School of Mining Engineering

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

APPLICATION OF DATA ANALYSIS AND MACHINE LEARNING TO DEVELOP A MAINTENANCE STRATEGY FOR LOAD-HAUL-DUMP (LHD) MACHINES AT BOOYSENDAL MINE

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Report Declaration

I declare that this research report is my own unaided work. It is being submitted for the degree of Master of Science in Engineering at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other university.

I have familiarised myself with the University of the Witwatersrand Student Academic Misconduct Policy (SAMP). I hereby declare that the work I am submitting for assessment is my original work. I affirm that I have not plagiarised, misrepresented, or colluded with any other person or source. I have properly acknowledged, cited, and referenced all the sources that I have used in my work. I also declare that where I have used artificial intelligence (AI) tools it has only been as a means of guidance. The ideas and arguments presented in my work are my original thoughts and interpretations. I acknowledge that any academic misconduct, such as plagiarism or collusion will result in serious consequences. According to the SAMP, these consequences may include a reduced grade, a fail mark, or disciplinary action. The Faculty of Engineering and the University of the Witwatersrand have my consent to investigate any potential academic misconduct in my work. This investigation may include the use of similarity and AI detection software to check the originality of my work. I undertake to abide by the decision of any such investigation.

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03 day of October , 2024

(month) (year)

“An inspirational quote”

“Don’t feel entitled to anything you didn’t sweat and struggle for.” — Marian Wright Edelman

ABSTRACT

This report focuses on applying data analysis and machine learning to develop a maintenance strategy for load-haul-dump (LHD) equipment at Northam Platinum's Booysendal underground mine. This operation predominantly relies on trackless mobile machinery, with a significant emphasis on LHD machines. The mine maintains daily records of mechanical equipment breakdowns. However, Booysendal's reliance on a reactive "run-to-failure" maintenance system has led to operations outside a predefined maintenance plan.

The objective of this research was to apply data analytics to understand trends in the dataset and extract meaningful insights regarding LHD breakdowns. It aimed to develop a predictive maintenance model for LHD machines using appropriate machine learning models. Lastly, to design a data-driven maintenance strategy based on insights from data analysis and machine learning (ML).

The hydraulic system and transmission components were found to contribute 80% towards downtime. The K-Nearest Neighbours (KNN) regressor was chosen as the best regression model, achieving the lowest Root Mean Square Error (RMSE) of 2.02, while the Support Vector Machines (SVM) classifier was selected as the best classification model with the highest accuracy of 60%. Recommendations on how the predictive models could be improved were highlighted.

Finally, a hybrid maintenance strategy is proposed for proactive optimisation. The strategy entails integrating predictive analytics, real time condition monitoring and threshold-based alerts to enable proactive maintenance actions. The proactive actions include ensuring availability of critical spares and conscientizing LHD operators on failures related to bad operating practises.

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviation	**Description**
AI	Artificial Intelligence
ARMA	Autoregressive Moving Average
DBN	Deep Belief Networks
DNN	Deep Neural Network
DT	Decision Trees
Eh	Engine Hours
EPFAN	Electric Power Fan
EVS	Explained Variance Score
FIT	Failure In Time
KNN	K-Nearest Neighbours
KPI	Key Performance Indicator
LHD	Load-Haul-Dump
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ME	Maximum Error
ML	Machine Learning
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
MTTF	Mean Time To Failure
OEM	Original Equipment Manufacturer
R^2	R-squared
RBF	Radial Basis Function
RF	Random Forest
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
RSF	Random Survival Forests
RUL	Remaining Useful Life
SAE	Stacked Autoencoder
SVM	Support Vector Machine
TBF	Time Between Failures

LIST OF EQUATIONS

1 INTRODUCTION

1.1 Research Background and Context

The study was carried out at the Booysendal mine, which is one of the mines that constitute the Northam Platinum Limited Group. The fully mechanised mine adopts a bord and pillar mining method at shallow mining environment. Northam Platinum's Booysendal mine is a large-scale, mechanised platinum group metals (PGM) operation located on the eastern limb of South Africa's Bushveld Complex in Mpumalanga Province. The mine began operations in 2013 and is divided into North and South mines. Declines are used as the primary form of access for men and materials into the underground environment.

The Bushveld Igneous Complex in South Africa is a cornerstone in the global production and reserves of platinum group metals (PGMs), including platinum (Pt), palladium (Pd), rhodium (Rh), osmium (Os), iridium (Ir), and ruthenium (Ru), accounting for more than 70% of the world's known mineral reserves (Gibson et al., 2023). In line with mechanisation strategies, several mining operations within South Africa have transitioned to trackless mobile mining equipment to enhance operational efficiency. A prime example is Booysendal Mine, managed by Northam Platinum Limited, which extensively uses trackless mobile machinery, especially Load-Haul-Dump (LHD) machines, to bolster production within the Bushveld Complex. Booysendal Mine relies on LHD machines for conveying ore from stoping and development sections to the main conveyor belts. The optimal availability of this equipment is important for cost reduction and maintaining high production rates (Wolff & Schmitz, 2017). The study by Wolff and Schmitz (2017) highlighted the mine's potential for increased production and economic improvement through strategies like enhanced planning and optimised mining methods.

The mine keeps daily records of mechanical equipment breakdowns. These records detail types of failures, associated downtime, and availability, providing insights into LHD machine operational health. The profound impact of LHD machine breakdowns on daily production targets has been evident, with instances revealing substantial downtimes leading to reduced availability and production rates (Khethani, 2022). According to MacIntyre (2013), the prolonged recovery periods are attributed to uncoordinated and unplanned LHD maintenance practices. This highlights the criticality of understanding the parameters influencing breakdowns.

This research endeavours to develop a machine learning-based maintenance strategy for LHD machines, with emphasis on both the prediction of maintenance needs and an in-depth analysis of trends in breakdowns. Predictive capabilities aim to enhance scheduling and planning, while analysing breakdown aids in formulating an optimised maintenance strategy. Therefore, development of a comprehensive predictive machine learning (ML) model, using the mine's two years of daily operational data, forms the crux of this research.

1.2 Problem Statement

Booysendal Mine's reliance on a reactive maintenance system, known as the "run-to-failure" approach for its LHD machines, has resulted in operations outside a predefined maintenance plan. Despite resource allocation to enhance LHD maintenance practices, this approach has led to significantly low equipment availability and utilisation. Reports from Northam Platinum Limited (2020) indicate that LHD machine availability and utilisation is around 78% and 70%, respectively. This is below the minimum acceptable benchmark of 85% (Khethani, 2022). The LHD machines at the mine significantly surpass their designed operational hours, averaging 21,787 hours without refurbishment compared to the intended 13,500 hours. This extended operational duration escalates the risk of failures, causing unplanned downtime and expensive repair endeavours (Khethani, 2022).

These challenges directly hinder the mine's ability to meet production targets, posing a substantial risk to operational efficiency and cost-effectiveness.

The current maintenance strategy for LHD machines at the mine faces significant challenges, particularly in terms of accurately capturing failure or breakdown information. The lack of uniformity in the “naming” and categorisation of failure types contributes to inconsistencies and delays in comprehensive understanding of the issues. For example, similar failure types are often captured using differing phrases. The absence of detailed reports on the actions taken by artisans, with breakdowns reported solely by operators makes it difficult to design an efficient maintenance strategy.

To address these challenges, a data-driven maintenance strategy for LHDs based on data analysis and ML models has been developed and proposed for adoption by the mine. This includes a new and improved data capturing system for LHD breakdowns and related maintenance information.

1.3 Justification for Research

Operating as a board and pillar mine, Booysendal Mine stands as a significant contributor within the mining industry, playing an important role in meeting the global demand for minerals and metals. The reliance on trackless mobile equipment, particularly LHD machines, is key in material movement and production processes. The reliability and availability of these machines directly dictate production efficiency, operational costs, and overall business profitability. Consistent machine availability ensures smooth operation, leading to lower operational costs related to repairs and spare parts. Frequent breakdowns can result in missed production targets and reduced revenues. High reliability reduces unplanned maintenance and extends equipment lifespan, enhancing overall business profitability through increased productivity and cost savings.

Dayo-Olupona, et al (2023) demonstrated a proposed ML-based maintenance strategy aimed at enhancing equipment reliability, cut maintenance costs, and minimise downtime. In order to prevent breakdowns, this strategy fostered an efficient and profitable mining operation, important for sustained growth. An example of a relevant case study that supports the effectiveness of ML-based maintenance strategies in enhancing equipment reliability and reducing costs involves a large machine manufacturer that implemented a predictive maintenance system for mining equipment. This strategy focused on identifying early signs of engine failure, such as temperature and pressure fluctuations. Applying deep learning models to monitor sensor data allowed the company to successfully predict and address potential issues before they resulted in costly breakdowns, significantly reducing downtime and enhancing operational efficiency (Mosaic, 2024).

The use of machine learning (ML) in maintenance strategies is justified due to its ability to analyse large volumes of data and identify patterns in equipment performance that are not easily detectable through traditional methods. ML models can predict when components are likely to fail, allowing for proactive interventions that reduce unplanned downtime and costly repairs. The "run-to-failure" approach leads to frequent breakdowns and increased operational costs due to unforeseen failures, making production unpredictable. Predictive maintenance using ML offers several advantages, such as improving equipment availability and reliability by anticipating failures based on real-time data.

1.4 Research Objectives

This research focuses on developing maintenance practices for LHD machines at Booysendal Mine through data analysis and ML applications. The primary objectives are as follows:

- To apply data analytics to identify the trends in the dataset and extract meaningful insights regarding breakdowns of LHDs at Booysendal Mine.
- Develop predictive maintenance models for the LHD machines using appropriate ML models.
- Design a data-driven maintenance strategy based on insights from data analysis and ML.

1.5 Structure of the Research Report

The report starts with Chapter 1 which discussed the research background, presented the problem statement and objectives and provided an overview the methodologies employed. The subsequent chapters cover the following:

- Chapter 2: Explores literature on LHD machines, LHD downtime, types of LHD machines used at Booysendal Mine and the LHD’s critical components and associated failure types. The following is also explored: mining equipment key performance indicators (KPIs), maintenance strategies for LHDs, maintenance costs, machine learning models applicable to predictive maintenance of mine production equipment.
- Chapter 3: Methodology: Details the methodology used in the research, focuses on data collection methods, describes analysis techniques and the application of ML models.
- Chapter 4: Results and Findings: Provides analytical insights into operational downtime, discusses the impact of breakdowns and proposes a maintenance strategy based on the study's findings.
- Chapter 5: Conclusions and Recommendations: Reviews all prior chapters, highlights contributions to achieving research objectives, emphasises key findings and their implications.

2 LITERATURE REVIEW

2.1 Load-Haul-Dump Machines

This section covers literature on LHD downtime, machine functionality, types of failures, critical components prone to breakdowns, and equipment performance indicators. These insights inform feature selection for a predictive model aiming to enhance maintenance and decrease machine downtime. The LHD machines operate in underground mining operations to load and transport ore or waste material from mining face to the tips. LHDs are critical equipment in the mining process as they can have a significant impact on productivity, safety, and profitability of mining operations (Mohammadi, et al., 2017). Their design, performance, automation, maintenance, and reliability are critical factors that affect underground mining operations (Fourie, 2016).

2.1.1 LHD downtime

Downtime refers to the period during which a machine is not available for use or is inoperable, typically because of unforeseen maintenance or breakdowns (ToolSense, 2024). There are generally two broad categories of downtime, i.e. planned and unplanned downtime. Planned downtime refers to scheduled maintenance that is expected and accounted for, such as regular servicing or inspections. Unplanned downtime, on the other hand, refers to unexpected equipment failures, which can severely disrupt operations and lead to inefficiencies, (Mobley,2002). In the mining industry, reporting downtime is important. If any downtime is not reported, the machine's availability and utilisation may be incorrectly calculated, which could have an impact on the production schedule. LHDs, like any other machinery, are prone to breakdowns and failures resulting in downtime.

A study by Kecojevic et al. (2016) analysed the impact of LHD downtime on the productivity of underground mining operations. The study found that

LHD downtime significantly impacted production and recommended that maintenance strategies be developed to reduce downtime (Kecojevic, et al., 2016). The study recommended that the mine should ensure that LHDs are well-maintained, employees are well-trained, and there is adequate supervision. The amount of tonnage produced is greatly impacted by the delay in repairing LHDs. Minimising downtime is one of the important factors for maximising tonnage output. This can only be achieved on assumption that design factors such as tramming distances are optimal. Minimising downtime is important for achieving high productivity. In general, the longer the downtime, the more costly it is for the mining operation. The downtime must be minimised by ensuring that LHDs are well-maintained and that repairs are carried out promptly.

Several studies show that a shortage of spare parts caused numerous prolonged downtimes for LHDs at a trackless mine in the eastern limb (Mbhalati, 2015). In the study by Mbhalati (2015), it was illustrated that it can take an entire shift up to two days to repair a LHD machine that had damaged its rear axle if spare parts are not available. Another study by Musingwini and Moyo (2017) analysed the factors affecting LHD utilisation at a platinum mine in Zimbabwe. The study found that the most significant factors affecting LHD utilisation were the availability of LHDs, spare parts, and the time taken to repair LHDs.

A study by Leeuw (2018) analysed the productivity of LHD operations and found that the most common problems affecting LHD productivity were the lack of maintenance, lack of training, and lack of supervision. It is important for this study to investigate how long it takes to repair various types of machine failures or breakdowns and the causes in the delays of repair work. It would also be beneficial to develop a predictive maintenance model to aid in the management of the ordering and stocking of spare parts as this has been reported in literature as a primary cause of the delays in repairs.

Mean Time Between Failure (MTBF) measures the average time that equipment functions without experiencing failures or stoppages (Sharma, et al., 2019). The MTBF assists the mine in assessing equipment reliability and predicting its performance in the long run. It indicates the duration for which the equipment can operate without encountering failure or needing maintenance. Comprehending MTBF facilitates the mine's ability to preplan and allocate equipment effectively. To determine the MTBF equation 1 is used (Sharma, et al., 2019)

$$\text{MTBF} = \frac{Total\ Operational\ Time}{Number\ of\ Failures}$$

Equation 1: MTBF

To better understand the downtime of an LHD, the MTBF should be investigated. MTBF for the LHD machine and its parts is often determined using data from the mine. Table 2.1 below lists four subsystems for LHD machines running in two mines during a 12-month period that had the lowest MTBF values (the highest failure frequency). These MTBFs for each LHD subsystem can be useful for a comparative analysis to the MTBFs at Booysendal Mine. It will help the mine to compare its MTBF with that of other mines for benchmarking purposes.

Table 2.1: Critical LHD subsystems with regards to MTBF in engine hours (Eh) (Paraszczak, 2000).

Mine A		**Mine B**	
Subsystem	**MTBF (Eh)**	**Subsystem**	**MTBF (Eh)**
Electrical	74	Electrical	77
Frame*	75	Frame*	94
Engine	84	Engine	100
Hydraulics	202	Hydraulics	248
Machine overall	31.7	Machine overall	36.2

Table 2.1 presents a comparison of the MTBF for various subsystems and overall machine performance for two different mining operations, labelled as Mine A and Mine B. Mine B consistently shows higher MTBF values across all subsystems and overall machine reliability compared to Mine A.

2.1.2 Booysendal Mine LHD machines

Booysendal Mine uses a variety of diesel LHD machines to support its mining operations. These LHD machines are important for the efficient transport of mined material within the underground environment. Among the notable manufacturers and models employed at the mine are the AARD 5.5-tonne LHD, GHH 3.2-tonne LHD, and Sandvik 7-tonne LHD. The AARD 5.5-tonne LHD, GHH 3.2-tonne LHD, and Sandvik 7-tonne LHD are considered notable for several reasons, primarily related to their design, performance, and suitability for specific mining applications. AARD 5.5-tonne LHD: Known for its compact design, the 5.5-tonne capacity makes it suitable for narrow-vein mining and small to medium-sized operations. GHH 3.2-tonne LHD: This smaller LHD is ideal for very narrow-vein mining, where space is extremely limited. Sandvik 7-tonne LHD: With a larger capacity, the Sandvik 7-tonne LHD is favoured in larger underground mining operations where higher throughput is needed.

The AARD 5.5-ton LP machine is designed for underground mining by AARD. With its 5.5-tonne payload capacity, it efficiently handles ore and waste material. The "LP" denotes "Low Profile," suitable for confined underground spaces. Low-profile LHDs are characterised by their reduced overall height to fit in narrow mining headings. The height is often in the range of 1.8 to 2.5 meters. The width is around 1.5 to 2.5 meters. These dimensions are designed to ensure that LHDs can operate efficiently in narrow and low mining headings. Figure 2.1 shows an Aard LHD from Aardme website.

Figure 2.1: Aard LHD (Aardme, 2023).

The GHH SLP 3.2-tonne LHD is compact and agile. Its 3.2-tonne capacity, designed for manoeuvrability, suits tight underground spaces. "SLP" means "Super Low Profile." GHH's reliable equipment, like the SLP LHD, ensures material handling efficiency in spatially restricted areas. Figure 2.2 shows an LHD from GHH website.

Figure 2.2: GHH LHD (Ghh Mining Machines, 2023).

SLP LHD machines typically refer to equipment designed for extremely confined underground mining environments. These machines usually have a height of less than 1.8 meters, with some models being as low as 1.5 meters or even lower. The width is also minimised, often ranging between 1.5 to 2.2 meters, to navigate narrow tunnels and stopes.

Impact mining equipment (2024) states that the LS170 Loader is a compact, powerful and multipurpose LHD loader, designed with the operator's safety as a priority and ergonomically designed for maintenance ease in mind. With a 7-tonne payload, it excels at moving large volumes of material efficiently. "LS" suggests "Low Seam," ideal for low-clearance environments. Low-seam machines like the LS170 are designed for operations in low-clearance mining environment, which typically refers to mining heights that range from 1.2 to 1.8 meters. Sandvik's innovation and reliability make the LS170 crucial for Booysendal Mine's productivity and safety. Figure 2.3 shows an LHD from Sandvik.

Figure 2.3: Sandvik LHD (Impact Mining Equipment, 2023).

2.1.3 Critical components of LHDs and their associated failure types

The understanding of the components of the LHD are critical for analysis of breakdowns of these machines. The maintenance of these components is high priority at Booysendal Mine in order to achieve production targets. Here are the main components of an LHD machine (GHH Fahrzeuge, 2024; Siddiqui, et al., 2022; Tampier, et al., 2021; Zichen, 2021; GMI wheels, 2019; Paraszczak, et al., 2014):

i. Bucket: The bucket is the part of the machine that is used for loading, hauling and dumping material. It is designed to withstand heavy loads and has a capacity of several tonnes.
ii. Boom: The boom is the arm that supports the bucket and allows it to move up and down. It also enables the operator to control the position of the bucket for efficient loading. A boom lift is used to control wheel deflection.
iii. Dump cylinder: Is used to move the bucket up and down.
iv. Hydraulic system: The hydraulic system is the use of fluid power to operate functions on the LHD such as loading, hoisting, dumping, and steering. The hydraulic system comprises components such as a hydraulic pump, control valves, dump valve, hydraulic cylinders, and hoses. The hydraulic system is responsible for powering the movements of the LHD machine.
v. Engine: Is the major driving component of the LHD. It provides the motive power that propels the LHD either forwards or backwards. The fuel of choice in LHDs is diesel. In addition, the engine also drives the hydraulic system which powers the loading components such as the bucket and boom and also provides steering. The cooling system includes a water pump, radiator, and thermostats. The fuel system includes filters and injectors.
vi. Cabin: The cabin is where the operator sits and controls the LHD machine's operations. It is designed to provide a comfortable working environment and has various controls, including joysticks, pedals, and switches, for operating the machine.

vii. Wheels/Tracks: Transmit the power of the engine through the transmission system to the ground, and by rotating, causing the LHD to move.

viii. Torque converter: The torque converter functions as a hydraulic linkage connecting the engine and transmission. Engine power is converted to usable levels through the principle of fluid coupling. Components include shaft bearings, seals, impeller, shaft and couplings.

ix. Transmission: is the component that allows gears to be changed according to the load and road conditions. Allows the LHD to be operated through a range of gears. Components of transmission are bearings, seals, gears, clutch plates and control valve.

    Drive shaft: Transmits the power from the transmission to the wheel axles. Main components include the drive flanges and the universal joints.

Overall, these components work together to enable the LHD machine to load, haul, and dump material. The functional capabilities of LHD components enables the mining of resources to be efficient and work at full capacity.

The characterisation of expected damage for critical LHD components provides important insights for designing proactive maintenance strategies and data inputs for predictive modelling. Table 2.2 summaries the typical damages for critical LHD components; this also includes repairs or maintenance needs for each component of the LHD machine:

Table 2.2: Typical breakdowns per component (Jakkula, et al., 2020)

Component	**Expected Damage or Breakdowns**	**Maintenance Needs**
Bucket	Wear and tear, damage to the bucket edge, deformation or cracking of the bucket body.	Regular inspections, welding repairs, and replacement of worn-out parts.
Boom	Wear and tear, damage to the boom structure, corrosion and wear due to friction.	Periodic inspections, routine lubrication, and replacement of damaged/worn-out components.
Hydraulic system	Leaks, contaminated fluid, worn-out hoses or seals, malfunctioning valves, pumps or cylinders.	Regular replacement of hydraulic fluids, filters, hoses, and seals; periodic inspections to identify wear/damage.
Engine	Wear and tear, loss of power, oil leaks, cooling system issues.	Regular replacement of filters, belts, hoses; periodic inspections to identify wear/damage.
Cabin	Damaged windows, malfunctioning controls, dirty or damaged seats.	Periodic cleaning, replacement of damaged seats, inspection of controls.
Wheels/Tracks	Wear and tear, damage to the wheels/tracks, problems with bearings, misalignment of wheels.	Regular inspections, lubrication, and replacement of worn-out parts.

Regular inspection is the systematic evaluation of machinery to ensure they are in safe operating condition and periodic inspection is the systematic examination of machinery to assess their condition and detect any potential issues before they lead to failures.

Table 2.3 lists the sub-systems of an LHD, each of which is linked to a particular failure category (Bala, et al., 2018). Depending on the kind of breakdown, different subsystems may take different amounts of time to repair. The length of time it takes to correct a problem will depend on its complexity and severity as well as on the knowledge and resources at hand.

Table 2.3: Sub-systems classification of LHD (Bala, et al., 2018)

Sub-system	**Failure type**
Engine (E)	Piston-cylinder, radiator
Brake (Br)	Oil leakage, brake jamming
Body (Bo)	Bucket wear out, welding
Tyre/wheel (Ty)	Tyre puncher, rim failure
Hydraulic (H)	Leakages, suspension system
Electrical (El)	Cable reel, socket, sensor
Transmission (Tr)	Gear train wear out, lubrication
Mechanical (M)	Structural failure, chassis

Table 2.4 gives an overview of LHD components and breakdown types, along with their associated durations. Understanding the time required for each type of repair, maintenance teams can effectively plan and allocate resources to minimise downtime and optimise LHD performance at Booysendal Mine. The information provided in Table 2.4. is obtained from a previous benchmark conducted at the mine by Khethani (2022). The study by Khethani (2022) aimed to determine the expected duration required for the replacement or repair of each component. The duration represents the maximum hours expected to repair or replace specific components, assuming that all the necessary parts are readily available. The values were obtained from the internal reports of the mine, relying upon the experience

of the artisans. The reliability of these values can be considered moderate, given that they are based on the experience of skilled artisans working at the mine. However, their accuracy depends on several factors: the availability of parts, the specific circumstances of each breakdown, and the consistency of working conditions. Since these values were derived from internal reports and are not benchmarked against external standards, they may vary in practice. Therefore, while these estimates are useful for scheduling maintenance, they should be treated as approximate rather than absolute.

Table 2.4: Component/Breakdown type and expected time to repair (Khethani, 2022)

Component/Breakdown type	**Duration (hours)**
Engine	8
Hydraulic pump	3
Overheating	0.5
Transmission oil leak	0.5
Hydraulic oil leak	1.5
Not starting	0.5
Brakes	8
Tyre damage	0.5
Propshaft	7
Boom not moving	4
Fittings	1.5
Hoses	1
Lights	0.5

LHDs are important components of underground mining operations, allowing for efficient material transportation inside confined spaces transport rock from the excavation face, either to the processing plant or continuous haulage systems. However, like any complicated machinery, LHDs are prone to malfunctions, which can delay mining operations. Understanding which components are most likely to fail is critical for developing appropriate maintenance methods to ensure the dependability. LHD breakdowns are often complex, including multiple subsystems such as the transmission, hydraulic system, drive unit, tyres, bucket, and brakes. Failures in these components can cause unexpected downtime, affecting production schedules and overall operational efficiency. As a result, a complete examination of the variables contributing to LHD breakdowns, particularly the important components vulnerable to failure, becomes important for establishing targeted and proactive maintenance approaches in the mining industry.

A study done by Samanta et al (2004) offers a comprehensive assessment of the LHD machine's components, shedding light on their reliability, availability, and maintainability. The study identifies the transmission, drive unit, and hydraulic subsystems as significant contributors to machine unavailability with 7%, 6%, and 5% of working hours, respectively. These components emerge as key areas that demand special attention for maintenance and improvement (Samanta, et al., 2004). Talan, et al (2018)'s investigation found that hydraulic, transmission, and engine failures were common throughout the whole fleet of loading equipment. Critical subcategories were discovered to be hydraulic oil leakages, leaks in other components, overheating, gear-shifting issues, and not taking load (NTL) issues (Talan, et al., 2018).

A study by Manenzhe et al (2019) found that fittings and hoses, electrical systems, air conditioning system, engine, brakes, and transmission formed part of the top twenty percent which accounted for eighty percent of LHD fleet failures. Jakkula et al. (2019) identified the bucket attachment system, steering direction main spool, lift cylinder rod, engine supporting block, and hose as major potential failures in LHD machine. A review of these studies shows that the distribution of failures by component seems to be different from case to case. It is important to investigate the percentage contribution of each critical component of the LHD in the Booysendal context.

2.1.4 LHD performance indicators

Numerous studies have investigated performance indicators specifically related to LHDs. Accomplishing the required operation and efficiency target is one of the challenges for mining companies. This requires proper performance measuring of mining equipment (Mohammadi, et al., 2015). Key Performance Indicator (KPI) studies are useful to quantify the performance of production equipment in the mining industry (Arputharaj, 2015). The design and performance of LHD machines are important for efficient underground mining operations. Availability is the measure of how many hours the machine is available for work (Mohammadi, et al., 2017). Utilisation is characterised as the proportion of the time in hours the machine is used to the overall hours it is available (Arputharaj, 2015). Understanding how these KPIs describe LHD performance at Booysendal serves as a foundation for shaping maintenance strategies and provide a framework for evaluating the effectiveness of proposed interventions. This will ensure alignment with the research objectives aimed at enhancing maintenance efficiency and operational performance of LHD machines at the mine.

Overall equipment effectiveness (OEE) presents a relationship that is used to determine the equipment's effectiveness (Ádám, 2023). OEE is derived from availability, performance, and quality (Ádám, 2023). OEE includes six sources of productivity losses, which are breakdowns, setup and adjustments, small stops, reduced speed, start-up rejects, and production rejects (Dermawan & Iriani, 2022). KPIs assume a fundamental role within the mining industry, especially in the realm of process monitoring and control (Gackowiec, et al., 2020). These metrics serve as essential benchmarks, providing valuable insights into the efficiency, effectiveness, and overall performance of mining operations. Downtime affects OEE by reducing machine availability and lowering equipment utilisation rate.

The OEE is determined as indicated in Equation 2 (Dermawan & Iriani, 2022).

$$\mathrm{OEE} = \mathrm{Availability} \times \mathrm{Performance} \times \mathrm{Quality}$$

Equation 2: OEE

Availability is a measure of how far the machine can continue to operate and equation 3 represents the formula to calculate availability (Dermawan & Iriani, 2022). Downtime affects the efficiency of equipment due to reduced availability.

$$\mathrm{Availability} = \frac{\text{Loading time} - \text{Downtime}}{\text{Loading time}} \times 100\%$$

Equation 3: Availability

Performance is derived from factors that cause the process to function at lower than the optimal possible speed when operational. The performance is determined using Equation 4 (Dermawan & Iriani, 2022).

$$\mathrm{Performance} = \frac{\text{Operating period} - \text{Speed Losses}}{\text{Operating period}} \times 100\%$$

Equation 4: Performance

Quality accounts for factors that result in performance losses, hence reducing the overall efficiency of the equipment. Where 100% quality means the outputs are high quality with zero faults and it is determined using Equation 5.

$$\mathrm{Quality} = \frac{\text{Net Operating period} - \text{Defect Losses}}{\text{Net Operating period}} \times 100\%$$

Equation 5: Quality

A study conducted by Pereira, 2018 indicated that MTBF, Mean Time To Repair (MTTR), Mean Time To Failure (MTTF), and Failure In Time (FIT) as the primary mathematical concepts employed in Reliability Engineering. Hours are used to express the measures. MTBF is a reliability metric used to quantify the frequency of failures occurring within a certain timeframe for repairable items or components (Pereira, 2018). The MTBF metric measures the duration during which the equipment operates without disruptions. It is important to point out that MTBF is specifically applicable to items that may be repaired. The MTTR is important for ensuring availability as it impacts both scheduled and unscheduled maintenance. Selvik and Ford (2017) assert that MTTR determines the time it takes to repair a piece of equipment and restore it to operational status. It is determined by adding the overall duration of repairs conducted within a specific timeframe and then dividing this sum by the total number of repairs.

MTTF refers to the duration between the first failure of a component on a certain piece of equipment (Sifferlinger & Rath, 2016). It is applicable to systems that cannot be repaired and covers the complete lifespan of a system. These items include lights, batteries, and hydraulic hoses. The MTTF is calculated by dividing the total number of hours in service for all devices by the total number of devices. The FIT, is a metric that quantifies the frequency of failures and the number of failures that occur per billion hours (TDK Product center, 2024). When analysing the duration values provided for different components and breakdown types, the FIT metric could be used to understand how frequently these failures might occur over a large period.

2.1.5 Maintenance strategies for LHDs

Maintenance strategies include various approaches to upkeep and management of assets within an organisation. These strategies aim to ensure the continuous functionality of equipment, minimise downtime, and optimise operational efficiency. Table 2.5 shows some common types of maintenance strategies along with their benefits and disadvantages:

Table 2.5: Maintenance strategies (Upkeep, 2024; Manwinwin, 2023; Teixeira, et al., 2020; Gackowiec, 2019).

Maintenance Strategy	**Definition**	**Benefits**	**Disadvantages**
Preventive Maintenance	Scheduled inspections, tasks, or repairs to prevent equipment failures.	Reduces likelihood of unexpected breakdowns.	Can be costly if performed too frequently. May lead to unnecessary maintenance costs.
Corrective Maintenance	Corrective maintenance is the category of maintenance tasks that are performed to rectify and repair faulty systems and equipment.	Reduce emergency maintenance orders. Increase employee safety. Reduce service interruption.	Unpredictability. Interruption to production. Shortened asset lifespan.
Predictive Maintenance	Uses data to predict equipment failure and performs maintenance just before.	Minimises downtime by addressing issues proactively. Reduces unnecessary maintenance. Optimises equipment performance.	Requires sophisticated sensors and expertise. High initial implementation costs.
Condition-Based Maintenance	Monitors real-time equipment condition and performs maintenance based on it.	Identifies potential failures before they occur. Maximises asset life. Reduces unnecessary maintenance.	Requires complex sensor systems and data analysis. Downtime possible if predictive measures are inaccurate.
Proactive Maintenance	Anticipates potential failures by continual	Reduces likelihood of failures. Focuses on	Demands ongoing commitment and investment in improvements.

Maintenance Strategy	Definition	Benefits	Disadvantages
	improvement and prevention.	root causes to prevent recurrence. Minimises downtime.	May be challenging to identify all potential failure points.

Each strategy has its advantages and drawbacks, and the choice of the most suitable strategy depends on factors like the type of equipment, available resources, industry requirements, and the organisation's goals. Often, a combination of strategies or a hybrid approach can be more effective in addressing the diverse needs of different equipment and systems within an organisation. The choice of the best maintenance strategy for LHD machines depends on various factors such as the specific operational environment, the criticality of the machines, available resources, and the organisation's objectives. Given the critical role of LHD machines in mining operations, for instance a combination of predictive and condition-based maintenance might be especially effective.

These strategies enable proactive maintenance actions based on real-time data, ensuring optimal performance, reducing downtime, and avoiding unexpected failures. However, each organisation needs to assess its specific needs, technological capabilities, and available resources before choosing the most suitable maintenance strategy for their LHD machines (Gackowiec, 2019). Based on the mentioned considerations, a maintenance strategy for LHD machines that meets the research objective can be developed. Talan et al (2018) used a Risk-Based Maintenance (RBM) plan to establish a maintenance strategy for mine loading equipment, specifically LHDs.

Several studies have emphasised the significance of understanding breakdown time in relation to planned and unplanned maintenance. Planned maintenance refers to scheduled and corrective maintenance, whereas unplanned occurs on a random basis as reactive or emergency maintenance (Pampana, et al., 2022). Understanding breakdown time and the distinction between planned and unplanned maintenance contributes to the objective of refining maintenance strategies (Mohammadi, et al., 2017). It supports the aim of shifting from reactive to proactive maintenance approaches, aiming to minimise downtime and improve equipment reliability. Talan et al (2018) emphasises the importance of risk-based maintenance plans. The adoption of a proactive and risk-based maintenance plan could significantly improve inspection and maintenance scheduling. Optimal inspection and preventive maintenance scheduling can significantly enhance the benefits derived from mining equipment (Angeles & Kumral, 2020). An improved equipment performance and increased reliability can enhance the overall productivity in mining operations.

To pinpoint the most detrimental factors influencing equipment availability is crucial to have dependable failure and downtime reporting mechanisms in place. Incorporating problem identification and performance measurement systems into maintenance programs (Vladimir, et al., 2014) resonates with the research objective of developing a structured maintenance framework. It emphasises the need for comprehensive systems to identify issues beforehand, aligning with the goal of predictive maintenance formulation.

2.2 Maintenance Cost

Mining equipment entails a substantial capital investment. Occurrences of equipment failures leading to associated downtime result in a significant escalation of operating, production, and maintenance costs, and in certain instances, revenue losses (Dayo-Olupona, et al., 2022). Acknowledging this, maintenance experts have reached a consensus that pre-emptive replacement of components before they fail (preventive maintenance) can prove more economically practical under certain conditions than corrective replacements after failure (Narayan, 2004).

The critical task lies in determining the suitability of preventive replacement for a specific component and, if warranted, identifying the optimal timing for such actions. Two conditions must be met to justify the preventive replacement of a component. Firstly, preventive maintenance is economically sensible when the condition of the component deteriorates over time. The second criterion is that the cost of preventive maintenance should be lower than the cost associated with corrective maintenance (Hottinger Brüel & Kjær, 2023).

According to Hottinger Brüel and Kjær (2023), Figure 2.4 depicts that the costs of corrective replacements rise with the passage of time. Simultaneously, the frequency of corrective replacements reduces as the time interval increases, given that fewer preventive replacement actions are required. The total cost comprises the sum of these two cost components. If both conditions are satisfied, a graph of cost per operating unit of time versus operating time can be plotted. At a specific point in time (time t), a minimum cost point emerges, presenting the optimal time for preventive replacement of the component. This thorough analysis allows for strategic decision-making regarding maintenance practices, ensuring both cost-effectiveness and operational efficiency (Hottinger Brüel & Kjær, 2023).

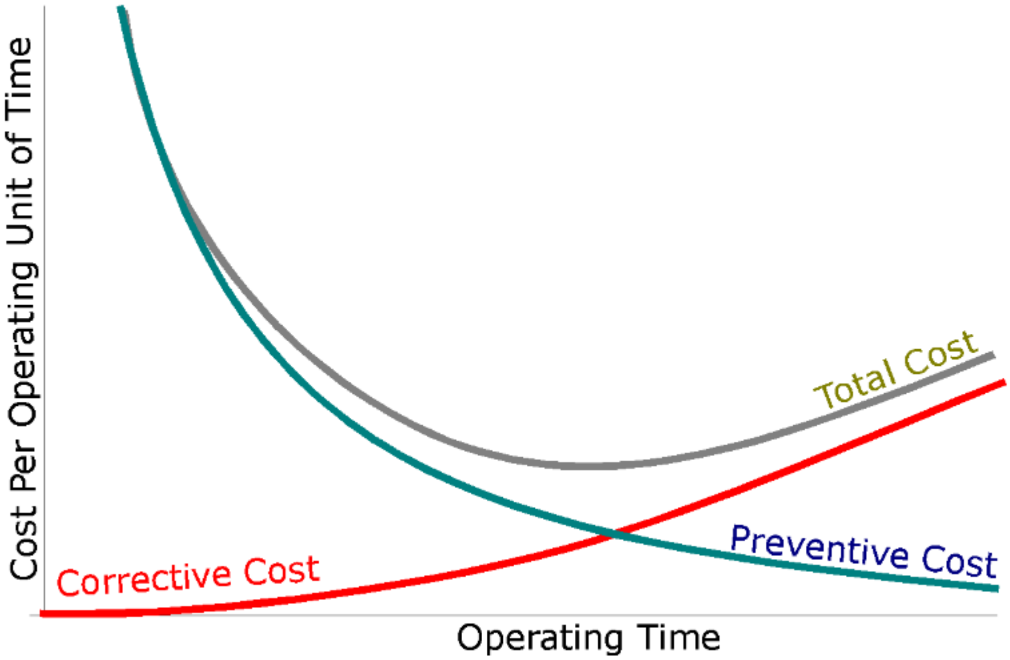

Figure 2.4: Cost per Operating Time Unit vs. Operating Time (Hottinger Brüel & Kjær, 2023).

2.3 Overview of Machine Learning

ML is the ability of a digital computer or a computer-controlled robot to do actions that are typically associated with intelligent beings such as learning from previous experiences (Vishnukumar, et al., 2017). ML can handle predictive and preventive maintenance procedures and is therefore relevant for this study (Yeardley, et al., 2022). ML is the process of solving a practical problem by:

- Gathering a dataset, and
- Building a statistical model based on that dataset, the types of ML are either supervised, unsupervised, semi-supervised, or reinforced (Burkov, 2019).

Supervised learning uses labelled input and output data (i.e. desired inputs and outputs), and the algorithms determine how to achieve the desired inputs and outputs. Supervised learning algorithms learn from observations, identify patterns, and make predictions. It allows the data modelled to analyse the predictions made and correct the algorithms until a high level of model performance is reached (Delua, 2021). There are two main subcategories of supervised learning, namely: classification and regression. Classification refers to a prediction model that uses a mapping function to estimate a relationship between input factors and separate output variables, which may be categorised or labelled (Gupta, 2021).

There exist various algorithms used for classification; some common classifiers include Naïve Bayes, K-nearest neighbour (KNN), random forest (RF), decision trees and logistic regression (Terra, 2023). Regression is a statistical procedure that aims to ascertain the relationship between the target output variables and the features of the input in order to make predictions about the new data (Great Learning Team, 2023). There are several types of regression algorithms that are frequently used in the field of machine learning, these include linear regression, polynomial regression, decision tree regression and random forest regression (Terra, 2023).

Unsupervised learning aims to detect patterns, structures, or representations in the incoming data without the need for explicit direction or feedback. Clustering and dimensionality reduction are two primary subcategories of unsupervised learning (Ghahramani, 2003) Semi-supervised learning uses the combination of supervised and unsupervised learning, small amount of labelled data and large amount of unlabelled data are used (GeeksforGeeks, 2023). Reinforced learning is a type of ML technique that enables an agent to learn in an interactive environment by trial and error using feedback from its own actions and experiences (Adler, 2019).

These algorithms play key roles in various machine learning tasks and applications, each suited for different types of data and objectives. The application areas of ML in maintenance extend from the intelligent maintenance optimisation models to more practical applications such as cost budgeting of maintenance projects and selecting optimal repair methods (Pokorni, 2021).

The application of ML consists of seven distinct general steps, as shown in Figure 2.5. The mentioned steps are important components of any machine learning procedure and play a key role in enabling the development of machine learning models.

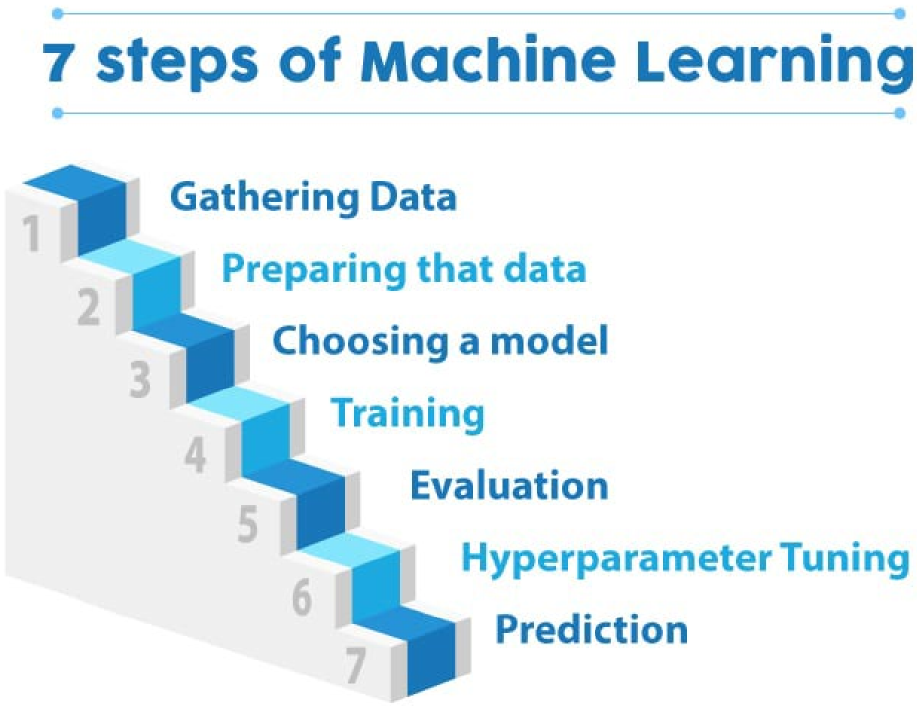

Figure 2.5: Steps of ML (Great Learning Team, 2023).

The following general steps are applied in ML and will guide the approach followed in this report (Crabtree, 2024; Great Learning Team, 2023; Javatpoint, 2021; Kapoor, 2020):

i. Gathering Data: This entails gathering the requisite data for the research project. Data collection can be sourced via a variety of channels, including files, the internet, and databases. Enhancing the accuracy of the model can be achieved by collecting enough and high-quality data. Data collection facilitates the identification of data-related issues.

ii. Preparing that data: The data should be cleaned to facilitate its preparation for training. Errors, noise, and missing values should be removed. The data is divided into separate training and test sets. Data cleaning is necessary to resolve quality issues.

iii. Choosing a model: After finishing the process of data preparation, the next step involves the selection of a machine learning model. Various models are available for selection, such as linear regression, decision trees, and random forest. The selection of a model is dependent upon the nature of the data and the specific problem at hand.

iv. Training: The subsequent stage involves the training of the model. The model undergoes training to enhance its performance and achieve improved outcomes in addressing the problem at hand. Various machine learning algorithms are employed to train the model using the datasets. The process of training a model is necessary to enable it to understand and evaluate various patterns, rules, and features.

v. Evaluation: After the completion of training, it is necessary to assess the performance of the model prior to its deployment. It entails evaluating the model on new data that it had not seen during the training process. Key performance indicators commonly used to assess the effectiveness of a model include accuracy, precision, recall, and mean squared error.

vi. Parameter or Hyperparameter Tuning: Upon doing an evaluation of the model, it may be necessary to adjust its hyperparameters to improve its performance. This is referred to as parameter tuning or hyperparameter tuning. Hyperparameter tuning techniques include grid search and cross validation.

vii. Prediction: Upon completing the training of the machine learning model and identifying the optimal combination of hyperparameters, the process then moves into the final stage. The objective is to apply the model in practical situations and assess its feasibility. It is important to keep in mind that the outcomes of the models are frequently used in a larger decision-making procedure. This means that the accuracy and reliability of the model's outcomes can affect the final decisions. Inaccuracies in the model's results could lead to flawed decisions.

2.4 Application of Machine Learning in Mining Machinery Maintenance

A study by Rihi, et al. (2022) explored the challenges within mining maintenance, notably focusing on the limitations of traditional approaches like reactive and preventive maintenance. It highlighted the emergence of predictive maintenance, necessitating real-time equipment monitoring for failure forecasting. The context emphasises the significance of Industry 4.0 technologies, AI, and big data analytics in facilitating real-time monitoring in smart mines (Rihi, et al., 2022). The paper does not explicitly mention a specific model but discusses various AI-driven fault diagnosis and prognosis approaches. These include neural networks, deep learning-based methods and their applications in fault detection, identification, prediction, and degradation assessment. Examples of the deep learning methods explored were Deep Neural Network (DNN) Deep Belief Networks (DBN,) Stacked Autoencoder (SAE) and Long Short-Term Memory (LSTM) (Rihi, et al, 2022). The article dives into several challenges, including the difficulty in modelling high-complexity phenomena for future failure prediction due to missing future-condition data. It highlights the need for comprehensive historical data and sophisticated models to compensate for this absence. Debates persist between model-based and data-driven fault diagnosis approaches, posing challenges in fault identification methodologies (Rihi, et al, 2022). Challenges in forecasting future failures align with the research objective of constructing a robust ML model for LHD machines. The importance of using historical data and advanced AI-driven methods to predict potential equipment failures is emphasised. Addressing complexities in fault diagnosis and emphasising AI-driven fault prognosis methods directly relates to constructing an optimised maintenance strategy.

Another research study by Kruczek, et al. (2019) revolved around the challenges of maintaining mining machinery, emphasising the significance of proper maintenance in ensuring uninterrupted mine’s production. It discusses various maintenance methods, from breakdown maintenance to planned preventive maintenance, highlighting the limitations and costs associated with each. The focus is on the emergence of predictive maintenance, emphasising its importance in continuous monitoring and planning repairs based on the observed degradation process (Kruczek, et al., 2019) Regarding the model used, the article introduces an advanced data analysis system based on cloud technology for predictive maintenance in mining machines. It highlights the system's efficiency and adaptability to various types of machines, aiming to process enormous datasets efficiently.

The cloud-based approach is advocated for its accessibility and utilisation of cloud computing methods for data processing. The paper discusses the significant variables measured online for LHD machines and how this extensive dataset contributes to condition monitoring. It demonstrates algorithms for damage detection and repair indication using machine-operating data (Kruczek, et al, 2019). The challenges outlined relate to the complexities of analysing extensive datasets from mining machines. These challenges encompass varying operational conditions, impulse-ridden signals, and the need for highly efficient algorithms and data analysis methods to process such data effectively (Kruczek, et al, 2019).

The paper's emphasis on predictive maintenance aligns with the objective of constructing robust ML models for anticipating equipment failures. It highlights the significance of continuous monitoring and predictive maintenance methodologies for extending machine lifetimes. The challenges presented, particularly in analysing extensive and varying datasets, are directly linked to crafting an optimised maintenance strategy. This aligns with the objective of streamlining maintenance practices within the mine, emphasising the need for advanced fault detection and assessment techniques for enhanced operational efficiency and extended equipment lifetimes.

A study by Bisht et al (2021) indicated that being able to predict the time of the LHD's breakdown enables mining operations to be planned and LHD maintenance activities to be organised. The LHD breakdown hours can be expressed as a time series and are dependent on several complex elements. Traditionally, the Autoregressive Moving Average (ARMA) model has been used to represent time series. But as neural networks and computing power have advanced, time series have been modelled using a variety of deep neural networks (Bisht, et al., 2021). The study showed that time series analysis can be used to optimise LHD maintenance and operations.

2.5 Application of Machine Learning in Other Machinery Maintenance

In the study conducted by Rahman and Mahbub (2022), the application of classification models on maintenance records through a text mining approach in an industrial setting was investigated. The paper investigates the utilisation of text mining in industrial maintenance to predict failures from maintenance records. Employing Naive Bayes and SVM classification algorithms, the study focuses on binary classification of text data to forecast potential equipment failures (Rahman & Mahbub, 2022). The findings suggest that both models such as Naive Bayes and SVM demonstrate acceptable accuracy and excellent performance in classifying failure from maintenance records.

This approach presents an opportunity for maintenance teams to predict impending breakdowns, allowing proactive measures to prevent failures in industrial settings (Rahman & Mahbub, 2022). The significance lies in shifting from a preventive-based maintenance approach to a proactive strategy. In order to predict failures in advance, the proposed technique empowers maintenance teams to take preventive measures, potentially reducing unnecessary maintenance costs. This proactive methodology aligns with the objective of designing an enhanced maintenance strategy, aiming to optimise maintenance practices within industrial environments. Using classification models aligns with the goal of enhancing maintenance strategies by enabling proactive identification of potential failures, therefore contributing to streamlined and optimised maintenance practices within industrial settings.

Voronov (2020)'s thesis highlighted the importance of heavy-duty trucks in global logistics and the necessity for their high availability to ensure uninterrupted transport operations. The challenges of traditional maintenance approaches, involving frequent component replacements and inefficiencies, drive the exploration of prognostic methods for individualised vehicle maintenance plans. The focus is specifically on lead-acid batteries within heavy-duty trucks and the complexities in developing physical degradation models due to the lack of accessible battery health sensing and detailed chemistry knowledge (Voronov, 2020). The thesis contributed by developing ML or deep learning models, specifically Random Survival Forests (RSF) and Recurrent Neural Networks (RNN), for predictive maintenance.

The approach uses large sets of logged vehicle operation data to estimate conditional reliability functions, particularly concerning the degradation and remaining useful life of lead-acid batteries. It addresses challenges such as dealing with multiple data readouts for a specific vehicle and data quality issues like imbalanced datasets and complex variable dependencies (Voronov, 2020). The data-driven approach faces hurdles such as dealing with uninformative variables, complex dependencies, imbalanced datasets, and the need to estimate uncertainty in predictive estimates (Voronov, 2020).

Studying battery degradation for the LHD machines at Booysendal Mine offers tailored insights for refined battery maintenance. These insights allow precise predictions regarding battery lifespan and failure, enabling optimised maintenance schedules. Understanding degradation patterns in Booysendal Mine operational context, costs associated with premature replacements can be minimised, optimising resources and maximising battery lifespan. The thesis aligns with the objective of constructing ML models for predictive maintenance, focusing on estimating component degradation and remaining useful life based on logged vehicle operation data.

Fan and Fan (2015) focused on using time series models for system reliability analysis, specifically in the context of construction equipment. The predictions derived from these models include the expected number of failures per interval, conditional reliability, and unreliability, MTBF, and the determination of an optimum overhaul and system operation plot. The study explored the impact of incorporating TTR as a predictor, emphasising its significance in equipment reliability analysis. The deployment of time series models for predicting TBF and TTR as parameters is discussed, showcasing the models' ability to offer insights into maintenance strategy selection. The research highlights the importance of considering TTR in reliability analysis and failure forecasting for construction equipment, providing valuable information for making informed management decisions.

The time series models, particularly the ARMA model, proved effective in predicting failure patterns.

The study concluded by emphasising the suitability of time series models to forecast reliability metrics and support maintenance decision-making in construction equipment management (Fan & Fan , 2015). In the study done by Shafi et al (2018), researchers explored the effectiveness of four classifiers—Decision Tree, SVM, k-Nearest Neighbours (k-NN), and Bagging Tree (Random Forest)—across different vehicle systems: ignition, fuel, exhaust, and cooling. They evaluated these classifiers using metrics like accuracy, precision, recall, and F1 score with 10-fold cross-validation. SVM consistently outperformed other classifiers, achieving 96.6% accuracy in the ignition system. Similar trends were observed in the fuel, exhaust, and cooling systems.

The study emphasises SVM's importance in handling small datasets. The proposed Vehicle Monitoring and Fault Predicting System aims to reduce automotive system faults using ML and wireless communication. The study also proposed future work that involves refining classification performance and expanding the dataset to include various vehicle types (Shafi, et al., 2018). Kusumaningrum et al (2021) developed diagnostic and prognostic models for fault prediction in an electric power fan (EPFAN) motor using ML algorithms—specifically SVM and RF. The grid-search results indicate that RF consistently outperformed SVM in terms of accuracy, precision, and recall. Diagnostic modelling achieved an impressive 97% accuracy, while prognostic modelling reached 89.6%. Cross-validation results further validate the algorithms' performance without overfitting.

The study also explores tuning parameters, demonstrating that a smaller number of decision trees in RF can achieve similar accuracy. SVM accuracy analysis suggests that the radial basis function (RBF) kernel with a carefully chosen regularisation value yields the best results. Overall, the proposed models, especially using RF, show promise in predicting normal/abnormal conditions and remaining useful life (RUL) in EPFAN (Kusumaningrum, et al., 2021).

Hildreth and Dewitt (2016) conducted a study where logistic regression was employed to forecast the economic success or failure of 378 single axle dump trucks. The predictions were based on cost and use criteria derived from average fleet data, resulting in correct outcomes. The models underwent both internal and external validation to determine a predictive accuracy of around 70 percent. This level of accuracy is adequate for managers to safely prioritise their efforts on machines that are likely to fail (Hildreth & Dewitt, 2016). The study also noted that it is very critical to develop an early warning system to identify issues associated with individual machines.

The study by Achouch et al (2023) aimed to develop a predictive maintenance model for the TA-48 compressor, using ML algorithms and time series analysis to predict the residual life of the compressor. Logistic regression, SVM, and Naïve Bayes algorithms were employed for failure prediction, with an additional approach fixing time intervals (X hours) for prediction. Time series analysis involved LSTM neural networks for predicting RUL. Logistic Regression, SVM, and Naïve Bayes exhibited low prediction rates. LSTM demonstrated superior performance in predicting RUL (Achouch, et al., 2023).

2.6 Literature Review Summary

The literature review focuses on LHD machines, important equipment in underground mining operations, emphasising their functionality and specific models at Booysendal Mine. LHD machines play a key role in production, highlighting the importance of proper maintenance and reliability. Downtime of LHDs impacts production, requiring effective maintenance strategies to minimise disruptions. Studies reveal that shortages of spare parts contribute to prolonged downtimes, underlining the importance of well-maintained critical components. KPIs are essential for assessing LHD performance, while breakdown time is important for planning maintenance. Proactive maintenance adoption could enhance inspection efficiency, with preventive maintenance proving economically advantageous in minimising costs. The literature underlines the significance of predictive maintenance as a maintenance strategy.

ML can handle predictive and preventive maintenance, facilitating a need to shift from reactive to proactive approaches. ML-based systems and predictive analytics are instrumental in predicting breakdowns, helping in proactive maintenance strategies. Challenges in analysing extensive datasets from mining machines underline the need for advanced algorithms and predictive models to accurately predict equipment failures. Specific studies employing text mining and classification models demonstrate their efficiency in predicting and preventing breakdowns. This comprehensive review helps in selecting appropriate maintenance strategies based on equipment importance and resource availability. Random forest and logistic regression are highlighted as critical ML algorithms in the literature review which can address the objectives of this study. The literature review explored the two main types of ML algorithms that are necessary to consider; these include regression and classification. Data preparation, selecting an appropriate ML algorithm, and model evaluation and parameterisation are important in order to build the optimal model.

The sources supporting the need for this research, including academic journals, reports, and case studies, have highlighted the need of conducting this study. These sources align with the research objectives and validate the importance of the research topic. The literature review revealed that predictive maintenance can significantly reduce downtime and unnecessary maintenance at Booysendal Mine. It emphasised the utilisation of historical data to predict equipment breakdowns, highlighting the importance of proactive maintenance strategies.

3 RESEARCH APPROACH

3.1 Introduction

The research methodology focuses on the strategy employed to achieve the research objectives and resolve the problem statement. The fulfilment of these objectives is through the construction of a research design tailored to address the research questions and objectives. The methodology includes outlining the techniques for gathering data and explaining the approaches taken for analysing the data to derive conclusions and solutions. The data processing, data analysis and machine learning performed in this study was carried out using Python programming language applied in Jupyter notebooks.

3.2 Research Methods

This study employs a mixed-methods approach, integrating both qualitative and quantitative methodologies to comprehensively explore and address maintenance challenges of LHD machines at Booysendal Mine.

3.2.1 Qualitative research

The qualitative research approach involved transforming and mapping qualitative raw data in the maintenance records for the years 2021 to 2022 into useful information for data analysis and modelling. The following steps are undertaken:

- **Literature review:** A comprehensive review of studies about downtime and related breakdown or failure types of underground trackless mobile machinery, particularly LHDs.
- **Qualitative commentary analysis:** Systematic analysis of qualitative comments provided by operators in the daily breakdown reports.

- **Thematic coding and contextual insights:** Thematic coding of breakdown or failure types to identify recurring themes or prevalent issues highlighted in the qualitative comments.
- **Triangulation of qualitative and quantitative data:** Merging of qualitative insights from breakdown reports with quantitative analyses to form a comprehensive understanding of LHD maintenance challenges, providing depth and context to statistical findings.

3.2.2 Quantitative research

The quantitative research approach is categorised in two methods. These are data analysis and ML model development:

- **Data analysis**: Employing statistical analysis tools to leverage historical data from daily breakdown reports from 2021-2022 to quantify breakdown occurrences, durations, and their impact on LHD downtime.
- **Machine learning model development:** Using historical data to train and develop predictive maintenance models for LHD machines. This quantitative approach aims to forecast downtime and the underlying contributing breakdowns, aiding in proactive maintenance planning.

3.3 Sources of Data

Data was sourced from the daily breakdown reports from the years 2021 to 2022. These reports contain detailed information on breakdown occurrences, their duration, and qualitative comments by operators regarding the issues faced. A review of similar case studies will also provide supplementary data to support the research.

3.4 Research Validation

The research validation process aims to ensure the credibility, reliability, and accuracy of the findings and methodologies employed in the study on LHD maintenance strategies at Booysendal Mine. In thoroughly validating data sources, data quality, predictive models, and ensuring transparency and consistency throughout the research process, credibility and reliability is sought to be maintained.

3.5 Data Acquisition

The original dataset contained information about all the equipment (i.e. drill rigs, LHDs, utility vehicles, etc.) at Booysendal Mine for the years 2021 and 2022. The details were recorded by control room operators during each shift, which lasts for 8 hours. The morning shift (MS), afternoon shift (AS), and night shift (NS) operators and artisans report stoppages to the control room via telephone. The data is captured and stored in different folders and sub-folders in worksheets within various workbooks on the mine's shared drive. Each worksheet represents daily recordings of equipment breakdowns, availability, and production. Each workbook collects worksheets of daily recordings for a week. Each sub-folder contains weekly workbooks for a specific month. Monthly sub-folders are arranged in folders representing the data for each year. Different colour coding within excel was used to describe special cases such as when there was no stock or operator available, equipment was on service or completely damaged. The original data in each daily worksheet contained the following columns:

- Mine Captain (or Mine Overseer)
- Section
- Equipment Description
- Make of Original Equipment Manufacturer
- Total standing time, including start time and end time (grouped by shift).

- Bucket/panels (grouped by shift).
- Location (grouped by shift).
- What was report by TM 3 Operator (grouped by shift), refers to the type of breakdown
- Repaired by (grouped by shift)
- Feeback by Artisan (grouped by shift)
- Downtime DS
- Downtime AS
- Downtime NS
- Availability %
- Production DS
- Production NS
- Production NS
- Total Production
- Utilisation %

3.6 Data Cleaning and Wrangling

Data cleaning is the method of identifying and removing errors or missing information in a dataset. Data wrangling is the process of transforming and mapping raw data into a more useful format for further analysis. It is typically a more comprehensive than cleaning. Poor data quality can lead to inaccurate analysis. Data cleaning and wrangling ensure that the data is accurate and complete.

The data underwent cleaning to correct errors which were detected. Rows wherein errors were found were subsequently deleted. The following major errors were detected:

- Time-related columns containing text.
- Durations of downtime exceeding 8 hours in a shift.
- Recording of information in wrong columns.

- Availability percentages which were negative.
- Utilisation calculation and values which could not be explained satisfactory.
- No details on “Feedback by Artisan”.
- A possible misrepresentation or ambiguity regarding “Total standing time”.
- Instances where downtime was recorded but no explanation of the type of breakdown given.
- Instances where the explanation of the type of breakdown is given but no downtime is recorded.

The process of consolidating the data which was from multiple sources into a unified file required the use of Python libraries such as *os*, *pandas*, and *zipfile*. However, this merging operation assumed a consistent structure across all data sources, which was not always the case. Consequently, some rows in the merged dataset were misaligned and needed to be corrected.

During the merging process, only columns deemed relevant to the study's objectives were retained. Several columns, including "mine captain," "section," "buckets/panels," "start time," "end time," "location," "reported by," "repaired by," "production," "availability," and "utilisation," were omitted. Although columns like availability, utilisation, and production could have provided valuable insights, they were excluded due to uncertainties regarding their inputs or insufficient data availability. This resulted in the removal of over 27 columns, leaving only 13 columns out of the initial 40. Rows related to equipment types other than LHDs were filtered out and deleted.

As part of the data refinement process, two new columns were introduced: "Failure mode" and "Failed component." "Failure mode" identifies the specific type of failure responsible for a breakdown, while "Failed component" denotes the component that malfunctioned. The records for

"Failure mode" were derived from the “What was reported by TM 3 Operator” columns. However, inconsistencies arose due individual failure modes being expressed using different phrases, sometimes up to five or six variations for the same type of breakdown. To address this, the inputs were encoded into distinct modes and categorised by the author. Phrases representing the same failure mode were consolidated into fewer categories, reducing around 100 different descriptions to 17 distinct failure modes. The corresponding failed components were then linked to each failure mode, establishing a clear relationship between types of failures and affected components, as depicted in Table 3.1.

Table 3.1: Failure mode with their critical components

Number	Failure mode	Critical component
1	Articulation problem	Steering system
2	Brake failure or damage	Braking system
3	Canopy and frame damage	Cabin or frame
4	Collision Avoidance System (CAS) faulty	Other
5	Electrical or wiring or battery issue	Electrical system
6	Engine cutting off	Engine
7	Engine not starting	Electrical system
8	Lights not working	Electrical system
9	Limited or no bucket or boom movement	Bucket or boom
10	No forward or reverse movement	Transmission
11	Oil leak or damaged hose	Hydraulic system
12	Other	Other
13	Overheating	Cooling system
14	Propshaft damaged	Transmission
15	Torque converter problem	Transmission
16	Transmission failure	Transmission
17	Tyre or wheel damage	Wheels or tyres

Table 3.1 highlights various failure modes and their corresponding critical components, with many issues cantered around the transmission, electrical, and hydraulic systems. This breakdown provides clear guidance for prioritising maintenance efforts, with transmission-related problems being particularly critical, followed by steering and braking issues that affect safety. The values in the downtime columns were converted from their original format, which represented time in hours and minutes, into a decimal format denoting hours. As a result, the final data frame, named "lhd," comprised 13 columns and 4326 entries. The columns included in this data frame are as follows:

- Year
- Equipment Description
- Make
- Downtime MS
- Failure mode MS
- Failed component MS
- Downtime AS
- Failure mode AS
- Failed component AS
- Downtime NS
- Failure mode NS
- Failed component NS
- Downtime total

Further data wrangling involved merging the Downtime MS, Downtime AS, and Downtime NS columns into a single "Downtime" column, followed by a similar process for the "Failure mode" and "Failed component" columns. Subsequently, the “Downtime total” column was deleted.

A new column named "Category" was introduced to categorise downtime. This categorical variable was designed to classify the continuous downtime variable into four classes based on its proportion to the total shift time (8 hours), as illustrated in Table 3.2. For instance, downtimes comprising less than 25% of the shift duration (i.e., less than 2 hours) were assigned to category A. The need for categorising or labelling downtime arises from the requirement of classification models, which rely on categorical target variables.

Table 3.2: Classification of downtime with respect to shift time

Percentage of Shift Time	**Downtime less than or equals to**	**Category**
25%	2.00	A
50%	4.00	B
75%	6.00	C
100%	8.00	D

Rows where downtime was not recorded were removed. The resulting data frame, named lhd2, comprises 7 columns and 936 entries. The columns in this data frame are as follows:

- Year
- Equipment Description
- Make
- Downtime
- Failure mode
- Failed component
- Category

Both data frames, lhd and lhd2, were employed for data analysis purposes. The lhd data frame was primarily used for shift-based data analysis, whereas the lhd2 data frame was predominantly employed for holistic data analysis and machine learning tasks. The selection between the two data frames was largely determined by choosing the data frame that facilitated the simplest code depending on the specific analytical approach being undertaken. The finalised datasets represent data collected from Booysendal Mine between 2021 and 2022, specifically focusing on LHDs. These datasets record the downtimes experienced by each LHD during this period, associating each downtime occurrence with the type of breakdown (failure mode) and the failed component. The manufacturer of the LHD equipment is included in the dataset.

Table 3.3:LHDs from different manufacturers

LHD number	**OEM**	**Total**
13;14;30;02;11;21;31;08;10;15;24;25;16;34;17;22;09;36;07;29;35;19;18;20;23;32;33;12;309;37;38;308;112; 40;39;44;45;48;46;47;01;03;49;103;109;04 and 06	Sandvik	47
203;204;205;201;202;206;301;302;303;327;311;313;317;312;324;325;312C;327C;314;323;42 and 43	GHH	22
101;108;102;104;106;105;110;107;309;307;111;41;14;112 and 14	AARD	15
Null	Unspecified	31

Table 3.3 shows the distribution of LHD machines across different Original Equipment Manufacturers (OEMs) at Booysendal mine. Sandvik leads with 47 units, identified by specific numbers. GHH follows with 22 LHD machines, while AARD has 15 units. There are 31 LHD machines which are listed as "unspecified" regarding the OEM, reflecting incomplete data.

3.7 Data Analysis

The employment of Python libraries including os (i.e., to interact with the operating system), pandas (i.e., for structured data manipulation and analysis), and zipfile (i.e., for the creation, reading, writing, appending, and extracting of ZIP files).

The data analysis process includes various steps to explore and derive insights from the cleaned dataset. The following summarises the process followed to analyse the data:

i. Examination of the distribution of objects of analysis

- Number of LHDs
- Frequency of occurrence of breakdown per LHD
- Number of LHDs per original equipment manufacturer (OEM)
- Frequency of occurrence of breakdown per OEM

ii. Analysis of downtime

- Descriptive statistics of downtime
- Histogram of downtime
- Cumulative probability curve of downtime
- Frequencies and average downtime per failure mode
- Pareto chart of failure modes vs downtime
- Frequencies and average downtime per failed component
- Pareto chart of failed component vs downtime
- Bar charts of total and average downtimes per shift
- Bar charts of total and average downtimes per OEM
- Total and average downtimes per LHD (highlighting LHDs responsible for 80% of the number of failures)

iii. **Analysis of failure modes**

- Frequencies of failure modes
- Frequencies of failed modes per shift
- Frequencies of failure modes per OEM

iv. **Analysis of failed components**

- Frequencies of failed components
- Frequencies of failed components per shift
- Frequencies of failed components per OEM

3.8 Machine Learning

Regression and classification ML models were employed to address different aspects of the research problem, namely:

- Regression for prediction of downtime based on failure modes and,

- Classification of downtime categories (as shown in Table 3.2) based on failure modes.

The regression models run were the Decision Tree (DT), k-Nearest Neighbours (KNN), Random Forest (RF), and Support Vector Machine (SVM) regressors. The classification models run include the DT, KNN, RF, and SVM classifiers. The selection of these machine learning models—DT, KNN, RF, and SVM—for both regression and classification tasks are well supported by their ability to handle a wide range of data types. DT and RF are known for their flexibility to model non-linear relationships, while KNN is useful for pattern recognition. SVM is good at finding the best boundaries for classification and regression tasks, making these models suitable for capturing diverse patterns in the dataset. Fenner (2020) provides an overview of machine learning models, including DT, KNN, RF, and SVM.

Fenner (2020) further discusses the mathematical foundations of these models, explaining how they work under different conditions and what parameters influence their performance. DT use parameters like max_depth and min_samples_split. KNN use n_neighbors parameter to determine the model performance. RF uses bootstrap and max_features parameters. SVM uses kernel and gamma parameters.

The general processes followed for the regression and classification models are summarised in Table 3.4. The subsequent parametrisation, grid search ranges for hyper-parametrisation and the final best hyper-parameters used to run the regression and classification models are summarised in Table 3.5 and Table 3.6, respectively.

Table 3.4: General process followed for the regression and classification models.

Process Step	**Regression**	**Classification**
i. Data preprocessing	Predictor = “Failure mode” Target = “Downtime”	Predictor = “Failure mode” Target = “Category”
ii. Data splitting	The data was split into 80% training and 20% testing sets.	
iii. Hyperparameter tuning	Grid search ranges used to train each model using various parameters within these ranges and then select the best parameters.	
iv. Model training	Best parameters selected during hyper-parametrisation used to train model.	
v. Model evaluation	Root mean squared error (RMSE) used to select the best model with the lowest RMSE. The selected model is recommended for predictive maintenance modelling	Accuracy, precision, recall, and F1 score used to select the best classification model that has the highest performance metrics. The selected model is recommended for predictive maintenance modelling.

Table 3.5: Regression Models (Predictor variable = “Failure mode”, Target variable= “Downtime)

Regression model	**Grid search parameters**	**Hyper-parameters**	**Best parameters**
DT	Maximum depth	None, 5, 6, 10, 20, 50, 100	10
	Minimum samples split	1 ,2, 5, 10, 40, 150	2
	Minimum samples leaf	1, 2, 3, 17, 50	1
KNN	Nearest neighbours	2, 5, 10, 50	50
	Weight function	"uniform", "distance"	"distance"
	Power parameter for the Minkowski metric	1,2	2
RF	Number of estimators	1, 3, 5, 50, 100, 400	3
	Maximum depth	None,3, 5, 10, 12, 15, 50	12
	Minimum samples split	1, 2, 3, 5, 10, 50	2
	Minimum samples leaf	1, 2, 3, 4, 5, 10, 50	1
	Maximum features	"auto", "sqrt", "log2"	"log2"
SVM	Types of kernels	"linear", "rbf", "poly"	"rdf"
	Regularisation parameter	0.05, 0.2, 0.5, 1.0, 5, 10	0.2
	Kernel coefficient	"scale", "auto"	"scale"

The model validation metrics used for the regression models are briefly described as follows:

- RMSE: measures how far off the predictions are from the actual values in the same units as the target variable. The model with the lowest RMSE will be selected.
- Mean Absolute Error (MAE): measures the average absolute differences between the predicted and actual values. It is less sensitive to outliers as compared to RMSE.
- R-squared (R^2): measures the proportion of the variance in the target variable that is explained by the model, it ranges from 0 to 1. It is calculated as 1 - (residual sum of squares / total sum of squares), where the residual sum of squares is the sum of squared differences between actual and predicted values, and the total sum of squares is the sum of squared differences between actual values and the mean of the actual values.
- Explained Variance Score (EVS): measures the proportion of variance in the target variable that is explained by the model.
- Maximum Error (ME): represents the maximum residual error between predicted and actual values. It provides an idea of the worst-case scenario in terms of prediction error.

Table 3.6: Classification Models (Predictor variable = “Failure mode”, Target variable= “Category”)

Classification model	**Grid search parameters**	**Hyper-parameters**	**Best parameters**
DT	Maximum depth	None, 2, 10, 20, 50, 100	2
	Minimum samples split	2, 5, 10, 50	2
	Minimum samples leaf	1, 2, 4, 10, 50	1
	Maximum features	"sqrt", "log2", None	Sqrt
KNN	Nearest neighbours	11, 50, 100, 300	11
	Weight function	"uniform", "distance"	"uniform"
	Algorithm	"auto", "ball_tree", "kd_tree", "brute"	"auto"
	Power parameter for the Minkowski metric	1, 2	1
RF	Number of estimators	5, 10, 50, 100	10
	Maximum depth	None, 2, 10, 20, 100	2
	Minimum samples split	2, 5, 10	2
	Minimum samples leaf	1, 2, 4, 10	2
	Maximum features	"sqrt", "log2", None	"sqrt"
SVM	Regularisation parameter	0.1, 1, 10, 100	0.1
	Kernel type	"linear", "rbf", "poly"	"linear"
	Kernel coefficient	"scale","auto"	"scale"

The model validation criteria used for the classification models are briefly described as follows:

- Accuracy simply measures how often the classifier correctly predicts. The accuracy is defined as the ratio of the number of correct predictions and the total number of predictions. This was regarded as the most important classification metric as it directly impacts the objective of correctly predicting downtime category.

- Precision measures the accuracy of the positive predictions made by the model.
- Recall, also known as sensitivity or true positive rate, is a performance metric used in binary classification tasks.
- F1 Score is the harmonic mean between precision and recall. The range for F1 Score is [0, 1]. It tells how precise the classifier is (how many instances it classifies correctly), as well as how robust it is.

3.9 Development of a maintenance strategy

The literature review, data analysis results and selected machine learning models will be used to inform decision about the selection and development of a maintenance strategy. The insights about the contribution of the specific LHDs, type of OEM, failed components and failure modes on downtime will allow for an informed targeted focus on these factors. Further in-depth root cause analysis can then be carried on the factors that have the largest contribution towards downtime. The selected regression and classification models can be used to continually predict downtime and the level of downtime category to be expected as daily LHD data is being updated. This will allow for real-time understanding of equipment performance and the impact it is having on downtime.

3.10 Data validation process

A clearance from Booysendal Mine authorised mining manager responsible for maintenance of LHD equipment was obtained. This clearance adheres to legal and ethical guidelines, ensuring compliance with data protection laws and maintaining confidentiality. The formal written authorisation from

Booysendal Mine's management permits the researcher to access and use historical breakdown reports and qualitative data from 2021 to 2022 for the study on LHD maintenance challenges.

The data validation process started with the comprehensive cleaning and preparation of the data and a thorough documentation thereof. Any assumptions and uncertainties identified in the data preparation process were communicated. Inconsistencies encountered were investigated, addressed and documented. Cross-referencing findings with on-site observations and case studies was carried out to ensure coherence between data sources.

3.11 Methodology chapter summary

The research method involves a systematic methodology created to address the research problem effectively and achieve the study's objectives. It includes various stages, each designed to contribute to the understanding and resolving identified issues. One of the initial steps involved in the research approach is data cleaning and wrangling. This process involves preparing the raw dataset for analysis by removing inconsistencies, handling missing values, and ensuring data integrity. Following data cleaning, the data analysis process begins, aiming to derive insights and patterns from the cleaned dataset. This involves using various analytical techniques such as histograms, frequency tables, descriptive statistics, and Pareto charts to explore different aspects of the data, including failure components, downtime, and operational patterns. The research approach directly contributes to achieving its objectives. Initially, through data analysis methods like histograms and descriptive statistics, it aims to understand breakdown trends in LHD machines at Booysendal Mine, meeting the first objective.

Using regression and classification algorithms in machine learning, the research develops predictive maintenance models. These models forecast downtime based on failure mode and classify failure categories, fulfilling the second objective. Regression and classification models are used to predict downtime based on failure mode and classify failure categories, respectively. These models undergo data pre-processing, training, hyperparameter tuning, and evaluation to ensure optimal performance. Insights from data analysis and ML guide the design of a data-driven maintenance strategy. In identifying key patterns, the research formulates proactive maintenance approaches to minimise downtime and enhance equipment performance, aligning with the third objective.

Data validation ensures the accuracy, consistency, and quality of data by checking for errors before processing. Ethical clearance Ethical clearance is the approval granted by management to ensure that a research study adheres to ethical standards, protecting participants' rights and well-being. It involves obtaining necessary clearances and agreements from relevant stakeholders, such as Booysendal Mine, to access and use the data responsibly while maintaining confidentiality and adhering to regulatory requirements.

4 ANALYSIS AND FINDINGS

4.1 Introduction

The analysis of results offers a thorough examination of LHD breakdowns at Booysendal Mine from year 2021 to 2022. Analysing the results from data analysis and ML, will aid in providing insights about underlying contributors on downtime. The findings from this research can help the management to make strategic decision and improve the overall efficiency and sustainability of LHD operations at Booysendal Mine.

4.2 Data analysis of LHD machines

4.2.1 Examination of the distribution of objects of analysis

For the study, 115 LHDs were analysed to study their contribution to downtime, failure modes and frequency of breakdowns. The LHDs were from different manufacturers, namely: Sandvik (41% of 115 is equivalent to 47 LHDs), GHH (19% of 115 is equivalent to 22 LHDs) and Aard (13% of 115 is equivalent to 15 LHDs), However, a sizable number of LHDs (27% of 115 is equivalent to 31 LHDs) were categorised as unspecified. The unspecified LHDs were a consequence of data missing from the original reports.

The bar chart in Figure 4.1 shows the frequency of breakdown occurrence per LHD, this was also done by a section in the data analysis code that used data in the equipment description column to tally how many times a specific LHD appeared in that list. Among the LHDs, LHD33 has the highest number of breakdowns, with a frequency of approximately 48, while LHD46 has the lowest, with a frequency of around 2. The LHDs experiencing the highest number of breakdowns, listed in descending order, are LHD 33, LHD 12, LHD 37, LHD 11, and LHD 34. The top 5 LHDs with the highest breakdowns are selected to prioritise maintenance efforts, as these LHDs likely contribute the most to operational downtime. The top 5 LHDs are from the same manufacturer, namely: Sandvik.

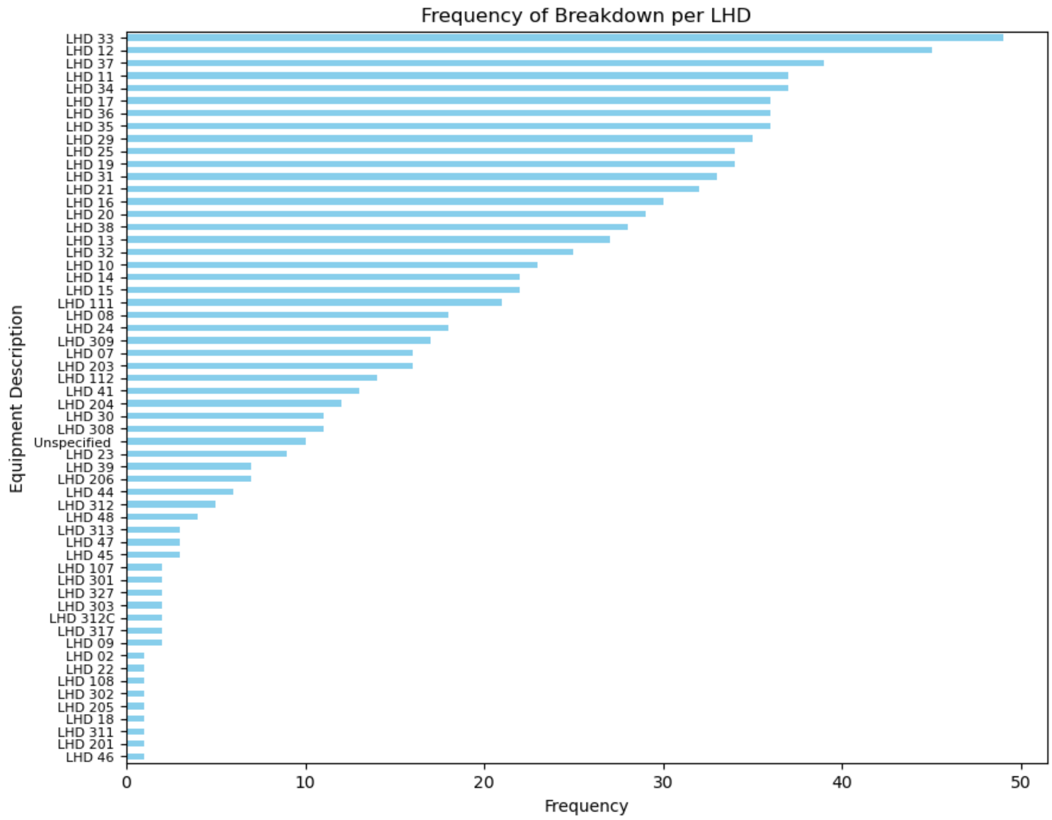

Figure 4.1: Frequency of breakdown per LHD

Figure 4.2 shows the contribution of each equipment manufacturer to the frequency of breakdowns. The breakdown distribution among the machines is as follows: Sandvik machines contributed approximately 83% to the 936 total number of breakdowns which is equivalent to 777 breakdowns. Aard machines contributed 9% (i.e. 84 breakdowns), GHH machines contributed 7% (i.e. 66 breakdowns), and the remaining 1% of the breakdowns were attributed to unspecified machines. Sandvik machines have the highest breakdowns. This could be attributed to Sandvik machines being the majority of the investigated LHDs.

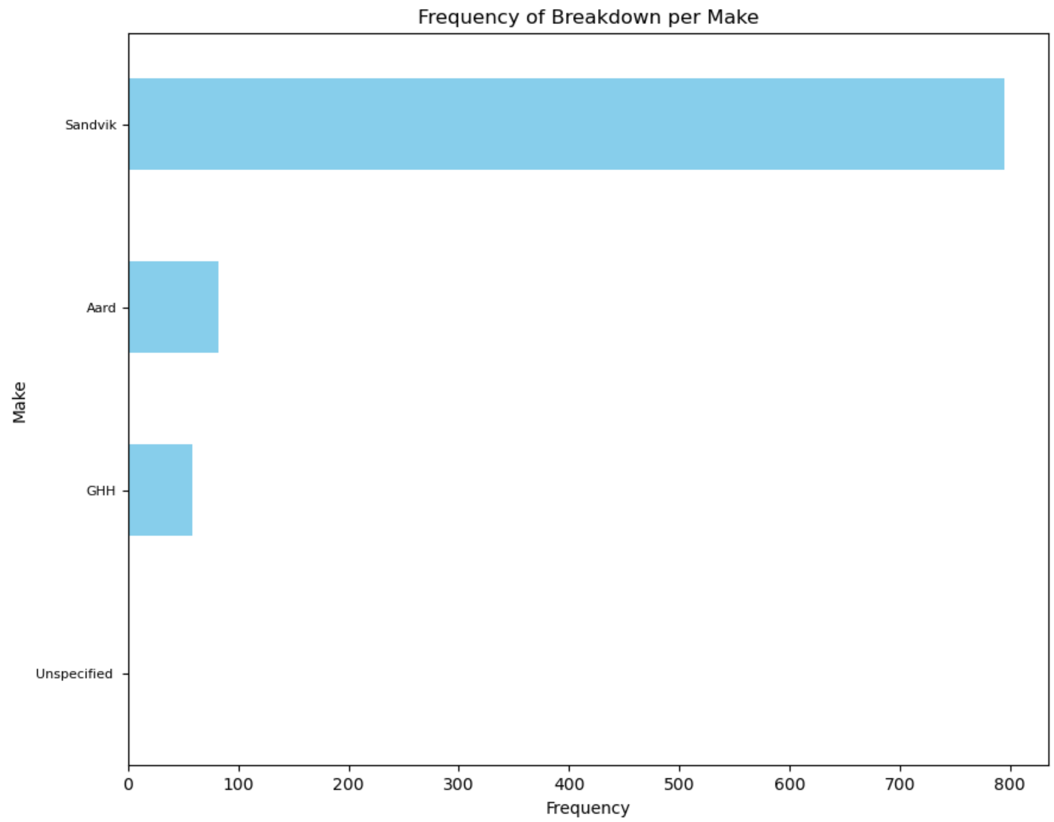

Figure 4.2: Frequency of breakdown per make

4.2.2 Analysis of downtime

i. Descriptive statistics of downtime

The mode of the LHD downtime is 5.25 hours which is higher than the mean of 2.50 hours as shown in Table 4.1. The median downtime of all LHD machines is around 1.73 hours (less than the mean and mode). The highest downtime value is 6.75 hours, and the minimum is 0.017 hours meaning the data has a wide range of values with a moderately high variability. The standard deviation (i.e. 2.03 hours) is moderately high.

Table 4.1: Descriptive statistics of downtime

Count	936
Mean (Hours)	2.50
Standard deviation (Hours)	2.03
Minimum (Hours)	0.017
Quartile 1 (Hours)	0.73
Median (Hours)	1.73
Quartile 3 (Hours)	4.66
Maximum (Hours)	6.75

ii. Histogram of downtime

Figure 4.3 shows the histogram of downtime. The distribution of downtime is positively skewed, majority of the downtime hours experienced are less than the mean. From Figure 4.3, it is observed that downtimes of less than an hour are frequently occurring. This short downtime hours could be representing minor breakdowns which occur frequently but can be repaired speedily. There also a considerable number of downtimes ranging from 5 to 6 hours; this could be due to particular failure mode/s that occur frequently and also take a long time to repair. There is less occurrence of downtimes of more than 6 hours.

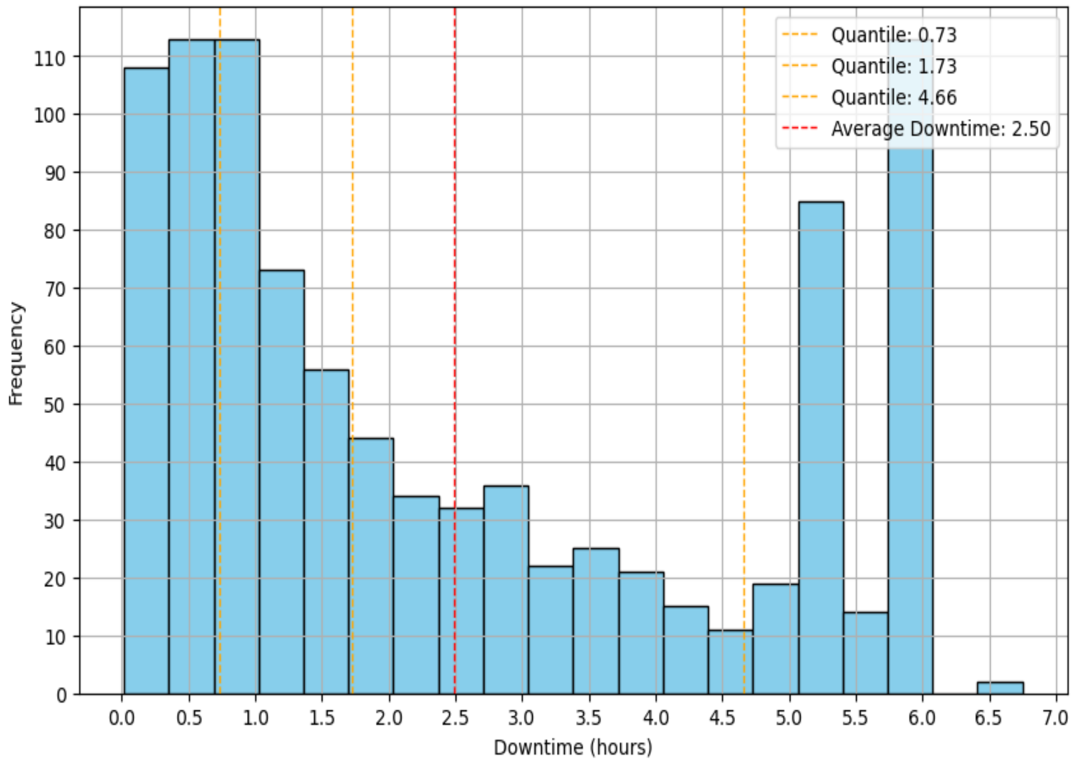

Figure 4.3: Histogram showing downtime in hours and associated statistics.

From Figure 4.3, it can also be noted that 25% of the observed breakdowns have a downtime of less than or equals to 0.73 hours. Half the breakdowns have a downtime of less or equals to 1.73 hours while 75% of the downtimes are less than or equals to 4.66 hours.

iii. Cumulative probability curve of downtime

Figure 4.4. shows cumulative probability curve of downtime. There is a probability of approximately 40% that the greater than the average downtime of 0.25 hours. The probability that the downtime will take more than 4 hours of the shift (i.e. half the shift) is 30%. The probability that the downtime will take more than 6 hours of the shift (i.e. 75% of the shift) is less than 1%. The understanding of the probability distribution of downtime will help in the prioritisation of those downtimes and associated failure modes which are most likely to occur.

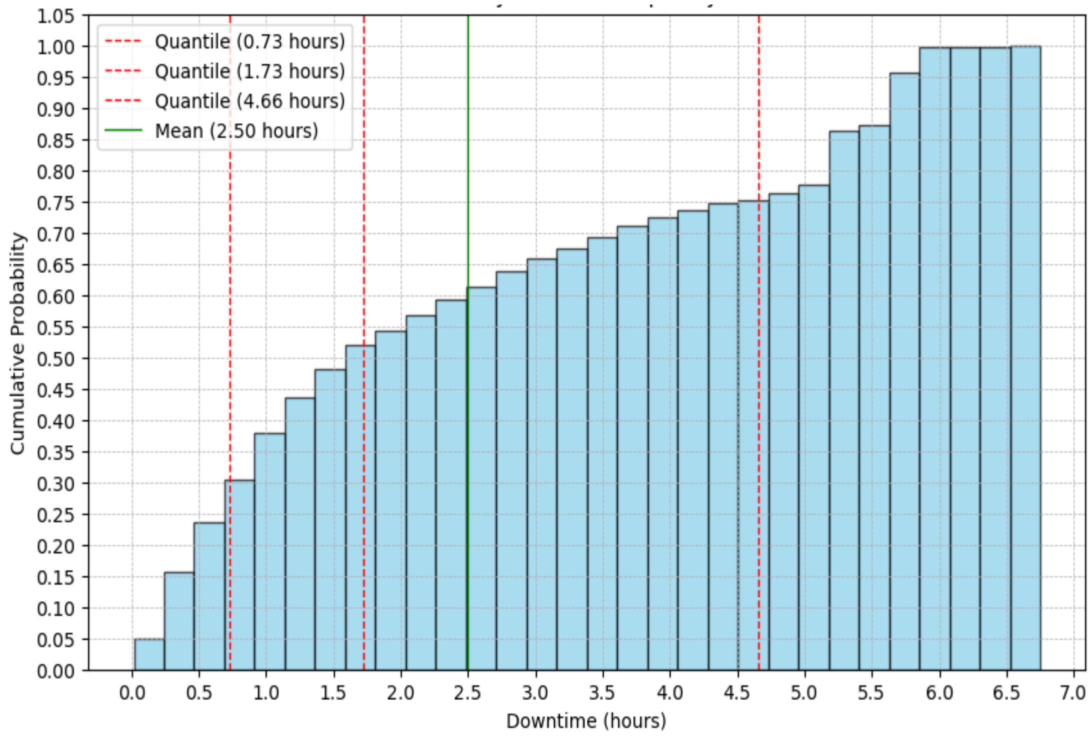

Figure 4.4: Cumulative probability curve of downtime in hours.

iv. Frequencies and average downtime per failure mode

Figure 4.5 shows frequencies of downtime per failure category. *"Oil leak or damaged hose"* have the highest cumulative frequency downtime of 194 occurrences. This is followed by the *"Engine not starting"* and *"No forward or reverse movement"* with 132 and 101 occurrences. *"Lights not working"* contributed the least to the frequency of 13 occurrences followed by *"CAS faulty"* with the frequency of 20 occurrences, *"Transmission failure"* with the frequency of 20 occurrences, and *"Electrical or wiring or battery issue"* with the frequency of 21 occurrences. Talan et al. (2018) highlighted oil leaks as the main component that failed. The study by Manenzhe et al. (2019) also found fittings and hoses as the main failure which is the same as damaged hose. Samantha et al. (2004) identified transmission failure as the main contributor to machine unavailability.

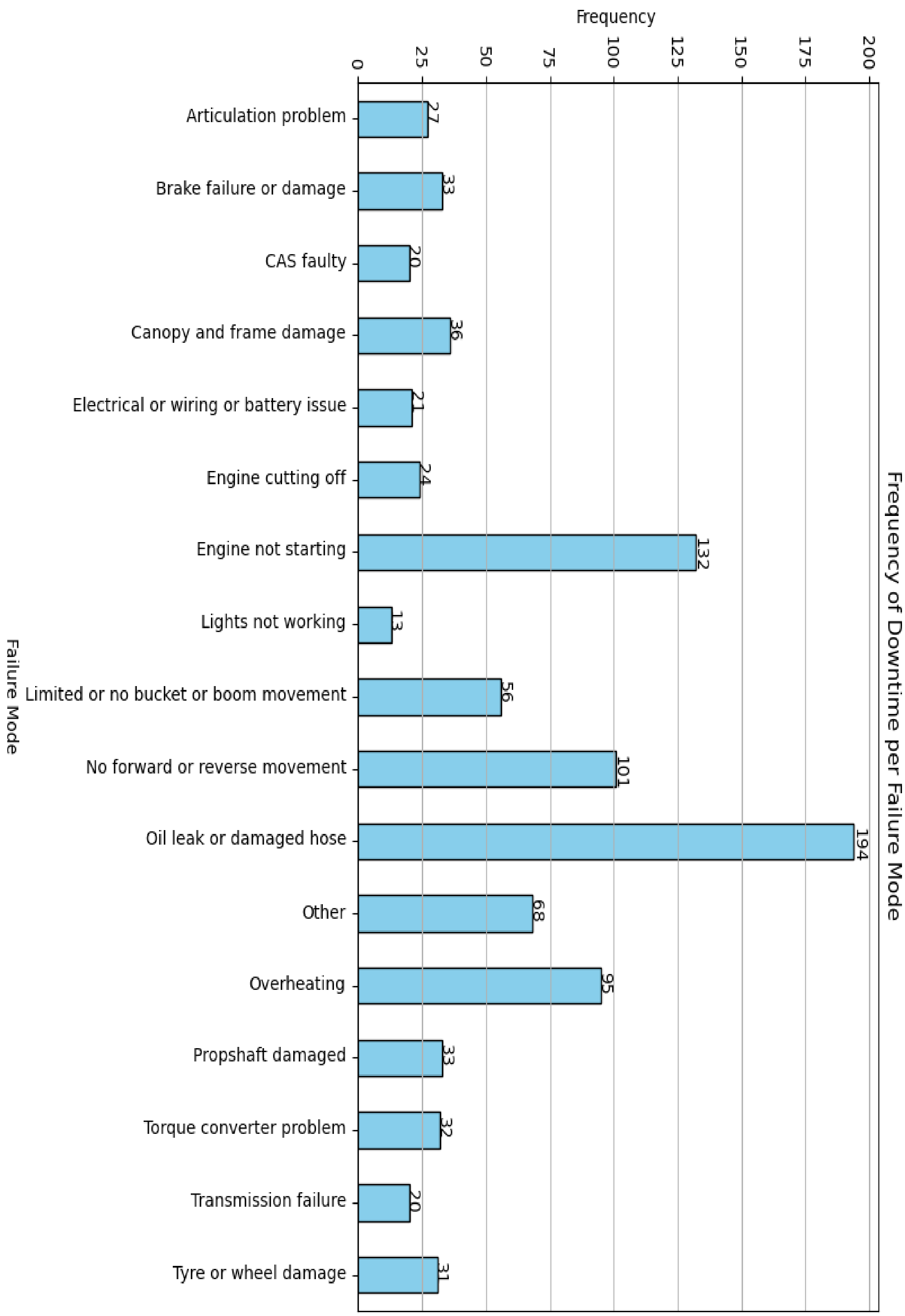

Figure 4.5: Frequencies of downtime per failure category.

Figure 4.6 shows average downtime per failure category. *"Canopy and frame damage"* has the highest average downtime of 3.99 hours, followed by the *"Electrical or wiring or battery issue"* and *"Propshaft damaged"* both with an average downtime of 3.74 hours. *"Lights not working"* had the least average downtime followed by *"Engine not starting"* with 0.73 and 1.64 hours, respectively.

"Light not working" have the lowest cumulative downtime and average downtime of all failure modes. The occurrence of failure modes with the highest cumulative frequency does not always correlate with the highest average downtime. While certain failure modes may occur frequently, their impact on downtime can vary depending on factors such as repair time, severity of the issue, and efficiency of maintenance procedures. Prioritising based solely on cumulative frequency may not accurately reflect the actual impact on downtime.

The study conducted by Khethani (2022) as discussed in the literature review, suggested that fixing a not starting problem should take at least 0.5 hours. However, the actual data analysis in table 4.2 shows it takes 1.64 hours. Similarly, the literature indicates that repairing an oil leak should take 1.5 hours, but the data shows it takes 2.34 hours. The literature suggests that fixing lights not working should take 0.3 hours, yet the actual time recorded is 0.73 hours. Overheating from the literature review shows 0.5 hours but the actual data analysis shows 2.39 hours. The time required to fix breakdowns, as shown in the data analysis, exceeds the estimates provided in the literature. This variance could be due to incompetency or a shortage of spare parts.

Human factors could play a significant role in the variance between the actual time required to fix breakdowns and the estimates provided in the literature. These might include supervision, slow response to breakdowns, skills competency and communication gaps. Ineffective supervision could lead to delays in decision-making, poor prioritisation of tasks, which can extend repair times. Delays in responding to a breakdown, such as slow reporting from operators or artisans, can prolong the repair time. Incompetency of the artisans could increase the time taken to diagnose and fix issues compared to the estimates in the literature. Poor communication between operators, artisans, and supervisors can delay the breakdown reporting process or create misunderstandings regarding the necessary repairs.

Table 4.2: Average downtime per failure mode from Khensani versus data analysis

Failure mode	**Khensani (hours)**	**Data analysis (hours)**
Not starting	0.5	1.64
Oil leak	1.5	2.34
Lights not working	0.5	0.73
Overheating	0.5	2.39

No failure modes have an average downtime greater than 75% of shift hours. Only two failure modes (*"Lights not working"* and *"Engine not starting"*) have an average downtime of less than 50% of shift hours. *"Transmission failure", "Propshaft damaged"*, *"Electrical or wiring or battery issue"* and *"Canopy and frame damage"* have an average downtime of more than 50% of the maximum downtime which is 6.75 hours. A balance should be sought to minimise breakdowns from highly frequent failure modes; while minimising the downtime of those failure modes that are less likely to occur but have a larger downtime when they do breakdown.

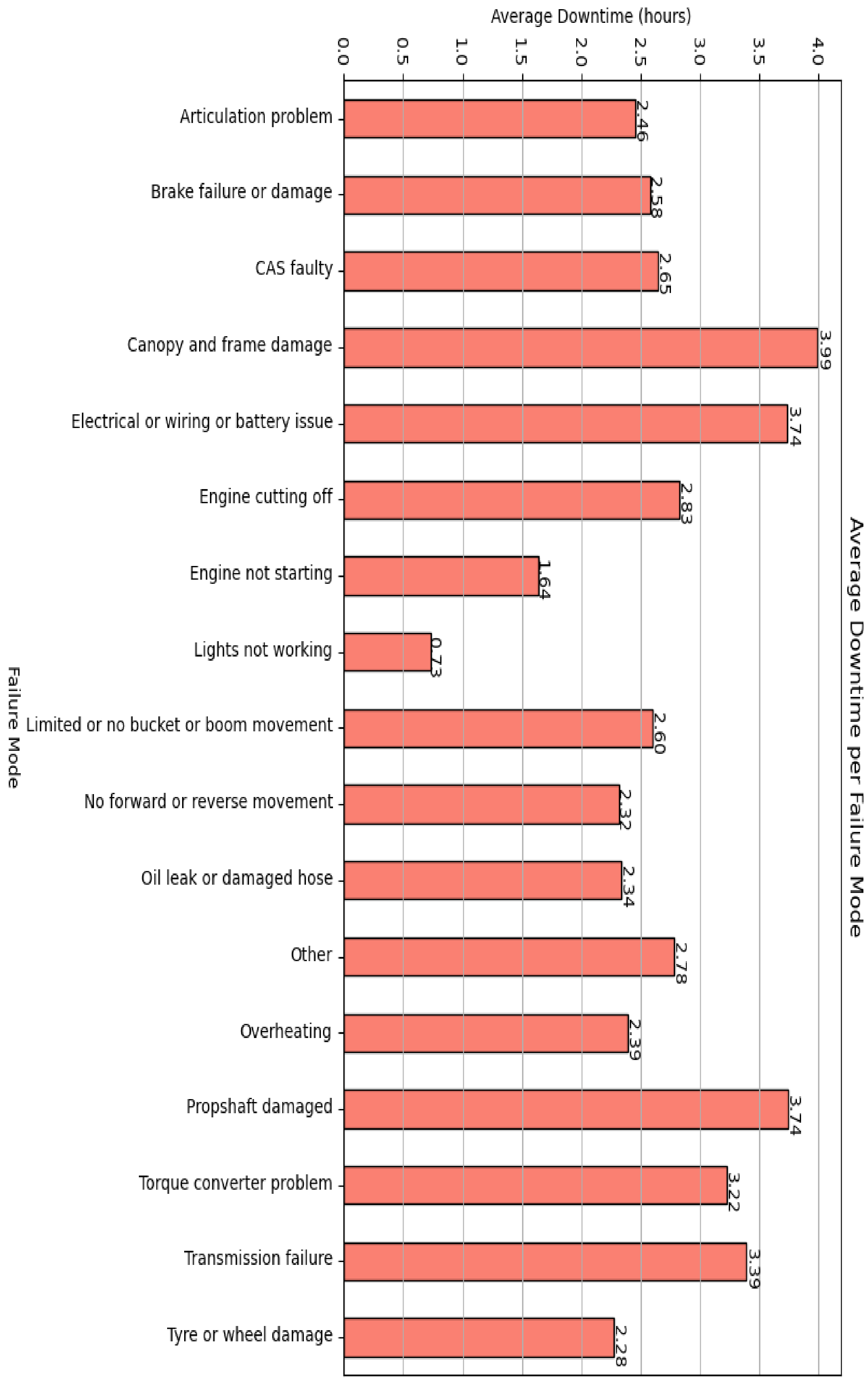

Figure 4.6: Average downtime per failure category.

v. Pareto chart of failure modes vs downtime

Figure 4.7 shows a pareto chart of failure modes versus downtime. The majority of downtime occurs as a result of the following failure modes, namely torque converter problem, damaged propshaft, canopy and frame damage, limited or no bucket or boom movement, other, engine not starting, overheating, no forward or reverse movement, and oil leak or damaged hoses. These failure modes contribute to 80% of the downtime. Focusing on these failure modes can result in an 80% reduction in downtime. Among these, the most frequent failure modes identified in both Figure 4.5 and a Pareto chart are oil leak or damaged hoses, engine not starting, no forward or reverse movement, and overheating. These are the primary areas where efforts should be concentrated to minimise downtime effectively.

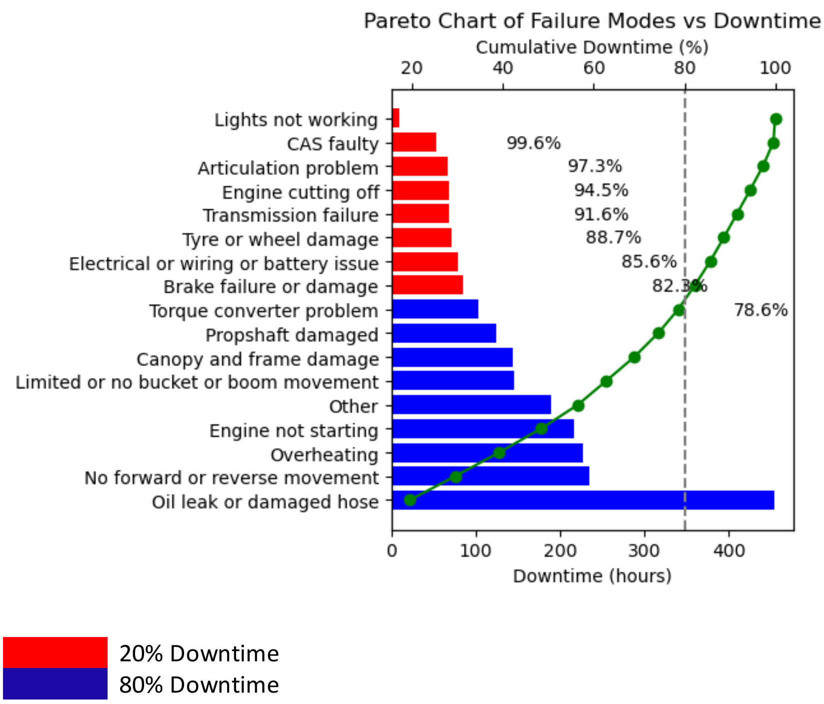

Figure 4.7: Pareto chart of failure modes versus downtime in hours.

vi. Frequencies and average downtime per failed component

Figure 4.8 shows the frequency of downtime per failed component. The *"Hydraulic system"* failed more than any other component with a frequency of 194. Followed by the *"Transmission"* and *"Electrical system"* with 186 and 166 occurrences of failure, respectively. *"Engine"* and *"Steering system"* have the lowest frequency of downtime with 24 and 27 instances, respectively.

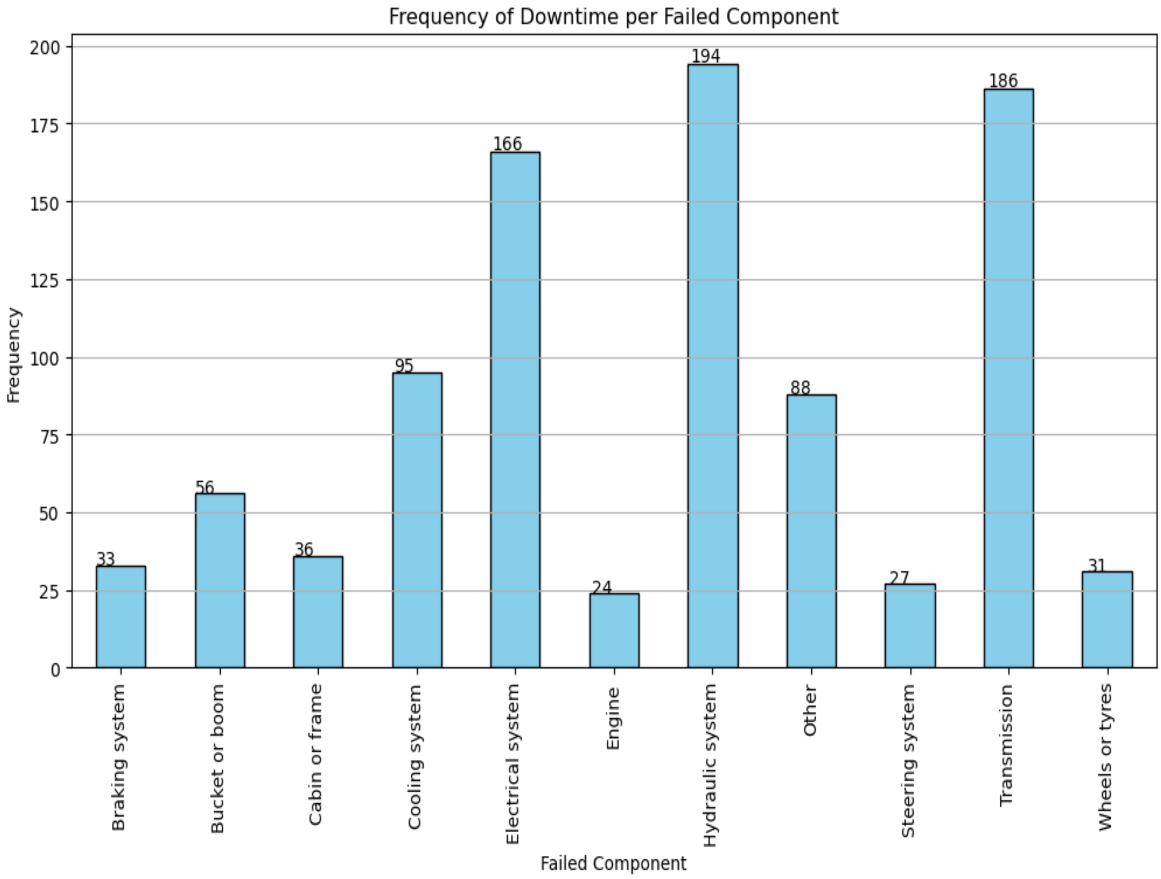

Figure 4.8: Frequency of downtime per failed component.

Figure 4.9 shows the average downtime per failed component. The *"Cabin and frame"* component has the highest average downtime of 3.99 hours. The *"Electrical system"* has the lowest downtime average of 1.83 hours. The rest of the other components have a relatively similar average downtime between 2.3 and 2.8 hours.

The components with the highest and lowest frequency of downtime were found to be different from those with the highest and lowest average downtime. This is as a result of some components that fail more easily than others but would require less time to repair, having a lower average downtime. Other components fail less (i.e. lower frequency of occurrence) take longer to repair, resulting in higher average downtime hours. This finding is important in the establishment of the maintenance strategy. Nonetheless, the "*Transmission*" component is of concern and warrants a special mention. It has a high frequency of downtime as well as a high average downtime. Meaning, transmission fails regularly, and it is also time consuming and complex to repair.

Components like the engine, hydraulic system and brakes have been found to have a lower downtime average than the ones presented by Khethani (2022). Whilst there is no component with an average of downtime more than half shift (4 hours) period, the cabin or frame component was close to 4 hours. Except for wheels and tyres, steering system, electrical system and cooling system, the rest of the components had average downtimes larger than the mean. No failure components have an average downtime greater than 75% of shift hours.

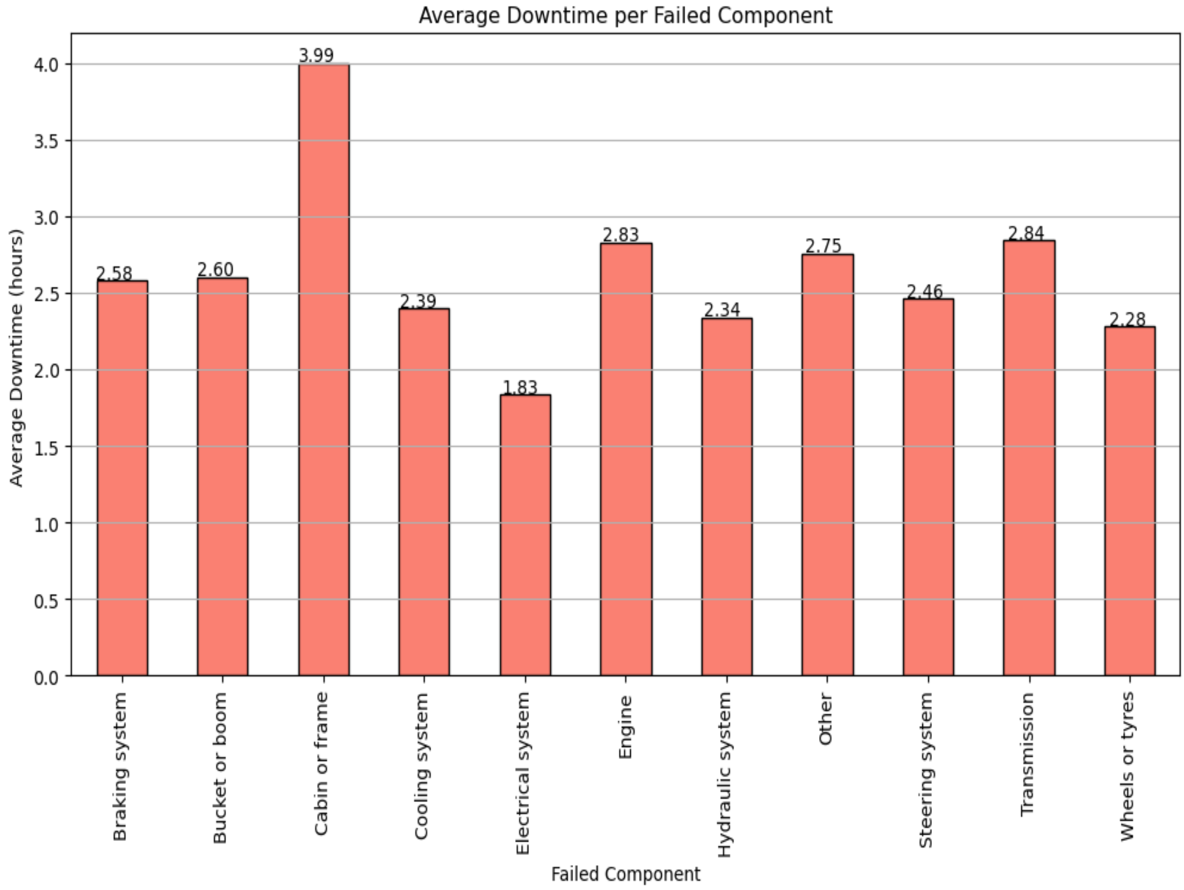

Figure 4.9: Average downtime per failed component.

vii. Pareto chart of failed component vs downtime

Figure 4.10 shows the pareto chart of failed component versus downtime. The following components contribute towards 80% of downtime: Transmission, hydraulic, electrical system, cooling system and components classified as “other”. That means if the focus is on these failure components, downtime can be reduced by 80%. The *“Transmission”* and “*Other*” failed components have downtime averages greater the mean downtime of LHDs which is 2.5 hours. This highlights the large impact the *“Transmission”* is having on downtime.

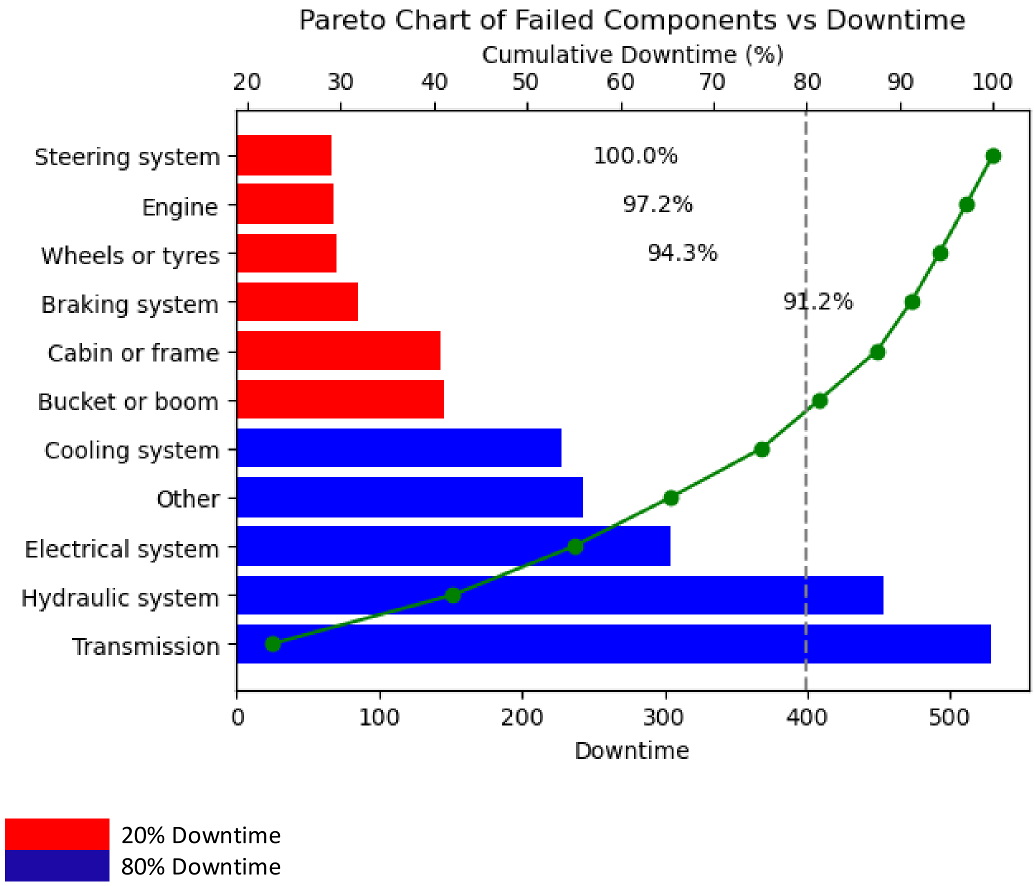

Figure 4.10: Pareto chart of failed component versus downtime in hours.

viii. Bar charts of total and average downtimes per shift

Figure 4.11 shows totals hours of downtime per shift. There is a difference between the night shift and the other shifts (morning shift and afternoon shift). The night shift has 1802.03 hours of downtime while morning and afternoon shifts have 840.17 and 811.00 hours, respectively. These findings suggest that the NS has more machine downtime.

Figure 4.12 shows the average downtime per operational shift. It shows that the night shift experiences an average downtime of 0.42 hours per shift, while both the morning and afternoon shifts experience an average downtime of 0.19 hours per shift. This indicates that each breakdown during the night shift takes an average of 0.42 hours to resolve, which is significantly longer compared to the morning and afternoon shifts, where each breakdown takes an average of only 0.19 hours to resolve.

The more downtime hours and larger downtime average experienced during the night shift may be due to various reasons, including challenges in spare parts organisation, labour issues, and little supervision. Organising spare parts becomes particularly challenging during the night shift, possibly due to limited resources or accessibility. Unlike the day shift, which benefits from a greater number of forepersons available to address breakdowns efficiently. Night shift typically operates with fewer supervisory staff. For example, the morning shift typically has more robust supervisory presence such general engineering supervisors, forepersons, and mine overseers. The night shift often operates with one or two mine overseers and relies heavily on a limited number of supervisors to manage breakdowns and maintenance tasks. This discrepancy in supervision levels between shifts can contribute to the challenges faced by the night shift in effectively addressing and resolving equipment breakdowns in a timely manner.

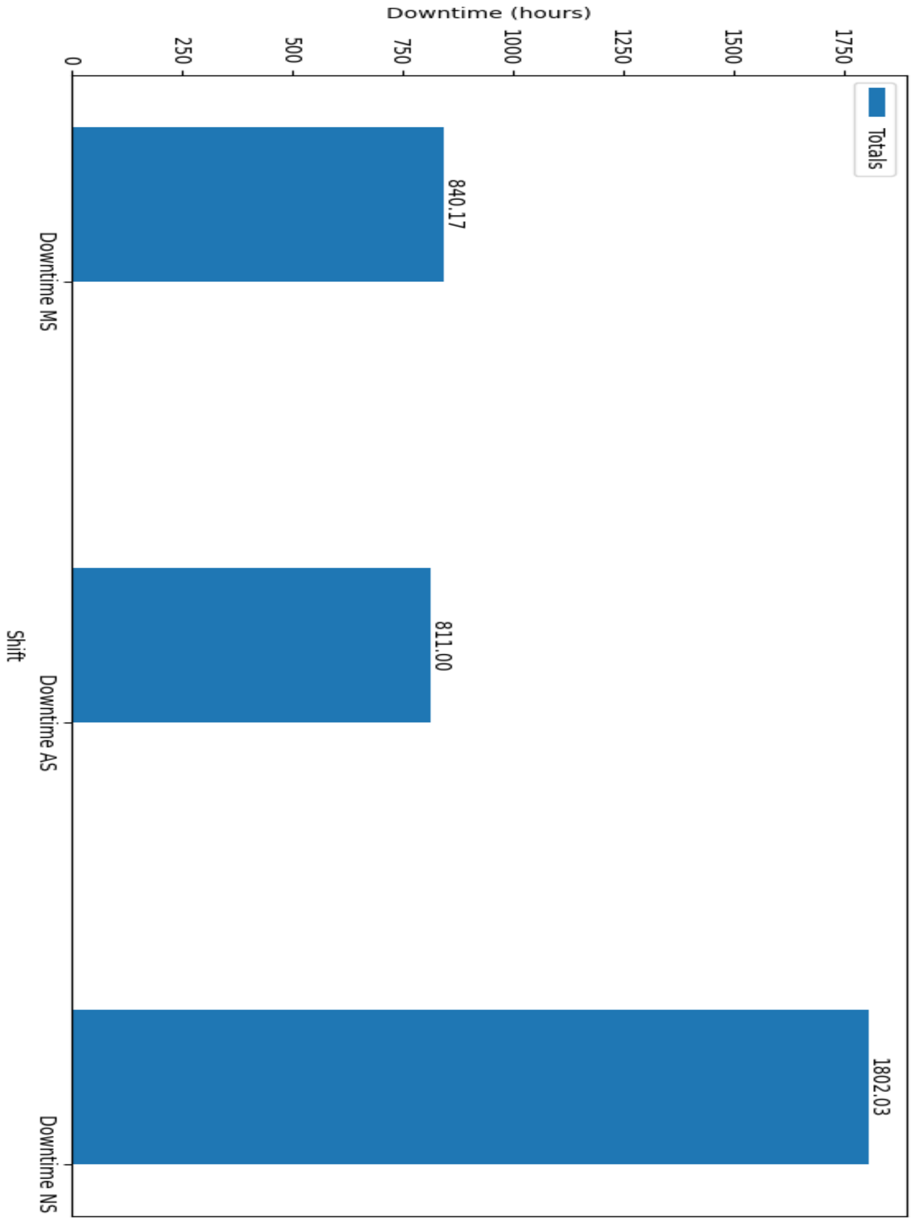

Figure 4.11: Totals and averages per operational shift.

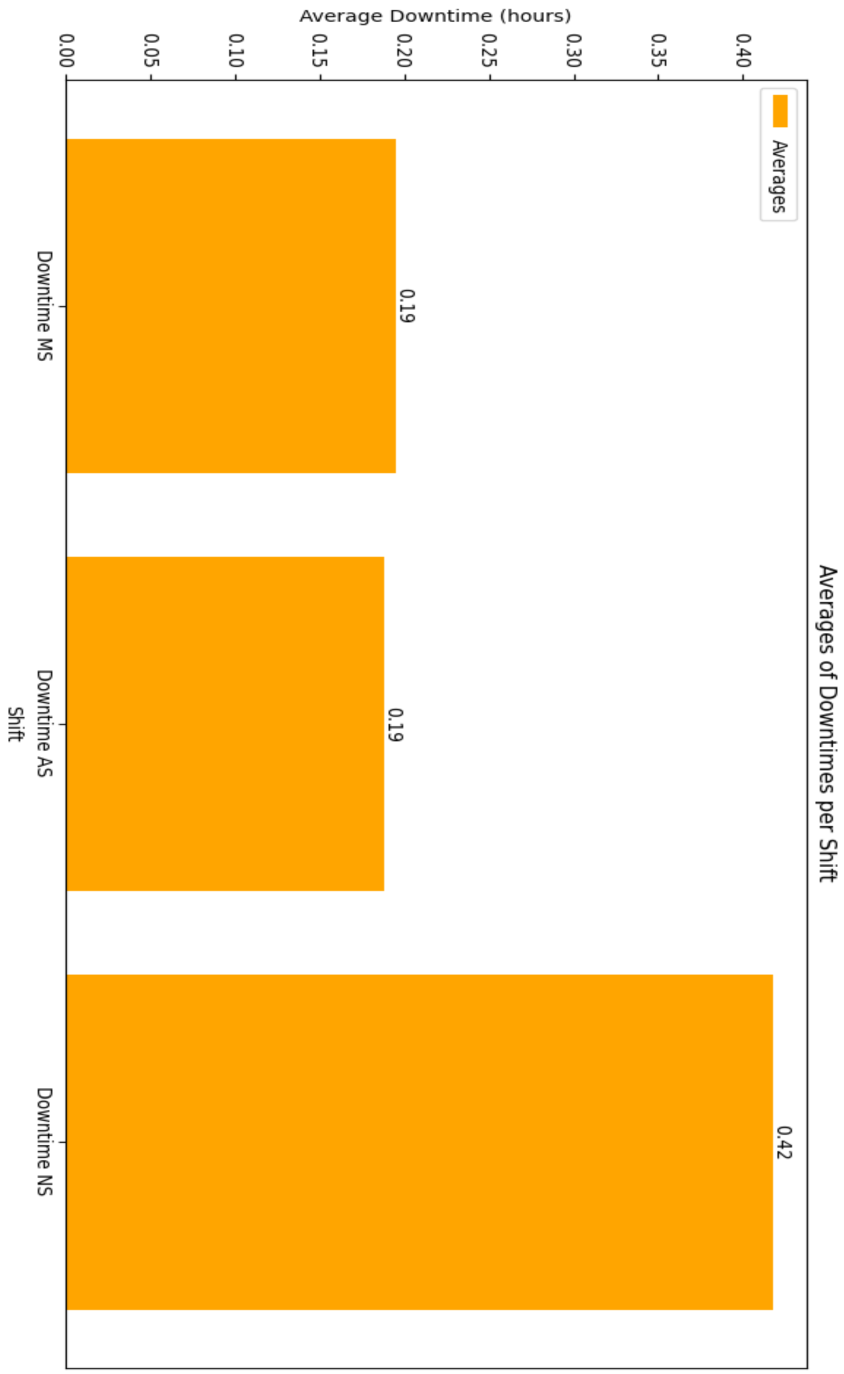

Figure 4.12: Averages of downtime per operational shift.

ix. Total and average downtime per LHD (highlighting the LHDs responsible for 80% of the downtime)

The number of LHDs contributing to 80% of the total downtime is 21, with LHD-33 which approximately accounts 140 total downtime hours, the highest among them. Following LHD 33, the next four LHDs with high total downtimes are LHD-12, LHD-11, LHD-36, and LHD-29, as shown in Figure 4.13. The LHDs with highest average downtimes are LHD-317, LHD -22, LHD-18, LHD-02, and LHD-20, as illustrated in Figure 4.14. There is no LHD that appears in both the top 5 contributors of highest average downtime and the LHDs contributing 80% of downtime. This suggests that all LHDs are experiencing unpredictable problems or failures. To effectively manage downtime, it is advisable to prioritise addressing the LHDs contributing to 80% of the downtime. It is possible that some of these LHDs with the highest average downtime might be from the same shift, experiencing failures that take long to repair or have reached their useful life. When comparing to the data from the frequency of breakdown per LHD, it was found out that LHD-33 has the highest frequency of breakdowns, as well as several other LHDs such as LHD-11 and LHD-12. It is important for the maintenance strategy to flag the problematic LHDs and then carryout a root-cause analysis on a continuous basis so as to reduce the impact of LHD failures.

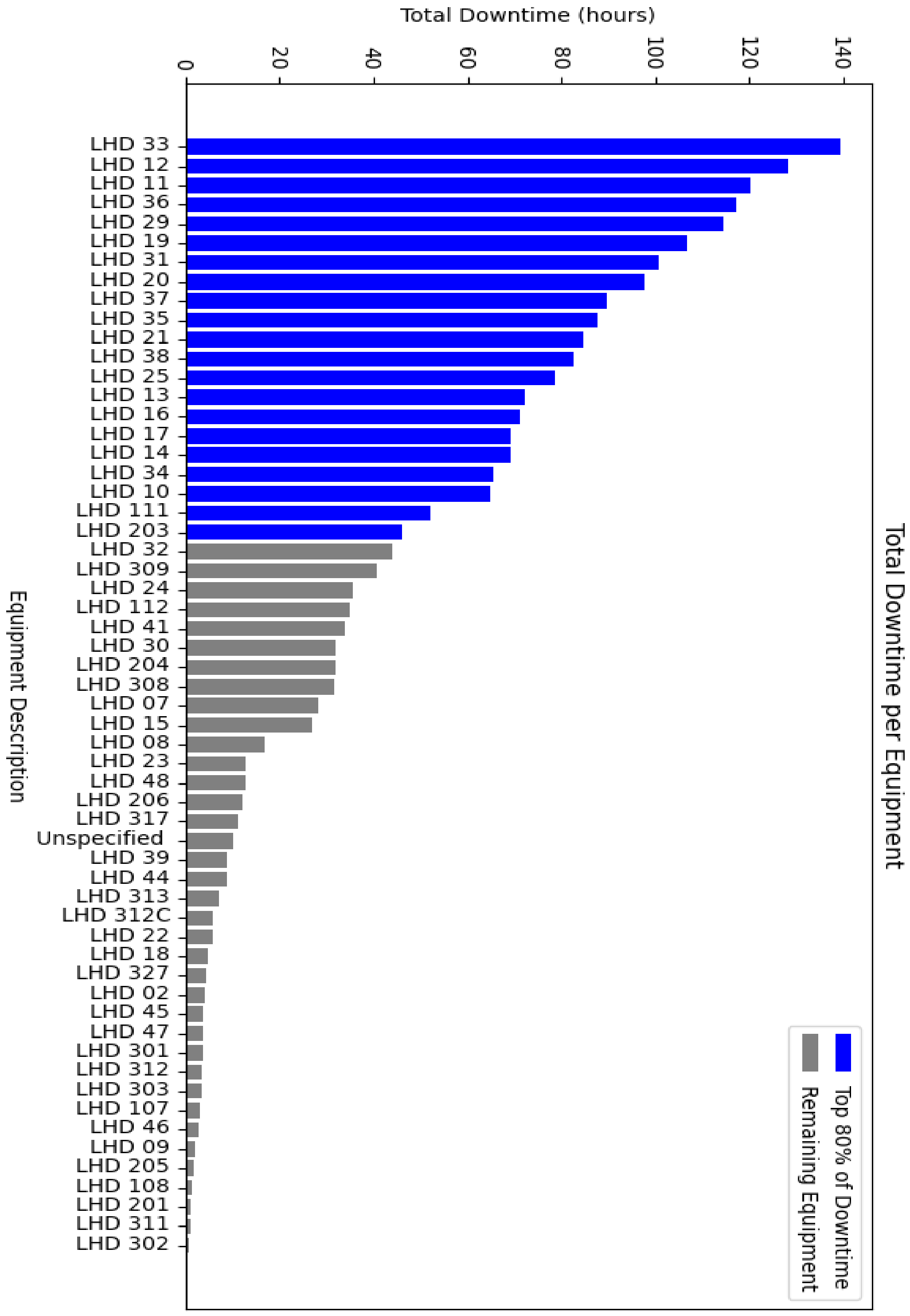

Figure 4.13: Total downtime per equipment.

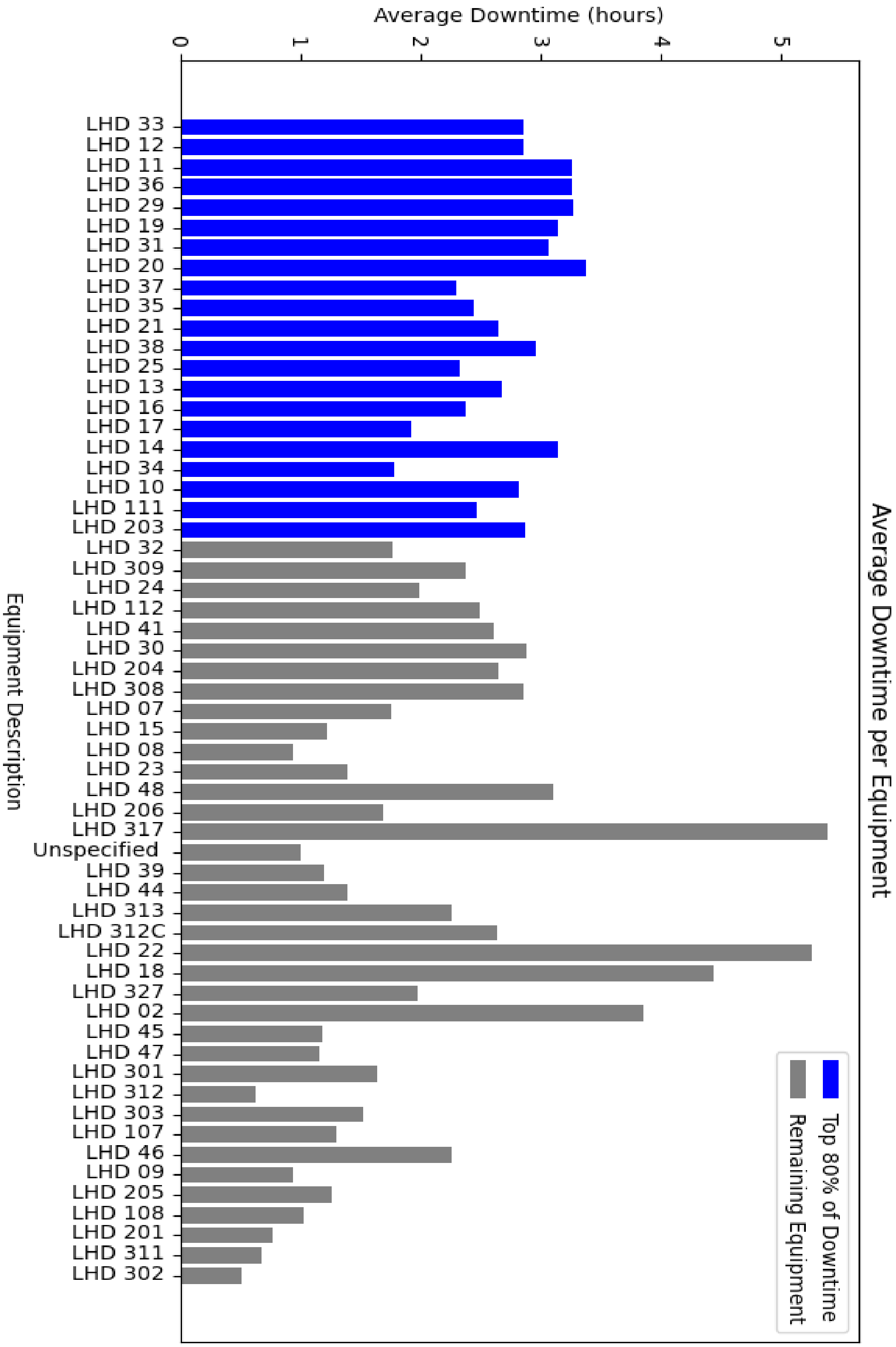

Figure 4.14: Average downtime per equipment.

x. Downtime contribution per OEM

The LHDs from the OEM Sandvik are found to be the ones having the highest downtime at 86.3%, followed Aard at 8.2%, GHH at 5.5% and unspecified at 0.1% as shown in Figure 4.15. The high downtime of Sandvik as an OEM is found to be consistent as Sandvik is the highest frequency of breakdowns, compared to other makes in the OEM group. Although Sandvik has more LHDs in the group than any other make, it did not justify the extremely high contribution to downtime as well as the high frequency of breakdowns, hence there is a need for a focused study of the Sandvik's LHDs.

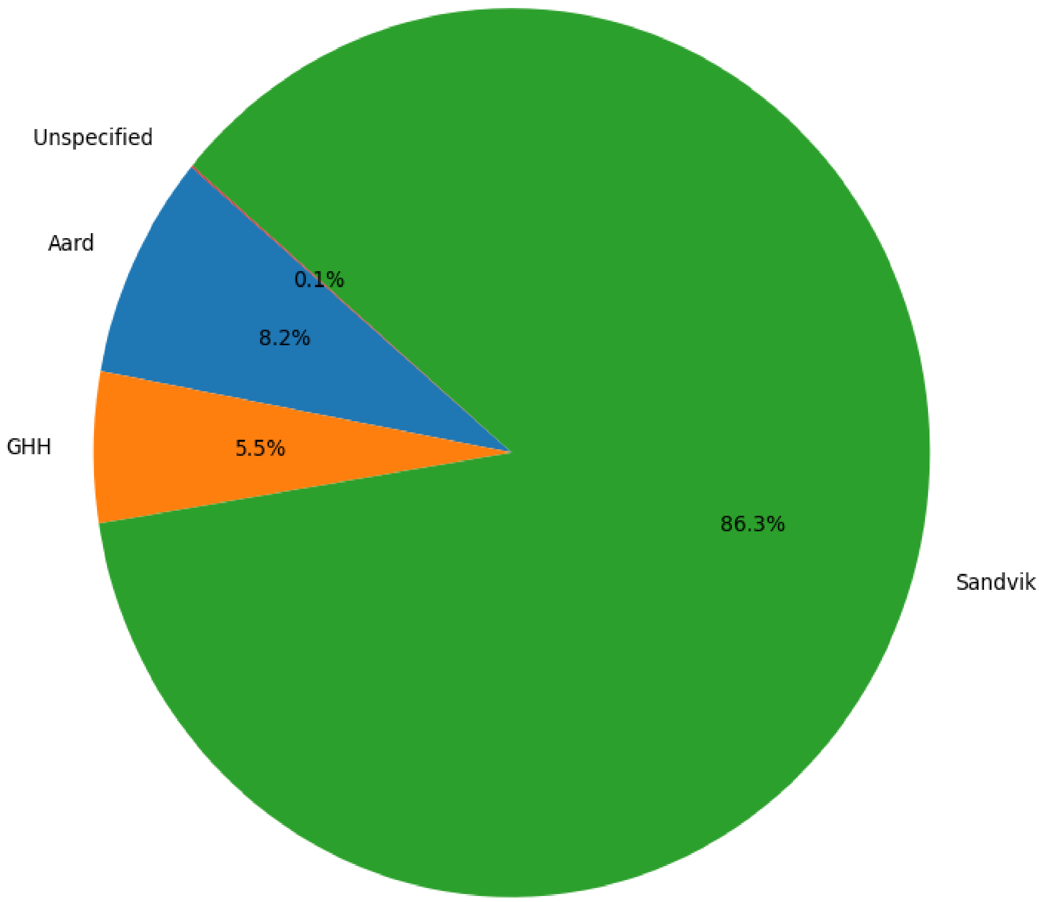

Figure 4.15: Distribution of downtime by LHD make.

4.2.3 Analysis of failure modes

i. Frequencies of failure modes

The occurrence of failure modes is not specific to shifts; however, there are slight differences in the quantities of each failure mode as shown in Figure 4.16. The frequency of failure modes varies slightly across shifts, with different modes prevailing in each shift. For instance, canopy and frame damage occurs 12 times in both the MS and AS. Similarly, engine cut off occurs 12 times in AS and NS, while engine not starting is observed 42 times in AS and NS. Propshaft failure occurs 11 times in MS and NS, while torque converter problems occurred 12 times in MS and NS. Despite these variations in occurrence, the sizes of each failure mode are nearly identical across all shifts.

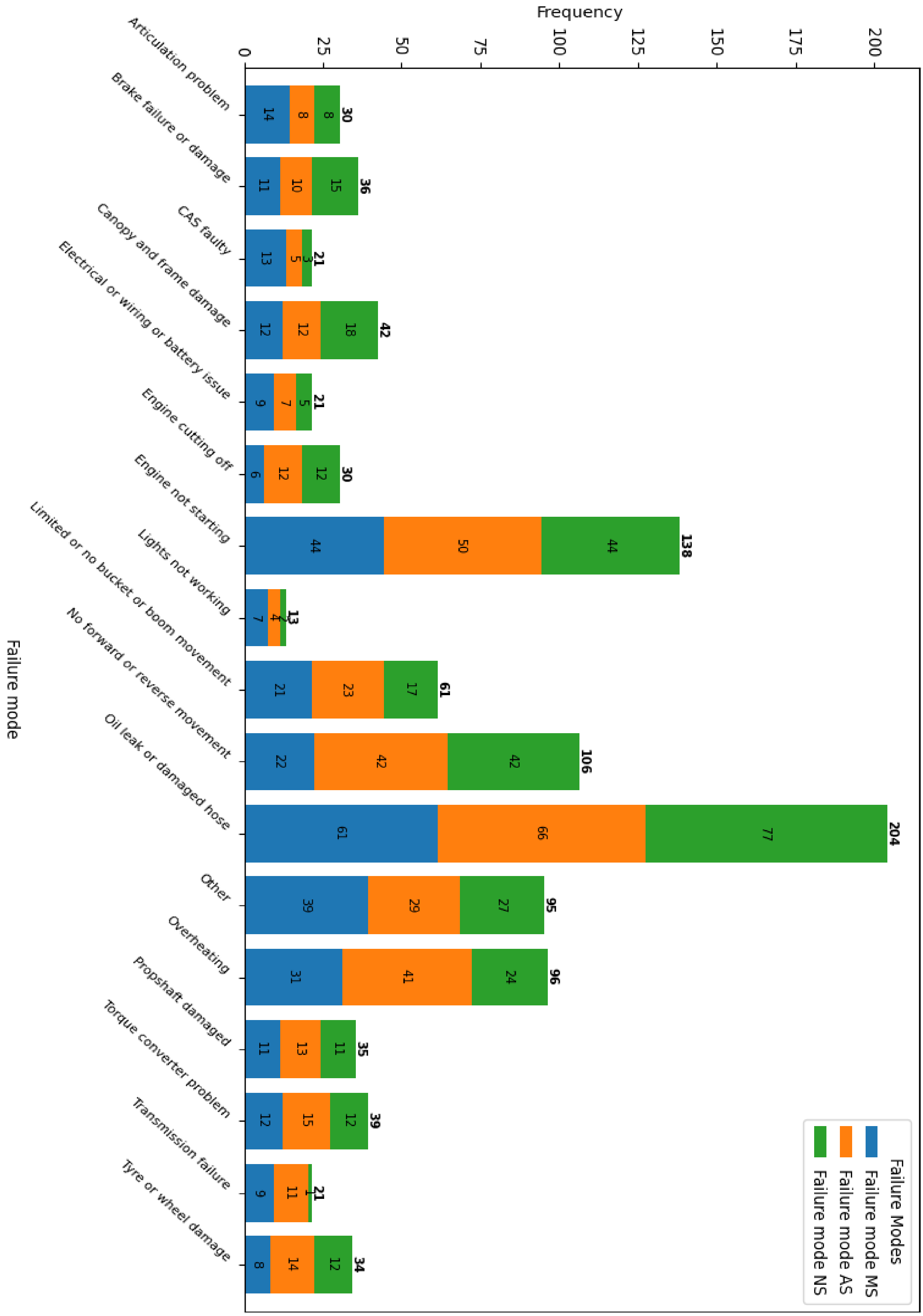

Figure 4.16: Frequencies of categories in each failure category.

ii. Frequencies of failure modes per OEM

Articulation issues are the most common failure mode for Aard. GHH LHDs have a problem of "brake failure or damage. Sandvik LHDs face a variety of challenges, including articulation difficulty and brake failure/damage. Sandvik LHDs tend to not perform well at Booysendal mine compared to other OEMs, based on practical observations. Similar to the previous investigation, hydraulic and brake-related issues are prevalent. The unspecified category contains fewer failure modes as shown in Figure 4.17.

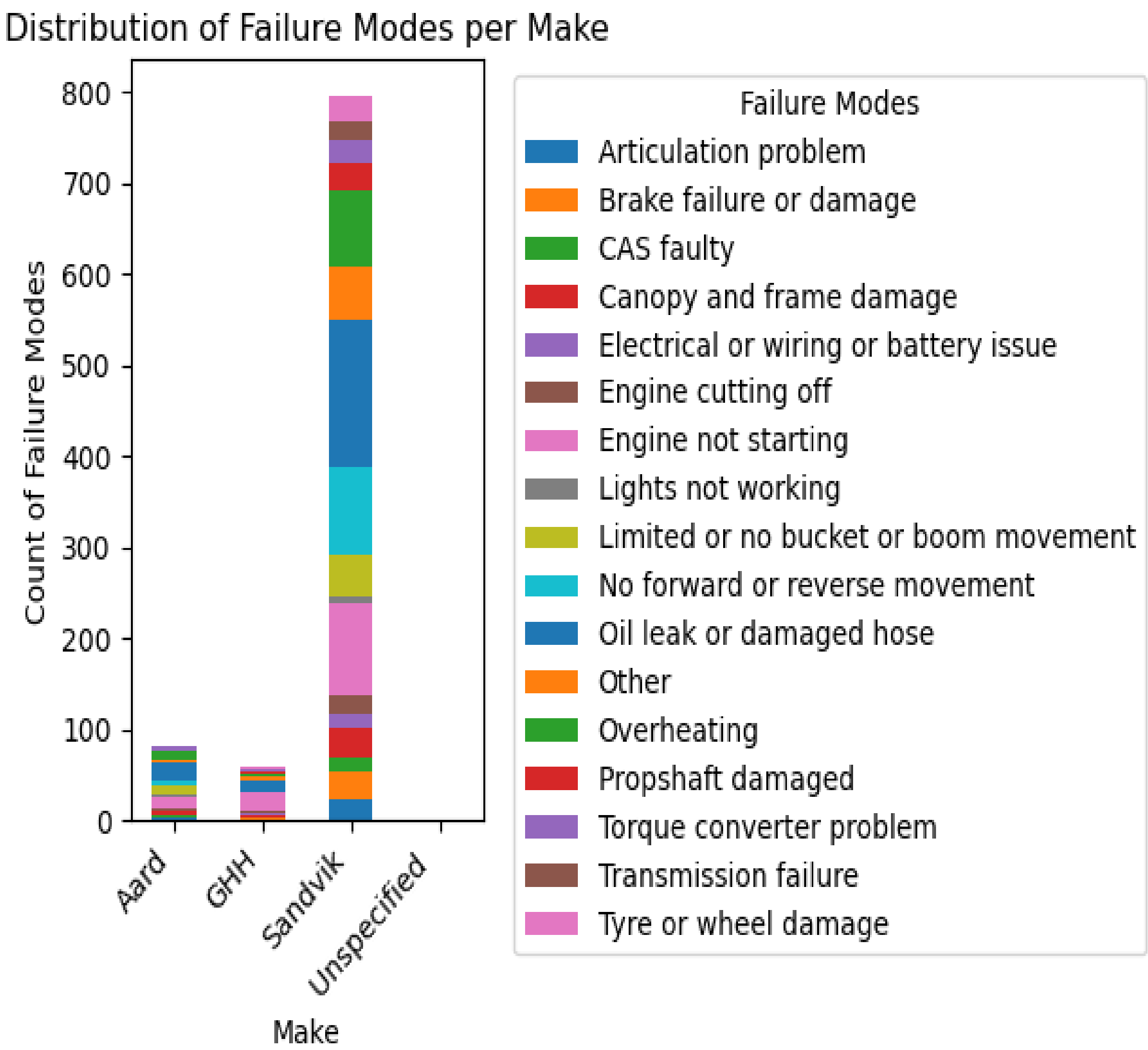

Figure 4.17: Distribution of failure modes per LHD make.

4.2.4 Analysis of failed components

i. Frequencies of failed components

Figure 4.18 shows the frequencies of categories in each failed component. The distributions across operational shifts (i.e., morning, afternoon, and night shift) are not slightly different, but there are some discrepancies. Electrical systems and mechanical issues (transmission and hydraulic systems) show a higher frequency during the night shift. Problems related to wheels or tires show consistent distribution across all shifts. It is possible that during night shifts, there could be less supervision, leading to increased component failures. The limited supervision in night shift on-site, can result in slower decision-making and minor issues may go unnoticed until they become significant. Operators working night shifts are more prone to fatigue, which can reduce their concentration and reaction times. The fatigued operators may be less alert to operational protocols, increasing the risk of breakdowns.

The hydraulic system category has the highest overall frequency, with 202 occurrences in total. Both the engine and steering systems have the lowest frequency, each with 30 occurrences in total. Further investigation must be conducted to address any potential operational concerns. "Other" is a major concern since it contributes 116 occurrences of failed components.

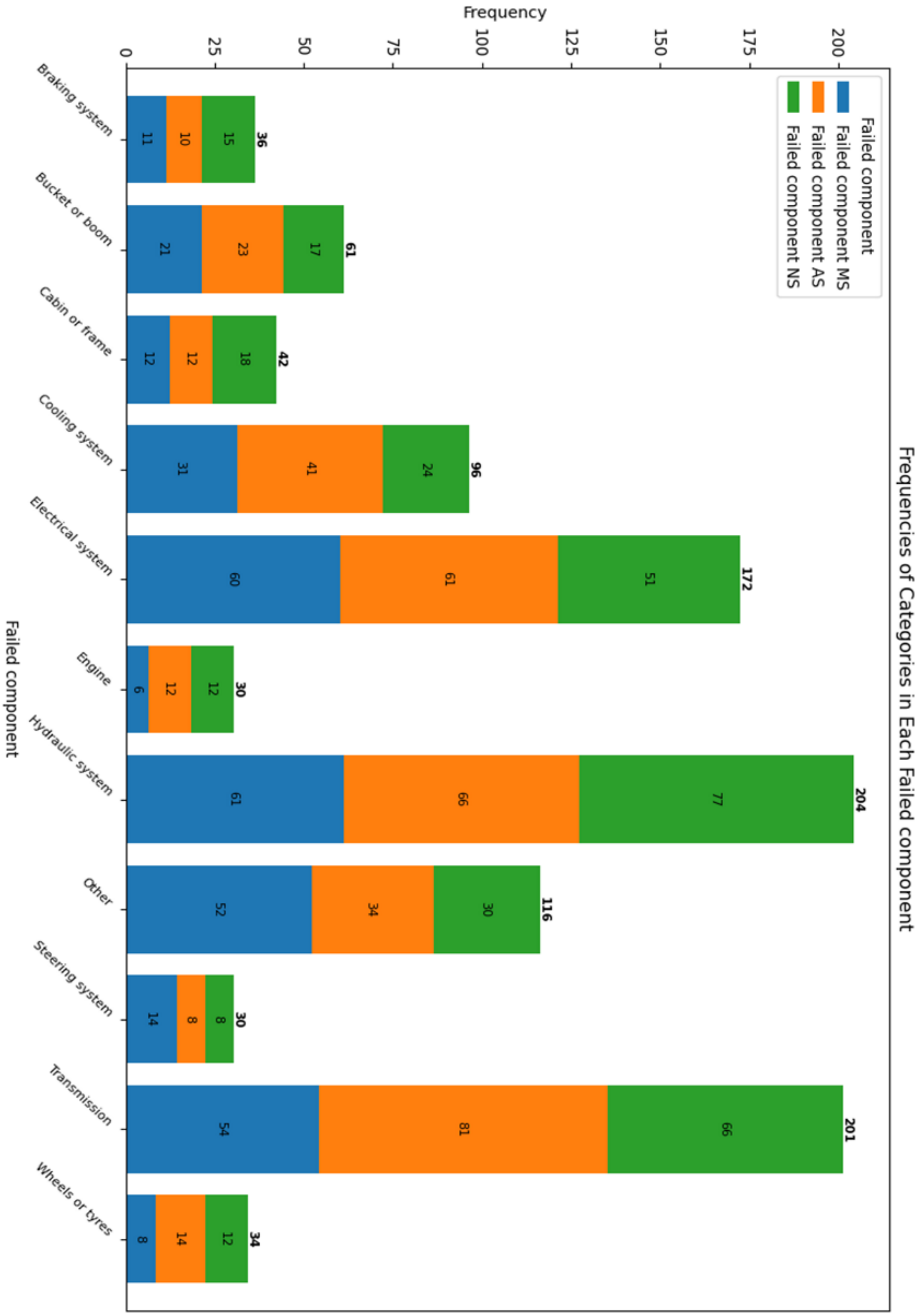

Figure 4.18: Frequencies of categories in each failed component.

ii. Frequencies of failed components per OEM

Figure 4.19 shows the distribution of failed component per make. Sandvik LHDs experience the most problems in its hydraulic system and transmission. Aard LHDs are have the highest problems with hydraulic system and electrical system. GHH machines have the highest problem with electrical system and hydraulic system. The hydraulic system is the most dominant component failure across all OEMs. The hydraulic system has been highlighted is the most common failure in the previous sections and literature review. According to the literature review in the study by Samanta et al. (2004), transmission emerges as a significant contributor to machine unavailability. A study by Manenzhe et al. (2019) also identified fittings and hoses as the primary contributors to breakdowns. On average, transmission is the most common failure across all these studies.

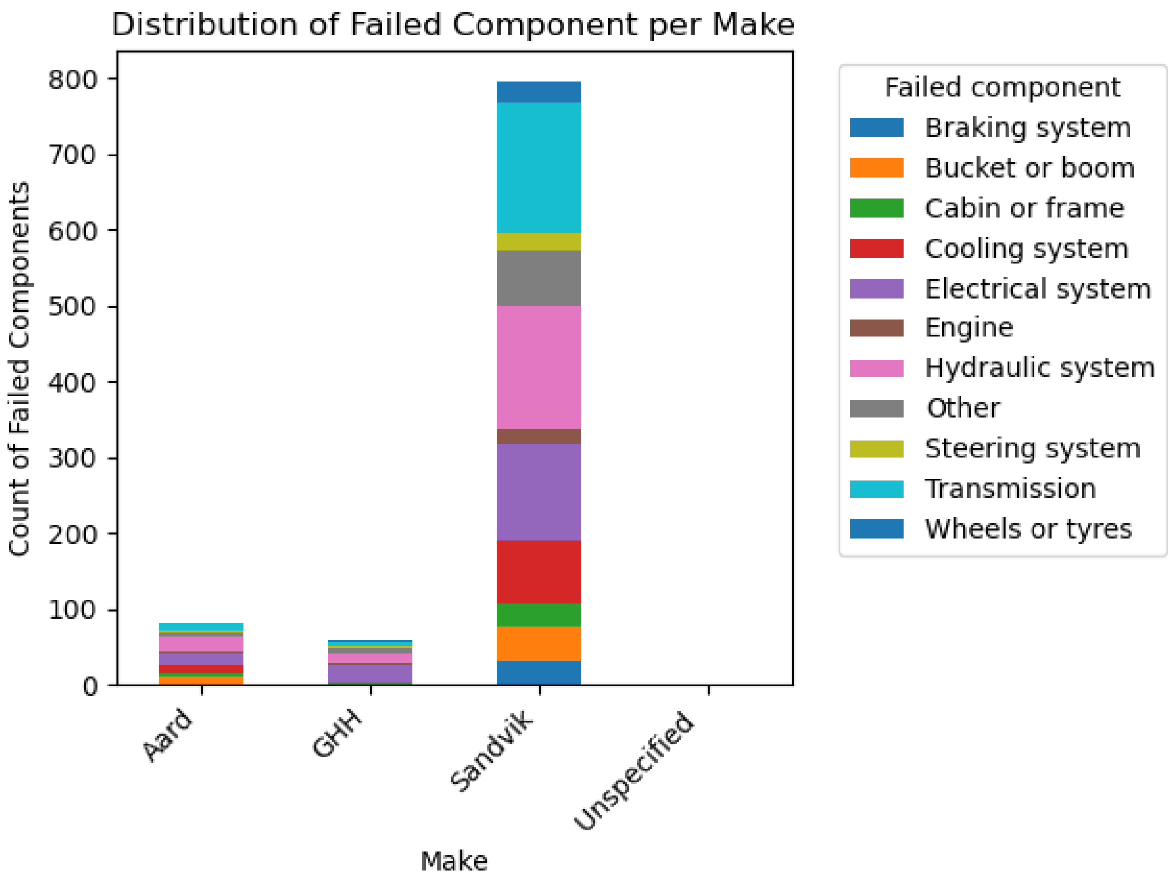

Figure 4.19: Distribution of failed component per make.

4.3 ML models

4.3.1 Regression models

The KNN regression model was found to be the best predictive regression model to predict the downtime of an LHD machine since it has the least Root Mean Square Error (RMSE) of 2.02 hours and the best R^2 and Variance Error (VE). Support Vector Machine (SVM) was the worst performing regressor when looking at RMSE, R^2, Variance Error (VE) and Maximum Error (ME) but provided the best Mean Absolute Error (MAE), as shown in Table 4.3. The RMSE of 2.02 hours means that the model will predict the downtime with an error equivalent to 25% of the shift.

The performance of the regression models needs further improvement. It is suspected that since the data had to undergo extensive cleaning by deleting most of it as detailed in sub-section 3.3, the inherent patterns, interactions and variability in the training data may have been lost. The enhancements in data collection proposed in sub-section 4.4 will increase the quality of the data and it expected that this will subsequently improve the models' performance.

Table 4.3: Regression models using Decision Tree (DT), K-Nearest Neighbours (KNN), Random Forest (RF), and Support Vector Machine (SVM).

Model	**RMSE (Hours)**	**MAE (Hours)**	**R^2**	**Variance Error (VE)**	**ME (Hours)**
DT	2.05	1.82	0.053	0.065	4.29
KNN	2.02	1.76	0.083	0.091	4.37
RF	2.06	1.81	0.061	0.074	4.42
SVM	2.07	1.69	0.032	0.047	5.11

4.3.2 Classification models

Accuracy was deemed the most important classification metric for the selection of the best performing classifier since it directly measures how accurately downtime categories were classified. Precision was still useful to analyse instances of false negatives and false positives, providing an opportunity to investigate anomalies in expected classes versus predicted classes. SVM classifier displayed the highest accuracy (60%) and highest measures of precision and recall. As a result, SMV was chosen since it still displays highest accuracy while also maintaining better precision than the other classifiers. The worst performing classifier was found to be KNN. DT displayed the highest F1-score.

Table 4.4: Classification models using Decision Tree (DT), K-Nearest Neighbours (KNN), Random Forest (RF), and Support Vector Machine (SVM).

Classification Model	**Accuracy**	**Precision**	**Recall**	**F1**
DT	0.596	0.461	0.596	0.509
KNN	0.479	0.390	0.479	0.430
RF	0.585	0.455	0.585	0.507
SVM	0.601	0.472	0.601	0.481

Although SVM displayed the best classification metrics, further improvements on these models are necessary. It is suspected that since the data had to undergo extensive cleaning by deleting most of it as detailed in 3.3, the inherent patterns, interactions and variability in the training data may have been lost. The enhancements in data collection proposed in 4.4 will increase the quality of the data and it expected that this will subsequently improve the models' performance.

4.4 Maintenance Strategy Development

The maintenance strategy used for this study will be a combination of predictive maintenance (PdM) and condition-based maintenance (CBM), which is commonly referred to as hybrid maintenance. Based on a review of historical breakdown data, it has been determined that some components, namely the transmission and hydraulic system, show higher frequencies of failure with 186 and 194 occurrences, respectively compared to other components. These particular components require special attention and must be readily available in stores. Hence, it is important to implement hybrid maintenance strategies that align with the observed trends of these failures. Hybrid maintenance proves to be extremely useful in the early detection of possible breakdowns and reducing the amount of operational downtime.

The application of machine learning models and data analysis has had a significant impact on the maintenance strategy by identifying critical components that show frequent failures. This has enabled the implementation of targeted maintenance initiatives aimed at reducing downtime. Predictions of component failures were developed using machine learning models, which relied on historical data patterns. The combination of machine learning models with condition-based monitoring provides valuable insights into the health of LHD machine. This helps the maintenance crew to schedule maintenance tasks based on actual equipment conditions.

The ML algorithms have a prediction accuracy of 50%, which is quite moderate due to the challenging dataset. The data quality is not great as it was overly cleaned, removing many variables that influence downtime. While the model performs well in general, there is a need to improve the dataset fed into the model to select the appropriate maintenance strategy. Data capturing can be improved by implementing a standardised Excel spreadsheet containing all potential breakdowns of an LHD machine. In this system, the control room operator will simply select the actual breakdown from a predefined list within the automated excel spreadsheet, ensuring consistency and completeness in recording breakdowns.

Integrating machine learning models into the maintenance strategy can have a substantial impact on daily practical decisions in various aspects, including predictive maintenance scheduling, CBM, and spare parts management. In integrating machine learning models into the maintenance schedule, maintenance teams are empowered to make well-informed decisions based on data on a daily basis. This integration results in increased equipment reliability, less downtime, and improved productivity. In the maintenance strategy, integrating new data sets into existing models can significantly enhance the prediction of downtime and downtime categories based on failure modes, in that way improving preventative maintenance strategies.

Planning for spares

Based on the insights derived from ML and data analysis, the stocking spares for components that show higher failure frequencies of failure will be prioritised. These components include transmission, hydraulic system (hydraulic cylinders, hydraulic hoses and hydraulic pump) and electrical system, these components must always be on site. The other critical components that must be on site include torque converter, propshaft, engine, and safety devices (Proximity Detection Systems (PDS)). Predictive maintenance can assist in forecasting which parts are likely to require replacement in the future. It is important to maintain communication with the supplier to prevent stock shortages, and spare parts should undergo regular review. Emergency spares are indispensable and must always be readily available in stock.

Purchasing of spares

The critical components like transmission, hydraulic system and electrical system must be purchased in advance to avoid any delays in production. The mine must choose the supplier based on reliability, quality, pricing, and lead time. Suppliers should meet the mine's requirements. Orders should be placed in a timely manner, and their status monitored. Upon receipt, the person receiving the stock must inspect it to verify quality and quantity and maintain records of all spare parts purchases, including invoices and receipts.

4.4.1 Hybrid maintenance strategy

The hybrid maintenance strategy is summarised using Figure 4.20 diagram design using Microsoft Excel default shapes tools. The proposed elements of hybrid maintenance strategy are summarised below:

- **Predictive analytics integration:** Advanced analytics and ML algorithms used predict potential equipment failures based on historical and real-time data.
- **Real time condition monitoring:** Continuously monitoring equipment conditions using daily check-up/inspection report data to detect anomalies and deviations from normal operating parameters. Combining real-time inspection data with predictive analytics to enhance the accuracy of failure predictions.
- **Threshold-Based Alerts:** Set predictive thresholds to trigger maintenance actions just before the equipment reaches critical failure points. Provide immediate alerts based on real-time condition monitoring to address any sudden deviations indicating potential failures.
- **Proactive maintenance actions:** Implement proactive maintenance tasks based on predictive analytics to prevent imminent failures. Conduct targeted repairs or component replacements indicated by real-time condition monitoring data to avoid potential failures.

- **Continuous evaluation and improvement:** Integrate feedback from implemented maintenance actions into the predictive models for ongoing learning and refinement. Update predictive algorithms and condition monitoring parameters based on observed equipment behaviours and actual maintenance outcomes.

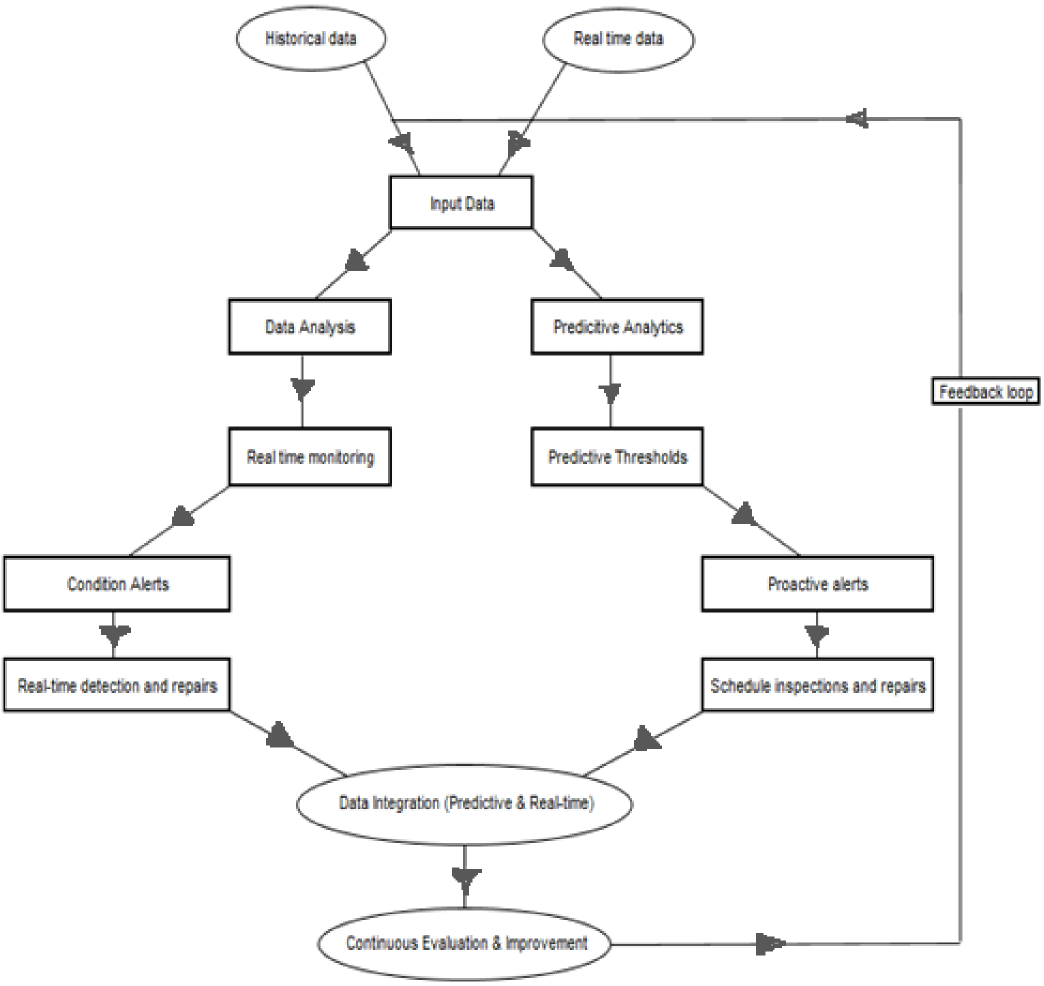

Figure 4.20: Hybrid Maintenance Strategy diagram.

4.5 Chapter Summary

The data provides an overview of Booysendal Mine's LHD machines. The dataset indicates that LHD machines from Sandvik are predominant at Booysendal Mine, comprising the majority of the fleet. The unspecified LHD machines resulted from incorrect data entry during the merging process. Oil leaks or damaged hoses are the most frequent failure mode across all shifts from 2021 to 2022. The oil leak has the highest frequency of 204 failure modes. NS has the highest downtime hours of 1802.03. This could be due to labour shortages, minimal supervision, and poor availability of spare parts during NS hours. The distribution of downtime from the histogram shows positive skewness. Hydraulic system and transmission contribute to 80% of downtime as shown in pareto chart. The average duration of downtime is 2.50 hours.

The ML models used for this study include KNN regressor, KNN classifier, decision tree classifier, multiple linear regression, multi polynomial regression, RF classifier, RF regressor, SVM regressor, and SVM classifier. The top regression model chosen is the KNN regressor, achieving an RMSE of 2.02. For classification, the SVM classifier was identified as the best model with an accuracy of 60%.

Lastly, the proposed hybrid maintenance strategy combining Predictive Maintenance (PM), and Condition-Based Maintenance (CBM) outlines a proactive approach to minimise downtime and optimise equipment performance while continually adapting to operational needs. This summarises the key insights and findings from the data, providing a comprehensive overview of the LHD operations and associated analyses at Booysendal Mine.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This is the last chapter of the research study, and it break downs the discussion of the overall research by looking at all the five chapters and how they aided in fulfilling the objectives of this research study. The key findings, complimentary studies and recommendations better summarise the contribution of applying ML models to develop a LHD maintenance strategy for underground mining environment.

5.2 Summary of Chapters

5.2.1 Introduction

This research emphasises Booysendal Mine's heavy reliance on LHD machines for efficient production, highlighting the important role these machines play in daily production. Frequent LHD machine failures, as recorded, have a significant negative impact on production, making it necessary to address the challenges posed by the current reactive maintenance system. The study aims to develop a predictive maintenance strategy using historical data to proactively manage LHD performance in order to reduce downtime. The research seeks to improve the reliability of mining equipment, enhance productivity, and lower operational costs by shifting from reactive to predictive maintenance.

5.2.2 Literature review

The literature review elaborated on LHD downtime and its impact on the mine’s productivity in the underground environment. Kecojevic et al. (2018) recommended implementing maintenance strategies to reduce downtime. Musingwini and Moyo (2017) found that a lack of spares affects LHD availability. Sharma et al. (2019) mentioned that MTBF enables the mine to assess and predict equipment reliability in the long run. Investigating MTBF is central to understanding LHD downtime. The literature review also stressed the significance of understanding critical components and their associated failure types. KPI studies were useful for quantifying LHD machine performance at Booysendal Mine. Maintenance strategies should ensure continuous equipment function to enhance operational efficiency.

The literature review detailed two main subcategories of supervised learning: classification and regression. Classification algorithms include KNN, RF, decision tree, and logistic regression. Regression algorithms encompass linear regression, polynomial regression, decision tree regression, and random forest regression. The literature review highlighted seven important steps of ML in developing ML models. It also focused on ML application in mining machinery maintenance, where Rihi et al. (2019) emphasised the significance of predictive maintenance and discussed various models to predict failures using historical data. Hildreth and Dewitt (2016) conducted a study where logistic regression predicted failures of 378 single axle dump trucks in non-mining machinery maintenance.

5.2.3 Methodology

The research methodology focused on ML methods, including RF, logistic regression, and KNN. It outlined steps to develop an appropriate ML model. The dataset was collected from daily breakdown reports of Booysendal Mine from 2021 to 2022. To meet the study's objectives, the dataset from 2021 to 2022 underwent cleaning, removing unnecessary columns. The process of consolidating data from multiple sources into a unified file required the use of Python libraries such as os, pandas, and zipfile. Data analysis comprised histograms, frequency tables, bar charts, descriptive statistics, and downtime categories. The structure of the cleaned dataset was used to construct the model. Various ML models were evaluated, and the best one was selected.

5.2.4 Results and findings

The LHD makes used in the study include Sandvik, GHH, Aard, and unspecified, accounting for 40.9%, 19.1%, 11.3%, and 28.7%, respectively. Among the failure modes, oil leak had the highest frequency with 204 occurrences, while lights not working had the lowest frequency with 13. NS has the highest downtime of 1802.03 hours compared to other shifts. This can be due to little supervision and shortage of spare parts. The average duration of downtime is 2.50 hours. Hydraulic system and transmission contribute to 80% of downtime as shown in pareto chart. The hydraulic system has the highest frequency of 204 occurrences while transmission has 201. Sandvik equipment contributes significantly to downtime, accounting for 86.3%. The probability that downtime will take more than 75% of the shift is 0.75.

Regarding ML models, the dataset contained 936 missing values, all of which were dropped. The process of consolidating data from multiple sources into a unified file required the use of Python libraries such as os, pandas, and zipfile. ML models employed include KNN regressor, KNN classifier, decision tree classifier, multiple linear regression, multiple polynomial regression, RF classifier, RF regressor, SVM regressor, and SVM classifier. The KNN regressor was chosen as the best regression model, achieving an RMSE of 2.02, while the SVM classifier was selected as the best classification model with an accuracy of 60%. Finally, a hybrid maintenance strategy is proposed for proactive optimisation.

5.3 Conclusions

The research focused on developing an effective maintenance strategy at Booysendal Mine through the application of data analysis and ML techniques. The primary objective was to create a predictive maintenance strategy using historical data to manage LHD performance and reduce downtime. A thorough literature review explained the impact of LHD downtime on mine productivity and examined various maintenance strategies, including the lack of spares, MTBF, and two main supervised learning categories. The methodology applied ML models such as RF, logistic regression, and KNN, leveraging Python libraries for data consolidation. Data analysis involved descriptive statistics, histograms, frequency tables, and downtime categorisation, leading to the selection of the best ML models. Sandvik, GHH, and Aard LHD makes were studied, with the hydraulic system and transmission contributing 80% to the downtime. The KNN regressor and SVM classifier were identified as the best models, with respective performances of RMSE at 2.02 and 60% accuracy. The study proposes a hybrid maintenance strategy to proactively optimise LHD performance.

5.4 Research Observations

5.4.1 Initial and complimentary studies

Predictive Maintenance in Mining Machines (Kruczek, et al, 2019) and ML Models for Predictive Maintenance (Voronov, 2020). Both studies align with Booysendal Mine's focus on predictive maintenance. They offer insights into developing predictive models for machinery, similar to the approach proposed in the Booysendal Mine data. Kruczek, et al., emphasising cloud-based predictive systems which is a recommendation for Booysendal Mine LHD data storage. Voronov's work on ML models for battery lifespan, parallel the aim of optimising LHD maintenance for extended equipment lifetimes by focusing on component-based prediction and analysis.

Grinding Mill Case Study (Rihi, et al, 2022): Rihi's exploration of challenges in mining maintenance and the emergence of predictive maintenance resonates with Booysendal's emphasis on predictive modelling. The discussion on AI-driven fault diagnosis methods corresponds to Booysendal's analysis of breakdowns, repairs, and maintenance needs for operational efficiency.

Application of Classification Models on Maintenance Records (Rahman & Mahbub, 2023). This study aligns with Booysendal's exploration of maintenance records. The text mining approach for predicting failures could complement Booysendal's thematic analyses of breakdowns and repairs, providing additional predictive insights into maintenance categories.

These case studies, collectively, support Booysendal Mine's efforts by providing methodologies, tools, and insights that parallel or complement the strategies proposed or implemented in the Booysendal LHD operations. They offer varied approaches, from predictive modelling and AI-driven fault diagnosis to text mining for predictive maintenance, reinforcing the importance of proactive strategies to optimise maintenance practices and operational efficiency.

5.4.2 Key findings and observations

The failure types for each make show varying frequencies. Oil leak emerges as the most prevalent failure mode, emphasising the critical need to address this issue. NS requires more attention as it experiences the highest number of breakdowns compared to other shifts. The distribution of downtime durations demonstrates positive skewness. Transmission issues serve as the primary contributor to downtime, necessitating targeted maintenance strategies in this area. Missing values were addressed by dropping them to maintain the integrity of the analysis. Various ML models were employed to analyse the dataset. The KNN regressor and SVM classifier were identified as the best-performing models for regression and classification tasks, respectively.

5.5 Research Contributions

The research conducted at Booysendal Mine will assist the Eastern Limb Bord and Pillar trackless mines in conducting further studies on maintenance strategies to improve equipment efficiency. It will also help local mines identify trends, compare breakdowns, and determine if similar issues arise across different OEMs, enabling them to develop strategies to minimise these breakdowns. The research shows patterns in downtime and production across various manufacturers. The analysis of LHD breakdowns over a two-year period allows the mine to observe losses and make informed decisions. Various visualisations highlight key performance indicators (KPIs), providing valuable insights into optimising maintenance strategies.

5.6 Limitations of Research Findings

The accuracy of the ML models is influenced by the quality of the dataset, any missing data could affect the reliability of the predictive maintenance strategy. The study focuses solely on LHD machines, which may not fully capture maintenance challenges for other types of mining equipment. External factors such as operator behaviour, artisan behaviour, slow response to breakdowns and poor communication were not incorporated into the models, potentially limiting the scope of the predictive strategy in real-world. The study relies on historical data from a specific mine, Booysendal, which may limit the generalisability of the results to other mining operations with different mining conditions. No other research papers can be found with common conditions and focus in order to compare findings and results.

5.7 Recommendations

The efficient and reliable operation of Booysendal Mine depends on strategic maintenance practices and data-driven decision-making. To enhance the overall maintenance strategy and optimise equipment performance, several recommendations are proposed. Monthly coaching sessions for LHD operators should be implemented to help them understand which components failed most frequently, so that breakdowns can be minimal. LHD operators with fewer breakdowns in that particular month should be compensated accordingly. Critical components that fail regularly should be added to the checklist for operator awareness. Fault finding must be thorough, ensuring that only the correct component is ordered and replaced after a proper fault analysis by a Competent Person, rather than relying solely on reports from LHD operators or artisans.

The mine should ensure the availability of critical spare parts at the workshop to minimise downtime during repairs. Transitioning to a predictive maintenance approach is also recommended to expect potential issues and reduce costs associated with unplanned repairs. Expanding qualitative data collection across diverse operational aspects will provide a more holistic understanding of equipment performance and maintenance needs. Comparative analyses should be conducted on breakdowns within Booysendal Mine and other mines to validate findings and identify broader trends. Developing a real-time monitoring dashboard for condition-based maintenance will enhance visibility into equipment conditions, enabling proactive decision-making. A standardised Excel spreadsheet should be developed to capture all possible failure modes and their respective components, with specific codes assigned to each failure component and updated as needed.

5.7.1 Suggestion for Future Research Work

Trackless mines should establish a seed fund where mines contribute a designated amount of money to support institutions in conducting research on mining equipment. This initiative would help mines stay informed about high-risk components and ensure that spare parts are always available. Mining interns should be employed to conduct time studies, enabling data collection and storage for future research. Each trackless mine should have a dedicated data science division focused on data analysis and collection, allowing management to make informed decisions. The engineering team must collaborate closely with researchers to develop practical, feasible solutions rather than purely theoretical ones. Machine learning models should also be tested by researchers at the mine to evaluate their impact on reducing breakdowns and to ensure their effectiveness in real-world applications.

Comparative studies across multiple mining sites, incorporating different equipment manufacturers and operational settings, would also be valuable in validating the effectiveness of predictive maintenance strategies across diverse conditions. Research should investigate the development of real-time, AI-driven monitoring systems that can detect potential failures more effectively, integrating Internet of Things (IoT) technologies for continuous data collection. Future work should consider cost-benefit analyses of predictive maintenance strategies versus traditional reactive approaches.

6 REFERENCES

Aardme, 2023. Aardme. [Online] Available at: https://www.aardme.com/content/dam/brands/aard/documents/low-profile-equipment/AARD-55-LP-LHD%20(1).pdf [Accessed 16 December 2023].

Achouch, M., Dimitrova, M., Dhouib, R., Ibrahim, H., Adda, M., Karganroudi, S., Ziane, K., Aminzadeh, A. (2023). Predictive maintenance and fault monitoring enabled by machine learning: experimental analysis of a TA-48 multistage centrifugal plant compressor. *Applied Sciences, 13*(1790), pp.1-19.

Ádám, B. Á., 2023. Comparison of OEE-based manufacturing. Hungary, Budapest University of Technology and Economics.

Adler, S., 2019. Intelligentautomation.network. [Online] Available at: https://www.intelligentautomation.network/decision-ai/articles/a-basic-guide-to-reinforcement-learning [Accessed 05 April 2024].

Angeles, E. & Kumral, M., 2020. Optimal inspection and preventive maintenance scheduling of mining equipment. *J Fail.Anal and Preven, 03 August*, Volume 20, pp. 1408-1416.

Arputharaj, M. M., 2015. Studies on availability and utilisation of mining equipment - An Overview. *Internation Journal of Advanced Research in Engineering and Technology*, 6(3), pp. 14-21.

Bala, R. J., Govinda, R. M. & Murthy, C.., 2018. Reliability analysis and failure rate evaluation of load haul dump machines using Weibull distribution analysis. *International Information and Engineering Technology Association*, 05(02), pp. 116-122.

Bisht, V., Kumar, S., Agrawal, A. K., Siddiqui, M. A. H., & Chattopadhyaya, S. (2021). Prediction of breakdown hours of load haul dumper by long short-term memory network. *Materials Science and Engineering*, Volume 1104, pp. 1-6.

Burkov, A., 2019. The Hundred Page Machine Learning Book. [Online] Available at: http://ema.cri-info.cm/wp-content/uploads/2019/07/2019BurkovTheHundred-pageMachineLearning.pdf [Accessed 18 June 2022].

Crabtree, M., 2024. datacamp. [Online] Available at: https://www.datacamp.com/blog/what-is-machine-learning [Accessed 13 March 2024].

Dayo-Olupona, O., Genc, B., Bada,. S. & Celik,. T., 2022. Predictive maintenance: a viable maintenance option for machines/equipment/plants in mining and mineral processing. Turkey, IMCET.

Delua, J., 2021. www.ibm.com. [Online] Available at: https://www.ibm.com/blog/supervised-vs-unsupervised-learning/ [Accessed 24 February 2024].

Dermawan, A.. R. & Iriani, Y., 2022. Analysis of forging machine effectiveness using overall equipment effectiveness (oee) and six big losses methods (case study: pt x). *Jurnal Darma Agung*, 30(3), pp. 195-210.

Fan, Q. & Fan, H., 2015. Reliability analysis and failure prediction of construction equipment with time series models. *Journal of Advanced Management Science*, 3(3), pp. 203-210.

Fenner, M. E., 2020. Machine Learning with Python for Everyone. 1st ed. Boston: Pearson Education.

Fourie, H., 2016. Improvement in the overall efficiency of mining equipment: a case study. *Journal of the Southern African Institute of Mining and Metallurgy*, 116(3), pp. 275-281.

Gackowiec, P., 2019. General overview of maintenance strategies. *Sciendo*, 2(1), pp. 126-139.

Gackowiec, P., Podobinska-Staniec, M., Brzychczy, E., Kühlbach, C., & Özver, T. (2020). Review of key performance indicators for process monitoring in the mining industry. *Energies, 13*(5169), pp.1-20.

GeeksforGeeks, 2023. geeksforgeeks. [Online] Available at: https://www.geeksforgeeks.org/ml-semi-supervised-learning/ [Accessed 16 December 2023].

Ghahramani, Z., 2003. Unsupervised learning. In: Advanced Lectures on Machine Learning. Berlin: Springer Berlin Heidelberg, pp. 72-112.

GHH Fahrzeuge, 2024. teikom.rs. [Online] Available at: https://teikom.rs/upload/items/documents/1533642685.pdf [Accessed 12 March 2024].

Ghh Mining Machines, 2023. ghhrocks. [Online] Available at: https://ghhrocks.com/wp-content/uploads/2020/09/GHH-SLP-6-Spec-Sheet.pdf [Accessed 16 December 2023].

Gibson, B.A., Nwaila, G., Manzi, M.S., Ghorbani, Y., Ndlovu, S., & Petersen, J. (2023). The valorisation of platinum group metals from flotation tailings: A review of challenges and opportunities. *Minerals Engineering*, Volume 201, pp. 1-24.

GMI wheels, 2019. gmiwheels. [Online] Available at: https://gmiwheels.com/underground-mining-wheels/ [Accessed 12 March 2024].

Great Learning Team, 2023. Mygreatlearning. [Online] Available at: https://www.mygreatlearning.com/blog/what-is-machine-learning/ [Accessed 12 March 2024].

Gupta, S., 2021. Springboard. [Online] Available at: https://www.springboard.com/blog/data-science/regression-vs-classification/ [Accessed 11 March 2024].

Hildreth, J. & Dewitt, S., 2016. Logistic regression for early warning of economic failure of construction equipment. North Carolina, University of North Carolina at Charlotte.

Hottinger Brüel & Kjær, 2023. hbkworld. [Online] Available at: https://www.hbkworld.com/en/knowledge/resource-center/articles/optimum-preventive-maintenance-replacement-time [Accessed 25 December 2023].

Impact Mining Equipment, 2023. Impact mining. [Online] Available at: https://impactmining.com.au/underground-loaders-lhd/sandvik-ls170 [Accessed 16 December 2023].

Impact Mining Equipment, n.d. Sandvik LS170 Loader. [Online] Available at: https://impactmining.com.au/underground-loaders-lhd/sandvik-ls170-loader/ [Accessed 25-07-2024].

Jakkula, B., Govinda Raj, M., Murthy, C. S., (2019). Fuzzy-FMEA risk evaluation approach for LHD machine – A case study. *Journal of Sustainable Mining*, vol.18, no.4, pp 257-268.

Jakkula, B., Govinda, R. M., & Murthy Ch. S. N. (2020). Maintenance management of load haul dumper using reliability analysis. *Journal of Quality in Maintenance Engineering,* vol.26, no.2, pp.290-310.

James, G., Witten, D., Hastie, T., Tibshirani, R., & Taylor, J. (2023). *An Introduction to Statistical Learning with Applications in Python* (1st ed.). New York: Springer.

Javatpoint, 2021. javatpoint. [Online] Available at: https://www.javatpoint.com/machine-learning-life-cycle [Accessed 13 March 2024].

Kapoor, D., 2020. medium. [Online] Available at: https://medium.com/analytics-vidhya/machine-learning-101-the-7-steps-of-a-machine-learning-process-9439f3ef97eb [Accessed 13 March 2024].

Kecojevic, R., Komljenovic, M. & Kecojevic, A., 2016. Impact of LHD downtime on mine production. *International Journal of Mining, Reclamation and Environment*, 30(06), pp. 429-441.

Khethani, P., 2022. Weekly major component report, Lydenburg: Northam Platinum.
Kruczek, P., Gomolla, N., Hebda-Sobkowicz, J., Michalak, A., Sliwiński, P., Wodecki, J., Stefaniak, P., Wyłomańska, A., & Zimroz, R. (2019). Predictive maintenance of mining machines using advanced data analysis system based on the cloud technology. *Proceedings of the 27th International Symposium on Mine Planning and Equipment Selection - MPES 2018*. (Poland).

Kusumaningrum, D., Kurniati, N. & Santosa, B., 2021. Machine learning for predictive maintenance. Indonesia, IEOM Society International.

Leeuw, P., 2018. LHD-inhibiting factors in Southern African underground mines. *Journal of the Southern African Institute of Mining and Metallurgy*, 118(08), pp. 819-824.

Manenzhe, M., Telukdarie, A., & Medoh, C. (2019). Maintenance strategy optimisation for load haul dumpers used in the South African underground hard rock mine. In *4th North American International Conference on Industrial Engineering and Operations Management*. Retrieved from https://doi.org/10.46254/NA04.20190075.

Manwinwin, 2023. manwinwin. [Online] Available at: https://www.manwinwin.com/preventive-maintenance/ [Accessed 18 December 2023].

Mbhalati, W., 2015. LHD optimization at an underground chromite mine. *The Journal of The Southern African Institute of Mining and Metallurgy*, Volume 115, pp. 313-320.

Mobley, R. K. (2002). An introduction to predictive maintenance (2nd ed.). Elsevier Science.

Mohammadi, M., Rai, P., & Gupta, S. (2017). Performance Evaluation of Bucket-based Excavating, Loading, and Transport (BELT) Equipment - An OEE Approach. *Archives of Mining Sciences, 62*, 105-120.

Mohammadi, M., Rai, P., & Gupta, S. (2015). Performance Measurement of Mining Equipment. *International Journal of Emerging Technology and Advanced Engineering, 5*(12), 240-248.

Mosaic, 2024. *Mosaic Data Science.* [Online]
Available at: https://mosaicdatascience.com/wp-content/uploads/2024/03/Predictive-Maintenance-Modeling-for-Industrial-Machinery-2.pdf

Musingwini, S. & Moyo,. P., 2017. Factors affecting the utilization of load-haul-dump machines in the mining industry. *Journal of Industrial Engineering International*, 13(04), pp. 529-538.

Narayan, V., 2004. *Effective maintenance management: risk and reliability strategies for optimizing performance*. Industrial Press Inc.

Northam Platinum Limited, 2020. An Assessment of Machine Availability and Utilization, Lydenburg: Northam Platinum.

Pampana, A. K., Jeon, J., Yoon, S., Weidner, T. J., & Hastak, M. (2022). Data-driven analysis for facility management in higher education institution. *Buildings,* vol.12, pp1-19.

Paraszczak, J., 2000. Failure and downtime reporting — a key to improve mine equipment performance. CIM Bulletin, 93(1044), pp. 73-77.

Paraszczak, J., Svedlund, E., Fytas, K. & Laflamme, M., 2014. Electrification of loaders and trucks – a step towards more sustainable underground mining. *Renewable Energy and Power Quality Journal*, 01(12), pp. 81-86.

Pereira, P., 2018. Reliability based models to evaluate the financial consequences of mining equipment component selection and purchasing decisions, Golden, Colorado: Colorado School of Mines.

Pokorni, S. J., 2021. Current state of the application of artificial intelligence in reliability and maintenance. Military Technical Courier, 69(3), pp. 578-587.

Rahman, U. & Mahbub, M. U., 2022. Application of classification models on maintenance records through text mining approach in industrial environment. *Journal of Quality in Maintenance Engineering*, Volume 17, pp. 203-219.

Rihi, A., Baına, S., Mhada, F., Elbachari, E., Tagemouati, H., Guerboub, M., & Benzakour, I. (2022). Predictive maintenance in mining industry: grinding mill case study. *Procedia Computer Science.* Morocco.

Samanta, B., Sarkar, B. & Mukherjee, S. K., 2004. Reliability modelling and performance analyses of an LHD system in mining. *The Journal of The South African Institute of Mining and Metallurgy*, pp. 1-8.

Selvik, J.T. and Ford, E.P., 2017. Down time terms and information used for assessment of equipment reliability and maintenance performance. *System Reliability*, pp.43-66.

Shafi, U., Safi, A., Shahid, A., Ziauddin, S., & Saleem, M. (2018). Vehicle remote health monitoring and prognostic maintenance system. *Journal of Advanced Transportation,* vol.*2018*, pp. 1-10.

Sharma, N. R., Hemant, A. & Mishra, A. K., 2019. Maintenance schedules of mining HEMM using an optimization framework model. *Journal Européen Des Systèmes Automatisés*, 52(3), pp. 235-242.

Siddiqui, M. A. H., Chattopadhyaya, S., Sharma, S., Assad, M. E. H., Li, C., Pramanik, A., Kilinc, H. C. (2022). Real-Time Comprehensive Energy Analysis of the LHD 811MK-V Machine with Mathematical Model Validation and Empirical Study of Overheating: An Experimental Approach. *Arabic Journal for Science and Engineering, 47*(11), 9043–9059.

Sifferlinger, N. and Rath, G., 2016. Functional Safety and Mean Time to Fail for Underground Mining Proximity Detection Device in No-Go-Zones. *IFAC-PapersOnLine*, *49*(20), pp.31-36.

Talan, S., Yadav, D. K., Rajput, Y. S. & Bhattacharjee, S., 2018. Risk based maintenance planning for loading equipment in underground hard rock mine: case study. *International Scholarly and Scientific Research & Innovation*, 12(5), pp. 343-349.

Tampier, C., Mascaró, M. & Ruiz-del-Solar,. J., 2021. Autonomous loading system for load-haul-dump (LHD) machines used in underground mining. *Applied Sciences*, 11(8717), pp. 1-27.

TDK Product center, 2024. product.tdk. [Online] Available at: https://product.tdk.com/en/contact/faq/power-supplies-0020.html [Accessed 16 March 2024].

Teixeira, H. N., Lopes, I. & Braga, A. C., 2020. Condition-based maintenance implementation: a literature review. *Procedia Manufacturing*, Volume 51, pp. 228-235.

Terra, J., 2023. Simplilearn. [Online] Available at: https://www.simplilearn.com/regression-vs-classification-in-machine-learning-article [Accessed 11 March 2024].

ToolSense, 2024. www.toolsense.io. [Online] Available at: https://toolsense.io/maintenance/idle-time-definition-difference-to-downtime-and-how-to-calculate-it/ [Accessed 24 February 2024].

Upkeep, 2024. upkeep. [Online] Available at: https://upkeep.com/learning/corrective-maintenance/ [Accessed 13 March 2024].

Vishnukumar, H., Butting, B., Müller, C. & Sax, E., 2017. Machine learning and deep neural network—Artificial intelligence core for lab and real-world test and validation for ADAS and autonomous vehicles: AI for efficient and quality test and validation. In: IEEE, pp. 714-721.

Vladimir, K., Boris, G., Aleksey, K. & Pavel, G., 2014. Preventive maintenance of mining equipment based on identification of its actual technical state, Kemerovo, T.F: Gorbachev Kuzbass State Technical University.

Voronov, S., 2020. Machine learning models for predictive maintenance, Sweden: Linköping University.

Wolff, C., & Schmitz, B. (2017). Determining Cost-Optimal Availability for Production Equipment Using Service Level Engineering. In 2017 IEEE 19th Conference on Business Informatics (CBI) (pp. 176-185). Thessaloniki, Greece: IEEE. doi:10.1109/CBI.2017.47

Yeardley, A. S., Ejeh, J. O., Allen, L., Brown, S. F., & Cordiner, J. (2022). Integrating machine learning techniques into optimal maintenance. *Computers & Chemical Engineering,* vol.166, pp.1-13.

Zichen, 2021. fuchenglhd.com. [Online] Available at: https://fuchenglhd.com/blog/the-ultimate-guide-about-lhd-machine-2/ [Accessed 24 February 2024].