# A METHODOLOGY FOR DEVELOPING PREDICTIVE GEOMETALLURGICAL MODELS (PGMs) FOR PRODUCTION PLANNING. CASE: EXISTING COPPER CONCENTRATOR

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## ABSTRACT

A PGM is a quantitative analysis tool aimed at assisting planning teams to deliver objective and reliable mining production plans for a specific mine-plant complex.
This methodology comprises eight development stages:

1. Information gathering (geology, mining, and concentration)
2. Selection of representative samples
3. Laboratory testing program: design & supervision
4. Construction of Base Case simulators
5. Simulation of productive scenarios
6. Generation of TPH and recovery models
7. Geostatistical estimation of models' inputs
8. Model validation

Concentrator´s equipment, operational data, and physical constraints are collected. This information combined with suitable scaling software, such as JK SimMet and FlotSoft, allows the construction of simulation base cases for comminution and flotation circuits.

Industrial-scale simulations are ran using these base cases and laboratory results as inputs.

The simulation results (comminution and flotation) generate a database with candidate variables for model construction. The variables in the model should meet at least two requirements: be independent and estimable through geostatistical techniques.

Model inputs include variables related to mineral characteristics (specific gravity, comminution indices, and flotation results). These variables tend to be regular from a statistical perspective, following a Gaussian distribution, with low or no presence of outliers and minimal dispersion. Geostatistical speaking, there is a small nugget effect and extended estimation ranges facilitating the

estimation process, meaning that a much smaller number of samples is needed compared to the required number when estimating copper grade.

Considering past projects, this methodology has shown an unbiased average weekly error of 5%.

Finally, during the development of these models, it is possible to identify some bottlenecks allowing to assess/develop improvement projects to prevent future production drops that are not visible with current operational information.

## INTRODUCTION

Geometallurgy is a very wide mining related subject with multiple study areas and applications. This article will focus on one small area with practical implications for production planning. This article aims to introduce a methodology consisting of eight developing stages. Geometallurgy teams could follow the steps to end up with a predictive geometallurgical model (PGM) to be used by the planning teams to produce robust and traceable production plans in an existent copper concentrator.

The methodology uses best practices (or rational practices) for each developing stage, for instance for samples selection and laboratory testing. Also, the methodology uses well known metallurgical equations, metallurgical formulas, and process simulators software. The methodology could be considered as an auditable methodology and by extension, the PGMs are auditable as well.

A PGM allows the planning team to prepare robust and trustable production plans. Using the PGM to run/evaluate different mine plan scenarios could be used as an optimizing tool of the existent mine-plant complex.

This article will walk the reader through the development stages with the objective of understanding the rationale behind the methodology more than specific details.

## METHODOLOGY

The first stage of this methodology is collecting information of the mine-plant complex. First, the existent geological and mining information such as: deposit genesis, geology model, block model, and geological units (GU). Then, current mine plan and run of mine (ROM) particle size distribution are necessary. Finally, information regarding half (or quarter) existent drill core from previous drilling campaigns is requested. On the concentrator side, "As Built" information is requested, for instance: Flowsheet, equipment´s technical information (size or dimensions, installed power, nominal capacities, etc) as well as operational data from PI system (or similar), plant surveys, flotation conditions (pH, reagents formula, reagents dosage, rpm, air flow, slurry level, etc).

The second stage is dedicated to select variability representative samples to run some laboratory tests. The sample selection process requires a current mine plan and an agreement for the period used to develop the PGM, as well as an agreement on the minimum number of samples to be selected. As a reference, total number of variability samples range between one sample per million ton to 1 sample per two million tonnes. Also, normally a 5-year plan period in the future is a commonly used starting point. For this article a 5-year plan is used only as an example.

By intersecting the 5-year plan with the block model and the GUs it is possible to see the mass contribution of each GU in the 5-year plan. The blocks of each portion of GU in the 5-year plan allow to generate a grade histogram. There will be as many histograms as GU participating in the 5-year plan. The representative samples are selected according to the criteria that follows:

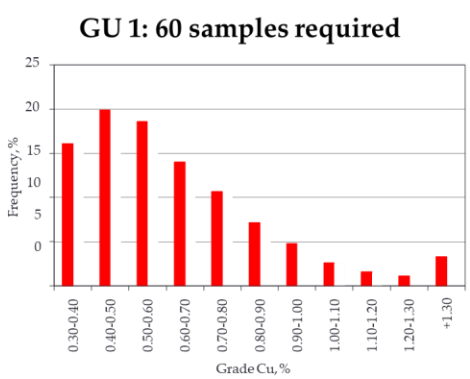
- The number of samples by GU should match the percentage of each GU in the 5-year plan
- The grades of representative samples should mimic the grade histogram by GU
- The samples within a GU should cover the whole volume occupied by the GU. In other words, samples should be taken in a way that prevent clustering
- The mass of each variability sample should be enough to run the laboratory testing program
- Minimum number of samples by GU should be 30

Examples of this criteria are explained in the flowing figures:

| Mass within mine plan, % | Identification | Number of samples |
|---|---|---|
| 20 | GU 1 | 60 |
| 25 | GU 2 | 75 |
| 55 | GU 3 | 165 |
| **100** | | **300** |

Table 1. Number of samples selected matching mass distribution criteria

Samples grades selection is explained using Graph 1




Assuming sixty samples for GU 1 obtained from mass proportion criteria, the histogram is used to selected grades, as follows:

Range Cu% 0.30 – 0.40: 60 x 0.16 = 10 samples

Range Cu% 0.41 – 0.50: 60 x 0.20 = 12 samples

Range Cu% 0.51 – 0.60: 60 x 0.18 = 11 samples

Etc.

Graph 1. Number of samples to be selected by grade range

In addition to grades criteria indicated in Graph 1, to prevent clustering, the samples should be selected from all possible regions within the GU volume of 5-year plan.

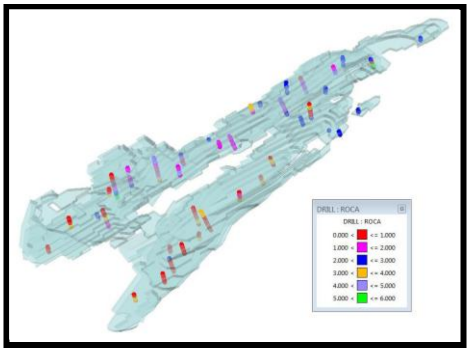



Figure 1. Example of spatial selection of samples within a GU

The third stage is the definition of a testing program and special protocols if required. The metallurgical test is defined by the process, as well as the software used to simulate/scale industrial results. It is important to remember that test results will be used as inputs to simulate feasible productive scenarios. In the case of a copper concentrator, the test program must follow the actual Flowsheet. Considering a typical comminution circuit, it starts with a gyratory crusher follow by a SAG mill, pebbles crushing and ball mills. Sometimes, the SAG mill is replaced by HPGR crushers. In these two examples, if the simulation software is JK SimMet for example, the comminution testing could be quite simple. A SMC and a Bond Ball Work Index could be enough to provide variability data results to feed the simulator. There are some occasions where a company uses a different simulation software, in those cases, it is necessary to understand which are the software´s inputs and which are the tests that provide those inputs.

In the case of flotation, there are different software to simulate/scale a flotation circuit, the authors use FlotSoft. The same principle used in comminution applies in flotation. The test program should follow the actual circuit and the lab test results should provide the inputs for the simulation software.

In the case of the flotation testing program, the flotation tests are executed under specific conditions (air flow, agitation, particle size distribution, reagents, etc) that emulate actual industrial circuit conditions. These protocols help make sure the test results reflect actual industrial results as close as possible. The results from these tests should provide the inputs for the simulation/scaling task.

The fourth stage is to build the base cases for comminution and for flotation. The base cases are built using the adequate software to mimic the actual circuits, one for the comminution circuit and another for the flotation circuit. The main feature of these base cases is that they were built using operational data from a long period of time (six months to one year) and consider all the equipment features that make the concentrator unique. For instance, equipment size, installed power, dimensions of mills, ball charge level, ball mills speed, etc. In the case of flotation circuit, flotation cells model and dimensions, rpm, air flow, etc. The base cases are finished when the results of the base case are very close to the industrial results at stream level and at general level. Also, as part of the methodology process, the plant operation team must approve both base cases before any simulation would take place.

Figures 2 is an example of what a comminution circuit looks like in a simulator software such as JK SimMet and Figure 3 is an example of what a flotation circuit looks like in a simulator software such as FlotSoft.

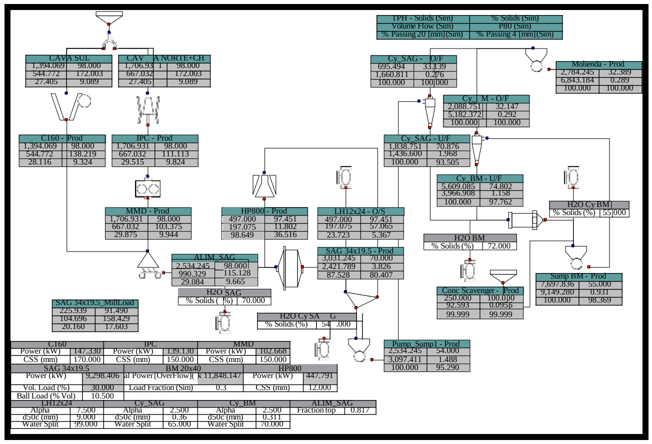


Figure 2. Comminution Circuit, Base Case Example

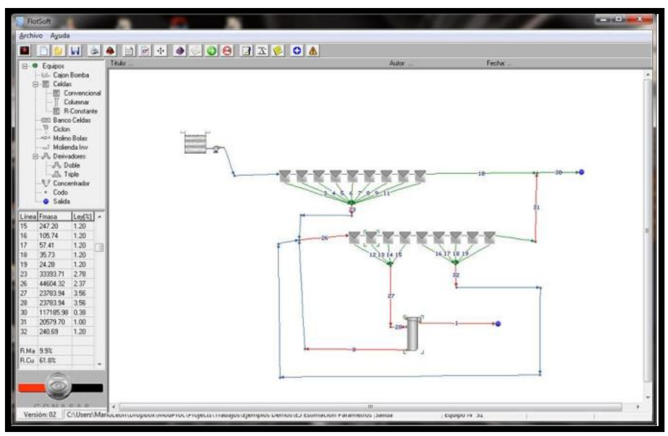
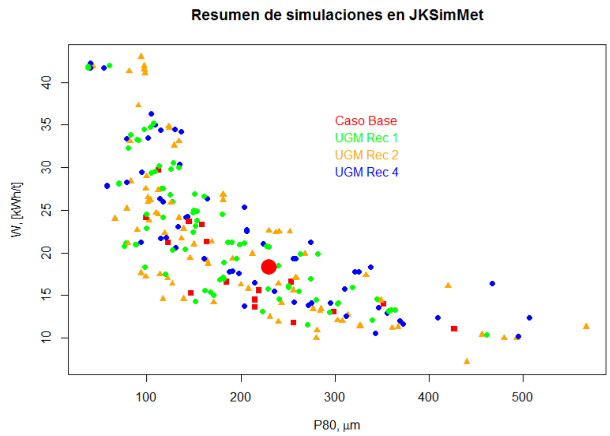


Figure 3. Flotation Circuit, Base Case Example

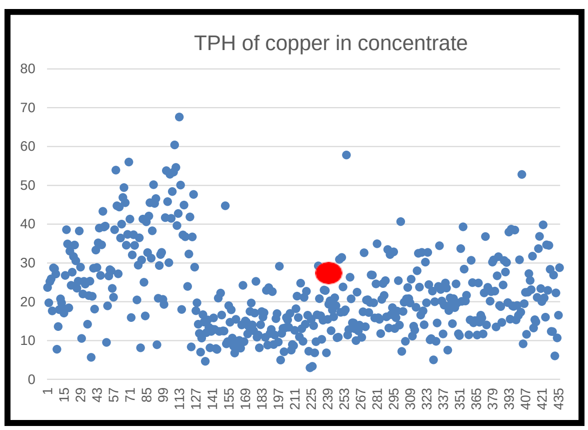
The fifth stage is the simulation of productive scenarios using each variability sample testing results as inputs over the base cases developed in the previous stage. The main idea is to simulate different productive scenarios by using each one of the representative samples. This simulation process is required for comminution as well as for flotation. The inputs are different with each sample. For instance, in comminution the SAG indexes are different for different samples or sometimes if the SAG indexes are similar the Ball Mill Index is different and vice versa, or sometimes when all indexes are similar, the specific gravity is different. The same happened in flotation simulations, different inputs are translated as different representative samples. It is very rare that two samples from different locations share the exact features.

The comminution simulations show consumed power by each equipment and particle size distribution by stream along the circuit, then it is possible to calculate the specific power consumption (SPC) as a function of P80 to flotation. Why is P80 chosen as a key variable? Because P80 is the link between comminution and flotation, also P80 is an operational control variable used in every concentrator, and P80 data is normally available for future conciliation process. Graph 2 shows a typical distribution of SPC vs P80.




Graph 2. Example of SPC *vs* P80

In the case of flotation simulations, it is very difficult to show an outcome with one variable since copper production or copper recovery are multivariable dependant. For flotation, the data results are more commonly handled as a table. However, to have an idea of what a graph of flotation results looks like, Graph 3 shows ton per hour of copper produced as concentrate in a flotation circuit by each representative sample at different P80.




Graph 3. TPH of copper as concentrate by sample

The sixth stage is the generation of predictive models, ton per hour of ore processed in comminution and copper recovery. Normally, the way to use these models is by selecting blocks from a block model and then adding the technical data contained in those blocks, therefore the model requires the use of variables that can be weighted averaged (also known as additive variables). It is accepted that TPH is not a variable that can be averaged. Therefore, the first predictive model requires a little reminder, the definition of SPC.

$$SPC\left(\frac{kwh}{t}\right) = \frac{Power\ (kw)}{Ton/H} \quad \text{Equation 1}$$

Since, SPC is considered an averaged variable, the way to obtain a TPH predictive model is to go through the generation of a SPC model. From equation 1 it is possible to see that:

$$\frac{Ton}{H} = \frac{Power\ (kw)}{SPC\ (\frac{kwh}{t})} \quad \text{Equation 2}$$

As a conclusion, once a predictive SPC model is obtained, TPH is calculated using equation 2 as follows. SPC model assigns (kwh/t) to each block, the weighted average from a group of blocks ($SPC_{wa}$) can be used to describe the hardness of ore processed in a specific comminution circuit at a specific P80. Usable power in comminution (UPC) can be determined from operational data, then TPH for a group of blocks could be calculated as follows:

$$TPH\ group\ blocks = \frac{UPC\ (kw)}{\text{SPCwa}\ (\frac{\text{kwh}}{\text{t}})} \quad \text{Equation 3}$$

For the recovery model, the situation is similar. Recovery is not considered an additive variable; therefore, it is necessary to find an additive variable and then use this additive variable to calculate recovery. In this case, the definition of industrial recovery is as flows:

$$Recovery\ (\%) = \frac{Ton\ of\ concentrate\ x\ Concentrate\ Grade}{Ton\ Ore\ Processed\ x\ Ore\ Grade} \quad \text{Equation 4}$$

From equation 4 is possible to see that ton ore processed (TPH) and ore grade (head grade, feed grade, etc.) are known. First TPH comes from equation 3 and head grade is information from the blocks. Therefore, if a model for copper produced in flotation can be generated from flotation simulations, then a predictive recovery model is also obtained.

$$Recovery\ (\%) = \frac{Model\ for\ Copper\ Produced}{Copper\ Fed\ to\ Flotation\ Circuit} \quad \text{Equation 5}$$

In this case, copper produced as concentrate in flotation is an additive variable, therefore as in the TPH model, copper produced by block as well as copper fed to flotation circuit can be both averaged and used in equation 5 to calculate Recovery.

How to generate both SPC and Copper Produced models?

Using simulations data, it is possible to create a matrix containing all variables that could explain the SPC or the Copper Produced by flotation. Statistics correlation help to uncover which are those independent variables that can be included in a predictive model. After selecting these variables, it is a matter of hard work, experience, and well know formulas and equations to find the relationship between variables that translate into a predictive model.

The seventh stage is geostatistical estimation of models' inputs. The most important regionalized variables studied in mining are grades. These variables exhibit significant spatial variability which require using tight grid spacing. In a gold mine, the maximum grid spacing is about 30 m, while in a porphyry copper mine, is in the range of 60 m. These variables are statistically characterized by a high coefficient of variation, a Lognormal distribution with the presence of high outliers, and a high variance, resulting in a coefficient of variation greater than 1.0. From a geostatistical perspective, the variograms have a short range and a significant nugget effect. Constructing a block model is challenging and requires careful consideration of the geological units within the deposit. Generally, mine-to-plant conciliation presents biases.

Besides grades, there are variables used in geometallurgy that need to be estimated, for instance: specific gravity (density), comminution indexes, and flotation indexes. These variables; however, are much more favorable to be estimated, exhibiting normal behavior with small coefficients of variation and little or no outliers, large estimation ranges, and almost negligible nugget effects. Wider grid spacing can be used compared to grid spacing for grades. Conciliation between block model data and concentrator is normally close and unbiased. Some examples of this type of behavior are shown in the next figures

Work Index (Wi): The figures show the variogram at a Chilean mine, along with a profile of the block model. The estimation range is about 500 m.

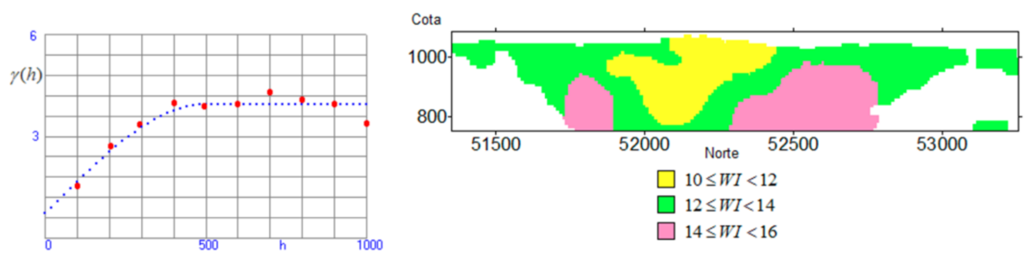



Figure 4. Wi estimation

Flotation Index: In this case, the histogram is close to a normal distribution, and the variogram has an estimation range of about 180 m.

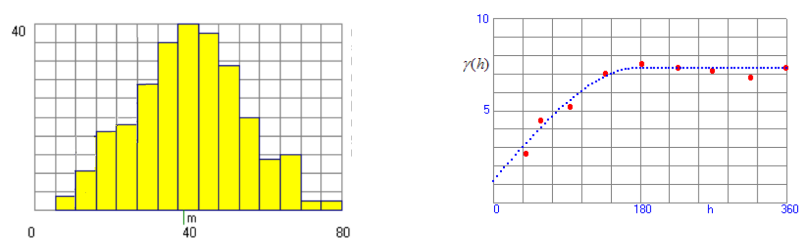
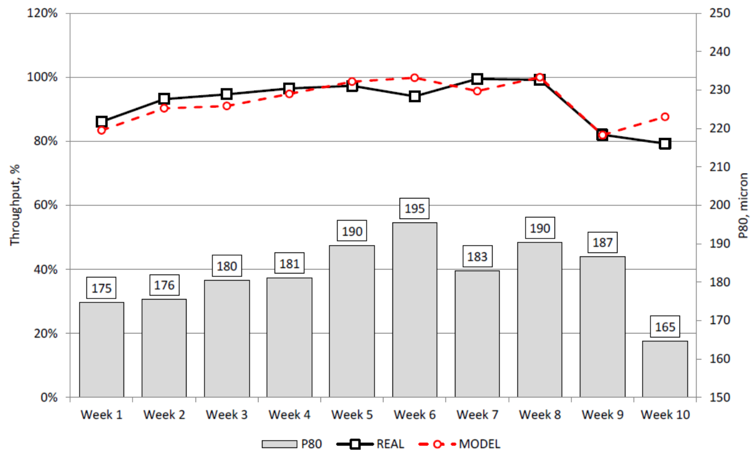


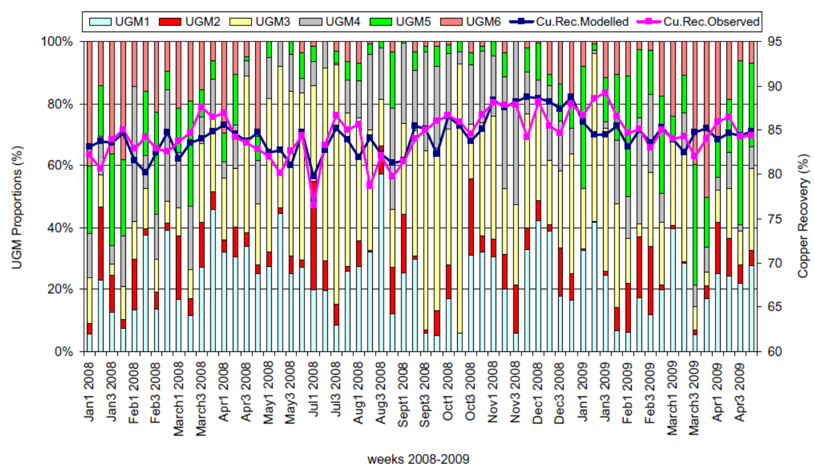

Figure 5. Flotation index estimation

The last stage of the methodology is the validation of predictive models. To validate the PGM is suggested run conciliation exercises in a weekly basis. Validation is the strongest argument to adopt and to trust these PGM. The variables included in the models are selected by statistics; therefore, a rational validation of the model´s fitting such as the conciliation process showing the actual deviation every week is the argument that will prevail over all others.

Some examples of conciliation exercises are presented in Graphs 4 and 5



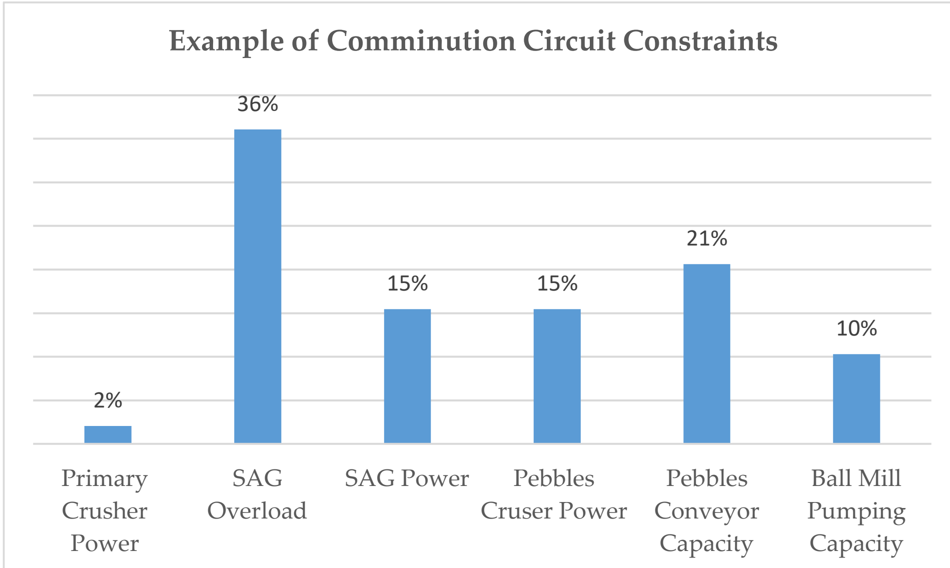

Graph 4. TPH conciliation Exercise, Caserones (2017).




Graph 5. Recovery Conciliation Exercise, Collahuasi (2009)

## ADDITIONAL REMARKS

During the process of generating these PGMs, it is possible to find some interesting and useful collateral information. For example, Graph 6 shows a statistical analysis of the comminution simulations results. The graph shows the times a simulation stopped because of a physical constraint (power, capacity, etc.). Organizing this information in a graph allows project teams to rank the projects that have the greatest impact on production or are the most efficient in capital usage.




Graph 6. Main Constraints Statistics After Simulation Runs

## CONCLUSIONS

This methodology allows to generate predictive models for TPH and Recovery to help planning teams to produce robust and auditable production plans.

Since the predictive models use variables that can be estimated by Geostatistics methods to block level, the planning team is able to examine different block arrangements and objectively define the best production plan.

Projects developed over the last 15 years show an unbiased deviation of 5% from actual results on weekly basis.

Collateral information during model development can be used to evaluate and rank improvement or debottlenecking projects.

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