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Optimizing maintenance strategies through data-driven analysis: Case study of a manufacturing company in South Africa Pietermaritzburg

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ABSTRACT

The increasing complexity of industrial systems and pressure on businesses to achieve operational excellence have made maintenance a strategic function in modern manufacturing. This study examined how data extracted from IBM Maximo can be leveraged in the process of evaluating and optimizing maintenance strategies within a South African manufacturing firm.

The research focused on eight key production departments within the organization and analysed historical maintenance data spanning the period 2021 to 2025. The study adopted a quantitative, post-positivist research approach and employed structured methods to extract, process, clean and integrate workflows to transform raw maintenance records into analytical datasets. Descriptive statistics, correlation and regression analyses were applied to uncover the relationships between maintenance activities and asset reliability.

The findings revealed significant variations across departments in maintenance workload distribution, work type composition, and asset performance. Preventive maintenance was found to increase breakdowns in the month of execution but demonstrated lagged reliability improvements in subsequent months. At the same time, predictive maintenance was underutilized, resulting in statistically insignificant effects. Corrective maintenance exhibited the most significant immediate impact on breakdown frequency, increasing failures during the month of execution.

The study concluded that (Computerised Maintenance Management System (CMMS) data holds great potential for driving continuous improvement when converted into actionable insights. The observed interdepartmental differences and maintenance behaviour patterns formed the foundation for recommending a targeted approach to reliability enhancement. A data-driven feedback loop is proposed to support maintenance teams in refining task intervals, focusing attention on high-risk assets, and systematically tracking the long-term impact of maintenance interventions.

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List of Abbreviations

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
CM	Corrective Maintenance
CMMS	Computerized Maintenance Management System
COVID-19	Coronavirus Disease 2019
IoT	Internet of Things
ISO	International Organization for Standardization
KPI	Key Performance Indicator
MTBF	Mean Time Between Failures
MTTR	Mean Time To Repair
MTTD	Mean Time To Detect
MTW	Mean Time Waiting
NLP	Natural Language Processing
OEE	Overall Equipment Effectiveness
PM	Preventive Maintenance
PDM	Predictive Maintenance
PMP	Planned Maintenance Percentage
RCM	Reliability-Centered Maintenance
ROI	Return on Investment
SCADA	Supervisory Control and Data Acquisition
TPM	Total Productive Maintenance

1. CHAPTER 1: INTRODUCTION

In today's competitive business landscape, efficient maintenance practices are crucial for maintaining operational efficiency and competitive advantage. Maintenance is no longer viewed as a reactive function aimed at responding to equipment breakdowns, but a strategic business pillar that directly influences production efficiency, cost asset longevity, and overall operational resilience (Baglee & Knowles, 2010).

The evolution of maintenance from reactive to preventive and predictive strategies has been significantly fuelled by the availability of digital tools such as Computerized Maintenance Management Systems (CMMS). These systems have enabled organizations to store vast amounts of historical maintenance data to track asset performance and generate maintenance work orders (Lopesa, et al., 2016). However, despite this digital capability, CMMS data is often not fully exploited. Many organizations still use these systems primarily for compliance and record-keeping rather than for driving proactive maintenance, according to Bengtsson, et al. (2020). The data collected over time on equipment failures, preventive maintenance activities, corrective actions and asset downtime present an opportunity to evaluate the effectiveness of existing maintenance strategies and unlock valuable insights for optimization. However, this opportunity is missed if the data remains dormant or is used only for reporting compliance (Bengtsson, et al., 2020).

This study aims to examine data from the CMMS of a South African manufacturing firm to pinpoint opportunities for enhancing machine reliability. The analysis commences with the extraction of historical data pertaining to equipment failures, maintenance operations and asset performance during a specified timeframe. The raw data is subjected to comprehensive cleaning and preparation to ensure that it is organized and appropriate for analysis. Subsequent to data compilation, the study classifies equipment into pertinent categories and performs a comprehensive analysis of historical failure incidents. The analysis focuses on discerning patterns in failure frequency, recurring issues and the operational impact of specific failures. The study draws from proven maintenance theories, including reliability-centred maintenance (RCM) and total productive maintenance (TPM) to generate actionable insights and propose evidence-based recommendations for minimizing equipment failures and optimizing maintenance costs.

1.1. Background

1.1.1 Asset Management and Maintenance in the Manufacturing Sector

The Manufacturing Industry is one of the most significant sectors in South Africa, employing over 1,507,000 people, according to Stats SA (2022). Manufacturing companies rely on complex systems and machines to achieve business objectives. Therefore, it is paramount that machines are kept operational and reliable to ensure that equipment failures do not stand between the business and its objectives. The reliability of a machine is defined as the likelihood that a machine will perform its prescribed operation for a specified period under defined conditions (Ross, 2020). Failure of a manufacturing machine to perform its function when required is undesirable, and machine maintenance is one of the processes put in place to prevent equipment failures. The SS-EN13306 (2017) standard defines maintenance as a set of technical, administrative and managerial activities carried out to retain or restore equipment to a state that allows it to deliver its function.

The ISO 55000 (2014) standard refers to five types of assets that companies invest in to enable their operations and make them competitive, namely human, financial, intangible, information and fixed assets (buildings and machinery). All these assets come together to produce a healthy and operating company. Physical assets often demand the greatest share of capital and operating costs, making their effective management critical for organizational sustainability (Parida & Kumar, 2006). The management and maintenance of machinery is particularly vital in manufacturing companies where production is dependent on the health of machines. Figure 1.1 depicts different asset lifecycle stages defined in ISO 55000 standard. Asset life begins at the point when a need for an asset is identified and ends at the point where the asset is disposed of. Throughout the lifecycle of an asset, the asset spends most of its time in the operation and maintenance phase. This is the phase where value is extracted from the asset and where maintenance comes into play.

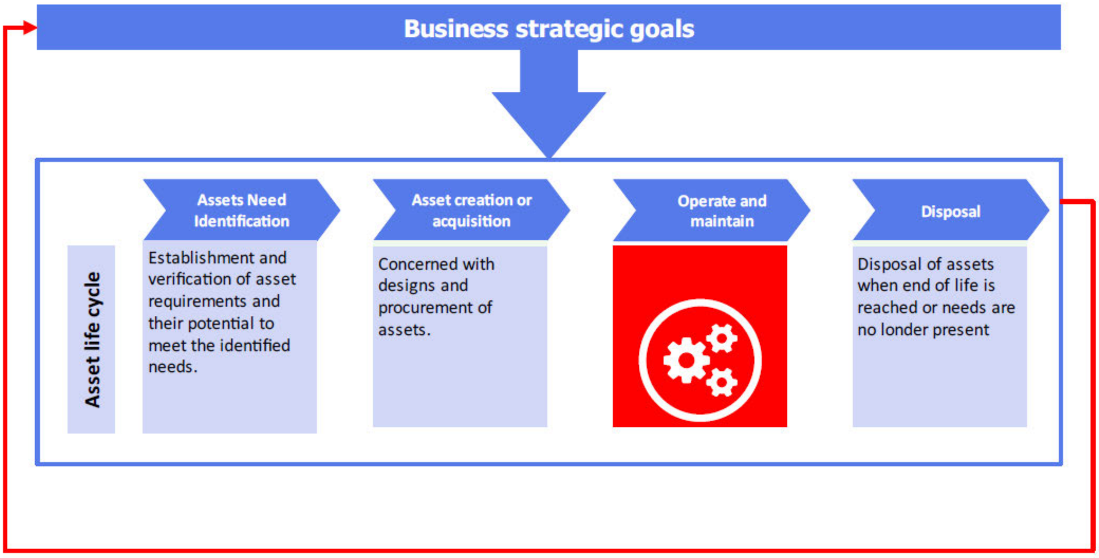


Figure 1.1: Asset Lifecycle (International Organization for Standardization, 2014)

1.1.2 Maintenance transformation over the years

The need for machine maintenance has existed since the invention of the first machines. The recorded history suggests that maintenance existed in Egypt as early as 600 B.C. (Poor, et al., 2019). Over the years, the complexity and scale of machinery increased and necessitated changes in the maintenance approach to ensure that the maintenance met the needs of the time. Maintenance practices have evolved alongside industrial development, shifting from reactive "fix-when-it-fails" approaches to proactive and predictive strategies (Nowakowski, et al., 2019). Chapter 2 expands on this transformation and highlights the role of Total Productive Maintenance (TPM) and Reliability-Centred Maintenance (RCM) frameworks that underpin this study. These two frameworks have been widely adopted across modern industry and continue to shape contemporary maintenance thinking and practice.

However, despite the adoption of TPM and RCM, companies still face challenges in translating these strategies into measurable improvements due to a number of challenges. Incomplete or fragmented data is one of the challenges faced by organizations. This highlights the importance of tools such as CMMS, which collect and structure maintenance data to support organizations moving from reactive to data-driven predictive and reliability-centred maintenance approaches.

1.1.3 Introduction of CMMS

The dependency on digital solutions for managing physical assets has grown over the years, as organizations seek to improve efficiency, reliability and decision-making. One of the most significant technological developments in this area has been the CMMS. The need to develop computerized maintenance systems was identified before the 1960s. However, the IT infrastructure to support the development of such a system was not in existence before 1960 (Mirka , 2009). With the development of microcomputers during the third industrial revolution, the possibility of having computerized maintenance systems became a reality with what was described by Mullin (1989) as state-of-the-art CMMS of the late 1980s. These systems had limited functionality and were mainly used as repositories for work orders and asset records (Mirka , 2009). This development marked the beginning of a shift away from purely manual processes to digital maintenance management systems.

Industry 4.0, introduced at the Hannover Fair in Germany in 2011, marked a new era characterized by the Internet of Things, artificial intelligence and machines that have the ability to process data and turn it into actionable insights (Nazanin & Farzad, 2020). This was followed by Industry 5.0 in 2020, which emphasizes human-machine collaboration to improve mass production and the creation of smart factories (Varshney, et al., 2024). These advancements in technology, computing and information systems have propelled the development of CMMS from simple record-keeping tools into integrated platforms that support preventive and predictive maintenance, spare parts management, performance reporting and other key modern maintenance processes (Lopesa, et al., 2016).

1.2. Problem Statement

Maintenance departments across many industrial organizations find themselves investing heavily in CMMS platforms to digitize their maintenance operations. These systems produce and retain vast quantities of maintenance-related data. However, studies have shown that this data is neither systematically examined nor utilized to guide the formulation and enhancement of maintenance programs (Bengtsson, et al., 2020). This data is often used passively for documentation or compliance purposes rather than proactively to drive strategic decisions (Bengtsson et al., 2020; Dalle Mule & Davenport, 2017).

This underutilisation creates a disconnect between maintenance execution and strategic planning. While established frameworks such as RCM and TPM advocate for data-driven approaches to reliability improvement, research suggests that organizations still lack effective feedback loops that use performance data to refine and adapt their maintenance plans (Efthymiou, et al., 2012). As a result, preventive tasks may be performed too frequently, wasting labour and resources, or too infrequently, increasing the risk of asset failures and production interruptions (Bengtsson et al., 2020; Mahabir & Pun, 2022). CMMS data underutilisation also limits opportunities for continuous improvement and prevents organizations from fully realising the system's intended benefits, including enhanced asset reliability, reduced downtime, and more efficient resource utilisation (Hoffmann & Lasch, 2025).

1.3. Research Objectives

This study is centred on the overarching goal of establishing how CMMS data can be used to evaluate and improve maintenance strategies at manufacturing companies in South Africa. The specific research objectives are as follows:

I. To extract and categorize historical maintenance data from the CMMS;

II. To analyse the effectiveness of current maintenance strategies by examining patterns in asset reliability, failure frequency, downtime and maintenance costs;

III. To assess the relationship between preventive maintenance and asset performance metrics;

IV. To identify inefficiencies in current maintenance practices, such as over-maintained or under-maintained assets;

V. To propose data-driven recommendations for optimizing maintenance frequencies, task prioritization and resource allocation; and

VI. To demonstrate the practical value of a data-informed feedback loop in improving maintenance outcomes and supporting continuous improvement.

This study addresses the identified gap in the utilisation of CMMS data for maintenance decision-making by aligning each research objective with a specific aspect of the problem. The extraction and categorisation of historical maintenance data address the issue of underutilised information within CMMS platforms. The analysis of maintenance strategies and asset performance responds to the lack of data-driven evaluation of maintenance effectiveness. The identification of inefficiencies targets the disconnect between maintenance execution and strategic planning. The development of data-driven recommendations and feedback mechanisms aims to establish a structured approach to continuous improvement, thereby addressing the absence of feedback loops identified in the problem statement.

1.4. Research Questions

To address the above objectives, the study seeks to answer the following research questions:

I. How can historical maintenance data from the CMMS be structured and analysed to evaluate the performance of existing maintenance strategies?

II. What insights can be gained from trends in failure data, work order frequency, and downtime records across different asset categories?

III. Is there a measurable relationship between the frequency of preventive maintenance tasks and asset reliability indicators such as asset failure frequency?

IV. Which assets contribute disproportionately to operational disruptions?

V. What opportunities exist to revise maintenance schedules or improve task effectiveness based on empirical data analysis?

VI. How can CMMS data be integrated into a continuous improvement framework for maintenance strategy development?

1.5. Hypotheses Development

Based on the research objectives, the following testable hypotheses are formulated:

H1. Proactive maintenance activities have a statistically significant negative relationship with breakdown frequency.

H2. Increased corrective maintenance activity is positively associated with higher breakdown frequency.

H3. Delays in maintenance execution are positively associated with increased breakdown frequency.

1.6. The Importance of the Study and Research Problem

This research has relevance in both theory and practice. On a theoretical level, it contributes to the subject of maintenance management by illustrating how structured data analysis may be used in real-world CMMS datasets in order to guide strategic decision-making. This is achieved by putting up a practical framework for the formulation of data-driven strategies, which helps to bridge the gap between traditional maintenance theory and modern data analytics.

From a pragmatic point of view, this research has the potential to bring about direct benefits for manufacturing enterprises in South Africa. The benefits include:

- Improved equipment reliability through better-informed maintenance schedules;
- Reductions in unplanned downtime and associated production losses;
- More efficient use of maintenance resources, including labour and spare parts;
- Lower maintenance costs through targeted interventions and the elimination of unnecessary tasks; and
- The enhanced ability to track and measure maintenance effectiveness using KPIs.

Within maintenance teams, the research fosters a cultural shift toward continuous improvement and decision-making that is driven by data. This is accomplished by giving a structured approach to data analysis that can be adopted in different organizations. This can enable maintenance personnel to progress beyond compliance-based execution and actively contribute to strategic objectives. Additionally, the findings from this study can serve as a reference point for other industrial companies in South Africa and worldwide that are looking to optimize their maintenance strategies by making use of data assets that are already in existence. In this sense, the research contributes towards the achievement of operational excellence and to the general progress of maintenance best-practices in the Manufacturing Industry.

1.7. Scope of the Study

The scope of this research is focused on the analysis of maintenance data extracted from the IBM Maximo CMMS platform of a South African manufacturing firm. The dataset spans the period 2021 to 2025 and pertains to the company’s Pietermaritzburg site. The study focuses on critical assets that have a significant impact on production output and operational continuity.

Data types to be analysed include:

- Preventive maintenance work orders,
- Corrective and reactive maintenance work orders,
- Failure history data,

- Asset master data, and
- Downtime records and root cause analyses.

Real-time data from SCADA or condition monitoring systems is not included into the study. However, the framework could be further developed to include such data in future research. In addition, the impact of organizational culture, human factors or external supply chain disruptions are excluded from the analysis. These factors are acknowledged as influencing variables but fall outside the scope of this study. This scope definition seeks to keep the study focused on the actionable results that can be acquired directly from the CMMS data.

1.8. Limitations of the Study

Several limitations were recognized in the pursuit of this study:

i. **Data Quality**
   - CMMS data may contain inconsistencies or inaccuracies due to some data being manually entered into the system and possibly resulting in entry errors, missing records or inconsistent recording practices.

ii. **Generalizability External Validity**
   - The study is based on data from a single organization and may not be directly generalizable to other organizations, industries or geographical contexts. The reliance on a single site inherently constrains the external validity of the findings, and adaptation may be necessary before applying them in different contexts.

iii. **Time Constraints**
   - The analysis is constrained by the available time for data processing and interpretation as defined by the academic research timeline.

iv. **Non-Quantifiable Factors**
   - Cultural and human factors that influence maintenance outcomes, such as people skill levels, are not quantified in the data but may impact results.

v. **Technology Scope**
   - The study solely focuses on CMMS data and does not include Real-time data from SCADA or condition monitoring systems.

1.9. Structure of the Report

This thesis is structured into five chapters, each addressing a critical element of the research process:

- **Chapter 1: Introduction**
    - Introduces the research background, problem statement, objectives, significance, scope and limitations.
- **Chapter 2: Literature Review**
    - Provides a review of existing research and conceptual frameworks related to maintenance strategies, CMMS and data-driven decision-making.
- **Chapter 3: Methodology**
    - Describes the research design, data extraction procedures, analytical methods and validation techniques used in the study.
- **Chapter 4: Data Analysis**
    - Presents the results of the data analysis using visualizations, statistical summaries and interpretation of findings.
- **Chapter 5: Conclusion**
    - Summarizes the key findings, revisits the research questions and provides recommendations for practice and future research.

2. CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter provides a comprehensive review of the literature relevant to the optimization of maintenance strategies using CMMS data. It begins by tracing the evolution of maintenance practices from traditional reactive approaches to more proactive preventive and predictive maintenance strategies. This historical view helps to contextualise current industry practices and the shifts that have taken place over the years of maintenance existence. Thereafter, the review focuses on the role of CMMS in modern maintenance environments. It explores the structure of CMMS data storage, the ways in which this data has been utilised by scholars, and the challenges associated with CMMS data quality.

In addition, this chapter also examines TPM and RCM maintenance philosophies that are widely adopted in modern manufacturing industries. The understanding of these frameworks provides a theoretical basis for interpreting how CMMS data can be aligned with structured maintenance planning principles. The review also addresses how maintenance performance is evaluated by exploring approaches to measuring maintenance effectiveness, including commonly used key performance indicators such as Mean Time Between Failures (MTBF) and Overall Equipment Effectiveness (OEE).

The literature reviewed was sourced from peer-reviewed journal articles, academic textbooks, and industry reports accessed through databases such as Google Scholar and ScienceDirect. The search keywords used to identify relevant studies included "*maintenance strategies", "CMMS data", "predictive maintenance", "RCM",* and *"TPM"*. Preference was given to recent and highly cited publications to ensure that the review reflects current developments in industrial machine maintenance and data-driven decision-making.

2.2. Evolution of Maintenance

Maintenance management has changed significantly over the years. It has evolved from simply fixing machines when they break to a strategic, data-driven pillar of industrial reliability and performance that is increasingly putting emphasis on proactive maintenance strategies that leverage technology and data. At each phase of the industrial revolution, a maintenance transformation has come with it. The term 'industrial revolution' was used to describe the economic growth of Britain from 1760 to 1840 by economic historian Arnold Toynbee (Coleman, 1956). This term has been used from that time to refer to a sudden change in industry. Each industrial revolution phase brought about different challenges to maintenance and necessitated the transformation of the maintenance field. Various maintenance strategies have emerged to characterize and guide maintenance practices through each phase.

2.2.1 Reactive maintenance

Industry 1.0 was a transformation of society from hunters to agriculture characterised by mechanization, steam power and the transformation of transportation (Varshney, et al., 2024). This was the era when the engine was invented by James Watt in 1765 (Wahid, et al., 2021). During this time, breakdown maintenance was known to be the way to conduct machine maintenance. The idea behind this approach is to operate the equipment until it fails, at which point maintenance is performed to restore its functionality (Afolalu, et al., 2021). This approach is commonly known as 'reactive maintenance' or "run to failure", and it does not involve pre-planned maintenance activities, but actions are taken only after a failure has occurred. Reactive maintenance is one of the most traditional approaches to equipment management due to its simplicity and perceived short-term cost savings (Jooste, 2007). However, over time, it has been established that while it may reduce immediate maintenance expenditure, its broader implications for operational efficiency, safety and asset longevity are significantly more complex and often detrimental in the long-term. As a result, this approach is used on equipment that is not critical to production, safety and product quality (Afolalu, et al., 2021). The run-to-failure approach is still used in the modern industry and applied to suitable assets.

The relevance and application of the run-to-failure approach in modern industry are supported by the work done by Jooste (2007) in his assessment of South African industrial maintenance practices. In this research, it was noted that despite advancements in technology and maintenance in organizations globally, many South African industries still relied heavily on reactive maintenance due to constraints such as limited resources, lack of planning capability, and workforce skill gaps.

2.2.2 Preventive maintenance

The reactive maintenance approach was sufficient until around 1870, when Industry 2.0 came to light (Poor, et al., 2019). Industry 2.0 era was the time when complex electrically powered machines that enabled significant production growth were developed. With this advancement, the economic and operational consequences of unplanned downtime associated with reactive maintenance started becoming a problem. This was particularly a challenge in mission-critical industries such as aviation, manufacturing and utilities (Nowlan & Heap, 1978). The growing need for failures to be prevented rather than reacted to necessitated a philosophical shift in industrial maintenance practice, and preventive maintenance emerged. Preventive maintenance was established when military operations recognized the need to service aircraft components based on usage hours, regardless of visible wear, to prevent failures (Nowlan & Heap, 1978).

Preventive maintenance is concerned with identifying machine components that are likely to fail after a certain period and replacing these components before the failures happen. The strategy allows for work to be executed under planned circumstances, which reduces machine downtime and costs while preventing unplanned production interruptions (Piqueras & Fernandez-Crehuet, 2020). In the post-war industrial boom of the 1950s and 1960s, preventive maintenance gained traction as organizations sought to improve the reliability of increasingly complex machinery. There was a strong understanding that components wear over time and establishing the time it took for the components to wear out was critical in implementing effective preventive maintenance strategies (Nowlan & Heap, 1978). As a result, strategies initially focused on time-based schedules, where servicing was carried out at fixed intervals, regardless of the condition of the equipment. Later developments introduced usage-based or meter-based approaches, triggering maintenance based on operating hours, cycles or production volumes (Wireman, 2004).

According to Afolalu et al. (2021), preventive maintenance plays a critical role in sustaining the design life of equipment by conducting scheduled inspections, lubrication, cleaning and component replacements. It improves asset availability, reduces the risk of catastrophic failures, and supports a safer working environment. These benefits made preventive maintenance a fundamental element of asset-intensive industries of the 20th century. The study by Jooste (2007) on maintenance performance across multiple industries in South Africa revealed some important insights into the local adoption of preventive maintenance. The study noted that while many companies had implemented preventive maintenance schedules, their execution and effectiveness varied widely. This was a result of a myriad of issues, including poor planning systems, a lack of workforce training, and inadequate performance monitoring.

From Jooste's (2007) study, it was noted that about 78.7% of scheduled preventive maintenance tasks were completed on time, with significant variations across sectors. This variation in job completion suggested systemic issues in work scheduling and execution. The study called for improved CMMS integration and better alignment of preventive maintenance plans with operational goals.

2.2.3 Predictive maintenance

Transition to predictive maintenance

Preventive maintenance was a significant step towards failure prevention. However, preventive maintenance came with the risk of over-maintenance. The equipment could be serviced unnecessarily, leading to the wasteful use of labour and materials (Mobley, 2002). This was realised shortly after preventive maintenance started gaining traction. As a result of the search for maintenance strategies to address the shortfalls of reactive and preventive maintenance, predictive maintenance emerged as an evolution of preventive maintenance. The earliest signs of predictive maintenance appeared in the late 1960s and early 1970s in highly sensitive and critical industries like aerospace and nuclear energy (Mobley, 2002).

This was a maintenance strategy that would be more tailored and maintain equipment based on its actual condition rather than a rigid schedule. In addition, it was realised that the continuous monitoring of equipment critical parameters such as vibration, temperature and lubrication quality could provide early warning signs of equipment degradation. Predictive maintenance only gained broader industrial relevance from the 1980s onward, as microelectronics, computing power and sensor technologies became more accessible.

Predictive maintenance fundamentally revolves around monitoring asset health in real time or near real time and predicting failures before they occur (Carvalho, et al., 2019). This is achieved through:

- Continuous or periodic data collection, e.g. vibration, temperature, oil quality,
- Analysis of data trends to detect degradation patterns, and
- Forecasting potential failure points using statistical or machine learning models.

Predictive maintenance seeks to maintain the equipment only when necessary. This approach optimizes maintenance costs and improves reliability (Carvalho, et al., 2019). Importantly, predictive maintenance is not merely condition monitoring but the creation of actionable predictions enabling strategic planning, parts procurement, labour allocation and downtime minimization (Carvalho, et al., 2019).

Empirical research has shown that predictive maintenance delivers better results when compared to traditional maintenance strategies. Thomas and Weiss (2021) conducted a study in United States manufacturing facilities and showed that companies that relied more on predictive maintenance achieved 18.5% less unplanned downtime compared to those focused mainly on preventive maintenance. In addition, the same firms experienced 87.3% fewer defects. These findings suggest that predictive maintenance not only improves machine reliability but also product quality (Thomas & Weiss, 2021).

Implications for modern industry

Nowadays, the paradigm of Industry 4.0 has fuelled the aggressive development of predictive maintenance by enabling the integration of the Internet of Things (IoT) devices, machine learning algorithms, and cloud-based analytics (Ocheni, et al., 2024). Studies such as Ocheni, et al.'s (2024) emphasize that predictive maintenance now forms a crucial pillar of modern manufacturing systems.

Numerous studies conducted on predictive maintenance and its integration with IoT, smart sensors, machine learning and data analytics have consistently found that predictive maintenance plays a crucial role in improving machine reliability, product quality and workplace safety. A systematic literature review conducted by Rojas, et al. (2025) encompassed 166 high-impact studies and highlighted that AI-driven predictive maintenance strategies significantly reduce unplanned downtimes and enhance worker safety. It also highlighted that the integration of smart sensors and machine learning algorithms facilitates real-time monitoring and early fault detection, which enable proactive maintenance actions that prevent equipment failures and associated safety risks.

Challenges in adopting predictive maintenance

However, even though maintenance has evolved into modern practices that rely on modern technology, the implementation of predictive maintenance still faces numerous challenges in industry. One of the problems is the initial investment required to implement predictive maintenance. The deployment of IoT sensors, integrating them with CMMS platforms, developing predictive algorithms and training personnel, represent considerable upfront costs (Zonta, et al., 2020). In many cases, companies do not have this capital and are faced with sticking to alternative maintenance strategies or implementing predictive maintenance on a few selected critical assets. In addition to the initial cost challenge, Hoffmann and Lasch (2025) pointed out that many organizations remain sceptical about the return on investment from the implementation of predictive maintenance, which makes the justification of upfront costs difficult.

For machine learning algorithms, it is paramount that the data is accurate for the models to produce reliable results. Moreover, CMMS contains important information about the assets, which forms key input to predictive model construction (Diez-Olivan, et al., 2019). Many organizations struggle with inaccurate CMMS data containing missing, inconsistent or biased entries. According to a study by Diez-Olivan et al. (2019), poor-quality historical data limits the accuracy of predictive models and can lead to incorrect maintenance decisions, thereby introducing new risks rather than eliminating them. This challenge of data accuracy is also highlighted in the study by Hoffmann and Lasch (2025), which pointed out that poor data quality, insufficient historical data or fragmented data systems hinder the effectiveness of predictive maintenance.

2.2.4 Integrating maintenance strategies in modern industry

These studies show that even though maintenance strategies have significantly evolved from reactive to predictive maintenance, predictive maintenance is not a silver bullet to the challenges of maintenance. Maintenance challenges are complex and require organizations to adopt a multifaceted approach to maintenance that considers their specific contexts, resources and capabilities. All maintenance approaches still have a place in modern industry, as Thomas and Weiss (2021) note that organizations typically rely on a blend of reactive, preventive and predictive strategies selected according to operational and asset criticality. Table 2.1 contrasts the defining features, advantages, limitations and typical applications of reactive, preventive and predictive strategies. While the adoption of new technologies is becoming a norm in the search for suitable and effective maintenance approaches in modern industrial maintenance, particularly in contexts involving high operational demands, the literature also recognises that the key may not solely lie in adopting cutting-edge predictive maintenance technologies but rather in optimising what organizations already have (Al-Turki, 2011). However, for such optimization to be effective, the presence of a well-implemented Computerized Maintenance Management System is essential.

Table 2. 1: Comparison of reactive, preventive and predictive maintenance

Feature	Reactive Maintenance	Preventive Maintenance	Predictive Maintenance
Definition	Maintenance performed only after failure occurs (“run to failure”).	Scheduled maintenance at fixed intervals or based on usage, regardless of condition.	Maintenance triggered by actual condition and predictive analytics.
Trigger	Equipment breakdown.	Time-based or usage-based schedules.	Real-time or periodic monitoring, IoT sensors, and predictive models.
Advantages	Simple and minimal planning needed.	Reduces unplanned downtime, improved safety, predictable workloads.	Optimizes costs, minimizes downtime, enhances safety and product quality.

Limitations	High downtime, costly for critical or high value assets, create unsafe conditions.	Risk of over-maintenance, resource waste.	High upfront investment, requires accurate data and skilled workforce.
Typical Application	Non-critical or low-cost equipment where downtime has little impact on production.	Regular servicing of commonly used production equipment to reduce breakdowns.	Monitoring of high-value or critical machinery to detect faults before failure.

2.3. CMMS Data Storage

CMMS is an integrated software solution designed to track, schedule and manage maintenance activities, including work orders, equipment history, spare parts inventory and labour allocation (Mobley, 2002). Modern CMMS platforms capture vast amounts of data, including failure modes, mean time between failures (MTBF), and equipment utilization (Crespo Marquez & Iung, 2008). Moreover, CMMS platforms typically store a mix of static master data and transactional data, which are combined to support a closed-loop system of planning, execution, feedback and improvement (Muchiri, et al., 2011). According to Ahmad and Kamaruddin (2012), the following elements are typically stored in CMMS as master data.

- *Asset register:* A complete inventory of physical assets, including descriptions, asset IDs, location, commissioning dates and technical specifications.
- *Maintenance task library:* Standardised task descriptions, including job procedures, tools required, safety instructions and estimated durations.
- *Bill of materials*: Lists of parts, materials and spares associated with each asset, including supplier information and re-order thresholds.
- *Equipment hierarchies:* Logical grouping of assets that facilitates the assignment of maintenance at different levels.
- *Failure codes and root causes*: Standardised codes used to classify the types of equipment failures, aiding in data analytics and fault trending.

On the other hand, transactional data in CMMS encompasses dynamic records. These include work orders, downtime logs, labour hours, materials and services (Rambe & Bester, 2020).

- **Work orders** include predictive, preventive, corrective and breakdown maintenance. Each work order typically includes job descriptions, asset identifiers, fault codes, required tools, safety instructions, scheduled and actual start and end dates, technician or artisan assignments, parts consumed, and feedback or notes after task completion (Carnero, et al., 2023).

- **Downtime logs** provide information about the duration, frequency and root causes of machine downtime. This information is vital in performing calculations for key performance indicators like MTBF and MTTR (Muchiri, et al., 2011).

- **Labour details** provide details about involved people's identifications, hours worked and labour rates. Accurate labour tracking allows cost attribution to individual jobs and supports workforce productivity assessments (Muchiri, et al., 2011).

- **Materials and service records** track spare parts, consumables and contracted services used in maintenance activities. These entries often include part numbers, inventory locations, unit costs, quantities issued, suppliers and procurement references. This supports inventory optimization, cost tracking and the identification of material consumption trends (Bengtsson, et al., 2020).

Historically, CMMS platforms were primarily used as digital logbooks to support reactive maintenance, focusing on recording breakdowns; issuing work orders; and managing spare parts inventory (Mobley, 2002). Their role was largely administrative, namely supporting maintenance teams after equipment failures had occurred. The evolution of maintenance over the years from reactive to predictive has necessitated additional functionality in the CMMS platforms to remain relevant. Modern CMMS systems serve as data-driven decision-support tools, integrating information from smart sensors, IoT devices and condition monitoring systems to support real-time equipment health monitoring (Crespo Marquez & Iung, 2008).

2.4. CMMS Data Utilization

2.4.1 Gap in CMMS data utilization

While CMMS capabilities have undoubtedly improved significantly over the years, a gap in the utilization of the rich data they generate still persists. Dalle Mule and Davenport (2017, p. 113) state that: "*Cross-industry studies show that on average, less than half of an organization's structured data is actively used in making decisions and less than 1% of its unstructured data is analysed or used at all*". This underuse represents a missed opportunity to improve asset reliability and improve maintenance efficiency.

2.4.2 Approaches adopted in existing studies

However, there are existing studies that have analysed CMMS data to extract insights for maintenance improvements. In most cases, these studies have primarily focused on machine-level data rather than delving into the component level. This can be a problem as production machines are assemblies of components like motors, drives, gearboxes, etc., arranged in a certain way to perform a specific function (Ivanov, et al., 2025). Figure 2.1 illustrates a typical production machine, highlighting that it comprises interconnected sub systems and components working together to deliver a specific output. Typically, when a machine experiences a breakdown, it is due to the failure of one or more of these individual components. Therefore, analysing maintenance data at the machine level can obscure the identification of specific component failures, potentially leading to less effective recommendations.

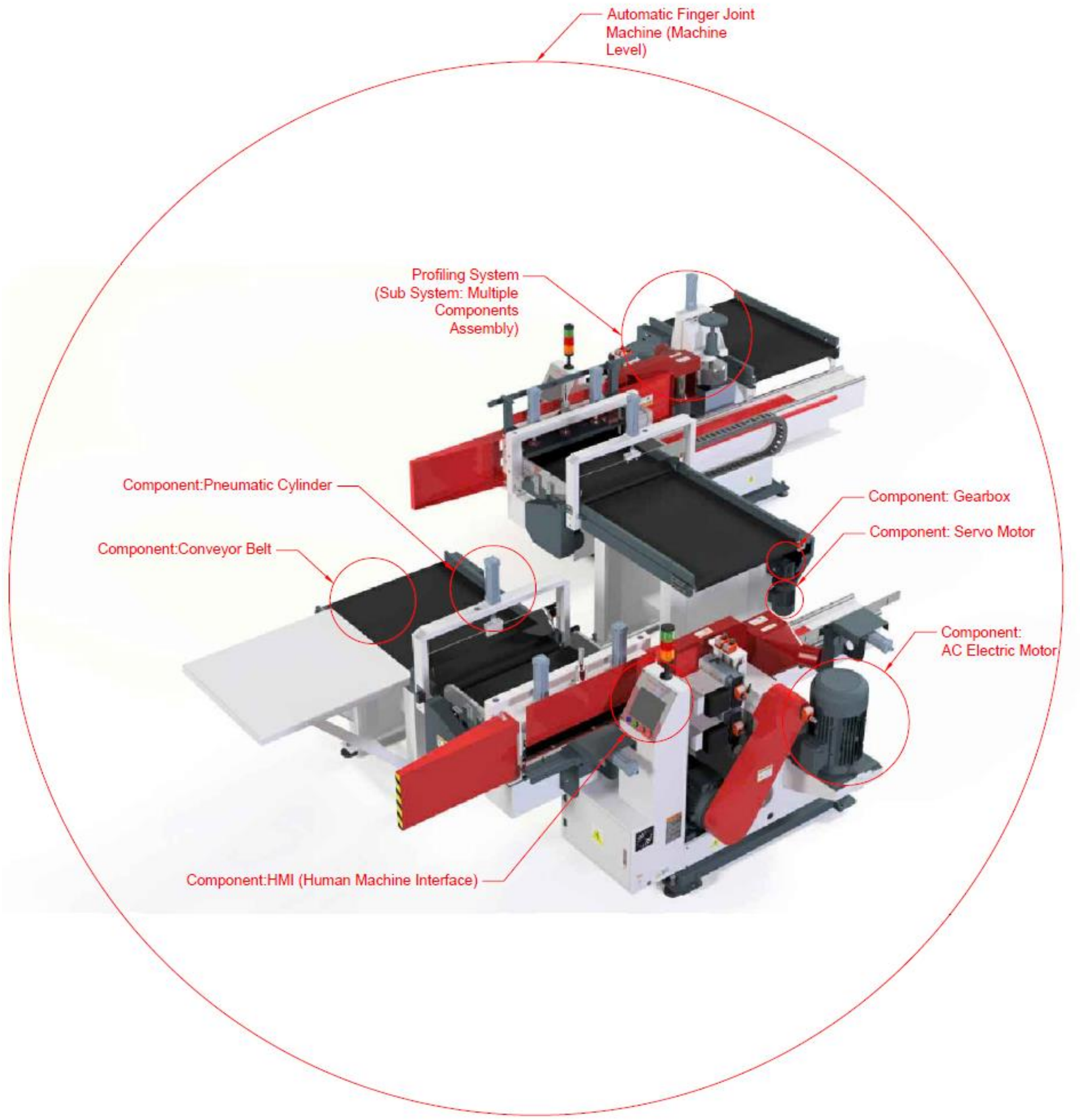


Figure 2 1: Typical production machine (GrabCAD, 2025)

Recent studies advocate for a component-level approach in maintenance data analysis. For instance, a study by Ucar, et al. (2024) emphasized the importance of focusing on key components in predictive maintenance applications. Similarly, research by Gawde, et al. (2023) reviews two decades of data-driven approaches for multi-fault diagnosis in industrial rotating machines and highlights the importance of component-level analysis in improving fault detection and maintenance planning. The importance of component-level analysis in maintenance planning is further highlighted by the work of Labib (2004) in a study on a decision analysis model for maintenance policy selection using a CMMS. The study developed a decision analysis model for maintenance policy selection using CMMS data. This model emphasized the need for detailed failure data at the component level to inform maintenance decisions. It showed that in analysing failure modes and their frequencies, organizations can prioritize maintenance activities based on the criticality and failure rates of individual components, leading to more efficient resource allocation and reduced downtime.

However, despite these recognized benefits of component-level analysis, many real-world implementations still fall short. This is reflected in empirical studies such as that of Hoseinie, et al. (2018) who conducted a reliability analysis on a fleet of face drilling rigs operating in a Swedish underground mine. The researchers employed three different modelling approaches, namely white-box, black-box and simulation, to understand failure behaviour and improve maintenance strategies. However, the focus remained at the machine level, treating each drilling rig as a single unit. Although the study acknowledged the complex structure of these machines, it did not isolate failure data at the component level. This abstraction limited the ability to derive targeted insights for individual parts such as hydraulic systems, drilling arms or control units, which are often the causes of failures.

Similarly, Garcia and Salgado (2022) explored how the type of machine component and the conditions of use influence preventive maintenance strategies in multistage industrial machines. The study recognized the influence of components on maintenance needs but largely treated machines as cohesive systems rather than dissecting them into their constituent parts. The analysis was designed to help decision-makers choose optimal maintenance policies for machines used under different operational conditions but lacked in-depth failure mode data at the component level. For instance, instead of examining failure rates of gearboxes, drive motors or bearings individually, the study evaluated general categories of equipment such as presses or cutting machines. This high-level analysis lacks the resolution needed to pinpoint recurring failures or wear trends within individual components. As such, it does not fully capitalize on the diagnostic power of CMMS data.

Bengtsson et al. (2020) also conducted a case study in a plant that manufactures driveline components for heavy construction vehicles. They investigated the use of CMMS data to improve maintenance practices in a heavy commercial vehicle manufacturing company using breakdown data extracted from CMMS. The data analysis focused on frequency of breakdowns, Mean Time Waiting (MTW), Mean Time To Repair (MTTR), and Mean Time To Detect (MTTD). Notable in their analysis of 386 work orders is that the analysis remained at the machine level and did not delve into component-level failures. This limited the specificity of the recommendations for maintenance improvements.

2.5. CMMS Data Quality

2.5.1 Unstructured data issues

In addition to these analytical limitations, Bengtsson et al.'s (2020) study highlighted a broader issue common in CMMS-related research, which is data quality. The issue of unstructured, inconsistent and inaccurate data is reflected in multiple studies that use CMMS. Scholars have adopted various methods to work around the data quality issue. Bengtsson et al. (2020) found that a substantial amount of data is entered as free text in CMMS. They concluded that the lack of standardization posed challenges in data analysis, necessitating the development of a structured approach to extract meaningful insights from unstructured data.

Stenström, Parida and Aljumaili (2015) also emphasized the challenges posed by free-text entries in maintenance records. They pointed out that free text entries complicate data retrieval and analysis and advocated for the integration of natural language processing (NLP) techniques to interpret unstructured data and enable the extraction of actionable insights. They also suggest the implementation of text-mining algorithms capable of processing linguistic patterns to extract meaningful information. The study additionally demonstrates the use of keyword extraction and clustering techniques to classify fault descriptions and identify recurring failure patterns. This approach helps with the automated analysis of large volumes of textual maintenance records.

Beyond technical solutions, another contributor to unstructured data issues is poor data-entry practices. Artisans may enter ambiguous or inconsistent descriptions in CMMS fields due to usability challenges or insufficient guidance on standardized reporting (Tretten & Karim, 2014). Such practices introduce subjectivity and reduce the reliability of the information captured. Therefore, addressing unstructured data issues may also require cultural and procedural changes, including training and standardized data-entry protocols, to improve data quality and support more reliable maintenance decision-making.

2.5.2 Structured data Issues

While unstructured data receives considerable attention, structured CMMS data also come with its own set of quality challenges. A literature review conducted by Aljumaili and AL-Chalabi (2016) explored how the quality of data influences decision-making processes in maintenance management. It identified key data quality dimensions, namely accuracy, completeness, timeliness and consistency, that significantly affect the reliability of maintenance decisions. The study highlighted that poor data quality can lead to incorrect diagnostics, inefficient planning and increased downtime. It demonstrated this by conducting an analysis using data before and after data cleaning, showing the impact of poor data quality. This underscored the importance of data cleaning and indicated how flaws in the data can lead to wrong conclusions.

All these studies highlighted the importance of considering data quality when working with CMMS data and ways of handling the poor data quality one would inevitably encounter. From free-text entries and inconsistent formats to incomplete or inaccurate records, data quality challenges are a recurring theme across empirical investigations. Together, the studies emphasize that without addressing both structured and unstructured data challenges, the potential of CMMS data to inform effective maintenance decision-making is severely limited.

However, despite the widespread acknowledgment of poor data quality as a barrier, only a limited number of studies offer systematic and repeatable frameworks to address these issues. The majority of existing research remains diagnostic, focusing on identifying and describing data problems and their operational consequences. This indicates a maturity gap in the literature, where recognition of the problems has outpaced the development of solutions.

The data quality challenges identified in the literature have important implications for the reliability and interpretation of the findings in this study. Issues such as missing records, inconsistent data capture, and variability in how maintenance activities are logged in CMMS may introduce bias and affect the accuracy of calculated indicators such as failure frequency and maintenance work type distribution. In addition, the presence of unstructured or ambiguous data entries may limit the precision with which relationships between maintenance activities and asset reliability can be established. This introduces a level of uncertainty in the statistical results, particularly in correlation and regression outputs, where the strength and significance of relationships depend on data consistency. As highlighted in prior studies, poor data quality may lead to either overestimation or underestimation of maintenance effects, which has direct implications for the validity of conclusions drawn from the analysis.

2.6. Decision-making Frameworks

Having quality data without a structured methodology for selecting optimal maintenance strategies in complex industrial settings can also impact the effectiveness of the outcome. Over the years, several structured decision-making models have gained traction for selecting appropriate maintenance strategies. One of these models is the Multi-Criteria Decision-Making model, which is useful in situations where a balance between competing priorities such as cost, risk, asset criticality, downtime impact and resource constraints is required

The Analytic Hierarchy Process (AHP) is one of the most widely used multi-criteria decision-making techniques to solve decision problems (Lopesa, et al., 2016). The AHP decision-making tool breaks down complex problems into a hierarchy of goals, criteria and alternatives. It uses pairwise comparisons to assign weights and calculate a priority ranking of options, incorporating both subjective judgments and objective data (Saaty & Vargas, 2012). The practical application of AHP was seen in a study by Garg and Deshmukh (2006). The study proposed an AHP-based model, which was used to evaluate maintenance strategies by assigning weights to criteria such as cost, equipment criticality and downtime impact. Their study showed how subjective managerial preferences could be formalised into a repeatable decision model.

AHP has also been used in conjunction with other models, like in the study conducted by Kirubakaran, et al. (2016), which aimed at selecting the best strategy for a pump in the paper industry and applied the AHP model combined with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The TOPSIS model ranks alternatives by measuring their distance from a hypothetical ideal solution and the worst outcome. The alternative closest to the ideal and farthest from the negative ideal is considered the best (Behzadian, et al., 2012). In Kirubakaran et al.'s (2016) study, AHP was used to determine the weigting of the options, and TOPSIS was used to derive the final ranking of maintenance alternatives. The outcome of the study was improved efficiency in the mainteinace strategy selection process.

Similarly, Prasanta (2004) applied AHP combined with a risk-based decision support system to select optimal maintanance strategies for oil pipelines. The system prioritised pipeline segments for inspection and maintenance by evaluating five key failure risks, namely corrosion, external interference, construction/materials defects, acts of God and human error. Through the formation of the hierarchical model of risks and alternatives, stakeholders were able to conduct pairwise comparisons and determine failure likelihoods for each segment. The outcome of this process was targeted inspection plans, which reduced overall failure risk and demonstrated a cost reduction of over 60% compared to traditional blanket inspection methods.

Garg and Deshmukh (2006) demonstrate how CMMS-enabled multi-criteria decision-making models provide maintenance managers with quantitative tools to evaluate strategy alternatives based on diverse factors such as cost, risk, downtime impact and criticality. However, a key challenge remains the subjectivity involved in assigning weights to decision criteria. This is particularly an issue where decision-making is dominated by a few individuals. Even though AHP attempts to reduce inconsistency through pairwise comparisons and consistency indices, results can still be biased by managerial perceptions, which needs to be taken into consideration when applying these models. In South African manufacturing contexts, where managerial expertise and data availability vary significantly across organizations, reliance on subjective judgments may undermine replicability.

2.7. TPM and RCM Maintenance Philosophies

It is clear that CMMS contains a vast amount of equipment-related information, including equipment maintenance plans. The performance of equipment is highly dependent on the quality of maintenance plans that are developed and kept in CMMS. Therefore, it is imperative that these plans are developed through structured processes guided by proven maintenance philosophies such as TPM and RCM.

TPM is a maintenance philosophy formulated by a Japanese citizen, Seichi Nakajima, and was formally introduced in Japan around 1970 (Ahuja & Khamba, 2008). On the other hand, RCM was developed by engineers from United Airlines for the aviation industry, with the aim of improving the profitability of operating airlines (Wilmeth, et al., 2020). RCM and TPM are not distinct philosophies but rather complementary. The RCM and other maintenance strategies are packaged in TPM to bring focus to maintenance as an essential aspect of the business (Mahabir & Pun, 2022).

RCM is about analysing possible equipment failures, considering its function and operating context. It is a methodology focused on maintaining system function through the identification of critical failure modes and their consequences (Moubray, 1997). Moreover, RCM emphasizes understanding how and why equipment fails and seeks to craft maintenance activities to prevent those specific failures. The implementation of RCM follows a structured process that involves defining system functions; identifying functional failures; determining failure modes and their effects; and selecting appropriate maintenance tasks (Hipkin, 1993). It focuses on the analytical analysis of maintenance data using the following analytical tools (Mahabir & Pun, 2022):

i. Root cause analysis;
ii. Failure mode and effect analysis; and
iii. Criticality analysis.

The outcomes of RCM are maintenance strategies designed to prevent specific component failure modes, and sometimes, equipment is redesigned if the analysis outcome is deemed unacceptable (Nowlan & Heap, 1978). The types of maintenance could be a combination of preventive, predictive and corrective maintenance. Mahabir and Fai Pun (2022) note that RCM underpins the analytical backbone of TPM. TPM integrates RCM into a holistic framework that emphasizes maintenance as a core business process and includes culture, collaboration and continuous improvement (Ahuja & Khamba, 2008). TPM emphasises getting participation from different stakeholders in the maintenance of machines across a company (Wireman, 2004). Furthermore, TPM is known for creating step changes in company performance, improving employee morale, and creating visible changes in the workplace (Suzuki, 1994).

A key objective of TPM is the elimination of the so-called "six big losses", which are the primary causes of inefficiencies in manufacturing. These include equipment failures, setup and adjustment losses, idling and minor stoppages, reduced equipment speed, defects in the production process, and reduced yield (Ahuja & Khamba, 2008). TPM addresses these losses by shifting some traditional maintenance responsibilities to operators, who are empowered to carry out routine activities such as cleaning, lubrication, inspections and minor adjustments. This creates a sense of order and discipline around the machine while allowing maintenance professionals more time to focus on more complex tasks, including scheduled inspections and preventive repairs (Nakajima, 1988).

One foundational concept in TPM is the assumption that equipment follows the bath-tub failure curve, which suggests that failure rates are high during the early and late stages of equipment life and relatively low during the mid-life (Hipkin, 1993). TPM further distinguishes between two types of equipment-related losses, namely sporadic losses, which are sudden and noticeable, often due to shifts in operating conditions; and chronic losses, which are persistent, harder to detect and often stem from issues such as poor design, sub-optimal operating procedures, or a lack of maintenance skills (Nakajima, 1988). Addressing sporadic losses typically involves restoration to original conditions, while tackling chronic losses demands innovative problem-solving and systemic improvement (Hipkin, 1993). The successful implementation of TPM requires cultural change, cross-functional collaboration and a strong commitment to continuous improvement.

TPM is concerned with the following 8 pillars of maintenance, namely (Hipkin, 1993):

i. Autonomous maintenance,
ii. Focused improvement,
iii. Planned maintenance,
iv. Quality Maintenance,
v. Early equipment management,
vi. Training and education,
vii. Safety health and environment, and
viii. Administration.

The implementation of maintenance plans developed through the TPM and RCM theories is key to the success of maintenance. Up until the maintenance plans are executed on the shopfloor, the value of maintenance plans is not realised. It is important that preventive and predictive maintenance activities are performed at the right time, with the correct tools, procedures and skills to ensure the desired results (Mobley, 2002). In modern maintenance practices, the CMMS acts as the critical link between planning and execution, ensuring that maintenance tasks are scheduled, tracked and completed as intended. However, the African industrial context is characterised by fragmented maintenance cultures and data-governance infrastructure required to sustain these frameworks. Additionally, resource constraints, including funding shortages and limited training opportunities, hinder the institutionalization of preventive and predictive practices (Jooste, 2007). These contextual realities become stumbling blocks in sustaining these frameworks in Africa, and they need to be considered when designing or implementing maintenance improvement programmes in African industries.

The practical implementation of TPM and RCM relies on the availability and analysis of maintenance data. In this study, these theoretical frameworks are operationalised through the application of statistical techniques to CMMS data. The employed statistical methods serve as a quantitative extension of these frameworks and enable data-driven validation of maintenance strategies. The principles of RCM, which emphasise failure patterns and maintenance optimisation, are reflected in the analysis of failure frequency, MTBF, and breakdown trends. Similarly, TPM's focus on continuous improvement and performance measurement is aligned with the use of key performance indicators and inter-departmental comparisons conducted through correlation and regression analysis.

2.8. Measuring Maintenance Effectiveness

Ideal maintenance can be defined as one where there are minimal corrective events while just enough preventive and predictive maintenance is being done (Rastegari, 2017). The other type of maintenance, which is undesirable, is breakdown maintenance. The impact of machine breakdowns is enormous, and these should be systematically prevented. Bengtsson et al. (2020) stated that the cost of unplanned machine stoppage is about five times that of planned stoppage. In the current times, where cost efficiency is a significant driver in competitiveness, it is undeniable that reducing unplanned stoppages can add significant value to a company. However, this must be done without adding excessive planned maintenance, which can also result in unnecessary costs, as pointed out by Bengtsson et al. (2020). Alsyouf (2007) argued that beyond a certain threshold, additional preventive maintenance delivers diminishing returns. This highlights a tension in the literature between advocating for more proactive maintenance and recognising the risk of over-maintenance.

An ideal outcome of maintenance is the complete elimination of unplanned downtime, with planned downtime being used effectively to execute maintenance activities in line with a defined strategy (Mobley, 2002). However, achieving this ideal is difficult, particularly as assets progress through various stages of their lifecycle during the "operate and maintain" phase (Nowlan & Heap, 1978). Several factors, namely the increasing probability of failure with age; human error during maintenance or operation; and the effectiveness of the selected maintenance strategies, can each, or in combination, contribute to unplanned machine downtime (Moubray, 1997). In practice, these factors frequently occur, making unplanned downtime an inevitable part of asset management.

To gauge how well maintenance is being carried out, Key Performance Indicators (KPIs) have been traditionally used. The KPIs provide quantifiable metrics to assess the effectiveness of maintenance activities. Common KPIs cited by Mobley (2002) include:

- **Mean Time Between Failures (MTBF)**

  This KPI indicates the average time between equipment failures. A higher MTBF is desirable as this indicates better machine reliability. MTBF is calculated as follows:

$$\text{MTBF} = \text{Total Uptime}/\text{Number of Failures}$$

- **Mean Time to Repair (MTTR)**

This KPI measures the average time required to repair equipment, indicating maintenance efficiency. A Lower MTTR is desirable as this indicates a quicker recovery from failures. MTTR is calculated as follows:

MTTR= Total Downtime/Number of Repairs

To explain the link between MTBF and MTTR, Figure 2.2 depicts a timeline of a typical machine experiencing two failures. As shown, MTBF represents the interval from the completion of one repair to the occurrence of the next failure. The phases of Mean Time to Detect (MTTD), Mean Time to Repair (MTTR) and Mean Time to Failure (MTTF) all fall within the MTBF span, with MTTR reflecting the average time to recover from a failure. Hence, MTBF and MTTR play a critical role in minimizing downtime and enhancing overall equipment effectiveness (OEE).

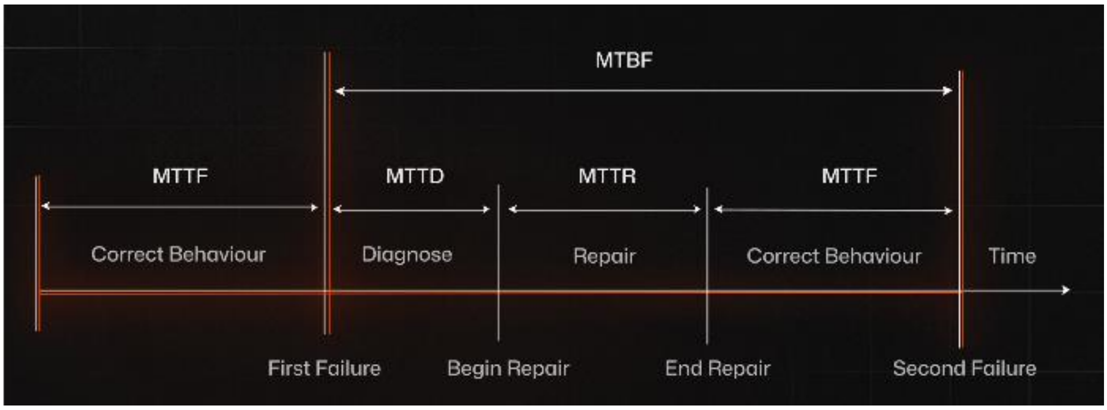


Figure 2.2: Typical machine timeline (Zenduty, 2024)

- Overall Equipment Effectiveness (OEE) - Combines availability, performance and quality metrics to provide a view of equipment productivity. In some cases, the individual components of OEE are measured individually and discussed at different levels in the organization. OEE is calculated as follows:

OEE=Availability × Performance × Quality

Availability=Operating Time / Planned Production Time

Performance = Ideal Cycle Time × Total Units / Operating Time

Quality =Good Units / Total Units Produced

Planned Maintenance Percentage (PMP) - Represents the proportion of maintenance activities that are planned versus unplanned, highlighting the proactivity of maintenance strategies. PMP is calculated as follows:

$$PMP = (\text{Planned Maintenance Hours} / \text{Total Maintenance Hours}) \times 100$$

These KPIs are widely adopted in industry but their sufficiency has been debated. Some scholars have pointed out that MTBF's reliance on a constant failure distribution assumption is problematic as real assets seldomly fail in a uniform fashion but rather follow a bathtub-shaped failure pattern with variable hazard rates (Bowles, 2002). On the other hand, research also criticises the bathtub curve concept itself, suggesting that it applies to as few as 10–15% of cases and may oversimplify early-life failure dynamics (Klutke, et al., 2003).

In responding to these shortcomings, recent studies have advanced reliability modelling beyond traditional constant failure-rate assumptions. Belyi et al. (2017) demonstrate that Bayesian parametric models provide a more flexible approach to reliability analysis by accurately capturing bathtub-shaped hazard functions. The model integrates prior knowledge and updates predictions with new data, enabling the dynamic representation of asset failure behaviour. Their findings show that with such accurate information about asset deterioration, a far more effective optimization of preventive maintenance schedules can be achieved. This highlights the limitations of conventional MTBF-based approaches and reveals the need for more flexible, data-driven models in maintenance strategy development.

Similar criticism is documented in the literature regarding the use of OEE, which has been criticized for oversimplifying the complex interactions between availability, performance and quality, thus potentially mask underlying operational challenges. Van De Ginste et al. (2022) point out that OEE does not adequately account for production changeovers, which are an inseparable part of modern manufacturing systems. OEE treats changeover time as downtime, even though the equipment is actively used to switch between products. This limitation makes OEE less applicable in mass-customized manufacturing contexts, where adaptive throughput and operational versatility are required. Additionally, recent studies have highlighted ambiguities in OEE definitions across industries and call for standardized approaches like ISO 22400 to improve comparability (Di Luozzo, et al., 2023).

Another prevalent gap in the literature on the use of such KPIs is the lack of a clear connection between these KPIs and strategic financial outcomes such as ROI. A number of empirical studies associate improved maintenance performance like higher availability and MTBF with productivity and profitability gains (Alsyouf, 2007), but literature on the direct impact on ROI from specific KPI improvements remains scarce. This view is reinforced by Lundgren et al. (2020), who show that despite the acknowledged importance of financial indicators in maintenance performance frameworks, they are still applied far less frequently than operational measures such as OEE and MTBF. As a result, the research base remains fragmented, with limited guidance on how operational improvements in maintenance can be translated into quantifiable ROI outcomes. There is a clear need for multi-site studies, particularly those examining CMMS and predictive maintenance programs, where associated KPI improvements are linked directly to standardized financial metrics.

3. CHAPTER 3: METHODOLOGY

3.1. Introduction

This chapter outlines the details of the research design adopted in the study. The design was guided by the widely recognised Research Onion framework proposed by Saunders, Lewis and Thornhill (2019). The research onion provides a layered approach to structuring the research design, beginning with broad philosophical considerations and progressively narrowing down to specific data collection and analysis techniques. The illustration in Figure 3.1 visually maps the methodological layers.

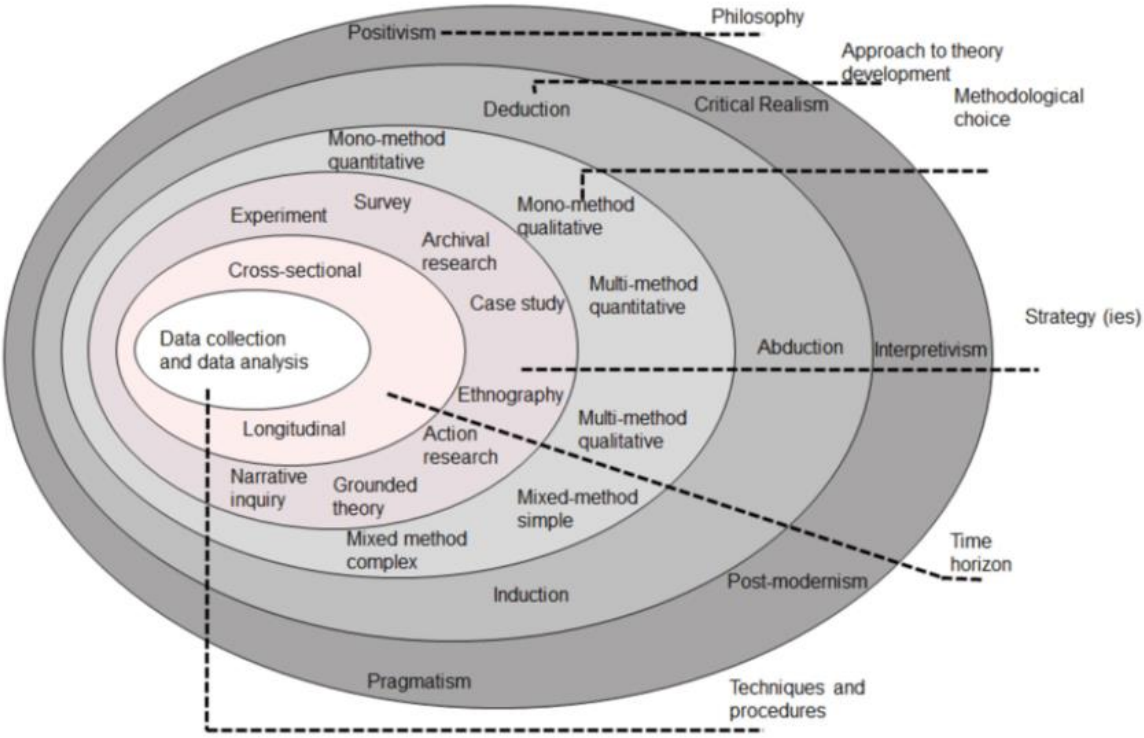


Figure 3. 1: Research onion framework (Saunders, et al., 2019)

The chapter begins by introducing the concept of research and research design. It then delves into the philosophical paradigm underpinning the study, clarifying the ontological, epistemological and axiological assumptions that shape the research. This philosophical view provides the foundation for selecting an appropriate research design and approach. Building on this foundation, the chapter addresses the research strategy, specifying the case study approach adopted and its justification in relation to the research objectives. The choice of time horizon, the study site and the sampling strategy are discussed within the context of ensuring validity and reliability.

Subsequent sections focus on the practical layers of the research onion. They address the data collection methods, the tools and instruments employed, and the analytical techniques applied to derive and interpret the findings. Each method is justified with reference to its suitability for answering the research questions. Ethical considerations are also addressed to demonstrate compliance with responsible research conduct. This is followed by the last section of this chapter, which discusses the data handling, confidentiality and security measures taken to align with relevant data protection regulations.

3.2. Research

The term 'research' is often used loosely to define a number of activities that are not necessarily research in academic terms. An understanding of the concept of research is fundamental to any academic inquiry. Research is a systematic and purposeful activity aimed at generating new knowledge or deepening existing understanding about a subject of interest. The definition provided by Leedy and Ormrod (2015) states that research is "a systematic process of collecting, analysing and interpreting data in order to increase our understanding of a phenomenon about which we are interested or concerned". This is congruent with the definition by Creswell and Creswell (2018), which describes research as a methodical approach where investigators propose a hypothesis or inquiry, collect relevant information, and seek to resolve or explain the issue through analysis. These definitions highlight some of the key characteristics of research, which are structured, intentional, evidence-based and contribute meaningfully to a particular field.

In the context of this study, research was applied to the sphere of physical asset management. The study examined how secondary data from IBM Maximo CMMS can be utilised to inform maintenance strategy decisions. The study aimed to identify opportunities for enhancing maintenance performance by analysing maintenance data, including MTBF, unplanned downtime frequency, and the relationship between maintenance activities and breakdowns. Therefore, this study aimed to add practical value by offering insights into data-driven maintenance and also to contribute to the academic discourse on reliability-centred maintenance.

3.3. Research Paradigm

This study is grounded in the post-positivist research paradigm, which is well-suited to the quantitative research approach employed in this study. Post-positivism builds upon the philosophical foundations of positivism, but recognizes the complexity and imperfect nature of empirical observation. Positivism upholds the view that the world is governed by absolute laws and truths that can be objectively observed and measured, but post-positivism adopts a more cautious stance and acknowledges the limitations of absolute objectivity in understanding social phenomena (Leedy & Ormrod, 2015). The Secondary data used in this research is objective and quantifiable, but the post-positivist view recognizes potential limitations such as human understanding of the data, which is always partial and influenced by the limitations of measurement tools and interpretive frameworks. The post-positivist paradigm is predicated on the assumption that the phenomena under investigation follow lawful, predictable patterns and that cause-and-effect relationships can be uncovered through systematic inquiry. However, it also accepts that these findings are probabilistic rather than absolute. In line with this, the study does not claim to definitively "prove" hypotheses but rather aims to increase the likelihood that certain patterns and relationships exist within the maintenance data (Leedy & Ormrod, 2015).

Objectivity remains a cornerstone of credible and rigorous research (Creswell & Creswell, 2018). Therefore, it is important that personal biases, preferences and subjective influence are removed from the research process to ensure that findings are valid, replicable and generalizable. The post-positivist view is that objectivity and complete neutrality is unattainable in practice (Creswell & Creswell, 2018). However, the researcher remained aware that biases can influence both the design and interpretation of the results in this study. The use of standardized data collection tools, validated metrics, structured data handling procedures, statistical analysis techniques and a focus on validity and reliability were used to minimize the researcher's biases.

The positivist paradigm emphasises replicability, which refers to the ability of other researchers to repeat a study using the same methods and data sources and obtain similar results (Leung, 2015). Replicability is one of the key characteristics of inquiry within post-positivist epistemology as it ensures that the research findings are not biased but reflect underlying causal relationships that are consistent and observable across contexts (Leung, 2015). According to Mertens (2014), replicability contributes to the credibility of research findings by providing a mechanism for independent verification, thus enhancing the robustness of scientific claims. In this study, replicability was supported by the use of clearly defined maintenance data extracted from a structured CMMS database, along with standardized analytical techniques such as time-series analysis, failure trend evaluation and correlation testing. The study also documented the data preparation steps, analytical models and statistical procedures used. This enables other researchers working with similar datasets in other comparable organizations to validate the findings through independent analysis.

In addition, the post-positivist paradigm supports generalizability, which refers to the extent to which the findings from the study can be reasonably expected to hold true for similar datasets or contexts under investigation (Leung, 2015). In post-positivist research, generalizability is achieved by identifying patterns or relationships that hold true across different settings or populations. In the present study, the analysis of historical CMMS data is used not only to identify opportunities to optimise maintenance strategies for the equipment at the chosen organization, but also to derive principles that may be relevant to other manufacturing environments where similar equipment, operational conditions and maintenance systems are in place. For instance, insights about the impact of preventive maintenance frequency on asset uptime could inform strategy development in other plants that utilise CMMS technology.

3.4. Research Design and Approach to Theory

Research design can be viewed as a detailed blueprint that guides the collection, measurement and analysis of data in a study. Kumar (2019) defines the research design as a roadmap that guides the investigation, aiding in the attainment of answers to research questions in a valid, objective, precise and cost-effective manner. Research design provides the overall structure through which research objectives are operationalised, ensuring that the study is systematic. There are several key considerations in research design, including decisions about sample selection, data sources, data collection tools and methods of analysis. A robust research design is one of the key elements to producing findings that are credible, replicable and applicable.

According to Creswell (2018), there are three primary types of research designs, namely qualitative, quantitative and mixed methods. These designs should not be considered as entirely distinct, but rather as existing along a continuum. On one end of the continuum, there is qualitative research, which focuses on understanding human experiences through open-ended questions, observation and inductive reasoning. On the other end lies quantitative research, which involves testing theories through an analysis of numerical data collected via structured instruments and using a deductive process. Mixed methods research falls between the two and combines both qualitative and quantitative elements to enrich the study's outcomes. Creswell highlights that the differences between these designs go beyond the use of words versus numbers or open versus closed-ended questions. Instead, they are shaped by deeper philosophical assumptions, the overall strategies employed, and the specific methods of data collection and analysis.

A quantitative research design was employed in this study to objectively analyse extracted maintenance data and identify patterns, trends and statistical relationships related to maintenance performance. The data investigated in this study included information such as asset downtime, failure frequency, work order completion rates and proactive maintenance schedules, which are mostly numerical and structured in nature. This made the data well-suited for statistical analysis and quantitative analysis (Creswell & Creswell, 2018).

The quantitative design also enabled the use of deductive reasoning, whereby the theoretical constructs based on TPM and RCM models were used. It assessed the practical implementation of these models within the context of manufacturing companies. This was achieved through the interrogation of extracted data to validate these models and determine whether real-world maintenance behaviour and planning practices conform to or diverge from these theoretical ideals. Where inconsistencies and inefficiencies were observed, the study proposed data-driven improvements that align more closely with the desired outcomes.

3.5. Study Site

The study is conducted within a large, vertically integrated industrial manufacturing company operating in Pietermaritzburg, South Africa. This company is characterized by a complex production environment where multiple processing stages are interdependent, and where operational continuity is crucial for meeting production targets and customer delivery expectations. The organization's asset base comprises a broad range of mechanical, electrical and control system equipment distributed across multiple departments and production lines. These departments are configured to support the transformation of raw materials into semi-finished products. The operation is such that not all products pass through every machine, but certain production machines are dedicated to key product streams that generate the majority of the company's revenue and profitability.

This site was selected as the focus of the research due to its extensive use of CMMS technology, its high degree of equipment integration, and its established organizational emphasis on performance monitoring and continuous improvement. The organization has invested significantly in both preventive and predictive maintenance strategies, and maintains comprehensive digital records of work orders, maintenance schedules, equipment hierarchies and asset-related feedback. These attributes make it a suitable environment for conducting a study that relies exclusively on secondary data analysis to examine the link between maintenance strategy execution and asset performance outcomes. Even though each department maintains its own maintenance plans and schedules, the system allows for the consolidation and export of maintenance data across the site, which is required for the fulfilment of the study's objectives.

One of the key operational characteristics of the study site is its high dependency on the reliability of equipment to maintain a smooth and sequential flow of production. Production stoppages in one department frequently have cascading effects, disrupting upstream or downstream processes. In such environments, even relatively minor equipment failures can result in significant production delays, quality risks, missed delivery timelines and increased operational costs. This interdependency reinforces the strategic importance of asset reliability and justifies the focus of the study on key performance indicators such as MTBF and unplanned downtime hours and frequency.

3.6. Target Population and Sampling

A population is defined as the complete set of elements or entities that possess some common characteristic defined by the sampling criteria established for a study (Cooper & Schindler, 2014). In the context of this study, the target population refers not to human subjects, but to the population of physical assets managed within the company's CMMS. The population comprises all registered equipment assets that are subject to preventive, predictive, corrective and breakdown maintenance interventions, and for which relevant maintenance data is available.

According to Kumar (2019), the reliability of research findings is strongly influenced by how the sample is selected. The main goal of sampling is to ensure that the results drawn from the sample closely reflect those of the broader population, while staying within resource limits. If a sample is genuinely representative, even a small number of units can provide accurate insights about the entire population. Kumar (2019) highlights the following two principles when selecting a sample:

i. Avoiding selection bias – Selection bias involves intentionally distorting findings or using inappropriate methods to obtain desired outcomes due to personal interests.
ii. Aiming to achieve the highest level of accuracy possible with available resources.

The study adopted a purposive sampling method to concentrate the analysis on the most critical and high-impact equipment. Given the diversity of the asset register, the sample was limited to the eight primary production departments and excluded support departments and overhead cranes. These eight departments were selected based on their significant contribution to overall maintenance workload and operational criticality, as they process core product streams that generate the majority of the company's revenue. These departments represent the organisation's full set of production machines and house high-value, production-constraining assets, making them strategically critical to the business mission. When equipment fails in these departments, it sets off a chain reaction that disrupts both upstream and downstream processes, thus magnifying the effect of any maintenance inefficiencies. Therefore, by focusing the analysis on these departments, the study captured parts of the operation where maintenance performance has the greatest impact.

The maintenance data used is from January 2021 to June 2025. This four-year window was chosen to represent a recent and relevant period during which the company maintained consistent use of its CMMS and associated feedback processes. The timeline sought to exclude the COVID-19 period, where the use of CMMS might have been inconsistent. The period provides a sufficiently long timeline to conduct a trend analysis and assess the consistency or deterioration in reliability over time.

3.7. Data Integration and Analysis Workflow

To support the study's objective, a structured data integration and analysis workflow was employed. This process focused on transforming raw maintenance data into a coherent, analysable format suitable for statistical evaluation and insight generation. The workflow consisted of five key stages as depicted in Figure 3.2.

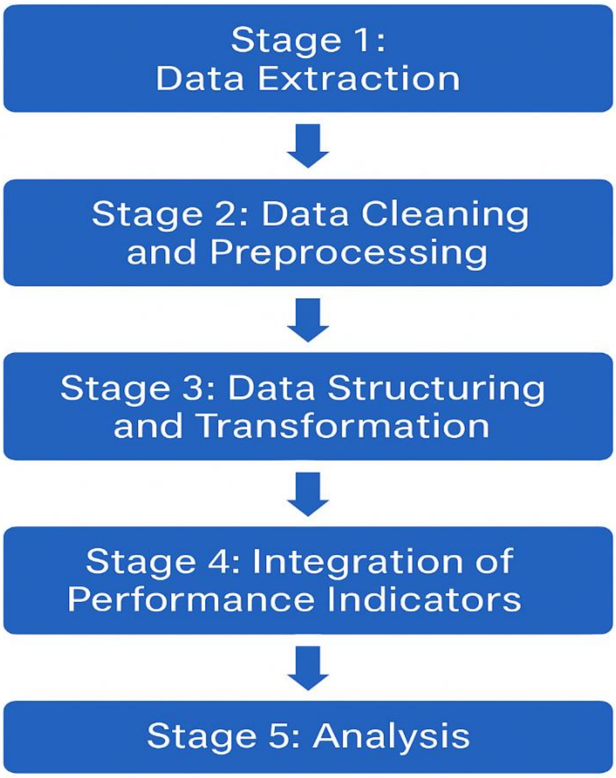


Figure 3. 2: 5-stage data processing workflow

3.7.1 Stage 1: Data extraction

The initial step involved the extraction of three datasets from Maximo, namely the asset location master data, maintenance work order history, and maintenance work order feedback history. Each dataset was extracted following a predefined template to ensure data consistency, completeness and traceability.

Asset location master data

This dataset contained information such as the location's unique identifier, site identifier, description, type and status. The extraction followed the asset location template presented in Appendix A. The resulting dataset was then filtered to include only locations associated with the eight primary manufacturing departments. Subsequently, crane-related locations were excluded to ensure that the analysis focused exclusively on process-related assets. Data was retrieved for asset locations within the Pietermaritzburg site that were recorded as having an active operating status.

It is important to note that location data was used rather than asset data. In Maximo, asset locations serve as virtual representations of the physical areas or systems where equipment is installed. Within these virtual locations, corresponding virtual assets, which represent the real equipment, reside. Under normal circumstances, each location is expected to have one associated asset. However, it is not uncommon at the study site for Maximo locations to exist without corresponding assets, due to factors such as:

- Assets temporarily removed for off-site repair without being re-assigned upon return.
- Newly installed assets have not yet been created in Maximo.
- Historical data migration inconsistencies.

As a result, location data provides a more comprehensive and representative view of the actual number of assets, their departmental distribution, and the diversity of asset types within the manufacturing system. Considering these factors and the comparative evaluation presented in Table 3.1, the decision was made to base the analysis on location-level data rather than asset-level data.

Table 3. 1: Asset vs location data considerations

Criterion	Asset Data	Location Data
Information Availability	Provides detailed reliability inputs such as asset age, installation date, and repair history. This will be useful for future life-cycle studies.	Sufficient for this study's trend and regression analysis but limited for detailed future investigations.
Accuracy	Often incomplete due to asset movements or poor update management.	More accurate and stable as location information is static from the machine installation date.
Work Order Logging	Work may be logged on different assets in the same Maximo location, causing fragmented histories.	All work recorded under one location, giving a clearer view of recurring or environmental issues.
Analytical Focus	Enables asset-level fault and maintenance analysis, identifying specific defects or repair issues.	Focuses on broader system or environmental trends affecting multiple assets.

Data Completeness	May be incomplete if maintenance technicians fail to select the correct asset when raising work orders.	Every work order requires a location, ensuring complete coverage of all maintenance activities.
Suitability for Trend Analysis	More suitable for micro-level or equipment-specific reliability studies.	Better suited for system-level trend analysis, where the goal is to understand department- or machine-level maintenance performance and strategy effectiveness.
Ease of Data Integration	Requires frequent data cleaning and cross-checking with location data to ensure accuracy.	Easier to integrate with work order and failure data since location is a mandatory field in Maximo.

Maintenance work order history

This dataset included details such as work type, task descriptions, reported and completion dates, and responsible craftsperson. The extraction process was guided by the work order data template provided in Appendix A. The work order data used was from January 2021 to June 2025 and this was extracted for only the selected eight departments.

Maintenance work order feedback history

This dataset included information on work order numbers, descriptions, summary feedback, and detailed feedback. The extraction template used for this dataset is also included in Appendix A. Similar to the other datasets, this data covered the period January 2021 to June 2025 and was limited to the same eight departments to maintain consistency across datasets.

3.7.2 Stage 2: Data cleaning and pre-processing

Following the extraction of raw CMMS data, a robust data merging, cleaning and validation process was undertaken to ensure the accuracy, consistency and reliability of the dataset prior to analysis. CMMS data, especially when manually entered over long time periods, often contain discrepancies and gaps that can compromise analytical results if not properly addressed (Mobley, 2002). The cleaning procedures in this study included a multi-step approach, combining rule-based validation with cross-field consistency checks.

Pre-processing

The first step in data pre-processing included creating department and asset class columns in the locations data table. The department data was extracted from the "Location id" field, while the asset class information was extracted from the "Location Description" field. The assets were categorized into asset classes, including pumps, gearboxes, motors, heat exchangers, compressors, and other mechanical or electrical components. This grouping enabled a structured analysis and prioritization of asset groups rather than individual assets. It also allowed for the number of assets per class to be determined, facilitating a quantitative understanding of commonly occurring asset types overall and within each department.

The next step involved pre-processing the work order dataset to incorporate the asset class information developed in the locations table. The "Location ID", which was common to both datasets, served as the linking key for merging and transferring the asset class field from the locations table to the work order table. To validate the accuracy of the assigned asset classes and prevent mis-classification resulting from work orders logged under incorrect locations, a rule-based filter was applied. This filter examined the work order descriptions to identify instances where the textual content suggested a different asset class from that assigned via the location linkage. The verification results were captured in a new column containing the updated or confirmed asset class values.

The summary and detailed feedback fields from the feedback table were subsequently merged into the work order table using the work order number as the linking key. In addition, a new composite column was created by concatenating the summary and detailed feedback text. This enabled the identification of work orders lacking feedback entries and enabled text-based analyses in subsequent stages.

Data cleaning

Firstly, verified work order statuses were verified against the artisan's feedback. A common anomaly in CMMS systems is that work orders are marked as "completed", which implies the task was physically done and completed, but the corresponding feedback notes indicate that the task was deferred, partially completed, or not done at all. These inconsistencies were flagged through a rule-based filter developed in Power Query, which compared the recorded status codes with textual feedback fields. The resulting evaluation generated an additional column containing revised or validated status values.

Secondly, labour booking records were examined for feasibility and alignment with scheduled durations. Instances have been observed where the booked labour time significantly exceeds the scheduled work time. For example, bookings of several days against a task that was scheduled for just one hour. Such cases indicate input errors or flawed timekeeping and were investigated by reviewing timestamps and task types. Work orders showing implausible labour and task durations were excluded from time-based performance calculations to avoid distortion.

Other data quality checks included validating the chronological sequence of timestamps. This ensured that data misrepresentations, such as a task being closed before it is reported in the system, were prevented. Furthermore, work orders lacking corresponding feedback were excluded from the dataset to preserve analytical accuracy and integrity.

3.7.3 Stage 3: Data structuring and transformation

Cleaned data was then structured into analysis-ready tables, with records grouped and aggregated at appropriate levels (e.g., per asset, per month). Data transformations were applied to derive new variables where necessary to bridge the gap between operational records and analytical modelling. The derived variables included:

- MTBF, calculated by dividing the total operating time by the number of failures recorded. This measure was available at the machine level but not at the individual location or asset class level.
- The Pro-active maintenance coverage ratio, reflecting the proportion of proactive maintenance actually executed.
- Task delay indices, measuring average delays between reported and actual execution dates.

3.7.4 Stage 4: Integration of performance indicators

The fourth stage in the analytical framework involved the integration of key performance indicators with the cleaned and structured maintenance data. This step was critical to establishing empirical relationships between maintenance strategies and asset reliability outcomes. The CMMS data provide rich insights into maintenance tasks, schedules and frequencies. However, the result of these strategies must ultimately be measured in terms of their impact on asset performance. Therefore, the integration of KPIs allowed the research to go beyond descriptive analytics and into performance-based evaluation.

Three key technical performance indicators, Mean Time Between Failures, labour cost and unplanned downtime hours and frequency, were integrated into the dataset to assess the relationship between maintenance strategy and asset reliability. These indicators are widely accepted in the field of reliability engineering and maintenance management as valid measures of equipment performance (Mobley, 2002).

Given that the manufacturing organization where the research was conducted is characterised by a sequential flow of material through interdependent machines and departments. MTBF is an important measure as any unplanned failure, even if relatively minor, can trigger a chain reaction, disrupting upstream and downstream operations. These disruptions can delay product delivery, reduce order fulfilment capacity, and undermine customer satisfaction. Ultimately, compromised reliability poses a reputational risk and reduces the organization's ability to secure future business, affecting short-term revenue and long-term sustainability (Campbell & Reyes-Picknell, 2015).

Unplanned downtime hours, as a complement to MTBF, provide insight into the cumulative duration of these interruptions. MTBF focuses on the frequency of failures, while unplanned downtime captures their impact in terms of lost production time (Campbell & Reyes-Picknell, 2015). In the context of this study, unplanned downtime is considered significantly more disruptive than planned downtime. Planned downtime can be proactively scheduled around production cycles, thus allowing for the building of inventory buffers and advance communication with customers and stakeholders. This flexibility allows the business to minimise customer disruption and maintain delivery commitments even during maintenance activities (Muchiri, et al., 2011). In contrast, unplanned downtime is sudden and unpredictable, offering no opportunity for mitigation or contingency preparation. Unplanned downtime leads to missed production targets; delays in customer orders; and increased pressure on other parts of the system to recover lost throughput. The additional adverse outcome of unplanned downtime could be overtime labour, emergency spares procurement and quality risks, further inflating operating costs and eroding profitability.

Maintenance cost proxies are necessary to evaluate the financial efficiency of the maintenance strategy. Cost considerations are essential because a maintenance system that maximises uptime but does so at disproportionately high cost may be unsustainable. Rising maintenance expenditure without corresponding reliability improvements directly affects the organization's operating margin and, by extension, its competitive positioning (Thomas & Weiss, 2021). As the company's core objective is profitability through reliable and efficient production, the maintenance strategy must strike a balance between performance and cost-effectiveness.

The assessment of these three indicators, namely MTBF; unplanned downtime hours and frequency; and maintenance cost proxies, were assessed at the departmental and asset class levels. This allowed for a comparative analysis across similar assets deployed in different departments, and also supported a longitudinal analysis to identify trends over time.

3.7.5 Stage 5: Analysis

This combination of technical performance with strategy execution data laid a foundation for addressing the main research question: Do the existing maintenance strategies contribute effectively to asset reliability and operational outcomes, and how can they be improved using data-driven insights? The next stage of the research involved applying a range of quantitative analytical techniques to uncover actionable insights and inform model development. Several assumptions had to be made regarding the structure and completeness of the CMMS dataset. Firstly, downtime was proxied using recorded maintenance work hours, as direct downtime logging was not consistently available across all assets. Secondly, it was assumed that work orders were accurately classified into preventive, corrective and predictive categories, despite the possibility of inconsistencies in data entry. Thirdly, it was assumed that the recorded timestamps and work durations reasonably reflect actual maintenance activities, enabling meaningful comparison across departments and asset classes. These assumptions were necessary to enable structured quantitative analysis and are consistent with approaches adopted in similar CMMS-based studies. The following analytical methods were employed to extract meaning from the data and build an understanding of asset performance:

- Descriptive statistics were used to summarise existing locations, trends in execution rates, maintenance frequency, failure occurrences and work order completion over time. This provided a view of operational performance and variability across departments.

  A Pareto analysis, which posits that a minority of causes typically account for the majority of outcomes (Pareto, 1897), was used to identify assets likely to contribute most to operational performance outcomes. This principle helped in isolating the small proportion of assets that contributed disproportionately to failures or downtime. The focus on this top-tier group of critical equipment also allowed for a meaningful evaluation of maintenance strategies effectiveness without being diluted by non-essential data.

- Correlation analysis was conducted to assess relationships between variables such as preventive maintenance frequency and asset downtime. These results informed the identification of potential causal links. Correlation analysis also provided an initial basis for testing the direction and strength of relationships proposed in the study hypotheses.

- Regression modelling was used to identify predictors of asset reliability and determine focal areas for targeted reliability improvements. This modelling enabled the formulation of recommendations grounded in statistically validated patterns, such as how changes in execution compliance may impact reliability outcomes. Regression analysis was further used to test the statistical significance of the hypothesised relationships between maintenance strategies and breakdown frequency, as well as to assess differences in maintenance effectiveness across departments and asset classes.

- Control charts and Pareto analysis were also incorporated to visualise maintenance-related process behaviour over time and isolate the most critical contributors to inefficiencies. These visual tools supported continuous improvement efforts by focusing attention on the few factors causing the majority of the problems.

The ultimate objective of this stage was to develop a conceptual or data-driven model that explains the relationships between executed maintenance and asset performance results. This model serves as a tool for predictive insights, as well as a framework for refining existing maintenance strategies. Throughout the process, all analytical procedures were documented, and statistical assumptions were tested to ensure the reliability and validity of the results.

3.8. Ethical Considerations

Ethical responsibility is one of the key elements of the research process. Ethical considerations ensure that the study upholds academic integrity, respects data ownership, and avoids harm in the analysis or reporting of results (Saunders, et al., 2019). This research made exclusive use of historical maintenance data extracted from the CMMS. The research did not involve interaction with human participants, which obviated the need for informed consent or participation risk mitigation procedures. In addition, personal identifiers such as the names of maintenance personnel or sensitive human resource records in the CMMS database were deliberately excluded from the analysis. As such, the study avoided the risks associated with the use of personal or confidential employee information.

Permission to access and use the CMMS data for research purposes was formally obtained from the organization. All data was anonymised to protect the identity of the company and prevent the unintentional disclosure of commercially sensitive information. Company name, system identifiers and department names were either omitted or generalized to ensure that findings cannot be traced back to the organization by external readers. The research was reviewed for ethical compliance by the UKZN internal oversight process and conducted in accordance with the principles of responsible data stewardship.

According to Resnik (2015), ethical research should ensure honesty, objectivity, and transparency in data analysis and reporting. This study sought to uphold these principles when handling the extracted data. The data was not manipulated to support preconceived ideas. The analytical procedures were applied consistently and transparently, with the results presented in an unbiased manner.

In line with the principles discussed by Odebrecht (2025), all data used in this study was handled in a secure manner, with restricted access and no external distribution beyond the academic requirements of this thesis. The research results are intended solely for academic purposes and shall not be used for operational performance evaluations, employee assessments, or punitive actions within the organization.

3.9. Data Handling and Governance

The study involved large amounts of data that could be commercially sensitive or proprietary. Therefore, proper data management was a vital component of this research project. In alignment with the organization’s cybersecurity policies, the use of removable storage devices such as USB drives was avoided. This policy is consistent with the best-practices for minimizing the risk of malware infections and data breaches (Dumitru, et al., 2022). To comply with these internal controls and ensure data security, the study utilized the company’s secured OneDrive cloud storage platform for all data storage, access and backup needs. The use of OneDrive ensured compliance with enterprise-grade encryption standards, access control and versioning features, which were essential for maintaining the confidentiality and integrity of the research data.

Data cleaning and analysis was conducted using Microsoft Excel and R. These tools were chosen for their flexibility and general acceptance in academic and industrial research (Masuadi E, et al., 2021). Excel was mainly used for the initial data structuring, validation and visual inspections of outliers. R supported advanced analyses, including the calculation of key performance indicators, correlation assessments and regression modelling. All scripts and processing steps were documented and stored alongside the raw data within the OneDrive environment. This supported the traceability and reproducibility of findings. In line with the ethical best-practices and data minimization principles outlined by Saunders, Lewis and Thornhill (2019), only data relevant to the research questions was retained for the duration of the study. No printed hardcopies or copies on portable storage such as USBs or external drives were made. Access to the data and tools was limited to the researcher and authorized academic supervisors only.

Once the research objectives were met and the final thesis was submitted, data used in this study was discarded. Since all research data was stored on the organization's secure OneDrive platform, deletion was conducted digitally and permanently within that environment. The files containing raw and processed maintenance data, intermediate analysis results, and any extracted reports were removed from the OneDrive directory by the researcher. The OneDrive system also cleared the data from its recycling bin and backup cache after the standard retention period. These steps were intended to ensure that no residual data remained accessible beyond the research lifecycle.

4. CHAPTER 4: ANALYSIS

4.1. Introduction

This chapter presents the results of the data analysis undertaken to address the research objectives and questions outlined in Chapter 1. The analysis is based on structured and cleaned datasets extracted from the CMMS of the case study organisation, following the methodological stages described in Chapter 3. These stages included data extraction, cleaning and preprocessing, structuring and transformation, integration of performance indicators, and statistical analysis.

The chapter is organised thematically to progressively build from global patterns in maintenance activity across the entire asset base to more granular levels at departmental, asset-class and individual critical asset levels. At each level of analysis, the relationships between maintenance strategies, preventive maintenance, predictive maintenance, corrective maintenance and breakdowns, and reliability indicators such as MTBF, downtime are explored.

In line with the research questions, the chapter focuses on identifying trends, correlations and disparities across maintenance practices. It culminates in regression models that test the quantitative relationship between proactive maintenance frequency and asset failure rates, which form the cornerstone of this research inquiry. The results are presented in both tabular and graphical formats, supported by statistical summaries and correlation heatmaps, to provide an evidence-based foundation for the discussion in Chapter 5.

4.2. Dataset Overview – Assets and Locations

The first step to understanding the maintenance dynamics within the organisation was to examine the distribution of assets across different operational departments. Each department has distinct production purposes and functions, which require specialised equipment. However, the machines in these departments are generally composed of similar classes of assets, such as motors, cylinders, rollers and control systems. Therefore, it was anticipated that there would be common asset classes recurring across departments, even though their relative volumes might differ.

The Maximo dataset on asset locations revealed that a total of 19151 locations exist within the key production departments analysed. The distribution of asset locations per department is shown in Figure 4.1. From Figure 4.1, it can be seen that 73% of these asset locations are concentrated within the top four departments, indicating a highly uneven distribution of equipment across the plant. This uneven spread is significant as it implies that the bulk of maintenance activity is inherently tied to a few departments. With this distribution, it is expected that the bottom four departments would contribute less to overall maintenance demand despite playing critical roles in specific stages of production.

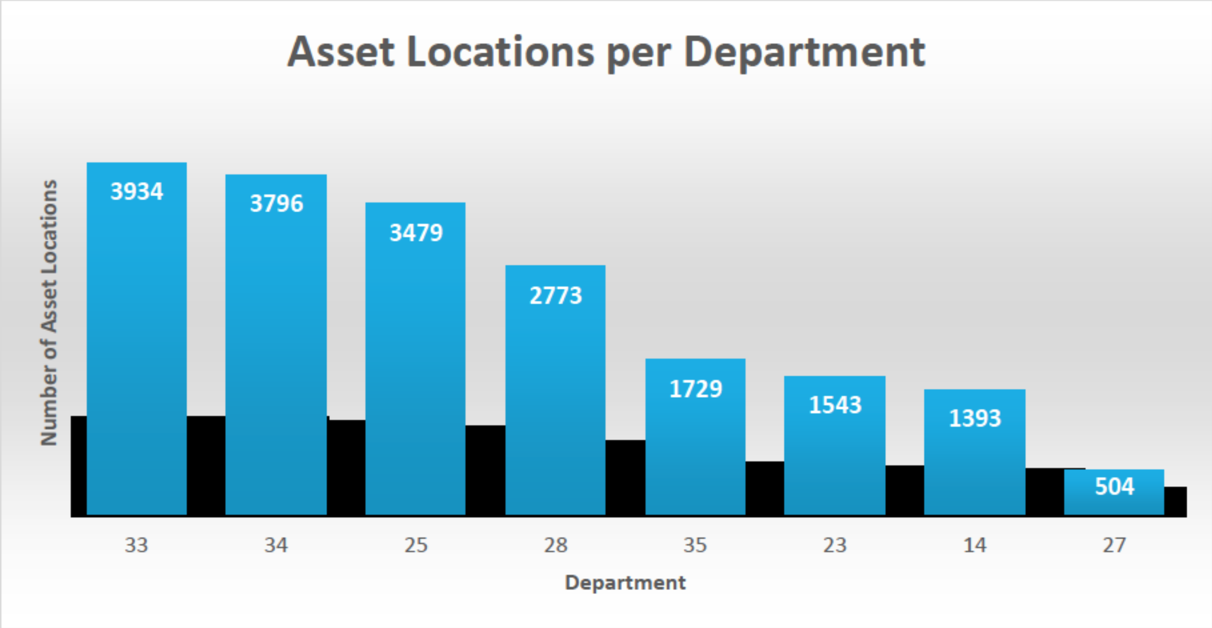


Figure 4. 1: Distribution of asset locations per department

Given that each asset location has a single asset, the count of asset locations is therefore equivalent to the total number of assets within the organization. Therefore, the total number of assets in this study is 19151, classified into 1075 asset classes. However, from the total number of assets, it was observed that 12827 are concentrated within the top ten asset classes, representing 66.9% of the overall asset base in the key production departments. This distribution is summarised in Table 4.1, which shows the number of assets per asset class. This finding demonstrates that despite the breadth of equipment installed across the organization, a relatively small group of asset classes dominates the operational landscape.

The understanding of this distribution is crucial for the course of the analysis as it highlights where the majority of maintenance effort and resource allocation is likely to be concentrated. It also provides a clear indication of which asset classes should be prioritized in subsequent analyses to generate credible results and recommendations with the greatest potential impact on organizational performance.

Table 4. 1: Top 10 assets by count and distribution per department

	Department								
Asset Class	**14**	**23**	**25**	**27**	**28**	**33**	**34**	**35**	**Total**
motor	251	133	775	45	321	536	460	189	2710
	18.02%	8.62%	22.28%	8.93%	11.58%	13.62%	12.12%	10.93%	14.15%
cylinder	183	109	415	50	242	591	443	257	2290
	13.14%	7.06%	11.93%	9.92%	8.73%	15.02%	11.67%	14.86%	11.96%
control system	72	174	276	42	409	559	282	181	1995
	5.17%	11.28%	7.93%	8.33%	14.75%	14.21%	7.43%	10.47%	10.42%
roller	46	0	377	0	365	306	297	154	1545
	3.30%	0.00%	10.84%	0.00%	13.16%	7.78%	7.82%	8.91%	8.07%
pump	42	79	244	34	124	189	145	77	934
	3.02%	5.12%	7.01%	6.75%	4.47%	4.80%	3.82%	4.45%	4.88%
gearbox	145	32	169	2	92	131	262	56	889
	10.41%	2.07%	4.86%	0.40%	3.32%	3.33%	6.90%	3.24%	4.64%
valve	7	38	30	7	34	292	310	152	870
	0.50%	2.46%	0.86%	1.39%	1.23%	7.42%	8.17%	8.79%	4.54%
drive	96	25	60	16	47	187	258	50	739
	6.89%	1.62%	1.72%	3.17%	1.69%	4.75%	6.80%	2.89%	3.86%
fan	86	47	91	30	134	120	41	24	573
	6.17%	3.05%	2.62%	5.95%	4.83%	3.05%	1.08%	1.39%	2.99%
filter	6	29	62	0	3	114	52	16	282
	0.43%	1.88%	1.78%	0.00%	0.11%	2.90%	1.37%	0.93%	1.47%
Total									**12827**
									67%

In addition, Table 4.1 shows that the distribution of assets is not uniform across departments, either in terms of absolute numbers or proportional representation within each departmental asset base. For example, Departments 27 and 23 do not record any roller assets, whereas the roller asset class is the fourth-largest overall when aggregated across all departments. This highlights how departmental function influences asset composition. This information was key in contextualising maintenance activities by department and by asset class. It provided the foundation for the subsequent analysis of the different work types and enabled meaningful comparisons between departments and asset classes.

4.3. Dataset Overview – Maintenance Work

An analysis of reported maintenance work orders from January 2021 to June 2025 provided information about maintenance activities and how these are distributed across the organization's departments. The Maximo dataset shows that a total of 430,748 work orders were generated during this period. Similar to the distribution of assets, these work orders are not evenly spread across departments. According to Figure 4.1, Department 33 recorded the highest volume of reported work, with 97,975 work orders, accounting for almost a quarter of total maintenance activity. This high volume is consistent with the large number of asset locations operating in this department. Departments 23 and 25 followed with 66,991 and 63,243 work orders, respectively. Together, these three departments account for over half of all reported maintenance work during the review period.

To enable a direct comparison between departments, a ratio of work orders per asset location was calculated and summarized in Figure 4.2. This normalization revealed that Departments 25, 28, 33, 34 and 35 fall within a relatively moderate range of 11 to 25 work orders per asset location, suggesting a more balanced distribution of maintenance effort relative to their asset base.

In contrast, Departments 14, 23 and 27 exhibit disproportionately high ratios, all above 40 work orders per asset location, with Department 27 having generated the highest number of work orders per asset location of 59. These values are significantly higher than those observed in the other departments, indicating either elevated maintenance demand, recurring reliability challenges, or potential gaps in preventive and predictive practices. This normalization of the data exposes departments where asset reliability pressures are more pronounced and where optimisation strategies may yield the greatest impact.

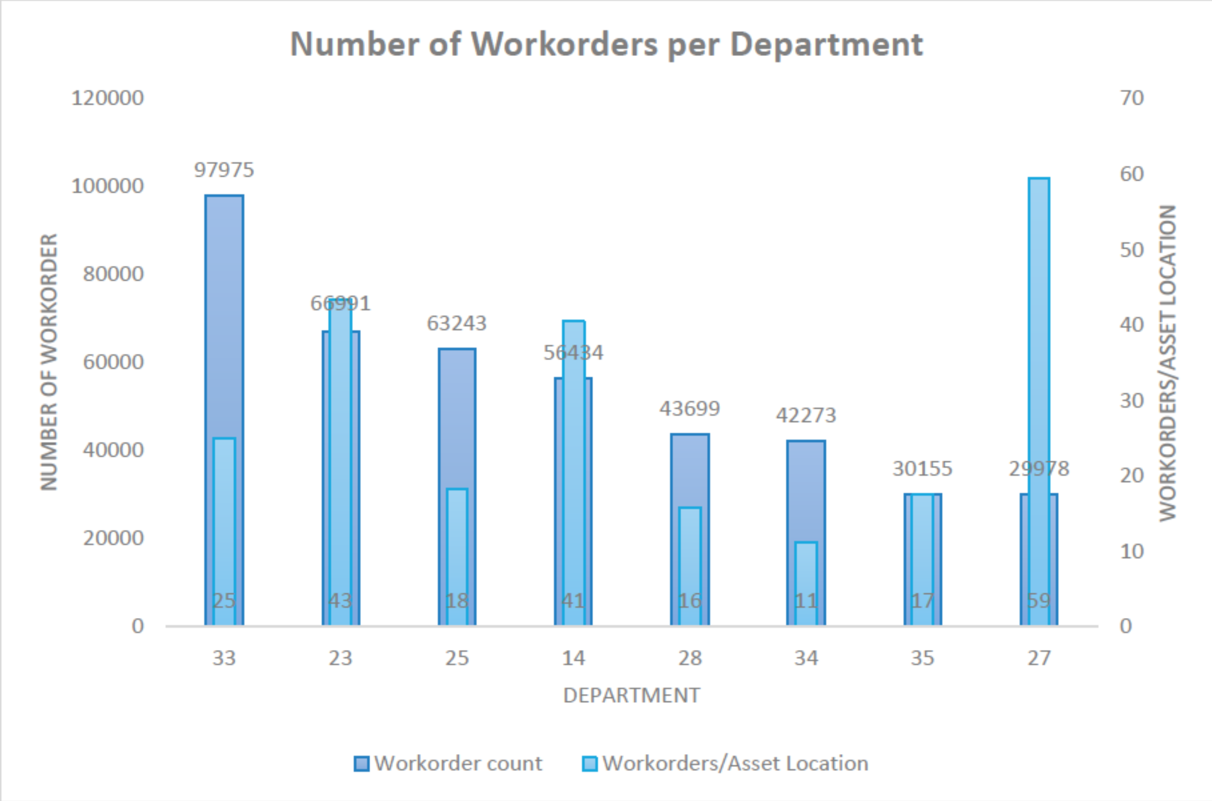


Figure 4. 2: Maintenance work per department

The analysis presented in Figure 4.2 considers the count of maintenance work orders, which provides an indication of how frequently maintenance teams interact with equipment. However, these interactions are very different in nature. For example, an artisan resetting a drive that has tripped during production, a task that may take five minutes, represents a very different type of intervention compared to an artisan performing a planned roller replacement to prevent a potential failure. The fundamental differences between these scenarios are twofold:

I. A drive reset results from an unplanned failure and is therefore recorded as a breakdown, whereas a planned roller change is recorded as preventive maintenance.

II. The duration and impact of the tasks differ considerably. While the drive reset requires only a few minutes, a roller replacement demands significantly more time. Crucially, preventive interventions such as an eight-hour roller change are intended to avert longer and more disruptive breakdowns. For instance, if the roller is not proactively replaced, its eventual failure could result in a 12-hour breakdown, along with additional adverse outcomes such as higher repair costs and increased product scrap (Muchiri, et al., 2011).

With this view in mind, it becomes clear that the count of work orders alone is not sufficient to provide meaningful insights into maintenance dynamics. While count data provides an indication of how often assets require attention, the hours data highlights how demanding those interventions are. As a result, the analysis was broadened to consider not only the count of maintenance work undertaken but also the time invested in each activity and the types of activities. This provided a more comprehensive understanding of the interplay between PM, CM and PDM, while also revealing how these patterns differ across departments. Moreover, it provided an indication of the labour cost implications of proactive maintenance measures.

The results shown in Figure 4.3 summarizes the analysis of all maintenance work hours per department. From the figure, it is evident that the top 3 departments by work order count still remain the top 3 by recorded hours. However, the order changes as Department 33 recorded the highest number of work orders, but according to the hours analysis, it has recorded the third highest number of hours. This suggests that while department 33 produces the largest number of work orders, each work order on average requires less time. The jobs are likely smaller, routine inspections or preventive in nature rather than major corrective repairs. On the other hand, Department 27 appeared moderate in the count analysis but emerges as one of the most resource-intensive areas when considering hours, averaging 116.8 hours per location. This indicates fewer but highly labour-intensive jobs. This trend is congruent with that observed in Department 23. This combined analysis provides a clearer picture of departmental maintenance burdens and supports more targeted resource allocation.

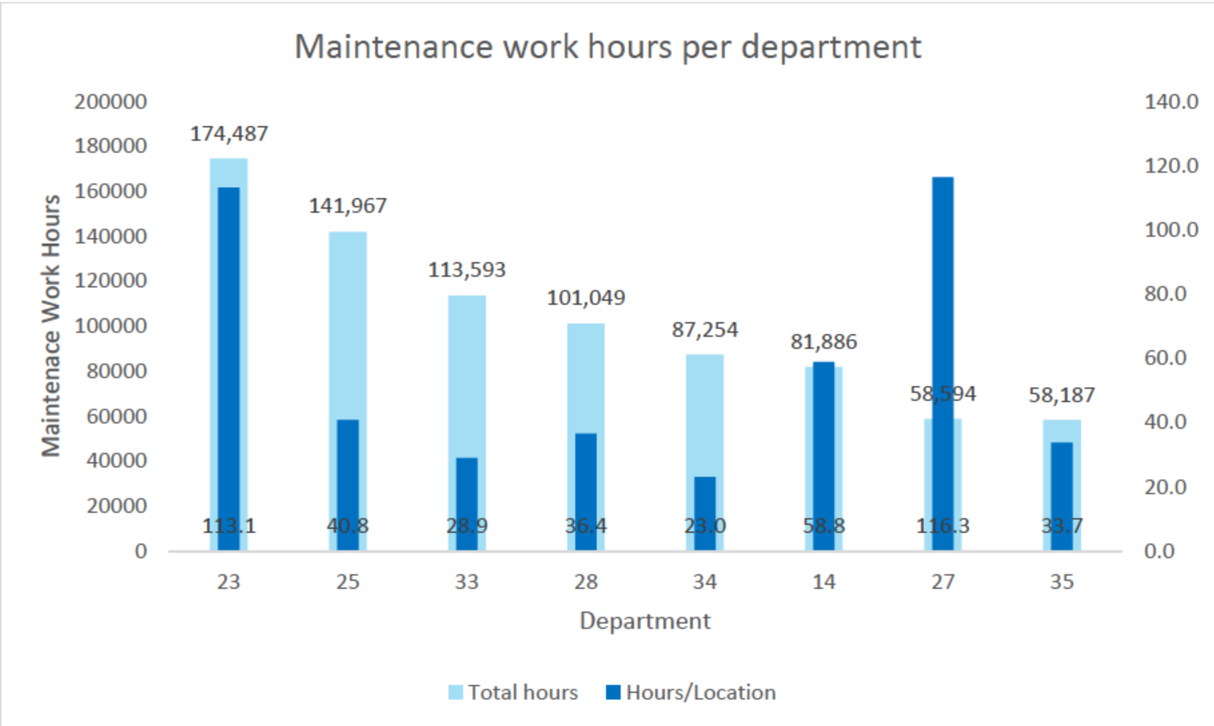


Figure 4. 3: Maintenance work hours per department

To further understand the types of maintenance activities that departments focus on, the data was analysed by work type. PM and PDM activities are expected to reduce breakdown maintenance. For this reason, PM and PDM work hours were grouped and analysed per department, as shown in Figure 4.4. The effectiveness of these maintenance interventions can be assessed by comparing them with the BDM work hours incurred, which are depicted in Figure 4.5.

From Figures 4.4 and 4.5, it can be noted that the departments with the highest investment in preventive and predictive maintenance do not always experience the lowest breakdown work hours. For example, Department 23 shows the highest PM and PDM, with an average of 44.5 hours per location, yet it also records the second largest BDM hours per location. This suggests that despite substantial proactive maintenance activity, the department continues to experience frequent breakdowns. Possible explanations include deteriorated asset conditions, high operational intensity or misalignment between the implemented maintenance strategies and actual failure modes. Additionally, the imbalance could reflect the over-maintenance of certain assets and under-maintenance of others within the same department.

On the other hand, Department 34 shows the lowest average PM and PDM hours per location, at approximately 8.8 hours, yet it does not exhibit the highest breakdown frequency or downtime. This suggests a relatively effective maintenance strategy where limited proactive effort yields comparatively stable reliability outcomes. This pattern may indicate that maintenance activities in this department are well targeted, assets are in better condition, or operational demands are less severe compared to other departments. The total PM and PDM maintenance have direct implications for maintenance costs as Departments investing aggressively in preventive and predictive maintenance, such as Department 23, incur higher labour and material costs upfront without necessarily achieving proportional reductions in breakdown-related downtime. Therefore, cost-reduction initiatives should not only focus on decreasing maintenance hours, but rather on optimizing how and where proactive maintenance is applied.

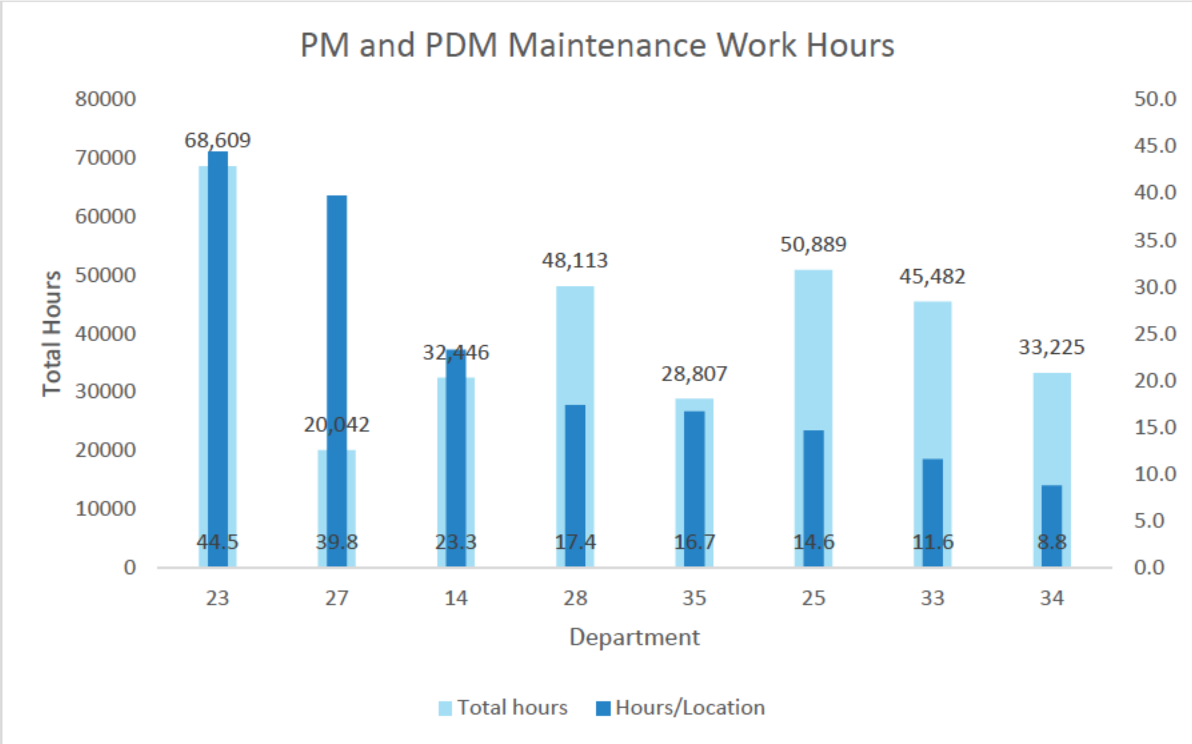


Figure 4. 4: PM and PDM work hours per department

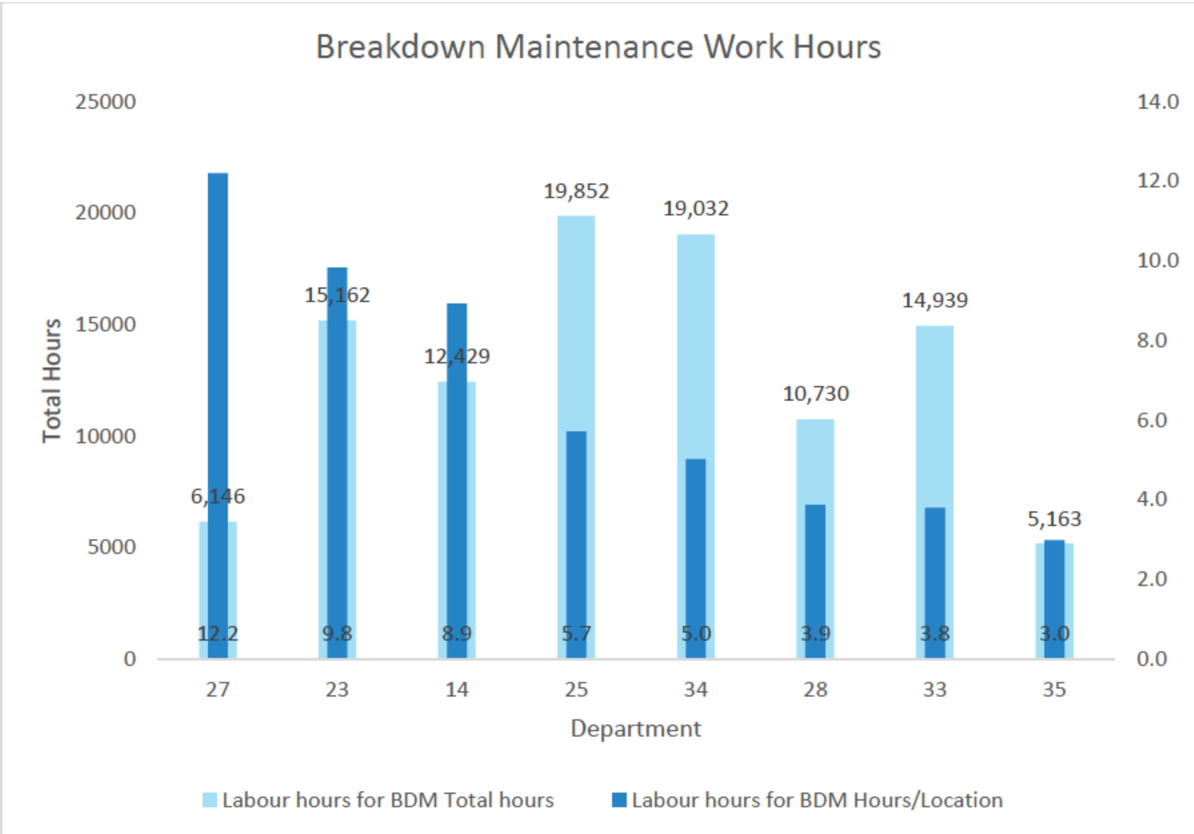


Figure 4. 5: BDM work hours per department

4.4. Key Assets Maintenance Work

Section 4.3 established that asset classes are not equally represented, with two-thirds of the total asset base concentrated in the top ten asset classes. To gain a clearer view of maintenance on these critical assets, the data was analysed, focusing exclusively on this group. At the outset, it was observed that 128,060 of the 430,478 work orders were recorded against the top ten asset classes. This indicates that although these assets constitute two-thirds of the base, they account for only one-third of all recorded maintenance activity.

This finding is reinforced by the analysis of average recorded work orders per asset class presented in Table 4.2. The results show that in most departments, the key asset classes receive fewer work orders per asset compared to the departmental average for all assets. For instance, cylinders are consistently significantly below the departmental average in all departments. This suggests that these assets attract relatively less recorded maintenance effort. An initial interpretation of this disparity could be that an insufficient maintenance effort is being directed towards these key asset classes. However, such a conclusion would be premature without considering the nature of the work performed. Lower maintenance volumes are not necessarily undesirable. For instance, if these asset classes generate relatively fewer breakdown work orders but higher levels of preventive and predictive maintenance, the reduction in overall work order volume would actually reflect a positive outcome, which would be improved reliability supported by proactive maintenance practices. While most assets have below average workorders per asset, certain asset classes stand out with higher-than-average maintenance activity in specific departments. For example, gearboxes in Departments 14, 27 and 33 show significantly higher recorded work orders than the departmental average. This may be an indication of extensive proactive maintenance or localized reliability challenges. The large variation between departments, reflected in the high standard deviation values for several asset classes, also suggests that asset performance and maintenance practices are not uniform across the organization.

Table 4. 2: Average recorded work orders per asset class

	Dep 14	Dep 23	Dep 25	Dep 27	Dep 28	Dep 33	Dep 34	Dep 35	Mean	Std deviation
Overall Department workorders/asset class	41	43	18	59	16	25	11	17		
motor	8	4	9	11	4	13	3	10	8	4
cylinder	6	9	2	12	1	6	2	1	5	4
control system	8	21	3	19	4	5	3	3	8	7
roller	22	0	12	0	7	31	5	15	12	11
pump	20	5	7	66	4	17	3	7	16	21
gearbox	45	2	20	28	5	84	2	45	29	28
valve	2	6	4	13	8	0	0	0	4	5
drive	7	26	11	19	8	7	2	7	11	8
fan	24	63	11	18	4	21	3	1	18	20
filter	9	80	8	0	26	4	0	98	28	39
Average workorders/ key asset class	15	22	9	19	7	19	2	19		

Work orders/Asset class < Work orders/Asset class for all assets in the department

Work orders/Asset class <= Work orders/Asset class for all assets in the department

Table 4.2 does not provide insight into the type of work being undertaken on these key assets as it only reflects the relative distribution of recorded work orders. To address this, the data was further disaggregated by work type and summarised in Figure 4.6. The results indicate that the main driver of maintenance activity across all asset classes is preventive maintenance, which represents the largest share of work orders. This pattern is consistent across nearly all departments, suggesting a strong emphasis on preventive strategies in the organization. The exception is Department 34, where PM does not dominate to the same extent, pointing to a different maintenance profile. When this information is viewed together with Table 4.2, it becomes clear that Department 34 not only records the lowest average number of work orders on these key asset classes, but is also the only department where every key asset class falls below the overall departmental average of work orders per asset. This suggests that key assets in Department 34 may be receiving comparatively less attention, which raises questions about whether maintenance practices in this area are sufficiently proactive.

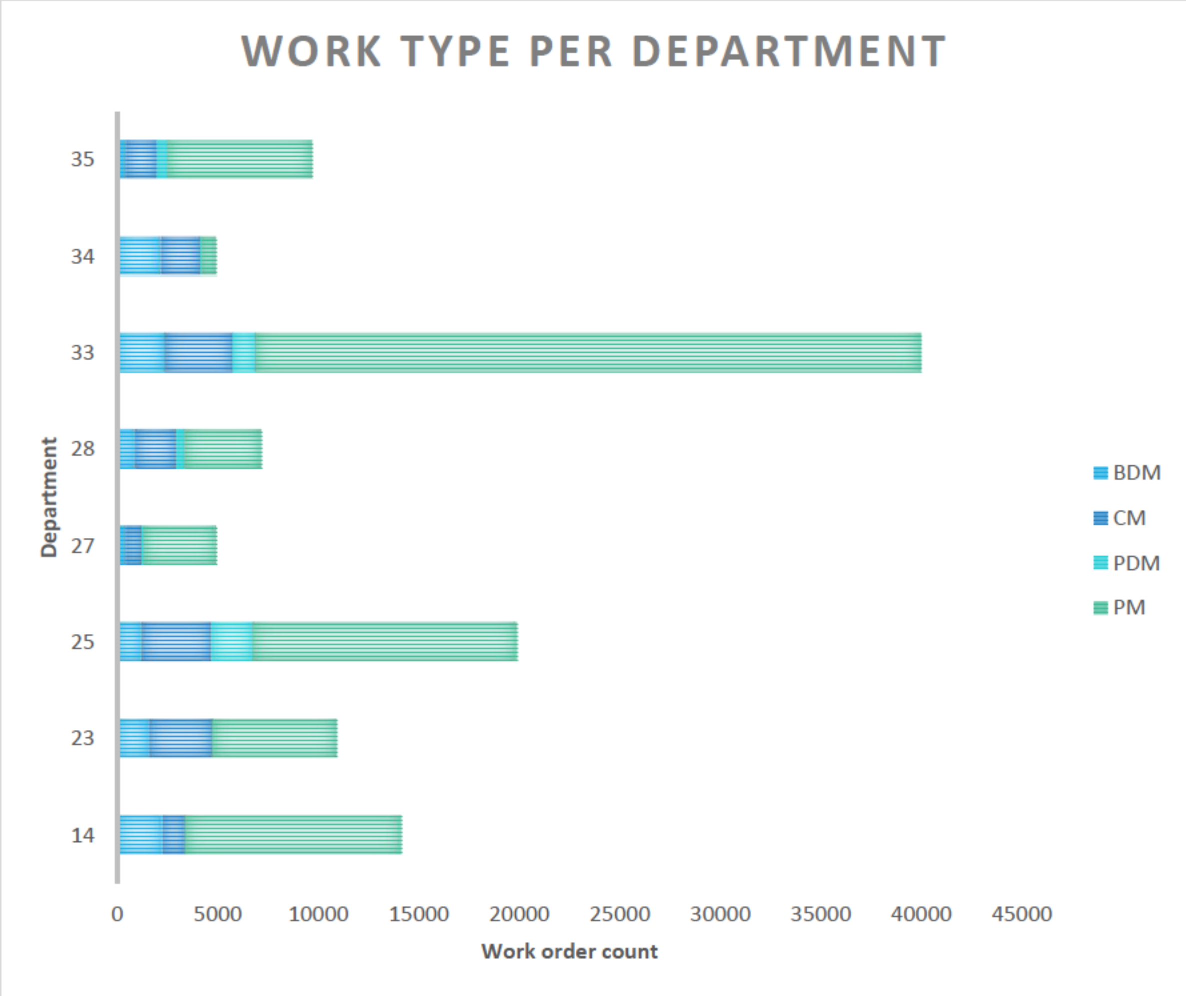


Figure 4. 6: Work type recorded per department

4.5. Key Assets Breakdowns

Since one of the key objectives of maintenance is to reduce unplanned downtime, which impacts productivity through both the frequency of failures (mean time between failures) and the duration of delays, as discussed in Section 3.7, an assessment was conducted to evaluate the extent to which the top asset classes contribute to breakdown events.

Figure 4.7 shows the maintenance breakdown work hours per asset class, with red-highlighted categories representing those within the top ten asset classes by count. For this analysis, it was assumed that machine downtime is closely aligned with the maintenance work time recorded in the CMMS. Even though minor differences are expected, for instance, a machine may be returned to production by the maintenance team while follow-up activities such as verification or clean-up continue, it was considered that these discrepancies would be small enough to be insignificant in the context of this study.

The results show that six of the top ten asset classes also appear amongst the ten highest contributors to recorded breakdowns, while eight of the top ten feature within the top twenty contributors overall. In contrast, filters and valves rank significantly lower, at 28th and 88th respectively, accounting for only 0.9% and 0.2% of total breakdowns. These are relatively minor shares compared to other asset types. Overall, the combined contribution of the top ten asset classes amounts to 31.9% of all recorded breakdowns, or approximately one-third of the total. This finding underscores the significance of these assets and directs focus as they not only dominate the installed asset base of but also account for a disproportionately high share of breakdown hours.

Figure 4.7 also shows that the table, conveyor, saw and rewinder asset classes appear amongst the top ten contributors to breakdown hours. However, these asset classes are not amongst the most common in the plant, ranking 11th, 13th, 28th and 135th respectively, in the overall distribution of operating asset classes. This outcome may be explained by certain assets within these classes experiencing isolated major breakdown events during the review period, which disproportionately increased their contribution to total downtime.

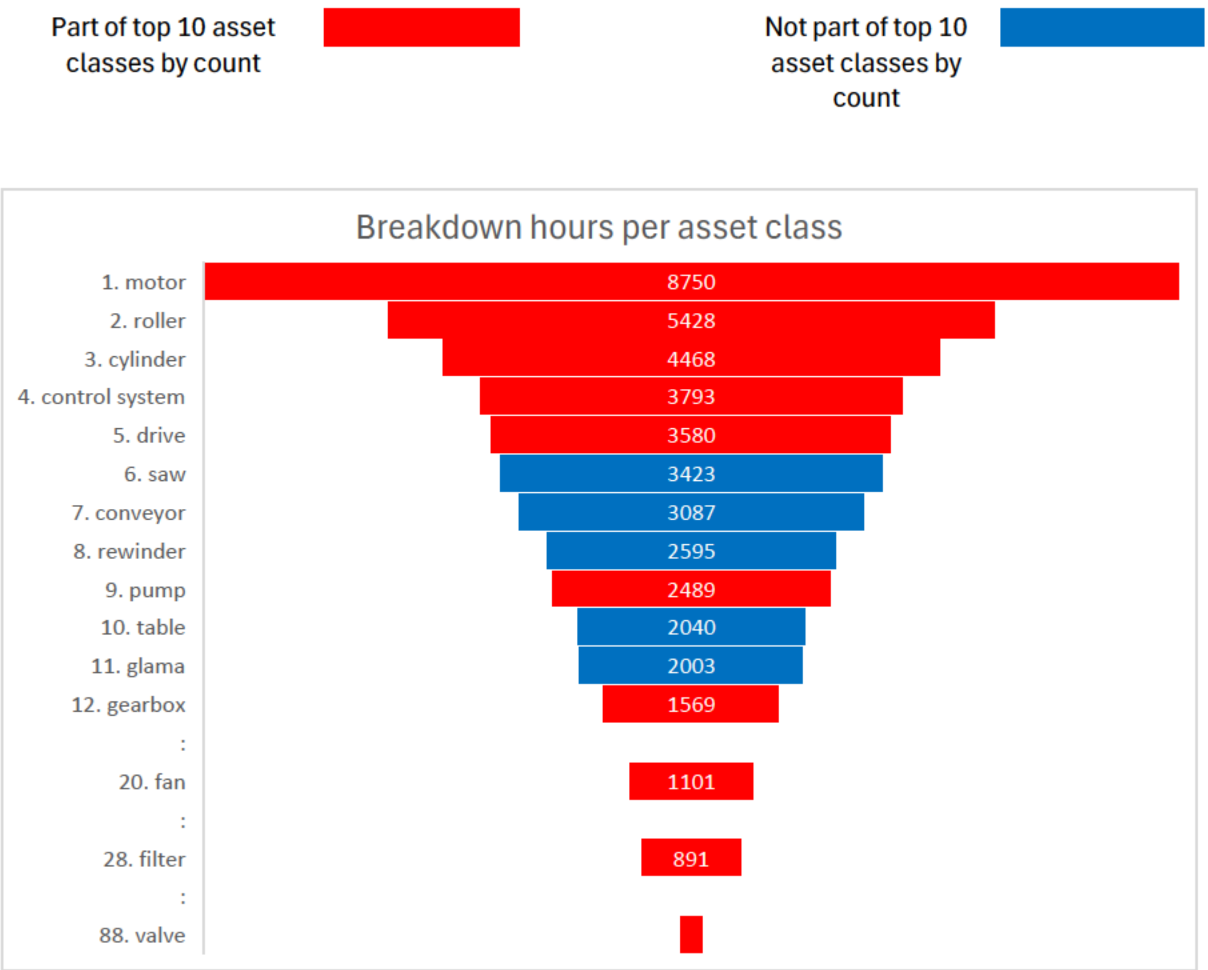


Figure 4. 7: Recorded breakdown hours per asset class

4.5.1 MTBF analysis of the top 10 asset classes

To develop an understanding of the frequency of failure of the top ten asset classes by count, Mean Time Between Failures was calculated. For this analysis, a daily method was applied, which clusters all failures occurring on the same day into a single event. This avoids overstating the frequency of failures in cases where multiple work orders are raised for the same incident. The average interval (in days) between these daily events was then calculated, and MTBF computed according to Equation 4.1:

$$MTBF = \frac{\sum_{i=1}^{n-1} Date_{i+1} - Date_i}{\mathrm{n}-1}$$

Equation 4.1: Daily MTBF calculation

The analysis presented in Figure 4.8 shows significant variation in MTBF across asset classes, which is indicative of differences in reliability and maintenance effectiveness. Gearboxes stand out with the highest MTBF value of 80 days, which suggests fewer failures related to gearboxes. This implies that gearbox failures occur less frequently, which may be related to effective preventive strategies or an inherently more robust design. In contrast, rollers have the lowest MTBF, which reflects their frequent failure and potentially high wear nature. Cylinders and motors also show a relatively low MTBF of 17–23 days, which suggests that they are amongst the more failure-prone classes.

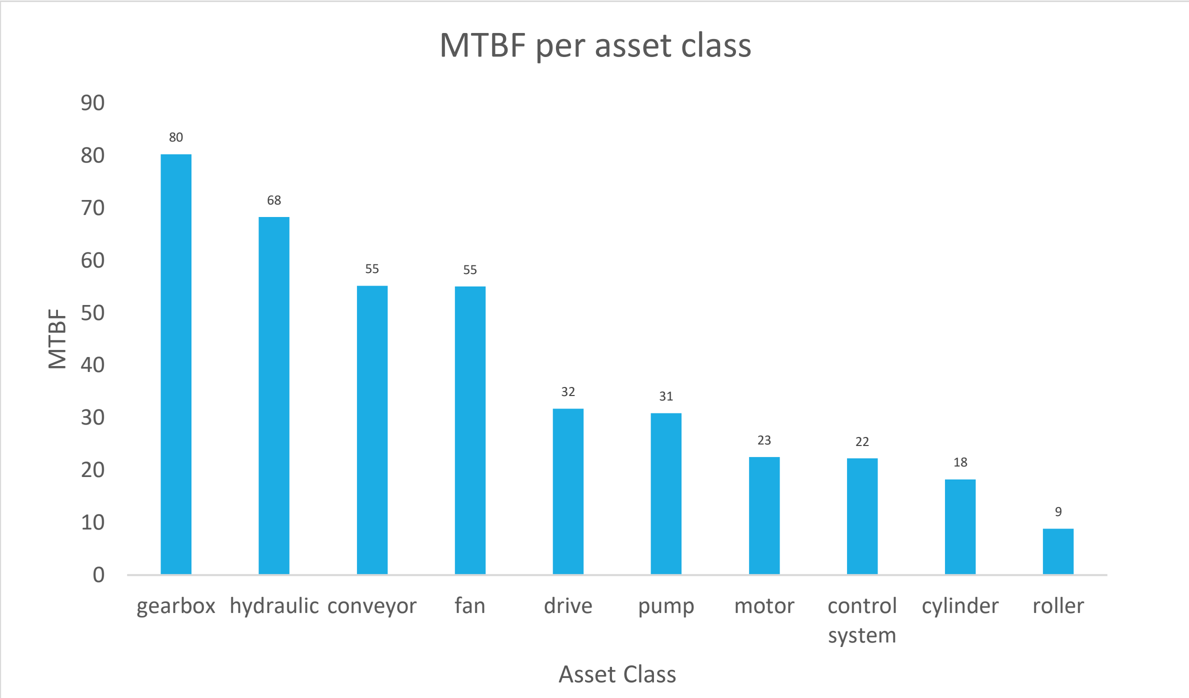


Figure 4. 8: MTBF of top to assets by count

Variations across departments cannot be identified through the analysis presented in Figure 4.8, which can result in missed improvement opportunities. To address this gap, MTBF was also analysed per department, as shown in Table 4.3. This analysis provides a more granular view, revealing that asset reliability is not uniform across the organisation. At the aggregate level, six of the eight departments record MTBF values within a narrow range of 16 to 29 days. In contrast, Departments 27 and 35 stand out with significantly higher average MTBF values of 76 and 114 days, respectively, which is indicative of stronger reliability performance of assets in these departments. Across the dataset, asset classes exhibit varying MTBF values. The most notable inconsistency is observed in gearboxes, where MTBF ranges from as low as 6 days in Department 14 to as high as 359 days in Department 35. This is reflected in a high standard deviation of 126, which is indicative of uneven reliability performance. This variation is likely driven by differences in load profiles, operating environments, maintenance practices or the quality of maintenance work. By contrast, the lowest variation is observed in rollers, which have a standard deviation of only 5 days. However, despite this consistency, rollers also exhibit the worst MTBF overall, indicating that they consistently perform poorly. This suggests that the frequent failures of rollers are less influenced by departmental or environmental factors.

Table 4. 3: MTBF of top 10 asset classes by count

	Department								
Asset Class	**14**	**23**	**25**	**27**	**28**	**33**	**34**	**35**	**Stand deviation**
gearbox	6	93	46		28	15	15	359	126
hydraulic	47	32	66	260	38	11	34	57	79
conveyor	5	10	47	51	78	49	13	189	59
fan	32	17	44	41	23	66	59	159	45
drive	25	8	13	13	45	8	11	132	42
pump	13	31	27	10	24	18	14	109	33
motor	3	11	9	112	9	5	3	28	37
control system	6	8	8	75	13	5	10	53	26
cylinder	5	9	9	48	20	6	6	43	18
roller	18		7		9	3	8	8	5
Departmental Average	16	24	27	76	29	19	17	114	36

4.6. Correlation Analysis

This section presents results from correlation analysis which supplements the analysis in the preceding sections by providing deeper insight into whether maintenance interventions are effectively influencing reliability outcomes. The analysis is presented at three levels of aggregation. First, global correlations across the entire asset base establish overall patterns within the organisation. Second, departmental-level correlations highlight localised differences that may be linked to operational conditions or maintenance practices. Finally, asset-class and critical asset correlations provide granular insights into whether specific equipment categories respond as expected to preventive and predictive maintenance.

4.6.1 Global analysis

Figure 4.9 presents a heatmap comparison of Pearson and Spearman correlation coefficients between different maintenance work types. The results are shown for the same month, one-month and three-month lags. The results are shown for all asset classes in the dataset and the top 8 asset classes ranked by total population count. Having seen that valves and filters are not major contributors to the breakdowns as discussed in section 4.5, these classes were removed from the list of top 10 and as a result a top 8 was evaluated in this section.

The left-hand panel displays Pearson correlations, which capture linear associations, while the right-hand panel displays Spearman correlations, which measure monotonic relationships. The intensity of the colour shading represents the strength and direction of the correlation, ranging from –1, which is a strong negative relationship shown in blue, to +1 which is a strong positive relationship, shown in red. The interpretation of correlation strength and direction follows the guidelines presented in Table 4.4, adapted from Lynne (2012).

Table 4. 4: Interpretation of correlation results

	Interpretation	
0.00 to 0.19	Very weak	0.00 to -0.19
0.20 to 0.39	Weak	-0.20 to -0.39
0.40 to 0.59	Moderate	-0.40 to -0.59
0.60 to 0.79	Strong	-0.60 to -0.79
0.80 to 1.00	Very strong	-0.80 to -1.00

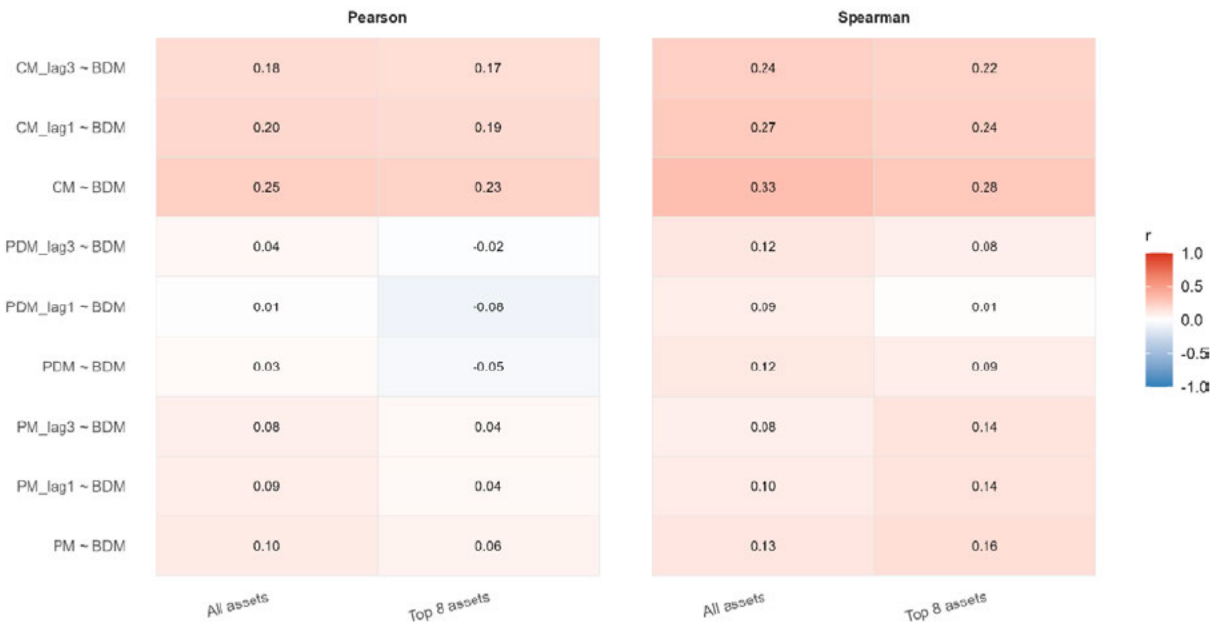


Figure 4. 9: All assets and top 8 correlation analysis results

On a global level, the data indicate a weak positive correlation between corrective maintenance and breakdowns. The association is stronger in the same month that corrective maintenance is conducted compared to when a one-month lag is applied. For all assets, Pearson's correlation between CM and BDM is 0.25, with Spearman's rank correlation slightly higher at 0.33. This outcome remains consistent for the smaller group of top eight assets, with Pearson's correlation at 0.23 and Spearman's correlation at 0.28. These findings suggest that higher levels of corrective maintenance tend to align with a slight increase in breakdowns. This reflects the inherently reactive nature of CM, where interventions occur after deviations have already manifested. In some instances, failures escalate to complete breakdowns before corrective action is applied.

In contrast, both predictive maintenance and preventive maintenance exhibit very weak correlations with breakdowns across Pearson and Spearman measures for both the total asset base and the top eight assets. The results hover close to zero, indicating that increases or reductions in PDM and PM activity have a negligible immediate impact on breakdown levels. This weak relationship suggests that overall, predictive and preventive maintenance practices are not sufficiently effective in mitigating breakdowns within the period under review.

It is important to emphasise that this does not imply that all asset classes exhibit a negligible correlation between PM, PDM and BDM. Instead, this represents the net aggregate outcome when considering the collective of all assets. At the individual asset-class level, the results reveal a notable variation. To illustrate this, the three-month lagged PM results are presented as a histogram in Figure 4.10. From this figure, it is evident that the majority of asset classes exhibit Spearman correlation values ranging between –0.25 and 0.25. However, the distribution also highlights that certain asset classes demonstrate moderate to strong correlations between PM and BDM, located outside this central range. This suggests that while the overall impact of PM on breakdowns may appear negligible at the aggregate level, meaningful relationships exist within specific asset categories, warranting closer asset-level investigation.

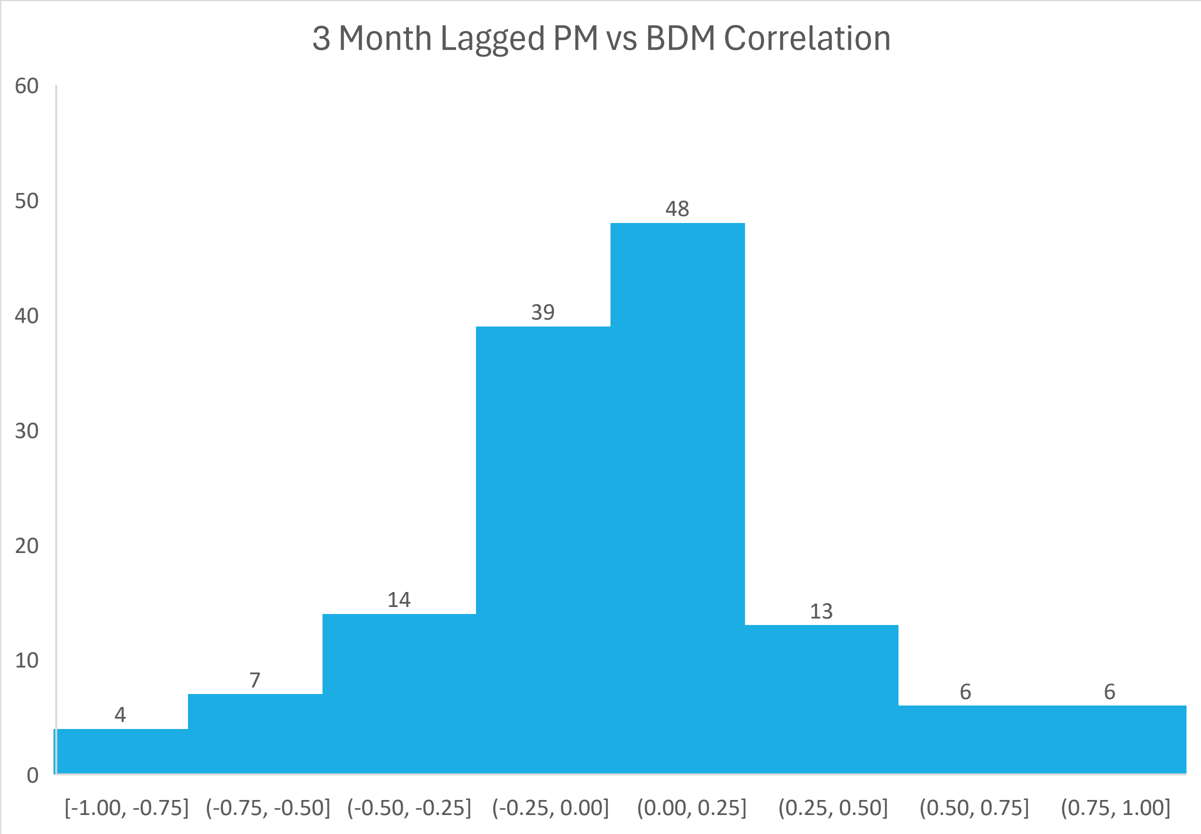


Figure 4. 10: Distribution of three-month lagged PM Vs BDM correlations

4.6.2 Departmental-level analysis

The data was further disaggregated to the departmental level to assess whether correlations varied across different operating areas. Figure 4.11 presents the Spearman correlations for all assets in the respective departments, including same-month, one-month lag and three-month lag values for corrective maintenance, predictive maintenance and preventive maintenance.

The results show that correlations differ considerably across departments, revealing important localised dynamics not visible in the global analysis. A key observation is the presence of more negative Spearman correlations for PM and PDM versus BDM at the departmental level than that observed in the aggregate results. Departments 14 and 34 display three-month lagged PM–BDM correlations of –0.12 and –0.19, which fall within the negligible or very weak range. This suggests that higher levels of preventive maintenance in these departments are only minimally associated with fewer breakdowns. However, this pattern is not consistent across the dataset, as all other departments exhibit positive PM–BDM correlations. Department 35 stands out, with a moderate positive correlation of 0.56 at a three-month lag, indicating that higher levels of preventive maintenance coincide with increased breakdowns. This may point to poor workmanship or the inadequate execution of preventive strategies in this department. Another pattern worth noting is that PM correlations become increasingly negative with longer lags in most departments, supporting the notion that preventive maintenance may have a delayed effect on breakdown reduction.

The results for predictive maintenance also show inconsistencies across departments. Departments 27, 28 and 33 display negative one-month lagged PDM–BDM correlations of –0.22, –0.10 and –0.28 respectively. These values indicate that increased predictive activity in these departments has a negligible to weak association with fewer breakdowns in the following month. Notably, these are the only departments with negative correlations, whereas all others show positive, albeit weak, associations. Department 14 stands out with a moderate positive correlation of 0.48. This implies that predictive maintenance is either closely triggered by breakdowns or that identified issues are not addressed timeously or effectively to prevent failures. It is also worth noting that several departments show more negative values at the one-month lag than in the same month and three months. This may reflect the delayed nature of predictive maintenance, where findings often lead to interventions in subsequent months.

The corrective maintenance analysis results show consistently positive correlations across all departments, with the strongest associations observed in the same month. This reinforces the global findings that CM is inherently reactive and closely tied to breakdown activity. Departments 25, 33 and 35 record the highest moderate correlations of 0.48, 0.41 and 0.42 respectively. This pattern may be driven by stronger adherence in these departments to the practice of recording follow-up work orders, thereby reinforcing the apparent relationship between breakdowns and corrective interventions.

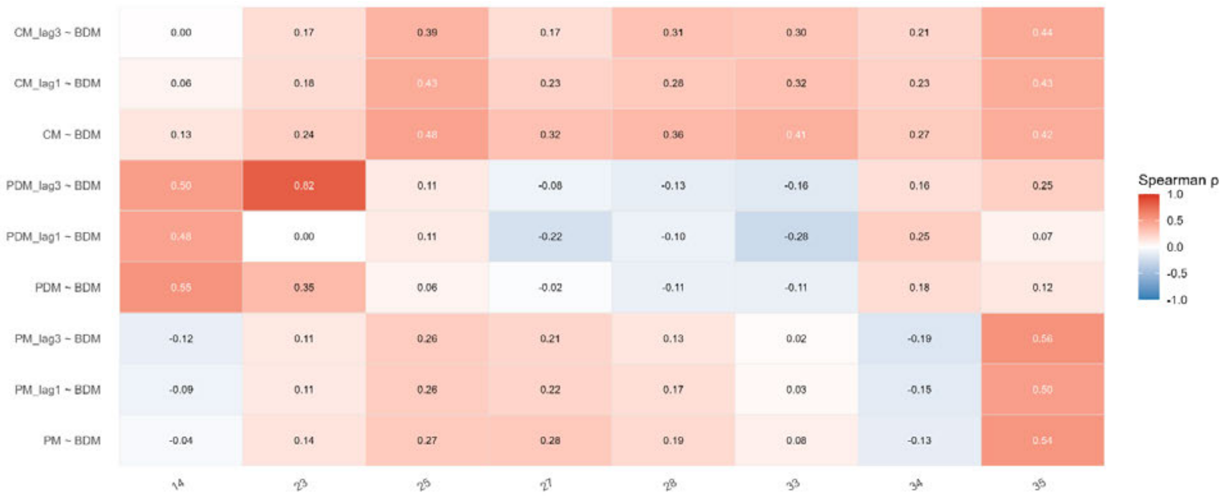


Figure 4. 11: All assets per department Spearman's correlation analysis results

To examine these correlations more closely, the analysis was repeated for the top eight assets by department. The results, depicted in Figure 4.12, show that all Spearman's correlations are positive, except for the PDM–BDM relationship in Departments 33 and 14. This implies that the increased frequency of PDM and PM activities does not result in reduced breakdowns in the majority of departments. However, Department 33 consistently exhibits a weak negative PDM–BDM correlation across both the all-assets and top-eight-asset analyses, suggesting a degree of consistency in the application of predictive maintenance techniques across different asset groups. In contrast, Department 14 shows a weak negative PDM–BDM correlation for the top eight assets, while at the same time presenting a moderate positive PDM–BDM correlation in the all-assets analysis. This shift highlights a stronger departmental focus on predictive maintenance for key assets.

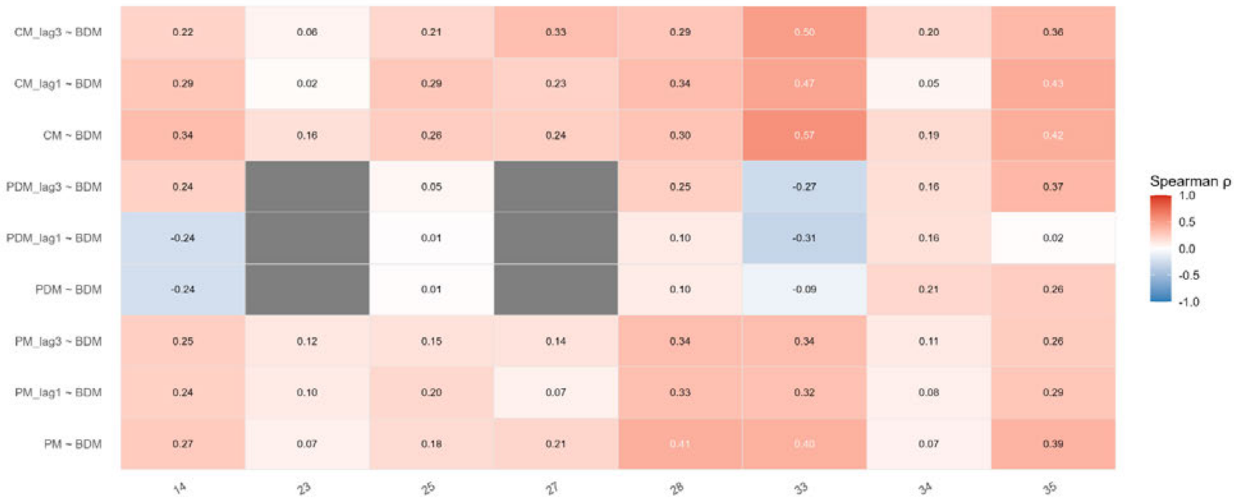


Figure 4. 12: Top 8 assets per department Spearman's correlation analysis results

4.6.3 Asset-Level analysis

At this point, an understanding of global, departmental and top-eight asset group maintenance patterns has been established. However, to build a robust foundation for developing effective maintenance strategies and identifying gaps, it is necessary to examine the differences at the individual asset-class level. Such analysis enables a direct evaluation of maintenance plans for specific asset classes within particular departments and helps to identify both weaknesses and strengths that could be adapted or transferred to other areas in order to enhance overall plant maintenance value delivery. To achieve this, further analysis of the data was conducted at the asset-class level within each department, with the results presented in Appendix B.

The results show that maintenance performance for the same asset classes is highly uneven across departments, with clear evidence of both strengths and weaknesses. For example, motors in department 28 exhibit a moderate Spearman correlation between PM and BDM at t−1, suggesting an opportunity to analyse and extend these maintenance practices to other departments, such as Department 25, where a risk-enhancing effect was observed for the same asset class. The analysis also highlights an insufficient number of PM and PDM work orders in several departments, represented in grey where N < 10, which signifies data scarcity and potential gaps in proactive maintenance execution. For example, within the motor asset class, Department 28 shows an insufficient PDM count. At the same time, Department 25 demonstrates the existence of a PDM strategy, albeit with only a weak protective effect on breakdown occurrences. Similarly, for pumps, where no department shows an adequate PDM count, there are clear opportunities to develop maintenance strategies guided by RCM and TPM principles.

4.7. Regression Analysis

To complement the correlation analysis, regression models were fitted to quantify the effects of proactive maintenance, which combined PM and PDM and CM on breakdown counts. The dependent variable was the monthly number of breakdown work orders, aggregated by department and asset class. Independent variables included contemporaneous and lagged values of proactive activities and CM at 1-month and 3-month intervals, as well as execution delay measures for both proactive and corrective work. This structure allowed for an assessment of the immediate and delayed effects of maintenance practices on breakdown incidence.

Given the non-negative integer nature of the outcome variable, models were specified as generalized linear models with a Poisson distribution and log link function. Where over-dispersion was present, a Negative Binomial regression was adopted as a more appropriate alternative. The general form of the model was:

$$\begin{aligned}\ln\left(E[\,BDM_{it}\,]\right) = \quad & \beta_0 + \beta_1\, PM_{it} + \beta_2\, PM_{i,t-1} + \beta_3\, PM_{i,t-3} + \beta_4\, PDM_{it} + \beta_5\, PDM_{i,t-1} + \beta_6\, PDM_{i,t-3} \\ & + \beta_7\, CM_{it} + \beta_8\, CM_{i,t-1} + \beta_9\, CM_{i,t-3} \\ & + \beta_{10}\, ProactiveDelay_{it} + \beta_{11}\, ProactiveDelay_{i,t-1} + \beta_{12}\, ProactiveDelay_{i,t-3} \\ & + \beta_{13}\, CMDelay_{it} + \beta_{14}\, CMDelay_{i,t-1} + \beta_{15}\, CMDelay_{i,t-3} + \varepsilon_{it}\end{aligned}$$

Where $\mathrm{BDM}_{i,t}$ represents the breakdown count for department or asset class i in month t. Department-level fixed effects were incorporated in the pooled regressions to control for unobserved heterogeneity across operational areas. Poisson regressions were estimated using the base R glm() function with family = poisson(link = "log"), and Negative Binomial regressions were fitted using MASS::glm.nb(). The analyses were implemented in R using the tidyverse and lubridate packages for data processing and visualization, and MASS for the count-data modelling.

4.7.1 Global analysis of all assets and top 8 assets

At the global level, the regression models provided a view into how proactive maintenance activities and their execution delays influence breakdown maintenance events. The results for all assets and top 8 are presented in Tables 4.5 and 4.6. For all assets, PM activities in the current month (t) were associated with a 2.2% increase in breakdowns ($p < 0.001$), while for top 8 breakdowns increased by 2.0%. This counterintuitive result suggests that preventive and predictive interventions may sometimes introduce short-term disturbances or latent defects that lead to breakdowns in the same month. This could be attributed to poor work quality, inadequate post-maintenance testing, or maintenance-induced failures such as improper re-assembly or incorrect settings after servicing.

However, after three months (t−3), PM showed a protective effect, reducing breakdowns by 2.1% ($p < 0.001$) for all assets and 2.3% ($p < 0.001$) for top 8 assets. This lagged benefit supports the theoretical expectation that the positive impact of proactive interventions manifests after a time delay, once the equipment has stabilized following maintenance. The consistency of this lag effect suggests that the benefits of PM accumulate gradually over subsequent months. The corresponding regression line plots are presented in Figures D1 and D2 in Appendix D. In contrast, predictive maintenance activities were found to be statistically insignificant, which may indicate a limited implementation of PDM practices within the organization.

The results for all assets showed that delays in executing proactive (PM and PDM) work worsened performance, as each additional day of delay increased breakdown frequency by 0.1% ($p = 0.003$) at t + 3. This highlights that the adverse impact of delayed execution becomes more pronounced in future periods. It was also noted that this effect and magnitude were similar for delays in corrective maintenance work execution, which showed a breakdown frequency increase of 0.2% ($p<0.001$). This finding highlights the importance of timeous work execution as a critical determinant of maintenance effectiveness.

Corrective maintenance work was strongly and positively associated with breakdowns, with current CM activity linked to a 9.1% increase in BDM events ($p<0.001$). This was also evident in the top 8 assets, as current CM activity was linked to a 5.5% increase in BDM events ($p < 0.001$). This aligns with the correlation results and reinforces the notion that CM tasks are reactive in nature. This effect might also point to possible problems with the poor quality of CM work execuion.

Table 4. 5:Global regression results for all assets

Model_Family	Predictor	Estimate	StdError	Stat	P-value
NegativeBinomial	CM	0.091	0.004	24.347	0.000
NegativeBinomial	CM_Delay	0.001	0.000	3.544	0.000
NegativeBinomial	CM_Delay_lag1	0.001	0.000	7.441	0.000

NegativeBinomial	CM_Delay_lag3	0.002	0.000	9.139	0.000
NegativeBinomial	CM_lag1	0.049	0.004	12.643	0.000
NegativeBinomial	CM_lag3	0.038	0.004	10.021	0.000
NegativeBinomial	PDM	0.016	0.012	1.280	0.200
NegativeBinomial	PDM_lag1	-0.001	0.013	-0.087	0.931
NegativeBinomial	PDM_lag3	0.003	0.013	0.247	0.805
NegativeBinomial	PM	0.022	0.003	8.471	0.000
NegativeBinomial	PM_lag1	-0.005	0.003	-1.564	0.118
NegativeBinomial	PM_lag3	-0.021	0.003	-8.201	0.000
NegativeBinomial	Proactive_Delay	0.000	0.000	-0.571	0.568
NegativeBinomial	Proactive_Delay_lag1	0.001	0.000	2.305	0.021
NegativeBinomial	Proactive_Delay_lag3	0.001	0.000	2.975	0.003

Table 4. 6: Global regression results for top 8 asset classes

Model_Family	Predictor	Estimate	StdError	Stat	P-value
NegativeBinomial	CM	0.055	0.006	9.800	0.000
NegativeBinomial	CM_Delay	0.000	0.000	-0.763	0.445
NegativeBinomial	CM_Delay_lag1	0.000	0.000	-0.083	0.934
NegativeBinomial	CM_Delay_lag3	0.000	0.000	0.769	0.442
NegativeBinomial	CM_lag1	0.021	0.006	3.661	0.000
NegativeBinomial	CM_lag3	0.015	0.006	2.714	0.007
NegativeBinomial	PDM	0.015	0.008	1.850	0.064
NegativeBinomial	PDM_lag1	0.001	0.009	0.072	0.942
NegativeBinomial	PDM_lag3	0.008	0.008	0.907	0.364
NegativeBinomial	PM	0.020	0.005	4.189	0.000
NegativeBinomial	PM_lag1	-0.001	0.005	-0.247	0.805
NegativeBinomial	PM_lag3	-0.023	0.005	-4.606	0.000
NegativeBinomial	Proactive_Delay	0.000	0.000	0.473	0.636
NegativeBinomial	Proactive_Delay_lag1	0.001	0.000	1.575	0.115
NegativeBinomial	Proactive_Delay_lag3	0.000	0.001	0.271	0.787

4.7.2 Departmental analysis of all assets and top 8 assets

The departmental-level regression analysis provided a more granular view of the maintenance–breakdown relationship. It mitigated the possibility that global results were disproportionately influenced by variations in work-order recording discipline across departments. Each department was analyzed individually for the entire asset base and the subset of the top eight critical assets.

On all assets and top 8 departmental analyses, PM again showed the dual effect of short-term increases and lagged reductions in breakdowns, as shown in Table C-1 and C-2 in Appendix C. Departments 23 and 33 demonstrated the most potent protective effects in the all-assets analysis, where each PM work order executed in the previous three months reduced breakdowns by 2.6% ($p<0.001$) and 3.2% ($p<0.001$) respectively. The regression line plots are shown in Figures D-3 and D-4 in Appendix D to visually demonstrate the lagged protective effect of preventive maintenance. These results reflect the effectiveness of maintenance strategies in these departments. However, these departments did not rank highest when the analysis was limited to the top eight assets. In that subset, Department 25 showed the most substantial proactive effect, where work orders executed at lag three ($t-3$) reduced breakdowns by 3.0% ($p=0.013$), as shown in Table C-2 and Figure D-5. This finding suggests that Department 25's maintenance plans are targeted and effective for its critical assets.

The highest sensitivity to proactive activities execution delays for all assets was also noted in Department 25, where every additional day of delay in proactive work corresponded to a 0.3% ($p < 0.001$) increase in breakdown frequency. This delay effect, coupled with the observed weak protective influence of preventive maintenance for all assets of 1.7% ($p=0.029$) at $t-3$, may render proactive interventions in Department 25 largely ineffective. These results of delayed maintenance work point to potential inefficiencies in maintenance scheduling, inadequate resource co-ordination, or poor adherence to planned work execution timelines.

Corrective maintenance remained the dominant and statistically significant predictor of breakdown frequency across all departments. Departments 34, 33 and 14 exhibited the strongest risk-enhancing effects of 14.8% ($p<0.001$), 14.3% ($p<0.001$) and 12.1% ($p<0.001$) respectively for all assets' current-month CM activity. Similar trends were observed for the top eight assets, with Departments 34 and 14 still demonstrating the highest risk-enhancing effects. This points to structurally embedded relationships within departmental maintenance practices rather than being isolated to specific asset classes.

4.7.3 Diagnostic assessment

To evaluate the adequacy and statistical robustness of the regression models, a diagnostic assessment was conducted across both the global and departmental analyses. The objective was to examine model fit, significance and explanatory power to ensure the reliability of the inferences drawn from the CMMS-based data.

Global Model Diagnostics

The diagnostic assessment of the global and top 8 asset-class models showed that the negative binomial specification delivered statistically significant improvements relative to their respective null models. The global model showed a likelihood-ratio of 30742.9 while the top 8 was 3268.4 ($p<0.001$) as shown in Table 4.7. This means that maintenance activites, PM, PDM, CM and their lags and delays in execution, provide measurable predictive information about breakdown behaviour at both scales of analysis. The all-assets model achieved a McFadden pseudo-R^2 of 0.302, which is indicative of a strong improvement in the model fit. In contrast, the Top 8 model produced a pseudo-R^2 of 0.214, which also indicated meaningful improvement, but reflected a more moderate explanatory contribution. This difference suggests that maintenance activities and breakdown relationships are more stable when viewed at an aggregated organisational level, where large sample sizes smooth out fluctuations. Both models demonstrated acceptable dispersion values close to 1, confirming that the Negative Binomial specification is appropriate for the over-dispersed nature of breakdown counts.

In evaluating the balance between model fit and complexity, the global and Top 8 models reported BIC values of 71,219.2 and 12,226.4 respectively. These values provide useful reference points for future modelling work as they allow subsequent models to be compared against these benchmarks to determine whether additional complexity meaningfully improves explanatory power.

Table 4. 7: Model diagnostics results for all assets and top 8

Group	Model_Family	N	df_resid	AIC	BIC	logLik	null_logLik	pseudoR2_McFadden	Dispersion	LR_stat	LR_df	LR_p
All assets	NegativeBinomial	34374	34351	71016.52	71219.2	-35484.3	-50855.7	0.302	1.10532987	30742.94	16	0
Top 8 assets	NegativeBinomial	3166	3143	12060.97	12206.42	-6006.49	-7640.69	0.214	1.02032231	3268.40	16	0

Departmental Model Diagnostics

The diagnostic evaluation of departmental-level models revealed variations in how maintenance activities predict breakdown behaviour across the organisation. Across all departments, the likelihood-ratio statistics were large and highly significant ($p < 0.001$), showing that PM, PDM, CM and their lagged and delayed versions provide meaningful predictive information about breakdowns at the departmental scale.

For the all-assets models, Departments 14, 23, 33 and 34 exhibited the strongest overall model performance as shown in Table 4.8. These departments produced the highest improvements from the null models with values of 5042.9; 7508.6; 5623.7 and 5752.9 respectively. The McFadden pseudo-R^2 values ranged from 0.318 to 0.360, indicating that the predictors explained a substantial proportion of the improvement in model fit relative to the null model. These results suggest that these departments have more stable maintenance activities and breakdown relationships. The dispersion values across all departments remained close to 1, supporting the suitability of the Negative Binomial specification.

When restricting analysis to the Top 8 critical asset classes, Departments 14, 33 and 34 remained the strongest performing departments with pseudo-R^2 values of 0.350, 0.280 and 0.337 respectively. These values align with the patterns observed in the all-assets models, which highlights the stability of maintenance activities and breakdown dynamics in these departments. The top 8 assets analysis showed a substantial reduction in Department 23's LR statistic, attributed to the observed dramatic decrease in sample size, which reduces statistical power. Additionally, as shown in section 4.2, Table 4.1, Department 23 contains only seven of the eight critical asset classes as it did not record any roller assets. This results in reduced variability in breakdown behaviour and simplifies the model structure, which limits the magnitude of improvement over the null model for this department.

Table 4. 8: Departmental model diagnostics results for all assets and top 8

Asset Group	Department	Model_Family	N	df_resid	AIC	BIC	logLik	null_logLik	pseudoR2_McFadden	Dispersion	LR_stat	LR_df	LR_p
All	14	NegativeBinomial	3574	3558	8982.9	9088.0	-4474.4	-6995.9	0.360	1.035	5042.857	16	0.000
All	23	NegativeBinomial	5367	5351	13436.5	13548.5	-6701.3	-10455.5	0.359	1.229	7508.553	16	0.000
All	25	NegativeBinomial	5418	5402	9717.5	9829.7	-4841.8	-6630.6	0.270	1.094	3577.713	16	0.000
All	27	NegativeBinomial	2156	2140	4223.9	4320.4	-2094.9	-2767.3	0.243	1.026	1344.658	16	0.000
All	28	NegativeBinomial	5233	5217	7513.9	7625.4	-3739.9	-4583.6	0.184	1.034	1687.283	16	0.000
All	33	NegativeBinomial	5314	5298	10717.1	10828.9	-5341.6	-8153.4	0.345	1.131	5623.705	16	0.000
All	34	NegativeBinomial	4902	4886	12361.4	12471.8	-6163.7	-9040.1	0.318	1.145	5752.900	16	0.000
All	35	NegativeBinomial	2410	2394	3510.9	3609.3	-1738.4	-2229.3	0.220	1.139	981.735	16	0.000
Top 8	14	NegativeBinomial	436	420	2027.4	2096.7	-996.7	-1533.1	0.350	1.052	1072.902	16	0.000
Top 8	23	NegativeBinomial	367	354	1466.8	1521.5	-719.4	-843.2	0.147	0.990	247.633	13	0.000
Top 8	25	NegativeBinomial	452	436	1616.2	1686.1	-791.1	-908.6	0.129	1.084	234.946	16	0.000
Top 8	27	NegativeBinomial	273	257	716.3	777.7	-341.1	-394.3	0.135	1.078	106.287	16	0.000
Top 8	28	Poisson	434	418	1358.7	1423.8	-663.3	-740.8	0.105	1.342	154.932	15	0.000
Top 8	33	NegativeBinomial	426	410	1934.3	2003.2	-950.1	-1319.7	0.280	1.120	739.126	16	0.000
Top 8	34	NegativeBinomial	433	417	2004.9	2074.1	-985.5	-1486.3	0.337	1.053	1001.778	16	0.000
Top 8	35	Poisson	345	329	704.3	765.8	-336.1	-414.6	0.189	1.287	157.006	15	0.000

4.8. Hypothesis Testing Results

The results of the statistical analysis were used to evaluate the hypotheses developed in Chapter 1. The outcomes are summarised as follows:

H1: Proactive maintenance activities have a statistically significant negative relationship with breakdown frequency.

> The regression results indicate that preventive maintenance exhibits a lagged relationship with breakdown frequency, where increased PM activity contributes to improved reliability over time. However, the immediate-period effect suggests a short-term increase in breakdown risk, likely due to execution-related factors. Predictive maintenance did not show strong statistical significance across the models, indicating limited current impact. Therefore, this hypothesis is partially supported, as the expected relationship is observed over time rather than immediately.

H2: Increased corrective maintenance activity is positively associated with higher breakdown frequency.

> The analysis shows a strong positive relationship between corrective maintenance activity and breakdown frequency within the same period. This confirms that corrective maintenance is reactive in nature and reflects existing equipment failures rather than preventing them. Therefore, this hypothesis is supported.

H3: Delays in maintenance execution are positively associated with increased breakdown frequency.

The statistical analysis indicates that delays in maintenance execution are associated with higher breakdown risk. The results suggest that where maintenance activities are not executed on time, the reliability benefits of those interventions are reduced, increasing the chances of subsequent failures. This pattern supports the view that maintenance timeliness is an important factor in asset performance. However, the strength and significance of this relationship may vary across maintenance types and analytical models, and should therefore be interpreted in relation to the broader regression results presented in this chapter. On this basis, this hypotheses is supported, as the results indicate a positive association between maintenance execution delays and breakdown frequency.

5. CHAPTER 5: DISCUSSION

5.1. Introduction

The purpose of this study was to evaluate how computerised maintenance management system data can be structured and analysed to provide insights into the performance of existing maintenance strategies within a manufacturing organisation in Pietermaritzburg, South Africa. The overarching objective was to determine whether a data-driven approach could identify inefficiencies, highlight opportunities for improvement, and inform the development of more effective and proactive strategies that enhance asset reliability and improve value delivery through maintenance.

This chapter consolidates the key empirical findings presented in Chapter 4 and demonstrates how the study has addressed the research questions. It links the evidence obtained from the organisation's maintenance records to the research objectives outlined in Chapter 1 and to broader asset-management theory. The chapter further identifies gaps in existing practices; proposes evidence-based recommendations; and outlines opportunities for future research and practical implementation within the South African manufacturing context.

5.2. Overview of Findings

5.2.1 Objective 1- Data structuring and analysis

The first objective of the study was to structure the organization's CMMS data in a manner that enables a meaningful interpretation of maintenance patterns at the global, departmental and asset-class levels. The CMMS dataset initially lacked support for detailed analysis due to a number of challenges. These challenges were anticipated, as this is well-documented in global literature, which notes that CMMS datasets often contain large volumes of information but limited analytical value due to poor data architecture and inconsistent user practices (Aljumaili & AL-Chalabi, 2016). The challenges included:

- Missing assets in Maximo locations
- work orders assigned at high-level locations instead of specific equipment
- work orders assigned to the wrong asset locations
- Unrealistic times and dates in the work orders
- Incorrect statuses of work orders
- Insufficient details on the work order feedback

The data had to undergo a restructuring process, which involved correcting asset hierarchies, aligning work orders with the correct equipment, removing erroneous records, standardizing timestamps and validating maintenance histories across locations. Once these steps were done, the data provided a valuable and multi-dimensional view of maintenance activity across the organization over the chosen period. This restructuring was critical because the success of subsequent analyses depended on the accuracy of imput data. This finding aligns with Bengtsson et al. (2020), who emphasize that structured CMMS data enables meaningful analysis and supports data-driven maintenance decision-making.

5.2.2 Objective 2- Insights from trends and equipment failure data

The second research objective focused on interpreting what the structured CMMS dataset revealed about the organization's asset behaviour, failure dynamics and maintenance demands. A key finding was that maintenance activity and failure patterns were highly uneven across asset classes. Certain asset classes like motors, gearboxes, pumps and cylinders, accounted for a disproportionately high share of work orders and downtime. This confirmed the theoretical expectation of the Pareto pattern, indicating that a small subset of critical assets drives the majority of the organization's maintenance workload and reliability challenges (Moubray, 1997).

This finding is further supported by reliability-centred maintenance literature, which emphasises that failure behaviour is not uniformly distributed across assets, and that maintenance strategies should be informed by historical failure patterns and asset criticality rather than applied uniformly (Nowlan & Heap, 1978). The observed concentration of failures within specific asset classes highlights the importance of focusing maintenance efforts on high-impact assets, as also noted in maintenance optimisation studies that advocate prioritisation based on failure frequency and operational consequence (Mobley, 2002).

Number of work orders

This pattern remained despite the normalization of work orders by asset population size. Several departments still recorded substantially higher work order volumes than others despite comparable asset counts. Given that preventive maintenance is the dominant work type in all departments except Department 34, these variations largely reflect differences in the intensity and frequency of PM execution across the organization. Such inconsistency points directly to the co-existence of over-maintenance in some areas and under-maintenance in others, suggesting that PM programmes are not being applied in a balanced or risk-aligned manner. However, when interpreting these patterns, several contextual factors must be taken into account.

a. Age of equipment

According to the bathtub principle, failure rate is highest during early “infant mortality” and late “wear-out” phases (Dhillon, 2006). This behaviour is visually depicted in Figure 5.1. Therefore, departments operating ageing or near end-of-life equipment would be expected to generate higher maintenance demands than departments operating assets in their stable life phase. This lifecycle-driven variation underscores the importance of age profiling in interpreting CMMS maintenance volumes.

In the context of this study, the majority of assets are operating within the useful life phase, where failure rates are relatively stable and influenced primarily by maintenance practices and operating conditions. However, a subset of asset classes exhibiting higher breakdown frequency and maintenance demand may be transitioning into the wear-out phase, where age-related deterioration becomes more prominent. This combination of stable and ageing assets within the system helps in explaining the uneven distribution of maintenance workload across departments.

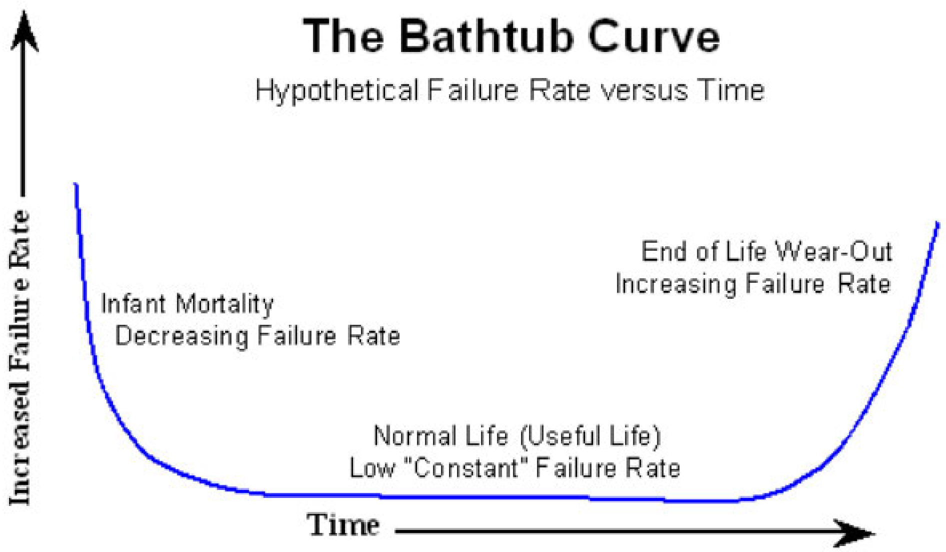


Figure 5. 1: Bathtub curve (Wilkins, 2002)

b. Equipment type and criticality

RCM emphasises that maintenance should be driven by asset function, failure modes and consequences of failure, not by uniform work-order volumes. As a result, similar assets located in different departments may require different maintenance strategies because they operate under different functional roles, loading conditions and risk profiles.

c. Production loading and operating context

Duty cycle and throughput volumes also affect maintenance requirements. Departments that serve as bottlenecks or carry higher production loads tend to accumulate more mechanical stress, elevating maintenance needs. On the other hand, under-loaded machines may exhibit lower activity despite similar asset populations. Fluctuations in market demand also introduce additional complexity by shifting production pressure across departments, periodically changing which machines function as bottlenecks. These dynamics highlight the need to view maintenance patterns through the lens of a broader operational context. There is no universal target for work orders per asset, and organizations are instead encouraged to benchmark internally, monitoring ratios across departments over time rather than against external norms (Wireman, 2015). The ratios calculated in this study therefore represent a foundational baseline for internal comparison and future performance tracking.

Maintenance types

The observed behaviour of maintenance activities added further nuance to this imbalance. Regression results indicated that increases in PM work orders were associated with higher breakdown counts in the contemporary month, likely linked to intrusive maintenance, human error or temporary destabilisation after major interventions. However, this was followed by a delayed protective effect, where PM activity conducted three months earlier reduced breakdowns. This lagged benefit suggests that PM effectiveness manifests only after equipment has stabilised, making the timing and sequencing of preventive tasks a critical strategic consideration.

Complementing this, the analysis also revealed a systemic under-application of predictive maintenance. In addition, PDM volumes were low relative to failure-critical asset classes and regression results showed no statistically significant effect of PDM on breakdown reductions. The statistical insignificance does not necessarily imply that PDM is ineffective, but rather signals that the organisation is not employing enough condition-based maintenance to achieve detectable reliability improvements.

Corrective maintenance patterns in the current month and in lagged periods were consistently associated with increases in breakdowns. This reinforced the theoretical expectation that organisations heavily reliant on corrective work tend to experience repeated breakdowns (Wireman, 2015). This is particularly evident in departments with persistent CM-heavy workloads.

Downtime analysis added another layer to understanding asset behaviour. Several asset categories that were not amongst the highest in maintenance frequency surfaced in the top 20 of asset classes by downtime hours contribution. This highlighted that some assets may be failing less frequently but resulting in long breakdowns. This underscores the importance of integrating downtime, severity and failure mode characteristics when setting maintenance priorities. Asset classes with both high severity and a moderate-to-high frequency of breakdowns should be prioritised for increased PM or targeted PDM interventions.

Departmental analysis

Department-level patterns provided further insight into the behavioural and operational factors shaping these outcomes. Some departments demonstrated a relatively mature preventive maintenance culture, with PM showing a relatively significant lagged influence in breakdowns reduction as seen in Department 33. However, others were characterised by highly reactive maintenance profiles and frequent breakdowns, like Department 34. These differences may be an indication of varying skill levels, production pressures, supervisory inconsistency or different asset age distributions. These departmental discrepancies highlight that maintenance performance is not solely a function of technical practices but also reflects organisational culture, leadership and local resource allocation.

Top 8 asset classes maintenance

This inconsistency in maintenance effort also spills over to key asset classes, as results showed that they experience different levels of maintenance activity depending on the department. Gearboxes and pumps experience the highest variation across departments, with standard deviations of 28 and 21 work orders per asset class, respectively. Although some variation in maintenance activities across departments is expected, as discussed above, the magnitude of these differences raises concerns about the consistency of standards and the presence of departmental silos that hinder the standardisation of maintenance practices.

5.2.3 Objective 3 – Relationship between PM and reliability indicators

The empirical analysis provided a multifaceted answer to the question: Is there a measurable relationship between the frequency of preventive maintenance tasks and asset reliability indicators? It revealed a complex relationship between preventive maintenance and reliability indicators. The correlation analysis initially suggested an unexpectedly weak relationship between PM frequency and breakdown counts, with many global correlation coefficients clustered around zero or slightly positive. This weak relationship indicates that increased PM activities did not translate into improvements in reliability across the organization. At face value, such results could challenge the theoretical assumption that PM reduces failure frequency and improves MTBF. However, a deeper interrogation reveals that this interpretation would overlook the underlying contextual dynamics of PM interactions with equipment health.

The weak global correlations are best understood as a reflection of noise within the dataset and the confounding influence of multiple maintenance activities occurring simultaneously. PM does not exist in isolation but forms part of a larger maintenance system. For example, departments experiencing deterioration of machines may simultaneously increase PM, PDM and CM. Correlation analysis, being bivariate and simplistic, cannot disentangle whether PM is driving failures downward or whether failures are prompting more PM work.

The regression analysis offered a clearer picture, which enabled the independent effects of PM to be estimated while holding other predictors constant. At the global level, PM demonstrated a dual effect, an increase in breakdown risk in the same month (t) followed by a statistically significant reduction in breakdowns at lagged intervals, particularly at three months (t−3). This dynamic aligns with established reliability theory and the Bathtub Principle, which recognizes that maintenance interventions can result in short-term reliability deterioration through infant-mortality effects (Afolalu, et al., 2021). However, an additional mechanism likely amplifying this immediate risk is the quality of work execution. Incomplete PM tasks, improper reassembly, missed inspection points, incorrect lubrication, poor torquing and inadequate testing can inadvertently elicit new failure modes in equipment. These execution-related defects counteract the intended reliability benefits of PM and explain why the risk-enhancing effect is more pronounced in the current month.

At a departmental level, departments with high PM volumes, such as Department 33, exhibited the strongest risk-enhancing effect in the current month, suggesting that execution quality is a key concern. The lagged protective effect was still present, confirming that PM ultimately contributes positively to reliability, but its influence was masked by substantial short-term risk. In contrast, departments with lower PM volumes displayed more muted risk-enhancing behaviour but weaker lagged benefits, implying that PM volume produces a measurable influence on failure-rate dynamics.

5.2.4 Objective 4 – Assets association to costs and operational disruptions

The empirical findings make it clear that the organisation's cost and disruption patterns are heavily concentrated in a relatively small subset of assets. The identified top 8 asset classes attract large volumes of proactive work, which comes at a certain cost. However, the most significant cost burden arises from breakdowns of these assets.

As established in Chapter 2, maintenance literature consistently emphasises that unplanned maintenance is the most expensive and operationally disruptive form of intervention. The high cost associated with this type of maintenance is driven by:

- Emergency labour call-outs and overtime, which inflate labour costs and strain maintenance budgets.
- Shift disruption, which diverts resources away from planned and preventive activities, potentially leading to additional breakdowns.
- Expedited procurement processes, which force the bypass of standard supply chain procedures, resulting in inflated material and service costs.
- Collateral damage to adjacent components, which increases repair scope, cost and downtime duration.
- Extended downtime due to inadequate planning and co-ordination, compounding production losses.

In addition, RCM theory highlights that the hidden costs of unplanned failures, such as reduced equipment life, chaotic work environments, higher inventory requirements and reduced plant stability, compound over time (Moubray, 1997). This information can be used to refine cost understanding and direct focused attention toward departments such as Department 34, which exhibits an overwhelmingly reactive maintenance profile. This implies that allocated budget, labour and managerial effort in this department are disproportionately consumed by firefighting activities rather than proactive control.

The cost and downtime implications become more evident in the analysis of key asset classes maintenance, such as cylinders. The misalignment between maintenance effort and downtime contribution further escalates the costs, as high-risk assets under-maintenance result in more frequent breakdowns and escalating costs. Conversely, the over-maintenance of low-risk assets results in unnecessary PM costs without proportional reliability gains. Therefore, the cost implications revealed by the analysis result reflects the challenges related to reactive exposure and strategic misalignment.

5.2.5 Objective 5 – Identification of improvement opportunities

The results of the study revealed several opportunities to revise and optimize maintenance schedules and improve task effectiveness. The lagged PM effects observed in the regression analysis suggest that the current PM programme is not fully effective at preventing machine failures, as reflected in the relatively small PM coefficients across the models. This pattern indicates that PM activities may not be fully aligned with the underlying failure behaviour of assets in terms of interval and task content. Strengthening these elements has the potential to enhance the protective lagged effects of PM and improve its overall contribution to reliability. This observation is consistent with maintenance literature, which highlights that ineffective interval selection and poorly defined maintenance tasks can reduce the effectiveness of preventive maintenance programmes (Wireman, 2004).

The risk-enhancing effect of PM suggests that workmanship quality, procedural clarity, post-maintenance testing and technical competence are not consistently at a level that supports reliability improvement. When maintenance execution introduces new failure modes, the intended benefits of PM are reversed. The data indicate that improving the quality of PM execution represents a strategic opportunity to reduce the magnitude of the short-term risk penalty and strengthen the long-term reliability gains. This aligns with TPM literature, which emphasise that maintenance quality and operator competence are critical determinants of reliability outcomes (Nakajima, 1988).

Another opportunity lies in the enhancement of PDM coverage and utilization. The general statistical insignificance of PDM in both correlation and regression models suggests that predictive maintenance is not sufficiently adopted across departments. Expanding vibration analysis, oil diagnostics, thermography and other condition-monitoring techniques could create earlier failure detection and reduce unplanned CM and BDM workloads.

Timeliness work execution represents a further area of opportunity. Delayed PM, PDM and CM were all associated with increased breakdown risk in the regression findings. This suggests that improvements in planning, scheduling and resource availability could reduce operational risk. Departments with chronic delays would benefit from identifying bottlenecks in their maintenance workflow, whether due to manpower, planning capacity, procurement processes, equipment accessibility, and developing corrective actions.

Accurate data structuring is widely recognised in the literature as a prerequisite for effective maintenance analysis and decision-making (Bengtsson, et al., 2020). The issues with work-order allocations represent a major systemic improvement opportunity. Ensuring that maintenance tasks are allocated to the correct locations and assets would aid the organization in gaining a more accurate understanding of equipment-specific failure patterns. This would also enable a refinement of PM schedules to align with actual asset behaviour, rather than generic departmental assumptions. This re-alignment would significantly enhance the predictive power of future analyses and strengthen the organisation's ability to implement a continuous improvement approach.

5.2.6 Objective 6 – CMMS data integration to a continuous improvement framework

Continuous improvement is pivotal to TPM, ISO 55000 and lean maintenance principles. However, it requires stable and reliable performance indicators, systematic feedback loops, and the ability to track the impact of interventions over time (Nakajima, 1988). The structured data generated in this study provides a firm foundation for these capabilities as it converted fragmented maintenance records into reliable performance information that can be used to monitor trends and evaluate outcomes.

Data governance and quality control are important key determinants of success for achieving continuous improvement. CMMS data must be accurate, standardised and consistently maintained, which requires well-defined processes and routines. This involves establishing clear data-entry rules; the periodic validation of asset hierarchies and work-order classifications; and accountability for accurate feedback reporting. Without a robust data-governance process, the reliability indicators generated from the CMMS cannot be trusted and may mislead decision-making.

Continuous improvement depends on the ability to measure performance trends and the effect of interventions over time. Therefore, asset-level MTBF, PM-to-BDM ratios, delay ratios, CM backlog trends and lag-adjusted PM effectiveness metrics baselines would have to be established to enable the Integration of CMMS data into continuous improvement. The tracking of these indicators on a monthly or quarterly basis would then provide a foundation for identifying deterioration patterns, assessing the impact of schedule changes, and refining strategies. Tracking the lagged effects highlighted by regression analysis is particularly important as traditional maintenance KPIs typically focus on same-month outcomes, which can obscure PM's true contribution to reliability.

Another critical step would be to connect these CMMS insights to knowledge-sharing structures, such as RCA sessions, planning meetings, PM review workshops and cross-departmental learning forums. These platforms would serve as the formal mechanisms for interpreting and verifying CMMS against field experience, which will enable data to become a living input into decision-making rather than being viewed as a retrospective reporting tool. This will also ensure that reliability insights inform planning, budgeting, resource allocation and strategic asset management.

The sustainability of such continuous improvement can be bolstered by digital integration. CMMS insights must connect with broader operational systems. This includes linking maintenance KPIs with IoT-enabled condition-monitoring data and Supervisory Control and Data Acquisition (SCADA) systems to enable the real-time tracking of equipment health and performance. These links can enable automatic update maintenance dashboards and data-driven interventions.

5.3. Conclusion

The results of the study demonstrated that CMMS data becomes meaningful for strategic decision-making only when rigorously structured, cleansed and contextualised. The raw Maximo dataset was constrained by a number of issues, which made the analysis not possible. However, following the process of cleaning and validating the dataset, the identification of maintenance patterns that were previously obscured was made possible. This confirms that the core challenge with maintenance data is not its scarcity, but rather the lack of structured, accurate and interpretable data. It is this limitation that prevents organisations from fully leveraging CMMS information as a strategic asset for maintenance optimisation and continuous improvement.

Drawing together the insights from all six research questions, the study concludes that historical maintenance data holds substantial potential to guide reliability improvement. However, this potential is only partially realised in the current organisational context. The findings reveal a maintenance landscape characterised by inconsistent data practices; the uneven execution of proactive work,;varying departmental maintenance cultures; and a considerable gap between the theoretical expectations of PM/PDM and their realised effectiveness in practice.

The results from the study have shown that preventive maintenance improves reliability only after a lag of one to three months, while poor execution quality leads to a spike in failures immediately after PM activities. Predictive maintenance, meanwhile, remains underdeveloped, limiting early defect detection.

Corrective maintenance and delays in scheduled work emerged as strong indicators of future breakdowns, highlighting the need for better planning, scheduling and resource allocation.

From the results of the study, the organisation is well-positioned to integrate CMMS data into a continuous-improvement framework, but significant enablers must be addressed before this can be fully achieved. These include strengthening asset-level work-order allocation; improving execution quality; improving planning and scheduling processes; adopting lag-based KPIs; expanding predictive maintenance; and reinforcing cross-departmental learning structures. The structured analysis in this study provides a roadmap for the organisation and other industrial entities with similar maintenance challenges to transition from non-value-adding maintenance practices towards a targeted, risk-based, data-driven and reliability-centred asset management strategy that delivers sustained value improvement.

5.4. Recommendations

Based on the study's findings, several actionable recommendations are proposed to improve the organisation's maintenance effectiveness and support a transition toward reliability-centred operations.

Improve preventive maintenance execution quality (High priority)

The most immediate recommendation is to strengthen PM execution quality, with a focus on mitigating the risk-enhancing effect observed in the current month. This can be achieved by establishing clear PM procedures, improving artisan competency through targeted skills development, and introducing systematic post-maintenance testing before machines are released back into production. A formal "maintenance quality verification" step should be embedded into PM workflows to reduce workmanship-related failures. This intervention should be treated as a high priority and implemented within a 3 to 6 month timeframe, given its direct impact on reducing maintenance-induced failures.

Optimise preventive maintenance strategies and intervals (High priority)

A second recommendation is to re-design and optimise PM schedules to better align with asset criticality, observed failure behaviour and asset failure modes. The organisation should review PM intervals, content and resource allocations for key asset classes, especially those with high downtime contributions. The findings indicate that departments should prioritise optimisation efforts by focusing first on asset classes that are both highly represented and high-risk. For example, Department 33, where cylinders make up a significant proportion of the asset population yet receive comparatively limited preventive attention, provides a clear case for targeted PM re-design. In addition, the organisation should adopt successful maintenance plans for specific asset classes from departments that have demonstrated higher levels of effectiveness, as established by the asset class analysis results. Transferring proven PM and PDM strategies from these high-performing areas can accelerate organisational learning and promote standardisation across the organization. The focus on risk-based maintenance programmes will also help in eliminating over-maintenance where it offers limited value and increase the focus on assets that have a high impact on reliability. A phased pilot implementation of these optimised PM strategies should be conducted over a 6 – 12 month period on the top critical asset classes before broader rollout.

Expand predictive maintenance capability (Medium priority)

Formalising and expanding predictive maintenance beyond periodic inspections to an integrated, real-time condition-monitoring framework is imperative. This should include scaling up traditional techniques, such as vibration analysis, thermography and oil diagnostics, as well as adopting IoT-enabled condition-monitoring technologies that provide continuous data streams. Integrating these live condition-monitoring feeds with CMMS data at the asset level would allow maintenance teams to detect the early signs of deterioration and prioritise interventions based on actual equipment health rather than fixed intervals. It is recommended that a 36-month pilot project be initiated, focusing on the implementation of continuous vibration analysis and thermal monitoring. The project should target the identified top 8 critical and high-speed rotating assets such as motors, hydraulic pumps, and fans in Departments 23, 25, and 33.

Improve maintenance planning and scheduling discipline (Medium priority)

The study showed that delayed PM, PDM and CM significantly increase future breakdown risk, indicating that delays are not merely administrative issues but direct contributors to equipment instability. In the next 6 months, the organisation should also improve planning and scheduling processes to address this gap. The review of resource allocation may also be required to ensure that sufficient artisans, planners, supervisors and specialist resources are available to execute scheduled work. KPIs focused specifically on PM, PDM and CM delays should also be introduced to monitor performance in this critical area. This should be supported by weekly maintenance planning reviews and tracked through schedule compliance metrics. Reducing execution delays will help prevent minor defects from escalating into major breakdowns.

Strengthen CMMS data integrity and accuracy (Medium priority)

The organisation should strengthen CMMS data integrity, beginning with consistent asset-level work-order allocation and routine data audits. Improved data structures will support a more accurate future reliability analysis, facilitate the identification of further improvement opportunities, and enable more effective decision-making. This should be reinforced through system validation rules and periodic data quality audits conducted on a monthly basis.

Furthermore, it is recommended that additional CMMS fields be made mandatory to ensure the consistent capture of critical data. This should include ensuring that all key asset locations are linked to defined assets, that all breakdown work orders logged against these locations include recorded downtime, and that breakdown feedback follows a standardised structure e.g., problem, cause, remedy.

Establish asset-class reliability specialists (Medium priority)

It is recommended that the organisation appoint dedicated specialists for the identified top eight critical asset classes. These individuals should focus on developing and refining maintenance plans, ensuring the quality execution of these plans, facilitating the repair processes for these assets, and managing associated spare parts effectively. In addition, they should facilitate the transfer of lessons learned across departments to promote standardisation and accelerate the adoption of best maintenance practices. Establishing these specialist roles will play a pivotal role in improving the reliability of these key assets and overall plant reliability. The first step towards achieving this should be the appointment of motor and cylinder specialists within the next 12 months.

Implement a data-driven continuous improvement framework (Long-term priority)

Once data quality and structure have improved, the developed analytical model should be embedded directly within the live CMMS data. This integration will enable the model to provide real-time feedback on the effectiveness of maintenance practices. It will also generate live performance indicators, highlight inefficiencies, and identify opportunities for improvement on a continual basis.

5.5. Contribution to the Body of Knowledge

This study contributes to the body of knowledge by demonstrating how CMMS data can be transformed from basic work order records into an analytical resource for maintenance optimisation. This research provides a systematic framework for structuring, cleaning and analysing CMMS data in a manner that reveals previously hidden patterns in asset behaviour, failure dynamics and maintenance effectiveness. The findings position this study as a key pathway to addressing the widely recognised challenge of CMMS underutilisation in industry. The research also provides a pragmatic and analytical framework that bridges the gap between traditional maintenance theory, such as RCM and TPM, and contemporary data analytics approaches. Through the integration of lag-based regression models with traditional descriptive and correlation techniques, the study advances the methodological understanding of how preventive, predictive and corrective maintenance activities interact over time. The study highlights the importance of evaluating maintenance effectiveness through time-sensitive models rather than same-month indicators.

The study also provides new insights into the maturity of the maintenance strategy within resource-constrained manufacturing environments, particularly in the South African context, where empirical research on CMMS-driven optimisation remains limited. It extends theoretical discussions on RCM and TPM by linking them to practical organisational realities, such as departmental behaviours, execution quality, data governance and scheduling delays, which influence breakdown patterns. The integration of IoT-enabled predictive maintenance concepts further broadens the literature by illustrating how modern, real-time monitoring tools can complement traditional PM programmes to strengthen reliability.

Additionally, the study contributes to a cultural and organisational shift toward continuous improvement by providing a replicable analytical approach that can be adopted in other manufacturing environments in South Africa and beyond. The findings support operational excellence within the case organisation and contribute broadly to the advancement of maintenance best-practices, offering a reference point for industries seeking to unlock the strategic value of their existing CMMS data assets.

5.6. Future Research

Future research could focus on explicitly exploring the content and execution quality of PM tasks. This can be done by linking CMMS-derived insights with field observations, interviews or time-and-motion studies to evaluate how maintenance procedures are performed in the field. An understanding of the contributing factors to the risk-enhancing effect of PM would support the development of targeted interventions to reduce post-maintenance failures.

Future research could also consider pulling production and operational data, such as machine utilisation, load profiles or process conditions, into maintenance modelling. Combining CMMS data with operational parameters would provide a more comprehensive understanding of failure predictors and enable more accurate predictive models. These models could be further buttressed by incorporating additional asset characteristics, including equipment age, operating environment and more granular asset-level histories, once CMMS data integrity has improved.

This study could also be extended to include comparisons across different organizations to test whether the findings hold in other industrial settings, and to benchmark levels of maintenance maturity. Such comparisons would make it possible to identify common challenges that transcend the individual facility, and to develop practical strategies that strengthen maintenance practices across the industry.

6. REFERENCES

Afolalu, S. A. et al., 2021. Evaluation of effective maintenance and reliability operation management – A review.. *E3S Web of Conferences,* Volume 309, pp. 1-9.

Ahmad, R. & Kamaruddin, S., 2012. An overview of time-based and condition-based maintenance in industrial application. *Computers & Industrial Engineering,* 63(1), pp. 135-149.

Ahuja, I. & Khamba, J., 2008. Total productive maintenance: Literature review and directions. *International Journal of Quality & Reliability,* 25(7), pp. 709-747.

Ahuja, I. P. S. & Khamba, J. S., 2008. Total productive maintenance: Literature review and directions. 25(7), pp. 709-747.

Aljumaili, M. & AL-Chalabi, H., 2016. Data Quality of Maintenance Data: A Case Study in Maximo CMMS. pp. 1-7.

Alsyouf, I., 2007. The role of maintenance in improving companies' productivity and profitability. *International Journal of Production Economics,* 105(1), pp. 70-78.

Al-Turki, U. M., 2011. A framework for strategic planning in maintenance. *Journal of Quality in Maintenance Engineering,* 17(2), pp. 150-162.

Baglee, D. & Knowles, M., 2010. Maintenance strategy development within SMEs: the development of an integrated approach. *Control and Cybernetics,* 39(1), p. 276–303.

Behzadian, M., Otaghsara, S., Yazdani, M. & Ignatius, J., 2012. A state-of the-art survey of TOPSIS applications. *Expert Systems with Applications,* 39(17), p. 13051–13069.

Belyi, D., Popova, E., Morton, D. P. & Damien, P., 2017. Bayesian failure-rate modeling and preventive maintenance optimization. *European Journal of Operational Research,* 262(3), p. 1085–1093.

Bengtsson, M., Fridholm, V. & Salonen, A., 2020. The Possibilities of Improving Maintenance Through CMMS Data Analysis. *IOS Press,* 13(1), pp. 249 -259.

Bowles, J., 2002. Commentary – Caution: Constant failure-rate models may be hazardous to your design. *IEEE Transactions on Reliability,* 51(3), p. 375–377.

Campbell, J. & Reyes-Picknell, J., 2015. *Uptime: Strategies for Excellence in Maintenance Management.* 3rd ed. Boca Raton: CRC Press.

Cao, Y., Liu, S., Fang, Z. & & Dong, W., 2020. Reliability Allocation for Series-Parallel Systems subject to Potential Propagated Failures. *Quality and Reliability Engineering International,* 36(2), pp. 565-576.

Carnero, M., Martínez-Corral, A. & Cárcel-Carrasco, J., 2023. Fuzzy multicriteria evaluation and trends of asset management performance: A case study of Spanish buildings. *Case Studies in Construction Materials,* Volume 19, pp. 1-34.

Carvalho, T. et al., 2019. A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering,* Volume 137, pp. 1-10.

Coleman, D. C., 1956. Industrial Growth and Industrial Revolutions. *Economica,* 23(89), pp. 1-22.

Cooke, R. & Paulsen, J., 1997. Concepts for Measuring Maintenance Performance and Methods For nalysing Competing Failure Modes. Reliability Engineering and System Safety. 5(2), pp. 135 - 141.

Cooper, D. & Schindler, P., 2014. *Business research methods. 12th ed. New York: McGraw-Hill Education.* 12th ed. New York:: McGraw Hill Education.

Crespo Marquez, A. & Iung, B., 2008. A review of e-maintenance capabilities and challenges. *Journal of Systemics Cybernetics and Informatics,* 6(1), pp. 1-5.

Creswell, J. & Creswell, J., 2018. *Research design: Qualitative, quantitative, and mixed methods approaches.* 5th ed. Thousand Oaks: SAGE Publications.

Dalle, M. L. & Davenport, T., 2017. What's Your Data Strategy?. *Harvard Business Review,* 95(3), p. 112–121.

Dhillon, B. S., 2006. *Maintainability, Maintenance, and Reliability for Engineers.* 1st ed. Boca Raton: CRC Press Taylor & Francis Group.

Di Luozzo, S., Starnoni, F. & Schiraldi, M. M., 2023. On the relationship between human factor and overall equipment effectiveness (OEE): An analysis through the adoption of analytic hierarchy process and ISO 22400. *International Journal of Engineering,* 15(2), pp. 1-13.

Diez-Olivan, A., Ser, J. D., Galar, D. & Sierra, B., 2019. Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0. *Information Fusion,* Volume 50, pp. 92-111.

Dumitru, R., Genkin, D., Wabnitz, A. & Yarom, Y., 2022. The Impostor Among US(B): Off-Path Injection Attacks on USB Communications. *ArXiv,* pp. 1-18.

Efthymiou, K., Papakostas, N., Mourtzis, D. & Chryssolouris, G., 2012. On a Predictive Maintenance Platform for Production Systems. *Procedia CIRP,* 3(12), pp. 221-226.

García, F. J. Á. & Salgado, D. R., 2022. Analysis of the Influence of Component Type and Operating Condition on the Selection of Preventive Maintenance Strategy in Multistage Industrial Machines: A Case Study. *Machines,* 10(5), pp. 1-18.

Garg, A. & Deshmukh, S., 2006. Maintenance management: literature review and directions. *Journal of Quality in Maintenance Engineering,* 12(3), pp. 205-238.

Gawde, S. et al., 2023. Multi-fault diagnosis of Industrial Rotating Machines using Data-driven approach : A review of two decades of research. *Engineering Applications of Artificial Intelligence,* Volume 123, pp. 1-39.

GrabCAD, 2025. *Finger Joint Automatic Machine.* [Online]
Available at: https://grabcad.com/library/finger-joint-automatic-machine-1
[Accessed 17 August 2025].

Hipkin, I., 1993. A comparison of two maintenance strategies: reliability-centred maintenance and total productive maintenance. *S.-Afr.Tydskr.Bedryfsl,* 24(4), pp. 124-129.

Hoffmann, M. & Lasch, R., 2025. Unlocking the Potential of Predictive Maintenance for Intelligent Manufacturing: a Case Study On Potentials, Barriers, and Critical Success Factors. *Schmalenbach Journal of Business Research,* Volume 77, pp. 27-55.

Hoseinie, S. H., Al-Chalabi, H. & Ghodrati, B., 2018. Comparison between Simulation and Analytical Methods in Reliability Data Analysis: A Case Study on Face Drilling Rigs. *Data,* 3(2), pp. 1-12.

Institute Swedish Standards, 2017. *SS-EN 13306:2017 Maintenance – Maintenance terminology,* Stockholm: Swedish Standards Institute.

International Organization for Standardization, 2014. *ISO 55000:2014 – Asset management – Overview, principles and terminology,* Geneva: ISO.

Ivanov, V., Evtuhov, A., Dehtiarov, I. & Trojanowska, J., 2025. Overview of Manufacturing. In: Fundamentals of Manufacturing Engineering Using Digital Visualization. In: *Springer Tracts in Mechanical Engineering.* s.l.:Springer, Cham, pp. 15-35.

Jooste, J., 2007. maintenance performance in the south african industry. *The South African Journal of Industrial Engineering,* 18(1), p. 117–133.

Kirubakaran, B., Ilangkumaran, M. & Karthikeyan, M., 2016. Maintenance Strategy Evaluation Based On AHP – TOPSIS. *Journal of Advances in Chemistry,* 1(1), pp. 5744-5750.

Klutke, G.-A., Kiessler, P. C. & Wortman, M. A., 2003. A Critical Look at the Bathtub Curve. *IEEE Transactions on Reliability,* 52(1), pp. 125-129.

Labib, A., 2004. A decision analysis model for maintenance policy selection using a CMMS. *Journal of Quality in Maintenance Engineering,* 10(3), p. 191–202.

Leedy, P. & Ormrod, J., 2015. *Practical research: Planning and design.* 11th ed. Boston: Pearson.

Leung, L., 2015. Validity, reliability, and generalizability in qualitative research. *Journal of Family Medicine and Primary Care,* 4(3), pp. 324-327.

Lopesa, I. et al., 2016. Requirements specification of a computerized maintenance management system – a case study. *Procedia CIRP,* 52(1), pp. 269 -273.

Lynne, C., 2012. Correlations. *Medsurg nursing: official journal of the Academy of Medical-Surgical Nurses,* 21(3), pp. 171-172.

Mahabir, R. & Fai Pun, K., 2022. *Improving CMMS-integrated Equipment Reliability and Availability with the IS0 41001: 2018 Standard Compliance at an Industrial Organisation: A Case Study.* University of the West Indies, St Augustine, Trinidad and Tobago, The University of the West Indies.

Masuadi E, et al., 2021. Trends in the Usage of Statistical Software and Their Associated Study Designs in Health Sciences Research: A Bibliometric Analysis. *Cureus,* 13(1), pp. 1-7.

Mirka , K., 2009. The advancement of maintenance information technology A literature review. *Journal of Quality in Maintenance Engineering,* 15(1), pp. 5-16.

Mobley, R. K., 2002. *An Introduction to Predictive Maintenance.* 2nd ed. Amsterdam: Elsevier Inc.

Moubray, J., 1997. *Reliability-Centered Maintenance.* 2nd ed. New York: Industrial Press Inc.

Muchiri, P., Pintelon, L., Gelders, L. & Martin, H., 2011. Development of maintenance function performance measurement framework and indicators. *International Journal of Production Economics,* 131(1), p. 295–302.

Mullin, A., 1989. *The application of information technology to asset preservation in Ford of Europe.* London, IET.

Nakajima, S., 1988. *Introduction to TPM: Total Productive Maintenance.* 1st ed. Portland: Productivity Press.

Nazanin, P. & Farzad, Y., 2020. Industry Revolutions Development from Industry 1.0 to Industry 5.0 in In manufacturing. *Journal of Industrial Strategic Management,* 2(5), pp. 44-63.

Nowakowski, T., Agnieszka, T. & Sylwia, W.-W., 2019. Evolution of Technical Systems Maintenance Approaches – Review and a Case Study. In: A. Burduk, E. Chlebus, T. Nowakowski & A. Tubis, eds. *Intelligent Systems in Production Engineering and Maintenance.* cham: Springer, pp. 169 -181.

Nowlan, F. S. & Heap, H. F., 1978. *Reliability Cetred Maintenance.* 1 ed. california: United Airlines.

Ocheni, E. S., Nwabueze, M. O., Egbelana, S. O. & Alade, B., 2024. Big Data for Predictive Maintenance in Industry 4.0: Enhancing Operational Efficiency and Equipment Reliability. *International Journal of Computer Applications Technology and Research,* 13(10), pp. 37-51.

Pareto, V., 1897. The New Theories of Economics. *Journal of Political Economy,* 5(4), p. 485–502.

Parida, A. & Kumar, U., 2006. Maintenance performance measurement (MPM): issues and challenges. *Journal of Quality in Maintenance Engineering,* 12(3), pp. 239-251.

Piqueras, R. & Fernandez-Crehuet, M. J., 2020. Data Analysis for the Preventive Maintenance of Machinery. *Studies in Engineering and Technology,* 7(1), pp. 1-8.

Poor, P., Zenisek, D. & Basl, J., 2019. *Historical Overview of Maintenance Management Strategies: Development from Breakdown Maintenance to Predictive Maintenance in Accordance with Four Industrial Revolutions.* Pilsen, Czech Republic, IEOM Society International, pp. 495-500.

Prasanta, K. D., 2004. Decision Support System for Inspection and Maintenance: A Case Study of Oil Pipelines. *ieee transactions on engineering management,* 51(1), pp. 47-56.

Rambe, P. & Bester, J., 2020. Using historical data to explore transactional data quality of an African power generation company. *South African Journal of Information Management,* 22(1), pp. 1-12.

Rastegari, A., 2017. *Condition Based Maintenance in the Manufacturing Industry: From Strategy to Implemetnation,* Västerås: Mälardalen University Press Dissertations, Mälardalen University.

Rojas, L., Peña, Á. & Garcia, J., 2025. AI-Driven Predictive Maintenance in Mining: A Systematic Literature Review on Fault Detection, Digital Twins, and Intelligent Asset Management. *Applied Sciences ,* 15(6), pp. 1-36.

Ross, S. M., 2020. *Introduction to Probability and Statistics for Engineers and Scientists.* 6th ed. Los Angeles: Elsevier Inc..

Saaty, T. & Vargas, L. G., 2012. *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process.* 2nd ed. New York: Springer.

Sala, R., Pirola, F., Pezzotta, G. & Cavalieri, S., 2022. Data-Driven Decision Making in Maintenance Service Delivery Process: A Case Study. *Applied sciences,* 12(15), pp. 1-17.

Saunders, M., Lewis, P. & Thornhill, A., 2019. *Research methods for business students.* 8th ed. Harlow: Pearson Education Limited.

Suzuki, T., 1994. *TPM In Process Industries.* 1 ed. New York: Taylor & Francis Group.

Thomas, D. & Weiss, B., 2021. Maintenance Costs and Advanced Maintenance Techniques in Manufacturing Machinery: Survey and Analysis. *International Journal of Prognostics and Health Management,* 12(1), pp. 1-29.

Thomas, D. & Weiss, B., 2021. Maintenance Costs and Advanced Maintenance Techniques in Manufacturing Machinery: Survey and Analysis.. *Int J Progn Health Manag,* 12(1), pp. 1-29.

Tretten, P. & Karim, R., 2014. Enhancing the usability of maintenance data management systems. *Journal of Quality in Maintenance Engineering,* 20(3), pp. 290-303.

Ucar, A., Karakose, M. & Kırımça, N., 2024. Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends. *Applied Sciences,* 14(2), pp. 1-40.

Van De Ginste, L., Aghezzaf, E. & Cottyn, J., 2022. The role of equipment flexibility in Overall Equipment Effectiveness (OEE)-driven process improvement.. *Procedia CIRP,* Volume 107, pp. 289-294.

Varshney, A. K. et al., 2024. The Development of Manufacturing Industry Revolutions from 1.0 to 5.0. *Journal of Informatics Education and Research,* 4(1), pp. 1230-1242.

Wahid, J., Abdullah, A. & Salleh, B., 2021. Proving Into Urban Linkage Theory: The Case Study of India Street, Kuching, Sarawak. *International Journal of Social Science Research,* 3(3), pp. 30-40.

Wilkins, D., 2002. The bathtub curve and product failure behaviour: Part 1 – The bathtub curve, infant-mortality and burn-in. *Reliability HotWire,* Issue 21.

Wilmeth, R. G., Energy, X. & Usrey, M. W., 2020. reliability-centered maintenance: a case study. *Engineering Management Journal,* 12(4), pp. 25 - 30.

Wireman, T., 2004. *Total Productive Maintenance.* 2nd ed. New York: Industrial Press.

Wireman, T., 2015. Benchmarking Fundamentals. In: 3rd, ed. *Benchmarking Best Practices for Maintenance, Reliability and Asset Management: Updated for ISO 55000.* New York: Industrial Press, pp. 80-81,93-95.

Zenduty, 2024. *MTBF, MTTR, MTTF, MTTA: Incident Metrics Explained.* [Online]
Available at: https://zenduty.com/blog/mtbf-mttr-mttf-mtta-incident-metrics-explained/
[Accessed 21 October 2025].

Zonta, T. et al., 2020. Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering,* Volume 150, pp. 1-17.

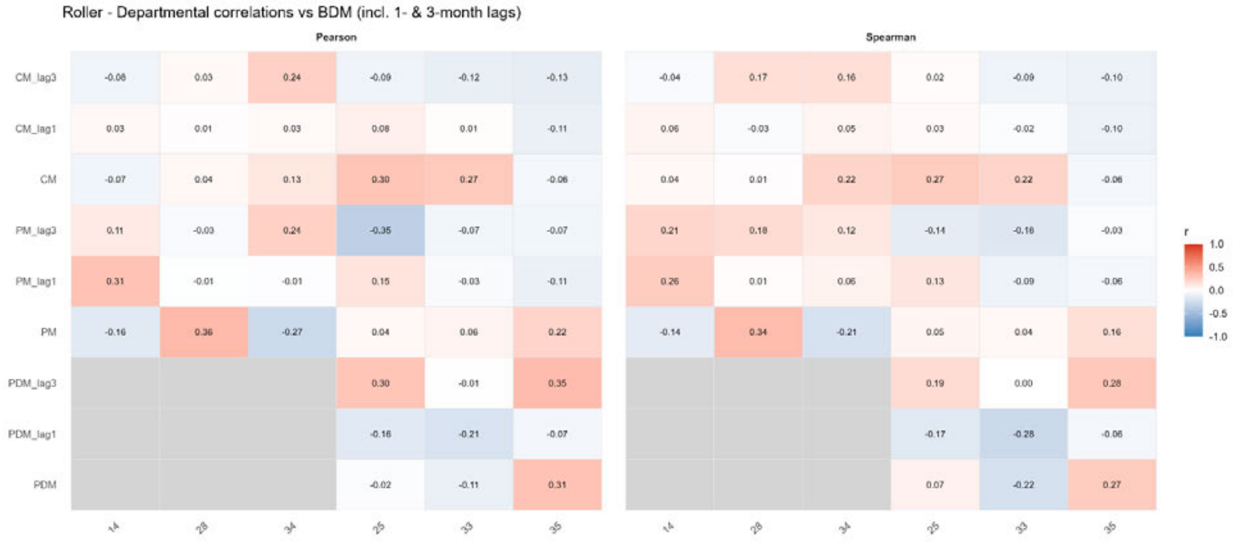
7. APPENDIX A

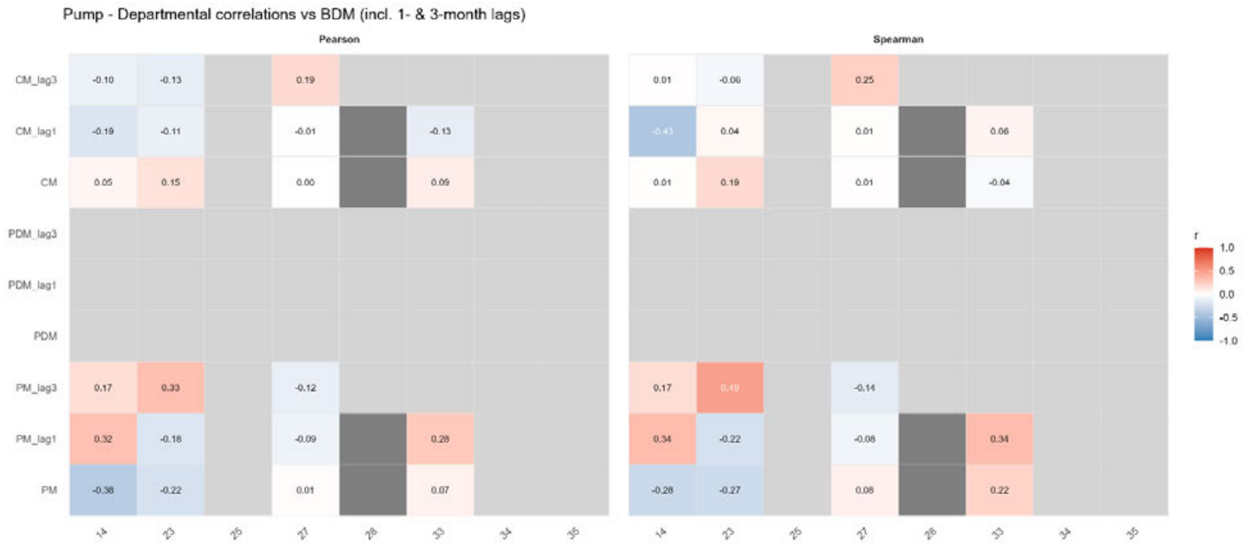
Location Data Extraction Template				
location id	description	type	status	site id

Work order Data Extraction Template														
work order number	asset number	work order description	location id	work order status	Craft	schedule finish date	schedule start date	actual finish date	actual labour cost	actual labour hours	actual start date	target start date	reported date	work type

Feedback Data Extraction Template			
work order number	workorder description	Summary feedback	Detailed feedback

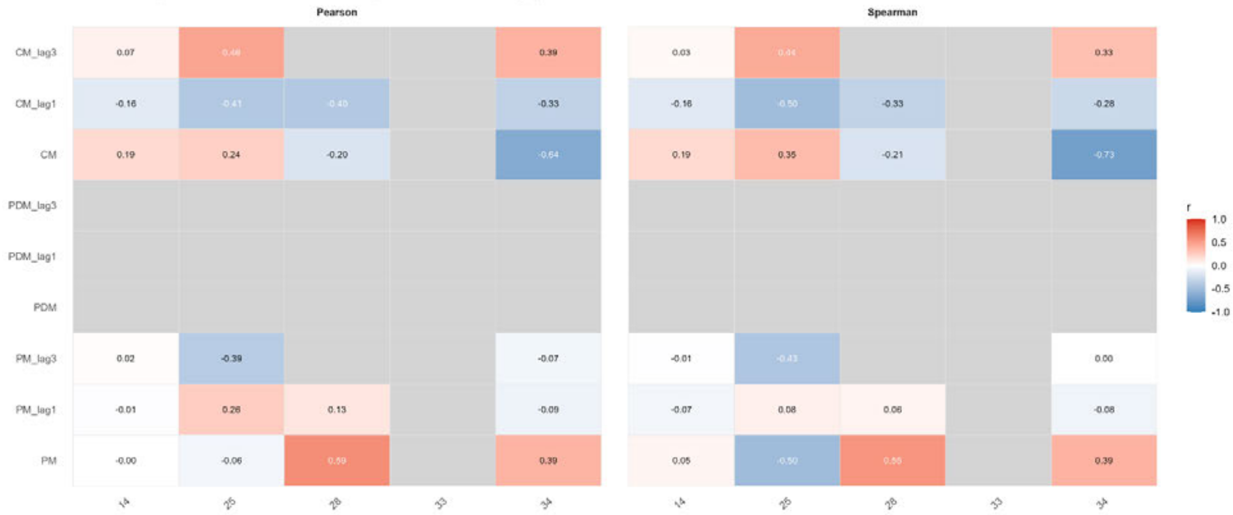
8. APPENDIX B


Roller - Departmental correlations vs BDM (incl. 1- & 3-month lags)
Pearson
Spearman

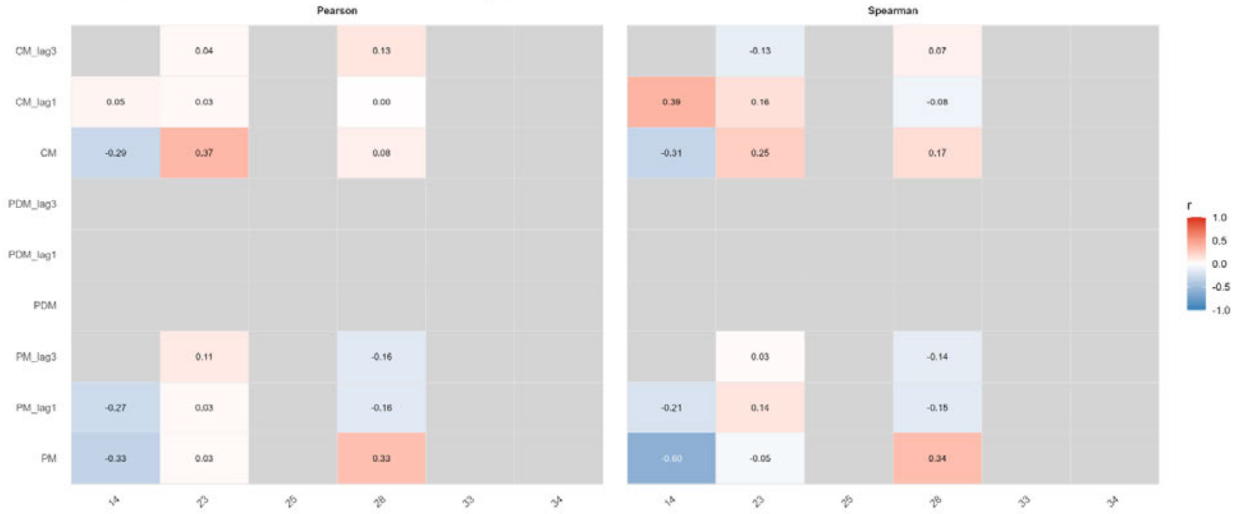

Pump - Departmental correlations vs BDM (incl. 1- & 3-month lags)
Pearson
Spearman

Motor - Departmental correlations vs BDM (incl. 1- & 3-month lags)

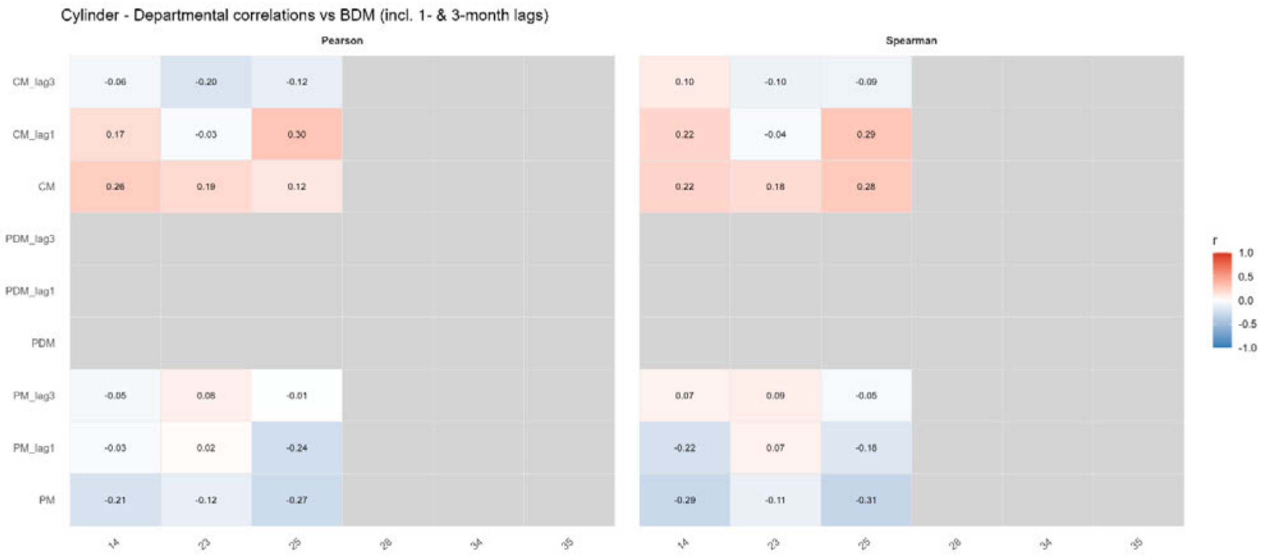
Gearbox - Departmental correlations vs BDM (incl. 1- & 3-month lags)

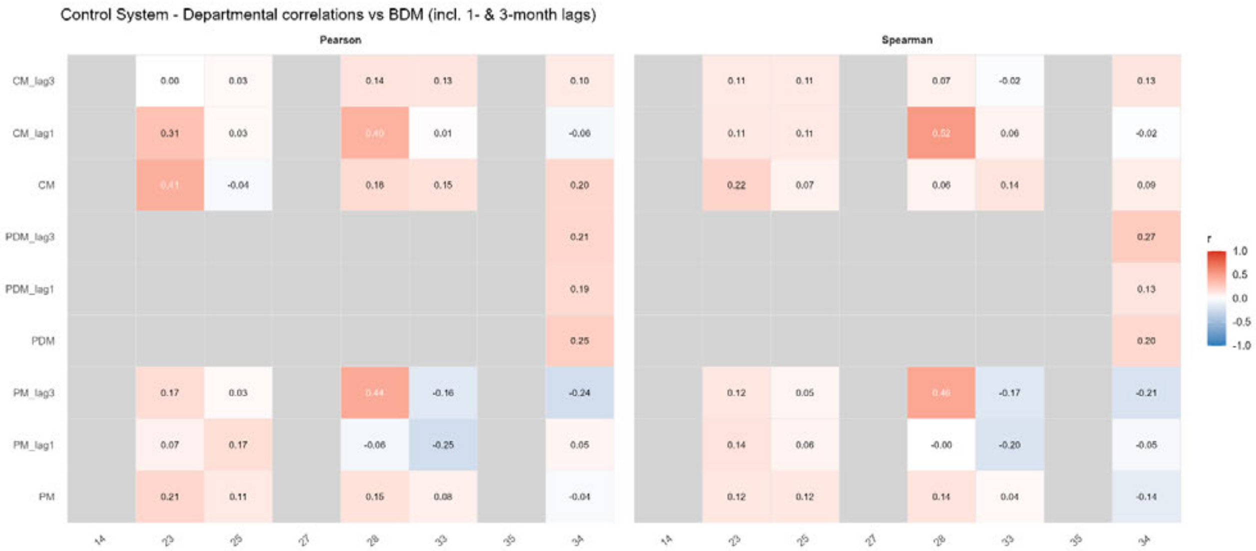


Fan - Departmental correlations vs BDM (incl. 1- & 3-month lags)



Drive - Departmental correlations vs BDM (incl. 1- & 3-month lags)


Cylinder - Departmental correlations vs BDM (incl. 1- & 3-month lags)
Pearson
Spearman
CM_lag3
CM_lag1
CM
PDM_lag3
PDM_lag1
PDM
PM_lag3
PM_lag1
PM
14
23
25
28
34
35
r
1.0
0.5
0.0
-0.5
-1.0


Control System - Departmental correlations vs BDM (incl. 1- & 3-month lags)
Pearson
Spearman
CM_lag3
CM_lag1
CM
PDM_lag3
PDM_lag1
PDM
PM_lag3
PM_lag1
PM
14
23
25
27
28
33
35
34
r
1.0
0.5
0.0
-0.5
-1.0

9. APPENDIX C

Table C-1: Departmental Regression analysis results for all assets

Entity	Model_Family	Predictor	Estimate	StdError	Stat	Pvalue
14	NegativeBinomial	CM	0.121	0.014	8.412	0.000
23	NegativeBinomial	CM	0.076	0.008	10.034	0.000
25	NegativeBinomial	CM	0.078	0.009	8.534	0.000
27	NegativeBinomial	CM	0.022	0.012	1.802	0.072
28	NegativeBinomial	CM	0.100	0.009	10.734	0.000
33	NegativeBinomial	CM	0.143	0.012	12.414	0.000
34	NegativeBinomial	CM	0.148	0.012	12.592	0.000
35	NegativeBinomial	CM	0.026	0.021	1.277	0.202
14	NegativeBinomial	CM_Delay	0.001	0.001	2.761	0.006
23	NegativeBinomial	CM_Delay	0.000	0.001	0.269	0.788
25	NegativeBinomial	CM_Delay	0.000	0.000	1.078	0.281
27	NegativeBinomial	CM_Delay	-0.001	0.001	-1.532	0.125
28	NegativeBinomial	CM_Delay	0.001	0.000	1.896	0.058
33	NegativeBinomial	CM_Delay	0.000	0.000	-1.037	0.300
34	NegativeBinomial	CM_Delay	0.000	0.000	1.228	0.219
35	NegativeBinomial	CM_Delay	0.001	0.001	1.504	0.132
14	NegativeBinomial	CM_Delay_lag1	0.001	0.001	2.381	0.017
23	NegativeBinomial	CM_Delay_lag1	0.001	0.001	1.247	0.212
25	NegativeBinomial	CM_Delay_lag1	0.001	0.000	3.048	0.002
27	NegativeBinomial	CM_Delay_lag1	0.002	0.001	2.512	0.012
28	NegativeBinomial	CM_Delay_lag1	0.001	0.000	2.961	0.003
33	NegativeBinomial	CM_Delay_lag1	0.001	0.000	1.916	0.055
34	NegativeBinomial	CM_Delay_lag1	0.001	0.000	1.427	0.153
35	NegativeBinomial	CM_Delay_lag1	0.002	0.001	2.865	0.004
14	NegativeBinomial	CM_Delay_lag3	0.001	0.001	2.655	0.008
23	NegativeBinomial	CM_Delay_lag3	0.001	0.001	1.303	0.192
25	NegativeBinomial	CM_Delay_lag3	0.002	0.000	6.174	0.000
27	NegativeBinomial	CM_Delay_lag3	0.004	0.001	4.341	0.000
28	NegativeBinomial	CM_Delay_lag3	0.002	0.000	3.540	0.000
33	NegativeBinomial	CM_Delay_lag3	0.000	0.000	-0.059	0.953
34	NegativeBinomial	CM_Delay_lag3	0.001	0.000	1.793	0.073
35	NegativeBinomial	CM_Delay_lag3	0.002	0.001	2.139	0.032
14	NegativeBinomial	CM_lag1	0.075	0.015	5.171	0.000
23	NegativeBinomial	CM_lag1	0.033	0.008	4.235	0.000
25	NegativeBinomial	CM_lag1	0.024	0.009	2.508	0.012
27	NegativeBinomial	CM_lag1	-0.003	0.012	-0.212	0.832
28	NegativeBinomial	CM_lag1	0.072	0.009	7.687	0.000
33	NegativeBinomial	CM_lag1	0.071	0.012	5.906	0.000
34	NegativeBinomial	CM_lag1	0.103	0.012	8.561	0.000
35	NegativeBinomial	CM_lag1	0.013	0.021	0.631	0.528
14	NegativeBinomial	CM_lag3	0.088	0.014	6.451	0.000
23	NegativeBinomial	CM_lag3	0.033	0.008	4.134	0.000

25	NegativeBinomial	CM_lag3	0.003	0.009	0.362	0.717
27	NegativeBinomial	CM_lag3	0.005	0.013	0.384	0.701
28	NegativeBinomial	CM_lag3	0.078	0.009	8.236	0.000
33	NegativeBinomial	CM_lag3	0.039	0.011	3.405	0.001
34	NegativeBinomial	CM_lag3	0.094	0.011	8.400	0.000
35	NegativeBinomial	CM_lag3	0.002	0.022	0.108	0.914
14	NegativeBinomial	PDM	-0.160	0.088	-1.812	0.070
23	NegativeBinomial	PDM	0.030	0.437	0.068	0.946
25	NegativeBinomial	PDM	0.046	0.023	1.983	0.047
27	NegativeBinomial	PDM	0.055	0.130	0.419	0.675
28	NegativeBinomial	PDM	-0.016	0.054	-0.289	0.773
33	NegativeBinomial	PDM	0.010	0.018	0.561	0.575
34	NegativeBinomial	PDM	-0.011	0.074	-0.151	0.880
35	NegativeBinomial	PDM	0.046	0.054	0.854	0.393
14	NegativeBinomial	PDM_lag1	-0.150	0.092	-1.629	0.103
23	NegativeBinomial	PDM_lag1	0.136	0.439	0.309	0.757
25	NegativeBinomial	PDM_lag1	0.033	0.023	1.424	0.155
27	NegativeBinomial	PDM_lag1	-0.224	0.135	-1.656	0.098
28	NegativeBinomial	PDM_lag1	-0.416	0.084	-4.941	0.000
33	NegativeBinomial	PDM_lag1	-0.005	0.018	-0.271	0.787
34	NegativeBinomial	PDM_lag1	-0.130	0.076	-1.712	0.087
35	NegativeBinomial	PDM_lag1	-0.061	0.060	-1.015	0.310
14	NegativeBinomial	PDM_lag3	-0.037	0.089	-0.416	0.677
23	NegativeBinomial	PDM_lag3	-0.360	0.520	-0.693	0.488
25	NegativeBinomial	PDM_lag3	0.040	0.024	1.664	0.096
27	NegativeBinomial	PDM_lag3	-0.371	0.136	-2.726	0.006
28	NegativeBinomial	PDM_lag3	-0.147	0.074	-1.984	0.047
33	NegativeBinomial	PDM_lag3	-0.009	0.018	-0.512	0.609
34	NegativeBinomial	PDM_lag3	-0.027	0.075	-0.356	0.722
35	NegativeBinomial	PDM_lag3	0.029	0.053	0.549	0.583
14	NegativeBinomial	PM	0.013	0.007	1.922	0.055
23	NegativeBinomial	PM	0.030	0.007	4.602	0.000
25	NegativeBinomial	PM	0.020	0.008	2.496	0.013
27	NegativeBinomial	PM	0.029	0.008	3.878	0.000
28	NegativeBinomial	PM	0.021	0.008	2.630	0.009
33	NegativeBinomial	PM	0.040	0.007	5.540	0.000
34	NegativeBinomial	PM	0.008	0.009	0.924	0.356
35	NegativeBinomial	PM	0.024	0.008	3.114	0.002
14	NegativeBinomial	PM_lag1	-0.008	0.008	-1.017	0.309
23	NegativeBinomial	PM_lag1	0.003	0.008	0.387	0.699
25	NegativeBinomial	PM_lag1	0.001	0.008	0.137	0.891
27	NegativeBinomial	PM_lag1	0.013	0.008	1.755	0.079
28	NegativeBinomial	PM_lag1	-0.006	0.010	-0.585	0.559
33	NegativeBinomial	PM_lag1	-0.009	0.008	-1.160	0.246
34	NegativeBinomial	PM_lag1	-0.007	0.012	-0.553	0.580
35	NegativeBinomial	PM_lag1	0.008	0.008	0.944	0.345

14	NegativeBinomial	PM_lag3	-0.016	0.006	-2.537	0.011
23	NegativeBinomial	PM_lag3	-0.026	0.007	-3.501	0.000
25	NegativeBinomial	PM_lag3	-0.017	0.008	-2.180	0.029
27	NegativeBinomial	PM_lag3	0.001	0.008	0.177	0.860
28	NegativeBinomial	PM_lag3	-0.010	0.006	-1.645	0.100
33	NegativeBinomial	PM_lag3	-0.032	0.007	-4.861	0.000
34	NegativeBinomial	PM_lag3	-0.021	0.011	-1.868	0.062
35	NegativeBinomial	PM_lag3	-0.019	0.009	-2.080	0.038
14	NegativeBinomial	Proactive_Delay	-0.002	0.002	-1.256	0.209
23	NegativeBinomial	Proactive_Delay	-0.003	0.001	-3.153	0.002
25	NegativeBinomial	Proactive_Delay	0.001	0.001	1.013	0.311
27	NegativeBinomial	Proactive_Delay	0.000	0.001	-0.363	0.717
28	NegativeBinomial	Proactive_Delay	0.001	0.001	1.073	0.283
33	NegativeBinomial	Proactive_Delay	0.000	0.001	-0.160	0.873
34	NegativeBinomial	Proactive_Delay	-0.002	0.001	-1.579	0.114
35	NegativeBinomial	Proactive_Delay	0.001	0.001	0.532	0.595
14	NegativeBinomial	Proactive_Delay_lag1	-0.003	0.002	-1.624	0.104
23	NegativeBinomial	Proactive_Delay_lag1	-0.001	0.001	-0.542	0.588
25	NegativeBinomial	Proactive_Delay_lag1	0.001	0.001	1.522	0.128
27	NegativeBinomial	Proactive_Delay_lag1	0.003	0.001	1.850	0.064
28	NegativeBinomial	Proactive_Delay_lag1	0.002	0.001	2.081	0.037
33	NegativeBinomial	Proactive_Delay_lag1	-0.001	0.001	-1.002	0.317
34	NegativeBinomial	Proactive_Delay_lag1	0.000	0.001	0.261	0.794
35	NegativeBinomial	Proactive_Delay_lag1	0.001	0.001	1.209	0.227
14	NegativeBinomial	Proactive_Delay_lag3	-0.001	0.002	-0.732	0.464
23	NegativeBinomial	Proactive_Delay_lag3	0.000	0.001	0.081	0.935
25	NegativeBinomial	Proactive_Delay_lag3	0.003	0.001	3.678	0.000
27	NegativeBinomial	Proactive_Delay_lag3	0.002	0.001	1.371	0.170
28	NegativeBinomial	Proactive_Delay_lag3	0.001	0.001	0.953	0.340
33	NegativeBinomial	Proactive_Delay_lag3	0.000	0.001	-0.162	0.871
34	NegativeBinomial	Proactive_Delay_lag3	-0.001	0.001	-0.888	0.375
35	NegativeBinomial	Proactive_Delay_lag3	0.001	0.001	0.527	0.598

Table C-2: Departmental regression analysis results for top 8 assets

Entity	Model_Family	Predictor	Estimate	StdError	Stat	Pvalue
14	NegativeBinomial	CM	0.134	0.026	5.218	0.000
23	NegativeBinomial	CM	0.051	0.011	4.441	0.000
25	NegativeBinomial	CM	0.014	0.012	1.190	0.234
27	NegativeBinomial	CM	0.025	0.033	0.750	0.453
28	Poisson	CM	0.036	0.012	2.893	0.004
33	NegativeBinomial	CM	0.054	0.010	5.673	0.000
34	NegativeBinomial	CM	0.108	0.017	6.304	0.000
35	Poisson	CM	0.052	0.024	2.202	0.028
14	NegativeBinomial	CM_Delay	0.001	0.000	1.350	0.177
23	NegativeBinomial	CM_Delay	-0.001	0.001	-0.654	0.513
25	NegativeBinomial	CM_Delay	-0.001	0.000	-1.590	0.112
27	NegativeBinomial	CM_Delay	-0.003	0.002	-1.497	0.134
28	Poisson	CM_Delay	0.000	0.000	0.243	0.808
33	NegativeBinomial	CM_Delay	-0.002	0.001	-2.524	0.012
34	NegativeBinomial	CM_Delay	0.000	0.001	0.322	0.748
35	Poisson	CM_Delay	-0.002	0.001	-1.555	0.120
14	NegativeBinomial	CM_Delay_lag1	0.000	0.001	0.339	0.735
23	NegativeBinomial	CM_Delay_lag1	0.000	0.001	0.251	0.802
25	NegativeBinomial	CM_Delay_lag1	-0.001	0.001	-1.713	0.087
27	NegativeBinomial	CM_Delay_lag1	-0.001	0.002	-0.337	0.736
28	Poisson	CM_Delay_lag1	0.000	0.001	0.323	0.747
33	NegativeBinomial	CM_Delay_lag1	0.000	0.001	0.177	0.860
34	NegativeBinomial	CM_Delay_lag1	0.000	0.001	0.421	0.674
35	Poisson	CM_Delay_lag1	-0.001	0.001	-0.845	0.398
14	NegativeBinomial	CM_Delay_lag3	-0.001	0.001	-1.088	0.276
23	NegativeBinomial	CM_Delay_lag3	0.000	0.001	0.286	0.775
25	NegativeBinomial	CM_Delay_lag3	0.000	0.001	-0.704	0.481
27	NegativeBinomial	CM_Delay_lag3	0.002	0.001	1.310	0.190
28	Poisson	CM_Delay_lag3	0.000	0.001	-0.166	0.868
33	NegativeBinomial	CM_Delay_lag3	-0.001	0.001	-1.653	0.098
34	NegativeBinomial	CM_Delay_lag3	0.002	0.001	2.636	0.008
35	Poisson	CM_Delay_lag3	0.000	0.001	-0.389	0.698
14	NegativeBinomial	CM_lag1	0.067	0.026	2.608	0.009
23	NegativeBinomial	CM_lag1	0.006	0.012	0.466	0.641
25	NegativeBinomial	CM_lag1	0.023	0.012	1.927	0.054
27	NegativeBinomial	CM_lag1	0.046	0.031	1.472	0.141
28	Poisson	CM_lag1	0.033	0.012	2.720	0.007
33	NegativeBinomial	CM_lag1	0.012	0.010	1.205	0.228
34	NegativeBinomial	CM_lag1	0.062	0.017	3.630	0.000
35	Poisson	CM_lag1	0.023	0.025	0.915	0.360
14	NegativeBinomial	CM_lag3	0.094	0.024	3.885	0.000
23	NegativeBinomial	CM_lag3	-0.003	0.013	-0.208	0.835
25	NegativeBinomial	CM_lag3	-0.001	0.011	-0.115	0.908

27	NegativeBinomial	CM_lag3	0.006	0.030	0.203	0.839
28	Poisson	CM_lag3	0.026	0.012	2.124	0.034
33	NegativeBinomial	CM_lag3	0.013	0.010	1.272	0.203
34	NegativeBinomial	CM_lag3	0.056	0.016	3.412	0.001
35	Poisson	CM_lag3	0.052	0.026	2.051	0.040
14	NegativeBinomial	PDM	-0.362	0.294	-1.231	0.218
25	NegativeBinomial	PDM	0.006	0.017	0.339	0.735
27	NegativeBinomial	PDM	-29.820	1627009.791	0.000	1.000
28	Poisson	PDM	0.055	0.027	2.050	0.040
33	NegativeBinomial	PDM	0.000	0.009	0.021	0.983
34	NegativeBinomial	PDM	0.012	0.059	0.195	0.845
35	Poisson	PDM	0.124	0.053	2.318	0.020
14	NegativeBinomial	PDM_lag1	-0.208	0.293	-0.710	0.478
25	NegativeBinomial	PDM_lag1	-0.002	0.017	-0.098	0.922
27	NegativeBinomial	PDM_lag1	-29.628	1623398.738	0.000	1.000
28	Poisson	PDM_lag1	-0.653	0.269	-2.427	0.015
33	NegativeBinomial	PDM_lag1	-0.010	0.009	-1.111	0.267
34	NegativeBinomial	PDM_lag1	-0.091	0.063	-1.452	0.147
35	Poisson	PDM_lag1	-0.130	0.071	-1.821	0.069
14	NegativeBinomial	PDM_lag3	0.160	0.280	0.569	0.569
25	NegativeBinomial	PDM_lag3	0.019	0.017	1.097	0.273
27	NegativeBinomial	PDM_lag3	-29.780	2306617.091	0.000	1.000
28	Poisson	PDM_lag3	-0.036	0.057	-0.624	0.533
33	NegativeBinomial	PDM_lag3	-0.007	0.009	-0.770	0.441
34	NegativeBinomial	PDM_lag3	0.002	0.061	0.026	0.979
35	Poisson	PDM_lag3	0.158	0.054	2.925	0.003
14	NegativeBinomial	PM	0.039	0.018	2.131	0.033
23	NegativeBinomial	PM	0.003	0.009	0.333	0.739
25	NegativeBinomial	PM	0.017	0.012	1.400	0.161
27	NegativeBinomial	PM	-0.003	0.012	-0.284	0.777
28	Poisson	PM	0.038	0.010	3.899	0.000
33	NegativeBinomial	PM	0.050	0.010	5.064	0.000
34	NegativeBinomial	PM	-0.062	0.037	-1.654	0.098
35	Poisson	PM	0.070	0.015	4.578	0.000
14	NegativeBinomial	PM_lag1	0.047	0.018	2.566	0.010
23	NegativeBinomial	PM_lag1	0.002	0.011	0.200	0.841
25	NegativeBinomial	PM_lag1	0.021	0.013	1.645	0.100
27	NegativeBinomial	PM_lag1	-0.016	0.011	-1.438	0.150
28	Poisson	PM_lag1	-0.014	0.012	-1.200	0.230
33	NegativeBinomial	PM_lag1	0.004	0.010	0.415	0.678
34	NegativeBinomial	PM_lag1	-0.036	0.046	-0.783	0.433
35	Poisson	PM_lag1	0.004	0.016	0.264	0.791
14	NegativeBinomial	PM_lag3	0.012	0.019	0.605	0.545
23	NegativeBinomial	PM_lag3	-0.019	0.010	-2.002	0.045
25	NegativeBinomial	PM_lag3	-0.030	0.012	-2.473	0.013
27	NegativeBinomial	PM_lag3	0.004	0.012	0.355	0.723

28	Poisson	PM_lag3	-0.018	0.009	-1.878	0.060
33	NegativeBinomial	PM_lag3	-0.028	0.010	-2.683	0.007
34	NegativeBinomial	PM_lag3	-0.032	0.047	-0.681	0.496
35	Poisson	PM_lag3	-0.023	0.017	-1.363	0.173
14	NegativeBinomial	Proactive_Delay	-0.004	0.002	-2.129	0.033
23	NegativeBinomial	Proactive_Delay	0.002	0.002	1.263	0.206
25	NegativeBinomial	Proactive_Delay	-0.001	0.001	-0.699	0.485
27	NegativeBinomial	Proactive_Delay	0.010	0.004	2.623	0.009
28	Poisson	Proactive_Delay	0.000	0.001	-0.319	0.750
33	NegativeBinomial	Proactive_Delay	0.001	0.001	0.929	0.353
34	NegativeBinomial	Proactive_Delay	0.001	0.002	0.643	0.520
35	Poisson	Proactive_Delay	-0.001	0.002	-0.368	0.713
14	NegativeBinomial	Proactive_Delay_lag1	-0.007	0.002	-3.481	0.001
23	NegativeBinomial	Proactive_Delay_lag1	0.005	0.002	2.663	0.008
25	NegativeBinomial	Proactive_Delay_lag1	-0.001	0.002	-0.953	0.340
27	NegativeBinomial	Proactive_Delay_lag1	0.014	0.004	3.782	0.000
28	Poisson	Proactive_Delay_lag1	0.002	0.000	3.195	0.001
33	NegativeBinomial	Proactive_Delay_lag1	0.000	0.001	-0.403	0.687
34	NegativeBinomial	Proactive_Delay_lag1	0.001	0.001	0.931	0.352
35	Poisson	Proactive_Delay_lag1	0.000	0.002	0.084	0.933
14	NegativeBinomial	Proactive_Delay_lag3	-0.008	0.002	-3.562	0.000
23	NegativeBinomial	Proactive_Delay_lag3	0.007	0.002	3.774	0.000
25	NegativeBinomial	Proactive_Delay_lag3	0.001	0.001	1.068	0.285
27	NegativeBinomial	Proactive_Delay_lag3	0.001	0.004	0.142	0.887
28	Poisson	Proactive_Delay_lag3	0.000	0.001	-0.171	0.864
33	NegativeBinomial	Proactive_Delay_lag3	0.000	0.001	-0.556	0.578
34	NegativeBinomial	Proactive_Delay_lag3	-0.002	0.002	-1.183	0.237
35	Poisson	Proactive_Delay_lag3	-0.002	0.002	-0.875	0.382

10. APPENDIX D

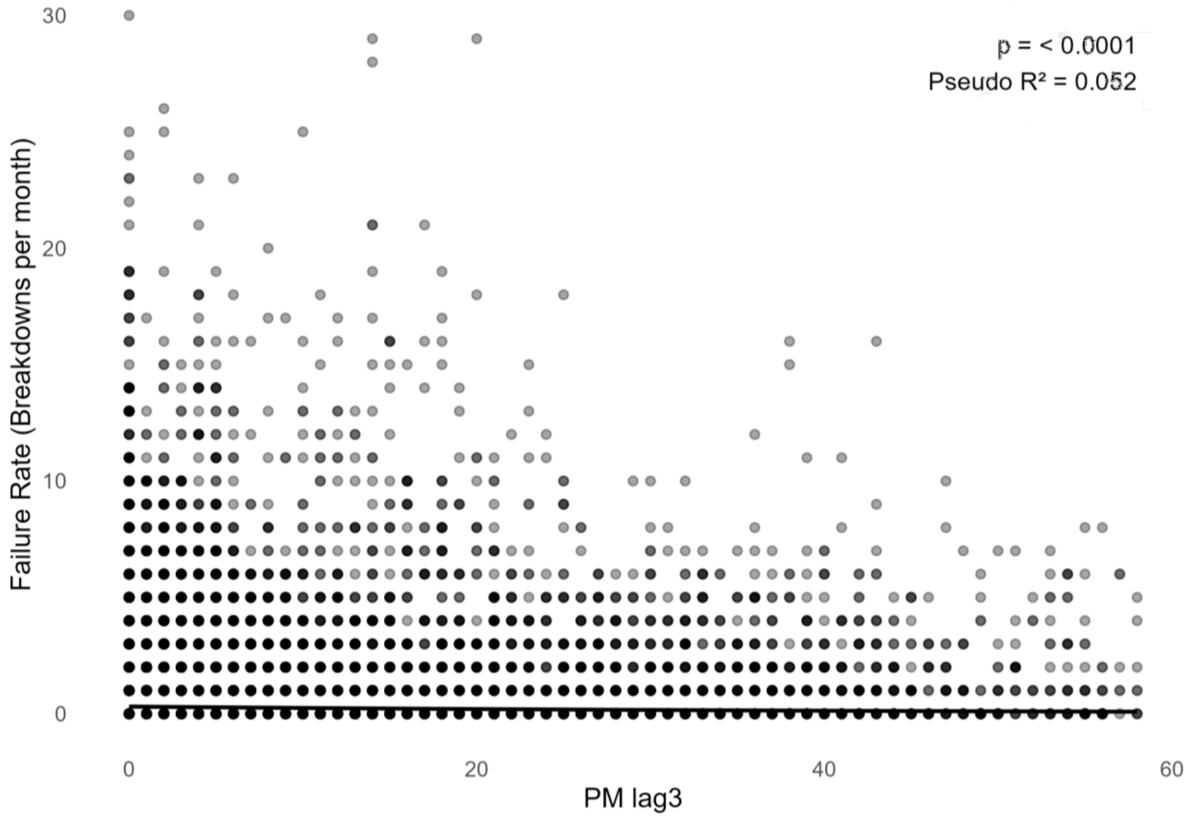


Figure D-1: All assets Regression Line Plot -PM c Failure Rate (Lagged effect t3)

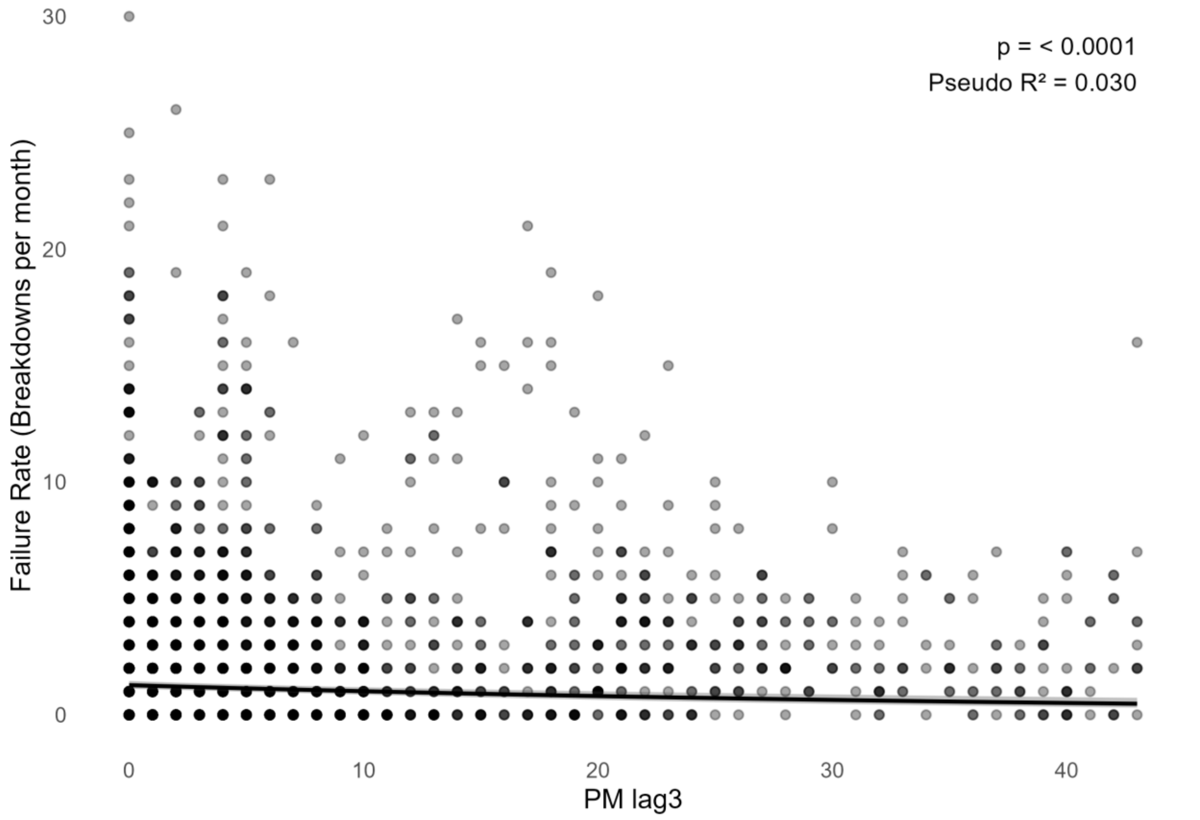


Figure D-2: Top 8 Assets Regression Line Plot -PM c Failure Rate (Lagged effect t3)

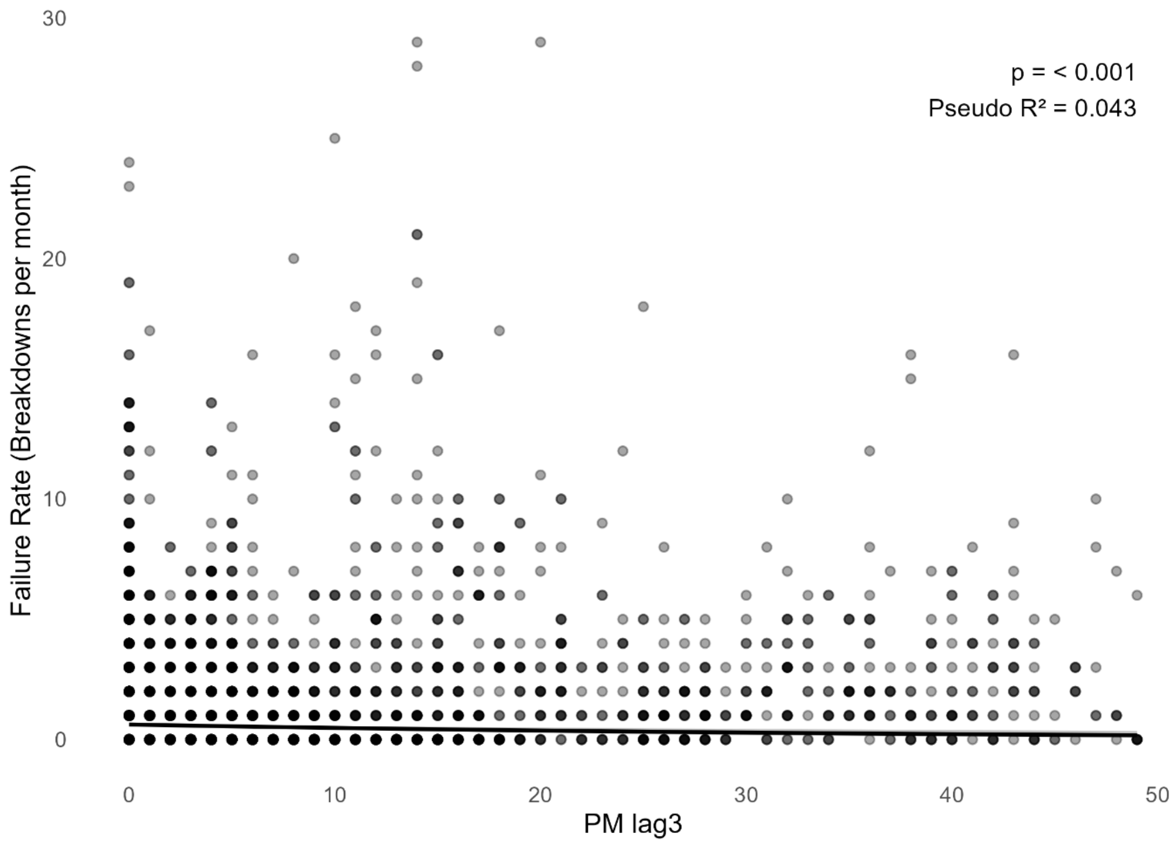


Figure D-3: Department 23 All Assets Regression Line Plot -PM vs Failure Rate (Lagged effect t3)

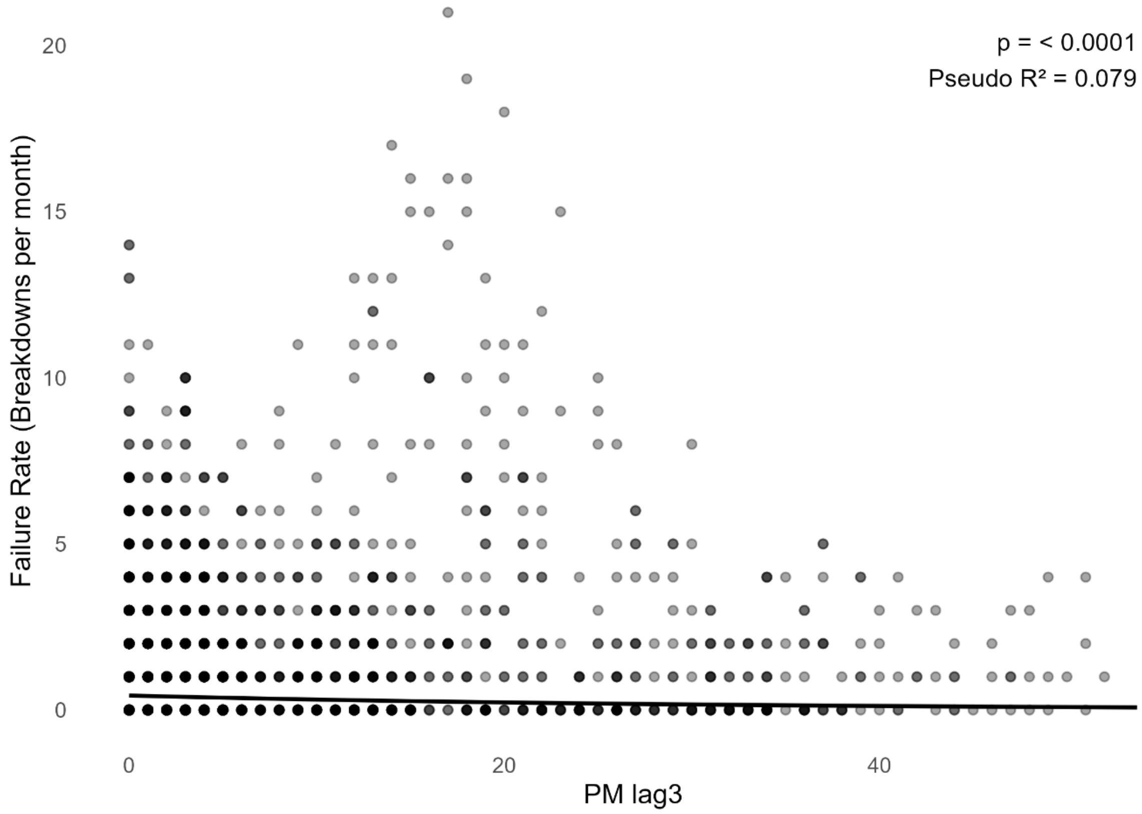


Figure D-4: Department 33 All Assets Regression Line Plot -PM vs Failure Rate (Lagged effect t3)

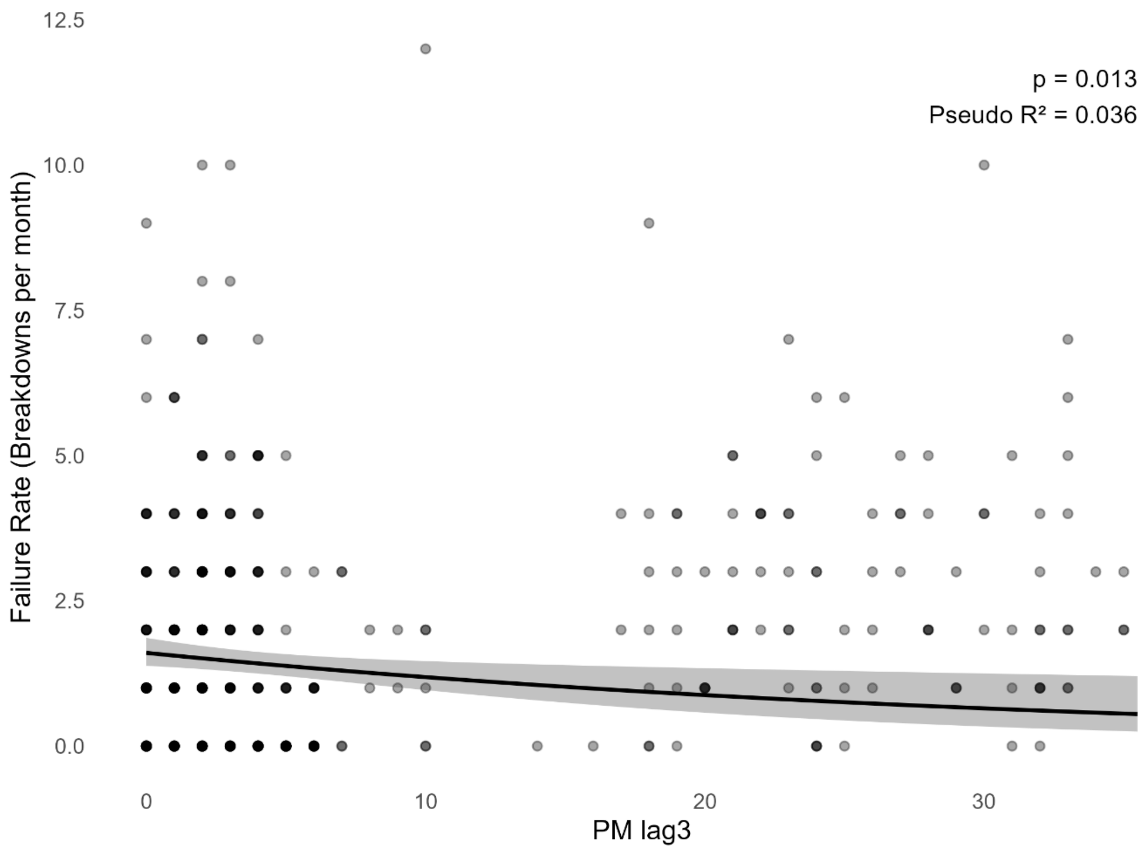


Figure D-5: Department 25 Top 8 Assets Regression Line Plot -PM vs Failure Rate (Lagged effect t3)

11. ETHICAL CLEARANCE

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

25 June 2025

Sandile Aubrey Zuma (209533270)
Grad School of Bus & Leadership
Westville Campus

Dear SA Zuma,

Protocol reference number: HSSREC/00008692/2025
Project title: Optimizing maintenance strategies Through Data-Driven Analysis: Case study of a manufacturing company in South Africa Pietermaritzburg
Degree: Masters

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 21 May 2025 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL**.

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number.

PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

Incidents of adverse events and serious adverse events (AEs and SAEs) should be reported in writing to HSSREC, the study sponsors, and any regulatory authority (where appropriate), within 7 working days of the occurrence for local sites and 14 days for all other South African sites.

This approval is valid until 25 June 2026.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

HSSREC is registered with the South African National Health Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Doctor Shamila Naidoo (Interim Chair)

/nng

Humanities and Social Sciences Research Ethics Committee
Postal Address: Private Bag X54001, Durban, 4000, South Africa
Telephone: +27 (0)31 260 8350/4557/3587 **Email:** hssrec@ukzn.ac.za **Website:** http://research.ukzn.ac.za/Research-Ethics