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Abstract

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Keywords

Mining operations, hard rock, productivity, Monte Carlo

RESEARCH ARTICLE

Analysis of the key performance indicators between lithologies on mine to crusher

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Abstract

The evolution of the mineral economy requires greater technological developments to find a better use of resources and reserves through the relationships between the characteristics of the rocks and the need to enable the entire mining enterprise. This study focuses on the development of new rock blasting technologies that result in a more optimized fragmentation according to the lithology in the feed of the primary crusher. This methodology is known as Mine to Crusher, through which it becomes possible to minimize costs in the future prospecting of the mine and maximize productivity. For this methodology to be developed, it was necessary to implement the Mine to Crusher model. Through this project, the key performance indicators (KPIs), such as average productivity, availability and utilization of the equipment, and a nominal capacity observed in the crushing circuit, were analyzed. Furthermore, by observing the results, it became possible to evaluate the KPIs must be adjusted for better equipment performance and better development and planning of the mining project. Through this project, it was possible to carry out a probabilistic analysis of the project's KPIs using a Monte Carlo simulation. At the end of the work, it became possible to verify the relationship between more compact and less compact lithologies, where there is a difference in results depending on the lithology and properties evaluated. At the end of the evaluations, a difference in the penetration rate and productivity between the CI and FI lithologies of 26.99% and 26.78% respectively was verified. It is also possible to verify that when carrying out sensitivity tests for lithologies, friable lithologies require a reduction in a fixed time of 6%, whereas more compact lithologies require an increase of up to 2% in their time.

Keywords: mining operations, hard rock, productivity, Monte Carlo

1. Introduction

Technological innovations in the mineral sector are reaching increasingly high levels, progressing mineral extraction and processing in an efficient and sustainable manner through the approach of Industry 4.0 [1]. The mining enterprise can be categorized into two major operational processes, namely, mining and mineral processing [2]. The management of these activities through the collection and treatment of operational data contributes to a better use of mineral resources, ensuring sustainability and minimizing the costs of mining operations.

The complexity of open pit mining operations presents an uncertain and dynamic production environment [3], which depends on the global economic sector, the rock, and its geotechnical characteristics. Although the mineral industry has very diversified parameters, it uses tools to address the market fluctuations more coherently and with greater coverage, proposing factors that directly influence the viability of the enterprise.

In general, drilling and blasting operations are the ones that demand the most production costs at the mine, with blasting accounting for around 30% of direct production costs, mainly impacting the quality of rock fragmentation. For these parameters to be controlled, there are two qualities of parameters to be evaluated, which are considered as controlled as the geometric parameters of the mine (hole diameter, burden, spacing, stemming, sub-drilling, hole length, charge length, charge weight and delay time) and uncontrollable, such as the effects of

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dismantling occurring through flyrock, ground vibrations, and airblast [4,5].

Currently, due to the scarcity of raw materials, some mineral deposits have been found to have a lower mineral content and greater hardness, thus requiring greater planning of the project. In addition, minerals found with greater hardness or mechanical strength require a high fragmentation energy and, consequently, greater energy expenditure in drilling, blasting, and crushing operations. Thus, the control of operational indicators, or key performance indicators (KPIs) [6], is of fundamental importance to ensure the viability of the enterprise.

The key performance indicators are also defined as quantitative or qualitative information that highlights performance throughout the organizational process, be it in terms of efficiency, effectiveness, or level of satisfaction [7]. The increase in competitiveness among companies favors the implementation of a more efficient production planning and control system, presenting a higher quality of data and resources to be obtained as a result of the project to be developed [8].

Regarding the mining indicators, O'Neill [9,10] evaluated and revised the key performance areas (KPAs) and their respective environmental development in mines in South Africa, warning of the necessary care when using the term KPI, as some researchers confuse it with KPA. The success of the factors used explicitly or implicitly reflects the strategic vision of the organization. In addition, KPIs are part of the development of a specific KPA and can be used to find the best version and optimization of the factors to be analyzed [11].

Through research developed, verified and analyzed, an improvement in KPIs values makes it possible to quantify the impacts on equipment productivity, aiming for better results, lower costs and maximized efficiency of the production systems [12]. Productivity management allows for a consistent reduction in operating costs in a mine. However, care must be taken with the productivity used in the process, which is classified as global and effective.

Hartman [13] defines rock blasting as a set of processes with the ability to facilitate and obtain an extraction of ore from rock through the progression of an optimized mining front that is appropriate to the size of the material to be processed. Generally, the explosives used are composed of chemical mixtures, which when properly initiated by a sufficiently energetic external agent, release energy that ore fragmentate, thus generating heterogeneous particles in a short period of time.

Blasting with explosives is the first stage of rock fragmentation, with further fragmentation occurring in the later stages of the mining production chain, such as loading, transport and crushing. The control and technological development of rock blasting with explosives directly impacts the productivity of these activities. A study of optimized mine operations and KPIs related to blasting with explosives, which impacted the particle size of the material to be processed. Without such analysis, through the low quality of the blasting of the material to be fractured, the need to perform a secondary blasting results in unnecessary costs for mine operation [14].

For the performance keys to be analyzed, an evaluation through simulation is necessary, in which Monte Carlo simulation was used. Through this type of simulation it is possible to verify the effect of the predictive variables adopted during the drilling and blasting stages as well as the estimation of unknown values using known variables. From this simulation, it is possible to evaluate using a probabilistic approach based on deterministic parameters. Therefore, this means of simulation seeks, through the stochastic generation of randomized numbers, to generate an interval for a given purpose [4,15–18].

In this study, the productivity and other performance metrics of mining activities were analyzed. Additionally, the behavior of the equipment used in such activities was analyzed via a probabilistic simulation for better adaptation of the transport parameters.

Furthermore, the productivity and other performance indicators of mining activities were analyzed, considering drilling, blasting, loading, haul and primary crushing. Additionally, the behavior of the equipment used in such activities was analyzed via a probabilistic simulation for better adaptation of the transport parameters. When possible the KPIs were analyzed according to different lithologies of the mine under study. The operational database included: rock drills for the drilling operation, the shovel type for loading the material onto trucks, which carry out the haul to the final stage of the project, and the primary crushing, represented by the gyratory crusher. The blasting design parameters and characteristics of the explosives were considered in relation to blasting with an explosive database.

2. Materials and methods

The mine in this case study is located in the northeastern area of the Iron Quadrangle in the state of Minas Gerais, Brazil. Approximately 18 lithotypes of iron formation and different host rocks, most of which were classified as compact hematite, were mapped in the region. In lenses across the entire mine, friable hematite was observed, mostly in the bottom of the pit. The friable itabirite was usually observed in the upper portion of the mine, and the compact itabirite has a deep formation in the syncline base below the friable itabirite. Figure 1 shows the percentage of mass to be mined and, consequently, the annual production estimated by lithology.

The mining of iron ore from the case study occurs in an open pit mine via drilling, blasting, loading (through hydraulic diesel shovels), hauling (trucks), and primary crushing (gyratory crusher). The database and the calculated operational parameters were collected and standardized using statistical methods to increase the accuracy of the analysis and validate the empirical conclusions to be investigated. For each parameter analyzed, analyses were performed for three different ore lithologies: very compact itabirite (VCI), compact itabirite (CI), friable itabirite (FI), and compact hematite (CH). The operational parameters analyzed are briefly described in Table 1, and through these parameters, it is possible to evaluate the fleet of rock drills and ideal trucks, judging the need for improvement in each phase according to the results presented.

A rotary rock drill with tricone bits was initially used in oil drilling; however, given their efficiency and productivity, they began to be used in mining projects [19]. Drilling can be subdivided into two stages, namely, rotary cutting and rotary grinding of the material [20]. At the beginning of the drilling process, a hole is created that, through the shear force and the friction of the material in contact with the tricone drill bit, releases the energy necessary for rock breaking and eliminates the rock fragments with the aid of compressed air through the space created. The diameters used for such equipment can vary between 0.20 and 0.45 m, with an operating range between 50 and 120 rpm. The equipment has the disadvantage of limiting the performance of inclined holes, which are recommended to have a maximum angle of 18° [21].

During this study, it was necessary to perform statistical analyses of the data, thus evaluating the necessary investigation parameters according to Table 1. Through the collected data, graphs such as histograms, descriptive statistics (boxplot) and scatterplots were elaborated. To obtain the best optimization of the parameters assessed, Monte Carlo simulations were performed, with the main objective of optimizing the operational times.

After the analysis of the statistical parameters with the boxplot, it was possible to analyze the data by lithology through Monte Carlo simulation and to observe the behavior of the lithology on the influence of the investigated statistical parameters; this can help to optimize the model and even adapt it according to the values analyzed.

For a concise and accurate optimization analysis, it was necessary to choose the most appropriate probability distribution. For this, Minitab® software

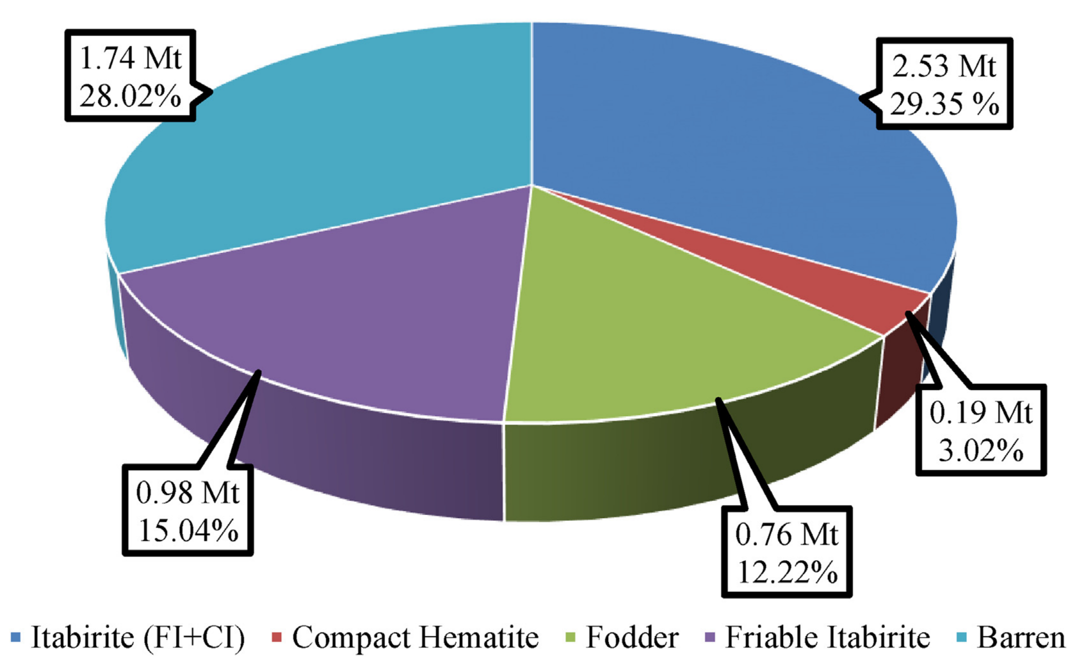

Fig. 1. Production by lithology.

Table 1. Operational parameters evaluated in the operation with respect to drilling, loading and transport.

Parameters	Formula	Description
Availability (A)	$A(\%) = \frac{Hc - Hm}{Hc}$	Parameters in which the equipment are analyzed through the availability, utilization and operating performance for drilling, as well as for loading or haul.
Utilization	$U(\%) = \frac{Hd - Ho}{Hd}$	
Operating performance (OP)	$OP(\%) = \frac{Ht}{Hc}$	
Productivity (P)	$P(\mathrm{m/h}) = \frac{\mathrm{Length}}{HT}$	Indicator of production per hour, by loading, haul or drilling equipment.
Number of holes (N_f)	$\sum$ number of holes	Total number of holes related to the production of the mine and the blasting design.
Loading cycle time (T_{cc})	$T_{cc}\ (\mathrm{min}) = T_c + T_h + T_m + T_d + T_v$	Time that the equipment takes to load and a truck.
Fixed time (F_T)	$F_t\ (\mathrm{min}) = T_{wl} + T_m + T_c + T_{wd} + T_d$	Total operational time of the haul, from loading to haul material.
Penetration rate	$Tx(\mathrm{m/h}) = \frac{\mathrm{Length}}{Ht}$	Rate performed per rock drill per hole, depending exclusively on the length and hours worked.
Payload (P_m)	$P_m(t) = $ useful mass	Equipment payload.

Hc: Calendar hours. Hm: Maintenance hours. Ht: Hours worked. HT: Total hours. Hd: Available hours. Ho: Idle hours. T_c = Load time. T_h = Haul time. T_m = Time for maneuvers. T_d = Dumping time. T_v = Travel time (empty). T_d = Dump time. T_{wd} = Wait dump time. Twl = Wait load time.

was used, which enables the complete analysis from an add-on model to the computational Monte Carlo simulation tool, Minitab Workspace®.

In the simulations performed with Minitab Workspace®, the model used refers to a nonparametric method that allows an analysis of the parameters up to the range of ±3σ, corresponding to a 99.7% confidence interval of the samples relative to the standard deviation. Therefore, approximately 100,000 replicates were simulated to present a model that was more efficient at the selected confidence interval and has the highest possible adherence. A 95% confidence interval of the samples was considered in its development, i.e., ±2σ.

The Monte Carlo simulation model follows the appropriate standard where there is an ability to implement solvable variables according to the reality of the problems. For this, the model is used as a function of failures and randomized variables, where this model is described as $g(x_1, x_2, \ldots, x_n)$ and its variables to be investigated are the values of $x_1, x_2, \ldots, x_n$ and the probability performed by the system, known as p_d [22]. The estimated probability zone can be verified in Equation (1).

$$p_d = \frac{1}{N}\sum_{i=1}^{N} I(x_1, x_2, \ldots, x_n) \tag{1}$$

Where, N is independent of the values of $x_1, x_2, \ldots, x_n$, based on the probability distribution and I is a function where [22]:

$$I(x_1, x_2, \ldots, x_n) = \{1 \text{ if } g(x_1, x_2, \ldots, x_n) \le 0 \ \ 0 \text{ if } g(x_1, x_2, \ldots, x_n) > 0 \tag{2}$$

At the end of these probabilistic analyzes using the Monte Carlo method, the sensitivity of the variables is worked on, seeking to improve the system as a whole. To this end, the Spearman rank correlation analysis is used, which facilitates the measurement of the probability for each variable in the model [16].

3. Results

3.1. Drilling and blasting

The drilling equipment used in the mine was a Caterpillar model, CAT MD 6420; this equipment is of the rotary type, which includes a mast of 13 or 16 m [21].

From the data collected, it was possible to determine the statistical values for the KPI's A, U, and OP of drilling; after measuring the hours of operation of the rock drill, the data was statistically analyzed, as shown in Table 2.

Through the available data, it was feasible to measure and analyze the drilling times and the number of boreholes, per the analyzed period. Table 4 shows the number of total boreholes per period, the rate of borehole drilling, and the rate of borehole loss per lithology studied. As can be observed in Table 3, for the more compact lithologies, the rate of borehole loss was relatively higher compared to that of the more friable lithologies.

Table 2. Statistical analysis of the A, U and OP data from the MD6420 rock drill fleet.

Parameter	Minimum	Maximum	Mean	Median	Standard deviation
DF (%)	33.10	85.81	60.53	61.29	11.44
UF (%)	35.15	80.93	67.10	67.86	7.93
OR (%)	21.65	52.47	40.42	42.86	8.18

Table 3. Analysis of the holes drilled by the MD6420 rock drill according to the lithology, considering the rate of borehole drilling and the rate of borehole loss.

N_f	Borehole rate	Lithology		
		CI	FI	CH
41,725	T_x (%)	86.22	12.28	1.50
	T_{xp} (%)	2.86	1.52	4.31

N_f: Number of holes. T_x: Borehole drilling rate. T_{xp}: Borehole loss rate.

When evaluating the data through statistical analyses optimizing the generated parameters, the boxplot was elaborated, and the performance of the drilling process for each lithology was possible to assess. For lithologies with similar geotechnical characteristics to the intact rock, the penetration rate was low, given the compactness of the rock [23]. According to Quaglio [24], both rock drilling and productivity will increase as a result of the limited penetration rate because the advancement pressure of the rock increases proportionally to the penetration velocity until the limit. When this limit is exceeded, it is inferred that the equipment will have a high level of wear, thus minimizing the penetration rate.

Analyzing the Uniaxial Compressive Strength (USC) of Figure 2, it was possible to compare the increase in borehole losses to the UCS because it increases the difficulty of drilling the rock, thus increasing costs. For this purpose, at the blasting design project has to be cautious, fundamentally considering the minimization of the errors generated and the unnecessary costs through hole loss.

Figure 3 shows the average penetration rate per lithology, indicating that CH has a lower strength than the other lithologies, and the CI requires more resources due to the higher UCS, therefore, it becomes evident that the competence of the rock is directly related to the penetration rate, with there being a higher penetration rate for the FI than for the CI, as seen in the figure, indicating greater ease of penetration of the rock.

In Figure 4, it is observed that the productivity of CH is higher, thus correlating with the penetration rate of Figure 3, attesting to the lithology with a lower UCS will be easier to drill; thus, it will have a greater penetration rate.

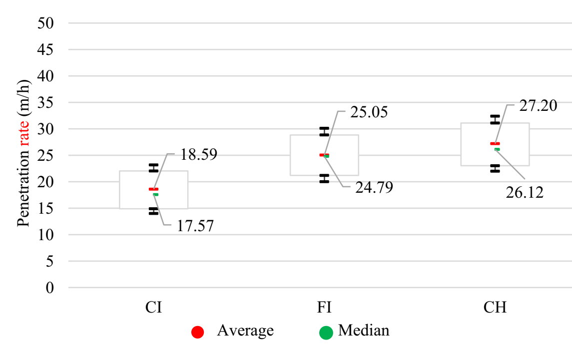

Fig. 3. Boxplot of penetration rate by lithology, CAT MD 6420 rock drill.

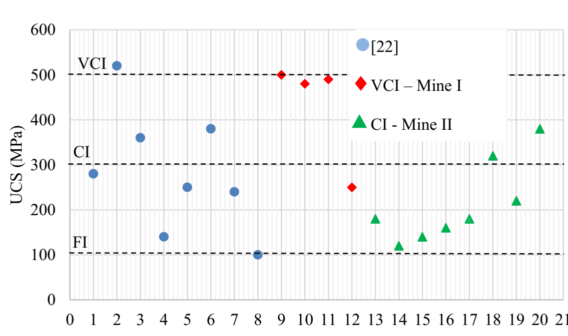

Fig. 2. Categorization of itabirites according to the UCS, where VCI is very impact Itabirite, and CI is Itabirite compact.

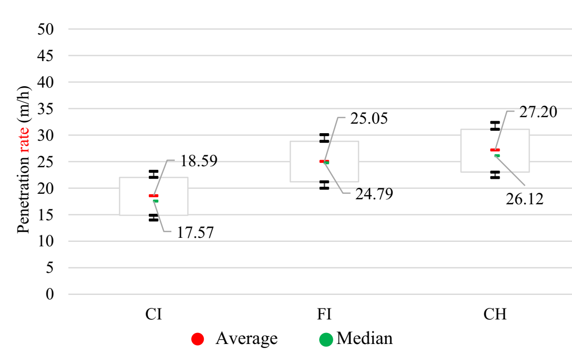

Fig. 4. Boxplot of the overall productivity rate of CAT MD 6420 drill rigs by lithology.

3.2. Loading and haul

The hauling of fragmented material by trucks is one of the costly steps in the production process of mine operations. The control and optimization of the related parameters can contribute to the efficiency of operations and minimization of operational costs. For better haul performance-related indicators, with the objective of better optimization, some simulations were performed. Conorado & Tenorio [6] addressed different simulation scenarios to aid decision-making, mainly evaluating productivity as a KPI. This work showed the importance of adequacy in the mode of data treatment and, consequently, the proportionality between productivity and operational costs.

Adherence to the mine KPI values is important for the operational continuity and development of mineral operations. Upadhyay & Askari-Nasab [25] used KPIs for the simulation of discrete events through an optimization tool, generating short-term mine production plans with loading and haul data. In the mine, two types of loading and haul equipment were used, according to Table 4. To maximize productivity, the parameters *HT*, *OP*, payload, productivity, and loading cycle time were analyzed.

Table 4. Loading and transport equipment of the mine in operation and their respective nominal capacities.

Parameter	Shovels	Trucks
Caterpillar	CAT 7295HR	CAT 793
C_n (t)	45.4	240
Komatsu	Komatsu 23000XPC	Komatsu 830E
C_n (t)	45.5	250

C_n: Nominal capacity.

Figure 5 shows the mean loading cycle time due to the sampling percentiles of the CAT 7295HR and 2300XPC shovels. The statistical values of the CI, CH, and FI + CI lithologies were measured for the loading time, thus providing sufficient data for the elaboration of Boxplot to understand how the equipment works regarding the lithology. As observed in Figure 5, the most friable lithologies have the fastest loading time, as expected.

The representative values of the average load per cycle (*payload*) of the shovels are shown in Figure 6 for the lithologies CI, CH, and FI + CI. Different behaviors are observed for the different lithologies. The CI and FI + CI lithologies in Figure 6 for CAT 7295 HR present very close values, making it difficult to identify differences in the payload of this equipment, as in Figure 6 to 2300 XPC. However, the presence of a mixture of lithologies presents a higher payload, and it was possible to infer that in such samples, the mix of CI and FI produces a result that is much higher than that of CI.

Through the average productivity per lithology, it was possible to evaluate an increase in productivity due to the friability of the sample (Fig. 7 to CAT 7295 HR). Figure 7 to 2300 XPC shows the mean productivity of the material is approximately the same for all materials.

In Figure 8, the mean load data are very similar for all lithologies. However, the mixed samples (IF + IC) have a higher capacity for the average transport load, in contrast to the other lithologies.

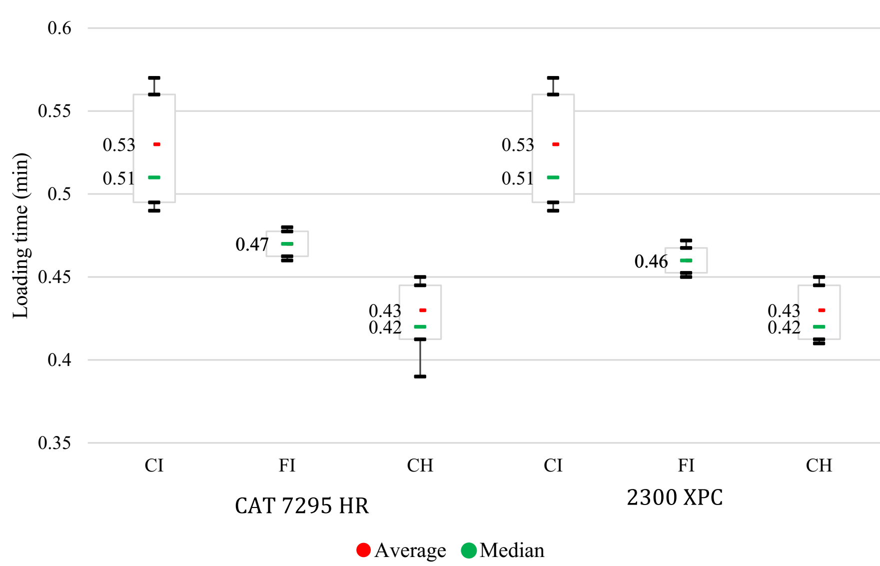

Fig. 5. Boxplot with processed loading cycle times for the CAT 7295HR and 2300XPC by lithology.

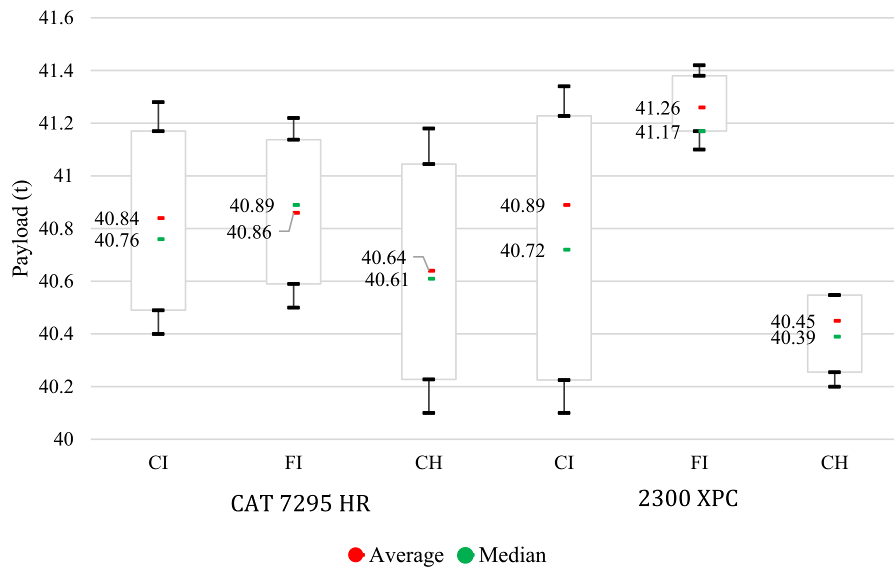

Fig. 6. Boxplot with processed payload values of the (A) CAT 7295HR and (B) 2300XPC per lithology.

When finalizing the sample evaluations via boxplot, it was important to evaluate the times related to operations via Monte Carlo simulation in order to optimize the parameters through a probabilistic analysis and adjustments to the arrangements in which the data are presented. For this purpose, the behavior of the transport equipment was analyzed as a function of total times, correlating them with the fixed time and thus optimizing the parameters resulting from the cycle time.

Before starting the simulation, the probability distributions of the data for the loading equipment were analyzed. Thus, the best distributions of the generated data were evaluated, as observed in Table 5, using Minitab® software. The methodology consisted in analyzing the behavior of the distributions for each time, verifying the behavior of the samples, and enabling the selection of the best method to be inserted in the Minitab Workspace®, thus enabling a more optimized simulation of the evaluated parameters.

Through the Monte Carlo method simulation, the parameterized data were investigated and presented in a graph with the 95% confidence interval.

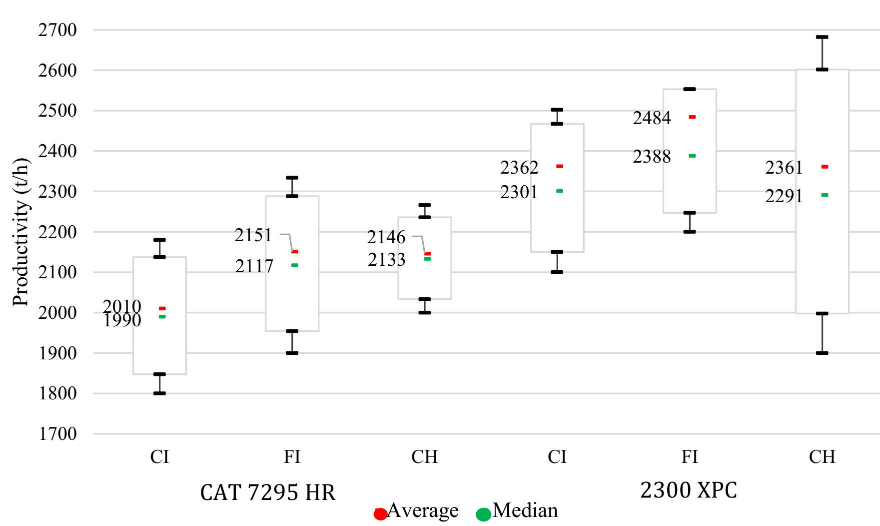

Fig. 7. Boxplot with processed productivity values of the (A) CAT 7295HR and (B) 2300XPC by lithology.

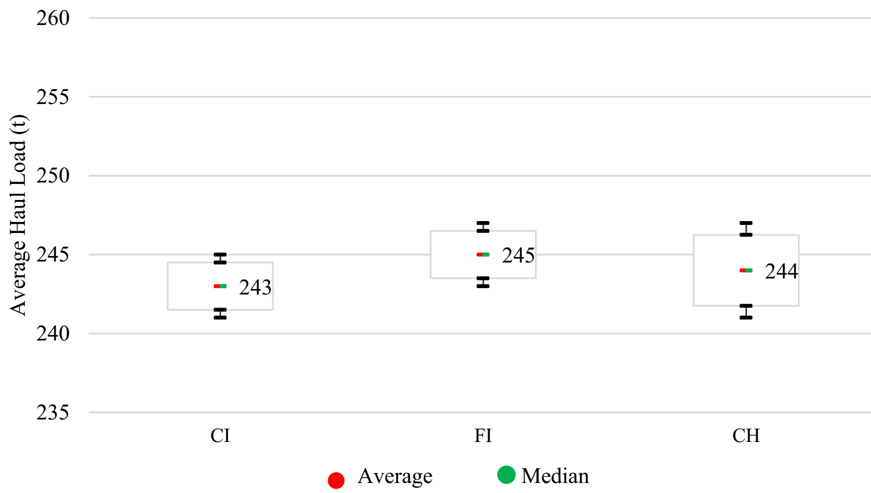

Fig. 8. Average haul load by CAT 793 and Komatsu 830E trucks per lithology.

Table 5. Probability distributions for the fixed time analysis parameters in relation to the lithologies presented.

Parameter	Lithology		
	Hematite	Itabirite	Compact Itabirite
T_{wl}	Lognormal	Normal	Weibull
T_m	Normal	Normal	Normal
T_c	Lognormal	Lognormal	Lognormal
T_{wd}	Normal	Lognormal	Normal
T_d	Weibull	Lognormal	Normal

The investigation variables were optimized through the available parameters. When optimizing the fixed time, adjustments were made to the model regarding the degree of sensitivity of the parameters for each distribution involved in the system.

Figures 9–11 show the behavior of the parameters in relation to the results of the Monte Carlo simulations for each lithology (hematite, itabirite, and compact itabirite, respectively). Figures 9 and 10

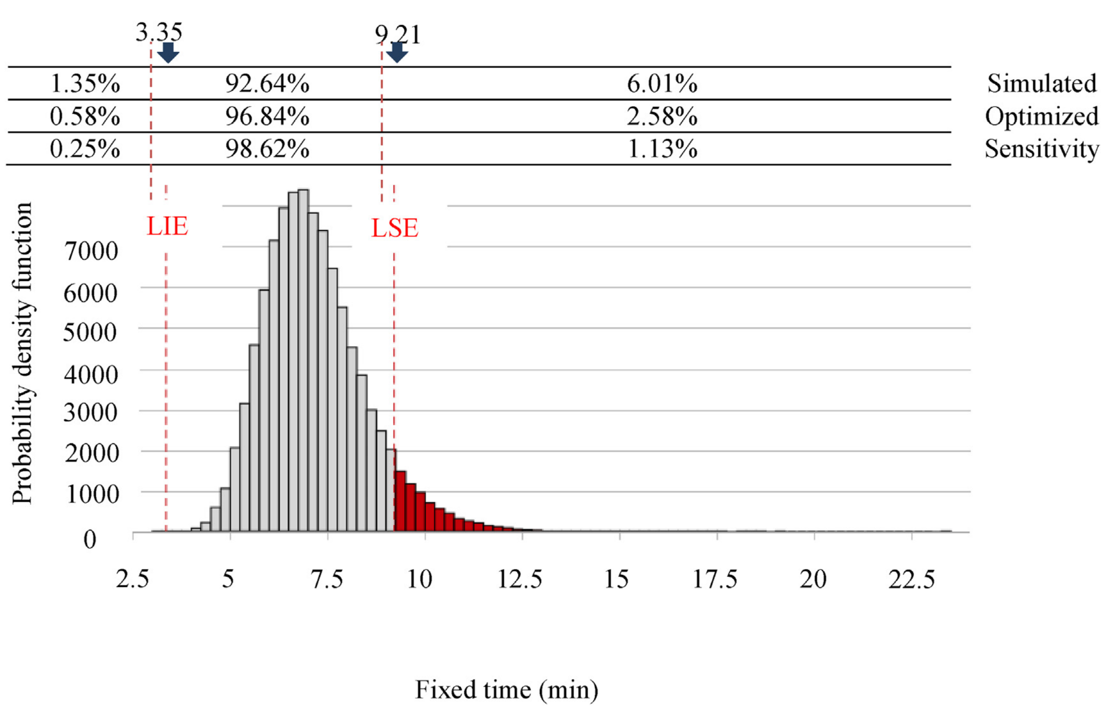

Fig. 9. Results of the Monte Carlo simulation for the total fixed time of the trucks for the hematite.

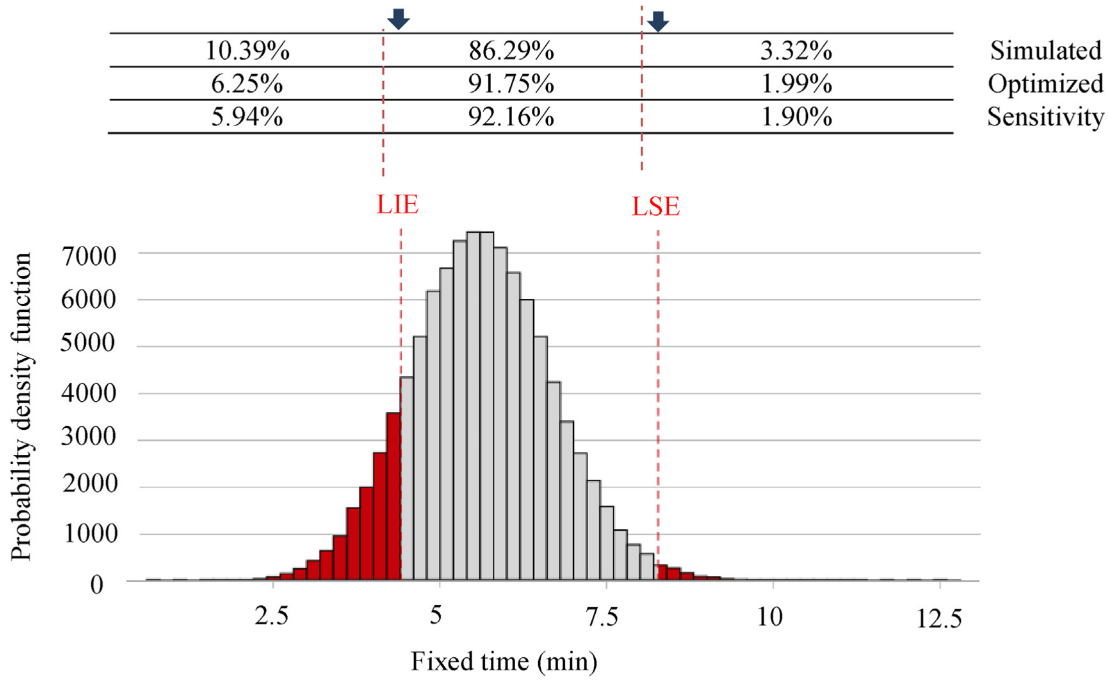

Fig. 10. Results of the Monte Carlo simulation for the total fixed time of the trucks for itabirite.

show that as the simulation sensitivity and optimization of the simulated parameters were done, the percentage of samples in the confidence interval increased. Also, in Figure 9, it was possible to observe that the samples are in the confidence interval between 3.35 and 9.21 min, corresponding to approximately 92.64% of the samples present in the observed interval. Figure 10 shows approximately 86.29% of its samples within the confidence interval between 4.41 and 8.27 min. However, in Figure 11, the optimizations appear in a confidence interval between 4.70 and 4.80 min, containing approximately 87.01% of the samples within the confidence interval, and it was assessed that after sensitivity analysis, there was a small drop in the percentage of samples in the interval.

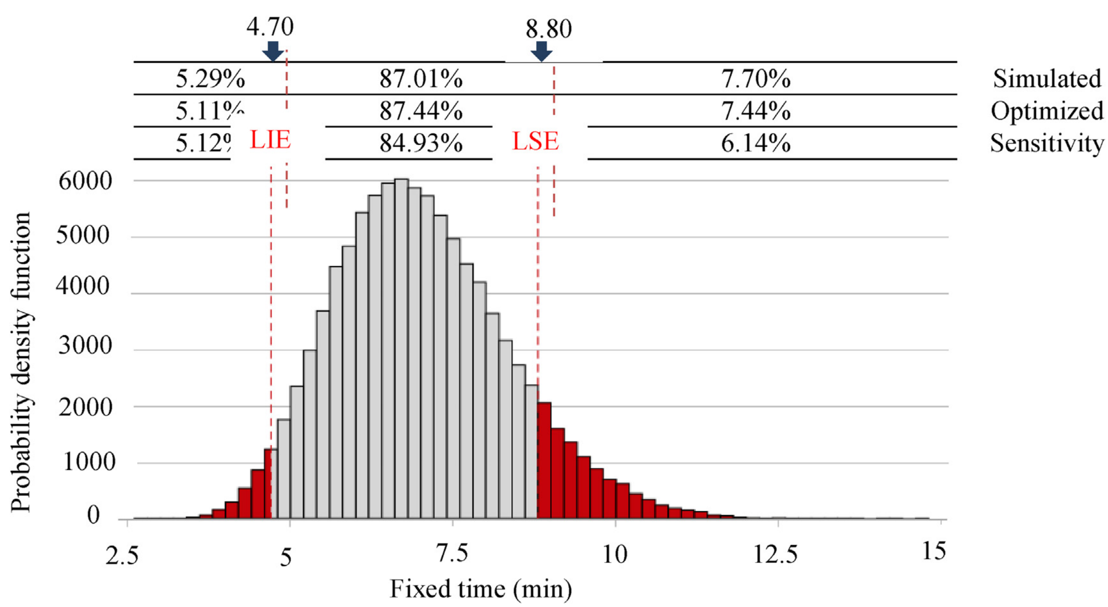

Fig. 11. Results of the Monte Carlo simulation for the total fixed time of the trucks for the compact itabirite.

After simulating the data using the Monte Carlo method, it was possible to ascertain the statistical parameters generated during the execution of the project, as observed in Table 6. The table shows that as the model was optimized, its mean time tended to decrease, thus demonstrating that the equipment was being optimized and minimizing parameters such as time lost in loading or waiting for dumping. However, the same does not occur for itabirite; as the parameters are optimized, the mean increases, thus demonstrating the presence of waiting time of the vehicle when hauling the material of such lithology. This issue requires more accurate analysis of more data for decision-making.

In addition to the statistical data table, it was possible to analyze the difference between the calculated and simulated data for the fixed time, thus verifying the difference between a deterministic and a probabilistic model, mainly highlighting if there was a great variability between the applied methods. Table 7 shows a small variation, thus demonstrating a greater variation between the lithologies of −8.83%.

3.3. Primary crushing

The primary crusher used in the mine is a cone-type rotary crusher manufactured by Metso Outotec. The technical specification of the equipment can be verified in Table 8 [26]. The crusher works above its nominal capacity but below the technical specification, as recommended by the manufacturer, thus avoiding problems such as sudden stops for corrective maintenance. The project specification addresses a particle output of 150 mm above the closed position length specification, also verifying the occurrence of some failure by the crusher or in previous phases.

When analyzing the database of the material to be fed and the product of the crushers, it was found that they are composed of particle sizes previously defined by the project, according to a dry sieving analysis. The feed and product curves are shown in Figure 12, which can evaluate the degree of fragmentation of the passing material in the crusher and the sizes of the passing product and the feed. According to Figure 12, the values measured relative to the size of the passing particles in the particle size of the feed in the range between 80% (P_{80}) and 50% (P_{50}) passing are 778 and 110 mm, respectively. For the primary crusher product, the range 80% and 50% passing are 122 and 87 mm, respectively.

Once the parameter to be evaluated in the crushing was established, such as the productivity of the equipment, the statistical analysis was performed to verify the behavior of the equipment productivity when performing the fragmentation and if it is performing the work properly, as observed in Table 9.

Through the data analysis, it was possible to observe that the crusher reached its maximum productivity below its nominal capacity of the primary crusher of 4350 t/h. When working in its tipping mode, there was a loss in productivity when loading. However, before performing the actual crushing, it is advisable to perform a scalp for the P_{50} material, and most of this material is found below the break range of the crusher, thus generating unnecessary costs. In addition, at least 10% of all crushed material has a specification greater than the OPL of the crusher, which is the maximum size to be used in the next steps. So that the efficiency is maximized and improved, the blasting of the material should be performed to leave the material with larger fragments.

4. Discussions

4.1. Drilling and blasting

Through the results generated by drilling and blasting, a difference was observed among the resistances of the different lithologies. According to Mariano [20], the same correlation found in this article was observed due to the geometry of the blasting and how it could influence the crushing of the material. During the development of the work and through the

Table 6. Statistical results according to the optimization performed in the Monte Carlo simulation due to the lithologies present in the field.

Lithology	Monte Carlo	N	Mean	Standard deviation	Minimum	Median	Maximum
H	Simulation	100,000	7.1787	1.344	3.2312	7.0082	23.4706
I		100,000	5.6219	1.0761	0.6916	5.6046	12.5705
CI		100,000	7.0217	1.3623	2.7516	6.91	14.6342
H	Optimization	100,000	6.2137	1.3546	2.4481	6.0345	17.3682
I		100,000	6.0431	1.0723	1.6921	6.0287	13.3546
CI		100,000	6.8665	1.3673	2.4753	6.745	14.4508
H	Sensitivity analysis	100,000	5.7254	1.1532	2.4407	5.5991	14.8882
I		100,000	6.5743	1.0743	1.8599	6.5592	12.3346
CI		100,000	6.3909	1.385	2.3352	6.2588	13.8222

Table 7. Analysis of the mean total deterministic and probabilistic fixed times for each verified lithology.

Comparison between the deterministic and probabilistic mean fixed times				
Lithology	Probability associated with standard deviation (%)	Deterministic mean fixed time (min)	Probabilistic mean fixed time (min)	Variation (%)
H	98.62%	6.28	5.7254	−8.83
I	92.16%	6.34	6.5743	3.70
CI	84.93%	6.75	6.3909	−5.32

Table 8. Technical specification of the cone-type rotary crusher, Metso Outotec.

Technical specification (t/h)	5220
Usual (t/h)	5000
Nominal capacity (t/h)	4350
Fragmentation capacity (t)	325
Specific parameters	**Dimensions**
Open position length (OPL) (mm)	1200
Closed position length (CPL) (ideal/performed) (mm)	127/150
Axis eccentricity (AE) (mm)	1073

analysis of previous works, a great correlation was verified between drilling and blasting equipment and primary crushing. It is also possible to evaluate, through a probabilistic study, the significant impact on the final productivity of comminution operations, as in the case of primary crushing. In this study, it was observed that the greater the strength of the rock is, the higher the rate of explosives required for blasting, making it necessary to have a greater number of holes in more compact lithologies due to the rock's competence, as found in [20].

The work developed by Oliveira [27] compares the USC of the rocks for each lithology (VCI: 271–302 MPa; CI: 5–50 MPa; and FI 0.25–5 MPa)

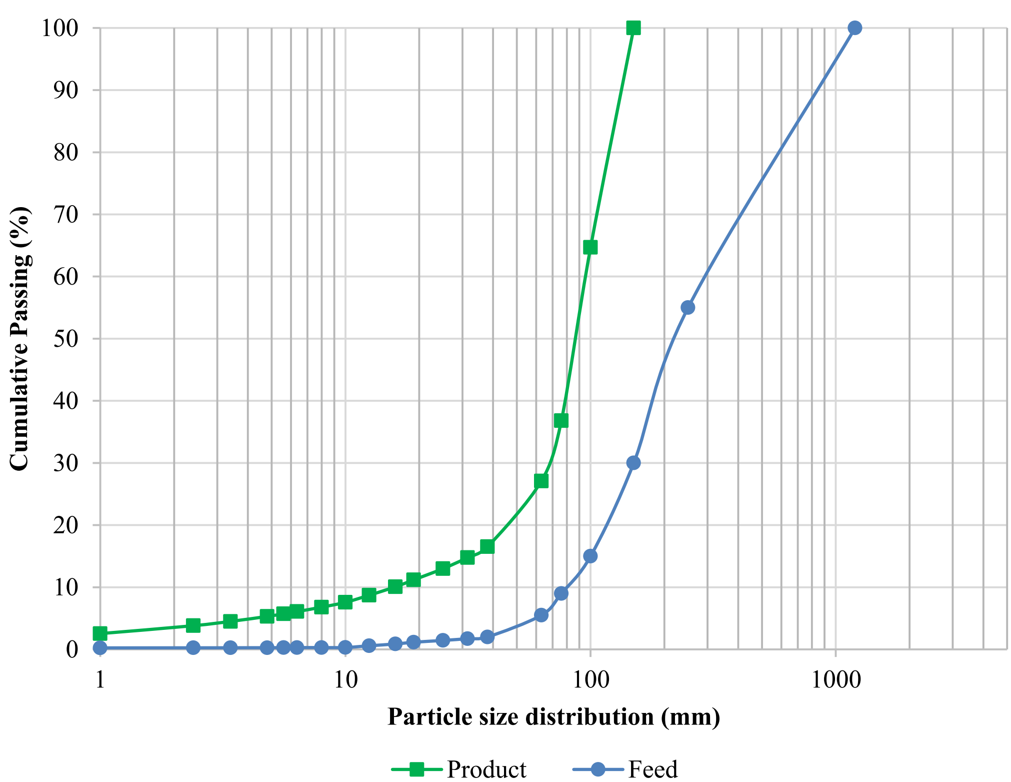

Fig. 12. Granulometric curve of the feed and design product for the primary crusher.

Table 9. Statistical analysis of the monthly productivity of the crushing circuit.

Parameter	Minimum	Maximum	Mean	Median	Standard deviation
Productivity (t/h)	2617	4085	3523	3561	406

despite presenting different values from the studies developed in this article, the proportion and correlation of the data are similar. Thus, the greater the compactness of the rock is, the greater its compression, requiring more efficient drilling to obtain the material.

It was worth noting that as the USC increased, there was a need to apply explosives, as shown in Table 5, making the process much more costly, thus influencing the need for an increasingly accurate optimization for the development of the project. Furthermore, it was possible to investigate the behavior of the USC of each lithology found to identify the compactness of the rocks [28,29].

4.2. Loading and haul

Related to the behavior of the loading equipment for each lithology, the Komatsu equipment presents a payload, productivity, and loading time that are higher than those of the Caterpillar equipment. Figure 8 shows that the lithology becomes more compact as the loading time increases. Regarding payload and productivity, in Figures 7 and 8, the mixed material (CI + FI) has higher KPI values than the others, thus identifying the possibility of a greater amount of compact material included in the mixture.

With respect to haul, there was no difference in the results among the different types of equipment. With a comparison between the lithologies studied, it was possible to verify that the haul cycle time was inversely proportional to the loading time; the more competent the rock was, the longer its cycle time and the shorter the loading time. The same comparison can be observed for the other times, such as the waiting time and other maneuver and waiting times. These results can be optimized and standardized, enabling the entire mine process [8] in a mine planning operational research to optimize all existing processes in terms of the improvement of the KPIs observed in the process. With the aim of optimizing these parameters, a Monte Carlo simulation was used to measure effectiveness the data for each lithology studied.

4.3. Crushing

When observing the data from the crushing plant according to Table 8, it is possible to verify that the crusher is used below its technical specification with around 95.78% of use; however, it works above its nominal capacity by 13%, indicating Therefore, this rotary type crusher eventually works in flood mode. Furthermore, the caveat is that although the expected ideal granulometry is 127 mm, a range of 150 mm is obtained in this operation, which is a result considered efficient for the operation. The productivity of the equipment was below the nominal capacity supported by the equipment, thus inferring that there were operational problems in the execution of the equipment or in previous steps. Thus, once again, the presence of a project that addresses a system as a whole was justified, such as the project performed by this article.

As observed by Mariano [15], primary crushing was the most affected phase of a project, positively and negatively linked to the blasting of the material. For example, the productivity of the crusher is mainly intended to qualify the quality of the blasting.

In Figure 11, at least 10% of the material, which was fragmented, was above the crushing OPL specification, thus requiring a sieve prior to the operation in order to improve the productivity and feeding capacity of the crusher itself and blasting process, thus minimizing costs in the crushing stage. The average productivity of the hours worked in the primary crushing circuit during the analyzed period was below the nominal capacity, for which the product physical availability × physical use results are on the order of 25–35%.

5. Conclusions

The database collected, and the values presented in this article characterize the current situation of the mine and its production during 2019, 2020, and 2021. Intact rock considerably decreases the penetration rate of the material and its productivity. When observing the morphological differences depending on the penetration rate and productivity, a considerable variation is observed, as seen in the graphs in Figures 3 and 4, where it is clear that the competence of the rock directly influences both parameters, resulting in more compact rock a need for higher penetration rates and lower productivity. Comparing, for example, two similar lithologies such as CI and FI, and knowing in advance that the compact material presents greater compactness and difficulty in penetration, it is possible to observe certain aspects in these graphs, where, through data measured in the field, it is observed that compact itabirite presents around 26.99% less penetration than friable itabirite. Furthermore, when observing the global productivity graphs in Figure 4, note this inference again where the IC productivity is about 26.78% lower than the friable morphology.

In the shovel loading phase, the more friable the blasting rock, the shorter the loading time. This fact can be verified, for example, due to the displacements of trucks, in the transport phase of the fragmented material, whether to the FI or CI, where the morphology of the rock directly affects the transport time, where the more compact the rock, the greater relative to its weight, and therefore, the greater the difficulty of transporting it. Furthermore, the primary crushing analysis demonstrated the need to add new phases of crushing or to improve the blasting process.

Monte Carlo simulation results show that as the compactness of the ore increases, the haul cycle becomes longer, thus affecting productivity. The present study will be useful for further study of the productivity of the chain of operations from blasting to primary crushing. When carrying out the sensitivity analysis, it was verified that it is possible to improve productivity by adjusting the fixed time, depending on this methodology, where it is possible to observe that it can be reduced by 6% for friable lithologies and that productivity increases for the material that is more compact, in this case the compact itabirite, this fixed time becomes necessary to increase it by around 2%, as shown in the graphs in Figures 9–11.

Ethical statement

The authors state that the research was conducted according to ethical standards.

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Data availability statement (DAS)

The data in this article cannot be distributed due to the confidentiality of the company's data.

Conflicts of interest

The authors declare no conflict of interest.

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