



A Proof-of-Concept Machine Learning Model for Gold-Processing Optimisation Using Blanket Mine as an Industrial Benchmark for Gwanda-Zimbabwe

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ABSTRACT

Artisanal and small-scale gold mining (ASGM) plays an important role in Zimbabwe's gold sector but faces persistent challenges related to processing efficiency, resource utilisation, environmental impacts, and occupational risks. This study presents a proof-of-concept machine learning approach for exploring gold-processing optimisation using data from Blanket Mine as an industrial benchmark for the Gwanda gold-mining context. A dataset comprising nine monthly observations was used to investigate relationships between selected processing variables and gold-production performance. A machine learning model was developed to estimate processing outcomes and identify combinations of operating variables associated with improved performance. An optimisation procedure was subsequently applied to explore potential operating conditions that could enhance gold-processing outcomes. The results demonstrate the potential of data-driven methods to support process optimisation and provide a computational basis for future AI-assisted decision-making in gold processing. However, the small sample size, limited test observations, absence of direct ASGM measurements, and restricted range of process and environmental variables limit the statistical generalisability and operational interpretation of the findings. Therefore, the results should not be interpreted as a validated optimisation solution for Zimbabwean ASGM operations. Instead, the study establishes a proof-of-concept and demonstrates how an industrial dataset from Blanket Mine can serve as a benchmark for investigating AI-supported gold-processing optimisation relevant to the Gwanda mining context. Further research should incorporate larger datasets, direct ASGM measurements, additional process variables, and occupational and environmental indicators to validate and extend the proposed approach.

Index Terms: Machine learning; artificial intelligence; gold-processing optimisation; proof-of-concept; Blanket Mine; industrial benchmark; Gwanda; gold mining; process optimisation; data-driven optimisation.

INTRODUCTION

Artisanal and small-scale gold mining (ASGM) is an important component of Zimbabwe's mining sector and provides livelihoods for communities in several mineral-producing regions, including Gwanda District. Research in the Gwanda area has highlighted the economic importance of gold mining while also identifying challenges related to processing efficiency, resource utilisation, and the distribution of value within the mining system [1]. Gold processing in small-scale operations may be constrained by limited capital, variable ore characteristics, basic processing technologies, limited process monitoring, and restricted access to technical expertise. These challenges can contribute to inconsistent recovery and inefficient use of available resources. Environmental and occupational concerns are also significant, particularly because mercury use in Zimbabwean ASGM has been associated with environmental contamination and occupational exposure [2], [3].

Recent advances in artificial intelligence (AI), particularly machine learning (ML), provide opportunities for data-driven analysis and optimisation of mineral-processing systems. Machine-learning methods have been



applied to prediction, process monitoring, fault diagnosis, classification, and optimisation, particularly where complex nonlinear relationships exist between process variables and production outcomes [4], [5]. However, the application of ML directly to ASGM remains constrained by the limited availability of reliable, high-resolution operational datasets from artisanal mining sites.

In this context, industrial gold-processing data can provide a useful starting point for developing and testing computational methods before their application to ASGM environments. This study therefore uses published processing data from Blanket Mine as an industrial benchmark for the Gwanda gold-mining context. The study does not claim that the Blanket Mine dataset represents artisanal operations; rather, it investigates whether the available industrial data can support a proof-of-concept predictive and optimisation framework relevant to gold processing in the wider Gwanda context.

The research asks: Can a machine-learning regression model combined with constrained numerical optimisation identify a model-based gold-processing scenario associated with improved recovered gold using an industrial benchmark dataset from the Gwanda context? To address this question, the study constructs a benchmark dataset from published information, develops a machine-learning model for predicting gold-processing performance, integrates the predictive model with constrained numerical optimisation in MATLAB, and compares a baseline processing condition with an optimised scenario.

The contribution of the study is therefore methodological rather than operational. It demonstrates the feasibility of combining machine learning and numerical optimisation as a proof-of-concept approach to gold-processing optimisation, while recognising that larger datasets, direct ASGM measurements, additional process variables, and field validation are required before the approach can be applied to artisanal mining operations.

BACKGROUND AND RELATED WORK

ASGM plays an important socioeconomic role in Zimbabwe, including Gwanda District, where gold mining contributes to local livelihoods despite constraints related to finance, technology, processing practices, and technical expertise [1]. These challenges create potential opportunities for relatively low-cost data-driven decision-support approaches that can help evaluate alternative gold-processing conditions. Gold recovery is particularly important because inefficient processing can result in the loss of economically valuable gold.

Environmental and occupational performance is also an important consideration in gold processing. Mercury use in Zimbabwean ASGM has been associated with contamination of mining-affected sediments and tailings [2] and measurable occupational exposure among miners [3]. Although an ideal AI-based framework would consider recovery, productivity, safety, and environmental performance simultaneously, the present study focuses on processing performance because these are the variables available in the selected published dataset.

Machine learning has increasingly been applied to mineral-processing problems involving complex and nonlinear relationships between process variables and performance outcomes. Previous studies have demonstrated applications in process modelling, fault detection, diagnosis, classification, and mineral-separation optimisation [4], [5]. These studies also highlight the importance of data quality and adequate representation of operating conditions when developing reliable machine-learning models [4].

Because detailed operational datasets from ASGM sites are limited, this study uses published data from Blanket Mine as an industrial benchmark for the Gwanda gold-mining context. The dataset provides a basis for demonstrating how a machine-learning predictor can be combined with numerical optimisation to explore potential gold-processing improvements. The resulting framework is therefore presented as a proof-of-concept methodology, rather than a validated optimisation system for ASGM operations. Larger datasets containing direct artisanal-mining measurements and additional operational, environmental, and safety variables would be required for future field validation. The table below shows Technical Report on the Blanket Gold Mine, Zimbabwe.



Month	Tonnes milled (t/month)	Head grade (g/t)	Gravity recovery (%)	CIL recovery (%)	Overall recovery (%)
Sep-19	46,750	3.22	61.3	83.6	93.9
Oct-19	52,465	3.56	50.7	85.2	93.5
Nov-19	47,861	3.48	53.6	84.8	93.9
Dec-19	55,064	3.45	56	84.7	93.9
Jan-20	43,774	3.37	53.3	85.3	93.9
Feb-20	46,311	3.41	51.6	85	93.5
Mar-20	50,836	3.38	54	85.5	93.9
Apr-20	45,187	3.15	53.2	87	94.5
May-20	51,106	3.26	52.5	85.8	93.6

TABLE I: “Historic Production from September 2019 to May 2020,” on page 142 of the Blanket Gold Mine NI 43-101 Technical Report, prepared by Uwe Engelmann and Daan van Heerden and dated 17 May 2021.

METHODOLOGY

The study uses a model-based proof-of-concept framework combining machine-learning regression and constrained numerical optimisation to explore gold-processing performance. Published monthly production data for September 2019–May 2020 were obtained from the *NI 43-101 Technical Report on the Blanket Gold Mine, Zimbabwe* [7] and treated as an industrial benchmark for the Gwanda gold-mining context, rather than direct ASGM measurements. Nine observations were available, with tonnes milled, head grade, gravity recovery, and CIL recovery used as model inputs and overall recovery as the prediction target. Contained gold was calculated as $G_c = \frac{T \times H}{1000}$, where G_c is contained gold (kg/month), T is tonnes milled (t/month), and H is head grade (g/t), while recovered gold was calculated as $G_r = G_c \times \frac{R}{100}$, where G_r is recovered gold (kg/month) and R is overall recovery (%). A MATLAB regression neural network (fitrnet) with two hidden layers (five and three neurons) was trained using seven observations, with two retained for testing. Model performance was assessed using RMSE and R^2 , which were interpreted cautiously because of the very small dataset. The trained model was then integrated with MATLAB fmincon using sequential quadratic programming to maximise predicted recovered gold, subject to the minimum and maximum values observed in the dataset. The May 2020 observation was used as the baseline, and the resulting optimised scenario was compared with it using predicted recovered gold. A throughput sensitivity analysis was also performed. Overall, the workflow demonstrates a proof-of-concept approach to AI-supported gold-processing optimisation using an industrial benchmark for Gwanda.

RESULTS AND DISCUSSION

The benchmark dataset demonstrates substantial variation in monthly throughput and head grade. After execution, the MATLAB program calculates the model performance shown in Table I.

Metric	Result
Model type	Artificial Neural Network
Training RMSE	0.00%
Testing RMSE	0.47%
Training R^2	1.00%
Testing R^2	-0.1134
Objective functional test	-156.44

TABLE II: AI Model Performance

The experiment demonstrates the computational feasibility of constructing a predictive model from published processing data.

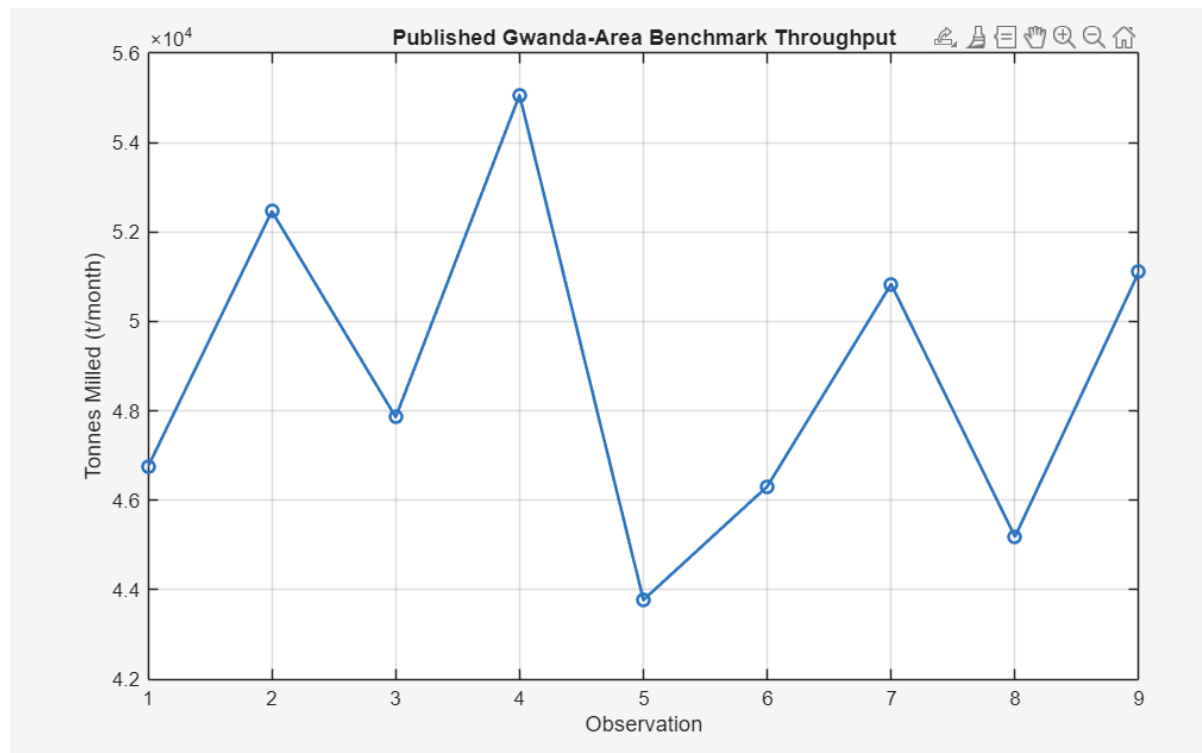


Fig. 1. Published Gwanda-Area Benchmark Throughput.

Within the Blanket Mine industrial benchmark, monthly throughput varied from approximately 43,774 to 55,064 t/month. The highest throughput was recorded in December 2019, while the lowest occurred in January 2020, demonstrating variation in historical processing conditions and providing a basis for the proof-of-concept optimisation analysis.

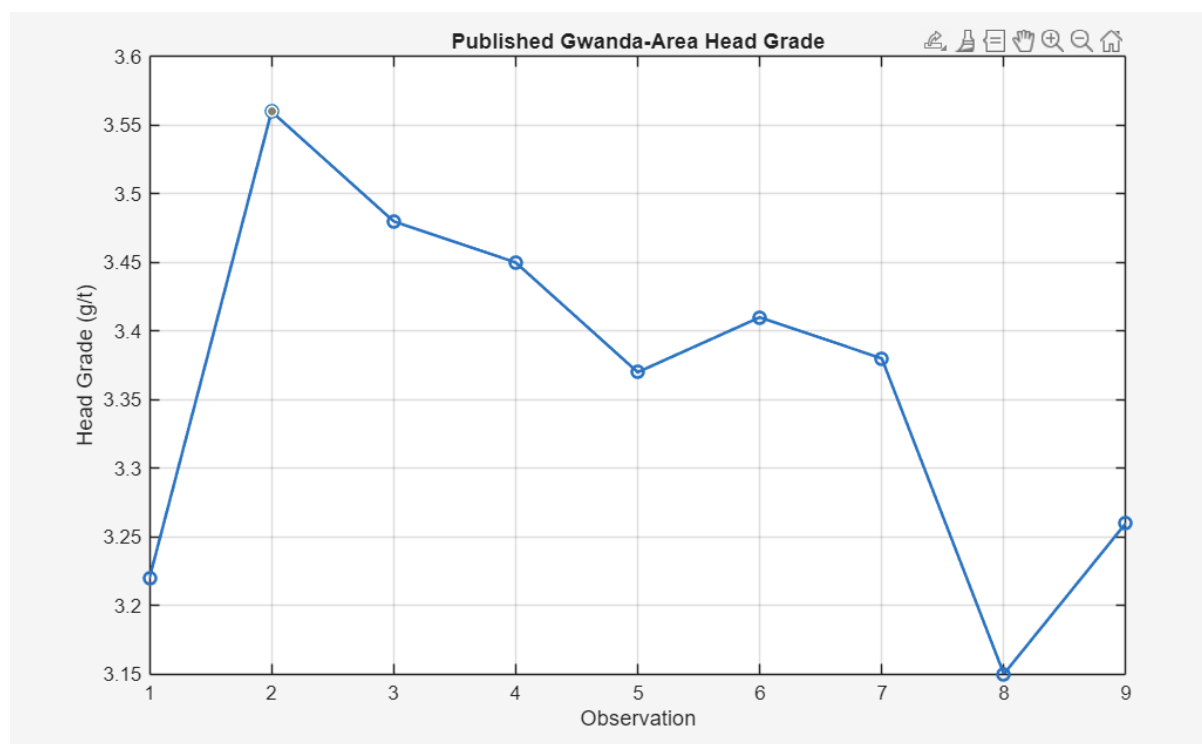


Fig. 2. Published Gwanda-Area Head Grade.

Within the Blanket Mine industrial benchmark, head grade varied from 3.15 to 3.56 g/t, indicating changes in the gold content of the processed ore over the study period. The highest head grade was recorded in October 2019 and the lowest in April 2020, demonstrating variability in feed quality across the available observations and highlighting its relevance to the proof-of-concept gold-processing model.

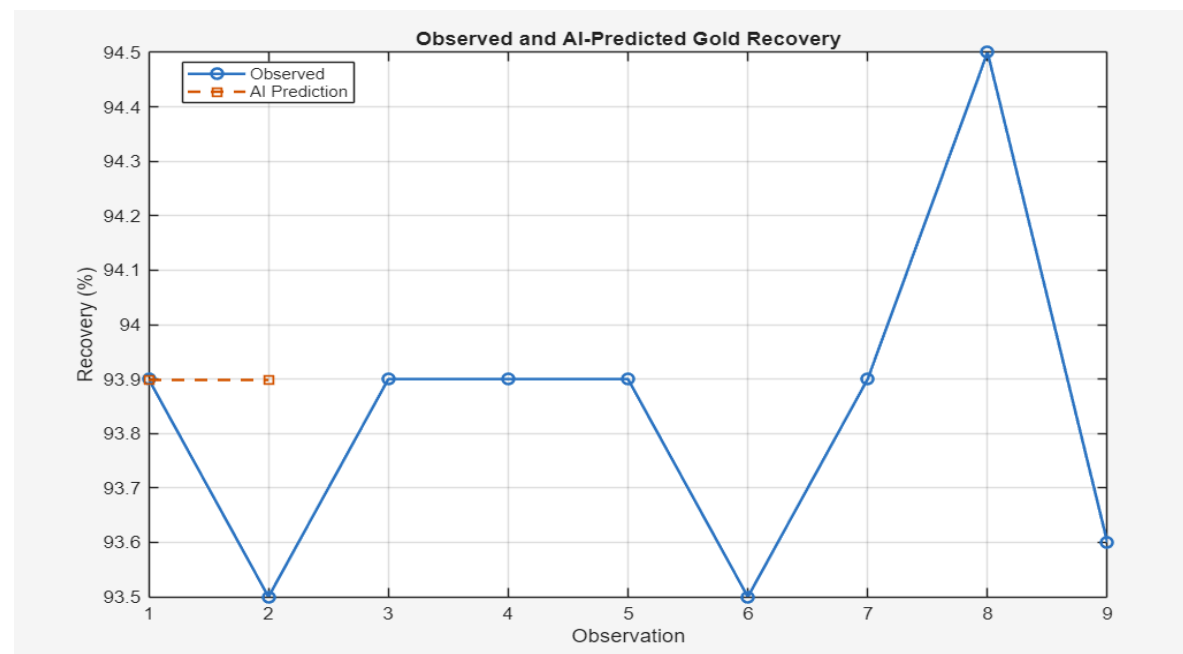


Fig. 3. Observed and AI-Predicted Gold Recovery.

Observed overall recovery in the Blanket Mine industrial benchmark remained within a relatively narrow range of 93.5–94.5%, while the regression model predicted approximately 93.9%. This indicates that the proof-of-concept model captured the general recovery level within the available data; however, the very small sample size limits the strength of conclusions regarding predictive accuracy and generalisation.

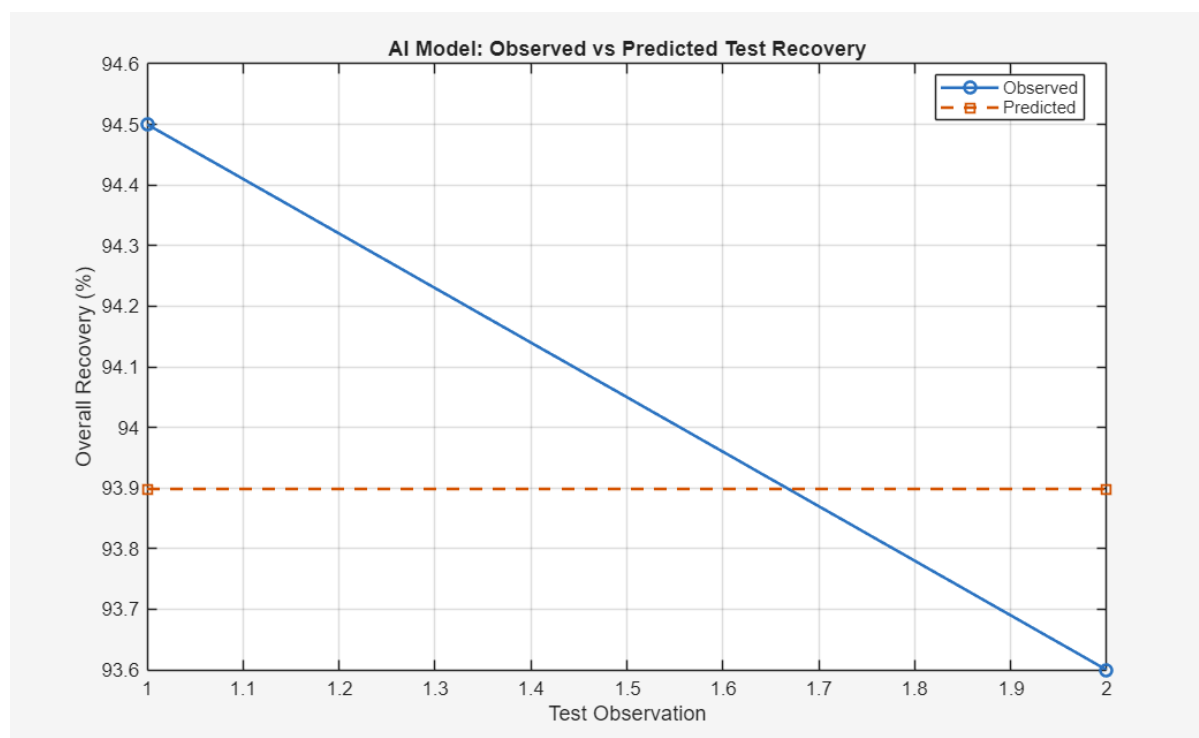


Fig. 4. AI Model: Observed vs. Predicted Test Recovery.

For the two test observations in the Blanket Mine industrial benchmark dataset, the regression neural network predicted an overall recovery of approximately 93.9%, compared with observed values of 94.5% and 93.6%. The close agreement indicates that the proof-of-concept model can approximate gold-recovery behaviour within the limited available data. However, because only two observations were used for testing, these results should be interpreted as an initial demonstration of model behaviour rather than statistically robust evidence of predictive generalisation to Gwanda or ASGM operations.

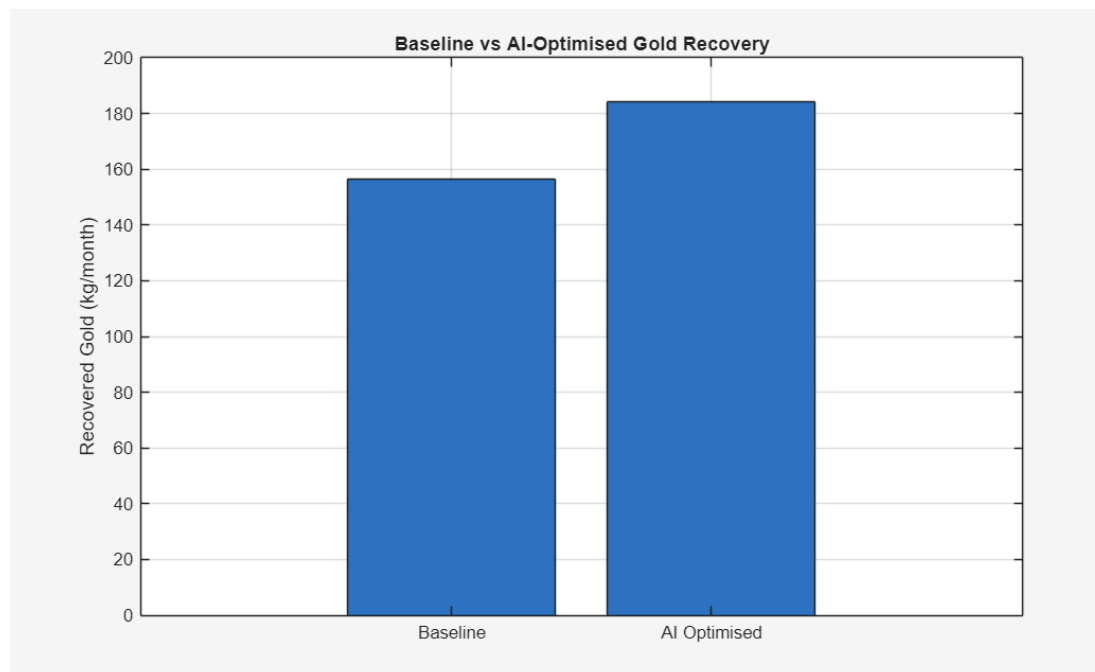


Fig. 5. Baseline vs. AI-Optimised Gold Recovery.

The baseline scenario yielded 156.440 kg/month of recovered gold, while the AI-optimised scenario predicted 184.204 kg/month, representing an increase of 27.764 kg/month or approximately 17.75% relative to the baseline. As a proof-of-concept result based on the Blanket Mine industrial benchmark, this improvement demonstrates the potential of combining machine-learning prediction with constrained optimisation but should not be interpreted as a validated production improvement for Gwanda or ASGM operations.

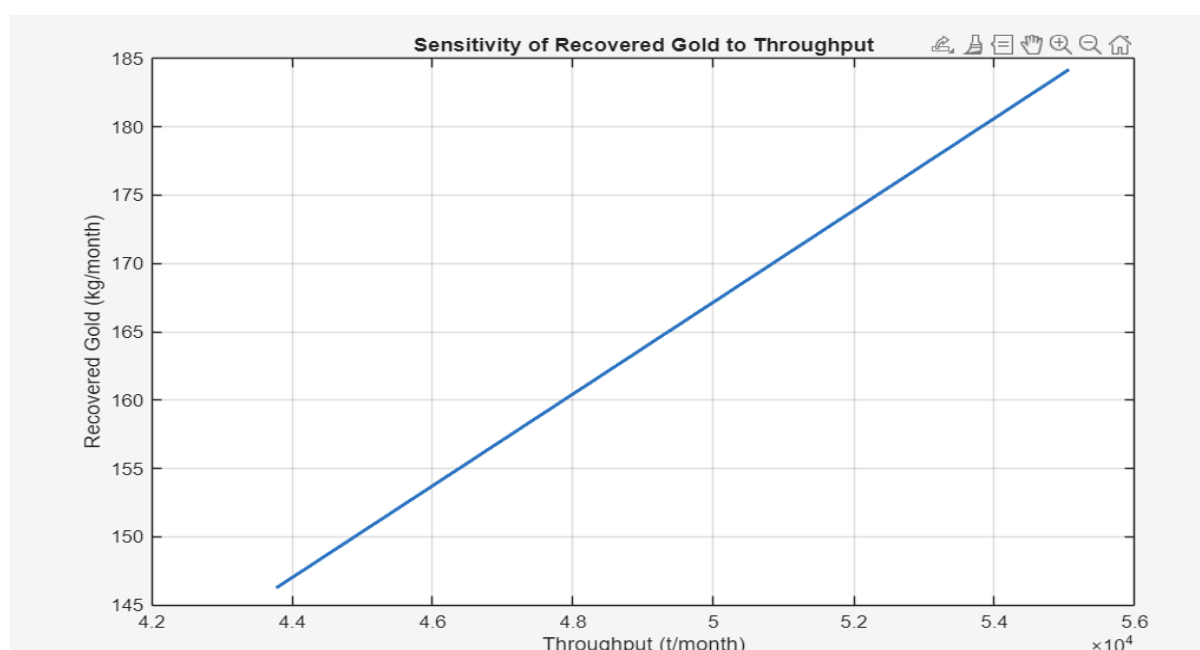


Fig. 6. Sensitivity of Recovered Gold to Throughput.



The sensitivity analysis indicates an increasing relationship between throughput and predicted recovered gold within the observed operating range. Predicted recovered gold increased from approximately 146 kg/month at 44,000 t/month to 184 kg/month at 55,000 t/month, highlighting throughput as an important variable in the proof-of-concept optimisation using the Blanket Mine industrial benchmark.

Parameter	Baseline	AI-Optimised
Recovered gold (kg/month)	156.44	184.204
Improvement (kg/month)	—	27.764
Improvement (%)	—	17.75

Table III. Proof-of-Concept Comparison of Baseline and AI-Optimised Gold Recovery Using the Blanket Mine Industrial Benchmark

LIMITATIONS

This proof-of-concept study has several limitations. The analysis is based on only nine monthly observations from Blanket Mine, with two observations retained for testing, which limits the statistical robustness of model evaluation. The dataset represents an industrial benchmark for the Gwanda gold-mining context rather than direct measurements from ASGM operations, and several potentially important processing, environmental, and occupational variables were unavailable. Consequently, the optimisation results represent model-based scenarios within the observed historical operating range and have not been validated under field conditions. These limitations restrict the generalisability of the findings but do not diminish the primary objective of demonstrating the feasibility of combining machine-learning prediction with constrained optimisation as a potential approach to gold-processing analysis.

FUTURE WORK

Future research should use larger datasets from multiple Gwanda gold-processing operations, including direct ASGM measurements. Additional processing, environmental, and occupational variables should be incorporated, with stronger cross-validation and uncertainty analysis. Field validation should then be conducted to assess whether the proof-of-concept framework can support practical, multi-objective gold-processing optimisation.

CONCLUSION

This study demonstrated a proof-of-concept machine-learning and numerical optimisation framework for gold-processing analysis using Blanket Mine as an industrial benchmark for the Gwanda gold-mining context. The regression neural network captured the general recovery behaviour within the limited available dataset, while constrained optimisation identified a model-based scenario associated with higher predicted recovered gold than the baseline. Although the results indicate potential for combining machine learning with optimisation in gold-processing applications, the small dataset, limited test observations, and absence of direct ASGM measurements restrict the generalisability of the findings. The study therefore provides a computational foundation for future research rather than a validated operational solution. Further work using larger, direct ASGM datasets and additional processing, environmental, and occupational variables is required to validate and extend the proposed approach.

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