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Prediction of energy consumption in grinding using artificial neural networks to improve the distribution of fragmentation size
[Predicción del consumo de energía en la molienda utilizando redes neuronales artificiales para mejorar la distribución del tamaño de la fragmentación]

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Resumen

El estudio se enfoca en la predicción del consumo energético en procesos de molienda empleando redes neuronales artificiales (RNA), la finalidad fue desarrollar un modelo predictivo basado en redes neurales artificiales para estimar el consumo energético en la molienda y mejorar la distribución del tamaño de fragmentación, que es crucial para la eficiencia de operaciones mineras y metalúrgicas. El consumo energético en la molienda representa parte significativa de los costos operativos e influye directamente en la rentabilidad de las operaciones, La RNA fue entrenada a partir de un conjunto de datos de 126 registros, los cuales se dividieron en 80% para el entrenamiento y 20% para el testeo del modelo. Los resultados de esta investigación destacan un rendimiento óptimo del modelo predictivo con las métricas de rendimiento como Error Absoluto Medio (MAE), Error Cuadrático Medio (MSE), Raíz del Error Cuadrático Medio (RMSE) y Coeficiente de correlación (R2), con valores de 0.78, 1.39, 1.18 y 0.98, respectivamente en la estimación del consumo de energía en el proceso de molienda. Finalmente, estos resultados indican que la RNA logró una predicción precisa del consumo de energía en el proceso de molienda, esto permitirá hacer una mejor panificación en la optimización de la energía.

Palabras clave: Consumo energético; molienda; modelos predictivos; RNA.

Abstract

The study focuses on the prediction of energy consumption in grinding processes using artificial neural networks (ANN). The purpose was to develop a predictive model based on artificial neural networks to estimate energy consumption in grinding and improve the fragmentation size distribution, which is crucial for the efficiency of mining and metallurgical operations. Energy consumption in grinding represents a significant part of operating costs and directly influences the profitability of operations. The ANN was trained from a data set of 126 records, which were divided into 80% for training and 20 % for model testing. The results of this research highlight optimal performance of the predictive model with performance metrics such as Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Correlation Coefficient (R2), with values of 0.78, 1.39, 1.18 and 0.98, respectively in the estimation of energy consumption in the grinding process. Finally, these results indicate that the ANN achieved an accurate prediction of energy consumption in the grinding process, this will allow better baking in energy optimization.

Keywords: Energy consumption; grinding; predictive modelling; RNA.

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1. Introduction

Energy consumption in grinding processes is an important aspect in the mining and metallurgical field, since it represents a significant part of operating costs and directly influences the effectiveness and profitability of operations (Holmberg et al., 2017). Grinding is a fundamental stage in the preparation of minerals, where the aim is to obtain particles of adequate size for subsequent processing and recovery of the metals of interest (Wang et al., 2022).

According to Aramendia et al., (2024) in their research mentions that currently, mining represents approximately 1.7% of final energy consumption worldwide, but this proportion is expected to increase significantly in the future due to economic growth and greater consumption of materials. This leads to greenhouse gas emissions from the combustion of fossil fuels, which is a cause for concern (Wang et al., 2021). In response to this problem, mining companies such as the Anglo-Australian multinational Rio Tinto, South African Gold Fields or the Chilean copper mining company Antofagasta are adopting strategies that prioritize the use of renewable energy in their operations, seeking to reduce their environmental footprint and contribute to the transition towards a more sustainable industry (Pouresmaieli et al., 2023; Strielkowski et al., 2021).

The fragmentation size distribution obtained during milling is a crucial factor for the efficiency of subsequent processes, such as flotation and leaching (Herrera et al., 2023). An optimal size distribution allows for better release of valuable minerals and greater recovery (Little et al., 2016; Pérez et al., 2020a). Therefore, improving the fragmentation size distribution has become a key objective in the industry (Balakrishnan et al., 2020).

In recent years, artificial neural networks have emerged as a promising tool to predict and optimize processes in the mining field (Abdollahi et al., 2019). Neural networks are mathematical models inspired by the functioning of the human brain, capable of learning complex patterns from data sets (Montesinos et al., 2022; Mustafa, 2023). These networks can be trained using historical data from grinding operations, considering variables such as the type of ore, feed size, mill rotation speed, among others (Bannoud et al., 2022).

The use of artificial neural networks to anticipate energy consumption in milling offers several advantages. Firstly, it allows obtaining more precise and reliable estimates of energy consumption, which simplifies decision making and programming of operations and not only can energy consumption be predicted in mining but in other industries as indicated by Cao. et al., (2021). Furthermore, these networks can identify patterns and non-linear relationships between input variables and energy consumption, which can help discover new control and optimization strategies (López et al., 2023).

Otsuki and Jang (2022) in their research use predictive neural networks to predict particle size distributions (PSD) in size reduction operations. The importance of accurately predicting PSDs is highlighted to avoid over-grinding and reduce energy consumption. The study used supervised ANN models to predict PSDs, with results that demonstrated an adequate fit with the experimental data. Furthermore, the applicability of ANN to simulate multiparametric systems in different fields is mentioned, and the lack of applications of ANN in the prediction of PSD in milling processes is highlighted, despite the high energy intensity of these operations in mineral processing plants.

In this framework, the purpose of this study is to build a predictive model based on artificial neural networks to estimate energy consumption in grinding and improve the fragmentation size distribution. To do this, a set of data collected from real mining operations will be used, which includes detailed information on operating conditions and the results obtained.

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The proposed model will be based on a supervised learning approach, where the neural network will be trained using real data from grinding operations and their respective energy consumption. Subsequently, tests and validations will be carried out to evaluate the accuracy and effectiveness of the model in predicting energy consumption and optimizing the fragmentation size distribution.

2. Materials and Methods

2.1 Materials

To carry out the research, 126 sample data were collected containing the input parameters P100, GPB, F80, P80 and Wi(kWh/t) that serve in ANN training and prediction of grinding energy consumption. Articles and magazines related to the topic were used for analysis and discussion, as well as the Python program in Colaboratory in the development of programming and Microsoft Excel for verification of results.

2.2. Procedure

The research methodology to be carried out through the use of artificial neural networks and search for the prediction of energy consumption in grinding was carried out according to Figure 1

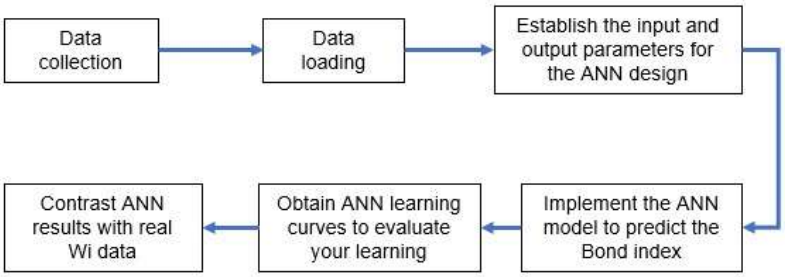

Figure 1. Flowchart for creating an artificial neural network

To determine the energy consumed in grinding (kWh/t), the Bond theory, which was established in 1951, is used; the study seeks to calculate energy consumption (Nikolić et al., 2022). This parameter indicates the amount of energy necessary, for each unit crushed, in the size reduction of a material from infinite dimensions to 100 microns, which is represented as the Bond index according to Riera et al., (2022) and is established accordingly. to the following equation 1.

$$W_i = \frac{10}{(\sqrt{D_{80}} - \sqrt{F_{80}})} \quad (1)$$

W_i : Bond index in kWh/t.
D_{90}: It is the 80% of material that passes (µm).
F_{90}: It is the 80% of the feed material that passes through the mill (µm).

The grinding phases will persist even when the grams of the finer material per rise reach stability. Usually, the trend of growth or decrease of the grindability index (g/rev) in the last three cycles will be reversed (Nikolić & Trumić, 2021). Once the balance is achieved, the grain distribution and classification of the finest material in the sieve (final product of the process) will be carefully examined to provide the 80% through size (P80). Then, the grinding index in a rod mill (Grp; g/rev)

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will be calculated by taking the average of the last three values of net grams of finer material per revolution of the mill. This index represents the work efficiency of the material, applicable to grinding in rod mills and is predicted using the expression in equation 2.

$$W_i = \frac{62}{({P_{100}}^{0.23} x\ Gbp^{0.625} x \left(\frac{10}{\sqrt{P_{80}} - \sqrt{F_{80}}}\right)} \quad (2)$$

W_i: Bond index in kWh/tc.
P_{100}: The dimension in microns of the cutting mesh used to complete the circuit (size of the product that passes through 100%).
Gbp: Grams of finer material (final product of the system) generated by each revolution of the rod mill, under equilibrium conditions with a circulating load of 100%.
F_{80}: The dimension in (µm) corresponding to 80% of the particles that pass through the mill feed.

P_{80}: The dimension in (µm) corresponding to 80% of the throughput of the final product of the grinding circuit.

From the above expression, Bond suggests the application of particular corrective factors in situations where the feed is excessively coarse, the reduction ratio in the mill is low or high, and in cases of variability in the uniformity of the material supplied to the mill (Valerevich & Sergeevich, 2019).

Likewise, Bond proposes that, in ball mill grinding, it is calculated according to equation 3.

$$W_i = \frac{44.5}{({P_{100}}^{0.23} x\ Gbp^{0.82} x \left(\frac{10}{\sqrt{P_{80}} - \sqrt{F_{80}}}\right)} \quad (3)$$

W_i: Bond index in kWh/tc.
P_{100}: The dimension in microns of the cutting mesh used to complete the circuit (size of the product that passes through 100%).
Gbp: Index that measures the grindability of the material in ball mills (g/rev.).

F_{80}: The dimension in (µm) corresponding to 80% of the particles that pass through the mill feed.

P_{80}: The dimension in (µm) corresponding to 80% of the throughput of the final product of the grinding circuit.

There is also the simplified Bond expression for homogeneous materials that is represented in the following equation 4.

$$W_i = \frac{1.6x\sqrt{P_{100}}}{Grp^{0.82}} \quad (4)$$

The work index that evaluates the energy efficiency of crushing and grinding circuits in the mining industry. The development of Fred C. Bond is used to estimate the energy required in these operations, it is a key tool in the design and optimization of mining metallurgical processing plants (Pérez García et al., 2020b).

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Given Bond's theoretical context, our research seeks to predict energy consumption in grinding, but using artificial neural networks, the factor that allows ANN to be predicted is the Adam algorithm, it is an optimization algorithm proposed in the field of stochastic optimization by authors Kingma and Ba (2015) from the University of Toronto. This method, known as an adaptive two-moment method, was initially designed to address stochastic problems, but is also applicable in deterministic optimization contexts (Rojano et al., 2021).

It is an algorithm designed to fit the specific architecture of a neural network, optimizing according to the unique characteristics of each structure using the stochastic technique, it helps facilitate the rapid optimization process that calculates and refines based on the input data, which ultimately improves training efficiency (Barrio, 2022). Each training step is automated throughout the process until the predetermined number of epochs is reached, taking into account the specified inputs, hidden neurons, and outputs which is determined by the expression in Equation 5.

$$ECM = \sum (OI - EI)\exp(2)/n \quad (5)$$

Where:
OI: observed values.
EI: estimated values.
n: Number of observations.

2.3 Methods

The methodological foundation of the research had a quantitative approach because it sought to measure and analyze descriptive statistics in Python programming in Colaboratory. A comparative descriptive analysis was done to evaluate the prediction obtained from estimated results. The quantitative approach with the combination of comparative descriptive analysis managed to consolidate a detailed and analytical view of the results (Kumar, 2021).

3. Results

3.1. Data collection

125 trials were taken from the study by Álvarez (2010), which were used in training the artificial neural network (ANN) architecture, which contained the following input parameters P100, Gbp, F80 and the target Wi (kWh/ t), as shown in Table 1.

Table 1. Data collection

N° assay	*P100*	*Gbp*	*F80*	*P80*	*Wi (kWh/t)*
1	500.00	5.37	2073.00	416.00	10.93
2	200.00	3.07	2073.00	152.00	9.76
3	175.00	20.83	2503.00	125.00	1.79
4	147.00	6.24	2503.00	137.00	5.31
5	175.00	3.82	2485.00	131.00	7.41
120	80.00	0.73	317.00	69.00	35.93
121	500.00	4.86	1523.00	281.00	9.45
122	200.00	4.52	1523.00	138.00	7.08
123	500.00	1.45	2097.00	282.00	22.90
124	200.00	1.22	2097.00	133.00	19.01
125	100.00	1.02	4154.00	81.00	17.52

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3.2. Data loading

The Pandas library was used to load the data obtained from data collection. Subsequently, the info () method was used to obtain information about the DataFrame, such as the type of variables, null values, number of columns and rows, etc. The first column represents the number of trials, while the next four columns, P100, Gbp, F80 and P80, are the inputs for our predictive model. The last column, Wi (kWh/t), became the target variable to predict.

3.3. Establish the input and output parameters for the ANN design

Table 2 shows the variables found in the data to be used, where no null value is identified. The variables P100, F80 and P80 are of type “integer”, while the variables Gbp and Wi are of type “float”.

Table 2. Identification of variables

Variable	Quantity	Type
P100	125	integer
Gbp	125	Float
F80	125	integer
P80	125	integer
Wi (kwh/t)	125	Float

P100, Gbp, F80 and P80 were established as input parameters. The Work index (Wi) was defined as a target, to predict the energy consumption (kWh/t) of the mill, when the size of the ore is reduced.

The analysis of the main variables was also carried out using a correlation matrix, between the input variables and the target Wi. Figure 3 shows the correlation matrix, where the correlation coefficient of 0.15 between P100 and Wi, likewise the coefficient between Gbp and Wi is -0.55, their negative correlation being very weak, so they influence inverse in the result of Wi. On the other hand, the F80 and P80 present a correlation coefficient of -0.26 and 0.26, respectively, with the Wi, which indicates weak correlation.

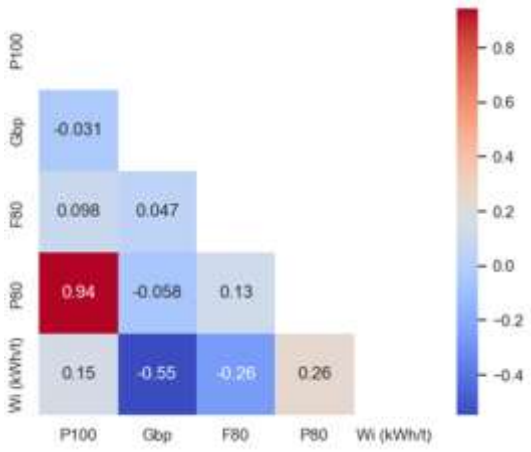

Figure 2. Correlation matrix of study variables

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3.4. Implement the ANN model to predict the Bond index

Table 3 shows the architecture of the ANN, whose purpose is to offer the expected and representative result. The activation function used was ReLU (Rectified Linear Unit) which allowed optimizing the efficiency and performance of the ANN. Furthermore, a learning rate of 0.01 and 1500 epochs were considered within the hyperparameters. Both and Dimitrakopoulos (2021), in their research to build a geometallurgical performance prediction model based on ball mill data, considered the recorded energy consumption, feed particles and product particle size, for which They used a neural network, comparing it with a linear model. In their study they used a single hidden layer neural network structure comprising 30 neurons offering the most stable predictions and showing a performance prediction error variation of 10.6%. In this study, three hidden layers were used with 24, 12, and 6 neurons each, which allowed us to obtain a more acceptable prediction.

Table 3. Architecture of the ANN

Layers	Number of neurons	Activation function
Input	4	
Hidden	12	ReLU
	24	
	6	
Output	1	

Figure 4 presents the final design of the ANN architecture, which has an input layer of 4 neurons, followed by three hidden layers with 12, 24 and 6 neurons respectively, and finally an output layer with a neuron to obtain the target of the Bond index.

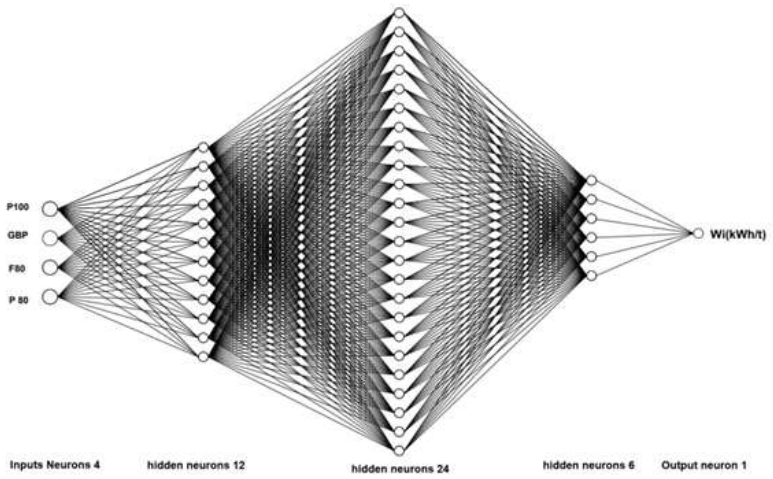

Figure 3. ANN diagram

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3.5. Obtain ANN learning curves to evaluate your learning

Figure 5 shows the learning curve, which highlights a marked convergence between the training loss curves as in the validation. As training progresses, the curves gradually decrease, reaching the mean square error (MSE) after 68 epochs in training and 70 epochs in validation, which indicates significant learning, achieving optimal performance to predict correctly. the Bond index efficiently. Otsuki and Jang (2022), in their study whose objective was to investigate the applicability of artificial neural networks to predict the particle size distributions (PSD) of factory products, obtained that the mean square errors (MSE) reached the best value after of 30 epochs in the test and 70 epochs in the validation. The results showed that the PSDs predicted by ANN fit very well with the experimental data after training, and they also calculated the root mean square error (RMSE) for each grinding condition, with results between 0.165 and 0.965. The results showed that the PSDs predicted by RNA fit very well with the experimental data after training, concluding that the developed RNA models can predict the PSDs of the milled products under different grinding conditions.

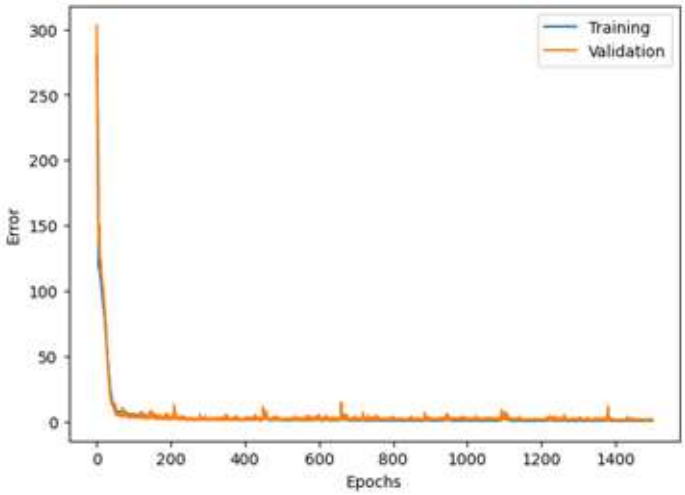

Figure 4. Evolution of the mean square error during training

Once the models are developed, it is necessary to validate them using different techniques. The performance metrics used in this study help determine the quality of the predictive models developed. The goodness-of-fit indicators are MAE, MSE, RMSE and R2. All indicators shown quantify how well a model fits a data set (Saldaña et al., 2023). Table 4 shows the adjustment and prediction capacity of the model to estimate the Bond index accurately, which is mainly evaluated by the RMSE and R2, which have reached a value of 1.182 and 1.181 respectively in training and a value of 0.984 and 0.984 in validation.

Table 4. Training and validation performance metrics

Metrics	Training	Validation
MSE	1.398	1.396
MAE	0.785	0.784
RMSE	1.182	1.181
R^2	0.984	0.984

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3.6. Contrast ANN results with real Wi data

Table 5 shows the results of the 20% of the sample that were used for testing, evidencing a significant similarity with the real results. The division of data for training and validation varies depending on the amount of data in each study. Otsuki and Jang (2022), in their study collected a total of 56 data sets and randomly divided into training data sets (40 data sets: 70%), validation (8 data sets: 15%) and training (8 data sets: 15%), for their grinding study, 56 experimental data sets were considered more than enough. Saldaña, et al. (2023), in their research divided the historical data into two groups, that is, the training set (70%) and the validation set (30%), while the fitted model was used to estimate the production after the application of the M2M strategy and simulate production, at different values of the mill rotation speed and lining age factors. Like Azizi, et al. (2020), in their study to investigate the application of three powerful Kernel-based supervised learning algorithms to develop a global model of the wear rate of grinding media based on input factors such as pH, percentage of solids, the loading weight of the balls and the rotation speed of the mill and the grinding time, the models were trained using 40 randomly selected data (representing 80% of the total data) and the remaining 10 data (which represent 20%) were applied for testing purposes. In this investigation, the 126 data were also divided into 101 (representing 80%) for training and 25 (representing 20%) for testing.

Table 5. Results of real and estimated Wi (kWh/t)

Wi (kWh/t) Real	Wi (kWh/t) estimated
8.16	8.23
7.40	9.25
16.86	16.12
37.31	34.32
29.88	28.32
1.66	1.76
6.88	6.70
10.64	10.97
11.35	11.31
10.89	10.49
13.39	13.44
30.62	27.72
6.28	6.21
22.90	22.22
17.52	17.63
4.88	4.90
6.88	6.70
13.11	11.11
5.66	5.47
14.04	12.85
12.08	12.16
21.34	19.52
6.32	5.86
40.28	39.60
9.45	8.51

Figure 6 shows the scatter plot between the real values and the prediction of Wi (kWh/t), which shows a determination coefficient R2 of 98%. Saldaña, et al. (2023), in their study, the adjustment through the application of artificial neural networks, for its part, turned out to be the model with the best adjustment indicators (MAE, RMSE and R2), where it obtained an R2 of 89%, whose architecture of the RNA corresponded to a multilayer perceptron. In this study, an R2 of 98% is a

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very strong indicator that the model is capable of making predictions very close to the real values of the variable Wi. This suggests optimal model performance and a high degree of confidence in the predictions, indicating that the ANN has achieved solid learning and effective generalization of the model, guaranteeing the prediction of the Bond index.

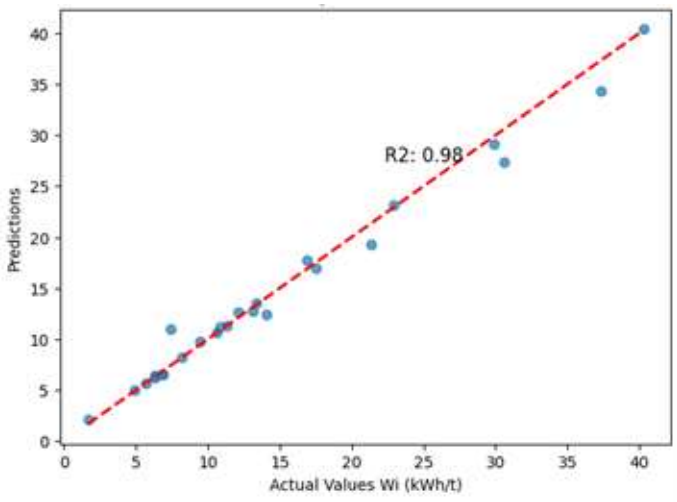

Figure 5. Scatter plot of actual values vs predictions

Table 6 shows the effectiveness of the implemented ANN, which is reflected in the results obtained, which guarantee high performance in the optimization of the parameters. The adjustment and prediction capacity of the model to estimate the Wi accurately is mainly reflected in the critical evaluation metrics; RMSE and R2, which have reached a value of 1.396 and 0.984 respectively. Otsuki and Jang (2022), in their research, trained six ANN models separately and obtained strong positive correlation coefficients (R2 > 0.90) in all models, which confirmed the statistical reliability of the models, they also obtained an RMSE for each grinding condition, and was between 0.165 and 0.965, which was lower than that found in the prediction of the crystallite size, with an RMSE of 3.34). The results indicated the applicability of ANN to predict particle size distributions (PSD), concluding that the proposed approach can be used not only for coal particles but also for other minerals/materials to predict their PSD in order to reduce consumption. of energy optimizing grinding conditions. Azizi, et al. (2020), in their study compared single-core and RNA-based techniques. They determined that the use of multi-core support vector machines benefits from a higher degree of correctness and generalizability in predicting the wear rate of grinding media. Meanwhile, the findings indicated that the model using the MK-SVM approach allows obtaining R2 values of 0.994 and 0.993 in training and testing, respectively, concluding that the MK-SVM technique can be used efficiently to predict and model grinding ball wear rates in the mineral processing industry. In this study, an R2 of 0.984 was also obtained in the test set, so the ANN model can be applied efficiently to predict Wi.

Table 6. ANN performance metrics

Metrics	Testing
MSE	1.396
MAE	0.784
RMSE	1.181
R^2	0.984

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4. Conclusions

In the research study, we focused on the implementation of artificial neural networks (ANN) to make predictions of energy utilization in the mineral grinding process based on the Bond index (Wi), achieving notable results. The ANN was trained from a data set composed of 126 records, which were divided into 80% for training and 20% for testing the model. Its structure was composed of 4 input neurons, 3 hidden layers and 1 output neuron, which represented the variable of interest, the energy expenditure in the grinding process.

The results achieved showed that the proposed model is capable of accurately predicting the energy consumption in grinding Wi (kWh/t) and improving the fragmentation size distribution. The model was based on the learning curve, which showed effective convergence and significant learning. Performance metrics such as MAE, MSE, RMSE and R^2 were 0.78, 1.39, 1.18 and 0.98 respectively, these supported the model's ability to accurately adjust and forecast energy consumption in grinding, indicating good accuracy in its performance.

Future work would be to explore the use of machine learning approaches in the mining domain and use more training data for artificial neural networks to further improve the accuracy and effectiveness of the predictive model. These techniques can allow the identification of more complex patterns and relationships in the grinding data, as well as the discovery of relevant variables that may influence energy consumption and fragmentation size distribution. Likewise, it is suggested to carry out comparative studies between different machine learning algorithms and evaluate their performance in relation to accuracy and effectiveness. This would provide a solid basis for the selection and development of more advanced predictive models in the grinding area of the mining industry.

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