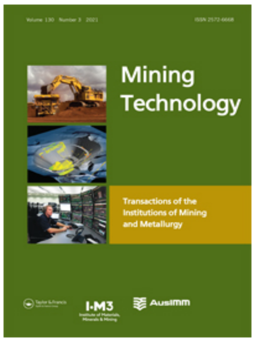


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Mining Technology
Transactions of the Institutions of Mining and Metallurgy

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ymnt21

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**To cite this article:** Pedro Henrique Alves Campos, João Felipe Coimbra Leite Costa, Vanessa Cerqueira Koppe & Marcel Antônio Arcari Bassani (2021): Geometallurgy-oriented mine scheduling considering volume support and non-additivity, Mining Technology, DOI: 10.1080/25726668.2021.1963607

**To link to this article:** https://doi.org/10.1080/25726668.2021.1963607

Published online: 12 Aug 2021.

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MINING TECHNOLOGY
https://doi.org/10.1080/25726668.2021.1963607

# Geometallurgy-oriented mine scheduling considering volume support and non-additivity

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**ABSTRACT**
In mine planning, metallurgical recovery is traditionally estimated in each block as a fixed value or a function of the block's primary geological attributes. Nevertheless, this variable has two characteristics that are often neglected. First, it is non-additive, which means that estimation and scaling procedures of such properties cannot be done based on linear techniques. Second, it is a process response variable, which means this variable value represents the response of the volume processed at the plant. The combination of these two properties results that the metallurgical recovery of each block is dependent on the blocks that will be mined and processed together with it at the plant. This paper demonstrates the difference between how metallurgical recovery is traditionally considered in mine planning, and how it should be. There are impacts on mine scheduling/blending, global metallurgical recovery estimation (total quantity of metal recovered) and total economic value.

**ARTICLE HISTORY**
Received 28 April 2021
Revised 14 June 2021
Accepted 28 July 2021

**KEYWORDS**
Mine planning; mine scheduling; metallurgical recovery; non-additivity; volume support

## Introduction

### *Mine planning*

Commonly, one of the main objectives of mine planning is developing a production schedule that maximizes the project's Net Present Value (NPV), subject to technological, operational, environmental, legal, and social constraints. Usually, the mineral deposit is represented by a set of regular three-dimensional blocks (mining blocks), each one of them containing estimated geological information such as grade, density, lithology, alteration, among others. These intrinsic rock properties are termed primary variables (Coward et al. 2009) and are often estimated through geostatistical techniques from drill-hole data.

In metallic mines, the ore is seldom mined in an acceptable form to be sold and used by different industries. Therefore, ore processing must concentrate the valuable metallic product and clean it from deleterious elements. A response variable measures the material response to a specific process. Metallurgical recovery is the response variable that measures the metal concentration process efficiency and, as well as geological variables, it is also estimated in each mining block. Traditionally, the metallurgical variable value is considered constant for every mining block in a particular domain or is estimated as a function of the primary geological attributes of each block, such as its grade.

Other variables can be assigned to each mining block, such as economic variables, e.g. commodity price and mining and processing associated costs. Along with the geological, process, and economic variables, the profit of mining and processing each block can be assessed through the economic benefit function. Mine planners use this economic benefit as a guide to define the block schedule, the order in which they should mine each block. Usually, the economic high-value blocks are mined before the low-value blocks. The idea is to obtain the highest revenue quickly to improve the project's NPV.

Besides aiming at optimizing economic value, short-term mine planners also seek the best operational efficiency. They are concerned with blending different blocks to provide material with specific characteristics to the processing plant with minimum possible variability. Blending can also cause an increase in mineral reserves. A particular lithology may not have the adequate characteristics to be processed alone, but it may reach the desired quality restrictions mixed with other lithologies. For example, in an iron ore mine, a lithology containing low Fe grade can be processed when combined with a high Fe grade one (Gomes et al. 2016).

Although scheduling is performed on individual blocks, mine operations do not extract blocks individually (Rossi and Deutsch 2014). The ore volume sent to the processing plant consists of several blocks mixed. This mixture partly occurs during the drilling and blasting operations. More mixture may occur if the blocks are sent to a stockpile before going to the

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processing plant or intentionally blended in short-term mine planning. The mill feed typically represents a blend of ore from multiple locations and sources (Wambeke et al. 2018). Dealing with mixtures of additive properties is not problematic, but that is not true with non-additive properties, which is presented next.

## Metallurgical recovery

Geometallurgy is the integration of geological, mining, metallurgical, environmental, and economic information into spatial models through geometallurgical variables (Dowd et al. 2016). Metallurgical recovery is a geometallurgical variable, historically inputted in the spatial mining blocks as a constant mean value of the processing plant's efficiency. As geometallurgy knowledge progressed, it has been clarified that geometallurgical variables are related to the interaction among geological/physical/mineralogical/chemical properties and industrial processes (Lishchuk et al. 2020). Hence, estimation of metal recovery based on chemical assays or quantitative mineralogical information became more common (Lishchuk and Pettersson 2021). A function which relates the process variable with primary-geological variables is a regression model. The grade-recovery regression plot is often used to display the metallurgical grade-recovery relationship (Dunham and Vann 2007).

Metallurgical recovery, however, has two characteristics that are often neglected when inputting it as a value to each block in mine planning. First, it is a non-additive variable. A variable is additive when it can be linearly averaged and scaled up, such as grades. For instance, consider the mixture of two blocks with one tonne of weight each and Au grades of 1 g/t and 2 g/t, respectively. The upscaled mixture of the blocks would result in two tonnes and an average Au grade of 1.5 g/t, the linear average of the individual blocks' grades. When a variable is non-additive, the average value for a mixture differs from the linear average of individual blocks. Consequently, linear scaling up and estimation techniques applied to this type of variable may result in biased averages.

The second characteristic is that metallurgical recovery regression models consider the volume or support in which the metallurgical recovery has been measured, the volume of several blocks processed by the processing plant. This ore volume processed is referred to here as 'feed volume'. Applying the regression model to a support which is different from the support used to build the model may lead to error and bias (Dunham and Vann 2007).

These two characteristics present a challenge for the traditional methods of mine scheduling. Mine scheduling algorithms require a metallurgical recovery value for each block. Nevertheless, the true metallurgical recovery depends on how the blocks will be mixed during the processing. And this mixture depends on the mine scheduling/blending, which makes the problem recursive.

Several authors have investigated geometallurgical modelling at block support (Dunham and Vann 2007; Bye 2011; Newton and Graham 2011; Dominy et al. 2018), how mine planning could change if geometallurgical models were considered (Bye 2011; Del Castillo and Dimitrakopoulos 2016; Morales et al. 2019), and how to integrate geometallurgical uncertainty into scheduling (Navarra et al. 2018; Sepúlveda et al. 2018; Kumar and Dimitrakopoulos 2019). Nevertheless, all the authors assign metallurgical recovery values to each block, which assumes that each block is processed alone. As ore processing occurs upon the feed volume support, the impact of support and non-additivity in mixtures of blocks should be considered. The metallurgical recovery value assigned to each block may either decrease or increase depending on how it is mixed with other blocks. The blocks mixed are the ones close to each other along with the mine scheduling. Wambeke et al. (2018) recognize that geometallurgical block estimates are inaccurate and propose an algorithm to adjust them based on mill observations. In this paper, we acknowledged this issue and evaluated the impact of mixing non-additive metallurgical recovery in mine planning.

In Section 2, an illustrative example is used to demonstrate that applying the regression model to the block support provides different results than that using it to the feed volume. When applying it to the feed volume, different schedules/blendings result in other metallurgical recoveries for each block, leading to different global metallurgical recoveries (quantity of metal recovered after processing all blocks) and different economical values. This situation is what we refer to as the recursive character of the problem.

In Section 3, an application example is used to evaluate the non-additivity and support impacts in mine planning when three aspects are considered: (i) distinct support differences between block and feed volume; (ii) different regression models; (iii) two primary geological variables not linearly associated with metallurgical recovery. Also, a comparison between the traditional approach of populating metallurgical recovery value and its scheduling is compared against a novel approach. The conventional process starts by filling a block model with metallurgical recovery values at the block support. Then traditional optimization and mine scheduling algorithms are applied to this block model. The novel approach consists of an iterative procedure (remember, it is a recursive problem). A possible block scheduling is performed, followed by upscaling the additive variables according to the feed volume. We use the proper

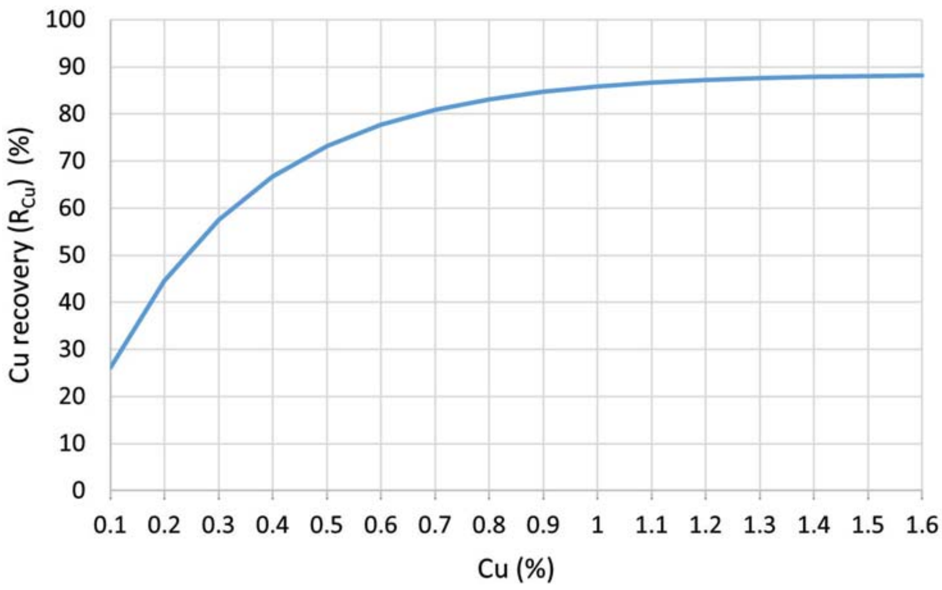


**Figure 1.** Regression model: copper recovery prediction based on the ROM elemental copper grade. Images are available in colour online.

regression model on the upscaled additive variables to obtain the metallurgical recovery at the feed volume support. Then, the result of this scheduling is assessed. Some other possibilities of schedules are run until a considered optimal one is found.

In Section 4, we discuss the results of the example presented, highlighting how to better consider metallurgical recovery in mine planning.

## Demonstration example

### *Regression model applied on block volume vs. feed volume support.*

To demonstrate that the regression model should only be used at the feed volume and not at the mining block support, consider the following hypothetical example. In a copper mine, there is only one processing route, in which copper recovery ($R_{Cu}$ (%)) can be estimated from Run of Mine (ROM) elemental copper grade (Cu (%)) by Equation (1), visually shown in Figure 1. This regression curve is not fictitious; it is a real estimated copper recovery model from a copper mine in Brazil (Wheaton Precious Metals 2019), used here to bring truth likeness to the example. Note that the relationship between recovery and grade is not linear (not additive).

$$R_{Cu}\ (\%) \;=\; 88.5 \times (1 - \exp(-3.5 \times \ \mathrm{Cu}\ (\%))) \quad (1)$$

For our example, feed volume consists of one tonne. Four ore blocks are mined in sequence and

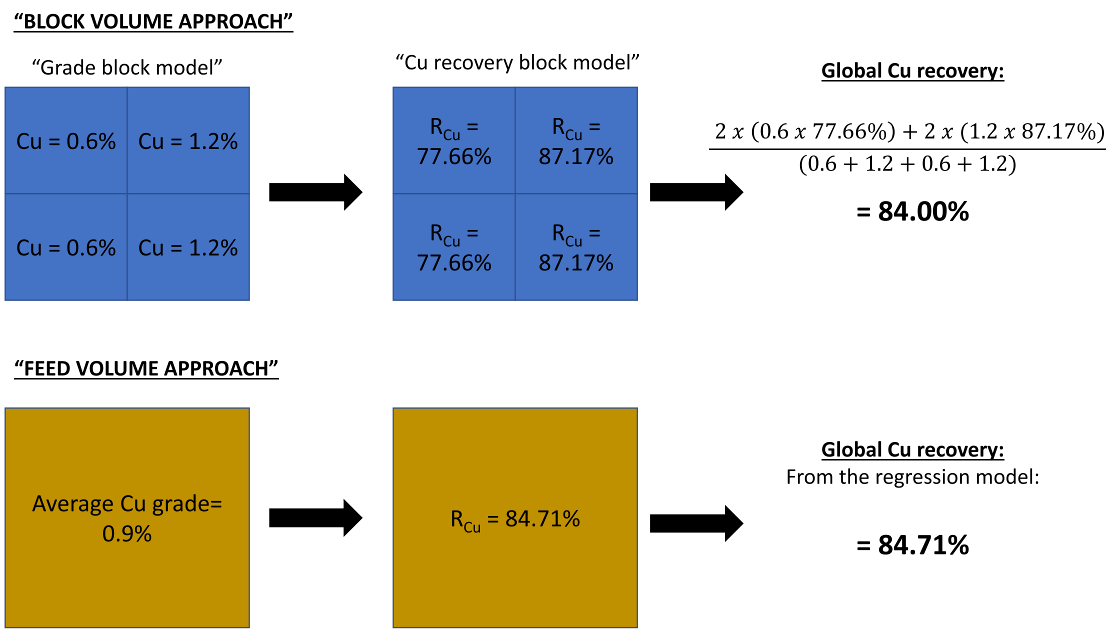


**Figure 2.** Differences in how to apply the recovery curve prediction. Images are available in colour online.

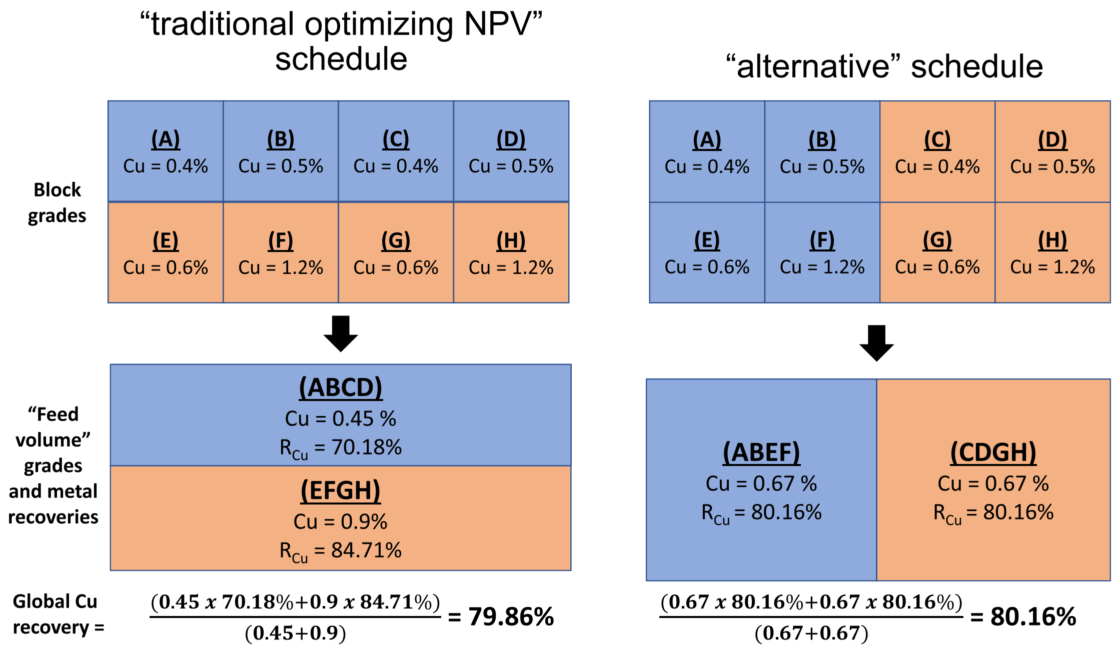


**Figure 3.** Different mixtures yield different global metal recoveries. Images are available in colour online.

processed (Figure 2). We considered that the four blocks have different copper grades but the same 0.25 tonnes of ore mass. 'Block volume approach' is the traditional application of the regression model (Equation 1) to each block grade, which results in four estimated copper recovery values. The mean copper recovery after processing all blocks (global copper recovery) is 84.00%.

Now, consider the 'feed volume approach' in which the four blocks are mixed, resulting in an average copper grade of 0.9%. Applying the same regression model on the mixed copper grade would result in a global metallurgical recovery of 84.71%, 0.71% more in global Cu recovery. From an economical and mine scheduling optimization perspective, each of the four blocks used to compound the mixture would have 84.71% of Cu recovery.

The most accurate approach is the second, as it mimics how the ore is processed in the mine operation. Once the ore arrives at the plant, there is no longer any perception of a block but rather a blend of extracted material (Del Castillo and Dimitrakopoulos 2016). Deutsch (2015) demonstrated that even when the ore is fed in batches to the processing plant, there is enough mixing of the materials such that mixture properties will dictate the process outputs more than the properties of any single block.

Therefore, as metallurgical recovery is a non-additive variable, metal recovery should be estimated based on the average grade of the feed volume (an upscaled mixture of blocks), which differs from that assessed for each block individually. Process responses set on a block-level may lead to erroneous recoveries. These differences in recovery estimation can significantly impact mine scheduling, global metal recovery, and total economic value.

## Regression model applied on feed volume and its impacts on schedule

Applying the regression model in the feed volume support rather than in the block support can change the 'best' block scheduling, impacting global metal recovery and economic value. Consider that the feed volume equals the volume of four blocks, each one weighing the same. For the eight blocks in Figure 3, two mixtures are to be processed one after another in the same period. In the 'traditional optimizing NPV' schedule, the high-grade blocks are mined before the low-grade blocks. Therefore, block E will be blended and processed together with blocks F, G, and H. The next feed volume is the mixture of the four remaining blocks (A, B, C, and D). The ABCD mixture has an average copper grade of 0.45%, which results in a metal recovery of 70.18% by applying the regression model. The mixture EFGH has 0.9% of copper, resulting in a recovery of 84.71%. After processing all blocks, global copper recovery is 79.86%. However, if scheduling changes and block A is mined and blended with blocks B, E, and F, as shown in the alternative schedule, the mixture ABEF will have an average copper grade of 0.67%, with copper recovery of 80.16%. The CDGH mixture average grade is equal to ABEF; then, it would result in the same copper recovery. Global copper recovery is then 80.16%, 0.3% higher than the first schedule. In other words, in this case, the alternative schedule

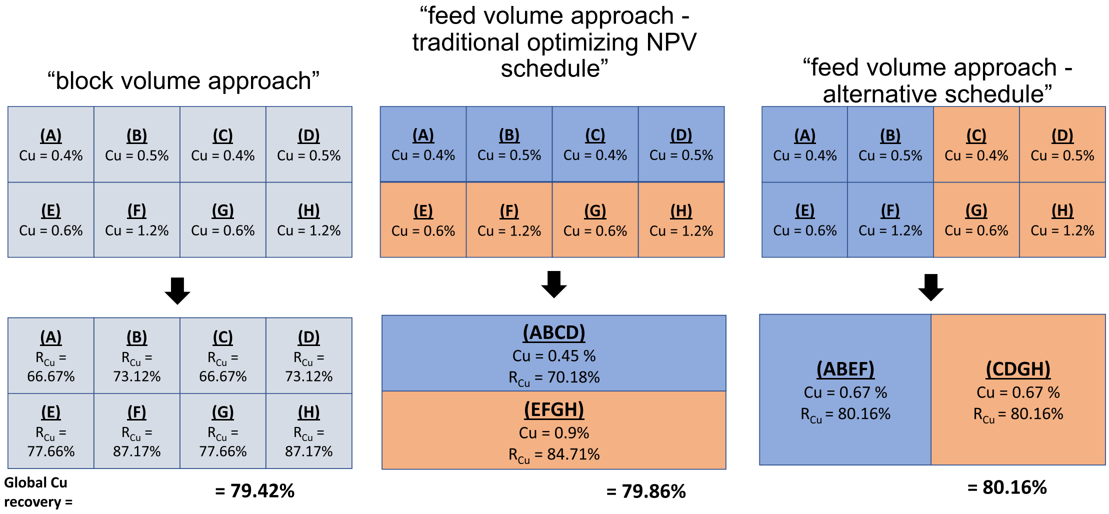


**Figure 4.** Difference between traditional 'block volume approach', 'feed volume approach-traditional optimizing NPV schedule' and 'feed volume approach-alternative schedule'. Images are available in colour online.

maximizes global copper recovery, even though it does not mine high-grade blocks before. In short-term planning, which seeks the best operational efficiency, this type of schedule is adequate.

### *Discussion of the demonstration example*

We demonstrated that applying the regression model to the larger volume support of the feed volume (which is the theoretically correct approach) results in a different global metal recovery estimation. Additionally, the 'best' block scheduling may change to another one.

The comparison between three situations is shown in Figure 4. 'Block volume approach' is the block-by-block method of estimating metallurgical recovery. Although this method is currently adopted in the mining industry, it is biased. If a 'traditional optimizing NPV' schedule (high-grade blocks before) is performed, a ABCD- and EFGH-mixture will occur, and the global metallurgical recovery will be 79.86%, not the 79.42% previously estimated. However, there is an alternative schedule that is better in terms of global copper recovery. The alternative programme increases even more the global copper recovery to 80.16%, this being an accurate prediction.

More studies on understanding the relationship and sensibility between scheduling and recovery predicted for the feed volume and its impact on global metal recovery and economic value are needed. In Section 3, an example on a synthetic two-dimensional database is performed.

## Non-additivity and support impacts – example application

### *Block model description*

To better assess the impact of considering upscaled mixtures of blocks in mine planning, consider a synthetic two-dimensional copper block model adapted from the Walker Lake dataset (Isaaks and Srivastava

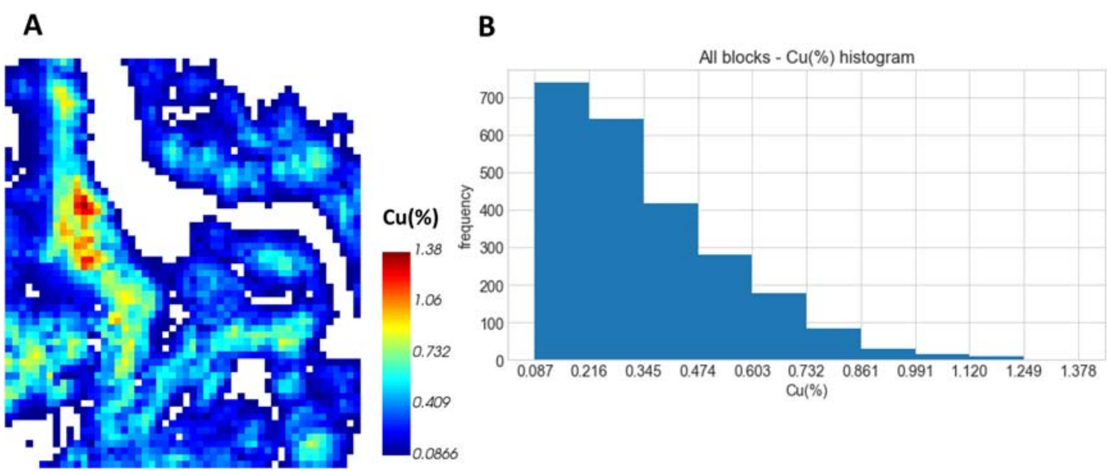


**Figure 5.** (A) Block model – Top view. (B) Copper histogram of the block model. Images are available in colour online.

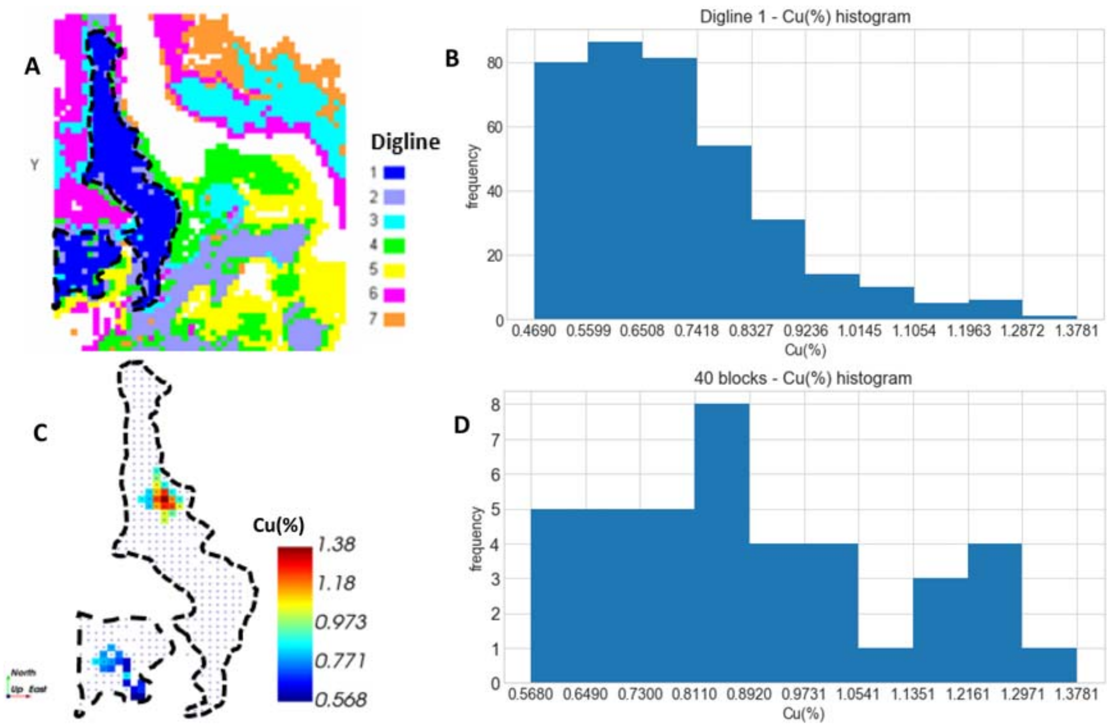


**Figure 6.** (A) Diglines of a synthetic copper deposit. (B) Digline1 copper histogram. (C) 40 blocks of the first digline with their copper grades. (D) 40 blocks copper histogram. Images are available in colour online.

1989). The block model and its copper histogram are shown in Figure 5.

Koppe et al. (2011) proposed a schedule where seven diglines were generated (Figure 6(A)). For this case study purposes, consider that the first digline is being mined. This first digline comprises the higher-grade blocks of the block model (Figure 6 (B)). For the short-term, 40 blocks of this digline were deemed free to be mined (Figure 6(C)) and must be extracted promptly, i.e. within a week. Each of these blocks has its copper grade, ranging from 0.57% to 1.38%, as seen in the histogram (Figure 6(D)). As this is a two-dimensional example, we could think of the blocks as being on the same bench, in two different mining faces, in an actual three-dimensional block model.

The impact of the support and the non-additivity of the metallurgical recovery is checked in this example for the following aspects: (i) differences in volume between block support and feed volume support; (ii) different regression models; (iii) considering two primary geological variables not linearly associated with metallurgical recovery.

**Table 1.** Scheduling scenarios with their feed volume/block volume relation and global metallurgical recovery.

| Scenario | Feed volume/block volume ratio | Scheduling Global Metallurgical Recovery |
|---|---|---|
| A ('block volume approach') | 1 | 84.30% |
| B | 4 | 84.31% |
| C | 8 | 84.32% |
| D | 10 | 84.33% |
| E | 20 | 84.41% |

## *Differences in volume between the block and the feed volume*

Five scenarios are compared to assess how the differences between block and feed volume affect global metallurgical recovery. The same previous regression model between copper recovery and copper ROM grade is used (Figure 1).

Scenario A is based on a feed volume/block volume ratio of one; that is, it is based on the premise that each mining block will be processed alone, one at a time. Scheduling to maximize global metallurgical recovery is performed, resulting in higher grade blocks being mined first. The global metallurgical recovery is 84.30%.

Although scenario A is the traditional method of considering a metallurgical recovery value in mine planning, it is not recommended to apply the recovery curve on each block, as illustrated in Figure 2, but on their combination, which mimics the volume sent to the processing plant. This volume depends on the mining block's dimensions and density, the throughput rate, and the processing plant's material residence time. For example, a plant with a throughput rate of 3,500 t/h and a total residence time of 6 h would mix 21,000 t of material. If each mining block has an average of 3,000 t, it will combine seven blocks.

Scenarios B, C, D, and E assume that the material fed to the plant is equivalent to the same volume of

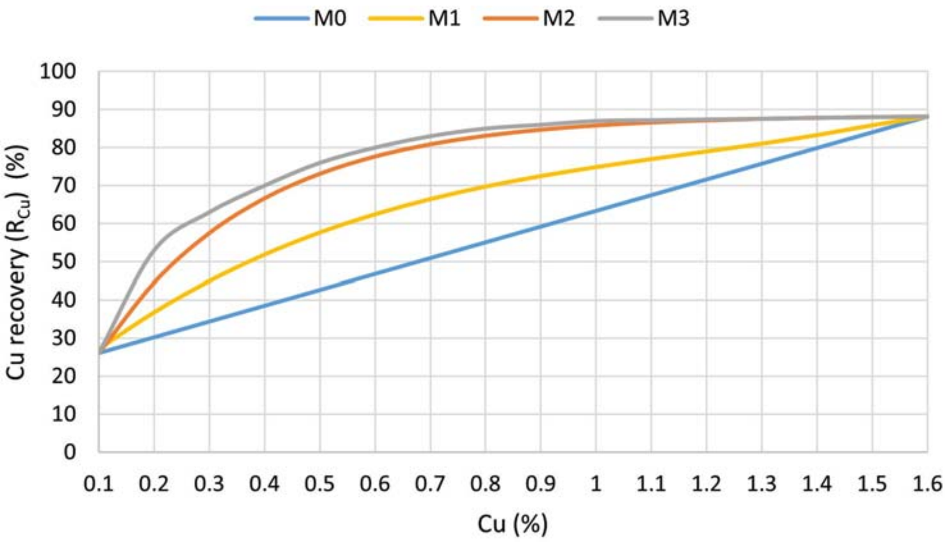


**Figure 7.** Different recovery regression models between Cu content in the feed (%) and Cu Recovery (%). M0 equation: $y = 41.358x + 21.999$. M1 equation: $y = 24.281x^3 - 85.192x^2 + 119.65x + 16.14$. M2 equation: $y = 88.5*(1\text{-EXP}(-3.5x))$. M3 equation: $y = -211.77x^6 + 1182.5x^5 - 2615.7x^4 + 2936.4x^3 - 1801.1x^2 + 616.78x - 19.683$). Images are available in colour online.

four, eight, ten, and twenty mining blocks, respectively. The order in which each mining block is mined and sent to processing on these scenarios does not differ from that of scenario A (all share the same schedule). However, their global metallurgical recovery results change (Table 1).

For the next analysis, feed volume is assumed to be equal to four blocks. Therefore, scenario B is the theoretically correct approach. As Scenario A is the traditional method of considering metallurgical recovery in mine planning, it is used for comparison purposes.

## Differences in the behaviour of the recovery regression model

The regression model between metallurgical recovery and the primary geological variable may have different behaviour, in some cases approximating a linear function. A sensibility analysis of how this regression model affects recovery proceeds. Four regression models are applied. Model 0 (M0) is a linear function. M1 is an order three polynomial. M2 is the previously explained regression model (Figure 1). M3 is a polynomial order six. They all have the same minimum and maximum copper recovery (Figure 7).

Considering the feed volume consists of four blocks, we can think of the estimation based on feed volume/block volume ratio of one (scenario A – ‘block volume approach’) as the biased estimation and scenario B (‘feed volume approach’) as the accurate estimation. The impact of each model is analysed on the difference between the scenarios (Table 2). Scheduling order of mining blocks is not changed among them.

For each model, there is a specific error between the biased and the accurate approach.

## Regression model considering two primary variables

Besides considering the difference between block-feed volume and the different regression models, grade and lithology are used to explain how the mixture of two primary variables may also impact the global metallurgical recovery estimation.

For assessing the lithology impact on metal recovery, consider the example of a real copper mine (Wheaton Precious Metals 2019), where metallurgical recovery varies as the mixture of lithologies in the ROM feeding the plant changes. In lesser quantity in the deposit, the oxidized ore has only 77% on average of metal recovery. In greater quantity in the deposit,

**Table 2.** Recovery regression model equations, global metallurgical recovery for each scenario and their difference.

| Model | Regression equation | Global metallurgical recovery estimation – Scenario A | Global metallurgical recovery estimation – Scenario B | Global metallurgical recovery error (Sc.A – Sc.B) |
|---|---|---|---|---|
| M0 – Linear | $y = 41.358x + 21.999$ | 60.99% | 60.96% | +0.03% |
| M1 – Polynomial 3 | $y = 24.281x^3 - 85.192x^2 + 119.65x + 16.14$ | 72.88% | 72.86% | +0.02% |
| M2 – Reference | $y = 88.5(1-\text{EXP}(-3.5x))$ | 84.30% | 84.31% | −0.01% |
| M3 – Polynomial 6 | $y = -211.77x^6 + 1182.5x^5 - 2615.7x^4 + 2936.4x^3 - 1801.1x^2 + 616.78x - 19.683$ | 84.29% | 85.56% | −1.27% |

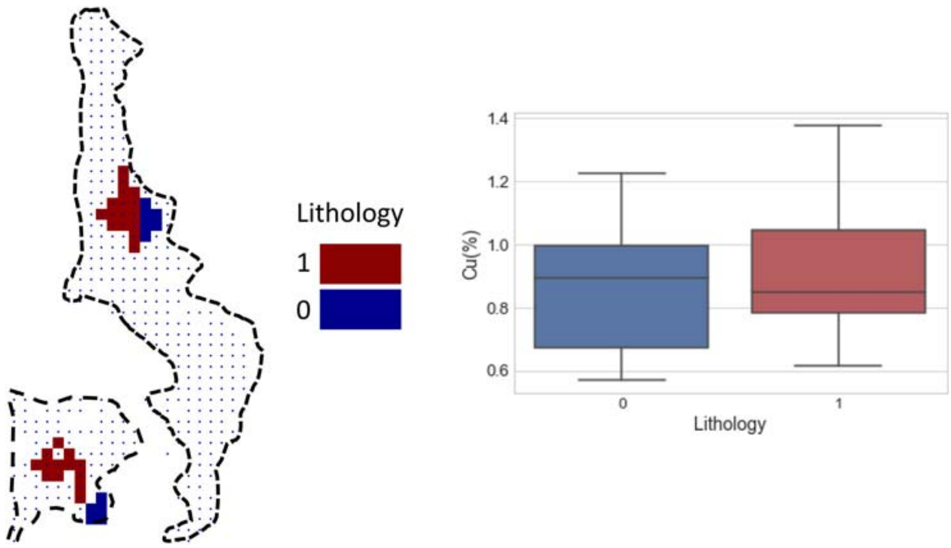


**Figure 8.** Lithology map and lithology-grade boxplot. Images are available in colour online.

the fresh sulphide ore has 90% metal recovery on average. A combination of up to 30% oxidized to 70% sulphide could be tolerated by the plant with no relevant impact. Above that proportion, the process loses effectiveness.

Reproducing a similar situation, a lithology variable is assigned to the blocks in our example study. Of the 40 blocks, 29 have lithology-1 type (fresh sulphide), and 11 have a lithology-0 type (oxide). Grade and lithology are not correlated (Figure 8).

The lithology and grade impact on metal recovery is represented by the regression models shown in Figure 9. Each curve is related to a different lithology proportion: 'Litho1 (100%)' refers to a mixture composed only by lithology-1 blocks. In contrast, 'Litho0' refers to a combination consisting only of lithology-0 blocks. 'Litho1 (75%)' curve is very close to the 'Litho1(100%)' curve. Nevertheless, the greater the proportion of lithology-0 blocks in the mixture, the worse is the metal recovery.

For our forty-blocks case study, two situations are compared (Table 3). Both use grade and lithology as primary variables associated with the metal recovery (Figure 9), but the first (A-GL) is based on the feed volume/block volume ratio of one (Scenario A - 'block volume approach'), while the second (B-GL) is based on the feed volume/block volume ratio of four (Scenario B - 'feed volume approach'). We can think of scenario A-GL as the biased estimation and scenario B-GL as the accurate estimation.

Therefore, the joint impact of the aspects mentioned (feed volume/block volume ratio, regression model, and grade and lithology variables) on the global metallurgical recovery is assessed. Scheduling order of mining blocks is not changed among them.

As with the example in Section 2, the biased 'block volume approach' has a lower copper recovery value than the accurate 'feed volume approach'.

### *Novel scheduling considering mixtures.*

The A-GL and B-GL scenarios considered the 'traditional optimizing NPV' schedule that mines the high-grade blocks before.

However, an alternative schedule which considers the 'feed volume approach' and how each block is mixed provides an accurate and greater global metallurgical recovery. This schedule, denominated novel 'mixture' scheduling, changes the order of mining for nine blocks out of forty (Table 4).

The differences between these scenarios may be better evaluated in economic value. Consider Equation (2), where:

- *Pcu = price of copper* (*US$/lb*)
- *Qcu = quantity of recovered copper* (*lb*)
- *C = all associated costs* (*US$/t*)
- *T = ore tonnage* (*t*)

$$\text{Economic Value (US\$)} = P_{cu} \cdot Q_{cu} - C \cdot T \quad (2)$$

Consider the copper price as 3.18 US$/lb, the sum of mining and processing costs equals 10.0 US$/t of ore. Each block has 3,000 t. The quantity of recovered copper is different for each scenario. Table 4 summarizes all the results. A-GL scenario is the biased 'block volume' traditional method of considering metallurgical recovery in mine planning. B-GL scenario is the accurate 'feed volume' approach, with a 'traditional optimizing NPV' schedule performed. B-GL - Novel 'mixture' scheduling is the accurate 'feed volume' approach with the best scheduling scenario.

In summary, A-GL is what mine planners predict. B-GL is what happens. B-GL – Novel 'mixture' scheduling is the best possible option that could happen.

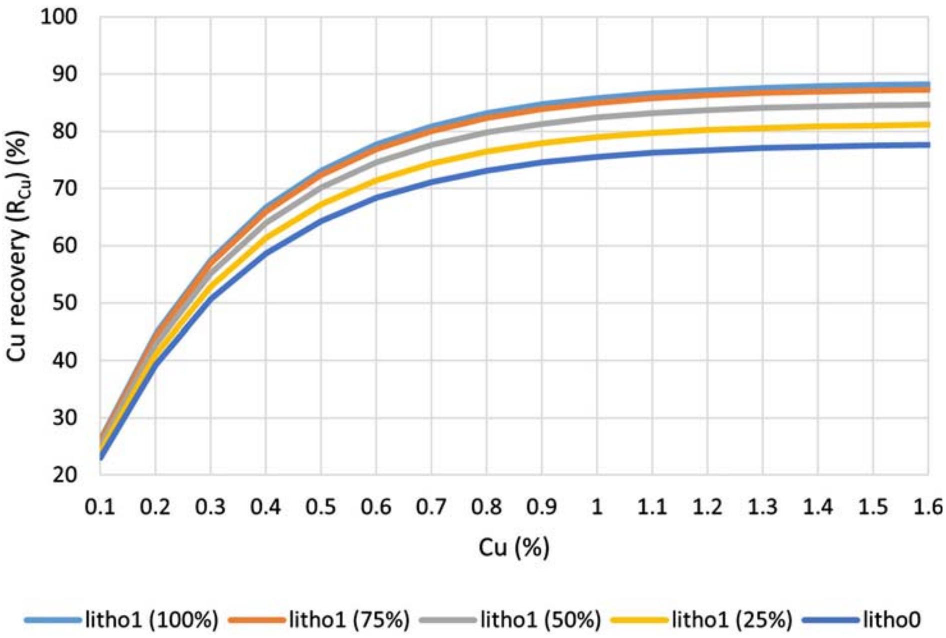


**Figure 9.** Regression model for each different lithology proportion. Images are available in colour online.

## Discussion

Non-additivity may impact metallurgical recovery estimation in different ways, depending on the joint impact of (i) the difference between feed volume and block volume, (ii) the regression model behaviour, and (iii) the primary variables associated with the metallurgical recovery estimation.

The feed volume/block volume ratio seems to have little impact, if considered by itself. For a ratio of up to twenty, the regression model can be applied on the block level with a global metallurgical recovery difference of 0.11%. It should be noted, however, that the blocks composing the feed volume are similar to each other in respect to copper grade, because of the 'traditional optimizing NPV' scheduling performed. This explains the little global metallurgical recovery difference. The more different the blocks composing the feed volume, the more inaccurate would be the global metallurgical recovery estimation based on block volume.

From the second analysis on, we fixed the feed volume to four. All the analysis compares the traditional scenario based on the feed volume/block volume ratio of one ('block volume approach'), which is biased, with the accurate scenario based on the feed volume/block volume ratio of four ('feed volume approach'). The use of different regression models indicates that for the linear and the order three polynomial, there is a positive bias. For the reference model and the order six polynomial, there is a negative bias. Global metallurgical recovery value is sensitive to the regression model used. Adopting inadequate regression model's behaviour may lead to excessive error in predicting the expected global metal recovery. Therefore, geometallurgical tests to assess the accurate relationship between recovery and primary variables are needed.

The third analysis included the lithology attribute. The A-GL scenario is the traditional 'block volume approach' with a 'traditional NPV optimization' schedule. This solution ignores how each block is blended with others to compose the feed volume. The B-GL scenario is based on the correct method of considering the feed volume. Applying the same scheduling, the difference between them is 1.17% in copper recovery.

Nevertheless, there is a better schedule than the 'traditional NPV optimization' programme in terms of global metallurgical recovery. The novel 'mixture' scheduling recognizes the benefit of mixing lithologies 0 and 1 in the 25–75% proportion. Consequently, this schedule changed the order of nine blocks, and

**Table 3.** Scheduling scenarios and their global metallurgical recovery.

| Scenario | Description | Scheduling global metallurgical recovery |
|---|---|---|
| A-GL | - 'Block volume approach'<br>- Regression model: based on Cu grade. Only litho1(100%) or litho0(100%) curves are assumed (not proportions).<br>- Schedule: high-grade blocks first | 81.67% |
| B-GL | - 'Feed volume approach'<br>- Regression model: based on Cu grade and lithology (proportions)<br>- Schedule: high-grade blocks first | 82.84% |

**Table 4.** Scheduling scenarios, their global metallurgical recovery and economic value.

| Scenario | Description | Scheduling global metallurgical recovery | Scheduling economic value |
|---|---|---|---|
| A-GL (Inaccurate) | - 'Block volume approach'<br>- Regression model: based on Cu grade. Only litho1(100%) or litho0 (100%) curves are assumed (not proportions).<br>- Schedule: high-grade blocks first | 81.67% | 65,233 US$ |
| B-GL (Accurate, but not the best schedule) | - 'Feed volume approach'<br>- Regression model: based on Cu grade and lithology (proportions)<br>- Schedule: high-grade blocks first | 82.84% | 83,284 US$ |
| B-GL – Novel 'mixture' scheduling (Accurate and best schedule) | - 'Feed volume approach'<br>- Regression model: based on Cu grade and lithology (proportions)<br>- Schedule aim: maximize mixture global met. recovery | 83.31% | 90,587 US$ |

provided a better result. Evaluating it in economic values, this schedule resulted in 90,587 US$, against 83,284 US$ of the accurate but not best B-GL schedule, and 65,233 US$ of the biased traditional method.

If non-additivity is ignored in the mixture of blocks, the combination of high feed volume/block volume ratio, non-linear regression model, and many primary variables correlated to metallurgical recovery can contribute to a very inaccurate estimation of global metallurgical recovery and sub-optimized scheduling.

All discussion here is based on the example results. Different feed volume/block volume ratio, regression model behaviour, and primary variables analysed may provide smaller or more significant differences, positive or negative bias. Each operation should evaluate its own characteristics from this geometallurgical perspective, as there is no universal rule.

## Conclusions

Project success can be impacted by a poor understanding of the characteristics of geometallurgical attributes. In particular, the support and non-additivity properties must be thoroughly thought out when considering geometallurgical variables in mine planning.

The support is related to the feed volume/block volume ratio. Plant capacity and block dimensions will determine how many blocks should be clustered to form and assess the mixture feeding the plant.

The non-additivity property requires that the non-linear behaviour be known. This can be accomplished by sampling and analysing ROM variables (inputs) and their metallurgical recovery results (outputs) to obtain a representative regression model.

Depending on the combination of feed volume/block volume ratio, regression model behaviour, and primary variables correlated to metallurgical recovery, the support and non-additivity may have, or not, a relevant impact on global metallurgical recovery estimation and, consequently, on the economic results. An optimal 'mixture' scheduling is useful to have both accuracy and optimality in global metallurgical recovery results and economic value of the project.

In the application example mimicking a copper mine, the traditional 'block volume approach' scheduling resulted in a global metallurgical recovery 1.64% lesser than the novel 'mixture' scheduling. As the latter is the theoretically correct approach, there is an inaccuracy of global metallurgical recovery and economic value forecasted with the current practice.

Each operation should evaluate its own characteristics to understand if the scheduling performed is accurate in predicting global metallurgical recovery and if it is the optimal one. If not, optimal scheduling may be obtained with an iterative algorithm that considers how to mix blocks in the feed volume, which is currently being investigated.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Data availability statement

The data used in this study are openly available in figshare at http://doi.org/10.6084/m9.figshare.14502087.

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