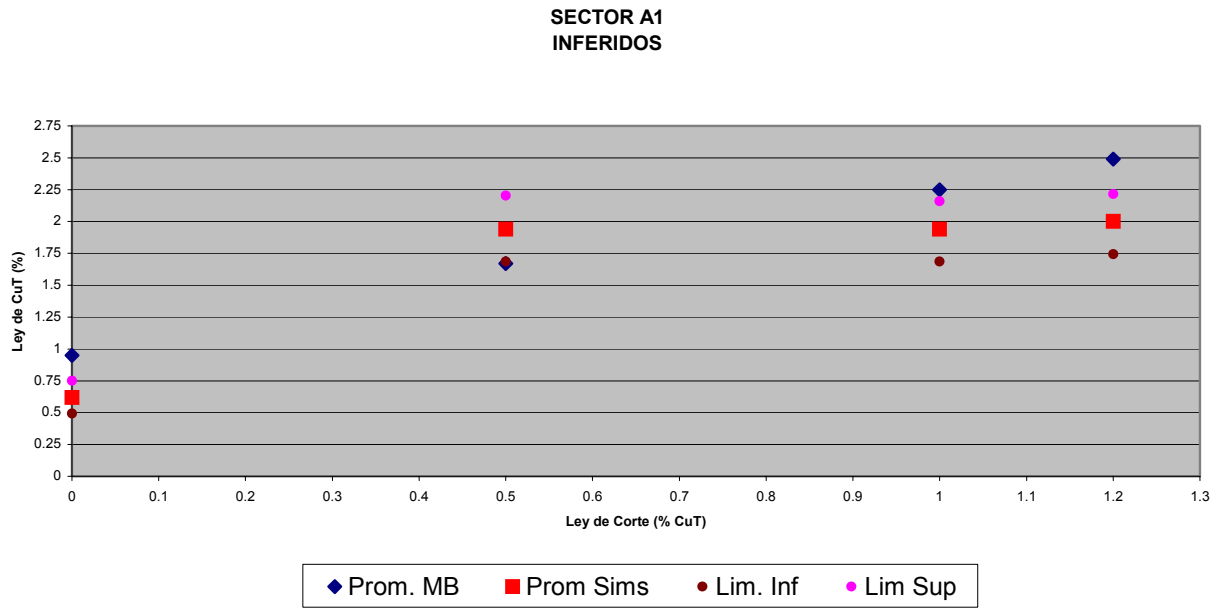


Figure 8(c): Inferred Resources, Sector A1 (Cut and Fill).

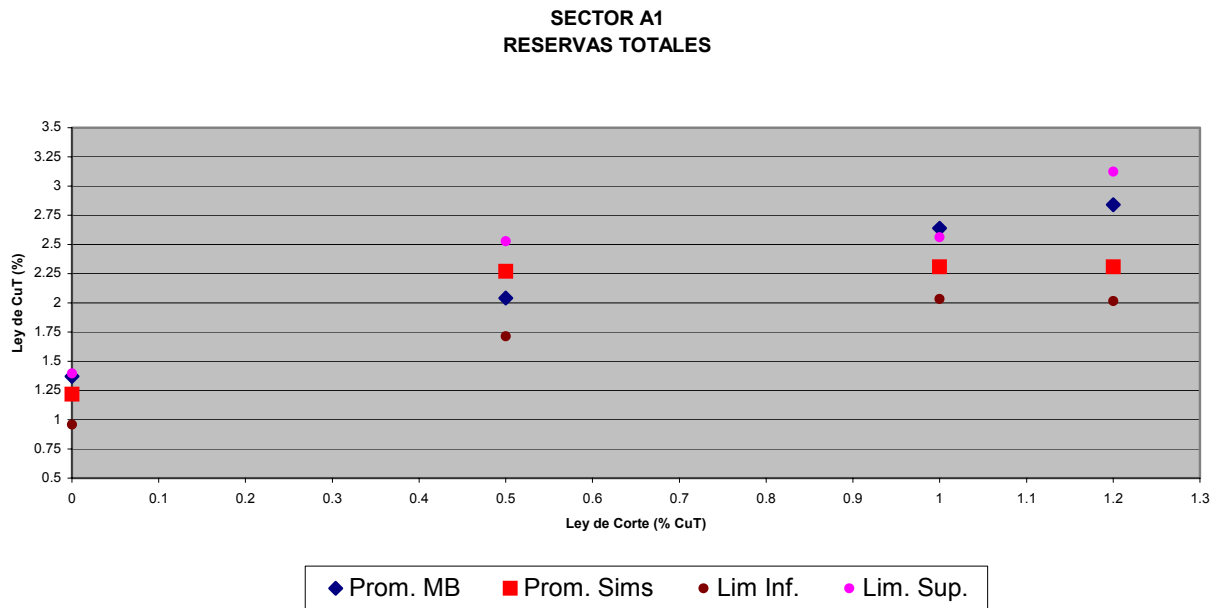


Figure 8(d): Total Resources, Sector A1 (Cut and Fill).