



FACULTY OF ENGINEERING AND TECHNOLOGY

DEPARTMENT OF MINING ENGINEERING

**A DATA-DRIVEN APPROACH FOR MODELING AND OPTIMIZATION
GOLD RECOVERY EFFICIENCY FROM THE FROTH FLOTATION
PROCESS AT WAGAGAI MINING (U) LTD**

CASE STUDY; WAGAGAI MINING (U) LIMITED

By

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This final year project report submitted to the department of Mining Engineering as a partial fulfilment of the requirements of the award of Bachelor of Science in Mining Engineering.

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ABSTRACT

Froth flotation is a cornerstone process in the mining industry for separating valuable minerals like gold from gangue, yet its efficiency is often compromised by the complex, non-linear interactions among various operational parameters (e.g., reagent dosage, particle size, pH). Traditional optimization methods heavily rely on subjective operator experience, leading to suboptimal and inconsistent gold recovery rates. This research addressed this challenge by developing and validating data-driven predictive models and an optimization framework to enhance gold recovery from the froth flotation process at Wagagai Mining (U) Ltd. Using 1,000 historical operational records, predictive models based on Multiple Linear Regression (MLR), Random Forest (RF), and Artificial Neural Networks (ANN) were developed after relevant feature selection (Modifier, Activator, Collector 1, Collector 2, Frother, and Residence Time). Model performance was evaluated using R-squared (R^2) and Root Mean Squared Error (RMSE). The ANN model demonstrated superior predictive performance (Testing $R^2 = 0.879$) compared to RF (Testing $R^2 = 0.819$) and MLR (Testing $R^2 = 0.556$), effectively capturing the complex relationships within the data. The best-performing ANN model was then coupled with a Genetic Algorithm (GA) to identify optimal process parameter combinations for maximizing gold recovery, constrained by operational limits. The GA optimization identified an optimal reagent dosage configuration that the ANN predicted could yield a maximum gold recovery of 99.06%. Sensitivity analysis on the optimized model revealed that Modifier (Na_2CO_3 , 38%), Activator (CuSO_4 , 25%), and Collector 1 (HB-33A, 20%) were the most influential reagents affecting recovery. A comparison with Wagagai Mining's existing practices showed historical monthly gold recovery fluctuating between 87.00% and 94.01%, significantly lower than the predicted optimum. The company's current approach involved inconsistent reagent dosing, often leading to over- or underdosing relative to the identified optimal levels. Implementing the ANN-GA optimized strategy is estimated to yield an annual reagent cost saving of \$657.01 while achieving substantially higher recovery. This study underscores the significant potential of integrating machine learning and genetic algorithms for optimizing mineral processing operations, offering a data-driven approach to improve gold recovery efficiency, reduce operational costs, and support more sustainable mining practices at Wagagai Mining and potentially similar operations.

DECLARATION

I **GIRAMIA TRINITY**, registration number BU/UG/2021/3393 declare that this research report was originally written and organized by me and has not been previously published, therefore presented as a requirement for the award of Bachelor of science in mining engineering.

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DEDICATION

I dedicate this report to my guardians for their unwavering love, support, and encouragement have been the driving force behind my academic pursuits, may the almighty God bless them abundantly.

APPROVAL

I GIRAMIA TRINITY, submit this report of my final year project to the faculty of engineering in the department of mining and water resources engineering for the examinations with approval of my supervisors

MR. MASERUKA BENEDICTO

Signature.....

Date.....18/11/25

MR. KWIKIRIZA MATHIAS

Signature.....

Date.....8th/05/2025

LIST OF ACRONYMS

ANN	Artificial Neural Networks
CNN	Convolutional Neural Networks
GA	Genetic Algorithm
IQR	Interquartile range
LR	Linear Regression
MAE	Mean absolute error
MLR	Multiple Linear Regression
MNLR	Multivariate Nonlinear regression
OOB	out-of-bag
PSO	Particle Swarm Optimization
R^2	coefficient of determination
RBNN	Radial basis function neural network
RF	Random Forest
RFECV	Recursive feature evaluation with cross-validation
RMSE	Root mean square error
SA	Simulated Annealing optimization algorithm
SVM	Support Vector Machines
VIM	Variable importance measurements
XRF	X-ray fluorescence

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5.1 Recommendations

Scale Up Optimization to Industrial Operations. While the optimization in this study was performed using laboratory scale historical datasets, future work should implement the ANN-GA optimized parameters in full-scale flotation plants to assess real-world feasibility, variability, and economic performance.

Explore Hybrid Optimization Algorithms. Although Genetic Algorithms (GA) proved effective, exploring and comparing alternative or hybrid optimization algorithms such as Particle Swarm Optimization (PSO) or Differential Evolution (DE) could further improve robustness and convergence speed.

Consider Additional Input Variables. Include more diverse input variables such as ore mineralogy, feed size distribution, pulp temperature, and slurry viscosity to enhance model accuracy and generalizability across different ore types and plant conditions.

5.2 Conclusion

The ANN model was the most accurate in predicting gold recovery, with an R^2 value of 0.961.

GA optimization increased the predicted recovery to 99.06%, outperforming the company's results.

Modifier (Na_2CO_3) and Collector 1 (HB-33A) were the most influential reagents.

The developed approach reduced costs, improved efficiency, and outperformed the company's trial-and-error method.

Demonstrated the value of ML decision-making in mineral processing

5.3 REFERENCE

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