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Improving mixing model calibration using scenario simulation in block caving mines

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Abstract

Predicting ore grades and dilution in block caving mines is inherently complex due to the nature of the extraction method, where material flow and cave performance strongly influence outcomes. Numerous factors affect flow behaviour, including cave propagation, preferential flow, differential migration of fine and coarse fragments, draw cone geometry, lateral movement caused by airgap formation (rilling), and surface material displacement from toppling or large-scale failures.

Although extensive literature exists on grade prediction and flow modelling, discrepancies between forecasted and actual grades are still common. As a result, mixing models require frequent calibration to reflect new data, inputs and assumptions. This calibration is typically manual and iterative process, often requiring weeks of effort without necessarily improving understanding of the underlying cave behaviour.

This paper presents the application of a scenario-simulation approach in which hundreds of model realisations are generated by systematically varying key inputs and assumptions. Statistical analysis of the results in 2D and 3D outputs enables identification of the parameter combinations that best improve grade forecasts and provides insight into the influence of different mixing mechanisms across the footprint and at individual drawpoints.

Keywords: *block caving, material flow modelling, scenario simulation, mixing model calibration*

1 Introduction

Creating a production schedule for a block cave mine presents numerous challenges due to the various inputs and assumptions involved. The reported tonnage and grades by period are particularly crucial results. Predicting grades is essential, as it forms the basis for economic evaluation and determining the reliability of forecasts and life of mine plans. This prediction relies on data from the block model and the application of different mixing algorithms. The mixing parameters simulate the dynamics of mixing within the cave, making it one of the key assumptions. Once the mine is operational, it is vital to regularly update these parameters to ensure the most accurate predictions for the future of the cave.

This paper outlines a study that uses the marker mixing (MMIX) model (Khodayari 2022) implemented in PCBC software (Diering 2000). The automation of the calibration process enables the simulation of hundreds of scenarios in a short amount of time. This approach aims to enhance understanding of the dynamics of caving, allows for a review of mixing mechanisms, and makes use of all available input data from operations.

An initial example is presented in Figure 1, which compares actual tonnage (Figure 1a) and copper grade with forecasts generated by the PCBC model (Figure 1b). It becomes evident from period 40 onwards that the grade forecasts do not accurately reflect the cave's reality. Notably, the model overestimates the predicted grade, creating a misleading expectation regarding the grade results. This discrepancy arises because the

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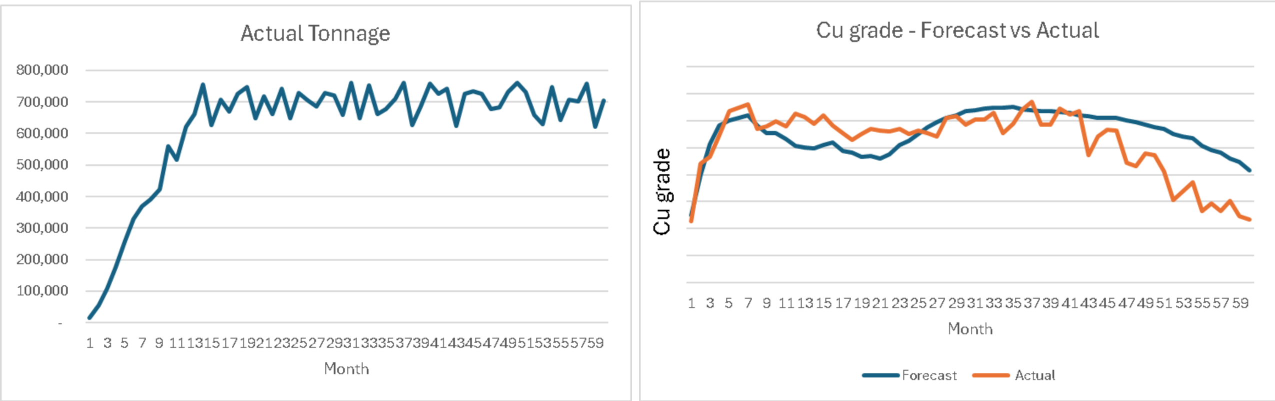
model fails to account for the complexity of cave behaviour. Therefore, it is essential to calibrate the mixing model to enhance our understanding of the cave and improve grade predictions.



(a) (b)

Figure 1 (a) Actual tonnage; (b) Forecast (PCBC model) grade versus actual grade

The potential prevailing movement mechanisms in a block cave are illustrated in Figure 2. Understanding these mechanisms is crucial, as they significantly affect dilution and ore reserve calculations in a block cave mine. The three primary mechanisms involved are vertical mixing, rilling and erosion. Other factors, such as fragmentation, also play a vital role in the evaluation of any block cave mine. Fragmentation has a strong influence on several aspects, including drawpoint spacing, the entry of dilution and the overall ore recovery. Fragmentation characteristics will impact other inputs to the mixing model, such as fines migration and vertical mix (Diering 2010).

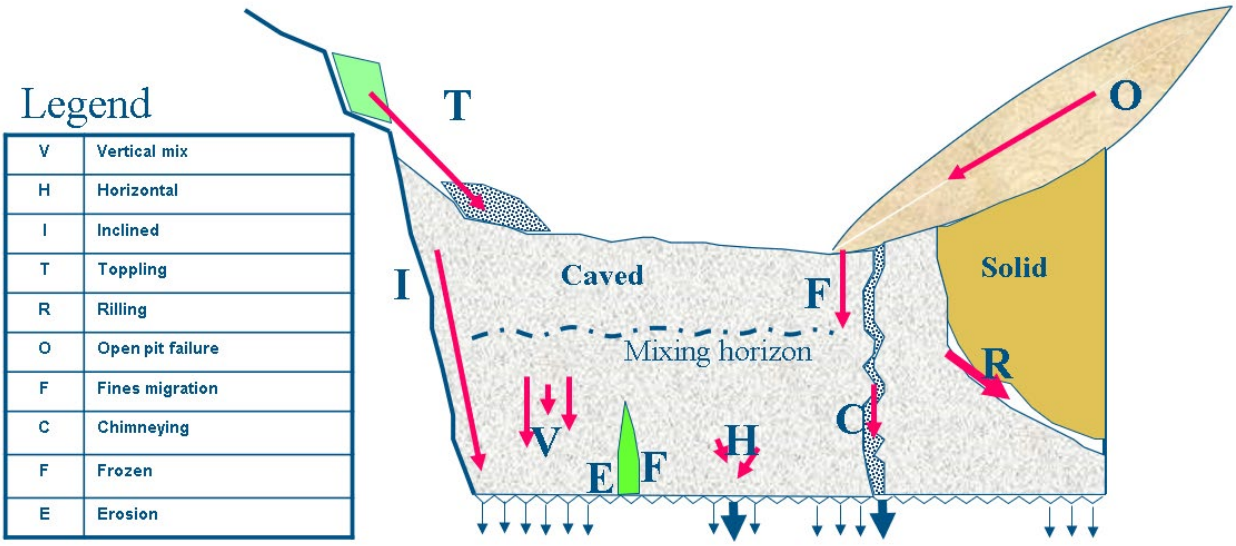


Figure 2 Block caving movement mechanisms

MMIX uses the same fundamental concepts for flow modelling as a depletion engine in the PCBC Production Scheduler. However, instead of working with fractions of material that mix during the flow process, MMIX employs discrete markers whose movements are tracked within each draw column (Khodayari & Diering 2022). Furthermore, most movement mechanisms can be modelled in MMIX, enabling the generation of complex scenarios that simulate the behaviour of the cave. An example of its application is shown in Figure 3, where the cave propagation is controlled by various cave back shapes that represent the formation of airgaps and material mixing. This allows for the vertical and horizontal movement of markers. Finally, once the markers break through the surface, external material (shown in black) is added to account for dynamic dilution resulting from mechanisms such as toppling or open pit failures.

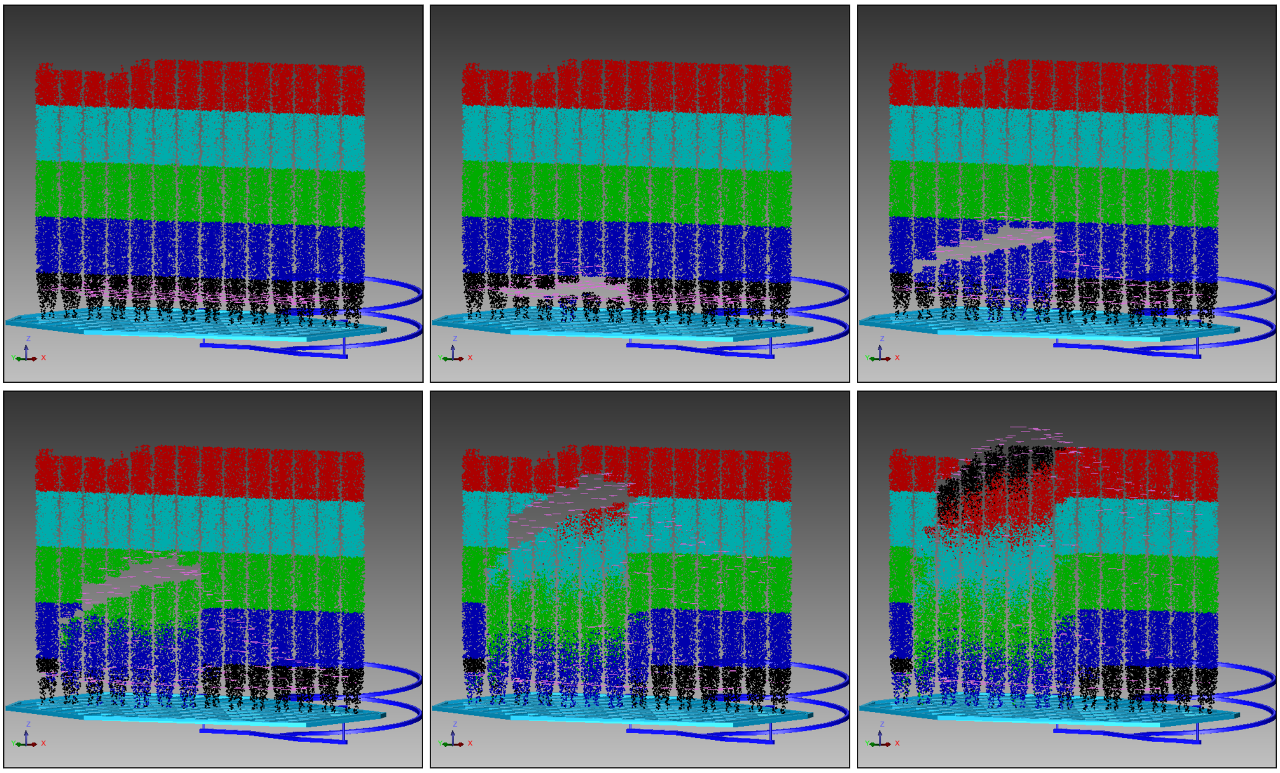


Figure 3 Marker mixing execution in different periods

The calibration process is typically iterative and manual, requiring regular updates to inputs and assumptions as cave considerations and actual data become available. These adjustments can be applied to MMIX and may take hours or even days to be analysed correctly to identify the combination of mixing assumptions that best interpret cave behaviour.

There is an option to automate the calibration process, which enables the running of hundreds of scenarios and the analysis of results using statistical tools. This automation provides a quicker understanding of the relationships between inputs and outputs, enhancing the modelling of block caving movement mechanisms. As a result, it aims to improve the grade forecast but also translates the complexity of overall cave behaviour into a more reliable, long-term life of mine prediction.

2 Scenario simulation approach

The scenario simulation approach has been used in previous studies and is discussed in two papers by Villa et al. (2022) and Villa & Mikulich (2024). In this implementation (Figure 4), the model is simpler as it allows MMIX to be run by changing inputs automatically and collecting results for analysis using statistical tools.

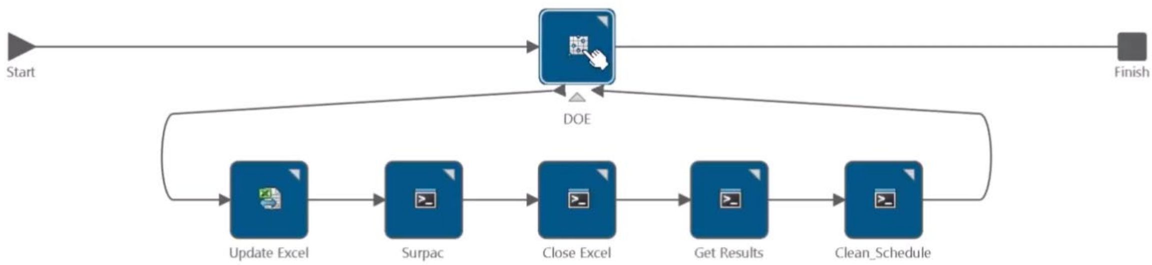


Figure 4 Simulation model for marker mixing simulation in PCBC-Surpac

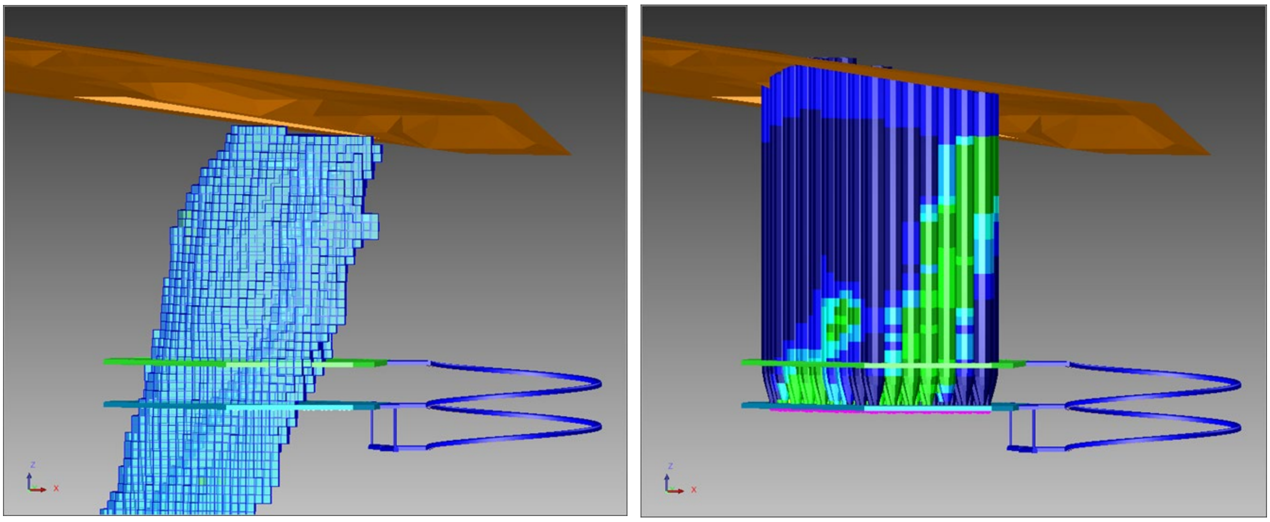
The simulation model for MMIX consists of the following components:

- Design of experiment (DOE): this part executes the workflow for PCBC-MMIX by simulating a wide range of alternatives using specific inputs, constraints, and cave considerations.
- Update Excel: this function takes the new inputs generated by the DOE for MMIX and updates the corresponding MMIX inputs in Excel.
- Surpac: this component runs both PCBC-MMIX with the updated inputs and assumptions, and saves the results in the production schedule Excel file.
- Close Excel: this step allows to close the Excel file to avoid problems for the next simulation.
- Get results: each run is stored in a separate Excel file for each scenario simulated, which includes all typical PCBC reports and run information for future analysis.
- Clean_Schedule: this process involves cleaning all Excel reports in preparation for the next run.

2.1 PCBC model

The PCBC model was created using fictious data; however, the data replicate the reality of a block cave operation. The layout contains 254 drawpoints distributed across 15 tunnels. The main objective of this model is to calibrate the copper (Cu) grade, with mineralisation contained into the orebody shown in Figure 5a; the surrounding area contains only dilution.

Figure 5b illustrates the PCBC model, which features draw columns at each drawpoint that distribute the Cu grade across the footprint. Some drawpoints commence extraction with dilution from the footwall (FW), while others have longer ore fractions predominantly located at the centre of the footprint. Additionally, several drawpoints connected to the hanging wall (HW) begin ore extraction but quickly transition to dilution. This combination creates a complex mixing scenario, as the rock properties of the orebody can lead to varying mixing behaviours between the footwall and hanging wall.



(a) (b)

Figure 5 PCBC model. (a) Block caving layout and block model; (b) Slice file created based on grade from block model and grade distribution

2.2 Marker mixing set-up

MMIX enables various block caving movement mechanisms to be modelled, as illustrated in Figure 3, by using specific inputs. In this model, the inputs were defined by minimum and maximum values, and a DOE approach will generate a comprehensive combination of all the inputs used. Table 1 describes the parameter inputs and values used in this model.

Table 1 Marker mixing parameter inputs and values used

Marker mixing inputs	Description	Minimum	Maximum
Base_Frozen	Proportion of base slice which is frozen	0	0.5
Erosion	Rate at which frozen material is added to mobile material for depletion	0	0.05
HT_Frozen	Height to top of frozen material	0	200
VMIX1	Probability for one slice up	0.30	0.90
VMIX2	Probability for two slices up	0.15	0.45
HMIX	Side movement probability	0.0001	0.1
Fines_Mov	Preferential movement Fines versus Coarse	0.5	0.7
Rill_Slope	Rill slope angle	30	50
Swell	Swell factor	1.2	1.4

2.2.1 Draw cone geometry adjustment

The frozen and erosion inputs are valuable tools for simulating changes to the draw cone geometry without the need to create a new slice file. This capability makes it possible to quickly and effectively analyse different draw cones during simulations. Figure 6 illustrates how the frozen and erosion inputs are applied.

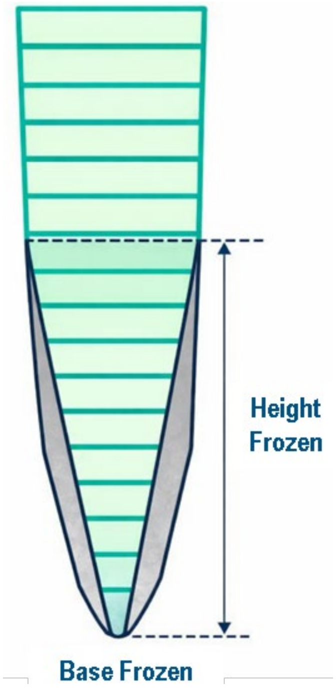


Figure 6 Draw cone geometry adjustment using frozen and erosion mechanisms

Base_Frozen: percentage of the drawpoint which is assumed to be frozen at the base of the column. The amount of frozen material per slice will decrease linearly from this base value to 0 at the Height_Frozen value. Set this value to 0 to avoid use of frozen material. Typical values would be in the range from 0.1 to 0.6. For a cave with coarse fragmentation, a lower value would be used. For fine fragmentation, a higher value would be expected since the smaller fragments would take longer to establish the full draw cone.

Height_Frozen: height value at which the percentage of frozen material in each slice will reach 0.

Erosion: the erosion rate at which material will be removed from the frozen material and allowed to contribute to the flowing material. This is done using random numbers every time material moves through a slice which contains frozen material. For example, if a marker is to be moved from the current slice to a lower slice and the erosion value is 0.05, and the random value is >0.95, then the marker will be depleted from the frozen material, or it will be depleted from the mobile material (bottom bin). Typical values for erosion would range from 0.02 to 0.1.

2.2.2 Mixing probabilities

MMIX is a dynamic model in which mixing occurs after depletion, resulting in an empty slice. This empty slice is then filled by moving markers both vertically and horizontally according to the probabilities established for VMIX1, VMIX2 and HMIX. The process can be managed by adjusting the input values during the simulation to discover the optimal combination that represents the movement within the cave. Figure 7 describes the depletion process and how these inputs are applied.

VMIX1: this is the probability for replenishment from the next slice up.

VMIX2: this is the probability for replenishment from two slices up. Usually VMIX1 > 2*VMIX2. If slice thickness is small, then higher values for VMIX2 would be recommended.

HMIX: this is the probability for replenishment from a neighbouring drawpoint. It is usually very low, e.g. 0.03.

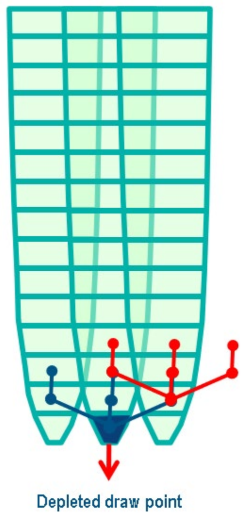


Figure 7 Depletion and mixing probabilities applied for marker mixing

2.2.3 Swell and fines movement

The swell factor (ratio of the expanded volume to the original volume) is a crucial parameter in simulating caving flow. Under the same conditions, a higher swell factor results in slower movement of caved material down the draw column.

Fines migration plays a significant role in the flow mechanism; it occurs when fines-designated markers preferentially move over coarse-designated markers. Within the cave, fines material moves faster than coarse material, which can impact the depletion grade, particularly when there is a substantial difference in grade between areas with varying percentages of fines material (Khodayari & Diering 2022).

2.2.4 External material

This approach facilitates the seamless integration of external materials into the flow domain after the cave breaks through at the surface. This concept has been successfully implemented in various models, including PCSLC (Villa & Diering 2010) and has also been applied within template mixing (Diering 2007). Figure 8 illustrates an example of external material, illustrated in black, that has been incorporated into the mixing model.

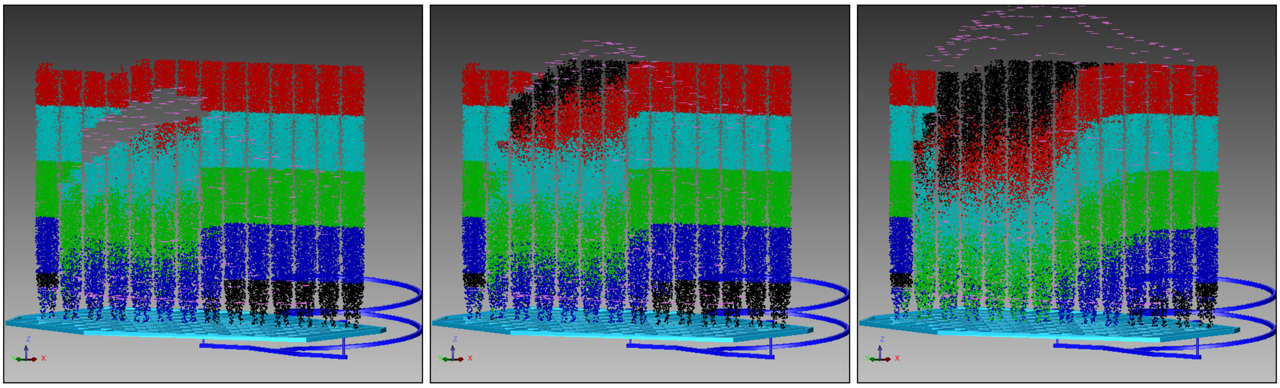


Figure 8 External material (black colour) applied for marker mixing

2.2.5 Cave backs and rilling

The cave back can be incorporated into MMIX by calculating the height of these surfaces at each drawpoint and capturing the cave growth for each period. Figure 9 illustrates the set of cave back shapes used in this example.

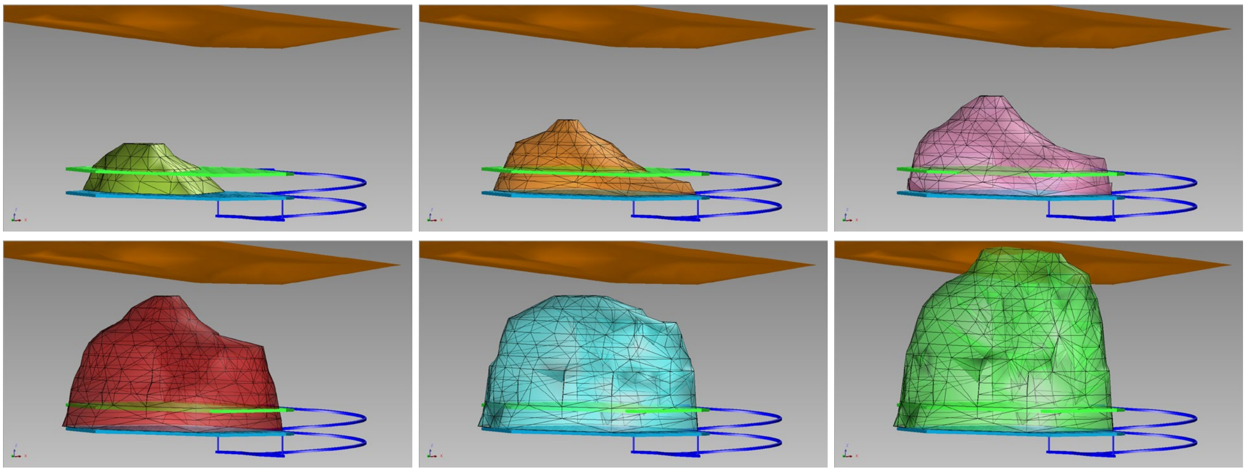


Figure 9 Cave back interpretation in different periods

The rilling mechanism will activate when the cave backs are used, enabling material to move laterally through the airgap. This is an additional input included in the simulation to analyse the sensitivity of the rilling angle used by MMIX.

2.2.6 Using smart markers, cave trackers and beacons with MMIX

Cave back monitoring has advanced through the integration of smart markers, cave trackers, and other types of beacons. These tools are now standard in cave operations, allowing material movement to be visualised – whether it occurs vertically or laterally. This information can be used in MMIX to gain insights into material movement, calibrate mixing probabilities, and compare assumptions with actual data. Figure 10 displays the beacons employed in this study, showing MMIX results (small markers shown in blue, green and cyan) alongside real movement data from beacons (shown as red spheres).

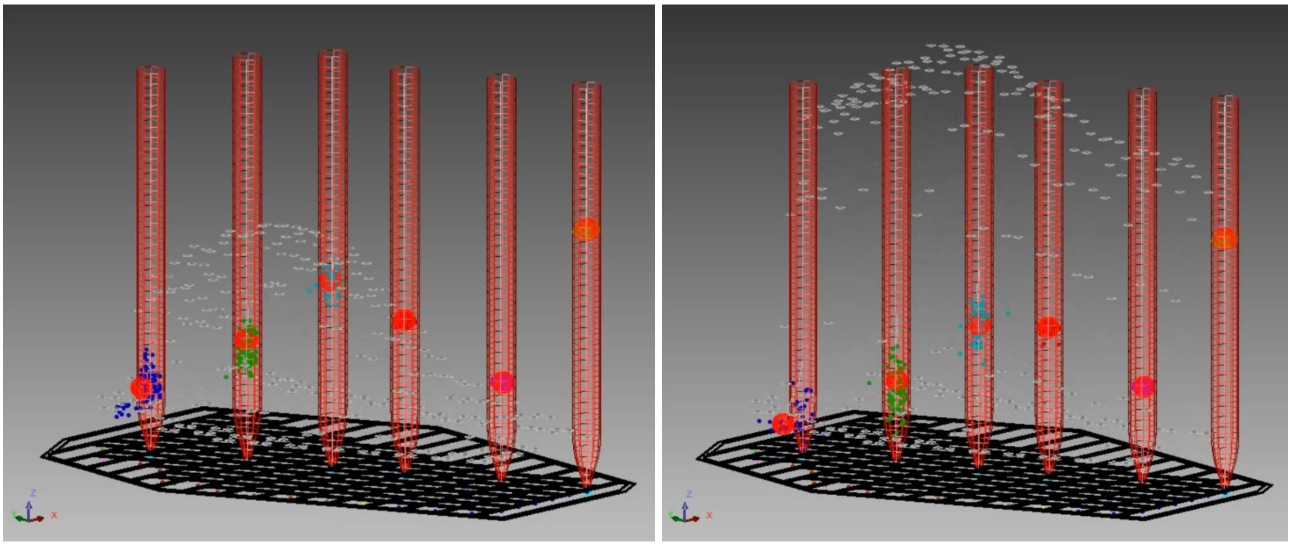


Figure 10 Visualisation of markers in different periods

2.3 Simulation model

The primary goal of this simulation model is to minimise the discrepancy between the actual Cu grade and the PCBC prediction using MMIX, as illustrated in Figure 1. An effective approach to calibrate the MMIX model involves replicating the monthly extracted tonnage, then comparing the PCBC Cu grade results against the actual Cu grade values. The aim is to reduce the Cu grade difference between the predictions and the real data over time. This strategy serves as the objective function for the simulation, which is outlined below:

$$Objective\ function = Minimise \sum_{k=0}^{n} abs(\mathrm{Cu_{act}} - \mathrm{Cu_{PCBC}})\, k \quad (1)$$

where:

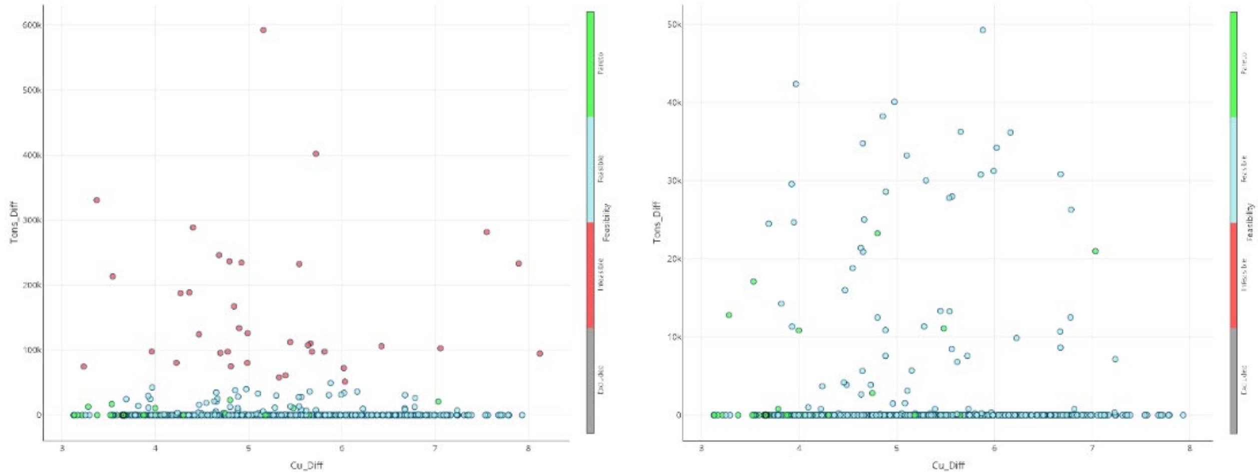
k = periods simulated based on actual tonnage extracted

$\mathrm{Cu_{act}}$ = Cu grade from actual data for each period

$\mathrm{Cu_{PCBC}}$ = Cu grade from PCBC simulated using MMIX for each period

2.3.1 Initial simulation results

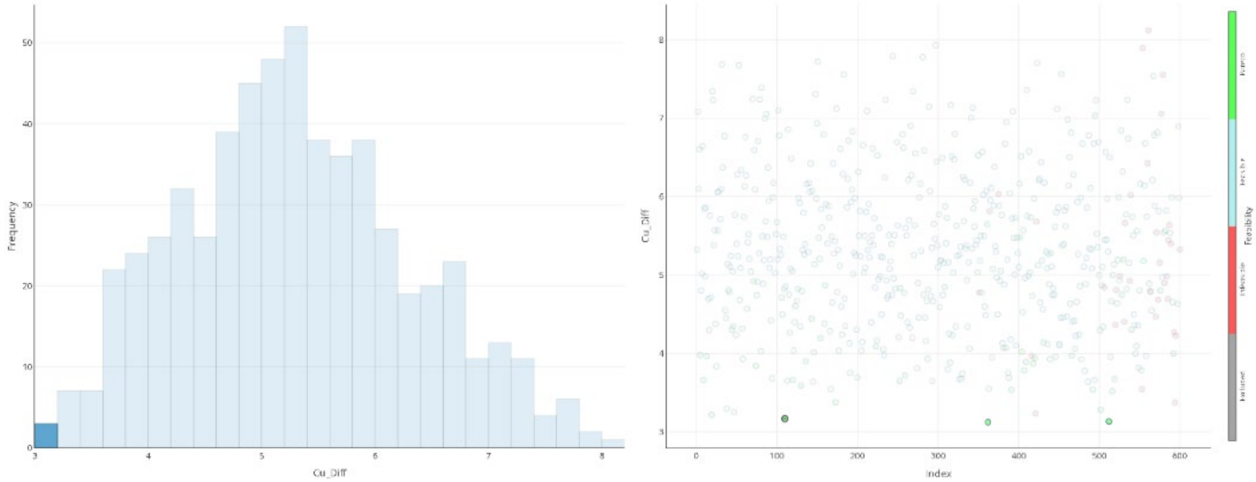
A total of 600 runs were simulated using the MMIX input combination outlined in Table 1. The entire process took approximately 10 hours, as each run lasted no more than 1 minute. Because the simulation relies on actual monthly tonnage extraction, in some cases depending on the inputs used, actual tonnage cannot be depleted, for example, due to cave back constraint or lateral probabilities of movement, Therefore a constraint was incorporated to ensure that the MMIX inputs used must extract at least 99.99% of the reported tonnage to qualify as a feasible calibration scenario. Figure 11a presents all runs, with the red dots indicating infeasible solutions, where the simulated tonnage fell below 99.99%. Figure 11b displays the results after filtering for feasible solutions, which consisted of 564 runs.



(a) (b)

Figure 11 Simulation result. (a) All 600 runs; (b) Filtering feasible results only – 564 runs

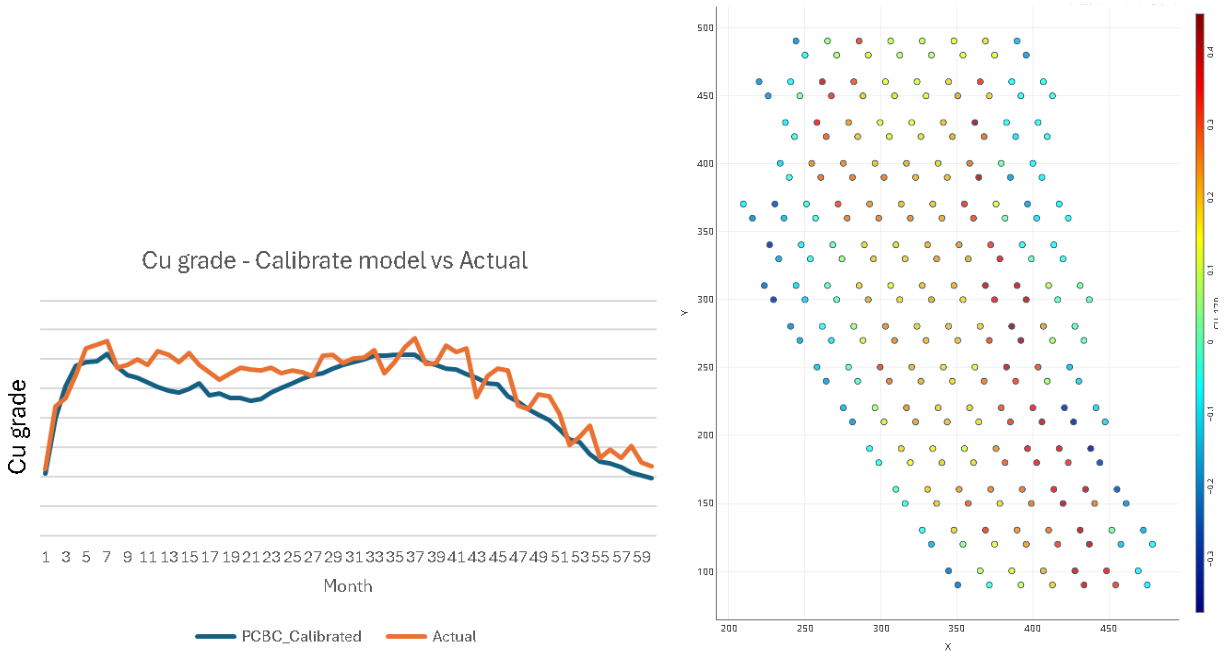
The next step involved selecting the best results through statistical analysis. Figure 12a presents a histogram of the Cu grade differences calculated from all runs. By focusing on the lowest-difference bar, one can filter and highlight four runs that exhibited good calibration results in Figure12b. These four runs represent the most promising scenarios for further analysis, allowing the MMIX inputs that contributed to these successful outcomes to be reviewed.



(a) (b)

Figure 12 Simulation result for entire layout. (a) Histogram selecting lowest Cu grade differences; (b) Cu grade difference per run based on histogram selection

When analysing the best scenario among the four initially selected, Figure 13a compares the calibrated PCBC model to the actual Cu grade results, showing promising outcomes. However, on visualising the total difference in Cu grade distributed per drawpoint in Figure 13b, several shifts from negative to positive differences across the footprint are noted. This fluctuation may create the false impression of successful calibration results, primarily due to using the same MMIX inputs across the entire layout.

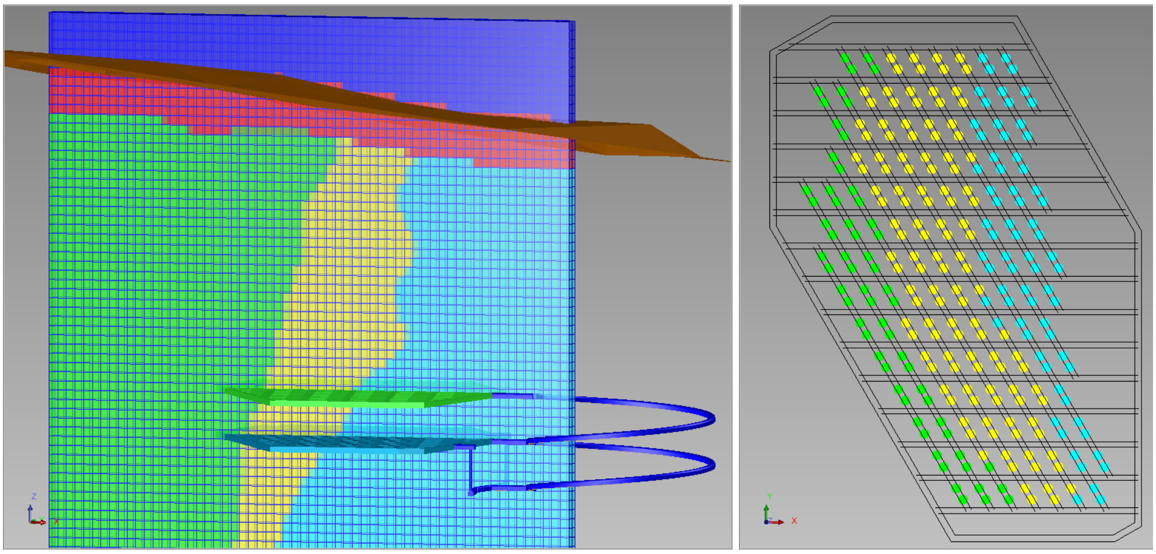


(a) (b)

Figure 13 Simulation result for entire layout. (a) PCBC-calibrated model versus actual Cu grade; (b) Cu grade difference per drawpoint plotted using XY coordinates

2.3.2 Analysis per sector

Three sectors were defined based on the rock type distribution and the location of drawpoints in the layout. It is essential to divide this analysis into sector groupings based on their proximity to the FW and HW, or if the sectors are covered by the orebody. Figure 14a presents a vertical section in the middle of the layout, illustrating the rock types. It highlights the FW (cyan), orebody (yellow), HW (green), and the top layer of overburden (red). Figure 14b shows the layout divided into three sectors: left sector (green), centre sector (yellow), right sector (cyan) and air (blue).



(a) (b)

Figure 14 (a) Rock type block model; (b) BC layout divided into three sectors – left, centre and right

The analysis of the 600 runs was conducted by sector. At this point, it is possible to perform additional statistical analyses to identify similarities and correlations between the sectors. This will make it possible to determine which mixing mechanisms are suitable for each sector and whether similar inputs can be applied across the sectors. Figure 15 illustrates the simulation results using a scatter plot, where numbers represent the total absolute difference calculated for Cu grade. The centre and left sectors show a positive correlation, while the right sector displays an inverse correlation. This suggests that different mixing mechanisms are affecting the material flow in the right sector compared to the left and centre sectors.

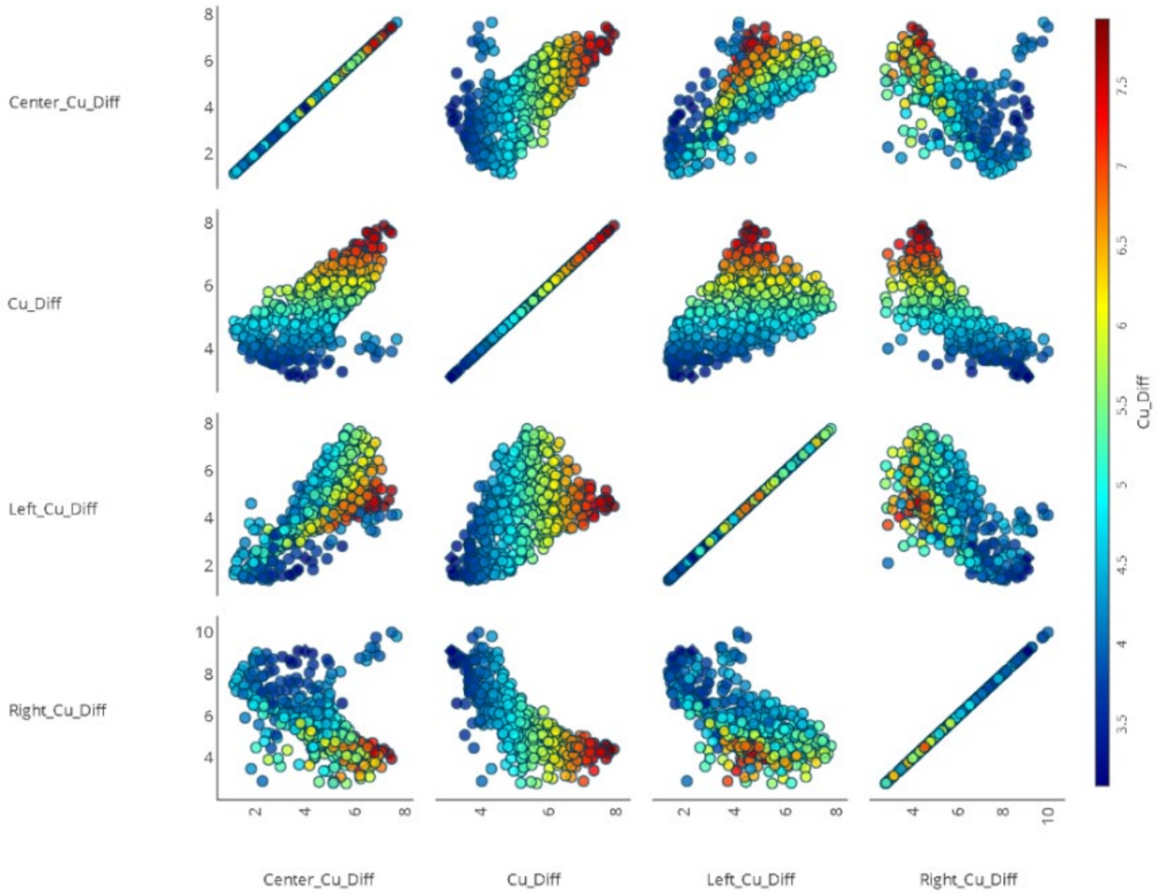


Figure 15 Simulation result – scatter plot to compare Cu grade per sector

Rock type composition can help identify correlations between reported Cu grades and the percentages of ore, FW, HW and overburden (dilution). Figure 16 allow correlations to be visualised, for example, the right sector shows a strong correlation with FW and ore percentages, the centre sector with ore and overburden dilution, while the left sector correlates with HW and ore percentages.

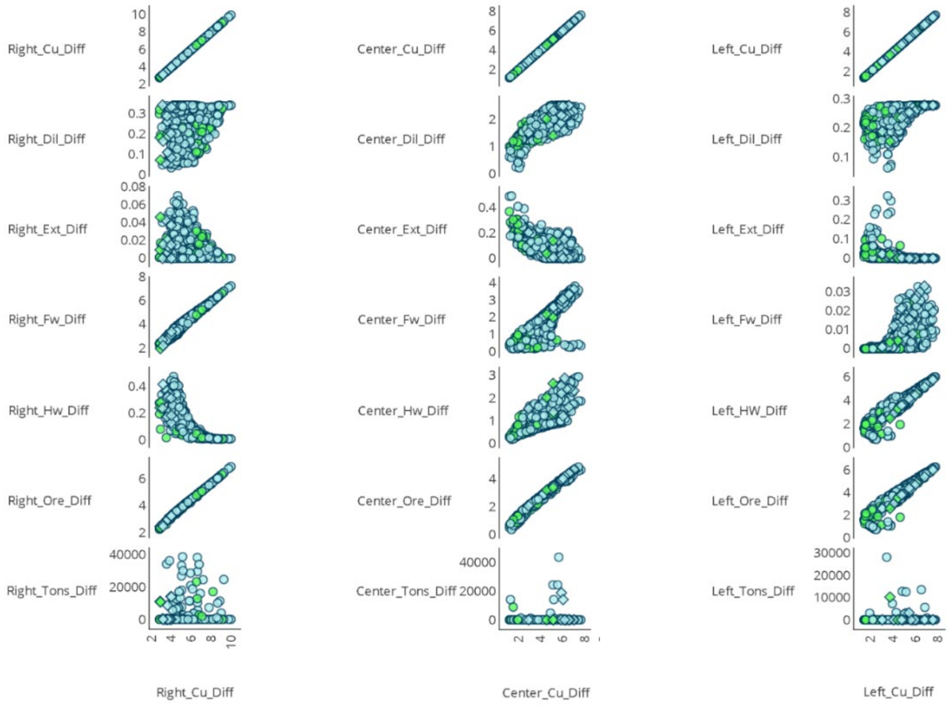


Figure 16 Scatter plot per sector to compare Cu grade with rock type percentage

Scatter plots can compare MMIX input and variations in Cu grade to identify correlations that indicate the dominant mixing mechanism. For example, Figure 17 shows that in the left sector of MMIX, HMIX has an inverse correlation, suggesting material flow is mainly controlled by vertical movement. In contrast, inputs like swell, rilling angle and fines movement show no correlation, indicating their variability does not follow a specific trend and needs further analysis.

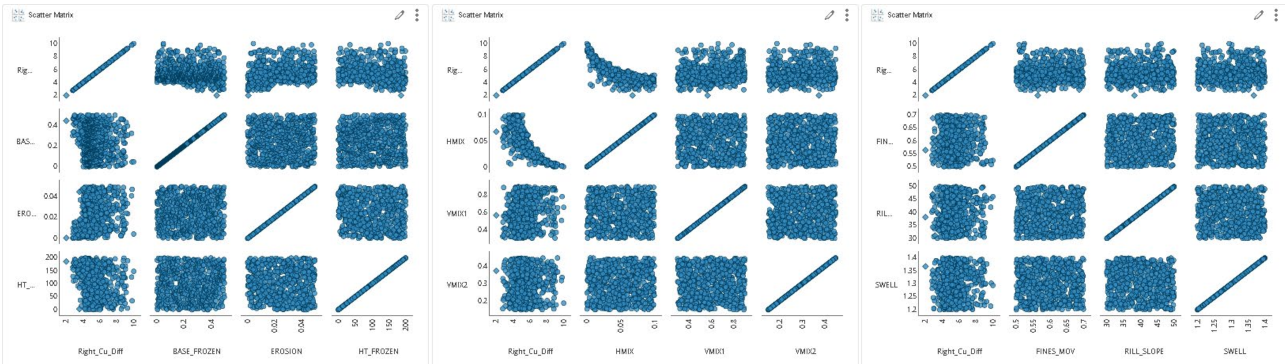


Figure 17 Scatter plot results to compare inputs and difference in Cu grade – left sector

One effective method for analysing results is to display the inputs along with the Cu grade difference using a histogram. This allows one to filter and highlight the scenarios that generate good calibration results, making it easier to identify the most important mechanisms and the obtain tentative values for specific inputs. For example, Figure 18 illustrates the outcomes for the right sector, where a filter could be applied dynamically by selecting the two columns with the lowest Cu grade differences. This is highlighted in dark blue in the top image in Figure 18 (Right_Cu_Diff). The nine graphs below that also highlight the inputs used to generate these scenarios. The conclusion is that the best results are linked to a high base and height frozen, combined with a low erosion rate. This suggests a reduction in the draw cone geometry is likely due to fine fragmentation associated with the FW.

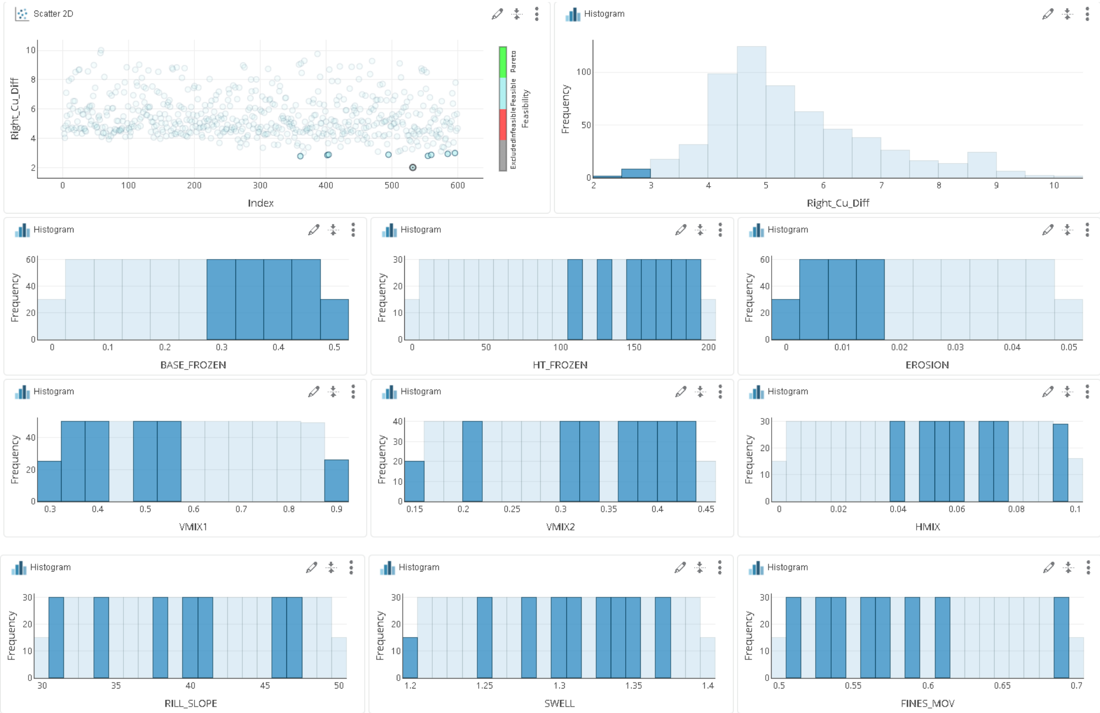


Figure 18 Histogram results – right sector

Using a similar analysis, Figure 19 presents histogram results for the centre sector, where the most favourable outcomes are linked to low HMIX probabilities. This indicates a higher degree of vertical movement. Additionally, this assumption is supported by the strong correlation with top dilution, suggesting that increased vertical mixing allows this type of material to be introduced more rapidly. In contrast to the right sector, frozen inputs do not display any specific trends; therefore, the reduction of the draw column geometry is not significant for the centre sector. The same analysis was done for the left sector (Figure 20), where best results are also associated with low HMIX probabilities.

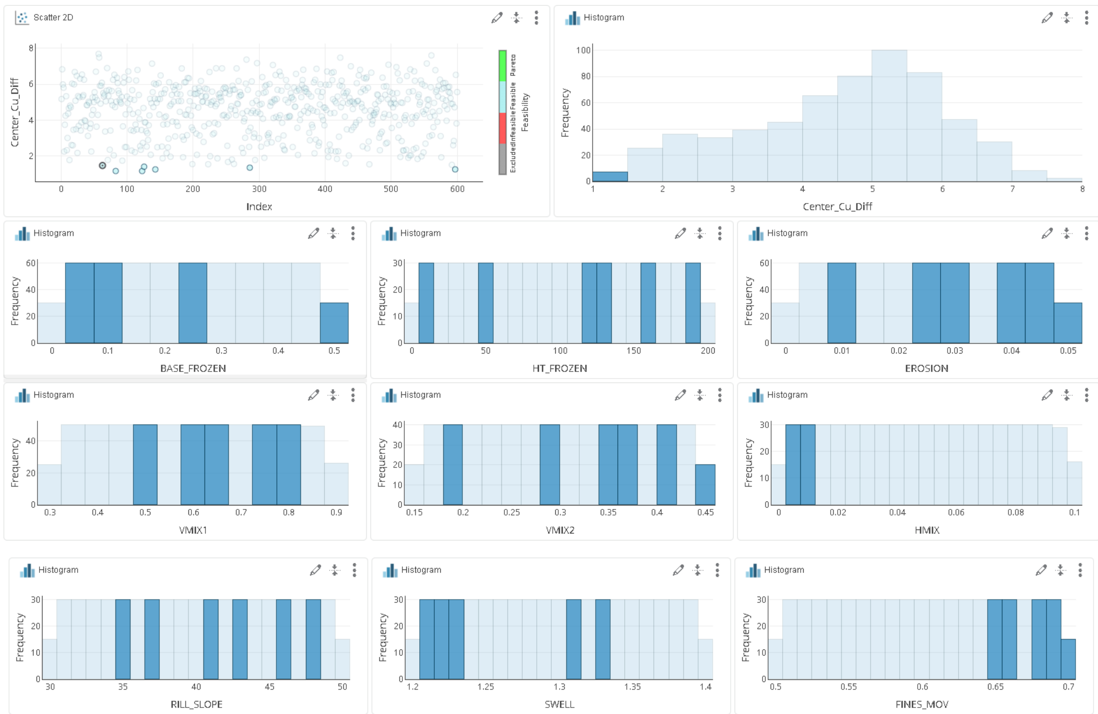


Figure 19 Histogram results – centre sector

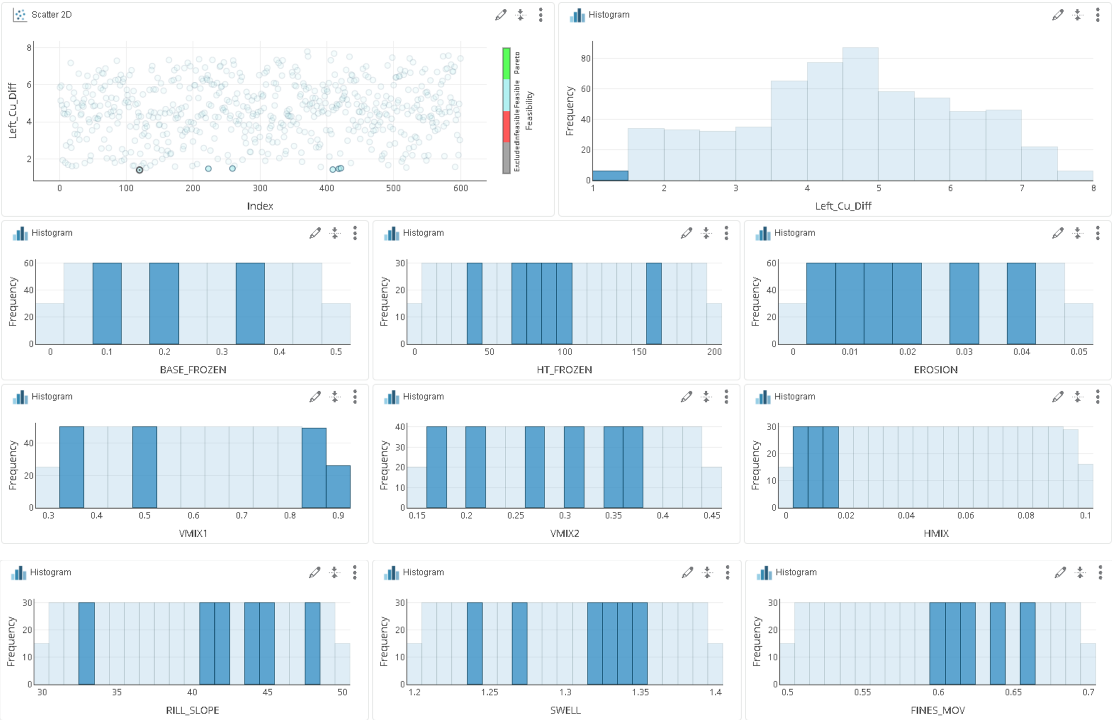


Figure 20 Histogram results – left sector

2.3.3 Calibrated PCBC run

After thoroughly analysing and revising the best scenarios for each sector, the best outcomes to create a new PCBC run with different MMIX inputs for each sector were selected. Table 2 presents the inputs used in the final run. Since inputs like Fines_Movement, Rill_Slope and Swell can use only one value per MMIX run, the average values were used in MMIX.

Table 2 Marker mixing inputs and values used

Marker mixing inputs	Right sector	Centre sector	Left sector	Average value (*)
Base_Frozen	0.543	0.102	0.099	–
Erosion	0.0005	0.0463	0.0195	–
HT_Frozen	106.3	6.7	19.8	–
VMIX1	0.698	0.558	0.523	–
VMIX2	0.304	0.287	0.264	–
HMIX	0.008	0.003	0.006	–
Fines_Mov (*)	0.61	0.66	0.55	0.61
Rill_Slope (*)	40.1	35.4	38.2	37.89
Swell (*)	1.27	1.23	1.26	1.26

The grade calibration results in Figure 21 show that the PCBC-MMIX calibrated run is effective overall, but the left and centre sectors require further work. While the right sector demonstrates accurate predictions by MMIX, the left sector underestimates and the centre sector overestimates the Cu grade. To enhance modelling effectiveness, it is necessary to closely review aspects like dilution inflow, fragmentation impact and cave propagation.

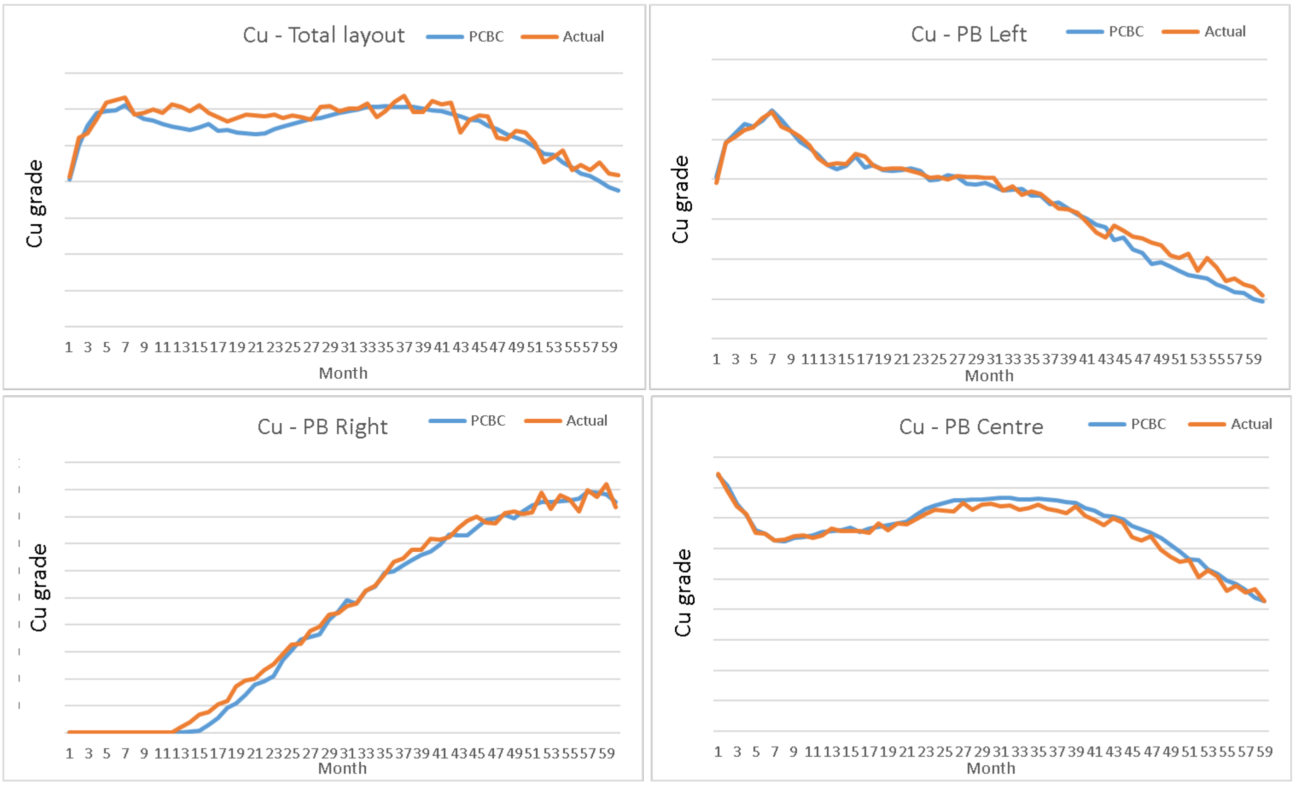
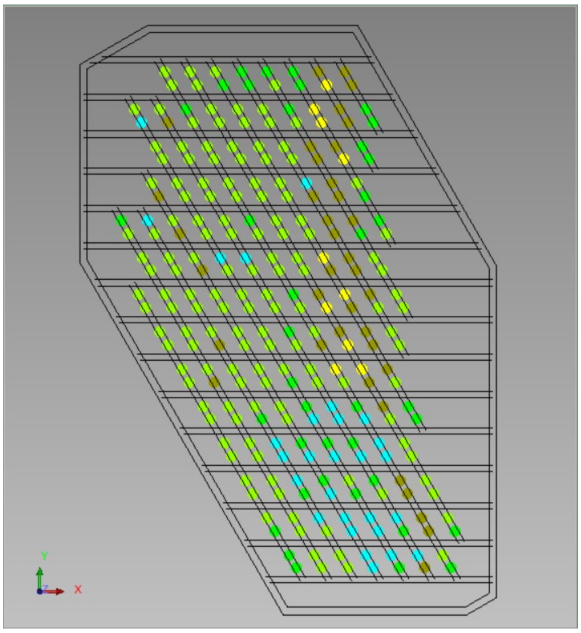


Figure 21 Cu grade calibration results – total and per sector

Finally, Figure 22 presents the differences calculated for each drawpoint. The overall layout indicates acceptable results, represented in green (indicating differences between -1% and 1%). There are no areas showing significant negative or positive differences for drawpoints located closer to the HW and FW, as was seen in the initial results. This confirms that the calibration conducted for each sector was an effective approach to represent the mixing behaviours and translate them into correct MMIX inputs.



	Colour	>= Lower bound	< Upper bound
1	r=0.4 g=0.0 b=0.8	-1.0	-0.4
2	blue	-0.4	-0.3
3	r=0.0 g=0.4 b=0.8	-0.3	-0.2
4	r=0.0 g=0.8 b=1.0	-0.2	-0.1
5	cyan	-0.10	-0.01
6	green	-0.01	0.01
7	r=0.6 g=1.0 b=0.0	0.01	0.10
8	r=0.6 g=0.6 b=0.0	0.1	0.2
9	yellow	0.2	0.3
10	orange	0.3	0.4
11	red	0.4	1.0

Figure 22 Cu grade calibration results – total and per sector

3 Conclusion

This study demonstrates that scenario simulation is an effective and scalable approach for calibrating mixing models in block caving operations. By automating the generation and evaluation of hundreds of MMIX runs, the method overcomes the limitations of traditional manual calibration, which is often time-consuming and provides limited insight into the underlying cave behaviour. The systematic variation of key inputs – combined with statistical analysis of both global and sector-level results – enables a deeper understanding of how different mixing mechanisms influence grade performance across the footprint.

Sector-based analysis proved essential. While uniform inputs across the footprint produced misleading improvements, dividing the layout into right, centre and left sectors revealed distinct mixing behaviours linked to geological domains. The right sector was strongly influenced by draw cone geometry parameters, whereas the centre and left sectors were dominated by vertical mixing, reflected in consistently low HMIX values. These findings align with correlations between Cu grade differences and rock type observations.

The final calibrated PCBC-MMIX run significantly improved the match between predicted and actual Cu grades, reducing deviations and strengthening forecast reliability. Although further refinement is needed for the centre and left sectors, the results confirm that scenario simulation provides a robust framework for ongoing calibration and for improving the interpretation of cave performance as new operational data become available.

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