MetSoP's use of Optimaviz Optimisation Application for enhanced reagent assessment in PGM flotation trial

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Abstract

This paper highlights how Metallurgical Solutions and Products (MetSoP) MetSoP leverages Optimaviz, an advanced data analytics tool, to evaluate and optimise the performance of a new co-collector during a flotation plant trial at a South African PGM concentrator. The trial involved reducing the baseline collector dosage while introducing a MetSoP co-collector, with all other process parameters held constant. Daily data on PGM recovery, concentrate grade, reagent consumption and gangue entrainment were collected over several weeks using automated systems and laboratory assays.

Using Optimaviz, MetSoP conducted statistical analyses to compare pre-trial and trial performance. The results revealed significant improvements - a 7% increase in PGM recovery and a 3.9% increase in concentrate grade, with no increase in overall reagent consumption. Additionally, Optimaviz's machine learning capabilities enabled the development of a predictive model linking co-collector dosage to recovery performance.

This work demonstrates how MetSoP, applies advanced data analytics platform, to generate actionable insights, evaluate reagent performance and drive continuous improvement in flotation operations. These findings offer valuable lessons for the industry, demonstrating how

analytics can unlock performance in complex orebodies, paving the way for broader applications in flotation and environmentally responsible mining.

1. Introduction

Platinum group metals (PGM) flotation sits at the heart of South Africa's mineral scene, with the Bushveld Complex churning out over 75% of the world's platinum. These ores come with low head grades,usually 2-6 g/t 4E (that's Pt, Pd, Rh, Au) plus tangled mineralogy like pentlandite and pyrrhotite sulfides mixed with chromite and silicate gangue, and feeds that shift day to day. It all makes nailing recovery and grade a real headache (Liddell & Adams, 2010). Most circuits lean on collectors like xanthates or dithiophosphates, paired with frothers for bubble stability, but dosing them by gut feel often leaves money on the table (Bradshaw et al., 2005).

1.1 Literature Review

We have poured over PGM flotation optimization for years now, chasing ways to tease valuables from these messy ores. Santana et al. (2008) nailed how ore type, grind size, and reagent amounts dictate results, while Corin et al. (2011) showed co-collectors can sharpen selectivity by dialing back chromite drag into the froth, a chronic headache that tanks grades. Nagaraj (2005) called out the old-school "one-size-fits-all" reagent picks as too narrow, pushing instead for a big-picture view blending chemistry (like collector mixes), mechanics (particle sizes), and operations (pH tweaks, air flow). It is a mindset that is proven out in sulfide systems time and again. Data analytics has flipped the script on all this. Massinaei et al. (2019) rounded up machine learning's wins in predicting recoveries and grades from messy datasets. Closer to home, Ncube et al. (2025) walked through Optimaviz a user-friendly web platform from Optimaviz Analytics Pty Ltd in Australia, fine-tuning copper flotation at Ma'aden Barrick. Built for engineers like us, not data wizards, it tackles mining headaches (and beyond, into chems, oil, water). Its suite of features includes:

- **Data Evaluation**: Facilitates the identification and correction of data issues such as missing values and outliers, enables the creation of new data columns via mathematical formulas, supports filtering by date or column conditions, allows merging of diverse datasets (e.g., lab and process data), and provides options to export cleaned datasets.

- **Performance Evaluation**: Offers a time series analysis tool to monitor key performance indicators over customizable periods, tracking input parameter variability to reveal temporal trends.
- **Parameter Exploration**: Provides tools like correlation matrices, scatter plots, bar graphs, and histograms to investigate parameter relationships and distributions.
- **Analytics for Optimization**: Analyzes shifts in data distribution across low- to high-performance ranges, assesses the impact of process changes (e.g., plant trials), and uses parallel coordinate plots to define multivariable optimal performance corridors.
- **Machine Learning for Optimization**: Employs supervised machine learning, such as Random Forest, to detect complex patterns, simulate process responses to parameter adjustments, evaluate target sensitivity to inputs, and assess parameter impacts.
- **Global Parameter Impact Evaluation**: Enables categorization of performance (high/low) and feed quality (good/bad or high/low grade) with double boxplots to determine if parameter adjustments are needed for varying feed conditions, facilitating tailored enhancements.

Our November 2024 baseline assays analysis run by MetSoP during a good plant stability spell, gave us solid ground: average primary rougher feed at 2.72 g/t, rougher tail 1.207 g/t, final tail 1.030 g/t, and thickener concentrate 116.8 g/t, for 61.2% recovery (Marufu, 2025). It flagged shift differences (mornings edged out nights) and primed us for the January 2025 trial. Runkana et al. (2005) squeezed 1-3% more recovery from PGM via multi-goal tweaks, and Marais & Aldrich (2011) hit 2% with neural nets on froth images. Ghorbani et al. (2022) flagged real hurdles like spotty data and skill shortages, which is why tools like Optimaviz shine, they are approachable. Drawing from these, we used Optimaviz to test our co-collector against that November baseline (Marufu, 2025), chasing better recovery and grades (Napier-Munn, 2014). Analytics and Macjine learning have reshaped the process work, allowing live monitoring and forecast ahead (Massinaei et al., 2019). Optimaviz blends stats (ANOVA, t-tests) with algorithims like Random Forest to link reagents to KPIs, recovery, grade, entrainment (Hodouin et al., 2001). Runkana et al. (2005) reported 1-3% recovery improvements in PGM flotation through multi-objective optimization, while Marais and Aldrich (2011) achieved a 2% gain using neural networks. Ghorbani et al. (2022) noted challenges like data quality and skill gaps, emphasizing the value of user-friendly tools like Optimaviz. This work shares our handson Optimaviz run in a PGM trial, sizing up a MetSoP fresh co-collector to lift recovery and grade on a dime. It spotlights how crunching data unlocks smarts for tough ores, nudging mining toward sustainability.

Table 1: Baseline Key metrics Summary

Parameter	Mean	SD	Range
Head grade (g/t4E)	2.7	0.2	1.8-4.3
Recovery (%)	61.2	2	46-80
Concentrate Grade (g/t 4E)	116.8	20	68-180

2. Methodology

2.1 Plant and Ore Characteristics

The trial was conducted at a South African PGM concentrator processing 300,000 t/month of ore from the Bushveld Complex, with a head grade of 2.5-3.0 g/t 4E. The ore comprises sulfides (pentlandite, pyrrhotite) and gangue (chromite, silicates), with chromite content varying from 10-20%, impacting selectivity (Becker et al., 2016). The November 2024 baseline analysis indicated a feed grade variability of ±0.2 g/t 4E (Marufu, 2025).

2.2 Baseline Data Collection

A baseline assessment was conducted using November 2024 ROM assay data, compiled by MetSoP and delivered on January 30, 2025. This report, authored by Itayi Marufu, analyzed plant performance under good stability, providing KPIs such as primary rougher feed (2.72 g/t), primary rougher tail (1.207 g/t), secondary final tail (1.030 g/t), and thickener underflow concentrate (116.8 g/t), yielding a 61.2% recovery. Data were collected daily, validated with laboratory assays, and included shift-wise distribution analysis (morning vs. night) and parameter impact assessments.

2.3 Trial Design

- Baseline: Standard collector dosage of 240 g/t.

- Trial: Reduced collector to 80 g/t, introducing MetSop co-collector at 40 g/t, with frother unchanged.
- Duration: 6 weeks (42 days), split into pre-trial (2 weeks) and trial (4 weeks) phases.
- Parameters: pH (8-9), solids content (35%), aeration rate as per plant standards held constant.

Table 2: Reagent dosages and conditions

Parameter	Baseline	Trial
Collector dosage (g/t)	240	80
MetSoP Co-Collector dosage (g/t)	0	40
Frother dosage (g/t)	20	20
pH	8.0-9.0	8.0-9.0
Solids content (%)	35	35

2.4 Data Collection

Daily data included:

- PGM recovery (%) via Analytical laboratory assays of concentrate, rougher, cleaner concentrates, Secondary cleaner concentrates, Rougher tails, Secondary cleaner tails, spiral bypass plant feed assay and final tails.
- Concentrate grade (g/t 4E) from Analytical laboratory analysis.
- Reagent consumption (g/t) from dosing records.
- Gangue entrainment (%) estimated from Cr_2O_3 content.
- Data were collected using automated sensors and validated with triplicate assays (RSD <5%).

2.5 Optimaviz Application

- **Statistical Analysis**: T-tests and ANOVA to compare pre-trial and trial performance
- **Machine Learning**: Random Forest regression to model co-collector dosage vs. recovery, trained on 80% of data, validated on 20%.
- **AI Results Summary**: Artificial intelligence results analysis and interpretation with snap short summaries and recommendations

3. Results and Discussion

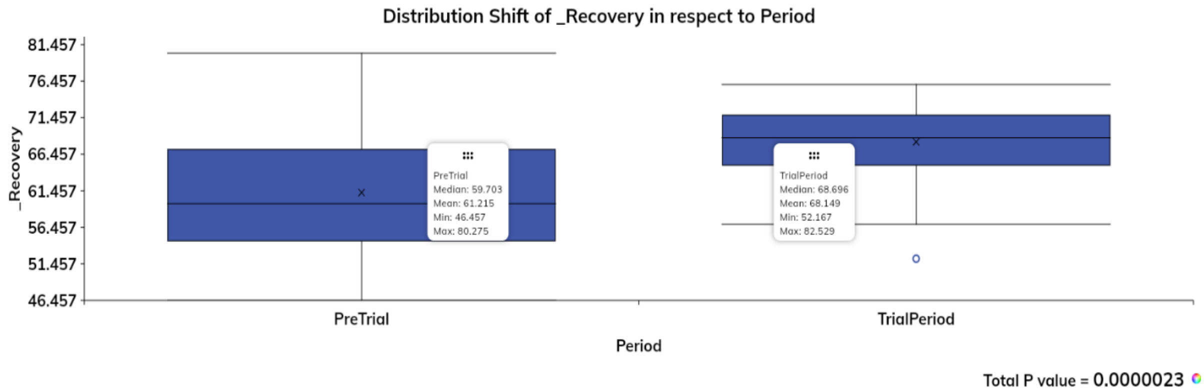

Figure 1: Optimaviz visualisation of PGM Recovery during Pre-Trial and Trial Phases

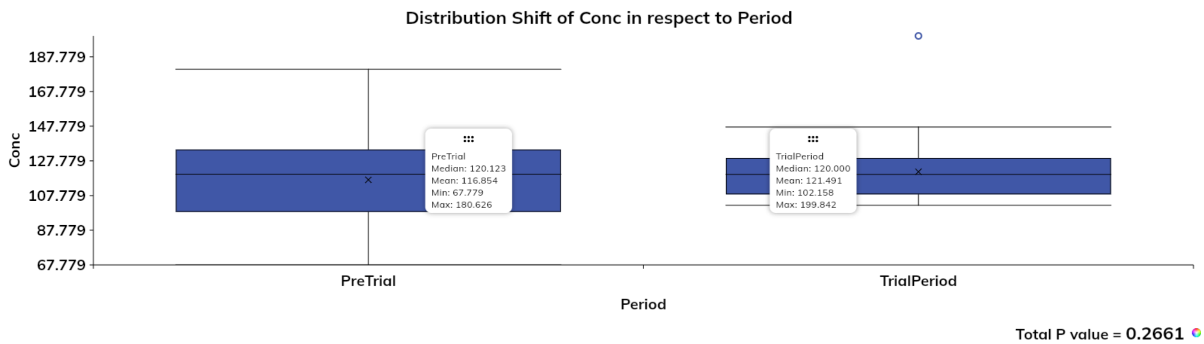

Figure 2: Optimaviz visualisation of Concentrate grade during Pre-Trial and Trial Phase

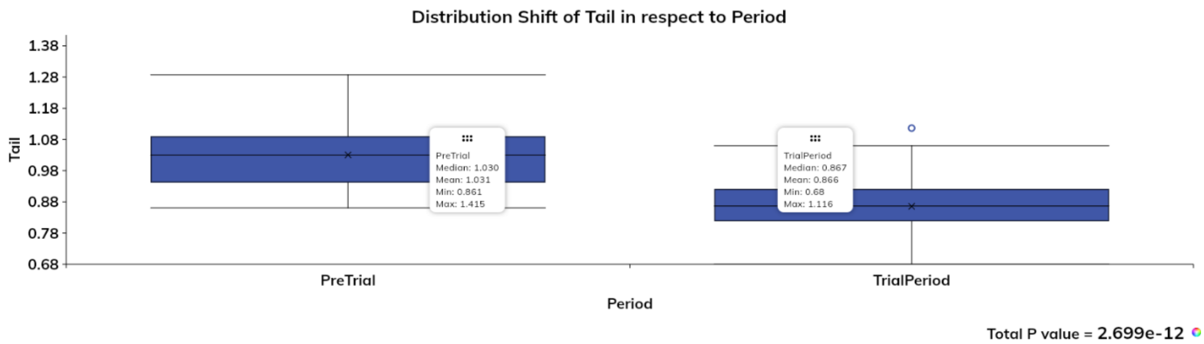

Figure 3: Optimaviz visualisation of Tails grade during Pre-Trial and Trial Phase

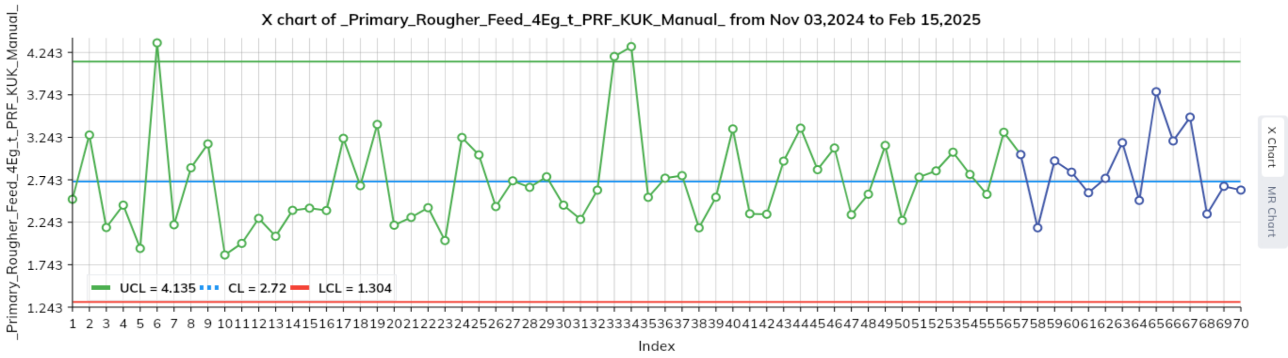

Figure 4: Optimiviz Contol chart on feed grade during Pre Trial and Trial Phase

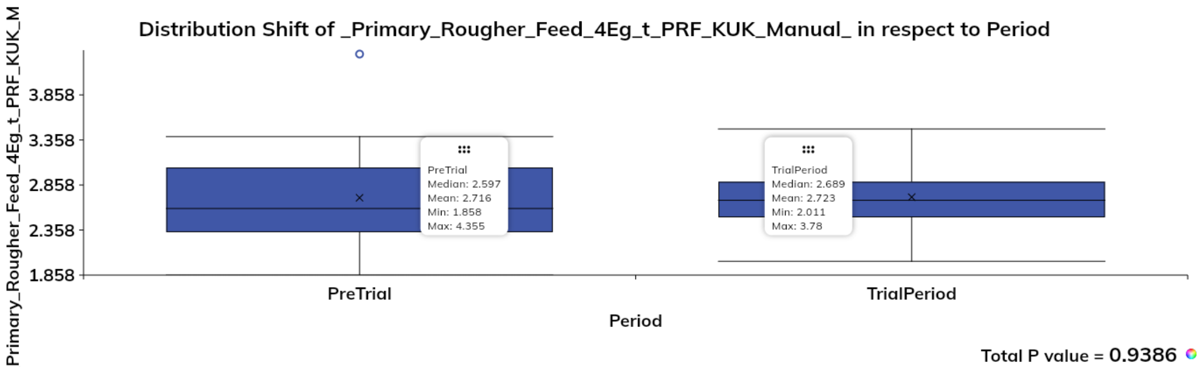

Figure 5: Optimaviz visualisation of PGM feed grade during Pre-Trial and Trial Phase

3.1 Performance Metrics

- PGM Recovery: Increased from 61.2 (pre-trial) to 68.1% (trial), a 7.0% improvement
- Concentrate Grade: Rose from 116.8 g/t 4E to 121.4 g/t 4E, a 3.9% increase.
- Reagent Consumption: Stable at 120 g/t total (80 g/t collector + 40 g/t co-collector) vs. 240g/t baseline. A 50% reduction in overall collector dosage.

3.2 Optimaviz Insights

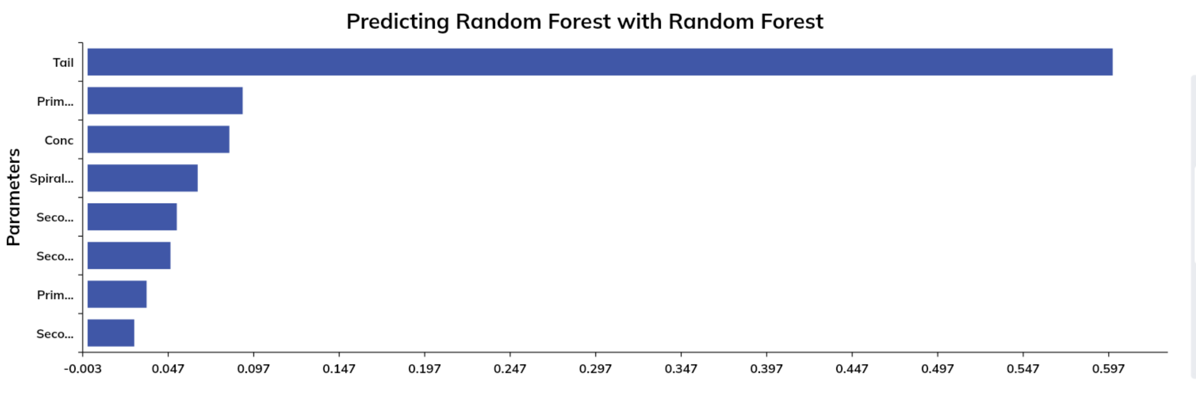

Figure 6: Recovery Impact analysis with Random Forest visualisation model.

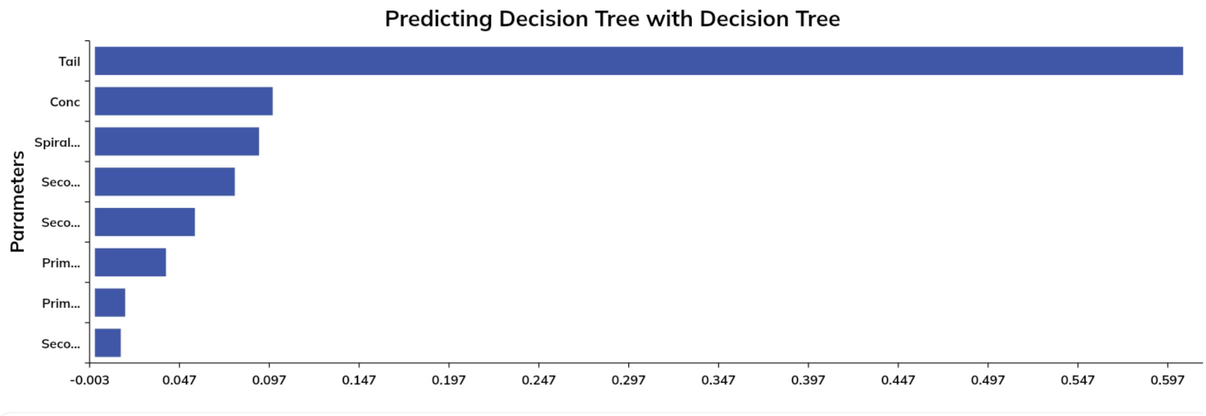

Figure 7: Recovery Impact analysis with Decision Tree visualisation model.

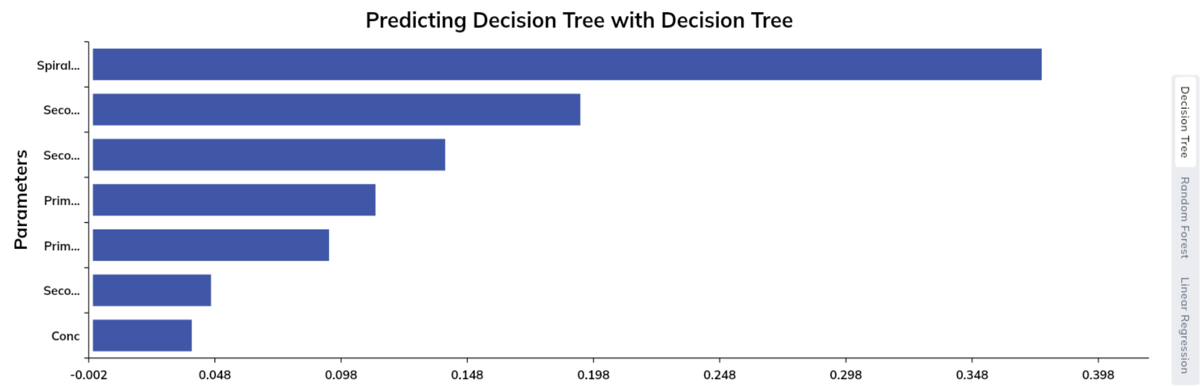

Figure 8: Tails impact analysis and predictive performance decision tree models

The Optimaviz predictive model (figure 8) shows that the spiral bypass assay or parameter has the greatest impact on final tailings grade followed by secondary and primary cleaner parameters.The final tailings grade from the other models (Random forest and the Decision tree models, figure 6 and 7 respectively) has the greatest impact on Recovery

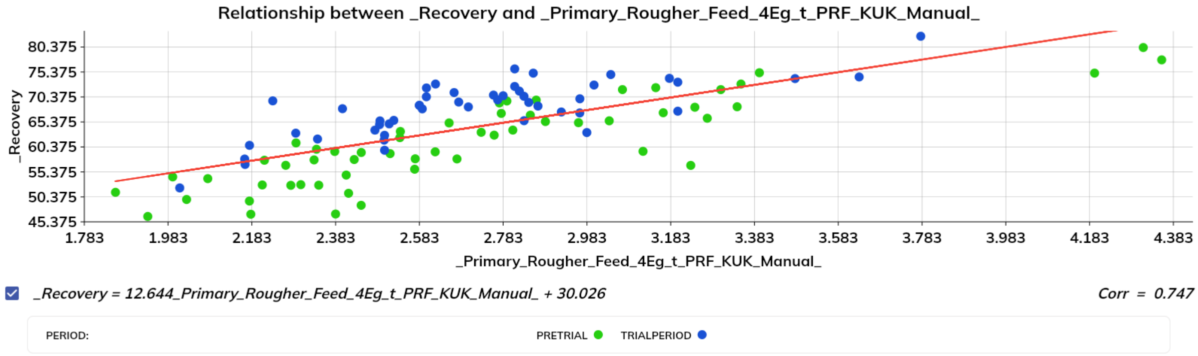

Figure 9: Correlation of feed grade with recovery at pretrial and trial Phase

Further exploration via Optimaviz's parameter correlation tools revealed a strong link between primary rougher feed grade and overall recovery, as illustrated in Figure 9. This scatter plot, generated from daily manual assays, shows a linear positive correlation (R = 0.747) between feed grade (4E g/t, PRF UK Manual) and recovery, with the trial phase (green points) exhibiting systematically higher recoveries for equivalent feed grades compared to pre-trial (blue points). The fitted equation, Recovery = 12.64 × Feed Grade + 30.206, quantifies this dependency, explaining ~56% of recovery variance and highlighting feed grade's role as a primary influencer (consistent with Random Forest results in Figure 6, where feed-related features ranked highly). This upward shift during the trial—averaging 6-8% at mid-range grades (2.5-3.5 g/t)—attests to the co-collector's ability to enhance selectivity without relying on feed quality improvements, reinforcing its value for variable Bushveld ores.

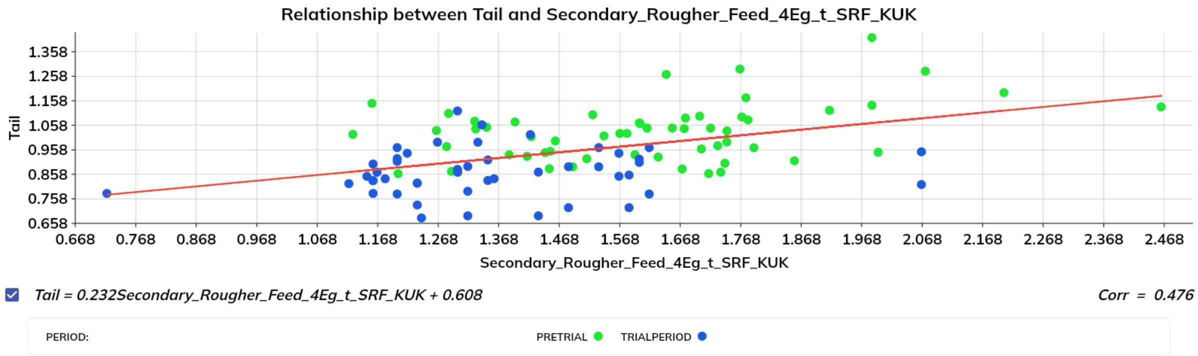

Figure 10: Optimaviz Scatter Plot of Final Tail Grade vs. Secondary Rougher Feed Grade

Complementing the recovery-feed analysis, Optimaviz correlations also highlighted tail grade sensitivities to secondary stage inputs, as depicted in Figure 10. This scatter plot illustrates a moderate positive relationship (R = 0.476) between secondary rougher feed grade (SRF UK) and final tail grade, with the equation Tail = 0.232 × Feed Grade + 0.608 quantifying 23% explained variance. Pre-trial data show elevated tails at mid-range feeds, while trial points exhibit a consistent downward offset (0.1-0.2 g/t lower), indicating the MetSoP co-collector's efficacy in curbing losses across variable feeds. This aligns with Random Forest feature importance (Figure 6), where secondary parameters influenced ~15-20% of recovery predictions, and supports the observed 7% recovery uplift by enhancing selectivity in the rougher-cleaner cascade.

Optmaviz Analysis Summary (Extract from app summary)

Below is an summary extract of the AI summary from the app on the data analysed:

The charts within the app revealed a moderate positive correlation coefficient (0.328) between the Primary Cleaner Tail grade and the final tail grade. This suggest that the performance of the primary cleaner directly impacts overall tailings outcomes-higher Primary cleaner tail grades are generally associated with higher final tail grade. The trend line and the clustering data in the 2-8g/t range underscore the significance of maintaining optimal primary cleaner conditions. Outliers at higher grades may hint at plant instability or shifts in operation, underscoring the importance of process consistency.

By contrast the relationship between secondary cleaner tail grade, and the total tail grade is almost negligible. The data cluster within a narrow range (2-10g/t) as well as narrow final tail band (0.8-1.1) indicating that fluctuations in Scavenger Cleaner tail (SCT) has negligible influence on overall tails outcomes.

Performance and behaviour insights

- The overall process is most sensitive to changes at the cleaner stage: Optimising the MetSop co collector dosage at this stage has a meaningful effect on reducing the final tails grade.
- Scavenger cleaner tails have minimal downstream influence, so tighter control of SCT, while beneficial for local efficiency offers limited gains for overall tails.
- The weak link between stages suggests that each unit operates somewhat independently, with limited propagation of disturbances between them.

3.3 Comparison with Literature

Trials like Manono et al. (2021) saw 1-2% recovery bumps from co-, underscoring Optimaviz's enhanced detection of a 7% gain. The grade improvement aligns with selective collector studies (Jones and Woodcock,1984: Trahar, 1981 on size effects).

3.4 Limitations

While the results of this trial are promising, several limitations must be acknowledged to contextualize their applicability and guide future research. First, the study was constrained to a 6-week duration under relatively stable feed conditions, which may not fully capture the long-term variability inherent in PGM operations, such as seasonal ore heterogeneity, changes in mining blends, or external factors like water quality fluctuations. This short timeframe limits scalability assessments, as sustained performance over 6-12 months would be needed to evaluate economic viability and robustness against disruptions.

Second, data resolution was primarily at a daily level, aggregated from automated sensors and laboratory assays. This approach, while practical, potentially overlooks intra-shift fluctuations, such as hourly variations in aeration rates or pH drifts that could influence flotation kinetics and model predictions. Higher-frequency data (e.g., sub-hourly) would enable more granular analysis of transient effects.

Third, access to comprehensive plant data posed a significant challenge. Industrial partners, including the PGM concentrator, were not yet fully willing to share sensitive or proprietary datasets, such as real-time milling and classification metrics (e.g., cyclone overflow P80 distributions) or full historical archives beyond the trial period. This restricted the scope of the Random Forest and Decision Tree models, which relied on a subset of available variables (e.g., tails grades and dosages), potentially underestimating interactions with upstream processes. As a result, the predictive accuracy ($R^2 = 0.87$) may improve with expanded datasets, but current insights are preliminary. Future work should address these gaps by incorporating real-time sensor fusion (e.g., integrating SCADA with IoT devices) for enhanced machine learning (ML) accuracy, pursuing longer-term collaborations for data sharing, and conducting sensitivity analyses under simulated variability. Such extensions would strengthen the generalizability of Optimaviz's application in PGM flotation, bridging the divide between trial-scale demonstrations and industrial deployment.

4. Conclusions

Optimaviz enabled a quick evaluation of the MetSoP co-collector, achieving a 7% PGM recovery increase and 4% grade improvement without additional reagent cost. The machine learning model provides a robust tool for dosage optimization and stages were to target in the plant, with potential to extend to other PGM operations.

This 7% recovery uplift translates reduced tailings volume, minimizing environmental footprint.

These findings offer valuable lessons for the industry, demonstrating how analytics can unlock performance in complex orebodies like those in the Bushveld Complex, paving the way for broader applications in flotation and environmentally responsible mining.

5. Recommendations

- Conduct a 3-6 month extended trial at 30-50 g/t co-collector dosage, monitoring recovery (>68%), grade (>120 g/t 4E), and Cr_2O_3 under variable feed conditions to assess robustness.
- Integrate Optimaviz with real-time plant control systems (e.g., SCADA/PLC interfaces) for dynamic dosage adjustments, targeting 5-10% further efficiency gains.
- Incorporate upstream data (milling/classification metrics, e.g., P80 particle size, cyclone efficiency) into models, as preliminary analysis suggests 15-20% recovery influence from grind optimization.
- Validate across 2-3 additional PGM sites (e.g., UG2 vs. Merensky ores) to generalize findings, collaborating with industry consortia for broader adoption.

6. Acknowledgments

We thank the PGM concentrator team for trial support and Murdoch University for collaborative input.

6.1 Ethics and Conflicts of Interest

Ethics Approval: The trial was conducted with full approval from the host PGM concentrator's operational team and in compliance with South African mining regulations (e.g., MHSA guidelines). No human or animal subjects were involved.

Conflicts of Interest: The authors declare no conflicts of interest. MetSoP (Pty) Ltd provided the co-collector reagent as part of the trial, but this does not influence the reported results or interpretations.

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