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Particle-based Approach to Predict Magnetite Separation from Iron Ore Tailing Piles

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Abstract

This research work aims to explore the intricate mineralogy and texture of the tailing piles of iron ore processing plants to present a particle-based prediction for magnetite recovery. Three samples were taken from different points of tailings piles of an iron ore processing plant. Davis tube tests were performed on each sample under various operating conditions. Process mineralogy studies were conducted to determine the mineralogy modal of the feed and product of each test. An Artificial Neural Network (ANN) model was used to make a model that related the grade and recovery of magnetite in the product to the mineralogy modal of the tailing piles. The magnetite grade and association index of feed, the magnetic intensity, and the water flow rate were the inputs to this network. The grade and magnetite recovery correlation coefficients were 0.954 and 0.86, respectively. The grade of magnetite in the feed emerged as a limiting factor on the grade and recovery of magnetite in concentrate. An increase of one unit in magnetite grade in the feed resulted in a 1.68 decrease in the recovery. The association index changes with the coefficients of -0.173 cause the changes in predicted magnetite recovery in the concentrate.

1. Introduction

In the recent years, with the increase in global demand and the rapid development of the iron and steel industries, the amount of tailings produced from iron mining and processing plants has increased [1]. Therefore, reprocessing tailings from iron ore processing plants is necessary from economic and environmental perspectives. However, this process is time-consuming and expensive [1, 2]. To provide optimal approaches for reprocessing iron tailings, it is crucial to establish accurate classifications and models that fully and accurately describe their metallurgical, economic, and environmental aspects. Currently, the modeling and optimization of mineral processing plants rely on general characteristics of the ore or bulk feed [3, 4]. Various attempts have been made so far to model and simulate iron ore magnetic separation circuits [5-7].

In magnetite ore processing, the Davis Tube Recovery (DTR) test is traditionally used to develop recovery and grade models. Its development dates back to 1921 when a previously manually performed test was mechanized. The model provides information about the quality of the concentrate and the iron recovery based on the iron grade in the feed [8]. The empirical model of the wet high-intensity magnetic separator (WHIMS) by Dobby and Finch (1977) indicates that the recovery of particles into the magnetic concentrate is dependent on the magnetic susceptibility and particle size [9]. King and Schneider (1995) developed an empirical magnetic separator model that considers particle properties and can forecast the behavior of each particle separately [9]. Rayner and Napier-Munn (2003) developed a model to predict the percentage loss of magnetic particles for a wet drum magnetic separator in a dense medium application [10]. Ersayin (2004) proposed a simplified approach called the pseudo-liberation approach for simulating the effect of liberation in

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WLIMS [11]. Metso reported a model for the LIMS that combines the discrete element method (DEM), computational fluid dynamics (CFD), and finite element method (FEM) [12]. In this model, each particle is supposedly treated separately. In most of the presented models, the variables of iron grade in the feed and magnetic sensitivity are considered the most important factors.

Regarding the reprocessing of tailings in iron ore processing plants including low-grade iron reserves, challenges arise due to factors such as low grade, mineralogical diversity, complex mineralization, low liberation degree for valuable minerals, and a high degree of interlock between iron-bearing and gangue minerals. These challenges make it difficult to obtain the desired grade and recovery [13-15]. Consequently, conventional models for the magnetic separation of iron tailings may not yield favorable results. Therefore, the most optimal approach to capitalize on tailings is by developing a tailing-metallurgy program based on modal mineralogy. This involves determining the mineralogical modal and combining it with the results of metallurgical tests to develop mineralogical-based approaches for the productive and optimal management of iron tailings (via tailing-metallurgy programs). The mineralogical approach of geometallurgical programs relies on particle and mineral properties. In this approach, often referred to as process mineralogy, process models are formulated using particle tracking methods. However, it is worth noting that this process model level is relatively less developed, and requires further attention and research.

The significance of Particle-based Separation Models (PSMs) stems from their utilization of rich and quantitative data derived from process mineralogy investigations, which employ Scanning Electron Microscopes (SEMs) and X-ray analysis. These models possess capabilities that surpass conventional data-based approaches, as they consider material properties [16, 17]. On the other hand, with the increasing demand for raw materials and the need to optimize existing circuits, modeling mineral processes based on particles becomes ever more crucial. This is due to the growing complexity of mineralogy and geology in ores, necessitating the development of optimal flowsheets for efficient extraction, as well as the reprocessing of waste and tailings from mine and mineral processing plants [3, 18, 19]. Recently, PSMs have been employed to model various mineral processing operations including flotation, magnetic separation, and grinding [20]. The particle tracking approach, introduced by Polat in 1995 used the characteristics of particles to investigate the kinetics of coal flotation [19]. Lamberg and Vianna (2007), utilized mineralogical data, surface composition, and particle size obtained from SEM-based image analysis systems to model the flotation process of lead-zinc-silver polymetallic ore [20]. Pascoe et al. (2007) applied a similar approach to calculate particle recovery in gravity separation processes using SEM-based image analysis data. This method involves classifying particles based on density and size and expressing recovery as the percentage of particles in each class that are recovered in the concentrate product [21]. Hannula et al. (2018) proposed a modification to particle tracking methods by incorporating neural networks to create generalized prediction models that provide continuous recovery probabilities [22]. Furthermore, Schach et al. (2019) developed a method for cassiterite ore that directly links particle tracking to distribution curves using Falcon apparatus. They utilized kernel density estimates to quantify continuous probabilities in the two-dimensional sample space defined by particle density and size [23]. However, the method is limited to less than 10 variables due to computational complexity and data density limitations. Therefore, variable pre-selection is necessary.

This study aimed to predict the behavior of magnetite minerals in the tailings of iron ore processing plants during the magnetic separation process. All the previously mentioned discussions focused on primary ores, which typically have higher grades and simpler mineralogy. However, reprocessing of tailings from iron processing plants presents challenges, due to mineralogical complexities and low grades. To address this, it is important to have a clear understanding of the particle recovery potential of tailings to develop effective approaches for revitalizing tailing piles. Although various experimental particle-based separation modeling approaches have been developed, there is a lack of investigation into predicting their performance under variable process conditions. This research work aims to fill this gap by investigating the performance prediction of a particle-based separation under different conditions (feed and operating conditions) for magnetic separation on a laboratory scale. To achieve this process, mineralogy studies were conducted on the feed and Davis tube test products of various samples. The mineralogical composition of iron ore tailings and Davis tube test products was determined. Finally, Artificial Neural Networks (ANN) were used as particle-based modeling approaches to predict the magnetic separation of magnetite from the tailings of iron ore processing plants.

2. Materials and Methods

2.1. Sample characteristics

The present study focused on the tailings of an iron ore processing plant located in the Kurdistan province of west Iran. These tailings are derived from the low intensity magnetic separation of magnetite iron ore using the dry method, and they accumulate in the form of piles near the processing plant. To obtain representative samples from the tailing piles, three samples were taken from different locations, identified as ST1, ST2, and ST3. Sampling points were selected based on the pattern of tailings accumulation, in different periods. Following the sampling process, several analyses were conducted on the three samples including chemical analysis through techniques like XRF (X-ray fluorescence) and titration, particle size analysis, and mineralogical studies utilizing XRD (X-ray diffraction), Optical Image Analysis (OIA), and Scanning Electron Microscopy (SEM). The results of the chemical analysis are presented in Table 1, while Figure 1 illustrates the findings of the particle size analysis. Based on the particle size analysis, d_{80} for three samples ST1, ST2, and ST3 is 4.7, 5.0, and 6.7 mm, respectively. ST3 has a coarser particle size distribution than the other two samples. In this sample, size fraction +1 -12.5 mm has the highest weight percentage (approximately 77%).

Table 1. Results of XRF of tailing samples of iron processing plant.

Code	SiO_2 %	CaO %	Fe(T) %	FeO %	K_2O %	MgO %	MnO %	Al_2O_3 %	S %	TiO_2 %	LOI %	Cu %
ST1	31.27	20.76	14.80	4.89	0.42	3.24	0.30	7.40	2.28	0.50	2.31	0.25
ST2	35.02	20.37	12.26	3.68	0.83	2.76	0.29	7.99	0.37	0.47	3.60	0.10
ST3	33.61	16.96	13.15	4.51	0.59	3.79	0.26	8.66	1.20	0.53	3.27	0.14

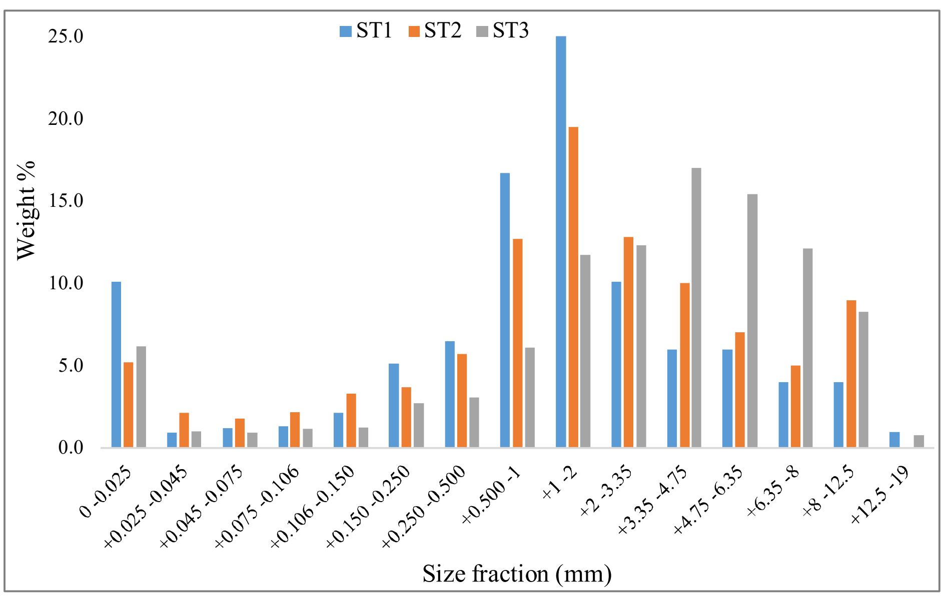

Figure 1. Particle size distribution of the three tailing samples of the iron ore processing plant.

Based on XRD analysis, diopside ($CaMg(SiO_3)_2$) has been identified as the most abundant phase in all of the tailing samples. Calcite and garnet are the next most abundant minerals after diopside, with their quantities being approximately equal across the samples. The mineralization and mineralogy studies of the primary reserve reveal that garnet-skarn and epidote-skarn are the two main exo-skarn zones in the studied area. This suggests that the abundance of garnet and epidote minerals in the tailings of the processing plant can be attributed to their prevalence in the primary ore. Additionally, changes in physicochemical conditions and the infiltration of low-temperature atmospheric waters have led to the formation of minerals like calcite and quartz from the transformation of garnet and pyroxene into low-temperature minerals in the primary ore.

Using OIA and SEM, it has been observed that the volumetric abundance of the two main oxide minerals, magnetite and hematite (as the primary iron minerals in the tailings), varies across the different size fractions of each tailing sample. In the larger size fractions, there are interlocks between iron oxides (predominantly magnetite) and silicate and carbonate gangues (as seen in Figure 2-A). Additionally, the gangues have been found as inclusions within iron oxides, exhibiting a relatively complex interlock. Analysis of the liberation degree of the oxide minerals in the tailings indicates that for fractions with a particle size smaller than 106 microns, the oxide metal minerals exhibit a degree of liberation exceeding 85% (Figure 2-B). The results of SEM have been used to determine the association index (AI) [24].

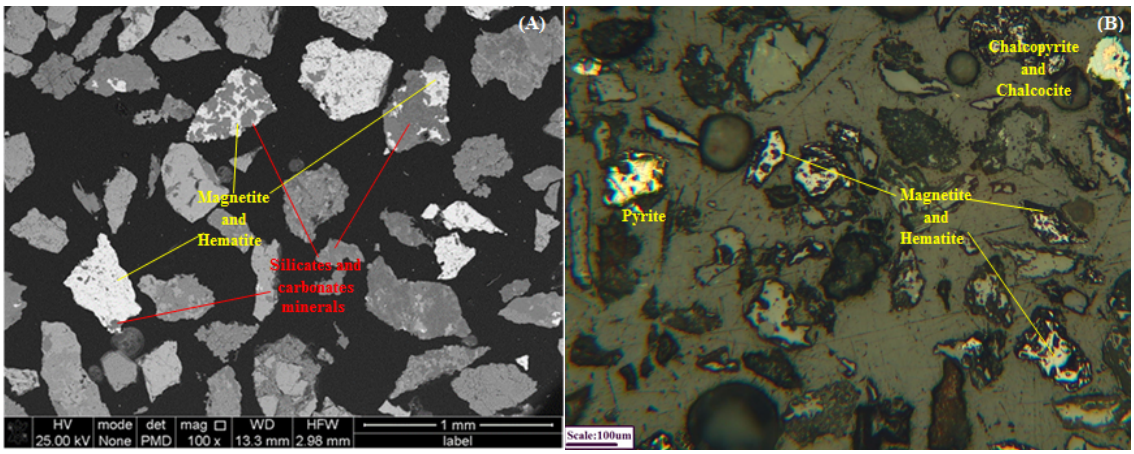

Figure 2. A) The interlock of iron oxide minerals and silicate and carbonate minerals in dimensions of +500 microns (BSE image), B) Liberation of iron oxide minerals in size of -106 microns (PPL image).

2.2. Test works

Conducting metallurgical tests is a crucial step in applying particle-based methods. These tests are specifically performed to assess the behavior of each tailings sample. Ideally, the data gathered from these tests should enable the prediction of the process behavior of various sections within the stockpiles. In this study, Davis tube tests were carried out to predict the grade and recovery of magnetite from iron ore tailings. Figure 3 provides an overview of the entire tests for the iron tailing samples. Based on the degree of liberation studies, as well as the difference in particle size of the examined samples, which were in two ranges of 0-8 and 0-15 mm; First, all the samples were crushed to the dimensions of 0-2 mm. In the next step, chemical and mineralogical analyses have been performed on the samples by classifying them in different fractions. Davis tube tests have also been performed for samples with different d_{80}.

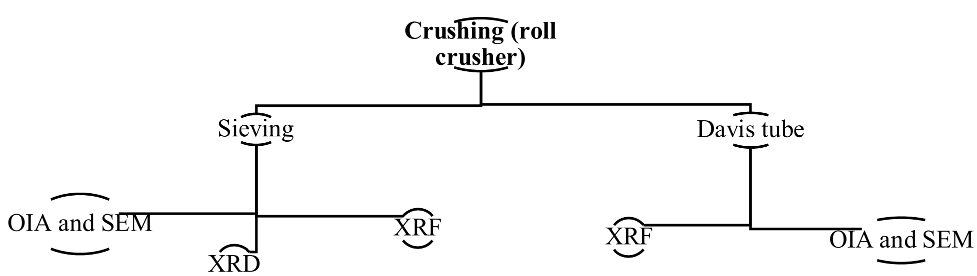

Figure 3. The overview of the analysis and tests performed to predict the recovery of magnetite from the iron tailings.

Davis tube tests were conducted under various operational conditions. These tests aimed to investigate the impact of changes in feed and Davis tube device variables. The variables related to the feed characteristics were the magnetite grade (Mag.) and association index (AI). The varied device variables included the Magnetic Intensity (MI) and water Flow Rate (FR) (Table 2). It is important to note that the separation time for all tests was set at 2 minutes, and other variables such as feeding and tube movement frequency remained constant. Following each test, the concentrate products and tailings were weighed and subjected to chemical and mineralogical analysis.

In a geometallurgical program modeling at the 3D level, particle information is utilized to develop the model. To achieve this, the XRF and quantitative mineralogy (XRD), SEM, and OIA at the particle level were employed to determine the chemical and mineralogical characteristics of the feed and products of Davis tube tests. Subsequently, the mineralogical modal was calculated for the feed, concentrate, and tailings of each Davis tube test using the Element-to-Mineral Conversion (EMC) method. The HSC chemistry software package provided by Outotec was utilized to implement the EMC method and calculate the mineral ratios. The EMC procedure, based on Non-Negative Least Squares (NNLS) estimation was chosen and manually entered the data obtained from the iron tailings piles into the software. In addition, the association index concept has been used to quantify the texture data (resulting from SEM microscopic studies) of iron tailing samples. The AI calculated based on the proportion of valuable minerals in the particles and interfacial surface area between valuable minerals with gangues [24]. Table 2 presents the intervals of variable variations for these tests. The changes in magnetite grade (calculated by EMC) in different tailing samples (ST1 to ST3) are from 13.20 to 26.00. The AI of magnetite also varies from 27.2 to 68.2 in three samples.

Table 2. Experimental variable variation intervals of Davis tube tests.

Variables	Range
Magnetite %	13.20 – 26.00
Association index	27.2 – 68.2
Magnetic intensity (G)	600 – 3000
Water flow rate (l/min)	0.2 – 0.5

2.3. Modeling and prediction

Magnetic separation is a comprehensible process that can be understood based on the behavior of individual particles in an ore. As a result, several experimental models have been developed to predict this process [7, 25, 26]. These models tend to be effective in predicting the behavior of a feed with a constant chemical composition and physical characteristics. However, when the composition of the feed changes, along with the corresponding alterations in the operating conditions required for effective enrichment, the existing mathematical models for magnetic separators become considerably complex. Consequently, predicting the process becomes challenging. The findings of current research conducted on the tailings of an iron ore processing plant indicate significant variations in feed composition across different areas of the tailing piles. Therefore, to develop a metallurgical model for tailings piles, it is essential to adopt an approach that can establish a connection between inputs and outputs under complex and variable conditions. Artificial Neural Network (ANN) is one such approach, capable of establishing meaningful communication in the presence of variability and complexity. Neural networks are designed based on biological neural networks and quickly adapt to process changes. ANN is considered a black-box approach for modeling real-world problems and relies on the utilization of training data sets (history) to predict outputs through appropriate weight-updating techniques.

As stated in Table 2, the input variables in Davis tube tests include magnetite grade, association index, magnetic intensity, and water flow rate. The investigated output variables are the grade and recovery of magnetite to concentrate. The file containing the data (in the form of an Excel file) including 42 values for each variable (168 data in total) has been uploaded into the software *R-studio*. It should be noted that to ensure data accuracy, each test was performed in three repetitions and their average was used for modeling. Figure 4 provides a visualization of the inputs and schematic image of the neural network that has been designed to predict the grade and recovery of magnetite from iron ore tailings. By carrying out different designs (networks with different numbers of layers and neurons), finally, the network includes an input layer, two hidden layers (with the number of neurons 30 and 20, respectively) and an output layer, considered the most optimal state. The network is designed with four input variables and two outputs (output layer) and consists of two hidden layers with 30 neurons in the initial hidden layer and 20 neurons in the second hidden layer, as well as 2 biases. In the designed network (Figure 4), feedforward algorithms with 10,000 training iterations were used to train the network. The learning rate was set at 0.0001, with an error target of 0.001. The Mean Square Error (MSE) method, as described by Equation 1, was employed to calculate the error. To determine the type of activation functions in the hidden layers and output layer, the performance of Rectified Linear Unit (ReLU), hyperbolic, and sigmoid, functions were checked by trial-and-error method. Based on the measured values for min.val.loss, min.loss and MSE function in the first hidden layer ReLU function (Equation 2), for the second hidden layer tanh (Equation 3) and the sigmoid function for the output layer (Equation 4) have provided the most suitable output.

$$MSE = \frac{1}{N}\Sigma(\hat{y} - y)^2 \quad (1)$$

$$f(x) = \max\ (0, x) \quad (2)$$

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (3)$$

$$f(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

In Equations 1 to 4, the variable "N" represents the number of rounds, "ŷ" stands for the predicted value, "y" represents the real value, and "x" denotes the input variables. Out of the 42 tests input to the neural network, 90% of the data (which is the data from 38 tests) was selected as the training data using the sample function either randomly or by default. The remaining 10% of the data (data from 4 tests) did not play a role in training the network but were chosen as the best data for the network. The training process of the proposed network was halted after nearly 600 training sessions. Figure 5 demonstrates the performance of the proposed network in terms of the convergence of the Mean Square Error (MSE) for the original training data and validation data. In this case, the network calculated the values of min.val.loss, min.loss, and MSE as 0.005, 0.008, and 5.36, respectively.

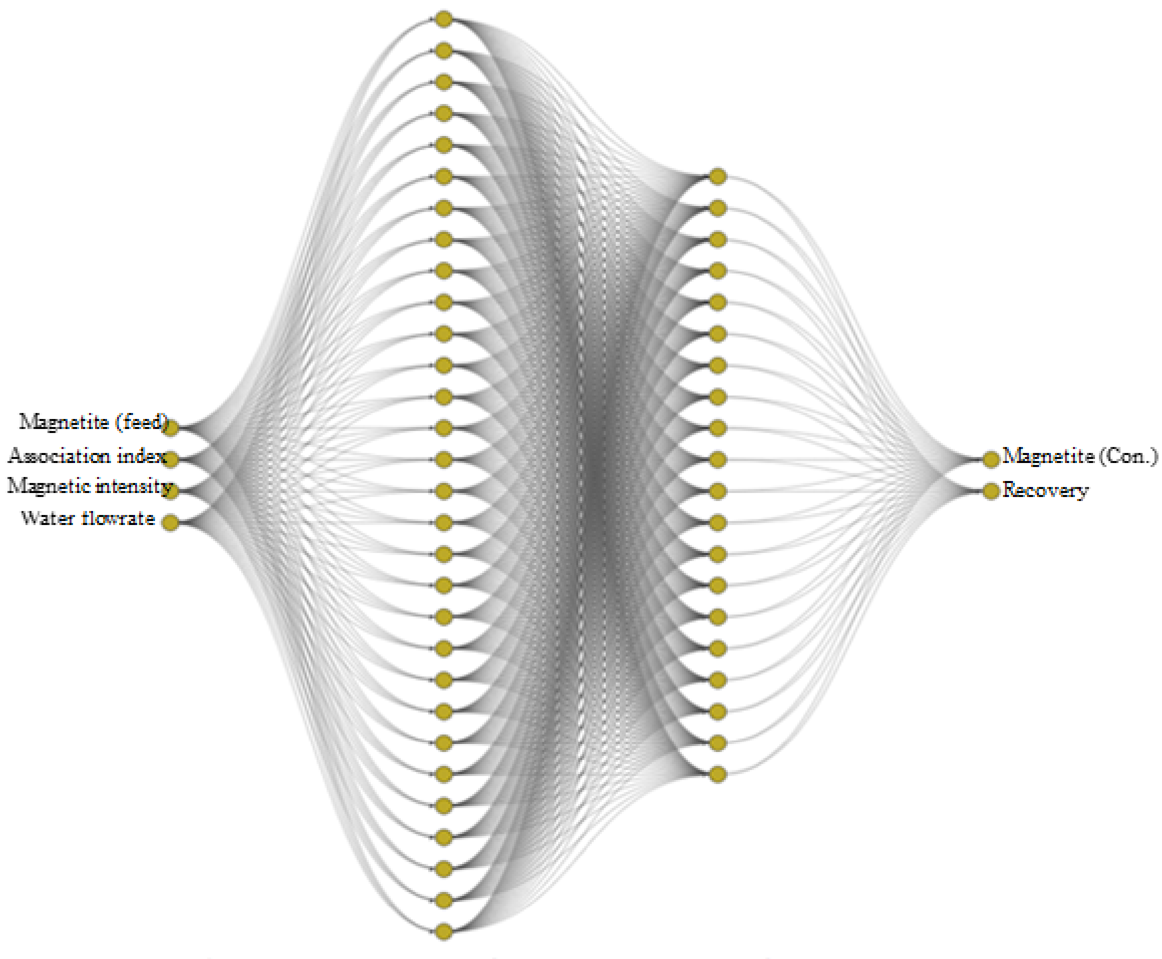

Figure 4. Schematic diagram of ANN for magnetic separation of magnetite from iron processing tailings.

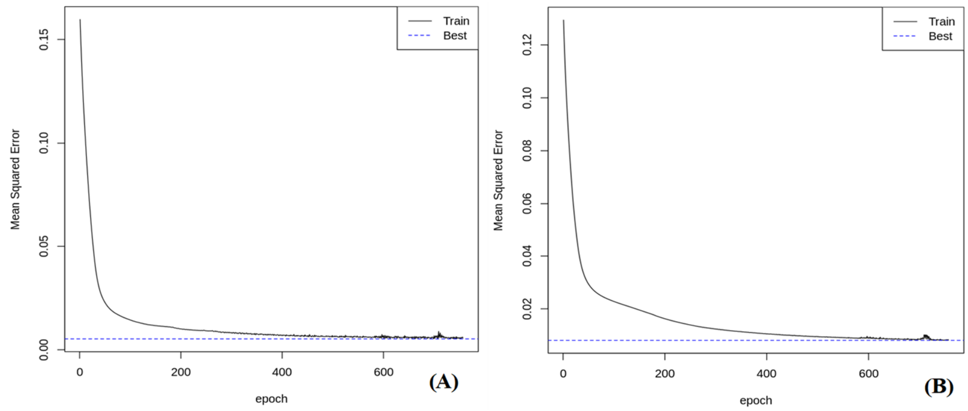

Figure 5. Checking the performance of the proposed neural network based on the convergence of the minimum error value A) random validation data, B) main train data.

3. Results and Discussion
3.1. Process mineralogy studies

Davis tube tests were conducted to investigate the behavior and make predictions about the grade and recovery of magnetite from different tailings piles in iron ore processing plants (as described in section 2-2). These tests involved performing chemical analysis and mineralogical studies on the concentrate and tailings. Through these studies, the grade and texture characteristics of magnetite were determined for each test. The grade of magnetite was calculated using the EMC method [24]. It is evident that as the liberation degree of magnetite increased, its grade in the concentrate also increased under a constant magnetic field intensity. Microscopic studies revealed that as the d_{80} (particle size) of the concentrate decreased, the interlocking between magnetite and gangue minerals decreased. It should be noted that the interlock of magnetite in the concentrate was mainly associated with hematite. The presence of hematite, resulting from the martitization phenomenon of magnetite (found at the edges of magnetite particles), contributed to the recovery of hematite in the concentrate. Figure 6, showing polished sections, indicates that hematite formed through the martitization of magnetite accounted for approximately 10-15 percent of the sample's volume when the size exceeded 500 microns. The phenomenon of martitization of magnetite to hematite has been observed at fines of even less than 25 microns.

Oxide-hydroxide types of iron such as goethite and, to a lesser extent, earthy hematite and limonite, can be found in magnetic concentrates. These metal minerals exist primarily in an interlocked form. As a result, in coarser grain sizes, the interaction between hematite, other iron-bearing minerals, and magnetite leads to their recovery into the concentrate. In smaller particle sizes (less than 106 microns); the majority of the concentrate consists of particles of metal minerals, with magnetite being the predominant component. Additionally, crystalline and earthy forms of hematite, goethite, pyrite, and chalcopyrite are other metallic minerals present. Most chalcopyrite crystals are interlocked within the non-metallic matrix, and less frequently they are interlocked with magnetite (as shown in Figure 7).

In a constant magnetic intensity, the grade of magnetite in the tailings has been observed to increase as the grade of the feed increases. In the tailings of the Davis tube test, magnetite is found in both intact and martitized crystal forms. Additionally, there are occurrences of magnetite being replaced by hematite and goethite. In some cases, the edges of magnetite crystals may also be replaced by titanium oxide compounds, specifically rutile-anatase. Consequently, the presence of magnetite in the non-magnetic portion can be attributed to the martitization of magnetite margins and the replacement of titanium oxide compounds in the magnetite margins (as shown in Figure 8).

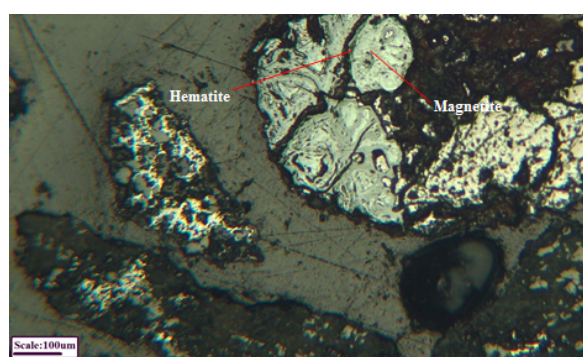

Figure 6. Recovery of hematite mineral to concentrate due to martitization of magnetite.

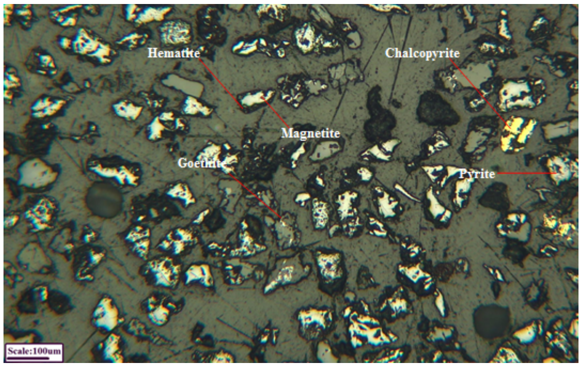

Figure 7. Recovery of hematite, pyrite, chalcopyrite, and goethite to concentrate due to interlocking with magnetite.

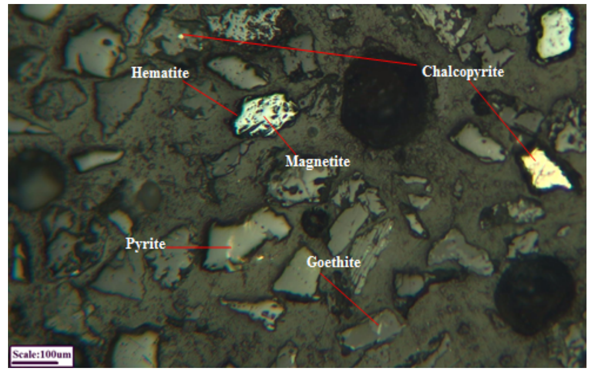

Figure 8. Presence of the magnetite, hematite, pyrite, chalcopyrite, and goethite in the tailings of Davis tube.

3.2. Predicting the grade and recovery of magnetite

To predict the grade and recovery of magnetite from tailings in iron ore processing plants, the first step involves determining the statistical parameters of the data obtained from Davis tube tests. The results of the statistical analysis of the input variables and outputs are presented in Table 3, which includes information such as the average, maximum, minimum, and standard deviation for the variables.

Table 3. Analysis of input data and output variables.

	Variables	Mean	Minimum	Maximum	Std. Dev.
Inputs	Magnetite	18.68	13.20	26.00	3.37
	Association index	51.49	27.20	68.20	10.91
	Magnetic intensity	1361.90	600.00	3000.00	697.37
	Water flow rate	0.35	0.20	0.50	0.15
Outputs	Magnetite	46.68	34.90	62.80	7.77
	Recovery	43.90	31.50	57.50	6.61

The grade and recovery of magnetite from the tailings of iron ore processing plants were predicted using an ANN modeled with the feed-forward algorithm. Figure 4 illustrates the architecture of the designed network. In this network, the input variables (Mag., AI, MI, and FR) labeled as Xi, are multiplied by the previously calculated weights (Wji) for each node in the hidden layer. Subsequently, the sum of all Xi × Wji is added to the bias value (bji), and finally, the operation is conducted using the activation function. Equations 5 and 6 provide a mathematical representation of these operations.

$$H_j = f\left(\sum W_{ji} \times X_i + b_{ji}\right) \quad (5)$$

$$Y = \left(\sum W_j \times h_j + \acute{b}\right) \quad (6)$$

In Equations 5 and 6, the variables and symbols have specific meanings: Hj represents network nodes, Wji denotes the weight of the parameter, Xi refers to the input parameter, bji represents the bias, Y represents the output, and Wj and b′ are sets of weights and bias values, respectively.

The selection of the optimal network geometry is based on two criteria: the highest R^2 value (coefficient of determination) and the lowest MSE value (mean squared error). The coefficient value is presented in Figure 9-A for the grade of magnetite. According to the figure, the neural network achieved good performance in predicting the grade of magnetite from iron processing tailings, with an R^2 value of 0.95 (MSE = 2.81). Figure 9-B presents the predicted results for magnetite recovery from iron processing tailings. The R^2 value, which indicates the goodness of fit between the predicted and measured data, is reported to be higher than 0.86 for magnetite recovery (MSE=6.40).

3.3. Effect of feed variables on the prediction of magnetite and recovery

A) Grade of magnetite

The influential variables related to the feed that impact the prediction of magnetite grade and recovery include the grade of magnetite in the feed and the association index. Figure 10-A illustrates the relationship between the magnetite grade in the concentrate, as predicted by the neural network, and the grade of magnetite in the feed. According to the findings, the grade of magnetite in the feed exhibits a direct proportionality to its grade in the concentrate. For every unit, increase in the grade of feed magnetite, there is an expected increase of 0.847 units in the amount of magnetite present in the concentrate. Figure 10-B illustrates the relationship between magnetite recovery, as predicted by the neural network, and the grade of magnetite in the feed. For every unit increase in the grade of feed magnetite, there is an expected decrease of 1.68 units in the amount of magnetite recovery.

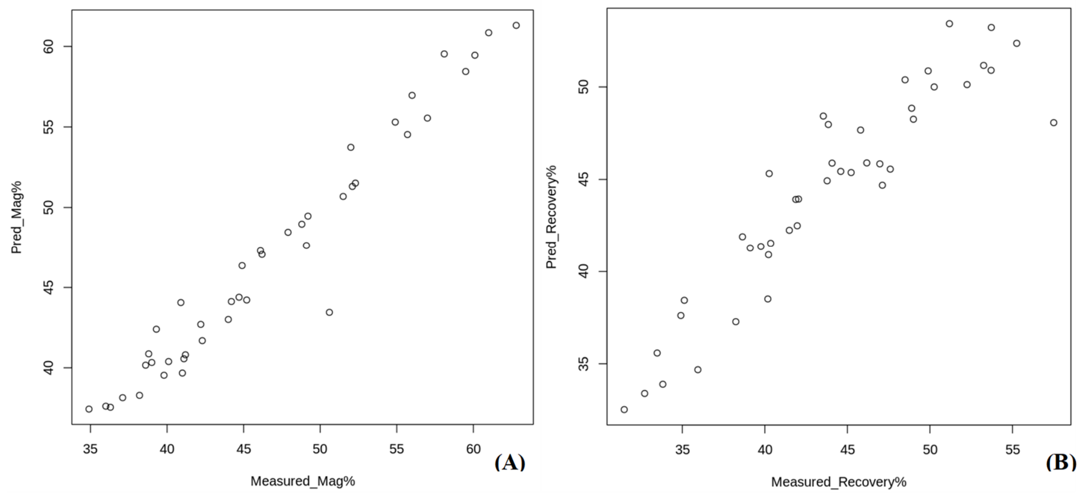

Figure 9. The relationship between the values predicted by the neural network, with the measured values for A) magnetite grade and B) magnetite recovery

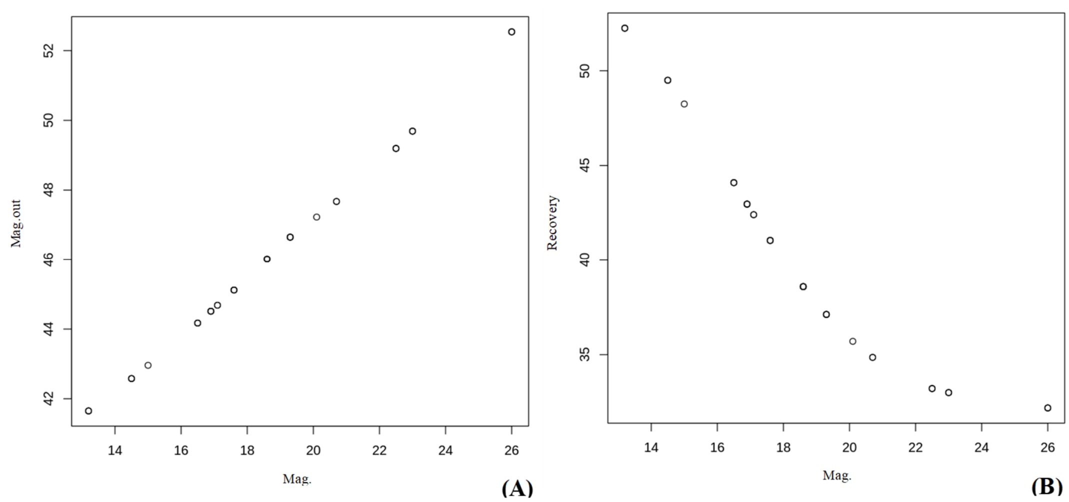

Figure 10. Relationship between A) magnetite grade in concentrate (predicted by neural network) and B) magnetite recovery (predicted by neural network) with feed grade.

B) Association index

Figure 11-A illustrates the correlation between the magnetite grade in the concentrate, as predicted by the neural network, and the association index of magnetite. The prediction made by the neural network suggests an inverse association between the magnetite grade and the mineral's association index in the feed. Specifically, as the association index of magnetite increases in the feed, the magnetite grade in the concentrate is projected to decrease with a factor of -0.297. Figure 11-B displays the correlation between the predicted magnetite recovery (determined by the neural network) and the association index of magnetite in the feed. The association index and recovery exhibit an inverse relationship, with a coefficient of approximately -0.173.

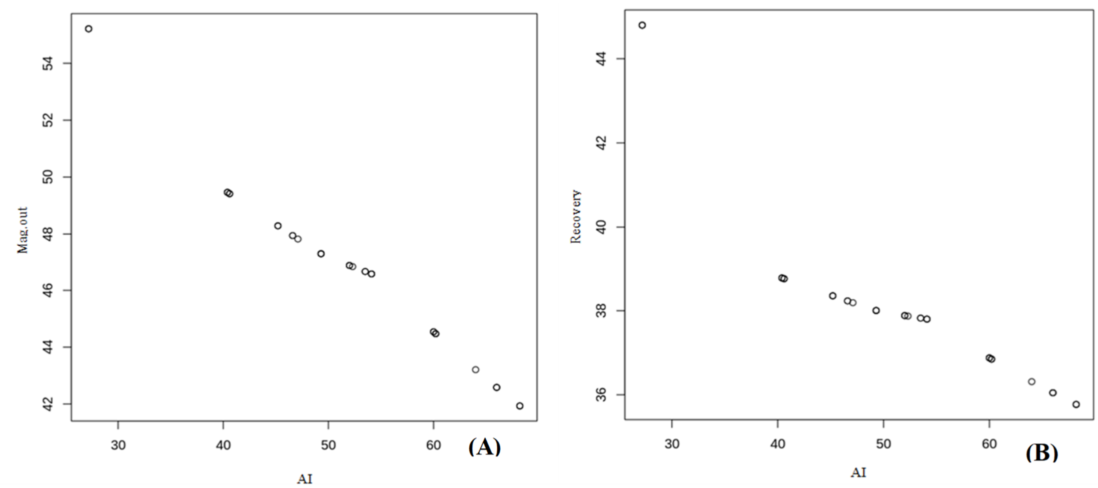

Figure 11. The relationship between the A) magnetite grade in the concentrate (predicted by the neural network) and B) recovery (predicted by the neural network) with magnetite association index in the feed.3-4 Validation of model

To validate the proposed model, magnetic separation, tests were performed by dry and wet methods on different samples of iron ore tailings. In each test, a sample weighing 50 kg was fed to the magnetic separator with a speed drum 50 (rpm) and the magnetic intensity mentioned in Table 4.

Table 4. Condition of magnetic separation tests.

Test No.	d_{80} feed (mm)	Fe (T) %	Magnetic intensity (G)	Water flow rate (l/min)	Speed of drum (rpm)
1	6.5	12.59	2500	Dry	35
2	2.0	14.05	1800	0.5	50
3	0.250	17.83	900	0.5	50

The results of magnetic separation tests are given in Table 5. In the magnetic separation performed with a magnetic intensity of 2500 G, approximately 22% by weight of the input load (with d_{80} = 6.5 mm) was transferred to the concentrated product (magnetic), and more than 77% by weight was transferred to the tailings (non-magnetic part). By decreasing the particle size to d_{80} = 2 mm and decreasing the magnetic intensity to 1800 G about 20.50% by weight of the feed with a grade of 38% of Fe (T) has been recovered into concentrate and about 80% by weight with a grade of 9% has been recovered into tailings. A magnetic separation test of 900 G has been performed for feed with d_{80} = 0.250 mm. According to Table 5, during this test, 18.90% by weight of the feed was transferred to the concentrate (or magnetic product) with a grade of 46.92% and 81% of it was transferred to the tailings with a grade of 9.42%. Using the EMC method; the amount of magnetite in the feed and products of each test was measured, the results are shown in Table 5. In the previous section, it was stated that with the increase of one unit in the magnetite grade of feed, its grade in the concentrate increases by 0.847 units. Examining the magnetite grade in the concentrate of magnetic tests (Figure 12) confirms this result.

Table 5. Results of magnetic separation tests.

Test No.		Weight (%)	SiO_2 (%)	CaO (%)	Fe (T) (%)	K_2O (%)	MgO (%)	MnO (%)	S (%)	Cu (%)	Magnetite %
1	Feed	100.00	36.01	20.31	17.83	0.59	4.44	0.29		0.14	10.65

	Con.	33.47	28.19	14.06	31.05	0.30	4.52	0.25	-	0.15	13.60
	Tail	66.53	39.95	23.46	11.18	0.73	4.40	0.31	-	0.13	9.10
2	Feed	100.00	31.15	16.85	19.65	0.43	5.58	0.25	1.47	0.28	11.58
	Con.	23.90	16.55	9.09	42.01	0.19	3.45	0.17	1.35	0.14	22.90
	Tail	76.10	35.73	19.29	12.63	0.50	6.25	0.27	1.51	0.33	8.00
3	Feed	100.00	33.48	16.95	13.54	0.62	3.97	0.26	0.80	0.14	13.10
	Con.	13.40	11.64	5.97	46.61	0.16	2.45	0.14	0.25	0.08	35.78
	Tail	86.60	36.86	18.65	8.42	0.69	4.20	0.28	0.88	0.15	9.60

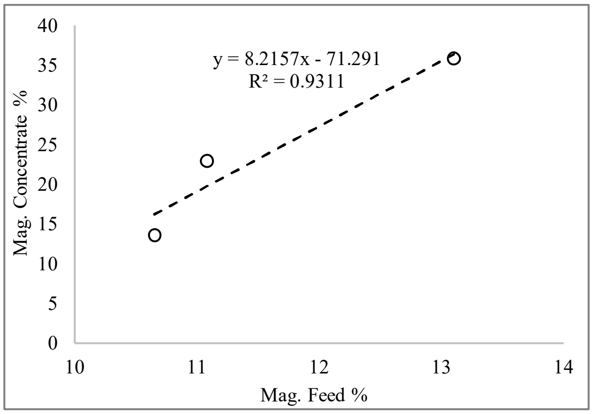

Figure 12. Changes in grade of magnetite in concentrate with changes in magnetite feed.

The concentrate and tailings of the magnetic separation tests were classified into different size fractions, and optical microscopic studies were performed on them. Based on the results, in the magnetic concentrate for the feed with d_{80} = 0.250 mm, where the magnetite AI was lower, the recovery of this mineral in the concentrate was higher. In such a way that in all fractions, magnetite abundance percentage is more than 40 percent by volume (Figure 13-A). But for the sample with d_{80} = 6.5 mm, as seen in Figure 13-B, the interlocking of magnetite with hematite, goethite, pyrite and chalcopyrite as well as gangue minerals causes the recovery of these minerals to magnetic concentrate (higher AI – decreasing of magnetite recovery).

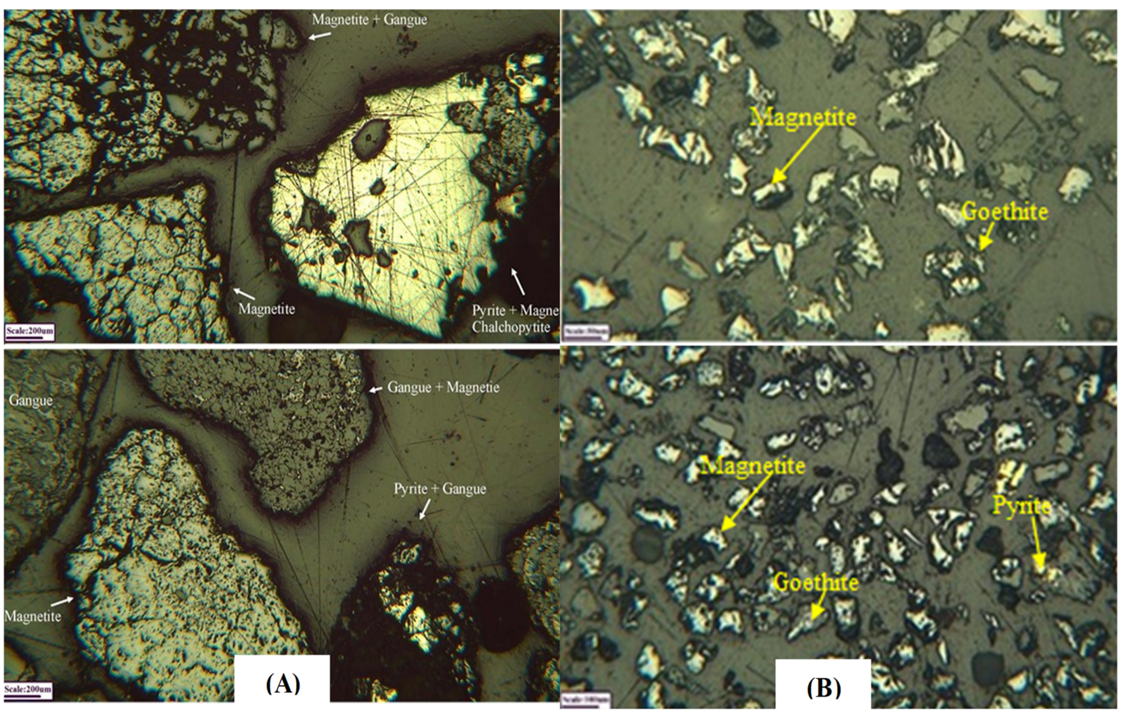

Figure 13. Image of concentrate of magnetic separation for A) feed with d_{80} = 6.5 mm and B) feed with d_{80} = 0.250. mm

4. Conclusions

Various empirical models have been developed to simulate magnetic separation, which is a commonly used method for processing iron ores. These models are built based on magnetic separation tests carried out under different operating conditions. They are useful for predicting the behavior of feed with consistent chemical composition and physical characteristics. However, when the feed composition varies, the existing mathematical models for magnetic separators become overly complex and predicting the process becomes highly challenging. The emergence of process mineralogy, along with the utilization of modern analysis techniques like SEM and XRD, has provided detailed particle-level data in the processing of mineral materials. Despite this wealth of information, current process models do not fully leverage these data, limiting the potential usefulness of this extensive dataset. To address this limitation, the present research aims to utilize process mineralogy data at the particle level to model magnetic separation and predict the grade and recovery of valuable mineral magnetite from iron ore processing plant tailings. By adopting a particle-based approach in the modeling of magnetic separation, the predictions can accommodate variable conditions found in tailings piles, which typically exhibit a wide range of mineralogical diversity.

Application of the neural network approach in modeling and predicting magnetite reprocessing from tailing piles of iron processing plants has proven effective in forecasting magnetite grade and recovery. The correlation coefficients between the measured and predicted data for magnetite grade and recovery were calculated as 0.95 and 0.86, respectively. Among the various variables considered, the magnetite grade of the feed was found to be the most influential in determining the predicted grade and recovery of magnetite by the neural network. For each unit increase in magnetite grade in the feed, the magnetite grade in the concentrate increased by 0.847 units, while the recovery decreased by 1.68 units. This suggests that the magnetite grade in the feed has a larger impact on the recovery than its effect on the concentrate's magnetite grade. This phenomenon can be attributed to other tailings texture variables, such as the association index, degree of liberation, and mineral interlocking, which affect magnetite recovery. Additionally, the association index of the studied variable exhibited a reverse relationship with the grade of magnetite in the concentrate and recovery. According to the output of the neural network, the predicted values for the grade and recovery of magnetite were found to vary with changes in the tailing piles such as alterations in the sampling location of the tailings and subsequently, modifications in the feed variables. Given these findings, it is possible to perform spatial modeling and develop a tailing piles blending plan based on the predicted results generated by the neural network.

References

[1]. Abaka-Wood, G.B., Zanin, M., Addai-Mensah, J., & Skinner, W. (2019). Recovery of rare earth elements minerals from iron oxide–silicate rich tailings–Part 1: Magnetic separation. *Minerals Engineering*, 136, 50-61.

[2]. Elvan, O.D. (2013). The legal environmental risk analysis (LERA) sample of mining and the environment in Turkish legislation. *Resources Policy*, 38(3), 252-257.

[3]. Pereira, L., Frenzel, M., Khodadadzadeh, M., Tolosana-Delgado, R., & Gutezmr, J. (2021). A self-adaptive particle-tracking method for minerals processing. *Journal of Cleaner Production*, 279, 123711.

[4]. Wills, B.A., & Finch, J. (2015). Wills' mineral processing technology: an introduction to the practical aspects of ore treatment and mineral recovery. *Butterworth-heinemann*.

[5]. Cui, J. & Forssberg, E. (2003). Mechanical recycling of waste electric and electronic equipment: a review. *Journal of hazardous materials*, 99(3), 243-263.

[6]. Dobbins, M., Dunn, P., & Sherrell, I. (2009). Recent advances in magnetic separator designs and applications. in *The 7th International Heavy Minerals Conference "What next", The Southern African Institute of Mining and Metallurgy*.

[7]. Svoboda, J. & Fujita, T. (2003). Recent developments in magnetic methods of material separation. *Minerals Engineering*, *16*(9), 785-792.

[8]. Schulz, N.F. (1964). Determination of the magnetic separation characteristics with the Davis Magnetic Tube. *Trans. SME-AIME,* 229, 211-216.

[9]. Parian, M. (2017). Development of a geometallurgical framework for iron ores. A mineralogical approach to particle-based modeling. *Luleå University of Technology.*

[10]. Rayner, J.G. & Napier-Munn, T. (2003). A mathematical model of recovery of dense medium magnetics in the wet drum magnetic separator. *International journal of mineral processing*, 69(1-4), 157-173.

[11]. Ersayin, S. (2004). Low intensity magnetic separator modeling: a pseudo liberation approach. *Mineral Processing and Extractive Metallurgy*, 113(3), 167-174.

[12]. Galvão, J.L.B., Andrade, H., Brigolini, G., Peixoto, R., & Mendes, J. (2018). Reuse of iron ore tailings from tailings dams as pigment for sustainable paints. *Journal of Cleaner Production*, 200, 412-422.

[13]. Cross, M. (2003). Modeling and Simulation of Mineral Processing Systems. *Proceedings of the Institution of Mechanical Engineers*, 217(1), 77.

[14]. Hilden, M.M. & Powell, M.S. (2017). A geometrical texture model for multi-mineral liberation prediction. *Minerals Engineering*, 111, 25-35.

[15]. Lotter, N., Baum, W., Reeves, S., Arrue, C., & Bradshaw, D.J. (2018). The business value of best practice process mineralogy. *Minerals Engineering*, 116, 226-238.

[16]. Carlson, R. (2019). Understanding geologic uncertainty in mining studies. *SEG Newsletter*,117, 21-29.

[17]. Frenzel, M., Kullic, J., Reuter, M., & Gutzmer, J. (2017). Raw material 'criticality'—sense or nonsense? *Journal of Physics D: Applied Physics,* 50(12), 123002.

[18]. Prior, T., Giurco, D., Mudd, G., Mason, L., & Behrisch, J. (2012). Resource depletion, peak minerals and the implications for sustainable resource management. *Global environmental change*, 22(3), 577-587.

[19]. Polat, M. (1995). Coal flotation kinetics: Methods for estimating distribution of rate constants. *The Pennsylvania State University.*

[20]. Lamberg, P. & Vianna, S. (2007). A technique for tracking multiphase mineral particles in flotation circuits. in Meeting of the Southern Hemisphere on Mineral Technology: 20/11/2007-24/11/2007. *Universidade Federal de Ouro Preto.*

[21]. Pascoe, R., Power, M., & Simpson, B. (2007). QEMSCAN analysis as a tool for improved understanding of gravity separator performance. *Minerals Engineering,* 20(5), 487-495.

[22]. Hannula, J., Kern, M., Luukkanen, S., Roine, A., van den Boogaart, K.G., & Reuter, M.A. (2018). Property-based modeling and simulation of mechanical separation processes using dynamic binning and neural networks. *Minerals Engineering*, 126, 52-63.

[23]. Schach, E., Buchmann, M., Tolosana-Delgado, R., Leißner, T., Kern, M., van den Boogaart, K,G., Rudolph, M., Peuker, U,A. (2019). Multidimensional characterization of separation processes–Part 1: Introducing kernel methods and entropy in the context of mineral processing using SEM-based image analysis. *Minerals Engineering*, 137, 78-86.

[24]. Kazemi, F., & Abdollahzadeh, A.A. (2024). Valorisation of iron ore tailing piles: utilisation of element-to-mineral conversion and association index to building mineralogical modal. *Canadian Metallurgical Quarterly*, 1-14.

[25]. Murariu, V. (2013). Simulating a low intensity magnetic separator model (LIMS) using DEM, CFD and FEM magnetic design software. *Proceedings of Computational Modelling*, 13.

[26]. Parian, M., Lamberg, P., & Rosenkranz, J. (2021). Process simulations in mineralogy-based geometallurgy of iron ores. *Mineral Processing and Extractive Metallurgy,* 130(1), 25-30.

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راهکار مبتنی بر ذرات برای پیش‌بینی جداسازی مگنتیت از باطله‌های باطله سنگ آهن

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کلمات کلیدی

مدل کانی‌شناسی
بازفرآوری باطله‌های آهن
مدل‌سازی
لوله دیویس

چکیده

هدف از مقاله حاضر شناسایی درگیری‌های کانی‌شناسی و پیچیدگی بافت دپوهای باطله کارخانه‌های فرآوری سنگ آهن در راستای ارائه یک مدل پیش‌بینی مبتنی بر ذرات برای بازیابی مگنتیت از باطله‌ها است. بدین منظور سه نمونه از نقاط مختلف دپوهای باطله یک کارخانه فرآوری سنگ آهن برداشت شد. بر روی هر نمونه آزمایش‌های لوله دیویس تحت شرایط عملیاتی مختلف انجام شد. مطالعات کانی‌شناسی فرآیند برای تعیین مودال کانی‌شناسی خوراک و محصول‌های هر آزمایش انجام شد. یک مدل شبکه عصبی مصنوعی (ANN) برای پیش‌بینی عیار و بازیابی مگنتیت (بر اساس داده‌های مودال کانی‌شناسی) مورد استفاده قرار گرفت. عیار مگنتیت، شاخص ارتباط خوراک، شدت میدان مغناطیسی و دبی آب، ورودی‌های شبکه عصبی مصنوعی طراحی شده، بودند. بر اساس نتایج، ضرایب همبستگی عیار و بازیابی مگنتیت به ترتیب ۰/۹۵۴ و ۰/۸۶ تعیین شد. عیار مگنتیت در خوراک مهمترین عامل محدود کننده عیار و بازیابی مگنتیت در کنسانتره است. افزایش یک واحدی در عیار مگنتیت در خوراک منجر به کاهش ۱/۶۸ واحدی در بازیابی می‌شود. تغییر شاخص ارتباط با ضریب ۰/۱۷۳- باعث تغییرات در بازیابی مگنتیت پیش‌بینی شده در کنسانتره می‌شود.

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