

School of Mining Engineering



UNIVERSITY OF THE
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**Productivity monitoring and improvement through
digitalisation of load-haul-dump (LHD) machinery
at Mimosa underground operations.**

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A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science in Engineering.

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DECLARATION

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“The future belongs to those who believe in the beauty of their dreams”

Eleanor Roosevelt

ABSTRACT

This study evaluates the impact of digital monitoring on the performance of underground Load-Haul-Dump (LHD) machines in a room-and-pillar mining operation at Mimosa Mine. The research aimed to (i) assess the limitations of the existing manual monitoring system, (ii) quantify the benefits of digitalisation via a Fleet Management System (FMS), and (iii) identify data-driven opportunities for productivity improvement. A quantitative approach was applied, integrating real-time telemetry from sensor-enabled LHDs with parallel manual records. Key variables: cycle time, payload, tramming distance, and loading rate were captured and analysed using Python scripting and Stata 15.

Results showed that the manual system consistently overstated tonnage and operating time, leading to an underestimation of productivity. These discrepancies were both statistically significant and operationally material. Productivity based on FMS data ranged between 36–37 tonnes per hour (tph), compared to 35.2 tph from manual data and a historical baseline of 34 tph. Although the effect size was small, even a 3% uplift translates into a potential annual net gain exceeding US\$1.7 million. Correlation analysis revealed that cycle time had a strong negative relationship with productivity ($r = -0.77$), tramming distance a moderate negative effect, while payload exhibited only a weak correlation. The loading rate was identified as a more actionable lever for operator performance management.

The FMS enabled high-resolution monitoring of variables such as cycle time and tramming distance, uncovering inefficiencies invisible to manual systems. These insights support targeted interventions to reduce tramming distances and cycle times, alongside the introduction of a digital performance management framework for LHD operators.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
BCM	Bank cubic metres
DM	Data Mining
FMS	Fleet Management System
KPI	Key Performance Indicator
LHD	Load haul dump loader
ML	Machine Learning
OEE	Overall Equipment Effectiveness
OEM	Original Equipment Manufacturer
T	Tonnes
Tph	Tonnes per hour
t/hr/km	Tonnes per hour per kilometre
TMM	Trackless mobile machinery

1 INTRODUCTION

1.1 Research Background

Mimosa mine geological and geographical setting is situated within the Wedza Geological complex of the Great Dyke of Zimbabwe. The Great Dyke is a layered ultramafic complex extending 550 kilometres across the country, having a maximum width of 11 kilometres. PGM and base metal deposits are found within its four chambers namely, Wedza Complex (Mimosa mine location), the Selukwe Complex, the Hartley Geological Complex and the Musengezi Complex (Implats, 2020). Mimosa is situated in the Midlands province, approximately 150 kilometres east of Bulawayo as shown in the map below.

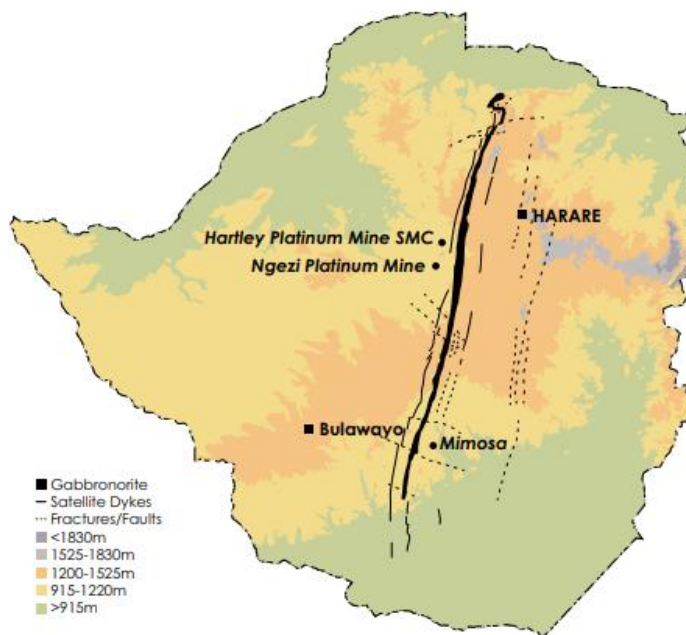


Figure 1: Mimosa mine location
(Mimosa Mining Company, 2023)

Mining operations on the Mimosa deposit commenced as far back as 1926 and have been conducted intermittently by several owners until the year 1998, when current operations were revived. Since then, production

capacity from underground activities has progressively grown from an initial 30 000 tonnes per month (tpm) of ore to the current 210 000tpm design capacity which was established in 2011 (Mimosa Mining Company, 2023). Mimosa is an underground bord-and-pillar mine that employs a series of drill-blast-support-lash cycles using low-profile trackless mobile mining machinery (TMM). Each production team is equipped with a single support bolter, drill rig and one or two load-and-haul dumpers (LHDs) depending on payload capacity. Although the mine is mechanised, production monitoring and productivity tracking are still conducted using manual data collection methods such as equipment checklists filled by operators and shift reports completed by operational personnel. This manual collection is prone to errors, manipulation, and delays in decision-making, which is pivotal to effective production planning and productivity improvement.

Furthermore, an analysis of production data at the mine has shown that lashing is a major constraint within the mining cycle for most production teams. This observation was made based on underground visits, discussions with site personnel, attendance of production meetings and analysis of historical production data. However, due to the limited amount of information provided by manual data collection methods on the process, productivity analysis has largely been deficient. Manual methods are not capable of accurately measuring critical variables that influence the lashing process such as cycle times, bucket fill factors, payloads and actual tramming distances within real time. Operator tracking and equipment pairing also becomes a complicated process within such a setup.

Consequently, planning KPIs have been based on historical performance and have not actually been tested for effectiveness within the actual production setup. Moreover, conflicts between the engineering and mining shifts reports generated using the manual system on-site make an accurate determination of productivity measures and constraints more challenging. Planning and decision-making are correspondingly negatively impacted as accurate and timely critical production information cannot be obtained.

Moreover, the unavailability of a digital system on LHDs creates an opportunity cost as the mine cannot leverage fully on available technology advancement in improving operations. Adopting a digital system creates opportunity for utilisation of data analytics and business intelligence tools towards further improvement in safety, cost and efficiency of operations. This failure to adopt available technology may result in a loss of competitive edge, thus further impacting operations negatively.

This research seeks to utilise digitalisation methods to close the above gaps. By establishing a digital management system for LHDs, it is anticipated that critical variables like payload, tramming distances and cycle times will be accurately determined. Such a system is expected to enable more accurate monitoring of LHD productivity. Analysis of the data generated is envisaged to provide useful insights for productivity improvement. In addition, the digital system is expected to provide a platform for further advancement in utilising available technology for improving safety, cost and efficiency of operations.

Digitalisation is a broad concept but basically involves applying digital technologies to improve operations and business performance. Application of these technologies across the mining value chain can bring significant benefits in improving safety, productivity and operational efficiency. Therefore, several mining companies have identified digitalisation as a strategic issue of focus to enable them to have safer, more efficient and profitable operations, thus gaining a competitive edge. Mimosa has also adopted digitalisation as part of its strategy to improve the bottom line and make operations safer. This research seeks to evaluate how digitalisation can be utilised to monitor performance and enhance productivity within the lashing process.

1.2 Problem Statement

Analysis of physical operations and manual production data collected at Mimosa shows that lashing is a constraint within the production cycle. A

single production rig and bolter is capable of drilling and supporting an area equivalent to 300 tonnes per shift. These targets have proven to be achievable when there are sufficient ends available to mine and the equipment is available and properly utilised. However, a single big capacity LHD is failing to meet its productivity target of 230 tonnes within a single shift. This is despite achieving planned availability levels for the machine and the availability of broken ore to move. Furthermore, more than 75% of the time, LHD productivity as measured by the manual system falls short of the mine planning target of 34 tonnes per hour. Improving the productivity of LHDs is therefore one of the key ways of increasing efficiency of operations and overall production output.

To effectively understand the hindrances to productivity of LHDs at the mine and how to improve it, it is essential to have an accurate system in place that measures all the key variables influencing the process. Data accuracy is crucial to enable data-based effective decision making in improving operational productivity. Reliable data is also useful in optimising mine planning processes so that performance measures are correctly set and monitored. Furthermore, variables such as loader cycle time, payload, tramming distances, loading rates, operator efficiency, availability and utilisation need to be determined based on objective and reliable data if improvement is to be made. This also avoids misdirected effort in adopting measures that can effectively address the productivity challenge.

However, productivity and fleet data at the mine is being gathered manually through paper-based shift departmental supervision reports and operator checklists. Data from these reports is then manually entered into Microsoft Excel, to generate the daily production reports used for production monitoring. This manual process is prone to errors and largely inefficient which creates the huge risk of misdirected effort in identifying and addressing critical production issues. Moreover, the manual data collection does not measure key variables such as cycle time, payload and tramming distances. Other factors such as loading rates, availability and utilisation are

not directly measured but calculated from it. Thus, data generated by the manual system is insufficient and risky to be utilised alone as baseline source information for production monitoring and improvement.

1.3 Justification for Research

This study is necessary as it seeks to close the above gaps and provide the following significant benefits to the organisation as well as to the industry and its stakeholders. These benefits include:

- Establishment of a more accurate system of measuring equipment operational KPIs by reducing human manipulation and errors. Beckmann, et al., (2016) discovered manual systems generates at least 2% inaccuracy in load counts for open pit mines. Studies show that a digital system is more accurate and produces more valid and reliable data (Howess & Forrest, 2011; Beckman, et al., 2016; Parkinson & Sommerville, 2016)
- Provision of value creation measurement opportunity through digitalisation of a mining fleet. Creagh, (2019) highlights how digitalisation is a stepwise journey with establishment of an FMS a critical step in measuring value creation as adoption of digital technology progresses in mining organisations.
- Exploration of optimisation opportunities that can be unlocked through digitalisation. Several studies have utilised FMS in optimisation of productivity with significant gains not only in production, but in safety and operational efficiencies as well. (Dessureault, et al., 2007; Fourie, 2016; Bullock, et al., 2017; Brzychczy, et al., 2020; Munyadzwe, et al., 2022).
- Unbiased data collection being used as the basis for making objective operational and planning decisions.
- Improved tracking of operational performance leading to enhanced productivity. Beckman, et al., (2016) outlined the significant benefits (21% production increase, cost reductions and improved safety)

obtained by White Foil mining operations by utilising FMS for this purpose.

- Provision of a foundation for further research to the mine, industry and academia There is a lack of publications covering the subject of digitalisation in the mining industry (Young & Rogers, 2019; Barnewold & Lottermoser, 2020)

1.4 Research Objectives

The aim of this study is to create a digital productivity monitoring system that measures essential LHD production data and demonstrates its application in enhancing productivity at the mine.

The project has the following objectives:

- To implement digital productivity management system for more accurate performance planning and monitoring of LHDs.
- To compare manual and FMS productivity measurements for accuracy and effectiveness.
- To identify factors affecting LHD productivity based on more accurate and comprehensive performance data.
- To recommend opportunities for LHD productivity improvement that maximise equipment performance and process efficiencies.

1.5 Research Questions

The research aims to answer the following questions:

1. What are the general requirements, challenges, and guidelines for implementing a productivity management system for underground TMMs?
2. How accurate and effective is a manual productivity monitoring system when compared to a digital system?
3. What is the impact of a digital monitoring system on LHD productivity?

4. What is the impact of LHD tramming distance, cycle time, payload and loading rate on productivity?
5. What are the opportunities for productivity improvement that can be derived from analysis of LHD digital production monitoring data at the mine?

1.6 Research Scope

The study is limited in scope by location, resources, time and operating context. It focuses on LHD underground mining equipment at Mimosa mine, whose payload capacity is at least 5t. It covers a period of about nine months and was conducted utilising existing infrastructure as much as possible, due to budgetary constraints. Other operational constraints that could influence productivity were not studied, including:

- Ventilation adequacy,
- Provision of required services to support mining,
- Adequate ground support,
- Adequate supervision and work allocation,
- Availability of equipment operators and operators' efficiency,
- Availability and reliability of the equipment chosen for the study.

1.7 Research Validation

Care was taken to validate the study through development of a sound methodology and procedures to maintain data integrity. The research methodology used for this study is based on literature review, input from industry practitioners and established historical mining methods. Consequently, the research design is of high validity. The data collected was also validated through other independent measures such as plant weightometer readings and also thoroughly discussed with various stakeholders at the mine for validity. Validation of the research study was also shown through comparative analysis of digital and manual productivity management system and the cost benefit analysis as seen in section 4.813

and 4.14. Use of the data in daily performance review meetings also confirmed its usefulness and practicability.

1.8 Structure of the Research Report

The report consists of five Chapters structured as follows:

- Chapter 1: Introduction
- Chapter 2: Literature Review
- Chapter 3: Research methodology
- Chapter 4: Results presentation and discussion
- Chapter 5: Conclusion and recommendations

2 LITERATURE REVIEW

2.1 Chapter Overview

This section provides a critical review of the literature relevant to the study. It explains the context of digitalisation and explores its benefits for the mining value chain, specifically focusing on how it enhances the productivity of TMMs, such as LHDs.

Productivity is defined and examined within the mining industry context, with an analysis of the various factors that affect it. The text also explores different types of productivity monitoring systems and evaluates the concept of fleet management systems (FMS) in detail. Furthermore, it analyses the factors influencing productivity and their respective impacts. Finally, it discusses relevant data analysis-based methods and other relevant operational techniques for evaluating and improving productivity.

2.2 Digitalisation Overview

Digital transformation or digitalisation has been consistently defined by scholars and industry practitioners as the utilisation of digital technology in enhancing and transforming organisational processes, efficiencies and models (Vial, 2019; Barnewold & Lottermoser, 2020; Lazarenko, et al., 2021; Maroufkhani, et al., 2022). It can also be understood as a process of organisational adaptation to contemporary technology utilising connectivity, pervasive data, and objective data-based decision-making (Young & Rogers, 2019). Consequently, this term will be used in this report to refer to the utilisation of digital technology in enhancing operational processes, productivity and ultimately, overall performance.

Four digital categories have been identified and are predicted to make a significant impact on the mining industry up to the year 2025 (World Economic Forum, 2017). Figure 2 shows each theme and the corresponding initiatives.

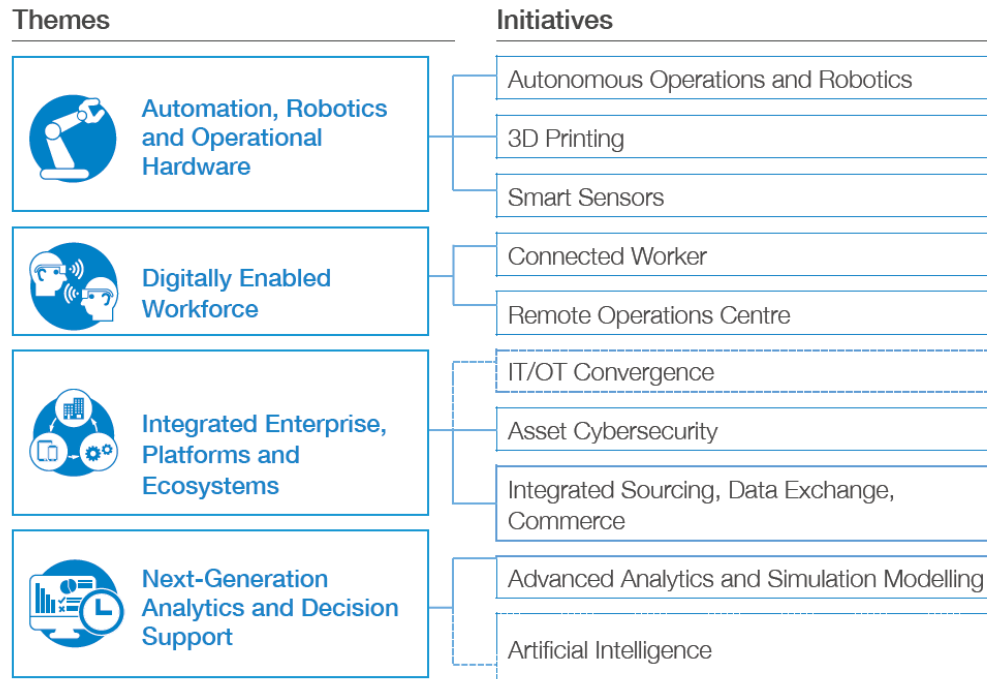


Figure 2: Digital themes and initiatives for the mining industry
(World Economic Forum, 2017)

This project seeks to leverage these themes and initiatives by utilising smart sensors on LHDs underground to enable automatic report generation on equipment productivity metrics. It seeks to analyse this data and demonstrate how it can be effectively utilised in improving LHD productivity. The study will also conduct a cost-benefit evaluation for implementing digitalisation within the operational context of the mine. This data, if available for all machines, has the potential to be utilised in integrated enterprise platforms to further add business value to the organisation.

Large amounts of such data can be analysed through advanced data analysis techniques to generate descriptive, predictive and prescriptive algorithms which can further boost productivity. Descriptive, predictive and prescriptive techniques are discussed further in Section 2.7.2. The study will utilise descriptive techniques to analyse the data generated and develop potential improvement initiatives. Predictive and prescriptive methods are expected to be the next stage of productivity implementation, subject to further studies. Adopting digitalisation is also expected to be a stepping

stone towards automation and improved control of production processes, where maximum benefits are anticipated.

Digitalisation is a proven method of improving processes across the mining value chain, thus changing visions, strategies, capacity and models of mining operations (Lazarenko, et al., 2021). Figure 3 summarises some of the benefits that can be realised by digitalisation along the mining operation lifecycle:

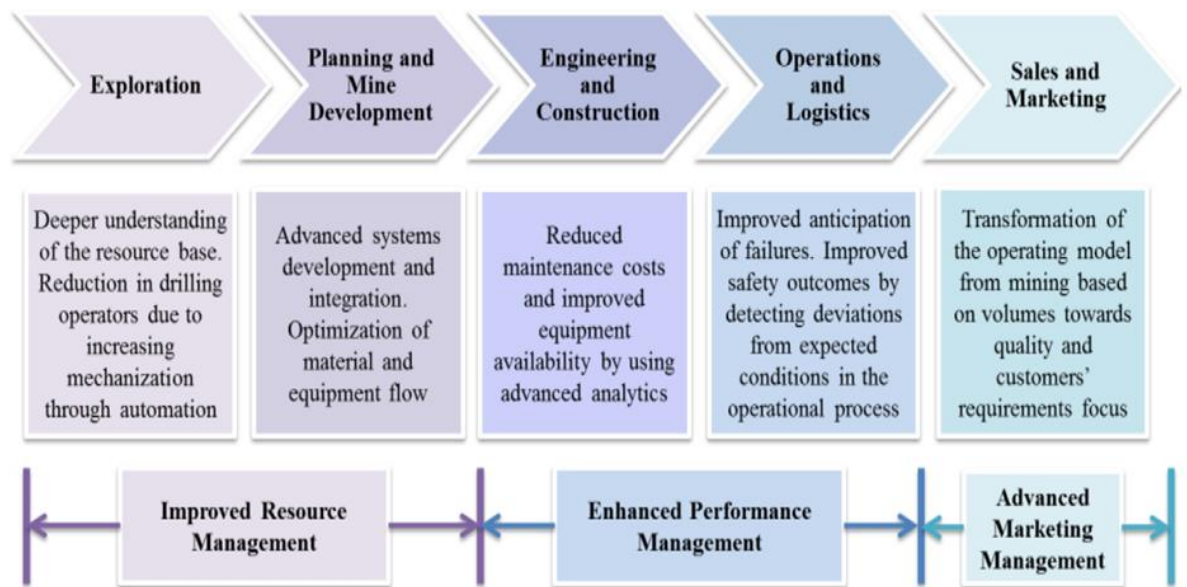


Figure 3: Digitalisation benefits on the mining project lifecycle
(Lazarenko, et al., 2021)

Figure 3 shows that digitalisation has brought about significant improvement in how mineral resources and reserves are managed from exploration up to the planning and mine development stages in the value chain. Improved performance management has also been realised in the engineering and construction as well as the operations and logistics stages of the chain. This study seeks to utilise digital technologies to improve the performance management of the loading and transportation of ore process.

Digitalisation has offered significant benefits to the mining industry. Productivity improvement has been identified as the main driver of digitalisation adoption in the mining industry (Lindholm, 2018). Other benefits include improvement of business processes, safety, health and environment (SHE) as well as operational costs and capital expenditure reduction (Maroufkhani, et al., 2022). It is envisaged that by introducing digital data collection and analysis, this project will lead to productivity improvement and ultimately better business performance. Further opportunities for performance improvement can also be potentially realised if the system is cascaded to other TMMs involved in the production process.

Industry practitioners have cautioned that digitalisation adoption is a journey unique to each operation which needs value addition to be measured at every step (Creagh, 2019). This project can be seen as one of the pilot projects relevant to the digitalisation adoption journey for not only LHDs, but for all TMMs at Mimosa. It seeks to evaluate the potential productivity improvement that can be unlocked by implementing digital data collection methods on selected LHDs at the mine. This project will be customised to adapt to the existing conditions at Mimosa mine for practicability. Creagh (2019) also identifies that for underground mines, digitalisation often starts in having equipment connected to a network and pursuing incremental steps to automation achievement. This study therefore forms part of the foundation required in achieving increasing levels of digitalisation which are crucial in improving productivity of mining operations.

Digitalisation is an area which needs to be given more attention by scholars in the mining industry as there is a scarcity of publications covering this subject (Maroufkhani, et al., 2022). Overall, academic studies detailing the approaches and methodologies adopted by mining companies in the progression of digitalisation are rare. Mining organisations have often collaborated with original equipment manufacturers (OEMs) and other technology suppliers in implementing digitalisation projects. However, much of the pertinent details on how these projects are implemented has not been

made available to other mining practitioners. The limited studies made available in the public domain often lack crucial details and practical insights to guide practitioners in implementing such systems within their operating context. This study also seeks to close that gap.

2.3 Productivity in the Mining Industry

The global mining industry has been facing major challenges of declining volume and cost productivity for some time since the year 2000 (EY, 2014). A benchmarking report compiled by McKinsey & Company (2015) showed that mining industry productivity was significantly lower than other related industries like steel making and oil refining. The publication also observed that underground mining's overall equipment effectiveness (OEE) performance averaged 27 percent, while open pit mining stood at 39 percent. Furthermore, it demonstrated that there has been a global downward trend in mining productivity as shown in the Figure 4.

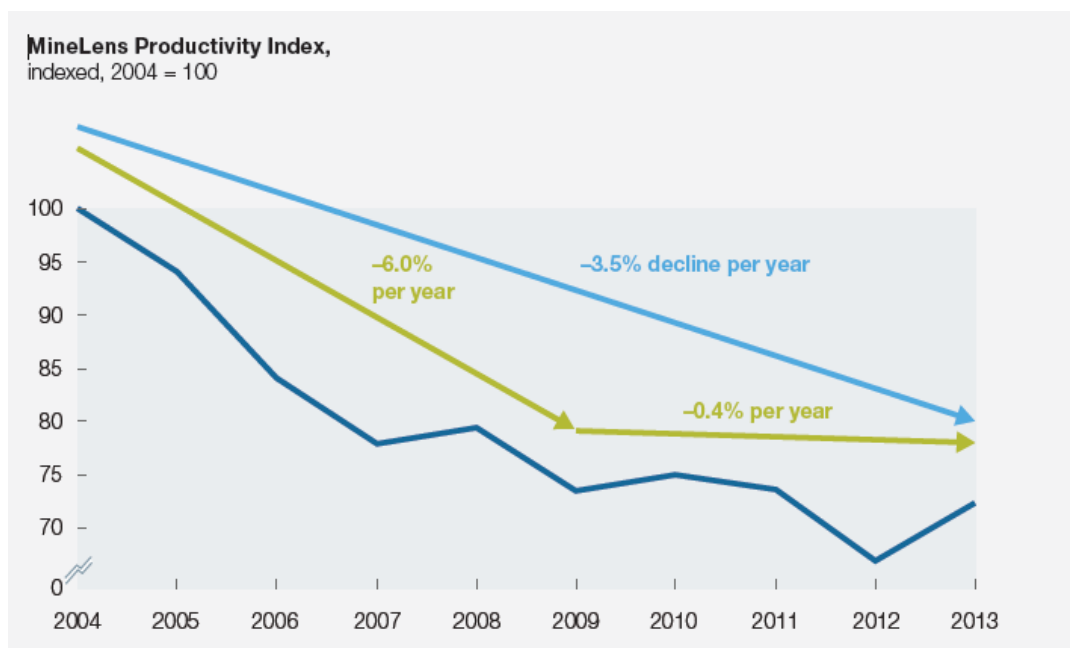


Figure 4: Mining productivity index data

(McKinsey & Company, 2015)

Consequently, over the past two decades the industry focus has been on improving productivity (PwC, 2024). According to this report, in response to investor demands to increase productivity from the year 2017, cost-cutting, digitalisation, automation and development of new technologies have been key strategic focus areas for the industry in answer to this call. Therefore, this research attempted to utilise digitalisation as a tool to effect productivity improvement in line with global mining strategies.

Although productivity in mining has been measured in a variety of ways, the foundational concept remains the same. Productivity has been consistently defined as an efficiency measure that captures the effective rate at which inputs are converted into outputs in production processes (Winters, 1993; Neingo & Cawood, 2014; Choudhary, 2015; Fourie, 2016; Korski, et al., 2017). It can be classified according to relevant inputs such as labour, cost, capital and assets or outputs such as volume. Productivity improvement can therefore be achieved in several ways that can increase this ratio such as generating more production output for a fixed set of inputs or reduced input as well as maintaining the same output using less input (Otto & Lindeque, 2021).

Productivity for mining companies can be analysed at both the corporate and operational levels (PwC, 2014). Evaluation of productivity at the operational level with focus on the primary activities along the operational value chain such as loading and haulage is key for productivity improvement (Munyadzwe, et al., 2022). Productivity metrics in excavation equipment contexts include availability, utilisation, overall equipment effectiveness, energy utilised, production tonnes moved and mining costs. Several metrics have been utilised in determining productivity such as unit cost, tonnes per employee, output per unit capital equipment, tonnes/bank cubic metres (BCMs) per hour, depending on desired objectives (Choudhary, 2015; Neingo & Tholana, 2016; Otto & Lindeque, 2021).

The approach taken by this study is to assess if productivity can be improved by increasing output using the same time input in terms of

available production shift hours. The focus of implementing the digitalisation project is to assess if production tonnes shift output can be increased by reducing the current lashing bottleneck in the production process. Measures such as OEE, while useful in determining productivity, focus mainly on optimising losses generated by equipment availability, performance and quality. These parameters will be assessed in the study as they directly affect production output. However, production output per shift provides a practical index directly relatable to end users in addressing the productivity challenge. Consequently, overall productivity will be assessed using the metric defined by Runge Mining Australia Pty Ltd (1993) which is mathematically expressed as:

$$Productivity = \frac{Production}{Operating\ time}$$

Equation 1: Productivity as a ratio of output over operating time

2.4 Productivity Management Systems in the Mining Industry

There is general agreement in literature on the importance of productivity management in mining operations and its role in improving productivity. Productivity management systems generate critical information which has been utilised in successfully managing and driving productivity improvements across mining operations over several decades (Wilke, 1979; Wright, et al., 1982; Kohler & Gentzler, 1988; Richard, 2004; Beckman, et al., 2016; Munyadzwe, et al., 2022). Consequently, such systems need to be capable of collecting accurate, readily accessible data in a timely manner to generate useful information for decision making (Wilke, 1979; Kohler & Gentzler 1988; Parkinson & Sommerville, 2016; Beckman, et al. 2016).

Several productivity monitoring or management approaches have been implemented in the mining industry which range from manual to full-fledged digital methods. Data collection, processing and analysis methods have

evolved from hand-written logs to real-time digital methods (Minnick, et al., 2023). This section explores the various approaches used in literature and evaluate their applicability to Mimosa mining operations.

2.4.1 Manual paper-based systems

Manual, paper-based systems, are among the most frequently used productivity monitoring methods in mining, especially for smaller operations (Johansson, 2010; Beckman, et al. 2016). In this system, production and equipment information is entered manually by equipment operators and production personnel into a paper-based system. This is the system that is currently in use at Mimosa mine. Operators of TMM log equipment operating information and downtimes for each shift. For LHDs, the following information is manually logged:

- Pre-start checks,
- Fuel consumed,
- Equipment release time,
- Mining delays affecting equipment utilisation,
- Engineering delays affecting equipment availability,
- Buckets loaded,
- Operating start and end times,
- Equipment engine hours,

This data is then manually entered from the equipment and shift checklists into Microsoft Excel spreadsheets to generate daily operational reports. The daily report shows the following:

- Date,
- Total number of buckets loaded per shift,
- Total estimated ore tonnage moved per shift,
- Total lashing/ productive time per shift,
- Total non-productive time per delay category,
- Total equipment available time per shift,

- Total maintenance and breakdown time,
- % availability per shift,
- % utilisation per shift.

The daily report does not measure payload but reports total tonnage moved by each LHD as the product of the recorded buckets moved and the bucket factor provided by the mine planning department. It does not report on actual cycle times but records the lashing time as reported by operators in their checklists. Categorised engineering and mining delays are also reported and the corresponding availability and utilisation measures. The daily report does not include any measure of tramming distances. Daily production meeting discussion is shaped around the key performance measures of productivity (tonnes per hour), ore lashing hours (in-shift utilisation), mining delays (utilisation challenges) and engineering delays (availability) in relation to production targets achievement. The weekly and monthly reports are a consolidation of totals and averages of the daily metrics for the corresponding periods.

Although the manual system captures most of the basic production data, it is ineffective in adequate production monitoring and productivity improvement. (Richard, 2004; Johansson, 2010; Howess & Forrest, 2011; Beckman, et al., 2016). This is due to the challenges that arise from using such a system which can be summarised as follows:

- Data is prone to input errors, thus making it of questionable accuracy and validity (Howess & Forrest, 2011). A study done by Beckmann, et al., (2016) found that manual input created errors at a rate of one load per 55 cycles for an open pit operation. Error sources in manual methods range from inaccurate data recording at source to data input errors into Excel spreadsheets and loss of checklists (Parkinson & Sommerville, 2016). At Mimosa, such errors have been identified several times, but such instances have not really been tracked to analyse their extent and impact. This project seeks to also evaluate

the accuracy of the manual methods in use at the mine by comparison with digital output,

- Data is subject to human manipulation, thus rendering it unreliable. Instances of collusion between equipment operators and engineering as well as mining personnel have been reported at Mimosa where equipment data is manipulated so that the shift report, especially in cases where production is sub-optimal, can be made acceptable to management.
- Data is often not recorded in real-time and there is a delay between when an event occurs, gets reported and the ability to take corrective action (Parkinson & Sommerville, 2016). This creates room for manipulation and delays decision-making critical for productivity improvement. However, recording and utilisation of real-time data is a stepwise progression in line with recommended approaches for technological deployment which will be discussed in Section 2.6 of the report. This study is a step towards achieving this desired objective.
- The method requires a lot of resources and is time-consuming (Parkinson & Sommerville, 2016). Several data capturers are required to timeously capture the equipment and shift information for TMMs at Mimosa, which makes the process very inefficient.
- Limited analysis can be done on data captured by such methods to improve operations as it often lacks sufficient amount of data features (Howess & Forrest, 2011) . For instance, at Mimosa crucial data such as cycle times and bucket fill factors are not captured by this system. This limits the capability of using data to improve the loading process of LHDs, and ultimately productivity.

Telephone and radio communication are often employed to complement the manual paper-based system. Mimosa does not have radio communication underground but uses a telephone system to mitigate against some of the challenges highlighted above. Telephone lines are available at the LHD grizzly tipping points underground and at waiting places in the production

sections. The rock breaker operator stationed at the grizzly serves as an independent check on recording and communicating tipped buckets. He notifies the surface control operator when the first bucket is tipped and records each time the LHD tips at the grizzly. Phone communication is also utilized by management for production monitoring during the shift. However, this method still does not capture critical metrics such as the tonnes per bucket for each LHD and is also insufficient to mitigate against collusion and data manipulation.

To address the challenges associated with manual systems, mining operations are moving from manual to digital methods for more effective productivity monitoring and improvement. Consequently, digital methods are reviewed below.

2.4.2 Digital systems/FMS

Original equipment manufacturers (OEMs) and other dedicated technology providers have developed various digital applications aimed at monitoring and controlling equipment usage for several years (Farrelly, et al., 2012). These systems have been developed and used in the mining industry for over five decades mainly to improve fleet productivity, although success has been hampered by technological and environmental limitations (Dessureault, et al., 2007; Bullock, et al., 2017; Afrapoli, et al., 2018). While usage of such systems is well developed and widely used in the open pit mining sector, adoption within the mining space came later and has been cyclical since the 1990s (Modular Mining Systems, 2011).

These systems have varying capabilities and organisations are at varying levels of adoption depending on several site-specific factors. Modern systems, commonly known as FMS utilise GPS, equipment on-board sensors, computers and wireless networks for data collection. They enable operations to collect a wide range of pertinent operational and machinery data in real time. Such data can be utilised in making better decisions and

further improvement and optimisation of operations (Richard, 2004; Parkinson & Sommerville, 2016; Ferreira, 2017; Erkayaoglu, 2019).

Several benefits have been experienced in using digital systems such as FMS according to studies conducted across several mining operations. These include:

- Truck and shovel open pit operations have reported gains in productivity of up to 15% coupled with cost savings (Dessureault, et al., 2007).
- Parkinson and Sommerville (2016) have shown how data obtained from these systems have been utilised to achieve significant productivity gains in the drilling, loading and hauling operations for several operations.
- Ferreira (2017) reported improvements in equipment utilisation, productivity, material movement, safety of operators and cost reduction as benefits encountered in underground mines that adopt FMS.
- Improved quality and flow of information have been major benefits of FMS (Johansson, 2010).

The following case studies experienced benefits because of specifically implementing FMS:

- White Foil operations - 18% cost reduction, 21% production improvement (Beckman, et al., 2016);
- Mogalakwena - improvement of OEE and ultimately productivity, which saw production turnaround in 2012 (Fourie, 2016);
- Glencore's Mount Isa Copper Operations (MICO)- Improvement in safety, productivity and efficiency (Bullock, et al., 2017).

Despite the immense benefits, several challenges have been experienced in implementing FMS, particularly in underground mining environments. Critical to the success of FMS is the adoption of the right strategy designed to provide contextual solutions relevant to the mining operations concerned

(Beckman, et al., 2016). The following section reviews the challenges gleaned from literature and highlights mitigation strategies to be implemented in conducting the study:

- Setting up requires significant capital cost for network infrastructure (Beckman, et al., 2016). This project will mitigate against this challenge by utilisation of already installed infrastructure as much as possible. Although this imposes limitations to the capability of the FMS system such as obtaining real-time data and tracking of machinery position, the strategy was considered optimal to meet the study objectives. The already installed underground network will be used to download FMS data whenever equipment goes through the workshop. Equipment comes to the workshop at the start and end of every shift as well as during the shift for major repair and maintenance work or fuel and lubes top-ups that may be required. Investments into updating the communication infrastructure were considered during pilot project closure phase.
- Possible damage to sensors as a result of underground mining conditions such as dust and moisture (Brzychczy, et al., 2020). This challenge was addressed mainly through the research and development (R&D) efforts by the OEMs partnered with in the project. The on-board sensors utilised were part of the standard telemetry systems developed by OEMs designed to withstand this challenge. Consequently, no cases of damage were experienced during the study.
- Physical limitations imposed by underground operations layout and regulatory constraints may hamper installation and maintenance of connectivity infrastructure required for such systems (Farrelly, et al., 2012). By utilisation of connection points already installed in strategic points such as underground workshops, the mine layout constraint will be mitigated. The mine legal department was included as part of the project team to assist in evaluating and advising on any legal and regulatory concerns.

- High equipment mobility, complex mining layouts and unfavourable mining conditions (Latum, et al., 1995). This challenge is mainly relevant if real-time data is required. This study focuses on an incremental step to technology adoption which has not yet reached the real-time data generation stage. As a result, the Wi-Fi-based downloads conducted in the workshop were considered adequate for this phase.
- Failure to use and analyse the immense data available for business improvement operations (Parkinson & Sommerville, 2016; Dessureault, 2019; Brzychczy, et al., 2020). The study addresses this gap by adopting suitable data analysis techniques that will demonstrate how productivity can be monitored, analysed and improved using FMS data.
- Ability to capture all the relevant key performance indicators (KPIs) (Parkinson & Sommerville, 2016). In this study, only a select few metrics were measured and consolidated based on inputs from consultations with operational mine personnel and OEM technical experts. Data collected covered all the needed productivity metrics.

Although FMS offers several benefits, this study focuses on how it can be utilised to improve equipment and process productivity. The following section discusses the factors that influence equipment productivity.

2.5 Factors Affecting Equipment Productivity

In mechanised mining, productivity is hugely dependent on how equipment is effectively utilised (Fourie, 2016). Equipment productivity has thus been underscored as a major determinant of productive competitiveness (Dindarloo, et al., 2016). FMSs are often utilised in maximising productivity and reducing operational cost through OEE measurements (Nel, et al., 2011). OEE is therefore a foundational concept that will be explored in this

study in relation to assessing the effectiveness of the current system and the implemented digital system.

OEE is a universally accepted measure, strongly entrenched in literature, that has been commonly used in both the manufacturing and mining industry to determine and improve productivity (Paraszcza, 2005; Elevli & Elevli, 2010; Choudhary, 2015; Dindarloo, et al., 2016; Fourie, 2016; Manyele, 2017; Deucker & White, 2017). Machinery OEE can be expressed by the formula:

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

Equation 2: OEE as a product of equipment availability, quality and performance

(Paraszcza, 2005; Elevli & Elevli, 2010; Choudhary, 2015; Korski, et al., 2017)).

Where:

OEE = Overall Equipment Effectiveness (%),

Availability = Availability of equipment (%),

Performance = Performance of equipment (%),

Quality = Quality of work done by equipment (%).

OEE considers the major sources of productivity losses encountered in equipment efficiency, commonly known as the six big losses (Elevli & Elevli, 2010). Table 1 shows how the six losses are related to the factors affecting

OEE for equipment in the manufacturing industry, where the concept originated from.

Table 1: Six major losses affecting OEE
(Elevli & Elevli, 2010)

Six Big Loss Category	OEE Loss Category	OEE Factor
Equipment Failure	Downtime Losses	Availability (A)
Setup and Adjustment		
Idling and Minor Stoppages	Speed Losses	Performance (P)
Reduced Speed		
Reduced Yield	Defect Losses	Quality (Q)
Quality Defects		

According to this model, in order to be effective, equipment needs to achieve high levels of each of the three OEE factors. Elevli and Elevli, (2010) further highlight how the parameters are mathematically calculated for manufacturing equipment in Table 2.

Table 2: OEE parameters calculation

(Elevli & Elevli, 2010)

Total Time				
Net Available Time			Scheduled Downtime	
Operating Time		Downtime Losses	$A = \frac{\text{Operating Time}}{\text{Net Available Time}}$	
Net Operating Time	Speed Losses			
			$P = \frac{\text{Net Operating Time}}{\text{Operating Time}}$	$P = \frac{\text{Actual Output}}{\text{Target Output}}$
Fully Productive Time	Defect Losses	$Q = \frac{\text{Fully Productive Time}}{\text{Net Operating Time}}$	$Q = \frac{\text{Good Output}}{\text{Actual Output}}$	

This framework can also be illustrated diagrammatically in Figure 5

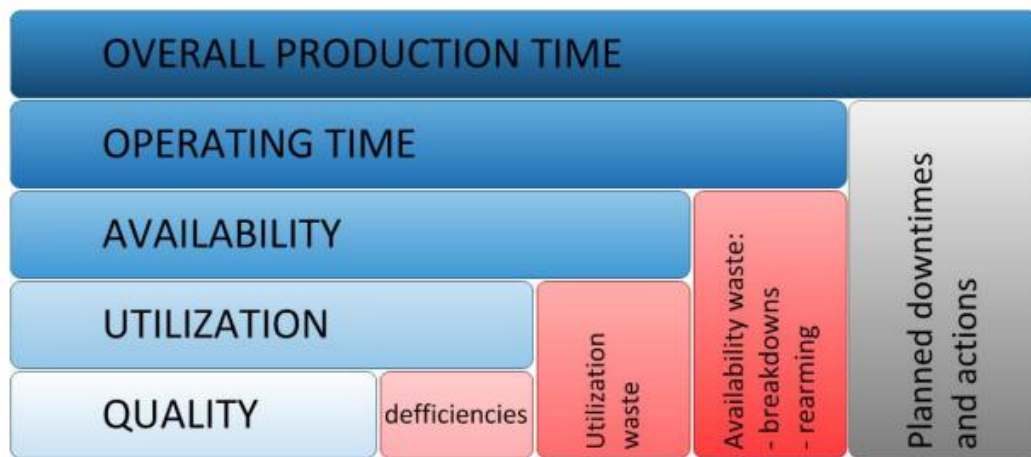


Figure 5: OEE indicators
(Korski, et al., 2017)

According to the framework, total productive time consists of net available time and scheduled downtime. This overall productive time baseline can be based on ordinary calendar hours or loading hours, depending on capital intensiveness of the equipment concerned or organisational reporting requirements (Elevli & Elevli, 2010). Downtime losses, such as unplanned equipment breakdowns, reduce net available productive time, and availability is the parameter that measures the ratio of operating time to the net available time. Speed losses or utilisation waste reduce operating time and utilisation is used to measure the performance aspect of OEE. Defect losses, further reduce net operating time and are used to determine the quality component of OEE.

Several studies have customised and utilised this framework in analysing the effectiveness of mobile equipment mining fleets such as shovels, trucks and loaders in both open pit and underground mining contexts (Paraszczak, 2005; Elevli & Elevli, 2010; Fourie, 2016; Korski, et al., 2017). It is important for organisations to develop OEE frameworks applicable to the type of equipment and operating context (Bamber, et al., 2003). Elevli and Elevli (2010), developed the framework shown in Table 3 for OEE of mining loading equipment, specifically shovels used in open pit mining.

Table 3: OEE parameters for mining loading equipment

TOTAL TIME (TT) 24 (hr/day)x 7(days/week)			LOSSES	OEE FACTOR
Actual Available Time (AAT)		Availability Losses	Nonscheduled time Scheduled maintenance Unscheduled maintenance Setup and adjustment Idle time Truck waiting time	Availability = $\frac{\text{Actual Available Time}}{\text{Total Time}}$
Net Production Time (NPT)		Performance Losses	Propel time Job condition loss Speed loss	Performance = $\frac{\text{Net Production Time}}{\text{Actual Available Time}}$
Valuable Production Time (VPT)	Quality Loss		Quality loss	Quality = $\frac{\text{Valuable Production Time}}{\text{Net Production Time}}$ Quality = $\frac{\text{Volume of Average Load}}{\text{Actual Bucket Capacity}}$

The model is similar to the manufacturing one with defect losses now corresponding to availability losses. Speed losses translate to performance losses equivalent to equipment utilisation, also known as use of availability (Fourie, 2016). Quality waste is customised to the ratio between average payload and the actual bucket capacity. It can also be expressed as the proportion of productive time that is used for the actual loading process. Paraszczak (2005) proposed productive efficiency as the third component of OEE instead of quality loss, which may not be applicable to mobile mining equipment. Fourie (2016) also used shovel loading rates and truck payload management as a productivity metric to measure OEE performance. Fourie (2016), modified the OEE formula for mobile mining equipment to:

OEE = Availability x Use of availability/Utilisation x Productivity x Quality of work done

Equation 3: OEE for individual or combined mobile equipment fleets

Where:

OEE = Overall Equipment Effectiveness (%)

Availability = Availability of equipment (%)

Utilisation/ Use of availability = Equipment utilisation (%)

Productivity = Operating tempo of equipment

Quality = Quality of work done by equipment (%)

Consequently, productive efficiency will be analysed as the third component of mobile equipment OEE in this report. Overall, OEE can therefore be considered an effective measure for analysing effectiveness of mobile mining equipment.

There is general agreement among scholars that the accuracy of the data collected is key to the relevance of OEE measurement if productivity is to be improved (Paraszczak, 2005; Elevli & Elevli, 2010; Dindarloo, et al., 2016; Fourie, 2016; Deucker & White, 2017). Consequently, the FMS will be utilised to collect actual operating hours, cycle times, tramming distances, and actual tonnes per payload using 'on-board' sensors fitted on LHDs. This will enable more accurate data collection to critically evaluate equipment availability, utilisation and productive efficiency. Data thus

generated will be free from bias and thus can be trusted to be the basis of analysing and improving equipment usage, and ultimately productivity.

2.5.1 Equipment availability

Equipment availability is the most common measure of equipment performance and can be defined as the ratio of machine uptime against the total or scheduled hours within a given production period (Paraszcza,2005; Dindarloo, et al.,2016). It is a broad concept that encompasses several metrics which provide guidance on equipment reliability and maintainability. Equipment uptime is the difference between the available hours and the downtime hours (Paraszcza, 2005).

Equipment downtime is one of the major contributors to production losses (Dindarloo, et al., 2016). Paraszcza (2005) underscored the importance of using reliable data to categorize downtime elements to identify and eliminate losses. Accurate availability data is often used to determine reliability and maintainability metrics such as mean time before failure (MTBF), mean time to restore (MTTR), and maintenance ratios (MR) (Hall & Daneshmend, 2003; Paraszcza, 2005). These indices are used as measures to monitor and improve equipment availability.

Mean time between failures/shutdowns (MTBF/MTBS) is a measure of equipment reliability that can be expressed mathematically as:

$$\text{MTBF/MTBS} = \text{Number of operating hours} / \text{Number of shutdowns/failures}$$

Equation 4: MTBF/MTBS is the average time between failures (Paraszcza, 2005)

An effective maintenance strategy results in higher MTBF by increasing the amount of time in between equipment failures (Stuart, 2022). Mean time between repairs (MTBR) measures the average time between necessary repairs while mean time to repair/restore (MTTR) indicates the time required

to restore functionality after a failure (Paraszcza, 2005). MTBR and MTTR measures effectiveness of maintenance practices, support, and administration efficiency. Maintenance ratio (MR) is the ratio of maintenance manhours to equipment operating hours. It can be used in maintenance planning and as an additional tool in replacement scheduling (Paraszcza, 2005).

Machine remote monitoring systems such as FMS can be utilised in improving machine availability metrics. Johansson (2010) outlines that FMS on underground LHDS can present the following benefits to improve availability:

- Improved maintenance scheduling through accurate recording of actual operating hours of various components such as engines, transmission and pumps,
- Improved diagnostic capability to enhance fault-finding and attendance to breakdowns,
- Generation of service alarms to enable components to be attended to before failure, thus improving predictive and planned maintenance practices.

Consequently, implementing FMS will result in higher MTBF and MTTR indices as well as overall availability. It also improves accuracy and efficiency of planned maintenance interventions, which reduces the MR, further improving availability.

Figure 6 shows a summary of the typical information helpful for equipment maintenance that can be generated by installed FMS system on various TMM.

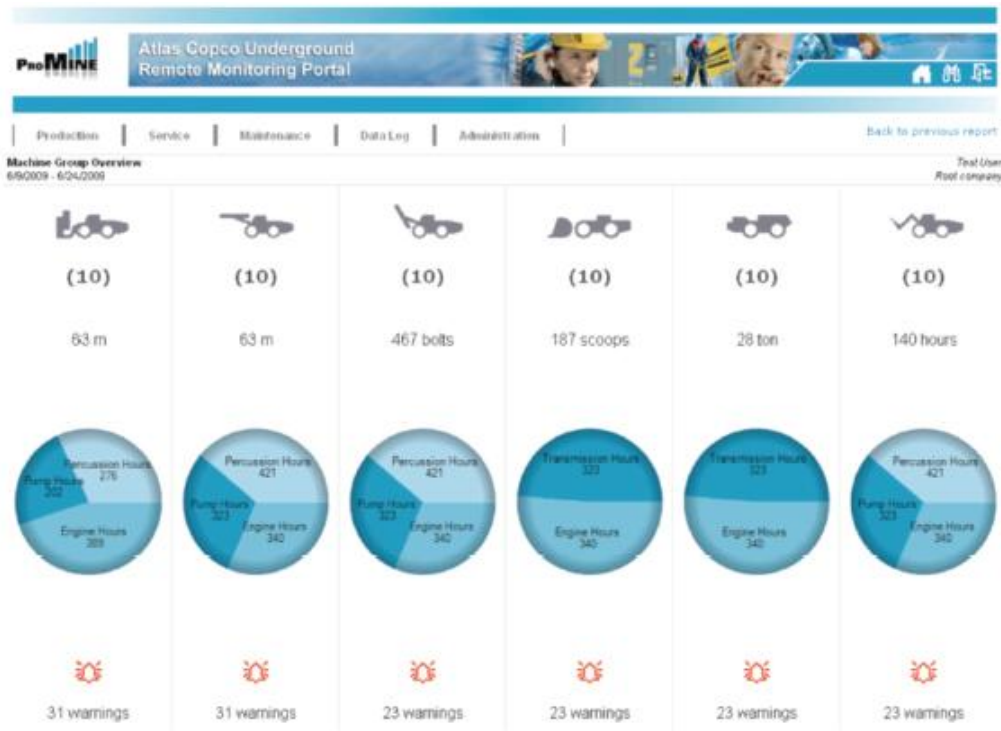


Figure 6: Summary of machine data captured by FMS
(Johansson, 2010)

The FMS utilised in this study had this functionality installed but the maintenance module was not part of this pilot study. Even though equipment availability is critical for productivity analysis and improvement, a detailed analysis of this factor is outside the scope of this report. This area is a broad subject that requires a separate study to enable its optimisation as there are several intervening variables that influence this parameter. Furthermore, availability focuses on the presence of the machine and does not necessarily influence how it is utilised. This research will therefore be focused on evaluating and improving how LHD equipment is utilised at the mine.

2.5.2 Equipment utilisation

Equipment utilisation also known as the “use of availability” is another key parameter that influences equipment usefulness and productivity. It can be

defined as ratio of an equipment's actual operating time against its uptime (Paraszczak, 2005; Fourie, 2016). Utilisation seeks to measure how the machine is used during its uptime while availability focuses on the presence of the machine for use.

Several factors affect equipment utilisation in mining which can be organisational, technical or geological (Brodny & Tutak, 2019). Paraszczak (2005) also asserts that equipment uptime needs to be categorised into idle and operating times to enable better analysis of utilisation. Idle time has been singled out as one of the six major losses that compromise effectiveness of any piece of equipment (Dindarloo, et al., 2016). Setting up of these categories can enable detection of any discrepancies between available and actual operating time (Paraszczak, 2005). Deucker and White (2017) advocated that utilised time can be further divided into:

- productive utilisation (time spent in direct revenue-generating productive work),
- support utilisation (time spent in necessary activities that support production),
- utilisation delays (equipment manned but doing indirect activities tasks like waiting),
- idle time (machine available but without operator) which should be considered as waste.

Operational inefficiencies that affect a machine's in-shift utilisation can be detected through analysis of these categories. Corrective action can thus be determined which can be used to improve equipment productivity.

FMS is expected to improve equipment utilisation and operational efficiencies due to its capability to provide visualisation of how the machine is used during the shift (Johansson, 2010). Figures 7, 8 and 9 show the typical graphical output generated by the FMS utilised in the pilot study which was utilised to analyse machine utilisation.

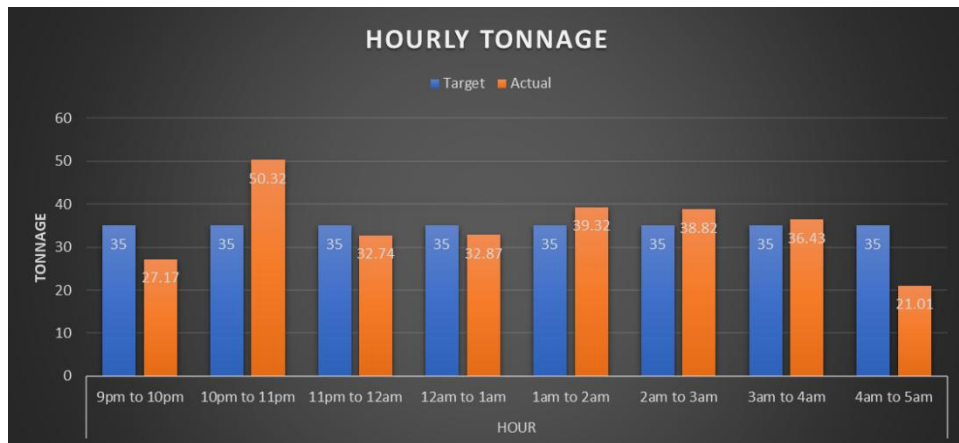


Figure 7: Hourly LHD actual tonnage vs planned

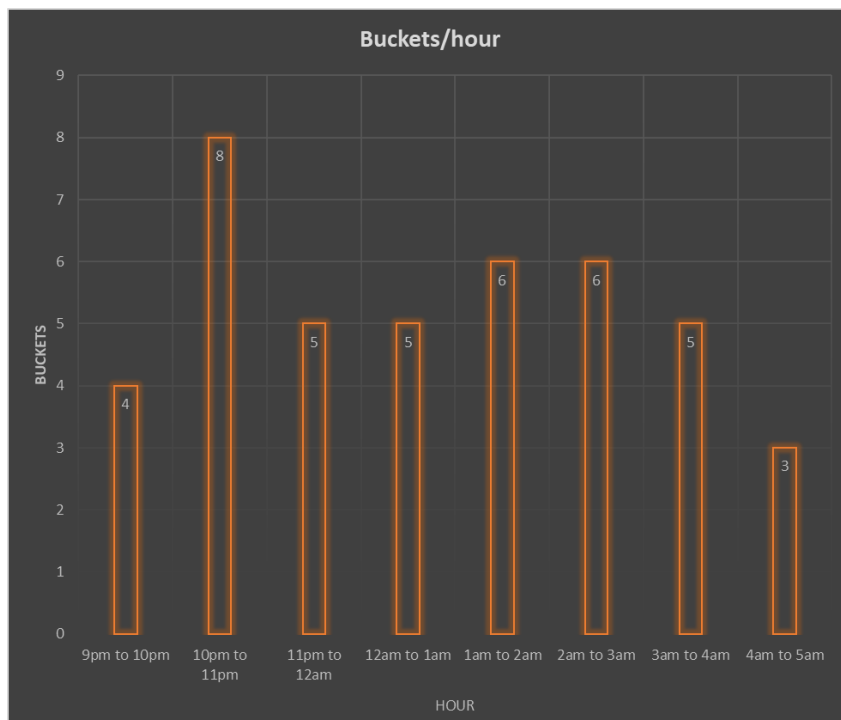


Figure 8: LHD buckets moved per hour

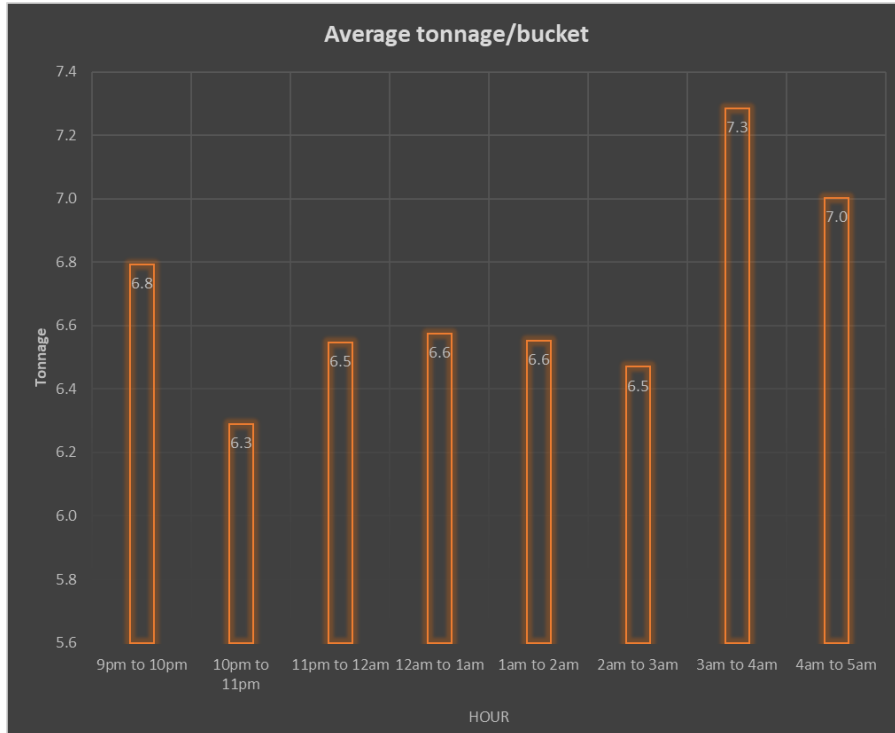


Figure 9: Average LHD payload per hour

This information clearly outlines the variations in machine utilisation during the shift which enables closer analysis of how the machine is working. Investigations can then be made based on this data to address the fluctuations in machine utilisation, so that productivity can be improved. In line with reviewed literature, the FMS used in this study collects equipment uptime data in doing revenue-generating work. A major weakness of the FMS system used for the project is that it cannot automatically record idle and support utilisation time. The research will therefore not be able to compare actual idle time. However, accurate determination of the actual productive time can be used as a starting point for utilisation analysis, with room for improvement. The system can be improved further if FMS can be utilised for capturing utilisation delays and idle time. Further studies can be used for evaluating this concept.

2.5.3 Productive efficiency/Quality

Equipment productive efficiency is another vital component of OEE that impacts productivity. It can be expressed as the ratio of the actual work done

by a piece of equipment measured against OEM specifications and the operating context (Paraszcza, 2005). It measures what the machine is producing against what it can be expected to produce when benchmarked using technical capability and similar operating conditions. Several authors have used this metric to represent the quality component of OEE for mining excavation equipment (Elevli & Elevli, 2010; Fourie, 2016; Korski, et al., 2017). Others such as Paraszcza (2005) argue that the quality component is not applicable to mining equipment and use productive efficiency instead to replace it. Overall, there is agreement among practitioners that productive efficiency can represent the quality parameter of OEE in mining equipment.

Productive rate or efficiency depends on several factors which ultimately determine performance. Operator skill, fatigue, motivation, attitude, managerial practices and operational state of the machinery, among others are key factors that can determine equipment productive efficiency (Paraszcza 2005; Dindarloo 2016; Brodney & Tutak 2019) (Brodney & Tutak, 2019). Another important consideration when measuring productive efficiency is that the units used to measure work done must be representative of the process being executed as well as the operating conditions (Paraszcza, 2005). Therefore, to gain a more complete picture of equipment productive efficiency all the necessary factors need to be considered.

A report by Leeuw & Mkhwanazi (2018) summarised the factors affecting LHD productive efficiency based on an analysis of 25 student reports covering at least 17 different underground mines. Most of the mines were room and pillar platinum operations based in Zimbabwe and South Africa. The analysis showed that operational inefficiencies underground accounted for 67% of LHD productivity inhibitors, which were a result of poor operator efficiency, supervision and management practices. The remaining 33% attributed to machine factors which were largely influenced by underground operating conditions. Consequently, it will be the focus of this study to utilise

FMS in evaluating operational factors that affect LHD productivity in underground operations at the mine.

Cycle time, operator efficiency and payload have been identified as the most significant factors affecting loading productivity for open pit mines (LaForest & Riggle, 2019). This is in line with recommendations made by Caterpillar Inc (2013) who published an OEM reference guide for users of surface mining equipment highlighting that these three variables are the most sensitive to mining unit costs as shown in Figure 10.

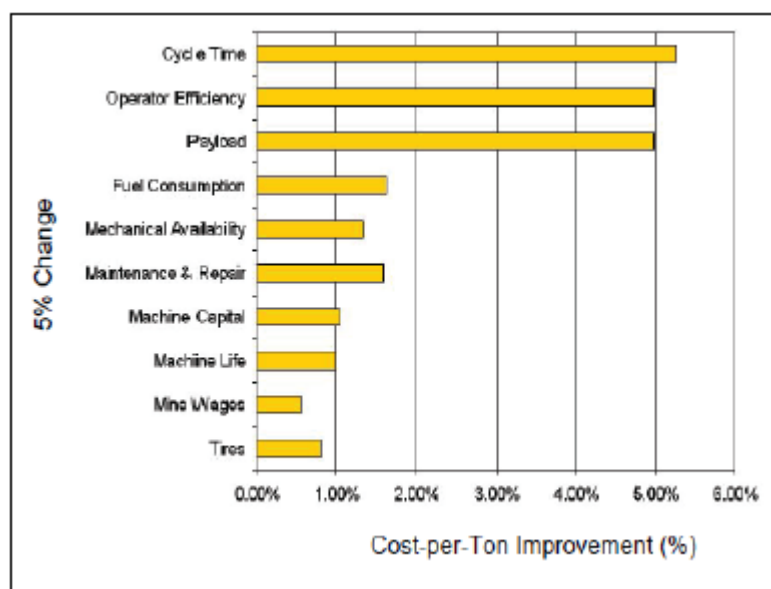


Figure 10: Sensitivity of mining unit costs (cost/tonne)
(Caterpillar Inc, 2013)

LaForest and Riggle (2019) propose that the use of FMS technology in optimising these three areas in operational management will produce the greatest productivity benefit. While this directly applies to open pit mining loaders, it would be helpful to evaluate the impact of these parameters on underground excavation work using LHDs. By using digital FMS, this study seeks to evaluate how these parameters are related to productive efficiency of LHDs.

Operator efficiency is a critical parameter that influences productivity of LHDs based on the above literature review. Loading rates, payload and cycle times are all dependent on operator efficiency to some extent. LaForest and Riggle (2019) outlines how FMS can be utilised to give operators feedback and training which can help improve productivity. Consequently, this research will seek to utilise LHD FMS data output in analysing operator efficiency and how it can be improved to enhance productivity. Care will be taken to utilise carefully considered efficiency measures to get adequate comparison measures.

Another benefit of FMS is that it can be utilised to improve safety by monitoring operator behaviour (Sandvik Zimbabwe, 2021). FMS is able to monitor unsafe operator work practices that damage machinery or create unsafe working conditions. FMS has been utilised to monitor the performance of mobile equipment operators in order to enhance safety and productivity (LaForest & Riggle, 2019). The FMS used in this study had the functionality of generating alerts to improper behaviour such as excessive speeding, improper gear changes and inefficient use of brakes. This data was utilised for training and coaching of operators to improve safety and productivity.

Equipment cycle time is one of the most significant factors influencing LHD productive efficiency, particularly in room and pillar mines. Load and haul cycle time is dependent on several factors that include haulage profile, dimensions, travel speed, operator efficiency, load times, haul times, traffic conditions and tramming distances (Leeuw & Mkhwanazi, 2018). Shorter cycle times generate ripple productivity benefits in room and pillar mines which include improved face availability, flexibility and ability to meet production targets. It can even lead to further optimisation of equipment fleet sizes, thus further improving costs. Analysis of cycle times is therefore imperative if LHD productivity is to be improved. This study will therefore seek to utilise digital FMS data in measuring cycle times and conducting relevant data analysis for productivity improvement.

Tramming distance is another critical parameter influencing LHD productivity. Long tramming distances are among the leading causes of poor LHD productivity encountered in underground room and pillar mines in Zimbabwe and South Africa (Leeuw & Mkhwanazi, 2018). It is generally recommended that tramming distances need to be kept within 150 metres as mining progresses for optimum LHD productivity (Harrison, 2006; Mbhalati, 2015; Sandvik, 2024). The Figure 11 shows how productivity changes with variations in tramming distances for a Sandvik LH208L loader as provided by the OEM.

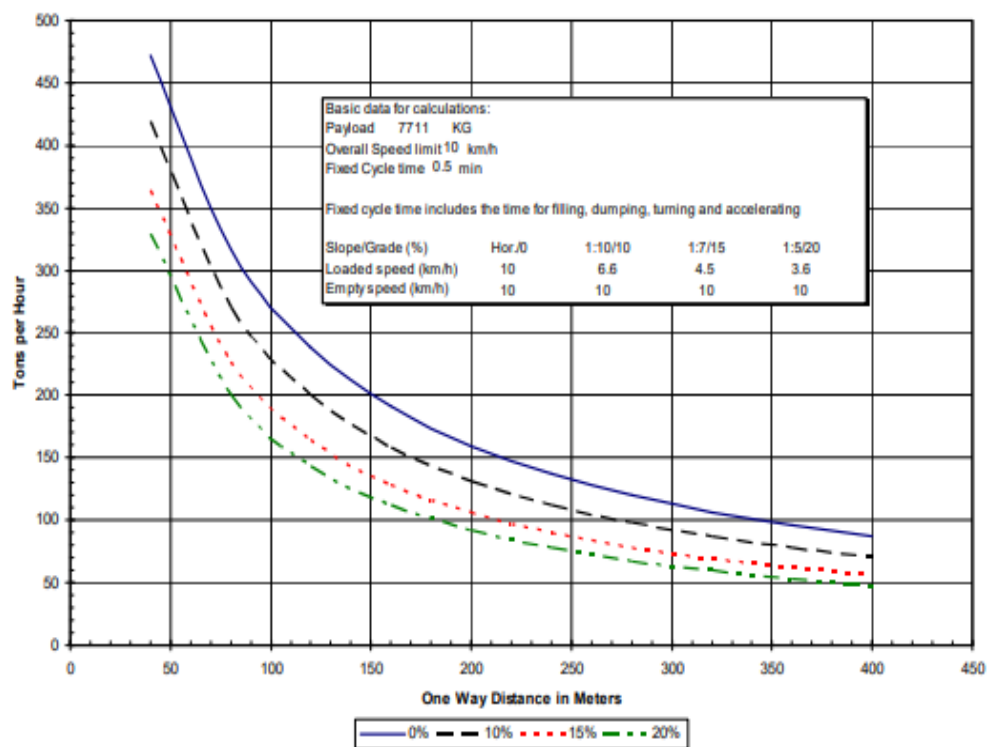


Figure 11: Sandvik LH208L productivity curve
(Sandvik, 2024)

As shown in Figure 11, productivity is inversely related to tramming distance and drastically reduces as optimum distances are exceeded at a given speed, cycle time and payload. The study will utilise FMS data output to investigate how critical variables such as tramming distances, cycle times, tonnes moved per kilometre, operator efficiency and payload influence LHD productivity at Mimosa mine. These metrics will be analysed to identify

potential sources of inefficiencies and come up with initiatives for production performance.

2.6 Technology Adoption Frameworks for Underground Mining Haulage Systems

A revolutionary or evolutionary approach can be taken by mining operations in adopting technological innovations. The former involves radical change whereas the latter represents small incremental changes (McCarthy, 2016). There is consensus among scholars and industry practitioners that the best results for digitalisation in underground haulage systems are obtained by adopting value-adding incremental progressive technological change (Scott, 1998; Pratt, 2016; Pratt, 2017; Creagh, 2019).

Such change has been successfully brought about in practice through collaborative partnerships between major industry players and original equipment manufacturers (OEMs) as well as various technology and services suppliers (Upstill & Hall, 2006; Bartos, 2007; Constable, 2022; The Minerals Council of Australia, 2022; WIPO, 2025). Examples of such alliances are BHP Billiton with Caterpillar, Rio Tinto with Komatsu and Codelco with DBT (Bartos, 2007). Through such alliances, technologies developed by OEMs and other technology suppliers are implemented at various mining sites in achieving incremental improvements in safety, costs and productivity.

Digitalisation of underground LHDs is a progressive journey. Figure 12 below shows the general model that demonstrates the anticipated changes until full digitalisation is achieved. Maximum benefits of digitalisation are expected when autonomous mining is reached.

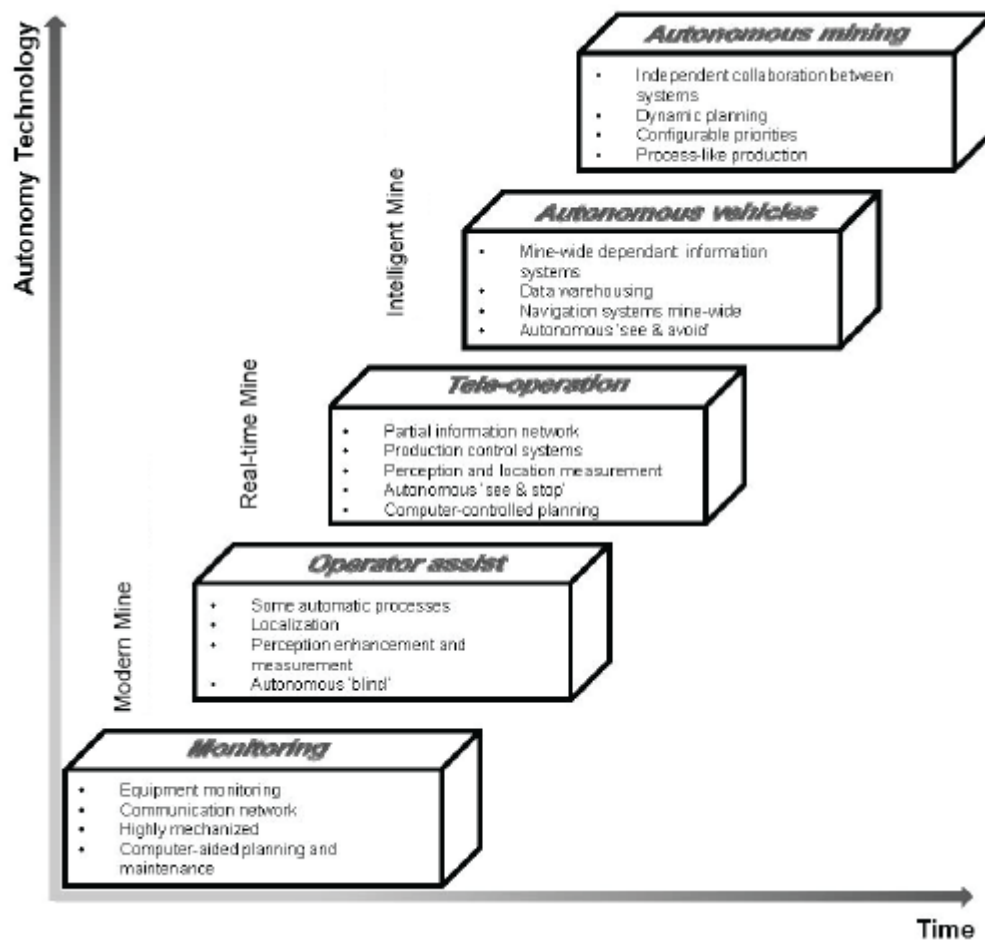


Figure 12: Incremental evolutionary stages for digitalisation of mining underground haulage systems
(Pratt, 2017)

The above model has been customised by OEMs such as Sandvik as they seek to collaborate with mining operations to implement digitalisation. Figure 13 below shows the proposed stages recommended by one of the major OEMs for Zimbabwean mines and the anticipated timelines based on their experience.

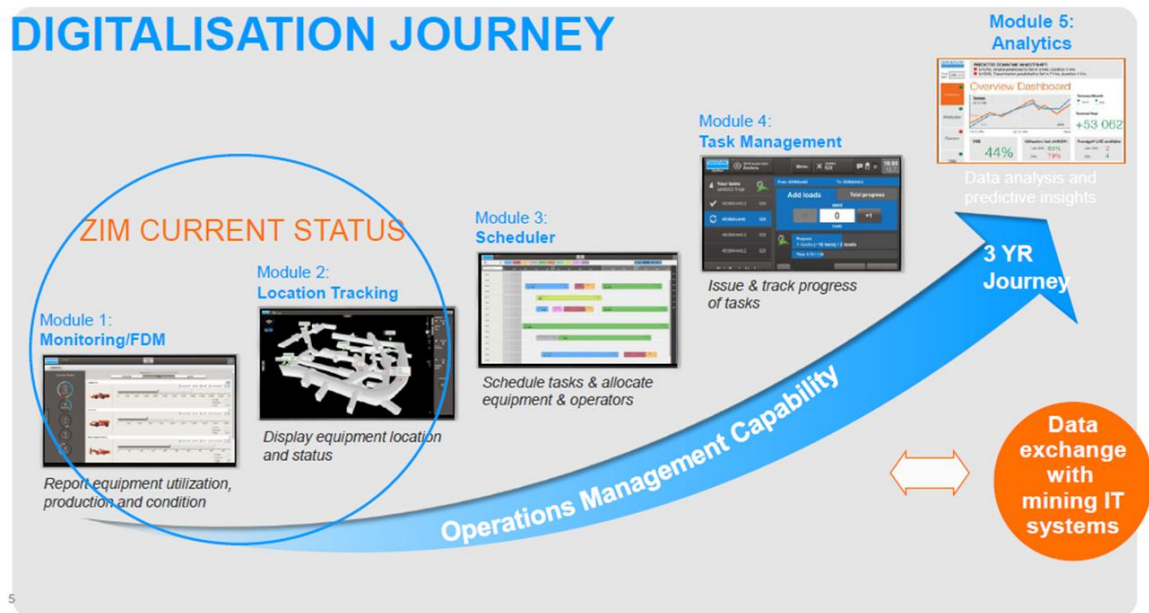


Figure 13: Proposed digitalisation journey for Mimosa underground TMM
(Sandvik Zimbabwe, 2021)

This study represents a pilot phase that focuses on the first stage of digitalisation, specifically targeting equipment productivity monitoring. It is expected that by implementing this project, value creation can be measured which will enable progression to further stages as well as extension of digitalisation to the remainder of the fleet.

A structured approach is considered necessary to achieve effective results when implementing digitalisation projects (McCarthy, 2016). In fact, the absence of a properly structured method has been one of the major causes of failure in implementing technology adoption projects in mines (Scott, 1998; Pratt, 2017). Furthermore, a lack of sufficient project management technical experience has been identified as one of the barriers to digitalisation within the mining industry (Cronin, 2017). It is critical therefore, that proper project management procedures be utilised in executing this project.

2.6.1 Project management procedures

Technical evaluation of mining projects typically goes through several project management stages. Figure 14 below shows the various stages and their respective differences in terms of scope, accuracy and purpose.

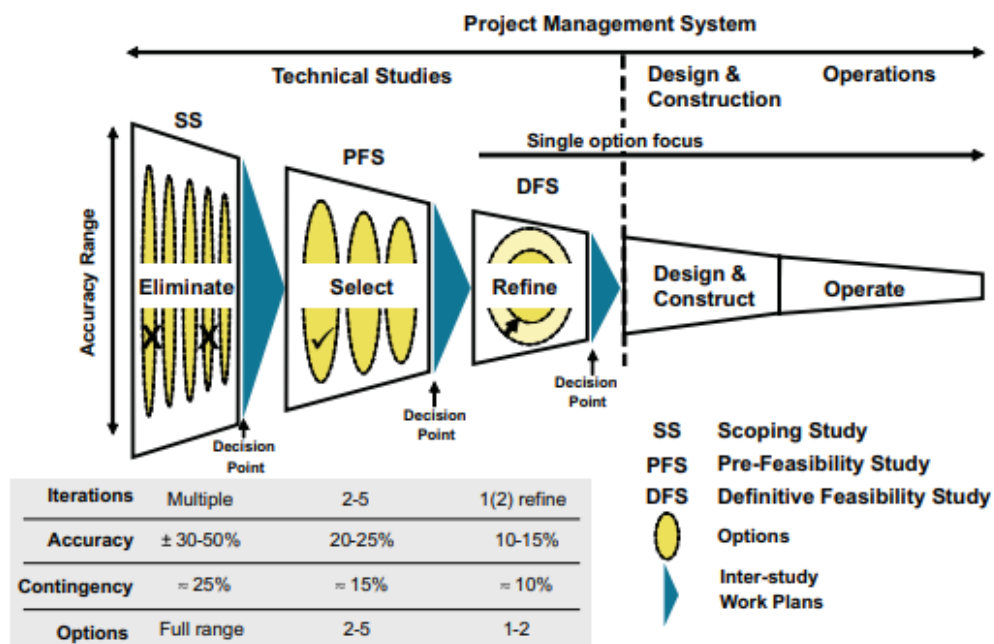


Figure 14: Typical mining project assessment phases
(Noort & Adams, 2006)

Scoping studies serve as the starting point whose purpose is to determine project options and eliminate unviable ones, with selected options proceeding to pre-feasibility stage for further evaluation. The definitive feasibility study refines the chosen option which is recommended for implementation. The level of accuracy increases as studies move from scoping to feasibility and implementation stages. Although this approach is widely used to mitigate project risks and uncertainty, in practice mining companies customise their approach depending on project size and their own internal processes as well as strategies (Luxford, 2006; Nort & Adams, 2006).

A similar approach was followed in conducting this study. It commenced with a desktop evaluation of the cost and benefits of installing digital monitoring systems on LHDs. This served as a scoping or order of magnitude evaluation which showed that there is potential to be derived in further evaluating the concept. Based on this recommendation, the scale of the project, and the Mimosa mine internal guidelines for studies of this nature, further feasibility studies were considered unnecessary. The pre-feasibility (PFS) and definitive feasibility (DFS) stages were skipped to proceed directly to project implementation through this pilot study.

Established project management techniques are crucial for success in implementing mining projects (Read, 2006; Luxford, 2006; Noort & Adams, 2006; McCarthy, 2016; Pratt, 2017). Since project management has developed into an established discipline, with properly maintained standards through the Project Management Institute, mining companies will do well in using such models than try to come up with entirely new ones (Read, 2006). Noort & Adams (2006) recommended the framework shown in Figure 15 for effective management of mining projects.

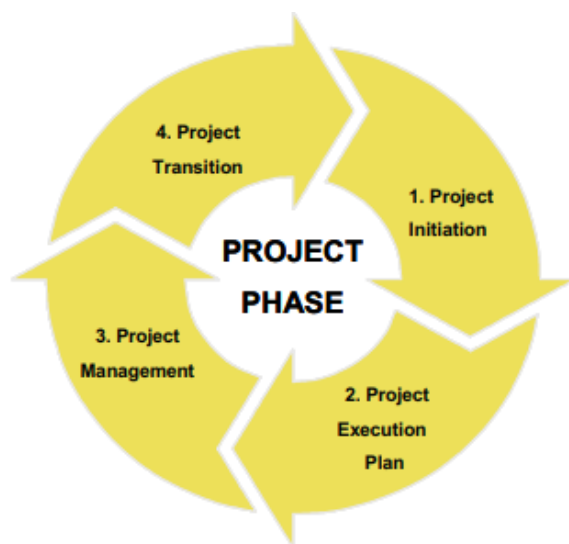


Figure 15: Project management framework for mining projects

Project initiation stage serves to evaluate if the project is worth pursuing and to lay the foundation for project execution planning. Project execution plan (PEP) outlines the detailed implementation plan, which includes work

breakdown structures, schedules and budgets. PEP serves as the foundation for the project management stage ensuring effective project delivery of all anticipated milestones. The project transition stage is the final phase, marking the closure of the current study or project or its transition to the next phase. Table 4 presents a summary of the activities required for each stage.

Table 4: Project management activities framework
(Noort & Adams, 2006)

Project stage	Activities
Project Initiation	• Project preparation and management-appointment of project sponsor, manager and customer • Project Charter development • Application for expenditure • Project manager briefing • Project procedures • Project kick-off meeting • Communication, filing and document control
Project Execution Plan	• Project work breakdown structure, • Project team composition, roles and responsibilities, • Project scheduling, • Setting milestones, • Budgeting, • Communication plan - meetings, reports and KPIs), • Risk assessment, • Procurement and contracts management plan
Project Management	• Team building and selection, • Progress and cost tracking, • Communication and reporting • Project evaluation and monitoring
Project Transition	• Project/ study completion • Project review • Filing and documentation • Closeout meeting • Initiation of the next phase

This approach is in line with established best practice guidelines set by international project management institutions. The Project Management Institute has developed its guides from inception in 1996 up to 2021 based on the five processes of:

- project initiation,
- project planning,
- project execution,
- project monitoring and controlling,
- project closure.

(Project Management Institute, 1996)

It is worth noting that since 2021, the Institute changed its process-based guide was changed to a principle -based one based one but that was mainly to accommodate flexibility in effective implementation of projects (Project Management Institute, 2021). However, the basic processes remain the same. Consequently, project management frameworks for mining and digitalisation projects have been developed following the process groups published by the Institute in earlier editions (Noort & Adams, 2006). This study followed the recommended process groups in project implementation which are documented in Chapter 3 of this report.

It has been argued by some researchers that sound project management alone is insufficient in implementing digital technological change in mining operations without change management (Scott, 1998; McCarthy, 2016; Pratt, 2017; Botha, et al., 2023). Project management is more focused on the technical side of delivering projects on time, schedule and within budget, while change management focuses on how people interact with the technological change (McCarthy, 2016). Change management is considered key in effecting digital technology changes in mining environments. Consequently, some change management frameworks have been developed for digitalisation in the mining industry.

2.6.2 Change management procedures

McCarthy (2016) developed a change management framework in implementing Modular Mining DISPATCH fleet management system, which can be summarised by Table 5 below:

Table 5: Organisational change management framework for adoption of FMS
(McCarthy, 2016)

Phase	Activities
1. Preparing for change	• understand the business reasons for the change; establish a sense of urgency • develop a vision for the changed state • assess the organisation's current state and ability to change • assess the magnitude of the change • select and prepare a change management team • prepare sponsor
2. Planning for change	• prepare the following change management plans: • communications plan • sponsor road map • resistance management plan • coaching plan • training plan
3. Implementing change	• implement change • measure progress • identify gaps • resolve issues and adjust plans • manage resistance and recognise show stoppers
4. Reinforce and transition	• gather feedback on change success (or failure) • audit compliance; identify root causes of non-compliance • identify and implement corrective actions • generate and celebrate short-term wins • integrate change into culture

The preparation phase evaluates the intended change and develops a risk profile that will guide the subsequent stages. Design and planning phase follow generating plans in line with company strategy that will direct change management efforts. Change implementation phase follows the design plan with data collection being done to adjust efforts accordingly. The final stage is focused on reinforcing the change so that it becomes incorporated into the organisational systems.

Botha, et al., (2023) developed a change management blueprint for implementing the fourth industrial revolution in mining operations, based on wide consultation with industry practitioners and stakeholders in South Africa. The recommended phases for the blueprint are shown in Figure 16

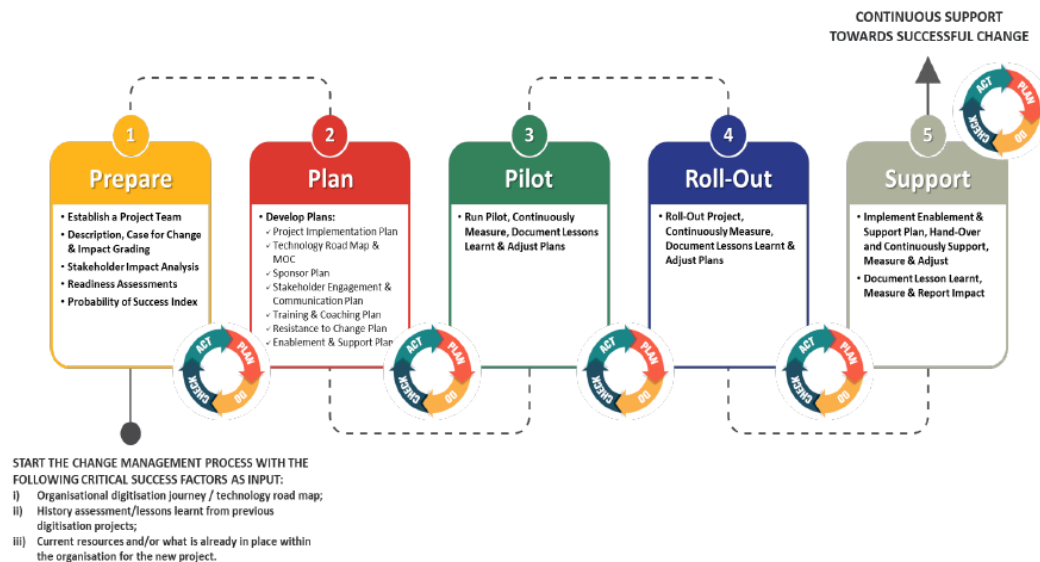


Figure 16: Change management blueprint summary
(Botha, et al., 2023)

The model highlights that before implementing technological change, it is beneficial to consider lessons learnt from previous technology adoption projects for the particular organisation. This input will assist in preparing for the anticipated change. Preparation involves setting up project teams, conducting a readiness assessment, stakeholder engagement and determining the anticipated value creation from the technology adoption. Project implementation plans then follow which must include communication and change resistance plans, among other issues. Following this, a pilot project needs to be conducted with progress measured and lessons learnt documented. The same process is conducted when implementing the roll-out project. Finally, the change needs to be supported for it to be reinforced within the organisation. At each step, it

recommends following the Plan-Do-Check-Act cycle for continuous improvement.

This study incorporated the change management frameworks recommended by both McCarthy (2016) and Botha, et al., (2023) in utilisation of the project management processes. Details of how this was done will be discussed in Chapter 3 of this report.

2.7 Data-Based Productivity Improvement Approaches

Although mining operations generate a large amount of data, analysis and utilisation of this data remain low within the industry (Parkinson & Sommerville, 2016; Dessureault, 2019; Brzychczy, et al., 2020; Barnewold & Lottermoser, 2020). A report by PWC (2014) noted that while several miners review performance data on a quarterly or monthly basis, they do not utilise or trust it for decision making. It further asserts that those that analyse and utilise daily productivity data are among the top 92% in terms of equipment productivity. FMS generates large amounts of data as it records distances, payloads, cycle times for each bucket as well as number of buckets and actual operating hours. This study seeks to close this lack of data analysis gap by implementing appropriate analytic tools to demonstrate how FMS data can be used to add value.

2.7.1 Statistical techniques

Several studies have implemented a variety of statistical techniques and approaches in data analysis of FMS output from mobile equipment, with the aim of improving productivity (Dessureault, et al., 2007; Fourie, 2016; Brzychczy, et al., 2020, Munyadzwe, et al., 2022). Statistics can be defined as the application of tools and processes in transforming raw data into useful information for decision making (Wegner, 2013). Descriptive, correlation, regression and data mining statistical techniques have been successfully applied in analysis of FMS data output for productivity assessment and improvement.

A study conducted by Fourie (2016) at Mogalakwena mine showed how descriptive statistics can be utilised on FMS data to improve productivity at an open pit mine. Infographics were compiled from the mine's modular dispatch FMS data to analyse the configuration of machinery downtime, in-shift delays and operational hours. This information was then used to identify opportunities and generate initiatives for productivity improvement. FMS data in that study was also utilised to develop baseline performance KPIs for each piece of equipment. Statistical analysis was carried out on historical production data from FMS to develop the best demonstrated performance, which was adopted as an improvement benchmark. Overall, the project resulted in improved OEE, which caused a ripple effect in reducing costs and achieving positive production turnaround at Mogalakwena mine.

Descriptive statistics were also utilised in this study to analyse FMS productivity data output on cycle times, payloads, tramming distances and tonnages moved. Averages were calculated to determine performance parameters of the equipment under study. The distribution of the data was also considered as part of exploratory data analysis to determine best ways of carrying out further analysis. Descriptive statistical analysis was also applied in the study to determine equipment performance benchmarks. Thomas (1999) advocated for the use of upper quartiles instead of averages as the acceptable standard of performance. The study recommends this approach to be progressively adopted in improving mine planning parameters and productivity. The research will analyse the mean, spread and distribution of the data to determine appropriate measures for benchmarking. Before carrying out detailed estimations or modelling exercises, descriptive statistical techniques will be employed to explore the data.

Another way descriptive statistics can be utilised with FMS data analysis is the use of graphical displays to capture key productivity shift data. Munyadzwe, et al., (2022) highlight that one of the major gaps in handling

of data in mining operations is how to present it to stakeholders for meaningful information to be extracted. The study sought to bridge this gap by presenting study results to stakeholders in suitable graphical format to enable proper analysis.

It is also common practice in the mining industry to generate, though descriptive statistical techniques, managerial dashboards and graphs summarizing a process or shift performance (Brzychczy, et al., 2020). This project also enabled the development of such managerial dashboards at the mine through installation of the FMS. These dashboards were developed in consultation with the mine technical team, OEMs and software providers to display key productivity data in appropriate graphs for productivity analysis. These graphs were utilised in shift review meetings and in providing decision makers with near real-time snapshots of key productivity information. The comparison of the mean productivity during the study period with historical performance can give indication of how these processes contributed to productivity improvement.

FMS productivity data analysis would be incomplete without the use of correlational and inferential statistics (Brzychczy, et al., 2020; Munyadzwe, et al., 2022). Correlational techniques involve the study of the relationship between two variables while inferential methods involve application of study results to the general population in statistical studies (Douglas, et al., 2012). The study utilises both techniques in data analysis as they are considered applicable and sufficient to meet the research objectives. Previous studies, although limited in the public domain, have demonstrated applicability of these methods to FMS studies involving mobile equipment((Dessureault, et al., 2007; Dindarloo, et al., 2016; Fourie, 2016; Bullock, et al., 2017; Brzychczy, et al., 2020; Latum, et al., 1995; Manyele, 2017; Munyadzwe, et al., 2022).

A study conducted by Munyadzwe, et al., (2022) illustrated how correlational analysis can be implemented in improving load and haul productivity at an open pit mine. The mine analysed data captured by the mine's modular

dispatch system to develop a productivity loss ranking model that can be utilised to improve load and haul performance. Correlational analysis was done on major time, tonnage and cost loss parameters influencing key performance indicators of the load and haul process. Pearson's correlation coefficient and coefficient of determination were calculated for parameters like costs, time delays and loading rate, among others. Microsoft Excel and R statistical software were used in data analysis. A regression model was developed and further tested on site data to improve validity. The result was a productivity loss ranking model which can be utilised in analysing productivity data and developing improvement initiatives.

The research conducted correlational analysis on FMS data similar to the above study. Relationships between key independent variables in relation to productivity will be explored through correlational and regression analysis. Differences between measurements developed by the manual system and those generated by FMS will be analysed for statistical significance through testing suitable hypothesis. Practical relevance of findings will also be assessed through the Pearson's correlation coefficient and coefficient of determination. While the correlation coefficient indicates strength of the relationship, the coefficient of determination is more meaningful as it defines to what extent the dependent variable is influenced by the predictor variable (Wegner, 2013). Microsoft Excel and Windows Stata 15 were utilised in data analysis. Regression analysis, which was used by Munyadzwe, et al., (2022) in developing the loss ranking model was not conducted in this study. This is because the author considered it unnecessary in satisfying the study objectives. It is recommended that this phase can be adopted as part of further study following the pilot project.

Although correlation does not necessarily imply causality, it is key in mining operations productivity management. Determining relationships between key variables influencing a production process enables key drivers of production efficiency to be identified. Thus, correlational analysis reveals the real factors impacting performance and guides in prioritization of

improvement initiatives. Furthermore, it is assumed that the trends and correlations would be more useful in driving performance improvement than just daily shift performance highlights. Pertinent issues affecting production, and their impact, normally get lost sometimes in day-to-day evaluations but trends analysis can expose these. This study sought to bridge this gap by utilising appropriate correlational and inferential statistical analysis.

2.7.2 Data mining, analytics and machine learning

Data mining (DM) and machine learning techniques can also be utilised in analysing FMS data in empirical studies. Data mining can be defined as an analysis technique used to discover and explore previously unknown, valid and actionable information from huge data sets (Pujari, 2001; Dessureault, et al., 2007; Brzychczy, et al., 2020). It uses a combination of machine learning, statistics, algorithms and retrieval of information (Dessureault, et al., 2007). Data mining has also been known as statistics at scale and speed (Ledolter, 2013).

Data mining tools can also be classified as descriptive or predictive depending on application. Descriptive tools are used to explore links and trends in acquired data and includes techniques such as sequence clustering, summarization, association and sequence discovery (Dessureault, et al., 2007; Larose & Larose, 2014; Brzychczy, et al., 2020). The same authors define predictive tools as those that utilise test data to make predictions and include classification, regression, time series analysis, and prediction techniques.

The mining industry is progressively adopting and implementing machine learning (ML) models in data analysis (Minnick, et al., 2023). ML is a subset of artificial intelligence (AI) that employs machines to learn analysis of patterns (Dessureault, et al., 2007). It utilises algorithms which enable comprehensive analysis of data to derive valuable information. Applications developed by ML can thus be utilised to speedily analyse data and automatically generate reports for insights generation. However, it is

important to understand how the ML application works to ensure that it generates the correct analysis.

Studies conducted by Dessureault, et al., (2007) and Brzychczy, et al., (2020) demonstrated how DM and ML techniques can be employed to generate useful insights from mobile mining equipment FMS output in both underground and open pit settings. Dessureault, et al., (2007) study applied DM tools on truck and shovel FMS data to identify patterns and relationships among critical production variables. Brzychczy, et al. (2020), on the other hand, adopted ML tools in a process mining (PM) approach to model the roof bolter operation as part of the business process management cycle aimed at process improvement. Both researchers used pertinent DM techniques to identify opportunities for productivity improvement in mobile mining equipment.

Dessureault, et al., (2007) applied data mining techniques on FMS data stored in a historian database which had been generated from 22 CAT trucks and 4 cable shovels at Phelps Dodge Baghdad Copper mine in Arizona, USA. They utilised Microsoft SQL Server 2000 Enterprise Manager, Analysis Manager and Query Analyser tools in processing FMS data. Dependency networks were applied to determine the presence and strength of statistically significant relationships between shovel waiting time and other operational variables. Online analytical processing (OLAP) cubes were also used in summarizing the quantitative data. They recommended Monte Carlo simulations and time series analyses to be conducted to further utilise deduced information. The study managed to identify that the mine controller had the biggest impact on productivity followed by machine operators. It is recommended that investment efforts be correspondingly applied to address these factors in order to achieve productivity improvement.

Brzychczy, et al. (2020) applied a PM methodology to identify productivity improvement opportunities for the underground roof support process. PM is an emerging data science discipline that seeks to develop insights about a

particular production process through analysis of data event logs generated during the process (Brzychczy, et al., 2020). Brzychczy, et al., (2020) applied supervised ML techniques for detailed mapping of the roof bolting process using FMS data collected from a working roof bolter. The data collected from sensors was detailed enough to allow the creation of event logs for the various stages of the bolting process conducted by the machine from travelling, idling, hole set-up, up to drilling.

Disco project management software was utilised in generating the process map. This software is offered by DISCO for project management solutions (DISCO, 2022). This data analytic method enabled identification of potential non-conformances, execution areas that had the highest impact and lost time inefficiencies when conducting the roof bolting process. This project can be considered a stepping stone to allow generation of event data for the mine production processes in order to gain actionable insights for productivity improvement.

FMS enables mining operators to generate huge datasets in real time whose analysis is pivotal to productivity improvement and increased industry competitiveness. Data analytics risk to be an expensive failure if not customized to meet organizational needs and improve processes (Young & Rogers, 2019). However, there is huge opportunity yet to be unlocked by proper analysis of the large amounts of data generated by mining companies (Barnewold & Lottermoser, 2020). The full spectrum of data analytics can then be fully utilised to get maximum benefit. Harris and Davenport (2007) summarise data analytic techniques, complexity and benefits they bring to organisations in Figure 17.

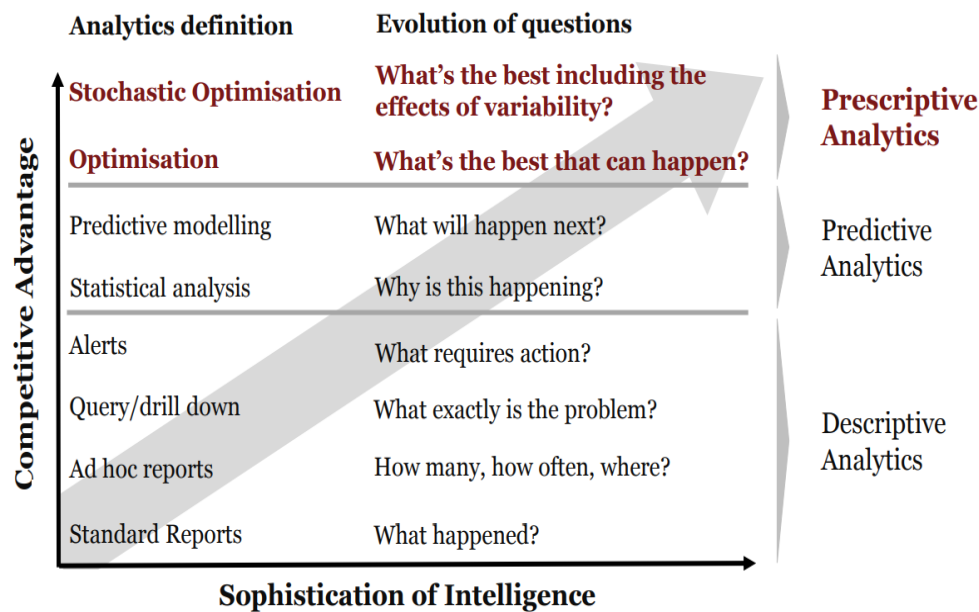


Figure 17: Evolution of analytics capability
(Harris & Davenport, 2007)

Figure 17 shows that while descriptive analytics is useful, it is predictive analytics that give more competitive edge to organisations (Harris & Davenport, 2007). This study falls within the descriptive category and is expected to be the starting point in utilising digital technology in TMM to boost competitiveness. With real time data, models can be developed to undertake stochastic optimisation which can be utilised in making decisions in real time to optimise performance. Optimisation of production processes can thus be achieved to further improve productivity and reduce costs. This will give mining organisations a more competitive edge, especially in times of depressed and fluctuating commodity prices.

Although real-time data could not be obtained during the study, the evaluation of value creation opportunities done can be utilised as part of the assessment to determine if investment in such infrastructure adds value. Furthermore, this review shows that it is highly likely that productivity can further be improved through application of suitable data analytics when large amounts of real time information are obtained.

2.8 Operational Process Improvement Techniques

The valid and reliable data output from FMS covering so many variables that influence mining processes enable mining operations to adopt a variety of process improvement techniques. Besides the statistical and data analytic productivity improvement techniques highlighted above, several process improvement methodologies can be adopted by digitalised operations. There are several methodologies available for operational and process improvement which include Lean, Six Sigma, Kaizen, total quality management (TQM), Define, Measure, Analyse, Improve and Control DMAIC tool, process mining (PM)) and theory of constraints (TOC).

Lean is a management philosophy that focuses on improving efficiency by reduction or elimination of activities that do not add value to improve customer satisfaction (Oliveir, 2024). The Define, Measure, Analyse, Improve and Control (DMAIC) tool is often used in conjunction with lean methods (Oliveir, 2024). Applying this approach enables small, incremental process improvement by mining companies through measurement and analysis of performance indicators (Munyadzwe, et al., 2022). Although it has its origins in the manufacturing industry, studies have shown that it can be successfully applied in the mining industry. Case studies include improvement of mining contractor performance for a copper mine in Chile (LeadPro, 2024). According to Munyadzwe, et al., (2022) the Lean concept is widely used in managing productivity at the operational level in mines. Rio Tinto have utilised this concept across its mining operations in Australia (Mottola, et al., 2011).

Kaizen is a continuous improvement approach which focuses on routine application of small incremental advances by teams in organisations to create sustainable reduction in waste and long-term productivity gains (American Environmental Protection Agency, 2024). It can be considered as the foundation of all lean production methods (Stuart, 2022). Kaizen is applicable to the mining industry and utilises a variety of tools. OKD mine in

the Czech Republic, applied this technique on 4 collieries over three years, and managed to increase revenues by US\$38 million (Vanek, et al., 2015).

TOC is a throughput improvement method that focuses on identifying constraints within a system and utilising focused steps to improve the whole system (Goldratt, 1990). This method has been successfully utilised in several mining studies. Finch and Elkington (2014) utilised TOC in tactical mine planning for a gold underground operation and in strategic mine planning for an open pit nickel project. Bloss, et al., (2020) outlined how TOC was used at Olympic Dam mine across the value chain to improve operational excellence.

TQM is a continuous improvement methodology that seeks to improve the quality of management in all activities at an organisation (Roberts, 1995). When correctly applied, TQM principles can be utilised to maximise productivity and minimise unit costs, even in a mining environment (Roberts, 1995). Scott (1998), however argues that this approach has not been as successful as expected in mining, although it has potential if mines start running like factories through utilisation of the right technology.

Six sigma is a method used for analysing production processes to improve quality by decreasing fluctuations in processes and elimination of non-conformances (Oliveir, 2024). It is a data-driven continuous business improvement strategy that is based on understanding processes and their variations (Mottola, et al., 2011). The Six Sigma method is a structured way useful in enabling better management and control of organisational processes (Pulakanam & Voges, 2010; Mottola, et al., 2011). The method has been used by Rio Tinto in effecting business improvement across its Aluminium operations in Australia (Mottola, et al., 2011).

Process mining is a process-focused approach towards analysis of digital data generated by sensors monitoring a process (Brzychczy, et al., 2020). Brzychczy, et al., (2020) has utilised FMS data on a roof bolter to adopt this technique in mapping out the roof bolting process as discussed in Section

2.7.2 of this report. The approach can also be customised and adopted for LHDs for further productivity improvement.

TOC is unique in the sense that it helps mining operations identify what needs to change for maximum results by identifying constraints whereas most of the other methods focus on how to implement continuous improvement change (Finch & Elkington, 2014). The author is aware that there may be several other tactical operational improvement techniques besides these. A full analysis of other methods is beyond the scope of this research. The two methodologies highlighted in the following section are meant to illustrate how FMS can be utilised further for productivity improvement.

2.8.1 Lean methodologies

Lean methodology has been defined by Womack & Jones (2003) as a structured, continual improvement approach to identification and removal of waste-adding activities that destroy value. Lean mining approaches have been commonly utilised in improving productivity and enhancing efficiencies (Cooper, 2011). Consequently, there is a growing number of studies advocating for adoption of these concepts in the mining industry for productivity improvement.

These methods are heavily reliant on having accurate and valid data readily available, otherwise they will be an expensive waste. This is where digital FMS can add value. The accurate and detailed data generated by FMS enables processes to be defined, measured and checked. Impact of continuous improvement initiatives can be directly quantified through use of FMS data. This enables lean mining and increased mining process control which is the foundation for automation. Increased automation is expected to improve productivity further.

The Define, Measure, Analyse, Improve and Control (DMAIC) problem solving methodology can be used as a tool for implementing lean concepts in continuous improvement (Cooper, 2011). It is derived from the Plan-Do-Check-Act cycle developed by Edward Deming (Deming, 1982). Figure 18 illustrates the DMAIC methodology:



Figure 18: DMAIC methodology
(Cooper, 2011)

This approach to solving challenges largely depends on availability of reliable and relevant data (Cooper, 2011; Parkinson & Sommerville, 2016). This is where FMS data can be of tremendous value. Sources of waste in a loading process can include inefficient processes like lower cycle time (Finch & Elkington, 2014). By capturing detailed cycle time data, the FMS can thus be utilised as a tool for productivity improvement, which enables techniques like DMAIC to be utilised for lean mining. Lean methods have been successfully utilised in improving processes for many industries Cooper (2011) highlights that with this method, areas of poor performance can be identified, and improvement can only be realised through measurements, checking and then measuring again. This methodology can

be effectively utilised using FMS data to achieve continual improvement and operational excellence.

2.8.2 Theory of constraints

The theory of constraints is an operational excellence technique that can be successfully implemented using FMS data output. The theory is based on the understanding that a constraint is present in every system which is the key to improving throughput (Fox & Goldratt, 1987). Fox and Goldratt (1987) presented the following five sequential focusing steps as the basis for continuous improvement:

1. **Identify the system's constraint(s).** – A constraint is a limitation to the system throughput which can be physical (equipment) or managerial (policy). Generally, policy constraints are more prevalent than physical (Goldratt, 1990). This is often the case in organisations yet to apply TOC (Finch & Elkington, 2014). It is important to identify and prioritise constraints according to how they affect performance goals for companies (Rahman, 1998).
2. **Decide how to exploit the system's constraint(s)**- This stage often involves making the most of already available resources within the organisation (Vorne Industries, 2024). It involves exploiting the physical constraint as much as possible and removing policy constraints.
3. **Subordinate everything else to the above decision**- Prioritise and support constraint by aligning resources accordingly. Throughput can only improve based on enhancing the constraint and not on non-constraint activities.
4. **Elevate the system's constraint(s)**-. This step often involves some capital investment to improve the bottleneck (Vorne Industries, 2024). It usually results in shifting of the constraint to another activity.
5. **If in any of the previous steps a constraint is broken, go back to step 1**- This step makes TOC a continuous improvement approach

and avoids organisational stagnation as a result of complacency. Ignoring this step has a negative impact on organisations. This final step may become necessary at any stage of the TOC process (Finch & Elkington, 2014) . This is what makes TOC a continuous process and also shows that there is no one size fits all for each situation.

This concept of TOC as a continuous improvement process is diagrammatically illustrated in Figure 19.

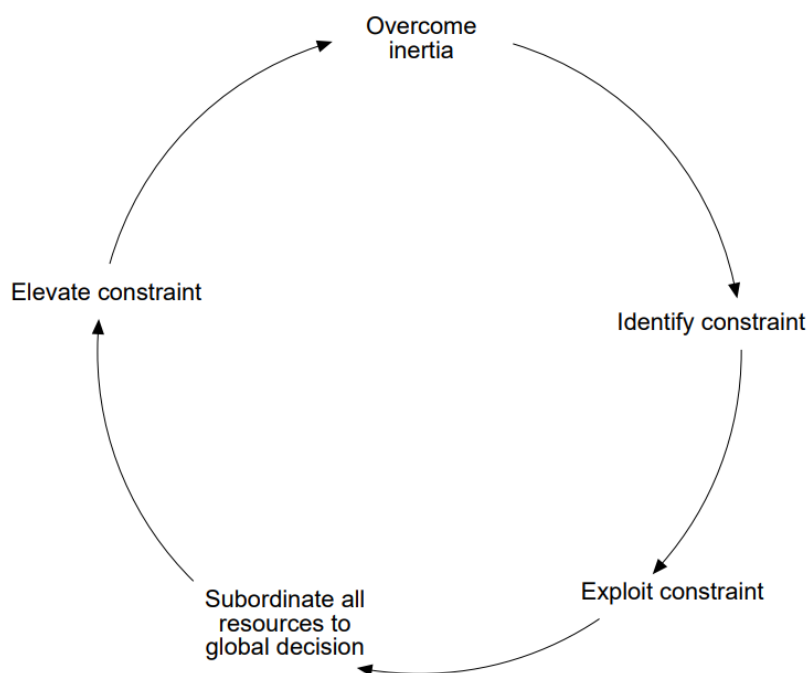


Figure 19: Illustration of TOC as a continuous process
(Rahman, 1998)

As can be seen in Figure 19, it is key to implement the fifth stage to prevent inertia in operations. This is a state where an organisation has stopped improving itself due to complacency generated by past successes (Vorne Industries, 2024).

While TOC originated from the manufacturing sector, it has also been utilised with success in the mining industry as well as other sectors (Cambitsis, 2013; Finch & Elkington, 2014). FMS data analysis is crucial in

enabling identification of constraints in operational processes as well as across the production value chain. Constraints can be objectively identified using the accurate data provided by FMS. The level of detail provided by FMS enables analysis of all key parameters influencing a process which is key in constraints identification and exploitation. If FMS is adopted in other interrelated activities such as drill and blast as well as support activities, it will further enable TOC application across the production value chain. The net effect of TOC application is throughput optimisation, which ultimately improves productivity.

2.9 Chapter Summary

Literature review showed that digitalisation is a key strategic focus for the mining industry for improving safety, productivity and ultimately competitiveness. The application of FMS technology has enabled mining operations to achieve these benefits. Manual systems were shown to have inaccuracy, bias, inadequate detail and data collection inefficiency challenges. However, implementation of FMS for underground LHDs faces several challenges which include significant capital expenditure, high equipment mobility and complex mining layouts. Other factors include legal requirements, poor project implementation, inadequate data capture and analysis.

To minimise capital requirements, the study is set up to utilise as much of the existing infrastructure as possible. Mobility and layout challenges are mitigated by the use of underground workshops as data collection points. Involvement of OEMs, technical experts and end-users in FMS set-up was used in the study to ensure capture of all essential data. Legal requirements are addressed through involvement of legal experts in the project team. Standard project management practices are adopted to ensure implementation success.

Equipment availability, utilisation and productive efficiency were identified as the key factors that influence OEE for underground LHDs, and ultimately productivity. FMS can be utilised in improving LHD availability as it offers additional diagnostic capabilities that enable improvement of both planned and corrective maintenance. Machine alerts on unsafe operator behaviour and machine parts maintenance resulting in cost savings, improved safety performance and availability. FMS shows detailed equipment utilisation variation in conducting revenue-generating work.

This enables operational management to analyse how equipment is utilised and generate improvement initiatives. These utilisation graphs will also be used in daily operational performance monitoring to maintain data relevance and enhance productivity improvement. Payload, cycle time, tramming distance and operator efficiency were shown to be the major factors impacting productive efficiency. Consequently, this study will utilise FMS data in analysing the relationship between these variables and productivity.

The review showed that effective project and change management is necessary in technology adoption initiatives for mining operations. Mining operations generally adopt technology in small incremental stages which have proven to be effective for the industry. Therefore, this research will focus on the initial step towards the digitalisation adoption journey for LHDs. The use of established project management guidelines in mining technology adoption projects has proven to be effective in delivering technological change. The study will therefore adopt these guidelines. Ineffective change management has been cited as the major hindrance towards technology adoption. Thus, change management frameworks developed towards digital technology adoption will therefore be utilised in the study.

Adoption of FMS in mining equipment also requires the application of several process improvement and operational excellence techniques. Collection of detailed data variables for the lashing process such as tramming distance, cycle times and loading rates enables identification of possible constraints in the lashing process. TOC can then be more

effectively applied in identifying, exploiting and elevating identified constraints for ultimate productivity improvement. Lean methodologies can also be more effectively utilised through FMS data. These methods are increasingly being used in the mining industry by major players for continual improvement.

3 METHODOLOGY

3.1 Chapter Overview

This chapter details the procedures and design that was followed in conducting this study. Data collection, validation, cleansing, transformation and processing methods are clearly outlined with the relevant justifications.

3.2 Research Design

3.2.1 Sample frame determination and sampling strategy

This study is a Longitudinal study collecting and analysing numerical data. The study followed a quantitative research design as it is the best approach to meet the study's objectives. Unlike qualitative methods, a quantitative approach ensures objectivity and utilises quantitative data (Johnson & Christensen, 2008). This enables detailed statistical analysis to be carried out, thus facilitating the extraction of meaningful information relevant to the study. The research was designed as a non-experimental correlational study that seeks to make deductions based on analysis of relationships between variables, without necessarily exploring causality. The study of cause-and-effect relationships is therefore outside the scope of this report. Quantitative data was collected through manual checklists and output files of the FMS system installed on the selected LHDs.

It is important to select a representative sample large enough to enable applicability of findings to the population utilised in quantitative research design (Sanders, et al., 2016). Sampling strategy is therefore key in the validity and applicability of results on the population or sampling frame. Sample size determination is a delicate balance between practicability, costs and the desired precision and statistical power of research (Garg, et al., 2024). Sample accuracy metrics used in determining sample size are the desired margin of error and confidence levels for the study, as well as anticipated response rate (Douglas, et al., 2012). For research studies, a

95% confidence level is considered acceptable and was therefore considered applicable to this study (Sanders, et al., 2016).

LHDs are considered big or small at the mine depending on bucket capacity. All LHDs whose capacity is at least 5 tonnes (t) per bucket are considered small and the mine has a strategy to scrap them off and progressively replace them with bigger LHDs. Consequently, the population considered for this study only focused on LHDs with at least 5t bucket capacity, which was 19. The total number of LHDs available at the mine is 24. Cochran (1977) formula is widely used in research for determining representative sample sizes for both finite and infinite population proportions (Adam, 2020; Nanjundeswaraswamy & Divakar, 2021; Garg, et al., 2024). Cochran's formula for sample size determination in finite populations is shown in Equation 4.

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

Equation 4: Sample size calculation for a finite population

Where:

- n_0 = required sample size for infinite population,
- N = population size

n_0 is calculated using Equation 5.

$$n_0 = \frac{z^2 pq}{e^2}$$

Equation 5: Required sample size for infinite population

Where:

- z = critical value at the desired confidence level (95% in the study)
- p = proportion of common attribute present in population (70.8% in this case as 19 out of 24 LHDs have at least 5T capacity)

- $q = 1-p$,
- e = desired margin of error or precision level

Table 6 shows the minimum sample sizes calculated for this study at different margins of error using Equation 4 and Equation 5.

Table 6: Sample size calculations using Cochran formula

Margin of error (e)	Population size (N)	Sample size for infinite population n_0	Minimum sample size (n)
1%	19	7910	19
1%	24	7910	24
3%	19	879	19
3%	24	879	23
5%	19	316	18
5%	24	316	22
10%	19	79	15
10%	24	79	19
15%	19	35	13
15%	24	35	15
20%	19	20	10
20%	24	20	11

As can be seen in Table 6, as the margin of error increases, the required minimum sample size decreases. The margin of error represents the precision required for the study. Calculations were conducted for 1%, 3%, 5%, 10%, 15% and 20% sampling error margins. Besides the formula-based approach, practical considerations are also essential in determining optimum sample size.

Practical considerations were also evaluated in determining the sample composition and size requirements for the study. A key parameter that affects the loading process are the prevailing ground conditions at the mine. The ground conditions determine the level of fragmentation which in turn

affects the digability of material to be mucked. In order to obtain a representative sample, it is essential for the LHDs in the sample to be stratified according to ground conditions. The operating areas of the mine were divided into three different ground control districts based on joint assessment between the production and rock mechanics department. To obtain a reasonable sample size, it was assumed that for practical significance, overall sample size needs to be at least 50% of the population of LHDs working in that district.

Based on this assumption, the minimum sample size required for practical representability was calculated for each cluster. Cluster-based sampling was utilised to reduce heterogeneity effects and improve representability of the sample. The LHDs were categorized into three classes based on the prevalent ground and operational conditions at the mine. Thus, care was taken when taking a sample representative of the underground mining conditions. Random samples from each category were selected by use of LHD identity cards drawn by operational management from each pool. A sample ratio of at least 50% from each category was utilised. Table 7 shows the characterisation of the sample.

Table 7: Sample size and identity characteristics

Ground control district (GCD)	Total number of LHDs (Population)	Number of 5t LHDs chosen (sample)	LHD sample ID
B	6	3	B3
			B5
			B6
C	6	3	C3
			C4
			C5
D	7	4	D3
			D4
			D5
			D7

As shown above, a total sample size of 10 LHDs were chosen from the population of 19 LHDs considered for the study. This sample was assumed to be representative of the LHDs being considered for the research study. The chosen sample size represents a 20% margin of sampling error based on the total population size. It is expected that the sampling error can be mitigated by the practical classification approach taken to improve precision of results.

This sample size was considered optimal since it is a pilot study, and precautions were taken to ensure representability of mine conditions. The observation period ranged from a minimum of six to a maximum of nine months. The period varied due to practical constraints such as availability of system spares and software licences required for the study. However, care was taken to obtain at least six months of data for each machine. The period was considered to generate enough data for robust statistical calculations.

3.2.2 Project management and implementation process

Project management principles were followed in conducting this research. The project implementation process is outlined in Table 8

Table 8: Project management and implementation process

1. Project Initiation
• Prepared project motivation presentation. • Senior management reviewed and approved the project. • Authorization was granted for project scoping and design. • Project sponsor (Head of Technical Services) and manager appointed (Senior Technical Services Manager). Customer identified and appraised (Mining Cluster Manager).

2. Project Team Formation

- Multi-disciplinary team was formed to pilot the project.
- Team consisted of essential technical skills (Production Engineer, Mobile Equipment Engineer, Mining Manager, Technical Services Manager, SHE Manager, SHE Officer, Mine Planning Engineer, Project Engineer, Project Administrator/Accountant, Legal Adviser).
- Funding constraints identified—thus existing equipment and infrastructure were to be leveraged. Unavoidable cost was the installation of FMS telemetry kits and On-board LHD weightometers which were required for 5 LHDs. Each kit cost ZAR150 000 on average per machine. On-board LHD weightometers also cost ZAR525 000 per machine.

3. Technical Consultation and Scoping

- OEMs consulted for technical input.
- Key study metrics defined based on OEMS input and wide consultative process.
- Consultative process included Epiroc, Sandvik OEMS, Production, Mobile Equipment, Procurement, Finance, Legal and SHE departments
- Key metrics identified: operator identity, payload, loading rate (number of buckets), cycle time, tramming distance for each LHD.
- OEMs recommended technical assessment of the chosen LHDs, compiled report indicating requirements for each machine, offered training of operators, maintenance personnel and users of FMS reports. They also provided baseline assumptions used for cost-benefit analysis of the project.

- OEMs provided standard kits for fitting into the machines which included all sensors.
- Real-time analysis required upgrading of mine communication backbone underground, which amounted to ZAR22.5 million. Initial scoping included real-time requirements and all TMMs. The desktop evaluation showed that significant benefits could be derived from adopting such a system. This consolidated scope was the one used to source funding. However, scope was revised later following Platinum price reductions, which necessitated budget cuts.
- Due to budget reductions encountered, decision was made to focus on LHDs based on OEM input and identification of lashing as the production constraint.
- Machines assessed for FMS-readiness.
- 5 of the LHDs were replacement machines delivered from the OEMs with FMS already installed. The remaining 5 needed to be fitted with standard retrofit kits and on-board weightometers to be able to utilise the FMS.

4. Setup and Implementation

- Set-up involved fitting the telemetry systems, setting up a local site office for OEMS where downloaded data was uploaded to the cloud platform based off-site. Designated users were then provided with online login credentials to be able to access the reports. Summary of the system is shown in Figure 20.
- OEMs provided technical assistance.
- Managerial dashboards configured for monitoring. Details included machine name, operator name, graphs showing LHD utilisation, buckets loaded per hour, tonnes moved per hour, payload and cycle time variations. Sample dashboard information is shown in Figure 21, Figure 23 and Figure 24. These reports could be filtered by time to get shift, daily, weekly and monthly data.

- , Access to Certiq and MySandvik software platforms was provided by OEMs for the trial period (6 months, extended to 9 months to ensure at least 6 months of data for each machine). This software generates the reports which are then accessed online by users.

5. Change Management and Stakeholder Engagement

- Stakeholder engagement identified as critical. Both formal and informal systems were used for stakeholder engagement. Formal approaches included monthly project meetings, daily, weekly and monthly production meetings and quarterly feedback meetings to the executive. Informal engagements were made in routine underground visits and discussions with LHD operators, maintenance personnel and production supervisors. Ad-hoc updates were also given to responsible line management.
- Objective of the engagements were to get buy-in from all stakeholders, identify challenges, sources of resistance to change, ensure project alignment, communicate scope changes, manage resistance and ensure project success at every stage.
- Stakeholders included LHD operators, maintenance personnel, production supervisors, executive management team, operational management team, project team members, worker leadership, SHE worker representatives, Postal and Telecommunications Regulatory Authority of Zimbabwe (POTRAZ), The Ministry of Mines and Mining Development of Zimbabwe.
- Management, operations, and maintenance teams were engaged.
- Communication via meetings, presentations, and informal discussions.

- Change management forms filled, signed, and filed. The forms captured a description of the operational changes introduced and acknowledgement by employees of the notified change.

6. Project Monitoring, Evaluation and Control

- Researcher participated in daily production meetings.
- End-users and operators consulted for feedback. Operators provided feedback on the user-friendliness of the operating platform and any issues encountered during operation of the FMS. Use of the FMS in tracking operator performance, production performance in terms of effectiveness. Possible room for improvement was also solicited. Effectiveness of the online platform was also assessed through stakeholder engagements.
- Routine underground visits were conducted.
- Report findings were presented to management for decision-making. Major platform used for reporting feedback was monthly project and quarterly management meetings. Issues reported on included operator feedback, machine alerts information, cycle time, loading rate, payload and productivity reports, online access of reports, project report, change management feedback.

7. Challenges and Mitigation Strategies

- **Funding constraints:** Overcome through stakeholder engagement, budgeting, cost-cutting, and vendor negotiations.
- **Resistance to change:** Addressed via continual engagement and change management.
- **Delays in spares and licenses:** Resulted in staggered start dates but ensured a minimum 6-month data collection period.
- **LHD availability issues:** Engaged maintenance teams for improved availability. Recommended maintenance department to

adopt the FMS maintenance module and evaluate if it can be integrated with existing planned maintenance systems.

- **Operator concerns-** Operators were worried that the FMS would be used as a punishing tool for recorded machine alerts and productivity differences with the manual system. The management was encouraged to use the tool for coaching and mentoring purposes and not for instituting disciplinary proceedings during the trial. Operators also wanted some motivation for adopting the change. Therefore, the management was urged to implement reward system based on the FMS data for operator performance. Lastly, the operators were made to understand why the FMS is more accurate for determining performance.

Figure 20 shows the set-up of the FMS that was used for the project.

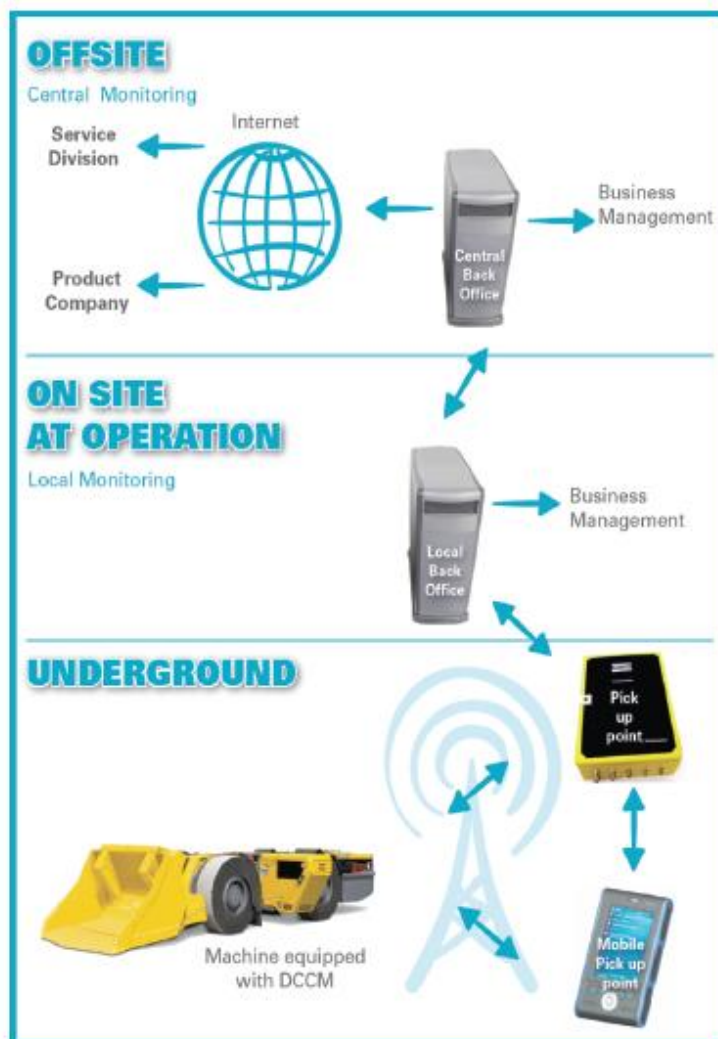


Figure 20: FMS set-up

(Johansson, 2010)

3.2.3 Project Scope and Budget

Original scope of the project was adjusted due to budget constraints. Table 9 shows the differences in aim, expected costs and anticipated benefits between the original and pilot project scope.

Table 9: Comparison between original and final project scope

Original scope	Final scope
Aim • To install FMS on all TMM • To upgrade underground communication infrastructure/backbone • To achieve real-time equipment monitoring • To implement data analytics for operational optimisation and maintenance improvement	Aim • To implement pilot FMS project on selected LHDS • To capture shift FMS data for each trial LHD • To utilise FMS in monitoring production performance • To evaluate impact of FMS on productivity improvement
Expected costs US\$2.6 million spread over three years	Expected costs US\$400 000 annual costs
Anticipated benefits • 10% reduction in downtime translating to net gain of US\$7.7 million per annum • 2% saving in fuel costs translating to US\$51 000 net annual gain • 5% increase in utilisation translating to net annual gain of US\$6.5M • Overall annual gain of \$14.4M	Anticipated benefits • 5% reduction in downtime on trial equipment translating to net gain of US\$6600 000 per annum • 2% saving in fuel costs for pilot LHDs translating to US\$27 000 net annual gain • 3% increase in utilisation for pilot LHDs translating to net annual gain of \$1.7M • Overall annual gain of \$2M

Table 10 shows the calculated costs for each option. The initial project scope involved 24 LHDs while the revised scope only consisted of 10.

Table 10: Comparison between initial and final project scope costs

Description	Initial Project scope	Revised project scope
Backbone Equipment	\$1,529,684.56	\$0.00
Tracking UG & Accessories	\$114,316.80	\$0.00
Machine Accessories	\$384,863.20	\$325,000.00
Rig and Bolter accessories	\$181,003.20	\$0.00
Other project costs (Admin, operational expenses)	\$90,000.00	\$40,000.00
Sub-Total	\$2,299,867.76	\$365,000.00
15% contingency	\$344,980.16	\$54,750.00
Grand Total	\$2,644,847.92	\$419,750.00

Scope of the project was greatly reduced after the decline in Platinum prices which necessitated the need to cut costs and suspend several project expenditures across the organisation. Following stakeholder engagement, motivation was submitted for management approval that showed how with a reduced scope, project expenditure could be reduced while maintaining some of the anticipated benefits. Costs for the pilot study were based on actual quotations instead of estimates used in initial scope setup.

3.3 Data Management

Data management was considered pivotal to the study validity and reliability. This section describes the data management approach that was followed by the study including data collection, validation, cleansing prior to analysis.

3.3.1 Data collection

Project data was collected through manual checklists and FMS output from January to November 2023. Both systems were utilised concurrently for each machine for data collection. Table 11 below compares the information collected by both systems:

Table 11: Comparison between data collected by FMS vs manual system

Manual system	FMS
• Operator name, • Shift start time, • Shift end time, • Machine hour meter readings, • Planned and unplanned, maintenance and repairs, • Downtime delays, • Mining and other utilization delays • Number of buckets	• Operator name, • Equipment operating time, • Date, • Productivity (tonnes loaded per hour), • Payload, • Cycle time • Trammig distance • Number of buckets • Machine alerts

FMS data was collected through use of telemetry systems and weightometer fitted by OEMs namely Epiroc and Sandvik on their respective LHDs. The data was downloaded using the underground Wi-Fi___33 network at the underground workshops as the machine was undergoing,

checks, refuelling, repairs and maintenance. Certiq and My Sandvik operating platforms were used in the study which then generated reports based on the downloaded data. Data was downloaded at the end of every shift and presented in the form of relevant managerial dashboards tracking key KPI. Figure 21 below shows the summary statistics shown on the production dashboard.

Night shift LHD 127			
Cumulative tonnage		100448.725	
ST7LP Production summary	Tramming distance (km)	Payload (Tonnes)	Cycle Time
	Max/Load	0.792	8.154
	Min/Load	0.199	5.544
	Av/Load	0.518	6.635
	Total	21.8	278.7
Tonnes per hour		39.3	

Figure 21: Summary statistics per LHD

The dashboard above shows a statistical summary of the maximum, minimum and average parameters for each LHD load. It also shows the total amount in each parameter per shift for each LHD. The three parameters are tramming distance, cycle time and payload. It also shows the overall productivity of the machine in tonnes lashed per hour. The machine identity and OEM as well as total tonnes moved since installation of the FMS are also shown. This information was utilised in production meetings to monitor performance. Furthermore, graphical displays for parameters of interest such as productivity, loading rate and payload were also generated by FMS as shown in

Figure 22, Figure 23 and Figure 24. The FMS platform also had filters embedded which allowed users to customise the reports they needed from the system. Filters included operator name, machine ID, time and efficiency parameters.

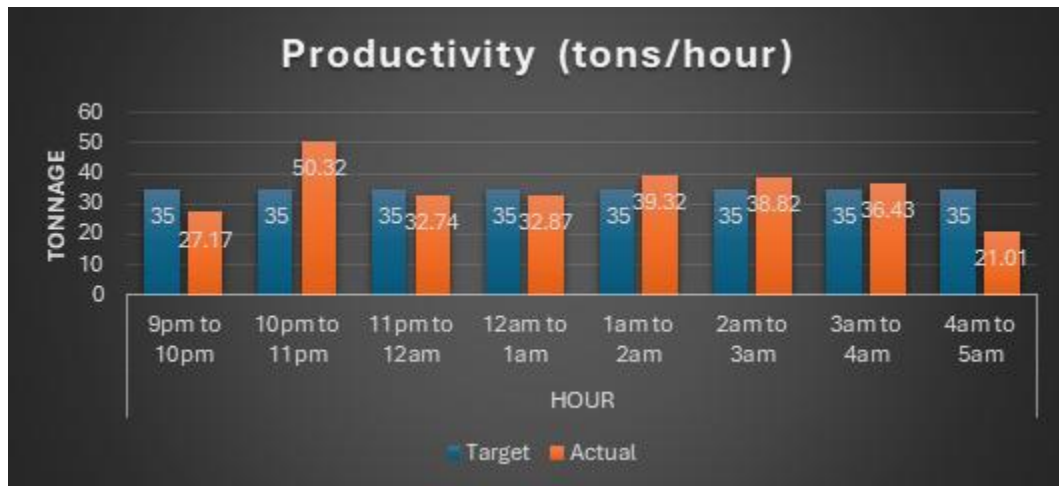


Figure 22: Graph showing LHD utilisation during the shift

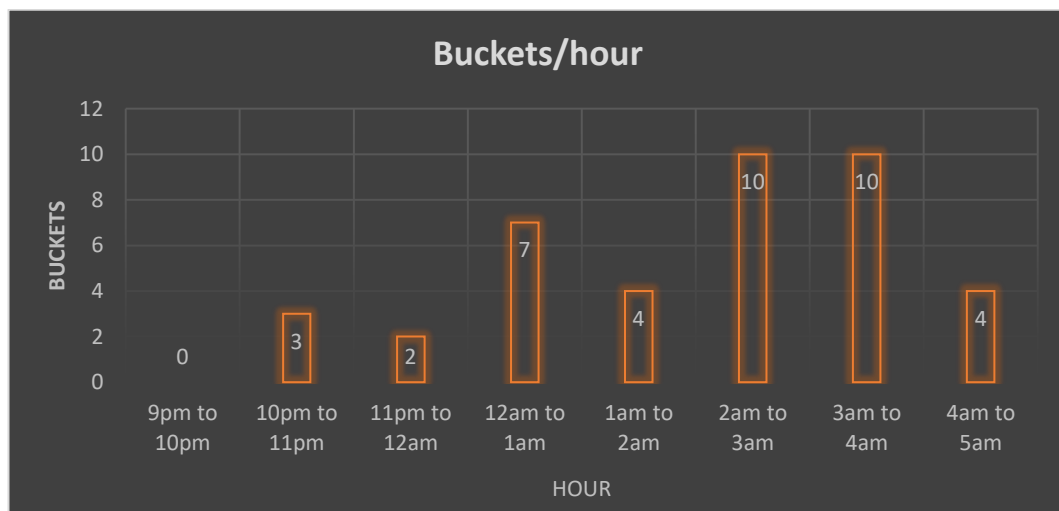


Figure 23: Graph showing variations in loading rate for an LHD during a production shift

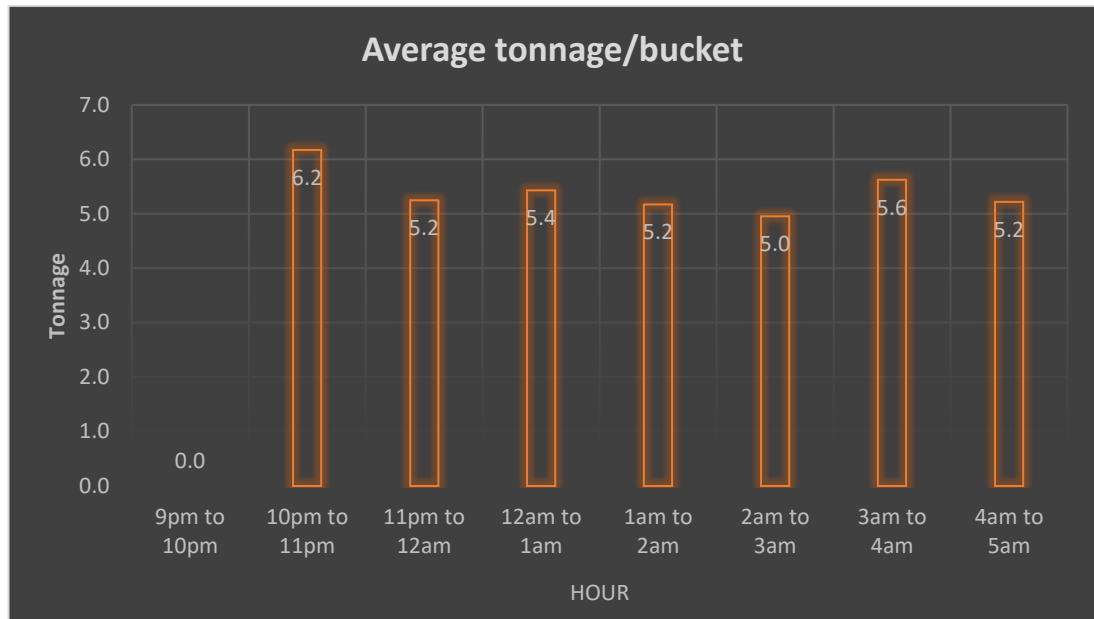


Figure 24: Graph showing payload variations during the shift

Moreover, the online platform enabled downloads of detailed customised statistical data. An example of data that could be downloaded per shift is shown in Table 12. Corresponding graphical displays could also be generated. This detailed data provided users with a level of granularity which cannot be matched by manual methods. Critical productivity analysis is therefore made possible by FMS, which is key for identification of previously hidden potential production bottlenecks. This paves the way for further initiatives towards productivity improvement.

Table 12: Detailed shift productivity statistics per machine

Bucket number	Date	Time	Tramming distance	Payload	Time taken /bucket
40	16/11/2023	4:44:50	0.193	6.03	00:03:55
39	16/11/2023	4:40:55	0.308	6.01	00:22:27
38	16/11/2023	4:18:28	0.141	4.14	00:11:07
37	16/11/2023	4:07:21	0.380	4.70	00:11:24
36	16/11/2023	3:55:57	0.169	4.37	00:05:35
35	16/11/2023	3:50:22	0.109	4.61	00:02:27
34	16/11/2023	3:47:55	0.318	6.57	00:09:09
33	16/11/2023	3:38:46	0.105	5.13	00:02:16
32	16/11/2023	3:36:30	0.281	6.98	00:08:37
31	16/11/2023	3:27:53	0.102	4.29	00:02:05
30	16/11/2023	3:25:48	0.304	6.12	00:08:10

Bucket number	Date	Time	Tramming distance	Payload	Time taken /bucket
29	16/11/2023	3:17:38	0.100	5.21	00:03:50
28	16/11/2023	3:13:48	0.342	8.12	00:10:53
27	16/11/2023	3:02:55	0.124	4.80	00:05:28
26	16/11/2023	2:57:27	0.218	5.96	00:06:29
25	16/11/2023	2:50:58	0.200	5.45	00:05:49
24	16/11/2023	2:45:09	0.130	1.99	00:03:08
23	16/11/2023	2:42:01	0.459	4.07	00:07:27
22	16/11/2023	2:34:34	0.102	4.75	00:06:05
21	16/11/2023	2:28:29	0.167	7.02	00:04:09
20	16/11/2023	2:24:20	0.288	5.95	00:04:39
19	16/11/2023	2:19:41	0.193	4.88	00:04:45
18	16/11/2023	2:14:56	0.442	5.43	00:11:17
17	16/11/2023	2:03:39	0.368	4.02	00:08:11
16	16/11/2023	1:55:28	0.322	4.47	00:06:49
15	16/11/2023	1:48:39	0.101	5.02	00:01:48
14	16/11/2023	1:46:51	0.298	6.52	00:31:38
13	16/11/2023	1:15:13	0.801	4.66	00:26:25
12	16/11/2023	0:48:48	0.502	4.35	00:12:10
11	16/11/2023	0:36:38	0.453	4.62	00:07:33
10	16/11/2023	0:29:05	0.160	5.58	00:04:53
9	16/11/2023	0:24:12	0.190	5.54	00:05:56
8	16/11/2023	0:18:16	0.482	6.46	00:09:32
7	16/11/2023	0:08:44	0.121	5.97	00:03:29
6	16/11/2023	0:05:15	0.752	5.48	00:28:24
5	15/11/2023	23:36:51	0.972	5.78	00:34:11
4	15/11/2023	23:02:40	0.847	4.71	00:26:50
3	15/11/2023	22:35:50	0.685	5.58	00:28:30
2	15/11/2023	22:07:20	0.157	5.45	00:02:49
1	15/11/2023	22:04:31	0.489	7.48	

Summary statistical data for this study was downloaded in csv format using the online platforms. The research database was then compiled for further analysis conducted in this study. Primary data was thus collected for use in the study, which greatly increases its reliability.

Care was taken through change management processes that operators; shift bosses and maintenance personnel are encouraged to record information as they normally do. This was done to eliminate accuracy bias so that the data collected could be a true representation of the prevalent

system as much as possible. The manual report was obtained from the Mine Planning department after its compilation by the data capturers as an MS excel file. The manual data was consolidated into a database stored in Microsoft Excel covering the study period.

3.3.2 Data validation

Data validation procedures were effected for tonnage and operating hours data collected by the FMS manual system. Routine verification of tonnes moved by the machinery were done monthly through comparison with conveyor weightometer systems and survey void calculations. Mined out voids in the respective areas gave an indication of the volume mined. Tonnage calculations were carried out using respective specific gravity. Back calculation was made to gain a representation of the tonnage moved by each LHD involved in the study. Weightometer measurements from the crusher feed conveyor and underground conveyor systems were also back calculated to get the tonnage moved by each LHD. Routine comparison was made of operating hours with engine and transmission hours. Calibration certificates were also checked for machine weightometer and kept valid during the study period.

3.3.3 Data cleansing and transformation

Data cleansing was considered before it could be utilised. The FMS data was not located in a data warehouse involving complex, multi-dimensional data as is normally the case in mines that have fully adopted FMS in their whole fleet. Correction of errors is necessary for FMS output as part of data cleansing before analysis can be conducted (Dessureault, et al., 2007). Main errors identified were in outliers which normally arose because of the FMS recording buckets for processes such as road scrapping with unusually high cycle times and abnormally low tonnages. These errors were flagged and excluded from the analyses. The corresponding manual data was also removed.

Data transformation was conducted before analysis could be conducted in statistical software. Transformation usually involves translation of data into consistent formats as readable by processing software (Dessureault, et al., 2007). Both FMS and manual data needed transformation before analysis could be conducted on the cleaned data. The manual and FMS Microsoft Excel databases needed consolidation to enable analysis required to meet the study objectives. FMS data generated per bucket needed to be summarized into shift data to enable comparison with the manual data. Thus, the FMS and manual shift data was consolidated into a single spreadsheet for each LHD. The manual and FMS data was later consolidated into a single database containing all machines. Then analysis was conducted using this transformed, cleaned and validated data.

3.4 Data Processing Methods

Descriptive, correlational and inferential statistical techniques were applied in processing acquired and transformed data. These techniques were considered relevant to be able to fully address the study objectives. Detailed statistical analysis was carried out utilising Microsoft Excel, Windows Stata 15 statistical software and python scripting.

Data were sourced from two measurement systems, manual shift reports and FMS, covering an identical sample of 3,616 records per system, distributed evenly across 10 LHD machines and day/night shifts. Variables included number of buckets, payload, tonnage per shift, run time, productivity (tph), cycle time, and tramming distance. Only the FMS system captured cycle time and tramming distance.

3.4.1 Exploratory data analysis

Exploratory techniques were used to understand the structure, distribution, and variability of key operational variables captured from both the manual and FMS data sources. Descriptive statistics were computed for each

numeric variable, including the mean, median, standard deviation, minimum, and maximum. In addition, the first (Q1), second (Q2/median), and third (Q3) quartiles were calculated to characterise the spread and central tendencies of the data distributions more comprehensively.

Visual analysis was conducted using histograms and box-and-whisker plots to support identification of skewness, outliers, and potential data quality issues such as missing or incomplete entries. These summary measures and graphical techniques enabled the development of an initial understanding of LHD performance patterns.

3.4.2 Measurement System Comparison and Statistical Testing

Statistical tests were used to evaluate the differences between manual and FMS measurement systems in assessing LHD productivity, measured in tonnes per hour (tph). The analysis was based on paired data collected from the same LHDs over the same shifts, allowing for a direct comparison of the recorded values from both systems. The methodology consists of three major stages: exploratory data analysis, inferential hypothesis testing, and effect size estimation to assess both statistical and practical significance.

Productivity for each LHD was calculated per shift in tonnes per hour (tph) by dividing the recorded tonnage by the operating time. Initially, exploratory statistics were conducted on the productivity (tph) for each method to gain insights into the central tendency, variability, and distribution characteristics. The summary statistics included the mean, median, standard deviation, and quartiles. Additionally, histograms were created to visually inspect the distribution of productivity in both measurement systems.

The goal was to determine whether the difference in productivity (tph) between the FMS and manual systems was statistically significant. Since

the data consisted of paired productivity values from the same LHDs and shifts, paired statistical tests were employed.

Before selecting the appropriate test, assumptions of normality were evaluated. The Shapiro-Wilk test was used to assess whether the distribution of differences deviated significantly from a normal distribution. The Shapiro-Wilk test statistic is given by (Douglas, et al., 2012):

$$W = \frac{(\sum(a_i x_i)^2)}{\sum(x_i - \bar{x})^2}$$

Where:

- x_i = ordered data.
- a_i = specific coefficients derived from tables for a given sample size.
- $\bar{x}$ = sample mean
- x_i = ordered sample values in ascending order.
- X_{nti} = the i^{th} sample if the data were ordered in descending order

Equation 6: Shapiro-Wilk test statistic

where a_i are constants generated from the means, variances, and covariances of the order statistics of a standard normal distribution, x_i are the ordered sample values, and $\bar{x}$ is the sample mean. A small p-value (typically < 0.05) leads to rejection of the null hypothesis (H_0) that the data is normally distributed.

The Anderson-Darling test was also used as a complementary normality test. The Anderson-Darling test statistic is given by (Douglas, et al., 2012):

$$A^2 = -n - S]$$

Where:

$$S = \frac{\sum[(2i - 1)]}{n} [\ln F(x_i) + \ln (1 - F(x_{n+1-i}))]$$

Equation 7: Anderson-Darling test statistic

Where:

- n = sample size.
- i = index of the ordered data point, from 1 to n .
- F = theoretical cumulative distribution function (CDF) of the specified distribution.
- x_i = ordered sample values in ascending order.
- X_{nti} = the i^{th} sample if the data were ordered in descending order

Here, $F(x)$ is the cumulative distribution function of the normal distribution. Lower p-values ($p < 0.05$) indicate significant deviation from normality.

Both tests confirmed the non-normality of the productivity differences. As a result, the Wilcoxon Signed-Rank Test—a non-parametric test—was employed. This test does not require the data to follow a normal distribution and is suitable for skewed or ordinal data. The test statistic (W) is calculated by ranking the absolute differences between paired observations, assigning signs based on the direction of the difference, and summing the ranks of positive or negative differences. The null hypothesis (H_0) is when median of the differences = 0 and is rejected if the p-value < 0.05 (Douglas, et al., 2012).

To evaluate the practical significance of the observed differences, effect size metrics were computed. The following effect size evaluations used were Cohen's d and Cliff's Delta (δ).

Cohen's d is a standardized measure of effect size that indicates the magnitude of difference between two group means (Cohen, 1988). Cohen's d is a parametric effect size calculated as:

$$d = \frac{(M_1 - M_2)}{S_{pooled}}$$

Equation 8: Cohen's d formula (Cohen, 1988).

where M_1 and M_2 are the means of the two groups (FMS and Manual), and S_{pooled} is the pooled standard deviation.

A Cohen's d of 0.2 represents a small effect (a subtle difference), 0.5 a medium effect (noticeable difference), and 0.8 a large effect (substantial difference), providing context for how meaningful the difference is in practical terms.

Cliff's Delta (δ) is a non-parametric effect size used when assumptions of normality or equal variances are violated (Cliff, 1993). Cliff's Delta compares all possible pairs of values between two groups—in this case, FMS and Manual. It works like this:

- For every pair of values (one from the FMS dataset and one from the Manual dataset), it checks:
 - If the FMS value is greater than the Manual value → count it as **+1**
 - If the Manual value is greater than the FMS value → count it as **-1**
 - If the two values are equal → **ignored** (or counted as 0)

The formula then takes the difference between the number of **+1s** and **-1s** and divides by the total number of possible pairs n^2 , where n is the number of observations in each group (assuming equal sizes) (Cliff, 1993).

The result, δ , tells how often one group tends to have higher values than the other, on average:

- A positive δ means FMS values are generally higher.

- A negative δ means Manual values are generally higher.
- A δ of 0 means there's no consistent difference between the two.

Values of $|\delta| < 0.147$ are considered negligible, $0.147 \leq |\delta| < 0.33$ small, $0.33 \leq |\delta| < 0.474$ medium, and ≥ 0.474 large (Cliff, 1993).

3.4.3 Multivariate Assessment of LHD Productive Efficiency

LHD productive efficiency was defined and calculated as the amount of material moved per unit of operating time and distance travelled, measured in tonnes per hour per kilometre (tph/km). This was computed for each LHD per shift. This normalised metric allows performance comparisons across machines operating over different haul distances.

Descriptive statistics were first used to summarise the efficiency values across all LHD units. Measures included the mean, standard deviation, minimum, maximum, and interquartile values. Visual analysis was performed using bar plots to show the distribution of efficiency per LHD and to identify high- and low-performing units. These summary metrics helped establish the general spread and variability of machine-level performance.

Subsequently, several operational variables captured by the FMS were analysed in relation to productive efficiency. These included:

- Average tramming distance per LHD per shift, to assess whether machines travelling longer distances exhibited lower efficiency.
- Average cycle time per trip, to evaluate the turnaround time impact on productivity.
- Average payload per trip, to test whether larger loads corresponded to higher efficiency.
- Average daily loading rate, to examine the influence of material transfer speed on output.

Each of these variables was summarised and compared visually across LHDs using aligned bar charts. Observed trends, such as inverse relationships between cycle time and efficiency, or the positive effect of loading rate, were qualitatively interpreted to identify key performance drivers.

To investigate human performance factors, operator-level analysis was conducted by linking LHD units to specific operators using a predefined operator-machine matrix. Mean productivity values per operator were calculated and compared across shifts and machines. This assessment helped isolate operator influence from mechanical or environmental factors and provided insights for potential operator training or performance management initiatives.

Finally, performance was evaluated by shift type (day vs night) to detect temporal differences in efficiency. For both shifts, averages were calculated for production tonnage, operating hours, and productivity (tph). Boxplots were generated to compare the productivity distributions, highlighting variations in median performance, spread, and presence of outliers between day and night operations.

3.4.4 Correlation of Operational Factors

To identify key drivers of LHD productivity and efficiency, Pearson's correlation analysis was conducted using shift-level data from FMS. Two dependent metrics, productivity (tonnes per hour) and productive efficiency (tonnes per hour per kilometre) were analysed against five operational variables. The independent variables included cycle time, bucket count, payload, tramming distance, and loading rate.

The Pearson correlation coefficient (r) quantifies the strength and direction of a linear relationship between two continuous variables. It ranges from -1 to 1, where values close to 1 indicate a strong positive linear correlation—meaning both variables increase together. The values close to -1 indicate a

strong negative correlation, where one variable increases as the other decreases. A value near 0 suggests little to no linear relationship. Correlation values are typically interpreted as follows: r between 0.70 and 1.00 (or -0.70 and -1.00) reflects a strong relationship, 0.40 to 0.69 (or -0.40 to -0.69) a moderate one, 0.10 to 0.39 (or -0.10 to -0.39) a weak correlation, and any r value below 0.10 as negligible.

The Pearson correlation coefficient (r) was calculated for each variable pair to measure the strength and direction of linear relationships. The formula used was:

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \cdot \sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

Equation 9: Pearson correlation coefficient (r) formula

Where:

- X_i and Y_i are individual sample values of variables X and Y
- $\bar{X}$ and $\bar{Y}$ are the means of X and Y
- n is the number of paired observations

Heatmaps were used to present the correlation results. Visual inspections of heatmaps were used to interpret the strength and direction of correlations between key operational variables. In the heatmap, each cell is color-coded based on the value of the r , allowing quick identification of strong positive (typically shown in dark red) and strong negative (dark blue) relationships.

3.4.5 Reconciliation of Production Measurements (FMS vs Manual) with Weightometer Readings

To evaluate the accuracy of production measurement methods, a reconciliation analysis was conducted comparing tonnage recorded by the

manual system and the FMS against weightometer readings from the conveyor belt. The weightometer readings served as the baseline reference. Tonnage data from all three sources were aligned per LHD over the same operational period. The percentage deviation of each recorded value from the weightometer reference was calculated, recorded and analysed.

3.4.6 Cost-Benefit Analysis

The cost-benefit analysis was conducted to evaluate the financial impact of implementing a Fleet Management System (FMS) across a fleet of 10 LHDs. The assessment focused on three targeted operational improvements: a 5% reduction in unplanned breakdowns, a 2% improvement in diesel efficiency, and a 3% increase in equipment utilisation. These outcomes were modelled using standard operational parameters such as daily working hours, productivity rates, and production days per year.

For each scenario, estimated gains were translated into additional tonnage moved or diesel saved, which were then monetised using fixed assumptions about commodity grades, recovery rates, and prevailing metal prices. Revenue gains were offset against associated production costs to derive net financial benefits for each component. The cumulative benefit was compared against the fixed annual cost of FMS implementation to determine the net annual gain.

The analysis used real operational data from the mine and incorporated benchmarks from equipment manufacturers and similar mining operations. This structured, assumption-driven approach allowed for a realistic evaluation of the potential return on investment from digitalising LHD operations through FMS.

3.5 Ethical Issues

This study does not require any special ethical clearance. However, the relevant permissions to collect data from the mine have been sourced in line with ethical practices. Ethical research practices were also followed in collecting, validating, transforming and analysing data. The highest standards of data management practices were followed to eliminate bias and manipulation.

4 RESULTS PRESENTATION AND DISCUSSION

4.1 Introduction

This chapter presents the results of the analysis conducted to evaluate LHD operational performance using data from both the Fleet Management System (FMS) and manual records. It begins with an exploratory data analysis to describe the structure and distribution of the dataset, followed by a comparative assessment of key metrics such as number of buckets, payload, run time, tonnage, and productivity. The chapter also includes correlation analysis to identify key relationships between operational factors influencing efficiency. Additional insights enabled exclusively by the FMS—such as cycle time and tramming distance—are explored to highlight the value of digital data collection. The results are then evaluated through statistical testing to determine the significance of observed differences between the FMS and manual systems. Finally, the chapter concludes with a cost-benefit analysis of FMS implementation and a discussion of its implications for productivity improvement, operational planning, and decision-making.

4.2 Univariate analysis of categorical variables

Table 13 summarises the frequency distribution of the sample data per shift and data collection method. Two shifts are recorded, day and night shifts. Each shift lasts 10 hours, with 7.5 hours allocated for loading in the designated working areas for that particular shift. There are two data collection methods: FMS and Manual.

Table 13: Frequency distribution of the sample data per data collection method

	Shift	Counts			Percentage		
		Day	Night	Total	Day	Night	Total
Data Collection Method	FMS	1808	1808	3616	25	25	50
	Manual	1808	1808	3616	25	25	50
	Total	3616	3616	7232	50	50	100

The table indicates that the data is evenly distributed across shifts and data collection methods. There are 3,616 records for each of the shifts, as well as 3,616 records for both FMS and manual data collection methods. This equal distribution means that each shift and each data collection method represent exactly 50% of the total observations. Such an even distribution is advantageous when comparing performance or operational metrics, as it minimises potential bias that could arise from unequal sample sizes.

Table 14 presents a non-uniform representation of 10 LHDs, illustrating a frequency distribution in which the top four LHDs—C5, D4, B5, and D7—each account for 12% of the total recorded instances, while D5 contributes only 7%. This uneven distribution could introduce bias, especially if the specific characteristics of each LHD significantly affect the comparison between the FMS and manual systems. However, the main focus of the study is the comparison of the systems themselves, rather than the individual performance of each LHD. Future research that seeks to analyse LHD-specific performance or the impact of individual LHDs will need to carefully consider this uneven distribution to avoid skewed results.

Table 14: Frequency distribution of the 10 LHDs

LHD ID	Count	Percentage Distribution (%)
C5	884	12
D4	852	12
B5	844	12
D7	832	12
B3	752	10
C4	736	10
B6	620	9
C3	608	8
D3	584	8
D5	520	7
Total	7232	100

Figure 25 illustrates the frequency distribution of 32 LHD operators within the database, indicating that some operators are represented much more frequently than others. This variability raises concerns about potential bias, as data from the more frequently recorded operators could disproportionately influence the findings. However, it is essential to note that the primary focus of the study is on comparing FMS and manual systems, rather than analysing the impact of individual operators. As a result, while this uneven distribution should be acknowledged, its direct effect on the study's main objectives may be limited. Nonetheless, future studies aiming to evaluate operator-specific performance or factors affected by individual operators will need to carefully consider this uneven distribution to avoid skewed results.

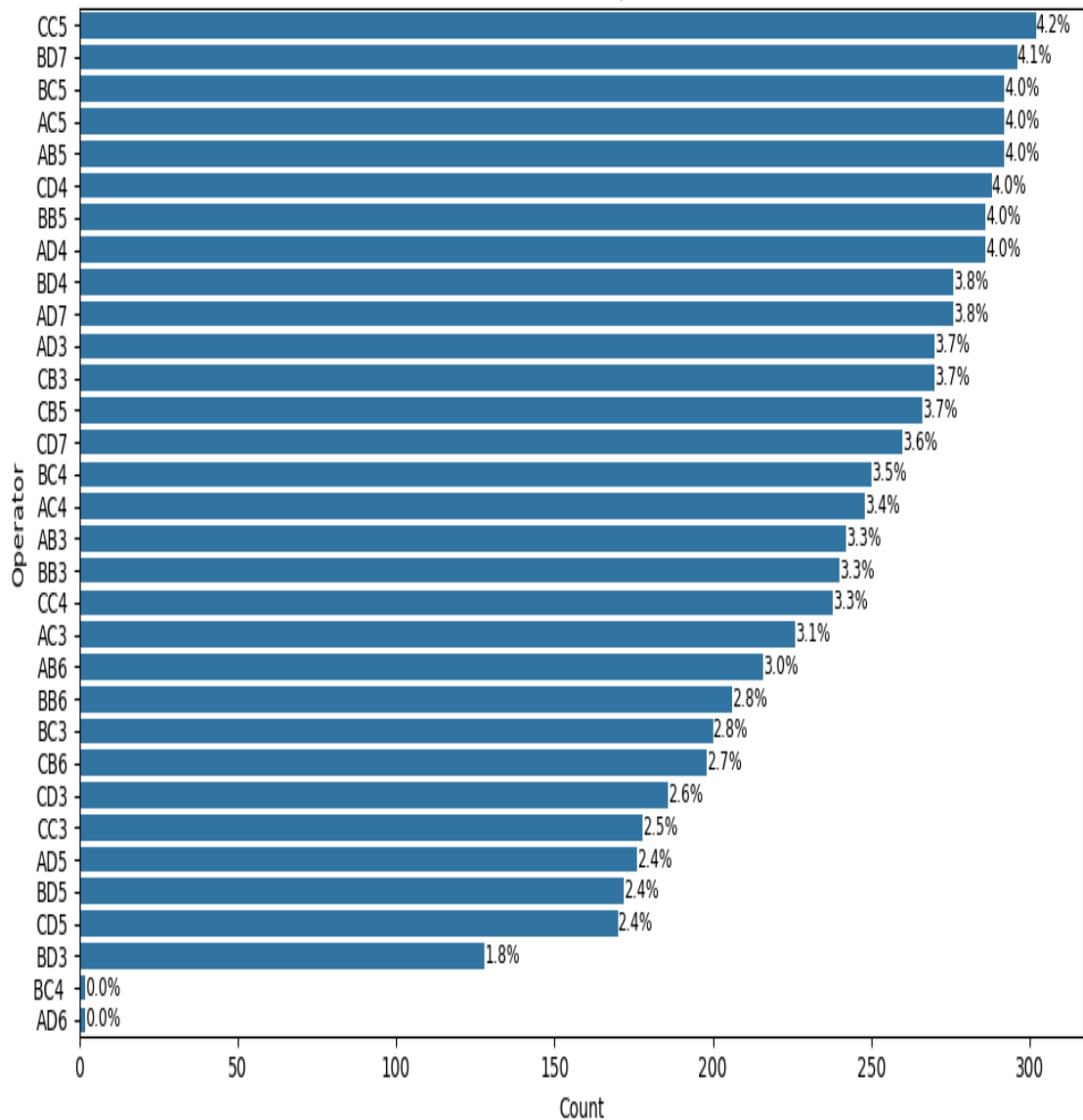


Figure 25: LHD Operators frequency distribution

4.3 Analysis on number of buckets per shift per LHD

Table 15 present the summary statistics of the productivity variables measured. These tables compare the statistics of the measured variables from the FMS and the manual system over the same period.

Table 15 shows the number of buckets per LHD per shift drawn from 3,616 records in both the FMS and manual datasets. The table shows notable similarities as well as small but meaningful differences. Both methods have the same sample size (3,616) and an identical standard deviation (15),

suggesting comparable variability in bucket counts per shift. Their minimum values are also the same at zero, indicating that each dataset includes shifts where no buckets were recorded—mainly cases where the machine was on planned maintenance. However, the mean number of buckets is slightly higher for FMS (45) than for manual (43) methods, implying that, on average, FMS records slightly more buckets per shift. Nonetheless, the planned number of an average of 48 buckets per LHD was not recorded by either system during the period of the study.

Table 15: Summary statistics of the number of buckets per LHD per shift (FMS vs Manual)

Statistic	FMS	Manual
Count	3,616	3,616
Mean	45	43
Standard deviation	15	15
Minimum	0	0
Maximum	90	78
1st Quartile (Q1)	39	38
Median (Q2)	46	45
3rd Quartile (Q3)	53	52

A closer look at the quartiles in Table 15 reveals further insights. For Q1, FMS reports 39 buckets while the manual system reports 38, suggesting that even at the lower distribution of 25%, FMS slightly outperforms manual recording. The median (Q2) values follow the same pattern: 46 for FMS compared to 45 for manual. At the third quartile (Q3), FMS records 53 buckets while the manual method captures 52. These consistent but small upward differences across all quartiles show that the FMS tends to report marginally higher productivity not just on average, but throughout the distribution of shift outputs. The maximum values further highlight a distinction whereby FMS records up to 90 buckets, whereas the manual method caps at 78. This higher number in the FMS data could reflect a more

precise or comprehensive recording processor possibly capture rare high-output shifts that were under-reported or missed in manual logs.

Figure 26 shows histograms that illustrate the differences between the FMS and manual systems in recording the number of buckets handled per LHD per shift. Both distributions are centred around the reported mean values—45 buckets for the FMS and 43 for the manual system—with peaks occurring in the 45–50 bucket range. Additionally, both distributions display a nearly symmetrical pattern. A noticeable spike at zero buckets indicates non-productive shifts; this spike is more prominent in the manual data, reinforcing earlier observations about potential omissions or downtime that may not have been accurately recorded.

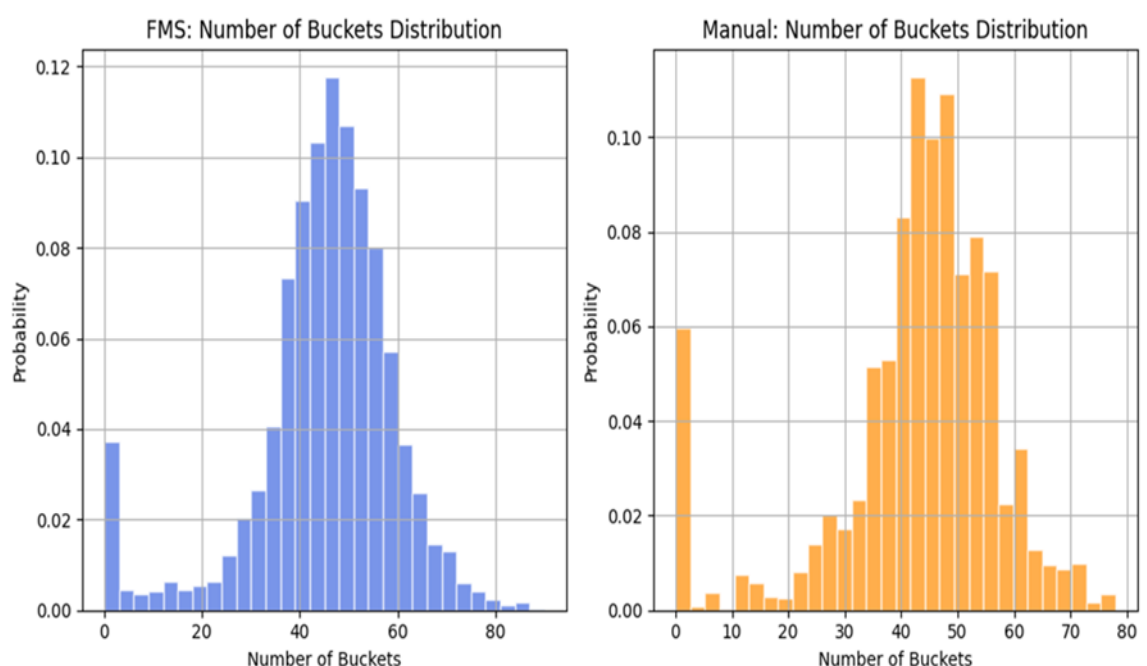


Figure 26: Histograms of number of buckets per LHD per shift (FMS vs Manual)

4.4 Analysis on payload per LHD per trip

Table 16 shows the payload per LHD per trip, highlighting substantial differences between the FMS and manual datasets. The FMS data, which

includes 3,616 trips, reports an average payload of 5.27t with a relatively high standard deviation of 1.21t. Payload values range widely from 0.00 to 7.71t, indicating that the FMS captures the full variability of actual operational conditions. In contrast, the manual dataset comprises only 3,400 recorded payloads, 216 fewer than the total number of trips. This gap highlights missing data in the manual system, likely resulting from human omission or data entry errors. Such issues are inherently mitigated by the FMS, which automatically captures and logs data in real time, ensuring completeness and accuracy.

The manual dataset also shows a narrow, tightly clustered distribution: the mean payload is 5.84t with an exceptionally low standard deviation of just 0.05t. Payload values are constrained between 5.81t and 5.93t. This lack of variability aligns closely with the theoretical payload target of 5.80t - 5.90t, indicating that the manual recordings are likely based on a fixed bucket factor provided by the mine planning department, rather than actual measured values. As such, the manual data reflects assumptions rather than real operational conditions, leading to an overstatement of actual tonnage moved by LHDs. On average, the FMS-measured payload is at least 10% lower than the manually assumed value, highlighting a systematic bias in the manual method. This reinforces the conclusion that the manual approach is unsuitable for accurately capturing operational performance, especially under conditions that vary from shift to shift.

Table 16: Summary statistics of payload per LHD per trip (FMS vs Manual)

Statistic	FMS	Manual
Count	3,616	3,400
Mean (t)	5.27	5.84
Standard deviation (t)	1.21	0.05
Minimum (t)	0	5.81
Maximum (t)	7.71	5.93
Q1 (t)	4.98	5.81
Q2 (t)	5.42	5.81
Q3 (t)	5.91	5.87

A comparison of the quartiles in Table 16 further illustrates the disparity between the two measurement systems. In the FMS data, Q1 is 4.98t, Q2 is 5.42t, and Q3 is 5.91t. These values show a wide interquartile range and reflect real differences in payloads across trips. Meanwhile, the manual dataset presents fixed or nearly identical quartile values whereby Q1, Q2, and Q3 are all around 5.81t – 5.87t, reinforcing the idea that manual figures are either estimated or standardised, lacking sensitivity to actual conditions. Overall, the FMS dataset provides a more accurate, variable, and realistic representation of payloads per trip, which can support both production analysis and operational optimisation. The manual dataset, by contrast, not only masks real variation but also suffers from incomplete records that further undermine its reliability.

Figure 27 shows histograms that clearly illustrate the stark contrast between FMS and manual systems in capturing payload per LHD per trip, and they strongly reinforce the descriptive statistics presented in Table 16. The FMS distribution (left) shows a broad, near-normal spread of payload values, centred around 5.27t, with a range extending from 0t to approximately 7.7 t. This reflects the true variability in operational conditions captured in real time by the FMS.

The small bar at zero further supports earlier observations of occasional non-productive or empty trips being properly recorded. In contrast, the manual system distribution (right) is extremely narrow and discrete, with most entries recorded at exactly 5.81t tonnes, and a few others near 5.87t and 5.93t. This aligns with the earlier findings that the manual system uses fixed or estimated payload values, derived from theoretical bucket factors rather than actual measurements. The complete lack of variability and clustering around the nominal value confirms that the manual data does not reflect actual trip-to-trip changes.

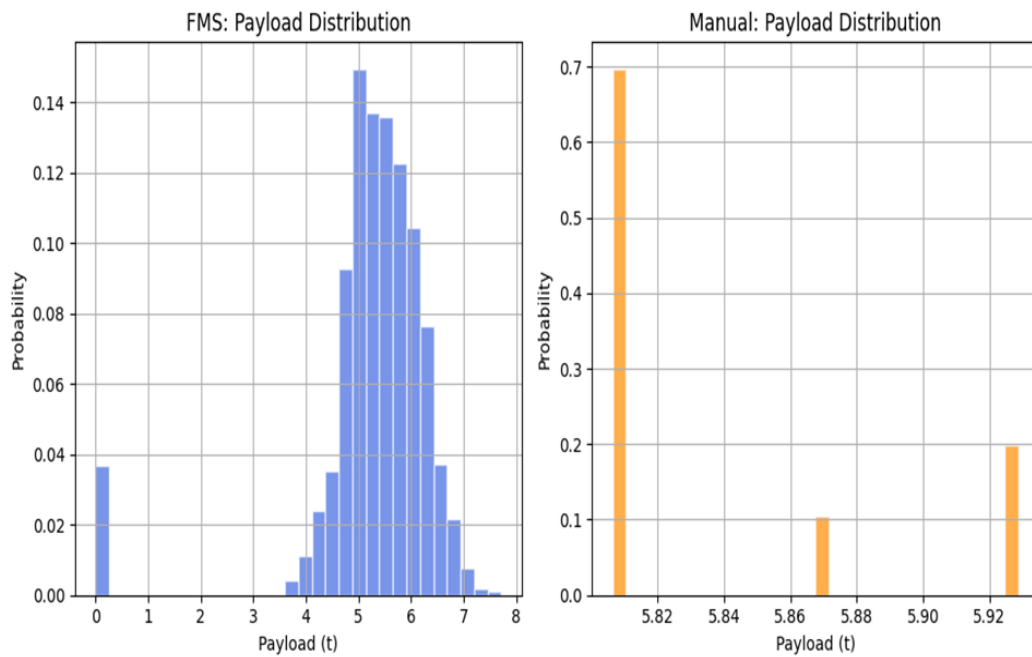


Figure 27: Histograms of payload per LHD (FMS vs Manual)

4.5 Analysis on tonnage per LHD per shift

Table 17 presents the summary statistics of tonnage per LHD per shift, comparing data from the FMS and manual recording systems across 3,616 recordings. Both datasets capture the general production trend, with average tonnages per shift falling slightly short of the mine's planned target of 255t per LHD per shift. The FMS data records a mean shift tonnage of 243.03t, whereas the manual system reports a slightly higher mean of 249.64t. Although the difference of just over 6t may appear modest, it suggests a consistent upward bias in the manual system, possibly due to the use of standardised assumptions rather than real-time measured data. These observations align with trends noted in daily, weekly, and monthly production engagements during the project, where manual reports often overstated actual performance compared to plant feed reconciliations.

In terms of variability, both systems show considerable spread in production figures, but the manual dataset is notably more dispersed, with a standard deviation of 88.76t, compared to 79.52t in the FMS data. The

maximum tonnage per shift recorded in the FMS dataset is 527.13t, significantly higher than the manual system's peak of 462.43t. This suggests that the FMS is more capable of capturing exceptionally high-performance shifts, which may be under-reported or missed in the manual system. Both datasets also report minimum values of 0 tonnes, corresponding to shifts with no production, typically due to planned maintenance, breakdowns, or other operational downtime.

Table 17: Summary statistics of tonnage per LHD per shift (FMS vs Manual)

Statistic	FMS	Manual
Count	3,616.00	3,616.00
Mean (t)	243.03	249.64
Standard deviation (t)	79.52	88.76
Minimum (t)	0	0
Maximum (t)	527.13	462.43
Q1 (t)	212.5	220.64
Q2 (t)	256.38	264.04
Q3 (t)	289.52	301.93

A comparison of the quartiles in Table 17 provides additional insights. In the FMS data, Q1 is 212.50t, Q2 is 256.38t, and Q3 is 289.52t. The manual dataset shows slightly higher values for each: Q1 = 220.64t, Q2 = 264.04t, and Q3 = 301.93 t. This consistent upward shift in the distribution confirms that the manual system generally reports higher production levels across all performance tiers. However, given the previously observed discrepancies in payload measurement (Table 16), these higher figures result from the multiplication of inflated or fixed bucket payloads by the number of buckets moved per shift, rather than actual weighed output.

Overall, both systems show a similar trend of underperformance compared to targets, however, the FMS system provides a more accurate, lower-variance, and realistic assessment of the actual tonnage moved per LHD per shift, as proven later in Section 4.13. In contrast, the manual data tends to overstate performance and lacks the precision necessary for reliable operational monitoring and performance optimisation.

Figure 28 shows histograms that illustrate the distribution of total tonnage moved per LHD per shift as recorded by the FMS (left) and Manual (right) systems, and they closely reflect the descriptive statistics in Table 17. The FMS distribution is tightly concentrated and resembles a bell-shaped (normal) distribution, centred around the mean of 243.03t, with most values falling between 200t and 300t. The smooth, symmetrical shape indicates consistent recording and reliable measurement of actual tonnage moved per shift, with fewer extreme values. The small bar at zero reflects the presence of non-productive shifts due to downtime, as captured accurately by the FMS.

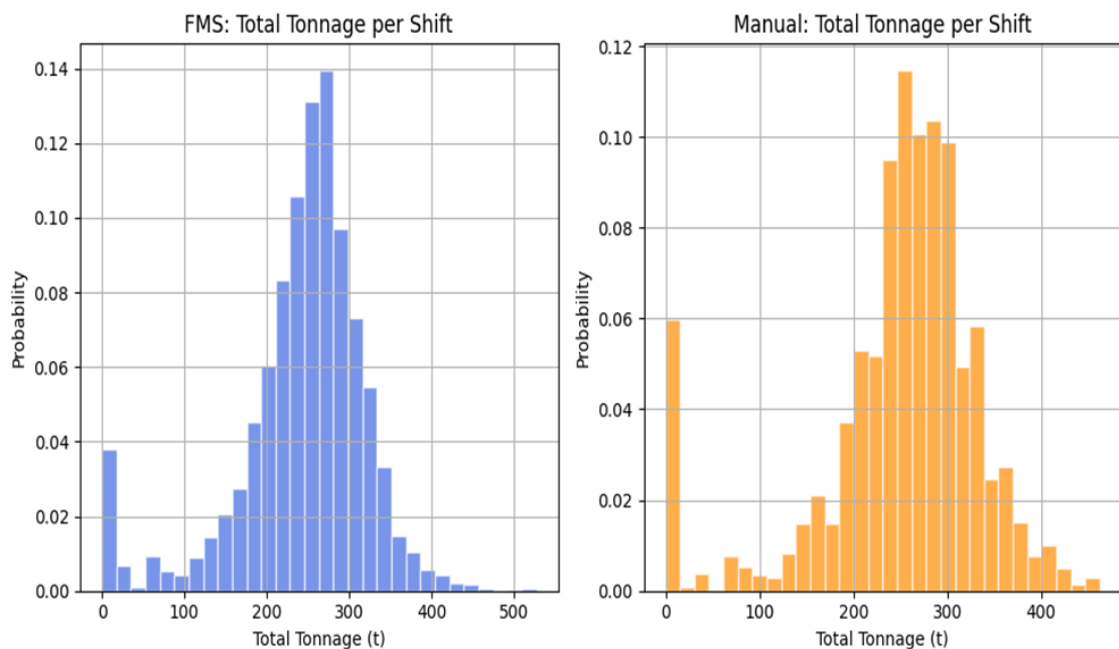


Figure 28: Histograms of total tonnage per LHD per shift (FMS vs Manual)

The manual system displays a more variable and irregular distribution compared to the FMS system. While it shares a similar central peak near the mean of 249.64t, it exhibits a wider spread and more pronounced tails on both ends. The right side of the distribution extends further, surpassing 450t, while the left side shows an unusually high frequency of zero-tonnage shifts. This suggests there may be inconsistencies or missing data entries. The histogram is also less symmetrical, indicating potential inaccuracies or overestimations in some shift records. These visual characteristics are

consistent with the manual dataset's higher standard deviation of 88.76, compared to 79.52t for the FMS system. Additionally, the presence of implausible or extreme tonnage values may result from applying fixed payload assumptions without validating them against actual run times or bucket counts.

4.6 Analysis on run time per LHD per shift

Table 18 presents summary statistics for run time per LHD per shift, based on 3,616 observations from both the FMS and manual recording systems. Although both datasets reflect the same number of shifts, they diverge meaningfully in terms of average run time. The FMS system reports a mean run time of 6.51 hours, while the manual system shows a higher average of 7.02 hours.

While both distributions have similar variability—standard deviations of 1.70 hours (FMS) and 1.77 hours (Manual)—the lower mean recorded by the FMS suggests a more accurate reflection of machine utilisation, particularly in capturing idle time, delays, or unplanned stoppages during the shift. The observed discrepancy is especially important when viewed in the context of the mine's planned target run time of 7.5 to 8 hours per shift. Neither dataset reaches this benchmark on average, but the manual system appears to significantly overestimate actual productive hours, likely due to rounding, standardised reporting, or omission of downtime in manual logs. This overstatement aligns with field-level observations made during project implementation, where manual shift reports tended to smooth over periods of inactivity, giving an inflated view of equipment utilisation.

Table 18: Summary statistics of run time per LHD per shift (FMS vs Manual)

Statistic	FMS	Manual
Count	3,616	3,616
Mean (hours)	6.51	7.02
Standard deviation (hours)	1.7	1.77
Minimum (hours)	0	0
Maximum (hours)	8.9	9.09
Q1 (hours)	6.53	7
Q2 (hours)	6.97	7.52
Q3 (hours)	7.38	7.92

A closer look at the quartiles in Table 18 reveals more insights. In the FMS dataset, the first quartile (Q1) is 6.53 hours, the median (Q2) is 6.97 hours, and the third quartile (Q3) is 7.38 hours. Comparatively, the manual system shows higher values across the board whereby Q1 = 7.00 hours, Q2 = 7.52 hours, and Q3 = 7.92 hours. This consistent upward shift in the manual data indicates a bias toward reporting higher utilisation across all shifts. The FMS data, in contrast, provides a more balanced distribution that reflects the true spread of LHD operational time during shifts, including underutilised periods that are critical for root-cause analysis and performance improvement.

While both systems report minimum values of 0.00 hours, which represent shifts where machines were completely idle (e.g., due to maintenance or breakdowns), the maximum run times are moderately similar at 8.90 hours (FMS) and 9.09 hours (Manual). This indicates that both systems are capable of capturing full-shift operations when they occur. However, the FMS's lower average and lower quartile values suggest a more conservative and accurate measurement of real operational conditions.

Although it was possible to compare the two measuring systems based on the number of buckets, payload, tonnage, and run time, comparisons of tramming distances and cycle times were not possible. This limitation arises

because the manual system did not capture these metrics. Nonetheless, Tables 19 and 20 provide summary statistics for the tramming distance per LHD (per trip and per shift) as well as the cycle time per LHD. These additional measurements are made possible by the FMS but are not available when using manual systems. Figure 29 shows histograms displaying the distribution of run time per LHD per shift as captured by the FMS (left) and Manual (right) systems. These distributions support the descriptive findings in Table 18, while further highlighting key differences.

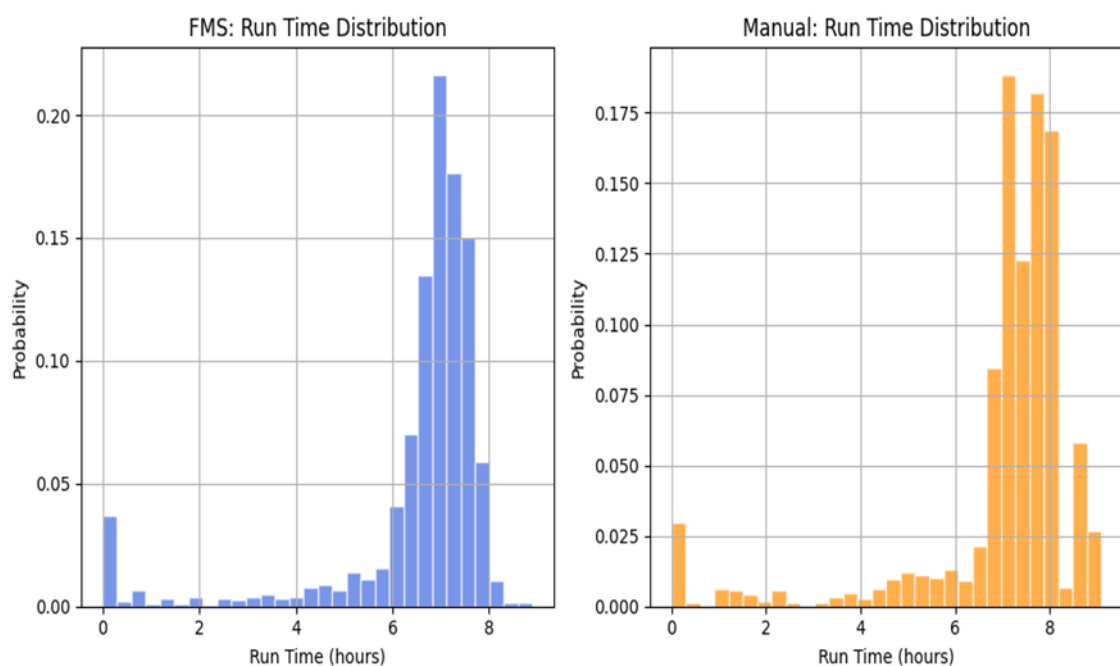


Figure 29: Histograms of run time per LHD per shift (FMS vs Manual)

The FMS distribution is closely clustered between 6.5 and 7.5 hours, with a clear peak near the mean of 6.51 hours. This distribution is negatively skewed, which reflects a realistic operational pattern where most machines operate for a significant portion of the shift. However, a small number of shifts experience reduced runtime, represented by the long-left tail and the small spike at 0 hours, indicating complete downtime due to breakdowns or planned maintenance. This suggests that the FMS effectively distinguishes between active and idle periods based on telemetry providing an accurate representation of machine utilisation.

In contrast, the manual distribution is more concentrated towards the higher end of the scale, with the mode and majority of values clustering around 7 to 8 hours, with a higher mean of 7.02 hours. However, there is also a significant number of recordings that exceed the planned loading time of 7.5 to 8 hours, indicating an overrepresentation of full-shift utilisation. The recorded engine-on time is presumed to represent active runtime without properly accounting for idling, waiting, or downtime.

4.7 Analysis on tramming distance per LHD

Table 19 presents descriptive statistics for tramming distance per LHD, reported both per trip and per shift, as measured exclusively by the FMS system. The dataset includes 3,616 records for each metric. On average, each LHD trip covers 0.43 km (430 meters), which is substantially higher than the theoretical planning target of 300 meters per trip. This suggests that, operationally, LHDs are travelling farther than intended, potentially due to inefficient tipping arrangements, layout constraints, route detours, or suboptimal loading management in underground.

Table 19: Summary statistics of tramming distance per LHD per trip/shift

Statistic	FMS	
	Per trip	Per Shift
Count	3,616	3,616
Mean (km)	0.43	18.23
Standard deviation (km)	0.13	5.54
Minimum (km)	0	0
Maximum (km)	1.86	35.52
Q1 (km)	0.35	16.1
Q2 (km)	0.41	18.94
Q3 (km)	0.5	21.64

Across a full shift, LHDs cover an average distance of 18.23 km, which also exceeds the planned target of approximately 13.5 km per shift. The

implications are significant such that LHDs are accumulating nearly 5 extra kilometres of travel per shift, which may lead to increased fuel consumption, higher maintenance costs, and excessive wear on drivetrain and tyres. This deviation from the mine plan indicates a disconnect between the mine's operational assumptions and actual field conditions, highlighting a need to revisit layouts, tipping strategies, and loading point-to-tipping logistics.

A closer look at the distribution reveals further insights. Per shift, the Q1 is 16.10 km, Q2 is 18.94 km, and Q3 is 21.64 km, indicating that the majority of LHDs are consistently travelling well beyond planned distances. At the trip level, Q1 = 0.35 km, Q2 = 0.41 km, and Q3 = 0.50 km, suggesting a moderately widespread and possible route variability among loading points. The maximum observed shift distance is 35.52 km, further underscoring the extent of possible inefficiencies in some areas of the operation.

Importantly, this data is completely absent in the manual system, where tramming distance is not recorded at all. As a result, manual reporting deprives decision-makers of a critical operational metric needed to optimise LHD deployment and shift design. The FMS not only enables tracking of actual distances per trip and per shift but also supports the analysis of performance in relation to route planning, cycle efficiency, and equipment wear. It provides a vital basis for data-driven interventions that can enhance both productivity and cost control. This confirms observations made by Johansson (2010) on the benefits of acquiring FMS and the reality observed in practical studies as reported by Bullock, et al., (2017).

Figure 30 shows histograms illustrating the FMS-recorded tramming distance distributions per load and per shift, offering valuable insights into actual LHD travel patterns underground. The per-load distribution is right-skewed, with most trips falling between 0.25 km and 0.50 km, and a clear peak near 0.43 km, which aligns with the previously reported average. This indicates that LHDs are regularly travelling farther than the planned 0.30 km per trip. It has a long tail extending beyond 1 km, suggesting occasional long hauls likely due to extended tipping locations, detours, or suboptimal

loading-to-tip layouts. The presence of near-zero or zero-distance trips may reflect aborted or idle trips, all of which are accurately captured by the FMS system.

The per-shift distribution presents a more symmetric, bell-shaped curve centred around 18–20 km, closely matching the previously reported mean of 18.23 km per shift and showing that most LHDs operate within a typical range. However, the presence of shifts exceeding 30 km or with zero recorded distance confirms the variability in haulage activity across different shifts.

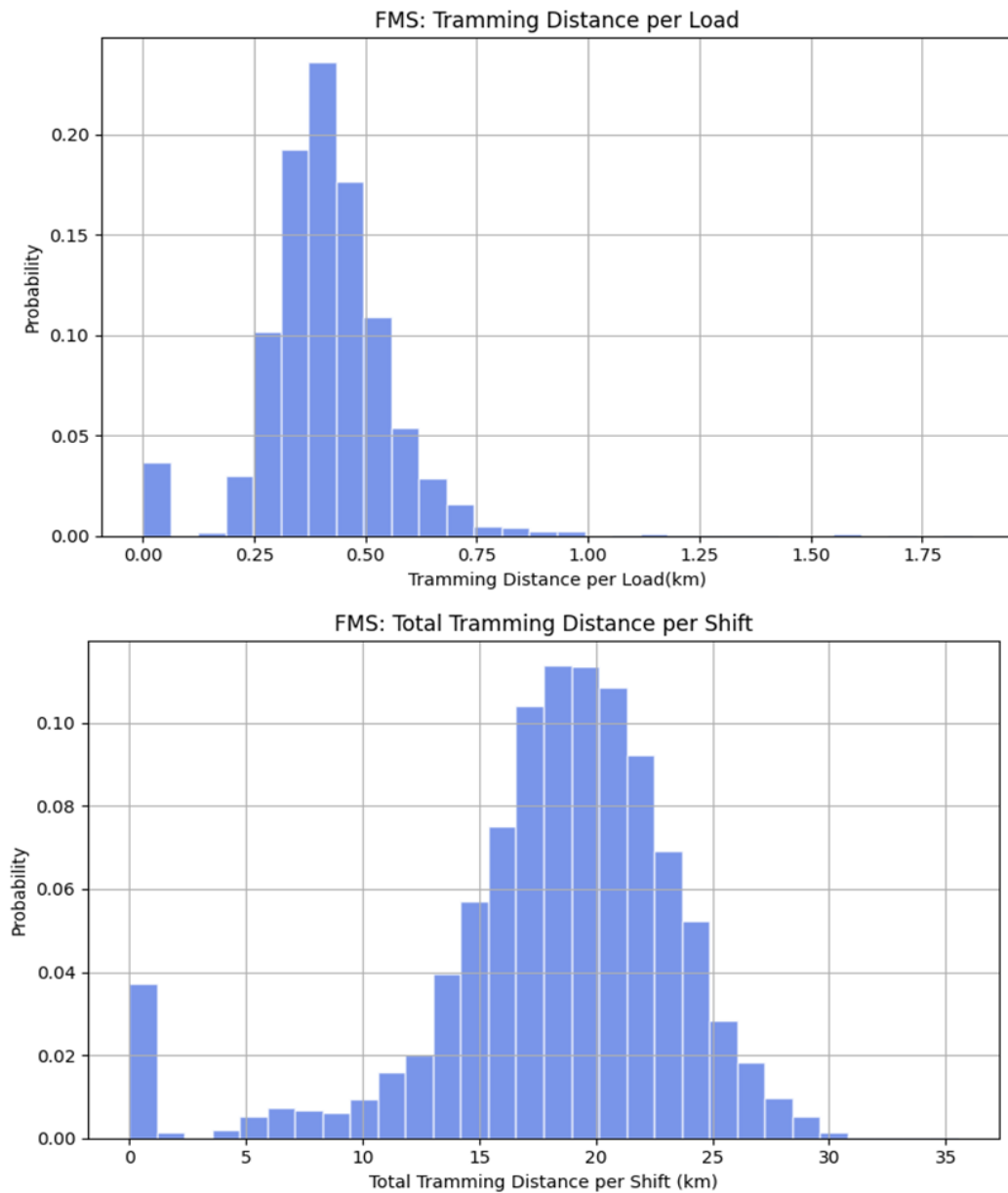


Figure 30: Histograms of tramming distance per LHD (per trip and per shift) – FMS

Importantly, these critical spatial metrics are absent from the manual data, which cannot account for route length or its impact on productivity. Overall, the FMS data not only provides a detailed and realistic representation of LHD travel distances, but also highlights key inefficiencies that support route optimisation, improved layout planning, and more accurate performance benchmarking.

Analysis on cycle time per LHD per trip

Table 20 presents the summary statistics for cycle time per LHD per trip, as captured by the FMS system across 3,616 records. The average cycle time is 0.15 hours (9 minutes), which slightly exceeds the planned benchmark of 0.14 hours (8.4 minutes). While this difference may appear marginal at the level of a single trip, it becomes operationally significant when considering that each LHD completes an average of 45 trips per shift (see Table 20).

When extrapolated across a full shift, this additional 0.01 hours per trip translates into a cumulative excess of approximately 0.45 hours per LHD per shift—nearly 30 minutes of extra loading cycle time per LHD per shift. This reduces the potential for completing additional trips and directly affects shift-level productivity and output.

Table 20: Summary statistics of cycle time per LHD per trip

Statistic	FMS
Count	3,616
Mean (hours)	0.15
Standard deviation (hours)	0.05
Minimum (hours)	0
Maximum (hours)	0.54
Q1 (hours)	0.13
Q2 (hours)	0.15
Q3 (hours)	0.17

The maximum observed cycle time of 0.54 hours (32.4 minutes), further highlighting the variability in performance, with some trips taking up to four times longer than the expected average. These extended cycles often result from operational bottlenecks, such as long tramming distances, tip congestion, or delays in loading and dumping. Supporting this interpretation, the FMS dataset in Table 19 revealed that the average tramming distance

per trip is 0.43 km, above the design target of 0.30 km. This increase in travel distance directly contributes to prolonged cycle times.

Examining the distribution provides more insight. Q1 is 0.13 hours, Q2 is 0.15 hours, and Q3 is 0.17 hours. This indicates that 75% of trips fall within a relatively tight band of cycle times, but even small variations—when multiplied by 45 trips per shift—can accumulate into meaningful delays. Moreover, the presence of a long upper tail (given Q3 = 0.17 hours), with a maximum of 0.54 hours, suggests isolated operational breakdowns or inefficiencies that merit targeted investigation.

Critically, this level of granularity is only available through the FMS system, which accurately captures start and end times for each cycle based on machine telemetry. In contrast, manual systems do not record individual trip durations and typically rely on shift-level summaries that obscure intra-shift variability. As such, manual data lacks the resolution to identify cycle time creep, let alone to associate it with underlying causes like tramming distances, queuing, or loading location.

By using FMS data, operators and planners can quantify the cost of inefficiencies and identify improvement opportunities—such as redesigning travel routes, optimising tipping locations, or addressing traffic congestion underground. These insights are crucial for increasing effective utilisation of LHDs and improving tonnage moved per shift.

Figure 31 shows a histogram illustrating the distribution of cycle time per load as recorded by the FMS system, offering detailed insight into the time taken by LHDs to complete a full load-haul-dump-return cycle. The distribution is slightly positively skewed, with most cycle times falling between 0.10 and 0.18 hours, and a peak around 0.14 to 0.15 hours. This matches the previously reported mean cycle time of 0.15 hours in Table 20, and the benchmark of 0.14 hours per round trip. This clustering near the

expected benchmark indicates consistent operational behaviour under typical conditions.

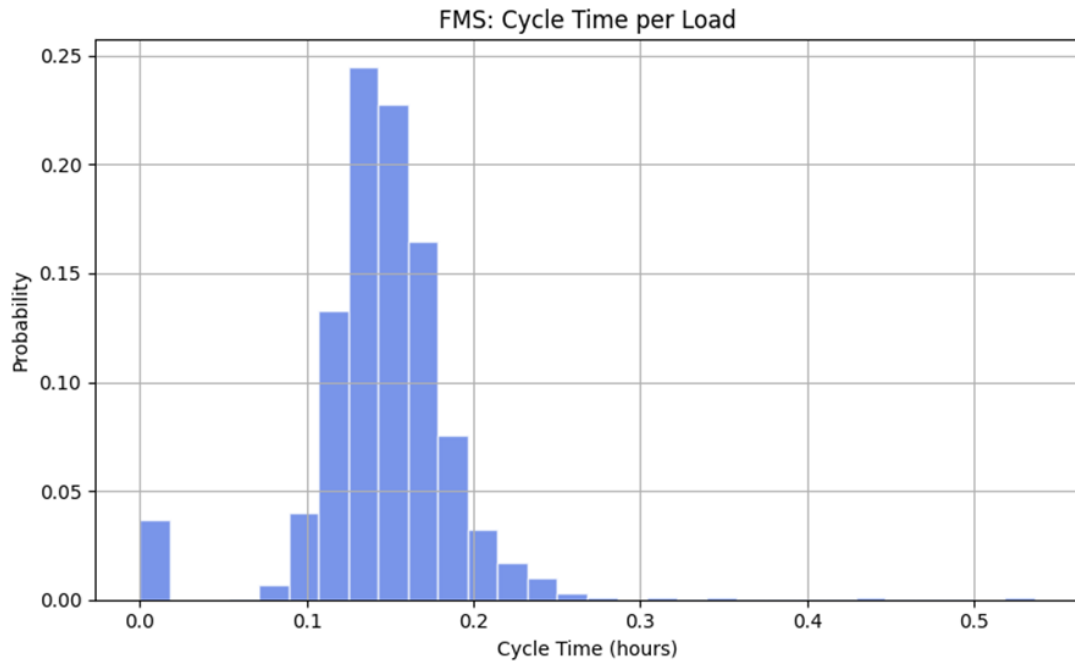


Figure 31: Histogram of cycle time per LHD per trip (FMS)

However, the long right tail shows that some cycles extend beyond 0.14 hours, with rare outliers approaching 0.50 hours, suggesting occasional delays. These may result from longer tramming distances, as identified in earlier analyses, or operational inefficiencies such as waiting at loading or tipping points, traffic congestion and mechanical interruptions. The small but distinct presence of near-zero cycle times likely represents either aborted or incomplete cycles, again demonstrating the FMS system's sensitivity in capturing real-time operational anomalies.

Overall, this distribution reflects the granularity and precision of the FMS system in tracking individual LHD movements. It not only confirms the average performance levels but also highlights performance variability that is essential for diagnosing bottlenecks and improving shift productivity. Unlike manual systems which do not track cycle time at all, the FMS enables quantitative analysis of efficiency at the trip level, offering a powerful

foundation for route optimisation, traffic management, and resource planning underground.

4.8 Analysis on LHD Productivity (tph)

To evaluate the overall production performance between the FMS and manual systems, this section presents results based on a composite productivity metric—tonnes per hour (tph), which is referred to as LHD productivity in this study. Instead of analysing individual variables such as the number of buckets, payload per bucket, cycle time, run time, and total tonnage moved separately, this integrated measure captures the combined effect of these factors in a single representative output. By normalising the tonnage moved over the actual operational time, tonnes per hour provides a practical and interpretable benchmark for comparing the efficiency of the two data collection systems.

The results generated compare LHD productivity derived from FMS and manual records. Table 21 summarises the statistics for LHD production (tph) for both the FMS and manual methods.

Table 21: Summary statistics for LHD productivity per shift for FMS vs Manual Systems

Statistic	FMS	Manual
Count	3,616	3,616
Mean (tph)	36.08	35.18
Standard deviation (tph)	10.23	16.63
Minimum (tph)	0	0
Maximum (tph)	80.12	289.12
Q1 (tph)	32.2	30.79
Q2 (tph)	37.02	35.81
Q3 (tph)	41.78	41.04

On average, FMS productivity is higher, with a mean of 36.08 tph compared to 35.18 tph recorded by the manual system. While the difference in means

appears modest (less than 1 tph), it consistently favours the FMS and reflects the cumulative benefit of more accurate payload and run time measurement discussed in earlier sections. Given the high number of observations ($n = 3,616$), even such a small difference may be statistically significant, as evaluated in the statistical testing that follows.

A more striking contrast is seen in the variability of the data. The standard deviation for the manual system is 16.63 tph, significantly higher than the 10.23 tph observed in the FMS data. This suggests that manual recordings of productivity are far more dispersed, which may result from inconsistent data entry, reliance on theoretical assumptions (e.g., fixed payload factors), or inaccuracies in recorded run time. The FMS system, by contrast, provides a more stable and tightly distributed range of productivity values, indicating greater measurement consistency and data integrity.

The extreme values also tell an important story. Both systems record a minimum productivity of 0.00 tph, reflecting complete downtime or idle shifts. However, the maximum productivity recorded by the manual system is 289.12 tph, which is anomalously high and well beyond the plausible operational range for LHDs. This likely reflects calculation errors or inflated tonnage or underestimated run time in the manual dataset. In contrast, the maximum FMS-recorded productivity is 80.12 tph, a value despite being high, remains within a realistic range given the known performance limits of LHDs.

Examining the quartiles provides further insight into the central tendencies of the distributions. The FMS values are consistently higher across all percentiles. These differences—though relatively small—are consistent and reinforce the observation that the FMS system measures productivity slightly more favourably and accurately, across the board.

Overall, the data suggest that while mean productivity levels from both systems are similar, the FMS system is more consistent, less error-prone, and free from extreme outliers that may distort performance analysis. The

manual data shows greater variability and unrealistic maximum values, highlighting its vulnerability to human error, assumption-based input, and calculation inaccuracies.

Figure 32 shows histograms presenting the distribution of LHD productivity (tonnes per hour) for both the FMS (left) and manual (right) systems. These distributions offer a direct comparison of how each system captures overall production efficiency.

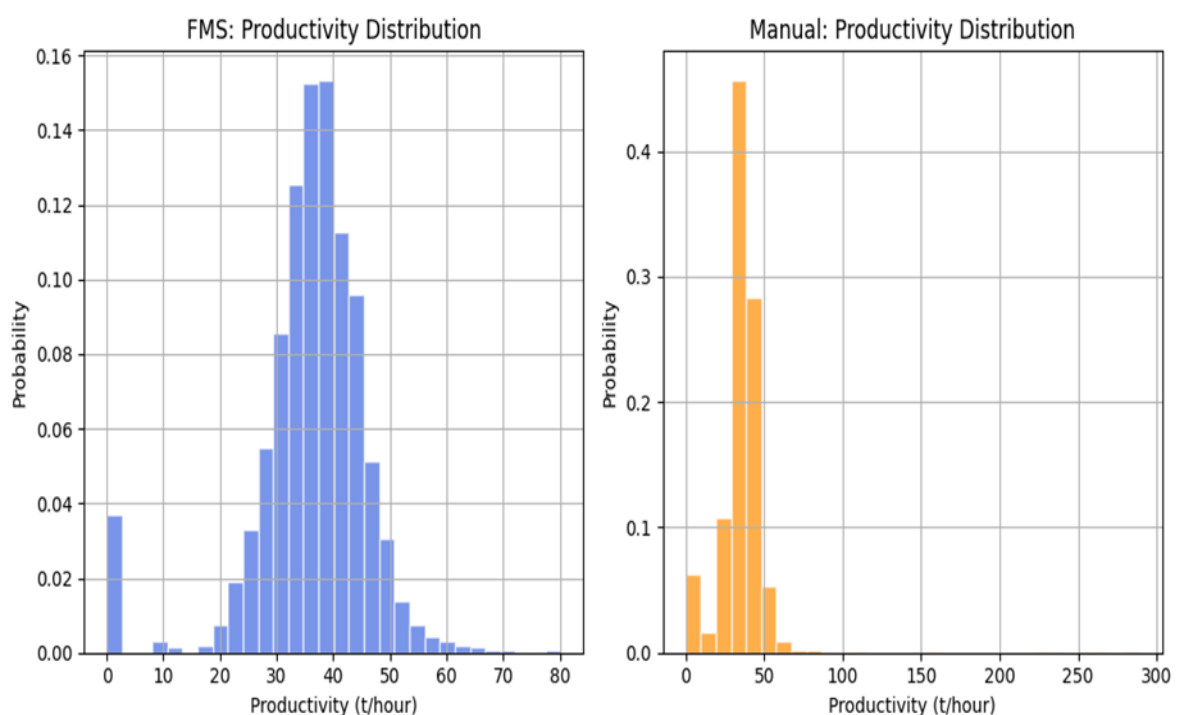


Figure 32: Histograms of productivity (tph) per LHD (FMS vs Manual)

The FMS productivity distribution is approximately normal, centred around 36 tph, with most values falling between 30 tph and 45 tph. This tight symmetric distribution and modest spread support the interpretation that the FMS system captures a reliable and consistent measure of actual productivity, with the ability to reflect both high-performing and low-performing shifts. The presence of a few values near 0 tph indicates shifts with no production likely due to downtime, while the absence of extreme outliers suggests good data quality.

By contrast, the manual system distribution is sharply peaked and heavily compressed, with most observations tightly clustered around 35–40 tph. The presence of implausible high values exceeding 200 tph—which are absent in the FMS data—points to data entry errors, inflated tonnage estimates, or underestimated run time in the manual calculations. This aligns with earlier findings of high variability and the extreme maximum value of 289.12 tph reported in Table 21.

Overall, the visual comparison confirms that the FMS system provides a more accurate, stable, and operationally meaningful assessment of LHD productivity, while the manual system suffers from over-simplification, limited sensitivity, and potential data distortions. These insights underscore the importance of transitioning to telemetry-based systems like FMS for performance evaluation and decision-making in production environments.

The following sections will discuss the results of statistical tests used to investigate whether the observed differences in LHD productivity are statistically and practically significant. Thereby confirming whether the FMS system offers a materially better basis for production monitoring and decision-making.

4.9 Statistical and Practical Significance of Productivity Differences in both FMS and Manual Systems

To analyse the differences in LHD productivity between the manual and FMS systems, statistical tests were conducted to determine whether these differences are both statistically and practically significant. The results of this analysis are presented in this section.

Since the continuous productivity values from both systems were recorded for the same LHD units and same shifts, the data consists of paired observations. Each FMS-recorded productivity value corresponds directly

to a manual entry for the same shift, making the use of paired statistical testing appropriate.

4.9.1 Testing for assumption of normality

Before comparing the productivity of LHD systems between FMS and manual methods, it was important to evaluate whether the differences between the paired values (FMS minus manual) followed a normal distribution. This assumption is crucial for applying parametric tests, such as the paired t-test. Given the large sample size ($n = 1,808$ for each group) and the presence of extreme values in the dataset, a thorough approach to test for normality was adopted. Two complementary statistical tests were used: the Shapiro-Wilk test and the Anderson-Darling test for normality. The null hypothesis for both tests is that the data is drawn from a normally distributed population (Douglas, et al., 2012). By using both tests, the analysis takes advantage of their complementary strengths, allowing for a more balanced and reliable assessment. Table 22 summarises the results of the normality tests, while Figure 33 provides a visual representation using a probability plot to assess normality.

Table 22: Results of normality tests for LHD productivity differences between FMS and manual system measurements.

Test	p-value	Conclusion
Shapiro-Wilk	1.13E-57	Reject H_0 (Not normal)
Anderson-Darling	7.85E-01	Reject H_0 (Not normal)

Both tests yielded p-values lower than 0.05, indicating that the null hypotheses are rejected. Consequently, it can be concluded that the differences between the FMS and manual system productivity values are not normally distributed. This finding violates the assumption of normality

required for the paired t-test. Therefore, the more appropriate statistical method is the Wilcoxon Signed-Rank Test, a non-parametric alternative that does not assume normality and is robust to skewed distributions (Douglas, et al., 2012).

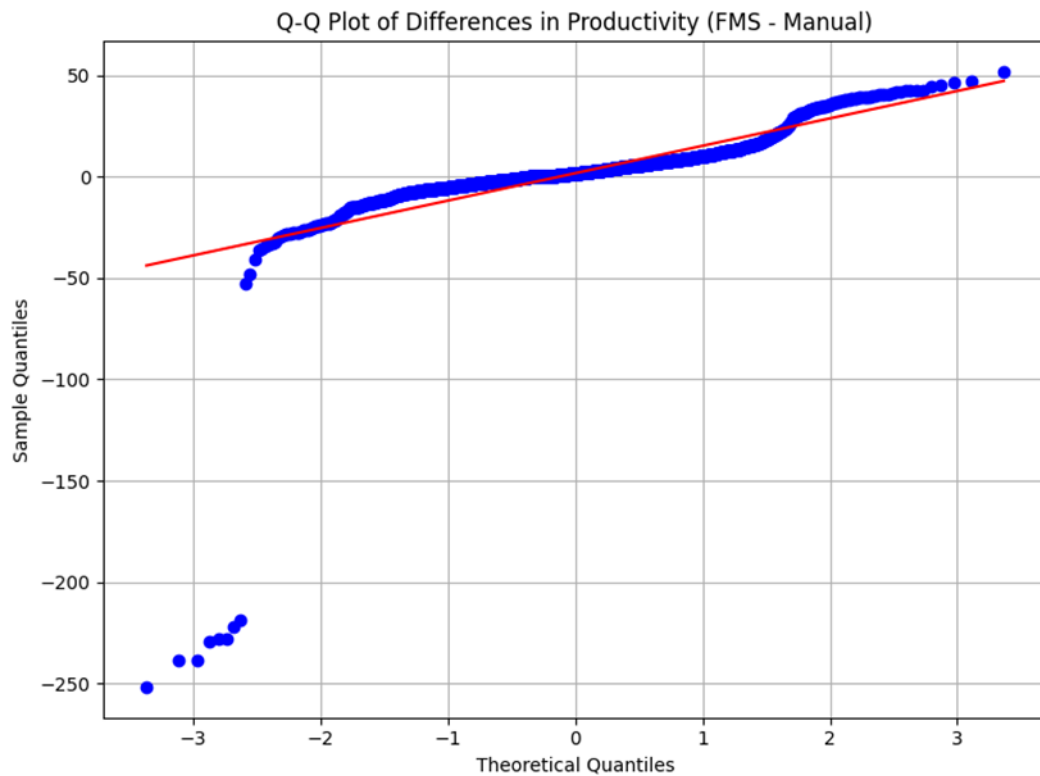


Figure 33: Q-Q plot comparing the differences in productivity between FMS and manual system measurements

The Q-Q plot confirms the results of the Shapiro-Wilk and Anderson-Darling tests as evidence by departures from the red line in Figure 33. The differences in productivity between FMS and Manual systems are not normally distributed, particularly due to extreme values in the tails. This further justifies the decision to use the Wilcoxon Signed-Rank Test, a non-parametric method that does not require the assumption of normality and is robust against outliers.

4.9.2 Statistical significance: Wilcoxon Signed-Rank Test

The null hypothesis of the Wilcoxon Signed-Rank test is that the median of the differences between the paired observations is zero—in other words, there is no difference in productivity measurements between the FMS and manual systems (Douglas, et al., 2012). The test produced a p-value of 4.53×10^{-25} , which is far below the significance level of 0.05. As a result, the null hypothesis is rejected. This indicates that the observed difference in productivity between the two systems is statistically significant and unlikely to have occurred by random chance. In practical terms, this means that the FMS and manual systems do not produce equivalent productivity measurements.

4.9.3 Practical significance: Cohen's d Test and Cliff's Delta

While the Wilcoxon Signed-Rank test confirmed that the difference in LHD productivity between FMS and Manual systems is statistically significant, it is important to go one step further. Statistical significance alone does not imply that the difference is meaningful in a practical or operational sense. In large datasets, even very small differences can result in low p-values. Therefore, it is essential to evaluate the magnitude of the difference indicating its practical significance to determine whether the change is substantial enough to matter in real-world decision-making. To assess the real-world impact of this difference, two effect size measures were calculated using Cohen's d and Cliff's Delta (Cohen, 1988; Cliff, 1993) and Table 23 summarises their output.

Table 23: Effect size test results

Metric	Value	Interpretation
Cohen's d	0.086	Negligible effect size
Cliff's Delta	0.169	Small effect size

Cohen's d , a parametric measure, yielded a value of 0.086, which is considered a negligible effect size. This suggests that the observed difference, while statistically significant, is small relative to the overall variability in productivity. However, given that the distribution of differences was found to be non-normal, reliance on Cohen's d alone may underestimate practical relevance. In contrast, Cliff's Delta, a non-parametric and distribution-free measure, produced a value of 0.169, indicating a small but consistent effect. This means that in approximately 58.5% of random pairings, FMS productivity values exceed those of the manual system. Importantly, Cliff's Delta is robust to outliers, unequal variances, and skewed data, making it a more reliable and appropriate indicator of practical significance under the current data conditions. Together, these results suggest that although the mean difference is modest, the FMS system offers a small yet consistently better reflection of actual productivity, reinforcing its operational value beyond just statistical metrics.

4.10 Multivariate Assessment of LHD Productive Efficiency

This section examines the productive efficiency of LHD machines, considering various operational factors enabled by the FMS system. The aim is to identify key drivers of efficiency and inform strategies for performance improvement.

The descriptive statistics for LHD productive efficiency, measured in tonnes per hour per kilometre (tph/km), are summarised in Table 24. The mean efficiency of 1.02 tph/km and standard deviation of 0.285, indicates a moderate level of variability across the LHD machines. The wide range (0.49 to 3.57 tph/km) highlights substantial differences in performance.

Table 24: Productive efficiency summary statistics

`. summarize Tonshrkkm`

Variable	Obs	Mean	Std. Dev.	Min	Max
Tonshrkkm	1,675	1.024983	.2850372	.495563	3.571949

Figure 34 illustrates the efficiency distribution across individual LHD machines. Notably, LHD B5 exhibited the highest efficiency (1.24 tph/km), followed by C5 and D7 (approximately 1.08 tph/km). LHDs B3, D3, D4, and D5 demonstrated average efficiencies around 1 tph/km, while C4, B6, and C3 showed the lowest efficiencies, averaging approximately 0.9 tph/km.

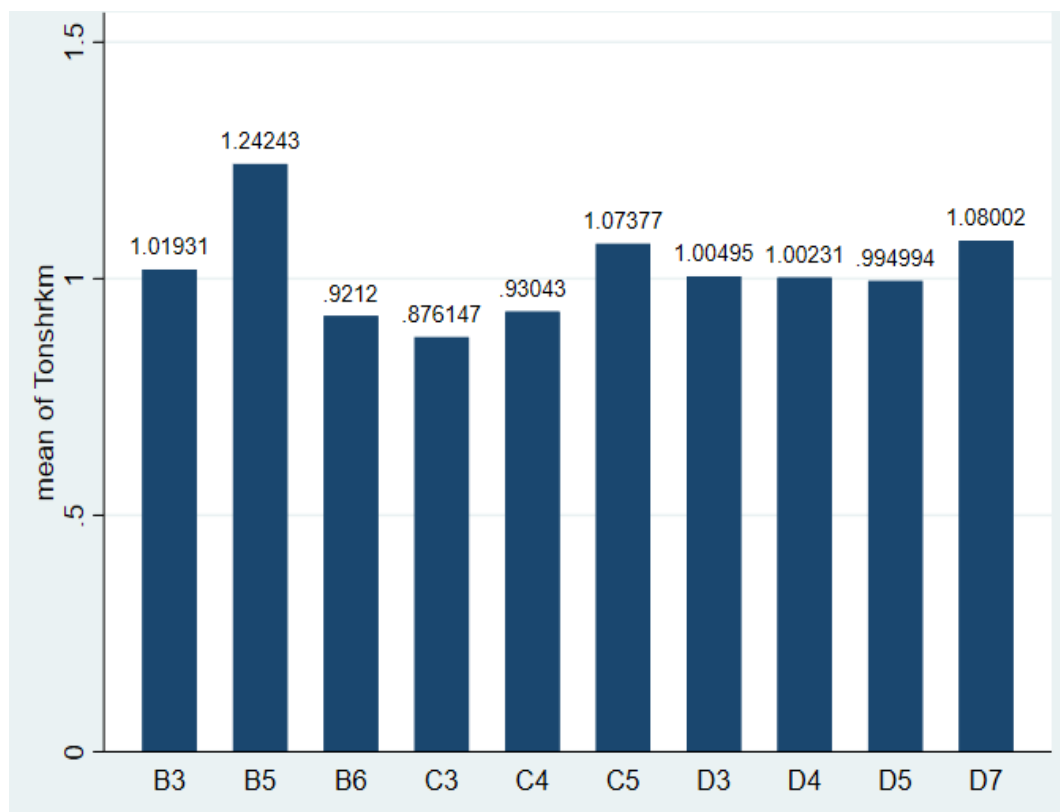


Figure 34: LHD productive efficiency snapshot

Figure 35 shows how tramming distance varies with the various machines. From the graph, it can be seen that B5, which had the highest productive efficiency, had the least tramming distance. C5 and D7, which were the

second highest in efficiency, also had lower tramming distances. The least productive machines had the highest tramming distance.

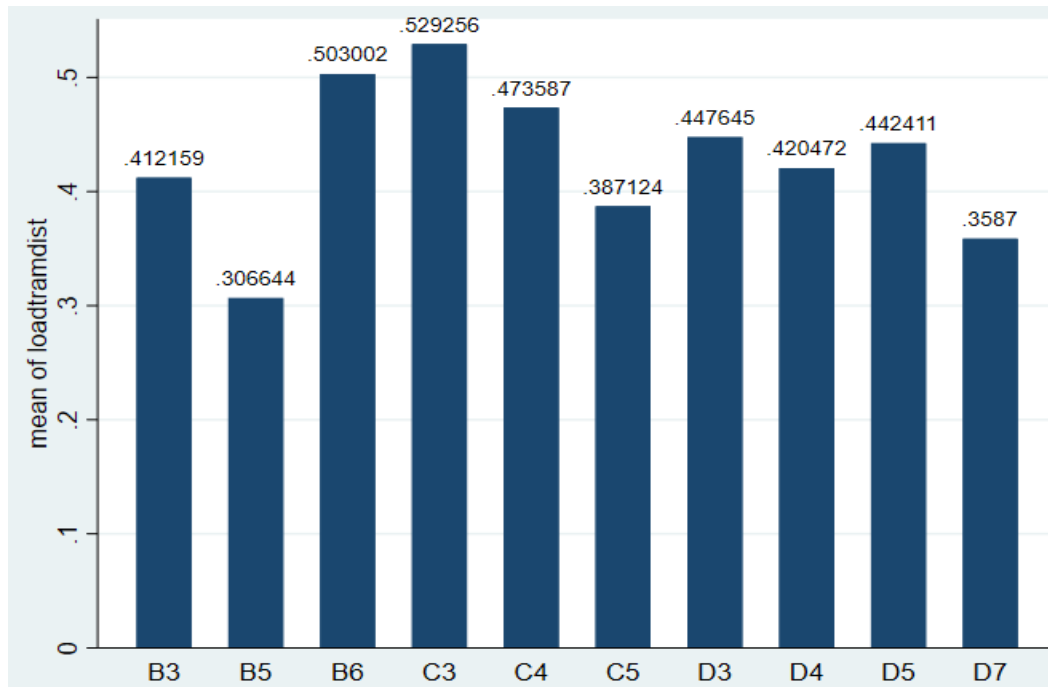


Figure 35: Mean tramming distance per LHD

Figure 36 indicates an inverse correlation between cycle time and efficiency. LHDs with shorter cycle times (B5, C5, D7) demonstrated higher efficiencies, highlighting the importance of minimising turnaround time.

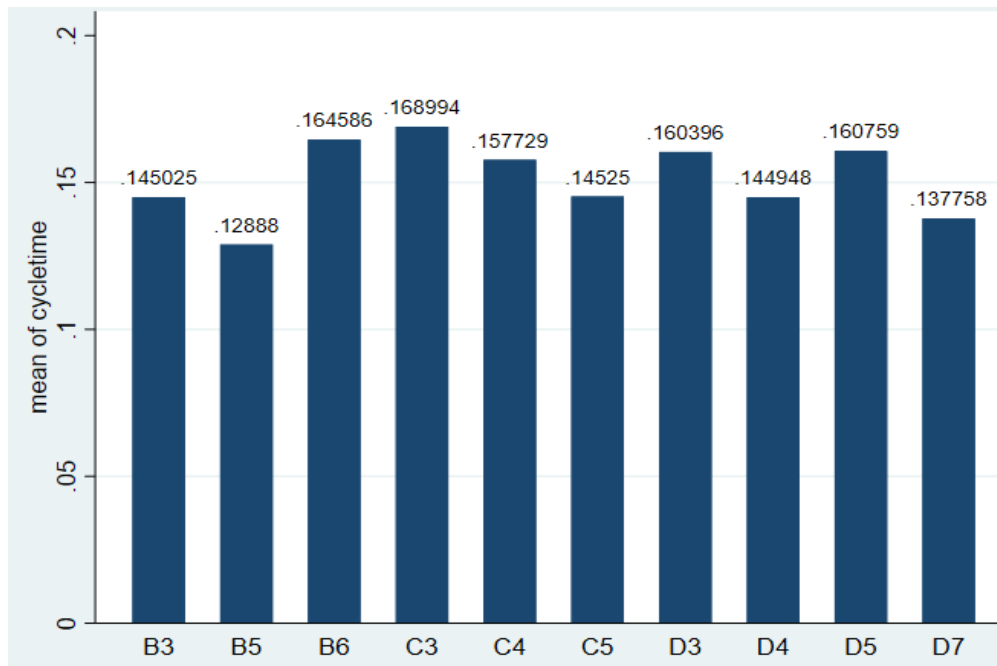


Figure 36: Mean cycle time per LHD

Payload, as shown in Figure 37, however, did not show a clear trend with efficiency. LHD B5, despite having the highest efficiency, had a relatively lower payload. This suggests that factors other than payload, such as cycle time and tramming distance, may have a more significant impact on productivity.

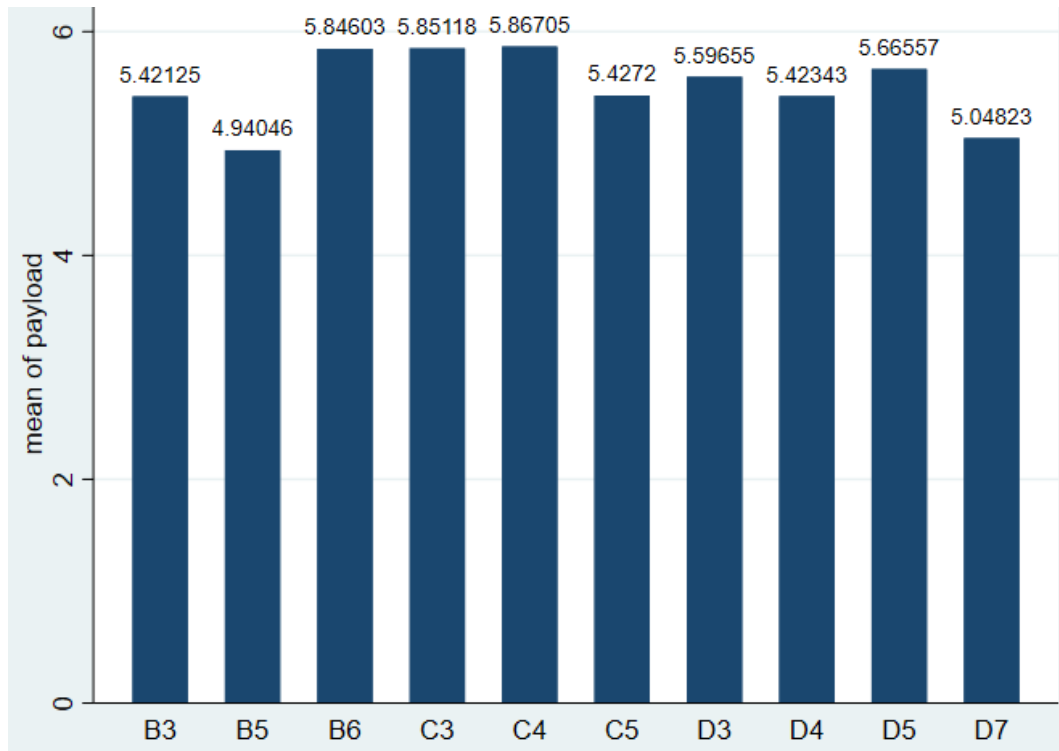


Figure 37: Mean payload per LHD

Figure 38 demonstrates a positive correlation between loading rate and efficiency. Machines with higher loading rates (B5, C5, D7) also exhibited higher efficiencies, indicating that faster loading contributes to improved overall productivity.

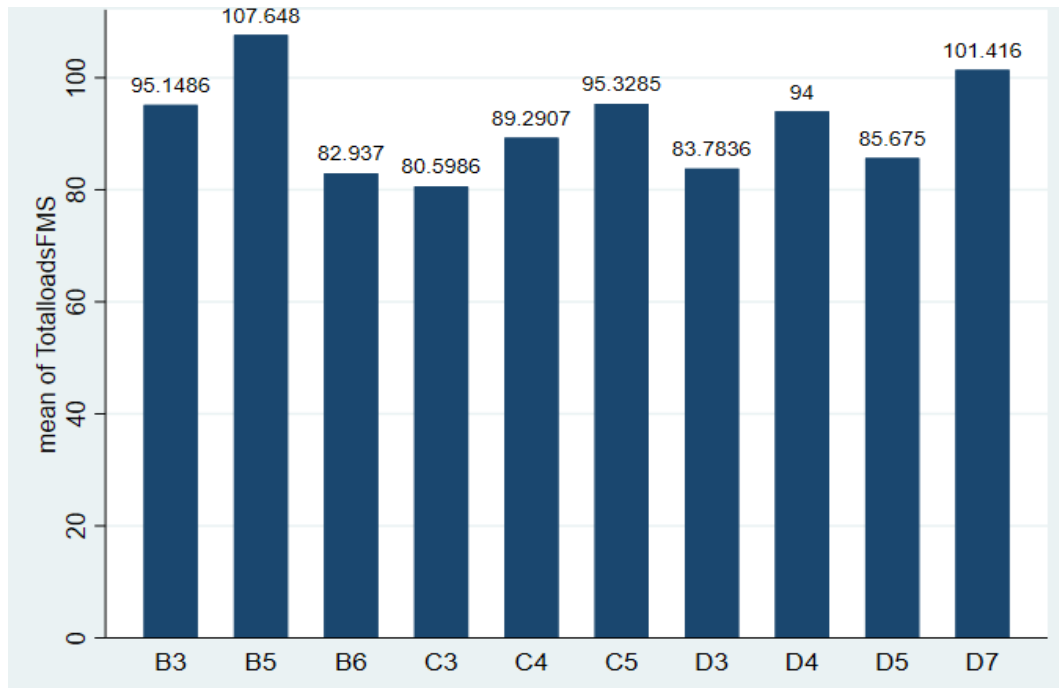


Figure 38: Mean loading rate per LHD per day

LHD machine efficiency can also serve as a proxy for operator efficiency, assuming other factors are held constant. Figure 39 shows how efficiency varied with each machine and its operator. Operator names and machines can be linked using the matrix shown in Table 25. This data can be utilised for targeted operator training and performance management initiatives, aiming to enhance productivity. The detailed information allows for the identification of best practices and areas for improvement.

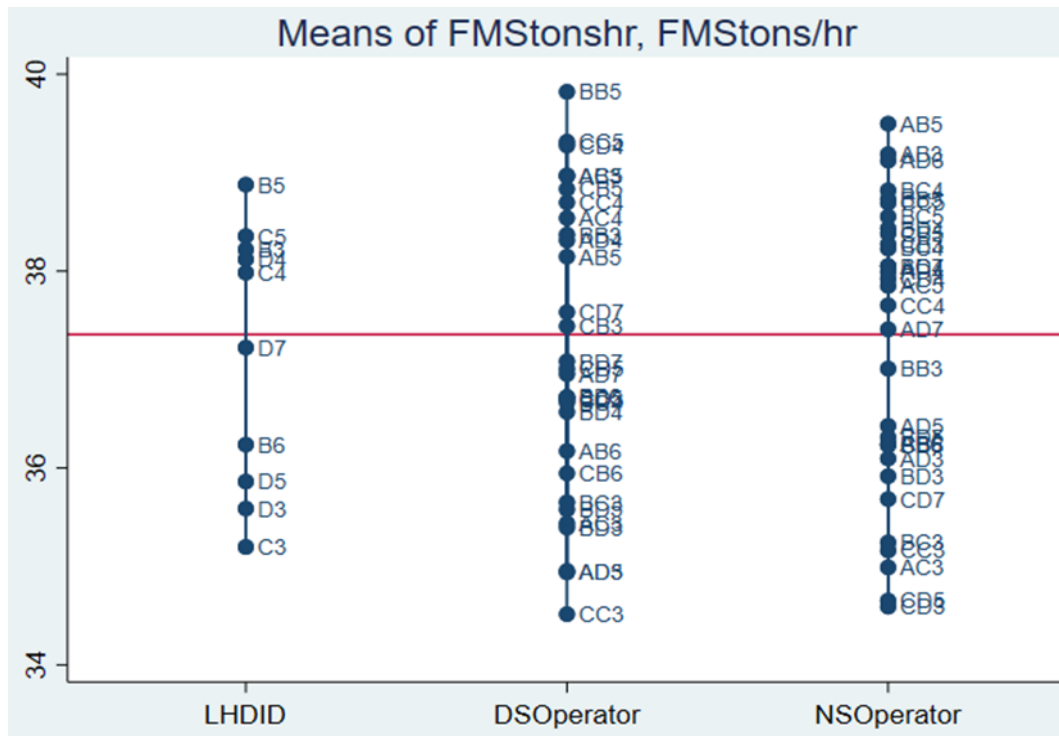


Figure 39: Mean productivity for each LHD and operator per shift

Table 25: LHD operator key

LHD sample ID	Operators		
B3	AB3	BB3	CB3
B5	AB5	BB5	CB5
B6	AB6	BB6	CB6
C3	AC3	BC3	CC3
C4	AC4	BC4	CC4
C5	AC5	BC5	CC5
D3	AD3	BD3	CD3
D4	AD4	BD4	CD4
D5	AD5	BD5	CD5
D7	AD7	BD7	CD7

Table 26 summarises the differences between the day and night shift daily production tonnage, operating time and productivity. The production tonnes moved, operating time, and productivity were higher in day shift than night shift. An average of 267t was moved in about 6.93 hours at a productivity

rate of 38.8 tph for the day shift. On the other hand, night shifts moved 237t on average within 6.61 hours, translating to a productivity rate of 36.04 tph.

Table 26: Summary of day and night shift productivity statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
DSFMStons	1,675	267.9468	71.66156	16.23513	527.1319
DShours	1,675	6.928207	1.33928	.3611111	8.899444
DSFMStonshr	1,675	38.8419	7.662314	9.379632	80.118
NSFMStons	1,675	237.1113	53.74526	29.08542	432.1544
NSFMShours	1,675	6.608925	.9044899	.6611111	8.058056
NSFMStonshr	1,675	36.04623	7.239288	16.08291	67.24083
SDSFMS ton~r	1,675	-2.795675	9.966023	-40.9004	31.84785

The productivity differences are further shown in the box and whisker plot in Figure 40. Day shift productivity is higher than night shift, with more outliers as well. The interquartile ranges are similar, with the day shift showing the higher values.

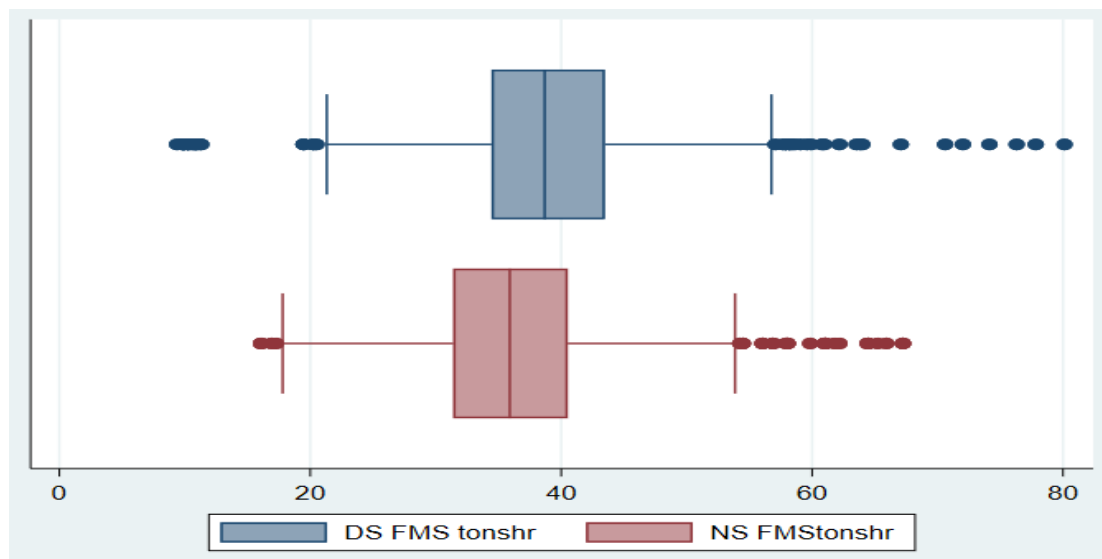


Figure 40: Box plot for day and night shift productivity

4.11 Correlation of Operational Factors

Figure 41 illustrates a correlation heatmap analysis. This matrix provides valuable insight into the statistical relationships between key operational variables influencing productivity and productive efficiency.

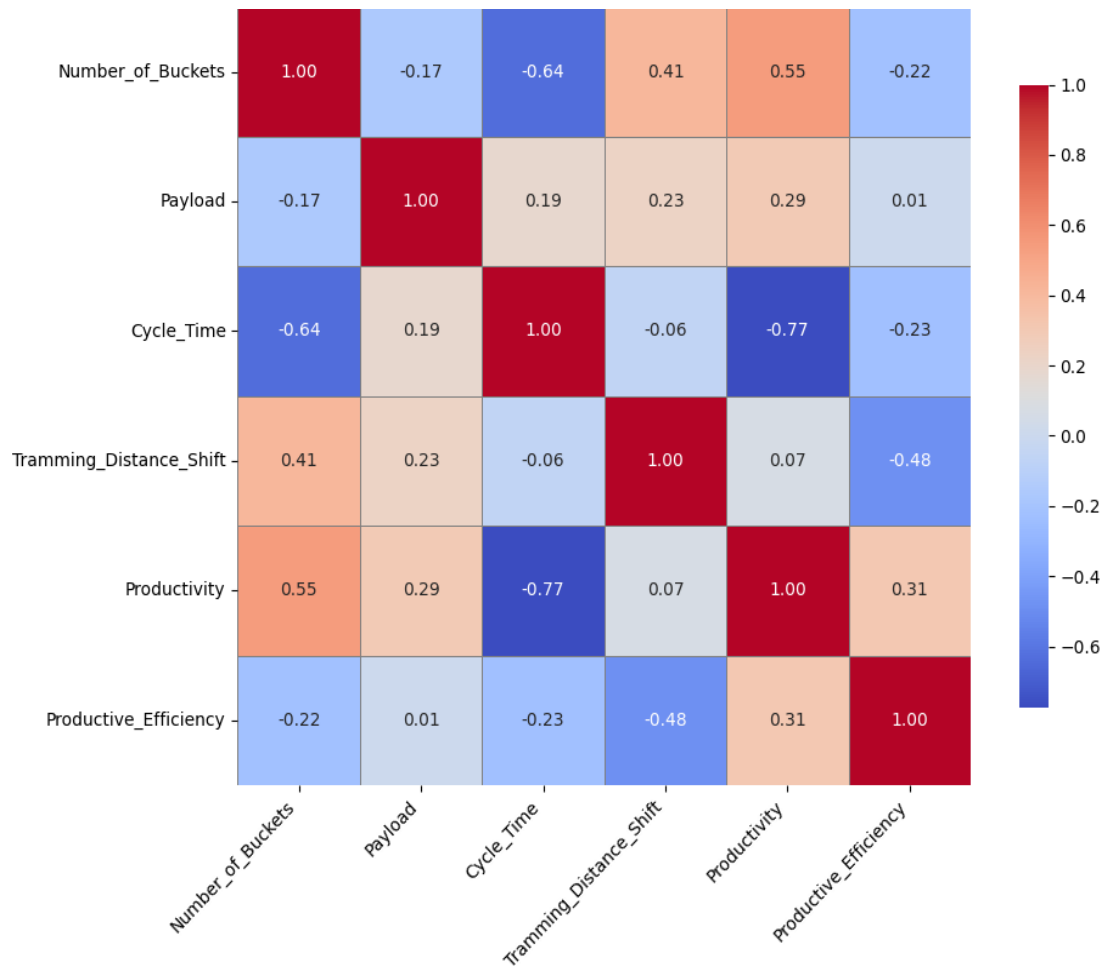


Figure 41: Correlation matrix heatmap of productivity factors

A strong negative correlation ($r = -0.77$) was observed between cycle time and productivity, suggesting that shorter cycle times are a key driver of improved performance. This relationship is reinforced by the operational findings in Figure 36, which showed that LHDs such as B5, C5, and D7 with the shortest cycle times also recorded the highest productive efficiency. This alignment between statistical and operational observations confirms the critical role of turnaround time in maximising production output.

Similarly, the number of buckets showed a moderate positive correlation ($r = 0.55$) with productivity, indicating that higher bucket counts are generally associated with more productive shifts. However, the relationship between payload and productivity was weaker ($r = 0.29$). This supports the earlier observation in Figure 37 that machines with lower payloads such as B5 can still achieve top performance. This suggests that while payload contributes to output, it is not the sole driver of productivity. Instead, how efficiently the payload is moved within each cycle matter more.

When the productive efficiency metric (tonnes per hour per kilometre) was analysed, there were additional insights. There was a moderate negative correlation ($r = -0.48$) between tramming distance and productive efficiency, showing that longer haul distances tend to reduce efficiency. This observation is consistent with Figure 35, where machines with shorter average tramming distances (B5, C5, D7) exhibited the highest efficiencies. The correlation between payload and productive efficiency was negligible ($r = 0.01$), again reinforcing that factors such as cycle time and travel distance outweigh payload figures in determining efficient operation.

A key enabler of this level of analysis is the FMS, which provided accurate, shift-level data on cycle time and tramming distance variables that are not measurable through manual systems. Manual tracking methods were limited to recording only the number of loads and payload estimates, which, as shown in the analysis, are insufficient for diagnosing the drivers of productive efficiency. Without the FMS, it would have been impossible to derive critical insights such as the strong inverse correlation between cycle time and productivity or the impact of tramming distance on efficiency. The FMS has therefore proven essential not only for real-time operational visibility but also for unlocking deeper performance analysis that can guide strategic improvements.

4.12 Reconciliation of Production Measurements (FMS vs Manual) with Weightometer Readings

The weightometer readings recorded at the conveyor belt were used as the baseline reference for evaluating the accuracy of different methods used to measure production tonnage as shown in Table 27. A comparison was conducted between the allocated weightometer figures and the tonnage recorded by both the manual tracking system and the digital FMS over the project period. The analysis aimed to assess the reliability and consistency of each method in capturing actual material movement.

Table 27 Total tonnage recorded by the FMS vs manual vs weightometer

LHD ID	Tonnage moved		Weightometer reconciliation (tonnes)	Percentage difference with tonnage reconciliation	
	Manual	FMS		Manual	FMS
B3	95,431	93,642	92,237	3.5	1.5
B5	110,894	108,075	105,913	4.7	2
B6	75,370	70,963	72,382	4.1	-2
C3	70,628	68,511	67,483	4.7	1.5
C4	91,615	93,189	94,587	-3.1	-1.5
C5	113,951	110,650	108,990	4.6	1.5
D3	69,990	65,650	66,634	5	-1.5
D4	109,001	106,129	104,537	4.3	1.5
D5	61,571	60,399	59,795	3	1
D7	107,149	101,572	102,588	4.4	-1

Overall, the manual system shows a wider deviation from the weightometer reading than the FMS. While differences with FMS range from 1 to 2%, corresponding manual figures range from 3 to 5 %. Therefore, the FMS is considered more accurate than the manual system in measuring production tonnages.

4.13 Cost-Benefit Analysis

This section presents the results of a cost-benefit analysis for the FMS system's impact on the performance of the LHD fleet, based on a trial involving 10 LHDs. The analysis investigates the financial effects of three desired minimum outcomes resulting from the system's implementation, which are:

- Reducing unplanned LHD breakdowns by 5%.
- Achieving a 2% improvement in diesel efficiency.
- Increasing LHD loading utilisation by 3%.

The goal is to quantify the expected benefits from these enhancements based on realistic production assumptions, while also factoring in the estimated annual implementation cost of US\$400,000. Table 28 outlines the assumptions, calculations, and the net financial benefit derived from the final scope of the initiative.

Table 28: Cost-benefit analysis of the FMS system

Component	Assumptions / Inputs	Calculation Steps
Breakdown Reduction (5%)	Loading hours = 10 LHDs × 15 hrs/day × 250 days = 37,500 hrs/year	Tonnage = 281.25 hrs × 23 tph = 6,468.75 t/year
	Breakdown rate = 37,500 hrs/year × 15% = 5,625 hrs/year	Metal (oz) = 6,468.75 t × 3.566 g/t × 79.2% = 18,269.51 g ÷ 31.104 g/oz = 587.34 oz
	Breakdown recovery = 5,625 hrs/year × 5% = 281.25 hrs	Revenue = 587.34 oz × \$1961,97 /oz = \$1,152,399.36
	Productivity = 23 tph	Cost = 587.34 oz × \$891.26/oz = \$523,498.04
	Grade = 3.566 g/t	Net Gain = \$ 1,152,399.36 - \$ 523,498.04 = \$628,901.32
	Recovery = 79.2%	
	Cost = \$891.26/oz	
Diesel Savings (2%)	Price (4E PGM) = \$1961,97 /oz	
	Tonnage hauled = 37,500 hrs per year × 23 tph = 862 500 t/year	Cost Saving = 21,562.50 l/year × \$1.29 /l = \$27,815.63
	Diesel cost per litre = \$1.29 /litres	
	Fuel efficiency = 0.8 t/litre	
	Diesel consumption = 862 500 t/year ÷ 0.8 t/litre = 1,078,125 l/year	
LHD Utilisation Gain (3%)	Diesel savings = 1,078,125 l/year × 2% = 21,562.50 l/year	
	Tonnage hauled = 37,500 hrs/year × 23 tph = 862,500 t/year	Metal (oz) = 25,875 t × 3.566 g/t × 79.2% = 73,078.04 g ÷ 31.104 g/oz = 2,349.47 oz

Component	Assumptions / Inputs	Calculation Steps
	Tonnage gains due to 3% utilisation increase = 862,500 t/year x 3% = 25,875 t	Revenue = 2,349.47 oz x \$1961,97 /oz = \$4,609,597.42
	Grade = 3.566 g/t	Cost = 2,349.47 oz x \$891.26/oz = \$2,093,992.16
	Recovery = 79.2%	Net Gain = \$4,609,597.42 - \$2,093,992.16 = \$2,093,992.16
	Cost = \$891.26/oz	
	Price (4E PGM) = \$1961,97 /oz	
Gross Total Benefit	Sum of all net gains	Net Gain = \$628 901.32 + \$27,815.63 + \$2,093,992.16 = \$2,750,709.10
Annual Implementation Cost	Fixed cost estimate = (\$400,000)	
Net Annual Benefit	Gross Benefit – Annual Cost	\$2,750,709.10 – \$400,000 = \$2, 350 709.10

As shown in Table 28, digitalisation is expected to deliver measurable improvements in equipment availability, utilisation, and operating costs. The baseline assumptions for this evaluation were informed by input from the Original Equipment Manufacturer (OEM), drawing on performance benchmarks from similar deployments at other mining operations. Projected gains in utilisation, fuel efficiency, and reduced breakdowns are grounded in the OEM's real-world experience across comparable sites. It is important to note that these anticipated gains will translate into actual financial benefits only if the additional tonnage is successfully hoisted, milled, processed, and ultimately sold. The assumption of increased hoisted tonnage is contingent upon the readiness and reliability of all upstream and downstream production processes to support the additional ore volumes.

The improvements from digitalisation are expected to be incremental, with full optimisation and value realisation projected to take a minimum of three years. The system's ability to deliver maximum benefit will depend on effective integration, operational maturity, and ongoing use of real-time monitoring and data analytics.

Beyond monetary returns, the system is also expected to enhance safety performance. By enabling machine-generated alerts for unsafe operating behaviour such as over speeding, FMS can play a key role in reinforcing safe work practices and reducing safety-related incidents.

4.14 Discussion

This section summarises the key findings from the data analysis concerning the research objectives. It also highlights practical opportunities for productivity improvement through the use of an FMS system.

4.14.1 Accuracy and limitations of the manual measurement system

The comparative results clearly demonstrate that the manual system overstates both production tonnage and operating time relative to the digital FMS. These discrepancies, analysed specifically in productivity measurements (tph) were found to be statistically significant and consistently biased. As a result, productivity calculated from manual records slightly underestimates actual performance. While the average variance in productivity appears small, its operational implications are significant, especially when multiplied across multiple LHD units and shifts. Statistical testing using Cliff's Delta revealed a small but consistent effect size ($\delta = 0.169$). This result indicates that in nearly 59% of the cases, productivity recorded by the FMS was higher than that of the manual system. Such consistency reinforces the practical value of FMS data for performance assessment.

Manual logs tend to inflate operating hours by overlooking idle time and delays, which distorts shift utilisation metrics and hampers the mine's ability to identify bottlenecks. In contrast, the FMS provides a granular, real-time view of machine activity, distinguishing clearly between productive and non-productive periods. This ability to isolate and measure downtime is critical for identifying hidden capacity and improving performance, a point strongly emphasised in the literature.

Likewise, the manual system's use of fixed bucket payload estimates leads to a systematic overstatement of tonnage moved. These static assumptions fail to reflect variability in loading conditions and introduce accumulating errors into shift reports and planning metrics. Over time, these inaccuracies complicate production reconciliation and undermine the reliability of manual tracking for performance monitoring.

While historical productivity norms at the mine have hovered around 34 tph, the study found that FMS-derived productivity values averaged between 36

and 37 tph. Furthermore, as shown in the cost-benefit analysis, a 3% uplift in productivity could yield a net annual gain exceeding US\$1.7 million. This supports a recommendation to adjust the productivity benchmark upward to 37 tph, aligning it with the mine's actual operational potential under digital monitoring.

In conclusion, while the manual system provides a general overview, it lacks the precision and completeness required for reliable performance management. The FMS system, by contrast, offers a robust platform for accurate benchmarking, early detection of inefficiencies, and targeted productivity improvements.

4.14.2 Impact of digitalisation on productivity

The introduction of FMS yielded two key benefits. First, productivity improved in absolute terms when FMS data was used as the primary measurement source. Manual productivity averaged 35.2 tph compared to 34 tph historically, likely due to the indirect influence of performance monitoring facilitated by the FMS. Meanwhile, productivity measured directly from FMS data was 36.1 tph, representing a notable improvement. Although causality cannot be established within this study's design, the alignment of higher values with the introduction of the system suggests a positive association.

Secondly, the FMS enabled the measurement of operational variables that were previously unrecorded, such as cycle time and tramming distance. These parameters proved critical in both understanding performance drivers and facilitating daily decision-making. For instance, excessive tramming distances can alert teams of misaligned tipping points and prompt corrective actions such as adjusting loading strategies. The ability to track and act on these variables in near-real time empowered operational personnel to address inefficiencies proactively.

Furthermore, awareness of being monitored on metrics such as cycle time and loading rate motivated operators toward better performance. This cultural shift towards accountability and transparency represents a key non-technical benefit of digitalisation and reinforces the system's broader role in continuous improvement.

4.14.3 Factors affecting productivity: Insights and implications

Among the operational variables examined, cycle time emerged as the most critical determinant of productivity. A strong negative correlation ($r = -0.77$) suggests that improvements in cycle time could explain up to 63% of the variance in productivity. Trimming distance also had a moderate negative effect on efficiency ($r = -0.48$), indicating that long hauls directly constrain performance. These findings confirm long-held industry assumptions, yet the availability of real-time FMS data now allows for quantification and continuous monitoring of these impacts. Optimising cycle time through improved fragmentation, haul road maintenance, and streamlined traffic flow can yield substantial productivity gains.

Payload showed only weak correlation with productivity ($r = 0.29$), suggesting diminishing returns from focusing on bucket filling alone. By contrast, loading rate showed a moderate positive relationship with productivity and offers a more actionable target for operator performance management. These correlations align with operational insights. For example, LHD B5, which had the shortest trimming distance and cycle time, also recorded the highest productive efficiency, despite having an average payload. This supports a shift in emphasis toward efficient material movement rather than only load volume.

4.14.4 Opportunities for productivity improvement

Several opportunities can be identified on improving productivity based on the research results. Initiatives to improve trimming distances can be

explored to improve productivity, with progress made measured at each step by an accurate system. Results show that most LHDs are operating above the mine planned one-way maximum tramming distance of 150m, which is in line with industry benchmarks. This shows that most tipping points are behind schedule in following mining progress. Studies need to be made on how to effectively close this gap and unlock a potential increase in productivity. It is recommended to create a taskforce involving personnel from planning, projects and production departments on how to address this challenge.

Cycle time proved to be the most critical factor affecting productivity. Initiatives to improve cycle time include operator training, proper haul road maintenance, haulage routes optimisation, improved fragmentation and good housekeeping. Haul roads need to be maintained clean and in good order to minimise delays due to uneven surfaces and road blockages. Tramming distances need to be optimised to minimise cycle times. Maintaining an optimum fragmentation that has good digability also optimises loading time, which further improves cycle time. It is recommended that the business improvement personnel at the mine activate targeted initiatives to optimise cycle time.

Payload, although it did not show much correlation with productivity is still important to be within reasonable ranges for maximisation of asset utilisation. Armed with this information, the monitoring and training of operators needs to be adjusted accordingly. Too much focus has been on filling buckets sometimes at the expense of the loading rate. The efficiency metrics derived from FMS can be used for LHD operators' performance management. Management can utilise these objective measures as KPIs for operators, which can be used for performance reviews and reward management. Strategies to motivate operators can thus be developed and implemented for productivity improvement.

5 CONCLUSION AND RECOMMENDATIONS

5.1 Summary

This chapter outlines the key conclusions that can be reached from the research findings as well as the corresponding recommendations.

5.2 Conclusions

The study established that the manual system is inaccurate for measuring production tonnes mined, LHD operating hours and ultimately productivity. It generates statistically different results from the more accurate FMS system and generally tends towards overestimation of both tonnage and operating hours. This creates challenges in monitoring as well as improving productivity. Adopting the FMS system can assist in removing such challenges and provide the operation with an efficient system capable of measuring productivity objectively. Accurate measurement of KPIs enables benchmarking and improvement of productivity based on objective data analysis.

The digital FMS demonstrated a significant influence in improving productivity. Even when measured by manual methods, the productivity showed a marked improvement ever since FMS was introduced. The productivity was higher than any historical milestones achieved. The use of FMS output in conducting review meetings and daily operational decision making could be attributed to this increase. Furthermore, effective change management and project management techniques may have contributed to the improvement.

Loading rate is moderately positively correlated with productivity and expected to influence it by about 24%. Trimming distance and cycle time show moderate to significant negative correlation with productivity. Cycle time had the most significant relationship, which contributes to about 59%

of productivity variations. Payload, on the other hand has little or no correlation with productivity.

Analysis of these relationships leads to the generation of several productivity initiatives. Proper haul road maintenance, optimised haul routes and optimum tramming distances can be explored further as initiatives to improve cycle time, and ultimately productivity. Objective statistics can be utilised for more effective KPI monitoring and operator performance management. Findings from the study can further be utilised to train, coach and motivate operators for realisation of improved productivity outcomes.

5.3 Recommendations

It is recommended that the FMS system be adopted for all LHDs for more effective tracking and improvement of productivity. Adopting this system will eliminate bias and inaccuracy challenges being experienced as a result of the inefficient manual system in place. It is also recommended that this system be further modified to be capable of providing real-time data. It is expected that real-time data will amplify benefits to be derived from this system and boost competitiveness of the operation.

The study also recommends the setting up of a productivity improvement taskforce to analyse and implement possible improvement initiatives derived from FMS data. A holistic approach is recommended in improving LHD productivity. Initiatives range from administrative controls, operational improvements, strategic and tactical planning and optimising factors influencing productivity. There is a need for the tramming distances at the mine to be significantly reduced and operator coaching to further improve cycle times. Targets need to be set and progressively measured using the FMS system until tangible improvement is realized. It is recommended to maintain tramming distances between 90 and 150m for optimum productivity.

Further study is also recommended to determine cause and effect relationships on the ore movement process. LHD operation is a multi-variate process that needs experimental studies to be done to determine causality. The FMS system can easily be used to achieve this due to its objective measurement capability. It is also recommended to explore operational improvement tactics such as the Theory of Constraints and DMAIC methodologies for productivity improvement using FMS. These approaches have been proven to be successful in improving productivity and will be aided greatly through the FMS.

It is also recommended to develop a system capable of digital measurement on all TMM. To obtain maximum benefits, installing FMS monitoring on other related processes such as drilling and rock support is recommended. This will enable accurate data collection not only for one part of the production process but for all the process cycles. Collection of such vast data, coupled with proper analysis techniques, will enable further application of process improvement approaches and technologies. Getting this data in real time will enable timely decision making which results in operational optimisation. This data can be a stepping-stone to automation, which will further improve productivity. Data mining and machine learning techniques can be applied on the collected vast data to derive previously unknown insights about the operation that can improve productivity. Ultimately, this approach is expected to improve productivity and ultimately competitiveness of the business.

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