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Towards the Application of Process Mining in the Mining Industry—An LHD Maintenance Process Optimization Case Study

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Abstract: Inefficiencies in mine equipment maintenance processes result in high operation costs and reduce mine sustainability. However, current methods for process optimization are limited due to a lack of access to structured data. This research aims to test the hypothesis that process mining techniques can be used to optimize workflow for mine equipment maintenance processes using low-level data. This is achieved through a process-oriented analysis where low-level data are processed as an event log and used as input for a developed process model. We present a Discrete-Event Simulation of the maintenance process to generate an event log from low-level data and analyze the process with process mining. A case study of the maintenance process in an underground block caving mine is used to gain operational insight. The diagnosis of the mine's maintenance process showed a loss of 23,800 equipment operating hours per year, with a non-production cost of about 1.12 MUSD/year. Process mining obtained a non-biased representation of the maintenance process and aided in identifying bottlenecks and inefficiencies in the equipment maintenance processes.

Keywords: underground mining; LHD maintenance process; DES; process mining

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1. Introduction

Mine equipment maintenance strategies have a significant impact on mining sustainability. Mining operations are dependent on equipment for excavation, transportation, and processing of minerals, and any downtime due to equipment failure can result in significant financial losses. Effective equipment maintenance strategies minimize the likelihood of equipment failures and improve their lifespan, reducing the need for frequent replacements and repairs, which leads to reduced resource consumption, energy use, and waste generation. This can contribute to the overall sustainability of mining operations by reducing their environmental impact and improving their economic viability. Proper maintenance of equipment can also ensure worker safety, minimize accidents, and reduce the potential for human health and environmental hazards associated with mining activities. Therefore, effective equipment maintenance strategies can help mining companies achieve their sustainability goals and contribute to the long-term viability of the industry [1].

There is a growing interest in the mining industry to innovate and adopt industry 4.0 technologies in its operations. This includes the use of data science approaches to analyze and improve mining processes [2,3]. However, there is still a significant gap in the implementation of data sciences in the mining industry [4]. This is projected to change in the next decade with the emergence and development of new data science technologies on a large scale. Such changes could positively impact mine asset management [5].

The maintenance cost in the mining industry is between 30% and 50% of the operating costs [6]. As a result, the mining industry has made significant efforts to attain high equipment availability and low operating costs through process optimization. Several efforts have been made to optimize the maintenance process using data science [7]. However, there is still significant uncertainty in terms of the quantity and quality of data to use when applying such techniques. Despite the advances in automation that have allowed an increase in data collection, the availability and use of such data by the industry for resource management are still lacking. Simulation techniques such as Discrete-Event Simulation (DES) have been important in addressing data challenges [8,9]. The availability of data allows for better monitoring of the mining operation's Key Performance Indicators (KPIs).

Current data science techniques used to analyze data include data mining algorithms and cluster elements with similar characteristics to machine learning algorithms for data-based decision-making. Process mining has emerged as a strong technique to analyze start-to-end processes in recent years.

Process mining (PM) is a novel research area composed of a set of techniques and algorithms to (1) extract (or mine) valuable process-related information from events (known as process discovery), (2) check the discrepancies between a process execution with a previously established process model (conformance checking), and (3) repair or extend a process model with information about the process execution (known as process enhancement) [9]. Process Mining can obtain a non-biased representation of the analyzed process. The input of PM algorithms is an event log, i.e., an ordered registry of (actual or simulated) data where each event that occurs during the process execution is registered and annotated with information about what and when it happened [10].

This research aims to present a case study on the application of PM in the mining equipment management system—specifically, the analysis of the maintenance cycle from a process-oriented worldview. We introduce the integration of DES and PM for the event log generation and analysis of the maintenance process from a low-level database. We believe that the application of PM in resource management will reduce the mean time to repair and enable analysis from the viewpoint of the maintenance cycle [10]. It will also support root cause detection and monitoring of asset management failures and generate better policies for resource management and mine sustainability. Achieving these objectives will allow, in the medium-to-long term, to increase the availability of the equipment, increase the Overall Equipment Effectiveness (OEE) of the mine, and improve the interaction between the different functional units.

The main contribution of this research is to set the first precedents, using a case study, regarding the implementation of PM to optimize the maintenance cycle of underground mining equipment and highlight the need for field implementation in the industry. In the following sections, we discuss the use of PM in the mining industry and its integration with DES. We then present the case study of DES and PM applications for maintenance process optimization. Finally, we discuss the results and conclusion.

2. Process Mining in the Mining Industry

Process mining is a relatively young discipline that has exponentially advanced in recent years. Since its inception, it has been applied in a wide range of industries, including healthcare [11], security [12], telecommunications [13], education [14], software [15], and aviation [16], among others [17]. This has permitted the development of specialized software, both commercial—e.g., Celonis, Disco, Minit—and open-source—e.g., ProM, BupaR, pm4py—[18].

A 2010–2019 review by Kulakli and Birgun [19] showed that PM in the mining industry is severely understudied despite the expansion of PM in various industries. In general, there has been an increased application of data mining research in underground mining, especially in the last five years, leveraged by the information boom. However, this trend is not reflected in PM. Until the end of 2018, only 5 studies on PM in underground mining have been published [20], and to date, not more than 10 studies that refer to PM implementation in mining can be found in the current literature.

The main reason has been limited knowledge of PM algorithms and tools and their opportunities in the industry. Second, there is a lack of event log-oriented data for process modeling and analysis with PM. The application of PM is expected to increase, such as data mining in the mining industry [21], despite these challenges. Several studies [22,23] have demonstrated the creation of event logs from low-level data from mine monitoring systems and domain knowledge to overcome this challenge. Brzychczy and Trzcionkowska [24] presented a methodology for the generation of appropriate event logs from sensors in underground mines, given the low level of abstraction of the data available in the monitoring systems of the longwall.

He et al. [25] proposed the use of PM to study and improve the response of rescue teams to fatal explosions caused by gases in coal mines in China. The authors used 50 cases from a historical event log for their analysis. Szpyrka et al. [26] presented the implementation of a data preprocessing methodology for the generation of an event log from low-level data in a longwall process and the application of conformance checking (an area of PM) to detect possible discrepancies in how the process has really been executed. Brzychczy et al. [27] presented a case study of PM application in the evaluation of the roof bolting process in an underground mine. Previous studies focused on the preprocessing of data to generate event logs from low-level abstraction data sources and the analysis of processes carried out in underground mining using process discovery, conformance checking, and process enhancement techniques.

The authors are unaware of any work in the literature that optimizes resource management processes using PM. Specifically, no applications were found in the optimization of the mine maintenance cycles. The application of PM to asset management in the mining industry could be beneficial. Such benefits include providing a clear vision of the processes carried out in the field, their main defects, and correlating equipment failure type (or operator) and the cause of the failure. An added benefit is the determination of whether the delay in repairing a piece of equipment is due to technical or logistical issues, lack or shortage of spare parts, etc. However, the limitations are rooted in the need for an appropriate quantity and quality of data in an event log format, trained personnel to develop areas of process analysis with PM, and implementing and managing the change necessary for adopting corrective actions.

3. Discrete Event Simulation and Process Mining

Several publications in the literature demonstrate the application of DES for the analysis of mining processes, maintenance planning, and physical assets management [8]. These studies have a clear bias toward evaluating what to repair and the impact of effective repair times. They do not analyze the maintenance policies and processes from when a piece of equipment fails until it is repaired and returned to the field. Despite the high potential of integrating DES with PM, this combination has not been extensively explored nor used in the literature. DES and PM are two orthogonal areas with differences in their goal and approach that can complement each other's drawbacks.

The main differences between PM and DES are the data source of the represented model, the ability to evaluate alternative scenarios, and the graphical representation of process models. The first differentiating point is perhaps the most relevant. While the simulation typically works from probability distributions to generate data, PM, as a data science discipline, works from the data to create an analysis from the viewpoint of processes instead of events, as is the case of DES. Process mining excels in cases where the different variations of the process are the subject of study. DES is also considered a forward-looking (what-if analysis) approach, while PM is mostly used as a back-looking approach [28]. This study integrates DES and PM to achieve our research objectives. We use DES with expert judgment as a middle layer to preprocess the low-level data collected from the mine's system and generate an appropriate event log for analysis with PM. To the best of our knowledge, this is the first study that integrates DES and PM to optimize the maintenance processes of underground mining equipment.

4. Case Study

The case study was performed on the largest block caving copper mine in the world, with over 4500 km of tunnels. The mine did not have a standardized maintenance process, although it had initiated work to formalize and standardize the maintenance process. Historically, the course of action in the event of an equipment failure was based on the operators and maintenance crews' experience, adopting previous practices and adding new ones as the need arose. Some of the established policies included implementing reliability-centered maintenance (RCM) to address and prioritize failures at a strategic level and total productive maintenance (TPM) to address failures at a tactical-operational level, which sometimes incorporated a first diagnosis given by the operator. The maintenance team believed that an ideal model (Figure 1) could be generated and implemented by the mine.

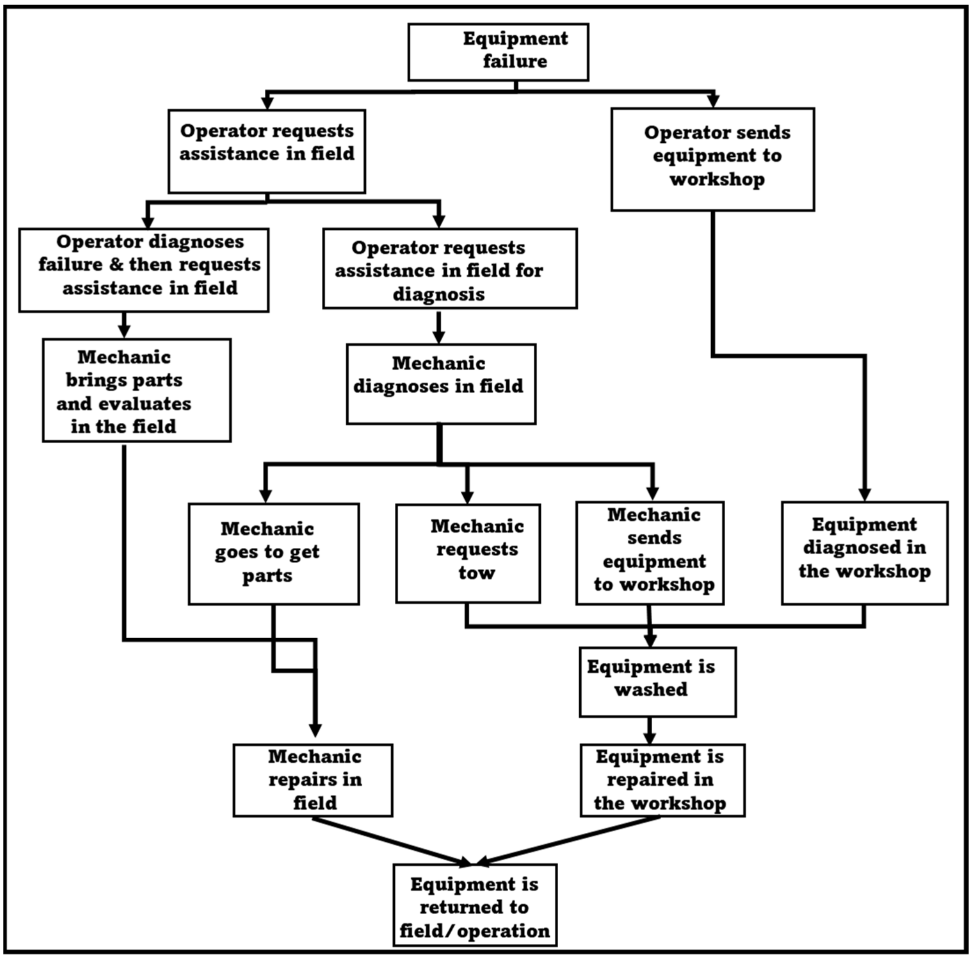


Figure 1. Ideal maintenance model for the LHD equipment, built based on expert judgment.

The model in Figure 1 was developed from the data obtained from the databases present in the systems, applications, and products management software (SAP) of the mine and expert opinion. Specifically, the databases consist of the orders and notices of production and maintenance requests for the LHD equipment. An interview with field experts involved in the maintenance process was conducted to understand the complete maintenance process from the time an LHD breakdown to its return to the field.

5. Solution Methodology

The workflow (Figure 2) included data extraction and transformation, system description and characterization, simulation modeling, and analysis with PM.

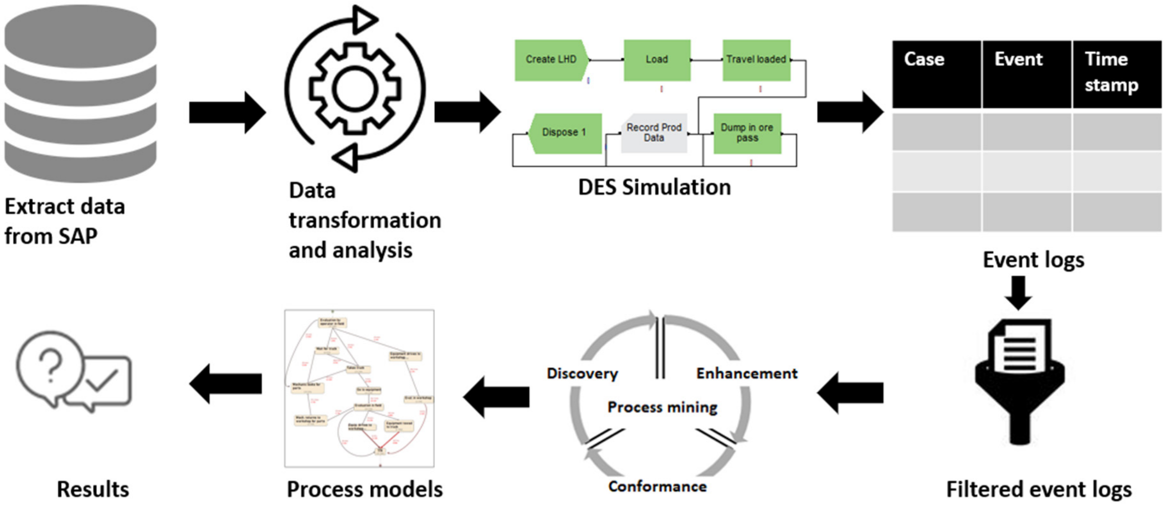


Figure 2. Solution methodology.

5.1. Data Collection and Processing

The databases used for this study were provided and reviewed together with experts from the mine maintenance section. The data were downloaded from the SAP system, which included the orders and notices records of the production and equipment maintenance. The data were collected for the years 2018, 2019, and 2020 (from January to June 2020).

The notices database (example in Table 1) consists of the requests made to the maintenance section to carry out a specific maintenance activity. It contains information such as the technical location of the failure, description of the technical location, notice code, description of notice, corresponding order code, duration of the maintenance, date and time of the start of the failure, date and time of the end of the failure, and classification of the failure.

Table 1. Example of Notices database.

Technical Location (Code)	Location	Maintenance Type	Description	Order Code	Duration of Failure (Hours)	Failure Start Date	Time at the Start of Failure	End of Failure Date	Time at the end of Failure
THLD-155-SES-BAL	Bucket LHD#155	2: corrective	Replace bucket pin	102030123	2.00	19 March 2018	13:00:00	19 March 2018	15:00:00
Code	Status	Stat. Syst.	Notice Code	Notice	Notice Descrip-tion	Time	Date	Created	Failure Code
X	New	MECE	21324565	PVEL001	HI234	15:20:39	19 March 2018	PVEL001	J20
Date modified	By	Part replaced							
20 March 2018	L Perez	MA1HT321							

The orders database (example in Table 2) is the record made by the maintenance team after the generation of the notice and once the maintenance commences. This contains information such as the technical location of the failure, name of the technical location, warning code, description, corresponding notice code, duration of the maintenance, date and time of the start of the failure, date and time of the end of the failure, failure classification, and actual cost of maintenance.

Table 2. Example Orders database.

Technical Location (Code)	Location	Actual Summed Cost (USD)	Notice Description	Notice Code	Order Code	Short Description of Failure	#	Code
THLD-155-SES-BAL	Bucket LHD#155	200.05	HI234	21324565	102030123	LHD bucket pin replacement	30	NP
Failure start date	Failure start time	Failure End date	Failure End time					
19 March 2018	13:00:00	19 March 2018	15:00:00					

The data were retrieved and ordered based on the order and notice codes. Records that showed inconsistencies were discarded as outliers or incomplete data. Such inconsistencies may be due to human error, as the team enters the data manually. The records for unplanned maintenance that present complete, coherent information and allow traceability of the evolution of the equipment over time are used. As a result, data from 2018 and 2019 were used for further analysis.

5.2. System Description and Characterization

The process analyzed was the production and maintenance cycle of the mine. It consisted of two interconnected environments—the production environment, made up of a tunnel system in which the LHD equipment extracts and transports the ore, and the maintenance area, which consists of a maintenance workshop with a capacity of 8 maintenance bays extendable to 10. The maintenance section was made up of a team of 16 mechanics in charge of 75 pieces of equipment, of which 36 were rock breakers, 15 jumbos (drill rigs), 2 secondary breaking jumbos, and 22 manual-operated mechanical LHDs. The LHD equipment studied has the system structure, components, and subcomponents presented in Table 3.

Table 3. LHD system, components, and sub-components.

System	Component	Subcomponent
Air Conditioning System (ACS)		
Electrical System (ELS)	Control system	
	Power system	
Structural System (SES)	Bucket	
	Bogie (framework)	
	Boom	
	Cabin	
	Chassis	
	Oscillating axle	
Hydraulic System (HIS)	Directional control system	Right steering cylinder
		Left steering cylinder
	Brake system	
	Lift and turn system	Right hoist cylinder
		Left hoist cylinder
		Tipping cylinder
Automatic Lubrication System (ALS)		
Motor System (MOS)	Diesel engine	
Fire Suppression System (FSS)		
Power Train System (PTS)	Torque converter-upper control	
	Differential	Front differential
		Rear differential
		Left front final drive
		Right front final drive
		Left rear final drive
		Right rear final drive
	Tire and Balance system	Right front tire
		Left front tire
		Right rear tire
		Left rear tire
	Transmission	

The operation and repair processes were characterized by modeling the time between failure (TBF) and time to repair (TTR) distributions. The Arena Input Analyzer software (v14.0) was used to model the data, as shown in Table 4. The input data modeled (Table 4) are historical data of subsystem failures collected from the SAP system for 2018 and 2019. The Weibull distribution (Table 4) is the most widely used distribution for equipment reliability modeling, and it is generally expressed as

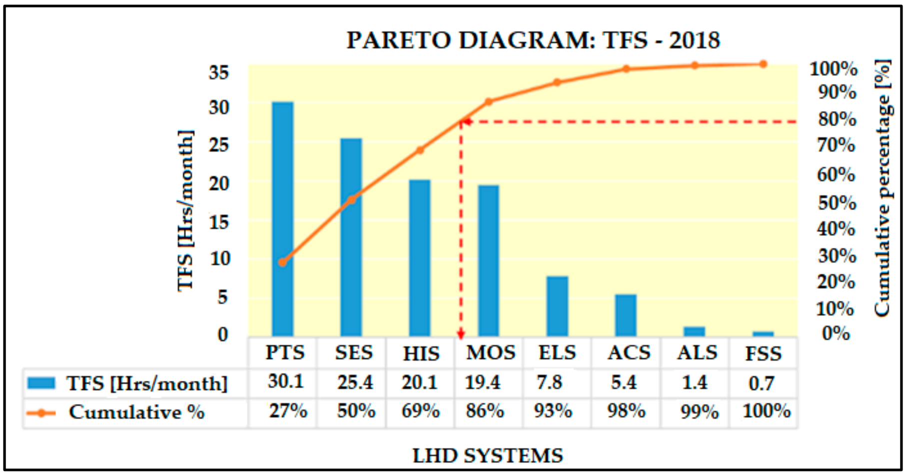
$$f(T) = \frac{\beta}{\eta}\left(\frac{T-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{T-\gamma}{\eta}\right)^{\beta}}$$

where $f(T) \geq 0,\ T \geq 0\ or\ \gamma\ ,\ \beta > 0,\ \eta > 0, -\infty < \gamma < \infty$, and β is the shape parameter; η is the scale parameter; and γ is the location parameter. The value of β determines the failure rate (early-life, constant, and wear-out failures).

Table 4. Probability distributions of subsystem failure.

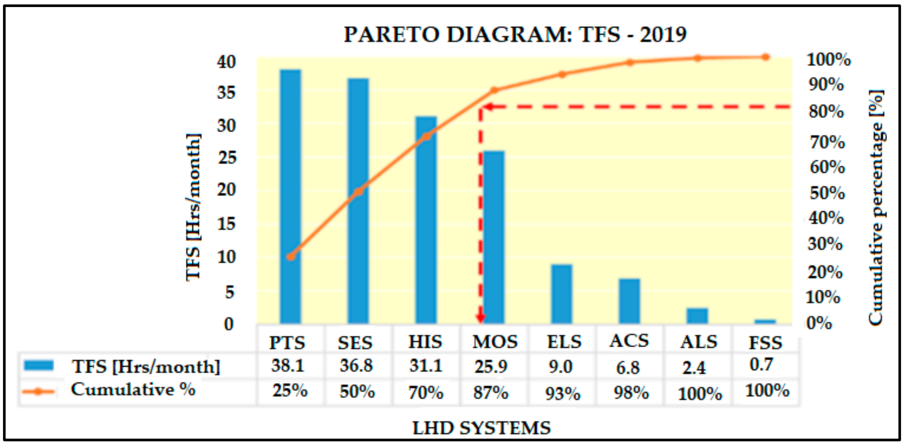
	TBF (Hrs.)		TTR (Hrs.)	
System	**Distribution**	**Expression**	**Distribution**	**Expression**
ACS	Weibull	WEIB (148, 0.631)	Exponential	EXP (3.8)
ELS	Weibull	WEIB (195, 0.807)	Weibull	WEIB (2.96, 0.761)
SES	Weibull	WEIB (189, 0.839)	Weibull	WEIB (3.6, 0.581)
HIS	Weibull	WEIB (140, 0.866)	Exponential	EXP (8.77)
ALS	Weibull	WEIB (92.7, 0.388)	Weibull	WEIB (4.32, 0.59)
MOS	Weibull	WEIB (137, 0.753)	Weibull	WEIB (3.27, 0.563)
FSS	Weibull	WEIB (4140, 0.649)	Weibull	WEIB (12.1, 0.786)
PTS	Weibull	WEIB (175, 0.772)	Weibull	WEIB (4.44, 0.567)

The most critical systems and components to be repaired can be determined based on the data. Standard metrics are used in physical asset management [29], which provide a strategic view and prioritize systems and time horizons for preventive maintenance. We perform a failure analysis using a Pareto diagram and a Jack-Knife diagram of global cost and reliability to understand equipment failure characteristics and analyze the LHD equipment maintenance process (Figures 3 and 4). Jack-Knife is a non-parametric approach used to estimate a sampling distribution for the failure data. Figures 3 and 4 show each system's time out of service or time from service (TFS) in 2018 and 2019.



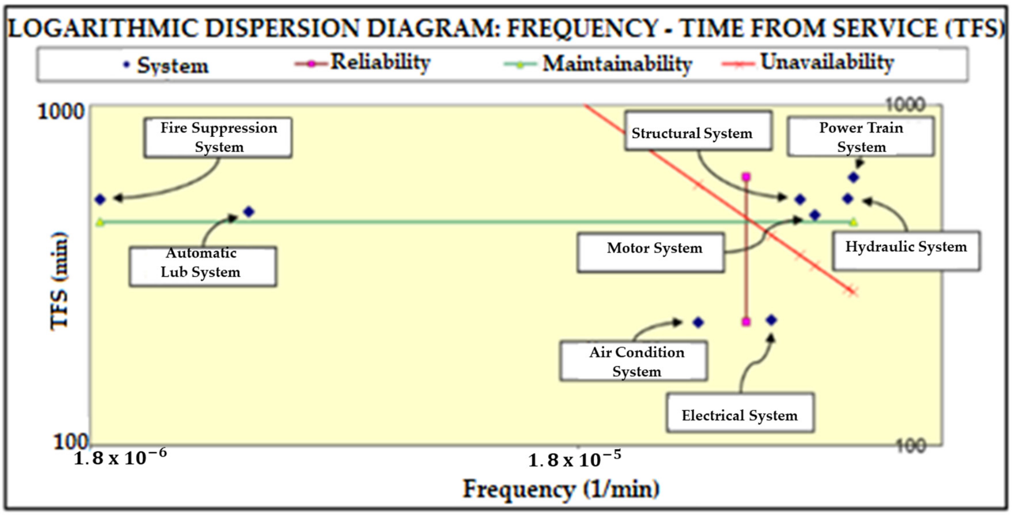
(**a**)

Figure 3. *Cont.*



(**b**)

Figure 3. Pareto diagram—LHD component failure analysis in (**a**) 2018 and (**b**) 2019.



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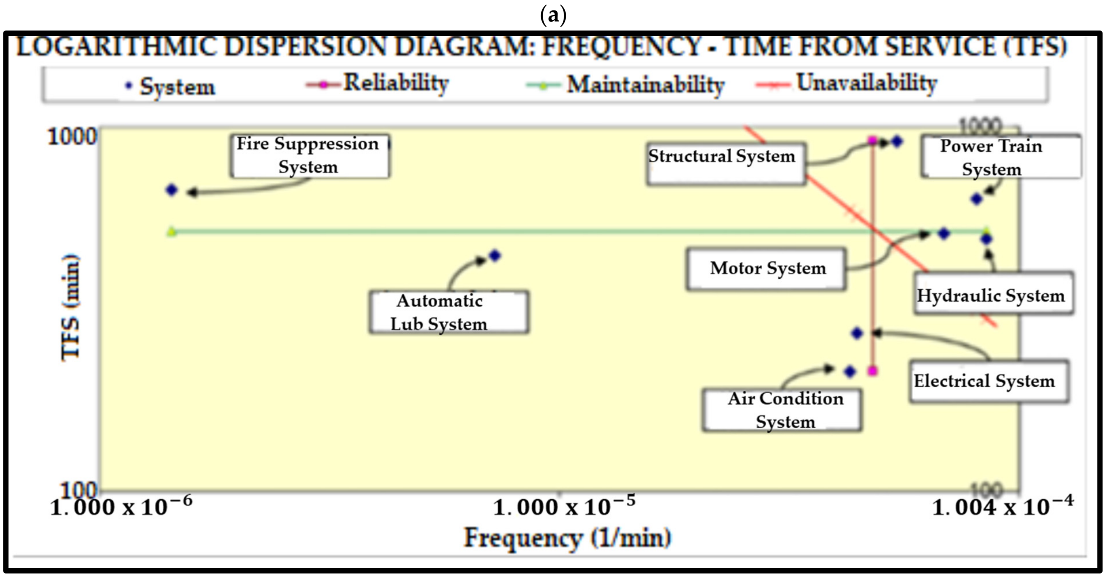


(**b**)

Figure 4. Jack-knife diagram—LHD component failure analysis in (**a**) 2018 and (**b**) 2019.

5.3. Simulation Modeling

The Pareto and Jack-Knife analysis and the implementation of an RCM-type maintenance policy effectively prioritize and determine which component to focus maintenance efforts on (e.g., PTS. SES. HIS) and outline a physical asset management strategy. However, they do not provide answers to how to optimize the maintenance process. We use PM to analyze the maintenance process from data, which allows the identification of failures, bottlenecks, and opportunities for improvement.

The mine does not capture the event log needed to perform PM analysis; therefore, we use DES to generate such data for the system studied. The DES is used to simulate the behavior of the time between failures and the effective time to repair at the system level using the distributions in Table 4. The production and maintenance cycle of the system is simulated using the Arena simulation software [30]. The LHD equipment is modeled as entities (objects that flow through the model) using the Create module in Arena (Create LHD in Figure 5). We then assign them attributes (Assign TBF and TTR in Figure 5) using the Assign module. The entities (LHD) go through the load-haul-dump production process (Equipment in production in Figure 5), keeping track of the time between failures. The equipment fails when the production time (after the equipment returns to the field) is greater than or equal to the TBF sampled from the input distribution (Table 4). The equipment then goes through the repair process based on TTR activity distributions (Activities in process in Figure 5). A record module is used to record production and activity times. The TBF is reinitiated once the equipment returns to the field (Reassign TBF to the repaired system in Figure 5).

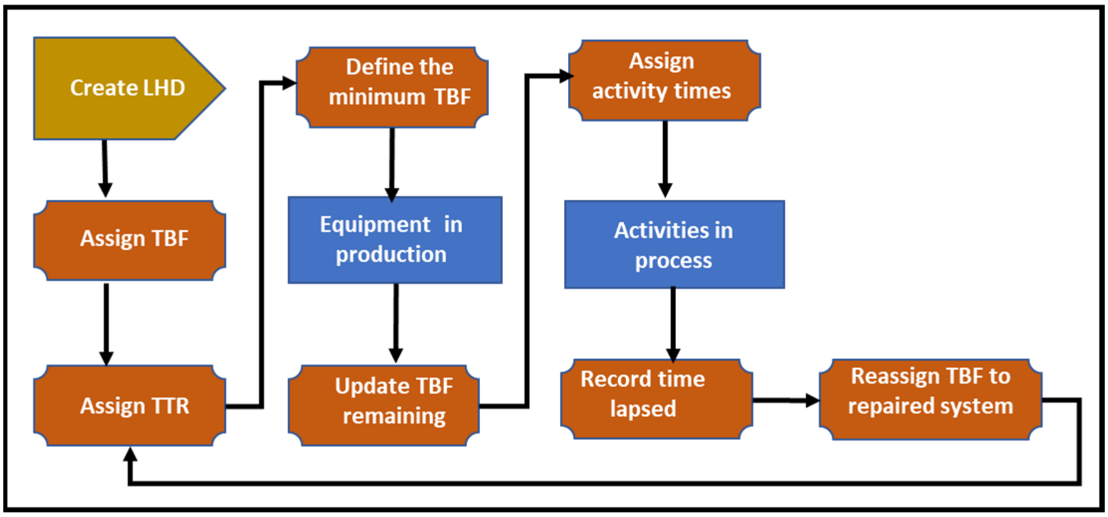


Figure 5. A flow diagram of the simulated LHD production system and maintenance processes.

Given that the mine's database did not generate logged data of the activities or contain all the data needed to perform the analysis, interviews with the mine's experts were used to generate the remaining data. The data generated from expert interviews were modeled deterministically (e.g., Operator evaluation time in the field) or with a triangular distribution where the minimum, mode, and maximum values are used (e.g., The time it takes for the mechanic to look for spare parts (Table 5)). Figure 5 shows a summarized flow diagram of the LHD maintenance process simulated in Arena. The DES model can be mathematically expressed as follows:

$$\{x_1(t), \ldots\ldots, x_p(t)\ \}\ t_0 \leq t\ \leq t_f$$

$$\{y_1(t), \ldots\ldots, y_m(t)\}\ t_0 \leq t\ \leq t_f$$

$$x(t) = \left[x_1(t), \ldots\ldots, x_p(t)\right]^T$$

$$y(t) = \left[y_1(t), \ldots\ldots, y_m(t)\ \right]^T$$

$$y_1(t) = f_1\left(x_1(t), \ldots\ldots., x_p(t)\ \right), \ldots.., y_m(t) = f_m\left(x_1(t), \ldots\ldots., x_p(t)\ \right)$$

$$y = f(x) = \left[f_1\left(x_1(t), \ldots\ldots., x_p(t)\ \right), \ldots.., f_m\left(x_1(t), \ldots\ldots., x_p(t)\ \right)\right]^T$$

Table 5. Probability distribution of maintenance process activities.

Activity	Values and Time Distributions (Seconds)
Operator evaluation time in the field	600
The time it takes for the mechanic to look for spare parts	TRIA (300, 600, 900)
The time the mechanic spends waiting for an unavailable tool	TRIA (750, 900, 950)
The time the mechanic waits for a truck to be available to go to the field	TRIA (1800, 2700, 3600)
The time it takes for the mechanic to receive, check, and drive the truck	300
Travel time from workshop to equipment	TRIA (1800, 1800, 7200)
Time for evaluation in the field by a mechanic	600
The time it takes for the mechanic to return to the workshop to look for spare parts	TRIA (1800, 1800, 7200)
The time it takes to tow the equipment to the workshop as a result of a major failure	TRIA (9000, 12,600, 57,600)
The time it takes for the equipment to travel to the workshop with a minor failure	TRIA (1800, 1800, 7200)
The time it takes for a piece of equipment to arrive at the workshop when transported by the operator	TRIA (1800, 1800, 7200)
The time it takes for a piece of equipment to be evaluated in the workshop	600
Queuing time for washing	TRIA (3600, 5400, 10,800)
The time it takes for a piece of equipment to be disassembled to remove an urgently needed part for another piece of equipment.	TRIA (3600, 7200, 10,800)
Waiting time for spare parts in the workshop	TRIA (600, 1200, 1800)
The time it takes for the mechanic to attend to an emergency before returning to the equipment	TRIA (1800, 14,400, 28,800)
The time that the equipment waits to be returned once it leaves maintenance	TRIA (1200, 4800, 6000)
The time that the equipment takes to return to the field since its withdrawal from the field	600
Equipment wash time	TRIA (1800, 2700, 10,800)

The input (e.g., LHD loading and travel times) and output (e.g., production, TBF) are given by the vectors $x(t)$ and $y(t)$, respectively, and f is the function that expresses the relationship between x and y over time t. The inputs x are in Tables 4 and 5. The output y is used for model validation and the event log data generation.

5.4. Creating an Event Log

We used the read/write module in Arena as the basis to generate an event log of activities and their simulated times. An example of the event log is presented in Figure 6. The log consists of a failure event ID number, equipment ID, the system component, current time (TNOW in seconds), time between failure (TBF in seconds), diagnosis time in the field (in seconds), and time searching for parts (in seconds), among others.

ID #	Equipment	System	TNOW (seconds)	TBF (seconds)	Time eval. Op in field (seconds)	T maint. search for parts (seconds)
7	LHD-1	6	536,247	26,430	600	565656956
12	LHD-1	8	994,291	39,333	600	530
15	LHD-1	1	1,464,157	189,224	600	565656956
23	LHD-1	2	2,244,755	17,705	600	565656956
32	LHD-1	2	3,842,587	114,831	600	608
55	LHD-1	6	7,780,448	39,041	600	518

Figure 6. A preview of the database generated from the simulation model. The arbitrary code "565656956" is used where activities were not performed.

The events are presented in chronological order. In cases where activities were not performed, an arbitrary code "565656956" was defined as default. The event log is the key input to the PM analysis. Therefore, it must be consistent and ordered to avoid compromising subsequent analysis.

5.5. Process Mining

We used a Directly-Follows Graph Process Discovery algorithm [31] through the Disco Process Mining tool [32]. Directly-Follows Graph was selected given the understandability of the resulting process models for non-experts in PM, its efficiency, and its implementation on most commercial and open-source PM tools.

The notations and PM concept used are defined as follows:

- Consider a set of global attributes A_{global} and $\{acName, timestamp, acID\} \subseteq A_{global}$, where $acName$ is the activity (case) name (e.g., diagnose LHD in the field), timestamp is the time stamp that an event occurs (e.g., LHD failure), and acID is the process identifier that the event belongs to (e.g., ID number in Figure 6).
- $V \in A_{global} \Rightarrow \mathbb{P}\left(V_{global}\right)$, where V_{global} is the set of global values V and $\mathbb{P}\left(V_{global}\right)$ returns all the possible values an attribute can take.
- $M_{global} = \left\{m \in A_{global} \nRightarrow V_{global} \,\middle|\, \forall at \in dom(m) : m(at) \in V(at)\right\}$ maps attributes to their correct values at.
- We define $\perp \in V_{global}$ such that $\perp \notin V(at)\, \forall at \in A_{global}$. That is, $\perp$ is a subset of the global values where $\perp$ is an arbitrary value for attributes with a missing, undefined, or unknown number.
- Therefore, for an event $e \in \xi$ with a known timestamp, associated activity name, and identifier, $e(acName) \neq \perp$, $e(timestamp) \neq \perp$, and $e(acID) \neq \perp$.
- The event log is in chronological order. Therefore, $e_j(timestamp) \leq e_k(timestamp)$ if e_j occurs before e_k and $e_j(acID) = e_k(acID)$ if e_j and e_k belongs to the same process (case) instance. Events related to the same process instance are known as the Trace.

Once the event log is uploaded to the Disco software, the tool displays the process variants developed during the maintenance cycle. Workflow filters are then used to perform the different analyses and draw inferences.

The following aspects were considered in the analysis:

- The opportunity cost of non-productivity must be considered when analyzing the process.
- Economic analysis can be used to determine the maintenance strategy to be followed. However, its execution can be improved regardless of the selected strategy.
- The event log used was generated from a simulation model that modeled the time between failures and the time to repair the LHD as distributions.
- The model was validated through expert opinions at the mine under study.
- The result of this analysis does not seek the direct implementation of PM as a standard by the mine but presents an opportunity for improvement.

The LHD equipment maintenance process is analyzed based on the components with the most frequent failure or the most complex and acute components. The event log generated had 25,644 case instances—that is, the maintenance process of 25,644 failures that occurred to 22 LHD equipment. The data were generated for a period of 5 simulated years. Among the instance, 30 variations of the process were observed, starting from the time a piece of equipment fails until it returns to the field. The foregoing gives notions of the low level of standardization and/or the dynamism of the process and the existence of multiple decisions. Two key decision-makers were identified, the operator and the maintenance team. Their decisions modify the analyzed process without prejudice to the fundamental role played by maintenance planners, analysts, and supply personnel.

Two maintenance environments are seen in the Disco software process flow—the workshop and the field. All maintenance carried out in the workshop must first go through the "Washing" activity (represented by the "Equipment queued for washing" activity in Figure 1), which generates a bottleneck. The role of the operator is recognized as the first diagnosis, which is reflected in two key decisions; the first is related to taking the equipment to the workshop or requesting the mechanic to diagnose the equipment in the field. The second is a diagnosis first by the operator and relating the diagnosis to the mechanic or ignoring it (Figure 1).

Additional activities were detected as part of the process during a conformity analysis with the field experts that could be considered bottlenecks or inefficiencies in the process. Conformance checking techniques compare observed behavior (i.e., event data) with modeled behavior (i.e., process models) to identify deviations. The impact of bottlenecks can be measured in terms of the time added to the maintenance cycle, which entails an opportunity cost defined by the economic value of the material that the equipment does not extract when it is unavailable. The identified activities and bottlenecks identified during conformance checking include the following:

Additional activities:

- Mechanic looking for spare parts.
- Mechanic travels by work truck.
- Mechanic tows the equipment.

Bottlenecks (process delays):

- Mechanic leaves to attend to an emergency.
- Equipment waiting to be extracted from the field.
- Equipment queued for washing.
- Mechanic waits for the work truck.
- The equipment is disassembled to remove an urgently needed part for another piece of equipment.
- The mechanic returns to the workshop to look for a spare part.
- Waiting for spare parts
- Mechanic waiting for tools.

Five key stages of the process are established and analyzed—diagnosis/initial evaluation, reaction time, failure prioritization, preparation process, effective maintenance, and return to field operations.

5.5.1. Diagnosis/Initial Evaluation

A process filter is first applied, eliminating all instances in which the "Wash" activity is carried out to obtain the instances of field maintenance. This has resulted in 7059 instances (27.5%) of the 25,644 total generated in the 5-year simulation. This value is close to the 30% defined by the field experts as a general rule.

Subsequently, the model is changed to show only the cases that included the "Washing" activity to obtain failures repaired in the workshop, resulting in 18,585 (72.5%) instances. The greater the complexity of these variants is, the higher the variability in the process itself is. Unlike failures repaired in the field, the process to repair in the workshop takes longer, with a mean time to repair (MTTR) of 8.2 h. It is evident that the faults repaired in the field are less acute, repaired faster, and less frequent (Table 6). Eliminating the bottlenecks in the process can significantly reduce the time to repair and have more people available for critical failures in the workshop or emergencies.

Table 6. Comparative summary of variants repaired in the workshop versus in the field.

Maintenance Location	Number of Instances	MTTR
Field maintenance	7059	21.8 min
Workshop maintenance	18,585	8.2 h

The evaluation of maintenance in the field revealed three inefficiencies in the process. The first was when the operator tells the mechanic that the breakdown can be repaired in the field but misdiagnoses the failure. This occurred in 1062 instances (4.14% of the total), on average, which is 212.4 instances per year. When a misdiagnosis was made, the maintenance process duration increased by 142.2 min, the equivalent of 503 h per year. The second error was when the operator indicated that the failure cannot be repaired in the field, yet it can. This failure occurred in 1669 instances (6.5% of the total) and, on average, 333.8 instances per year. Each time this diagnostic error was generated, the maintenance process duration increased by 112.3 min (625 h per year). The third error in the Diagnosis/Initial Evaluation stage occurred when the operator indicated that it can be repaired in the field but cannot. This failure occurred in 12,579 instances (49% of the total), which was 2515.8 instances per year on average. The maintenance process duration was increased by 16.2 min when such an error was made, resulting in an increase of about 679 h per year.

In the case of workshop maintenance, we analyzed the average time from failure until they reached the "Wash" activity depending on whether the operator requested assistance on-site first (16,335 cases—63.7% of the total cases) or took the equipment directly to the workshop (2250 cases—8.8% of the total cases). In the first instance, it is observed that the average time between the operator carrying out the evaluation in the field and arriving at the workshop for washing was 287.7 min. In contrast, in the second case, it was 73.9 min. This difference occurred because, in 30.6% of the cases in which the operator requested an on-site diagnosis from the mechanic, it was necessary to tow the equipment to the workshop, which had an average duration of 6.7 h. It did not include cases where the equipment was in a condition to be driven directly to the workshop.

It was deduced that 70% of the failures in which the operator requested a field diagnosis did not require towing, and the equipment could have been taken directly to the workshop. If properly diagnosed, this would have generated a saving of 213.7 min in 11,337 cases (44% of the total cases). If the operator had been trained to make a better diagnosis, the availability of the equipment could have increased by 8076 h per year.

5.5.2. Reaction Time

The reaction time of the mechanics was affected by the limited work truck fleet needed to go to the place where the LHD equipment was located. In 7038 instances (27.4% of the total), the mechanics had to wait for a truck, which increased the response time by 44 min per failure. This was equivalent to 1407.6 delays (1032 h) per year.

5.5.3. Failure Prioritization

The third stage of the process is the failure prioritization process. Once an operator requests assistance and a diagnosis of the failure is carried out in the field, it is classified according to whether the equipment needs to be towed and escorted to the workshop (major failure) or can travel to the workshop by itself (minor failure). This classification is relevant when planning which failures to prioritize, given that 4998 instances required towing, with an average transfer time to the workshop of 6.7 h. Comparatively, 11,337 instances did not require towing to the workshop and had an average transfer time of 57 min. In other words, approximately seven units with minor faults are equivalent to one unit with a major failure. This generates a trade-off that must be considered (Table 7). The effective maintenance time of an acute failure is greater than that of a minor failure. Equipment with an acute failure not removed and taken to a workshop can obstruct haulage ways, preventing its use by other equipment. Therefore, it is important to analyze each case to determine if it is possible to postpone the repair of an acute failure to accelerate the return to the operation of equipment with a minor failure.

Table 7. Comparison of minor and major failures repaired in the workshop.

Type of Failure	Number of Instances	Transfer Time	Unavailable Time Due to Transfer to Workshop
Minor Failure	11,337	57 min	2154 h/year
Major Failure	4998	6.7 h	6697 h/year

5.5.4. Preparation Process

The preparation process begins once the equipment enters the "washing queue" and ends when it reaches the maintenance bay. At this stage, several activities are considered bottlenecks, such as the queue for washing, waiting for tools, equipment disassembly to repair other more critical ones, maintenance breaks to address emergencies, and waiting for spare parts.

Of the instances evaluated, 9268 (36.1% of the total) maintenance tasks were paused to attend to an emergency, which takes an average of 246 min. Instances related to waiting in line to enter the wash were 3709 (14.4% of the total), with an average time of 106.7 min. Additionally, 73 (0.3% of the total) were related to the mechanic waiting for tools for about 13.9 min on average. Cases where the equipment must be disassembled to deliver parts to another piece of equipment with a higher priority to return to operations attributed to 1651 (6.4% of the total cases) instances (an average of 20.1 min). Finally, 5596 (21.8% of the total cases) instances were cases where the team had to wait for a replacement for about 144 min on average. The availability of tools had the least impact compared to other bottlenecks. Notably, the operating losses at this stage totaled 9958 h/year.

5.5.5. Effective Maintenance and Return to Operation

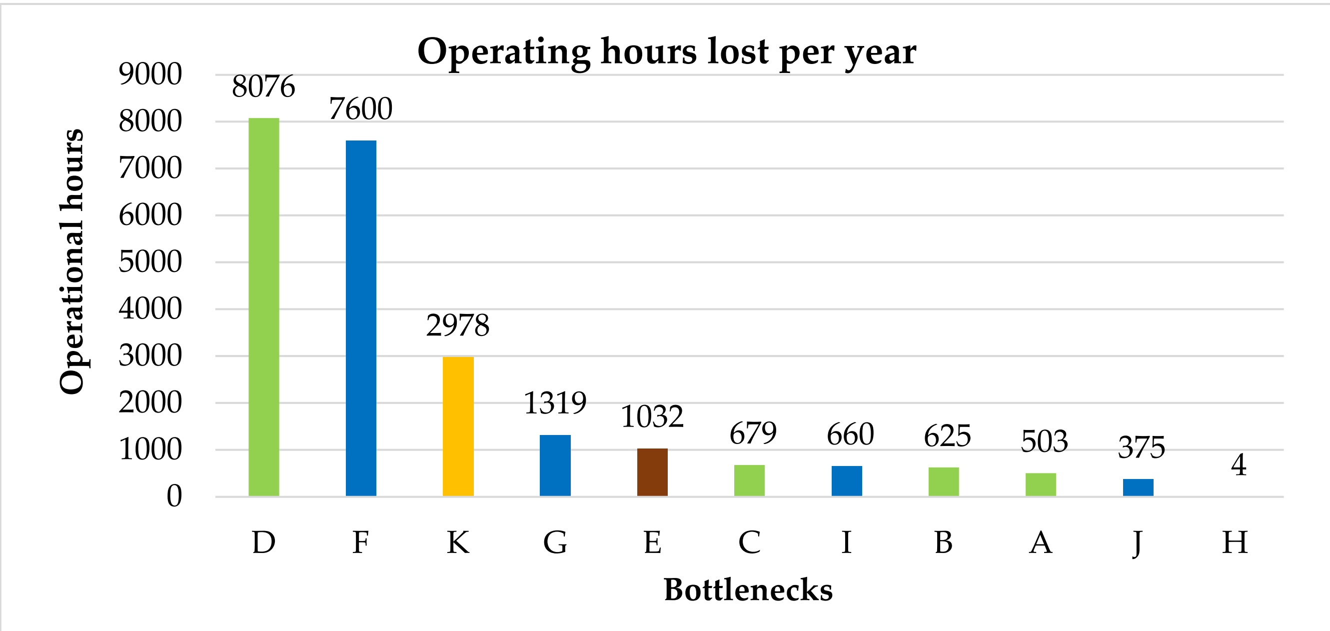
The last stage of the process is the effective maintenance and return to field operation stage. The analysis revealed that 25,644 instances had a MTTR of 6.0 h, with a median of 4.6 h. This indicated that a fair number of minor failures exist that deviate from the meantime to repair. On the other hand, 12,948 (50.5%) of the instances involve equipment waiting an average of 69 min for their return to the field after repair, equivalent to operating losses of 2978 h per year.

6. Results

Based on the LHD maintenance process analysis, an equivalent downtime was computed for the different bottlenecks. The downtimes represent the time that the equipment stops working while undergoing the maintenance process and incurs a non-productive opportunity cost. Table 8 shows the downtime of each non-productive activity and its corresponding opportunity cost. From Figure 7, it is evident that the greatest impact on lost operating hours is associated with the misdiagnosis by operators who requested towing from the field and could have traveled to the workshop without needing towing. This can be minimized through operator training and strengthening operator–mechanic relations, which also addresses other causes of operational loss.

Table 8. Opportunity cost due to downtimes in the LHD maintenance process.

Code	Operational Bottlenecks	Number of Cases per Year	Downtime Due to Failure (Minutes)	Annual Downtime (Hours)	Opportunity Cost (KUSD/Year)
A	Wrong initial diagnosis of the failure	212	142.2	503	24
B	Operator erroneously indicates that failure cannot be repaired in the field	334	112.3	625	29
C	Operator erroneously indicates that failure can be repaired in the field	2516	16.2	679	32
D	Operator requests towing but does not need towing	2267	213.7	8076	378
E	Mechanic must wait for a truck	1408	44	1032	48
F	Breaks due to other emergency maintenance	1854	246	7600	356
G	Equipment waiting for washing	742	106.7	1319	62
H	Waiting for tools	18	13.9	4	0.22
I	Equipment is disassembled to fix another	330	120	660	31
J	Equipment waiting for parts	1119	20.1	375	18
K	Equipment awaits return to operation	2590	69	2978	140
	TOTAL			23,852	1.12 M



	Diagnostic Stage
	Reaction Time Stage
	Preparation Stage
	Effective Maintenance Stage and Return to Operation

Figure 7. Pareto analysis of operating hours lost due to failure.

The second highest impact is given by the detention of maintenance to address other equipment failures that require urgent attention (Figure 7). This must be analyzed in depth to detect the root cause of these unforeseen events and favor operational continuity. The third highest impact on equipment availability is waiting for the equipment to be returned to the field after repair. This is a logistical factor that must be addressed urgently, given its impact.

Although the waiting time for washing is a bottleneck in the process, a cost–benefit analysis must be performed to determine whether it is economically feasible to build another washing station to speed up the process. An analysis must be performed to determine if there will be enough personnel to cater for the equipment by having more than one piece of equipment washed and prepared for maintenance. Finally, the option of having more work trucks available to transport maintenance personnel to the field should also be evaluated to determine its impact on operational losses.

Overall, a standardized maintenance procedure that determines whether a piece of equipment should be repaired in the field or the workshop, how long the maintenance should take on average, or if its performance is within normal limits will be beneficial to the mine. The maintenance manager is also interested in which mechanic has the shortest time to repair a piece of equipment and what the mechanic does differently.

Similarly, personnel who interact with the maintenance section, such as the equipment operator, should know their role in the maintenance cycle and how it affects the operation. For example, the operator must know when to ask for assistance in the field or take failed equipment to the workshop. The operators must understand activities that contribute to the better overall performance of the equipment.

7. Conclusions

This research applied PM in the analysis and optimization of the mine maintenance processes. The maintenance process of an LHD equipment in the largest underground copper mine in Chile was used as a case study. We identified the availability of generated logged data by a system and the quality and quantity of the data as pertinent challenges limiting PM use in the mining industry. To overcome this challenge, we employed DES, along with expert opinions and domain knowledge, to generate a database of 25,644 simulated instances for the production and maintenance systems of an underground copper mine. The DES output was validated by field experts. The equipment failure data were collected and filtered, and unplanned failures of the subsystems of the LHD equipment were identified. Five stages of the production and maintenance processes were analyzed, including diagnosis/initial evaluation, reaction time, failure prioritization, preparation process, effective maintenance, and return to operation. The analysis identified 11 non-productive activities and their lost time and opportunity cost. The total loss time was determined to be 23,800 h per year with a cost, due to non-production, of about 1.12 MUSD/year. It was determined that the highest productive time losses were associated with the misdiagnosis by operators who requested towing from the field and could have traveled to the workshop without the need for towing. The detention of maintenance to address other equipment failures that required urgent attention and waiting for the equipment to be returned to the field after repair also contributed significantly to lost productive time.

Although the data used to generate the log were obtained from the mine maintenance system and expert interview, it is recommended that future work use actual logged data generated by the system—an aspect that is difficult to achieve, particularly in the mining industry. We also recommend the field testing of the recommendations made to the mine, such as increasing the maintenance team truck fleet and training LHD operators to better diagnose equipment failures. The analysis performed in this research can be applied to other equipment, mining methods, and mine areas. Further research will study this aspect.

Using a case study, our research sets the first precedent regarding the implementation of PM to optimize the maintenance cycle of underground mining equipment and highlights the need for field implementation in the industry. Process mining obtained a non-biased representation of the process and aided in identifying bottlenecks and inefficiencies in the equipment maintenance processes. It provided quantifiable impacts of inefficiencies in the process, allowing for optimal decision-making.

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