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UNIVERSITY OF THE
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JOHANNESBURG

A COST-BENEFIT ANALYSIS OF TRANSITING TO FULL AUTONOMOUS SURFACE MINING MACHINES IN THE MINING INDUSTRY

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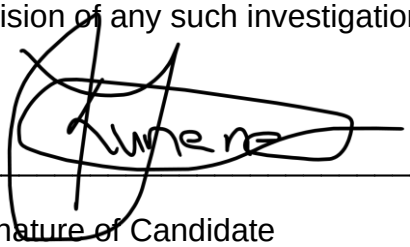
Supervisor: Prof. Glen Nwaila

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DECLARATION

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Abstract

The mining industry has continued to evolve and adopt necessary changes due to emerging digital technologies and automation. As a result, such an analysis has yet to be presented in the literature. This research project evaluates the anticipated costs and gains of adopting autonomous surface mining systems. It emphasises the extent of labour costs that may be saved, net production efficiency, and the payback period. This work employs case studies, statistical finance data, and cost curves to investigate the economic and functional parameters of the common, moving, cross-section autonomous mining complex. The results show that Autonomous Mining Systems (Dayo-Olupona et al., 2023) technology would allow efficiency increases and significant labour cost savings of over 60%, as there will be few employees on site, persons waiting for machines will not be idle, and machines will have less unproductive time. The Model-Based Maintenance (MBM) features of AMS significantly improve the working conditions of the machines, ensuring minimum idle time of the equipment while cutting costs by 15 to 20% of the maintenance costs, extending the lifetime of the machines. Integrating autonomous systems enhances production rates, decreasing unit costs to a low of US$20-US$30 at West Angelas and Hope Downs within twenty-four months after installation. This achieves a high level of production that reduces costs even further and makes returns on investment quicker.

There are, however, drawbacks to achieving complete implementation of autonomous mining technology, such as timeline, operation capital expenditure, expansion/equipment modification, and sociological worker redundancy. There are difficulties that have been found in the research as constraints, which could be resolved using Integrated and Intelligent Remote Operation Centres (I2ROCs) to enhance interactions between Information Technology (IT) and Operational technology for better decision-making and monitoring of systems. The initiatives are concerned with operationalising distributed control of various sites with automation in the mining industry, explicitly improving work health and safety outcomes. The present research project highlights the important initiatives that mining companies should adopt in recommending the introduction of autonomous systems while trying to contain any negative impact this development would otherwise have on the industry, the economy, and society. Lastly, in the future,

more levels of detail should be added to the models that allow coping with such processes as task distribution by Artificial Intelligence (AI), learning, and management of self-operating mining systems based on sensors and automatic control systems for cost management and performance enhancement.

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Thank you to my mother for guidance and support. Ever since, you have been my lodestar. Your prayers have been intervened in pleasant blindness for this. Love you again.

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Table of Contents

DECLARATION i

Abstract ii

Acknowledgements iv

List of Figures viii

List of Tables xi

List of Abbreviations xii

CHAPTER 1 1

1 Introduction 1

1.1 Background 1

1.2 Purpose of the Research Project 3

1.3 Problem Statement 4

1.4 Aim 5

1.5 Hypothesis 5

1.6 Research Objectives 5

CHAPTER 2 7

2 Literature review 7

2.1 Introduction 7

2.2 Challenges in Transitioning from Traditional Machines to Autonomous Machines in Surface Mining 9

2.3 Cost-Benefit with Semi-Autonomous Operations 10

2.3.1 Enhancing Maintenance Practices Through Predictive Maintenance 13

2.4 Machine Learning Approaches for Predictive Maintenance 14

2.4.1 Factors Influencing Machine Learning Model Selection for Predictive Maintenance Tasks 16

2.5 Innovations and Area Application of Predictive Maintenance in the Mineral Industry 18

2.5.1 Deterioration, diagnostic analysis, and prognostic assessments 18

2.6 Maintenance strategies for cost-benefit analysis of heavy equipment 19

2.6.1 Costs effective strategies 21

2.6.2 The strategy of preventive maintenance 21

2.6.3 Corrective maintenance 21

2.6.4 Condition-based maintenance 22

CHAPTER 3 23

3 Methodology 23

3.1 Introduction 23

3.2 Traditional Mining Data Analysis 23

3.2.1 Dump trucks ineffective time. 23

3.2.2 Shovel Ineffective Time 30

3.2.3 Inefficiencies in traditional mining 36

3.3 Equipment Maintenance Key Performance Indicators (KPI) Using Traditional Mining 37

3.4 Case Study 39

3.4.1 Rio Tinto's autonomous haul trucks 39

3.5 Integration of Machine Learning 40

3.5.1 Cascadia high precision Instrumentation 43

3.5.2 Benefits of using machine learning algorithms as opposed to traditional methods. 44

3.6 Industry Cost Curve Algorithm Development 47

CHAPTER 4 49

4 Findings 49

4.1 Labour Cost Saving with Autonomous Surface Machines 49

4.2 Industry Cost Curve Post Implementation of Autonomous Trucks 50

4.3 Machine learning and artificial intelligence on condition-based monitoring 71

CHAPTER 5 78
5 Discussion 78
CHAPTER 6 81
6 Conclusion and Recommendations 81
6.1 Conclusion.....81
6.2 Recommendations.....82
7 REFERENCES 84
8 Appendix 1: Supplementary files 91
9 Appendix 2: Supplementary Files 97

List of Figures

Figure 1. Benefits of using autonomous machines(Golbasi and Dagdelen, 2017). 11

Figure 2. Predictive maintenance chart. (Xia et al., 2022) 13

Figure 3. CRISP-DM framework (Sheuly et al., 2021) 15

Figure 4. Statistical-based and ML-based approaches for PdM (Sheuly et al., 2021). 17

Figure 5. Maintenance strategies analysis based on cost-benefit (Coble, 2010).20

Figure 6. Ineffective time waterfall study for the first quarter of the CAT777G dump trucks. 24

Figure 7. Pareto analysis for the first quarter for standby dump trucks. 25

Figure 8. Ineffective time waterfall study for the second quarter of the CAT777G dump trucks. 25

Figure 9. Pareto analysis for the second quarter for standby dump trucks. 26

Figure 10. Ineffective time waterfall study for the third quarter of the CAT777G dump trucks. 27

Figure 11. Pareto analysis for the third quarter for standby dump trucks. 28

Figure 12. Ineffective time waterfall study for the fourth quarter of the CAT777G dump trucks. 29

Figure 13. Pareto analysis for the fourth quarter for standby dump trucks. 30

Figure 14. Ineffective time waterfall study for the first quarter of the shovels. 31

Figure 15. Pareto analysis for the first quarter for standby shovels. 32

Figure 16 Ineffective time waterfall study for the second quarter of the shovels. 32

Figure 17. Pareto analysis for the second quarter for standby shovels. 33

Figure 18. Ineffective time waterfall study for the third quarter of the shovels. 34

Figure 19. Pareto analysis for the third quarter for standby shovels. 34

Figure 20. Ineffective time waterfall study for the fourth quarter of the shovels. ..35

Figure 21. Pareto analysis for the fourth quarter for standby shovels. 36
Figure 22. Cascadia Scientific approach data pipeline (Hernandez, 2022). 41
Figure 23. Productivity mapping of the dump trucks (Hernandez, 2022). 42
Figure 24. Heat map for road improvement analysis (Hernandez, 2022). 43
Figure 25. High-precision instrumentation (Hernandez, 2022). 43
Figure 26. Linear regression graph display (Shin and Yoon, 2020).....45
Figure 27. Gradient-boosted trees (Sahour et al., 2020). 46
Figure 28 Visuals of the complete cost curve. 48
Figure 29. Standby hours (No operator) for traditional mining operations in 2023. 49
Figure 30. Iron ore prices from 2000 to 2023 (Statista, 2024) 50
Figure 31. Iron ore mines cost curve 2010. 52
Figure 32. Iron ore mines cost curve 2011. 55
Figure 33. Iron ore mines cost curve 2012. 57
Figure 34. Iron ore mines cost curve 2013. 58
Figure 35 Iron ore mines cost curve 2014. 59
Figure 36. Iron ore mines cost curve 2015. 60
Figure 37. Iron ore mines cost curve 2016. 61
Figure 38. Iron ore mines cost curve 2017. 62
Figure 39. Iron ore mines cost curve 2018. 63
Figure 40. Iron ore mines cost curve 2019. 65
Figure 41. Iron ore mines cost curve 2020. 66
Figure 42. Iron ore mines cost curve 2021. 67
Figure 43. Iron ore mines cost curve 2022. 68
Figure 44. Iron ore mines cost curve 2023. 69
Figure 45 Condition monitoring oil pressure. 72
Figure 46. Feed temperature condition-based monitoring. 74
Figure 47. Return temperature condition-based monitoring. 75

Figure 48. Coolant temperature condition monitoring.....76

Figure 49. Booster pressure condition monitoring. 77

List of Tables

Table 1. The current implementation of autonomous trucks in operating mines (Parreira, 2013) 8

Table 2. Shovel equipment maintenance KPI using traditional mining (Workforce).....37

Table 3. Dump trucks equipment maintenance KPIs using traditional mining (Workforce).....38

Table 4. Steps to follow to train ML Models (Hernandez, 2022). 45

Table 5. Data input for the cost curve development. 47

Table 6. Data input description (Tholana, 2012).....47

Table 7. Iron Ore Mines Implemented Autonomous Trucks. 51

Table 8 Equipment health variables for dump trucks.....71

Table 9. Causes of abnormal oil pressure readings. 73

Table 10. Oil pressure condition monitoring. 73

List of Abbreviations

Parameters

AHS	Autonomous Haulage System
AI	Artificial Intelligence
AMS	Autonomous Mining Systems
BHP	Broken Hill Proprietary
ºC	Degree Celsius
CAN Bus	Controller Area Network Bus
CAGR	Compound Annual Growth Rate
CBM	Condition-based monitoring
CDL	Common Data Link
CM	Corrective Maintenance
CRISP-DM	Cross-Industry Standard Process for Data Mining
DAS	Data Acquisition System
DOH	Direct Operating Hours
DL	Direct Labour
DT	Dump Truck
ELT	Expected Learning Time
FMG	Fortescue Metals Group
GBT	Gradient Boosted Trees
GCI	Grid Convergence Index
GDP	Gross Domestic Product
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IIoT	Industrial Internet of Things
IoT	Internet of Things

IT	Information Technology
OP	Operational Technology
KPI	Key Performance Indicators
LRU	Line Replaceable Unit
M2M	Machine-to-machine
O.M	Operating and Maintenance Costs
S.B	Standby Cost
MBM	Model-Based Maintenance
ML	Machine Learning
MTBF	Mean Time Between Failure
MTTR	Mean Time to Repair
OP	Operational Technology
PdM	Predictive Maintenance
PLM	Product Lifecycle Management
PM	Predictive Maintenance
RTDs	Resistance Temperature Detectors
RTV	Real-Time Visibility
RUL	Remaining Useful Life
VF	Variable Frequency
VIMS	Vital Information Management System

CHAPTER 1

1 Introduction

1.1 Background

The performance of the equipment fleet is the main factor controlling the mine's operating expenses and production rate (Moradi Afrapoli and Askari-Nasab, 2019). The operability and efficiency of individual equipment, its role within a fleet, and dependencies among equipment, whether mutually inclusive or exclusive, impact the unit extraction cost of ore and overburden (Gölbaşı and Dagdelen, 2017). The operating cost of an equipment fleet typically constitutes a significant portion of the total operating cost in a mine. Chaowasakoo et al. (2017) stated that equipment operating costs include time-dependent expenses such as fuel and tyre consumption, spare parts and lubricants costs, maintenance crew wages, auxiliary tools, and more. Maintenance expenditures alone contribute to a substantial portion, around 40-50%, of the total operating cost of equipment (Gölbaşı and Dagdelen, 2017).

The equipment ages and the working components can deteriorate, leading to increased failure frequency and decreased availability (Alaswad and Xiang, 2017). The above stipulated can result in higher fuel consumption, maintenance expenditures, and production losses (Yahya et al., 2021). When equipment shows signs of wear and tear, scheduled maintenance is implemented as a proactive approach to address the natural wear and tear of equipment over time. As machines age, their components are more prone to failure, compromising their performance, efficiency, and reliability. Options considered for equipment repairs include complete overhauling, replacement with a new one, or purchasing a new one while keeping the old one (Shehadeh et al., 2021).

Mine managers often rely on subjective decision-making for maintenance due to the following factors (Ali, 2008): Limited access to comprehensive data hinders their ability to make fully informed, objective choices, leading them to depend on manufacturer recommendations, which are often based on average operating conditions and may not suit site-specific challenges. Unique mine conditions, such as varying ore hardness or climate, require tailored adjustments that rely heavily on the manager's experience. Managers use rough estimations and historical patterns to guide decisions without

advanced predictive maintenance tools or real-time monitoring systems. Additionally, the pressure to minimise downtime and control costs forces managers to prioritise immediate operational needs, often at the expense of long-term optimisation. Puronaho (2024) highlighted the need for more data-driven approaches to improve decision-making.

Dynamic factors can further complicate the equipment replacement problem throughout the mine's life. These factors include repetitive and multi-equipment replacements, periodic production target changes, and mine road profile variations (Abbasli and Mammadli, 2020). With the advent of automation technology, the option of autonomous operation is considered in equipment replacement decisions. Since transitioning from manual to autonomous operations can revolutionise a company's mining culture, this decision may go beyond the scope of a classical equipment replacement problem.

Autonomous mining operations began in the 1960s (Humphreys, 2020). Initially, the focus was on underground mines, with the primary motivation being safety. Over the years, other factors such as competition with other mining companies, increased production demand, economic extractability of low-grade ore, and the need to improve equipment productivity and reduce operational costs have driven mining companies to explore autonomous operations in underground and surface mines (Nwaila et al., 2022). In recent decades, various types of autonomous systems, including telerobotic, semi-autonomous, and full-autonomous, have been developed for mining activities, creating a competitive market in the industry (Gölbaşı and Dagdelen, 2017).

Autonomous off-highway trucks have gained significant popularity and market share among mining equipment. Initial reports from mines implementing autonomous trucks have shown increased productivity by 15-20% compared to manual truck operations (Walker, 2014). As trucks play an important role in surface mine operations and account for a significant portion of the total equipment operating costs, improved truck productivity can result in substantial cost savings for mining companies. Real-world data from mines also show that autonomous trucks have reduced tyre and fuel consumption per unit metric tonne of production and employee costs (Engholm et al., 2020).

Given these promising results, medium to large-scale surface mines are expected to consider autonomous trucks a viable option. Decisions about deploying autonomous trucks and drills are involved during the project feasibility phase of new mines or in

planning the remaining mine life in ongoing mining operations (Noriega and Pourrahimian, 2022). Such decisions require a long-term financial validation process that considers cost constraints, required truck capacities and numbers, changes in equipment performance due to ageing, fluctuations in haul road profiles, and time-dependent variations in production targets. The correlation among these factors may differ significantly between manual and autonomous primary mining machines.

Despite the increasing market share of autonomous machines on the surface, literature providing quantitative tools for investment validation and decision-making for the mining industry is limited (Singh et al., 2021). The research project presents a roadmap for the comparative evaluation of autonomous and manual machines in operations by integrating periodic variations in mining conditions and production targets into its methodology. The research project also presents the concept of equipment replacement and its mining applications.

1.2 Purpose of the Research Project

This research aimed to evaluate the cost-benefit impact of implementing autonomous mining technology in reducing operating expenses (OPEX) within mining operations. The study aimed to analyse how autonomous equipment enhanced efficiency, optimised operations, and increased productivity, resulting in lower maintenance and labour costs, improved safety, and reduced resource wastage. Examining the long-term savings and operational benefits, the research determined the viability of adopting autonomous technology in mining. It also explored the potential for improved accuracy, consistent production, and waste reduction, positioning autonomous systems as a transformative solution for sustainable and cost-effective mining practices.

The benefits of using autonomous mining technology to reduce OPEX in mining operations include the following:

(a) Increased Efficiency,

(b) Optimise mining operations,

(c) Increased productivity,

(d) Leading to more efficient use of resources and

(e) Lower OPEX.

For example, autonomous trucks can operate around the clock, reducing the need for human operators and increasing the number of loads hauled daily (Sánchez and Hartlieb, 2020). Mining can be a hazardous industry, and autonomous technology can help reduce the risk of accidents and injuries by eliminating the need for human operators in potentially dangerous situations, resulting in improved safety. For example, autonomous mining equipment can operate in areas unsafe for human operators, such as unstable or confined spaces (Molaei et al., 2020).

Autonomous mining equipment is designed to operate more efficiently and with fewer breakdowns than traditional mining equipment, reducing the need for maintenance and repair (Rogers et al., 2019). The output will be lower maintenance costs and reduced downtime, improving overall operational efficiency and reducing OPEX. Lower labour costs: Autonomous mining technology reduces the need for human operators, leading to lower labour costs (Rogers et al., 2019). The initial investment in autonomous mining technology can be high, and the long-term savings from lowered labour expenses can be considerable (Groshen et al., 2019). Autonomous mining technology can improve accuracy and precision in mining operations, leading to more consistent and predictable production (Matysek and Fisher, 2016)—waste reduction and overall efficiency, reducing OPEX. Overall, autonomous mining technology can lead to significant cost savings and operational improvements in mining operations, making it an attractive option for companies looking to reduce OPEX and improve their bottom line.

1.3 Problem Statement

Traditional mining involves manual labour, heavy machinery, and equipment requiring skilled operators (Lööw et al., 2019). The cost of labour, equipment, and maintenance is high. Business-wise, this extends the time needed to recoup initial investments (Knights and Yeates, 2019). In contrast, autonomous mining involves using advanced technologies such as robotics, machine learning (Shehadeh et al.), and artificial intelligence (AI) to operate mining equipment (Ali and Rehman, 2020). Autonomous mining will reduce labour costs and increase operational efficiency, as the machines can work continuously without needing breaks or rest periods (Goel and Gupta, 2020). The faster the positive return on investment (Sjödin et al., 2020).

1.4 Aim

This research project aims to investigate and quantify the potential cost reduction and production output benefits of implementing completely autonomous machines in mining operations. The focus is on reducing operational costs in areas such as labour and maintenance and improving production efficiency. Early return on investment (ROI) is the second but equally important focus.

1.5 Hypothesis

Autonomous mining systems can significantly improve efficiency, safety, and sustainability. They can also help prevent accidents and injuries while reducing operational costs and increasing productivity, as they eliminate the need for humans to perform in dangerous areas or conduct repetitive tasks. Autonomous mining systems are designed to optimise resource extraction, reduce environmental impacts, and improve overall mining performance. Therefore, investing in and developing autonomous mining technology will benefit the mining industry and have a positive return on investment.

1.6 Research Objectives

The following objectives were considered to achieve the aim and assess the hypothesis of this study.

- Evaluate the impact of autonomous machines on labour costs in mining operations, including the reduction in workforce required for manual machines in operations and associated labour expenses.
- Assess the potential savings in maintenance costs through autonomous machines, including the impact on equipment lifespan, maintenance schedules, and repair expenses.
- Investigate the impact of autonomous machines in operations on production output, including the potential for early ROI through increased productivity.

This chapter introduced the context and significance of autonomous mining technology in reducing OPEX and improving efficiency in mining operations. The research report is structured to comprehensively address the problem statement, research aim, and objectives. Chapter Two will present a detailed literature review, exploring existing

studies and technological advancements in autonomous mining. Chapter Three outlines the research methodology employed to evaluate autonomous systems' economic and operational impacts in surface mining. This study's research question is: Can implementing autonomous mining systems significantly reduce OPEX while improving safety, productivity, and return on investment in mining operations? This foundational chapter establishes the need for the research and sets the stage for the subsequent analysis of autonomous mining technologies and their transformative potential.

CHAPTER 2

2 Literature review

2.1 Introduction

The development and deployment of autonomous mining systems have gained significant attention in countries like Australia, Canada, Chile, and the United States of America to enhance mine productivity, safety, and efficiency (Kansake et al., 2019). The adoption of AMS has also been associated with social challenges, including job losses. The literature review explores the current state of knowledge regarding AMS, focusing on its potential benefits, limitations, and impact on the workforce and society. Existing frontiers of technological advancement in surface mining include current frontiers of technological advancement, which are increasingly shaped by the integration of automation, artificial intelligence (AI), and machine learning systems. These technologies have enhanced various aspects of mining operations, including mineral exploration, equipment operations, and safety improvements. Autonomous haul trucks are already in use, significantly improving efficiency and safety in surface mining operations. Machine learning algorithms are applied to optimise equipment usage, process automation, and even predictive maintenance, ensuring better performance in real-time mining operations (Ali and Frimpong, 2020). The focus is on creating intelligent systems capable of autonomous decision-making and interaction with complex environments, ultimately leading to safer, more efficient, and sustainable mining operations.

The mining industry has already primarily incorporated disruptive technology. For instance, advanced monitoring systems, according to Caterpillar (1999), real-time monitoring for equipment performance. Hexagon's Guardvant for fatigue monitoring and prevention of machine-to-machine (M2M) collisions are commonly used in the mines. Although complete autonomous mining has not been implemented yet, this research project will examine the transition from conventional to autonomous mining in detail. Rio Tinto visualisation uses a 3D gaming engine to facilitate a comprehensive view of their operations (Rio Tinto, 2019). Using this tool, they can soar above a site and dig into specific details required for their operations. It allows them to hover above

an excavator, track a haul truck, or scrutinise an orebody. The software integrates various aspects such as geology, geotechnical data, drill and blast information, production, and planning and presents a visual representation of surface and sub-surface features. An autonomous truck combines wireless communication, navigation, obstacle detection sensors, onboard sensor data processing hardware, dedicated movement actions, GPS for location tracking, and advanced local and supervisory control software (Parreira, 2013). Table 1 lists mining companies that have implemented autonomous dump trucks.

Table 1. The current implementation of autonomous trucks in operating mines (Parreira, 2013)

Start year	Mining company	Mine Site	Location	Manufacture	Truck Type	Capacity (metric tonnes)	Number
2008	Codelco	Gabriela	Chile	Komatsu	930E-AT	320	17
2008	Rio Tinto	West Angelas	Australia	Komatsu	930E-AT	320	5
2011	BHP	Navajo Mine	New Mexico	Caterpillar	Cat 793F	250	3
2012	Rio Tinto	Yandicoogina	Australia	Komatsu	930E-AT	320	22
2012	Rio Tinto	Hope Downs	Australia	Komatsu	930E-AT	320	19
2012	Fortescue	Solomon	Australia	Caterpillar	Cat 793F	250	54
2013	Rio Tinto	Nammuldi	Australia	Komatsu	930E-AT	320	30
2014	BHP	Jimblebar	Australia	Caterpillar	Cat 793F	250	18

Autonomous dump trucks have also been put to operational use in their company. Rio-Tinto Ltd is an Australian company engaged in mining and exploration activities. Autonomous dump trucks are used in construction activities at mining sites, listed in Table 1. BHP Billiton is a global mining company with various coal mines in different countries that have deployed autonomous haulers at the Navajo Mine in the US, Jimblebar in Australia, and Fortescue Metals Group. Fortescue Metals Group is an Australian mining company in iron ore extraction (Clout and Rowley, 2010). The company has also deployed autonomous dump trucks at its Solomon mine site. The information presented is based on data available as of September 30, 2021, and subsequent developments in autonomous mining technology have occurred since then.

Rio Tinto has ramped up its use of autonomous drilling machines at its Pilbara mines in Western Australia, adding a further nine machines to the existing ones to be twenty. The high technology allows an operator to control four autonomous or drilling rigs, which are operated at the same time within a single console from remote control.

Turner (2023) notes that the extraordinary results produced by the autonomous drilling systems of Rio Tinto have forced the company to take additional action. Recently, Rio Tinto upgraded a second set of four additional drills with autonomous drilling system technology at its Yandicoogina mine and the already seven at West Angelas. They want to be able to integrate nine more rigs by the end of the year, which shows how determined they are to move towards this significant technological edge (Arwoko et al., 2023).

2.2 Challenges in Transitioning from Traditional Machines to Autonomous Machines in Surface Mining

In a recent engineering white research project by the World Economic Forum, it is claimed that the mining and metals sector is comparatively low on the digital front compared to other industries, particularly those with high customer interfaces Forum (Forum, 2017). Since most activities occur in distant places, it is costly to move people. The problem has become worse of late because the metals or minerals encountered are smaller than what used to be the norm, and the active mine may not be worth the investment to build more houses. To deal with this situation, the progress of automation of field robotics is considered important (Nebot, 2007).

Konyukh (2002) observed that the integration of machine learning into open-pit mining proceeded steadily due to the existing industry culture and diverse cost-benefit ratios compared to underground mining. For surface mining, it felt that there was little room for further improvement, in this case, because a large pool of manpower was readily available that could easily accomplish the tasks by hand. Previously, the low labour cost meant little incentive to invest in sophisticated technologies. The activities or tasks required for surface mining could be completed with simple mechanised equipment and human supervision, decreasing the necessity for automation. In contrast, underground mining was pursued in more challenging and dangerous circumstances, which prompted the search for cutting-edge equipment to make operations easier and safer. Consequently, the mining industry's priority was more on hiring than on technology, derailing surface mining to utilise modern technologies like machine learning.

Recent pressures on costs, including increased fuel and labour costs, have changed the mode of operation in open-pit mines. Alarie and Gamache (2002) emphasised the effective automation of open-pit mining as it has challenges, such as the complexity of

the environment, including more enormous machines, the free will of machines without walls, and multiple objects within the same working space. Open pits are not static, and the weather changes occasionally, affecting the road leading to these machines and the machines themselves.

Barriers hindered productivity during the Fourth Industrial Revolution (4IR) advancement era. As a result, mining companies have considered applying automation technology for efficient operation in open-pit mining (Hongoro, 2021). There are other operations in the open-pit mining scope. Haul truck operations are, for now, the most conspicuous of all operations that involve automation, and for a good reason: these are machines that use constructed roadways, which do not change for a long-time duration; these machines take the same route from the point of extracting ore to a dumping area. Still, there is the issue of transferring the technology designed for underground operations into open pit operations, which is by no means a more manageable task and comes with technological challenges that must be overcome.

2.3 Cost-Benefit with Semi-Autonomous Operations

Mining companies like Rio Tinto, Glencore, and BHP have embraced autonomous machines to enhance their operations' productivity, safety, and cost-efficiency. According to Mulroy (2019), Rio Tinto's Pilbara iron ore operations in Australia have established the mining industry's most extensive fleet of driverless trucks. Their Autonomous Haulage System (AHS) comprises 130 dump trucks controlled from the Operations Centre in Perth, situated 1500km from the mine. Since 2018, this fleet has successfully transported over one billion metric tonnes of ore, using advanced global positioning system (GPS) technology for seamless coordination of the vehicles. According to (Golbasi and Dagdelen, 2017), the percentage of autonomous trucks in the company's entire truck fleet saw a significant increase from 9.2 per cent in 2014 to

17 per cent in 2015. The anticipated financial and operational advantages of autonomous trucks over manual ones can be summarised in Figure 1.

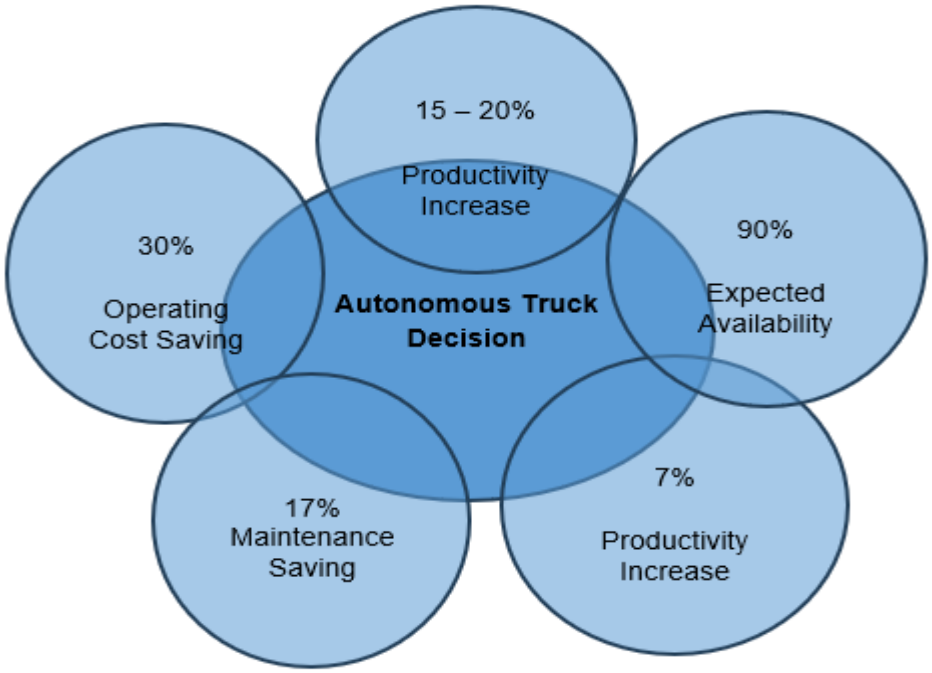


Figure 1. Benefits of using autonomous machines(Golbasi and Dagdelen, 2017).

The research project has examined the idea of complete autonomous surface mining as the detour of the activity in the future, claiming that economically, it has advantages and resolves the pain of change from crewed operations to driverless areas. In a systematic literature review, the author outlined the importance and prevalent use of novel technologies for autonomous mining and their potential benefits regarding operational efficiency and safety. The application of machine learning models along with artificial intelligence is emerging as one of the defining factors enhancing the automation of mining activities. Such advancement cannot be avoided when stakeholders stay aloof from such progress and situations change profoundly. Limited research focuses on unlocking the power of fully autonomous surface mining. A way can be paved for more sustainability, efficiency, and cost reduction in the mining industry in the future.

Markets and Markets (2017) stated that the mining industry's future market for mining automation was expected to reach US$ 3.29 billion by 2023, translating to a Compound Annual Growth Rate (CAGR) of 6.77 between 2017 and 2023. The growth results from increased attention to workers' safety, higher efficiency, and the need to

reduce overhead costs in the mining sector. The Asia-Pacific region has the prospect of being cemented as the topmost market for mining equipment and the adoption of automation technologies worldwide. Together with Rio Tinto, the FMG Group and BHP are among the big mining companies struggling to catch up with the new tendencies in that market. This pattern of digitalisation of mines, coupled with the worldwide growth of economies, has opened mining companies to new economies. Based on the Markets and Markets (2017), mining automation market participants include Atlas Copco (Sweden), Hexagon (Sweden), Komatsu (Japan) and Sandvik (Sweden). This research fashion can be applied to forecasting, so it is logical to consider its use in mining equipment facilities.

Based on the cyclical nature of the activity, the geographic mining industries are highly influenced in their conduct by the spatial dispersion of economic activities and their eventual relative contribution to the different national economic structures. As an illustration, its share of GDP in Australia comes to around 10.4%, while South Africa's share is almost 8.7% (Baxter, 2021). Mining operations across the globe differ in terms of the features of the minerals they mine, the mining engineering systems, and the modified machinery they use. The equipment, from mobile to stationary, has become more complicated due to technological improvements. These machines are now base-loaded with systems and subsystems, including electrical, hydraulic, mechanical, and control systems (Wakiru et al., 2021).

Maintenance of equipment usage, especially for operation in the mining field, is one of the highly controllable costs, although it has been slow to evolve compared to other industries. The goal of performing maintenance works is to avoid failures and enhance the whole functional system. Maintenance expenditure typically ranges from 40 to 70% of the installed capital cost and 20 to 60% of annual recurrent expenses when operating the system, depending on different parameters (Dayo-Olupona et al., 2023). Equipment maintenance has progressed and continues rapidly, shifting from a simple, functional requirement to a necessary business focus. The use of articulated maintenance principles has become the practice among top mining industries in the twentieth century to enhance maintenance programs and maintenance operations and maximise the operating period of the equipment (Dayo-Olupona et al., 2023).

Corrective, preventive or scheduled, and predictive are the three general categories of maintenance practices (Odeyar et al., 2022).In continuing with this note, predictive maintenance (PdM) has been increasingly popular in the industry's practical and

research fields, seeking cost savings, safety improvement, and reliability enhancement (Schwartz et al., 2020). There has been a transformation in Industry 4.0 regarding the relationship between the physical and digital worlds, which has induced an explosion of data development (Xiang et al., 2021; Elbazi et al., 2022). PdM applies this data and analytical techniques to predict the failure of equipment and perform maintenance just before the failure happens, allowing planning and scheduling of maintenance as necessary. The purpose of PdM is instead to augment existing maintenance processes rather than replace them, as it enables the organisation to use advanced maintenance politics based on the data rather than experience.

2.3.1 Enhancing Maintenance Practices Through Predictive Maintenance

Promoting rational outcomes and minimising downtime, predictive maintenance uses data-driven insights to anticipate equipment failures, streamline maintenance tasks, and deliver significant cost savings, safety enhancements, and heightened reliability. Despite these advantages, the cautious adoption of PdM in the mining sector highlights existing gaps in research. Customising PdM specifically for mining machinery, considering their unique failure modes and interconnected components, is in Figure 2. Developing cost-effective PdM implementation strategies and seamlessly integrating diagnostic and prognostic methodologies are imperative. Addressing these research gaps will strengthen the role of PdM in enhancing maintenance practices within the mining industry. Steenwinckel et al. (2021) proposed integrating data-driven and knowledge-driven approaches for fault diagnosis. Illustrated in Figure 2, the data-driven approach uses deep learning and machine learning techniques (Shehadeh et al. 2021).

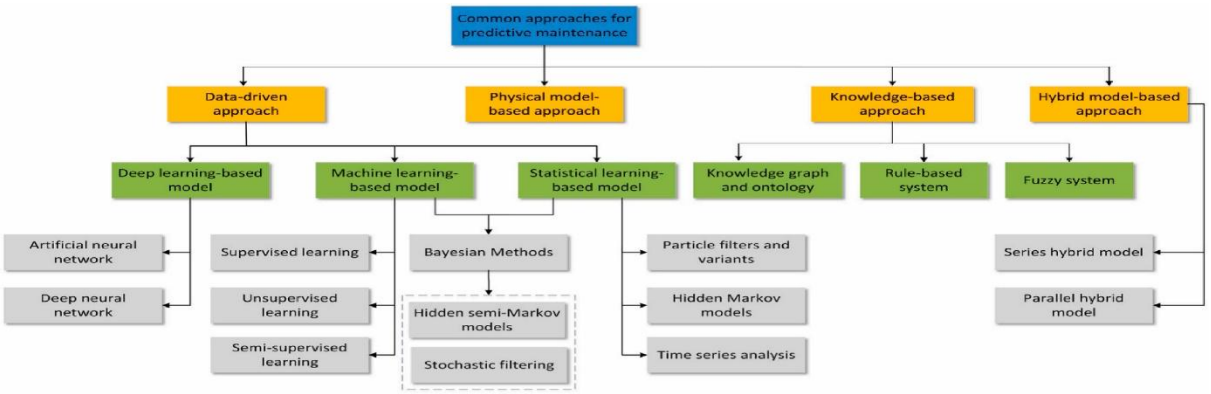


Figure 2. Predictive maintenance chart. (Xia et al., 2022)

Selcuk (2017) stated that if predictive maintenance was conducted effectively, the ROI could be as high as ten times, and production could increase by 25%. Nevertheless, the high cost of setting up and sustaining such PdM systems and training employees will prevent PdM from becoming commonplace (Napieraj, 2019).

2.4 Machine Learning Approaches for Predictive Maintenance

In machine learning modelling, it is possible to create predictive models for analysing the probability of equipment failure or forecasting the time of equipment's applicable life expiration (Shehadeh et al. 2021). In this phase, ML techniques can also be used to assess model quality and identify the problem areas that need improvement. The ML algorithms will find applications in the data-related stages for data cleaning and feature selection, which can be used as inputs for the predictive models. The same conclusion can be made within the framework that improving the efficiency and accuracy of PdM systems is possible by integrating ML within the Cross-Industry Standard Process for Data Mining (CRISP-DM) model. This section discusses the applications of different ML approaches described in the tested research projects.

The following types of ML approaches are used for implementing Predictive maintenance (Abbasli and Mammadli, 2020):

- In supervised learning approaches, concepts such as decision trees and support vector machines are used to model equipment failure based on the training dataset.
- Unsupervised learning approaches include clustering algorithms, which assist in identifying patterns in the data that correlate to potential failures.
- With reinforcement learning, there is a progression in the creation of models that can learn, and which would assist in maintenance rescheduling, devising total efficiency models, and
- Deep learning encompasses feeding complex large datasets into complex neural networks to produce the most accurate estimates of when failures will occur.

Figure 3 illustrates a decision-making flowchart for selecting appropriate modelling techniques in predictive maintenance.

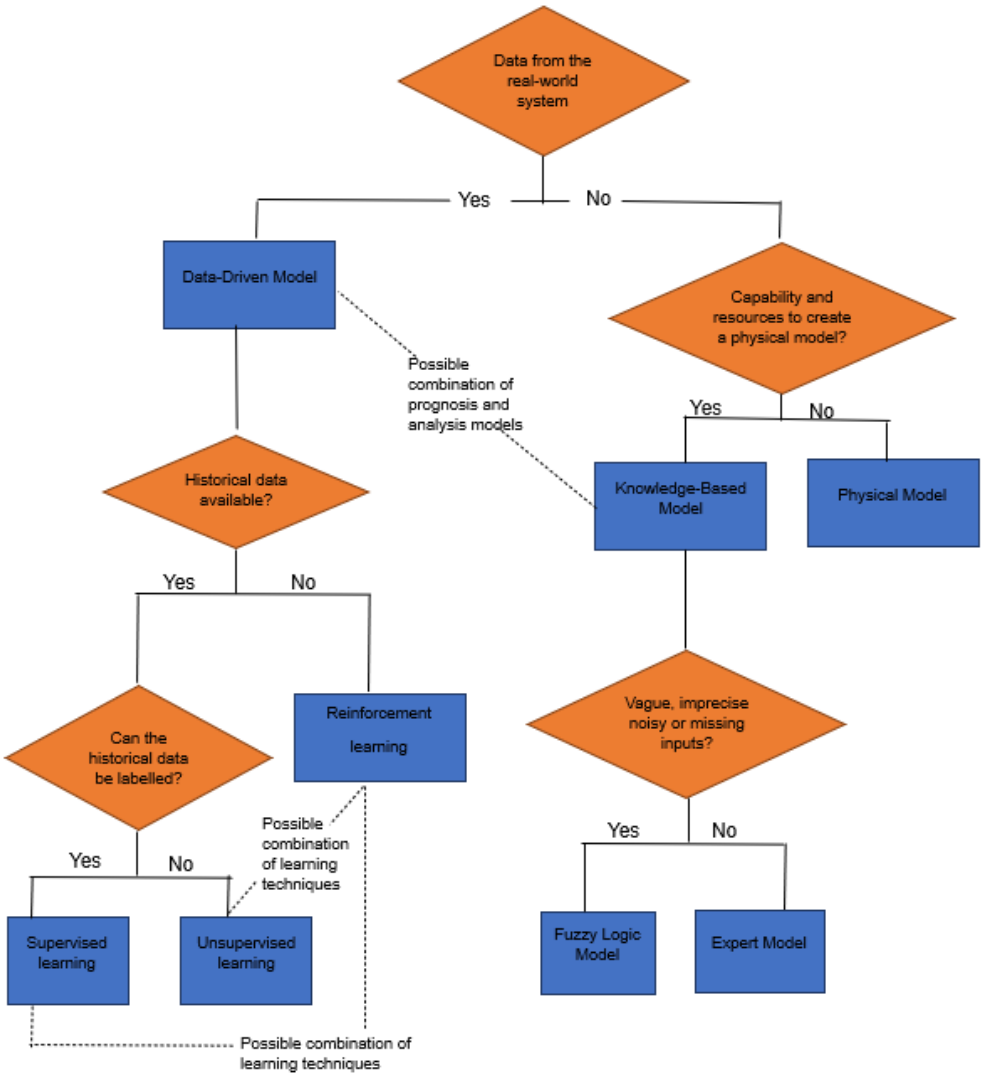


Figure 3. CRISP-DM framework (Sheuly et al., 2021)

Sheuly et al. (2021) highlighted integrating statistical and machine learning techniques in data analytics to enhance predictive modeling and decision-making processes. The authors applied these approaches to analyse power transfer units in their study, demonstrating how data-driven methodologies could improve operational efficiency and reliability. The research emphasised the synergistic use of statistical analysis for understanding historical patterns and machine learning algorithms for predictive insights, enabling more accurate identification of maintenance needs and fault detection. Combining these techniques, the study provided a robust CRISP-DM framework for optimising equipment performance and minimising downtime. The authors underscored the practical implications of such advancements in manufacturing

technologies, showcasing their potential for broader applications across industries. Their findings illustrate the growing significance of leveraging data analytics for predictive maintenance and operational excellence in complex engineering systems.

2.4.1 Factors Influencing Machine Learning Model Selection for Predictive Maintenance Tasks

In machine learning, some factors govern the selection of a model or technique. These include the type of application to be performed (classification, feature extraction, regression), the nature of the available data (for example, incomplete information, deficient information), and the representation of data samples (for example, images, time series, and text)(Jung, 2022). Any such factors, as outlined in Figure 4, should be considered when researching how to select the proper ML model for a specified PdM problem (Shehadeh et al. (2021).

Sheuly et al. (2021) have compared statistical and ML-based approaches to PdM. In their study, they have noticed that ML-based analytics are excellent in quite challenging analysis, which needs changes with time. ML detects anomalies and faults and even predicts the remaining useful life (RUL) in PdM (Bodo et al., 2020). A rationale for choosing the best-supervised ML method is provided (Ouadah et al., 2022). Vicêncio et al. (2020) described a diagram representing supervised or unsupervised ML methods helpful for different parts of PdM. For example, clustering, a type of unsupervised learning, may be used for anomaly detection. In contrast, regression, which is a type of supervised learning, may be used to focus on RUL estimation. Also, it stresses that supervised multilabel classification can be employed to evaluate health status, predict the failure state, or monitor changes in machinery over time.

Bleu-Laine et al. (2021) combined recurrent and convolutional neural networks to propose a classifier to predict adverse events. These classifiers constructed a simple binary classifier to gather information in significant parameters with correlation as an event evolution precursor. Susto et al. (2014) elaborately discussed the potential of ML applications in PdM on different classifier ensembles.

When data is used in real life, industrial usage must be completed, corrected, imperfectly labelled, or rarely feature a fault. For this aim, both (Cerquitelli et al., 2021) and (Cohen and Ni, 2022) developed different ML-based models. Cerquitelli et al. (2021) made a system using only unsupervised learning; on the other hand, Cohen

and Ni. (2022) used semi-supervised learning in their work on what is classified as anomalies even when the data set is partially labelled. Jittawiriyanukoon and Srisarku (2022) applied a weighted method in ML for decision support enhancement on support, scheduling, and schedule planning tasks. They have found such approaches highly effective as they facilitate multiclass classification and help avoid overfitting issues resulting from class imbalance (Figure 4).

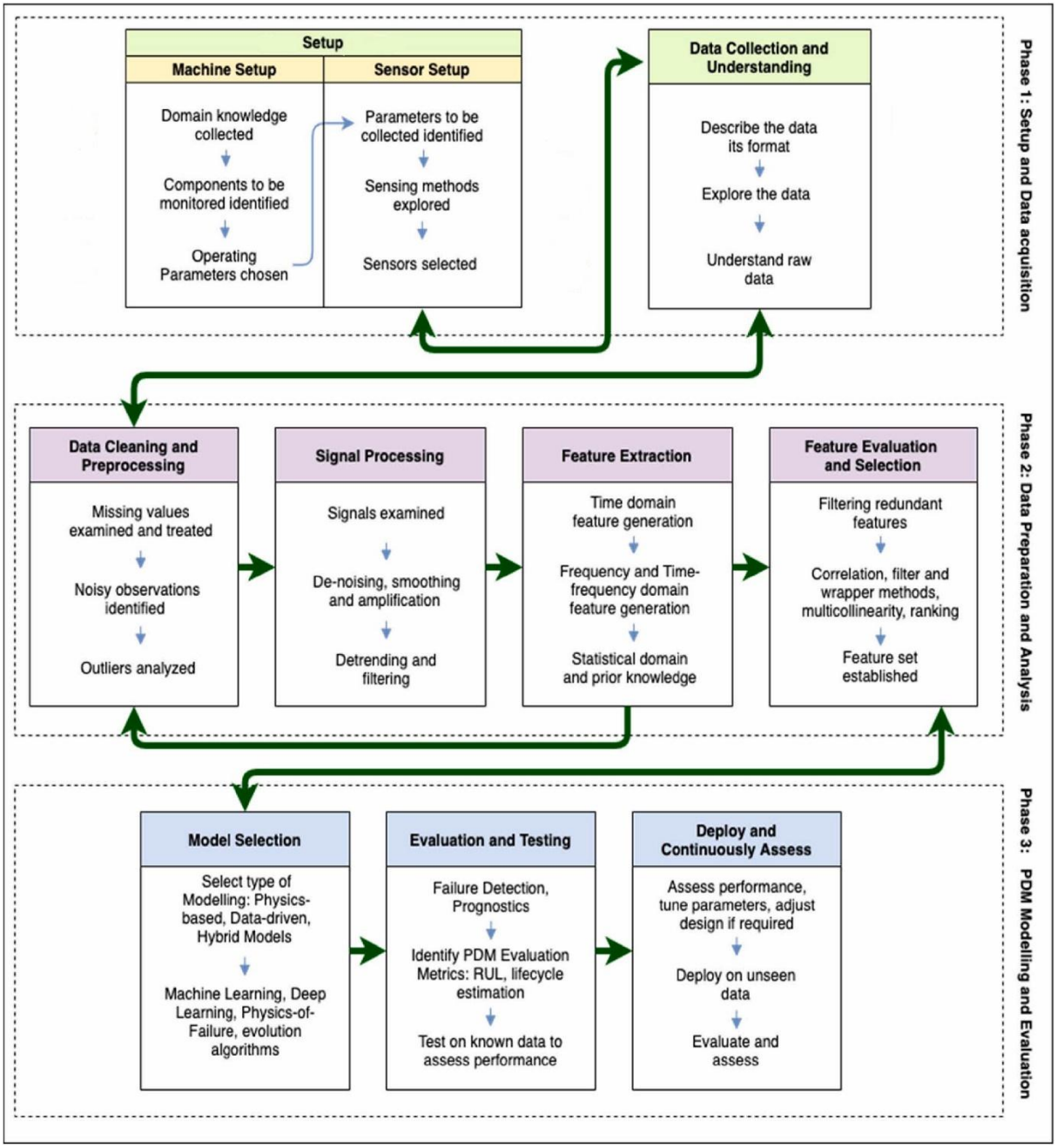


Figure 4. Statistical-based and ML-based approaches for PdM (Sheuly et al., 2021).

2.5 Innovations and Area Application of Predictive Maintenance in the Mineral Industry

Predictive maintenance is used in the mineral industry, including mining and mineral processing equipment, mining machinery, mineral processing machinery, and components (Sharma et al., 2022). A measured performance enhancement to shovel stone mining maintenance scheduling by using a performed parametric definition data model (Sharma et al., 2022). Identifying the electricity consumption of the Line Replaceable Unit (LRU) in a fixed jaw crusher, using intelligent machine learning models, enabled the prediction that the unit will remain in useful life (RUL). This process also highlighted the importance of Internet of Things (IoT) sensors and data analytics in the analysis (Dayo-Olupona et al., 2023).

Depiction of a cyber-physical system for early failure detection in vibrating screens, based on bench tests and multiphysical modelling. The functionalisation of robotic devices and the strategies used for mobile inspection systems illustrate that a mobile inspection robot for belt conveyor inspection has been designed (Rocha et al., 2021). Mining industries have concentrated on PdM and predictive models like deep learning for other mining equipment such as draglines, shovels, conveyor belts, wheel loaders, heavy trucks, and loaders (Dayo-Olupona et al., 2023). The references emphasise the relevance of ML models in Pdm, fault detection and diagnosis. They investigate using ML techniques for fault detection and diagnosis of mine machinery, focusing on the three sequential steps necessary to implement PdM for adequate maintenance support successfully (Dayo-Olupona et al., 2023).

2.5.1 Deterioration, diagnostic analysis, and prognostic assessments

In mining machinery, a holistic framework for classifying sensor data and degradation diagnosis is already available (Cofre-Martel et al., 2021). They used algorithms to build a classifier that would automatically separate healthy systems from the sick ones while also identifying the failure modes. Patil et al. (2021) proposed PdM strategies for mining machines that performed better than the classical approaches. These studies show how accurate diagnostics can aid in deciding the maintenance action to be taken and improve the availability of the asset. Degradation tracking is one measure of PdM that is concerned with understanding equipment wear and tear over time.

Aqueveque et al. (2021) developed a multiphysics simulation and test benching experiments based on a failure detection mechanism for vibrating screens in cyber-

physical space. The system successfully detected the wear progression of the vibrating screens, suggesting the viability of PdM in monitoring equipment deterioration. One area within prognostics is the anticipation of equipment health state in the future. Studies conducted by (Guerroum et al., 2021) and (Patil et al., 2021) demonstrated ML models that estimate the RUL of the mining equipment. These models, which were highly efficient compared to standard linear regression ones, made room for a proactive maintenance approach in resource allocation for stress and minimisation of downtimes.

The Grid Convergence Index (GCI) is a quantitative tool used to assess the reliability and stability of equipment maintenance trends in industrial operations. In mining machinery, GCI is a performance indicator by tracking the proportion of unscheduled and scheduled maintenance activities over time. It helps identify degradation patterns and offers insights into the effectiveness of existing maintenance strategies. Analysing GCI, operators can pinpoint recurring issues that lead to unscheduled breakdowns and evaluate the impact of predictive maintenance (PdM) interventions. This metric complements advanced diagnostic and prognostic techniques by providing a standardised framework for comparing maintenance performance across different operational periods. Incorporating GCI into assessments supports decision-making and aids in resource optimisation and downtime reduction, aligning with broader objectives of enhancing equipment reliability and operational efficiency.

2.6 Maintenance strategies for cost-benefit analysis of heavy equipment

Management profoundly influences the performance of heavy-duty surface mining machinery approaches described above, including the following three. Advanced strategies for the machines are preventive Maintenance (PM), corrective maintenance (CM), and condition monitoring (CBM), as presented in Figure 6. These maintenance strategies help optimise the overall cost associated with operation and equipment uptime. The issue then becomes what the advantages and the consequences of such

are about surface mining operations approaches such as PM, CBM or CM. The CBM alternative is the most optimal, with high and low operating costs.

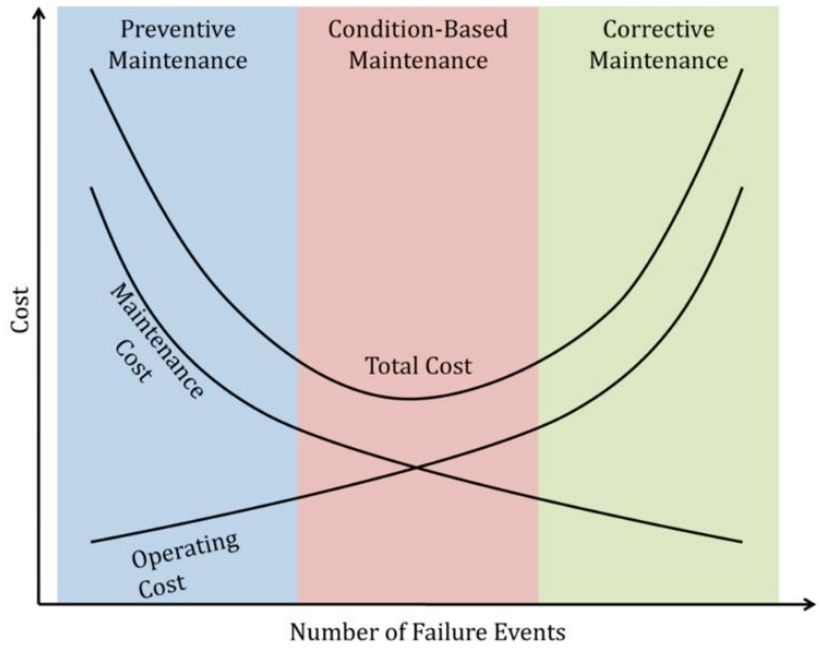


Figure 5. Maintenance strategies analysis based on cost-benefit (Coble, 2010).

Dependent factors include the quantity and reliability of heavy equipment, such as bulldozers, trucks, and primary crushers. The efficiency of the maintenance methods applied is critical in extending the intervals of equipment breakdowns and reducing the operation cost. There has always been a conventional way of thinking about maintenance methods, and this can be divided into three ways: PM, CM, and CBM. Each of these strategies has different risk financing, affecting the overall efficiency of mining operations. The PM expected all maintenance activities to be done on a goodwill basis, even without regard to the equipment's state. Even as it aims to eliminate breakdowns by undertaking stringent inspections and corrective repairs, it also results in excessive maintenance and costs.

The corrective maintenance approach is the task or activity that must be performed after a breakdown. The strategy lowers the amount of money that could be spent on a routine maintenance programme but spends time on nonproductive activities and costs, affecting production capacity and profitability. Condition-based maintenance is where equipment and its status are constantly checked, and maintenance is done when required. CM provides this alternative by acting on faults not after they have developed into breakdowns but before breakdowns occur. The report evaluates the measures implemented to surpass these three maintenance strategies in terms of their

associated operational costs and their overall influence on the total operating expenses of heavy surface mining equipment.

2.6.1 Costs effective strategies

The maintenance strategy must balance maintenance and operating costs to minimise the total cost. Costs arise from performing either routine or corrective maintenance, which is one of the poor operational efficiencies and is attributed to downtimes within the equipment. The research examined maintenance costs as being high and incorporating machine learning and artificial intelligence in the maintenance system helps reduce the cost. Here are findings with others on maintenance strategies to determine which of them, in terms of cost, was more efficient.

2.6.2 The strategy of preventive maintenance

Preventive maintenance aims to reduce the number of failure events by systematically inspecting and replacing parts. Maintenance targeting activity was considered costly because it demands unnecessary maintenance work in which activities change parts or lubricants of well-maintained components. This results in unwarrantable repair work and indirectly raises the overall maintenance cost. As for the operating cost, however, it is high. Because PM minimises the chances of an equipment breakdown and potential operational interruptions, operating costs are lowered. The overall expenditure was reasonable on the unsuspecting side. PM lowers risk and guarantees the reliability of high-quality equipment (Wang et al., 2020). The indirect cost of low-level and often distracting maintenance actions can be drastic.

2.6.3 Corrective maintenance

Corrective maintenance occurs when repairing or replacing individual components, but only if a failure occurs. The strategy eliminates expenditures on unnecessary preventive maintenance but has significant negative implications for equipment uptime, production, and continuity. Coble (2010) stated that maintenance costs are minimal as CM cuts expenses on unnecessary routine maintenance tasks and concentrates only on the actual maintenance needs. Maintenance actions are justified only if the equipment has broken down or malfunctioned. In contrast, operating costs are high. Since CM allows the equipment to fail, the period in which it lapses leads to considerable losses in production. So, even in this case, profitability is a problem because losses are due to unplanned breaks for most production processes. The total

expenditure increased further due to the consequent operating hours and indirect costs. Even though CM reduces maintenance costs, the losses resulting from loss of productivity and the costs of making emergency repairs raise the costs to another level, decreasing its attractiveness for critical equipment.

2.6.4 Condition-based maintenance.

Condition-based maintenance includes maintenance through the accepted definition of inspecting the machine's status over a set period. CBM uses health monitoring systems discussed in Chapter 4 (4.2), which include fault diagnosis, fault detection, prognostics, and maintenance planning, to arrange maintenance schedules efficiently (Acernese et al., 2021). The maintenance cost was reasonable for the CBM. Using resources to perform unnecessary maintenance actions is minimised, and, in turn, the overall maintenance costs are lowered. At the same time, this category of costs was also reported as moderate. In CBM, not only is the planning of maintenance action improved, but the scheduling of interventions is also implemented so that production does not stop. The operating expenses incurred due to the machinery being out of order can also be reduced.

As it turned out for the overall cost target, all three strategies brought problems of cumulative approach toward cost minus Direct Labour (Abbasli and Mammadli) plus Operating Maintenance Costs (Moradi Afrapoli and Askari-Nasab) minus Standby Costs (Sheuly et al.). They combine maintenance with operational expenditures simultaneously, decreasing both. In the case of heavy surface mining equipment, the maintenance strategy significantly determines the total ownership and operation costs. As a result, each of the maintenance and operating costs and total costs is graphically shown in Figure 49. Preventive maintenance is a strategy that minimises operating expenses by using maintenance strategies even if they incur higher maintenance costs. The idea behind CM is that it is more beneficial for a business to ignore routine maintenance costs since they will be compensated by increased downtimes or lack of productivity.

As an example of CBM, Maintenance must be performed only when necessary to save maintenance and operating costs. The overall balanced approach will also lead to minimal total cost. In realising CBM, mining companies have the potential to achieve significant cost reduction by increasing the RUL of asset parts, lowering downtime, and reducing the frequency of wasteful maintenance activities.

CHAPTER 3

3 Methodology

3.1 Introduction

The research project focuses on economic efficiency in moving towards complete autonomous surface mining, with minimal operating costs, workforce expenditure, and a short payback period. A systematic approach and multi-faceted examinations, such as the Cascadia scientific system with embedded ML and AI for the historical and live data stream, meet the research objectives. The methodology involves conducting case studies, financial analyses, and constructing a cost curve. This will ensure an adequate evaluation of the economic implications of integrating the autonomous systems against the benefits they are expected to realise.

3.2 Traditional Mining Data Analysis

Conventional mining infrastructure and cumbersome equipment require frequent maintenance, causing downtime and operational costs. Conversely, as Hamermesh (2021) explains, labour costs belong to a category that may rise very quickly and very profoundly if productivity does not increase proportionately. The outcome shall stress profitability and competitiveness. The productivity increase of a traditional mine is based on the physical work of people, and there are constraining factors like exhaustion, the safety of people, and inefficiency in processes (Bharatiya, 2023). The following report is based on the author's retrieved data from the Siguiri Gold Mine in Guinea. The focus was in 2023 to demonstrate the performance of conventional mining methods.

3.2.1 Dump trucks ineffective time.

The studied data covering the first quarter of 2023 highlights critical deficiencies in the functioning of the dump trucks CAT777G and shovels CAT6020B, see Figure 7. The waterfall graph portrays contrary aspects of their efficiencies mentioned above, namely the reasons for the status quo: breakdowns, maintenance, delays, and standby time. These results prompt the understanding that maintenance periods and breakdowns should be studied at the initial stages of developing fleet management strategies. As Onifade et al. (2023) noted, rectifying such shortcomings is important to improve

productivity and reduce idle time. Such approaches facilitate focused problem-solving by addressing stress points and optimising efficiency where change is recommended (Ediriweera and Wiewiora, 2021). Measures of such kind include more vigilance in the care of equipment, changes in job management, and resource movement. In the end, embracing this data-centric culture encourages enhancements and changes in the fleet's performance over time to sustainable levels.

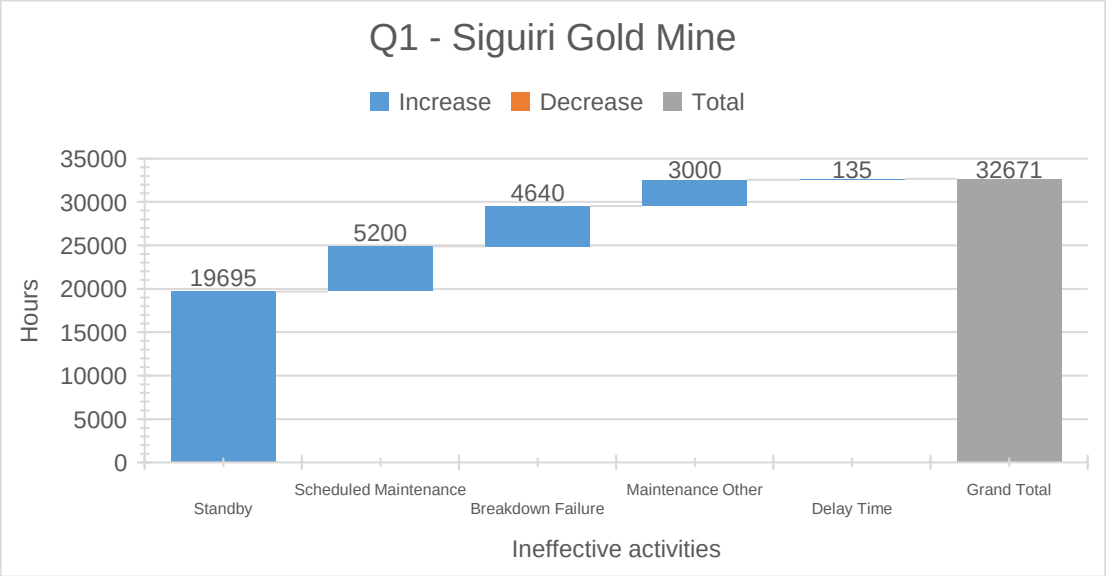


Figure 6. Ineffective time waterfall study for the first quarter of the CAT777G dump trucks.

In the first quarter, the dump trucks indicated by Figure 5 were inactive for 19,695 hours on standby, 4,640 hours on breakdowns and 8,500 hours in maintenance activities. Various reasons may cause considerable losses in usable operational time. The analysis shows a maintenance matrix indicating that 64% of maintenance activity is planned versus 36% reactive maintenance. The extreme skew is detrimental to the target maintenance ratio 80:20, in which scheduled maintenance constitutes 80% of the total maintenance window while only 20% is unscheduled maintenance. The 20% on the right-hand side constitutes the most problematic issues, accounting for 80% of the standby hours, and the 80% on the right-hand side constitutes the least problematic issues, accounting for 20%. The focus must be paid to the 20% of issues on the right-hand side. This is an important consideration given the need to reduce such discrepancies in the maintenance planning process and breakdown management of

organisational functions. Figure 7 below shows the Pareto analysis for standby (ineffective time) for the dump trucks conducted at the Siguiri open pit mine in Guinea.

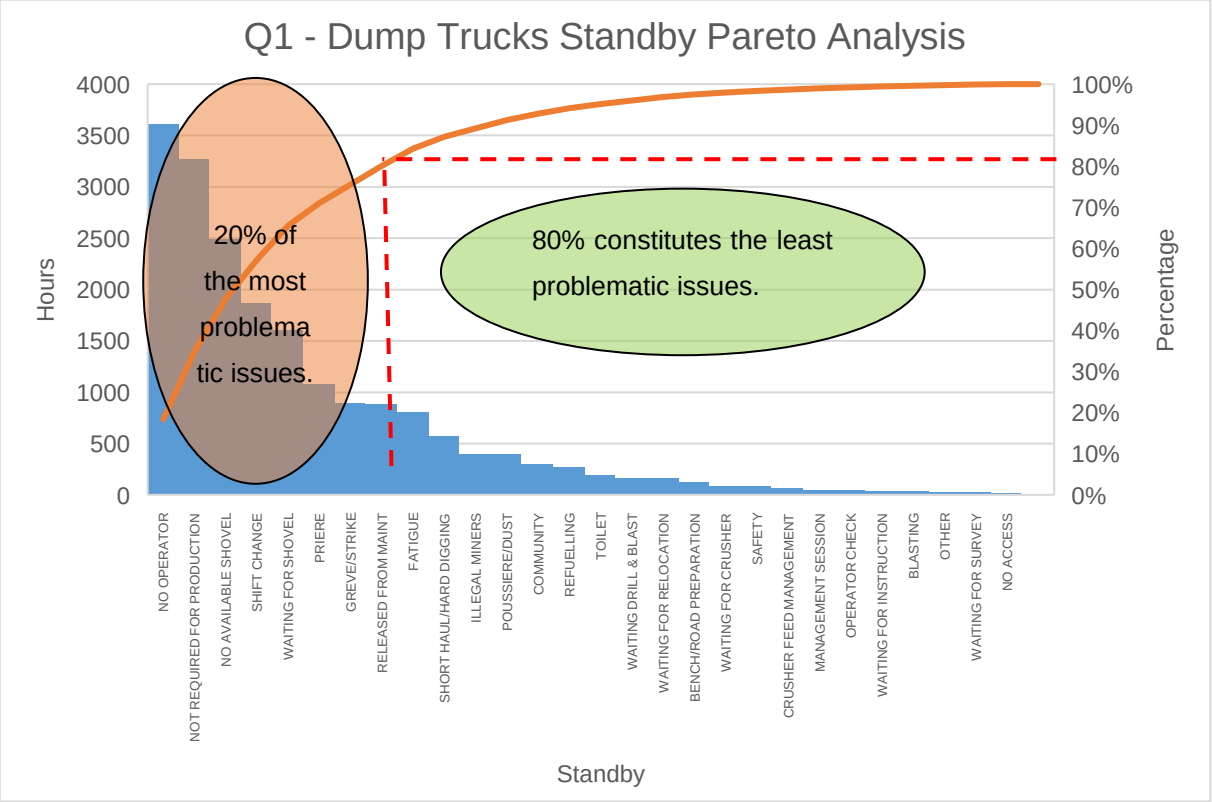


Figure 7. Pareto analysis for the first quarter for standby dump trucks.

Standby lost time was assessed using a Pareto analysis, as shown in the Pareto Breakdown in Figure 8 above. With over 3,500 hours, the most significant single contributor was designated for situations with no operator. The operators contributed 20 per cent to the 80 per cent lost time.

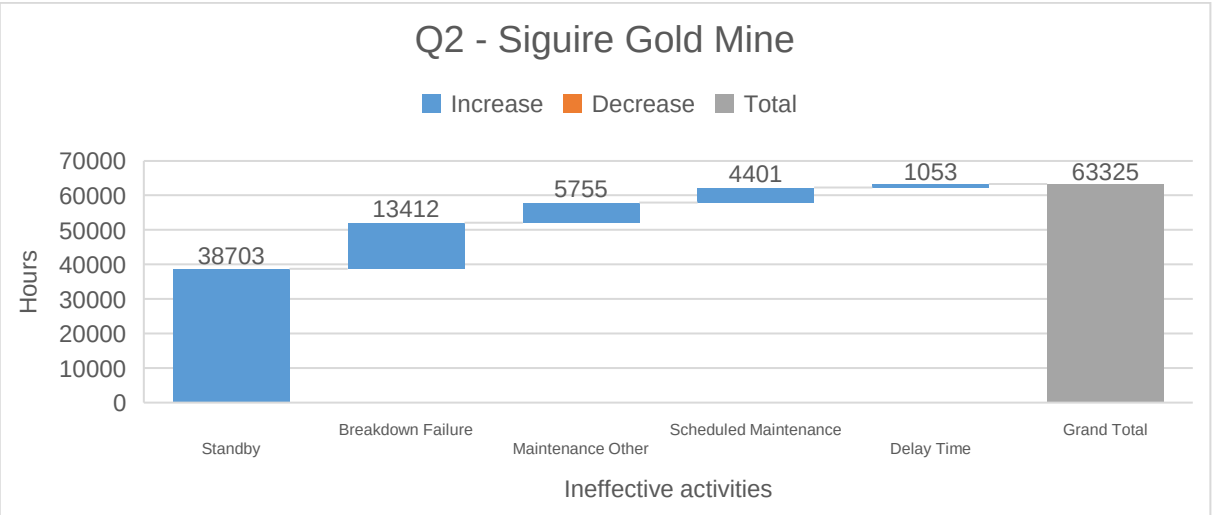


Figure 8. Ineffective time waterfall study for the second quarter of the CAT777G dump trucks.

The standby hours went marginally up from 19 695 to 20 073, suggesting slightly longer downtimes; see Figure 9. The impact of this rise will be elucidated through the Pareto analysis depicted in Figure 9 below. Looking at the Pareto chart, one can identify the main reasons for the most noticeable rise in standby hours. The root cause analysis will help better understand the reasons for such an increase and allow the focus on the most necessary measures in managing the growth. Studies of the Pareto chart and other data provide an overall image of the reasoning behind the deterioration in operative productivity. The overall picture is formulating adequate action plans to address the decline in production capability and performance.

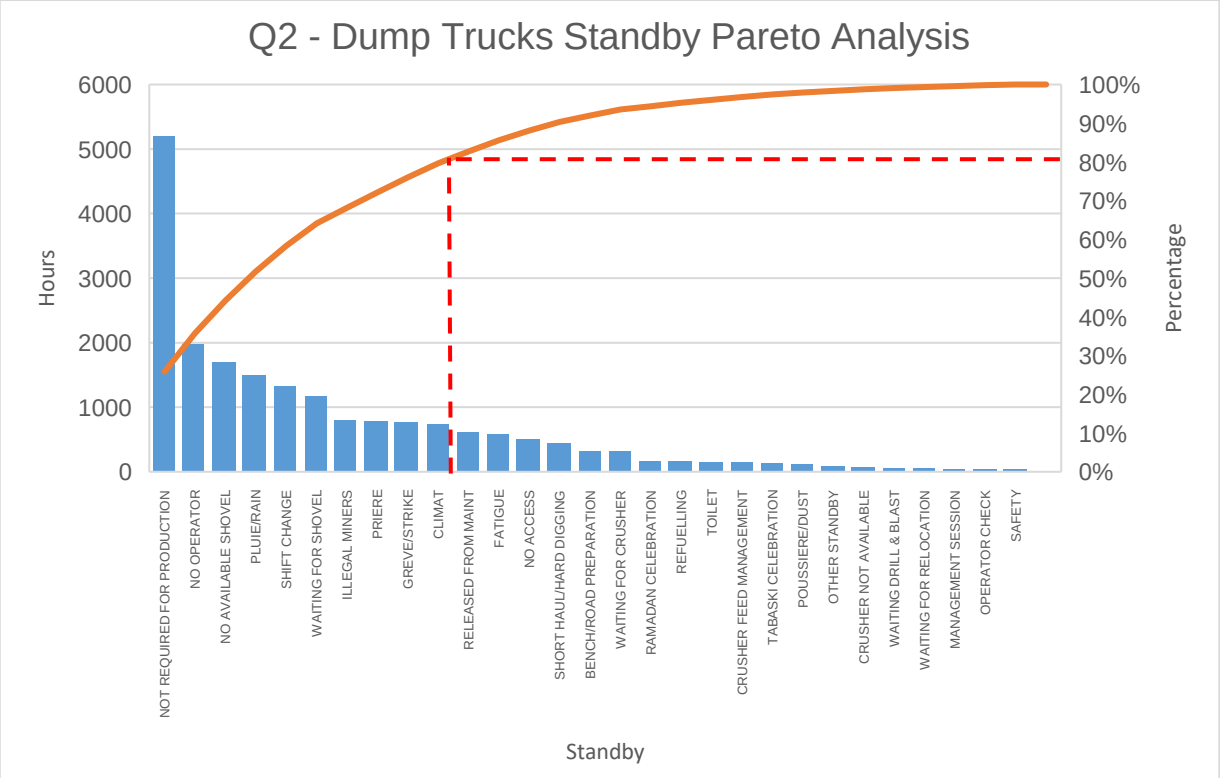


Figure 9. Pareto analysis for the second quarter for standby dump trucks.

As shown in Figure 10, during the second quarter, there was an increase in standby hours due to the absence of an operator, the absence of an available shovel, shift changes, and climate periods due to the weather. The aforementioned factors caused a significant inefficiency in the operation. A waterfall graph in Figure 9 lists the primary reasons for the ineffective time as we move towards quarter three. The graphical representation will help appreciate the trends contributing to the operational inefficiencies and highlight efforts to make positive changes regarding these issues through a targeted approach to addressing such operational inefficiencies. An ineffective work time management of excavator operators was related to eliminating

the root causes in the following clause to enable stakeholders to improve efficiencies and prevent inefficient work time. Such an emerging pattern can assist fleet management strategies as analysed through the established waterfall graph to achieve the best possible performance in the next quarter.

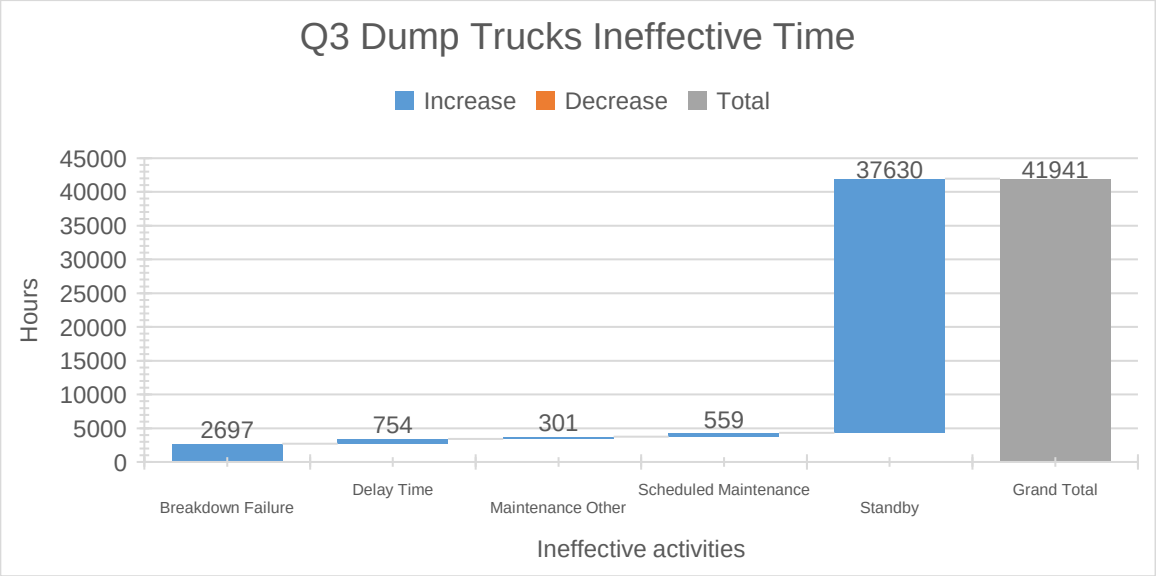


Figure 10. Ineffective time waterfall study for the third quarter of the CAT777G dump trucks.

During this period, standby hours had the most significant revelation, increasing from 20,073 to 37,630, which means there was a considerable increase in idle time. The consequences of this increase will be explained in further detail with the help of the Pareto analysis shown in Figure 11. Notably, the Pareto chart determines the causative factors of the increase in standby hours and has possibilities for change. The observations in the prescriptive chart are consistent. There is a picture for adequately analysing the increase and framing appropriate measures to counteract such an increase. Using the Pareto chart in conjunction with other parameters is most effective in assessing the impact of the technical documentation changes. As shown in Figure 12, using systemic and non-specific methods to analyse the data without 'tying' it to the expected changes in operational activity seems very promising. The global vision

is important not for 'introductory' or constructing efforts but for preventive strategies to enhance effectiveness and reduce unplanned external operating times.

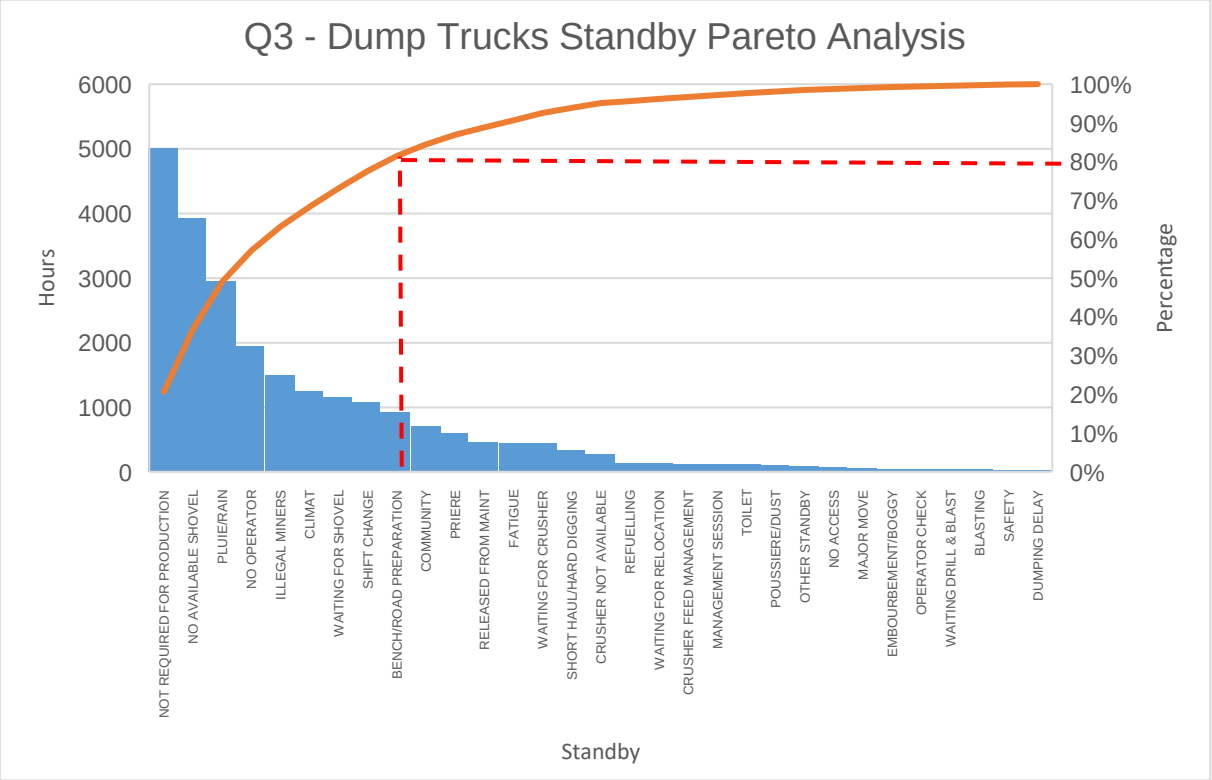


Figure 11. Pareto analysis for the third quarter for standby dump trucks.

The "non-production requirements" were the leading reason for this lapse and were followed closely by "no available shovel standby" as the secondary reason. These factors are more related to missed opportunities, highlighting engineering concerns that will negatively affect shovel reliability and availability, prompting more standby hours for truck-mounted shovels. The author encroaches into the last quarter of the year, and revisiting and discussing the lethargy observed during this period is important. Such issues need to be tackled proactively instead of leaving them for the next quarters since it would do nothing but enhance operational effectiveness and reduce the amount of downtime.

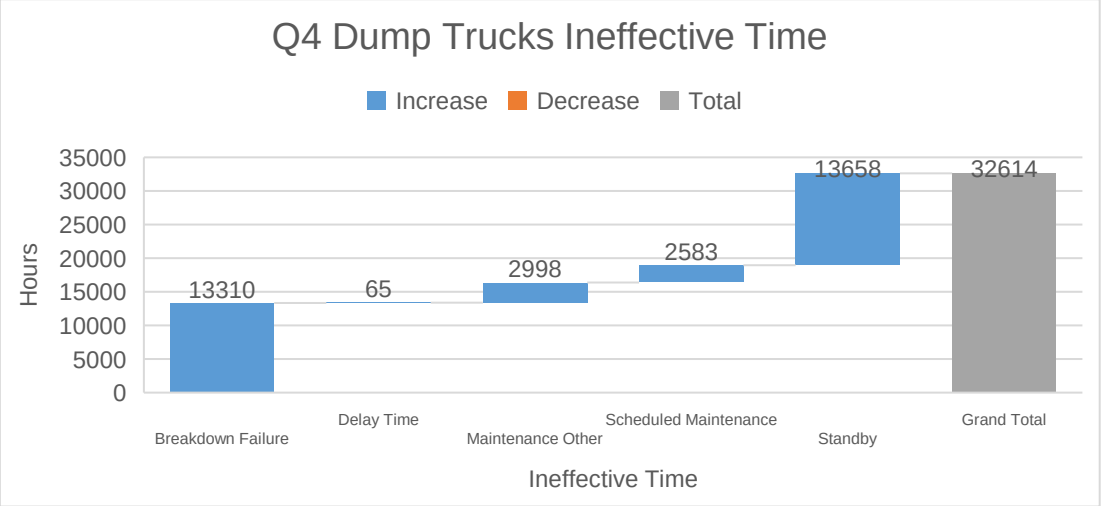


Figure 12. Ineffective time waterfall study for the fourth quarter of the CAT777G dump trucks.

In the last quarter of the year, the total number of equipment breakdowns increased, nearing the standby hours, which improved significantly by decreasing from 37,630 to 13,658 hours, as shown in Figure 12. Conversely, breakdown hours surged from 2,697 to 13,310 hours. The festive season contributed to this trend, as quality maintenance was impacted by senior management being on leave and maintenance teams losing focus. Production operators were a significant factor in equipment failures, with reckless driving significantly contributing. The analytical technique has advantages. It provides a platform for prioritising important issues that must be addressed and effectively delivering such initiatives to improve business performance.

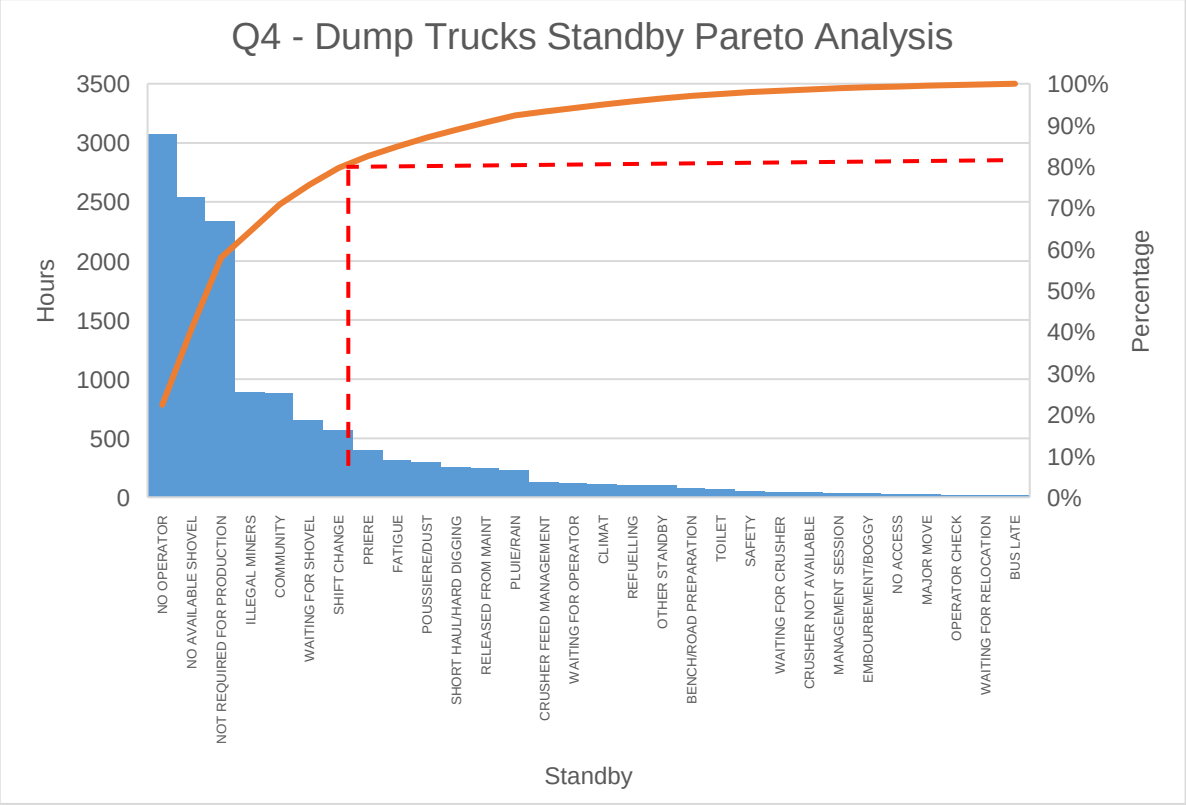


Figure 13. Pareto analysis for the fourth quarter for standby dump trucks.

At the close of the year (Figure 13), standby hours were increased significantly, with "no operator" once again being the leading cause of these minutes, followed closely by "no available shovel" and "not required for production". However, these observations highlight further maintenance limitations, specifically the factors related to the crew and the mean time between equipment failure. On the one hand, enhancing performance to reduce these factors reduces nonproductive time and increases effectiveness in subsequent quarters. The analyses should inform targeted interventions which can assist in minimising the negative impact of these factors and, therefore, aid in enhancing sustainable improvements in the management of fleets. There is a need for continuous monitoring, evaluation, and management control of the performance of operations to avoid adverse effects that may weaken the seamless operations of the business (Shimaponda-Nawa & Nwaila, 2024).

3.2.2 Shovel Ineffective Time

Examination of the shovels in Figure 14 revealed that unproductive standby time stood uncontested at 2753 hours, while delays came second at 1191 hours, followed by nonproductive mechanical faults on the shovel at hours. Figure 13 below illustrates that 1048 hours were lost due to the shovel's breakdown. However, there was also

quite a significant contribution of 1191 hours in scheduled maintenance, which was a good way of keeping the machine at an optimum functional capacity.

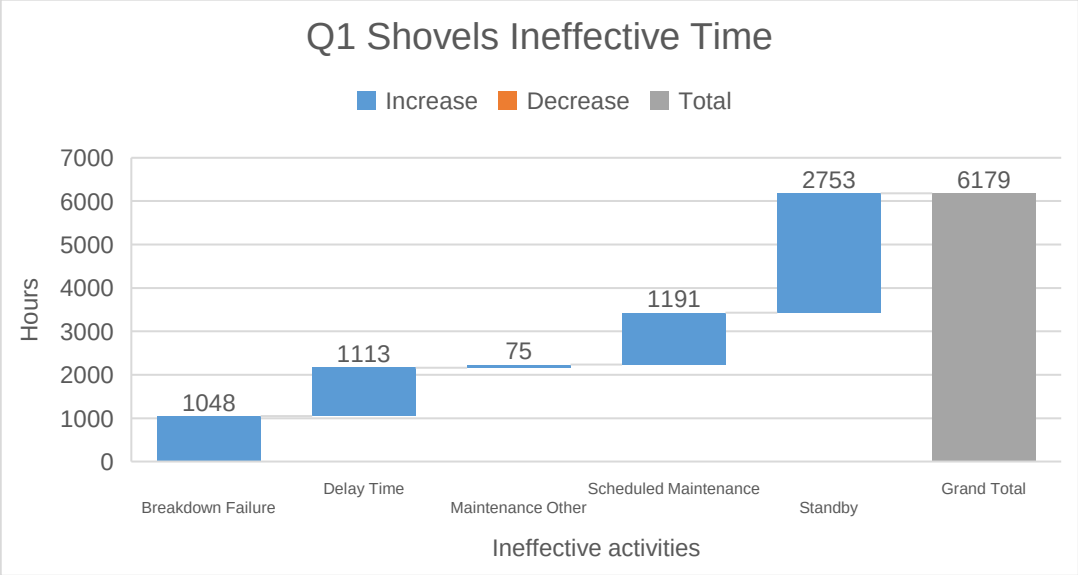


Figure 14. Ineffective time waterfall study for the first quarter of the shovels.

Looking at the time used in Figure 14, standby is the primary time consumer. The problem is efficiency enhancement, which can be achieved by proposing their use along with autonomous mining machinery, as demonstrated in the following graph in Figure 15. A Pareto analysis will explain the reasons for excessive nonproductive time for shovels to understand the problem better. Summing up these data, Boulter et al., 2015 argued the importance of the merger of shovel and truck activities so that the

necessary combined solutions are developed to improve the productivity of operations and decrease the nonproductive time of the mining activity.

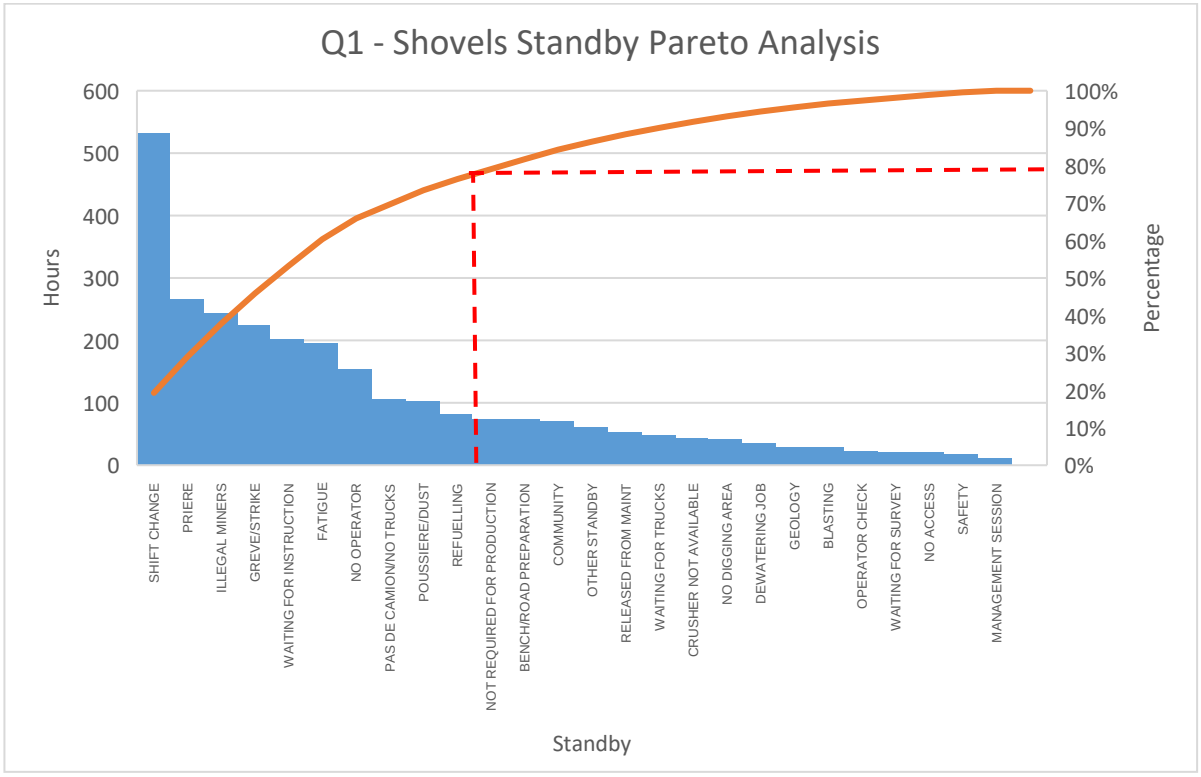


Figure 15. Pareto analysis for the first quarter for standby shovels.

In Quarter 2, a standby period, it contributed a large share of shovel ineffective time, which amounted to 2612 hours (Figure 16).

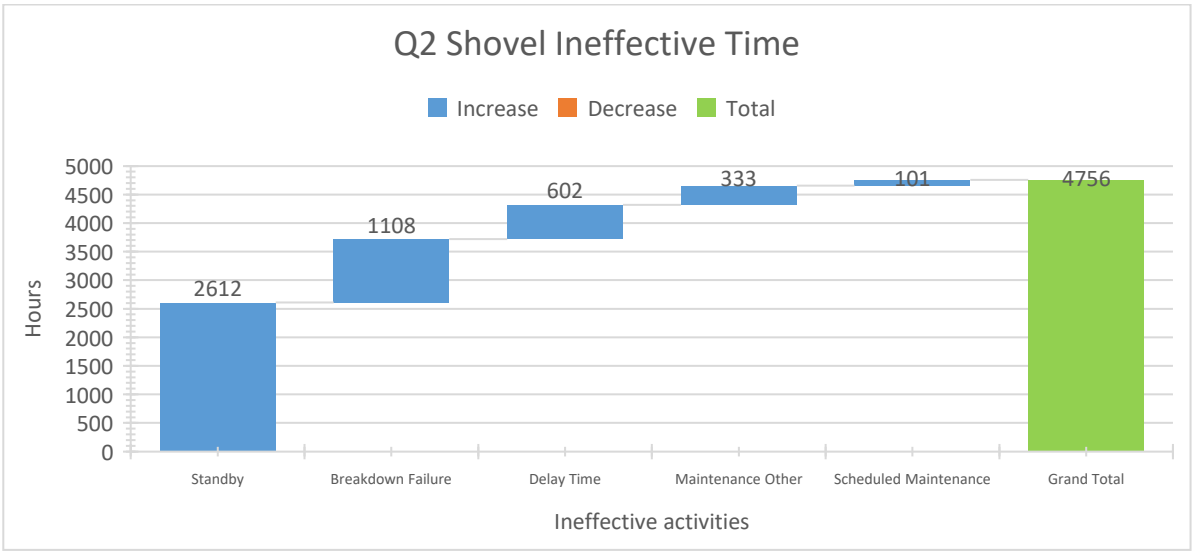


Figure 16 Ineffective time waterfall study for the second quarter of the shovels.

Figure 17 shows a Pareto graph to provide more analysis regarding standby. The graphical representation also highlights the factors that account for standby hours,

making it easier to implement measures to cut down on shovel standby time. Such stoppages were expected due to workforce-related issues, such as hours lost on shift changes, fatigue breaks, or other related reasons.

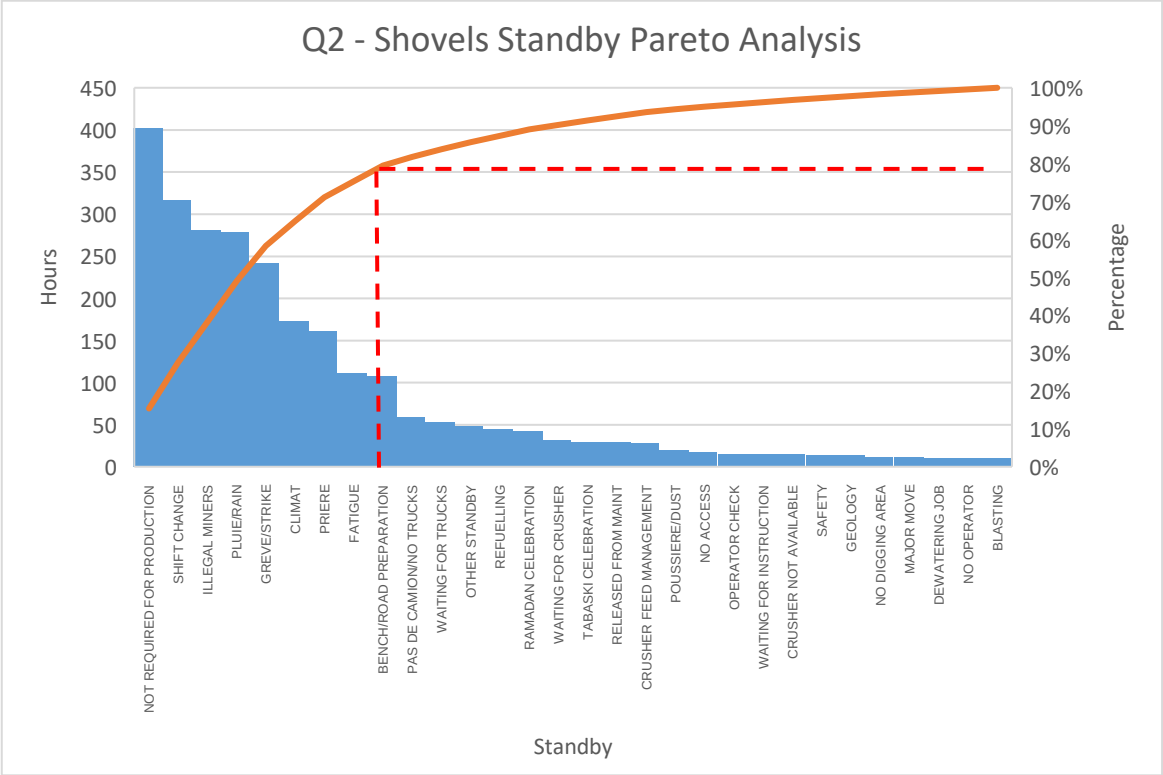


Figure 17. Pareto analysis for the second quarter for standby shovels.

In the third quarter, shovel inefficiencies were primarily due to the following specific factors: delays and idle periods, the latter being the most significant cause (upper middle portion in Figure 18). The indication that reliability is unimportant because breakdowns were rated much less impactful on shovel operation than standing by and delays.

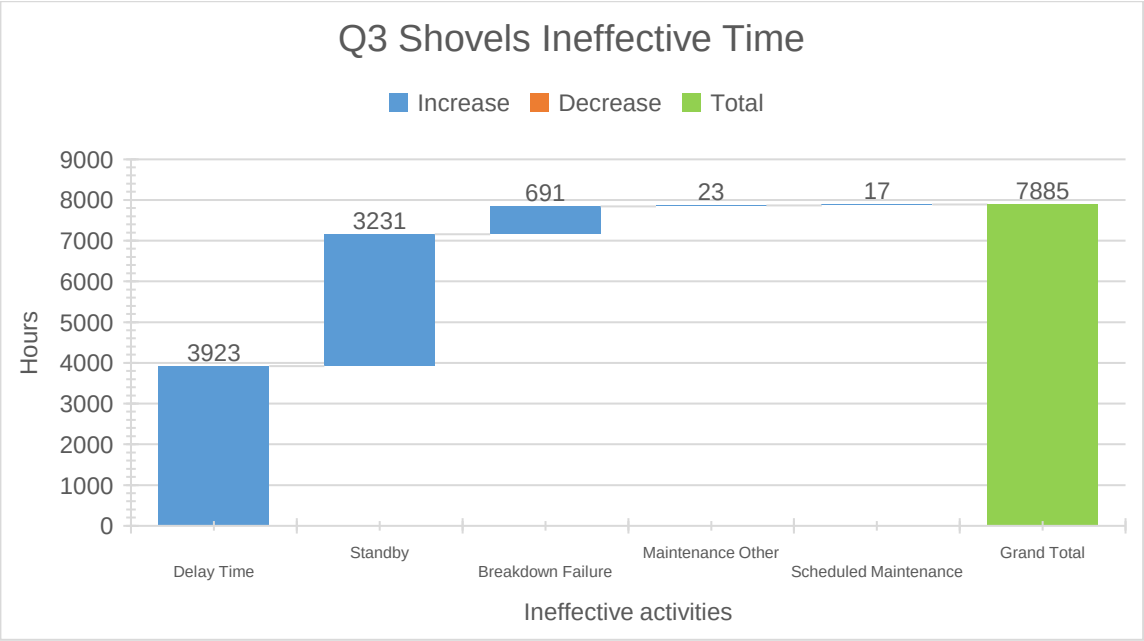


Figure 18. Ineffective time waterfall study for the third quarter of the shovels.

The Pareto analysis (Figure 19) details the standby time losses and, in this case, ranks shift change as the leading cause of them all. Other notable factors include prayer, rain from prayers, and fatigue. It was also noted that quarter three had increased levels of adverse weather, with rain being considered under safety concerns.

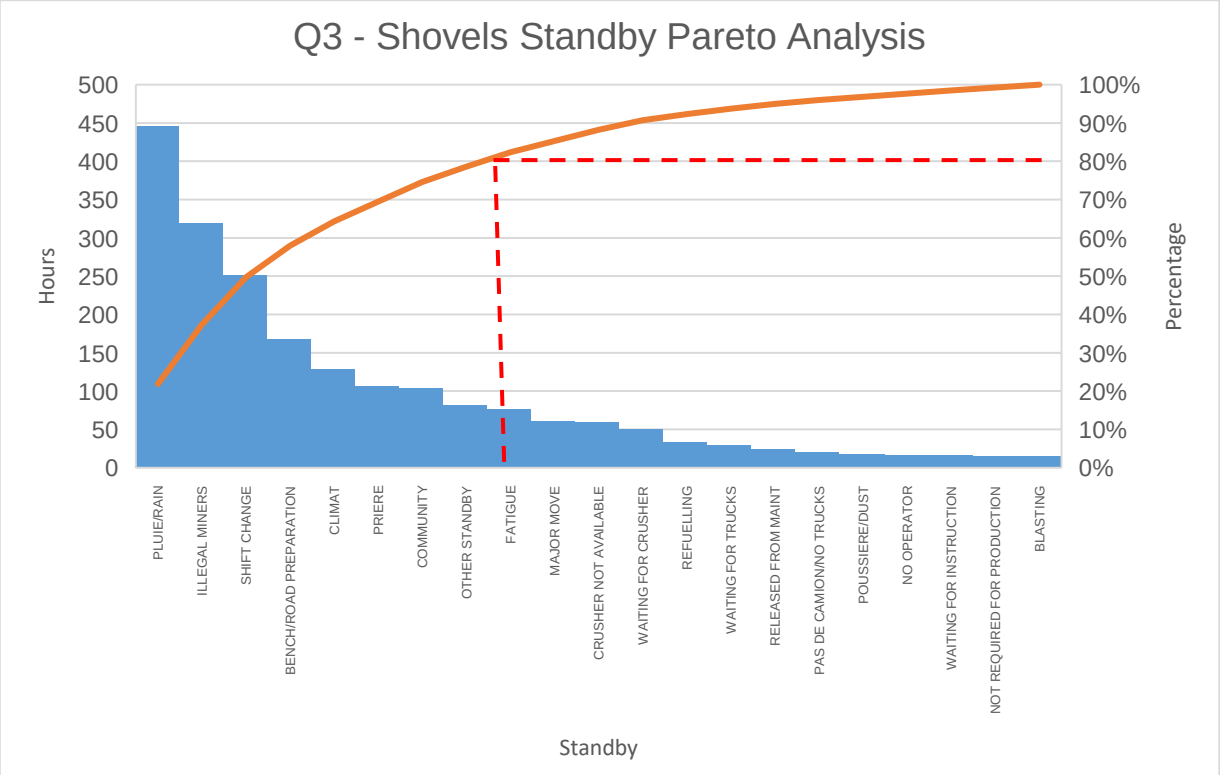


Figure 19. Pareto analysis for the third quarter for standby shovels.

In the last quarter, the shovel's ineffectiveness was accentuated due to the festive season (Figure 20). Machine breakdowns increased to a critical point, resulting in losses running into thousands of hours. The increase in breakdowns remained on standby and was still the single most contributing factor for ineffective time, which accumulated to 2208 hours.

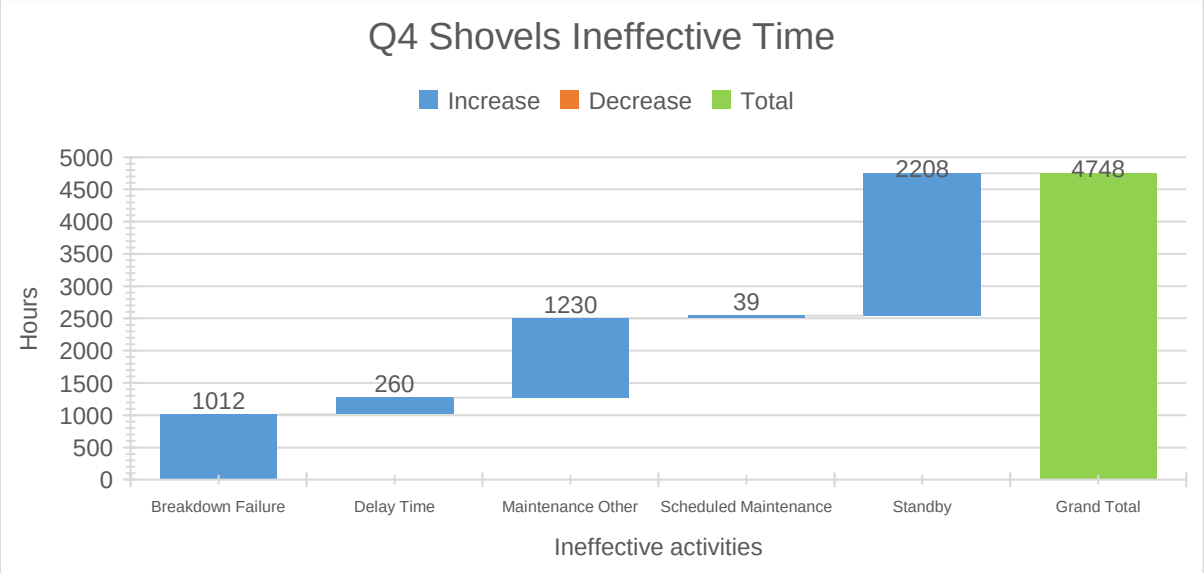


Figure 20. Ineffective time waterfall study for the fourth quarter of the shovels.

The structure of standby time indicated in Figure 21 reveals, in parts, the reasons related to community unrest and illegal miners, as well as the difficulties posed by such external factors. Consequently, the festive season is regarded as a high-risk production quarter due to the surrounding activities that hinder work operations. As much as workers are expected to work, it is reasonable to acknowledge that they may feel that their safety is threatened due to reckless behaviour from some of their colleagues. Other contributing factors during the festive season are that most senior management goes on leave, and employees undermine the skeleton leadership left to

run things. As a result, some employees come under the influence of alcohol. Explain and rationalise the decline in their productivity as they seek personal safety.

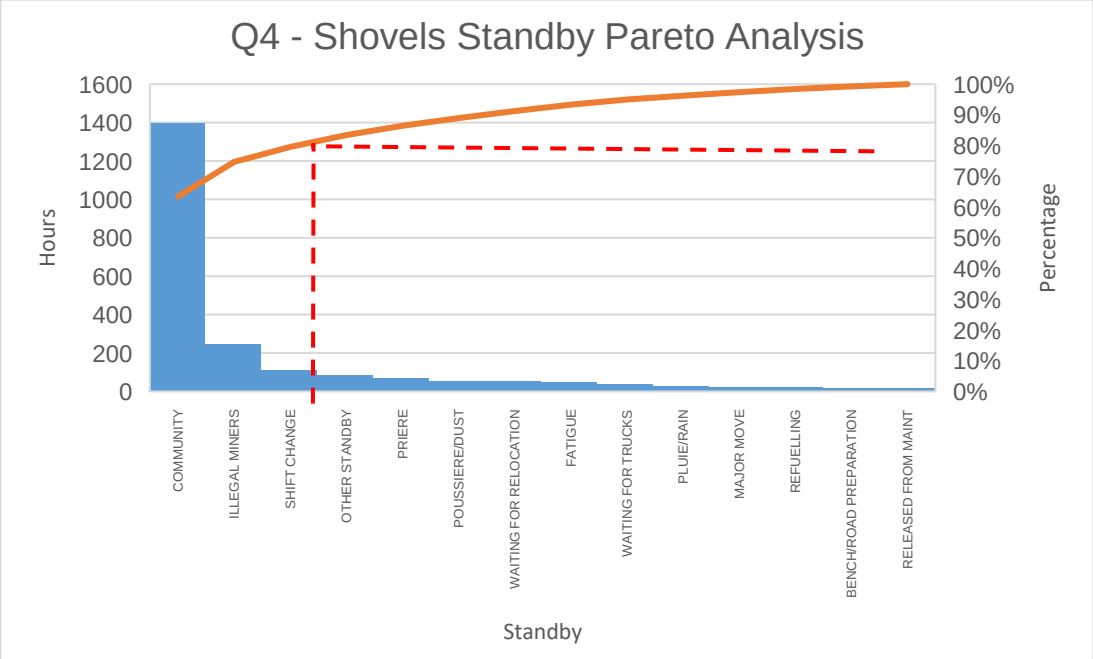


Figure 21. Pareto analysis for the fourth quarter for standby shovels.

3.2.3 Inefficiencies in traditional mining.

Across all the specific quarters mentioned, optimal utilisation relating to the labour factors always emerged as one of the factors that made operations of the old-fashioned style of mining inefficient. Human resources or human-related problems continued to abound in ways, such as poor attendance of the workforce, lack of skilled personnel, and disruption due to illegal mining activities by the locals during holidays. Self-imposed or imposed by management, such as forced shift bottlenecks, routine shifts, and fatigue breaks, were exposures to these shortcomings. Such labour-associated problems resulted in lengthy downtimes and inefficiencies in the safety and productivity of the working personnel. Resolving these challenges requires a more holistic strategy, such as changes in how the workers are managed, better skill improvement strategies, and improved relations with the community. Manners-Bell (2019) argues that inefficiencies related to labour can enhance the mining operation with a focus on resolving these hardships, as efficiency will be improved and all relevant stakeholders in the mining operations will be safe and productive with the aid of advanced technology and automation.

3.3 Equipment Maintenance Key Performance Indicators (KPI) Using Traditional Mining

The surface mining machinery required a more significant maintenance effort, which lessened its reliability. As a result, poor maintenance, irregular maintenance, failure to follow schedules, and shortage of important spares due to poor planning. After assessing the operational performance of the Siguiri mining site in 2023 using long-reach CAT6020B Shovels and CAT777G Dump Trucks. Tables 2 and 3 show the data for the subsequent quarters and the annual data, which covers the fleet percentages about availability, scheduled maintenance, unscheduled maintenance, mean time to failure (in hours) and mean repair time (in hours).

Table 2. Shovel equipment maintenance KPI using traditional mining (Workforce).

Shovel						
Cat 6020B	Q1	Q2	Q3	Q4	Average	Target
Availability	92%	80%	63%	74%	77%	85%
Scheduled Maintenance	20%	8%	2%	4%	9%	80%
Unscheduled Maintenance	80%	92%	98%	96%	91%	20%
Mean Time Between Failure (MTBF)Hrs.	32,26	24,63	12,6	32,18	25	50
Mean Time to Repair (MTTR)Hrs.	2,7	6,18	11,12	7,49	6,9	4

In Table *2* above, the review of the equipment's shovel engineering practicality in terms of business processes key performance indicators shows that overall availability stood at 77%, which is still below the goal of 85%. The actual scheduled maintenance was 9%, while over 80% was targeted, which is alarming as it depicts a situation where machines failed to operate due to unplanned breakdowns instead of planned breakdowns for engineering maintenance. One of the conditions for this degree of mobilisation was that at least 20% of the maintenance workload was for unanticipated maintenance. However, 91% of the maintenance fell outside this category. During this period, the machines had mechanical failures at a rate above the expected 20%. Applying the 80/20 rule for maintenance points out that 80% of the maintenance tasks to be undertaken should be predictive and planned preventive maintenance procedures. In contrast, only twenty per cent (20%) of the works should be broken down or corrective maintenance (Loan and Mushtaq, 2023). Establishing fairness in resource allocation shifts the focus towards the other tasks, the planning of which involves allocating a large share of resources to implement preventive measures.

The principle stipulates that money spent on nonproductive asset deterioration can and does have a favourable reaction when spent on productive, proactive actions like scheduling and conducting adequate and timely preventative measures. Such measures include inspections, preventive maintenance, repairs, and replacing parts before any breakdown occurs. Organisations undertake reactive maintenance approaches, most breakdowns are statistically proven very expensive, and they try to correct situations that would have been avoided. The apportioning of rules implies that planning and distributing resources in maintenance achieves efficiency, limits disturbances, and improves equipment performance over time.

The Mean Time Between Failure (MTBF) was estimated to be 25 hours, whereas the expected MTBF was 50 hours, in which excavations were estimated at barely 25 hours. The Mean Time to Repair (MTTR) was reported as 6.9 hours, which is above the 4-hour target, accomplishing that evident defect reported upon repair of the machine took about 7 hours to regain operational capacity. The engineering KPI performance of dump trucks is shown in Table 3.

Table 3. Dump trucks equipment maintenance KPIs using traditional mining (Workforce).

Dump Trucks						
Cat 777G	Q1	Q2	Q3	Q4	Average	Target
Availability	84%	67%	68%	71%	72%	85%
Scheduled Maintenance	53%	27%	21%	16%	29%	80%
Unscheduled Maintenance	47%	73%	79%	84%	71%	20%
Mean Time Between Failure (MTBF)Hrs.	35,21	26,85	23,78	62,84	37	50
Mean Time to Repair (MTTR)Hrs.	5,43	13,37	19,01	26,57	16,1	4

Table *3* above shows shovel engineering KPI, and management analysed that availability was an average of 72%, which was worse than the average availability target of 85%. Scheduled maintenance recorded an average of 29%, which was exceptionally low compared to the 80% target; such a trend is troublesome as it means that machines had stopped due to unforeseen breakdowns as opposed to it being maintenance downtime. Any breakdown that requires maintenance without planning is said to be unscheduled; on average, the GCI recorded 71% unscheduled maintenance, while 20% was anticipated. Even higher than expected, more mechanical breakdowns were ensuing.

Mean time between failures averaged 37 hours compared to what had been set at 50 hours, suggesting that the shovel could only operate for 37 hours before a breakdown was recorded. Excess of the MTTR was averaged at 16.1 hours against the allowed 4 hours in the restoration of reported defects. The restoration of the machine to operational level after reported defects took almost 16 hours on average.

3.4 Case Study

The author studied certain surface mining operations that have advanced and implemented the features of autonomous technologies. These case studies help demonstrate the costs involved, the maintenance and labour demand, and the return on investment from transitioning to full autonomy. Examining actual case studies, we can find applications of patterns, trends, and best practices that can inform strategic considerations for other mining companies.

3.4.1 Rio Tinto’s autonomous haul trucks

Rio Tinto's autonomous haul trucks have achieved a significant milestone in operations at prominent locations in Australia (Rio Tinto, 2018). These state-of-the-art Autonomous Haul trucks (AHT) began trial operations in 2008, and it has been reported that over one billion metric tonnes of ore and waste material have been successfully transported across five sites in the Pilbara region. Mining companies are embracing these changes and investing in automation to reduce their reliance on manual labour. The past few years have seen advancements by Rio Tinto in the mining industry, where the Tasmanian Yandicoogina and Nammuldi mines became the first in the world to deploy fully automated driverless trucks for hauling iron ore, a global first in the mining industry (Lindsay, 2016).

According to reports from other sites, this autonomous fleet accounts for around 25% of the total material movement in Rio Tinto's Pilbara mines (Rio Tinto, 2018). Each autonomous truck was reported to operate for an estimated direct operating hour (DOH) of 700 hours more than the conventional haul trucks operating in 2017, which averaged 470 hours. This translates to unit loading and hauling costs being about 15 per cent less without DOH.

Management described these advancements as highly significant, according to News (2015). A productivity increase of five billion US dollars was forecasted, focusing on the iron ore sector's commitment to achieving an additional 5 million US dollars in free

cash flow starting from 2021. This projection, before 2024, emphasised the sector's efforts to enhance operational efficiency and contribute to overall financial growth. Rio Tinto has designed prism modules to outfit 48 Komatsu and Caterpillar haul trucks over two years while incorporating autonomous technology. So far, approximately 20% of the Rio Tinto fleet in the Pilbara region, consisting of four hundred haul trucks, is self-operating (Sekar et al., 2019). Once these retrofit works are completed, the self-operating trucks constitute the entire Variable Frequency (VF) motor truck.

Rio Tinto's autonomous haul trucks are monitored and controlled by a central controller, which replaces the human driver with a supervisory system. The trucks are programmed to operate without a front look for movement, navigating designated haul roads and intersections without directing drivers (Pascoe, 2020). They use Global Positioning Systems (GPS) to guide them and monitor other vehicles' movements, speeds, and positions. Every step taken complies with complex technology, ensuring operations are conducted without delays and allowing the autonomous trucks to operate at total capacity while always maintaining full awareness of their surroundings.

3.5 Integration of Machine Learning

The author also improved the precision and forecast accuracy of the applied research machine learning methods. The historical data and machine learning methods can analyse patterns and relations among different characteristics of equipment utilisation performance, reliability, and availability, enabling better decision-making and forecasting. Algorithms in AI and machine learning could be employed to ascertain the main cost and benefit factors in autonomous surface mining so that considerations of the combinational effectiveness of the different aspects become more apparent.

As the mining industry advances technologically, core decisions regarding data management and utilisation become increasingly critical. While 85% of mining companies desire to adopt data-oriented approaches, only 37% have successfully implemented these practices, according to Hernandez (2022). Figure 23 highlights such advancements, displaying a sensor-powered data pipeline developed by Cascadia Scientific for fuel monitoring and maintenance conditioning. This system demonstrates the potential of integrating sensor technology to optimise resource management and enhance operational efficiency in the mining sector.

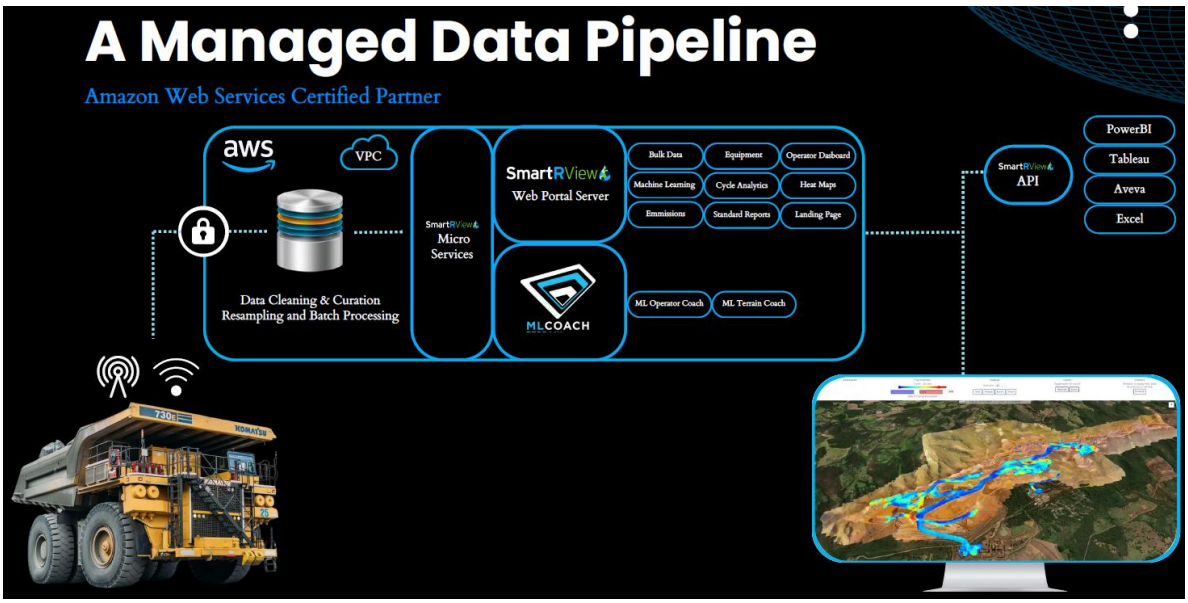


Figure 22. Cascadia Scientific approach data pipeline (Hernandez, 2022).

Figure 23 illustrates the evaluation of the performance and productivity of dump trucks in a mining operation. This assessment accounts for two critical factors: work allocation and work intensity. Work allocation refers to the distribution of tasks among the trucks to ensure optimal usage, while work intensity evaluates the workload each truck undertakes relative to its capacity. The figure visually represents sensor-enabled monitoring systems that provide real-time data on the trucks' operations, enabling precise analysis of their efficiency and overall contribution to the productivity of the mine. This data-driven approach ensures informed decision-making for improving fleet management. Insight into the actual working performance of the equipment helps in predictable maintenance, better machinery utilisation, and adequate equipment lifecycle management. Modern technologies include real-time oil condition monitoring, emissions control and reporting, and real-time performance monitoring (Hernandez, 2022).



Figure 23. Productivity mapping of the dump trucks (Hernandez, 2022).

Other benefits of the Cascadia system include terrain improvements for the haul roads, which enhance the quality and efficiency of haul roads, leading to smoother operations. Visual Representation of Haulage Networks, which generates detailed visualisations of haulage routes, allowing for the identification of areas with (Figure 23):

- High energy consumption
- Variable gradients
- Significant vibration levels
- Reduced speeds.

Generate reports to determine locations associated with frequent rack or ground impulse events. The Cascadia system's heatmap platform offers simple and impactful workflows to identify and analyse road network trouble spots. The image below, Figure 24, shows the "Heat Maps," where red indicates a poor haul road that requires improvement.

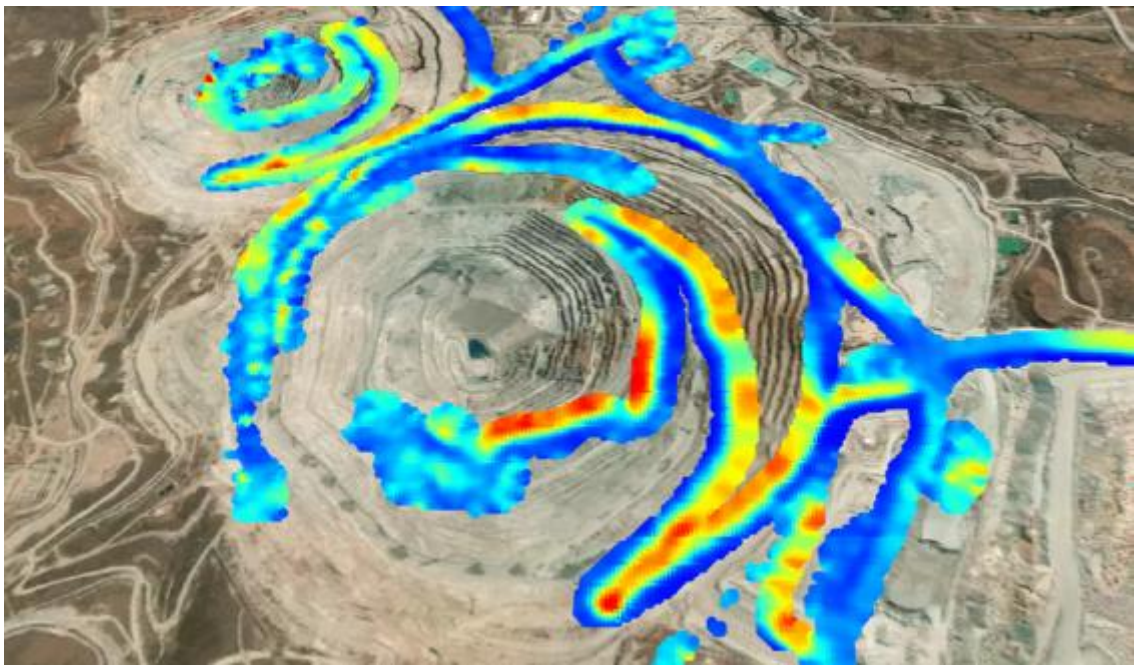
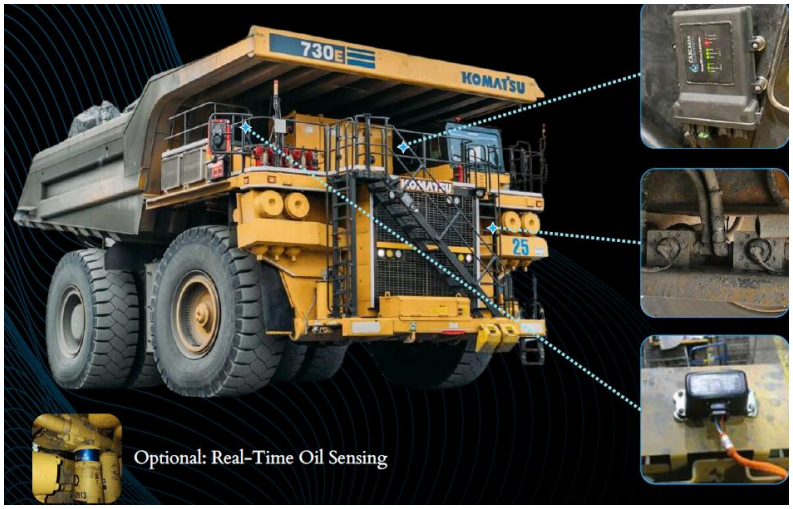


Figure 24. Heat map for road improvement analysis (Hernandez, 2022).

3.5.1 Cascadia high precision Instrumentation

The following instrumentation is installed on a dump truck: SmartRView Controller, fuel flow meter, and Global Navigational Satellite System (GNSS) (Geo-location accurate to three meters) shown below (Figure 25).



SmartRView Controller

- Nine-axis Motion Sensing, Pressure Based Altimeter.
- Vehicle Network Integration (CDL, PLM, CAN Bus)
- Edge Compute, Store & Forward (7 days of memory)
- Cellular, Wi-Fi, Ethernet

Cascadia Scientific Fuel Flow Meters

- Built for Mining
- >99% Consumption accuracy
- Temperature and Density Corrected

GNSS

- Geo-location accurate to three meters

Figure 25. High-precision instrumentation (Hernandez, 2022).

The paradigms provided by machine learning methods are better applications and industries (Shehadeh et al., 2021). The primary task of machine learning is to replace the manual approach whenever possible, reducing human effort and minimising the squandering of time and potential errors (Bharadiya, 2023).

3.5.2 Benefits of using machine learning algorithms as opposed to traditional methods.

According to Soofastaei (2020), machine learning algorithms can examine data from mining equipment to forecast machine failure and, therefore, assist in the performance of predictive maintenance, which reduces machine idle time and repair costs. The maintenance prediction method applies supervised learning—whereby these models will predict when maintenance will be planned or when the equipment will fail (Ouadah et al., 2022). Sensor measurements of this operational data, machine history and performance data, machine service, and active data will constitute the primary data source. Data labelled and supervised learning, such as regression, can train these models to predict when the machine fails or needs maintenance (Pesherova et al., 2022). Machine Learning tools help operate effectively by providing insights and responses at the different levels in organisations and businesses, aiding in fast decision-making in anticipation of changes in the environment or available opportunities.

Regression algorithms are effective in assessing the cost benefits of autonomous machines compared to conventional machines employed in surface mining processes because this method aids in modelling relationships among variables using empirical data (Baduge et al., 2022). Regression models provide numerical estimates of the relationship between the independent input variables and the dependent output variable (Kumari and Yadav, 2018). In the context of cost benefits, it helps to gauge the extent to which autonomous machines will cut costs or improve efficiency as opposed to conventional machines. The information used to administer the regression algorithm is based on both manual data collection and remote monitoring activities of the machines over six to twelve months.

3.5.2.1 Steps to follow on training machine learning models by Cascadia Scientific.

Cascadia collects haul cycle data and trains Machine Learning Models on every haul cycle (Table 4).

Table 4. Steps to follow to train ML Models (Hernandez, 2022).

1. Define a Question.	Which trucks in my fleet consume more than expected for their workload?
2. Define the Model Target.	Normalised Liters per Cycle.
3. Evaluate and choose correlated model inputs.	Truck ID, Metrictonnenage, duration, distance, vertical profile, zone, and Queuing time.
4. Select a Model Type.	Gradient Boosted Tree.
5. Establish model sensitivity and reliability targets.	Gradient Boosted Tree.
6. Train the model and evaluate its performance.	

3.5.2.1.1 Linear Regression

Linear regression is the classical means of assessing the relationship between a response variable and one or more explanatory variables through coefficient estimation using a least squares fit to the observed data; refer to the example graph in Figure 27. The technique is frequently used to anticipate subsequent actions of mining trucks. Linear regression is more robust than Gradient-Boosted Trees (GBT) for out-of-distribution samples because it uses the training data effectively to make inferences (Heuer et al., 2024).

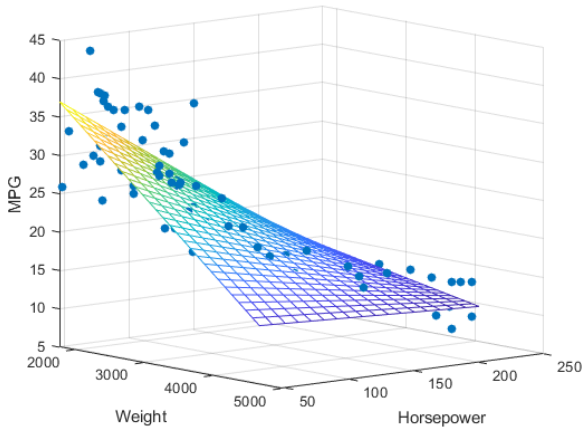


Figure 26. Linear regression graph display (Shin and Yoon, 2020)

3.5.2.1.2 Gradient Boosted Trees

Seeking improvement in model prediction, gradient-boosted trees combine simpler (weak) models. These models are useful for describing the antecedent behaviour of the trucks. Decision tree methods are not restricted to linear relationships and can manage the complexities of the system (Sahour et al., 2020). GBT works using the paths taken by decision trees, as seen in Figure 28, so it could do better with instances that did not exist in the past.

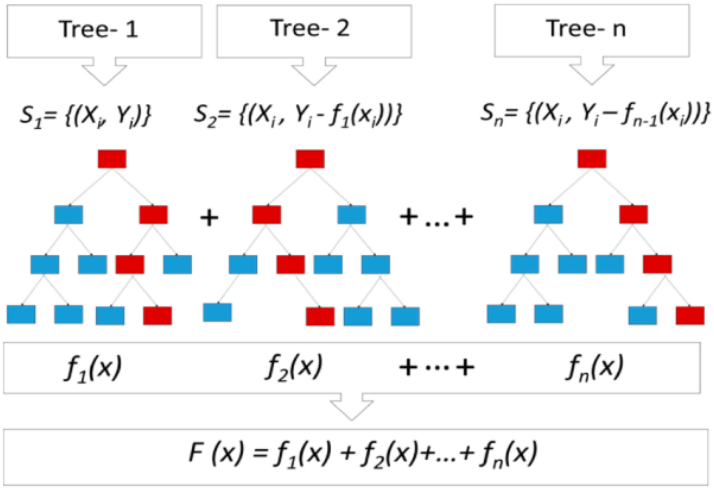


Figure 27. Gradient-boosted trees (Sahour et al., 2020).

The strategies of linear regression and gradient-boosted trees are focused on different aspects of the modelling and prediction processes. The linear regression model is most appropriate for forecasting behaviour, especially in out-of-the-distribution situations, as it is sensitive enough to the trained data (Mahmud et al., 2021). In contrast, as Era et al. (2022) noted, the most challenging aspects for gradient-boosted trees to analyse are non-linear patterns, which they excel at deciphering to describe past and future behaviours. Gradient-boosted trees may struggle with novel encounters or situations that have not been previously represented in the data. Despite this limitation, each method offers distinct advantages, making it possible to efficiently combine them for predictive modelling of mining trucks' operational aspects. In this research project, gradient-boosted trees were applied to the data outlined in sub-section 3.5.2.

3.6 Industry Cost Curve Algorithm Development

Cost curves can only be generated with the proficient version of Microsoft Excel. The author followed an algorithm based on the error bars and performed cost curves in Microsoft Excel (Tholana, 2012). The author was scientific enough to analyse data from Company Annual Reports. The author selected production data regarding metric tonnes treated and cash costs per unit, for example, one treated metrictonne. The data was organised by fixing the order of the mines or companies in ascending order of unit cash costs. The arranged data was then used to form a table, like Table 5.

Table 5. Data input for the cost curve development.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)	Unit cost $/t	X-Error (-)	Y-Error (-)	Y-Error (+)
Mine A	10,753	27	10,753	27	10,753	27	6
Mine B	7,898	32	18,651	32	7,898	32	1
Mine C	26,055	33	44,706	33	26,055	33	0
Mine D	15,440	34	60,146	34	15,440	34	0
Mine F	13,221	34	73,366	34	13,221	34	3

From left to right, the columns are defined as follows in Table 6.

Table 6. Data input description (Tholana, 2012).

Column	Description
Mine/Company Name	Lists the names of the mines or companies, denoted as Mine n or Company n.
Production	Provides production data, including metric tonnes treated or ounces/carats produced by Mine n or Company n.
Cumulative Production	It represents the X-axis of the curve, calculated by summing the current Mine or Company's production with the preceding entities' total production. Mathematically, cumulative production = (production of Mine n) + (production of Mine n-1) + ... + (production of Mine 1).
Unit Cost	Represents the unit cost of Mine n or company n as reported in the Annual Report or calculated and is plotted on the Y-axis of the cost curve.
X-error (-)	Captures the production data of Mine n or Company n.
Y-error (-)	Indicates the unit cost of Mine n or Company n.
Y-error (+)	Reflects the difference between the unit cost of mine (n+1) or company (n+1) and the unit cost of Mine n or Company n.

The first step required creating an XY scatter plot in Microsoft Excel. The plot shows the range with cumulative production values on the X-axis and unit cost values on the Y-axis, providing a graphical result like the one illustrated in Figure 34.

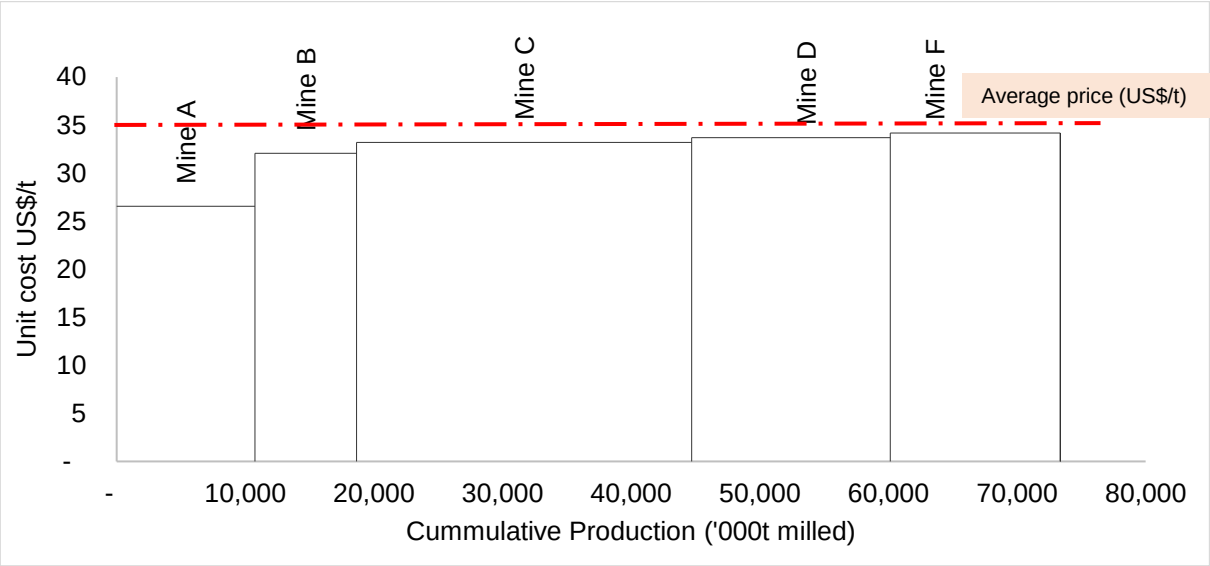


Figure 28 Visuals of the complete cost curve.

The industrial cost curve shown here, as illustrated in Figure 28, represents the relationship between cumulative production (in kilo metric tonnes milled) and unit cost (US$/t) across mines, with a red dashed line indicating the average iron ore price/t. Referring to Figure 28, Mine A is the least expensive operation, displaying the widest profit margin among all mines. In contrast, Mine F exhibits the lowest cost per unit of production. However, Mines D and F have costs per unit above the average price, indicating that these operations generate no economic profit or value. This concept directly aligns with the analysis in Chapter 4, which examines the cost-benefit of implementing autonomous dump trucks. Using a similar cost curve approach, Chapter 4 evaluates how autonomous systems can lower operational costs, potentially repositioning higher-cost operations to a more competitive stance on the curve. The results also highlight the potential for improved profitability and economic value through reduced unit costs, echoing the findings for Mines A and F. This framework provides a clear quantitative perspective on the economic impacts of adopting technological innovations.

CHAPTER 4

4 Findings

4.1 Labour Cost Saving with Autonomous Surface Machines

A comparison between traditional mining and autonomous mining machines showed noteworthy contrasts in terms of operational hours, keeping standby time as the primary factor. For the conventional industry process of mining, this study tracked non-labour operational overhead costs related to partitions for the operator's substitutions, e.g. other than shift replacements and combating exhaustion to a limit of four silent quarters of 2023. It has been revealed that there were a significant number of idle hours, which totalled three thousand six hundred hours idle in the first quarter of the year, decreasing to one thousand nine hundred in the second quarter and one thousand two hundred in the third quarter, then rising again in the fourth quarter to about three thousand one hundred hours. The standby hours captured within four quarter of the year 2023 indicate what amounts of foreseen inelastic time resources are placed in all the traditional mining procedures on human operators; Figure 29 illustrates this.

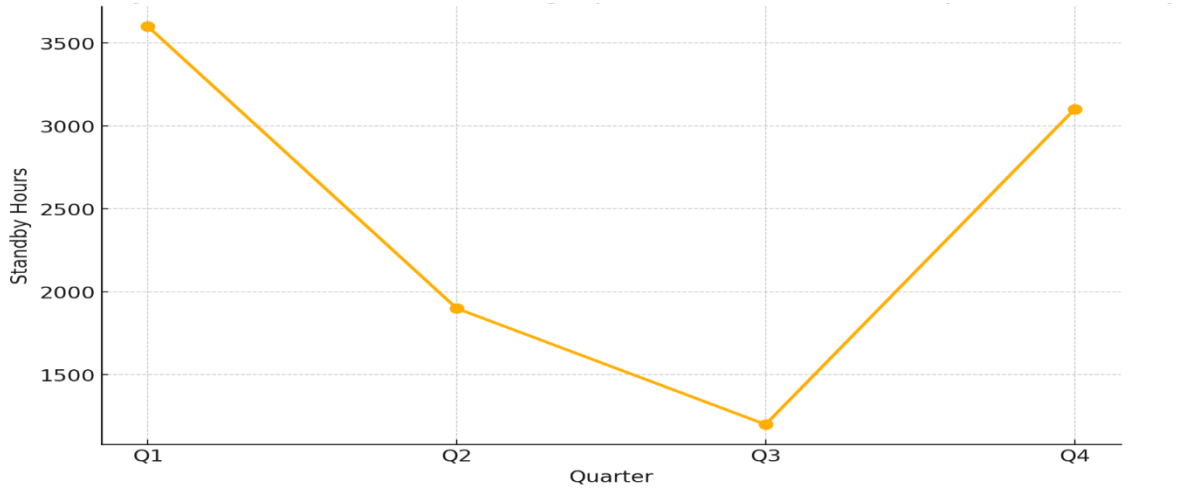


Figure 29. Standby hours (No operator) for traditional mining operations in 2023.

On the contrary, self-operating mining machines have low or practically no standby time concerning the same factors, as no workers require recovery breaks or shift changes. These factors combined result in continuous operation and reduce operational downtime, allowing for more operating hours within a given time. The graph

above reflects and vividly demonstrates the significant differences in suspended operational hours due to injuries from traditional mining methods and human-driven standby harassment. Autonomous machines address all these problems and, as a result, can perform work more uniformly and reliably.

The economic and production advantages are significantly appreciated when considering the plausible measures that must be undertaken to transition to autonomous mining levels. As noted previously, standby time is reduced, having a volatile effect on productivity and efficiency in operations. Not only does the reduction in time lessen the costs associated with wasted hours, but it also helps to increase output, as the machinery was expected to operate uninterrupted compared to conventional mining settings. The shift to autonomous mining technology can bring considerable improvements in both profit and the production scale of the mining processes.

4.2 Industry Cost Curve Post Implementation of Autonomous Trucks

The industry cost curve was prepared to illustrate the correlation between implementation costs and benefits from autonomous operations. Shaping the cost curve, decision-makers will comprehend all aspects regarding cost efficiency and the necessity of moving on to fully automated equipment for surface mining. Figure 30 below indicates the trend of iron ore prices from the year 2000 until the year 2023. An average price is considered a yardstick for measuring profitability or loss.

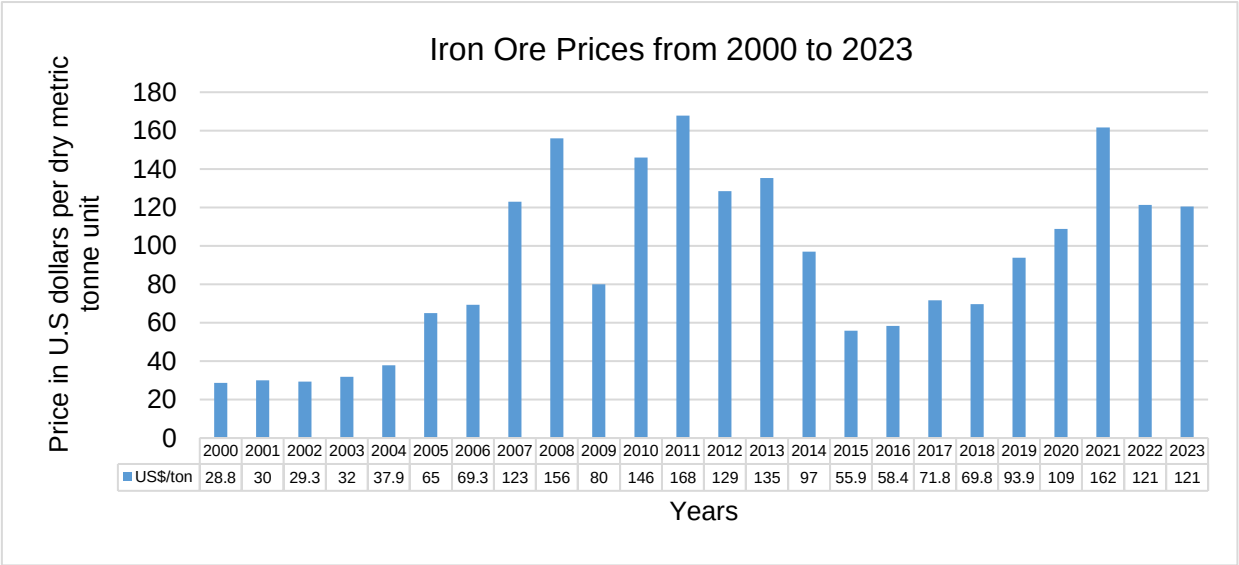


Figure 30. Iron ore prices from 2000 to 2023 (Statista, 2024)

The cost curves were used to identify any change after deploying autonomous dump trucks in surface mining. All the mines are in Australia and are owned by different mining companies. Operational efficiency and technological advancements are important in determining overall profitability among all unit cost factors, such as cut-off grade, mill head grade, and production scale. After introducing autonomous trucks, the research project concentrated on the production scale tracking and assumed constant to the other factors.

Five mines were analysed, as shown in Table 7 below.

Table 7. Iron Ore Mines Implemented Autonomous Trucks.

Start year	Mining company	Mine Site	Location	Manufacture	Truck Type	Capacity (metric tonnes)	Number
2008	Rio Tinto	West Angelas	Australia	Komatsu	930E-AT	320	5
2012	Rio Tinto	Yandicoogina	Australia	Komatsu	930E-AT	320	22
2012	Rio Tinto	Hope Downs	Australia	Komatsu	930E-AT	320	19
2013	Rio Tinto	Nammuldi	Australia	Komatsu	930E-AT	320	30
2014	BHP	Jimblebar	Australia	Caterpillar	Cat 793F	250	18

The assessment was performed on an annual basis throughout the years ranging from 2010 to 2023. It must be different from others, relating to mining facts of data used. Secondary data was sourced from hundreds of publications and research detailing the cost of all In-sustaining iron ore production. Year in and year out, tracking the movement or behaviour of unit cost and tonnages produced. The 2010 Iron ore mines cost curve is an additional deep dive into iron ore mines' cost structure and productivity (Figure 37). It analysed the unit cost, production, and price relationship from five mines listed in Table 1. This correlation, among other things, helps explain the interpretation of these mines' location and physical characteristics regarding cost and margin potential. The raw data used for the graph in Figure 31 can be found in Table 6 (Appendix 2).

The provided legend is used in an industrial cost curve to categorise mines based on their unit cost/t and metric tonnes milled. The three quartiles—lower, middle, and higher—are represented by green, yellow, and red, respectively. Mines are classified into these quartiles based on their relative cost efficiency and production levels. When a mine increases its unit cost/t or achieves high metric tonnes milled, it may shift its position on the cost curve, moving into the higher, middle, or lower quartile depending

on its performance. This classification allows for an easy comparison of operational efficiency and cost-effectiveness among different mines.

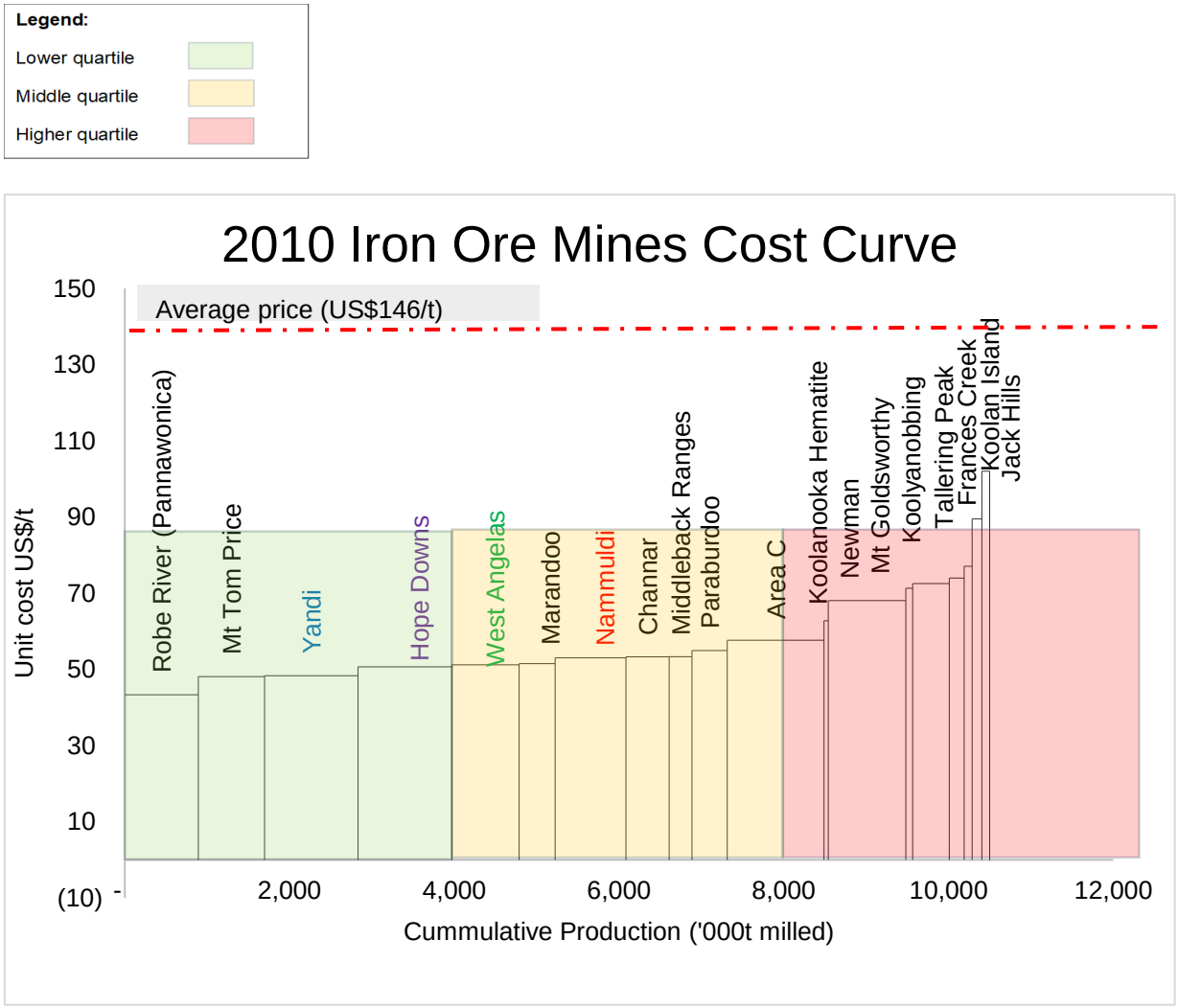


Figure 31. Iron ore mines cost curve 2010.

Using Figure 31, mines such as Yandi and Hope Downs are positioned in the lower quartile of the cost curve, with unit costs ranging between US$40 and US$55/t. These low-cost operations underscore their efficiency and competitiveness within the industry. Yandi achieves a cumulative production of approximately 5 million metric tonnes, while Hope Downs contributes around 4 million metric tonnes. Their combination of high production volumes and low unit costs highlights well-optimised processes and economically viable operations, positioning them well below the market average price of US$146/t. West Angelas and Nammuldi, on the other hand, are in the middle quartile of the cost curve.

These mines have unit costs between US$50 and US$60/t, reflecting slightly higher costs than the lower quartile. West Angelas produces approximately 5 million metric

tonnes, while Nammuldi has a lower output but remains a significant contributor. Their middle quartile positioning indicates a balance between moderate costs and substantial production volumes, displaying efficient operations with room for cost improvement. It is also noteworthy that Jimblebar was not listed on the Australian cost curve in 2010, highlighting its absence from significant production benchmarks. This exclusion may suggest that the mine was either not operational or not contributing significantly to production volumes during that period.

The margin profitability for the mine has been assured as it remains far below the mean market price, although the margins themselves are not as thick as those of the lower quartile. The cost elements may arise from variations in the mining technique, the grade of ore mined, or the efficiency of the facilities, pointing out that even though Yandicoogina is making gains in selling its product, its cost base structure lessens its competitiveness of low market price.

Mines within the Middle Quartile, such as Nammuldi, are moderately more costly, with estimated unit costs of about US$60 to US$70/t. Nammuldi has a production volume of approximately 3 million metric tonnes, which is lower than that of lower-quartile mines. Its placement in the middle quartile of the cost curve reflects a moderate balance between costs and production metric tonnes. It also indicates inefficiencies potentially due to unfavourable mining parameters, such as lower ore grades or higher stripping ratios. While Nammuldi remains below the market average price of US$146/t, its narrower cost margin highlights challenges in maintaining strong price competitiveness. Given its position in the middle quartile, there is a risk of financial strain as costs approach breakeven levels, emphasising the need for operational improvements to enhance efficiency and sustain competitiveness in a dynamic market.

The relationships between unit cost, production output, and average market selling price can be analysed using the 2010 iron ore mines cost curve and its quartile divisions. Mines like Yandi and Hope Downs, positioned in the lower quartile, effectively balance production volumes with low unit costs, achieving strong profit margins below the market average price of US$146/t. Middle-quartile mines such as West Angelas and Nammuldi maintain moderate costs and production levels, demonstrating a balance between revenue generation and operational expenses. Nammuldi, with its moderate production volume and higher costs, faces price pressures, underscoring the need for cost control and operational efficiency

improvements. Analysing unit costs about production metric tonnes provides valuable insights into a mine's competitive position and strategies for optimising profitability.

The Iron ore mines cost curve of 2011 (Figure 32) provides insights into the shifts in cost efficiency and production strategies among iron ore mines compared to 2010. The average iron ore price increase from US$146/t in 2010 to US$167.8/t in 2011 indicates a significant transformation in market conditions. This price rise altered the profitability thresholds for mines and cascaded cost structures and production strategies across the sector. The elevated price encouraged mines to maximise output and capitalise on higher revenue potential. However, this often came with increased operational costs as mines expanded production into areas with lower ore grades or higher stripping ratios. These adjustments are reflected in changes to the cost curve, as mines experienced upward shifts in their unit costs, leading to movements across quartiles.

The cost curve also highlights how certain mines, such as Yandi and Hope Downs, moved from the lower quartile to the middle quartile due to increased costs, while others, like West Angelas and Nammuldi, improved their efficiency and shifted to the lower quartile. These quartile changes underscore how mines adapted their strategies to balance production volumes and unit costs in response to the evolving market. Overall, the rise in average market price reshaped the competitive landscape by incentivising increased output, prioritising cost control, and emphasising operational efficiency to maintain profitability within the shifting economic environment.

The analysis below examines the positions of West Angelas, Yandicoogina, Hope Downs, and Nammuldi from 2010 to 2011, looking at the cost per metrictonne and production volumes to clarify the changes they would have undergone during the industry’s business. The raw data used for the graph in Figure 32 can be found in Table 7 (Appendix 2).

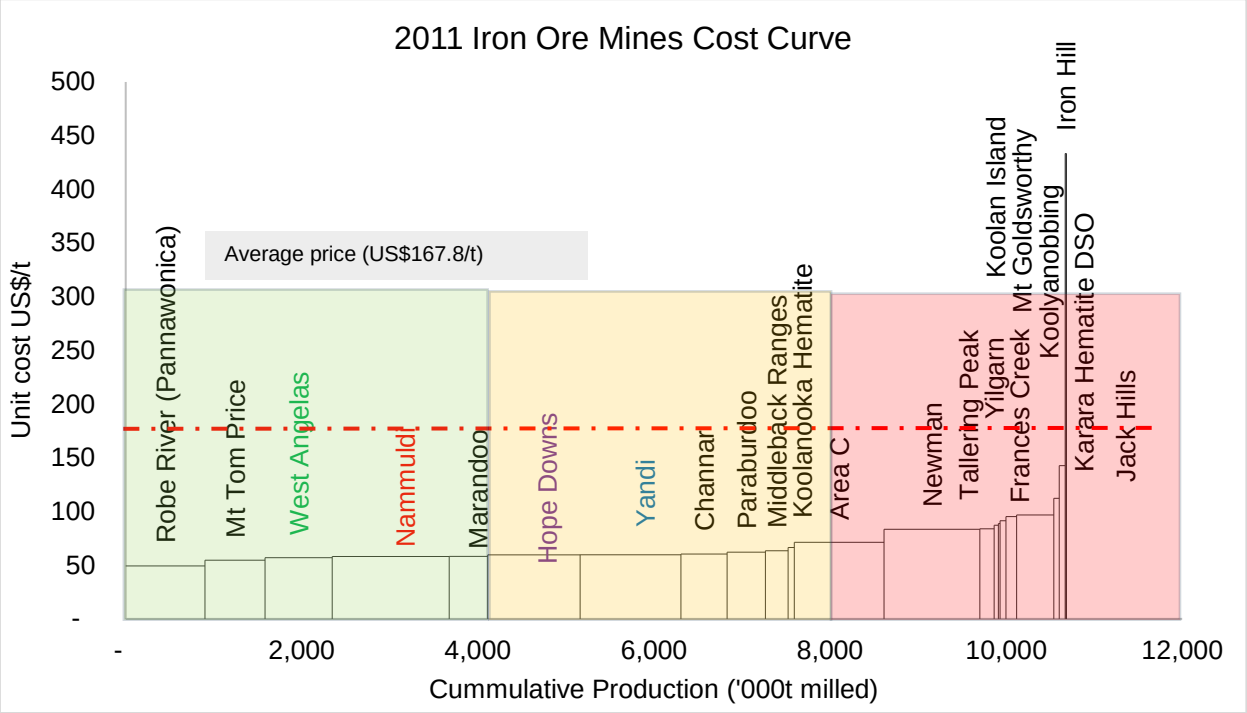


Figure 32. Iron ore mines cost curve 2011.

In 2011, West Angelas demonstrated its position in the lower quartile of the cost curve, with unit costs consistently in the US$50–US$60 range, despite increasing average prices and industry pressures (Figure 32). A significant factor contributing to this performance was the early adoption and implementation of autonomous technologies driven by forward-thinking management. Investing in automation early, the operation benefitted from enhanced efficiency, reduced labour costs, and improved consistency in production.

The sustained production volume of approximately 5 million metric tonnes further emphasises the impact of this strategic decision. Autonomous systems allowed the mine to optimise resource allocation, minimise operational delays, and enhance safety, contributing to steady output at low costs. This proactive approach by management stabilised costs and positioned West Angelas as a benchmark in operational excellence, displaying how early technological adoption can drive long-term competitive advantages. Yandicoogina, too, retained its middle quartile position and, albeit slightly this time, improved on cost-effectiveness, lowering its unit cost to below the range of US$50-60 in 2010. The explanation for the improvement in the cost

structure is that either improved mining or controlling costs can engage more productivity owed to higher average market prices.

Hope Downs could continue recording low unit costs in the lowest quartile within a similar gap in cost/t to West Angelas, which was also maintained at the US$40-US$50 band. The production volume stayed steady at around 4 million metric tonnes. The stable performance indicates that Hope Downs maintained its cost competitiveness, consistent with the industry direction of low-cost, high-volume strategies. For Nammuldi, however, the position has yet to change. Unit costs are still in the upper quartiles at US$60 - US$70/t K.U. unitar. The accumulated production volume for Nammuldi was approximately 3 million metric tonnes compared to 2010, which shows no change in production volume. The coexisting cost and volume pattern implies that although Nammuldi has not achieved considerable production gain, it has preserved productivity at higher price levels.

In the 2011 cost curve (Figure 32), the mines, like West Angelas and Hope Downs, bore a high, low-cost advantage while other mines, like Yandicoogina, made progress, and Nammuldi was stable but at higher costs. The juxtaposition shows the balance and realignment within an industry considered an outlier due to the prevailing high average pricing of iron ore over time. The trends help one understand how management strategies will be formulated to retain or increase market share, considering the cost and production structure changes. The 2012 cost curve for Iron Ore Mines (Figure 33) reveals increased inefficiencies, shifts, and fluctuations in production, reflecting ongoing technological progress and market challenges.

Average iron ore prices dropped sharply from US$167.8/t in 2011 to US$128.5/t in 2012, placing additional strain on the mines. This price decline heightened the challenges for operations, pushing them to maintain profitability under more significant economic pressure (Humphreys, 2014). Raw data used for the graph in Figure 33 can be found in Table 8 (Appendix 2).

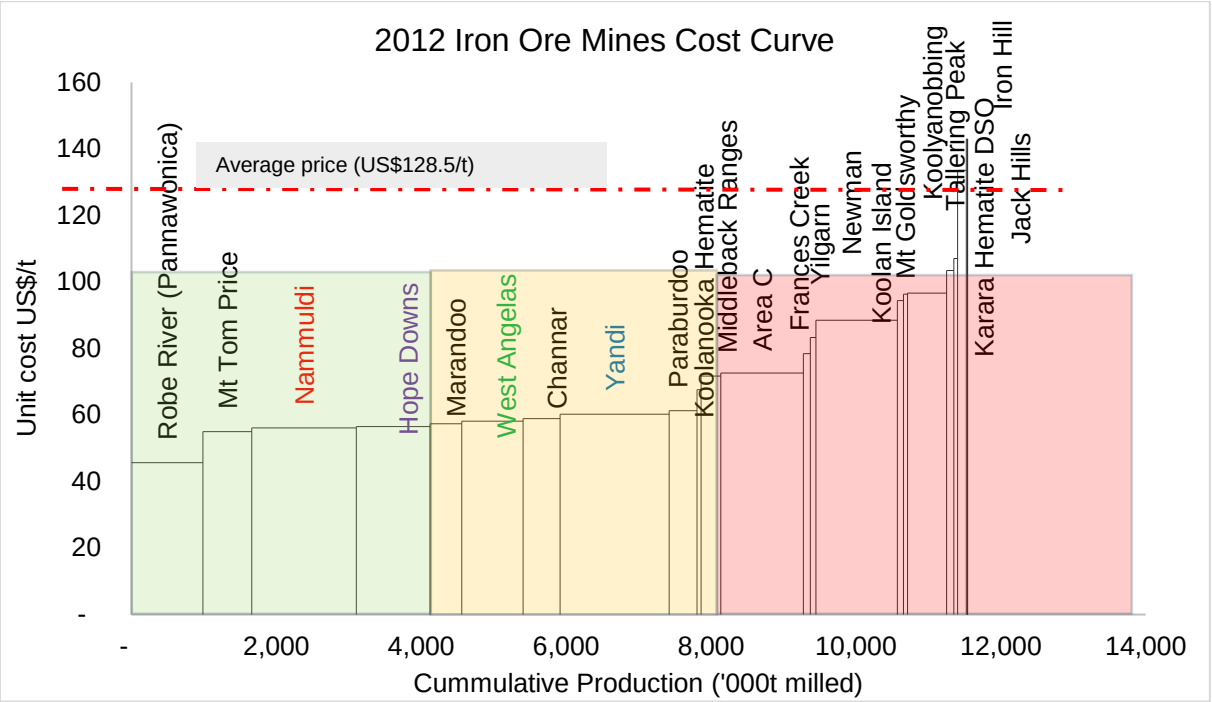


Figure 33. Iron ore mines cost curve 2012.

The 2012 cost analyses of these specific mining regions demonstrate how this new style of mine could cope with the case where there was a lower-than-average market price, even to the extent of emphasising cost control and production efficiency. Even those that were cost competitive in the lower quartile at unit costs of about US$40-US$50/t, such as Hope Downs, had the competitive edge of earlier incorporation of autonomous trucks and high crude steel production levels of 4 million metric tonnes, respectively. Using autonomous trucks since 2011, Yandicoogina was not as viable, sitting at the middle quartile of US$60/t, holding a high crude steel production volume of about 7 million metric tonnes, suggesting reasonable control of costs. Nammuldi, however, had the lowest range of unit costs at US$40/t - US$50/t, and moderate tonnage production volumes of 3 million metric tonnes came later, as the autonomous technology was not adopted until 2013 in Figure 34. The cost curve confirms the better position of early automation estimates/evaluation of measures to mitigate the harshness of shrinkage on market prices, unlike the later trades of new measures that suffered from lower margins and instability of market prices.

The evaluation also extended its observations to the cost curve for 2013 performance (Figure 34). The selling price affected none of the mines as the unit price rose to an upward movement of 135. The 2013 Iron ore mine cost curve in Figure 34 depicts a slight improvement in the average iron ore price, which stood at 128.5 in 2012 but has now improved to 135.4/t of iron ore. Further understanding of the cost curve also

suggests that formal relations started to take shape even as the market slump persisted and how mines endeavoured to contain their cost structures and levels of production within such circumstances, emphasising the role of autonomous technology implementation. Raw data used for the graph in Figure 34 can be found in Table 9 (Appendix 2).

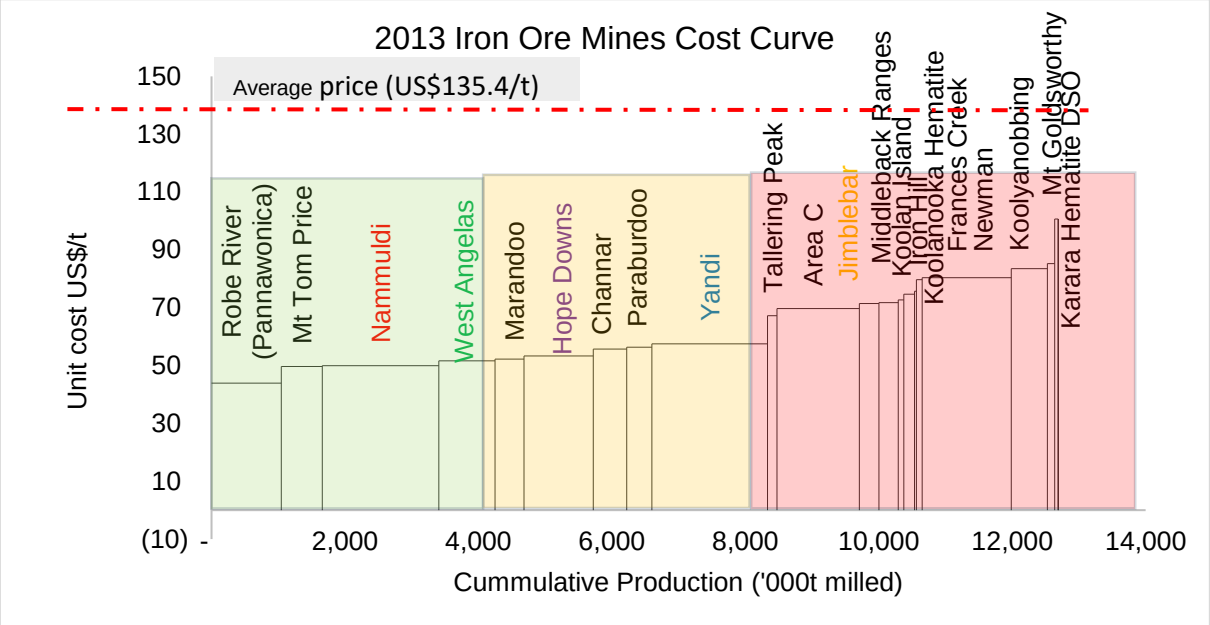


Figure 34. Iron ore mines cost curve 2013.

In 2013, West Angelas and Nammuldi remained stagnant. They were consistently ranked in the bottom quartile, sustaining unit costs of US$50/t to US$60/t. At the same time, Yandi Mine remained profitable in its second-year performance following the implementation of twenty-two autonomous dump trucks. Iron ore output increased from 7 to 8 million metric tonnes, while unit cost/t decreased from US$ 60 to 58t. Nammuldi mine did not display a leap in performance in the first year of the third autonomous dump truck implementation, with production volumes of 5 million and 4 million metric tonnes, respectively. These mines are still reaping the benefits of autonomous truck demand, launched in their early days, helping them remain competitive despite changes in market prices. Yandicoogina is less efficient in the lower quartile but remains competitive on production cost, with unit costs of about US$50 to US$60 and production capacity of about 6 million metric tonnes after further extending the adoption of autonomous technologies in place since 2011.

Finally, in Figure 35, Nammuldi, which used autonomous trucks as of 2013, is beginning to improve its cost efficiency and reduce the unit cost to US$50 - US$60/t. The moderate production volume of 3 million metric tonnes suggests only an initial

phase in using the new technology, with declines in costs eventually. Jimblebar's started with a high cost per unit in 2013, ranging from US$70/t - US$80/t. From a broader perspective, the 2013 cost curve highlights the need for automation and effective mining strategies, as the ore market is already characterised by such price volatility.

The 2014 iron ore mines cost curve (Figure 35) presents an opposing graph of changes in the mean price of iron ore/t, which now averages just US$96.95, down from US$135.4 a metrictonne in 2013. With the decrease in demand for such products, prices have dropped, exerting more pressure on the mines to revise their cost and production structures based on profitability in the present depressed market conditions. Raw data used for the graph in Figure 35 can be found in Table 10 (Appendix 2).

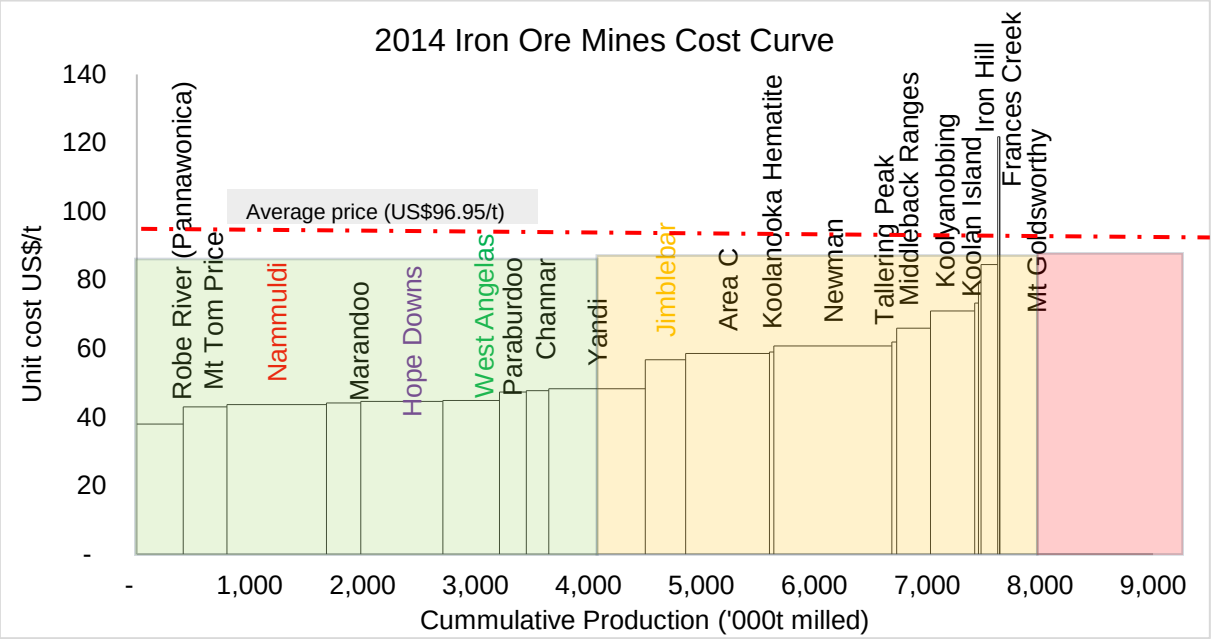


Figure 35 Iron ore mines cost curve 2014.

Nammuldi, West Angelas and Hope Downs remained lucrative in 2014, as they operated in the lower quartile with unit costs of US$40-US$50/t, producing million metric tonnes ranging from 1.6 to 4 million metric tonnes. Their continued low costs and even production show the immense advantage of early adoption of autonomous trucks in these mines, which enables them to enjoy healthy margins even in a low-price regime. With all the advantages associated with being in the lower quartile, Yandicoogina incurred unit costs of US$40-US$50/t, was able to produce 4.5 million

metric tonnes of production volume and attributed to its effective cost control post-adoption of autonomous trucking in 2011.

Jimblebar, however, still goes beyond its autonomous technology purchased in 2011 to affect a cost of US$ 50-60/t for production of 5 million metric tonnes per annum. The mine benefits from real-time monitoring, predictive analytics, and advanced fleet management systems that enhance efficiency and minimise downtime. Economies of scale and reduced labour costs from automation further lower production expenses. Continuous operation, improved safety, and energy efficiency also contribute to cost savings. Additionally, ongoing innovation and upgrades ensure that the technology remains effective and competitive. These combined efforts enable Jimblebar to maintain cost efficiency while maximising production output. For instance, in Figure 35, evidence from the cost curve for 2014 shows a mine closet diamond view event downer. The edge is seen in the new potential development compared to significant portfolios. In low commodity price periods, they are expected to remain cost-competitive and produce more than their followers.

In 2015, the iron ore mines cost curve 2015 (Figure 36) showed that iron ore reached an average low of US$55.85/t from the previous year's price of US$96.95/t, which is a drastic change. The situation evolved, and due to the further drop in the market price, attention was paid to actions and changes within the strategy to maximise cost efficiency in mining activities. Raw data used for the graph in Figure 36 can be found in Table 11 (Appendix 2).

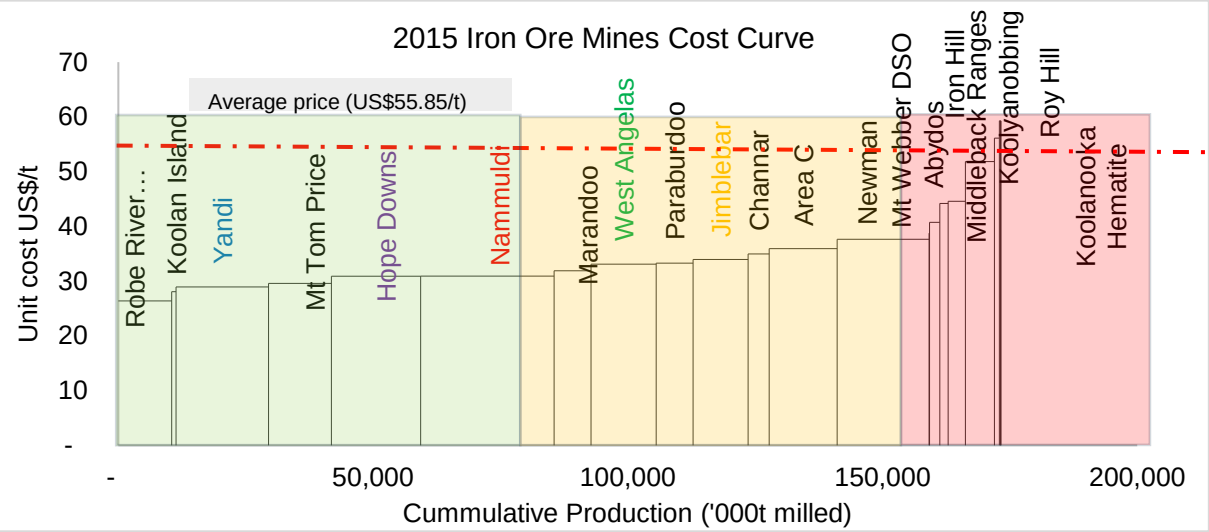


Figure 36. Iron ore mines cost curve 2015.

Hope Downs, an iron ore mine in Australia, also maintained a constant cost structure in 2015, recording costs per unit of US$31/t in the accounts of the lower quartile of unit costs. They improved by producing 59 million metric tonnes of production. Hope Downs Mine has displayed an early integration of how safe autonomous trucks can encourage market expansion where there is room. Due to similar reasons, Yandicoogina also noted unit costs of US$29, which allowed it to produce about 29 million metric tonnes of output despite Yandicoogina showing improvement in its cost structure. Nammuldi, the newcomer to this cutthroat environment, has been slowly progressing in efficiency since the introduction of autonomous trucks in 2013 and now falls toward the US$30/t - US$40/t range after steps to cut down costs further.

Jimblebar remains in the mid-cost tier at about US$30 to 40/t of production, with a stable 123 million metric tonnes annual output, and where improved technologies have been in use since 2011. In the 2015 cost curve, increasing distribution is observed in the curve, in which the first to embrace technological advancement, such as autonomous trucks, are most likely to recover from deep operating losses due to low unit operating costs and high output to those who have not yet enjoyed those advancements will always strive to remain competitive in business and have great difficulty cutting costs. Figure 37 portrays a stable yet low average iron ore price equal to 55.42 US$ per metric tonne; this price fell within the range of 55.85 per metric tonne recorded for the preceding year. The suspension of prices continues, making it compulsory for mining operations to seek ways to minimise costs and compete even when the market is unkind. Raw data used for the graph in Figure 37 can be found in Table 12 (Appendix 2).

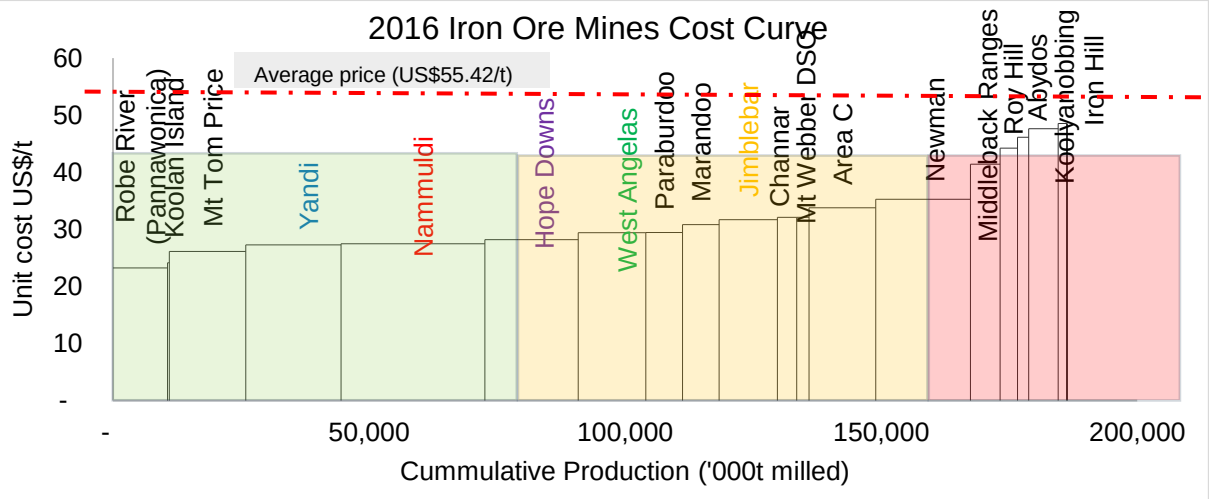


Figure 37. Iron ore mines cost curve 2016.

Weighted average cash cost figures for Yandi and Nammuldi remained in the lower quartile, with unit costs between 20-30 US$/t, while production volumes were 40 million and 80 million metric tonnes, respectively, in 2016. Those mines were among the introduced autonomous technology, keeping the costs low while ensuring that production does not fluctuate significantly. Hope Downs, which belongs to the middle quartile group on the same basis, focused on sustaining the unit economical cost at 28/t to sustain the tonnage of 90 million metric tonnes produced. West Angelas, the first–end user of autonomous trucks since 2008, managed to achieve additional cost reduction, stabilising the unit costs at US$20-30/t volume and moderate production of about 104 million metric tonnes, suggesting that operational optimisation is progressive. Completions of Jimblebar in adopting automation, having occurred in 2014, continued to reap the advantages of automation with unit cost coupled with tonnages of around 129 million metric tonnes remaining fixed at around US$40. The cost structure in the particular year emphasises the role of technological and cost management that enable mines to buy tools and implement changes, such as automating and optimising processes early and continuously, allowing the mines to survive for long periods in a low commodity pricing environment. Figure 38 shows that the average iron ore price is projected to increase slightly to US$71.76/t, rising from US$55.42/t in 2016. The inconsistency of healthy returns on mining operations remained, with an emphasis on cost structure and production output management. Raw data used for the graph in Figure 38 can be found in Table 13 (Appendix 2).

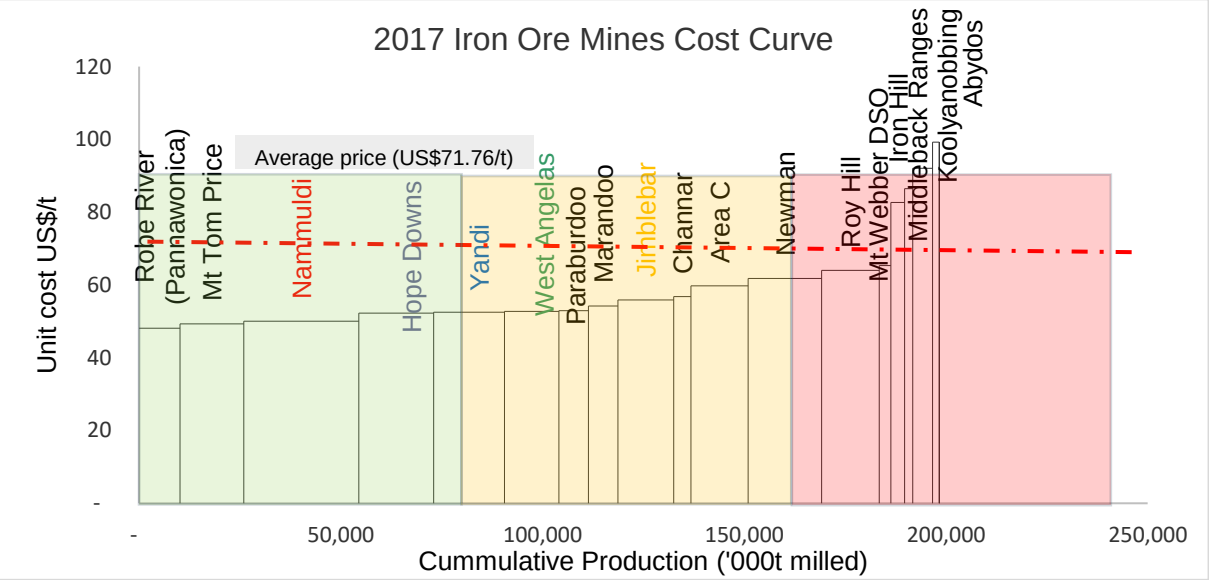


Figure 38. Iron ore mines cost curve 2017.

In 2017, Nammuldi remained in the lower quartile, whilst Yandi moved to the middle quartile. Hope Downs slightly moved to the lower quartile with unit cost figures of around US$45-55/t on production capacities of 80 million metric tonnes. Such mines that were the first to embrace driverless trucks have consistently scored exceptionally well in cost containment, hence poised to take advantage of the increasing market prices. Yandicoogina rated middle quartile but still saw it exploited unit cost of about US$52/t as it posted production volumes of 90 million metric tonnes, heightening the regard accorded the mine in the low-cost high-output axis. With a commendable record since using driverless trucks in 2012. Nammuldi almost doubled its unit cost from US$27/t to US$50/t with a drop in production to 54 million metric tonnes, projecting a gradual upturning of activities. Another mine that embraced autonomous technology in 2014 was Jimblebar, which managed to contain unit costs of around US$56/t on a production volume of 132 million metric tonnes. The 2017 cost curve cost mining companies which invest sufficiently in technology and efficiently manage costs illustrate that mines with appropriate technological deployment efficiency in operations can ride on improvements in the market price of their products without losing their competitiveness.

According to the 2018 Iron ore mines cost curve, shown in Figure 39, the average iron ore price also moderated, albeit marginally, to US$69.75/t, compared to US$71.76/t in 2017. A slight decline in market price may indicate a steady mood devoid of volatility. Cost management continues to be one of the critical elements for any mining business to remain profitable. Raw data used for the graph in Figure 39 can be found in Table 14 (Appendix 2).

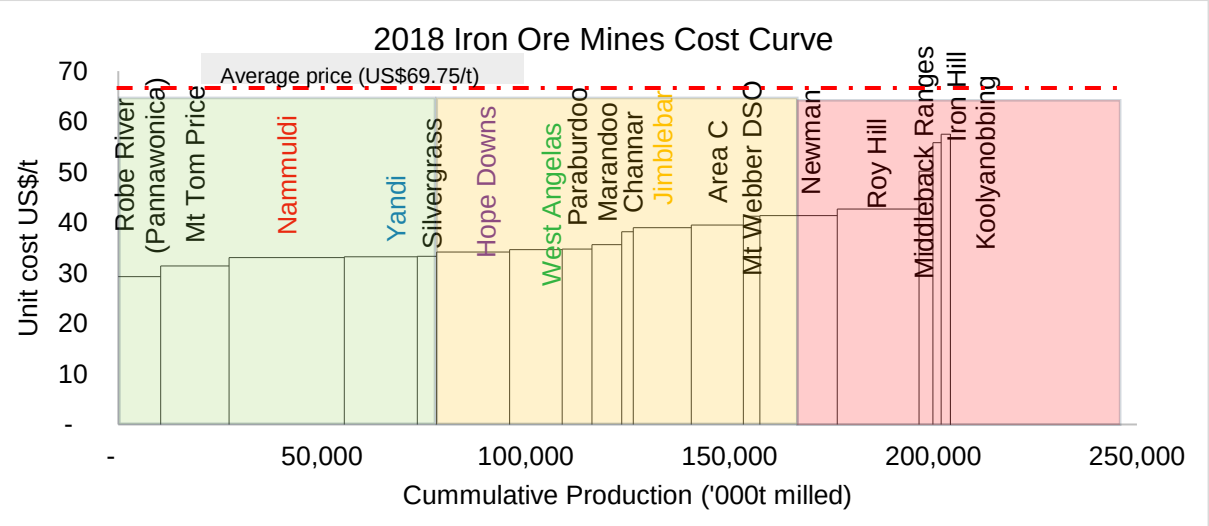


Figure 39. Iron ore mines cost curve 2018.

In 2018, unit costs improved to US$30-US$40/t mass-produced for evaluation purposes for West Angelas and Hope Downs, both in solid positions in the middle quartile geographical area with production volumes around 108 million and 96 million metric tonnes, respectively. With the onset of the competitive environment and the gradual incorporation of suitable technologies for commercial exploitation, this early adoption of autonomous trucks enables these mines to reduce their costs and optimise production rates, helping them remain competitive even with minor price variations. Ranking in the upper-half cost position, Yandicoogina had a unit cost of US$33/t for a 73 million metric tonnes significant output production volume, validating the company's cost-efficient strategy and high-volume production. Nammuldi has improved operational efficiency, reduced haulage costs, and enhanced overall production since employing autonomous dump trucks in 2013. These improvements have contributed to maintaining a profitable cost range of US$30/t to US$40/t while sustaining an average output of approximately 55 million metric tonnes annually. The 2018 cost curve shows the way forward, which includes dynamics of continued innovation and enhancement of efficiencies, which depicts how mines can remain profitable and competitive in the industry despite reduced prices for the operational market.

The 2019 Cost curve of iron ore mines (Figure 40) reveals an increase in the nominal average value of iron ore to US$93.85/t from US$69.75 in 2018. Improving market conditions helps the mines maintain their cost structure more effectively, as they can improve their income margins. Improving market conditions enables mines to maintain their cost structures more effectively, as higher commodity prices increase revenue and income margins. This additional income allows mines to cover fixed and variable costs more comfortably, invest in operational efficiencies, and absorb unexpected expenses without significant strain on profitability. Higher prices also create opportunities for reinvestment in technology and infrastructure, further stabilising cost

structures in the long term. Raw data used for the graph in Figure 40 can be found in Table 15 (Appendix 2).

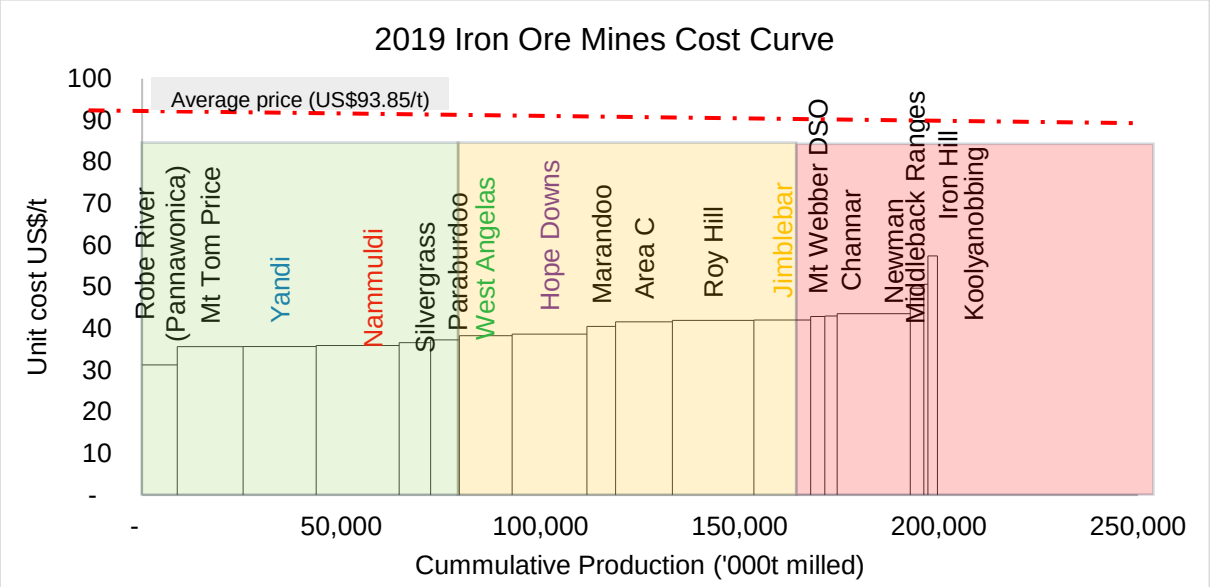


Figure 40. Iron ore mines cost curve 2019.

In 2019, Nammuldi and Yandi remained within the lowest quartile. The unit costs doubled, averaging between US$60 and US$70/t, and production levels of about 43 million and 64 million metric tonnes, respectively. The persistently low-cost structures and stable production rates of these mines indicate the advantages associated with the early adoption of operatorless trucks, which allow these mines to increase their profitability as prices rise. Yandicoogina, also in the lower quartiles, recorded unit costs of approximately US$30/t and production of 6 million metric tonnes, pointing to its operations' effectiveness and high performance. On the other hand, Hope Downs and West Angelas have rationalised their activities since adopting autonomous trucks, recording unit costs within the US$30–40/t band while sustaining volumes of production around 72 - 92 million metric tonnes, demonstrating continued improvement in cost management. Jimblebar improved on tonnages produced, which also increased the unit cost to US$42/t. The importance of integration and the cost control strategies as advanced in the 2019 cost curve underline the importance of technology to the mining industry; it explains how mining companies that focus on the two aspects would be able to take advantage of improvements in market prices of their commodities without losing their competitiveness.

Figure 41 indicates that the average iron ore price stood at US$93.85/t, the same as that of 2019. The price environment remains constant, encouraging the need to ensure

that the cost structures for the various mines are effective and that production is enhanced to improve revenues. Raw data used for the graph in Figure 41 can be found in Table 16 (Appendix 2).

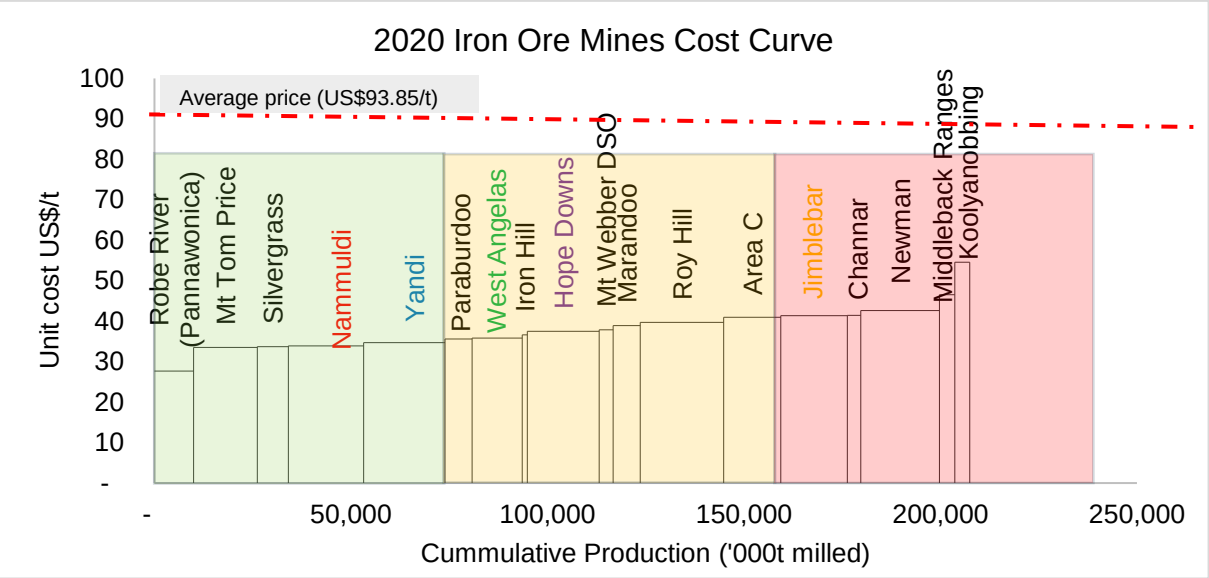


Figure 41. Iron ore mines cost curve 2020.

In 2020, West Angelas and Hope Downs proved their cost efficiency and operational stability. They remained in the middle quartile with unit costs within the US$20-US$30/t range and output volumes of about 93 million and 113 million metric tonnes. Their early investment in introducing autonomous trucks and constant process improvement has helped these mines achieve low costs, steady production, and a competitive edge. Yandicoogina, an example of a lower quartile mine, maintained unit costs of US$35/t and above, achieving a reasonable output of 73 million metric tonnes. Nammuldi, which has remained in the lower quartile, kept unit costs between US$30-US$40 and output levels at 53 million metric tonnes, highlighting gradual unit cost performance. Jimblebar, which has benefitted from an early investment in autonomous trucks since 2014, still stabilised unit costs at about US$40/t to US$45/t, producing a stunning volume of 176 million metric tonnes moved to the upper quartile. The 2020 cost curve developed by management regarding the placement of the elements integrates the use of technology and cost management efficiency, exhibiting that mines that embrace these elements are likely to perform much better even in a less volatile price environment.

According to the Iron ore mine cost curve of 2021 in Figure 42, the average price for iron ore increased from US$93.85 in 2020 to US$161.70 this year. Due to increased

market prices, mining ore producers maximised their profits by keeping costs low. Raw data used for the graph in Figure 42 can be found in Table 17 (Appendix 2).

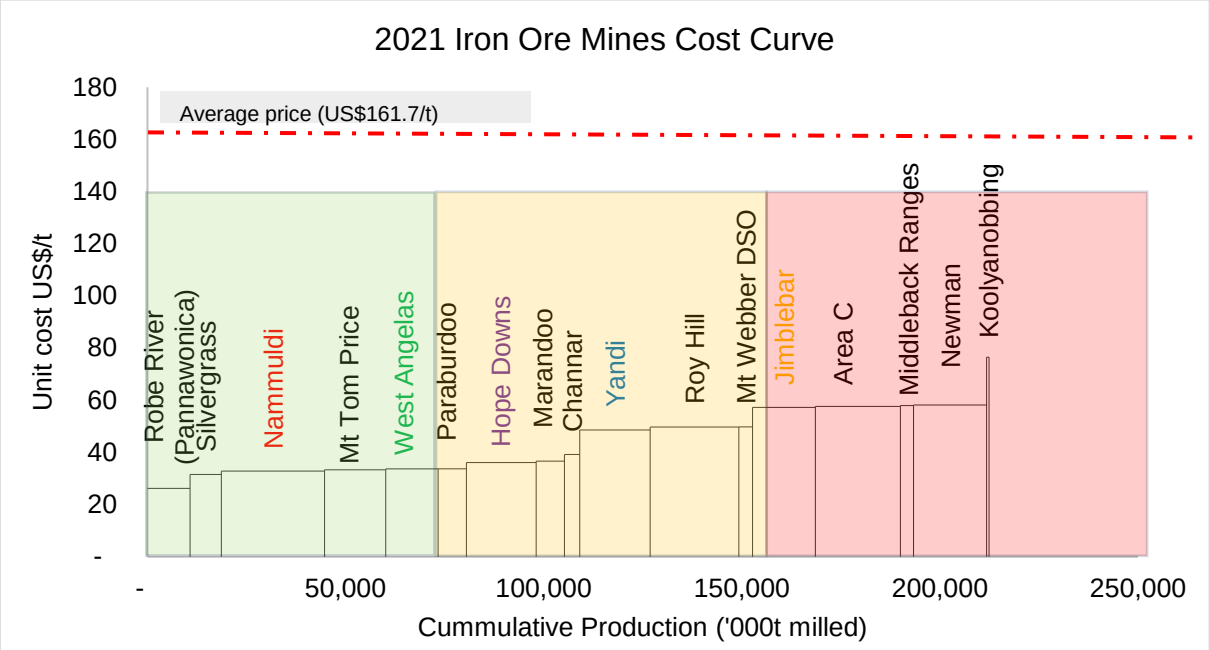


Figure 42. Iron ore mines cost curve 2021.

In 2021, West Angelas ranked first in cost competitiveness. It remained in the lowest quartile, with costs averaging US$30-40/t on production volumes of 73 million metric tonnes. Given the mature operations with early autonomous truck deployment, these mines can use the higher price levels to enhance profitability if such facilities are well maximised. Within the lower quartile, Nammuldi processed about 44 million metric tonnes and achieved lower unit costs of US$33/t, further consolidating efficient operations and tightening cost controls. Hope Downs, whose operational improvements have been gradual, occurred after the onset of autonomous operations in 2012, stabilised costs at around US$30-US$40/t while production levels hovered at about 98 million metric tonnes, which explains the improvements made on cost cuts. The information shows the advantage that the 2021 cost curve benefits from regarding technology acquisition, and maintaining such practices helps the mine high effectively.

The section has relied on internal estimates for market penetrations and submarket prices. According to Schmitt (2022), the cost of iron ore mines in 2021 was US$137.3/t. As demonstrated by the 2022 Iron ore mines cost curve Figure 43, the average price of iron ore plummeted to US$121.3/t, down from US$161.7/t in 2021. Factors such as average prices remained prominent, as price differentiation in the iron and steel industry did not drive market prices to enhance profitability or maintain a competitive

standing. Raw data used for the graph in Figure 43 can be found in Table 18 (Appendix 2).

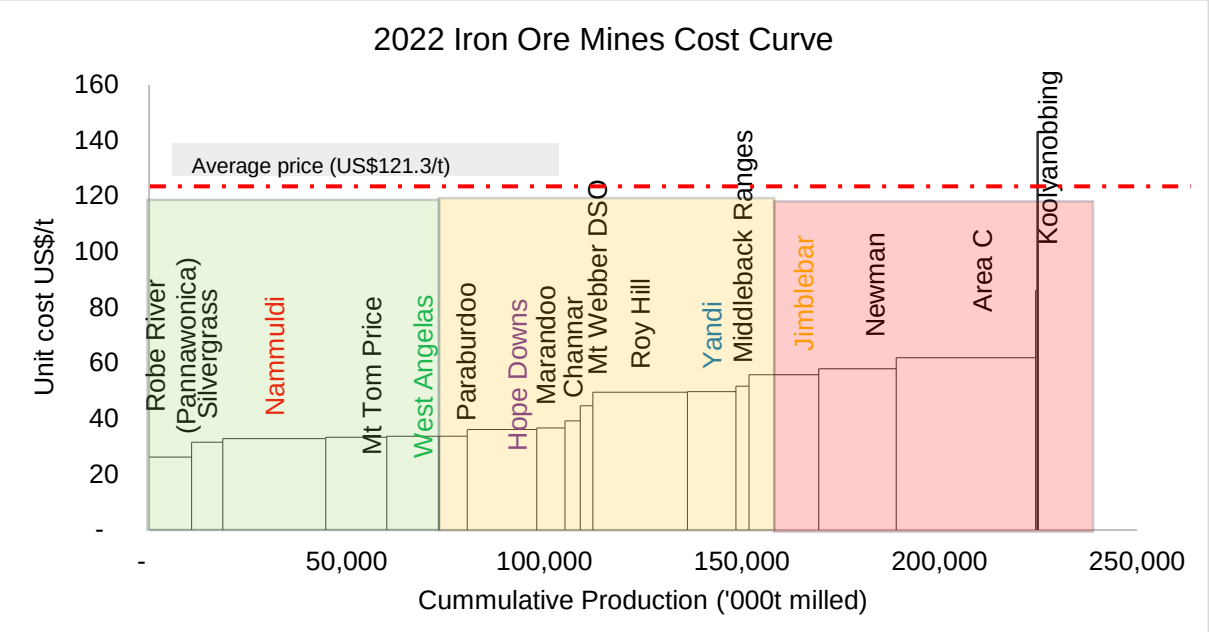


Figure 43. Iron ore mines cost curve 2022.

In 2022, the West Angelas and the Nammuldi continued to lead in cost efficiencies, remaining in the consultants' low-cost quartile with unit costs of around US$30-40/t and production volumes at about 73 million and 44 million metric tonnes, respectively. Their persistent low costs and production levels underscore the usefulness of advanced strategies such as early docking of autonomous trucks and operational optimisation, which allows these mines to withstand the changing market trends. Yandicoogina, on the middle quartile moving up, increased a unit cost to 50 US$/t and produced a phenomenal volume of 148 million metric tonnes, indicating excellent cost control and output efficiency parameters. Jimblebar continued to have a high cost per unit between 50 and 60 US$/t with a constant output of about 169 million metric tonnes, implying no significant changes. The 2022 cost curve also highlights the necessity for mines to use technological adoption to their full potential and, at the same time, operate efficiently in a complete price instability regime or other type of complexity.

Figure 44 reveals a modest decrease in the mean iron ore value to US$120.6/t compared to US$121.3/t in 2022. The marginal decline exemplifies that mining companies must remain astute in their cost structures and optimise production to

remain profitable in a competitive environment. Raw data used for the graph in Figure 44 can be found in Table 19 (Appendix 2).

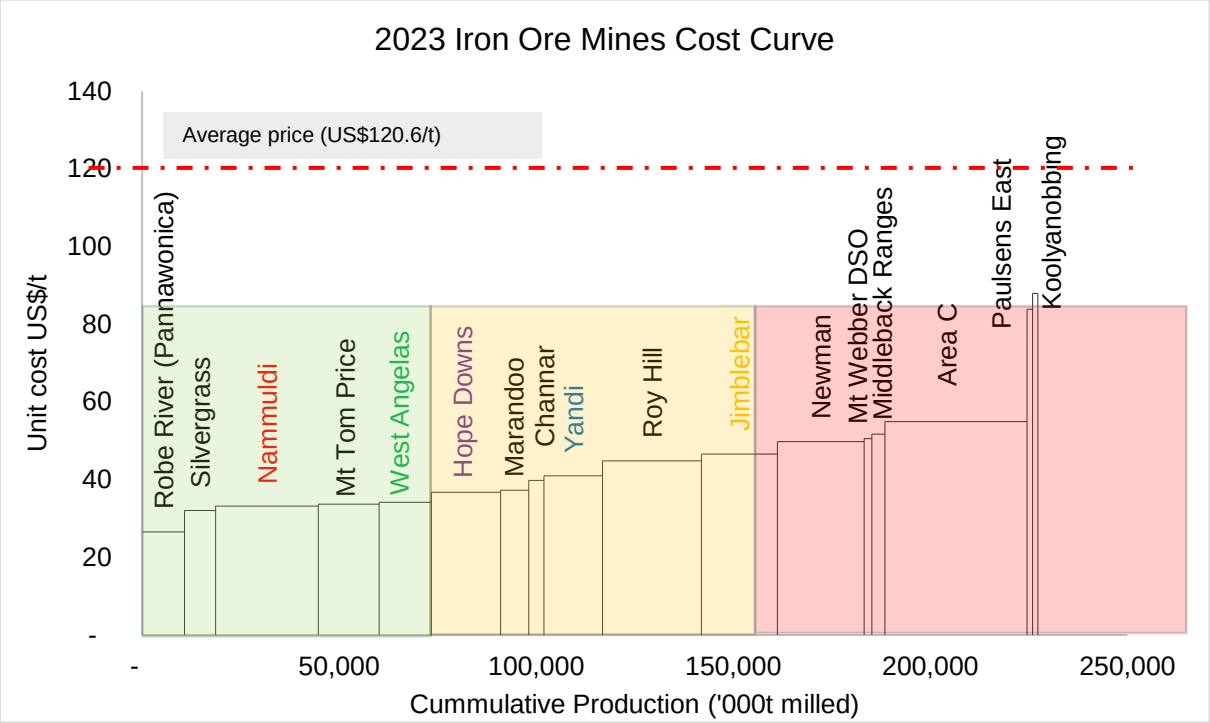


Figure 44. Iron ore mines cost curve 2023.

In 2023, West Angelas and Nammuldi still posted the lowest unit costs. They performed in the lower quartile range, with unit costs of about US$30-US$40/t and their respective production volumes of about 73 million and 44 million metric tonnes, respectively. These mines have continuously profited from the early adoption of autonomous trucks and operational strategies, remaining competitive despite moderate price fluctuations. Yandicoogina moved towards the lower quartile with unit costs of US$41/t and achieved high-volume productivity of 116 million metric tonnes, showing the efficiency of control over costs and high output productivity. Hope Downs, which has managed its costs better since the introduction of autonomous trucks in 2012 to the present day, has managed to keep unit costs within the range of US$30-US$40/t with output stability of about 90 million metric tonnes. Jimblebar improved and shifted from the upper to the middle quartile, with unit costs of US$47/t while production levels remained above 160 million metric tonnes.

In 2023, the cost curve showed that coupled with technology integration, effective cost control management enables a company or organisation to stay unrivalled in the market even with slight changes in the market environment. 2023, as a year in which the ongoing study ceased, enhances the importance of consensus on the requirement

for improvement of the ore mining market. Over the past decade, from 2010 to 2023, the implementation of autonomous haul trucks in Australian iron ore mines has undergone a complex evolution marked by challenges and operational successes (Long et al., 2024). The transition initially faced delays in achieving the anticipated cost efficiencies due to the steep learning curve associated with integrating and managing advanced technologies.

Factors such as system maintenance, optimisation processes, and the adaptation of operations to autonomous systems contributed to initial inefficiencies. Despite these hurdles, the integration of autonomous fleets has delivered notable progress in cost-per-metric tonne, aligning with the broader objective of improving cost structures amidst fluctuating iron ore prices (Richards, 2015). The data shows, however, that the unit cost per metric tonne did not record a hike, and years after any automation began, it fell (Aguiar, 2023). These changes are due to lower labour costs, better fuel efficiency, and better operational scheduling. It was not until later those greater yields began to appear, but on the other hand, the cost started to reduce during the early periods of moving autonomously.

In this critical transition period, mining teams had to come to terms with the new autonomous systems, which would take a decade for any economically practical way to use these trucks to be achieved. The phase was quite intensive, involving training, adaptation, and process improvement across the board, as both operators and technicians mastered the best ways to use the full potential of automation. In the later years of this period, mines saw excellent operational efficiency and increased metric tonnes produced as they surmounted the initial technical and logistical barriers (Ghosh, 2023). Overall, this evolution emphasises the necessity of adequate and comprehensive training, step-by-step assimilation, and constant modification of the workforce’s abilities and mining concepts to gain all advantages from technological innovations. Finally, the transition to autonomous mining has been regarded as a journey of challenges and yet undoubtedly worthwhile, showing that if automation is brought into such operations properly, enormous savings in costs and improved efficiency will be induced.

4.3 Machine learning and artificial intelligence on condition-based monitoring

Companies must strategically manage their maintenance budgets and expenditures to remain competitive, hence the need for this research. The research highlights that based on exploring practical business activities, it is known that appropriate resources in terms of capital investment are usually set on equipment maintenance. The introduction and availability of equipment in enterprises strongly impact productivity, profitability, and fulfilment of market needs. As a result, maintenance management is receiving increased attention in one way or another across different industrial sectors (Zhu, 1996).

The danger of contingency maintenance can be avoided by adequately managing maintenance and controlling factors. Relevant data and ideas acquired about the study of maintenance management provide direction toward this aim. This shift seeks to eliminate one of the significant sage detractors' maintenance by ensuring maintenance is performed only when the system demands it. The approach is called condition-based predictive maintenance and departs from the routine maintenance practice at specific intervals. The approach adopts and amalgamates several technologies, such as sensor measurement technologies, actionable data analytics, intelligent knowledge construction systems, and software systems, in successful maintenance management (Zhu, 1996).

This research highlights that machine learning was used to identify potential engine malfunctions, as detailed in Table 8 below, which outlines the following variables.

Table 8 Equipment health variables for dump trucks.

Variable	**Unit**
Oil Pressure	kPA
Coolant Temperatures	ºC
Fuel Temperatures	ºC

4.3.1.1 Oil pressure condition monitoring.

The following analysis was done for the week-in and week-out data but was not limited to historical data; real-time analysis was done; the same data can be pulled and analysed below in the Oil pressure analysis (Figure 45) for week 34 in 2024. Raw data used for the graph can be found in Supplementary Table 1 (Appendix 1)

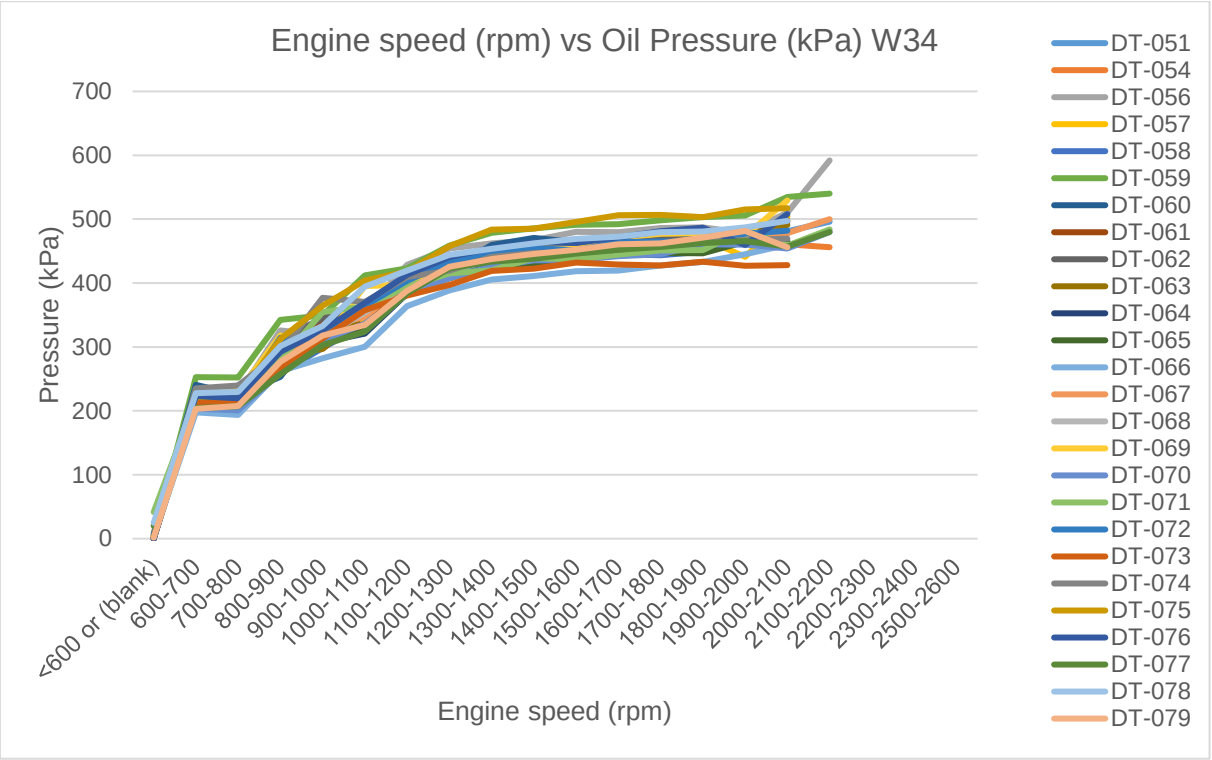


Figure 45 Condition monitoring oil pressure.

In Figure 45, no irregularities were identified. The graph illustrates engine speed (RPM) against oil pressure (kPa); irregularities or abnormalities can be identified based on deviations from the expected trend. Irregularities include outliers, where data points significantly deviate from the general pattern, and discontinuities, such as sharp breaks or unexpected jumps in the curve. Flat spots, where oil pressure remains constant despite increasing engine speed, and notable variability between individual units, such as one machine exhibiting a markedly different trend compared to others, are also considered irregular. On the other hand, abnormalities involve non-linear behaviour, such as oil pressure decreasing at higher RPMs or showing erratic changes that are inconsistent with typical engine performance.

Threshold violations, where oil pressure exceeds safe operational limits, and inconsistencies in the data, such as one unit showing behaviour vastly different from the majority, are critical signs of potential issues. Additionally, clusters of anomalies, where multiple data points from a specific unit or RPM range deviate collectively, may indicate systematic problems. Specific thresholds or statistical criteria, such as deviations beyond 10% of the average trend or exceeding manufacturer-defined oil pressure limits, can be used to identify and investigate these irregularities and abnormalities.

If abnormalities are identified, the causes, implications, and recommendations will be presented to the engineering team to address these issues promptly (Table 9).

Table 9. Causes of abnormal oil pressure readings.

Abnormal oil pressure readings	Causes
Low Oil Pressure:	Insufficient oil level
	Worn-out oil pump
	Clogged oil filter
	Oil leaks
	Engine wear (increased clearances in bearings)
High Oil Pressure:	Clogged oil passages
	Faulty oil pressure relief valve
	Oil that is too thick (high viscosity)
	Cold engine conditions (oil is thicker when cold)

The importance of oil pressure condition monitoring is discussed in Table 10 below.

Table 10. Oil pressure condition monitoring.

Importance of monitoring oil pressure	
Engine Health:	Consistent monitoring of oil pressure helps detect issues early. Abnormal readings can indicate problems like oil pump failure, clogged oil filters, or leaks.
Preventive Maintenance:	Regular monitoring allows timely maintenance actions, such as oil changes, filter replacements, and lubrication inspection.
Safety:	Maintaining proper oil pressure is important for safe engine operation. Low oil pressure can lead to inadequate lubrication, causing engine parts to seize or fail, resulting in catastrophic engine damage and potential safety hazards.
Performance Optimisation:	Ensuring that oil pressure is within the optimal range for given engine speeds helps maintain engine performance and efficiency.

4.3.1.2 Fuel feed return temperatures condition monitoring.

Monitoring dump trucks' fuel feed and return temperature is necessary primarily in surface mining operations, where heavy equipment operates in extreme environments. There is an enhancement in the engines' performance, fuel consumption, and lifespan. Temperature sensors are placed on the fuel feed and return systems to monitor the temperature of the fuel while being fed or bled back. There is involvement in using thermocouples or Resistance Temperature Detectors (RTDs) (Penny, 2014). Data Acquisition System (DAS) acquires and communicates temperature measurements from the sensors to the onboard computer/ remote site. The DAS is designed to access additional engine parameters, such as coolant or oil temperatures, to help assess the engine's overall condition (Arwoko et al., 2023).

Threshold-Based Alerts: Pre-set thresholds for fuel feed and return temperature were set up to trigger an alert if this temperature, like most operational ranges, exceeds or falls below the safety limit. There is an allowance for the operators to take the necessary preventive measures. Figure 46 below illustrates the performance of the fuel feed temperature and its distribution. In this case, the documentary review targeting tool DT072 indicated that the truck had a feed temperature that was too low, requiring further investigation. Raw data used for the graph can be found in Table 2 (Appendix 1)

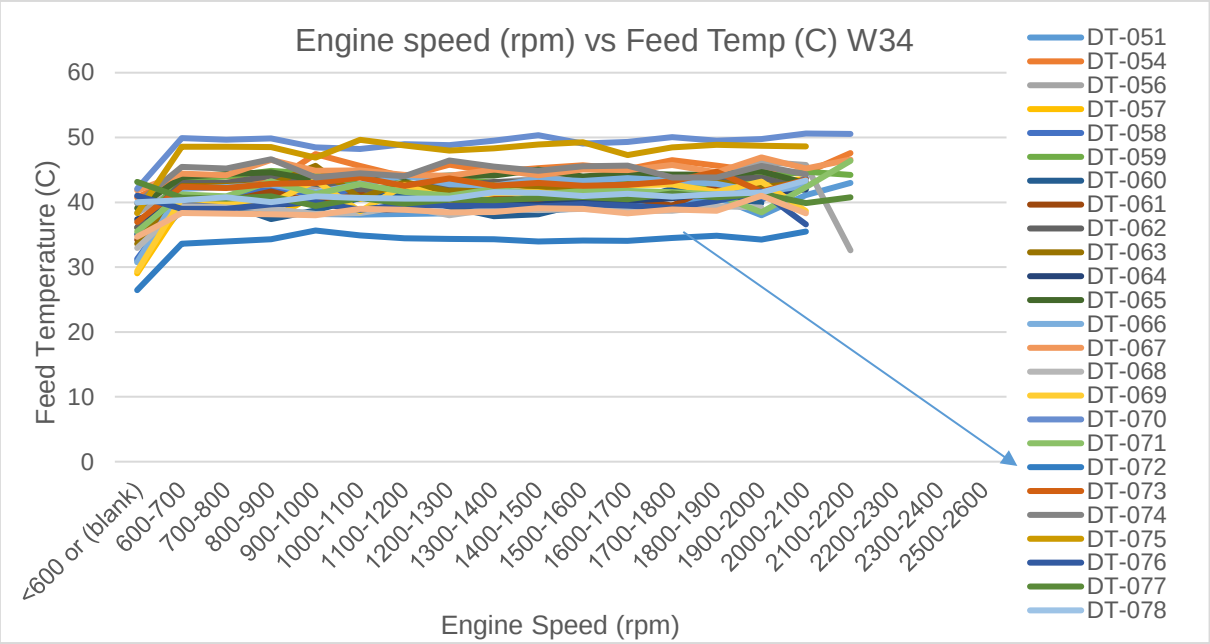


Figure 46. Feed temperature condition-based monitoring.

The chart provided in Figure 46 illustrates the relationship between engine speed (rpm) and average feed temperature (°C) for various trucks during week 34. Truck DT072 exhibits a distinct trend, where its average feed temperature is consistently lower than the trends of other trucks across the engine speed range. This anomaly may indicate potential operational inefficiencies, sensor calibration issues, or unique conditions specific to DT072, such as differences in load, maintenance status, or environmental factors. A further investigation into DT072's performance and operational parameters is recommended to determine the underlying cause of this deviation.

Figure 47. Return temperature condition-based monitoring. shows the fuel return temperature performance for the same fleet. The raw data used for the graph can be found in Table 3 (Appendix 1).

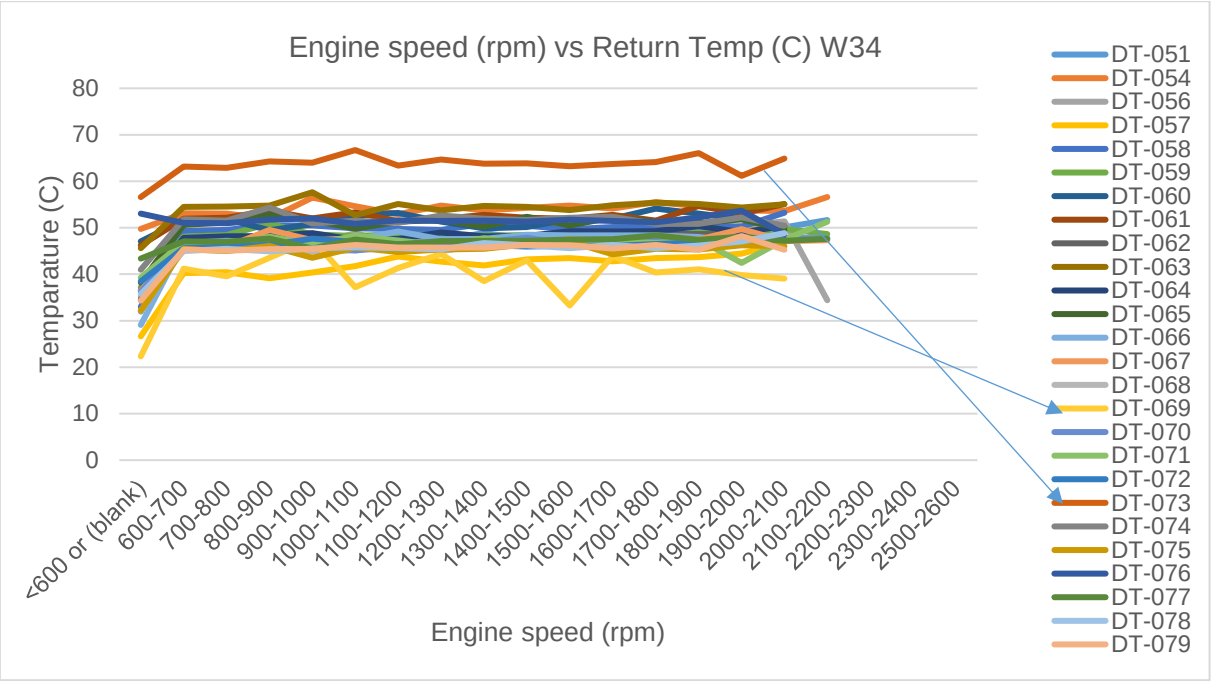


Figure 47. Return temperature condition-based monitoring.

Figure 47 highlights the elevated return temperature trends for truck DT073 compared to the other trucks. This discrepancy suggests potential underlying issues that may worsen over time. One root cause is an inefficient cooling system, which may fail to regulate the fuel's return temperature effectively. This could be due to clogged or malfunctioning radiators, reduced coolant flow, or degraded heat exchangers. Another potential issue might involve partial blockages or restrictions in the fuel return line, leading to heat accumulation. Prolonged high return temperatures could also result from a miscalibrated or damaged temperature sensor inaccurately reporting higher values. These conditions could contribute to fuel overheating, leading to long-term mechanical wear, reduced fuel efficiency, and potential damage to engine components. A detailed cooling system inspection, fuel return lines, and sensor functionality are recommended to confirm the root cause and prevent further complications.

4.3.1.3 Coolant temperature condition monitoring

Monitoring coolant temperatures and condition-based maintenance in surface mining dump trucks is important for prolonging these heavy machines' engine health, performance, and reliability in extreme and rigorous environments. The introduction of coolant temperature monitoring makes it possible to avert problems that could lead to the failure of the cooling system, such as manual internal heat classification (Figure 48), which would result in overheating and eventual damage to the engine. There is

the achievement of low downtime and low maintenance costs. Raw data used for the graph can be found in Table 4 (Appendix 1).

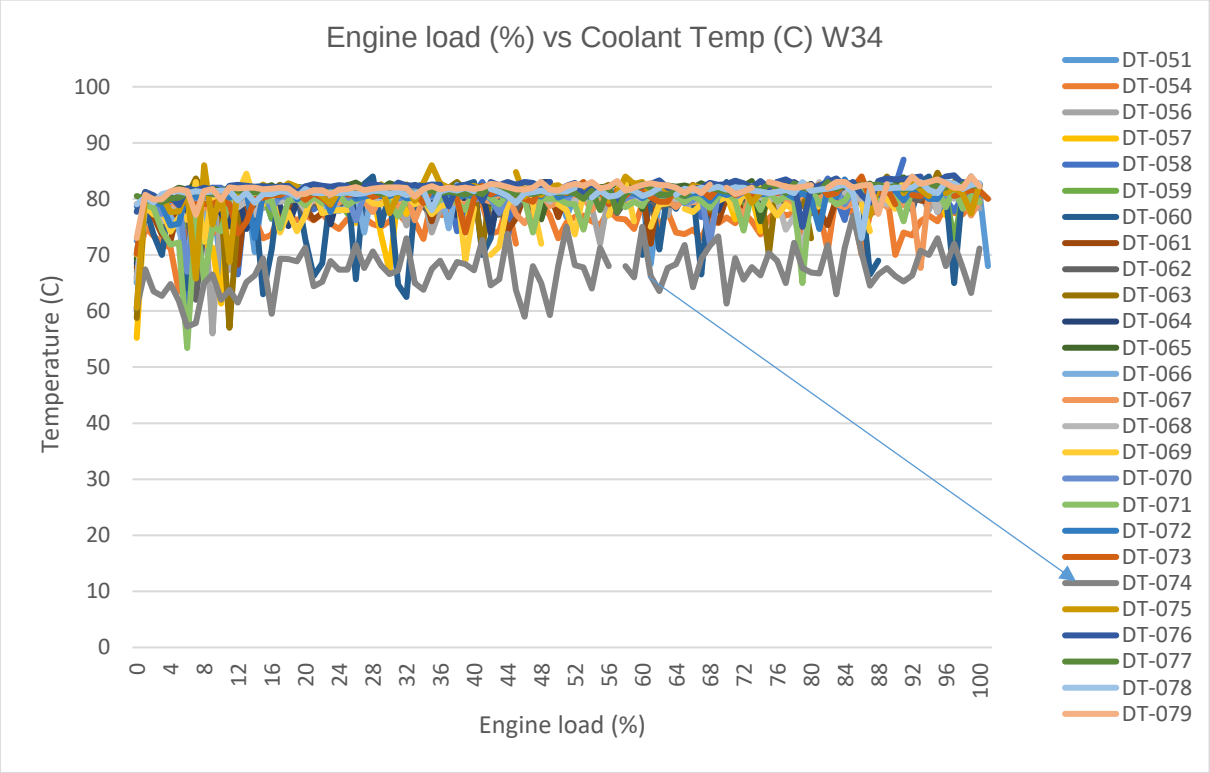


Figure 48. Coolant temperature condition monitoring.

The graph above demonstrates the lower limit on coolant temperature for DT074. Typical reasons for the coolant's depletion include a leak within the cooling vented system. Other causes include faulty radiators or radiator hoses, water pump leaks, engine block or cylinder head cracks and old gaskets (for instance, head gaskets) (Dubov et al., 2024).

4.3.1.4 Booster pressure condition monitoring

In surface mining dump trucks, the CBM of booster pressure (Figure 49) is important for boosting mining operations' reliability, safety, and efficiency (Dayo-Olupona et al., 2023). Booster pressure (the pressure provided by a turbo or hydraulic system) improves the performance of engines or systems used, particularly in surface mining. Effective monitoring of booster pressure is a preventative measure to avert unplanned downtimes or reduce maintenance pressure costs. Raw data used for the graph can be found in Table 5 (Appendix 1).

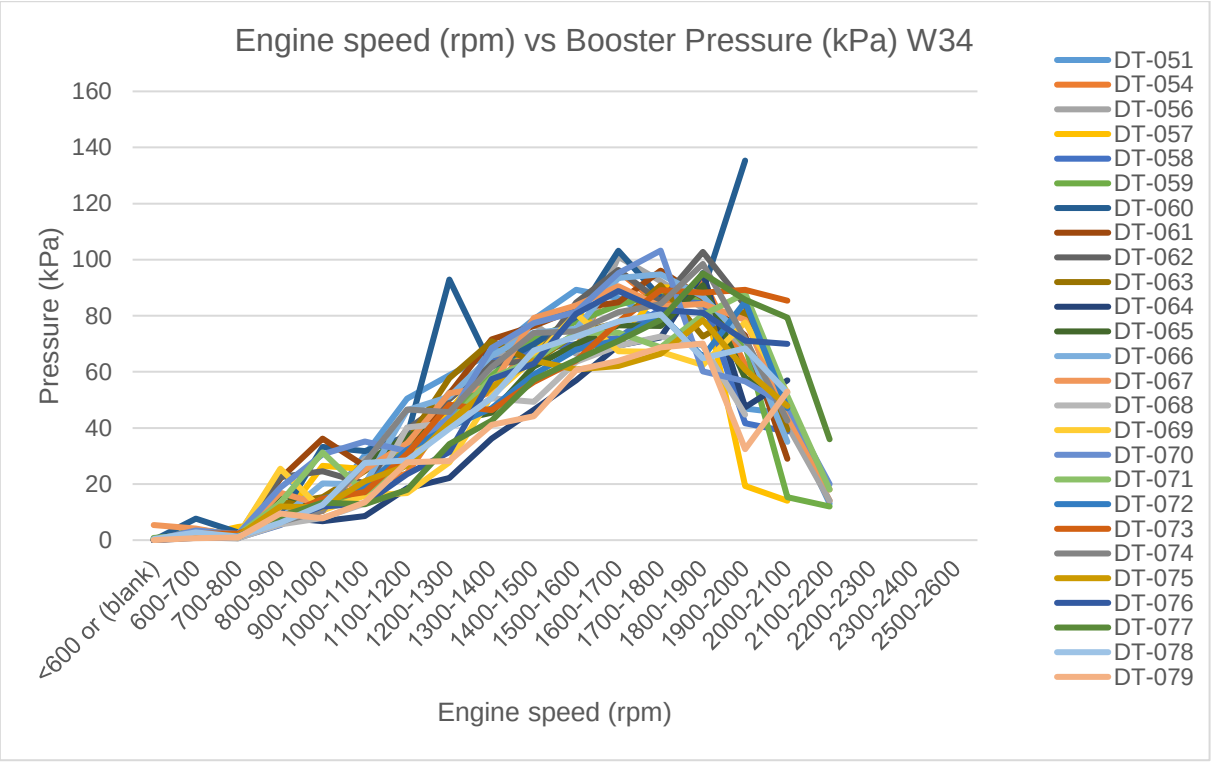


Figure 49. Booster pressure condition monitoring.

Condition-based monitoring is an advanced maintenance strategy directly related to real-time sensor data, data analytics, and predictive modelling to manage surface mining dump trucks better (Madahana et al., 2024). With the focus on parameters like booster pressure or coolant temperatures, CBM ensures that maintenance management changes are controlled with less distortion, with maintenance strategies progressing from set time intervals to when the equipment is due or nears due for servicing. Such a strategy presents massive advantages related to engineers' operational tasks: increased availability of machinery, lowered maintenance deployment, improved work safety, increased operational efficiency, and higher quality of in-service cycles of field assets. Preventive in character and aiming toward active, effective management of breakdowns and malfunctioning equipment operations, CBM results in lower downtime and more productive time during operation, affecting overall earnings (Peng et al., 2010).

CHAPTER 5

5 Discussion

The discussion concludes with findings and learnings regarding the cost-benefit analysis of adopting fully autonomous surface mining systems. As one of the core findings, it emerges that the outlay on labour is reduced with autonomous systems since there is no requirement for employing human operators, which incurs costs. The research project illustrated unique operating conditions of existing autonomous machines, which could provide readings up to 24 hours a day without operational breaks, instead of the systems that are said to have faced up to 37,630 hours of standby or operational inefficiencies within peak quarters. On the other hand, there was an increase of about seven hundred operational hours for autonomous trucks per truck annually, yielding a decrease of 15% in load and haul unit costs because of the considerable reduction of ineffective time.

As accepted learning, the efficiency improvements from the adoption of condition-based maintenance, wherein maintenance is performed only when there is a high probability of failure, increasing equipment availability. Maintenance costs were significantly reduced by up to 64% based on engine failure reduction. Figure 48 stipulated coolant temperature issues before failure; thereafter, the issue of engine overheating was promptly addressed before engine failure. The old ways had breakdowns that took 13,310 hours within a quarter (Figure 12) compared to the unscheduled maintenance in the autonomous machines. The CBM could also be associated with a favourable Expected Learning Time (ELT) as engrained mechanisms assisted in monitoring oil pressure and coolant temperature in real-time until there was no abnormal condition, enhancing operation efficiency and low risk of equipment failure, also prolonging machine longevity.

The research highlighted the perceptions of issues, such as the lack of trust from top management in doling out money to autonomous systems. The cost curve analysis showed that the return on investment should be expected to be realised later as the initial inversion was high. Other cost benefits, such as labour and maintenance, would be realised to neutralise the cost. The complete automation of mining machinery still has technical, economic, legal, and sociological obstacles before these machines become standard practice. From a technical aspect, the mining environment is highly dynamic and uncertain, which makes it challenging to operate autonomous systems. Unlike controlled environments such as warehouses or roadways, the conditions in a mine keep changing concerning geological factors, such as rock falls, landslides, or different ore grades.

These requirements show the increasing level of situational awareness and decision-making during action that must be demonstrable by autonomous machines, something that artificial intelligence and sensor technologies currently lie within the sans securely reliable ambit. There are adverse and non-operational conditions in mines, such as dust, average temperature, and vibrations, which are recognised to affect the sensors, yielding inaccurate data that can endanger operations. From an economic perspective, deploying fully autonomous mining machinery requires considerable capital investment at the very onset. In addition to the cost of the autonomous equipment, there are costs involved in installing reliable communication networks and advanced systems to process the data. In mining companies with small operations, the prominent starting outlay and the long payback time stand out as significant constraints.

Other applicable economic factors revolve around the ongoing maintenance expenses, software updates, cybersecurity, and training for a skilled workforce to manage these systems. Even though automation creates an opportunity to cut down on labour costs over the long term, the ROI could be challenging to determine due to commodity price shifts and other changes in the market. These concerns have arisen because of the regulations and safety issues governing the operation of robotic vehicles. In terms of regulations, autonomous vehicles operating in a mining environment have yet to be able to keep pace with this new technology. It is prevalent when a rule is void for those who want to manage autonomous systems in the mining industry. In such accidents, the question arises of who can be held responsible, making it difficult to answer these questions and find proper insurance. The need for common mechanisms for implementing best practices and interoperability limits the global geography of applying autonomous solutions.

The social factors and issues related to the workforce are yet another major drawback. Trade unions and the population of most regions do not accept the idea of using utterly automated mining machinery because they anticipate drastic unemployment and subsequent loss of livelihood. The mining industry, especially in underdeveloped countries, employs people, and automation should reduce the number of such positions. The resistance causes conflicts, strikes, and, most significantly, the slow uptake of technologies. Moving towards using fully autonomous mining processes means there is a need for a change in the workforce's skills. Therefore, by extension, workers must be given training programmes targeting supervisory roles in autonomous machines and systems.

There is a process that can be very gradual and expensive, bringing additional postponements to the introduction of autonomous mining machines. The research highlights the compelling advantages of fully autonomous mining machines, including enhanced safety, reduced operational costs through lower labour requirements, and increased efficiency in mining operations. These benefits are substantiated by findings that autonomous systems can reduce

labour costs by over 60% and lower maintenance expenses by 15–20% through optimised scheduling and predictive maintenance. However, the study also underscores significant challenges in achieving full automation. These include technical barriers, such as the dynamic and unpredictable nature of mining environments, economic considerations linked to high initial capital expenditures, and social and legal obstacles, particularly regarding workforce displacement and regulatory compliance. Addressing these multifaceted challenges is important to realising the full potential of autonomous mining technology. Meeting these challenges will necessitate the development of new artificial intelligence (AI) solutions and sensor tools that better regulate the machine's environment, strong regulatory policies that prevent investment risk, and stakeholder engagement in solving social challenges. It is only by adopting a multifaceted strategy that the mining sector will be able to achieve the full potential of fully autonomous mining machinery.

CHAPTER 6

6 Conclusion and Recommendations

6.1 Conclusion

At the strategic level, the research reveals that moving toward complete automation of the surface mining machines is advantageous for mining companies as it entails increased efficiencies, guarantees better safety, and enhances the profitability of their operations. The cost-benefit analysis shows that the profit levels of machines include reducing the operational workforce employed to run the machines. There is a reduction in maintenance costs since autonomous integrated systems can predict failures and schedule repairs using algorithms rather than human work. The occurrences of unplanned downtimes and breakdowns of the equipment will be less. Improvement in productivity and efficiency leads to faster payback, making the case for investment in autonomous systems for mainstream mining compelling. The transition to autonomous systems increases production output. It incorporates better resource allocation and minimal detrimental effects on the environment in mining operations, which is important for mining companies in the recent upsurge in regulations.

Despite its significant advantages, the research acknowledges the limitations and challenges of transitioning to autonomous surface mining. Substantial capital investment refers to the high initial costs associated with acquiring autonomous systems, including advanced equipment, technology integration, and employee retraining programs. These costs are further amplified by the need for periodic upgrades to prevent technological obsolescence as automation advances. The shift to the new ore extraction process prospects also brings concerns about the dislocation of the people who work for the mining companies and the economic implications of these changes to mining communities. There are also practical considerations, including integrating current technologies with autonomous systems and protecting automated systems from cyber-attacks. Overcoming these limitations requires that the company's financial management considers the ability building of the organisation, stakeholder support, and social and technological development.

6.2 Recommendations

These constraints indicate that, on the one hand, the transition to entirely autonomous surface mining machines is associated with sizable cost and productivity advantages. However, due diligence and management are required to address these risks and issues. Mining companies must develop remote solid operation centres to take full advantage of the expected change to fully autonomous surface mining. These ROCs, Integrated and Intelligent Remote Operation Centres or I2ROCs, and the works of (Shimaponda-Nawa and Nwaila, 2024) oversee and manage autonomous and human activities at multiple mining sites. However, I2ROCs are comparatively more advanced than a conventional command and control management system because the centres are digital and analytical, integrating intelligent technologies such as machine learning and artificial intelligence. They help make timely decisions, foresee upcoming failures, and organise the sequence of operations in the labour-intensive mining industry, which improves timing and safety. Mining companies are recommended to construct such centres to improve their effectiveness from the automation investments made in the first place.

The significance of I2ROCs is that they can draw together from across the globe wherever vertically dispersed mining takes place for control purposes, integration, and operationalisation. Remote operation centres facilitate the joint functioning of information technology and operational technology teams toward an inclusive management culture wherein decisions are made based on assessed data. They allow mining organisations to work around the clock while reducing idle time and enhancing productivity by permitting remote specialists to supervise operations in real time. Consolidating the functions of monitoring and managing operations, I2ROCs decrease the workforce requirement at sites and enhance worker safety by reducing the risk of working in adverse conditions. The stir, I2ROCs incorporation, is employed in the mining industry by companies looking to modernise their business processes in the digital era.

A specific area of continuing studies in the PhD programme should be developed to advance the development of new models that will enable the creation of a fully automated mine in real time. The research could focus on building an intelligent system enabling complex mining operations to be structured into a single model of, for instance, resource estimation, equipment management, logistical support, and safety, all within a fully automated and connected system. The research should address the issue of how integrating artificial intelligence and industrial Internet of Things

technologies may assist in reproducing and enhancing the performance of a mining operation through a digital mining twin. Such models would be important for understanding how to optimise production efficiency while minimising costs and being proactive in optimising the decision-making process against negative issues like predicting equipment failures and optimising resource loads. There are shaped economic models based on which an autonomous mining environment can be created and lined up activities in upcoming mining endeavours.

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8 Appendix 1: Supplementary files

Table 1. Sensor data for feed temperature.

	Average of Feed Temperature (C)											
Engine Speed	DT-051	DT-054	DT-056	DT-057	DT-058	DT-059	DT-060	DT-061	DT-062	DT-063	DT-064	DT-065
<600	31	41	38	29	31	36	35	34	36	34	37	39
600-700	39	44	42	39	41	44	40	40	43	43	40	44
700-800	39	44	42	40	40	44	40	40	43	43	40	44
800-900	39	43	41	38	42	45	37	42	44	43	40	45
900-1000	38	47	42	41	41	44	39	40	43	46	40	43
1000-1100	38	46	44	41	42	43	41	41	42	41	39	44
1100-1200	38	44	43	42	40	44	41	39	42	43	39	44
1200-1300	38	46	43	42	41	44	39	40	42	42	41	44
1300-1400	40	45	43	41	42	43	38	41	43	43	40	44
1400-1500	39	45	44	42	41	43	38	40	43	43	40	45
1500-1600	39	46	44	42	41	43	40	40	43	42	40	44
1600-1700	40	45	44	41	41	43	40	41	44	43	40	44
1700-1800	39	47	44	42	41	43	42	40	44	43	41	44
1800-1900	41	46	44	42	41	43	41	43	44	43	42	44
1900-2000	38	45	46	43	40	44	40	41	44	42	41	45
2000-2100	41	45	46	44	44	45		43	42	43	42	43
2100-2200	43	48	33			44						
2200-2300				39								
2300-2400												
2500-2600												
Grand Total	39	44	42	39	38	42	38	39	42	41	39	43

Average of Feed Temperature (C)														
Engine Speed	DT-066	DT-067	DT-068	DT-069	DT-070	DT-071	DT-072	DT-073	DT-074	DT-075	DT-076	DT-077	DT-078	DT-079
<600	31	42	33	29	42	36	26	37	40	38	41	43	40	35
600-700	42	44	39	41	50	41	34	42	45	49	39	41	40	38
700-800	42	44	39	40	50	41	34	42	45	49	39	41	41	38
800-900	43	47	39	40	50	43	34	43	47	49	40	41	40	38
900-1000	42	45	38	43	48	41	36	43	44	47	40	39	41	38
1000-1100	43	45	38	39	48	43	35	44	44	50	39	41	41	39
1100-1200	44	44	39	43	49	42	34	43	44	49	40	40	41	39
1200-1300	43	44	38	40	49	41	34	44	46	48	39	40	41	38
1300-1400	43	45	39	41	50	42	34	43	46	48	40	40	42	39
1400-1500	44	44	39	41	50	41	34	43	45	49	39	41	41	39
1500-1600	43	45	39	41	49	42	34	43	46	49	40	41	41	39
1600-1700	44	45	39	43	49	42	34	43	46	47	39	41	41	38
1700-1800	43	46	39	43	50	42	35	43	44	48	39	41	41	39
1800-1900	43	45	39	42	50	41	35	45	44	49	40	41	41	39
1900-2000	42	47	39	43	50	38	34	42	46	49	42	41	42	41
2000-2100	43	45		39	51	42	35	44	44	49	37	40	43	38
2100-2200		47			51	46						41		
2200-2300														
2300-2400					55									
2500-2600				44										
Grand Total	42	45	38	41	49	41	34	42	45	46	39	41	41	38

Table 2. Sensor data for return temperature.

Average of Return Temperature (C)												
Engine Speed	DT-051	DT-054	DT-056	DT-057	DT-058	DT-059	DT-060	DT-061	DT-062	DT-063	DT-064	DT-065
<600	32	50	35	27	33	37	47	46	35	46	37	38
600-700	48	53	47	40	49	48	52	52	48	55	48	51
700-800	48	53	47	40	50	48	52	52	48	55	48	51
800-900	48	52	45	39	50	51	49	54	48	55	48	53
900-1000	47	56	46	40	51	49	51	52	47	58	49	52
1000-1100	47	55	49	42	50	48	53	53	47	53	47	50
1100-1200	48	53	46	44	50	49	53	51	47	55	48	51
1200-1300	47	55	48	43	50	48	51	52	47	54	49	52
1300-1400	49	54	48	42	51	48	50	53	48	55	48	50
1400-1500	48	54	48	43	50	48	50	52	48	55	48	52
1500-1600	48	55	48	43	50	48	52	52	48	54	49	51
1600-1700	49	54	48	43	50	48	52	53	49	55	49	52
1700-1800	48	56	48	43	50	48	54	52	49	55	49	51
1800-1900	50	55	49	44	51	49	53	55	49	55	50	51
1900-2000	48	54	50	44	50	49	52	53	49	54	49	52
2000-2100	50	54	51	47	53	50		55	47	55	50	50
2100-2200	52	57	34			49						
2200-2300				38								
2300-2400												
2500-2600												
Grand Total	47	53	44	40	45	46	50	51	46	53	46	49

Average of Return Temperature (C)														
Engine Speed	DT-066	DT-067	DT-068	DT-069	DT-070	DT-071	DT-072	DT-073	DT-074	DT-075	DT-076	DT-077	DT-078	DT-079
<600	29	37	32	22	36	39	38	57	41	32	53	43	36	34
600-700	47	46	46	41	47	47	46	63	52	45	51	47	45	45
700-800	47	46	46	40	47	46	46	63	52	45	51	47	45	45
800-900	47	50	46	44	47	48	46	64	54	46	52	48	45	45
900-1000	47	47	45	47	46	46	48	64	51	44	52	46	46	45
1000-1100	48	48	45	37	45	48	47	67	52	46	51	47	46	46
1100-1200	49	46	46	41	46	47	46	63	51	45	52	46	46	46
1200-1300	48	47	45	44	46	46	46	65	53	45	51	47	45	46
1300-1400	48	47	46	39	47	48	46	64	52	45	52	47	47	46
1400-1500	48	47	46	43	48	46	46	64	52	46	51	47	46	46
1500-1600	48	48	46	33	46	47	46	63	52	47	52	47	46	46
1600-1700	48	47	46	44	46	47	46	64	52	44	51	48	46	46
1700-1800	48	48	46	40	47	47	47	64	51	45	51	48	46	46
1800-1900	48	47	46	41	47	47	47	66	51	45	52	47	46	45
1900-2000	47	50	47	40	47	42	46	61	52	46	54	48	47	48
2000-2100	48	47		39	48	47	47	65	50	46	49	47	49	45
2100-2200		47			48	51						48		
2200-2300														
2300-2400					54									
2500-2600				50										
Grand Total	46	47	44	40	45	47	46	63	50	43	51	47	45	44

Table 3. Sensor data for oil pressure.

Average of Oil Pressure (k Pa)												
Engine speed (rpm)	DT-051	DT-054	DT-056	DT-057	DT-058	DT-059	DT-060	DT-061	DT-062	DT-063	DT-064	DT-065
<600	9	1	0	9	0	2	0	0	6	4	0	4
600-700	213	224	222	227	209	253	241	213	230	215	209	209
700-800	213	224	225	232	211	252	225	208	225	210	208	209
800-900	300	296	326	304	259	343	253	299	311	288	275	292
900-1000	313	321	319	321	298	349	339	337	346	297	307	313
1000-1100	363	369	356	340	336	412	362	334	365	352	321	328
1100-1200	389	404	428	411	385	423	386	405	407	392	384	390
1200-1300	415	417	454	441	415	459	421	437	432	419	428	408
1300-1400	438	426	462	439	427	479	460	442	448	438	433	426
1400-1500	446	435	467	448	432	486	471	453	451	445	447	431
1500-1600	449	441	480	452	440	491	464	458	460	451	443	439
1600-1700	455	447	480	463	445	492	468	464	462	461	450	443
1700-1800	466	447	486	459	444	498	467	465	472	458	458	447
1800-1900	467	450	487	470	449	503	472	466	465	466	459	447
1900-2000	482	470	478	441	468	506	472	476	486	473	467	465
2000-2100	481	461	510	504	467	535		498	496	491	478	463
2100-2200	496	456	592			540						
2200-2300				500								
2300-2400												
2500-2600												
Grand Total	333	260	261	318	237	311	243	267	301	291	252	305

Average of Oil Pressure (k Pa)														
Engine speed (rpm)	DT-066	DT-067	DT-068	DT-069	DT-070	DT-071	DT-072	DT-073	DT-074	DT-075	DT-076	DT-077	DT-078	DT-079
<600	3	21	6	4	4	42	7	2	0	2	0	20	25	2
600-700	198	221	215	229	204	217	218	214	235	222	223	204	228	203
700-800	194	217	215	229	201	224	215	215	240	222	220	207	230	207
800-900	262	280	275	318	260	279	314	266	291	312	292	257	301	277
900-1000	282	332	315	306	310	355	313	314	377	364	326	303	333	318
1000-1100	300	347	354	396	336	364	365	357	371	404	369	324	394	334
1100-1200	364	402	399	397	382	395	404	381	410	418	413	384	420	388
1200-1300	388	427	421	434	408	415	433	397	419	458	441	423	444	426
1300-1400	405	439	435	452	426	420	448	419	441	484	455	434	454	438
1400-1500	411	444	444	456	436	439	455	422	447	485	464	438	462	446
1500-1600	419	448	444	461	436	437	451	432	447	496	463	446	469	452
1600-1700	419	456	451	471	442	445	464	429	452	506	472	452	473	461
1700-1800	427	459	456	477	445	451	465	428	461	507	481	457	480	462
1800-1900	433	469	460	478	461	452	465	433	467	503	487	463	481	471
1900-2000	445	466	475	474	460	483	477	427	467	515	460	466	487	482
2000-2100	460	478		529	454	459	482	428	470	517	508	457	497	456
2100-2200		500			480	484						480		
2200-2300														
2300-2400					488									
2500-2600				544										
Grand Total	285	367	291	347	302	350	334	284	319	286	317	314	346	291

Table 4. Sensor data for coolant temperature.

Average of Feed Temperature (C)												
Engine load (%)	DT-051	DT-054	DT-056	DT-057	DT-058	DT-059	DT-060	DT-061	DT-062	DT-063	DT-064	DT-065
0	70	67	66	55	60	66	66	68	65	59	68	69
1	80	75	77	80	80	79	79	79	79	81	80	81
2	80	73	77	80	78	79	74	77	78	80	78	80
3	80	72	76	75	74	77	70	74	75	79	77	80
4	78	71	78	80	78	79	80	73	79	80	78	81
5	79	63	74	79	79	77	80	79	78	79	81	82
6	79	74	76	79	58	75	64	69	79	81	78	82
7	74	77	73	75	83	81	81	76	62	84	76	83
8	77	77	80	72	82	80		81	75	81	82	78
9	82	74	56	71	82	80	76	81	78	82	79	82
10	66	76	79	61	82	81		80	81	79	78	81
11	81	77	67	82	80	81	70	80	78	57	75	82
12	82	76	79		67	76		68	81	76	81	82
13	81	78			82	80	81	81	81	82	75	81
14	71	76	81	80	81	75	80	81	78	81	80	81
15	81	73	78		82	81	63	82	80	80	81	82
16	76	74	79	81	81	77	71	81	79	82	81	82
17	80	78	80		82	81	83	77	81	83	79	81
18	79	77	79		81	80	80	78	79	81	75	80
19	80	76	79	81	81	81	81	80	80	80	80	82
20	81	77	80	80	81	80	73	79	77	79	80	82
21	81	76	79	81	78	81	66	76	80	81	80	82
22	81	77	79	81	79	81	69	78	78	81	81	82
23	80	76	79	80	79	80	81	80	80	82	76	81
24	82	75	79	79	82	80	81	81	80	80	81	82
25	81	76	78	79	79	77	83	81	78	81	81	82
26	81	76	79	76	79	81	66	82	80	82	79	83
27	80	77	80	82	81	81	83	81	80	79	75	82
28	81	75	79	81	82	80	84	80	80	80	81	80
29	81	75	80	74	81	79	75	81	80	82	82	82
30	81	76	80	67	83	81	81	81	79	81	80	83
31	81	78	80	81	82	81	65	79	80	82	81	82
32	81	76	75	77	80	80	63	81	81	83	81	82
33	81	76	80	81	82	77	79	81	80	82	83	82
34	81	73	81	80	81	80	82	81	79	81	82	83
35	81	80	74	81	82	78	80	76	77	82	80	81
36	80	77	78	81	81	81	80	81	80	80	82	82
37	81	77	81	79	81	81	79	81	80	82	82	82
38	80	80		81	74	81	82	80	80	83	77	83
39	81	76	79	78	79	81	83	81	80	82	81	82
40	81	78	82		81	80	83	81	80	82	82	82
41	79	79	81	81	83	81	70	82	80	71	82	82
42	81	74	80	80	80	79	73	80	77	82	74	79
43	81	74	81	81	81	81	82	81	77	82	81	82
44	81	79	80	82	73	79		74	80	81	80	82
45	81	72	78	82	82	80	83	77	78	82	81	82
46	80		81	80	81	82	82	81	81	82	81	81
47	80	76	79	80	80	81		78	78	82	81	82
48	80	79	80	80	82	80	82	81	81	79	83	76
49	81	77	82		82	80		81	80	82	83	82
50	81	73	79	81	82	80		77	79	82		82
51	77	76	80	80	82	80	81	81	80	81	81	82
52	81	77	82	81	82	81	82	83	79	82	82	82
53	81	77	82	80	82	81		81	80	81	81	80
54	81	76	79	80	80	81	79	81	80	81	81	81
55	80	75	72		82	81	81	82	80	82	82	82
56	81	78	81	80	82	80	82	81	80	83	82	82
57	81	77	79	81		81		81	78	82	82	82
58	79	76	79	81	83	81	81	81	80	83	81	81
59	81	75	81	81	82	81		81	80	82	82	82
60	81	79	80	82	82	80	70	81	79	82	81	78
61	68	78	78	82	81	81	82	72	80	83	80	82
62	80	75	80	81	82	81	71	82	79	82	81	82
63	81	78	77	80	82	81	81	81	79	82	81	82
64	81	74	82	81	81	80	78	79	79	82	81	82
65	81	74	79	81	81	81	81	81	80	82		82
66	81	75	79	81	80	79	82	83	80	82	81	82
67	82	73	79	80	77	81	67	80	79	81		83
68	82	76	79	82	82	82	82	78	80	78	82	82
69	80	76	81	81	81	79	81	76	80	82	78	82
70	80	77	80	81	80	80	83	80	80	81	82	82
71	80	76	79	76	82	81	81	81	81	81	81	82
72	81	78	82	79	81	79	82	77	80	81	81	82
73	81	76	80	81	82	81	80	81	81	81	82	83
74	81	74	80	74	79	80	81	82	80	82	78	76
75	81	77	80	82	82	80		80	80	70		81
76	81	78	79	78	81	81		82	80	83	82	82
77	80	77			82	81	80	79	80	81	82	82
78	82	78	80	81	82	81	81	81	80	81	83	82
79	82	74	83		81	75		81	79	82	82	82
80	81	78	81	80	82	81	82	78	80	73	83	81
81	82	78			81	79		78	80		81	81
82	82	71	80		84	80	83	75	81	83	81	82
83	80	81	80	80	80	81	83	80	80	82	82	81
84	81	77	80	82	76	81	83	82	80	82	82	83
85	81	78	79		83	80		82	80		82	81
86	81	70	80	82	82	81	81	80	79	81	82	82
87	82	77	79	81	81	80	67	78	79	82	83	83
88	81	78		83	83	81	69	82	79	82	82	80
89	82	81	82	81	82	82		82	79	84	83	82
90	83	70	79	82	82	82	80	82	80	82	82	83
91	83	74	81	82	87	81	82	80	81	82	80	84
92	83	74	81			81	78	82	80	82	83	82
93	81	76	81	81	81	81	83	80	80	82	83	82
94	80	77	78		83	81	84	80		81	83	82
95	81	76	82	82	78	81	78		79	85	82	83
96	82	79		77	80	81	81	79		82		81
97		78	78		78	73	65		80	83		82
98	81	77	79	82	80	81	82	79	80	81	83	80
99	82	79	80			82	82	82	80	81	83	82
100	81	79	78	82	83	80	81		79	83	83	82
Grand Total	78	73	73	74	71	75	72	74	76	75	76	78

Average of Feed Temperature (C)														
Engine load (%)	DT-066	DT-067	DT-068	DT-069	DT-070	DT-071	DT-072	DT-073	DT-074	DT-075	DT-076	DT-077	DT-078	DT-079
0	65	79	66	70	72	78	79	70	61	61	78	81	79	73
1	80	78	79	79	80	79	80	80	67	81	81	80	80	81
2	79	79	79	77	80	78	80	80	64	80	81	80	79	80
3	78	80	76	78	77	74	79	80	63	81	79	79	81	80
4	77	79	78	74	80	72	75	80	65	78	80	80	81	81
5	75	78	78	77	80	72	76	80	62	78	79	80	81	82
6	69	81	76	76	67	53	82	79	57	82	82	81	81	81
7	81	76	80	83	81	77	80	79	58	66	82	81	81	77
8	74	79	80	72	80	65	81	79	65	86	82	81	81	81
9	81	78	80	81	81	75	81	79	67	75	82	81	81	82
10	81	79	80	79	81	74	81	80	62	81	80	81	81	80
11	81	81	80	81	80	80	80	79	64	69	82	82	82	82
12	81		78	81	81	81	81	74	62	82	83	82	80	82
13	81	80	80	85	80	81	82	76	65	82	82	81	81	82
14	79	81	77	80	81	80	73	80	66	81	82	81	79	82
15	82	81	80	79	81	80	81	80	69	83	82	81	81	82
16	81	79	80	81	78	80	81	81	60	82	82	81	81	82
17	80	80	80	74	81	75	80	81	69	82	82	81	81	82
18	81	80	80	78	80	80	82	82	69	83	82	81	81	82
19	82	80	80	74	81	80	80	81	69	82	81	80	80	81
20	82	80	78	77	80	79	81	80	71	81	82	81	82	81
21	82	80	80	82	82	80	81	81	64	82	83	81	81	82
22	78	79	79	77	81	79	81	80	65	80	82	81	81	82
23	81	80	80	78	81	80	78	79	69	79	82	81	81	81
24	78	79	81	78	81	81	81	82	67	81	82	81	81	82
25	79	81	80	78	81	79	81	81	67	82	82	81	81	82
26	82	80	80	81	76	80	80	81	72	82	81	81	81	82
27	74	80	81	80	81	81	80	81	68	82	82	81	81	82
28	82	78	80	79	81	81	81	80	71	82	83	81	81	82
29	81	81	81	79	81	81	81	81	68	83	82	81	81	82
30	81	80	80	80	81	79	81	82	67	77	82	81	81	82
31	82	78	80	80	80	77	81	81	67	81	83	81	81	82
32	81	81	81	81	80	80	80	81	73	82	82	81	81	82
33	82	76	79	79	81	81	80	81	65	80	82	81	81	80
34	80	80	80	80	80	80	81	79	64	83	82	81	81	82
35	81	81	81	77	80	78	81	82	68	86	83	81	78	82
36	82	81	80	79	81	80	82	81	69	83	83	81	81	82
37	75	80	81	79	80	81	81	82	66	82	79	81	82	82
38	83	79	80	82	82	79	80	80	69	82	82	81	82	82
39	81	79	81	69	81	78	81	74	68	82	83	81	82	82
40	81	80	80	78	80	81	80	80	67	82	82	81	81	82
41	82	80	81		81	82	82	82	73	82	80	81		82
42	81	80	80	70	80	80	81	81	65	82	83	82	82	83
43	83	81	79	72	78	79	81	82	66	82	82	82	81	83
44	82	81		79	81	81	80	81	74		83	81	81	82
45	82	77	81	81	80	80	81	81	64	85	83	81	79	82
46	81	76		82	81	80	81	80	59	80	83	81	81	82
47	81	78	81	79	81	74	81	80	68	82	83	81	81	82
48	80	81	81	72	81	80	80	82	65	81	82	81	82	83
49	82	79	80		81	80	83	81	59	82	83	82	81	82
50	81	79	82	79	82	80	80	82	68	82		81	81	82
51	82	80	80	78	80	79	81	81	75	81	82	81	81	82
52	81	80	80	74	82	79	81	82	68	81	83	81	82	83
53	82	80	80	81	82	75	81	83	68	82	81	80		82
54	81	78	80	81	80	81	80	81	64	82	82	81	80	83
55	81	80	82		81	81	81	82	71	82	81	78	82	82
56	82	81	81	77	81	81	82	79	68	80	82	82	80	82
57	81	80	80	82	81	80	80	82		81	79	78	81	83
58	82	80	81	83	80	79	81	81	68	84	81	81	82	82
59	81	80	80	76	81	80	81	82	66	83	82	81	82	82
60	82	80	80		81	79	80	82	75	83	82	83	81	83
61	81	80	81	75	82	81	81	80	66	81	83	82	81	83
62	82	80	80	79	81	80	81	80	64	83	83	81	82	83
63	81	80	81	79	81	81	81	80	68	81	82	81		82
64	81	79	80		81	81	81	82	68	82	82	81	81	82
65	82	80	81	78	79	79	81	81	72	81	81	81	82	81
66	82	79	80	78	80	81	81	82	64	82	82	82	81	82
67	81	80	80	79	81	80	81	82	69	82	82	82	82	81
68	81	80	81	79	72	78	80	80	72	82	83	82	82	83
69	82	80	80	80	81	80	81	82	73	82	83	82	82	
70	82	81	81	80	82	81	81	82	61	82	83	81	82	82
71	82	79	80	78	80	80	81	81	69	81	83	81	82	81
72	82	77	81	81	81	74	82	81	66	82	83	82	82	81
73	82	81	81	80	81	81	81	80	68	79	82	82	82	82
74	81	81	80	82	81	78	81	81	66	81	83	82	81	
75	82	80	80	79	81	81	81	83	70	82	82	83	81	83
76	81	80	80	77	81	80	83	81	69	82	83	82	81	83
77	82	80	75	79	81	81	81	82	65	83	84	81	82	82
78	82	79	77	78	82	80	80	82	72	82	83	83	81	82
79	81	81	71		81	65	81	82	68	83	75	82	83	82
80	82	81	81	78	81	82	80	82	67	82	82	82	81	82
81	82	80	83	79	82	79	75	83	67	82	82	81	82	
82		81	81		81	80	82	81	72	83	83	83	82	82
83	82	79		80	82	79	80	81	63		84	82	82	83
84	83	79	81		79	80	84	83	71	82	82	83	83	83
85	80	79	81		81	82	81	82	77	82	83	82	81	82
86	82	80	80	79	82	82	83	84	70		81	83	73	82
87	82	80	80	74	81	82	81	80	65	77	79	83	82	83
88	82	81	81		79	80	81	81	67	82	83	83	82	77
89	83	79	79	80	82		82	82	68	82	84	82	82	83
90	82	81	81	78	82	80	82	79	66		84	82	82	
91	82	79		83	82	76	80		65	81	83	82	82	82
92	82	79	81	83	81	82	82	81	66	83	84	82	82	84
93	82	68	81		81	82	81	81	71	82	84	83	83	83
94	82	81	83	80	83	81	80	82	70	81		82	82	83
95	83	78	78			82	80	82	73		83	83	81	84
96	83	81	82	81	81	79	82		68	81	84	82	83	83
97	82	81	80		81	82		81	72	82	84		83	82
98	81	80	80	83	80	78	81	81	68	81	83	83	82	82
99	83	77	81		82	81	84	82	63	77	83	82	83	84
100	83	80	81	81	81	79	81	81	71	83	83	82	83	82
Grand Total	78	79	77	77	78	78	80	78	65	75	81	81	81	79

Table 5. Sensor data for booster pressure.

Average of Boost Pressure (k Pa)												
Engine Speed (rpm)	DT-051	DT-054	DT-056	DT-057	DT-058	DT-059	DT-060	DT-061	DT-062	DT-063	DT-064	DT-065
<600	0	0	0	0	0	0	0	0	0	0	0	1
600-700	3	1	1	1	1	4	8	2	3	2	1	3
700-800	2	1	1	5	1	2	3	1	2	2	1	1
800-900	25	6	10	7	5	13	8	22	22	13	8	16
900-1000	10	10	12	27	12	13	33	36	25	15	7	12
1000-1100	30	20	29	25	21	17	32	26	20	25	9	28
1100-1200	50	24	34	27	35	34	37	30	40	35	19	37
1200-1300	59	46	53	46	43	43	93	52	50	58	22	42
1300-1400	67	53	64	63	64	59	62	72	63	71	36	45
1400-1500	79	71	77	68	68	72	70	76	64	63	46	62
1500-1600	89	68	66	82	70	78	80	83	85	74	57	70
1600-1700	86	96	101	69	72	84	103	85	96	78	69	77
1700-1800	78	84	92	90	82	88	86	96	85	91	72	76
1800-1900	89	93	83	90	86	87	89	86	103	73	95	91
1900-2000	47	63	69	19	42	70	135	73	84	81	47	58
2000-2100	45	43	41	14	39	15		29	48	39	57	51
2100-2200	13	14	14			12						
2200-2300				14								
2300-2400												
2500-2600												
Grand Total	42	27	27	36	25	30	33	33	36	35	19	36

Average of Boost Pressure (k Pa)														
Engine Speed (rpm)	DT-066	DT-067	DT-068	DT-069	DT-070	DT-071	DT-072	DT-073	DT-074	DT-075	DT-076	DT-077	DT-078	DT-079
<600	0	5	0	0	0	1	0	0	0	0	0	1	0	0
600-700	2	4	2	2	3	2	2	2	2	2	2	2	3	1
700-800	1	1	1	2	2	2	1	2	1	2	1	1	1	1
800-900	8	17	6	25	19	13	7	8	6	12	7	8	6	10
900-1000	20	12	8	11	31	31	15	15	11	12	12	13	13	8
1000-1100	20	25	13	16	35	17	19	17	28	21	13	13	27	13
1100-1200	46	34	40	17	32	27	32	31	47	27	24	18	28	28
1200-1300	51	52	42	28	44	42	40	48	46	42	31	34	40	28
1300-1400	66	55	51	51	68	58	47	46	62	55	57	43	51	41
1400-1500	74	79	49	65	77	64	59	56	74	64	63	57	68	44
1500-1600	75	84	64	81	81	74	68	64	74	61	81	64	73	61
1600-1700	93	91	69	67	95	74	71	78	81	62	89	71	78	64
1700-1800	95	83	73	67	103	69	81	89	84	66	82	79	81	69
1800-1900	87	84	69	62	60	80	65	88	99	78	81	95	65	70
1900-2000	71	79	45	78	57	88	85	89	72	61	71	86	68	32
2000-2100	35	44		53	48	51	47	85	43	48	70	79	53	53
2100-2200		18			20	18						36		
2200-2300														
2300-2400					26									
2500-2600				20										

9 Appendix 2: Supplementary Files

Table 6. Input data for Australia's 2010 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	893	43	893
Mt Tom Price	804	48	1,697
Yandi	1,135	48	2,832
Hope Downs	1,139	51	3,970
West Angelas	817	51	4,787
Marandoo	437	52	5,225
Nammuldi	859	53	6,084
Channar	525	53	6,609
Middleback Ranges	277	53	6,886
Paraburdoo	428	55	7,314
Area C	1,175	58	8,489
Koolanooka Hematite	52	63	8,540
Newman	942	68	9,482
Mt Goldsworthy	83	71	9,565
Koolyanobbing	445	73	10,010
Tallering Peak	181	74	10,190
Frances Creek	96	77	10,287
Koolan Island	118	90	10,405
Jack Hills	95	102	10,500

Table 7. Input data for Australia's 2011 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	900	49	900
Mt Tom Price	682	55	1,583
West Angelas	763	57	2,346
Nammuldi	1,329	58	3,675
Marandoo	437	58	4,112
Hope Downs	1,050	60	5,161
Yandi	1,145	60	6,306
Channar	525	60	6,831
Paraburdoo	435	62	7,266
Middleback Ranges	258	63	7,524
Koolanooka Hematite	70	66	7,594
Area C	1,019	71	8,613
Newman	1,088	83	9,702
Tallering Peak	162	84	9,864
Frances Creek	48	87	9,912
Yilgarn	19	89	9,931
Mt Goldsworthy	67	91	9,999
Koolan Island	121	95	10,120
Koolyanobbing	422	97	10,542
Karara Hematite DSO	62	112	10,603
Jack Hills	68	143	10,671
Iron Hill	12	433	10,683

Table 8. Input data for Australia's 2012 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	986	46	986
Mt Tom Price	674	55	1,660
Nammuldi	1,443	56	3,104
Hope Downs	1,018	57	4,122
Marandoo	437	57	4,559
West Angelas	847	58	5,406
Channar	511	59	5,917
Yandi	1,506	60	7,422
Paraburdoo	385	61	7,807
Koolanooka Hematite	56	68	7,863
Middleback Ranges	272	72	8,135
Area C	1,140	73	9,275
Frances Creek	96	78	9,371
Yilgarn	77	83	9,448
Newman	1,124	88	10,573
Koolan Island	84	94	10,657
Mt Goldsworthy	56	96	10,713
Koolyanobbing	539	97	11,253
Tallering Peak	100	103	11,352
Karara Hematite DSO	52	107	11,404
Iron Hill	120	134	11,524
Jack Hills	18	143	11,542

Table 9. Input data for Australia's 2013 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	1,046	44	1,046
Mt Tom Price	615	50	1,660
Nammuldi	1,747	50	3,407
West Angelas	842	52	4,249
Marandoo	434	52	4,683
Hope Downs	1,038	53	5,722
Channar	501	56	6,223
Paraburdoo	377	56	6,600
Yandi	1,733	58	8,333
Tallering Peak	142	67	8,475
Area C	1,234	70	9,709
Jimblebar	293	71	10,003
Middleback Ranges	290	72	10,292
Koolan Island	84	73	10,376
Iron Hill	161	75	10,536
Koolanooka Hematite	28	76	10,564
Frances Creek	86	80	10,651
Newman	1,335	80	11,986
Koolyanobbing	541	84	12,527
Karara Hematite DSO	110	85	12,637
Mt Goldsworthy	53	101	12,690

Table 10. Input data for Australia's 2014 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	411	38	411
Mt Tom Price	387	43	798
Nammuldi	882	44	1,680
Marandoo	304	44	1,983
Hope Downs	727	45	2,711
West Angelas	501	45	3,212
Paraburdoo	238	47	3,450
Channar	199	48	3,648
Yandi	855	48	4,503
Jimblebar	358	57	4,861
Area C	742	59	5,603
Koolanooka Hematite	39	59	5,642
Newman	1,045	61	6,687
Tallering Peak	43	62	6,729
Middleback Ranges	300	66	7,029
Koolyanobbing	392	71	7,421
Koolan Island	33	73	7,454
Frances Creek	23	79	7,477
Iron Hill	148	85	7,624
Mt Goldsworthy	18	122	7,642

Table 11. Input data for Australia's 2015 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	10,475	26	10,475
Koolan Island	855	28	11,330
Yandi	18,155	29	29,485
Mt Tom Price	12,336	30	41,821
Hope Downs	17,522	31	59,343
Nammuldi	26,197	31	85,540
Marandoo	7,244	32	92,784
West Angelas	12,791	33	105,575
Paraburdoo	7,244	33	112,820
Jimblebar	10,804	34	123,623
Channar	4,136	35	127,759
Area C	13,340	36	141,100
Newman	18,041	38	159,141
Mt Webber DSO	96	39	159,237
Iron Hill	2,014	41	161,251
Abydos	1,635	44	162,886
Middleback Ranges	3,390	45	166,276
Koolyanobbing	5,697	52	171,973
Roy Hill	965	56	172,938
Koolanooka Hematite	281	59	173,220

Table 12. Input data for Australia's 2016 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	10,651	23	10,651
Koolan Island	347	24	10,998
Mt Tom Price	14,928	26	25,925
Yandi	18,609	27	44,535
Nammuldi	28,083	27	72,618
Hope Downs	18,227	28	90,844
West Angelas	13,200	29	104,044
Paraburdoo	7,173	29	111,217
Marandoo	7,141	31	118,358
Jimblebar	11,379	32	129,737
Channar	3,773	32	133,510
Mt Webber DSO	2,405	32	135,915
Area C	13,028	34	148,944
Newman	18,492	35	167,436
Roy Hill	5,790	41	173,226
Middleback Ranges	3,400	44	176,626
Abydos	2,186	46	178,812
Koolyanobbing	5,754	48	184,566
Iron Hill	1,724	49	186,290

Table 13. Input data for Australia's 2017 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	10,132	48	10,132
Mt Tom Price	15,816	49	25,948
Nammuldi	28,507	50	54,455
Hope Downs	18,560	52	73,015
Yandi	17,555	52	90,570
West Angelas	13,489	53	104,059
Paraburdoo	7,315	53	111,374
Marandoo	7,315	54	118,688
Jimblebar	13,831	56	132,519
Channar	4,269	57	136,789
Area C	14,176	60	150,965
Newman	18,218	62	169,183
Roy Hill	14,282	64	183,465
Mt Webber DSO	2,886	65	186,351
Middleback Ranges	3,400	83	189,751
Iron Hill	2,020	86	191,770
Koolyanobbing	4,915	92	196,685
Abydos	1,663	99	198,348

Table 14. Input data for Australia's 2018 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	10,402	29	10,402
Mt Tom Price	16,784	31	27,186
Nammuldi	28,285	33	55,472
Yandi	17,914	33	73,385
Silvergrass	4,739	33	78,124
Hope Downs	17,917	34	96,041
West Angelas	12,903	35	108,944
Paraburdoo	7,306	35	116,250
Marandoo	7,306	36	123,556
Channar	2,833	38	126,389
Jimblebar	14,240	39	140,628
Area C	12,778	40	153,406
Mt Webber DSO	4,053	41	157,459
Newman	18,991	41	176,450
Roy Hill	20,072	43	196,522
Middleback Ranges	3,400	50	199,922
Iron Hill	2,027	56	201,949
Koolyanobbing	2,277	57	204,226

Table 15. Input data for Australia's 2019 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	8,819	31	8,819
Mt Tom Price	16,535	36	25,355
Yandi	18,345	36	43,699
Nammuldi	20,833	36	64,532
Silvergrass	7,898	37	72,431
Paraburdoo	7,198	37	79,628
West Angelas	13,262	38	92,890
Hope Downs	18,778	39	111,668
Marandoo	7,198	41	118,865
Area C	14,256	42	133,121
Roy Hill	20,458	42	153,579
Jimblebar	14,259	42	167,838
Mt Webber DSO	3,550	43	171,387
Channar	3,101	43	174,488
Newman	18,355	44	192,844
Middleback Ranges	3,400	50	196,244
Iron Hill	1,028	51	197,272
Koolyanobbing	2,389	57	199,661

Table 16. Input data for Australia's 2020 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	9,960	28	9,960
Mt Tom Price	16,215	34	26,175
Silvergrass	7,898	34	34,073
Nammuldi	19,157	34	53,230
Yandi	20,704	35	73,934
Paraburdoo	6,896	36	80,830
West Angelas	12,752	36	93,582
Iron Hill	1,299	37	94,881
Hope Downs	18,282	38	113,163
Mt Webber DSO	3,550	38	116,712
Marandoo	6,896	39	123,608
Roy Hill	21,230	40	144,838
Area C	14,536	41	159,374
Jimblebar	16,933	41	176,307
Channar	3,420	41	179,727
Newman	20,016	43	199,743
Middleback Ranges	3,911	47	203,654
Koolyanobbing	3,802	55	207,456

Table 17. Input data for Australia's 2021 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	10,753	26	10,753
Silvergrass	7,898	32	18,651
Nammuldi	26,055	33	44,706
Mt Tom Price	15,440	33	60,146
West Angelas	13,221	34	73,366
Paraburdoo	7,141	34	80,507
Hope Downs	17,600	36	98,108
Marandoo	7,141	37	105,249
Channar	3,860	39	109,109
Yandi	17,769	49	126,878
Roy Hill	22,388	50	149,266
Mt Webber DSO	3,458	50	152,724
Jimblebar	15,860	57	168,584
Area C	21,461	58	190,045
Middleback Ranges	3,314	58	193,359
Newman	18,445	58	211,804
Koolyanobbing	614	77	212,418

Table 18. Input data for Australia's 2022 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	10,753	26	10,753
Silvergrass	7,898	32	18,651
Nammuldi	26,055	33	44,706
Mt Tom Price	15,440	33	60,146
West Angelas	13,221	34	73,366
Paraburdoo	7,141	34	80,507
Hope Downs	17,600	36	98,108
Marandoo	7,141	37	105,249
Channar	3,860	39	109,109
Mt Webber DSO	3,194	45	112,303
Roy Hill	23,932	50	136,235
Yandi	12,273	50	148,508
Middleback Ranges	3,314	52	151,822
Jimblebar	17,644	56	169,467
Newman	19,606	58	189,073
Area C	35,282	62	224,355
Koolyanobbing	315	86	224,670
Paulsens East	275	143	224,945

Table 19. Input data for Australia's 2023 iron ore mines industry cost curve.

Mine Name	Production ('000t milled)	Unit cost $/t	Cummulative Production ('000t milled)
Robe River (Pannawonica)	10,753	27	10,753
Silvergrass	7,898	32	18,651
Nammuldi	26,055	33	44,706
Mt Tom Price	15,440	34	60,146
West Angelas	13,221	34	73,366
Hope Downs	17,600	37	90,967
Marandoo	7,141	37	98,108
Channar	3,860	40	101,968
Yandi	14,866	41	116,834
Roy Hill	25,090	45	141,924
Jimblebar	19,283	47	161,206
Newman	22,014	50	183,220
Mt Webber DSO	1,961	51	185,181
Middleback Ranges	3,314	52	188,495
Area C	36,068	55	224,563
Koolyanobbing	1,412	84	225,975
Paulsens East	1,329	88	227,304