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Multivariable predictive models for the estimation of power consumption (kW) of a Semi-autogenous mill applying Machine Learning algorithms [Modelos predictivos multivariables para la estimación de consumo de potencia (kW) de un molino Semi - autógeno aplicando algoritmos de Machine Learning]

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Resumen

Esta investigación tuvo como objetivo desarrollar modelos de aprendizaje automático (ML) para estimar el consumo de potencia (Kw) en un molino Semi-autógeno en la industria minera. Empleando algoritmos de Machine Learning considerando diversas variables operativas para los diferentes modelos como se incluyen el Regresión Lineal Múltiple (RLM), Regresión Árbol de Decisiones (RAD), Regresión Bosque Aleatorio (RBA) y Regresión Redes Neuronales Artificiales (RRNA). La metodología adoptada fue de tipo aplicado, con un diseño experimental de enfoque descriptivo y transversal. Los resultados de la aplicación de estos modelos revelaron diferencias significativas en términos de eficiencia predictiva. El RLM y la RRNA destacaron con coeficientes de determinación (R^2) de 0.922 y 0.939, respectivamente, indicando una capacidad sustancial para explicar la variabilidad en el consumo de potencia. En contraste, los modelos basados en árboles (RAD y RBA) mostraron desempeño inferior, con R^2 de 0.762 y 0. 471. Al analizar métricas clave como el Error Absoluto Medio (MAE), el Error Cuadrático Medio (MSE) y la Raíz del Error Cuadrático Medio (RMSE), se confirmó que tanto el RLM como la RRNA superaron a los modelos basados en árboles. Estos resultados respaldan la elección de RLM y RRNA como modelos preferidos para la estimación del consumo de potencia en un molino Semi-autógeno.

Palabras clave: Machine Learning, molino Semi-autógeno, potencia (kW).

Abstract

This research aimed to develop machine learning (ML) models to estimate power consumption (Kw) in a Semi-autogenous mill in the mining industry. Using Machine Learning algorithms considering various operating variables for the different models such as Multiple Linear Regression (RLM), Decision Tree Regression (RAD), Random Forest Regression (RBA) and Regression Artificial Neural Networks (ANN). The methodology adopted was applied, with an experimental design with a descriptive and transversal approach. The results of the application of these models revealed significant differences in terms of predictive efficiency. The RLM and RRNA stood out with coefficients of determination (R^2) of 0.922 and 0.939, respectively, indicating a substantial capacity to explain the variability in power consumption. In contrast, the tree-based models (RAD and RBA) showed inferior performance, with R^2 of 0.762 and 0.471. When analyzing key metrics such as Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Root Mean Square Error (RMSE), it was confirmed that both RLM and RRNA outperformed the tree-based models. These results support the choice of RLM and RRNA as preferred models for estimating power consumption in a Semi-autogenous mill.

Keywords: Machine Learning, Semi-autogenous mill, power (kW).

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1. Introduction

In recent years, advances in sensor technology, data logging and storage strategies have resulted in the accumulation of a significant amount of production data in the databases of mineral processing facilities. Despite this, these valuable data repositories are rarely leveraged effectively to improve process modeling. Machine learning techniques have the ability to use this vast amount of data and generate predictive models by identifying patterns within the information (Murphy, 2022).

Efficient energy consumption is crucial in mining operations, especially in mineral processing. Crushing mills, responsible for up to 50% of a plant's electrical consumption, are particularly energy intensive (Hoseinzade et al., 2023). Improving the prediction of mill energy demand based on operational variables is an area of growing interest. (Peng et. al., 2023; Loor, 2020).
In mineral processing plants, the grinding stage becomes crucially important, accounting for approximately half of all costs associated with mineral processing (Wills and Finch, 2015). The semi-autogenous mill (SAG) is the main equipment used in this task, recognized for its economic efficiency by grinding large quantities of input material and occupying a reduced physical space (Codelco, 2019). The concept of "power" is directly linked to the amount of energy necessary to grind the mineral. This term plays a fundamental role in understanding and optimizing SAG mill performance, as it is intrinsically linked to the efficiency of the grinding process (Lopez et al., 2021).

The measurement and analysis of power in a SAG mill are key elements to adjust operations and achieve an optimal balance between grinding efficiency and energy consumption (Rosas, 2021). This focus on power, commonly expressed in kilowatts (kW), is evaluated by considering various operating parameters, such as mill load, mill speed, and specific mineral properties. Thus, power optimization in a SAG mill becomes an essential component to improve the profitability and sustainability of mineral processing operations (Salazar et al., 2014).

Various studies have explored the viability of predictive models for mill energy consumption, both at laboratory and industrial levels (Jayasundara et al., 2022; Heredia, 2016). These studies highlight the potential of machine learning techniques to model the complex and non-linear behavior of these teams, using algorithms such as multiple linear regression, Decision Tree, Random Forests and neural networks. (Venkata et al., 2024; Ghasemi et al., 2024)

These models incorporate critical operating variables, such as diameter, RPM and power, along with additional external variables. (Jayasundara et al., 2022). Having tools for accurately estimating energy consumption would allow short-term optimization of equipment and long-term planning of concentration plants. (Zou et al. 2023; Castro and Valenzuela, 2022). The aim is to develop and validate models of this type using real operational data from mills, focusing on the power used to determine energy consumption (Loudari et al., 2023). The objective of this research is to develop and validate predictive models based on Machine Learning algorithms, for the estimation of power consumption (kW) in a Semi-autogenous mill, incorporating multiple relevant variables, in order to improve energy efficiency and optimize operational performance in the grinding process.

2. Materials and Methods

2.1 Materials

For the purpose of carrying out this research, a specialized set of both hardware and software will be used. PCs with high processing performance to manage large volumes of data and execute machine learning algorithms. On the software side, Artificial Intelligence platforms and tools will

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be used, supported by specific libraries for machine learning in Python, such as TensorFlow or Scikit-Learn. This will allow you to take advantage of the flexibility and effectiveness of the Python language in the development of predictive models and data analysis for the proposed research. (Jung and Choi, 2021; Fu and Aldrich, 2020). The population, as seen in table 1, was made up of the performance record of a semi-autogenous mill.

Table 1: Database of the semi-autogenous mill

Download type	Diameter (m)	Length without cone (m)	Total lenght (m)	RPM	ø	*fb*	*f*	Po (g/cm3)	Power (kW)
Slit	3.85	5.69	5.69	10.35	0.48	0.12	0.12	2.8	404
Slit	3.9	5.1	5.1	16.75	0.78	0.25	0.34	3.35	1175
Slit	4.05	4.6	4.6	15.97	0.76	0.6	0.32	2.7	687
Slit	4.05	4.6	4.6	15.97	0.76	0.6	0.34	2.7	706
Slit	4.05	4.6	4.6	15.97	0.76	0.7	0.7	2.7	440
Slit	4.05	4.6	4.6	15.97	0.76	0.8	0.26	2.7	688
Slit	4.12	5.02	5.02	15.63	0.75	0.22	0.22	2.7	1012
Slit	4.12	5.02	5.02	15.63	0.75	0.22	0.33	2.7	1225
Slit	4.16	4.78	4.78	18.45	0.89	0.1	0.38	2.7	1063
…	…	…	…	…	…	…	…	…	…

2.2. Procedure

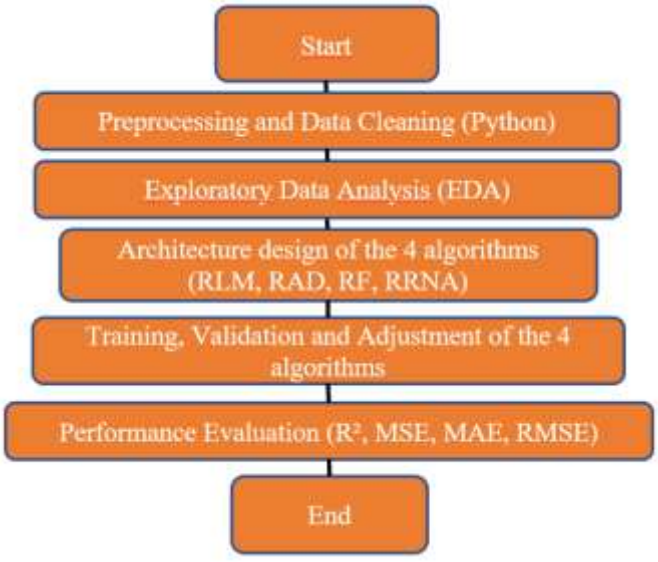

Figure 1. Flowchart of the proposed methodology.

The step-by-step process, as seen in the flow chart of the proposed methodology in Figure 1, begins with the preprocessing and cleaning of data, ensuring that the information is clean, relevant and structured appropriately for analysis. After them, exploratory data analysis (EDA) is carried out, helping us to identify patterns, trends and anomalies. This hassle-free approach is essential in the initial stages of data analysis, providing a solid foundation for more advanced analytical decisions. Next, the design of the 4 algorithms used for this article is developed, applying Multiple Linear Regression (RLM), Decision Tree (AD), Random Forest (RF) and neural network (RD), once each one has been designed with its hyperparameters. and appropriate

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libraries for each algorithm, where the data was divided for the training set 0.8 and test 0.2, the training for each model is determined differently from each other, adjusting its parameters, so that finally the 4 algorithms give us the evaluation of performance such as the Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Coefficient of Determination (R2) and to finish choosing the most robust model according to its algorithm (Khalifa et al., 2021; Jooshaki et al., 2021).

2.3 Methods

The methodology adopted was applied, with an experimental design with a descriptive and transversal approach. Besides. A supervised machine learning methodology was adopted, given its effectiveness in prediction based on historical data. In this approach, four algorithms are trained using a set of labeled data, meaning that each data input comes with a corresponding output (Toro, 2023).

Multiple linear regression uses several variables to predict a dependent one, assuming linear relationships. Decision trees build hierarchical structures based on data, useful for non-linear problems and easy interpretation. Random forests are ensembles of trees that combine predictions, robust and effective on large data sets. Neural networks, inspired by the brain, learn complex patterns through interconnected layers. The choice depended on the nature of the problem and the specific data (Howard and Gugger, 2020).

3. Results

3.1. Data collection

To carry out the Exploratory Data Analysis (EDA), we initially proceeded to detect null values, of which none were found, and then to generate a table that presents the descriptive statistics of the variables selected in the database. Priority was given to those columns considered most relevant for the construction of the predictive model. This table provides an overview and detailed overview of the key characteristics of the variables, providing an essential information base for the subsequent analysis and modeling phase. Table 2 presents detailed descriptive statistics of various relevant variables. The data were obtained from 29 observations and provide crucial information about the characteristics and performance of the study sample.

Table 2 Descriptive statistics performed on each variable

Variable	conteo	mean	std	min	25%	50%	75%	máx
Diameter (m)	29	6.21	2.08	3.85	4.12	5.82	7.23	10.2
Length without cone (m)	29	4.48	1.29	2.42	3.66	4.6	5.02	7.95
Total lenght (m)	29	4.90	1.43	2.44	3.66	5	5.86	7.95
RPM	29	13.13	2.42	10.09	11.23	12.38	15.63	18.45
ø	29	0.74	0.07	0.48	0.71	0.75	0.77	0.89
fb	29	0.27	0.22	0.1	0.12	0.17	0.3	0.8
f	29	0.26	0.11	0.11	0.19	0.25	0.31	0.7
Po (g/cm3)	29	2.83	0.33	2.6	2.68	2.7	2.8	4.1
Power (kW)	29	2589.14	2473.41	404	1063	1800	2840	10013

As seen in Table 2, it stands out that the standard deviations associated with these variables are relatively small, suggesting a certain cohesion and consistency in the data collected. This

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phenomenon indicates less dispersion around the means, which can be essential in predictive analysis. Special attention was paid to the variable to be predicted, Power (kW), and histogram and density plots were carried out to examine the distribution of its values. These graphs provide a detailed visual representation that makes it easier to understand the variability and patterns associated with this key variable in the context of the predictive model.

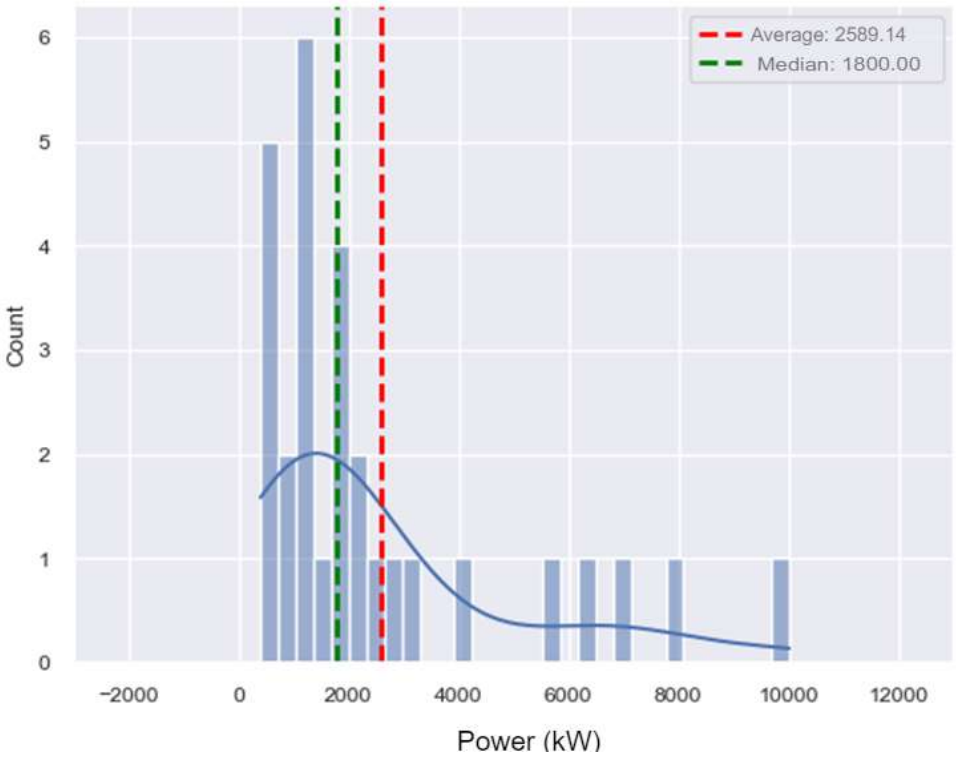

Figure 2. Power density histogram (kW) with vertical line of the mean and median

Figure 2 shows the histogram of the Power variable in kW, which is intended to be predicted using the developed models. It can be seen that the distribution does not follow a normal shape, presenting a positive asymmetry with an elongated tail towards the high values. This distribution is confirmed with the skeweness and kurtosis values greater than 0 reported in Table 3. Likewise, the figure includes vertical lines indicating the mean and median power, located at 2589.14 kW and 1800 kW respectively. A separation between the two is denoted, corroborating the absence of normality in the data due to the greater influence of the high extreme values on the mean.

Table 3. Asymmetry and kurtosis of the variable to be predicted Power (kW).

Parameter	Power (kW)
Skewness	1.69
Kurtosis	2.17

Table 3 reports the statistical metrics of skewness and kurtosis for the dependent variable Power in kW. An skewness coefficient of 1.69 was obtained, indicating the presence of a positively skewed distribution with a longer tail towards high values, as was also seen in Figure 2. On the other hand, the kurtosis value of 2.17 indicates a leptokurtic distribution more pointed than normal, with power values grouped around the average and decreasing rapidly towards the tails. These

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distribution shape indicators corroborate the non-normal and positive asymmetric behavior of the Power variable, validating the need to apply machine learning algorithms capable of adequately modeling these complex patterns to improve prediction.

The distribution histograms in Figure 3 confirm the non-normal behavior of the variables, with positive biases in RPM, density and power; as well as multimodal distributions in the dimensions of the mills. These complexities reinforce the suitability of using machine learning algorithms.

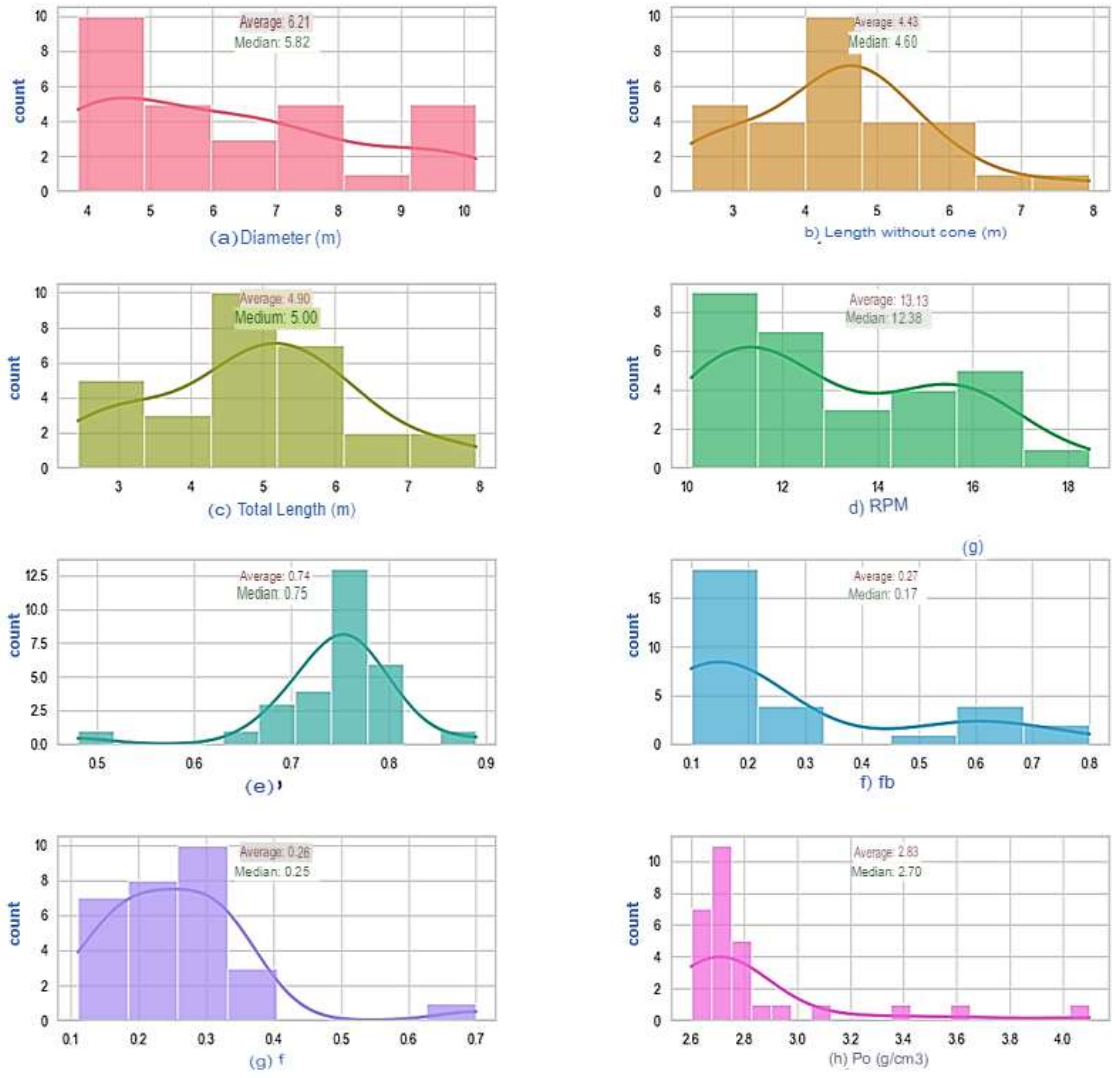

Figure 2. Distribution histograms for all variables

The different scatter diagrams reveal non-linear relationships between the independent variables of the process and the power in the mills. Curvatures and groupings are seen that show more complex interactions. This highlights the convenience of implementing machine learning techniques, which can model these intricate associations between multiple predictors and the

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electrical power response variable, having the most variable variable “ø” in its scatter plot, where its values are 0.65. to 0.85 as for the value to be predicted, it varies from 0 to 10,000 according to the Power (kW).

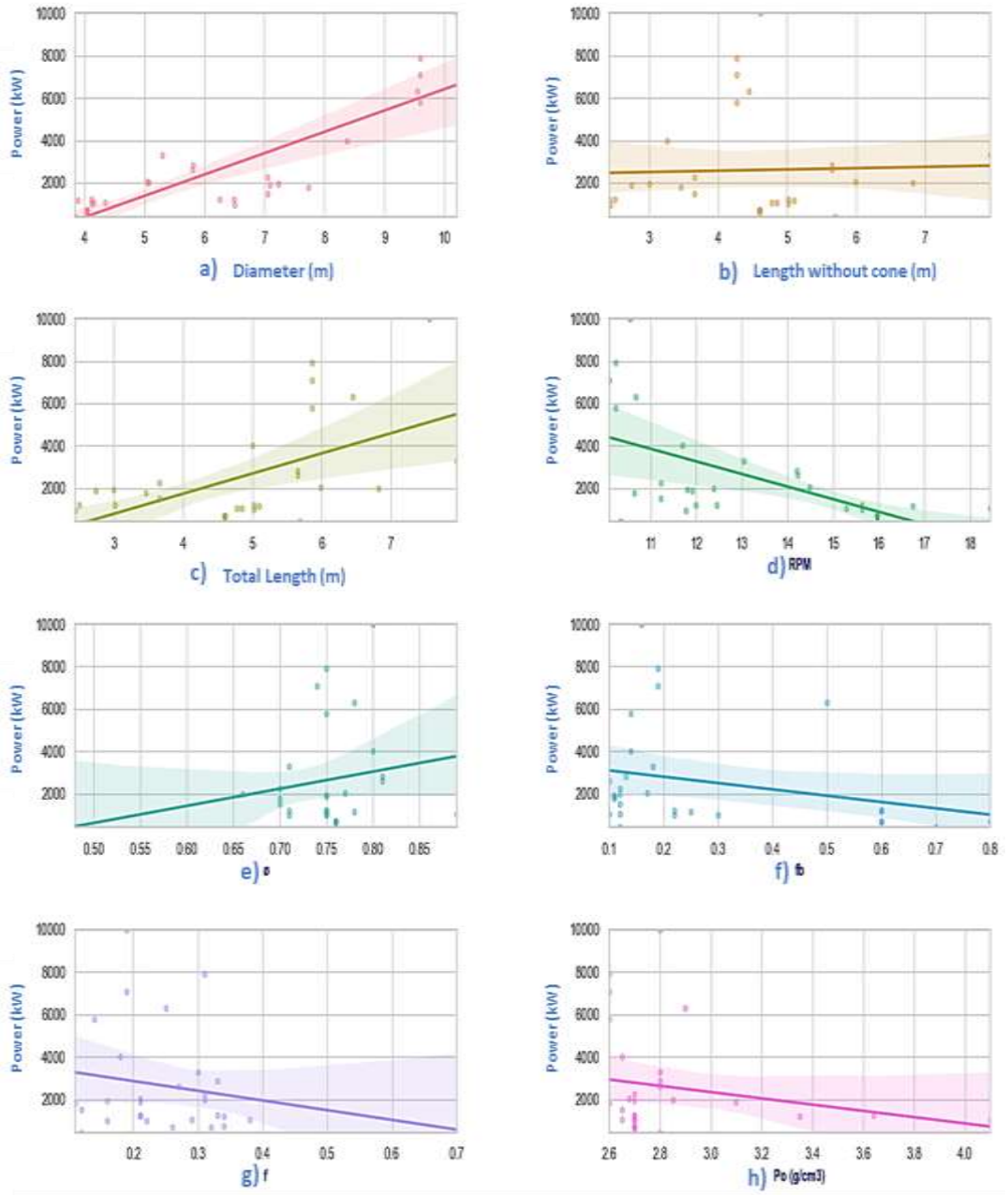

Figure 3. Scatter diagrams of each variable with the variable to be predicted Power (kW)

The different scatter diagrams reveal non-linear relationships between the independent variables of the process and the power in the mills. Curvatures and groupings are seen that show more complex interactions. This highlights the convenience of implementing machine learning techniques, which can model these intricate associations between multiple predictors and the

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electrical power response variable, having the most variable variable “ø” in its scatter plot where its values range from 0.65 to 0.85 as for the value to be predicted, it varies from 0 to 10,000 according to the Power (kW).

In the variable correlation analysis, in Figure 10, significant relationships were identified. On the one hand, a strong positive correlation was found between the total length and the length without cone. However, a strong negative correlation was observed between RPM and diameter, indicating that RPM is given and managed well with respect to the diameter of rock entering the mill.

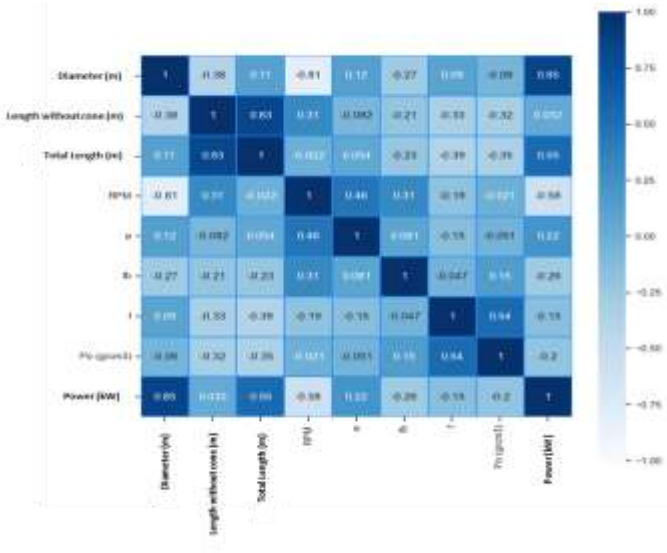

Figure 4. General correlation matrix

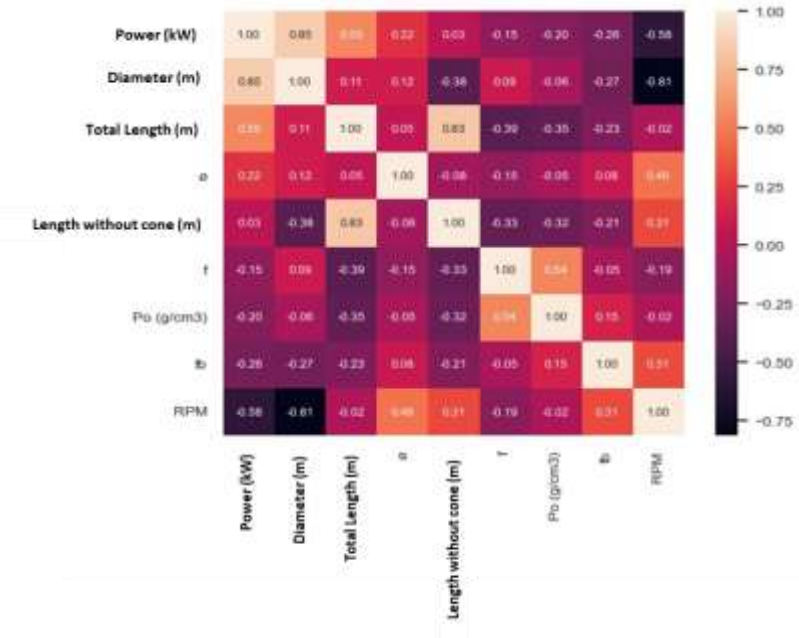

Figure 5. Ordered general correlation matrix centered on the Power variable (kW)

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On the other hand, when the correlation matrix is centered on the variable to be predicted, this matrix is ordered and there is a better correlation as seen in Figure 6, having a positive increase in the ratio of 0.85 according to the diameter and the power, therefore, is the relation given that the power is also affected by the diameter of each rock that enters the mill. On the other hand, for the negative correlation we have -0.81 between the RPM variable. and diameter.

3.1. Multiple Linear Regression Model (RLM)

Figure 6 shows us an ideal scenario, since the model predictions would be perfectly aligned with the real values. This is seen in a graph where all the points fall on the diagonal line, known as the "perfect prediction line." In the lower part of 1000 to 4000 there is minimal dispersion around this line, which means that the model is making accurate predictions and fits the data well. The point found at 8000 of the diagonal line is a little far away in the final part.

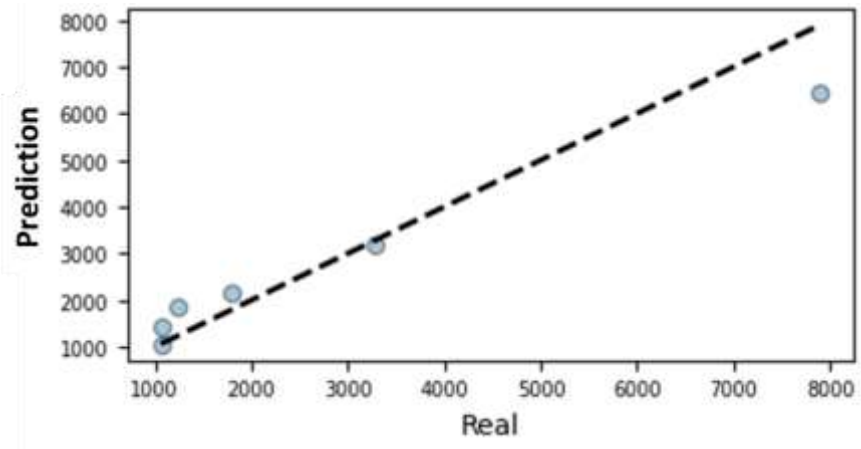

Figure 6. Predictions vs. Graph Real Values of the RLM model

shows us an ideal scenario, since the model predictions would be perfectly aligned with the real values. This is seen in a graph where all the points fall on the diagonal line, known as the "perfect prediction line." In the lower part of 1000 to 4000 there is minimal dispersion around this line, which means that the model is making accurate predictions and fits the data well.

The residuals would be distributed around zero uniformly, showing no discernible patterns. As seen in Figure 7 it resembles a normal distribution, with the majority of the residuals concentrated near zero and decreasing symmetrically towards the negative end ranging from - 1450 to - 1150 and having more quantity at the positive end that ranges from 250 to 520.

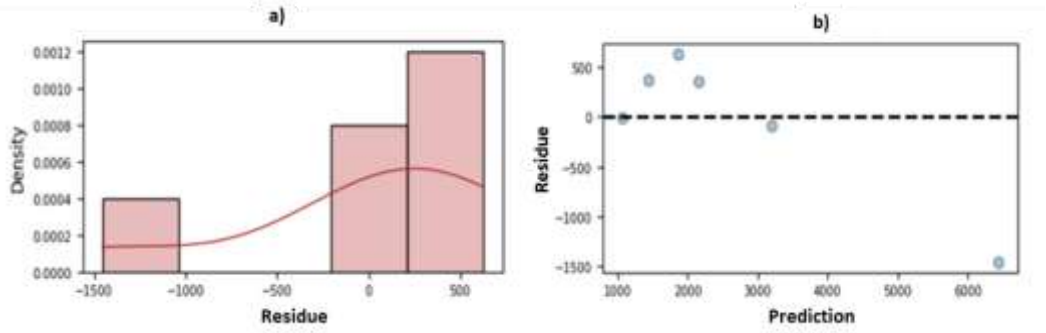

Figure 7. Graphs of the residual distribution of the RLM model

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The multiple linear regression model (RLM) presents promising results as seen in Table 4 according to the evaluation metrics. The mean absolute error (MAE) is 504.070, indicating acceptable precision in the predictions. The root mean square error (RMSE) is 681.874, which suggests a good fit of the model to the data, considering the magnitude of the errors. The mean square error (MSE) reveals a value of 464951.677, providing an additional measure of the model's accuracy. Furthermore, the coefficient of determination (R^2) stands out at 0.922, indicating that the model explains approximately 92.2% of the variability in the dependent variable of power (kW).

Table 4. Result of the RLM model with evaluation metrics

Evaluation metrics	Value
MAE	504.070
MSE	464951.677
RMSE	681.874
R^2	0.922

These metrics support the effectiveness of the RLM model in predicting the target variable, with low levels of error and substantial ability to explain variability in the data. These results support the validity and usefulness of the proposed model, providing a solid basis for its practical application and analysis in the context of the study.

3.2. Regression decision tree model (RAD)

These values were selected through a search process that maximized the model evaluation metrics. Limiting the tree depth (max_depth) to 3, along with the criteria of minimum samples to split and in a leaf, contributes to a more generalizable model and less prone to overfitting. The random seed provides reproducibility in the results.

These hyperparameters represent an effective balance between model complexity and generalization ability, suggesting a robust fit of the RAD predictive model to the data of interest.

Table 5: Best hyperparameters found for pruning used for the RAD predictive model.

Evaluation metrics	Value
max_depth	3
min_samples_split	5
min_samples_leaf	2
random_state	0

Figure 8 shows the decision tree created for the RAD predictive model. It is a binary tree with a maximum depth of 3 levels, according to the established hyperparameter. Each sheet represents conditions on attributes X that predict an output value $\hat{y}$.

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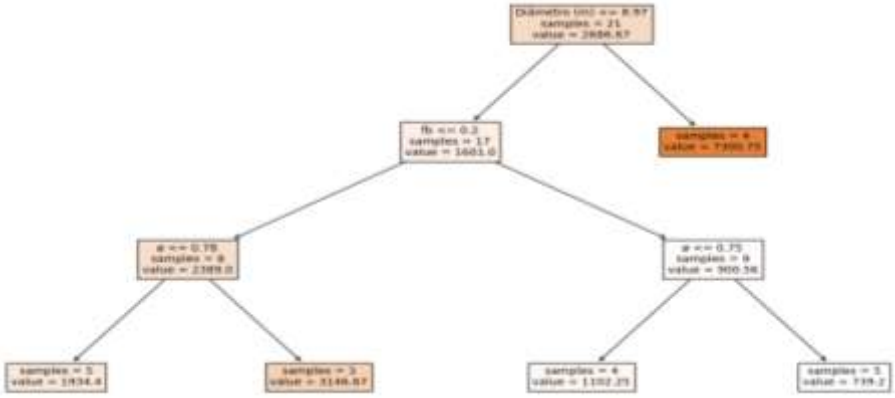

Figure 8. Structure of the tree created for the RAD model

Figure 9 shows a scenario in which the values are one further apart than in the multiple linear regression model. This is seen in a graph where all points are referenced near the diagonal line, known as the "perfect prediction line." In the range from 1000 to 4000, minimal scatter is observed around this wax line 1000 to 2000, which means that the model is making efficient predictions. And in the final part approaching the value 8000 and sticking to the diagonal line.

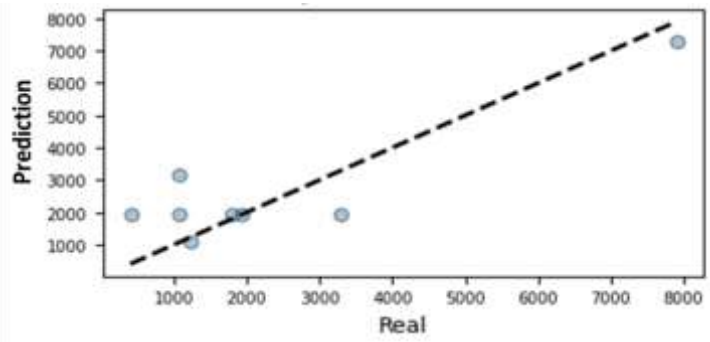

Figure 9. Predictions vs. Graph Real Values of the RAD model

For RAD the residuals would be distributed around zero uniformly, as seen in Figure 10 it resembles a normal distribution, with the majority of the residuals concentrated near zero and decreasing symmetrically towards the negative end that ranges from -1450 to - 500 and having more quantity at the positive end that ranges from 1250 to 2100. and with the curve pronounced at 0.

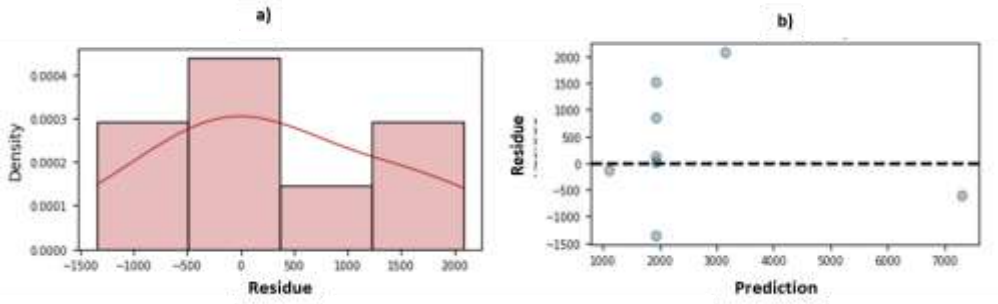

Figure 10. Graphs of the distribution of residuals of the RAD model

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In Table 6, the RAD model presents a positive performance, evidenced by the MAE of 838.233, MSE of 1,206,564.250, RMSE of 1,098.437 and an R^2 of 0.762. These metrics indicate that precision with respect to the RLM has dropped to 76.2%, even though it is in optimal conditions for predicting the variable to be predicted.

Table 6. RAD model result with evaluation metrics

Evaluation metrics	Value
MAE	838.233
MSE	1206564.250
RMSE	1098.437
R^2	0.762

3.3. Decision tree regression model (RBA)

Figure 11 shows that the error decreases as trees are added, but reaches a stabilization point around 155 trees. After that, these graphs represent limits for the search for the best values of the hyperparameters of the forest, as can be denoted by 85 as the min score, as a minimum and maximum 7 and 8.

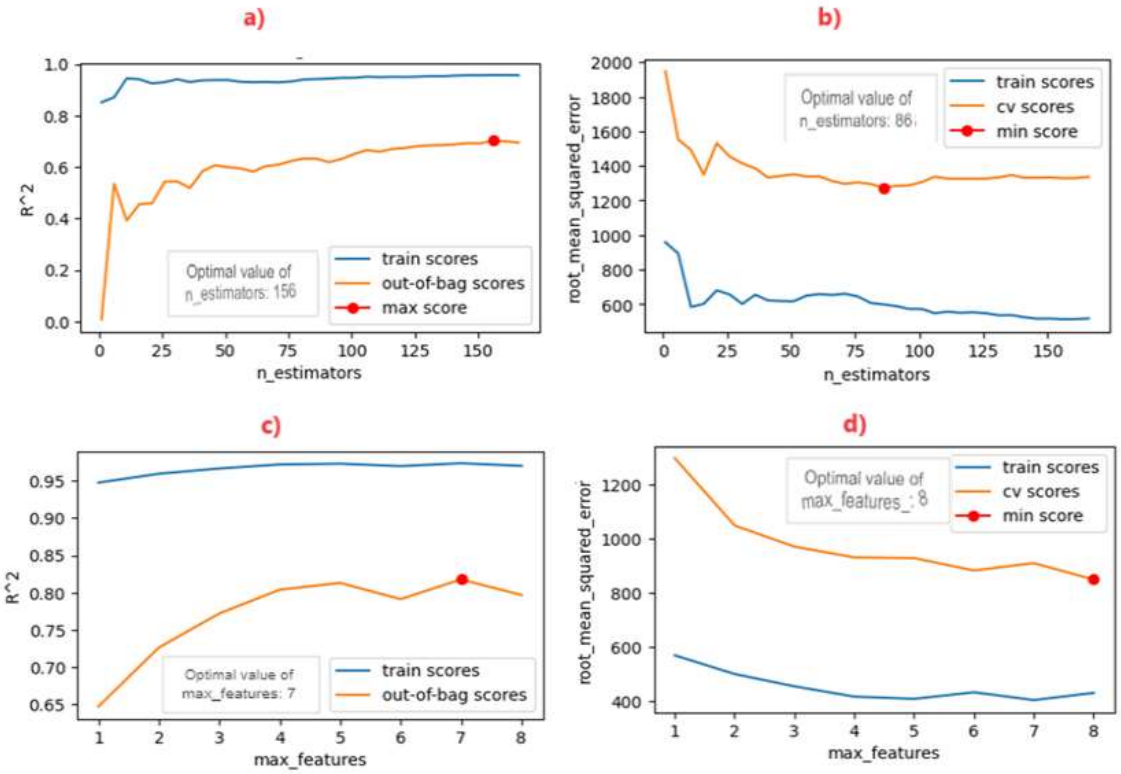

Figure 11. Graphs to find the best hyperparameter values of the RBA model.

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After the cross-validation process, the optimal hyperparameters for the Random Forest (RBA) predictive model were identified. These parameters include a maximum depth of 3, a maximum of 8 features per split, 155 estimators in the forest, utilization of all available cores for parallel work, and a random seed set to 0. This configuration was selected with the goal of achieve a balance between efficiency and generalization of the model.

Table 6. RAD model result with evaluation metrics

Evaluation metrics	Value
max_depth	3
max_features	8
n_estimators	155
n_jobs	-1
random_state	0

Figure 12 shows a scenario in which the values are one further apart than in the multiple linear regression model. This is seen in a graph where all points are referenced near the diagonal line, known as the "perfect prediction line." In the part varying from 1000 to 4000, minimal scatter is observed around this 0 to 4000 wax line, which means that the model is making efficient predictions.

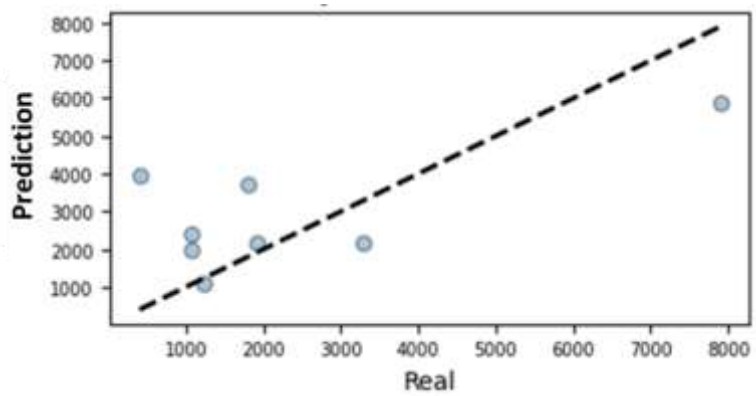

Figure 12. Predictions vs. Graph Real Values of the RBA model

For RBA the residuals would be distributed around zero uniformly, as seen in Figure 13 it resembles a normal distribution, with the majority of the residuals concentrated near zero and decreasing symmetrically towards the negative end that ranges from -2100 to - 700 and having more quantity at the positive end that ranges from 2100 to 3500.

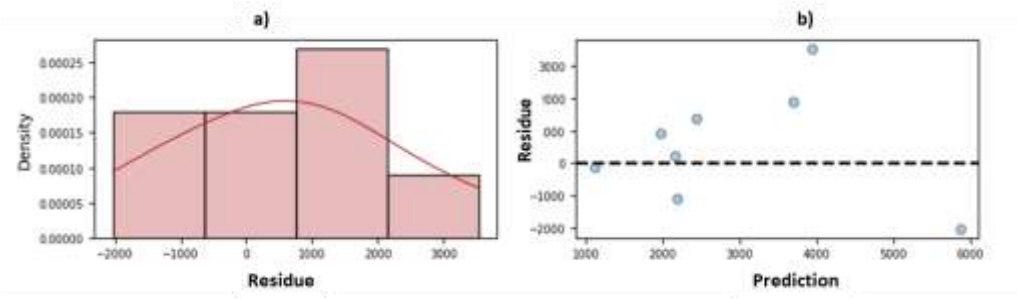

Figure 13. Graphs of the residual distribution of the RBA model

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The RBA model presents performance with evaluation metrics that reveal acceptable accuracy. With a MAE of 1319.871, MSE of 2,680,691.792, RMSE of 1637.282, and a coefficient of determination R^2 of 0.471, the model demonstrates its ability to make predictions in relation to the target variable. These metrics indicate some variability in the predictions, and although the model offers useful information, it is recommended to consider possible adjustments to further improve its performance.

Table 6. Result of the RBA model with evaluation metrics

Evaluation metrics	Value
MAE	1319.871
MSE	2680691.792
RMSE	1637.282
R^2	0.471

3.4. Decision tree regression model (RRNA)

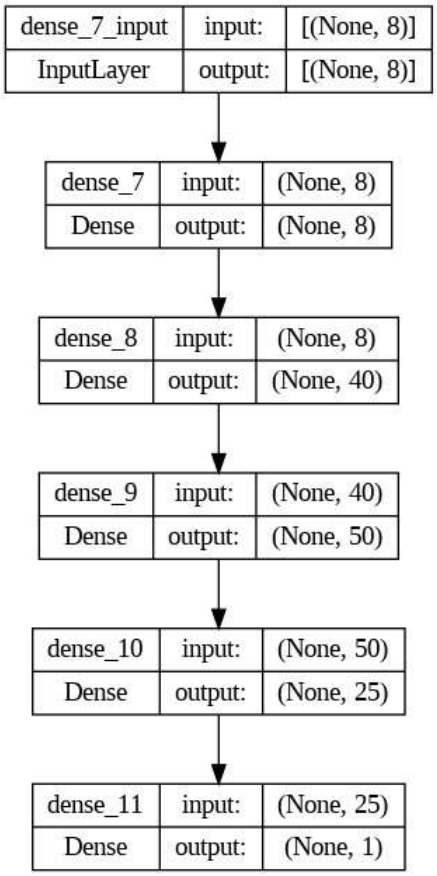

Figure 14. Structure of the RRNA

As seen in both Table 9 and Figure 14. Structure of the RRNA, the design of the neural network consists of a multi-layer architecture, with an input layer of 8 neurons, followed by four hidden layers with 8, 40, 50 and 25 neurons respectively, and finally, an output layer with a single neuron.

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Each connection between neurons has associated weights that determine the strength and direction of the connection according to its developed parameters.

Table 9. Architecture of the Artificial Neural Network used

Layer (type)	Output form	Parameters
Input layer (Dense)	(None, 8)	72
Hidden layer 1 (Dense)	(None, 40)	360
Hidden layer 2 (Dense)	(None,50)	2050
Hidden layer 3 (Dense)	(None, 25)	1275
Output layer (Dense)	(None, 1)	26

In Table 10 The neural network was trained for 900 epochs with a batch size of 30 samples per iteration, using the Adam optimizer and the mean squared error loss function. In the hidden layers, the ReLU activation function was implemented. These configurations were strategically chosen to facilitate efficient and rapid learning, with emphasis on optimizing model performance for the specific task.

Table 10. Best hyperparameters for the RRNA predictive model

Evaluation metrics	Value
epochs	900
batch_size	30
optimizer	adam
loss	mean_squared_error
Activation	relu

Figure 15 shows a scenario in which the values are one further apart than in the multiple linear regression model. This is seen in a graph where all points are referenced near the diagonal line, known as the "perfect prediction line." In the part varying from 1000 to 2000, a minimum dispersion is observed around this line is 1000 to 2000, which means that the model is making efficient predictions.

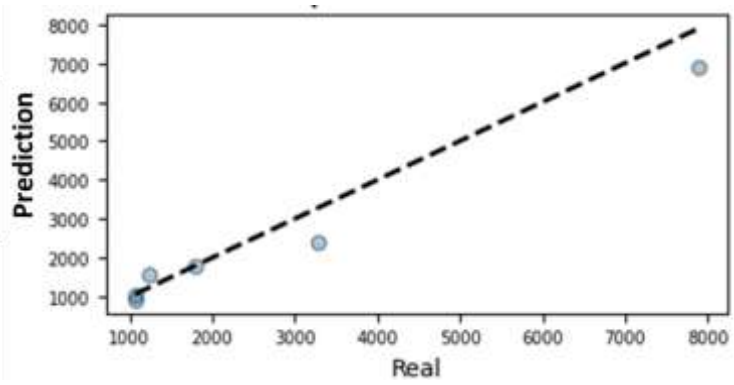

Figure 15. Predictions vs. Graph Real Values of the RRNA model

For RRNA the residues would be distributed around zero uniformly, as seen in Figure 16 it resembles a normal distribution, with the majority of the residues concentrated near zero and decreasing symmetrically towards the negative end ranging from -1000 to - 700 and having more quantity at the positive end that ranges from 10 to 350.

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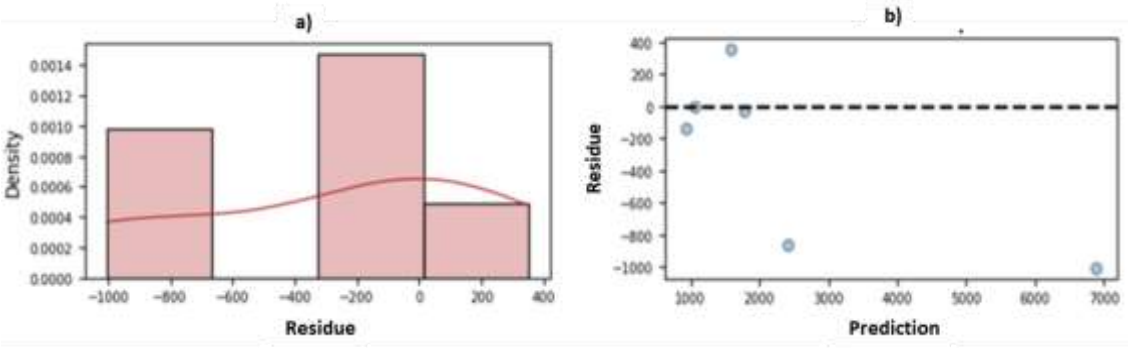

Figure 16. Residue distribution graphs of the RRNA model

The RBA model exhibits outstanding performance, evidenced by strong evaluation metrics: MAE of 476.9051, MSE of 426,711.6176, RMSE of 653.2317, and a high coefficient of determination R^2 of 0.929. These results indicate notable precision in the predictions.

Table 11. RRNA model result with evaluation metrics

Evaluation metrics	Value
MAE	476.9051
MSE	426711.6176
RMSE	653.2317
R^2	0.939

3.5. Comparison of all predictive models

Table 11: Results of the different models used

Evaluation metrics	RLM	RAD	RBA	RRNA
MAE	504.070	838.233	1319.871	476.9051
MSE	464951.677	1206564.250	2680691.792	426711.6176
RMSE	681.874	1098.437	1637.282	653.2317
R^2	0.922	0.762	0.471	0.939

The results highlight the superiority of the Multiple Linear Regression (RLM) model with an R^2 of 0.922, indicating that 92.2% of the variability in power consumption is explained by the model variables. The Artificial Neural Network (ANN) also shows impressive performance with an R^2 of 0.939. In contrast, the Decision Tree (RAD) and Random Forest (RBA) models exhibit inferior performance, with R^2 values of 0.762 and 0.471, respectively.

4. Conclusions

In conclusion, the results obtained from the different regression models used to estimate power consumption (kW) in a Semi-autogenous mill reveal valuable insights about the predictive efficiency and comparative performance of these techniques. The multiple linear regression model (RLM) stands out for its notable efficiency, evidenced by a high coefficient of determination (R^2) of 0.922. This result suggests that 92.2% of the variability in power consumption can be explained by the variables included in the model. Similarly, the artificial neural network (ANN) demonstrates a significant ability to capture complex relationships, with an R^2 of 0.939, pointing to its suitability for addressing non-linear patterns in the data.

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Regarding the evaluation metrics, the Mean Absolute Error (MAE) for RLM is 504.070, while for RAD and RBA it is higher, with values of 838.233 and 1319.871, respectively. In the case of RRNA, the MAE is the lowest, reaching 476.9051. Similarly, the Mean Square Error (MSE) is lower in RLM (464951.677) and RRNA (426711.6176) compared to RAD (1206564.250) and RBA (2680691.792). The Root Mean Square Error (RMSE) follows the same trend, being lower in RLM (681.874) and RRNA (653.2317) than in RAD (1098.437) and RBA (1637.282). These results support the choice of RLM and RRNA as preferred models for estimating power consumption in a Semi-autogenous mill. It is recommended to validate the models in real operational environments to support their usefulness in the mining industry.

Given these demonstrated predictive capabilities of both RLM and ANN to model power consumption, the use of these Artificial Intelligence techniques in real industrial applications with SAG mills is especially recommended. Its performance must be validated in each case, but the results obtained so far confirm its suitability and usefulness so that mining operations can better predict and manage this key parameter. These results support the choice of RLM and RRNA as preferred models for estimating power consumption in a Semi-autogenous mill. It is recommended to validate the models in real operational environments to support their usefulness in the mining industry.

References

Castro P. P., & Valenzuela M. A. (2022). Robust estimation and protection of locked charge in grinding mills. In 2015 IEEE Industry Applications Society Annual Meeting (pp. 1-11). IEEE. DOI: 10.1109/TIA.2017.2654998

Codelco Chile. (2019). MOLIENDA. Codelco Educa. https://www.codelcoeduca.cl/codelcoeduca/site/artic/20190109/asocfile/20190109005343/molienda_media_t__cnico_060119.pdf

Fu, Y., & Aldrich, C. (2020). Deep learning in mining and mineral processing operations: a review. IFAC-PapersOnLine, 53(2), 11920-11925. https://doi.org/10.1016/j.ifacol.2020.12.712

Ghasemi Z., Neumann F., Zanin M., Karageorgos J., & Chen L. (2024). A comparative study of prediction methods for semi-autogenous grinding mill throughput. Minerals Engineering, 205, 108458. https://doi.org/10.1016/j.mineng.2023.108458

Heredia Tejada H. J. (2016). Simulación y obtención de parámetros óptimos para la optimización de los revestimientos del Molino SAG 36 ft x 26.6 ft de la Minera Constancia–Hudbay. URI http://repositorio.unsa.edu.pe/handle/UNSA/1902

Hoseinzade Z., Mokhtari A. R., & Zekri H. (2023). Clay Minerals Characterization of the Miduk Ball Mill Output through Spectral Analysis. Ore Geology Reviews, 105629. https://doi.org/10.1016/j.oregeorev.2023.105629

Howard J., & Gugger S. (2020). Deep Learning for Coders with fastai and PyTorch. O'Reilly Media

Jayasundara C. T., & Zhu H. P. (2022a). Impact energy of particles in ball mills based on DEM simulations and data-driven approach. Powder Technology, 395, 226-234. https://doi.org/10.1016/j.powtec.2021.09.063

Jayasundara C. T., & Zhu H. P. (2022b). Predicting liner wear of ball mills using discrete element method and artificial neural network. Chemical Engineering Research and Design, 182, 438-447. https://doi.org/10.1016/j.cherd.2022.04.013

Jooshaki M., Nad A., & Michaux S. (2021). A systematic review on the application of machine learning in exploiting mineralogical data in mining and mineral industry. Minerals, 11(8), 816. https://doi.org/10.3390/min11080816

Jung D., & Choi Y. (2021). Systematic review of machine learning applications in mining: Exploration, exploitation, and reclamation. Minerals, 11(2), 148. https://doi.org/10.3390/min11020148

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Centre of Research and Training for Regional Development
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ISSN 2523-0905
DOI: https://doi.org/10.32829/eesj.v8i1.207

Khalifa R. M., Yacout S., & Bassetto S. (2021). Developing machine-learning regression model with Logical Analysis of Data (LAD). Computers & Industrial Engineering, 151, 106947. https://doi.org/10.1016/j.cie.2020.106947

Loor Cárdenas V. E. (2020). Aplicación de inteligencia artificial para el agendamiento y optimización del diseño de fases en minería a cielo abierto.

López P., Reyes I., Risso N., Aguilera C., Campos P. G., Momayez M., & Contreras D. (2021). Assessing Machine Learning and Deep Learning-based approaches for SAG mill Energy consumption. In 2021 IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON) (pp. 1-6). IEEE. DOI: 10.1109/CHILECON54041.2021.9702951

Loudari C., Cherkaoui M., Bennani R., Harraki I. E., Younsi Z. E., Adnani M. E., Baina K. (2023). Predicting energy consumption of grinding mills in mining industry: A review. In AIP Conference Proceedings (Vol. 2814, No. 1). AIP Publishing. https://doi.org/10.1063/5.0148768

Toro L. (2023). Como aplicar el Machine Learnig a la educación. OBS Business School

Murphy K. P. (2022). Machine learning: a probabilistic perspective. MIT press.

Peng J., Sun W., Xu J., Zhou G., Xie L., Han H., Li Q. (2023). Analyzing process parameters for industrial grinding circuit based on machine learning method. Advanced Powder Technology, 34(9), 104113. https://doi.org/10.1016/j.apt.2023.104113

Rosas G. A. A. (2021). Modelamiento y Diseño de un Sistema de Control de las Variables Críticas de un Molino Semiautógeno Mediante un Sistema Experto Basado en Control MPC y Lógica Difusa (Doctoral dissertation, Pontificia Universidad Catolica del Peru (Peru)). URI http://hdl.handle.net/20.500.12404/21199

Salazar J. L., Valdés-González H., Vyhmesiter E., & Cubillos F. (2014). Model predictive control of semiautogenous mills (sag). Minerals Engineering, 64, 92-96. https://doi.org/10.1016/j.mineng.2014.03.029

Venkata P., Pandya V., & Sant A. V. (2024). Data Mining and SVM Based Fault Diagnostic Analysis in Modern Power System Using Time and Frequency Series Parameters Calculated From Full-Cycle Moving Window. Journal of Operation and Automation in Power Engineering, 12(3), 206-214. DOI: 10.22098/JOAPE.2023.10819.1789

Wills B. A., & Finch J. (2015). Wills' mineral processing technology: an introduction to the practical aspects of ore treatment and mineral recovery. Butterworth-Heinemann. https://doi.org/10.1016/C2010-0-65478-2

Zou G., Zhou J., Song T., Yang J., Li K. (2023). Hierarchical intelligent control method for mineral particle size based on machine learning. Minerals, 13(9), 1143. https://doi.org/10.3390/min13091143