Risk Analysis in Short and Medium Term Mine Planning

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Abstract

The planning and sequence of exploration of an area from a mining deposit in an underground environment consists of evaluating mineral reserves and scheduling their exploration. Parameters such as mining methods in use, productivity constraints, exploration and treatment costs, geomechanical and geotechnical parameters and economic parameters such as metal prices are accounted for in mining reserves evaluations and the risk or uncertainty associated with the reserves should take into account the uncertainty associated with these parameters, as in the quantification of resources (estimated grades of ore in the deposit). For this purpose, the present work aims to present a method where the most important parameters are considered random variables with probability distribution inferred from experimental data.

Keywords: Mine Planning, Holt Exponential Smoothing, Bench-and-Fill, Risk, Mining Reserves, NSR

1. Introduction

Exploitation of natural resources, namely the extraction and processing of raw materials in the mining industry such as metals, used for the production of commodities, plays a major role in the way society has been evolving to complex civilizations during the last centuries and that continues to be the trend.

Whilst there are good prospects for past, current and future demand for transformed mineral products, the mining industry faces sustainable challenges characterized as the "combination of enhanced socioeconomic growth and development, and improved environmental protection and pollution prevention", Hilson and Murck (2000). In addition to the social and environmental issues addressed, new technical and financial solutions might become necessary for companies to remain competitive, as the more the industry matures, the more minerals will come from lower grade ore bodies and sometimes in deeper and severe geological conditions.

With this situation in mind, the purpose of this work is to create a stochastic model of the reserves estimates and profit in a way that can be translated into a risk throughout the mine planning, linking geostatistics with financial analysis and providing important information to assist in a decision-making process to better act in future events.

2. Forecasting, Simulation and Planning

To access the sources of uncertainty in the mining industry and control the corresponding risk it is important to understand the fundamentals of forecasting and simulation and how it can be integrated into a mine plan before presenting the methodology used in the current work.

Forecasting Methods

Metal prices (together with knowledge of the structure of the ore deposit to be exploited) represent the factor with the greatest impact on the financial performance of companies in the mining sector, however, the unpredictable changes caused by the fluctuation in the demand for these materials, make this component uncertain and volatile. To analyse data in a simple way, univariate analysis is used and, in the cases where data types show fluctuation patterns around an average value, i.e., the data is stationary in their mean, methods such the Holt method can be used, Makridakis et al. (1998).

Holt (1957) proposed a method in which the forecast values generated could capture the trend of the data. This model, known as the Holt linear method, or double exponential smoothing, is based on two smoothing constants α and β, with values between 0 and 1, and the number of forecast periods, k, translated into three equations, of level - (1), trend (slope) - (2), and forecast - (3):

$$N_t=\alpha Y_t+(1-\alpha)(N_{t-1}+T_{t-1}) \quad (1)$$

$$T_t=\beta(N_t-N_{t-1})+(1-\beta)N_{t-1} \quad (2)$$

$$P_{t,k}=N_t+kT_t \quad (3)$$

For the forecasting method to be started, Sharif and Hasan (2019) point to the need of initialization of N_0 as the estimate for the level and T_0 for the trend. For the present work, assuming that the data of the prices to be predicted have a regular and slightly erratic behaviour, we take $N_0=Y_0$ and $T_0=Y_1-Y_0$.

Monte Carlo Simulation

Monte Carlo simulations are part of a computational method originating in the 1940s, developed by scientists who tried an alternative to the trial-and-error method, to solve a problem in the development of nuclear weapons at the Los Alamos National Laboratory. The general idea is to establish a model that generates random values from a variable with known probability distribution.

As a way of selecting the probability distribution for one variable when historical data is available, Thomopoulos (2013) proposes to use graphical methods such as Q-Q Plot, which consists of comparing quantiles of the data sample to be analysed with the specific theoretical probability distribution quantiles and observing the quality of fit of the data. Therefore, the author advises that we start by confronting the data with more common probability distributions, such as normal, exponential, lognormal, gamma, beta and Weibull.

Kolmogorov-Smirnov (KS) Test can also be used to compare a set of data with a reference probability distribution. As noted by Hassani and Silva (2015), KS Test is used to compare the empirical cumulative distribution function of the data, F_{obs}, with the theoretical cumulative distribution function, associated with the null hypothesis that the sample comes from the theoretical distribution, F_{exp}.

The variables to be simulated can be considered discrete, if the result set is in a list of possible values, or continuous when the variable takes on any value specified in a range. In the context of this work, the variables to be considered will be continuous and the inverse transform method will be chosen for generating values of a random variable, through a probability distribution. In this paradigm, taking x, a continuous variable in the domain [a, b], f (x) is called the probability density function. The cumulative distribution function of x, in domain [0,1], corresponds to equation (4):

$$F(x)= \int_{a}^{x} f(x)dx \quad (4)$$

Considering a number u, from a pseudo-random number generator between 0 and 1, which generates from a standard uniform distribution, u ~ U (0,1), it is possible to obtain the value of x through the inverse function of F(x), represented by equation (5):

$$x= F^{-1}(u) \quad (5)$$

Risk Analysis in mine planning

The Monte Carlo method can be used to assess the uncertainty of future estimates and allows the creation of plans that can mitigate possible risks. Rendu (2002), explains that the risk depends on the parameters that control the value of the project and the uncertainty with which these parameters are known.

The objective of risk analysis and management consists firstly on quantifying the uncertainty of a set of factors, characterizing which are the most important factors for the joint uncertainty and in realizing how they can reduce the uncertainties, and what improvements they bring to the value of the project.

Dimitrakopoulos et al. (2002) identify the tonnage and the expected metal content of the deposit to be exploited, as the main technical risk factors in a mining project. With regard to economic parameters, capital costs, operating costs and the price of metals are included as the main factors of uncertainty.

3. Methodology

All data used for the present work, except for metal prices, were obtained through the Neves-Corvo copper, zinc and lead mine that is owned by SOMINCOR (Sociedade Mineira de Neves-Corvo S.A.) which is a subsidiary of Lundin Mining.

The purpose of this work is to present a method that quantifies the financial risk of a mining investment decision, by calculating the probability distribution of profit distribution, that can be allocated to a tool that translates the performance of a project, Net Smelter Return (NSR). A diagram summarizing to this idea is shown in figure 1.

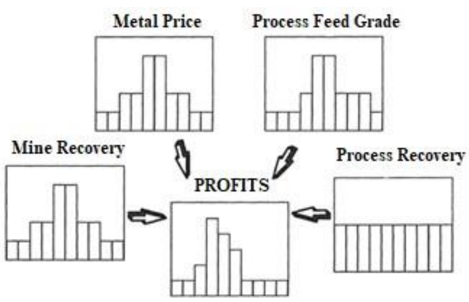

Figure 1 - Schematic representation for Monte Carlo simulations – Adapted from Armstrong M. (1994)

Zinc Price Forecasting

This next section describes the methods used for zinc price forecasting in the short-term horizon, i.e., up until 3 months in the future. For this work, a sample from the Federal Reserve Bank of St. Louis (FRED) comprising monthly prices from February 2006 up until February 2021 was chosen, as figure 2 shows.

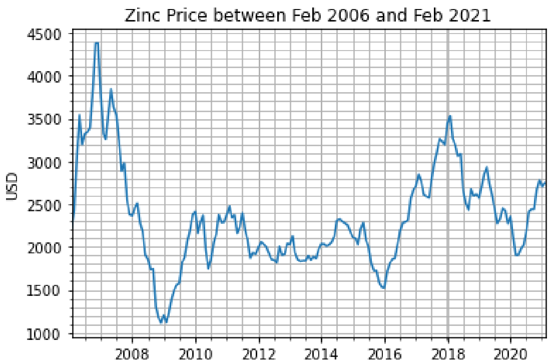

Figure 2 - Zinc Price between Feb 2006 and Feb 2021

In addition to the simple visualization of our dataset that indicates an evidence for stationarity, a test named Dickey and Fuller (DF) statistic was executed.

Using the *adfuller* function under the Statsmodels package in the Python programming language, gives the result of -2.67 for the test statistic and 0.08 for the p-value and comparing with a Dickey-Fuller table with critical value of -2.58, considering 181 observations, we can assume with more than 90% confidence that our data is stationary.

Using Holt's method with parameters $N_0 = 2219.725$ and $T_0 = 207.921$, the combination with alpha = 0.6 and beta = 0.7 was chosen as this was the iteration that gave the minimum error, MAPE = 9.658%, and whose values appeared to be best adjusted, as shown in figure 3 from January 2020 until May 2021.

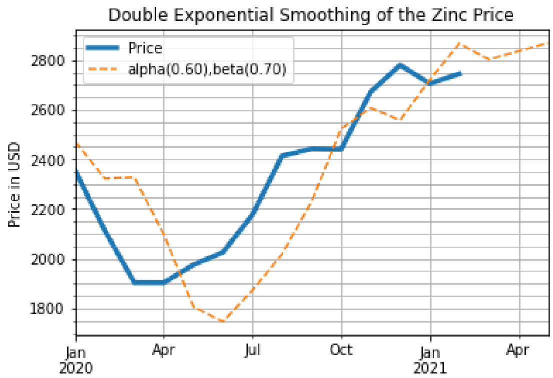

Figure 3 – Zinc Price Forecast

One might consider this to be a high-risk scenario as these predictions are pointing to high values of zinc. With that said, in a business environment it is crucial to consider the uncertainty associated with economic recoveries as some countries are still facing lockdowns due to the COVID-19 pandemic despite the vaccine rollout in developed countries and its possible migration to less developed nations give some optimism about a rebound in zinc demand. Also, as mentioned by the S&P Global, an almost 3% percent rise in zinc production to 14 million mt is expected this year, so, with such diversified information about the future, it becomes crucial to have sophisticated judgments of experts in order to adjust current trends for anticipated changes, Eggert (1987).

Mining Recovery

In mine exploitation, considering a specific area of production, not all the material considered as valuable by the mine planning is extracted. That proportion between the actual quantity extracted and the quantity planned to be extracted is defined as the mining recovery.

Data analysis was carried out using a sample from 17 observations from different areas of the

Neves-Corvo mine where the underground mining method Bench-and-Fill was used.

The estimation of the cumulative distribution function (CDF) of the mining recovery variable can be achieved plotting the graph of the empirical CDF given by equation 6, on the y axis against the actual sample values on the x axis. Fitting an equation to the graph, generating pseudo-numbers from a standard uniform distribution and, then using equation 5 to the best fitted equation of the CDF generates a random number from the CDF. Figure 4 shows the CDF of the mining recovery and its respective best fitted equation.

$$F[x(i)]=w_i=\frac{(i\text{-}0.5)}{n},\ i=1\ to\ n \qquad (6)$$

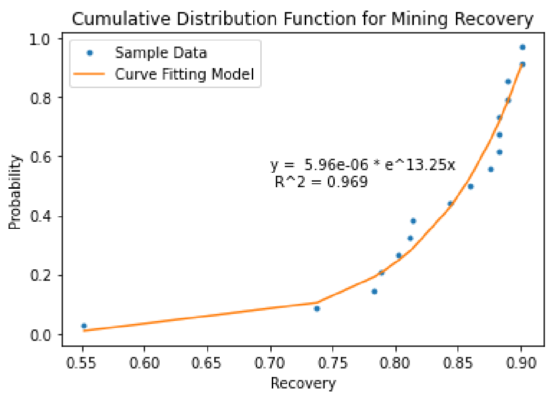

Figure 4 – CDF for mining recovery and respective equation

Zinc Head Grade

Taken as one of the riskier factors in a project valuation, head grade can be viewed as the quantity of metal present in the material entering the processing plant during production. When the mine is still in its pre-feasibility and feasibility stages, grade distribution becomes a factor of great uncertainty as our knowledge of the deposit characteristic is limited. As pointed by Rendu (2002), reducing this uncertainty can be accomplished taking additional sampling as well as finding geostatistical methods that use simulations to model the grade distribution within a deposit.

Due to the lack of data necessary to use geostatistical methods to model grade distribution of the deposit, an alternative to model this uncertainty was necessary using the actual values of head grade entering the zinc processing plant and modelling their uncertainty. For that purpose, 59 observations of head grades feeding the Zn processing plant of the Neves-Corvo mine were obtained.

Using graphical methods as proposed by Thomopoulos (2013) and observing the quality of fit of the data with a normal distribution, with parameters mean and standard deviation the same as the sample, we can conclude that our assumption is valid, as figure 5 shows that the line is close to the line intercepting the lower left part of the graph through to the upper right side with coefficient of determination equal to 0.984.

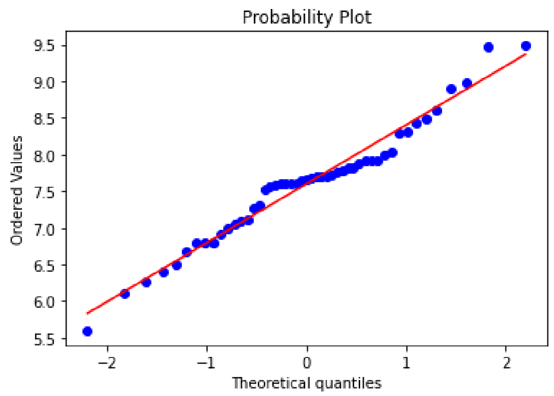

Figure 5 - Probability Plot using the normal distribution

Taking forward our assumption that the data comes from a normal distribution, using the *kstest* function from the *stats* model in Python the KS test attributed a test statistic of 0.1349. Comparing with the critical value of approximately 0.174 from a KS test table, as the test statistic is less than the critical value, we can accept with 95% confidence (α=0.05) that our data comes from a normal distribution.

Profit Risk Assessment

Various works on ore valuation using NSR have been carried out throughout the last three decades, Annels (1991), Hustrulid (2013), Wills and Finch (2016) all of which agree that this concept was created in polymetallic base-metal mines to describe the revenue received from the smelter for the concentrate produced, Bargmann (2000), Goldie and Tredger (1991). However, they differ in accounting for commercial costs, as some include smelter deductions, treatment and refining costs as well as distributions costs on the NSR calculations like Goldie and Tredger (1991), while others take into account only smelting and refining charges ignoring costs such as freight and insurance, Hustrulid (2013).

Adopting Goldie and Tredger (1991) approach NSR can be related to Gross Revenue and Commercial Costs as in equation 7:

$$NSR = Gross\ Revenue - CC \tag{7}$$

Gross Revenue can in turn be defined as the product of the price of metal and the quantity of concentrate produced in the processing plant, as equation 8 shows:

$$Gross\ Revenue = Metal\ Price * Quantity\ of\ Metal \tag{8}$$

Additionally, quantity of metal can be defined, as in equation 9, by the product of the tonnage of mine, the grade z(x), the mining and processing plant recoveries. The operational margin of mine can be attained subtracting the NSR, also known as net revenue, from the operational costs as equation 10 shows.

$$Quantity\ of\ Metal = Ton * z(x) * MR * PR \tag{9}$$

$$Operating\ Margin = NSR - Operating\ Costs \tag{10}$$

Finally, it is important to define the concept of cut-off grade which is the minimum amount of metal that one ton of material must contain before this material is sent to the processing plant, Rendu (2014), helping distinguish ore from waste, seeing as the former profitable to exploit while the latter it is not. For this work equation 11 relating the Production Costs (PC) with the metal price, mining and plant recoveries (MR and PR respectively) and the NSR in percentage, was used to evaluate this parameter.

$$Z_0 = \frac{PC}{Metal\ Price*MR*PR*NSR} \tag{11}$$

A value of 0.5 was used for the NSR in equation 11, as Wellmer et.al (2008) presented as a typical value for a Zn mine return. Goldie and Tredger (1991) defined this value as mine netback given, as the ratio of net revenue to gross revenue, and presented a typical Canadian mine netback of 43%. The selection for the former instead of the latter comes with the assumption that Wellmer et.al (2008) achieved this result with studies conducted more recently and with more updated data. More importantly, this choice of taking mine netback constant instead of calculating on a weekly basis, as achieved by the Monte Carlo simulations is justified by the fact that the commercial costs were taken as part of the General and Administrative (G&A) costs as more precise data on Commercial Costs was not available.

Using the ratio between net revenue in equation 7 and gross revenue in equation 8 gives the NSR variation in percentage. Figure 6 illustrates these results, for the next three months, in a scenario where it is expected that the zinc metal prices continue to soar, as figure 3 shows. For the calculation of the gross revenue using equation 8 it was used the zinc price forecast using the Holt's method with parameters alpha = 0.6 and beta = 0.7 for the months of March, April and May being 2802.713 USD, 2835.642 USD and 2868.572 USD, respectively. Then, for the calculation of the quantity of metal in equation 9, processing plant recovery was kept constant at 80% and the values of mining recovery and zinc head grade are each of the simulated. Finally, the value of tonnage of mine is the one that produces one tone to be milled.

It can be observed that the values of mine netback are in range of around 93% to 98%, due to the lack of precise data in transportation, freight, insurance and marketing costs that make up the commercial costs. The rule of thumb when dealing with a zinc concentrate NSR is to establish the mine netback in values around 50% as noted by Wellmer et.al (2008).

Keeping the value of mine netback to 50%, calculations of possible cut-off grades for the next three months were achieved as the results in figure 7 show. From that, no increasing or decreasing pattern is found over time and is also notable that a high density of values is less than 6% of grade. Taking into account the information above it is essential that the uncertainty in the NSR calculations and cut-off grades are integrated in the creation of mine plans to better access the risk in the decision-making process, by incorporating ways to reduce this risk and maximizing mining profits.

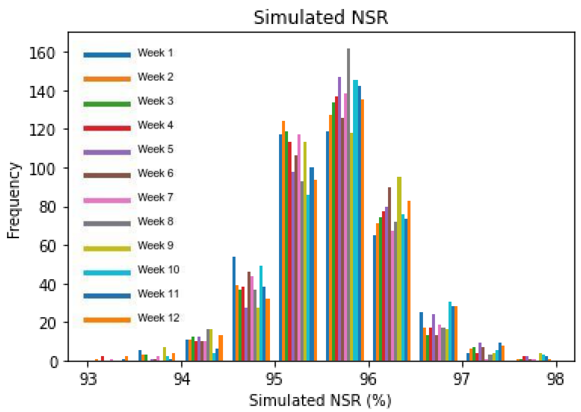

Figure 6 -Simulated NSR in percentage

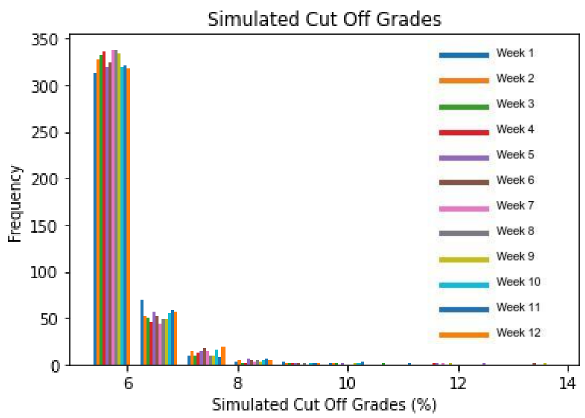

Figure 7 -Simulated Cut-Off Grades

4. Conclusions

The first major accomplishment of this work was to present a methodology that quantifies the financial risk of a mine planning decision, represented by the probability distribution of the NSR, which was the chosen parameter to quantify the performance of the exploitation of determined area of an orebody.

Future metal prices were forecasted in a short-term horizon (3 months) using a dataset of the monthly prices, representative of the global market from the last 15 years. Holt's method achieved the best predictions, coinciding with the underlying trend for the most recent observations.

Fitting the mining recovery data distribution with an exponential equation and performing Monte Carlo simulations using the inverse transform method, resulted in a distribution function that quantifies the mining recovery uncertainty.

As no model of the orebody was available, samples of the zinc head grade were obtained and the probability distribution of the data was assertively assumed to have a normal distribution.

Using the forecasted and simulated results, two models were created: one model of the percentage NSR (mine netback) and another for the cut-off grades that can be quantified in a risk throughout the timeframe of the mine plan. Values of zinc cut-off grade in the range between 5% to 6% are the most expected using 50% NSR and not accounting for dilution.

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