

Application of geometallurgy to develop predictive models for acid consumption on Tschudi copper heap leach operations

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Abstract

This study presents the application of geometallurgy to develop predictive models for acid consumption at the Tschudi copper heap leach operations in Namibia. The acid heap leach process, integral to the extraction of copper from low-grade ore, requires a substantial amount of sulphuric acid, which is a major cost driver. Accurate prediction of acid consumption is vital for budgeting and cost management. The model development utilized historical processing data, including mineralogical and lithological composition of the ore, to predict acid consumption during the curing and leaching stages. Multivariate regression analysis was employed to establish relationships between mineral species and acid consumption, resulting in a predictive model that considers the geological variations within the ore body. The model incorporates three distinct leaching stages, each characterized by exponential changes in acid consumption, and is calibrated using actual plant data to improve accuracy. The findings reveal that, after calibration, the model predicts acid consumption with an average error of 5%, with significant reductions in error for slow kinetic regions. This model offers a robust tool for enhancing operational efficiency, improving acid usage estimation, and optimizing overall leaching costs in heap leach operations.

Keywords: Copper; Heap Leaching; Acid, Modelling; Geometallurgical

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1. Introduction

The Tschudi copper mine, located in northern central Namibia near the town of Tsumeb, employs an acid heap leach process to extract copper from low-grade ore. This process is followed by solvent extraction and electro winning to produce American Society for Testing and Materials (ASTM) standard copper cathodes. A significant amount of sulphuric acid (H_2SO_4), sourced externally, is consumed in this process. Since H_2SO_4 is the primary reagent and a major cost driver, it is crucial to develop a tool that accurately predicts acid consumption, allowing for precise budgeting and estimation of overall leaching costs.

To accurately forecast acid consumption, it is essential to establish the geological and metallurgical characteristics of the ore. The total amount of acid consumed during leaching is influenced by the geological composition of the ore (Radwany and Barton, 2022). Exploration data reveals that the geological makeup of the Tschudi ore deposit includes varying proportions of highly weathered, transitional, and fresh lithologies, which contain a mix of oxides,

sulphides, carbonates, and silicate minerals (McKinney et al., 2009). In such an ore body, the lithological and mineralogical variations depend on the mining location. These geological features, however, are not directly linked to acid consumption, making it challenging to predict the acid requirements for the ore. This study aims to develop a mathematical model that can accurately predict acid consumption for the Tschudi ore, based on prior processing and exploration data.

1.1 Overview of the Tschudi orebody and acid consumption

The sulphide and non-sulphide copper minerals within the Tschudi deposit are hosted in carbonate and siliceous sandstone minerals, located in the northern part of the Otavi Mountain Land (McKinney et al., 2009; Herman, 2017). The mineral paragenesis varies across different sections, resulting in diverse combinations of pyrite, chalcocopyrite, bornite, chalcocite, covellite, malachite, and azurite (Herman, 2017). These mineral matrices are consistent regardless of location and depth within the ore body (Kamona, 2017). Table 1 presents the results of various petrographic analyses to determine the mineral paragenesis of the Tschudi deposit (Kamona, 2017).

Table 1 Tschudi copper deposit mineral paragenesis (Kamona, 2017)

Time	Early stage		Intermediate stage			Late stage
	Primary sulphides		Secondary sulphide enrichment			Oxide enrichment
Sample No.	Pyrite	Chalcocopyrite	Bornite	Chalcocite	Covellite	Malachite/ Goethite/Azurite
P4B-6						
P4B-7						 
P4B-8						 
P5A-1						 
P5A-2						 
P5A-3						
P5A-4						  
P5A-5						 

The different colours represent the different mineral phases and their relative sequence of formation within the Tschudi deposit.

Key:

-  Pyrite
-  Chalcocopyrite
-  Bornite
-  Chalcocite
-  Covellite
-  Malachite
-  Goethite
-  Azurite

This low-grade deposit's mineralization impregnates sandstones and conglomerates originating from a dolomite footwall (Augustein, 2017). Arenite sandstones transition from the carbonate-rich dolomite footwall, containing varying proportions of carbonate minerals (Augustein, 2017). The variation in the proportion of these carbonate minerals leads to differences in acid consumption. Table 2 presents the primary geologically identifiable minerals and lithologies within the orebody, along with the logging codes used to determine the relationship between mineralogy and acid consumption.

Table 2 Mineralogy and lithological classification of the Tschudi deposit (McKinney et al., 2009)

Classification	Code	Description
Copper bearing Minerals	OX	Oxide minerals, contain malachite and azurite
	CC	Secondary sulphide minerals which constitute chalcocite and covellite
	BN	Bornite
	CPY	Chalcopyrite
Limestone Minerals	MAG	Undefined Magnesite
	DOLO	Undefined dolomite
	CALC	Calcrete
Lithology	AREN	Arenite- standard sandstone term if not arkosic or quartz rich
	ARQZ	Quartz arenite, grey, generally glassy, hard, medium grained, quartz rich
	ARBL	black arenite, dark grey to black colour, fine medium grains

The Tschudi process uses agglomeration to pre-treat the crushed ore. During agglomeration, concentrated sulfuric acid is introduced to the ore, converting minerals into easily leachable sulphates (Bouffard, 2005; Saldana et al., 2019). This acid, used in the agglomeration process, is termed curing acid (Merritt 1971). The amount of curing acid supplied is determined by the required end pH, which controls the necessary solution chemistry for leaching (Free, 2010). The geochemical composition of the ore dictates the amount of acid needed to achieve the desired pH level (Free, 2010; Yousef et al., 2016).

During the leaching stage, a weak acid solution is applied on top of the heaps, percolating down to dissolve minerals into solution (Dhawan et al., 2008; Zambak, 2014; Ghasemi and Azizi, 2017). The acid used in this stage is referred to as leach acid. At this point, the dissolution kinetics of minerals are critical in determining overall acid consumption. According to Scheffel and Miller (2015), key factors to consider when modelling acid consumption with a geometallurgical approach during leaching include:

- Lithology and its variations within the ore deposit: Calcite and quartz were found to have the highest and lowest acid consumption, respectively.
- Equilibrium between the pH of the aqueous solution and the rock mass: Higher pH levels result in greater acid consumption.
- Ionic concentration of the system, determined by the bisulfate complexes of dissolved metal ions.
- Acid generated as a by-product of side precipitation processes.

To estimate acid consumption, the industrial heap is treated as an unsteady state reactor with considerable variability, considering the factors mentioned above (Bennett et al., 2012; McBride et al., 2014). Various modelling techniques have been used to estimate the kinetics of mineral dissolution and reagent consumption (Dixon and Hendrix, 1993; Bennett et al., 2012; Crundwell, 2013; McBride et al., 2014; Othusite and Muzenda, 2015; Cai, 2016; Bampole and Mulamba, 2017). Different components of this heterogeneous system consume and generate acid, with minerals on the heaps reacting electrochemically, chemically, or through diffusion. The reaction rate can be controlled by reactant dissolution, chemical reaction at the particle phase, or product dissolution at the reaction site. The electrochemical dissolution of minerals (M) in an aqueous solution containing an oxidant (B^{2+}) is described by equation 1:



This generic equation (Eq. 1) has been used by researchers to develop kinetics models that govern mineral dissolution and lixiviants. Table 3 lists these models and their principles.

Table 3 Summary of general models for mineral dissolution mechanism

Model ID	Model	Development Principles
Afewu, 2009	$S_{H_2SO_4(a)} = -\rho_b k_{GAC} C_{H_2SO_4(a)} - 0.75 \rho_b k_{Cu} C_{Cu(s)}^\phi C_{H_2SO_4(a)}^\eta$	The shrinking-core hypothesis is used to inform an empirical power-law regression. Rate of consumption is unaffected by changes in temperature or viscosity. In this case, the system is assumed homogeneous.
Crundewell, 2013	$r_{diss} = k_a \left(\frac{k_c [B^{2+}]}{k_a + k_c^1 [B^+]} \right)^{0.5}$	Charge diffusion is the mechanism used for leaching. The rate of the reaction does not depend on the stoichiometry, the surface, or the products that are generated.
Vilca, 2013	$A_{Cu} = c_0 + c_1 \cdot pH + c_2 \frac{Fe^{3+}}{Fe^{2+}} + c_{12} \frac{Fe^{3+}}{Fe^{2+}}$ $r_i = k_i(T) \cdot f_i(c_{reagents}) \cdot f_i(C_{minerals})$	The linear regression model approach is used here on the shrinking core model. The amount of acid consumed or produced is determined by the nature of the ore solution and its minerals.
McBride et al, 2014	$\frac{dr_m}{dt} = \frac{1}{B} \frac{M_i}{\rho x_i} \left(D_{eff} r_m r_0 \frac{(c_m - c_0)}{(r_0 - r_m)} \right)$	The shrinking core diffusion mechanism is used. Heaps are thought to be evenly saturated. The dissolution is influenced by particle size and concentration gradient.
Othusitse and Muzenda, 2015	$[X] = \exp(a + bpH + c\phi + e \ln[L_1] + f \ln[L_2] \dots)$	The rate of dissolution is influenced by the ionic species that are present in the system as

		well as the electro potential. The geochemistry of the ore and the thermodynamics of the heap both affect the rate of the reaction.
Van Staden and Petersen, 2018	$X_{\text{acid}} = K_{\text{GO}} C_{\text{acid}}$ $\text{TAC} = \text{CAA} + 1000$ $* \sum_{\text{shifts}} \frac{M_{\text{acid}} (C_{\text{acid,irr}} - C_{\text{acid,drain}}) u. \Delta t}{\rho N_z \Delta z}$ $\text{GAC} = \text{TAC} - 1000 W_{\text{Cu}} X_{\text{Cu}} \frac{M_{\text{acid}}}{M_{\text{Cu}}}$	The mechanism of diffusion from mobile and immobile cell units of the heap is employed. The rate of reaction depends on the chemical reaction.

Based on Table 3, direct computation and curve fitting can be applied to evaluate mineral acid consumption. Computational rate relations were developed using rate laws (Charles, 2017). Before developing computational models, it is necessary to establish the dissolution rate, controlling mechanism, and equilibrium species (Dixon and Hendrix, 1993; Bennett et al., 2012; Crundwell, 2013; McBride et al., 2014; Othusite and Muzenda, 2015; Bampole and Mulamba, 2017). Large-scale geochemical systems contain various chemical species that react with one another and with the fluid system, making it challenging to determine essential parameters for daily predictive modelling using computational methods.

Regression analysis can extract experimental rates and constants to generate models for forecasting, allowing time-varying consumption to be fitted to a forecasting curve (Charles, 2017). Techniques such as simple regression, multivariate regression analysis, and LASSO parameter transformation have been employed in chemical process modelling. However, few regression models for industrial acid use consider mineralogy (Chowdhury et al., 2011; Santiago et al., 2018; Pedrosa et al., 2019). Analyzing data from large-scale industrial datasets can benefit from these methodologies. As a result, regression analysis is utilized in this study to develop predictive models that accurately estimate acid consumption based on the ore's mineralogical composition.

2. Materials and Methods

The data utilized for the study was sourced from the Tschudi plant's historical processing repository. The repository contained mineralogical and lithological data from past historical exploration and metallurgical testwork, which were used to generate a normative model that predicts mineralogy using sequential copper tests and analytical assays and calibrated with Scanning Electron Microscope (SEM) data analysed by Intertek Laboratories in Perth Australia. Daily 6 hourly samples of the process feed (ore) for each leach panel constituting of up to 120 samples per panel were analyzed for their mineralogical and lithological composition using the normative model. The exact amount of acid consumed during the curing and leaching processes was tracked from process data and recorded. Once the leaching process was completed, tailings samples were collected using a drill rig, and tailings analysis was used to reconcile the actual data.

The repository's data was exported to Excel. Before modelling, curing acid tons were converted to kilograms per ton (kg/t) of treated ore through data processing procedures. Standardizing the measurement unit eliminated the need for the panel's weight. Leach acid consumption was

predicted over time, with the amount of acid consumed at each stage reported in kg/t. Consumption was monitored every 15, 30, 60, 90, 120, 150, and 180 days. The 15-day interval was chosen due to the rapid acid consumption at the start of the leaching cycle, while the 180-day mark was used at the end, as all panels had been leached by then.

$$\text{Curing Acid} = \sum k_{\text{neutralization}} X_{\text{neutralization}} + \sum k_{\text{conversion}} (1 - X_{\text{conversion}}) \quad (\text{Eq. 2})$$

Where:

- k is the kinetic constant and,
- X is the mineral specie weight percent

$$\text{Curing acid} = k_n(\text{Ox, CC, Bn, Cpy, Dolo, Mag, Calc, AREN, ARBL, ARQZ})\text{wt\%} + k_c(\text{Ox, CC, Bn, Cpy, Dolo, Mag, Calc, AREN, ARBL, ARQZ})\text{wt\%} \quad (\text{Eq. 3})$$

$$\text{Curing acid} \left(\frac{\text{kg}}{\text{t}} \right) = \beta_0 + \beta_{\text{Ox}} \text{Ox} + \beta_{\text{Cc}} \text{Cc} + \beta_{\text{Bn}} \text{Bn} + \beta_{\text{Cpy}} \text{Cpy} + \beta_{\text{Dolo}} \text{Dolo} + \beta_{\text{Mag}} \text{Mag} + \beta_{\text{Calc}} \text{Calc} + \beta_{\text{AREN}} \text{AREN} + \beta_{\text{ARBL}} \text{ARBL} + \beta_{\text{ARQZ}} \text{ARQZ} \quad (\text{Eq. 4})$$

Using the data on curing acid and mineral species arrays from the panels, multivariate regression analysis was conducted to establish the relationship between curing acid consumption and the ore's mineralogical content, resulting in the constants in Equation 4. Table 4 presents the multi-regression constants and statistical analysis derived from the Tschudi process datasets. This model offers a simpler and more inclusive approach for industrial application compared to the models presented in Table 3.

Table 4 Multivariate statistical analysis of the analysed samples

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1855.212	4540.125	0.409	0.684	-7243.403	10953.826
Oxide (%)	-17.028	74.440	0.229	0.820	-166.209	132.153
Secondary sulfides (%)	-17.611	57.789	0.305	0.762	-133.422	98.201
Bornite (%)	-62.482	63.331	0.987	0.328	-189.401	64.438
Chalcopyrite (%)	-71.512	130.334	0.549	0.585	-332.707	189.682
Dolomite (%)	-17.574	45.296	0.388	0.700	-108.350	73.201
Magnesite (%)	-19.342	45.310	0.427	0.671	-110.144	71.461

Calcrete (%)	-15.183	45.382	-	0.335	0.739	-106.130	75.764
AREN (%)	-18.937	45.379	-	0.417	0.678	-109.878	72.004
ARBL (%)	-18.116	45.428	-	0.399	0.692	-109.155	72.923
ARQZ (%)	-18.408	45.411	-	0.405	0.687	-109.413	72.598

Mineral groups were tested individually, without the presence of other minerals, to determine their acid consumption. Table 5 displays these mineral classifications. Copper and limestone mineral groupings best matched the model in Table 4, demonstrating improved correlation, precision, and alignment with scientific mineral leaching characteristics. Although the model closely forecasted the curing acid required, it did not account for the entire sample, resulting in a higher error than the model that included all minerals in Table 4. To improve correlation, representation, and equation realism, Fit 1, Fit 2, and Fit 3 were generated using the data. Model Fit 1 was constructed through the application of lithological logarithms, while Fit 2 and Fit 3 excluded minerals with intra-correlation. Fit 1 best describes the scientific phenomenon.

Table 5 Curing acid model generation and best fit scenarios comparisons

	Mineralogy and Lithology	Copper Minerals	Limestone	Lithology	Copper and Limestone	Copper and Lithology	Limestone and Lithology	Fit 1	Fit 2	Fit 3
R Square	0,770	0,107	0,711	0,614	0,756	0,688	0,722	0,770	0,763	0,760
Standard Error	4,316	8,078	4,562	5,268	4,329	4,899	4,582	4,316	4,304	4,299
Significance F	0,000	0,134	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,684	0,000	0,001	0,000	0,024	0,000	0,468	0,833	0,769	0,483
Oxide (%)	0,820	0,029			0,705	0,671		0,207		0,818
Secondary sulphides (%)	0,762	0,021			0,110	0,994		0,528		0,531
Bornite (%)	0,328	0,046			0,143	0,012		0,068	0,030	0,132
Chalcopyrite (%)	0,585	0,771			0,581	0,076		0,696	0,881	

Dolomite	0,700		0,578		0,383		0,389	0,448	0,318	0,293
Magnesite	0,671		0,733		0,475		0,448	0,491	0,763	
Calcrete	0,739		0,000		0,000		0,099	0,000	0,000	0,000
AREN	0,678			0,000		0,000	0,447	0,164	0,288	
ARBL	0,692			0,000		0,000	0,457	0,153	0,014	0,337
ARQZ	0,687			0,000		0,000	0,466	0,636	0,437	0,223
Intercept	1855,212	31,549	8,057	286,225	9,905	290,456	-270,211	8,91	-10,938	-24,702
Oxide (%)	-17,028	-24,853			2,562	-4,094		11,47		1,476
Secondary sulphides (%)	-17,611	-17,275			-6,796	0,075		6,41		-4,147
Bornite (%)	-62,482	-25,601			-10,331	-51,656		-33,01	-28,258	-12,792
Chalcopyrite (%)	-71,512	10,942			11,645	-54,388		-10,32	-3,679	
Dolomite	-17,574		0,473		0,747		3,519	0,65	0,838	0,868
Magnesite	-19,342		0,362		-0,790		3,078	-0,78	-0,313	
Calcrete	-15,183		3,386		3,334		6,137	3,22	3,216	3,393
AREN	-18,937			-2,890		-3,337	2,872	-16,25	-7,854	
ARBL	-18,116			-2,854		-2,398	2,782	14,78	12,899	8,211
ARQZ	-18,408			-2,937		-2,779	2,741	0,64	1,032	1,501

2.1 Leach acid model development

Acid consumed as leach acid includes the acid consumed by both copper and gangue minerals in the ore, excluding the acid used as curing acid. Leach acid consumption can be calculated as the rate of consumption per day in kg/t/day, which varies with changes in the mineral composition of the ore throughout the leaching period. The daily rate of acid consumption for panels from the Tschudi heap is illustrated in Figure 1.

Although the panels had the same parameters except for their mineralogical and lithological compositions, consumption varied, indicating variability due to the geological constituents of the ore.

However, the panels exhibited a similar trend in acid consumption: an exponential increase at the beginning of the leaching stage, peaking, and then followed by an exponential decrease in daily consumption. The average change in daily consumption across panels is modelled in Figure 2.

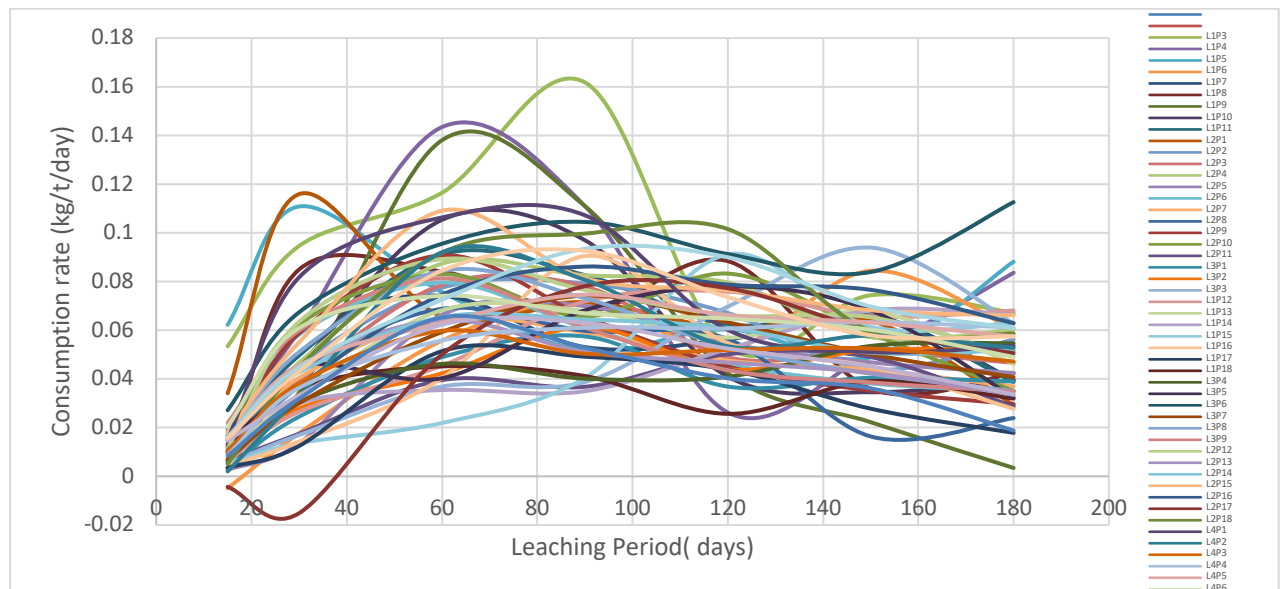


Figure 1 Daily acid consumption rate change as a function of leaching period on various stacked panels on Tschudi heap leach

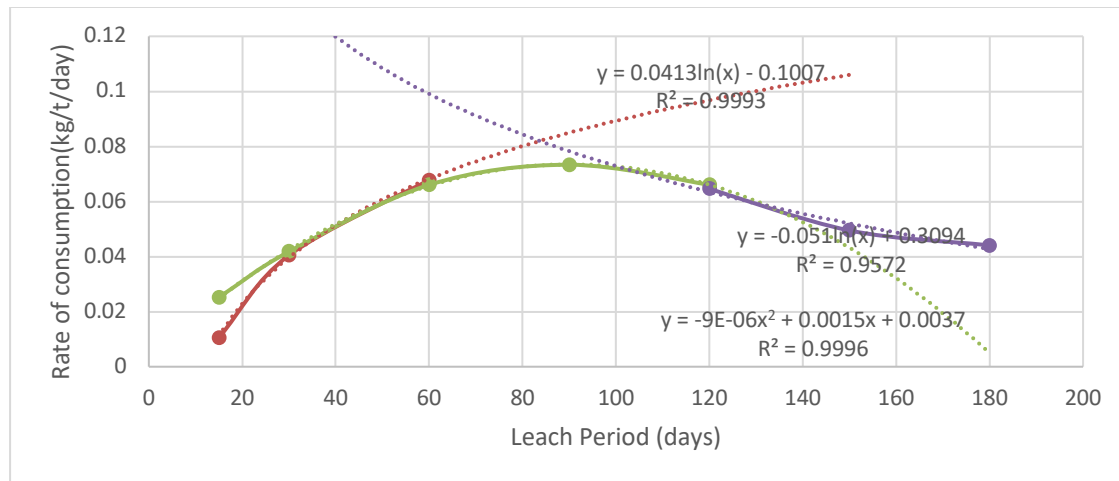


Figure 2 General modelling of the Tschudi processed ore daily leach acid rate of consumption trend over 180 leaching days.

The three general equations for the three leaching stages can be written as in equations 5 to 7.

$$Y = A_1 \ln(x) + C_1 \quad (\text{Eq. 5})$$

$$Y = A_2 x^2 + B_2 x + C_2 \quad (\text{Eq. 6})$$

$$Y = A_3 \ln(x) + C_3 \quad (\text{Eq. 7})$$

Where A , B , and C are constants related to the ore's mineralogical and lithological content. A multivariate analysis was conducted to develop a model that predicts these constants based on the ore's composition. The generated models are presented in Table 6.

Table 6 Multivariate analysis of the mineralogy and leach kinetic constants

	Oxide	Secondary sulphides	Bornite	Chalcopyrite	Dolomite	Magnesite	Calcrete	AREN	ARBL	ARQZ	Intercept
A ₁	0.03	0.00	-	0.29	0.00	0.01	-	0.00	(0.02)	(0.01)	0.09
C ₁	(0.10)	0.08	(0.25)	(1.04)	(0.02)	(0.02)	-	(0.11)	0.24	0.04	(0.56)
A ₂	(0.00)	-	(0.00)	(0.00)	-	0.00	0.00	(0.00)	-	-	0.00
B ₂	0.01	0.00	(0.02)	0.02	-	(0.00)	(0.00)	(0.01)	0.01	(0.00)	0.02
C ₂	-	-	-	(1.29)	0.07	-	0.01	-	-	-	(0.21)

A 3	(0.03)	0.04	0.1 4	(0. 23)	-	(0.0 1)	-	0.10	-	-	(0.42)
C3	0.19	(0.17)	(0. 72)	1.2 3	-	0.02	0.00	(0.5 2)	-	-	2.20

Using the model in Table 6, the constants A , B , and C were determined through Equation 4. These generated equations were then applied to the general equations (Equations 5 to 7). The models can be plotted, with the intersection of two models indicating the transition zone for the daily consumption rate.

2.2 Models Calibration

The generated models were tested against variable datasets with ores whose actual acid consumption had been previously determined, to assess the model's error level. An assay calibration method was adopted for the models, represented by the general equation shown in Equation 8:

$$Y = f(\theta, x) + \epsilon \quad (\text{Eq. 8})$$

Where Y is the estimated curing acid consumption, $f(\theta, x)$ is the non-calibrated multivariate function and ϵ is the error. The error component required to calibrate the model was obtained through multivariate analysis.

3. Results and discussion

The predictive models developed for curing and leach acid consumption were calibrated and evaluated using data obtained from the Tschudi copper heap leach operations. The models were based on mineralogical and lithological data collected from daily samples of the ore. These samples were analyzed for their composition, and the corresponding acid consumption was tracked throughout the curing and leaching stages.

3.1 Curing Acid Model Calibration:

The error analysis on the curing acid model before and after calibration is presented in Figure 3 (a) and (b). Before calibration, the non-calibrated model displayed a substantial error margin, with the estimated curing acid consumption differing from the measured values by an average of 5.7 kg/t, with a standard deviation of 3.09 kg/t. This discrepancy can be attributed to the complexity of the geological variations within the ore, which affects the acid consumption, but is not immediately apparent from basic mineralogical assessments. Upon calibrating the model using multivariate regression techniques, the error was reduced significantly. The minimum error decreased to 2.83 kg/t, the maximum error was reduced to 4.74 kg/t, and the mean error

dropped to 0.82 kg/t. This improvement demonstrates the effectiveness of calibration in refining the model's predictive accuracy.

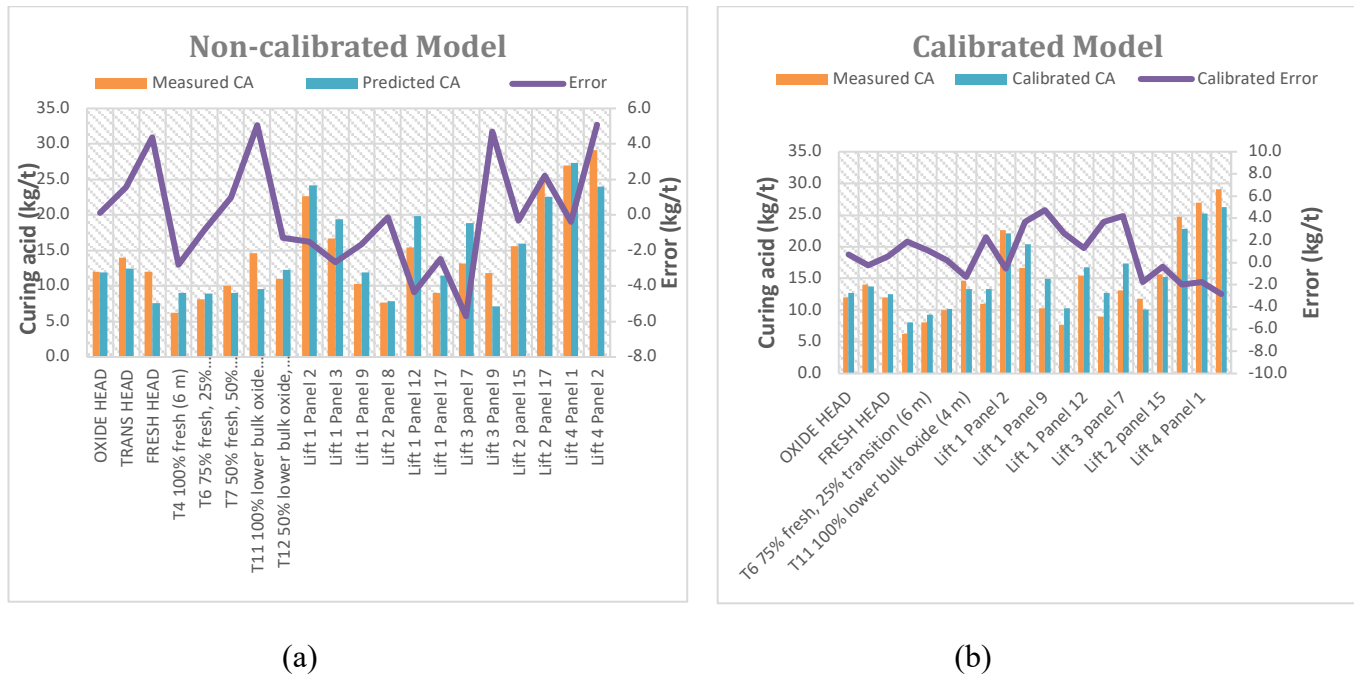


Figure 3 Comparison of the measured curing acid consumption with the estimates from (a) the non-calibrated curing acid model and (b) the calibrated curing acid model.

3.2 Leach Acid Model Calibration:

Similar to the approach described in Section 3.1, the leach acid consumption model was calibrated and subjected to error analysis as presented in Figure 4. Total leach acid consumption was predicted for 13 samples over a 180-day period. The model predicted leach acid consumption values within an average margin of error of 5%. However, some discrepancies were noted. Seven of the predictions overestimated acid consumption, with the highest over-prediction reaching 31%, while six predictions underpredicted consumption, with the lowest under-prediction at 32%. The error magnitude varied across different stages of the leaching process. In the initial kinetic stage, where acid consumption increased exponentially, the error was significant, and the model showed an apparent symmetry error within a 50% margin. As the leaching process moved into the peak kinetic stage, the error decreased, but it increased again during the slow kinetic stage. This pattern of error suggests that the model underestimates acid consumption in the slow kinetics phase.

By incorporating an error function into the constants that control the slow kinetic region (region with the highest error margin), the model's accuracy was further improved. After this adjustment, the error in the slow kinetic phase was significantly reduced, and error peaks over 200% were eliminated. The model's performance after calibration was assessed, with only three of the 13 samples exhibiting error peaks above 50%, as shown in Figure 5. The refined model now provides a more realistic prediction of acid consumption, minimizing the error margin and improving its practical applicability for the Tschudi mine operations.

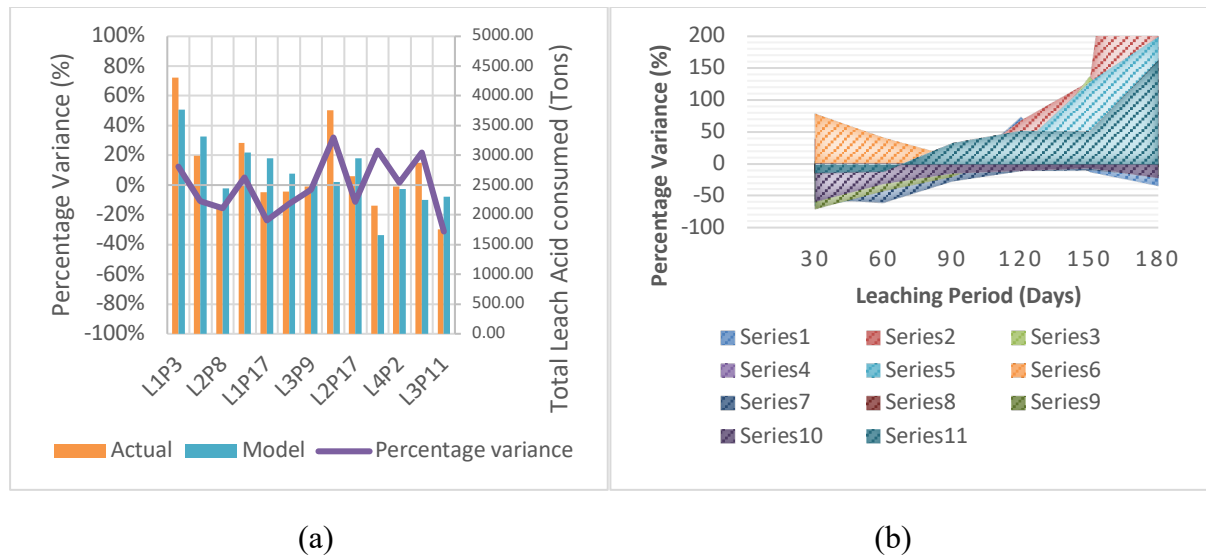


Figure 4 Comparison of (a) the actual total leach acid consumption with the non-calibrated model-generated values and (b) the percentage variance between the model-generated and measured values.

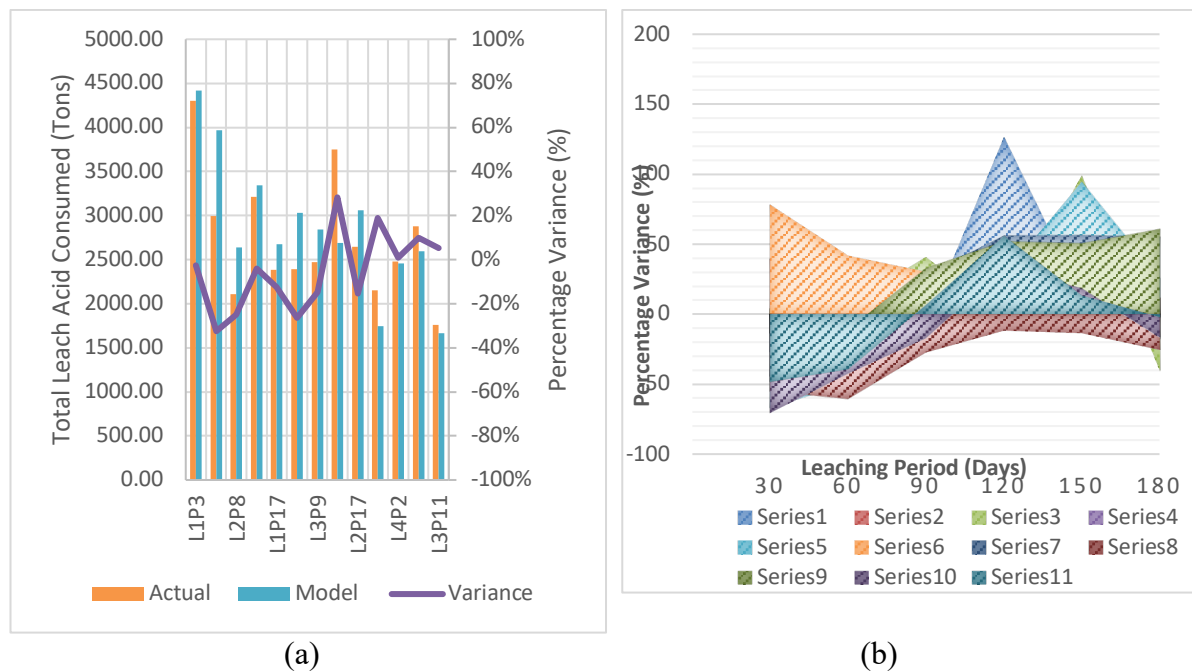


Figure 5 Comparison of (a) the actual total leach acid consumption with the calibrated model-generated values and (b) the percentage variance between the model-generated and measured values.

3.3 Model Validation and Practical Implications

The calibrated models were validated against historical data, and the results showed a much closer alignment between predicted and actual acid consumption, particularly when applied to large-scale datasets. The model's predictive power lies in its ability to account for variations in

mineralogical composition, which strongly influence acid consumption rates. This capability makes it a valuable tool for both operational optimization and cost estimation at Tschudi and similar heap leach operations.

4. Conclusion

This study successfully applied geometallurgy to develop a predictive model for acid consumption at the Tschudi copper heap leach operation. Multivariate regression analysis established relationships between the mineralogical and lithological composition of the ore and its corresponding acid consumption during the curing and leaching stages. The model's predictive accuracy was significantly improved through calibration using actual plant data, resulting in a mean error reduction of 5%. The model's ability to predict acid consumption with higher precision, particularly during the slow kinetic stage, offers practical benefits for managing acid costs and optimizing the leaching process.

The results suggest that this model could be applied to enhance the operational efficiency of heap leach operations by providing more accurate acid consumption forecasts, enabling better budget planning and resource management. Additionally, the methodology outlined in this study can be adapted for use in other copper and base metal heap leach operations with similar geological and mineralogical profiles.

5. Recommendations

It is recommended that further investigations be conducted to evaluate potential improvements in acid consumption prediction when processing ores with different mineralogical combinations and particle size distributions. This is particularly relevant because the error observed in the predictive model may be attributed to the poor liberation of certain minerals hosted within other mineral phases, such as carbonates and oxides hosted in sandstones. Furthermore, because the effect of solution ionic concentration was not considered in the development of the leach acid prediction model, further research should investigate its influence and assess the feasibility of incorporating an appropriate error function into the model to improve its predictive accuracy. Future studies should also consider replicating the methodology using more precise data parameterisation and curve-fitting regression techniques. In addition, the application of other process analysis software packages, such as MetSim and HeapSim, which have been utilised in previous studies, should be explored to assess their potential to improve the accuracy of the developed predictive models.

6. Acknowledgements

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