

Experimental Investigation of Copper Leaching from Flash Furnace Dust and Integrated Mathematical-Artificial Intelligence Modeling of Kinetics

Hassan Razzani^{1*}, Hassan Hashemipour¹, Amirhossain Karimi¹

¹ Chemical Engineering Department, Faculty of Engineering, Vali-e-Asr University of Rafsanjan, Iran

 h.razani@stu.vru.ac.ir*

Abstract

Hydrometallurgical methods, particularly leaching, provide an effective approach for recovering copper from low-grade materials. This study experimentally investigates the influence of temperature, time, and acid concentration on tank leaching of copper from flash furnace dust containing oxide and sulfide forms, focusing on recovery efficiency. Experimentally, increasing the temperature from 297 K to 317 K raised copper recovery from 53.8% to 69.3% (150 g/L H₂SO₄, 90 min), and the calibrated Shrinking Core Model (SCM) predicts that an increase of 30 K (from 300 K to 330 K, the upper value being a slight extrapolation) raises recovery at 100 g/L and 40 min by 19 percentage points (from 76% to 95%). Additionally, an artificial neural network (ANN) with a single hidden layer of 64 neurons achieved a mean absolute percentage error (MAPE, relative error) of approximately 2% ($R^2 = 0.98$) on an independent hold-out test set that was not used for training or architecture selection, demonstrating high predictive accuracy. By coupling the SCM with the ANN, used strictly for interpolation within the experimental window, the kinetic analysis was extended over the investigated range of operating conditions. The effective diffusion coefficient was correlated with temperature and acid concentration, yielding an apparent activation energy of 21.37 kJ/mol, which suggests that diffusion through the product layer is the dominant resistance in the leaching of flash furnace dust, although a contribution of the surface reaction (mixed control) cannot be excluded.

Keywords: Leaching, Flash Furnace Dust, Copper, Shrinking Core Model (SCM), Artificial Neural Network, Activation Energy

ARTICLE INFO

Article history:

Received

2025-07-08

Revised

2026-10-09

Accepted

2026-10-17

Published by

ISSN

Website

This is an open access article under the CC BY SA license



CV. Creative Tugu Pena

2963-6752

<https://attractivejournal.com/index.php/ajse>

<https://creativecommons.org/licenses/by-sa/4.0/>

@ 2026 by Authors

INTRODUCTION

Copper, a fundamental and widely used metal, occurs naturally in oxide and sulfide forms and is valued for its unique physical and chemical properties, making it essential in various industries [1]. As one of the earliest industrially recognized materials, copper plays a critical role in modern technology, particularly in the production of electronic equipment [2]. Global copper consumption has risen dramatically, from 550,000 tons in 1900 to 21.2 million tons in 2013, with projections estimating demand to reach over 42 million tons by 2030 and 78 million tons by 2050 [3].

Currently, approximately 80% of copper production derives from sulfide ores, with chalcopyrite being the most abundant and significant copper sulfide mineral [4]. A substantial portion of copper is produced through hydrometallurgical processes, primarily via leaching, where sulfuric acid is commonly used as an effective leaching medium for copper minerals [5], [6]. Factors such as mineralogical characteristics, particle size, acid concentration, temperature, and time significantly influence dissolution efficiency and kinetics [7]. In contrast, pyrometallurgical processes, such as smelting in flash furnaces, involve the oxidation of copper concentrate at high temperatures in an oxygen-rich atmosphere, producing copper matte, slag, and dust [8]. The dust generated from flash smelting contains significant copper content, which can be recovered through leaching. Flash smelting dusts are fine, largely crystalline materials that contain copper together with Fe, Zn, Pb and As [9]; they are commonly recycled to the smelter, which increases the circulating load of impurities [10], [8], or treated hydrometallurgically [11].

Temperature and acid concentration are critical parameters affecting the rate of dissolution and copper recovery during leaching. Studies have shown that higher temperatures enhance leaching efficiency by increasing reaction rates and improving mass transfer. For instance, Zhang et al. recovered 96.01% of the copper from arsenic-rich copper smelting dust by a two-stage leaching process whose sulfuric acid stage was operated at 90 °C with an initial H₂SO₄ concentration of 190 g/L [12]. Similarly, Liu et al. extracted 95.27% of the copper from copper smelting dust by potential-controlled oxidative leaching at 80 °C [13]. Elevated temperatures increase the rate constant of the surface reaction, according to the Arrhenius law, and the diffusivity of the reacting species, thereby accelerating dissolution. Higher acid concentrations also directly influence dissolution rates by increasing the number of active acid molecules per unit volume, thereby promoting collisions with copper particles and accelerating chemical reactions. This process facilitates the breaking of chemical bonds at the particle surface, releasing copper ions. Additionally, the concentration gradient between the particle surface and the surrounding medium enhances ion diffusion, further increasing reaction rates in the inner layers of the particle. Consequently, higher acid concentrations reduce the time required for complete dissolution and improve overall process efficiency. For example, Nicol and Akilan showed that the dissolution rate of chrysocolla in dilute sulfuric acid increases linearly with increasing acidity [14].

In modeling the leaching process, the Shrinking Core Model is widely applied in heap and tank leaching systems [15], [16]. This model describes three main stages: mass transfer from the liquid phase to the solid surface, diffusion through the product layer, and chemical reaction at the core surface. The SCM has proven effective in analyzing the dissolution behavior of copper-bearing materials such as chrysocolla and copper smelting slag and accurately describes the impact of operational parameters such as temperature, acid concentration and particle size [14], [17].

To enhance modeling accuracy and reduce the need for extensive experimental trials, artificial intelligence (AI) algorithms are increasingly utilized. In hydrometallurgy, artificial neural networks (ANNs) and other supervised machine-learning models have been successfully used to predict metal recovery in leaching systems, for example Al₂O₃ leaching recovery in an industrial Bayer process [18] and molybdenum extraction in the bioleaching of a spent catalyst, for which an ANN

reached $R^2 = 0.988$ on a test dataset [19]. However, these data-driven models are generally used as black-box predictors and do not provide physically meaningful kinetic parameters. In this study, tank leaching was employed to recover copper from flash furnace dust. The effects of operational conditions on recovery efficiency were investigated experimentally, and an AI-enhanced mathematical model was used to determine optimal operating conditions.

Although copper-bearing smelter dusts are an important secondary resource, to the authors' knowledge, kinetic studies based on the SCM have mainly addressed primary copper oxide and sulfide minerals [7], [14], [6], while studies on copper smelter dusts have focused mainly on their characterization, arsenic removal and process development rather than on the quantification of intraparticle diffusion parameters [9], [11], [12], whereas AI-based studies of copper leaching have been largely data-driven and have not been coupled with mechanistic kinetic models [18], [19]. Consequently, there is a lack of studies that (i) quantify the effective diffusion coefficient of the leachant within flash furnace dust particles as an explicit function of temperature and acid concentration, and (ii) combine a mechanistic SCM with an ANN trained on experimental data to extend the kinetic analysis over the operating window. To the best of the authors' knowledge, this is the first study to integrate tank-leaching experiments on flash furnace dust from the Sarcheshmeh Copper Complex with an ANN-assisted SCM, yielding an explicit Arrhenius-type correlation for the effective diffusion coefficient, $D(T, C)$. The specific contributions of this work are: (1) experimental quantification of the effects of temperature, acid concentration and time on copper recovery from flash furnace dust; (2) determination of the apparent activation energy and the concentration dependence of the effective diffusion coefficient; and (3) a hybrid SCM-ANN framework in which an ANN, validated on an independent test set, interpolates the experimental recovery data within the investigated window to support the kinetic analysis of this material.

METHOD

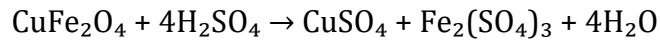
Flash furnace dust from the Sarcheshmeh Copper Complex was used as the primary feed for the leaching process. The elemental composition of the dust was determined by X-ray fluorescence (XRF); the results are provided in the Supplementary Material. Phase analysis indicated that approximately 69% of the copper was present in oxide form (mainly copper ferrite, CuFe_2O_4) and 31% in sulfide form ($\text{Cu}_4\text{Fe}_5\text{S}_8$). The dust was leached as received (without grinding or sieving), and a representative (assumed) particle radius of $r = 10\ \mu\text{m}$ ($0.001\ \text{cm}$) was adopted in the SCM (see the SCM formulation below). Because the particle size distribution of the dust was not measured, the values of D and D_0 reported below are apparent values conditional on this assumed radius. Since the product-layer diffusion time in the SCM scales with r^2/D , only the ratio D/r^2 is uniquely determined by the experimental data; this size-independent group is therefore also reported.

Leaching experiments were conducted in a 500 mL stainless steel reactor under atmospheric conditions, closed with a lid to limit evaporation. The slurry was mechanically agitated, and the temperature was kept constant during each experiment. Analytical-grade 98 wt% sulfuric acid ($\rho = 1.84\ \text{g/cm}^3$) was used as the stock reagent. Leaching solutions with target concentrations of 100, 125, 150 and 175 g/L H_2SO_4 were prepared by slowly adding the calculated volume of concentrated acid (approximately 5.5, 6.9, 8.3 and 9.7 mL per 100 mL of solution,

respectively) to distilled water in a volumetric flask, cooling to room temperature and making up to volume. The reactor was equipped with a stirrer and an adjustable heater. The parameters investigated were acid concentration, temperature and reaction time, while the pulp density was kept constant at 120 g/L. After each experiment, solid particles were separated from the solution, and the solution was analyzed to determine copper concentration and extraction efficiency. Copper concentration in the leach solution was measured using wet chemistry and atomic absorption spectroscopy (AAS) per standard protocols. At each sampling time, the sample was filtered and diluted, and copper was determined by AAS at 324.8 nm against matrix-matched standards.

Leaching experiments were performed using 12 g of dust in 100 mL of acid (pulp density of 120 g/L). The acid concentration was controlled directly by preparing solutions of known H₂SO₄ concentration (g/L), as described above; pH was neither used as a control variable nor as a measure of acid concentration, because in 100–175 g/L H₂SO₄ solutions the pH is close to or below zero and does not resolve differences in concentration. Copper recovery efficiency (X) was calculated as the ratio of dissolved copper concentration (g/L) to the total copper content in the initial dust, determined based on pulp density and copper grade. Specifically, $X = C_{Cu}V/(m \cdot w_{Cu})$, where C_{Cu} is the copper concentration in the leach solution (g/L), V is the solution volume (L) corrected for the volume of withdrawn samples, m is the mass of dust (g) and w_{Cu} is its copper mass fraction. Higher recovery efficiency indicates greater success in extracting copper from the dust.

The Shrinking Core Model (SCM) was employed to describe reactions where solid particles are consumed through dissolution or reaction, resulting in a shrinking unreacted core [15]. The dissolution of the main copper-bearing oxide phase (copper ferrite) in sulfuric acid can be represented as:



Copper oxide (CuO), if present, dissolves according to $\text{CuO} + \text{H}_2\text{SO}_4 \rightarrow \text{CuSO}_4 + \text{H}_2\text{O}$. The copper sulfide fraction is not expected to dissolve appreciably in non-oxidative sulfuric acid at the temperatures studied, except through oxidation by Fe³⁺ released during ferrite dissolution. This is consistent with the near-plateau of recovery observed at the lower temperatures (Table 1); the contribution of the sulfide fraction is discussed in the Results.

In the leaching process, the SCM accounts for several key resistances, including mass transfer and surface reaction resistance, effectively describing reaction progress. The model considers the following stages:

- A. Chemical reaction at the solid particle surface: Dissolution of copper oxides and sulfides occurs at the particle surface. Increasing temperature accelerates surface reactions, reducing dissolution time and enhancing leaching rates.
- B. Diffusion through the product (ash) layer: the leachant (H⁺/H₂SO₄) diffuses inward through the porous product layer to the surface of the unreacted core, while dissolved copper sulfate diffuses outward. Higher temperatures and acid concentrations improve mass transfer conditions and concentration gradients, accelerating this stage.
- C. Liquid-film mass transfer: under vigorous agitation and for the fine particles of the dust, the resistance of the liquid film was assumed to be negligible compared to the other resistances. Thus, only chemical reaction and diffusion

were considered in analyzing the effects of temperature and acid concentration on leaching rates. For spherical particles, the relationship between conversion (X) and time (t) under mixed control is expressed as [20], [16]:

$$t = A[1/2 - X/3 - (1 - X)^{2/3}/2] + B[1 - (1 - X)^{1/3}] \quad (1)$$

where the first term represents diffusion through the product layer (it is identical to the Ginstling–Brounshtein form $(A/6)[1 - 3(1 - X)^{2/3} + 2(1 - X)]$) and the second term represents chemical reaction at the surface of the unreacted core, and:

$$A = \rho r^2 / (M_w \cdot D \cdot C), \quad B = \rho r / (M_w \cdot K \cdot C)$$

Here, ρ (density of the reacting solid, taken as that of CuO, 6.315 g/cm³), r (representative particle radius, 0.001 cm = 10⁻⁵ m), M_w (molar mass of CuO, 79.54 g/mol), K (reaction rate constant, 0.0058 m/s [21]), C (acid concentration), and D (diffusion coefficient of component A) are defined. SI units are used in Eq. (1) (r in m, K in m/s, C in mol/m³), so that D is obtained in m²/s. Because ρ/M_w of CuO is used as a representative molar density of the reacting copper rather than that of the dust itself, D should be regarded as an apparent (effective) parameter. The surface reaction rate constant could not be determined independently from the present data; therefore, a literature value for copper dissolution [21] was used and kept constant. With this value, the characteristic time of the reaction term ($B \approx 0.13$ s at 100 g/L) is negligible compared with that of the diffusion term ($A/6 \approx 2$ h at 300 K and 100 g/L), so Eq. (1) effectively reduces to the product-layer diffusion model. The adequacy of this model was therefore checked independently against the experimental data (see Results).

To enhance modeling accuracy and reduce the need for additional experiments, AI algorithms were employed to generate supplementary data and predict system behavior. Artificial neural networks (ANN) were used to produce additional data and simulate process trends under various operational conditions. The ANN architecture included an input layer with three neurons (for temperature, concentration, and time), a hidden layer with 64 neurons and a ReLU activation function, and an output layer with one neuron and a linear activation function to predict recovery efficiency. Each data point used for the ANN consisted of temperature, acid concentration, time and the corresponding measured recovery (the complete dataset is provided in Supplementary Table S1). The input variables were normalized to [0, 1] by min–max scaling. To avoid information leakage between correlated time points of the same run, the data were divided by kinetic run into training, validation and independent hold-out test sets; the test set was not used at any stage of training or architecture selection. The network was trained with MSE as the loss function, and early stopping based on the validation loss was applied to limit overfitting. Candidate architectures with one or two hidden layers and different numbers of neurons per layer were evaluated using MSE and R^2 , and a single hidden layer with 64 neurons gave the best balance between prediction accuracy and model complexity. The final model was then evaluated on the hold-out test set using the coefficient of determination (R^2) and the mean absolute percentage error (MAPE, also referred to as relative error). The network, which has 321 trainable parameters, was trained with the Adam optimizer.

The ANN was used only as an interpolation tool within the experimental window. Its use in support of the SCM analysis does not imply validity at industrial

scale, which would require pilot- or plant-scale data. Calculations for diffusion coefficients and other mass transfer parameters were performed using MATLAB.

RESULT AND DISCUSSION

This section presents the results of experimental and analytical studies aimed at investigating the copper leaching process using sulfuric acid. The effects of acid concentration, temperature, and time on leaching performance are analyzed to elucidate their roles in dissolution rates and recovery efficiency. Additionally, AI-generated data are integrated into the SCM to predict and optimize process efficiency under various operational conditions.

It is expected that increasing temperature and acid concentration (as the reactant) enhances reaction rates and improves copper recovery efficiency. Higher temperatures play a critical role in increasing leaching efficiency by accelerating reaction rates and reducing diffusion resistance. Similarly, higher acid concentrations enhance mass transfer by increasing the concentration gradient, thereby improving recovery efficiency. Table 1 presents a subset of the experimental data (the complete dataset is given in Supplementary Table S1), confirming these trends. For example, at 150 g/L and 90 min, increasing the temperature from 297 K to 317 K raised recovery from 53.81% to 69.33%, whereas at 327 K and 105 min increasing the acid concentration from 125 to 175 g/L raised recovery only from 82.04% to 86.85%, and at 307 K and 125 g/L extending the time from 75 to 105 min increased it only from 56.29% to 57.91%. These comparisons indicate that, within the investigated ranges, temperature has a stronger influence on recovery than acid concentration and time.

Table 1. Selected Experimental Results for Copper Leaching under Various Operational Conditions

Temperature (K)	Acid Concentration (g/L)	Time (min)	Recovery (%)
307	125	75	56.29
307	125	105	57.91
327	175	105	86.85
327	125	105	82.04
297	150	90	53.81
317	150	90	69.33

Because the dissolution of copper oxide phases in sulfuric acid is generally fast [6], [14], the diffusion resistance within solid particles significantly affects reaction rates and process efficiency. Thus, understanding and calculating the diffusion coefficient and its influencing factors are critical for process optimization. The diffusion coefficient was calculated by fitting the SCM to experimental data. For each temperature and acid concentration, D was obtained by nonlinear least-squares minimization of the difference between the measured and SCM-predicted X (MATLAB), using the experimental data supplemented with ANN-interpolated points within the investigated window (see below). Since determining the precise temperature and concentration dependence of the diffusion coefficient requires extensive experimental data, which is time-consuming and costly, an ANN was

developed and validated to generate additional data within the operational range. It should also be noted that, at the lower temperatures, recovery approached a plateau well below complete extraction (e.g., 56.29% at 75 min and 57.91% at 105 min at 307 K and 125 g/L), which suggests that part of the copper, most likely the sulfide fraction, is refractory under non-oxidative conditions.

AI was employed as a powerful tool to generate supplementary (ANN-predicted) data through interpolation and curve fitting. The ANN-interpolated data were used only to provide a denser set of X-t points for the SCM fitting at the experimental temperatures and concentrations. They contain no information beyond that in the experimental data and were not used to compute any goodness-of-fit statistics. ANN predictions were used only within the experimentally investigated ranges of temperature, acid concentration and time (interpolation only).

On the independent hold-out test set, the ANN achieved $R^2 = 0.98$ and MAPE $\approx 2\%$. These metrics are complementary: R^2 expresses the fraction of the variance of the measured recovery that is explained by the model, whereas MAPE (relative error) expresses the magnitude of the prediction errors relative to the measured recovery. The combination of a high R^2 and a low MAPE therefore indicates that the ANN reproduces both the trends and the magnitudes of the experimental data, and, because the test set consisted of complete kinetic runs that were not used for training, the reported performance provides an estimate of generalization within the investigated window.

The variation of the diffusion coefficient with temperature and concentration is shown in Figure 1. The values plotted were calculated from the fitted correlation (Eq. 2, below) at the four acid concentrations (100–175 g/L) and four temperatures (297–327 K) investigated. The diffusion coefficient increases markedly with temperature and only weakly with concentration (see the discussion of Table 3 below).

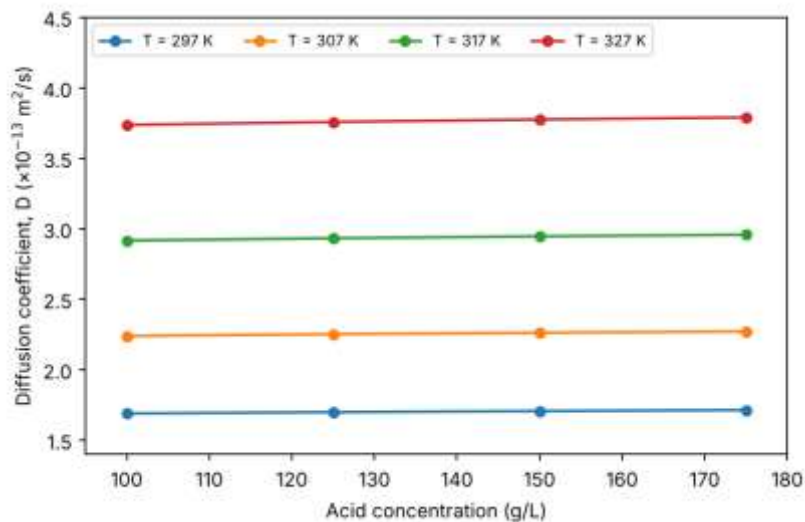


Figure 1. Variation of the Effective Diffusion Coefficient with Temperature and Acid Concentration (calculated from Eq. 2)

Higher temperatures reduce solution viscosity and increase the diffusivity of the acid species, which facilitates their transport through the pores of the product

layer to the unreacted core [17]. Higher temperatures also increase the fraction of molecules with energy exceeding the activation energy, thereby accelerating the surface reaction [22].

The diffusion coefficient is influenced primarily by temperature, exhibiting a direct relationship. Higher temperatures enhance the diffusion of reactant molecules, reducing the time required to achieve the desired copper concentration in the solution. This is attributed mainly to the reduced solution viscosity and the higher diffusivity of the acid species in the product layer. Consequently, higher temperatures increase the diffusion coefficient and reduce the time needed to reach a given conversion.

Increasing acid concentration enhances the concentration gradient between the particle surface and the surrounding medium, acting as a driving force for mass transfer and increasing the diffusion coefficient. Experiments with varying sulfuric acid concentrations showed faster and more complete copper dissolution at higher acid concentrations; however, as quantified below (Table 3), the dependence of the diffusion coefficient itself on acid concentration is weak within the investigated range, and the main effect of acid concentration is exerted through the driving force (C in Eq. 1).

The diffusion coefficient was modeled as a function of temperature and concentration as follows:

$$D = D_0 \cdot \exp(-E/RT) \cdot C^n \quad (2)$$

where D_0 is the pre-exponential factor, E is the activation energy, R is the gas constant, T is the absolute temperature, C is the acid concentration, and n is an empirical exponent describing the concentration dependence of the effective diffusivity (apparent concentration order). $D_1 = D_0 \cdot \exp(-E/RT)$ is the temperature-dependent (Arrhenius) part of the diffusion coefficient, i.e., the value of D at unit acid concentration; D_1 therefore differs from D_0 in that it includes the temperature factor and varies with T , whereas D_0 is a constant. The form of Eq. (2) follows Safari et al. [16].

To calculate the activation energy (E) and pre-exponential factor (D_0), linear regression of $\ln(D)$ versus $1/T$ at constant concentrations was performed, with results reported in Table 2. The R^2 values (0.979–0.984) indicate a good linear fit; the mean slope (-2571 K) gives $E = 21.37$ kJ/mol. At constant C , Eq. (2) gives $\ln D = \ln(D_0 C^n) - (E/R)(1/T)$; the slopes in Table 2 are therefore $-E/R$, and the intercepts are $\ln(D_0 C^n)$, not D_0 itself. The intercepts are negative simply because $D_0 C^n \ll 1$ m²/s. For example, at $C = 100$ g/L, $\exp(-20.755) = 9.69 \times 10^{-10}$ m²/s, which divided by $C^n = 100^{0.0253} = 1.124$ gives $D_0 = 8.62 \times 10^{-10}$ m²/s, consistent with the value reported below.

Table 2. Linear Regression Results for Diffusion Coefficient Parameters at Constant Concentrations

C (g/L)	-E/R	ln(D ₀ C ⁿ) (D in m ² /s)	R ²
100	-2568.0	-20.755	0.979
125	-2570.4	-20.749	0.981
150	-2567.6	-20.745	0.983
175	-2578.4	-20.741	0.984

To determine the concentration exponent (n), linear regression of $\ln(D)$ versus $\ln(C)$ at constant temperatures was conducted, with results shown in Table 3. The R^2 values near 1 validate the concentration dependence model. At constant T , Eq. (2) gives $\ln D = \ln D_1 + n \ln C$; the slopes in Table 3 therefore give n , and the intercepts give $\ln D_1$ (with $D_1 = D_0 \cdot \exp(-E/RT)$), which is why these values are negative. As expected, $\ln D_1$ increases with temperature.

Table 3. Linear Regression Results for Diffusion Coefficient Parameters at Constant Temperatures

Temperature (K)	n	$\ln D_1$ (D_1 in m^2/s)	R^2
297	0.0256	-29.53	0.973
307	0.0261	-29.24	0.983
317	0.0249	-28.98	0.982
327	0.0247	-28.73	0.974

Based on the regression results, the diffusion coefficient model parameters are: concentration exponent ($n = 0.0253$), activation energy ($E = 21.37 \text{ kJ/mol}$), and pre-exponential factor ($D_0 = 8.62 \times 10^{-10} \text{ m}^2/\text{s}$). Because r was assumed ($10 \text{ }\mu\text{m}$), the size-independent group $D_0/r^2 = 8.62 \text{ s}^{-1}$ is also reported; it allows D_0 to be recalculated once the actual particle size is known.

The concentration exponent ($n = 0.0253$) is close to zero, which means that, within the investigated range ($100\text{--}175 \text{ g/L}$), the effective diffusion coefficient depends only weakly on acid concentration: increasing C from 100 to 175 g/L increases D by only $(175/100)^{0.0253} - 1 \approx 1.4\%$. This does not contradict the positive effect of acid concentration on copper recovery, because in the SCM (Eq. 1) the acid concentration also appears explicitly in parameters A and B as the driving force for diffusion and reaction. The effect of C on the leaching rate is therefore exerted mainly through the bulk acid concentration (driving force), whereas its effect on the transport property D is marginal. Consistent with this interpretation, Eq. (1) predicts that the time required to reach a given conversion is inversely proportional to C (Figure 2: approximately 118 min at 100 g/L versus 67 min at 175 g/L for near-complete conversion at 300 K). Physically, this behavior is expected when the acid is present in large stoichiometric excess, as in the present experiments (pulp density of 120 g/L and $100\text{--}175 \text{ g/L H}_2\text{SO}_4$), so that intraparticle transport is governed mainly by the structure and porosity of the product layer rather than by acid concentration. Accordingly, the concentration term in Eq. (2) could be omitted with negligible loss of accuracy within the investigated range; it is retained for generality, but the correlation should not be extrapolated outside the investigated concentration range.

The apparent activation energy obtained in this work ($E = 21.37 \text{ kJ/mol}$) lies in the range typically reported for leaching processes controlled by diffusion through a product layer or by mixed control, and is well below the values generally associated with surface chemical-reaction control (above approximately 40 kJ/mol). Values below about 20 kJ/mol are commonly associated with diffusion control and values of $20\text{--}40 \text{ kJ/mol}$ with mixed control, so the value obtained here lies close to the boundary between these regimes. Because E was derived from the temperature dependence of D , which was itself obtained with a diffusion-dominated model, it

cannot on its own prove diffusion control. It lies between the values of 11.35 kJ/mol and 47.03 kJ/mol reported by Shi et al. for the product-layer-diffusion-controlled and the surface-reaction-controlled stages, respectively, of the pressure oxidative sulfuric acid leaching of copper smelting slag [17], and it is consistent with the small temperature effect observed for the diffusion-controlled dissolution of chrysocolla through its silica product layer [14]. Together with these comparisons, the value obtained here supports the conclusion that intraparticle diffusion is the dominant, though possibly not the only, resistance in the leaching of copper from flash furnace dust under the studied conditions. It should be noted that particle size affects the characteristic diffusion time but not the activation energy.

The kinetics of copper recovery were analyzed using the SCM, with the diffusion coefficient, a critical parameter, calculated as a function of temperature and concentration.

Figure 2 illustrates the SCM-predicted kinetics (Eq. 1 with D from Eq. 2 and $r = 10 \mu\text{m}$) of copper recovery efficiency (X) at a constant temperature of 300 K for various acid concentrations. The results show that increasing concentration slightly improves recovery efficiency at specific times. For example, at 60 minutes, the efficiency is approximately 0.95 for 150 g/L and 0.97 for 175 g/L, indicating a marginal improvement (2%). It should be noted that the SCM curves predict higher recoveries than those measured under comparable conditions (e.g., Table 1: 57.91% at 307 K, 125 g/L and 105 min, whereas the model gives $X > 0.95$ at 300 K, 100 g/L and 105 min). This indicates that the model, calibrated with an assumed particle radius and a literature value of K , overestimates the leaching rate of the as-received dust, most likely because part of the copper (the sulfide fraction) is refractory and because the dust has a size distribution rather than a single particle size. The SCM curves in Figures 2–4 should therefore be interpreted as trends rather than as absolute recoveries. Overall, concentration changes within this range have a limited impact on recovery rates, suggesting that other factors, such as particle size or temperature, should be prioritized for process optimization.

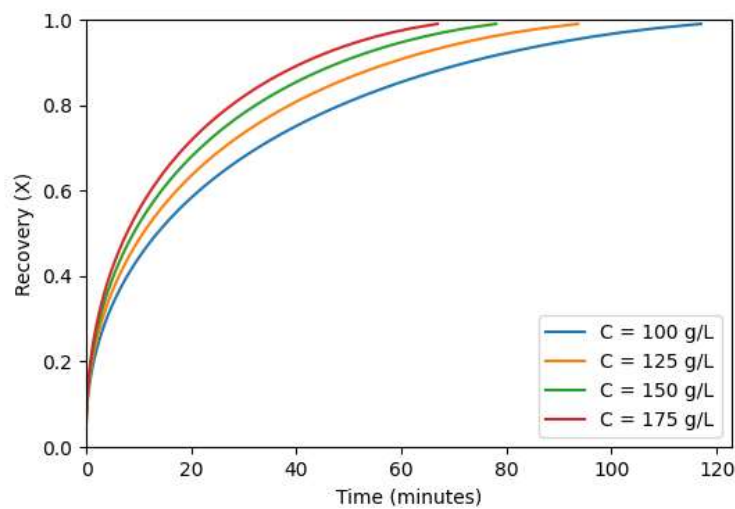


Figure 2. Kinetics of Copper Recovery Efficiency (X) at 300 K for Various Acid Concentrations (SCM prediction, $r = 10 \mu\text{m}$)

Figure 3 shows the SCM-predicted kinetics of copper recovery efficiency (X) at a constant concentration of 100 g/L for different temperatures. Increasing temperature significantly enhances recovery efficiency. For instance, at 40 minutes, the predicted efficiency is 0.76 at 300 K and 0.95 at 330 K; the latter temperature lies slightly above the highest experimental temperature (327 K) and is therefore a mild extrapolation of the SCM. These findings highlight temperature as a critical parameter for optimizing recovery efficiency.

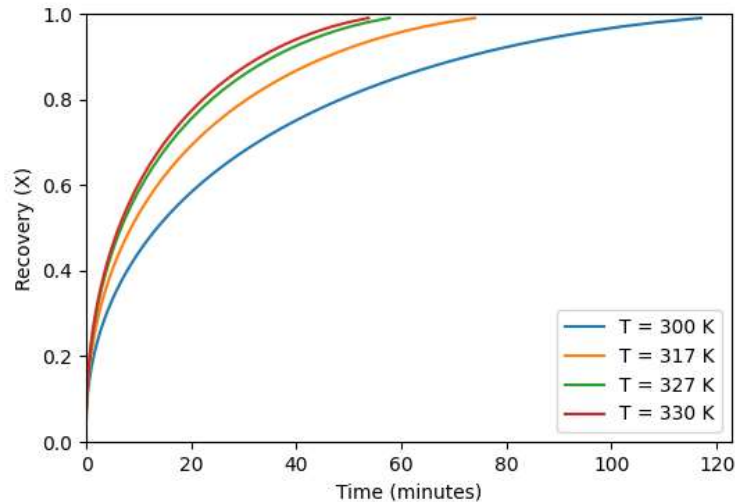


Figure 3. Kinetics of Copper Recovery Efficiency (X) at 100 g/L for Various Temperatures (SCM prediction, $r = 10 \mu\text{m}$)

The effect of particle size on recovery kinetics was also evaluated theoretically using the SCM; Figure 4 is therefore a model prediction, and no leaching experiments with size-classified fractions were performed in this study. Figure 4 illustrates the impact of particle size on recovery efficiency at a constant temperature (300 K) and concentration (100 g/L). Smaller particle sizes significantly improve recovery efficiency and reduce the time required to achieve a given efficiency. For example, at 100 g/L and 300 K, achieving 96% efficiency requires about 90 minutes for $10 \mu\text{m}$ particles (Figure 2), whereas for $5 \mu\text{m}$ particles the required time is about four times shorter (≈ 23 minutes), because under product-layer diffusion control the time to reach a given conversion scales with r^2 . This trend is consistent for particle sizes of $7.5 \mu\text{m}$ and $15 \mu\text{m}$, with smaller particles consistently yielding higher efficiencies in shorter times. Because these results are extrapolations of a model calibrated on the as-received dust, they should be regarded as indicative trends only; experimental verification using size-classified dust fractions is recommended for future work.

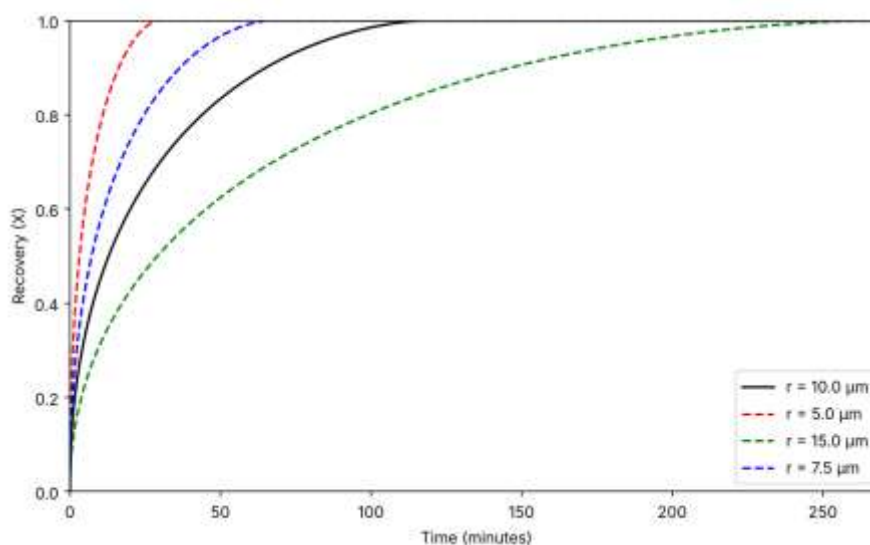


Figure 4. Effect of Particle Size on Copper Recovery Efficiency at 300 K and 100 g/L (SCM prediction; not experimentally validated)

CONCLUSION

This study shows that temperature is the most influential parameter in the sulfuric acid leaching of copper from flash furnace dust within the investigated ranges (297–327 K, 100–175 g/L H_2SO_4): it strongly increases the effective diffusion coefficient and the copper recovery, whereas acid concentration acts mainly through the driving force and has only a marginal effect on the diffusion coefficient. Using the Arrhenius equation and experimental data, the effective diffusion coefficient was found to depend strongly on temperature ($E = 21.37$ kJ/mol, between the 11.35 and 47.03 kJ/mol reported for the diffusion- and reaction-controlled stages of copper extraction from copper smelting slag [17]) and only weakly on acid concentration ($n = 0.0253$), indicating that diffusion through the product layer is the dominant resistance. Among the conditions reported in Table 1, the highest recovery (86.85%) was obtained at 327 K, 175 g/L H_2SO_4 and 105 min; however, at 327 K, increasing the acid concentration from 125 to 175 g/L raised recovery by less than 5 percentage points, so the lower acid concentration may be preferable when acid consumption and iron co-dissolution are taken into account.

The ANN, validated on an independent test set, provided reliable interpolation of copper recovery within the experimental window and supported the SCM-based kinetic analysis. Recovering copper from flash furnace dust can help reduce industrial waste; however, the behaviour of impurities (Fe, Zn, As) in the leach liquor, which is important for downstream processing, was not assessed in this work. However, limitations, including the specific range of temperatures and concentrations tested, the use of an assumed particle radius and of a literature value for the surface reaction rate constant, the deviation of the SCM predictions from the measured recoveries, the fact that the particle size distribution of the dust was not measured, and the fact that the particle-size effect (Figure 4) was predicted by the model but not verified experimentally, suggest that further research is needed to assess scalability to industrial applications. The final correlation for the effective diffusion coefficient, valid for the as-received dust (assumed $r = 10$ μm) at 297–327 K and 100–175 g/L H_2SO_4 , is:

$$D = 8.62 \times 10^{-10} \exp(-21\,370/RT) C^{0.0253} \quad (3)$$

where D is in m²/s, R = 8.314 J/(mol·K), T is in K and C is in g/L.

DATA AVAILABILITY

The complete experimental dataset (all leaching conditions and measured copper recoveries) and the XRF characterization results are provided as Supplementary Material (Table S1). Process-related information on the Sarcheshmeh Copper Complex that is covered by confidentiality agreements is not included; any additional data are available from the corresponding author upon reasonable request.

GLOSSARY

- SCM: Shrinking Core Model – A kinetic model used to describe solid–liquid reactions involving a shrinking unreacted core.
- ANN: Artificial Neural Network – A machine learning model used to predict complex nonlinear relationships.
- AAS: Atomic Absorption Spectroscopy – A technique for measuring metal concentrations in solution.
- Activation Energy (E): The minimum energy required for a chemical reaction to occur.
- Diffusion Coefficient (D): A parameter indicating how fast species diffuse through a medium.
- MAPE: Mean absolute percentage error – a metric used to quantify the prediction error of the ANN.

ACKNOWLEDGMENT

The authors would like to thank the Sarcheshmeh Copper Complex for providing the flash furnace dust sample used in this research. The authors also appreciate the support of the Laboratory of Chemical Engineering Department, Vali-e-Asr University of Rafsanjan.

FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

- [1] T. Watari, K. Nansai, and K. Nakajima, “Major metals demand, supply, and environmental impacts to 2100: A critical review,” *Resources, Conservation and Recycling*, vol. 164, Art. no. 105107, 2021, doi: 10.1016/j.resconrec.2020.105107.
- [2] M. A. H. Shuva, M. A. Rhamdhani, G. A. Brooks, S. Masood, and M. A. Reuter, “Thermodynamics data of valuable elements relevant to e-waste processing through primary and secondary copper production: a review,” *Journal of Cleaner Production*, vol. 131, pp. 795–809, 2016, doi: 10.1016/j.jclepro.2016.04.061.
- [3] B. W. Schipper, H.-C. Lin, M. A. Meloni, K. Wansleebe, R. Heijungs, and E. van der Voet, “Estimating global copper demand until 2100 with regression and

- stock dynamics," *Resources, Conservation and Recycling*, vol. 132, pp. 28–36, 2018, doi: 10.1016/j.resconrec.2018.01.004.
- [4] H. R. Watling, "The bioleaching of sulphide minerals with emphasis on copper sulphides — A review," *Hydrometallurgy*, vol. 84, no. 1–2, pp. 81–108, 2006, doi: 10.1016/j.hydromet.2006.05.001.
 - [5] D. Bingöl and M. Canbazoglu, "Dissolution kinetics of malachite in sulphuric acid," *Hydrometallurgy*, vol. 72, no. 1–2, pp. 159–165, 2004, doi: 10.1016/j.hydromet.2003.10.002.
 - [6] M. J. Nicol, "The kinetics of the dissolution of malachite in acid solutions," *Hydrometallurgy*, vol. 177, pp. 214–217, 2018, doi: 10.1016/j.hydromet.2018.03.017.
 - [7] M. D. Sokić, B. Marković, and D. Živković, "Kinetics of chalcopryrite leaching by sodium nitrate in sulphuric acid," *Hydrometallurgy*, vol. 95, no. 3–4, pp. 273–279, 2009, doi: 10.1016/j.hydromet.2008.06.012.
 - [8] H. Zhang et al., "Efficient and safe disposition of arsenic by incorporation in smelting slag through copper flash smelting process," *Minerals Engineering*, vol. 160, Art. no. 106661, 2021, doi: 10.1016/j.mineng.2020.106661.
 - [9] D. O. Okanigbe, A. P. I. Popoola, and A. A. Adeleke, "Characterization of copper smelter dust for copper recovery," *Procedia Manufacturing*, vol. 7, pp. 121–126, 2017, doi: 10.1016/j.promfg.2016.12.032.
 - [10] V. Montenegro, H. Sano, and T. Fujisawa, "Recirculation of high arsenic content copper smelting dust to smelting and converting processes," *Minerals Engineering*, vol. 49, pp. 184–189, 2013, doi: 10.1016/j.mineng.2010.03.020.
 - [11] A. Morales, M. Cruells, A. Roca, and R. Bergó, "Treatment of copper flash smelter flue dusts for copper and zinc extraction and arsenic stabilization," *Hydrometallurgy*, vol. 105, no. 1–2, pp. 148–154, 2010, doi: 10.1016/j.hydromet.2010.09.001.
 - [12] Y. Zhang, B. Jin, Y. Huang, Q. Song, and C. Wang, "Two-stage leaching of zinc and copper from arsenic-rich copper smelting hazardous dusts after alkali leaching of arsenic," *Separation and Purification Technology*, vol. 220, pp. 250–258, 2019, doi: 10.1016/j.seppur.2019.03.067.
 - [13] W.-F. Liu, X.-X. Fu, T.-Z. Yang, D.-C. Zhang, and L. Chen, "Oxidation leaching of copper smelting dust by controlling potential," *Transactions of Nonferrous Metals Society of China*, vol. 28, no. 9, pp. 1854–1861, 2018, doi: 10.1016/s1003-6326(18)64830-7.
 - [14] M. J. Nicol and C. Akilan, "The kinetics of the dissolution of chrysocolla in acid solutions," *Hydrometallurgy*, vol. 178, pp. 7–11, 2018, doi: 10.1016/j.hydromet.2018.04.001.
 - [15] F. Vegliò, M. Trifoni, F. Pagnanelli, and L. Toro, "Shrinking core model with variable activation energy: a kinetic model of manganiferous ore leaching with sulphuric acid and lactose," *Hydrometallurgy*, vol. 60, no. 2, pp. 167–179, 2001, doi: 10.1016/s0304-386x(00)00197-3.
 - [16] V. Safari, G. Arzpeyma, F. Rashchi, and N. Mostoufi, "A shrinking particle—shrinking core model for leaching of a zinc ore containing silica," *International Journal of Mineral Processing*, vol. 93, no. 1, pp. 79–83, 2009, doi: 10.1016/j.minpro.2009.06.003.

- [17] G. Shi, Y. Liao, B. Su, Y. Zhang, W. Wang, and J. Xi, "Kinetics of copper extraction from copper smelting slag by pressure oxidative leaching with sulfuric acid," *Separation and Purification Technology*, vol. 241, Art. no. 116699, 2020, doi: 10.1016/j.seppur.2020.116699.
- [18] S. Chehreh Chelgani and E. Jorjani, "Artificial neural network prediction of Al_2O_3 leaching recovery in the Bayer process—Jajarm alumina plant (Iran)," *Hydrometallurgy*, vol. 97, no. 1–2, pp. 105–110, 2009, doi: 10.1016/j.hydromet.2009.01.008.
- [19] S. Vyas, S. Das, and Y.-P. Ting, "Predictive modeling and response analysis of spent catalyst bioleaching using artificial neural network," *Bioresource Technology Reports*, vol. 9, Art. no. 100389, 2020, doi: 10.1016/j.biteb.2020.100389.
- [20] C. F. Dickinson and G. R. Heal, "Solid–liquid diffusion controlled rate equations," *Thermochimica Acta*, vol. 340–341, pp. 89–103, 1999, doi: 10.1016/s0040-6031(99)00256-7.
- [21] B. Jin, X. Yang, and Q. Shen, "Kinetics of copper dissolution during pressure oxidative leaching of lead-containing copper matte," *Hydrometallurgy*, vol. 99, no. 1–2, pp. 119–123, 2009, doi: 10.1016/j.hydromet.2009.07.004.
- [22] T. Wen et al., "Effect of microwave-assisted heating on chalcopyrite leaching of kinetics, interface temperature and surface energy," *Results in Physics*, vol. 7, pp. 2594–2600, 2017, doi: 10.1016/j.rinp.2017.07.035.

Copyright Holder :

© Hassan Razzani, Hassan Hashemipour, Amirhossain Karimi (2026)

First Publication Right :

© Asian Journal Science and Engineering

This article is under:

CC BY SA