Designing an AI-based Predictive Maintenance Framework to Improve OEE for an Automotive Manufacturer in South Africa

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ABSTRACT

This study presents a comprehensive approach to enhancing Overall Equipment Effectiveness (OEE) in an automotive manufacturing setting by integrating artificial intelligence and Internet of Things technologies with people and processes. The research applies the Design Science Research (DSR) methodology to develop, deploy, and evaluate an AI-driven predictive maintenance framework. The first phase involves a detailed exploratory data analysis to understand the current state of OEE and identify critical bottlenecks within the production line, particularly operating below OEE industry standards. The second phase builds on the insights gathered from a semi-structured survey conducted among field experts, leading to the formulation of a cohesive framework that synergises the socio-technical aspects of the manufacturing environment. The core of the study revolves around the design and development of a Bi-directional Long Short-Term Memory (Bi-LSTM) model artefact, capable of analysing sequential data to predict the Remaining Useful Life (RUL) of machinery, thereby pre-empting production halts. The model's predictive capability is rigorously tested and validated using historical IoT data, demonstrating a high degree of accuracy across different spot-welding locations. Overall, the study highlights the critical role of AI in transforming manufacturing processes, emphasising the need for continuous adaptation and improvement of predictive models to maintain operational efficiency. The proposed framework aims to serve as a strategic tool in lean manufacturing, contributing to smoother operations and improved OEE in automotive manufacturing settings.

KEYWORDS

Automotive manufacturing, Downtime, Fault prognosis, Internet-of-Things, Knowledge-based methods, Overall equipment effectiveness, Operations Management, Predictive maintenance, Production efficiency

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4IR - 4th Industrial Revolution

AI - Artificial Intelligence

AM - Autonomous Maintenance

ANN - Artificial Neural Network

ANT - Actor-Network Theory

ARIMA - Auto-Regressive Integrated Moving Average

BI-LSTM - Bi-Directional Long Short-Term Memory

CBM - Condition-Based Maintenance

CM - Condition Monitoring

DSR - Design Science Research

EDA - Exploratory Data Analysis

FMEA - Failure Mode and Effects Analysis

GDP - Gross Domestic Product

GDPR - General Data Protection Regulation

IoT - Internet of Things

IIoT – Industrial Internet of Things

JIPM - Japanese Institute of Plant Maintenance

LSTM - Long Short-Term Memory

ML - Machine Learning

MTBF - Mean Time Before Failure

MTTR - Mean Time To Repair

OTPM - Office Total Productive Maintenance

OEE - Overall Equipment Effectiveness

OM – Operations Management

PM - Planned Maintenance

PdM - Predictive Maintenance

POPIA - Protection of Personal Information Act

QM - Quality Maintenance

RF - Random Forest

RNN - Recurrent Neural Networks

RUL - Remaining Useful Life

SHE - Safety, Health, and Environment

STS - Socio-Technical Systems

SVR - Support Vector Regression

TE - Training and Education

TBM - Time-Based Maintenance

TPM - Total Productive Maintenance

CHAPTER 1. INTRODUCTION

1.1 Introduction

This chapter introduces the foundational elements of the study, focusing on the relationship between Overall Equipment Effectiveness (OEE) and the implementation of AI-based fault prognosis techniques within the South African automotive manufacturing sector. It sets the stage for understanding how the advancements of the 4th Industrial Revolution, specifically data-driven predictive maintenance methods, can enhance OEE by improving equipment availability, performance, and quality.

The chapter begins by outlining the purpose of the study in section 1.2, followed by a detailed background of the automotive industry in South Africa and the challenges it faces in section 2.2. The research problem is discussed in section 1.4, with the research questions and objectives outlined in section 1.5, providing a comprehensive rationale for the study. Additionally, key terms are defined in section 1.6, the delimitations of the study are outlined in section 1.7, and essential terms guiding the research are presented in section 1.8. The chapter concludes with a summary of the thesis structure in section 1.9 and a conclusion in section 1.10.

1.2 Statement of purpose

The purpose of this study is to delineate the correlation between Overall Equipment Effectiveness (OEE) and data-driven fault prognosis techniques derived from the advancements of the 4th Industrial Revolution. The study seeks to ascertain the influential factors that contribute to the effective implementation of predictive maintenance techniques, with the overarching aim of enhancing the OEE within the framework of a manufacturing environment in South Africa. This objective will be realised through the utilisation of artificial intelligence-based predictive maintenance methods.

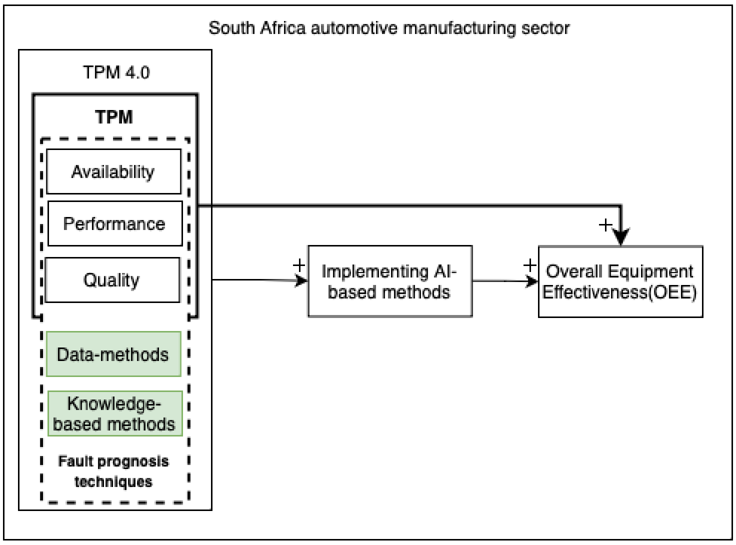


Figure 1: Dramatic representation, improving Overall Equipment Effectiveness (OEE). (Source: Author Constructed)

Figure 1 illustrates the potential relationship between conventional Total Productive Maintenance (TPM) techniques and data-based as well as knowledge-based fault prognosis techniques to enable effective AI-based maintenance techniques that could potentially result in improved OEE. The study posits that the inclusion of AI-based techniques that leverage data-based methods such as predictive maintenance and knowledge-based methods could potentially improve OEE within the automotive manufacturing context in South Africa and potentially lead to improved automotive production flow.

1.3 Background of the study

In South Africa, the manufacturing industry is a crucial component of the economy, contributing a significant 13% to the country's total GDP as noted by merSETA (2020). The motor vehicles, parts, and accessories sector alone accounts for an impressive 7% of the contribution (merSETA, 2020). The manufacturing sector has also been a reliable source of employment over time, and the automotive manufacturing sector has experienced steady growth in job opportunities. The South Africa automotive master plan, which governs the local motor industry, projects that employment within the industry will double by 2035 (merSETA, 2021). Given the automotive industry's leading role in the country's efforts to re-industrialise, it is evident that the manufacturing sector will continue to be a crucial force in driving economic development in South Africa.

However, in recent years, the industry has faced significant challenges due to increasing competition, strict regulations, covid-19 interruptions, and shifting customer demands, which have negatively impacted forecasted growth, increased production costs, and lowered output levels (merSETA, 2021). As a result, manufacturers and relevant practitioners are constantly exploring new techniques and methods of augmenting manufacturing processes to improve production efficiency, reduce production-related costs and improve product quality (Jan, 2023).

Efficiency can be defined as the extent to which a system or resource is utilised, while productivity refers to the degree of alteration in the characteristics, circumstances, and configuration of materials (Daneshjo, 2019). Production efficiency, therefore, means accomplishing a task or goal using the minimum possible resources, time, and effort (Chaurey, 2021). According to Chaurey (2021), efficiency involves maximising output while minimising input.

Improving efficiency is crucial for achieving long-term success and competitiveness in the automotive sector. To enhance efficiency, manufacturers can streamline processes, automate repetitive tasks, reduce waste, and optimise resource allocation. Production stops due to quality issues are one of the biggest contributors to production inefficiency and result in high costs, such as cost as a result of lost production, cost as a result of downtime, cost due to the time taken to identify errors in production, and costs as a result of production waste (Ayvaz, 2021).

Additionally, the cost of repairs and the deterioration of equipment may have significant implications on production efficiency. According to Ayvaz (2021), these costs may occur because of faulty or malfunctioning equipment, lack of well-trained workers, and other environmental factors, such as incorrectly configured equipment. Therefore, fault prognosis, which refers to the estimated amount of time a production environment is in operation before a failure occurs (Zhong, 2020), is critical in mitigating these costs and maintaining overall equipment effectiveness.

The possibilities created by Industry 3.0 resulted in the introduction of TPM, which resulted in an average downtime reduction of 53% and a decline in breakdowns by 54% on average in various industries (Jan, 2023). The Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), and Overall Equipment Effectiveness (OEE) were used as indicators for measuring downtime, performance, and quality improvements (Jan, 2023). Although the implementation of TPM brought about significant change to manufacturing environments, achieving zero downtime remains a challenge.

To improve production efficiency, manufacturers have relied on OEE, a performance metric that measures the effectiveness of manufacturing equipment and processes (Daneshjo, 2019). OEE considers three essential factors: availability, performance, and quality, which are used to calculate a single performance metric. By focusing on these key factors, manufacturers can optimise their production processes and identify areas for improvement.

By leveraging the data generated from inter-connected device networks and utilising data-driven approaches, practitioners can predict the likelihood of production disturbances, using asset, process and trend data generated from the equipment's historical performance and suitable Machine Learning (ML) models (Jan, 2023). According to Jan (2023), these ML models have allowed for the preparation of alternatives that are arranged in advance and proposed as recommendations with the end goal of reaching near-zero downtime. Additionally, recent developments in production environments and advancements in technology suggest that the ability to estimate the remaining useful life for machinery has started to play an increasing role in ensuring safe and reliable production environments (Ayvaz, 2021).

Industry-specific Internet of Things (IoT) solutions could potentially improve production efficiency, these technologies make it possible to detect events and respond promptly (Alsudani, 2023). According to Alsudani (2023), IoT solutions can also result in further cost savings, increased transparency, and process control. For example, using IoT data, fleet managers can control and track drivers as they are delivering parcels. The added transparency allows for more control as managers can monitor and assess routes travelled to identify and recommend optimal travel paths. IoT networks comprise interconnected, internet-connected electronic components referred to as things, that have the ability to collect and send data to various destinations using a wireless network without the need for human intervention(Alsudani, 2023). These networks act as enablers for the implementation of data-driven approaches such as condition monitoring and predictive maintenance for addressing manufacturing and production inefficiencies.

Predictive maintenance (PdM) refers to a cluster of scientific techniques, that can be used to detect possible failures that may not be easily identified from general preventative maintenance plans (Vanraj, 2016). PdM involves analysing data from various sources, such as sensors, machines, and other equipment, to predict when maintenance is needed. By detecting and addressing issues before they result in downtime or costly repairs, predictive maintenance can help manufacturers save time and dramatically reduce unplanned shutdowns and non-value maintenance activities (Vanraj, 2016). PdM has gained domination in the manufacturing industry (Ayvaz, 2021). This is because it has the potential to reduce maintenance costs and enable sustainable production environments.

At the core of predictive maintenance is the created possibility to predict the next interval during which an error may occur and trigger a response for suitable preventative measures to be implemented (Ayvaz, 2021). Unlike traditional preventative maintenance plans, which are typically based on predefined standards and professional bodies, predictive maintenance relies on real-time or historical data from equipment sensors, performance monitoring, and predictive analytics to identify patterns or anomalies that may indicate impending failures (Sunday, 2020). By leveraging these techniques, predictive maintenance aims to optimise maintenance activities, reduce costs, and enhance equipment availability, performance, and reliability.

Artificial Intelligence (AI) spans across multiple machine learning sub areas (Jan, 2023). These include automated configuration, planning, diagnostics, prognostics, and adaptions that contribute significantly towards the realisation of cyber-physical systems. In the last two decades, the world has experienced rapid growth in the use of AI-enabled systems within various industries (Jan, 2023). However, as stated by Jan (2023), a clear gap exists in research about how different industries have effectively utilised AI to fully achieve Industry 4.0. This includes obtaining a better understanding of the concerns and potential solutions that were identified and implemented in these settings.

Data generated by industrial systems are often noisy and, in most cases, require a lot of preparation before any experimentation may commence. Additionally, in order to enable faster and improved accuracy in judgement, heterogenous data such as image, video, and audio may need to be collected (Jan, 2023). This creates the need for additional production processes to be implemented and relied on, which remains a concern for production experts as this implies that for production to flow efficiently, the uptime of additional systems and processes must be taken into consideration. The implementation of additional AI-enabled systems and processes requires a lot of technical manpower (Jan, 2023). This includes domain experts, data scientists, AI engineers, and more, to fully understand production systems and design as well as develop and implement effective solutions. This creates an additional requirement for more technical roles and capabilities.

It is important to note that AI spans across multiple machine learning sub-areas, including automated configuration, planning, diagnostics, prognostics, and decision-making processes. These areas have the potential to revolutionise the manufacturing industry by optimising processes, reducing downtime, and improving overall productivity. AI-based predictive maintenance models can enable manufacturers to identify potential equipment failures before they occur, reduce unplanned downtime, and minimise maintenance costs.

However, implementing AI-based predictive maintenance models requires significant investment in infrastructure, technology, and personnel. It is essential to consider the potential risks and challenges associated with such implementation, such as the need for accurate and reliable data, adequate training of personnel, and the potential impact on the existing production environment. Additionally, it is important to consider the ethical implications of using AI-based predictive maintenance, such as data privacy and bias.

This study explores the implementation of AI-based methods to improve OEE for an automotive manufacturer in South Africa, which acts as a representative of automotive manufacturers in the country. The study highlights that production efficiency is a critical factor in enhancing the competitiveness and profitability of manufacturing organisations. The integration of data-based and knowledge-based manufacturing methods fused with TPM, an industry 3.0 concept, can lead to significant improvements in OEE and production efficiency.

1.4 Research problem

To boost production line profitability, minimising downtime and rejects is vital for efficiency and productivity. Increased uptime not only brings financial benefits but also enhances sustainability (Mitra, 2020). The gold standard for measuring manufacturing productivity is the OEE, which evaluates efficiency by considering factors like downtime, speed, and waste. Achieving an OEE score of 100% implies zero waste, no downtime, and maximum production line speed. The world-class standard for OEE currently stands at 85%, calculated based on equipment availability, performance, and quality rates (Suryaprakash, 2021).

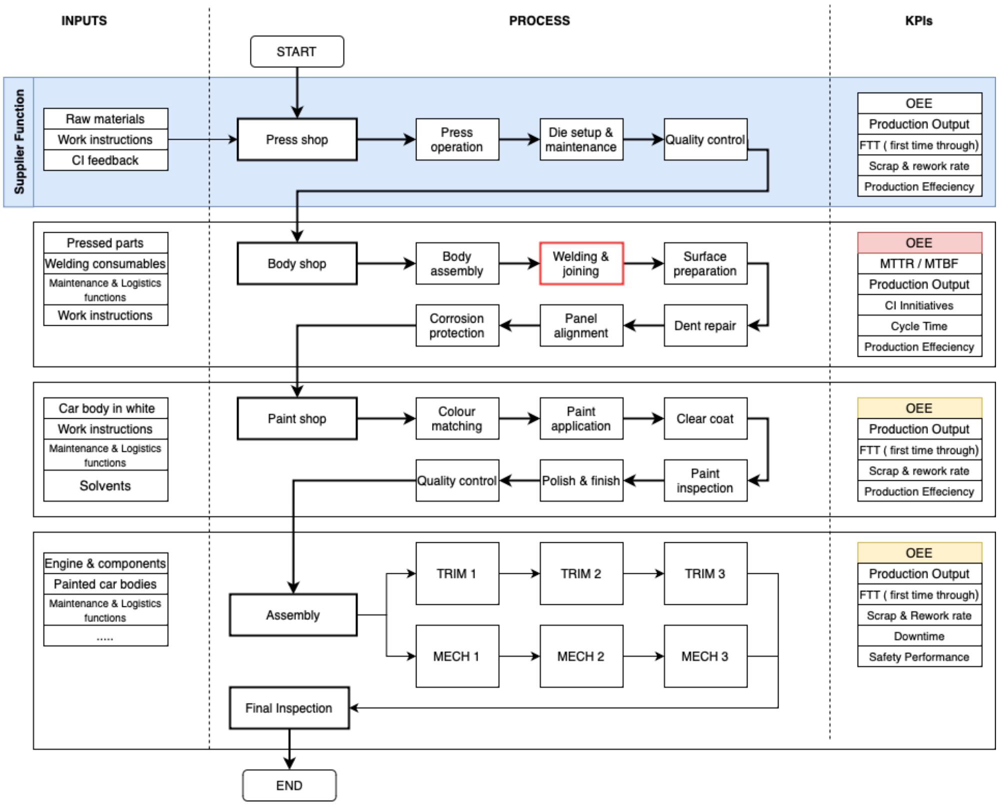


Figure 2: High-level process map of the automotive manufacturing process at Company X. (Source: Author constructed).

The focus of this study is Company X, an automotive manufacturing company based in South Africa. Company X operates over 20 stations as part of its production process. Figure 2 provides an overview of the automotive manufacturing process employed by Company X. The process begins with the supply of pressed parts and weldable consumables from an external press shop. These parts are then received and processed in the highly automated body shop, which leverages industry 4.0 technologies, such as embedded sensors for real-time data streaming. The result is a car body in white, ready for the paint shop.

Following the body shop, the vehicle proceeds to the paint shop, where multiple paint coats are applied, followed by a final polish and quality control. The completed car bodies are subsequently sent to assembly, where final trims and mechanical components, such as the engine and chassis, are installed. Prior to leaving the production line, each vehicle undergoes a thorough inspection to ensure there are no defects.

For further analysis, the welding and joining stations have been selected, with a particular focus on the spot-welding station. This station plays a critical role in the automotive manufacturing environment and is subject to time constraints and increasing costs due to quality-related production stops. Furthermore, the body shop's recent integration of IoT sensors and data streaming technologies presents significant possibilities for applying data-based fault prognosis techniques, in effort to improve weld quality and reduce resultant stoppages.

Company X has encountered a significant number of welds out of tolerance at the spot welding stations, resulting in increased downtime, compromised equipment performance, reduced quality, and higher overall costs. On average, spot welding stations experience an OEE below 75% and encounter numerous quality stops per week, leading to elevated costs and diminished quality. To address these issues, this study aims to enhance the OEE of spot-welding equipment by reducing downtime and improving weld quality through the application of AI-based techniques.

This study aims to adopt an operations management-based perspective to examine the use of artificial intelligence in streamlining the automotive manufacturing process to address production inefficiencies and improve OEE. Specifically, the study seeks to explore the role of production flow and its consequences for improved production efficiency and performance. The study will evaluate the effectiveness of AI-based predictive maintenance techniques in increasing station availability and production quality which remain a challenge for selected stations at Company X. The goal is to develop a framework that can be implemented within the South African automotive manufacturing context to improve the quality, availability, and performance of the automotive manufacturing process through the utilisation of AI-based approaches.

1.5 Research questions

1.5.1 Research objective

The primary goal of this study is to explore and define a fused approach that integrates techniques, such as Total Productive Maintenance (TPM), with AI-based methodologies to enable predictive maintenance in manufacturing environments. The objective is to enhance production efficiency and Overall OEE within an automotive manufacturing context.

1.5.2 Context

The implementation of predictive maintenance has emerged as a crucial strategy to optimise production processes. This approach entails the amalgamation of traditional manufacturing practices, such as TPM, with modern AI-driven techniques. By leveraging advancements from Industry 4.0, including IoT sensor-generated process data, there is potential to transform the existing TPM frameworks and further enhance OEE rates.

1.5.3 Questions

To address the above objective, the study will focus on the following questions:

1. What is the current state of OEE at Company X?:
2. How do technological readiness, AI and IoT integrations impact OEE?
3. How can a predictive maintenance framework, based on artificial intelligence, be developed to enhance OEE at Company X?

1.5.4 Research objectives

Based on the research question in section 1.4.3, the corresponding research objectives could be formulated as follows:

1. To assess the current state of OEE at Company X by conducting a comprehensive analysis to determine the baseline OEE at Company X, identifying areas of strength and opportunities for improvement is required.
2. Investigate the relationship between technological advancements, specifically AI and IoT integrations, and their effects on the OEE in an industrial setting, by conducting a semi-structured questionnaire to gather descriptive data from relevant stakeholders at Company X as part of formulate a solution proposal.
3. Develop an AI-based predictive maintenance model tailored for company X that aims to predict equipment failures, reduce downtime, and thereby enhance OEE.

The outcomes of this study are expected to contribute significantly to the manufacturing domain by elucidating the feasibility and potential benefits of merging traditional frameworks with AI-driven insights. By demonstrating how process data from IoT sensors and data-driven manufacturing methods can be seamlessly integrated, the study aims to provide a blueprint for improving OEE rates within automotive manufacturing contexts. Ultimately, this research seeks to bridge the gap between Industry 3.0 and Industry 4.0 practices, offering practical insights for manufacturers striving to enhance their production efficiency.

1.6 Rationale

TPM is a manufacturing program designed to maximise equipment effectiveness throughout the equipment’s lifespan (Chaurey, 2021). According to Chaurey (2021), the process aims to increase equipment availability and therefore reduce the need for further capital investment. Proper maintenance of machines is a very important attribute that will ultimately determine the achieved product quality (Chaurey, 2021). The optimisation and effective utilisation of machines is the responsibility of all production personnel, according to Nakajima (1989), the founder of TPM who further states that TPM is a plant improvement methodology that fosters continuous improvement in manufacturing processes through employee involvement, empowerment, and closed-loop outcome measurement, facilitating rapid iterations.

The use of TPM improves OEE and increases profitability (Chaurey, 2021). Through the introduction of TPM-based techniques on the production line, Company X has benefited significantly from increased profitability and reduced costs of production. The use of TPM has allowed for an integration of production and maintenance functions within the organisation. The cost of operations and maintenance in today's challenging market can make or break a business (Chaurey, 2021). Companies today are faced with challenges such as increasing demand on productivity, availability, quality, safety, and environmental concerns as well as decreasing profits. According to Chaurey (2021), the manufacturing sector in developing countries has experienced significant changes such as increased competition, and increased focus from customers on timely product delivery and product quality.

This study aims to evaluate the efficacy of AI-based predictive maintenance techniques to improve OEE for a particular station in an automotive environment using improvement in availability as the key measure of improvement. The empirical rationale for this study is based on the fact that existing approaches to maintenance have not been effective in practical factory settings due to challenges that arise from differing manufacturing environments (Ayvaz, 2021) and implementation challenges such as levels of technical expertise and experience. Therefore, there is a need to develop new approaches that consider the unique characteristics of each production line and setting as well as attempt to augment manufacturing processes using AI-based methods and complement industry 3.0 techniques such as TPM to further improve product quality.

The research is worth conducting because it seeks to add local research from a South African perspective to the existing pool of research on the use of AI-based techniques in conjunction with industry 3.0 methodologies for improved product quality. This study will contribute to the practice-oriented utility of research by providing insights into the effectiveness of a multi-source fusion method for downtime reduction improvement based on mechanisms, process data, and expert knowledge. This study's findings will also provide valuable information to manufacturing industries on how to improve the OEE of their manufacturing processes using process data generated from embedded IoT sensors. Ultimately, this research will help manufacturing industries reduce downtime, improve achieved quality, and remain competitive in an increasingly digital business environment.

1.7 Delimitations of the study

The implementation of fault prognosis systems can be categorised into three types: model-based, knowledge-based, and data-based, as described by Zhong (2020). Model-based systems require accurate mathematical descriptions of systems using physics and first principles, while knowledge-based methods rely on engineering experience and expertise as well as historical events. Data-based methods, on the other hand, determine the health of systems based on previously observed data.

For this study, the focus will be on knowledge-based and data-based methods. Knowledge-based methods will enable the exploration of accumulated knowledge and experience from experts, while the experimentation environment already has IoT-enabled devices, providing an abundance of sensor data required for data-based methods. Although model-based methods have the potential to outperform other methods with correctly designed experiments and selected parameters, the preparation required for such experiments is time-consuming and not core to the study. Within the scope of knowledge and data-based methods, the study will be delimited to the following:

i. The study assumes the performance of equipment is optimal when available and focuses on improving the availability aspect of a key station in production.
ii. The study may rely on a limited pool of experts with a specific set of knowledge, which may not capture the full range of knowledge and perspectives of existing processes.
iii. The study will only consider specific types of process data, such as data from sensors, which may not capture all relevant data required for effective fault prognosis.

iv. The study will consider process data, expert domain knowledge, and embedded mechanisms for the effective enablement of predictive maintenance in manufacturing environments.

1.8 Definition of terms

The study has the following key terms that need to be defined:

Data-based methods: Methods that rely on data analysis to inform decision-making and strategy development (Zhong, 2020).

Equipment reliability: The ability of equipment to perform its intended function under given conditions without failure for a specified period (Ngoma, 2020).

Fault prognosis: The process of identifying and predicting faults that are likely to occur in equipment and determining the actions necessary to prevent or mitigate them (Zhong, 2020).

Process data: Data that describes the steps and stages of a manufacturing process, including inputs, outputs, and quality control measures (Jan, 2023).

Overall Equipment Effectiveness (OEE): A performance metric that measures the effectiveness of manufacturing equipment and processes, by taking into consideration the availability, performance, and quality rate (Daneshjo, 2019).

Total Productive Maintenance (TPM): A maintenance strategy that involves the entire workforce in the maintenance of equipment to improve its reliability, availability, and maintainability (Nakajima, 1988).

1.9 Assumptions

For this study, the following assumptions were made:

I. The automotive organisation has already implemented TPM techniques as outlined in Industry 3.0 guidelines.

II. There is a need for a fused approach that takes into consideration multiple facets of manufacturing for the purpose of effective predictive maintenance.
III. Process data required and used for predictive maintenance purposes is reliable and accurate.
IV. Insights derived from the study can help different business units understand their role and contribution to the improvement of production efficiency using predictive maintenance.

1.10 Chapter Outline

The theoretical and practical implications of the study on the application of data-driven manufacturing models for improving OEE in an automotive manufacturing company in South Africa can be summarised as follows:

Theocratical Implications

1. Investigating the benefits, challenges, and motivation for AI-based predictive maintenance for automotive manufacturing in South Africa.
2. Identifying key factors necessary for the successful implementation of AI-based strategies in an automotive manufacturing environment in South Africa to improve the availability aspect of OEE.
3. Exploring the feasibility of a fused approach that incorporates embedded mechanisms with existing manufacturing environments, process data, and expert knowledge to enable predictive maintenance in an automotive manufacturing environment.

Practical Implications

1. Improving the OEE for an automotive manufacturer in South Africa by applying data-driven manufacturing models.
2. Enhancing production efficiency, reducing production-related costs, and improving product quality through streamlining processes, waste reduction, and resource optimisation.

3. Leveraging data-driven approaches, machine learning models, and IoT solutions to predict and prevent production disturbances, improve process control, and achieve cost savings.
4. Implementing predictive maintenance techniques based on AI, machine learning, and data analytics to detect and address potential equipment failures before they cause unplanned downtime and costly repairs due to outputted product quality issues.

Overall, the study's findings and implementation of data-driven manufacturing models and AI-based techniques for predictive maintenance can have significant implications for improving production efficiency, reducing costs, and enhancing the competitiveness and profitability of automotive manufacturers in South Africa. It can contribute to economic development, address industry challenges, and pave the way for the adoption of Industry 4.0 technologies in the manufacturing sector in South Africa.

1.11 Conclusion

In conclusion, this chapter establishes the essential foundation for the study, emphasising the critical role of AI-based fault prognosis techniques in enhancing Overall Equipment Effectiveness (OEE) within the South African automotive manufacturing sector. It highlights the transformative potential of the 4th Industrial Revolution, particularly through data-driven predictive maintenance methods, to improve equipment availability, performance, and quality. The chapter meticulously outlines the study's purpose, provides a comprehensive background of the South African automotive industry and its challenges, and details the research problem, questions, and objectives. Key terms are defined, delimitations of the study are specified, and essential terms guiding the research are presented. Finally, a summary of the thesis structure is provided, setting the stage for the detailed exploration and analysis in the subsequent chapters.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

In this chapter, the literature review delves into the historical and theoretical foundations of maintenance practices in the automotive industry, emphasising the significance of Overall Equipment Effectiveness (OEE). The chapter begins with a concise overview of the history of maintenance in automotive manufacturing environments in section 2.1, followed by a discussion on the importance of OEE in these settings in section 2.2. The chapter then reviews existing maintenance frameworks, including Preventive Maintenance, Condition-Based Maintenance, and Total Productive Maintenance in section 2.3, and explores AI-based techniques to reduce downtime, such as ARIMA, Fuzzy FMEA, and RNN-based frameworks in section 2.4. A critical evaluation of the literature is furnished in section 2.5. Section 2.6 provides a cross-sector analysis demonstrating the successful implementation of predictive maintenance methods for improved maintenance across various sectors. This is followed by an analytical framework integrating Socio-Technical Systems (STS) and Actor-Network Theory (ANT) in section 2.7. The chapter concludes with a conceptual framework that guides the research methodology in section 2.8.

2.2 A brief history of automotive production maintenance

In the 1960s, the concept of Total Productive Maintenance (TPM) emerged as a systematic approach to optimise the effectiveness of equipment and machinery in manufacturing (Jeon, 2011). TPM aims to minimise downtime, improve overall equipment efficiency, and involve all employees in the maintenance process (Madanhire, 2015). It was developed by Seiichi Nakajima (1988), who introduced the concept while working at the Japanese Institute of Plant Maintenance (JIPM), and defined TPM as a comprehensive system of maintenance that encompasses the entire lifespan of equipment across all divisions, including planning, manufacturing, and maintenance and emphasises proactive maintenance practices (Nakajima, 1988). Nakajima's pioneering work laid the foundation for TPM's widespread adoption in the automotive industry and other manufacturing sectors.

Another significant development in automotive production maintenance is the application of Lean Manufacturing principles. Originating from the Toyota Production System (TPS), Lean Manufacturing focuses on eliminating waste and improving efficiency throughout the production process (Kumar, 2022). It emphasises continuous improvement, standardised work, and a culture of problem-solving. Taiichi Ohno, an industrial engineer, and executive at Toyota, is often credited as one of the pioneers of Lean Manufacturing. His work in developing the TPS and implementing lean principles revolutionised automotive production and influenced the broader manufacturing industry (Womack, 2007)**.** The success of Lean Manufacturing in the automotive sector has been documented in numerous studies and has inspired the adoption of lean practices in other industries as well (Shah, 2007).

Overall Equipment Effectiveness (OEE) is a key metric used in automotive production maintenance to measure the efficiency and productivity of equipment (Madanhire, 2015)**.** It provides insights into equipment availability, performance, and quality. OEE gained prominence as a performance measurement tool within the Total Productive Maintenance framework (Nakajima, 1988). OEE's systematic approach to assessing equipment effectiveness has helped manufacturers identify and address bottlenecks, reduce downtime, and improve overall productivity.

Predictive maintenance has emerged as a cutting-edge approach in automotive production maintenance, complementing the rich history of traditional practices. With the integration of AI-based techniques, manufacturers can now proactively monitor and predict equipment failures, minimising downtime, and optimising maintenance processes (Theissler, 2021). Theissler (2021) further emphasises that companies that leverage machine learning algorithms data analysis and predictive maintenance systems can detect subtle anomalies in machinery performance and identify potential issues before they escalate into major breakdowns. This data-driven approach allows automotive factories to schedule maintenance activities based on actual equipment conditions, rather than relying on fixed time intervals or reactive repairs**.** Predictive maintenance, along with the established practices of TPM, Lean Manufacturing, and OEE, form a comprehensive framework that enables manufacturers to enhance efficiency, reduce costs, and improve product quality in the dynamic landscape of automotive production maintenance.

The integration of AI-based techniques and predictive maintenance continues to shape the future of the industry, paving the way for even more advanced and efficient maintenance strategies. This research study focuses on leveraging machine-learning-based methods to effectively reduce downtime and improve quality for a specific station within a South African automotive manufacturing context. With the aim of meeting contemporary productivity requirements and ensuring operational reliability, it is crucial for manufacturing environments to explore intelligent management strategies that enable proactive scheduling of production and maintenance activities while minimising costs (Zhang, 2018).

2.3 The Significance of OEE in Automotive Manufacturing Environments

The manufacturing sector faces formidable challenges in its pursuit to ensure timely product delivery to customers. These challenges arise from various factors, including the dynamic nature of the business environment, demanding expectations from customers, pressures from suppliers and governments, and the occurrence of equipment breakdowns (Gupta, 2012). Consequently, manufacturing systems often operate below their optimal capacity, leading to low productivity and soaring production costs. A significant study conducted by Mobley in 1990 revealed that maintenance activities within factories account for 25-30% of the total production costs (Mobley, 1990). The study by Mobley (1990) further highlights that the quality of maintenance plays a vital role in determining business profitability. Recognising the increasing significance of maintenance functions in safeguarding availability, product quantity, safety compliance, and maintenance costs, manufacturers have sought effective solutions.

In response to the maintenance challenges encountered in manufacturing environments, the Japanese have developed and introduced the concept of TPM. TPM is a new culture and attitude towards maintenance (Gupta, 2012), that encompasses several pillars that form the foundation for achieving optimal equipment performance in manufacturing operations (Adesta, 2018). According to Adesta et al (2018), these pillars include Autonomous Maintenance (AM), where operators take responsibility for routine equipment upkeep; Planned Maintenance (PM), which focuses on scheduled maintenance activities to prevent breakdowns; Quality Maintenance (QM), integrating quality management practices into maintenance; Training and Education (TE), developing knowledge and skills of maintenance personnel; Early Equipment Management (EEM), considering maintenance aspects during equipment design and procurement; Safety, Health, and Environment (SHE), ensuring a safe and sustainable work environment; and TPM in Administration (TPMIA), extending TPM principles to administrative processes as well as Office TPM (OTPM) which focuses on applying TPM principles and practices throughout the organisation. By emphasising these pillars, companies can enhance productivity, quality, safety, and efficiency while driving continuous improvement.

OEE is a performance metric that is commonly used within the TPM framework to measure and assess the effectiveness and efficiency of equipment. OEE considers factors such as equipment availability, performance rate, and quality rate to determine the overall effectiveness of equipment utilisation. While OEE is not a distinct TPM pillar, it is often used as a key performance indicator to monitor and improve equipment performance as part of the TPM implementation process (Gupta, 2012). The goal of TPM is to maximise equipment effectiveness, with OEE serving as a key metric for measuring the achieved equipment effectiveness (Waeyenbergh, 2002). Additionally, the OEE measurement is an effective way of analysing the effectiveness of a single machine or an integrated manufacturing system (Nakajima, 1988). In practical terms, OEE is determined by multiplying three key factors:

OEE = Availability rate x Performance rate x Quality rate

Equation (1) below provides a formula to quantify the availability rate, which encompasses the total duration of unplanned downtime, process set-up and changeovers, and any other unforeseen stoppages (Jasiulewicz-Kacmarek, 2016):

$$\boldsymbol{Availability = \frac{Net\ Operating\ time}{Planned\ operating\ time} = \frac{O_t}{P_t}} \qquad (\mathbf{1})$$

According to Jasiulewicz-Kacmarek (2016), the performance rate is calculated using (2) below:

$$\boldsymbol{Performance\ = \frac{Net\ Operating\ time}{operating\ time} = \frac{O_{nt}}{O_t}} \qquad (\mathbf{2})$$

Where:

The calculation of net operating time involves determining the ratio between the number of goods produced by a machine during its theoretical time of operation (Ct). It is crucial to define Ct as it directly relates to the speed at which a machine operates. Consequently, it is essential to establish Ct standards for each process to accurately define the performance of the machine.

Equation 3 below allows the calculation of the quality rate by subtracting the quantity of rejects and reworks from the output during running time, and then dividing the result by the total output produced.

$$\boldsymbol{Quality\ = \frac{Actual\ output - Rejects}{Actual\ output} = \frac{O_{pt-}\ R_{pt}}{O_{pt}}} \qquad (\mathbf{3})$$

The implementation of OEE aims to identify operational areas that necessitate improvement in both production and maintenance divisions (Jasiulewicz-Kacmarek, 2016). By analysing the OEE metrics and performance indicators, organisations can pinpoint specific areas that require enhancements to optimise operations and productivity (Jasiulewicz-Kacmarek, 2016). In conclusion, the significance of OEE in automotive manufacturing environments cannot be understated. By calculating the product of availability rate, performance rate, and quality rate, OEE provides a comprehensive assessment of equipment utilisation and identifies areas for improvement. Ultimately, OEE contributes to optimising operations, enhancing productivity, and driving success in automotive manufacturing environments.

2.4 A Review of Existing Frameworks Used in Maintenance

The automotive industry relies on effective maintenance techniques to ensure optimal vehicle performance, reliability, and safety. This section provides a comprehensive review of the existing maintenance techniques employed in the automotive industry. The review aims to identify and evaluate the effectiveness of preventive maintenance, condition-based maintenance, reliability-centred maintenance, and total productive maintenance. Additionally, it explores the integration of advanced technologies, such as data analytics and prognostics, in maintenance decision-making processes.

2.4.1 Preventative & Predictive Maintenance

Preventive maintenance has a long history in the automotive industry and remains a fundamental maintenance technique employed to ensure optimal manufacturing performance and longevity (Corman, 2017). It involves regularly scheduled inspections, servicing, and component replacements to prevent failures and mitigate potential issues before they occur (Guariente, 2017). The advantages of preventative maintenance include reduced downtime, extended equipment lifespan, and decreased overall maintenance costs (Zonta, 2020). According to Zonta et al. (2020), organisations can minimise the risk of unexpected breakdowns, optimise manufacturing reliability, and improve safety by proactively addressing maintenance needs. However, one disadvantage of preventive maintenance is that it may lead to unnecessary maintenance actions if components are replaced prematurely and require production interruptions at predetermined intervals (Swanson, 2001).

To address this limitation, advancements in sensor technologies and data analytics have paved the way for predictive maintenance (Zonta, 2020). By leveraging real-time process data and analytics algorithms, predictive maintenance enables the anticipation of failures, allowing for more targeted maintenance interventions and further optimising maintenance strategies (Theissler, 2021). A proactive maintenance strategy uses preventative and predictive maintenance activities which result in the prevention of equipment failure occurring (Swanson, 2001).

2.4.2 Condition-Based Maintenance

Condition-based maintenance also referred to as Condition-based monitoring (CBM), is a crucial technique employed in various industries, including automotive manufacturing, to assess the health and performance of equipment and machinery (Ahmad, 2012). According to Ahmad et al. (2012), CBM involves the continuous monitoring of parameters such as vibration, temperature, pressure, and electrical signals to detect any deviations from normal operating conditions. In the context of automotive manufacturing, condition monitoring could play a vital role in ensuring the optimal functioning of production machinery and processes.

One of the primary advantages of Condition Monitoring (CM) in automotive manufacturing is its capability to identify potential faults and failures before they result in expensive breakdowns (Ramere, 2021). By continuously monitoring the condition of critical components such as engines, transmissions, and other vital systems, manufacturers can detect early warning signs of deterioration or malfunctions. This enables timely preventive maintenance or corrective actions to be taken, reducing the risk of unexpected failures, and minimising production downtime.

Unlike PdM, which leverages advanced data analytics and machine learning techniques to anticipate future equipment failures or performance issues, CBM prioritises maintenance activities based on observed equipment condition thresholds (Ahmad, 2012). Ahmad et al. (2012), further notes that in real industrial practice, it is often challenging to accurately determine failure limits solely based on specific monitoring parameters. This is because the definition and classification of equipment failure can vary across different contexts and applications.

2.4.3 Time based Maintenance

Time-based maintenance (TBM), also known as periodic-based maintenance, is a traditional maintenance approach that determines maintenance actions based on the analysis of failure times (Ahmad, 2012). TBM operates under the assumption that equipment failures follow a predictable pattern represented by a bathtub curve, which includes burn-in, useful life, and wear-out phases (Elbeling, 1997). During the burn-in phase, failure rates are expected to decline, followed by a relatively constant failure rate during the useful life of the equipment. However, in the wear-out phase, equipment failure rates increase. The TBM process involves analysing failure characteristics through statistical investigations and reliability modelling based on gathered failure time data (Ahmad, 2012). This enables maintenance teams to identify patterns and make informed decisions about maintenance activities.

TBM has both challenges and advantages in maintenance management. One of the main challenges is the reliance on fixed time intervals for maintenance actions, which can lead to either unnecessary maintenance or missed maintenance opportunities, additionally decision modelling is time consuming and not always stable (Ahmad, 2012). This approach may result in higher costs due to excessive maintenance activities or increased risks of equipment failure if maintenance is not performed at the right time. Additionally, TBM assumes that failure rates follow a predictable pattern, which may not always hold true for complex systems with varying operating conditions. On the other hand, TBM offers certain advantages, such as simplicity and ease of implementation (Kim, 2016). TBM also enables the establishment of routine maintenance procedures, which can help prevent catastrophic failures and extend the useful life of equipment.

2.4.4 Total Productive Maintenance

TPM is a comprehensive approach to maintenance management that aims to maximise the productivity and reliability of equipment in an organisation (Madanhire, 2015). It incorporates various maintenance techniques such as preventive maintenance, predictive maintenance, and autonomous maintenance under its third pillar (Adesta, 2018). According to Adesta (2018), the maintenance program aims to optimise Mean Time Before Failure (MTBF) and Mean Time To Repair (MTTR) as part of the preventative and predictive pillar. Preventive maintenance involves regular inspections and planned maintenance activities to prevent equipment breakdowns, while predictive maintenance utilises data analysis and monitoring to identify potential issues before they occur.

TPM offers significant advantages in enhancing equipment effectiveness and minimising downtime (Suryaprakash, 2021). This is achieved through the implementation of preventive and predictive maintenance techniques, which play a crucial role in reducing unexpected breakdowns. By conducting regular inspections, scheduled maintenance activities, and utilising data analysis for predictive maintenance, organisations can proactively address potential issues before they escalate. As a result, the occurrence of equipment breakdowns is minimised, leading to improved overall equipment availability and increased productivity.

Furthermore, according to Suryaprakash (2021), TPM recognises and addresses six types of waste that are categorised into three groups: defect loss, speed loss, and downtime loss. Defect losses refer to the production of defective or non-conforming products, which can result in rework, scrap, customer dissatisfaction, and additional costs. Speed losses occur when equipment operates below its maximum potential, leading to reduced output and longer cycle times. Downtime losses encompass unplanned or planned interruptions in production, including equipment breakdowns, changeovers, and delays. By identifying and addressing these specific types of losses, TPM provides a structured approach to waste reduction.

Nevertheless, TPM does possess certain limitations. The implementation of TPM can be a time-consuming and a resource-intensive endeavour (Madanhire, 2015). It necessitates substantial investments in training, equipment upgrades, and the cultivation of a maintenance-oriented culture within the organisation (Sohal, 2010). Moreover, TPM may encounter resistance from employees who are unfamiliar with assuming maintenance responsibilities or view it as an additional burden to their current roles. Furthermore, the effectiveness of TPM relies significantly on the collection and analysis of accurate data, which can be challenging to accomplish without the presence of robust systems and technologies.

In conclusion, TPM is a comprehensive maintenance approach that integrates various techniques to optimise equipment performance and reduce downtime. Its advantages include improved equipment effectiveness, increased reliability, and a culture of continuous improvement. TPM implementation involves working towards an ideal manufacturing scenario, aiming for zero breakdowns, zero defects, zero abnormalities, and zero accidents (Suryaprakash, 2021). Achieving this ideal state requires continuous improvement and the wholehearted commitment of every individual in the organisation, ranging from operators to top-level management.

2.5 Overview of AI-Based Techniques to Reduce Downtime

In the modern manufacturing landscape, achieving operational excellence and maximising productivity are critical for organisations to thrive in a highly competitive environment. The integration of human expertise, machinery, technical abilities, and cutting-edge technology holds great potential for driving innovation and improving manufacturing outcomes (Chaurey, 2021). In this context, an important aspect is the ability to predict machine downtime and station availability accurately. The following section provides an overview of applied algorithms and techniques specifically aimed at achieving this goal. By leveraging machine learning algorithms and data analysis, predictive maintenance systems can detect subtle anomalies in machinery performance and identify potential issues before they escalate into major breakdowns, contributing to overall operational excellence and enhanced manufacturing productivity.

2.5.1 ARIMA Based techniques for predicting machine status

Many existing studies have contributed significantly to the detection of throughput bottlenecks that increase downtime (Chen, 2023).Techniques such as auto-regressive integrated moving average-based (ARIMA) have been used to accurately predict future machine status (Wu, 2007). The improved forecasting strategy involved building models multiple times based on dynamic datasets to ensure that derived predictions relied solely on true observations and not previous forecasts. The approach automates the process of ARIMA modelling based on the Box-Jenkins methodology and demonstrated using vibration characteristics in rotating machinery. While the approach presents an effective approach to predicting prognostics heath in machines, it assumes a linear relationship exists between observed and forecasted values. This assumption may not hold true in real-world scenarios where non-linear patterns and relationships may exist in production stations.

2.5.2 Fuzzy Failure Mode and Effects Analysis

Failure Mode and Effects Analysis (FMEA) is a proactive risk assessment tool widely utilised in the automotive manufacturing industry to identify and mitigate potential failures and associated risks (Godina, 2021). According to Gordina (2021), FMEA has been extensively employed for waste reduction in this sector by identifying failure modes that contribute to production inefficiencies, defects, and rework. Gordina (2021) further states that by analysing failure modes, their potential effects, and the likelihood of occurrence, automotive manufacturers can prioritise improvement actions and implement preventive measures. However, despite its usefulness in quantifying risks, FMEA has limitations when it comes to dealing with qualitative defects that involve subjectivity, uncertainty, and the lack of specialised technicians for visual inspection. These limitations highlight the need for a more comprehensive approach, which led to the development of the fuzzy FMEA.

Fuzzy FMEA, has been widely applied in various industries beyond automotive manufacturing (Godina, 2021). According to Godina (2021), it offers a general method for fuzzifying risk-indexed parameters using appropriate membership functions. Several studies have highlighted the advantages of implementing fuzzy FMEA, demonstrating its effectiveness in addressing risk associated with failure modes. For example, its application in the automotive spare parts industry using the fuzzy best-worst method and multi-objective optimisation (Godina, 2021). This study highlights that fuzzy FMEA allows for the identification of critical causes that were previously overlooked, providing a flexible and accurate analysis of complex problems characterised by subjective and imprecise information. Overall, fuzzy FMEA has proven to be a valuable approach for mitigating the limitations of traditional FMEA and improving risk assessment.

2.5.3 Data-level Fusion approaches for maintenance modelling

A data-level fusion model developed for degradation modelling by Liu (2013), leveraged condition or performance sensor signals to accurately estimate the remaining lifetime for partially degraded systems in a given station (Liu, 2013). Liu et al. (2013) emphasises the use of multiple sensor data to represent the condition of engineering systems to improve downtime prediction accuracy. The approach followed includes the process of selecting relevant data sources, processing the data sources and a data fusion process to collectively enhance prognostic based model-based degradation. The aim of the study was to expose the need for including fused data as compared to relying solemnly on individual sensor data because composition of health index data for a given machine outperforms individual sensor information. A key shortcoming of this study is that it only focused on one failure mode for a station whereas a production station will be confronted by multiple failure modes daily.

2.3.3. A comparative study on predicting equipment wear and tear as well as station availability.

In 2017, a comparative study on the use of machine learning algorithms for smart manufacturing explored the use of Random Forest (RF) classifiers to determine wear and tear of equipment by comparing the performance of feed forward based artificial neural networks and support vector regression models to accurately predict station availability (Dazong, 2017). The study exclusively explores the use of three machine learning algorithms namely ANNs, SVRs and RFs which may have limitations in capturing the complex relationships and patterns that exist in the collected data from a particular station, due to the complex nature of station interdependencies. The study concludes that extraction is an essential pre-processing step during which raw data representing station failure is converted to a format supported by machine learning algorithms.

2.5.4 RNN-Based Framework for throughput prediction

A study by Chen (2023) resulted in the development of an RNN-based framework that focused specifically on throughput prediction within automotive production systems. Forecasting the temporal variations in system throughput holds significance from the viewpoints of system operation and production control. This enables plant managers to promptly determine if any modifications are necessary to fulfil the daily production demands and to effectively arrange essential resources and personnel accordingly (Chen, 2023). Chen (2023) sheds further light on the compelling evidence that establishes a strong correlation between system throughput and machine status data, as indicated by previous research findings. The study then focuses on developing a method that can accurately predict the achieved throughput for a given production line.

The research findings lay the foundation for recognising the sequential nature of the resulting data, which stems from the amalgamation of data derived from various sources, including IoT-enabled assets and process data. This recognition is crucial in highlighting the necessity for a selected methodology capable of effectively handling high-dimensional or sequential data, while also providing contextual understanding of the interdependencies among multiple production systems. A study by Zhang et al (2018) focused on the use of Long Short Term Memory (LSTM) algorithms combined with IoT sensor data to monitor engine performance, characterise system failure and determine useful life expectancy (Zhang, 2018). The LSTMs ability to capture process data within a cycle as input for the subsequent cycles made it more attractive as compared to RNN algorithms, which have no way of representing long-term memory, due to the vanishing gradient problem.

2.5.5 Bi-directional Long short-term memory for remaining life prediction (RUL)

In Zhang's (2018) study, the author addresses the challenge of effectively monitoring performance degradation in dynamic systems such as manufacturing machines and aircraft engines. Conventional machine learning algorithms encounter difficulties in adapting to the intricate and non-linear characteristics inherent in these systems. However, with the advancements in computational hardware, Deep Learning, specifically the Long Short-Term Memory (LSTM) network, emerges as a promising solution (Zhang, 2018). The LSTM network exhibits the ability to discern patterns within time series data, thereby making it well-suited for predicting the Remaining Useful Life (RUL) of a system.

In Zhang's (2018) study, the author introduces a novel approach for tracking system performance degradation and predicting the RUL. The proposed method involves the utilisation of a bi-directional LSTM network. By employing this bi-directional LSTM architecture, the model can effectively capture the temporal dependencies and patterns present in the system's data. This enables accurate tracking of performance degradation over time and reliable estimation of the system's RUL. The use of bi-directional LSTM represents a significant advancement in the field, offering improved capabilities for system monitoring and predictive maintenance. The bi-directional LSTM network has demonstrated superior performance compared to other commonly used machine learning techniques such as Support Vector Regression (SVR), Deep

Convolutional Neural Network (DCNN), and bi-directional Recurrent Neural Network (RNN). The bi-directional LSTM network achieved a significant reduction in prediction error, surpassing these techniques (Zhang, 2018).

Table 1 below summarises the strengths and limitations of the reviewed predictive maintenance techniques.

Technique	**Strengths**	**Limitations**
ARIMA	- Accurate at forecasting future machine state - Dynamic model building based on datasets ensure predictions are based on true observations. - Box-Jenkins ARIMA approach allows for time and effort saving. - Ideal for detecting bottlenecks	- Approach assumes a linear relationship exists between observed and forecasted values. - Approach may not accurately capture complexities and non-linear system dynamics. - Approach does not consider the potential influence of external factors on machine health (e.g., environmental conditions) - Approach relies heavily on robust datasets
Fuzzy FMEA	- Comprehensive risk assessment process - Address qualitative defects involving subjectivity.	- Selection of membership functions involves a certain level of subjectivity. - Requires a significant amount of data and expert knowledge to

Technique	Strengths	Limitations
	- Improved failure mode accuracy compared to traditional FMEA. - Flexible risk assessment process that extends beyond automotive manufacturing. - Easy to integrate with other methods (e.g., multi-objective optimisation)	establish accurate membership functions. - Computational complexity can increase time and computational resources required for analysis; this can also limit its applicability in high-speed production environments.
Recurrent Neural Networks (RNN)	- Allows for operational efficiency by accurately forecasting temporal variations. - Framework provides insights into the interdependencies between machine performance and achieved throughput. - Effectively handles high-dimensional or sequential data	- Effectiveness of the algorithm depends on the availability and quality input of the data. - Missing or noisy data can negatively impact model accuracy and reliability. - Computational complexity can be high especially when dealing with large datasets or complex production systems. - Model performance may vary when applied to different production systems or datasets. - Finding optimal set of hyperparameters can be

Technique	Strengths	Limitations
		a time-consuming iterative process.
Bi-directional Long short-term models	- Effectively captures the temporal dependencies present in the systems data. - Accurately tracks performance degradation. - Enables reliable estimation of the systems Remaining Useful Life (RUL) estimation. - Superior performance compared to other techniques. - Overcomes the vanishing gradient problem, enabling the capturing of and representation of long-term memory data. - Enables proactive maintenance strategies and improved adaptability to complex systems. - Ideal for time series data	- Computational complexity required for implementing and training bi-directional LSTMs. - Requires a significant number of labelled datasets for training, to effectively learn and capture complex patterns in system behaviour. - Relies on carefully chosen hyperparameters such as network architecture, layer sizes and learning rates. - Varying algorithm performance based on chosen datasets. - Finding optimal set of hyperparameters can be a time-consuming iterative process

Table 1: Strengths and Limitations of Predictive Maintenance Techniques (Source: Author Constructed)

2.6 Cross-Sector Implications

The use of predictive maintenance has been applied across multiple sectors such as manufacturing, aviation, and consumer goods production. The study titled "Predictive Maintenance System for Production Lines in Manufacturing: A Machine Learning Approach Using IoT Data in Real-Time" focuses on the manufacturing sector, specifically within a consumer goods manufacturing plant in Turkey(Ayvaz, 2021). The researchers developed a predictive maintenance system that leverages real-time data from IoT sensors embedded in manufacturing equipment to anticipate potential failures. By applying machine learning algorithms, including Random Forest and XGBoost, the system could predict equipment failures and notify operators in advance, allowing for preventive measures to be taken before any production stops occurred. This approach not only minimised unplanned downtime and associated costs but also contributed to the digital transformation of the production process, enhancing overall efficiency and sustainability.

In the study Long short-term memory for machine remaining life prediction, Zhang explores the use of Long Short-Term Memory (LSTM) networks to predict the remaining useful life (RUL) of aircraft engines(Zhang, 2018). LSTM, a deep learning architecture known for its ability to handle time series data, is employed to model the degradation of engine performance. By analysing historical sensor data from various engine components, the LSTM network generates a health index that accurately reflects the engine's current condition. This health index is then used to predict future degradation and estimate the RUL. The bi-directional LSTM (BD-LSTM) network, which processes data forwards and backwards, enhances prediction accuracy by smoothing the data and mitigating noise. Evaluations using NASA’s C-MAPSS dataset demonstrated that the BD-LSTM outperforms traditional machine learning models in tracking engine degradation and predicting failures, reducing prediction errors significantly.

Finally, the study "Artificial Intelligence for Industry 4.0: Systematic Review of Applications, Challenges, and Opportunities" examines the use of AI-based predictive maintenance across various sectors within the manufacturing industry, with a specific focus on real-world case studies(Jan, 2023). In one case study set in a consumer goods manufacturing facility, the implementation of predictive maintenance involved utilising IoT sensors to gather real-time data from production machinery. Machine learning models processed this data to predict potential equipment failures, allowing for preventive actions that minimised unplanned downtime and maintenance costs. The study highlights that predictive maintenance not only enhances operational efficiency but also supports sustainability by extending equipment lifespan, reducing energy consumption, and lowering material costs due to reduced production waste. Moreover, the relevance of industry regulations and standards, such as ISO 55000 for asset management, is emphasised, as they ensure that predictive maintenance practices meet industry benchmarks for reliability and performance. Overall, the integration of AI-based predictive maintenance in manufacturing aligns with the goals of Industry 4.0, promoting smarter, more efficient, and sustainable production processes.

Considering these aspects shows how predictive maintenance can transform various sectors within the manufacturing industry. It highlights the importance of following industry regulations and standards to achieve the best results and create smarter, more efficient, and sustainable production processes in line with Industry 4.0 goals. The critical role of industry regulations and standards in shaping the implementation and adoption of predictive maintenance technologies cannot be overstated. Compliance with standards such as ISO 55000 for asset management ensures that maintenance practices are reliable and effective, fostering trust and consistency across the industry. Adhering to these regulations helps companies achieve optimal results by providing a framework that guides the proper implementation of predictive maintenance technologies, ensuring safety, efficiency, and sustainability.

2.7 Analytical Framework

2.7.1 Theoretical Framework: Socio-Technical Systems (STS)

Neglecting to address behavioural issues when introducing new machinery can lead to sociological complications in the workplace (Sony, 2020). Consequently, it is essential to consider behavioural aspects during the design and implementation of technologies. The application of socio-technical systems theory extends beyond technology design and work role redesign, encompassing various important domains (Sony, 2020). This application has yielded practical outcomes and theoretical advancements in the design and operation of socio-technical systems. Sony (2020) further states that socio-technical systems theory emphasises the significance of integrating social and technical factors during the design process, recognising that changes in one part of the system will affect other parts. To optimise the system, all components should be considered holistically.

Socio-technical analysis is conducted at multiple levels, including the primary work system, the entire organisation, and larger-scale macrosocial phenomena (Trist, 1981). Trist (1981) asserts that primary work systems are accountable for executing a specific set of activities within a clearly defined and bounded subsystem of the overall organisation. These subsystems can encompass one or multiple groups, comprising support staff, specialists, management, and necessary equipment and resources. These groups share a common purpose that aligns the individuals and their activities.

Originally proposed by Leavitt (1965), the socio-technical systems framework comprised four dimensions: people, task, structure, and technologies (Davis, 2014). The "people" dimension focuses on the individuals involved in the system, their roles, skills, and interactions. The "task" dimension refers to the specific activities and goals that need to be accomplished within the system. The "structure" dimension pertains to the organisational structure, including the formal hierarchy, communication channels, and decision-making processes. Lastly, the "technologies" dimension encompasses the tools, equipment, and technologies employed in the system.

However, as time progressed, this framework underwent development, resulting in a more extensive six-dimensional hexagonal structure that emphasises the interconnectedness among these dimensions (Davis, 2014). The expanded framework depicted in Figure 3 below includes two additional dimensions: environment and goals. The "environment" dimension recognises the influence of the external context on the system, encompassing factors such as the economic, social, and political conditions. The "goals" dimension highlights the overarching objectives and aspirations of the system, guiding the decision-making and direction of the organisation. According to Davis (2014), together, these six dimensions provide a comprehensive lens for analysing and understanding the socio-technical dynamics within a system.

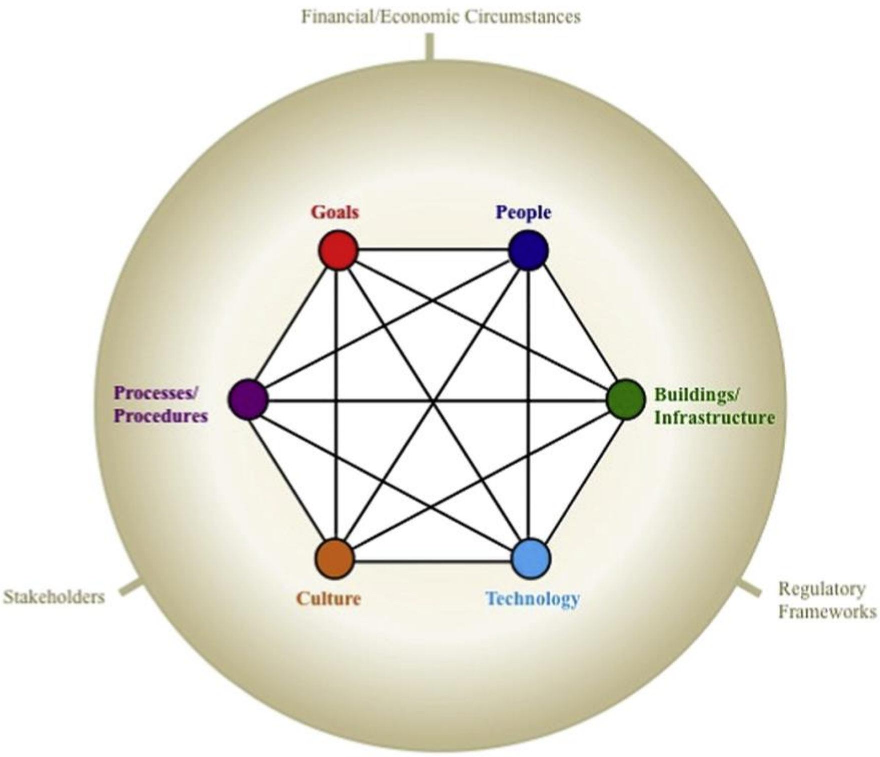


Figure 3: Socio-technical systems adapted from Davis et al (2014)

The study employs Socio-technical Theory as a valuable framework to gain insights into the various socio-technical factors that shape the current state of OEE at Company X. By applying this framework, the research aims to explore the intricate interdependencies between social elements, including employees and organisational culture, and technical elements such as machinery and production processes. These interdependencies significantly influence the achieved OEE and examining them through the lens of Socio-technical Theory enhances the researchers understanding of this complex relationship.

2.7.2 Theoretical Framework: Actor-Network Theory (ANT)

Actor-Network Theory (ANT) provides a compelling and innovative framework for examining the complex dynamics and interactions within the context of the study. As an analytical lens, ANT emphasises the interconnectedness and agency of both human and non-human actors, and how they collectively shape the outcomes and processes under investigation (Seuwou, 2016). In the context of this study, which aims to explore the implementation and effectiveness of AI-based techniques to improve OEE in manufacturing, ANT offers a valuable perspective to understand the intricate network of actors involved, such as employees, management, machines, sensors, and the broader socio-technical context.

By considering the relationships, negotiations, and translations among these actors, ANT allows for a nuanced analysis of the challenges, opportunities, and outcomes associated with the adoption and integration of AI-based techniques in the automotive manufacturing environment. Through its focus on the interconnectedness and agency of actors (Seuwou, 2016), ANT provides a rich framework for unpacking the complex socio-technical dynamics that influence the success and effectiveness of OEE improvement initiatives, ultimately contributing to a deeper understanding of the interplay between human and non-human actors in shaping manufacturing processes.

ANT encompasses four fundamental components, which include the actor and the actant as the first component (Seuwou, 2016). According to Seuwou et al (2016), these components are interconnected, forming a network that involves various factors. Actants can take various forms, such as individuals, groups, ideas, software, or physical objects, that contribute to the network by influencing and transforming the current situation. It is worth highlighting that actants may not necessarily initiate actions themselves, but rather bring about meaningful changes to established practices or concepts, thereby modifying, and improving the overall situation.

The second component of Actor-Network Theory entails the interconnected relationships among actors, which involve various forms of exchange such as monetary transactions, verbal or written communication, and the sharing of resources. These relationships may also involve the overlapping memberships of different networks (Seuwou, 2016). The third component focuses on the network itself, which can encompass individuals, groups, or ideas. This component also includes a series of actions and interactions, involving multiple mediators. Lastly, the fourth component pertains to the actual actions taken and emphasises the agency exhibited by both human and non-human actors, valuing and acknowledging their contributions (Seuwou, 2016).

In this study, ANT is employed to delve into the realm of AI-based technique implementation within automotive manufacturing settings, specifically aimed at enhancing equipment availability. ANT serves as a powerful tool for unravelling the intricate network of actors, including employees, management, machines, and the broader socio-technical context, all intertwined in the implementation process. With the introduction of new actors such as IoT-generated data from sensors, the network becomes even more complex. By incorporating these emerging data sources, ANT unveils the complex tapestry of challenges, limitations, and interactions that characterise these actors' roles. This framework will enable the researcher to develop a comprehensive understanding of the multifaceted social and organisational dynamics that profoundly influence the successful adoption and integration of AI-based techniques.

Through the integration of ANT, the research aspires to transcend the surface-level insights of AI-based technique implementation. The goal is to capture the subtle interplay of relationships, social dynamics, and hurdles that exert their influence on the outcome of these endeavours'. Within the intricate landscape of automotive manufacturing, characterised by its multifarious context. The research aims to reveal underlying insights that either facilitate or impede the success of these initiatives. The synergistic integration of ANT and quantitative analysis offers a unique avenue to illuminate the intricate relationships between actors, technologies, and socio-technical elements within the context of AI-based technique implementation, providing valuable insights for both academia and industry.

2.7.3 Conceptual Framework

The conceptual framework for the study integrates the dynamic interplay between social and technical elements, considering the agency of human and non-human actors. It recognises that technology design and implementation in socio-technical systems are influenced by social interactions, power dynamics, and network relationships. Socio-technical systems theory (STS) provides a holistic perspective by considering both social and technical factors, while Actor-Network Theory (ANT) emphasises the role of agency and network relationships in shaping technological outcomes. By combining STS and ANT, the framework explores the interconnectedness of social and technical elements, the influence of actors and their interactions, and the socio-technical transformations in the study context. This integrated approach enables a comprehensive analysis of complex dynamics and socio-technical implications, facilitating a deeper understanding of the interdependencies and factors relevant to the research questions.

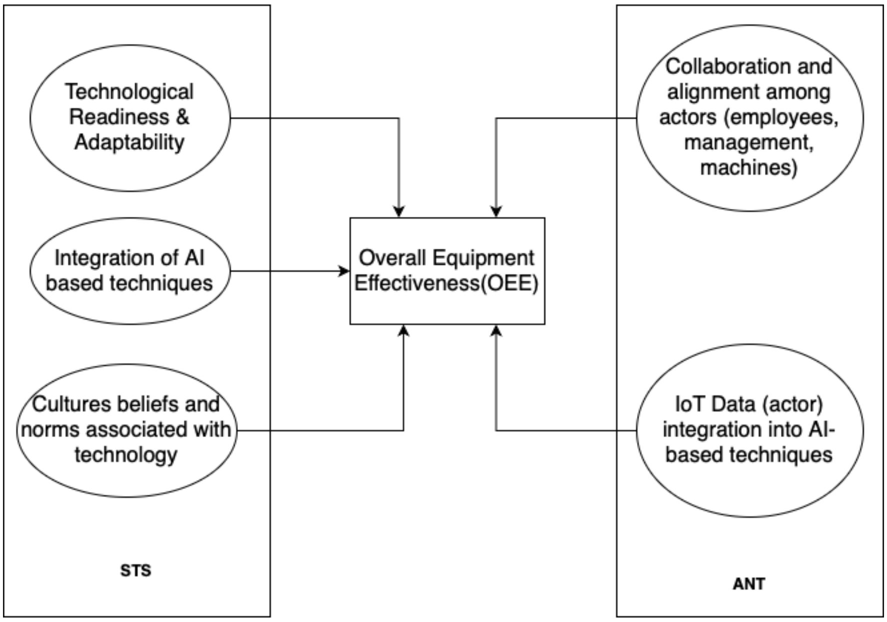


Figure 4: Conceptual framework to improve OEE (Source: Author constructed)

Figure 4 presents a conceptual framework that delineates the multifaceted influences on OEE within a company, approached from two theoretical perspectives: the Social Technical System (STS) and Actor-Network Theory (ANT). The STS side emphasises the importance of technological readiness and adaptability, the integration of AI-based techniques, and the cultural beliefs and norms associated with technology. These elements are crucial in understanding how the technological and organisational infrastructure currently supports OEE. On the ANT side, the focus shifts to the integration of IoT data into AI-based techniques and the collaboration among different actors in the organisation, including employees, management, and machines, highlighting the interplay between various stakeholders and the technological ecosystem.

The diagram aligns with the research questions by explicitly connecting these theoretical constructs to the practical concerns of assessing and enhancing OEE at Company X. The first question, regarding the current state of OEE, relates to analysing how each factor, such as IoT data, presented in the diagram contributes to the existing performance metrics. For the second and third questions, the diagram suggests that a thorough understanding and implementation of AI and IoT technologies, underpinned by an organisation’s technological readiness and a culture conducive to innovation, are key to the impact on OEE. Furthermore, it implies that developing a predictive maintenance framework to improve OEE necessitates not just technological integration, but also a strong alignment and collaboration among all actors involved, ensuring that both human and technological agents work cohesively towards the objective of enhancing OEE.

2.8 Conclusion of Literature Review

The literature review provides a critical analysis of maintenance practices in the automotive industry, focusing on Total Productive Maintenance (TPM), Lean Manufacturing, Overall Equipment Effectiveness (OEE), and predictive maintenance. TPM, developed in the 1960s by Seiichi Nakajima and the Japanese Institute of Plant Maintenance, optimises equipment effectiveness and involves all employees in the maintenance process. Lean Manufacturing, originating from the Toyota Production System (TPS), aims to eliminate waste and improve efficiency, significantly influencing automotive production.

OEE is a crucial metric within the TPM framework, offering insights into equipment availability, performance, and quality, helping manufacturers identify bottlenecks and improve productivity. The review highlights predictive maintenance as an emerging trend, utilising AI-based techniques to proactively monitor and predict equipment failures. This approach enables more efficient scheduling of maintenance activities based on actual equipment conditions rather than fixed intervals or reactive repairs.

The referenced literature discusses a study on the application of machine learning to boost the efficiency of maintenance practices in South Africa's automotive manufacturing. This research underscores the importance of intelligent management strategies for proactive scheduling to enhance production while curbing costs. Specifically, it aims to validate the impact of AI in improving equipment availability at a particular production station. Company X currently employs condition-based maintenance strategies, which depend on sensor data to initiate maintenance tasks. By incorporating a bi-directional LSTM (Long Short-Term Memory) network, the study seeks to refine this approach, using process parameters to predict availability outcomes and mitigate unplanned maintenance-related downtimes.

The referenced literature provides insight on how predictive maintenance has been used in multiple sectors such as manufacturing, aviation, and consumer goods production. It underscores the necessity of adhering to industry regulations and standards to achieve optimal results and foster smarter, more efficient, and sustainable production processes in line with Industry 4.0 goals. By examining cross-sector applications and the integration of advanced AI techniques, the review highlights the transformative potential of predictive maintenance in enhancing operational efficacy and setting new standards for maintenance operations.

Finally, the literature proposes the integration of a bi-directional LSTM into Company X's maintenance regime to predict quality-stops (Q-stops) and streamline operational management. This technological enhancement is anticipated to bolster product quality and reduce unexpected maintenance events, thereby fortifying overall operational efficacy. The research is focused on examining how AI-driven methods can improve equipment availability and operational efficiency within the automotive manufacturing sector, potentially setting a new standard for maintenance operations.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter of the study delineates the comprehensive framework and methodologies underpinning the research, aligned with the Design Science Research (DSR) approach. It begins by establishing the context for the DSR study, focusing on real-world challenges and opportunities such as those presented by novel technologies in production systems. The research progresses through the DSR framework which encompasses six phases: Problem Identification and Motivation, Objective Definition, Design and Development, Demonstration, Evaluation, and Communication (Peffers, 2007). This approach is mapped against specific research questions about OEE at Company X, ensuring a structured investigation into each query.

This chapter outlines the research methodology, detailing the approach, design, and data collection methods used. Section 3.2 describes the Design Science Research (DSR) approach, highlighting its practical focus on creating innovative solutions through iterative cycles. Section 3.3 explains the case study design aligned with DSR, focusing on Company X's OEE. The data collection methods, including IoT sensor data, semi-structured surveys, and experimental data, are detailed in Section 3.4. Section 3.5 discusses the purposive sampling strategy for selecting key data sources, while Section 3.6 details the research instruments, such as IoT sensors and Python-implemented bi-directional LSTM models. The data collection procedure and analysis strategies, including descriptive statistics and EDA, are covered in Sections 3.7 and 3.8, respectively. Sections 3.9 provides a detailed outline of how identified biases will be mitigated and the measures taken to address them. Section 3.10 and section 3.11 address the study's limitations and quality assurance measures, ensuring validity and reliability. Ethical considerations are discussed in Section 3.12, highlighting participant confidentiality and data protection. The chapter concludes with the importance of the DSR approach for achieving the research objectives and improving OEE through AI-based techniques.

3.2 Research approach

A Design Science Research (DSR) study typically finds its motivation in real-world challenges, such as issues related to production and capacity, as well as promising prospects like the incorporation of novel technologies and concepts (Aken, 2016). As highlighted by Aken (2016), the project's initial steps involve selecting a context where the identified problem holds significant importance or where potential opportunities exist. This setting enables the project to engage with management and other stakeholders, fostering a cooperative relationship with researchers to craft a workable solution. Throughout the improvement project, an extensive examination of the problem and its underlying causes is conducted (Aken, 2016). Additionally, the solution design often benefits from the collaborative input of local stakeholders and subsequent field testing. Aken (2016) further suggests that continuous refinement and testing at the local level contribute to the ongoing development of the solution.

DSR in Operations Management (OM), as highlighted by Dresch (2019), prioritises the pragmatic implementation of research to enhance operational efficiency and effectiveness. The research objective revolves around creating artifacts that analyse the influence of human behaviours and attitudes on productive systems (Dresch, 2019). According to Dresch et al., (2019), in the context of DSR for Operations Management, artefacts are pivotal elements that include constructs, models, methods, instantiations, and design propositions. These artefacts are developed to provide innovative solutions aimed at enhancing production systems. The methodologies employed in DSR span quantitative techniques, optimisation models, simulations, process modelling, and performance measurement, all essential in the creation and application of these artefacts. For the domain of automotive manufacturing, the study's artefact is an AI-based framework tailored to improve OEE.

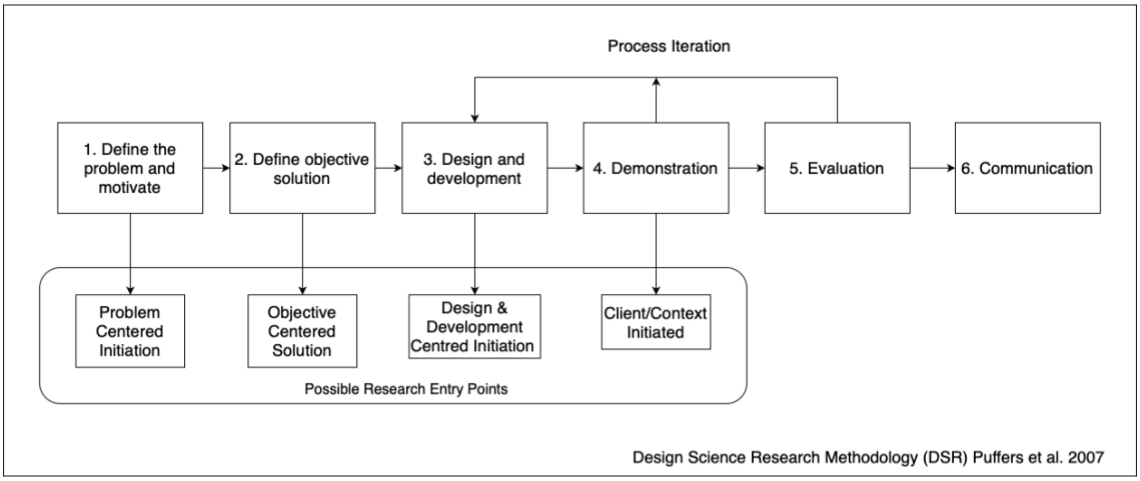


Figure 5: Design Science Research Methodology.

DSR as depicted in figure 5 is a research approach that involves iterative cycles of designing, developing, and evaluating innovative artifacts to address specific real-world problems (Gregor, 2013). According to Gregor et al (2013), the key strengths of DSR lie in its practical focus and the creation of solutions that can be implemented and evaluated in practical settings. DSR allows researchers to actively engage in the design and development process, drawing on theories and existing knowledge to guide their work.

The Design Science Research (DSR) methodology is a rigorous process that unfolds through six phases to guide the systematic creation of solutions (Peffers, 2007). It begins with Problem Identification and Motivation, where the fundamental issues necessitating intervention are pinpointed and described. This is followed by Objective Definition, where the desired outcomes of the solution are specified. The next phase, Design and Development, involves the actual crafting of the artefact intended to address the problem. In the Demonstration phase, the artefact's application is showcased to resolve the identified issue. The Evaluation phase involves a critical assessment of the artefact to determine its success in meeting its objectives. Finally, the Communication phase is where the insights and findings of the research are disseminated to a wider audience.

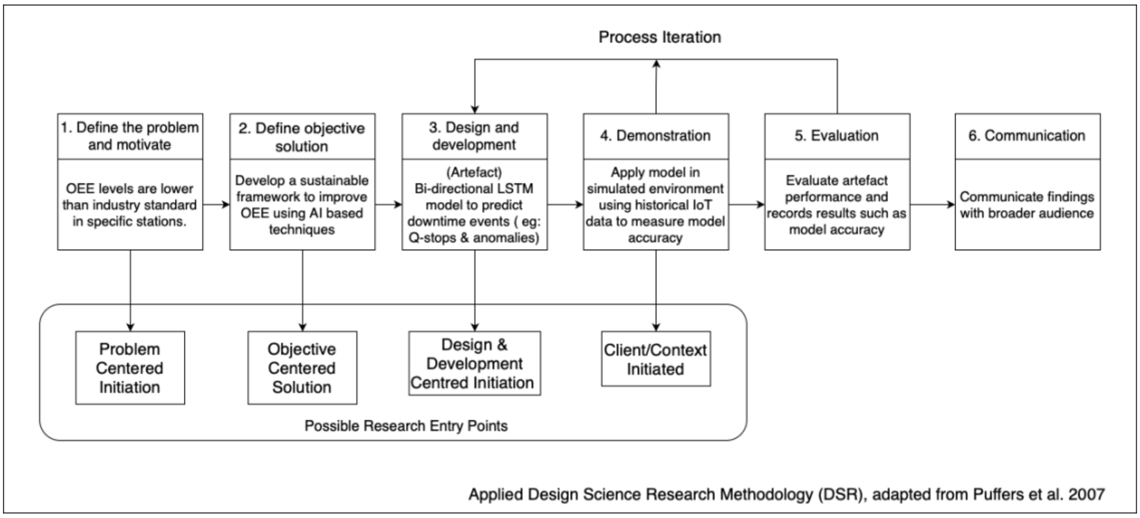


Figure 6: Applied DSR Methodology followed in the study.

Figure 6 depicts how the DSR methodology is followed to address each research question concerning OEE at Company X. The first research question, concerning the current OEE status, is answered during the "Problem Identification and Motivation" phase, where data analysis helps identify efficiency bottlenecks. The impact of technological readiness and the integration of AI and IoT on OEE, the second question, is explored in the "Define Objective" phase through a semi-structured questionnaire, establishing the link between technology integration and OEE performance in preparation for developing an AI based framework to improve OEE.

The third question, on the development of an AI-based predictive maintenance framework to improve OEE, is addressed across the "Design and Development," "Demonstration," and "Evaluation" phases. Here, a framework is crafted and tested for its ability to predict and mitigate production downtimes, with its performance critically analysed to ensure it meets the enhancement goals. Finally, the "Communication" phase ensures that the insights and solutions derived from these research questions are articulated and shared broadly, highlighting the DSR methodology's effectiveness in driving OEE improvements.

For the present study in the domain of operations management, the Design Science Research (DSR) approach is considered as the preferred methodological framework. DSR is suitable because it emphasises the creation and evaluation of innovative artifacts to address specific problems, which aligns with the objective of designing a framework to enhance OEE. The DSR approach allows for an iterative design and development process, enabling the researcher to create a practical solution by reducing downtime and improving output quality at a selected station(Peffers, 2007). Additionally, the use of a simulated environment in DSR provides a controlled setting for evaluating the effectiveness of the Bi-LSTM model. DSR offers a more focused and targeted approach to creating and evaluating artifacts to directly address the OEE improvement goals of the study.

3.3 Research design

A case study design is adeptly chosen for this research, as it aligns with the Design Science Research (DSR) framework detailed in Figure 6 to answer the posed research questions. It commences by examining the current state of OEE at Company X through the DSR's "Problem Identification and Motivation" phase, where the case study's depth allows for an analysis of quantitative metrics and qualitative insights. The "Define Objective" phase of DSR, which seeks to understand the impact of technological readiness and AI and IoT integration on OEE, is enriched by the case study's ability to dissect real-world applications and their varied outcomes as part of defining the objective solution.

Furthermore, the "Design and Development" and "Demonstration" phases of DSR are embodied in the case study's practical implementation of an AI-based predictive maintenance framework, where its efficacy is thoroughly evaluated within the operational context of the company. This hands-on approach paves the way for the "Evaluation" phase, which benefits from the case study's empirical data to refine the framework and assess its performance against the objectives. The DSR's concluding phase, "Communication," is where the case study's findings are articulated and shared, ensuring that each research question is not only addressed but also contextualised within the lived experience of the company, offering a robust and comprehensive view of the research's implications for enhancing OEE in automotive manufacturing settings.

3.4 Data collection methods

In a DSR study, data collection typically revolves around the iterative process of designing, developing, and evaluating innovative artifacts (Gregor, 2013)**.** The research problem focuses on using AI-based techniques to improve OEE for an automotive manufacturer. To achieve this within a DSR study, the data collection methods may include the following:

- **Historical Data**: Collecting historical data related to OEE and downtime, equipment performance, maintenance records, and other relevant variables from the automotive manufacturer. This data can serve as a baseline for evaluating the effectiveness of AI-based techniques in improving OEE.
- **Sensor Data**: Gathering real-time data from sensors installed on manufacturing equipment or production lines. This data can include parameters such as machine utilisation, energy consumption, temperature, vibration, or other relevant metrics. It provides input for training and testing AI models.
- **Semi-structured survey**: Administering a semi-structured survey to gather feedback from operators, maintenance teams, management, and other relevant personnel. This data can help understand their experiences, perceptions, and opinions regarding the use of AI-based techniques and their impact on OEE.
- **Experimental Data**: Setting up controlled experiments or pilot studies to test and evaluate AI-based techniques. This can involve implementing AI algorithms or models in a simulated or real manufacturing environment and collecting data on OEE metrics, equipment performance, and other relevant factors.

The data collection methods discussed above focus on gathering diverse quantitative data sources to assess the efficacy of AI-based techniques in enhancing OEE for automotive manufacturers in effort to improve operational efficiency.

3.5 Population and sample

To ensure a robust analysis, the study will employ purposive sampling to gather data from key sources. For an in-depth examination of the state of OEE at Company X, data will be extracted from IoT systems in a specific zone at compant X, capturing real-time OEE metrics over a three-month period, from September 1st to November 30th, 2023. The selection of this timeframe is a consequence of delays encountered in securing ethical clearance from the company. The focus will be on the body shop manufacturing station, which is noted for its high level of automation and downtime events due to technical reasons and, as such, provides a wealth of IoT data for analysis. To address the second research question, a semi-structured questionnaire, detailed in Appendix A and created using the Qualtrics platform, will be distributed to experts within the designated production environment. Regarding the third research question, data will be selectively collected from areas identified as having the lowest OEE, with particular attention paid to station equipment availability. This strategic approach to data collection allows for targeted insights into specific elements that influence OEE, ensuring that the study's findings are both relevant and actionable.

3.5.1 Case site

Company X, a South African automotive manufacturer, specialises in the production and assembly of premium luxury vehicles that are exported worldwide. The company's status as an automotive manufacturer in South Africa provides a distinctive industry and geographical context, offering valuable insights and perspectives for the research study. By conducting a comprehensive examination of Company X's performance using quantitative metrics, a thorough understanding of the organisation's current state of OEE can be attained.

3.5.2 Sample and sampling method

The sampling strategy for this research has been planned to align with the investigative needs of each research question, focusing particularly on OEE at

Company X. Purposive sampling is the cornerstone of the data collection process, especially for the first question which requires a deep dive into the current state of OEE. By deliberately choosing to extract IoT data from the body shop manufacturing station over a specified three-month period, the study capitalises on a time frame rich with operational data. This period was selected due to its potential to provide a comprehensive dataset following the delay in obtaining ethical clearance, ensuring that the data collected is not only ample but also pertinent to the highly automated processes that characterise the station.

In addressing the second research question, the study employs expert sampling through the distribution of a semi-structured questionnaire crafted with the Qualtrics platform. This questionnaire, detailed in Appendix A, is purposed for experts within the production environment, chosen for their specialised knowledge and experience. The intention is to gather qualitative data on the impact of AI and IoT integration on OEE from those with direct involvement and understanding of the technologies in use. Given that the population of experts for these highly automated manufacturing stations is inherently low, this form of purposive sampling ensures that the insights gleaned are informed by a high level of expertise, providing depth to the study's findings. By targeting these key individuals, the study aims to capture nuanced perspectives and informed observations, which are crucial for defining the objective solution.

For the third research question, selective sampling is utilised to pinpoint areas within the production environment that are underperforming in terms of OEE, with a particular focus on station equipment availability. This targeted approach allows the study to concentrate on zones where improvements can be most impactful, thus maximising the efficacy of the research. By selecting stations with the lowest OEE for data collection, the research can directly address the factors that critically affect equipment efficiency and availability, providing a clear path to enhancing operational performance through the proposed AI-based framework. This strategic selection of data sources, through various purposive sampling methods, underscores the study's commitment to the actionable exploration of OEE improvements.

3.6 The research instruments

The study will apply specific instruments to address the research questions outlined in Section 1.4.

1. To assess the current state of OEE at Company X:
   a. **IoT sensor data collection**: IoT sensors on manufacturing equipment will collect real-time data to measure machine availability, performance, and quality. The data will serve as an empirical basis for an objective assessment of OEE at Company X.
2. To explore the impact of technological readiness, AI, and IoT integrations on OEE:
   a. **Data analysis**: The study will undertake a detailed descriptive analysis of the data garnered from the semi-structured surveys. These findings will illuminate the current landscape of technological preparedness for AI adoption and IoT integration from a sociotechnical standpoint by delving into the insights provided by industry experts in the field. This approach will not only quantify the readiness levels but also encapsulate the qualitative perspectives that shape the integration of these technologies in the manufacturing environment.
3. To develop and validate a predictive maintenance framework using AI to boost OEE at Company X:
   a. **Python Software Implementation of a Bi-directional LSTM**: This research instrument, pseudo code detailed in Appendix B, will consist of a Python-implemented bi-directional LSTM model as part of developing a framework to enhance OEE using AI.
   b. **IoT sensor data collection**: IoT sensors on manufacturing equipment will collect real-time data to measure and represent the spot-welding process. This data will be pivotal in extracting features that can be used as predictors for the developed AI artefact.

Each step of this methodology is mapped to the corresponding research question, ensuring that the study's objectives are directly targeted through the selected data collection and analysis techniques. The goal is to not only understand the current OEE status and the effects of technological advancements but also to create and test a practical AI-powered tool to enhance maintenance practices and, consequently, OEE metrics.

3.7 Procedure for data collection

The study will implement a web-based questionnaire to capture expert insights on the operational efficiency at Company X, with a particular focus on OEE. This questionnaire will be disseminated via an online link, which will be shared with experts in Company X who will facilitate the distribution to selected experts through email. In tandem with this qualitative approach, a rigorous data clearance process, as stipulated by Company X, will be adhered to access a comprehensive batch of sensor data. This sensor data will encompass detailed OEE values for each station, recorded downtime occurrences at each station, as well as process-related data pertinent to the technologies deployed across the various stations. The analysis of this rich sensor data will be instrumental in providing a multifaceted view of the current OEE status at Company X, thereby contributing a quantitative dimension to the study's findings.

3.8 Data analysis strategies and Interpretation

To gain a comprehensive understanding of the current state of OEE at Company X, a combination of descriptive statistical techniques and Exploratory Data Analysis (EDA) will be employed. EDA will play a crucial role in enhancing the analysis of OEE by providing a deeper investigation into the data collected from IoT sensors. Descriptive statistical techniques will be initially applied to calculate standard measures such as the mean, median, and standard deviation of the OEE data. These measures will provide a summary and characterisation of the OEE performance within Company X. However, to further explore the data and extract valuable insights, EDA techniques will be utilised.

EDA involves employing visualisations, data profiling, and pattern recognition to uncover underlying patterns, relationships, and anomalies present in data (Tukey, 1977). Visualisations like scatter plots, histograms, and box plots will be generated to visually explore the correlations between OEE and other relevant variables, such as equipment downtime, availability, and performance rates. These visual representations will help identify any outliers, trends, or relationships that may significantly impact OEE performance. Moreover, EDA will assist in detecting potential data quality issues, such as missing values, inconsistencies, or data entry errors. By thoroughly examining the data, researchers can ensure the accuracy and reliability of the OEE analysis. Additionally, EDA techniques will also enable the researcher to segment the data based on different units, stations, or time periods. This segmentation will allow for a more granular analysis of OEE performance, facilitating the identification of specific areas or units that require improvement.

To gather feedback from a specific group of experts in the field, a web-based questionnaire will be conducted. The questionnaire will utilise a five-point Likert scale, providing respondents with options to express their opinions or ratings on various aspects related to the study. By employing this scale, the collected data can be statistically analysed through descriptive statistics, enabling researchers to derive meaningful insights and establish a quantitative foundation for the study (Savolainen, 2020). It is worth noting that participants for the questionnaire will be selected based on the analysis of the IoT data. This will allow for a targeted approach focusing on the station that needs intervention to improve OEE.

According to Zhang (2018), conventional machine learning algorithms face limitations in adapting to the intricate and non-linear characteristics of manufacturing systems and processes. In this study, the focus will be on implementing a bi-directional LSTM, as proposed by Zhang (2018), to predict performance degradation leading to downtime and compromised quality. The research will begin with the formulation of the prediction model and provide a theoretical background on the selected algorithms. The primary challenge in tracking the system lies in capturing the non-linearity associated with system variation and data uncertainty (Zhang, 2018). In response to these challenges, the research introduces a novel approach to system modelling using deep learning techniques. Specifically, the study focuses on investigating the effectiveness of a Long Short-Term Memory (LSTM) structure in capturing the underlying variation patterns within time series data (Zhang, 2018). Additionally, to address the issue of data uncertainty, a bi-directional LSTM network is proposed. According to Zhang (2018), this innovative network architecture allows for information flow through LSTM cells in both forward and backward directions, enabling improved prediction accuracy, disturbance elimination, and smoother predictions. The derived algorithm will act as the foundational framework for improving OEE in other stations.

3.9 Addressing Potential Biases in Data Interpretation and Mitigation Strategies

When utilising descriptive statistical techniques and exploratory data analysis (EDA) to analyse OEE data from Company X, several potential biases could arise. One significant concern is representation bias(Giffen, 2022), where the data collected from IoT sensors might not be representative of all equipment or time periods, potentially leading to misleading conclusions about overall equipment effectiveness. To address this, it is essential to ensure that IoT sensors are uniformly distributed across all equipment and consistently collect data over a representative time frame(Giffen, 2022).

According to Giffen (2022), confirmation bias is another risk, where the researcher might interpret data in ways that confirm pre-existing beliefs or hypotheses. This can be mitigated by implementing blind analysis techniques, where the researcher analysing the data is unaware of the initial hypotheses, and by incorporating peer review and collaborative analysis to identify and correct any confirmation biases.

Measurement bias can also occur due to data quality issues such as missing values, inconsistencies, or errors, leading to biased results(Miguel, 2015). These can be addressed by employing data cleaning techniques and using EDA to detect and correct these issues early in the analysis process. Visualisations and pattern recognition techniques in EDA are also subject to biases. Visual bias can occur if scales or axes are manipulated, leading to misinterpretations(Giffen, 2022). To mitigate this, standardising visualisations using consistent scales and clear labelling is crucial, along with providing multiple visualisations to represent the same data from different perspectives.

In the machine learning implementation, algorithmic bias and model overfitting are significant concerns(Giffen, 2022). Using diverse and representative training data, applying fairness-aware algorithms, and implementing regularisation techniques and cross-validation can enhance the robustness of the bi-directional LSTM model, ensuring reliable and unbiased predictions(Zhang, 2018). Addressing these potential biases and implementing respective mitigation strategies will ensure that the OEE analysis at Company X is robust, reliable, and insightful.

3.10 Possible limitations and challenges of the study

The following limitations and challenges may exist, pertaining to the study:

- Due to existing company clearance processes, obtaining the IoT sensor promptly may be a challenge.
- The effectiveness of IoT sensor data collection relies on the installation and coverage of sensors on manufacturing equipment. Incomplete or insufficient sensor coverage may limit the comprehensiveness of data collection.
- Conducting an in-depth analysis using a bi-directional LSTM may require a significant amount of time.
- It may be challenging to ensure participation from all relevant stakeholders or to obtain responses that fully reflect their knowledge and expertise.
- The performance and applicability of the bi-directional LSTM framework designed and tested using Python and specific data from IoT sensors may vary when applied to different manufacturing settings or equipment. Generalising the framework's effectiveness beyond the specific context may require further validation and adaptation.

3.11 Quality Assurance

3.11.1 Validity

There are three established types of validity that should be considered (Creswell, 2018). Firstly, there is content validity, which examines whether the items effectively measure the content they were intended to assess. Secondly, predictive, or concurrent validity examines whether scores can accurately predict a criterion measure or correlate with other results. Lastly, construct validity assesses whether the items can measure theoretical constructs or concepts. According to Creswell (2018), in recent research, construct validity has emerged as the primary focus in establishing validity, emphasising whether the scores generated serve a practical purpose and yield positive outcomes when utilised in practical applications.

To ensure the validity of the research instruments described in the study, several criteria can be addressed. Firstly, for the assessment of the current state of OEE at Company X, multiple instruments are employed. The utilisation of IoT sensors installed on manufacturing equipment enables the collection of real-time data on machine availability, performance, and quality. This approach ensures content validity as the data collected directly measures the intended aspects of OEE. Additionally, a questionnaire is designed and administered to gather data from automotive manufacturing professionals involved in improving OEE. These questionnaires contribute to construct validity by assessing the professionals' perspectives and experiences regarding OEE improvement.

In the exploration of AI-based techniques implemented in automotive manufacturing settings, data analysis plays a crucial role. The quantitative analysis conducted on existing datasets related to equipment availability ensures construct validity by examining real-world data and identifying patterns and correlations. This analysis contributes to content validity as it directly addresses the research question regarding the challenges and limitations of AI-based techniques.

3.11.2 Reliability

Reliability refers to the consistency or predictability of an instrument (Creswell, 2018). For multi-item instruments, the most crucial aspect of reliability is internal consistency, which measures how consistently sets of items on the instrument behave (Creswell, 2018). According to Creswell (2018), it is essential because the items in the selected research instrument scale should be evaluating the same underlying concept, and as a result, these items should demonstrate appropriate intercorrelations.

To ensure reliability in the study, several measures can be implemented. Firstly, the use of IoT sensor data collection in assessing the current state of Overall OEE at Company X provides consistent and objective measurements of machine availability, performance, and quality. This real-time data collection method contributes to the consistency and predictability of the instrument. Secondly, the administration of questionnaires to automotive manufacturing professionals involved in improving OEE adds to the internal consistency of the research instrument. By designing the questionnaire items to evaluate the same underlying concept of OEE improvement, the responses can be analysed for appropriate intercorrelations.

Lastly, the implementation of a Python software framework for OEE enhancement ensures internal consistency by utilising the same methodology and process data generated by IoT sensors. By maintaining consistency and aligning the research instruments with the underlying concept of OEE improvement, the study can effectively meet reliability standards in evaluating and measuring OEE in the manufacturing context.

3.12 Ethical considerations

Ensuring the study's ethical integrity and compliance with Company X's policies is of paramount importance for this study. In order to meet these requirements, the researcher will diligently follow a set of guidelines. Firstly, obtaining proper approvals and permissions from relevant stakeholders, including the company's management or ethics committee, will be a priority before initiating any data collection or research procedures. This step guarantees adherence to company policies governing research activities.

Furthermore, upholding participant confidentiality and data protection will be a central focus. To accomplish this, the researcher will obtain informed consent from survey participants and employ appropriate measures to anonymise sensitive information. By prioritising participant autonomy and privacy, ethical standards will be upheld throughout the study. Moreover, responsible data handling, storage, and sharing practices will be strictly followed to prevent any unauthorised access or breaches of Company X's data security policies. Maintaining open lines of communication and actively collaborating with the company's representatives will facilitate ongoing compliance with ethical guidelines and policies, ensuring the successful execution of this study with the utmost ethical consideration.

3.13 Conclusion

This chapter provides a robust framework for investigating the research questions and objectives. By adopting the DSR approach, the study ensures a systematic process for developing and evaluating the AI-based predictive maintenance framework, setting the stage for empirical analysis and results presentation. This comprehensive methodology equips the research with the necessary tools to achieve its objectives and improve OEE through innovative AI-based techniques.

Additionally, the literature review synthesises key insights from previous studies on maintenance practices and the application of AI in predictive maintenance, emphasising the critical role of integrating socio-technical systems and actor-network theory in understanding the complex dynamics of manufacturing environments. By highlighting the gaps in current knowledge and the need for a comprehensive framework to improve OEE through AI-based predictive maintenance techniques, the chapter lays a solid foundation for the empirical investigation in the following chapters.

3.14 Proposed schedule and timelines

Figure 7 below provides a detailed timeline for the research project.

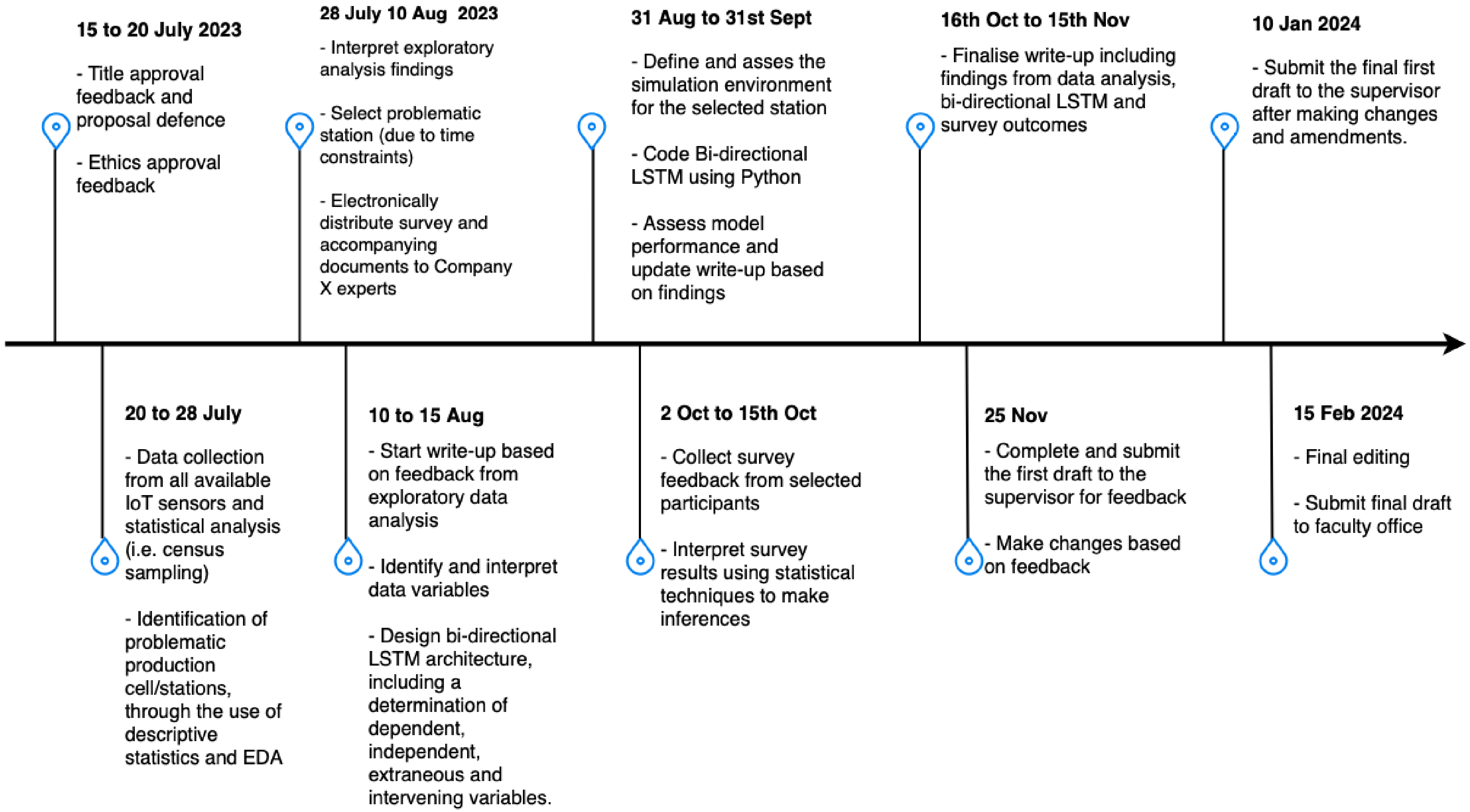


Figure 7: Detailed timeline for the research project

RQ #		State Research Question or Objective	Prop/hyp #	State Proposition or Hypothesis	Data collection detail	Data analysis method
1		What is the current state of OEE at Company X?	1	Implementing an AI-based Predictive Maintenance framework has the potential to significantly enhance Overall Equipment Effectiveness (OEE) in the automotive manufacturing process.	Sensor data from various stations with recorded OEE and downtime values for the specified period.	Descriptive Statistics
2.		How do technological readiness, AI and IoT integrations impact OEE?	2	Empowering Proactive Manufacturing Excellence: Leveraging AI for Early Anomaly Detection and Preventive Maintenance in	Semi-structured survey shared with selected participants.	Descriptive statictical analysis

RQ #		State Research Question or Objective	Prop/hyp #	State Proposition or Hypothesis	Data collection detail	Data analysis method
				Automotive Production through the development of an AI based framework.		
3.		How can a predictive maintenance framework, based on artificial intelligence, be developed to enhance OEE at Company X?	3	The AI-based Predictive Maintenance framework can contribute to improving product quality in automotive manufacturing. By analysing historical data and real-time performance parameters, the framework can identify correlations between equipment	Sensor data collected from various stations at Company X consiting of asset information and process information of selected area for improvement.	Data Mining Machine learning algorithms Sequential data analysis using Bi-directional LSTM.

RQ #		State Research Question or Objective	Prop/hyp #	State Proposition or Hypothesis	Data collection detail	Data analysis method
				conditions and product quality deviations, enabling the prediction of production interuptions.		

Table 2: Consistency table: research questions, propositions, data collection, and data analysis

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

Chapter 4 systematically employs the DSR methodology to delve into the intricacies of OEE in the context of automotive manufacturing. Section 4.2 is pivotal as it aligns with the first phase of DSR, identifying the problem through robust exploratory data analysis. The section is comprehensive, encompassing the collection methods, data description, cleaning procedures, OEE data analysis, downtime data analysis at selected stations, and a cluster analysis to discern patterns influencing OEE at Company X. This meticulous approach sets the stage for an in-depth understanding of the operational challenges.

The narrative progresses in Section 4.3, which aims to define the study's main objective, constructing an OEE improvement framework specifically for automotive manufacturing. This section discusses the insights drawn from a semi-structured questionnaire distributed to industry experts. The responses inform the creation of a holistic framework that integrates both social and technical dimensions, essential for the successful implementation of OEE strategies. Section 4.4 then details the development of the study's central artefact, an AI-based predictive maintenance model designed to anticipate production interruptions, allowing for pre-emptive action to reduce downtime.

The latter sections of the chapter, 4.5 to 4.6, delve into the application and validation stages of the research. Sections 4.8 and 4.9 describe the demonstration and evaluation of the artefact using a simulated environment crafted from real-world IoT data, aimed at assessing the artefact's accuracy and effectiveness. Sections 4.7 and 4.8 discuss the second demonstration phase, focusing on the artefact's generalisability across different operational contexts. Concluding the chapter, Section 4.9 offers a visual representation of the framework, encapsulating the communicative aspect of the study and underscoring the practical implications of the research in enhancing OEE in the automotive sector. It's important to highlight that all the analyses conducted, along with the developed artefact, are securely housed in Company X's private GitHub repository.

4.2 Identifying the Problem (Current State of OEE at Company X)

In alignment with the first phase of the Design Science Research (DSR) methodology, identify the problem and motivate, the study conducts a rigorous assessment of OEE at Company X using a suite of Exploratory Data Analysis (EDA) techniques using Python and Jupyter Notebook renowned for their robust analytical capabilities. This comprehensive analysis utilises descriptive statistics to summarise the data, while kernel density estimates, time series plots, and Exponentially Weighted Moving Average (EWMA) methods are applied to discern patterns and trends within the OEE metrics. Additionally, downtime analysis provides insights into operational interruptions, and cluster analysis is used to categorise and understand the characteristics of different downtime events. These EDA techniques are applied to OEE, and downtime data extracted for the period of September 1st to November 1st, 2023. This methodological approach enables the identification of key areas for potential enhancement, setting the stage for targeted improvements in the production process.

4.2.1 Data Collection Methods

To acquire a comprehensive understanding of OEE's status within Company X, data from IoT-embedded sensors was systematically gathered using Jupyter Notebooks, see Appendix F. These sensors are installed across various manufacturing stations characterised by highly automated processes. The selection of these stations was executed following a thorough performance analysis aimed at identifying areas with substantial downtime or significant periods of non-production across the production of vehicles. The overarching goal was to target these stations for improvements, thereby enhancing overall operational efficiency, using data-driven techniques.

4.2.1 Data description

The dataset from Company X's industrial facility is a rich repository of production downtime events, offering a detailed temporal lens through which operational inefficiencies are examined. It includes a variety of incident records, each contributing to a holistic understanding of production dynamics. This compilation not only presents a chronological sequence of events but also serves as a foundation for in-depth analysis. The 'MessageText' column within this dataset is particularly noteworthy, as it provides qualitative narratives of each incident. These narratives are invaluable for a nuanced understanding of each event from the Actor-Network Theory perspective, treating messages as actants within the broader network of the production environment. During the period 1st of September to 31st of November 34,012 downtime events and 101656 OEE records were collected.

4.2.2 Data cleaning and preparation

For the IoT data extraction and wrangling, the process was geared towards harnessing the vast amount of raw data generated by connected devices in the study's operational environment. The initial challenge was to aggregate the data from various sources and sensors, into a coherent and structured repository. Data wrangling techniques were employed to extract the relevant metrics, such as equipment uptime, downtime durations, and performance efficiency, process data generated by automotive manufacturing equipment as well as OEE values for all stations in the production environment. Given the heterogeneity of IoT data formats, it was essential to implement a normalisation routine to standardise the data, facilitating comparative analysis.

Validation checks were performed to confirm the accuracy of the timestamps and sensor readings, ensuring temporal alignment and data fidelity. After the validation phase, the focus was on transforming the IoT data into a format that was compatible with the analytical tools such as Python and Jupyter Notebook plugins, which involved restructuring the data into a tabular form and indexing it for efficient querying. The wrangling process also included dealing with missing data points, either by imputing values based on established patterns or by excluding periods of incomplete data where imputation would not be reliable, using the code snippet in appendix G. By the end of this rigorous data preparation phase, a robust dataset containing 101656 OEE measures and 34,012 downtime performance records for a selected production area and was in a form amenable to the sophisticated analytical techniques required for the study emerged.

4.2.3 Analysing OEE Levels

In the analysis of OEE data using a Jupyter Notebook, a comprehensive approach was undertaken to understand the distribution and trends of OEE values in the body shop at Company X. After preparing the data by filtering specifically for the body shop zones and further removing entries with a PlannedOEE and OEE value above 100% as outliers. Throughout the three months, descriptive statistical measures, including mean, median, standard deviation, and quartiles, were generated using specific Python functions, providing an essential summary of the OEE dataset.

This was followed by a visual examination of the OEE distribution. A histogram, enhanced with a Kernel Density Estimate (KDE), was plotted to visualise the spread and density of OEE values, offering insights into the central tendencies and variability of the data**.** Furthermore, to observe how OEE values fluctuated over time, a time series plot was created. This plot graphically represented the OEE values against their corresponding dates, effectively illustrating trends, patterns, or anomalies over the specified period. These visual and statistical explorations are fundamental in identifying areas for operational improvement and understanding the temporal dynamics of equipment effectiveness in the production process.

	PlannedOEE	OEE
count	1.718760e+06	1.718760e+06
mean	1.290300e+02	6.422881e+01
std	4.416523e+01	3.298052e+01
min	9.700000e+01	0.000000e+00
25%	9.700000e+01	6.564000e+01
50%	9.900000e+01	7.305934e+01
75%	1.800000e+02	8.269369e+01
max	2.030000e+02	1.561540e+03

Figure 8 : Descriptive Statistics for OEE over 3-month period

The dataset presented in figure 8 indicates a stark contrast between PlannedOEE and actual OEE values, with PlannedOEE demonstrating a high level of consistency and minimal variation, as evidenced by its tight clustering around a mean of approximately 97.66 and a low standard deviation of 0.94. The actual OEE, however, reveals a broader variability and a substantially lower average efficiency, with a mean of around 73.96% and a standard deviation of 8.10. The disparity is further highlighted by the median values; the PlannedOEE's median matches its mean, suggesting a symmetric distribution, whereas the OEE's median is notably lower than its mean, indicating a potential skewness in the data. The minimum value for OEE of 0.72, suggest possible outliers or episodes of significantly reduced efficiency. This disparity between planning and execution underscores potential operational inefficiencies or measurement discrepancies that warrant further investigation to understand the root causes and to bridge the gap between expected and actual performance.

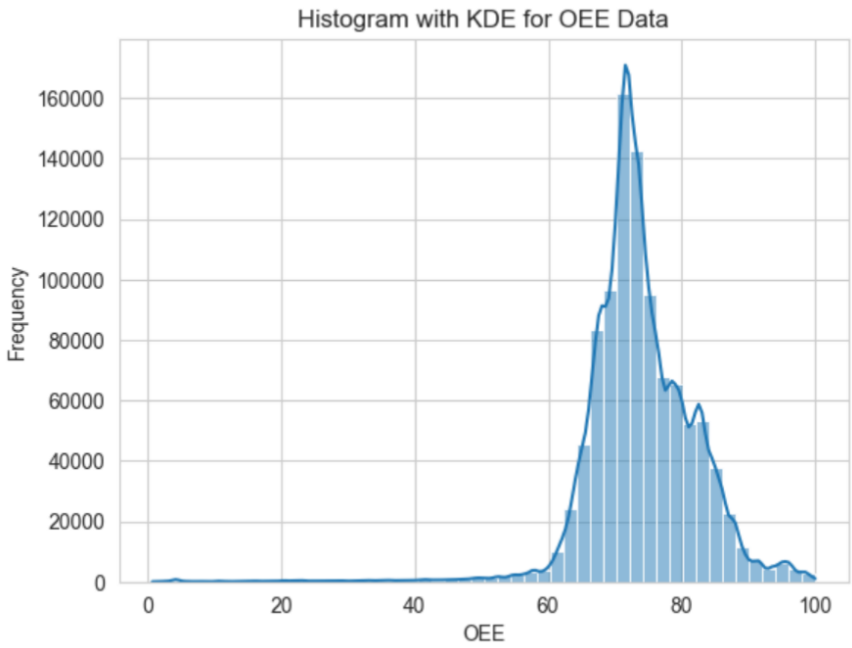


Figure 9: OEE Histogram with kernel density estimate (KDE), source: Company X

A Kernel Density Estimate (KDE) is a statistical technique used to estimate the probability density function of a continuous random variable, which helps in understanding the underlying distribution of data points. In the provided histogram, see Figure 9, enhanced with a KDE for OEE data, a bimodal distribution is observed, indicating two predominant efficiency levels in the operational performance. The pronounced peaks near 70-75 and 100 suggest that equipment tends to operate either at near-maximum efficiency or at a moderately lower efficiency level, with less common operational efficiencies in between. The long tail towards the lower end and the presence of a small histogram bar near zero point to outliers or rare instances of very low OEE values, implying potential operational issues or measurement errors. This visualisation underscores the need for further investigation into the operational processes to understand the dichotomy in performance levels and to address the data quality concerns suggested by the distribution's shape.

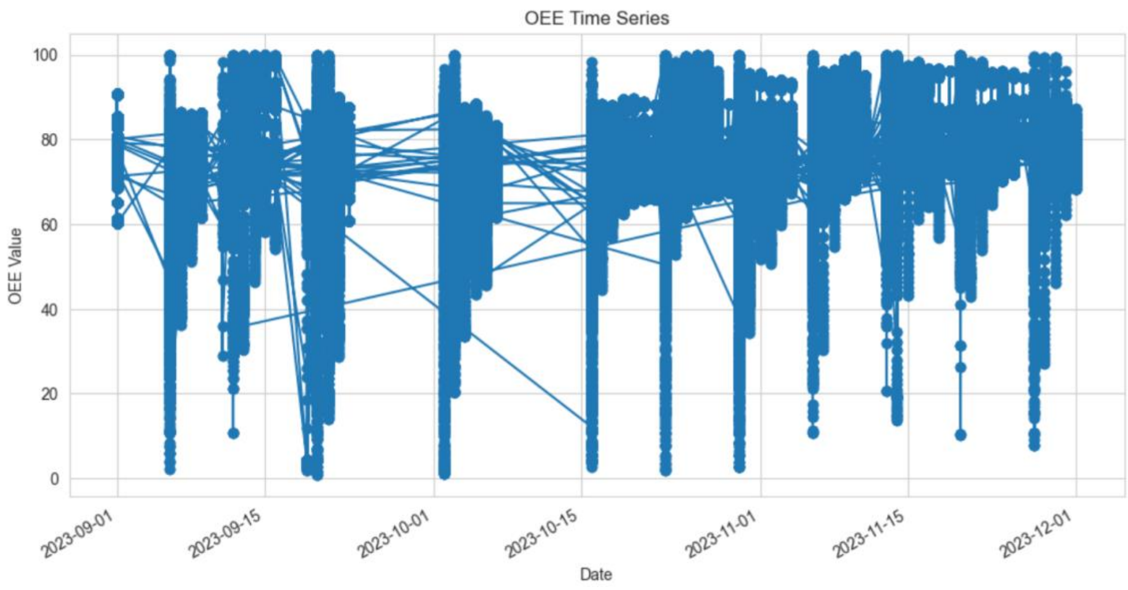


Figure 10: Time series plot of OEE in area ZONE_Z2

The time series plot of the OEE data depicts a highly variable and dynamic operational environment, with no discernible long-term trend in equipment effectiveness over the observed period. The data points are densely packed, suggesting a frequent fluctuation in OEE values, which obscures potential subtle trends and makes it challenging to extract clear patterns. Periodic peaks and troughs hint at possible regular fluctuations in performance, yet these are not immediately evident due to the plot's complexity. Notably, there are sporadic dips approaching zero, indicating moments of significantly reduced operational effectiveness, which could signal equipment shutdowns or malfunctions.

In contrast, a recurring attainment of values at or near 100 may reflect instances of peak performance or a ceiling effect in the data, where 100 represents the maximum possible value. This pattern of reaching the upper limit consistently could also mask genuine variability in optimal performance. The presence of these extreme values, both high and low, suggests a need for further analysis to determine if they represent actual operational events or data outliers. Employing data smoothing techniques, such as moving averages or examining aggregated data over larger time intervals, could provide additional insights and a clearer understanding of the underlying operational trends.

4.2.1 Exponentially weighted moving average of OEE

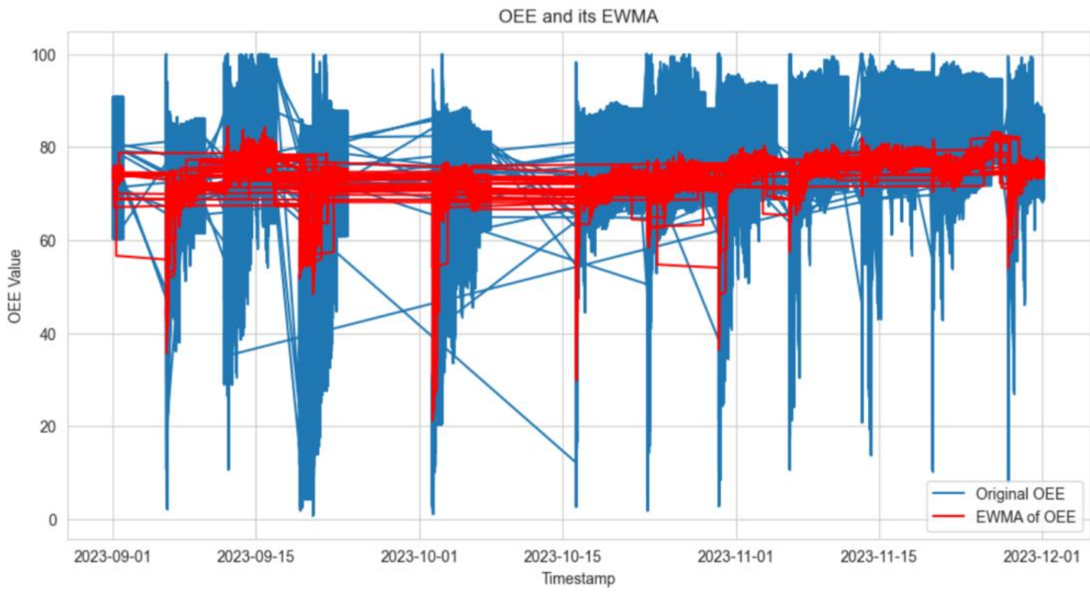


Figure 11: OEE Exponentially Weighted Moving Average (EWMA) in area ZONE_Z2

The provided plot in Figure 11 juxtaposes the raw OEE values against their Exponentially Weighted Moving Average, illustrating a stark contrast between the volatile daily operations and the smoothed-out trends. The original OEE data, depicted in blue, is characterised by substantial fluctuation, with frequent spikes and dips that suggest erratic operational performance or data anomalies. In contrast, the red EWMA line mitigates these fluctuations, offering a more stable view of performance over time and indicating an absence of significant long-term trends. While the EWMA curve subtly responds to changes in the data, it does not capture the extreme values, thereby filtering out short-term aberrations and highlighting more sustained shifts in operational efficiency.

The moments where the OEE hits the extremes of 100 or drops near zero are notably muted in the EWMA, pointing to their transient nature and the possibility of sensor limitations. Overall, the plot reveals a process that, despite the short-term inconsistencies and interruptions, maintains a level of control when viewed through the lens of the EWMA, with no clear indication of long-term performance degradation or improvement. The lack of a pronounced long-term trend in the EWMA could suggest that the process is under control but subject to frequent, short-term disturbances for example quality stops & short stops, otherwise referred to as Q-stops.

```
Area
ZONE__Z2    73.246721
ZONE__Z1    74.661306
ZONE__Z3    79.879883
Name: OEE, dtype: float64
```

Figure 12: Average OEE for Areas in the Bodyshop

The data presented in Figure 12 illustrates the average OEE for three distinct zones in production extracted using python commands, with ZONE_Z2 recording the lowest average OEE at approximately 71.13%, indicating potential room for operational improvement. Area ZONE_Z1 shows a slightly higher OEE at around 73.09%, while area ZONE_Z3 stands out with the highest effectiveness at approximately 79.19%, reflecting a comparatively better performance over a 3-month period. These figures highlight the variances in efficiency across the areas, suggesting that while area ZONE_Z3 is closer to optimal OEE performance, areas ZONE_Z2 and ZONE_Z1 might benefit from a detailed analysis to identify and rectify the underlying causes of their lower OEE scores.

A station in area ZONE_Z2 was selected for further analysis in effort to identify areas in which the application of AI can increase the uptime of equipment thus improving OEE. As a point of departure, the KPINames in area ZONE_Z2 with the lowest OEE levels were selected for inspection. To identify these areas, a Python command was used to filter the data for the lowest OEE values on average for all KPINames in area ZONE_Z2 over a three-month window.

	KPIName	Average OEE
0	SN41_2	68.813355
1	SN41_1	68.836012
2	SG41_2	69.075844
3	SG42_2	69.106462
4	SN41_3	69.660768
5	SN41_4	69.698627
6	AS42_1	70.604062
7	AS42_3	70.963472
8	AS41_1	70.967619
9	AS41_3	71.074358

Figure 13: Average OEE for worst KPI stations in area ZONE_Z2

The OEE values in Figure 13 range approximately from 68.1% to 71.1, which suggests that there might be room for improvement, as OEE scores are often benchmarked at higher percentages for world-class performance (usually 85% or above is considered excellent). The list identifies which stations are the worst performers in terms of OEE, providing a targeted list for where to focus improvement efforts. This could involve investigating reasons for lower performance, such as machine malfunctions, compromising availability, process inefficiencies, or quality issues at these stations or KPI areas. To further explore these KPINames, the availability of the areas will be assessed using the downtime data generated from embedded IoT sensors on the equipment in these KPI areas.

4.2.2 Downtime Duration Analysis

For further analysis, downtime data for all KPIName in area ZONE_Z2 were filtered for, from the original dataset and further analysed.

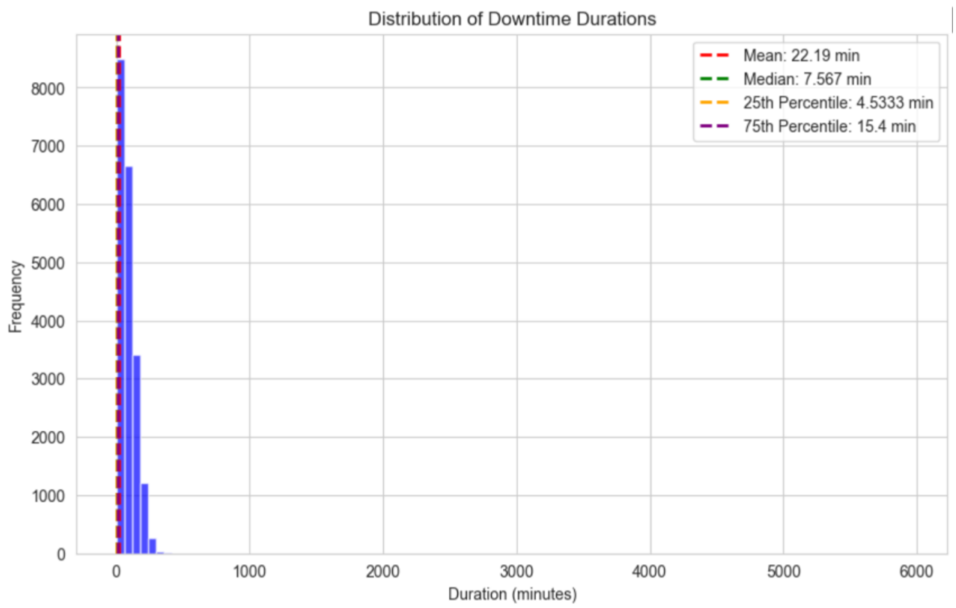


Figure 14: Distribution of downtime durations in Zone_Z2

The descriptive statistics of downtime data indicate that among the 34,012 recorded events in area ZONE_Z2, the average downtime is approximately 22.19 minutes. The substantial standard deviation of about 91.45 minutes reveals a broad range of downtime durations among the events, suggesting inconsistency in the lengths of these occurrences. Notably, the minimum recorded downtime is 0 minutes, indicating instances with negligible downtime, while the first quartile (25%) confirms that a quarter of the events have short durations of 4.53 minutes or less. The median value, at 7.57 minutes, is considerably less than the mean, pointing to a right-skewed distribution where most of the downtime events are brief, yet a minority consist of significantly extended disruptions. This is further emphasised by the maximum downtime recorded at a striking 5,931.68 minutes, highlighting the presence of outliers or particularly severe events that disproportionately raise the average. Such a distribution pattern is typical in operational contexts and underlines the potential benefits of investigating and addressing the root causes of the prolonged downtimes to enhance OEE.

4.2.1 Downtime Classification Analysis

In the realm of operational management, the scrutiny of downtime classifications stands as a cornerstone for enhancing process efficiency and equipment utilisation. By delving into the granular details of each downtime incident, categorised by underlying causes such as technical malfunctions, organisational bottlenecks, or quality issues, it is necessary to embark on a data-driven journey to distil actionable insights from the vast sea of operational data. This analysis not only highlights the prevalence and impact of various classifications but also charts a course for targeted interventions. With each classification serving as a beacon, signalling specific operational vulnerabilities, the ensuing examination promises to shed light on the intricate tapestry of production dynamics and pave the way for strategic improvements within the industrial ecosystem.

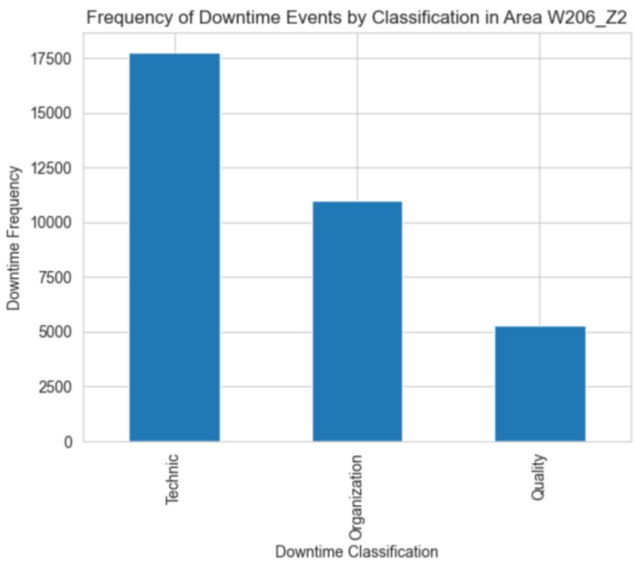


Figure 15: Frequency of Downtime Events by Classification

The bar chart provided in Figure 15 portrays the distribution of downtime events across three distinct classifications: 'Technic', 'Organisation', and 'Quality' in area ZONE_Z2. It is evident that technical issues are the predominant cause of downtime, with the frequency of such events surpassing those attributed to organisational and quality-related causes during the 1st of September to the 31st of November. This prevalence suggests a substantial impact of equipment failures, system errors, and technical malfunctions on operational productivity.

Organisational issues constitute the second most common source of downtime, pointing to potential areas for process optimisation and management interventions. Quality-related downtimes, while the least frequent, still represent a noteworthy cause of operational delays, and addressing them could lead to further enhancements in production efficiency. Collectively, this classification underscores the multifaceted nature of downtime events and highlights the critical areas where targeted improvements could significantly improve OEE.

The predominant frequency of technical issues highlights a pressing need for a systemic approach that not only addresses the mechanical and technical aspects but also integrates the human and organisational elements that contribute to overall efficiency. The substantial impact of organisational issues on downtime further emphasises the interplay between technology and the social components of the workplace, including workflow processes, team dynamics, and management practices. By adopting a socio-technical perspective, the organisation can holistically address the complex and interconnected causes of downtime, recognising that solutions must harmonise the technical infrastructure with the human elements to foster a resilient and efficient production system. This holistic approach can lead to more sustainable improvements and a more agile response to the challenges faced in operational environments.

4.2.1 OEE and Downtime Correlation Analysis

This section presents a correlation analysis for the ten stations with the lowest OEE, detailed in Figures 20 through 22. Technical issues are found to be the predominant cause of downtime, suggesting a focus area for improvements. Organisational factors also play a significant role, indicating potential for process optimisation. The analysis underscores the need for a balanced approach to operational efficiency, leveraging

AI techniques to enhance equipment availability and reduce downtime, thus improving OEE metrics across the board.

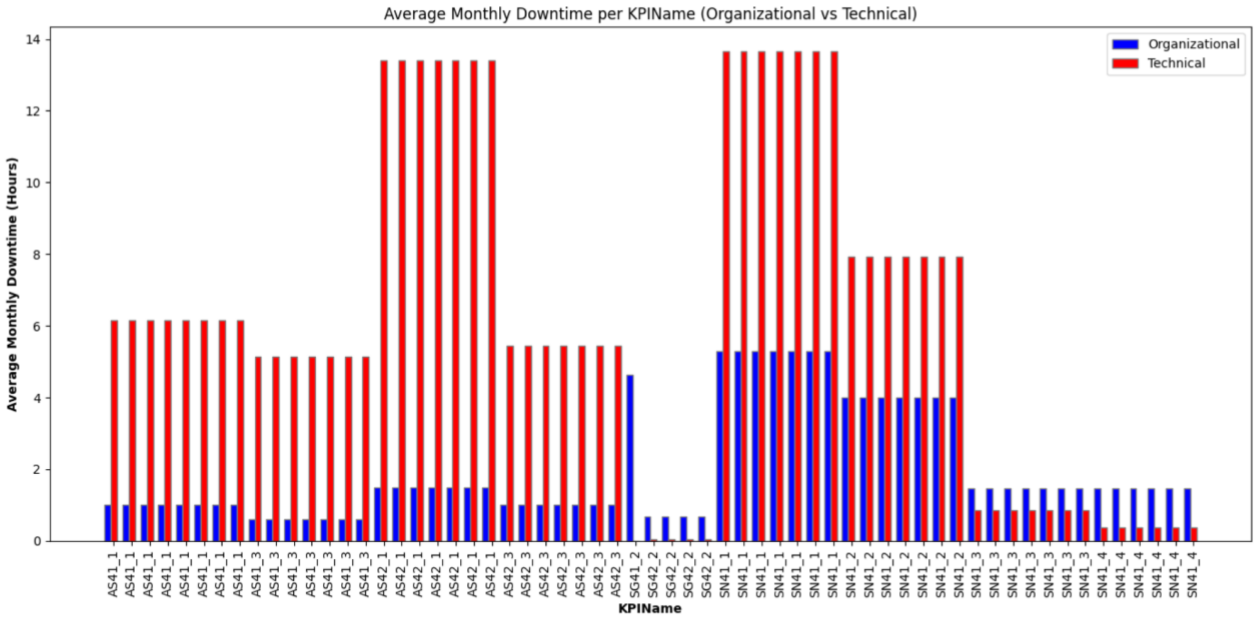


Figure 16: Average Monthly Downtime Analysis by KPIName, differentiating Organisational (blue) and Technical (red) contributions.

The bar chart in figure 16 presents a comprehensive breakdown of average monthly downtime by KPIName, delineated into organisational and technical categories, emblematic of a socio-technical systems approach where both human (ANT - Actor-Network Theory) and technical factors are considered in operational performance. ANT here underscores the interplay between human actors, organisational structures, and technical entities, all contributing to the system's overall behaviour.

The visualisation reveals that technical reasons (red bars) predominantly contribute to downtime across several KPIs, suggesting that technical system components and interactions might be areas ripe for enhancement. Organisational downtime (blue bars) also impacts certain KPIs, indicating potential areas for improvement in workflow, communication, and management practices. KPIs with the highest aggregate downtime, such as those with the tallest bars in the chart, should be prioritised for further analysis. These KPIs could benefit from a deeper investigation into the socio-technical dynamics at play, possibly leveraging insights from ANT to understand and mitigate the root causes of downtime.

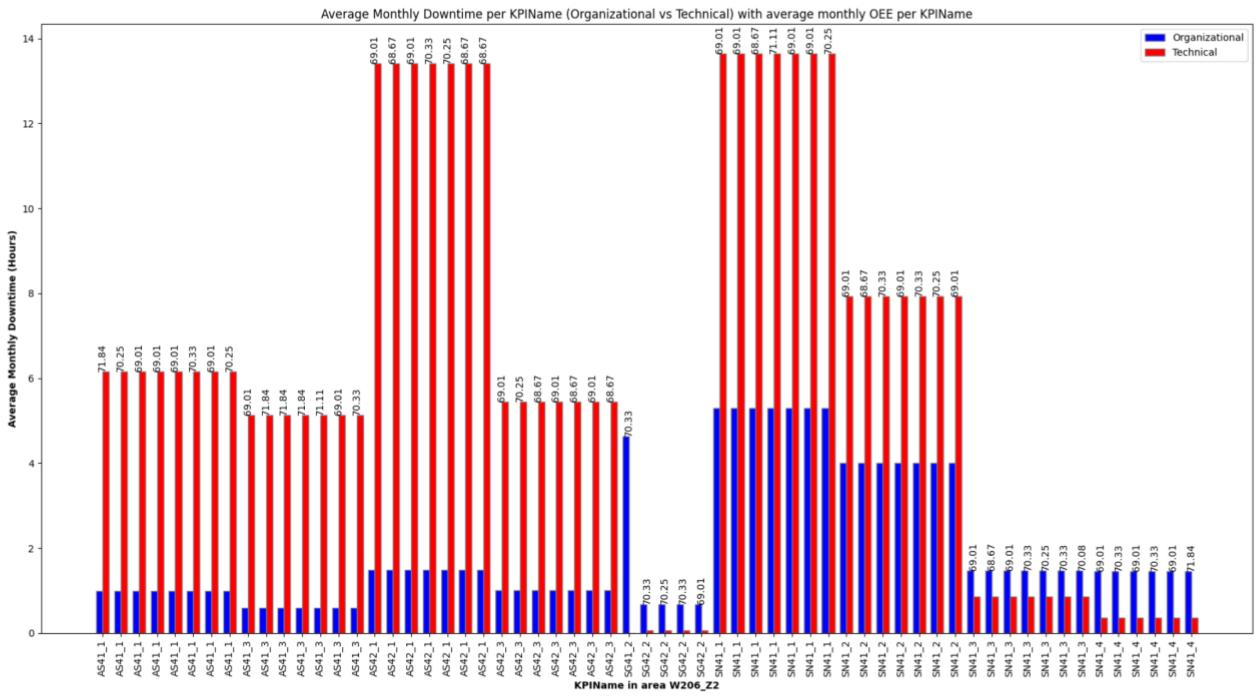


Figure 17: Dissection of Average Monthly Downtime by KPIName, juxtaposed with Average Monthly OEE percentages.

The horizontal bar chart in Figure 17 provides a visualisation of average monthly downtime across various KPIs, segregating the downtime into organisational (blue) and technical (red) factors, with the superimposed numerical values indicating the average monthly OEE per KPIName. This visual arrangement facilitates a socio-technical analysis, revealing the dual impact of process-oriented and equipment-related issues on OEE. KPIs that exhibit a substantial portion of technical downtime, particularly those coupled with low OEE figures, emerge as critical focal points for further investigation and intervention.

These insights are crucial for operational managers and process engineers in pinpointing areas of concern, where technical improvements or organisational reforms could lead to substantial gains in productivity and efficiency. The chart serves as a strategic tool, guiding the prioritisation of maintenance efforts, the optimisation of workflows, and the allocation of resources to enhance OEE within the production environment.

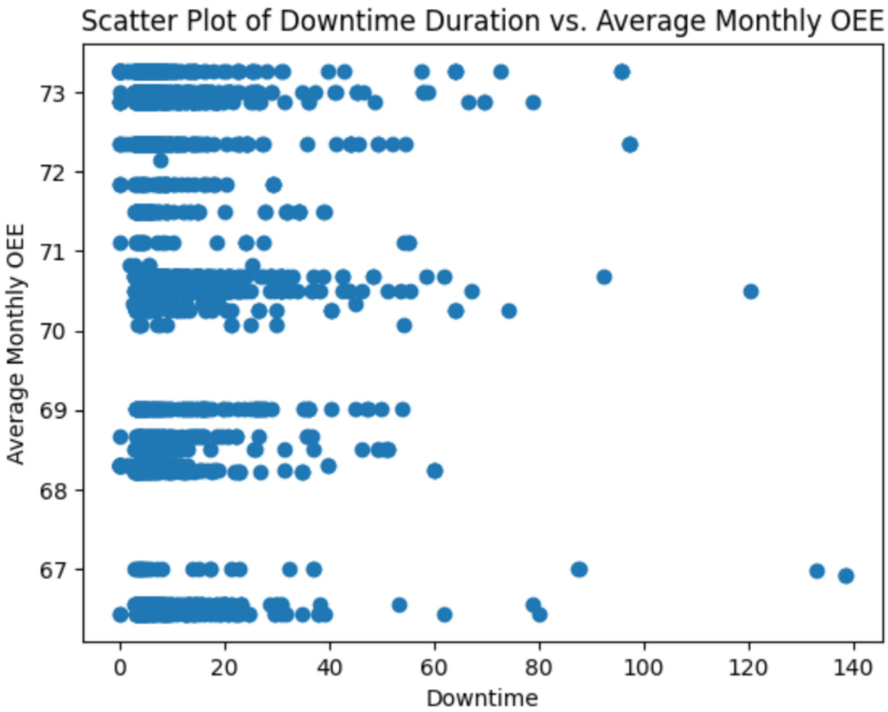


Figure 18: Decoding Downtime: Unveiling the Relationship Between Equipment Availability and Overall Equipment Effectiveness (OEE)

The scatter plot presented in Figure 18 delineates the interrelationship between 'Downtime' and 'Average Monthly OEE', revealing notable data trends. It shows marked clustering at regular intervals on the 'Downtime' axis, suggesting that downtime often occurs in predictable, short bursts. These short interruptions are frequent and seem to be managed effectively, as indicated by the 'Average Monthly OEE' which remains consistently stable across these incidents.

This stability suggests an operational resilience that effectively mitigates the impact of these brief downtimes. Moreover, the lack of a strong negative correlation between increased downtime and reduced OEE suggests that the operational process may have adaptive mechanisms to maintain effectiveness. Outliers, particularly at higher downtime durations, stand out and merit additional analysis to deduce their causes and impacts. It is also noteworthy that longer periods of downtime do not universally result in lower OEE, hinting at robust downtime management or system performance. These insights underscore that improvement efforts should not only aim at curtailing downtime but also at understanding and bolstering the production process's robustness to both short interruptions and prolonged downtimes, ensuring sustained high OEE.

4.2.2 Cluster Analysis

In this section, a K-Means clustering algorithm is applied as an analytical tool to discern the underlying patterns within Company X's operational data, specifically examining the interplay between 'Average OEE' and 'Total Downtime per KPIName'. Figures 19 and 20 unveil the results of this clustering, which aims to identify natural groupings in the dataset, thus providing a deeper understanding of the operational dynamics at play. The strategic application of K-Means clustering is instrumental in revealing distinct performance profiles across the stations, highlighting areas where efficiency is optimised and pinpointing those where downtime unduly strains productivity. This approach is particularly adept at shedding light on the variance in performance and guiding the focus towards stations that exhibit significant potential for improvement through targeted AI-enhanced interventions. By analysing these clusters, the aim is to extract actionable insights that can drive data-informed decisions, optimising OEE and reducing downtime in a concerted effort to advance the operational prowess of Company X.

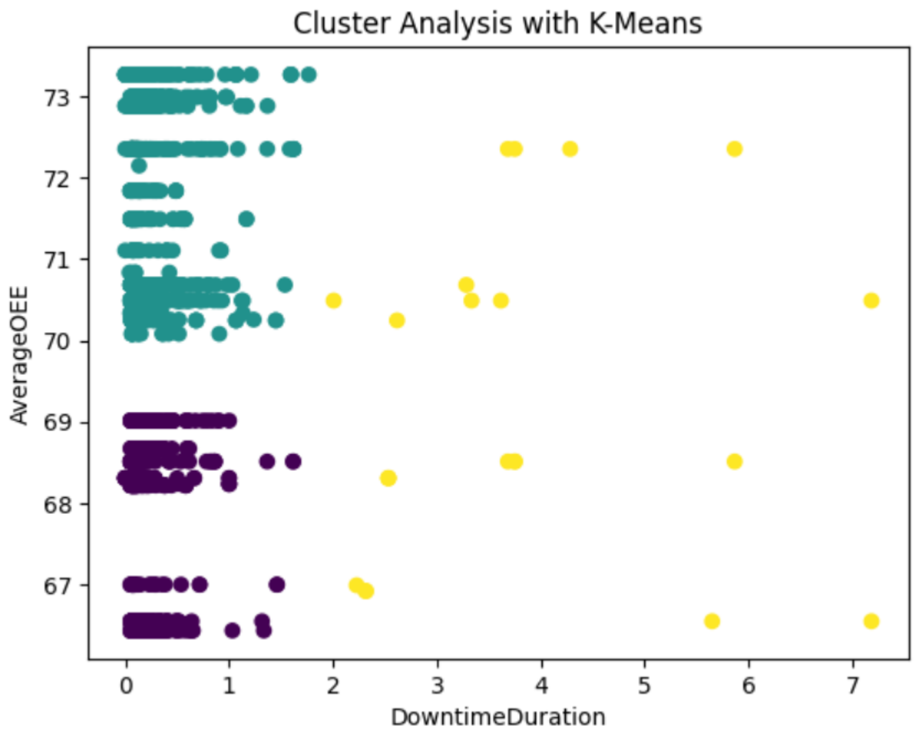


Figure 19: K-Means Clustering of Average OEE vs Downtime duration per KPIName

The scatter plot in Figure 19 showcasing the K-Means cluster analysis reveals several natural groupings within the data, highlighting distinct operational profiles based on 'DowntimeDuration' and 'AverageOEE'. Notably, the majority of data points cluster around regions indicative of higher OEE and shorter downtimes, suggesting a positive operational scenario where efficiency is maintained. However, the presence of outliers, particularly in the realm of extended downtimes, signals exceptions that may require individual scrutiny. The distribution of clusters suggests varying performance across the stations, with some demonstrating optimal efficiency and others lagging, possibly due to technical issues or process inefficiencies. This visual analysis, therefore, provides a strategic map for operational management, pointing towards areas with potential for improvement and stations that exemplify best practices, guiding targeted interventions to increase productivity and reduce downtime within the company's ecosystem.

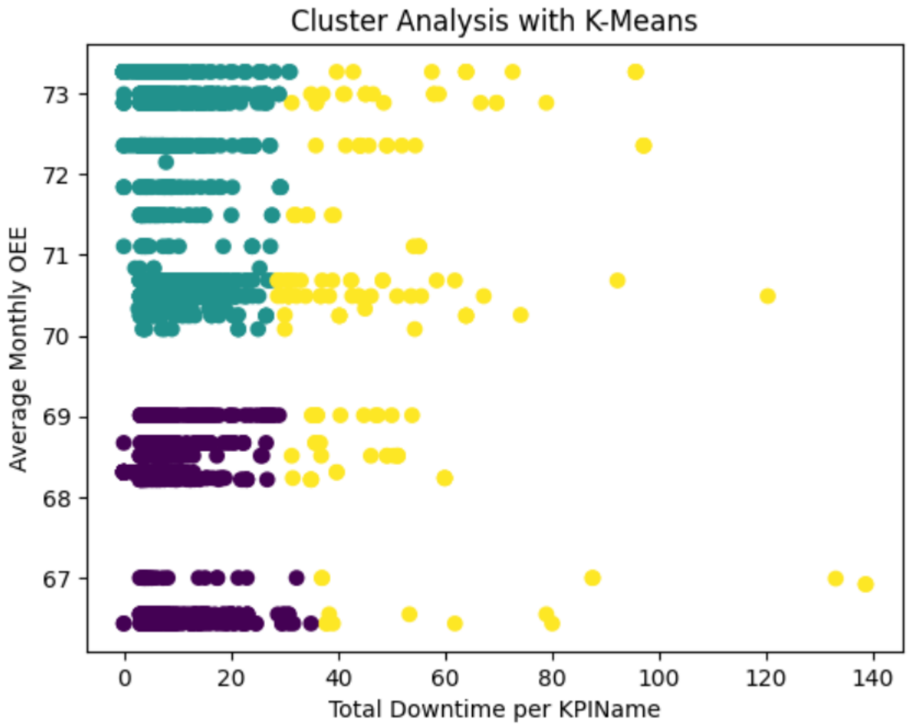


Figure 20: K-Means Clustering of Average OEE vs Total downtime per KPIName

The scatter plot in Figure 20 further presents a K-Means clustering analysis juxtaposing 'Total Downtime per KPIName' on the x-axis against 'Average Monthly OEE' on the y-axis for area ZONE_Z2 KPINames. The clustering has yielded distinct groups, indicated by varying colours, that signify different performance strata within the dataset. A majority of data points cluster in the zone of lower total downtime and higher OEE, suggestive of efficient operational segments. As total downtime increases, a dispersal of OEE values is observed, revealing a heterogeneous performance within these segments. Significantly, some data points extend into the higher downtime range, potentially signaling outlier stations or operational periods with acute disruptions.

This plot elucidates the operational landscape's complexity, highlighting stations or periods where an optimal balance between downtime and OEE is achieved, contrasted against others that might benefit from focused improvement initiatives due to their higher downtime and lower OEE figures. The study therefore further focuses on identifying key technologies and processes used in stations with longer downtime durations and reduced OEE levels as part of the third phase of DSR, which is developing the AI artefact. The goal is to identify key manufacturing technologies used in these stations and to leverage AI capabilities to predict downtime occurrences and pre-emptively inform stakeholders in advance.

4.3 Define Objective Solution

This section provides the context and preparatory steps that lead to the definition of the objective solution, which is the second phase in the DSR methodology. It begins with a semi-structured survey shared with participants at Company X, limited to 16 due to delayed ethics clearance and a slow response rate. The survey participants, as depicted in Figure 20, are strategic-level individuals involved in day-to-day operations, with the majority being Data Analysts and/or Data Engineers, and significant representation from Plant Engineers, Production Managers, Technology and IT Specialists. These roles are pivotal for providing insights into the integration and impact of technological readiness, AI, and IoT on OEE.

The subsequent figures and sections cited (Figures 21 to 26) detail the survey findings on perceptions of OEE's importance, the challenges of implementing OEE initiatives, the integration of data-driven decision-making, participation in OEE improvement initiatives, familiarity with AI and machine learning, and the adequacy of related training. These findings contribute to understanding the current state of OEE and the factors affecting its optimisation, thereby informing the development of the solution objective.

4.3.1 Position Profiles of respondents

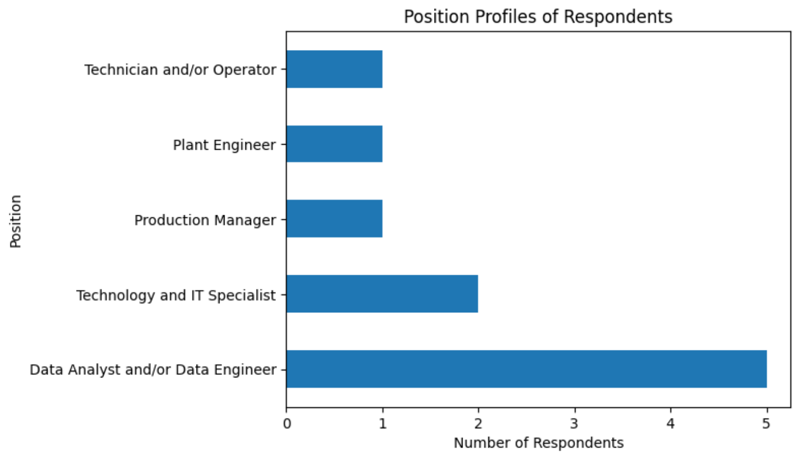


Figure 21: Position Profile of Survey Respondents

The bar chart in Figure 20 illustrates the distribution of position profiles among the respondents of the survey. Most participants identify as Data Analysts and/or Data Engineers, indicating a strong representation from individuals likely to be well-versed in data manipulation, analysis, and system design. The second most common role is that of Plant Engineers, professionals typically responsible for overseeing operational aspects, maintenance, and the efficient running of manufacturing processes. The survey also saw participation from Quality Control Managers and Operations Managers, roles that are integral to the management of production quality and business operations, respectively.

4.3.2 Understanding the importance of OEE in the automotive manufacturing process

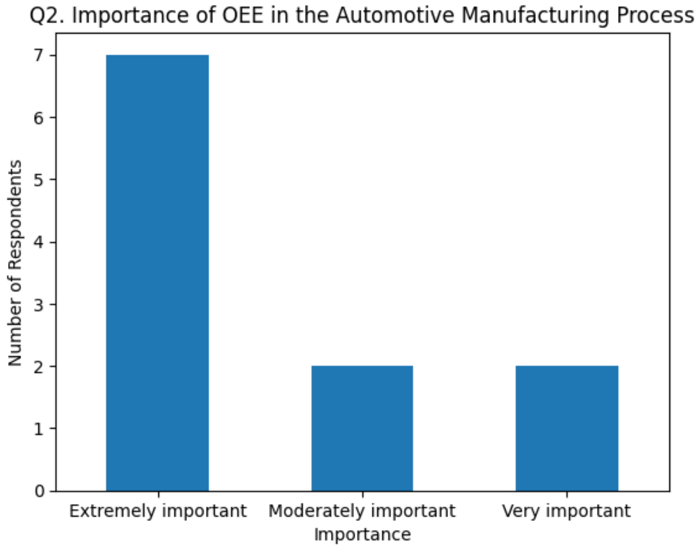


Figure 22: The importance of OEE in the automotive manufacturing process.

The bar chart in Figure 22 presents survey respondents' perceptions of the importance of OEE in the automotive manufacturing process. The results indicate a strong consensus on the significance of OEE, with the majority deeming it 'Very Important' and a substantial number considering it 'Extremely Important'. These responses underscore the critical role that OEE plays in the automotive industry, reflecting a recognition that maximising the effectiveness of equipment is crucial to operational success. Notably, there are some participants who rate OEE as 'Moderately Important', suggesting that while they acknowledge its value, they may perceive other factors as equally or more significant in the manufacturing process. Absent from the chart are the categories 'Not at all important' and 'Slightly important', which indicates a unanimous agreement among the respondents on the positive impact of OEE on manufacturing efficiency and productivity in the automotive sector.

4.3.3 Challenges faced when implementing OEE improvement initiatives.

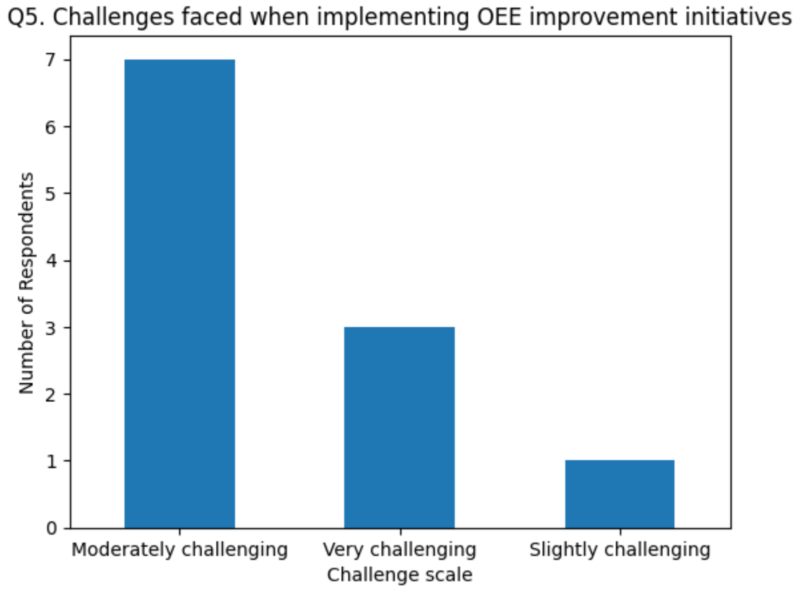


Figure 23: Challenges faced when implementing OEE initiatives.

The bar chart in Figure 23 depicts the respondents' ratings regarding the level of difficulty they encounter when implementing OEE improvement initiatives. Most participants rate the challenge as 'Moderately challenging', indicating that while there are certainly obstacles to enhancing OEE, they are not insurmountable with the right strategies and resources in place. A smaller group considers it 'Very challenging', suggesting that in their experience, significant barriers exist that complicate the improvement of OEE. Some respondents find it 'Slightly challenging', which could imply that they have effective processes or less complex environments that facilitate OEE improvement efforts. Notably, there are no responses in the extremes of 'Not at all challenging' or 'Extremely challenging', which could indicate a consensus that while OEE improvement is not straightforward, it is neither trivial nor prohibitively difficult across the board.

4.3.4 Data-driven decision-making practices integration into workflow

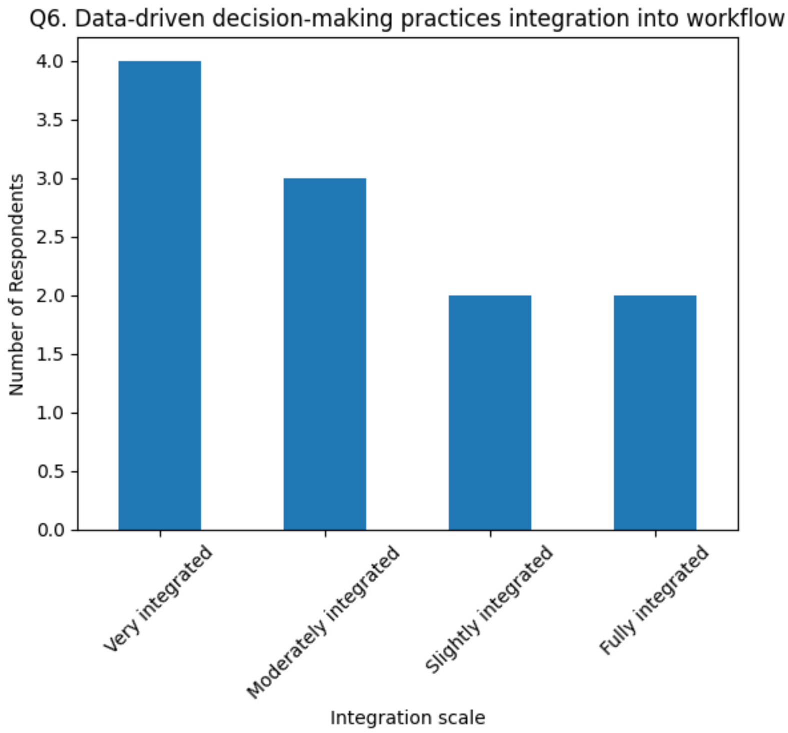


Figure 24: Data-driven decision-making practices integration into workflow.

The chart in Figure 24 illustrates the extent to which data-driven decision-making practices are incorporated into the workflows of the respondents. A significant number of respondents indicate that their decision-making is 'Moderately integrated' with data-driven practices, suggesting that while data is a part of their decision-making process, there may still be room for greater integration. The 'Very integrated' response also has a notable number of entries, pointing to a substantial group that heavily relies on data for making decisions. Interestingly, 'Fully integrated' received the fewest responses, which may imply that achieving complete integration of data into decision-making is still an aspirational goal for many. There are some respondents who feel their processes are only 'Slightly integrated', indicating that data plays a minimal role in their decision-making.

4.3.5 Participation in OEE improvement initiatives

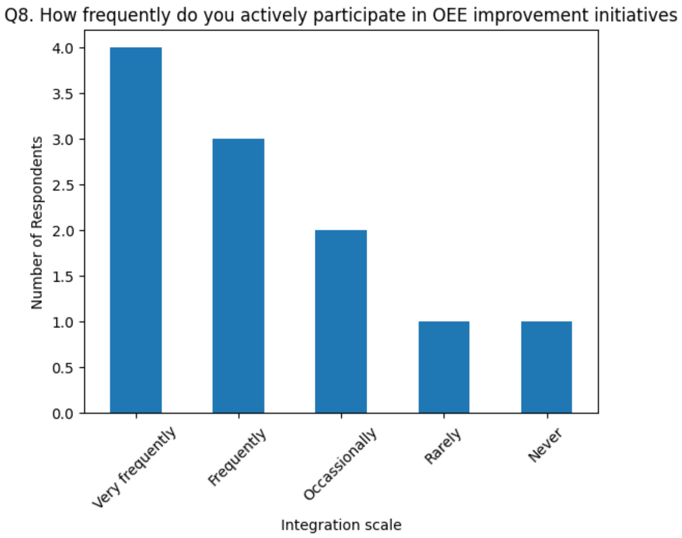


Figure 25: Participation in OEE improvement initiatives.

The chart in Figure 25 provides insight into the frequency of active participation in OEE improvement initiatives by respondents. A prominent level of engagement is observed, with the most common response being 'Frequently', indicating that a good number of respondents are regularly involved in efforts to enhance OEE. This is followed by those who participate 'Occasionally', suggesting a fair degree of involvement, although less consistent. Notably, a substantial proportion of respondents are at the 'Very frequently' level, showing a strong commitment to continuous improvement in their operations. There are a smaller number of respondents who indicate 'Rarely' participating in such initiatives, hinting at possible barriers to engagement or differing priorities. Interestingly, there are some respondents who 'Never' participate, which could point to missed opportunities for optimisation or a lack of awareness of the importance of OEE improvement initiatives. Overall, the data reflects a positive trend towards regular involvement in improving equipment effectiveness in the company.

4.3.6 Familiarity with AI or machine learning in OEE improvement initiatives

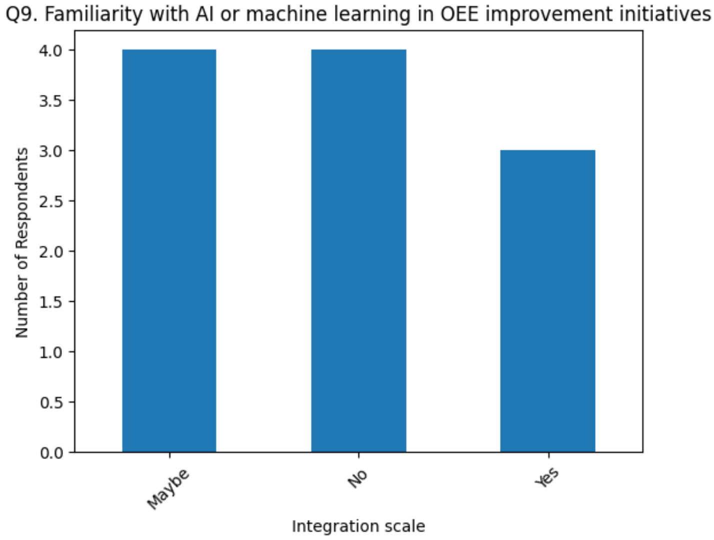


Figure 26: Familiarity with AI or machine learning in OEE improvement initiatives.

The bar chart in Figure 26 reflects the familiarity of respondents with the application of AI and machine learning in OEE improvement initiatives within the company. Most of the participants indicate that they are indeed familiar with the use of AI and machine learning, highlighting a significant level of awareness or engagement with these technologies in OEE contexts. A considerable number of respondents are uncertain, as denoted by the 'Maybe' category, suggesting that there may be varying levels of understanding or implementation of such technologies in their work environments. Notably, a smaller group of respondents admit to not being familiar with AI and machine learning applications in OEE, pointing towards a potential area for growth in knowledge and application within the company. This distribution underscores the importance of educational and training initiatives to enhance the adoption and effective use of advanced technologies in manufacturing processes.

4.3.7 Adequacy of AI and machine learning training provided to staff involved in OEE initiatives.

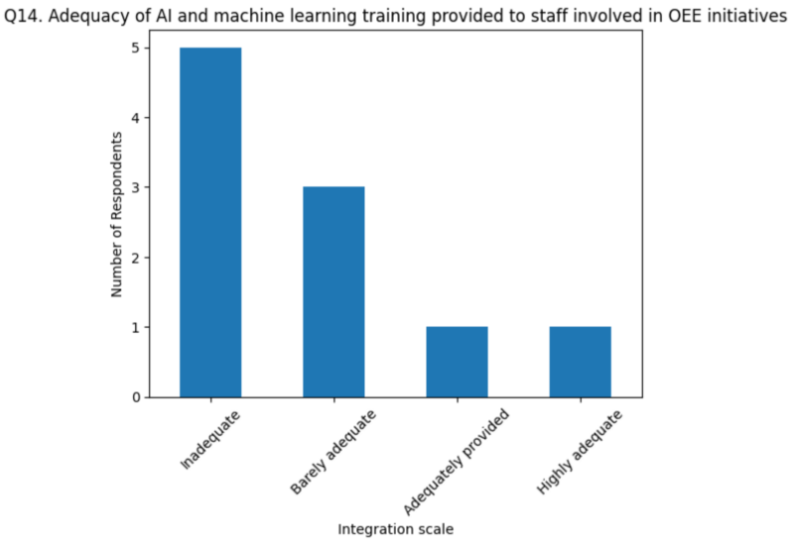


Figure 27: Adequacy of AI and machine learning training provided to staff involved in OEE initiatives.

The bar chart in Figure 27 gauges respondents' opinions on the adequacy of AI and machine learning training provided to staff involved in OEE initiatives. Most of the responses indicate that the training is seen as 'Adequately provided', which suggests that the current training programs meet the basic requirements for staff to engage with AI and machine learning in the context of OEE. A smaller number of respondents feel that the training is 'Barely adequate', pointing to potential gaps in the training that could be addressed to improve efficacy. On the positive side, a proportion of respondents rate the training as 'Very adequate', signifying a higher level of satisfaction with the training's comprehensiveness and applicability. Notably, no responses indicate 'Inadequate' or 'Highly adequate' training, which could mean that while extreme deficiencies or excellence in training are not perceived, there is room for enhancement to shift the perception towards higher adequacy.

4.3.8 Cross-functional collaboration between teams at Company X

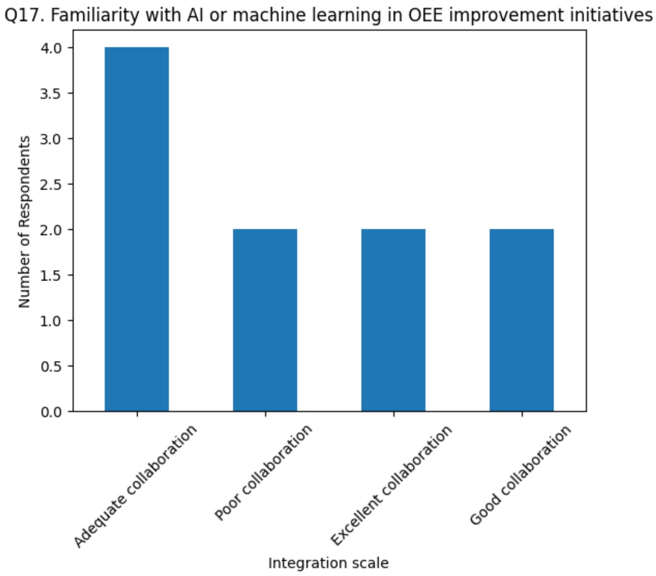


Figure 28: Quality of collaboration among cross-functional teams at Company X

The bar chart in Figure 28 assesses the quality of collaboration among cross-functional teams in Company X. Most responses indicate 'Adequate collaboration', suggesting that while teamwork across different departments is generally sufficient, there might be room for improvement. A significant number of respondents perceive the collaboration as 'Good', which reflects a positive working synergy among various teams. However, 'Poor collaboration' and 'Very poor collaboration' have also been noted, albeit to a lesser extent, implying that some employees are experiencing challenges in cross-departmental interactions. There are no responses in the 'Excellent collaboration' category, indicating that there is an opportunity for the organisation to strive towards more optimal collaborative practices. Overall, the responses suggest a need for enhanced efforts to foster better interdepartmental teamwork.

4.3.9 Conclusion

In conclusion, the findings presented in this section offer valuable insights into the current state of OEE and the factors influencing its optimisation within Company X. Through a semi-structured survey, strategic-level individuals across various departments provided essential perspectives on the integration and impact of technological readiness, AI, and IoT on OEE. The survey revealed a strong representation of roles such as Data Analysts, Data Engineers, and Plant Engineers, indicating a diverse set of expertise contributing to the understanding of OEE dynamics. Notably, respondents acknowledged the significance of OEE in the automotive manufacturing process, with a consensus on its importance for operational success.

While challenges exist in implementing OEE improvement initiatives, the data-driven decision-making practices are moderately integrated into workflows, underscoring the potential for leveraging data analytics to enhance OEE. The survey also highlighted a positive trend towards active participation in OEE improvement initiatives, although there is room for increased engagement, particularly among cross-functional teams. Furthermore, familiarity with AI and machine learning in OEE contexts is prevalent among respondents, suggesting a readiness to adopt advanced technologies for optimising equipment effectiveness. However, the adequacy of AI and machine learning training provided to staff involved in OEE initiatives may require further attention to address potential gaps and ensure comprehensive skill development. Lastly, while collaboration among cross-functional teams is generally perceived as adequate, opportunities exist to improve interdepartmental teamwork for more optimal outcomes. Overall, these insights lay the groundwork for defining the objective solution in the subsequent phase of the Design Science Research methodology, guiding the development of strategies to enhance OEE and drive operational excellence within Company X.

4.4 Design and Development of Artefact.

4.4.1 Introduction

This section presents the third phase of the Design Science Research (DSR) methodology, 'Design and Development', where the study embarks on the application of advanced predictive modeling techniques to enhance the uptime of manufacturing technologies. Drawing on insights from Zhang et al.'s study Long Short-Term Memory for Machine Remaining Life Prediction (Zhong, 2020) the research concentrates on the utilisation of Long Short-Term Memory (LSTM) networks. These networks, which fall under the umbrella of Deep Learning, are particularly advantageous for modeling the complexities of dynamic systems such as manufacturing machinery. The LSTM's proficiency in monitoring performance degradation and forecasting the Remaining Useful Life (RUL) of machinery is central to this phase, as it involves the creation and refinement of a tool designed to predict and extend the operational life of manufacturing equipment, thereby underpinning the study's contribution to the field of predictive maintenance.

The approach to be discussed entails two pivotal objectives: firstly, the conversion of raw sensor data into a coherent health index, which provides a more interpretable representation of the system's current condition. Secondly, the analysis of historical degradation data to forecast future health statuses with a high degree of accuracy. This predictive capability is grounded in the LSTM network's intrinsic ability to recognise complex patterns over time, which has been validated to outperform other machine learning techniques in the context of system degradation prediction, as evidenced by evaluations using NASA's C-MAPSS dataset (Zhang, 2018).

Implementing such predictive maintenance models stands to significantly bolster operational efficiency, minimising downtime and extending the functional longevity of critical production assets. The aim of the study is to prove the feasibility of applying AI based techniques to improve OEE within an automotive manufacturing environment by reducing equipment downtime. A key element of OEE is the availability of equipment, using the downtime data and OEE data from company X collected for a 3-month period this section focuses on analysing the performance of the key production areas. After conducting the analysis key findings highlight technical, organsational and quality issues compromising OEE performance in various areas of production. A cluster analysis performed in section 4.1.2 points to challenges with short downtimes due to technological disruptions impacting the availability of equipment.

As total downtime increases, a dispersal of OEE values is observed, revealing a heterogeneous performance within these segments. Significantly, some data points extend into the higher downtime range, potentially signalling outlier stations or operational periods with acute disruptions. This section will focus on using a Long short-term memory deep learning algorithm to improve the availability for a poorly performing technology within a selected KPNIname in area ZONE_Z2. Due to time constraints, the study focuses on improving the availability of equipment by applying AI techniques as well as making recommendations for organisational amendments to improve OEE levels, for a specific asset experiencing high volumes of errors.

The analysis of the downtime and OEE dataset collected, which tracks downtime events in a production environment, revealed several key insights regarding performance and classifications. The KPIName 'SN41_1' was identified as one of the worst performing stations as well as AS21, both overall and specifically within the 'Technic' classification, with total downtimes of approximately 135.94 hours and 95.56 hours, respectively. Additionally, the most common classifications were determined. In the 'Classification1' category, 'Technic' was the most frequent, occurring 1,557 times. For 'Classification2', 'Spotweld' topped the list, being recorded 320 times. These findings offer a clear view of the areas where inefficiencies are most pronounced and suggest where improvements might be most effectively targeted.

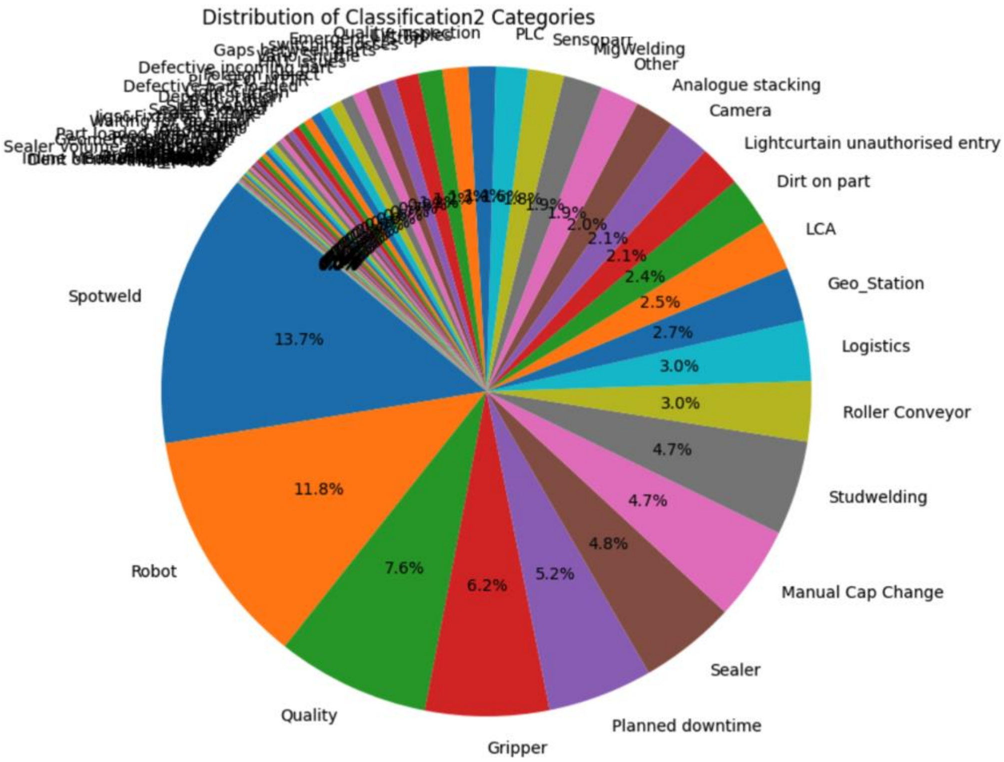


Figure 29 : Distribution of downtime classifications in Area ZONE_Z2

The pie chart in Figured 29 illustrates the distribution of 'Classification2' categories within Area ZONE_Z2. It clearly highlights that 'Spotweld' is the predominant category, accounting for 13.7% of the classifications. This is followed by other significant categories such as 'Robot' and 'Quality', which represent 11.8% and 7.6% respectively. Other categories like 'Gripper', 'Sealer', 'Manual Cap Change', 'Studwelding', 'Roller Conveyor', 'Logistics', 'Geo_Station', and several more, are also represented, each making up a smaller portion of the pie, ranging from 2.1% to 5.2%. Spotwelding technology will therefore be used as a further basis of exploration with the main goal of identifying technical errors that impact equipment uptime.

The accurate prediction of a machine's Remaining Useful Life is a focal point of this paper, highlighting its significance in maintaining operational efficiency and safeguarding against unexpected downtimes. However, forecasting RUL accurately presents numerous challenges due to the complex and evolving nature of machine degradation. By adopting LSTM networks, which excel in processing time series data and understanding long-term patterns, these challenges can be effectively addressed. This section aims to investigate how a LSTM-based methodologies can significantly enhance the precision of RUL predictions, thereby revolutionising maintenance practices in industrial settings. Given the constraints of time, this study will concentrate specifically on spot-welding for a distinct machine located at a particular station. This station was selected due to its record of having the amongst highest frequency of iq-stops, making it an ideal candidate for in-depth analysis and observation.

4.4.2 Formulating the Predictive Maintenance Problem for AI Application

This study focuses on analysing sensor data collected over a series of 'n' time steps, represented as X = [x(1), x(2), …, x(n)], alongside corresponding system states Y = [y(1), y(2), …, y(n)]. The objective is to monitor and understand the performance of spot-welding systems, specifically in terms of OEE by measuring downtime. The process involves deciphering the patterns of change in Y by examining fluctuations in the sensing data X. This is mathematically expressed as x(n) being a function of its historical values [x(n-1), x(n-2), …, x(1)] and similarly for y(n) as defined in (4) below:

$$\boldsymbol{x(n) = f\,[x(n\ 1), x(n\ 2),, x(1)] \Rightarrow y(n) = g\,[y(n\ 1), y(n\ 2),, y(1)]} \qquad (4)$$

This formula (4) emphasises two critical points: firstly, the present performance of the system is influenced by its historical performance, and secondly, the trajectory of system performance is reflected in the alterations of the sensing data. In the realm of spot welding, system performance, related to OEE and minimising downtime, can be quantified through either physically established parameters or a defined health index, denoted as system state Y in the analysis.

$$\boldsymbol{Y' = [y\,(n+\ 1), y\,(n+\ 2), y\,(n+\ 3), \ldots]} \qquad (5)$$

$$y'(n+1) = \ g\ [y'(n), y'(;n-\ 1), \dots, y'(2)] \qquad (6)$$

This research incorporates methodologies like those used by Zhang et al, (2018) in analysing historical sensing data. This approach is focused on identifying and understanding the functions f and g, which represent the evolution of the system over time. By unraveling these functions, the study aims to facilitate predictions about future system performance. The predictive model relies on the function g, as detailed in (5) and (6), to anticipate how the system will behave moving forward. This predictive capability is crucial for effective planning and management of system operations. It is important to distinguish between the predicted system states, labeled as Y', and the actual values, Y. By establishing a failure threshold, y_threshold, the study seeks to predict the RUL as the interval until the system state surpasses this threshold, as formulated in (7) below.

$$RUL_{predict} = inf\left\{k \colon y'_{(n+k)} \leq y_{threshold}\right\} \qquad (7)$$

A significant challenge in this process is dealing with the non-linear nature of system variations and uncertainties in data, which may result from external disturbances or sensor inaccuracies. To tackle these challenges, Zhang et al, (2018) propose a system modeling approach using a Long Short-Term Memory structure. Renowned for its efficacy in discerning patterns in time-series data, LSTM is particularly suited for this application (Zhang, 2018)**.** Additionally, to address uncertainties in the data, a bi-directional LSTM network is suggested. This network facilitates information flow in both directions through the LSTM cells, enabling forward predictions and backward adjustments to minimise disturbances and enhance prediction accuracy. This methodology is expected to significantly improve OEE and reduce downtime in spot-welding operations by offering more precise predictions of system performance and accurately predicting Q-stops.

4.4.3 Data Collection

To get a suitable extract of spot-welding data a focused approached was applied to collect data for the most problematic KPIName more specifically, where the downtime occurred because of the following errors from spotwelding guns 'Bosch welding control is not ready', 'Bosch welding quality stop’, ‘Bosch welding cooling water error', 'Robot stopped by submit', 'High contact resistance'. A subset of the OEE and downtime was extracted using Python.

Extracting specific data from a manufacturing dataset, such as spot-welding errors, involves a systematic approach. Initially, essential libraries like Pandas are imported for data handling. A crucial step is to closely inspect the dataset to understand its structure and the nature of the data it contains. The core of the process involves filtering the data based on predefined error categories relevant to the study, such as specific types of spot-welding errors. This is achieved through conditional filtering in Pandas, a Python library, isolating rows that match these error categories. Following the extraction, the data may require wrangling, including tasks like handling missing values or removing duplicates.

After successfully extracting a targeted subset of OEE and downtime performance data in section 4.1.3 and utilising specific error descriptions auto generated by the system. To enrich this dataset, the OpenSearch API was used for adeptly retrieving spot welding process data corresponding to the identified KPINames over a three-month period. This task presented a notable challenge, primarily because the OEE and downtime datasets for specific operational areas lacked direct, mappable common fields. However, a deeper dive into the spot-welding asset data revealed a solution: the 'Hostname' and technical location columns emerged as a key link, creating the possibility to precisely query specific devices within a station based on their KPIName. This approach not only allowed for a direct connection between specific OEE performance indicators and individual spot-welding assets to be forged but also set the stage for integrating essential IoT process data with the asset.

4.4.4 Extracting Spot Asset and Process data

After executing and extraction of the spot-welding data, the descriptive analysis of the 'ASSET' and 'Header' columns reveals notable details. The dataset contains a total of 25,284 records for both columns, indicating a comprehensive collection of entries.

Within the 'ASSET' column, there are 218 unique configurations, with the most prevalent configuration version being 'Cfg_0404_1.1.4', which appears 1,259 times. This suggests a common configuration setting across a subset of the spot-welding machines. As the focus is on area ZONE_Z2, the next step is to filter this dataset for a subset of spot guns in this area.

In the process of refining the Asset DataFrame to focus on specific spot-welding stations, a new 'Device Name' column was created. The creation of this column involves parsing the 'Topic', used by the IoT sensor to publish data for each unique device, to extract the 'UniqueId' of each device by converting the string entries into dictionaries and retrieving the 'UniqueId'. This setup is particularly geared towards filtering the dataset to include only those assets linked to specified stations, namely 'AS41', 'AS42', and 'SN41', which are known to report spot welding errors in OEE data as identified during the exploratory data analysis phase in the problem identification and motivation phase of the research. The successful data extraction sets the phase for feature engineering, which is instrumental in identifying key predictors from the process data.

4.4.5 Feature Engineering & Dimensionality Reduction

In predictive modeling, one of the most crucial decisions involves the selection of features used within a model (Miguel, 2015). As Miguel (2015) notes, the right set of features is essential to providing a robust evidential base for predictions. The chosen number of features directly corresponds to the model’s dimensionality. Selecting many dimensions can introduce several complexities. One such issue is data sparsity, which arises when the vast number of dimensions expands the possible combinations of feature values to such an extent that gathering sufficient data becomes impractical (Miguel, 2015). Another related challenge is the curse of dimensionality, which refers to various problems that occur when working with high-dimensional spaces, often impeding the model's performance. Miguel (2015) also points out that a large set of features may significantly increase the computational resources and time required for training and making predictions, potentially making some models impractical for certain applications, such as real-time analysis.

Feature engineering encompasses two fundamental techniques (Miguel, 2015). The first method entails the expansion of the feature space through the conception and integration of new features that did not exist within the original dataset. Such an endeavor may also involve the synthesis of novel features through the combination of pre-existing ones, a task that typically demands expert knowledge from the field of application to navigate effectively. It is crucial to note that this aspect of feature engineering is time-intensive and often involves a substantial amount of iterative experimentation. The second methodology is the contraction of the feature space, commonly referred to as feature reduction (Miguel, 2015). This method is characterised by the deliberate selection of a subset of features deemed most consequential for the prediction of the output variable, extracted from the larger original set.

Furthermore, a strategy known as dimensionality reduction is employed to refine the feature set. This strategy is a transformative process where the comprehensive set of features is converted into a new, more manageable set with fewer features. An archetypal technique within this domain is Principal Component Analysis (PCA), which generates new input features, termed principal components. These components are the linear aggregates of the initial input features and are instrumental in the simplification of the feature space (Miguel, 2015). It is worth noting that there are various alternatives that can be applied for effective feature engineering.

Another approach is to use tree-based methods for feature reduction, which are especially effective in handling heterogeneous data types and complex, non-linear relationships inherent in datasets (Miguel, 2015). According to Miguel, these methods, including algorithms like Random Forest and Gradient Boosting, and work by constructing a multitude of decision trees during training, providing insights into feature importance based on how they improve the model's performance. In the context of spot-welding data, tree-based methods can be particularly beneficial. They can discern the most relevant features - such as specific welding parameters, material properties, or operational conditions - by evaluating their impact on the predictive accuracy regarding welding quality or equipment efficiency. This approach not only aids in reducing the dimensionality of the data but also enhances the interpretability of the model, making it easier to understand and communicate the key drivers behind spot-welding performance.

In predictive modeling for spot welding machine availability, several features are critical for operational efficiency and reliability. The study zeroes in on one spot location, employing a tree-based method to simplify the dataset before model creation. Key factors include the specific 'Spot Name/Location,' which influences machine availability due to unique characteristics, and 'Material Thickness at each Welding Point,' which impacts process efficiency. 'Number of Q-stops' reflects operational interruptions and affects productivity. 'Welding Parameters' like current, voltage, and weld-time are vital as they differ across spots and significantly affect efficiency and downtime.

The detailed analysis of the dataset, comprising 206 features, highlights the intricacies involved in spot welding. Key features include 'WP_MirrorValuePosition', which reflects the positioning of equipment, and 'Gun.GU_TransformerCnt_description_en', which describes the welding gun's attributes, both are crucial determinants of performance. Additionally, features like 'WP_TipWearState_description_en', denoting the condition of the welding tip, and operational parameters such as 'WP_GhostRunMode', 'WP_GeometryCoefficient', and 'WP_RespCurrentSensor', are integral to a comprehensive understanding of machine availability in spot welding operations.

Each of these features, ranging from technical specifications to environmental conditions, intertwines to paint a comprehensive picture of the factors influencing machine availability in spot welding processes. The study will focus on identifying critical features that can be used to predict a specific Q-stop for a given spot number. It is important to note that part of the encoding will be to flag a Q-stop as a 1 and a non-q-stop as a 0 enabling the possibility of a flag that will indicate a q-stop in production or not, for various q-stop types in the developed supervised machine learning classification model.

The preprocessing of the data involved cleaning and preparing the dataset for model training a tree-based random classifier, to identify critical features for the first model iteration. This included handling missing values, removing unnecessary columns, and specifically addressing the variety of error types listed in the 'WP_MonitorErrorCode_description_en' column. Unique error types such as 'Q-Stop spot based error', various conditional errors, and absolute errors were identified, and a binary encoded column was created for each Q-Stop error type.

Moreover, the script normalised several columns deemed important for model consistency, including 'WP_SheetThickness', 'WP_SgDeflection', and 'WP_Energy', among others. Non-numeric values were converted to NaN and rows containing these were dropped to maintain dataset integrity, as indicated by the change in row count before and after this cleaning step. The normalisation process was carried out using the StandardScaler, a module of the Scikit-learn library, and the resulting normalised columns were then exported to CSV files for further use.

The second part of the process involved separating features and the target for model training. The target was one of the binary-encoded Q-Stop error types, and the features included the normalised columns. The dataset was split into training and test sets with a standard 70-30 split. A RandomForestClassifier was trained on the data, feature importance was quantified to gauge the predictive influence of each attribute. The seven most impactful features were identified and employed to configure a SelectFromModel, with the inclusion threshold set by the importance of the seventh-ranked feature. These pivotal features, along with their relative importances, were illustrated in a bar chart in Figure 30, offering a visual representation of the features most instrumental for the model's predictive accuracy.

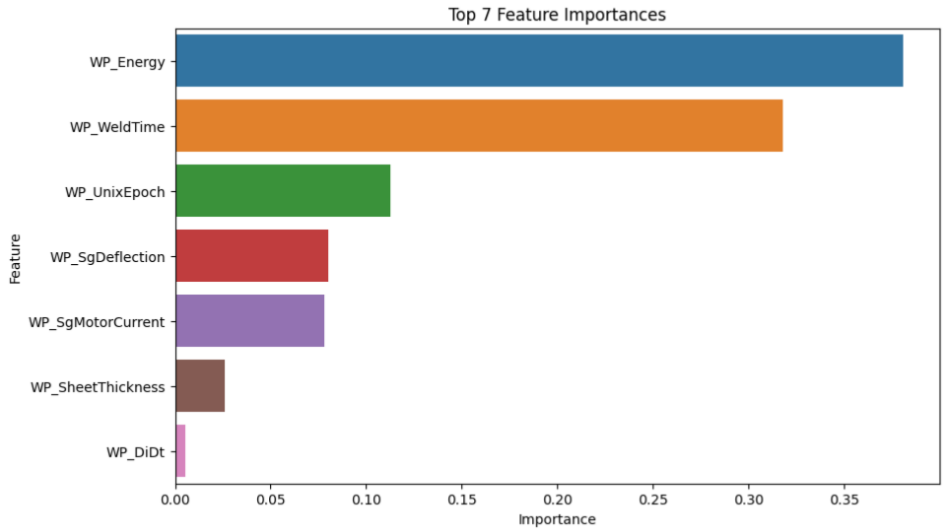


Figure 30: Top 7 Features in Spot Welding Process Data

The bar plot provided in Figure 30 depicts the relative importance of the top seven features as determined by a RandomForestClassifier. 'WP_Energy' appears to be the most influential feature with the highest importance score, followed by 'WP_WeldTime' and 'WP_UnixEpoch'. The importance scores of 'WP_SgDeflection', 'WP_SgMotorCurrent', 'WP_SheetThickness', and 'WP_DiDt' are lower, indicating they have less impact on the model's decision-making process. Given this visualisation, it is evident that 'WP_Energy' is the predominant feature, which could be a critical factor in the predictive model, particularly influencing the output variable, likely related to a manufacturing or process control quality error. 'WP_WeldTime' and 'WP_UnixEpoch' also play significant roles but are not as dominant. The other features contribute to varying degrees but are less significant compared to the top three.

Due to time constraints and the complex nature of feature engineering, these top seven features have been selected for intensive analysis. This is a common approach in machine learning projects, balancing the need for a thorough investigation of features against the practical limitations of project deadlines. The selected features are set to be the focus of further model development, with an emphasis on the iterative process of refinement and stakeholder collaboration to improve the model's performance in practical scenarios. This approach underscores the iterative nature of machine learning projects and the DSR methodology, where initial models are refined over time as more is learned about the feature's influence and as more data becomes available. It is a reminder that while the current model highlights certain features as key, continuous improvement is essential for maintaining accuracy and reliability in predictive applications.

4.4.6 Predicting Remaining Useful Life for Equipment

Guided by a RandomForestClassifier for feature selection, the stage was set to evaluate the Bidirectional Long Short-Term Memory (Bi-LSTM) model's performance. The Bi-LSTM's proficiency in detecting sequential patterns made it well-suited for the complex temporal data in manufacturing. After detailed feature engineering and pre-processing, as discussed in section 4.3.5, the focus shifted to a dataset from spot weld number 60001223, which included 659 instances and 45% Spot-based Q-stop errors. Although the study concentrated on a singular Q-Stop error type for clarity, the model's versatility suggests potential for broader application to various spot-welding error categories in the future.

	t-statistic	p-value
WP_SheetThickness	6.328190	4.591720e-10
WP_SgDeflection	0.199871	8.416433e-01
WP_WeldTime	-18.597269	2.431813e-62
WP_UnixEpoch	-12.544508	1.634727e-32
WP_SgMotorCurrent	5.213454	2.486005e-07
WP_DiDt	-4.664766	3.744835e-06
WP_Energy	-18.927555	4.252578e-64

Figure 31 : Statistical Analysis of Feature Significance

The analytical process undertaken to ascertain the statistical significance of various manufacturing features with respect to the binary target variable binary_encoded_Q-Stop spot based error yielded insightful results, as summarised in Figure 31. The t-tests conducted across multiple parameters highlight the variance in mean values between two distinct groups classified by the presence or absence of the Q-Stop spot based error. For instance, the feature WP_SheetThickness exhibits a notable t-statistic of 6.328190, accompanied by a p-value of approximately 4.59×10^{-10}, suggesting a statistically significant difference in group means and underscoring its potential predictive power. Conversely, WP_SgDeflection shows a t-statistic of 0.199871 and a p-value of 0.8416433, indicating no significant difference and suggesting limited predictive utility.

In the case of WP_WeldTime and WP_Energy, both features demonstrate substantial negative t-statistics, -18.597269 and -18.927555 respectively, with p-values nearing zero, pointing to their significant difference in means and strong predictive relevance. WP_UnixEpoch and WP_SgMotorCurrent also present significant p-values and corresponding t-statistics, reinforcing the premise that these features may be influential in modelling the target variable. The negative t-statistic of WP_DiDt further confirms its potential as a predictor, given the low p-value of 3.74×10^{-6}. The synthesis of these statistical test outcomes offers a robust foundation for the feature selection process in developing a LSTM-based predictive model, as it identifies which features may have a meaningful impact on the prediction of Q-stop spot based errors.

Notable features, see appendix H**,** include right-skewness in sheet thickness, bimodal patterns in deflection and weld time, a pronounced gap between modes in Unix Epoch, multimodality in motor current, extreme skewness in DiDt, and distinct dual peaks in energy consumption. These characteristics imply complex underlying process dynamics that could be crucial for predictive modeling. The scatter plots correlate these parameters with the Q-Stop Error, revealing various degrees of dispersion and outliers that hint at non-linear relationships. The concentration of data points around lower error values, particularly in relation to parameters such as sheet thickness, deflection, and weld time, suggests that deviations from the mean values are potentially influential on process quality.

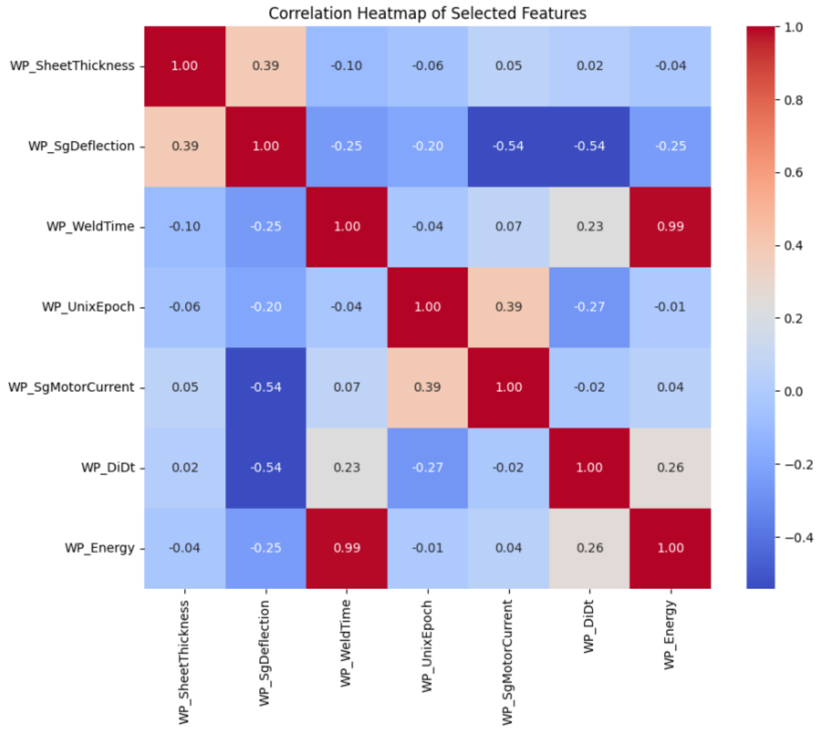


Figure 32:Correlation Heatmap of Selected Process Parameters

Building upon the initial exploration detailed in Appendix F, the correlation heatmap in Figure 32 provides further quantitative insight into the relationships between process parameters. Notably, a strong positive correlation is observed between weld time and energy, indicating a potentially direct relationship where changes in weld time are consistently associated with proportional changes in energy consumption. Conversely, there are notable negative correlations, such as between SgDeflection and both SgMotorCurrent and DiDt, suggesting that increases in deflection are associated with decreases in these parameters. These correlations underscore the interconnected nature of the manufacturing process variables, reinforcing the complexity of the system.

The heatmap also indicates a lack of strong correlation between many of the parameters, emphasising the need for a modeling approach that can capture these subtle relationships. LSTM networks, with their ability to model long-term dependencies and their robustness to noise and outliers can inherently learn the temporal sequences and the intricate patterns that simpler models might miss or overfit, providing an understanding that is critical for accurate prediction and effective control of the manufacturing process.

The Jupyter Notebook developed focused on the application of advanced data processing and Bi-directional Long Short-Term Memory models for analysing manufacturing data. Key steps involved converting timestamps to datetime format and sorting the data, followed by feature engineering to extract time-based characteristics like the hour of the day and day of the week, which were then scaled. The model included selected features related to the spot-welding process and time-based aspects, with the target variable being a Spot based Q-stop error. The preparation of the dataset for the LSTM involved creating sequences of data points, and the development of a Bi-directional LSTM model entailed layers designed for capturing temporal dependencies. This model was trained and tested on the IoT spot welding process data, emphasising its potential in predicting manufacturing outcomes and highlighting the comprehensive approach taken in the study for time-series analysis in manufacturing processes.

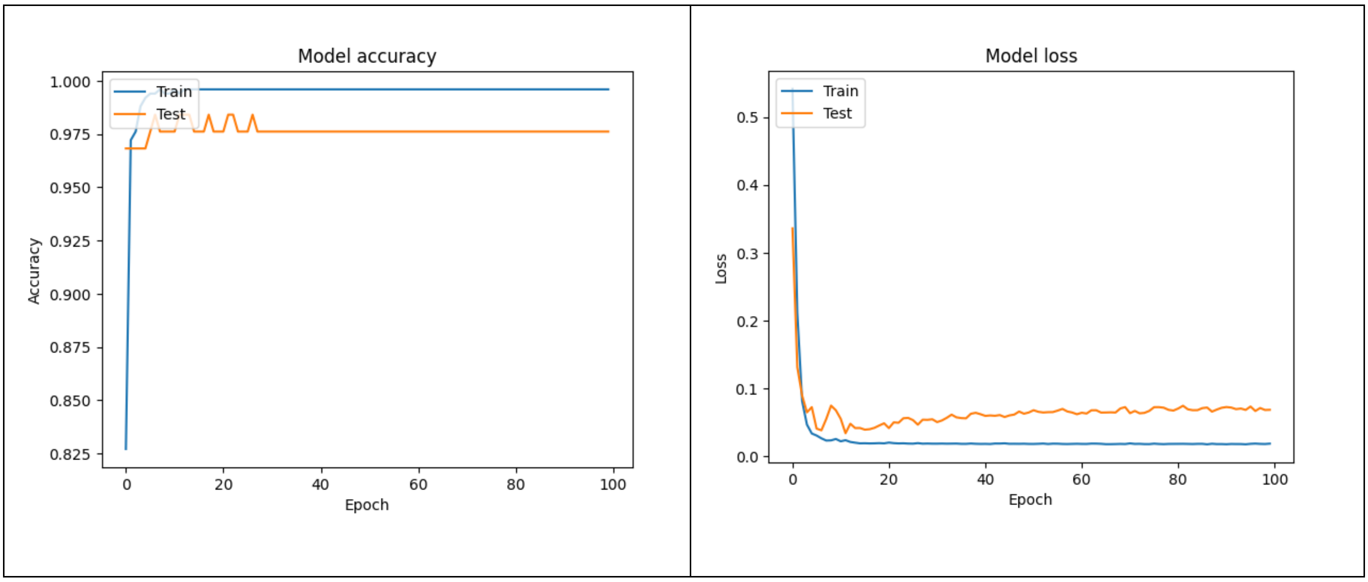


Figure 33: Training and test accuracy of the bi-directional LSTM model

Building on the methodologies described in Section 1.4.4 of the Jupyter Notebook, the empirical results from the Bi-directional LSTM model further validate the efficacy of the chosen techniques. The model's accuracy and loss graphs in Figure 33 reveal a high and stable accuracy above 95%, alongside a low and convergent loss for both training and test datasets, indicating a well-fitting model with excellent generalisation capabilities.

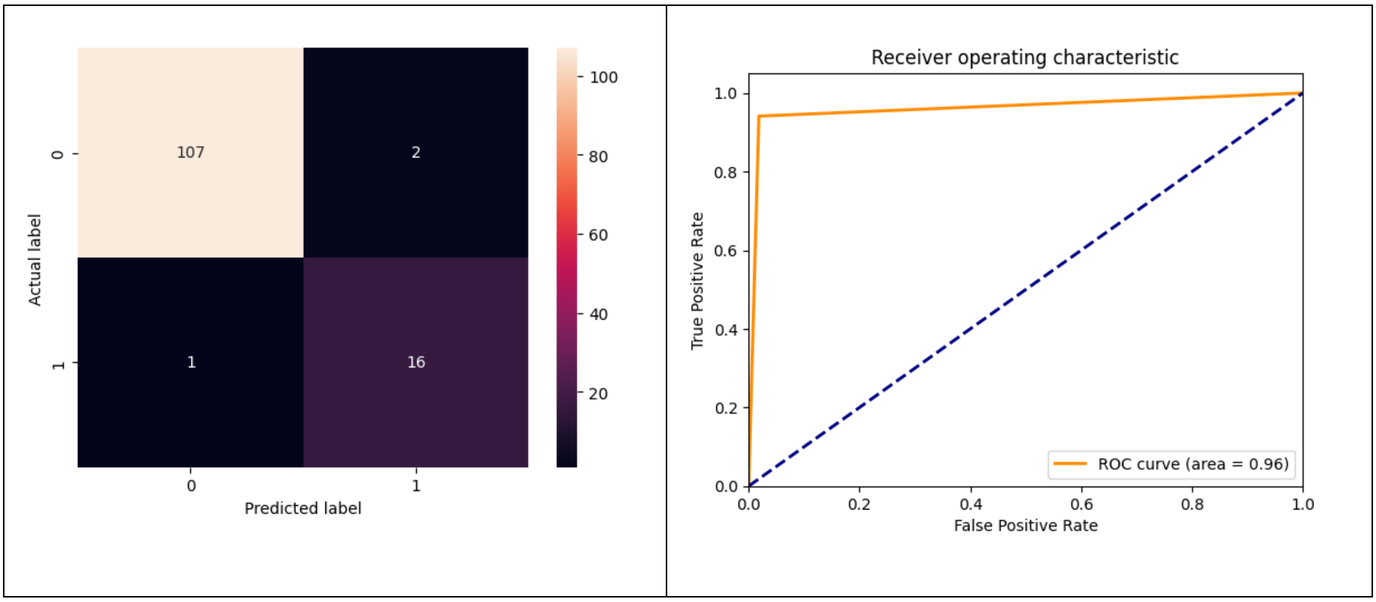


Figure 34: Confusion Matrix & ROC Curve for Bi-LSTM Model

The confusion matrix in Figure 34 solidifies this finding, displaying a notable precision in predicting the Spot based Q-stop errors with minimal false predictions. Moreover, the Receiver Operating Characteristic (ROC) curve, with an Area Under Curve (AUC) of 0.96, underscores the model's adeptness at distinguishing between the normal operation and the occurrence of Q-stop errors. These results not only demonstrate the model's robustness in handling time-series data specific to manufacturing processes but also underscore the successful capture of temporal dependencies and anomalies through the LSTM's architecture, providing a reliable tool for predictive maintenance within the manufacturing domain.

4.5 Demonstration – Phase 1

The evaluation of the model's performance was significantly enhanced using historical data, a strategy that came into play due to delays in obtaining ethical clearance and the extended process required for data access. To stay within the project's timelines, the research leveraged historical data from spot-welding operations, collected via embedded IoT sensors. This historical data provided a solid foundation for evaluating the Bi-directional LSTM model's accuracy. The use of historical data, reflective of real-world scenarios, was pivotal in accurately predicting Q-stops based on a series of critical features identified during the research. This approach highlighted the benefits of employing historical data for model evaluation, underscoring the model's adaptability and potential for application in various industrial contexts.

In the first phase of demonstration, the model was prepared and deployed in an .h5 file format. The deployed model's performance was tested using historical IoT data for the spot weld it was trained on. This process involved predicting and verifying a total of 600 spot-welding sequences to assess the model's prediction capabilities against actual outcomes. The verification process confirmed the model's high accuracy, as the predictions for the last sequences matched the actual outcomes significantly well. The results displayed a 99.52% accuracy in the model's ability to correctly predict spot-welding based Q-stops, which are encoded as '1', while '0' represents the absence of a Q-stop.

Accuracy was quantified by comparing the model's predictions to the actual events, with the results encapsulated in a percentage format that provides an intuitive grasp of the model's performance. Additionally, a confusion matrix in figure 35 was computed, offering a more granular view of the model's predictive capabilities by displaying the true positives, true negatives, false positives, and false negatives.

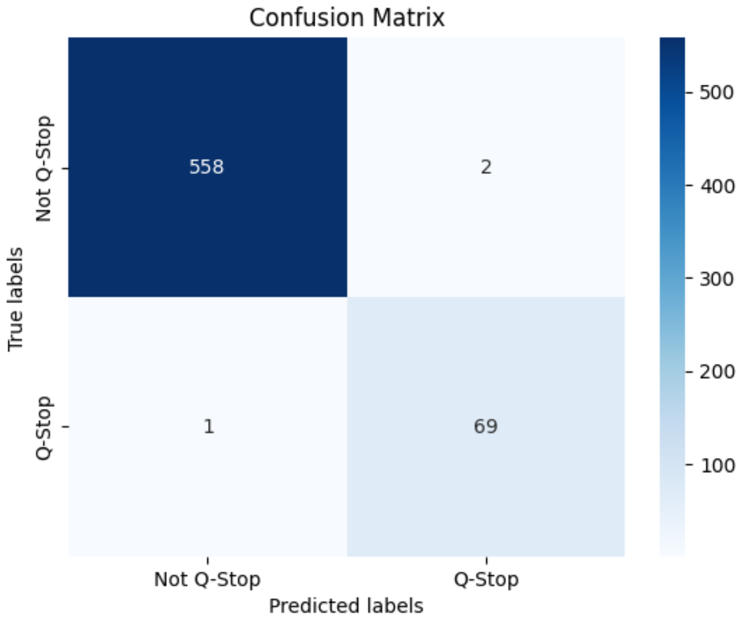


Figure 35: Model Accuracy Confusion Matrix

Overall, the model's deployment and the observed results underline the importance of using historical data in developing robust predictive tools that can significantly contribute to improving OEE by reducing unexpected downtime, enhancing quality control, and ensuring that equipment performance remains at an optimal level. However, the scaling issue also emphasises the need for ongoing model management and improvement to ensure sustained effectiveness.

4.6 Evaluation – Phase 1

Achieving a 99.52% accuracy rate in predicting Q-stops within the given weld sequences can have a substantial impact on reducing downtime in production. In practical terms, this level of accuracy means that the model can correctly identify and predict potential faults or quality issues in 99.52% out of 100 welding operations for a given spot weld location. This predictive capability allows for proactive interventions, where maintenance can be scheduled before a failure occurs, thus minimising unplanned stoppages that would otherwise interrupt the manufacturing process. By doing so, it not only enhances the availability component of OEE but also supports consistent production quality and performance. In essence, this high degree of predictive accuracy serves as a strategic tool in lean manufacturing, contributing to smoother operations, better product quality, and ultimately higher productivity.

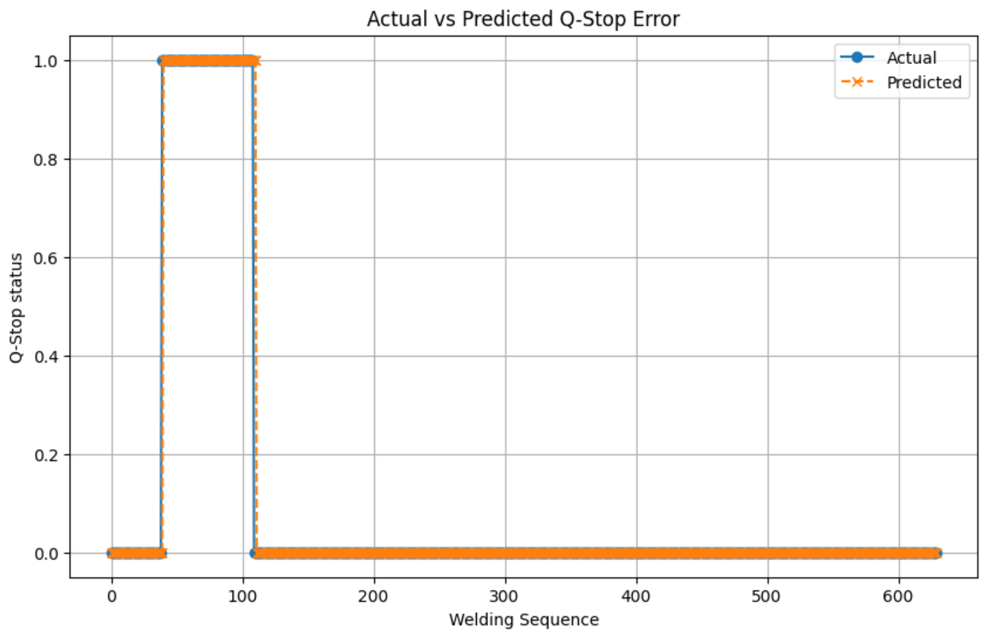


Figure 36: Comparison of Actual and Predicted Quality Stop Incidents in Welding Sequences

The line chart presented in Figure 36 provides a visual comparison between the model's predictions and the actual occurrences of Q-stops, showcasing the precision of the developed artifact. This initial demonstration, a crucial part of the methodology, was designed to exhibit the artifact's predictive capabilities. To verify the model's applicability across various spot-welding locations, it is essential to extend its application to a distinct spot-weld location, one that was not included in the model's training dataset. This step will help to confirm the model's generalisability and effectiveness in diverse welding scenarios.

4.7 Demonstration – Phase 2

Following the development, deployment, and rigorous testing of the predictive model using historical IoT data, the analysis was expanded to include additional spot-welding locations that exhibited a high incidence of Q-stop errors. These spots were selected from the dataset to provide a comprehensive view of the model's performance across various conditions. The methodology was further enhanced by incorporating a series of supplementary tests. These tests utilised historical IoT data points from other spot welds, specifically chosen from instances that were not part of the model's initial training phase. This extension into a broader range of welding scenarios during the demonstration phase allowed for a more robust validation of the model's predictive capabilities.

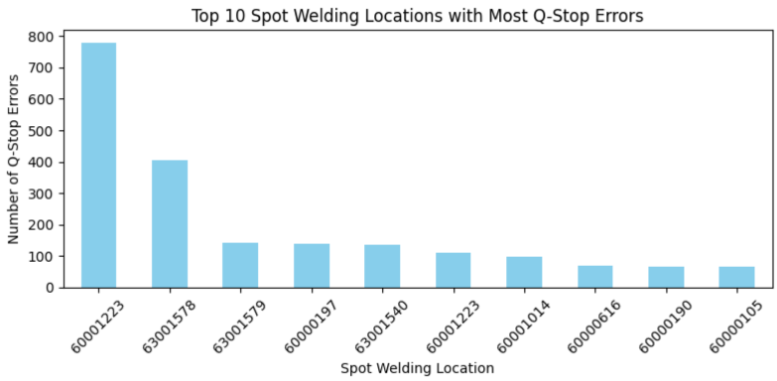


Figure 37: Comparison of Actual and Predicted Quality Stop Incidents in Welding Sequences

The additional testing phases were instrumental in assessing the model's generalisability and effectiveness in accurately forecasting Q-stop errors across a wider array of welding locations, thereby ensuring that the model's utility was not confined to the conditions it was originally trained on but extended to novel, unseen environments within the production setting. Spot 63001578 was selected for further analysis, after normalising the data points and feeding the model a sequence of data points, the following results were obtained.

The Demonstration Phase 2 expanded with the integration of advanced data pre-processing, feature engineering, machine learning model loading, and predictive analysis. Initially, the analysis incorporated essential libraries such as NumPy, pandas, Matplotlib, TensorFlow, scikit-learn, and seaborn to facilitate data manipulation, visualisation, and machine learning processes. A pre-trained LSTM model, trained on spot 60001223, was loaded using TensorFlow's Keras API, signifying the readiness for predictive analysis on the welding process data.

During the feature engineering phase of the study, the features 'WP_SheetThickness', 'WP_SgDeflection', 'WP_WeldTime', 'WP_UnixEpoch', 'WP_SgMotorCurrent', 'WP_DiDt', and 'WP_Energy' were selected as input variables after conducting an extensive tree-based analysis of influential features.

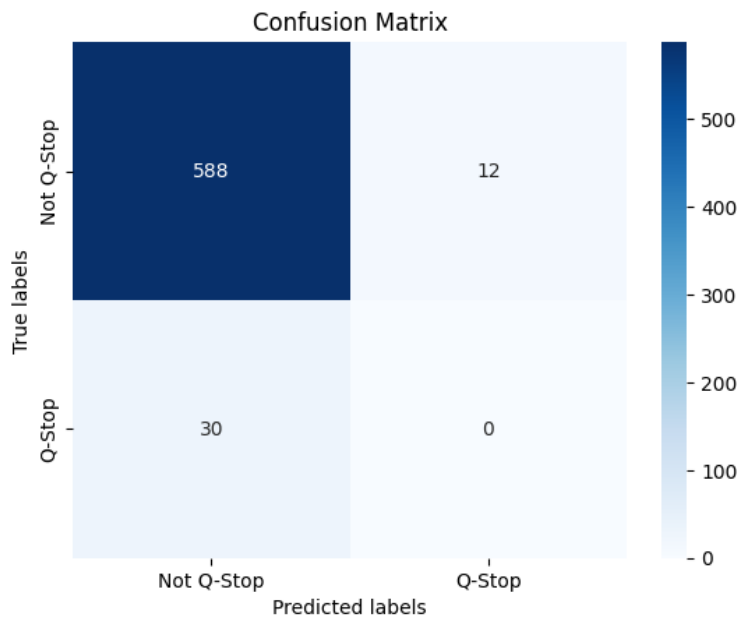


Figure 38: Spot-Welding Q-Stop Prediction for unknown spotweld

The analysed confusion matrix reveals a significant discrepancy between the true labels and the predictions made by the classification model for Q-Stop instances in spot-welding processes. The model demonstrates a high number of true negatives (588) but fails to correctly identify any true positives for Q-Stop events, which indicates a critical shortfall in its predictive accuracy for this specific category for a different spot-welding location. The absence of true positives signifies that the model did not correctly predict any of the Q-Stop occurrences when applied to an unknown spot weld. Additionally, the model’s accuracy dropped to 93.33% from 99.52% after changing the spot-welding location, further signifying the importance of capturing the temporal nuances for each unique spot-welding location.

4.8 Evaluation – Phase 2

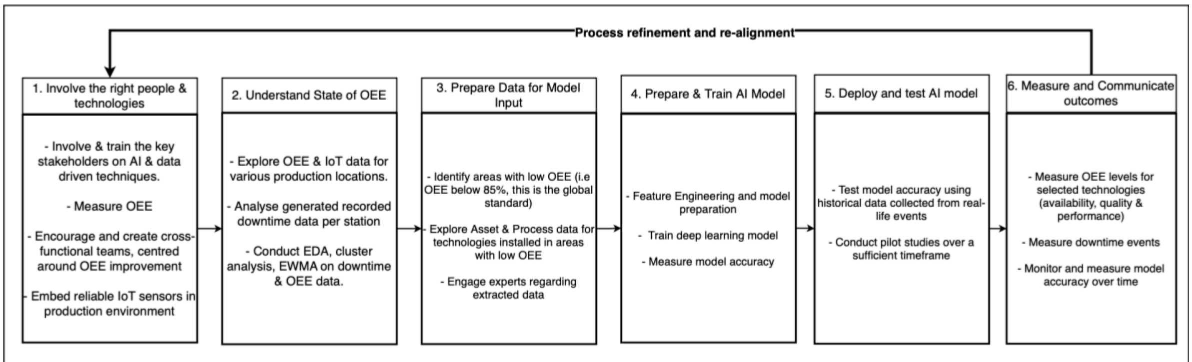
The findings in the second phase of evaluation underscore the importance of context in the models' training data, spot-welding processes can vary significantly across different locations, with each spot potentially exhibiting unique characteristics and defect patterns. These nuances are crucial for the model to learn to make accurate predictions. The homogenisation of training data across various spot-welding locations may dilute these contextual nuances, leading to poor model performance on specific spot-welding tasks.

Therefore, to enhance model accuracy, it is recommended to adopt a localised training approach where separate models are trained for each distinct spot-welding location. This strategy would allow each model to learn the specific error patterns and conditions of its respective location, leading to improved predictive accuracy and better support for quality control in spot-welding operations. This approach aligns with the growing trend towards personalised and context-aware machine learning models in manufacturing and quality assurance.

4.9 Communication

In the Design Science Research for Company X, an automotive manufacturer in South Africa, a critical issue was identified at the spot-welding station, a significant contributor to the production line inefficiency. The zones' OEE was found to be at 70%, well below the industry standard of 85%, with the spot-welding joining technology being responsible for 13% of the total downtime from September to November 2023. The proposed solution is the adoption of AI-driven predictive maintenance aimed at proactively signalling potential stoppages for timely intervention in effort to increase the availability of manufacturing equipment.

The study at Company X demonstrated that employing a Bi-Directional LSTM model within an AI-integrated framework significantly improved the predictive maintenance of spot-welding stations when validated in a simulated environment using historical events. Initial tests showed high accuracy in predicting equipment failures, but further testing across different locations highlighted the need for location-specific training to maintain accuracy. The findings advocate for the development of localised, context-aware AI models, tailored to the unique characteristics of each spot-welding site, to ensure the achievement of industry benchmarks and elevate overall production excellence.



Proposesd AI based Framework to improve OEE in automotive manufacturing. (source : author constructed)

The proposed framework to enhance OEE in automotive manufacturing is a blend of social and technical elements, ensuring a harmonious implementation. It begins with engaging the right people and technologies, underscoring the importance of involving key stakeholders in AI and data-driven techniques training, and establishing cross-functional teams cantered around OEE improvements. This social foundation is crucial for fostering a culture of continuous improvement and collaboration. Concurrently, the technical backbone is formed by embedding reliable IoT sensors within the production environment, providing the necessary data infrastructure for advanced analysis.

As the framework progresses, understanding the state of OEE is achieved through the exploration and analysis of OEE and recorded downtime data, with methodologies such as EDA, cluster analysis, and EWMA applied to downtime and OEE data. This phase sets the stage for the preparation of data for model input, where areas with subpar OEE are identified, and a deeper dive into asset and process data is conducted, integrating technical expertise and data insights. The subsequent stages involve preparing and training AI models with feature engineering and leveraging historical data to test model accuracy, leading to deployment and rigorous testing.

The final phases are dedicated to measuring outcomes and communicating them, which involves monitoring OEE levels and downtime events, emphasising the technical efficacy and social adaptability of the framework to the dynamic environment of automotive manufacturing. This comprehensive approach ensures that both the people at the helm and the technologies employed are in sync, driving towards the unified goal of optimising equipment effectiveness and manufacturing excellence.

4.10 Conclusion

Chapter 4 cohesively ties together the investigative and developmental strides made in addressing the research questions outlined at the beginning of the study. The initial research question sought to understand the current state of OEE at Company X. This objective was accomplished through data collection and analysis, with a special focus on downtime and availability data. Downtime, particularly the interruptions known as Q-stops, was identified as a significant factor affecting OEE. This discovery was instrumental in guiding subsequent phases of the research.

The second research question was addressed through an integrated analysis that combined the empirical OEE data with insights gathered from a semi-structured questionnaire administered to experts operating within the critical OEE zones of Company X. The insights gained from these dual streams of data underscored the necessity for a holistic framework. Such a framework emphasises the synergy between human expertise and technological prowess, fostering a collaborative team adept in pinpointing and rectifying OEE bottlenecks, thus enhancing the flow of production.

The third and final research question was explored through the application of the DSR methodology to conceive, develop, and evaluate a Bi-directional LSTM algorithm. This algorithm was tasked with predicting Q-stops and production interruptions by harnessing temporal data gleaned from IoT devices over a three-month period. The findings from the evaluation of this newly developed artifact shed light on the intricate dynamics of predictive maintenance. The artifact's outcomes demonstrate the critical role of advanced analytics in pre-empting production challenges, marking a significant advancement in the operational optimisation at Company X.

CHAPTER 5. DISCUSSION OF RESULTS

5.1 Introduction

The study applied the DSR methodology to demonstrate the validity of a framework developed to improve OEE through the engagement of people, technology, and processes. The main goal of a DSR research is to develop an artefact or recommendation to problem objections (Naik, 2023). DSR consists of 6 phases, namely (i) Identify the problem and motivate (ii) Define objective solution (iii) design and development, (iv) demonstration, (v) Evaluation and (vi) Communication (Peffers, 2007). This methodology provides a suitable guideline for designing and implementing a framework that can be used to improve OEE by leveraging AI capabilities. The artefacts developed in the study act as a point of departure into the exploration of the operational efficiency achieved through the implementation of AI techniques.

The aim of DSR is to address issues encountered in practical settings and to create broad strategies and solutions that can be adapted to similar situations (Naik, 2023). This study posits that enhancing OEE with artificial intelligence necessitates a comprehensive, cross-functional approach that deeply acknowledges the complexity of the problem context. Section 5.2 focuses on identifying and motivating the problem, using exploratory data analysis to pinpoint critical bottlenecks, such as a spot-welding station with an OEE of 70%. Section 5.3 defines the objective solution by developing a holistic framework that integrates people, processes, and technology, leveraging insights from a semi-structured survey among manufacturing experts. Section 5.4 covers the design and development of an AI-based framework, specifically using a Bidirectional Long Short-Term Memory (Bi-LSTM) model to predict and mitigate production interruptions. This perspective, adopting principles from Actor-Network Theory, allows for an exploration of the dynamic interactions between people, processes, technologies, and organisational structures, which is essential for the successful application and integration of AI in improving OEE.

5.2 Identify the Problem & motivate

The initial phase of the Design Science Research (DSR) methodology, focusing on identifying and motivating the problem, has been effectively applied in the context of Company X. This phase was critical for answering the first research question regarding the current state of OEE at the company. Exploratory data analysis was executed, enabling the identification of a crucial bottleneck at the spot-welding station, operating at an OEE of 70%, well below the industry standard of 85%. This station's shortfall, responsible for a significant 13% of total downtime, was most apparent from September to November 2023, representing a substantive impediment not only to the manufacturing flow but also to Company X's market competitiveness and demand fulfilment capabilities. This detailed analytical groundwork provides a solid foundation for the subsequent DSR phases, setting the stage for the development of targeted improvements and interventions to enhance the OEE at Company X.

5.3 Define Objective Solution

Incorporating the second phase of the methodology into the prior discussion, it becomes clear that this step was pivotal in addressing the second research question regarding the impact of technological readiness, AI, and IoT integrations on OEE at Company X. A semi-structured survey disseminated among manufacturing experts at the company, who provided vital insights into the current state and challenges of integrating these technologies into their manufacturing processes. The gathered data pointed towards the necessity of a cohesive framework that integrates people, processes, and technology, highlighting the role of IoT and the central importance of AI in driving this integration.

This informed response to the second research question, "How do technological readiness, AI, and IoT integrations impact OEE," laid the foundation for the objective solution, which was to develop a holistic framework.

The envisioned holistic framework, powered by IoT and centered around AI, aims to encapsulate the socio-technical elements of the manufacturing environment. By fostering a collaborative ecosystem where data analytics and predictive maintenance models are part of the operational culture, the solution seeks to enhance OEE. It is designed not just as a technical fix but as a transformative process that brings together cross-functional teams, leveraging their collective expertise to drive continuous improvement and operational excellence. This strategic approach, informed by empirical evidence and expert insights, propels the company towards a future where technology and human expertise converge to create a competitive and efficient manufacturing landscape.

5.4 Design and Development

This section signifies the third phase of the Design Science Research methodology, which concurrently serves as the juncture for addressing the third research question: How can an AI-based framework be developed to enhance OEE at Company X? In pursuit of this, the study delves deeper into the insights gleaned from the exploratory data analysis of OEE. A particular focus is placed on a spot-welding station that has been identified with an OEE score of 70%, notably below the industry benchmark of 85%. This station is selected and used for further investigation.

The investigation progresses to examine all spot-welding assets at the chosen station, utilising IoT asset data to isolate a specific spot-welding asset that is a source of frequent yet brief production halts. Subsequent to this pinpointing, a detailed extraction and analysis of the process data related to the identified asset are undertaken to discern patterns and behaviors that precipitate production interruptions, commonly known as Q-stops.

The culmination of this data extraction facilitates the deployment of a Bidirectional Long Short-Term Memory (Bi-LSTM) deep learning model. The selection of the Bidirectional Long Short-Term Memory (Bi-LSTM) model for this study was a deliberative process, anchored by a thorough review of relevant scholarly work.

Notably, Zhang's 2018 research, as detailed in the paper "Long short-term memory for machine remaining life prediction," which provided substantial evidence of the Bi-LSTM's capabilities. This particular model stands out due to its remarkable ability to capture and analyse time-dependent patterns within sequential data (Zhang, 2018), a critical feature when dealing with the complexities of equipment performance over time.

Implementing the Bi-LSTM model offers the distinct advantage of enhancing prediction accuracy for the Remaining Useful Life (RUL) of machinery. As stated by Zhang (2018), its bidirectional nature allows the model to process data in both forward and reverse time order, affording a comprehensive view of the equipment's operational timeline. This level of insight is crucial for developing proactive strategies to curb potential production halts, effectively minimising downtime and maintaining continuous productivity within the manufacturing pipeline.

5.5 Demonstration – Phase 1

In the first demonstration phase of the study, the Bi-directional LSTM model's effectiveness was evaluated using historical IoT data from spot-welding operations. Due to delays in obtaining ethical clearance and data access, historical data proved crucial, enabling the model to predict operational interruptions, or Q-stops, with a high degree of accuracy. The model was rigorously tested against 600 spot-welding sequences, showcasing a remarkable 99.52% accuracy rate in predicting Q-stops, with '1' indicating a Q-stop and '0' a non-Q-stop scenario. The model's predictions were further validated through a confusion matrix, which provided detailed insights into the true positives and negatives, as well as the false positives and negatives.

These findings affirm the value of leveraging historical data to refine predictive models, OEE by pre-empting downtime and maintaining equipment performance. The results underscore the model's potential applicability across various industrial settings, while also pointing to the necessity for continuous model management to maintain its efficacy over time.

5.6 Evaluation – Phase 1

In the first evaluation phase, the study demonstrated the predictive model's effectiveness, boasting an impressive 99.52% accuracy rate in forecasting Q-stops in welding sequences. This high level of precision means that out of 100 welding operations, the model can accurately anticipate faults or quality issues in nearly all instances, enabling pre-emptive maintenance and significantly reducing unplanned production downtime. This capability enhances the availability component of OEE and contributes to consistent production quality and performance. The model's predictions were corroborated with historical data, affirming its predictive strength. However, the study acknowledges the necessity for the model's continuous management and refinement to maintain its effectiveness. The next step involved applying the model to different spot-welding locations to validate its generalisability and effectiveness across various operational contexts, as part of the second demonstration phase.

5.7 Demonstration – Phase 2

In the second demonstration phase of the study, the predictive model's generalisability was put to the test by expanding the analysis to include additional spot-welding locations known for high incidences of Q-stop errors. This broader application was crucial to validate the model's robustness across various conditions and was supported by historical IoT data from new welding spots not included in the initial training set. The supplementary tests conducted indicated that while the model maintained a high predictive accuracy overall, its performance was notably lower when applied to an unknown spot weld, suggesting that each spot-welding scenario has unique temporal nuances that the model needs to learn.

The confusion matrix from the second phase of the study revealed a significant gap in the predictive model's performance when applied to a different spot-welding location. While the model showed a high number of true negatives, it failed to identify any true positives for the Q-Stop events, indicating a notable deficiency in its predictive capability for this specific operational issue when encountering new, unlearned scenarios. This resulted in a decrease in accuracy to 93.33% from the previously reported 99.52%, underlining the challenge of transferring learned patterns to new environments and the need to capture the distinct temporal dynamics of each welding location to ensure the model's reliability and effectiveness. The importance of ongoing model refinement to maintain effectiveness across diverse operational environments was highlighted as a key takeaway from this phase.

5.8 Evaluation – Phase 2

The key takeaways from the second evaluation phase highlight the critical role of contextual nuances in the training data of predictive models for manufacturing processes. It was found that each spot-welding location could have distinct characteristics and patterns of defects, which are essential for the model to capture for accurate predictions. The use of homogenised training data across various locations may not account for these differences, potentially compromising the model's performance on specific tasks.

To address this, a localised training approach is recommended, wherein individual models are developed and trained for each unique spot-welding location. This would enable each model to learn the error patterns and conditions specific to that location, thereby significantly enhancing predictive accuracy. Such a targeted approach can lead to better support for quality control measures in spot-welding operations and is in line with the emerging trends of creating personalised and context-aware machine learning applications in the realm of manufacturing and quality assurance.

5.9 Communication

The proposed AI-based framework for enhancing OEE in automotive manufacturing merges social dynamics with technical processes to form a unified strategy for improvement. The framework begins by establishing a solid foundation through the engagement of key stakeholders knowledgeable in AI and data analytics, and by fostering cross-functional teams focused on OEE enhancement. This collaborative social structure is supported by a technical infrastructure that includes reliable IoT sensors for data collection.

The process continues with a comprehensive analysis of OEE and IoT data, utilising methods such as EDA, cluster analysis, and EWMA on downtime and OEE data. Insights from this analysis lead to the preparation of data for AI model input, targeting areas with substandard OEE for improvement. An advanced AI model is then developed and trained, using historical data to refine its predictive accuracy. The final steps involve deploying the model, monitoring its performance, and communicating the outcomes to ensure continuous refinement of the manufacturing process. This approach not only bolsters the technical aspects of production but also adapts to the evolving landscape of automotive manufacturing, underscoring the interplay between technology and workforce development in achieving operational excellence.

5.10 Conclusion

This chapter has provided a thorough exploration and analysis of the study's findings, meticulously outlined through its structured sections. It began with an examination of the DSR methodology's application in enhancing OEE through the synergistic use of people, technology, and processes. A detailed review of the bi-directional LSTM artefact using historical IoT data has demonstrated the tangible benefits of AI integration in operational efficiency, using Company X as a case study. The critical assessment of the artefact underscored the iterative nature of the DSR approach, pivotal in refining the AI model to better predict and improve OEE. The findings highlight the indispensable role of AI in the operational advancement of the automotive manufacturing sector, suggesting that the integration of IoT and AI could significantly bolster OEE.

Moreover, the chapter navigated through the challenges and opportunities presented by technological readiness, adaptability, and the intricate interplay between social and technical elements within the manufacturing landscape. It posited that the adoption of AI-driven predictive maintenance could notably enhance the availability of critical manufacturing equipment, thereby improving OEE. In conclusion, this chapter underscores the promising potential of leveraging advanced AI techniques and IoT integration to elevate operational efficiency in the manufacturing domain. It encourages a continued exploration and application of these technologies, advocating for an integrated framework that harmonises technology with operational processes. As the study illustrates the successful application of AI in predicting and improving operational efficiency at Company X, it sets a compelling precedent for further research and development in this field.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

The objective of the study is to devise an integrated framework combining predictive analytics with effective coordination among people, systems, and processes to minimise downtime and align the spot-welding station's OEE with industry benchmarks by increasing the availability of equipment. AI is expected to refine production flows, bolster quality control, and improve predictive maintenance accuracy. During the design and development phase, the study evaluated AI's impact on operational efficiency through a questionnaire, practical demonstration using a Bi-Directional LSTM model, and analysis of downtime and IoT-generated data. The research involved an examination of the spot-welding station's data to uncover underlying patterns that could predict equipment failures and quality issues. The Bi-Directional LSTM model was specifically chosen for its ability to process complex time-series data and recognise long-term dependencies, making it ideally suited for the dynamic environment of automotive manufacturing.

The proposed AI-based framework for enhancing OEE in automotive manufacturing is a dynamic, iterative process that starts by mobilising the right mix of people and technologies, focusing on AI and data analytics training to foster a collaborative OEE-centric environment. Section 6.2 delves into the conclusions regarding the research questions, such as the current state of OEE at Company X, the impact of technological readiness, AI and IoT integrations on OEE, and the development of a predictive maintenance framework based on AI. Section 6.3 explores the theoretical implications of the research, particularly in relation to OEE and the Theory of Swift and Even Flow. Section 6.4 outlines strategic recommendations for Company X to enhance OEE through the integration of predictive maintenance techniques. Section 6.5 discusses the limitations encountered during the study, including procedural delays and the use of historical IoT data for validation. Section 6.6 offers suggestions for further research, emphasising the need for extended pilot studies and the development of a universal predictive maintenance model. Finally, Section 6.7

concludes the study, highlighting the successful application of AI in improving OEE and the importance of Design Science Research in driving operational improvements through advanced technologies.

6.2 Conclusions regarding the research questions

6.2.1 What is the current state of OEE at Company X

The current state of OEE at Company X is characterised by a level of 70%, which is below the industry benchmark of 85%. The spot-welding station is a significant contributor to this inefficiency, being responsible for 13% of the total downtime from September to November 2023. This indicates that there is considerable room for improvement in the company's operational efficiency for specific stations.

6.2.2 How do technological readiness, AI and IoT integrations impact OEE?

The Design Science Research methodology's second phase at Company X revealed how AI and IoT integrations could significantly boost OEE, due to current below standard levels at specific stations. Insights from experts via a semi-structured survey highlighted the need for a holistic framework that integrates technical and social aspects, thus shaping a culture of predictive maintenance and data-driven decision-making. This approach is set to enhance OEE and drive continuous improvement, merging AI with human expertise to push Company X towards a future of greater efficiency and a stronger competitive stance.

6.2.3 How can a predictive maintenance framework, based on artificial intelligence, be developed to enhance OEE at Company X?

The third phase of the DSR methodology is pivotal in developing an AI-based framework to improve OEE at Company X. The study intensifies with an exploratory data analysis focusing on a spot-welding station identified for underperformance, with an OEE score of 70% against an 85% industry standard. Detailed investigation of IoT asset data enables the pinpointing of specific spot-welding assets contributing to brief but frequent production interruptions known as Q-stops diminishing station availability. Following the identification, a thorough analysis of process data for these assets is conducted to detect patterns leading to these disruptions. This comprehensive data analysis leads to the application of a Bi-directional Long Short-Term Memory (Bi-LSTM) deep learning model, selected for its proficiency in capturing time-dependent data patterns critical in predicting machinery's Remaining Useful Life (RUL). The use of the Bi-LSTM model, as evidenced by Zhang's research, offers a nuanced view of machinery performance over time, allowing for proactive maintenance strategies that minimise downtime and sustain productivity, thus answering the question of how an AI-based predictive maintenance framework can be developed to enhance OEE at Company X.

6.3 Theoretical Implication

The empirical research and analysis conducted in this study have significant theoretical implications, particularly in the realms of Overall Equipment Effectiveness (OEE) and the Theory of Swift and Even Flow. By integrating predictive maintenance techniques into operational workflows, Company X stands to bolster its OEE and align its practices with the principles of swift and even flow.

The study's findings suggest that the proactive approach facilitated by predictive maintenance contributes directly to enhancing OEE. By pre-emptively addressing maintenance issues based on predictive cues, downtime is minimised, and equipment availability and performance are optimised. This aligns with the core tenets of OEE, which emphasise maximising equipment effectiveness through efficient utilisation and minimal downtime.

Furthermore, the integration of predictive maintenance supports the Theory of Swift and Even Flow by promoting smooth and uninterrupted production processes. By leveraging predictive insights to anticipate and prevent disruptions, operational workflows can be calibrated to maintain a steady and consistent flow of production activities. This ensures that resources are allocated efficiently, minimising bottlenecks and optimising throughput.

6.4 Recommendations

Considering the study's empirical research and analysis, several strategic recommendations emerge for Company X to bolster its OEE through the integration of predictive maintenance techniques. Initially, it is essential to cultivate a digitally literate workforce by providing expansive training in AI and IoT technologies. This initiative should encompass a wide array of learning opportunities, from hands-on workshops to ongoing educational programs, to nurture a culture steeped in technological proficiency.

Furthermore, the importance of a robust data infrastructure cannot be overstated. Investing in quality sensors and establishing rigorous data management protocols will ensure the fidelity of the data input into predictive models. In tandem, fostering a collaborative environment is paramount. By creating cross-functional teams that bridge various departments, Company X can enhance communication and leverage diverse perspectives, particularly in the realm of operational and maintenance decision-making.

Operational workflows must be recalibrated to assimilate predictive maintenance insights seamlessly, thereby enabling the operational processes to be agile and responsive to predictive cues. Initiating this integration with a pilot project at a single spot-welding station would allow for a controlled and measurable start, with scalability following the successful demonstration of value. Continuous performance monitoring forms the backbone of an iterative improvement strategy. By establishing and regularly reviewing predictive maintenance specific KPIs, Company X can refine its AI models and strategies based on tangible performance data. In parallel, maintaining a competitive edge requires an investment in advanced analytics, staying attuned to the latest AI developments that could further refine predictive maintenance tactics.

Managing organisational change is equally vital, as technological transitions can be disruptive. Supportive measures such as counselling and transparent communication about the benefits of new technologies are critical in securing employee buy-in. This approach also opens avenues for feedback, ensuring that the transition is inclusive and considers the insights of employees at all levels.

Resource optimisation is another area where predictive maintenance can yield significant dividends. By allocating resources efficiently, guided by predictive maintenance schedules, Company X can ensure that maintenance efforts are both effective and economical. Lastly, the company should leverage AI not merely as a predictive tool but as a catalyst for continuous operational improvement. By keeping AI models current and reflective of the evolving production landscape, the Company can ensure that its maintenance strategies are not only preventative but also progressively enhancing operational efficiency. Through the implementation of these recommendations, Company X can expect to see a marked improvement in its OEE, thereby reinforcing its manufacturing robustness and overall business performance.

The proposed predictive maintenance framework is not only applicable to the automotive sector but can also be scaled and adapted to various other manufacturing sectors. This scalability is enabled by the universal principles of predictive maintenance and the flexibility of AI-driven models to learn from diverse datasets. In the aerospace industry, predictive maintenance can monitor critical components like engines and avionics systems, ensuring safety and reducing the risk of unexpected failures. In electronics manufacturing, where precision and reliability are paramount, the framework can predict equipment failures in high-precision machinery, reducing defects and downtime, thereby increasing yield and efficiency. The pharmaceutical industry can adapt the framework to ensure the reliability of equipment used in drug manufacturing processes, maintaining high product quality and complying with stringent regulatory standards. In food processing, predictive maintenance can help maintain the operational efficiency of equipment, ensuring hygiene standards and preventing contamination by monitoring critical parameters that affect food safety and quality.

6.5 Limitations and Challenges

The study at Company X encountered limitations due to procedural delays in acquiring ethical clearance, hindering the launch of a pilot study critical for evaluating AI-driven operational enhancements. To mitigate this, the study capitalised on historical IoT data, utilising it to validate the artefact's accuracy within a simulated environment based on past data. This simulation served as an alternative for early evaluation, facilitating the discovery and resolution of potential challenges ahead of full-scale application. It also offered preliminary insights that were otherwise unattainable, aiding in the fine-tuning of the study. To further this effort, it is recommended that, as part of the artefact's rollout, a pilot study be conducted over a six-month period. This would allow for an extended data collection period, model training and continuous refinement as well as a thorough assessment of the artefact, ensuring its effectiveness and adaptability to Company X’s specific operational needs.

In broader terms, a study titled "Industry 4.0 skills: A perspective of the South African manufacturing industry" by Whisper Maisiri and Liezl van Dyk explores the skills requirements and development necessary for the successful adoption of Industry 4.0 (I4.0) technologies within the South African manufacturing sector(Maisiri, 2020). The study highlights the significant transformation in job roles and skills brought about by I4.0, emphasising the necessity for upskilling and reskilling to maintain competitiveness and productivity. Technological limitations such as data dependency, complexity, and integration challenges, along with ethical concerns like job displacement, bias, and privacy issues, are critical considerations in the application of AI models in this context(Maisiri, 2020).

The practical challenges of implementing AI technologies in the South African manufacturing industry are multifaceted. There is a significant workforce skills gap, with a pressing need for advanced digital skills, critical thinking, and problem-solving abilities, necessitating substantial investment in training and education(Maisiri, 2020). Financial constraints, including high implementation costs and limited access to technology, particularly affect smaller manufacturing companies. Additionally, organisational and structural barriers such as the need for alignment of HR strategies and fostering a culture of continuous learning and innovation complicate the adoption of AI systems.

Maisiri (2020) underscores the critical role of human resources in the transition to I4.0, highlighting the need for comprehensive strategies to manage workforce changes and ensure the development of necessary skills. Addressing the limitations of AI models and considering ethical implications are essential for the sustainable adoption of these technologies. Furthermore, overcoming practical challenges such as skills gaps, financial constraints, and organisational barriers is vital for the successful implementation of AI in the South African manufacturing industry.

6.6 Suggestions for further research

Further research into enhancing operational efficiency within manufacturing environments could benefit significantly from an expanded timeframe for conducting pilot studies. Such an extension would allow for comprehensive testing across specific stations, enabling the identification and analysis of unique challenges and opportunities inherent in each station. This detailed approach could reveal insights into station-specific processes, facilitating the development of targeted strategies for efficiency improvements. Moreover, a more prolonged period would provide the flexibility needed to iterate pilot programs, refining methods and approaches based on real-time feedback and performance data. Ultimately, a more extensive pilot phase would lay a more substantial foundation for scaling up successful practices across the manufacturing floor.

In parallel with these targeted station studies, future research should aim to develop a universal predictive maintenance model that transcends the specificity of single technologies. By leveraging a broader dataset that encapsulates diverse technologies, the model could learn to identify common patterns and anomalies that affect different types of manufacturing equipment. This universality would not only enhance the model's scalability but also its applicability across various sectors within the automotive industry. Additionally, enlarging the population group for questionnaires would offer a more representative understanding of industry-wide challenges and opportunities, leading to more generalisable findings.

Expanding the study to include multiple automotive manufacturers could provide a comparative analysis that identifies best practices and industry benchmarks. Furthermore, while the initial study concentrated on the availability aspect of OEE, subsequent research could take a more holistic approach, examining all three components of OEE, availability, performance, and quality, to foster a comprehensive enhancement of operational efficiency. To bring these theoretical frameworks to practical fruition, establishing focus groups dedicated to actualising specific use cases would be instrumental, ensuring that the research outcomes translate into tangible improvements on the production floor.

Future research should also provide tailored recommendations for implementing AI-based predictive maintenance in different manufacturing sectors. For instance, the aerospace industry could benefit from AI models that predict maintenance needs for critical components like engines and control systems, ensuring safety and reducing downtime. In electronics manufacturing, AI-driven predictive maintenance could monitor and optimise the performance of high-precision equipment, reducing defects and enhancing throughput. The pharmaceutical industry could utilise predictive maintenance to ensure the reliability of manufacturing equipment, maintaining high product quality and compliance with regulatory standards. Similarly, the food and beverage industry could apply predictive maintenance to improve the operational efficiency of food processing equipment, ensuring hygiene and reducing the risk of contamination.

Offering strategies for ensuring regulatory compliance is also crucial. Encouraging the adoption of relevant certifications such as ISO 55000 for asset management and ISO/TS 16949 for automotive sector quality management can provide a structured approach to compliance. Ensuring AI-based predictive maintenance systems comply with industry-specific regulations, such as FDA regulations for pharmaceuticals and FAA regulations for aerospace, is essential. Addressing data privacy and security concerns by ensuring compliance with regulations like POPIA & GDPR, especially when dealing with sensitive operational data, is another key aspect. Additionally, promoting standardisation in predictive maintenance technologies to ensure interoperability between different systems and devices is critical for sectors with diverse equipment and machinery.

6.7 Conclusion

The study, guided by the principles of Design Science Research in operations management, embarked on a mission to craft a framework capable of leveraging AI to enhance OEE within an automotive manufacturing context. The DSR methodology provided a structured approach, starting with the identification of the problem, suboptimal OEE at Company X and proceeding through the development and rigorous testing of AI-based solutions.

The framework's development was rooted in a deep understanding of the company's operational challenges, particularly the need to improve the availability aspect of OEE. Through a series of data exploration activities, the research examined the influence of technological readiness, AI integration, and the interplay of social and technical elements on OEE. The findings from these tests informed the creation of a predictive maintenance model using a Bi-directional Long Short-Term Memory network, which was then evaluated for its accuracy and effectiveness in a simulated environment reflective of real-world conditions.

The research not only demonstrated the practical benefits of AI in improving OEE but also laid out a clear path for its implementation. By adhering to the DSR methodology, the study ensured that the developed framework was both rigorously tested and finely tuned to the specific needs of Company X's manufacturing operations. The conclusion of this study highlights the successful application of AI in predicting and improving operational efficiency, thereby contributing significantly to the advancement of OEE within the automotive manufacturing sector. The study's outcomes serve as a testament to the power of DSR in driving innovation and operational improvements through the application of advanced technologies like AI.

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Appendix A: Specialist Questionnaire

Assessing the Impact of AI-based Predictive Maintenance on OEE Enhancement.

Start of Block: Block 1

Dear Sir / Madam

My name is Siphamandla Sifiso Phenyane. I am a master's student currently pursuing my Master of Management in Digital Business at the University of the Witwatersrand, Johannesburg. My supervisor is Dr Michael Sony. I am conducting a research study about designing an AI-based maintenance framework for the purpose of improving overall equipment effectiveness (OEE). The title of the study is **Designing an AI-based Predictive Maintenance framework to improve OEE for an Automotive Manufacturer in South Africa.**

As part of this study, I would like to invite you to take part in a questionnaire, which should take you no more than 20 minutes to complete. The questionnaire will be done online, and at your own convenience. With your permission, I would like to store the results in a private repository. This data will be stored in a database for 5 years and deleted thereafter. Only myself, as the researcher will have access to the data.

Your participation in this research study is strictly voluntary. Should you feel uncomfortable or unable to answer any of the questions, you are welcome to skip them. Please note that there will not be any direct benefits or payment from participating in this research study. There will be no loss of any services, benefits or rights you would normally have should you decide not to join.

Taking part in this research study will not have any direct costs incurred by you nor any risks transferred to you. Should you feel like you need more time to answer the questions for any reason whatsoever, you may stop and continue another time. This research study will be written up as a research report. The report will be available on the university library website. If you would like to receive a summary of this report, I would be happy to share it with you.

During the research activity, I will need to ask for some personal information about you, including your job title, years of experience, qualification, and department. The questionnaire will be confidential and anonymous. When I share the results of the research study, I will not include

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your name or any information that could be used to identify you. With your permission, other researchers may use the data collected from this research study, but your name and any personal information will not be used or shared.

If you have any questions during or afterwards about this research study, please feel free to contact me or my supervisor using the details provided below.

If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours in Research,
Siphamandla Sifiso Phenyane

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End of Block: Block 1

Start of Block: Block 2

Introduction

The purpose of this study is to delineate the correlation between Overall Equipment Effectiveness (OEE) and data-driven fault prognosis techniques derived from the advancements of the 4th Industrial Revolution. The study seeks to ascertain the influential factors that contribute to the effective implementation of predictive maintenance techniques, with the overarching aim of enhancing the OEE within the framework of a manufacturing environment in South Africa. This objective will be realised through the utilisation of artificial intelligence-based predictive maintenance methods.

Figure 1 illustrates the potential relationship between conventional Total Productive Maintenance (TPM) techniques and data-based as well as knowledge-based fault prognosis techniques to enable effective AI-based maintenance techniques that could potentially result in improved OEE. The study posits that the inclusion of AI-based techniques that leverage data-based methods such as predictive maintenance and knowledge-based methods could potentially improve OEE within the automotive manufacturing context in South Africa and lead potentially lead to improved automotive production flow.

End of Block: Block 2

Start of Block: Block 3

Study Background

Driving Economic Development: The Role of South Africa's Manufacturing Sector

In South Africa, the manufacturing industry is a crucial component of the economy, contributing a significant 13% to the country's total GDP as noted by merSETA (2020). The motor vehicles, parts, and accessories sector alone accounts for an impressive 7% of the contribution (merSETA, 2020). The manufacturing sector has also been a reliable source of employment over time, and the automotive manufacturing sector has experienced steady growth in job opportunities. The South Africa automotive master plan, which governs the local motor industry, projects that employment within the industry will double by 2035 (merSETA, 2021). Given the automotive industry's leading role in the country's efforts to re-industrialise, it is evident that the manufacturing sector will continue to be a crucial force in driving economic development in South Africa.

Adapting to Challenges: Enhancing Efficiency in South Africa's Manufacturing Industry

However, in recent years, the industry has faced significant challenges due to increasing competition, strict regulations, covid-19 interruptions, and shifting customer demands, which have negatively impacted forecasted growth, increased production costs, and lowered output levels (merSETA, 2021). As a result, manufacturers and relevant practitioners are constantly exploring new techniques and methods of augmenting manufacturing processes to improve production efficiency, reduce production-related costs and improve product quality (Jan, 2023).

Efficiency Enhancement Strategies in the Automotive Manufacturing Sector

Improving efficiency is crucial for achieving long-term success and competitiveness in the automotive sector. To enhance efficiency, manufacturers can streamline processes, automate repetitive tasks, reduce waste, and optimise resource allocation. Production stops due to quality issues are one of the biggest contributors to production inefficiency and result in high costs, such as cost as a result of lost production, cost as a result of downtime, cost due to the time taken to identify errors in production, and costs as a result of production waste (Ayvaz, 2021).

Industry 3.0 and TPM: Impact on Downtime and Manufacturing Efficiency

The possibilities created by Industry 3.0 resulted in the introduction of TPM, which resulted in an average downtime reduction of 53% and a decline in breakdowns by 54% on average in various industries (Jan, 2023). The Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), and Overall Equipment Effectiveness (OEE) were used as indicators for measuring downtime, performance, and quality improvements (Jan, 2023). Although the implementation of TPM brought about significant change to manufacturing environments, achieving zero downtime remains a challenge.

Enhancing Production Efficiency through OEE: Key Factors and Metrics

To improve production efficiency, manufacturers have relied on OEE, a performance metric that measures the effectiveness of manufacturing equipment and processes (Daneshjo, 2019). OEE considers three essential factors: availability, performance, and quality, which are used to calculate a single performance metric. By focusing on these key factors, manufacturers can optimise their production processes and identify areas for improvement.

Data-Driven Approaches and Machine Learning for Predictive Maintenance in Manufacturing

By leveraging the data generated from inter-connected device networks and utilising data-driven approaches, practitioners can predict the likelihood of production disturbances, using asset, process and trend data generated from the equipment's historical performance and suitable Machine Learning (ML) models (Jan, 2023). According to Jan (2023), these ML models have allowed for the preparation of alternatives that are arranged in advanced and proposed as recommendations with the end goal of reaching near-zero downtime. Additionally, recent developments in production environments and advancements in technology suggest that the ability to estimate the remaining useful life for machinery has started to play an increasing role in ensuring safe and reliable production environments (Ayvaz, 2021).

Challenges and Opportunities in Implementing AI-Based Predictive Maintenance for Enhanced OEE in South African Automotive Manufacturing

However, implementing AI-based predictive maintenance models requires significant investment in infrastructure, technology, and personnel. It is essential to consider the potential risks and challenges associated with such implementation, such as the need for accurate and reliable data, adequate training of personnel, and the potential impact on the existing production environment. Additionally, it is important to consider the ethical implications of using AI-based predictive maintenance, such as data privacy and bias.

This study explores the implementation of AI-based methods to improve OEE for an automotive manufacturer in South Africa, which acts as a representative of automotive manufacturers in the country. The study highlights that production efficiency is a critical factor in enhancing the competitiveness and profitability of manufacturing organisations. The integration of data-based and knowledge-based manufacturing methods fused with TPM, an industry 3.0 concept, can lead to significant improvements in OEE and production efficiency.

End of Block: Block 3

Start of Block: Block 7

Your Role

Before we commence, kindly choose a role below that closely aligns with your position in the company.

- ○ Production Manager (1)
- ○ Maintenance Manager (2)
- ○ Quality Control Manager (3)
- ○ Data Analyst and/or Data Engineer (4)
- ○ Plant Engineer (5)
- ○ Operations Manager (6)
- ○ Technician and/or Operator (7)
- ○ Continuous Improvement(CI) Team Member (8)
- ○ Technology and IT Specialist (9)
- ○ Executive and/or Thought Leader (10)

End of Block: Block 7

Start of Block: Default Question Block

Understanding and Importance of OEE

Q1
OEE is a performance metric that measures the effectiveness of manufacturing equipment and processes (Daneshjo, 2019). OEE considers three essential factors: availability, performance, and quality, which are used to calculate a single performance metric

Please rate your familiarity with OEE concepts

- ○ Not familiar at all (1)
- ○ Slightly familiar (2)
- ○ Somewhat familiar (3)
- ○ Moderately familiar (4)
- ○ Very familiar (5)

Q2 How important do you perceive OEE to be in the automotive manufacturing process?

- ○ Not at all important (1)
- ○ Slightly important (2)
- ○ Moderately important (3)
- ○ Very important (4)
- ○ Extremely important (5)

Q3 To what extent do you believe improvements in OEE can positively impact production efficiency?

- Extremely negative (1)
- Somewhat negative (2)
- Neither positive nor negative (3)
- Somewhat positive (4)
- Extremely positive (5)

End of Block: Default Question Block

Start of Block: Block 8

Maintenance and Challenges

Q4 How effectively do current maintenance strategies address OEE improvement goals?

- Not effective at all (1)
- Slightly effective (2)
- Moderately effective (3)
- Very effective (4)
- Extremely effective (5)

Q5 Rate the level of challenges faced in implementing OEE improvement initiatives.

- Not at all challenging (1)
- Slightly challenging (2)
- Moderately challenging (3)
- Very challenging (4)
- Extremely challenging (5)

End of Block: Block 8

Start of Block: Block 4

Data-Driven Decision-Making

Q6 To what extent are data-driven decision-making practices integrated into your workflow?

- Not at all integrated (1)
- Slightly integrated (2)
- Moderately integrated (3)
- Very integrated (4)
- Fully integrated (5)

Q7 Rate your confidence in interpreting data to drive OEE improvement decisions.

- Not confident at all (1)
- Slightly confident (2)
- Moderately confident (3)
- Very confident (4)
- Extremely confident (5)

Q8 How frequently do you actively participate in OEE improvement initiatives

- Never (1)
- Rarely (2)
- Occassionally (3)
- Frequently (4)
- Very frequently (5)

End of Block: Block 4

Start of Block: Block 5

Integration of AI and Technical Skills

Q9 Are you familiar with the use of AI or machine learning in OEE improvement initiatives within the South African automotive manufacturing industry?

- ○ Yes (1)
- ○ Maybe (2)
- ○ No (3)

Q10 On a scale from 1 to 5, how would you rate the variety of AI or machine learning techniques implemented in your OEE initiatives?

- ○ No variety (1)
- ○ Very little variety (2)
- ○ Moderate variety (3)
- ○ High variety (4)
- ○ Extensive variety (5)

Q11 On a scale from 1 to 5, rate the level of integration of AI-based techniques in your manufacturing processes.

- ○ Not integrated (1)
- ○ Slightly integrated (2)
- ○ Moderately integrated (3)
- ○ Very integrated (4)
- ○ Fully integrated (5)

Q12 On a scale from 1 to 5, indicate how frequently AI applications are used in your work environment.

- Never used (1)
- Rarely used (2)
- Occasionally used (3)
- Frequently used (4)
- Always used (5)

Q13 On a scale from 1 to 5, rate the change in the number of AI-based techniques used in your OEE initiatives over the past year.

- Decreased significantly (1)
- Decreased slightly (2)
- No change (3)
- Increased slightly (4)
- Increased significantly (5)

Q14 On a scale from 1 to 5, rate the adequacy of AI and machine learning training provided to staff involved in OEE initiatives.

- Inadequate (1)
- Barely adequate (2)
- Adequately provided (3)
- Very adequate (4)
- Highly adequate (5)

Q15 On a scale from 1 to 5, rate the level of technical skills your team possesses in relation to the current manufacturing technology.

- ◯ Very low level of technical skills (1)
- ◯ Low level of technical skills (2)
- ◯ Adequate level of technical skills (3)
- ◯ High level of technical skills (4)
- ◯ Very high level of technical skills (5)

Q16 In your opinion, how effective have AI-based techniques been in improving OEE in the South African automotive manufacturing sector?

- ◯ Not effective at all (1)
- ◯ Slightly effective (2)
- ◯ Moderately effective (3)
- ◯ Very effective (4)
- ◯ Extremely effective (5)

End of Block: Block 5

Start of Block: Block 9

Collaboration and Skill Development

Q17 On a scale from 1 to 5, rate the quality of collaboration between cross-functional teams in your organisation.

- Very poor collaboration (1)
- Poor collaboration (2)
- Adequate collaboration (3)
- Good collaboration (4)
- Excellent collaboration (5)

Q18 On a scale from 1 to 5, how would you rate the opportunities for skill development in relation to emerging technologies in your organisation?

- Very inadequate opportunities (1)
- Inadequate opportunities (2)
- Adequate opportunities (3)
- Good opportunities (4)
- Excellent opportunities (5)

Q19 On a scale from 1 to 5, rate the effectiveness of collaborative problem-solving efforts in OEE-related issues.

- Not effective at all (1)
- Rarely effective (2)
- Sometimes effective (3)
- Often effective (4)
- Always effective (5)

End of Block: Block 9

Start of Block: Block 6

IoT Integration

Q20 On a scale from 1 to 5, rate the extent to which IoT devices are utilised in your manufacturing processes.

- ○ Not utilised at all (1)
- ○ Rarely utilised (2)
- ○ Sometimes utilised (3)
- ○ Frequently utilised (4)
- ○ Always utilised (5)

Q21 On a scale from 1 to 5, rate the degree to which IoT data is used in decision-making processes in your organisation.

- ○ Not used at all (1)
- ○ Seldom used (2)
- ○ Used as much as other data (3)
- ○ Often the main data source (4)
- ○ The primary data source for decision-making (5)

Q22 On a scale from 1 to 5, rate the effectiveness of IoT data integration in improving manufacturing efficiency.

- ◯ Not effective at all (1)
- ◯ Slightly effective (2)
- ◯ Moderately effective (3)
- ◯ Very effective (4)
- ◯ Extremely effective (5)

End of Block: Block 6

Appendix B: Bi-Directional LSTM Pseudo algorithm

```
# Assuming I have input data X and corresponding target labels Y:
# Pre-process the data to convert it into a suitable input format.
# X shape: (num_samples, sequence_length, num_features)
# Y shape: (num_samples,)

# Step 1: Data Preparation
# Split the data into training and testing sets to evaluate the model's
performance on unseen data.
# A suitable splitting method will be used, ensuring a balanced representation of
classes in both sets.
X_train, X_test, Y_train, Y_test = split_data(X, Y, test_size=0.2,
random_state=42)

# Step 2: Model Construction
# Build a bi-directional LSTM model to capture patterns in both forward and
backward directions in the sequence data.
model = Sequential()
model.add(Bidirectional(LSTM(128, return_sequences=True),
input_shape=(sequence_length, num_features)))
model.add(Bidirectional (LSTM(64)))
model.add (Dense(1, activation='sigmoid'))

# Step 3: Model Compilation
# Compile the model with binary crossentropy loss and the Adam optimizer for
binary classification.
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Step 4: Model Training
# Train the model on the training set and validate its performance on the test
set.
model.fit(X_train, Y_train, epochs=10, batch_size=32, validation_data=(X_test,
Y_test))

# Step 5: Model Evaluation
# Evaluate the model's performance on the test set to understand its accuracy and
loss.
loss, accuracy = model.evaluate(X_test, Y_test, batch_size=32)
print(f"Test Loss: {loss}, Test Accuracy: {accuracy}")

# Step 6: Making Predictions
# Use the trained model to make predictions on new data.
predictions = model.predict(new_data)

# Step 7: Interpret Predictions
# Assuming the predictions are probabilities, apply a threshold to classify the
predictions into binary outcomes.
threshold = 0.5
binary_predictions = np.where(predictions > threshold, 1, 0)

# Now, binary_predictions contain the final binary outcomes based on the chosen
threshold.
```

Appendix C: Permission Letter

The University of the Witwatersrand,
Wits Business School

7 Settlers Way
Gately Industrial Township
East London, 5200
South Africa

24 June 2023

Dear Sir/Madam,

Re: Permission to conduct research at East London, Mercedes-Benz Manufacturing South Africa.

My name is Siphamandla Sifiso Phenyane.

I am currently employed as a Solutions Architect at the Mercedes-Benz IT Hub in South Africa. In my 6 years working for the brand, I have focused primarily on 4IR projects, with a strong emphasis on Big Data, IoT, and Machine Learning. To date, my team is responsible for the streaming of millions of data points to various projects at more than 16 manufacturing locations.

I am studying for a Master of Management in Digital Business at the Wits Business School at the University of the Witwatersrand. I am seeking permission to do research at Mercedes-Benz South Africa.

I am conducting research on the use of Artificial Intelligence to improve a key KPI, namely Overall Equipment Effectiveness (OEE) for a selected station in the body shop. The study focuses on using industry 3.0 techniques such as Total Productive Maintenance (TPM) to establish context and measure existing OEE performance for a particular station, to identify a station that will be at the center of the study. 4IR principles and concepts such as the Internet of Things (IoT), Machine Learning (ML), and Artificial Intelligence (AI) are then applied in a simulated environment to improve OEE and provide recommendations based on findings to the organization.

The research will entail collecting data from maintenance specialists or experts at the selected station in the form of an anonymous survey with the main aim of establishing a solid foundation on the current state of OEE for the station.

I request permission to get access to sensor/IoT data stored in OpenSearch for a 6-month window. This data pertains purely to the process parameters resulting from conducting tasks in a particular station.

Participants will be asked to give their written or verbal consent before the research begins. Their responses will be treated confidentially, and identities (their names and the name of the organization) will be anonymous unless otherwise expressly indicated. Individual privacy will be maintained in all published and written data resulting from the study.

The results will be communicated in my academic dissertation.

The research participants will not be advantaged or disadvantaged in any way. They will be reassured that they can withdraw their permission at any time during this project without any penalty. There are no foreseeable risks in participating in this study. The participants will not be paid for this study.

All research data will be destroyed 1 year after the study.

I, therefore, request permission in writing to conduct my research at your organization. The permission letter should be on your organization's headed paper, signed and dated, and specifically referring to me by name and the title of my study.

Please let me know if you require any further information. I look forward to your response as soon as is convenient.

Yours sincerely,

Siphamandla Phenyane

Siphamandla
0631802937
706212@students.wits.ac.za

Supervisor: DR Michael Sony
0117173817
michael.sony@wits.ac.za

Appendix D: Supervisor letter supporting submission.

Michael Sony 07:40
Re: Email Supporting submission
To: Siphamandla Phenyane

Hi Siphamandla,

The approval is hereby granted for submission.

Dr Michael Sony, PhD
Senior Lecturer / Program Director – PDM-DB: Digital Business | Wits Business School

E : michael.sony@wits.ac.za
T : +27 11 717 3817
W : www.wbs.ac.za

2 St Davids Place, Parktown,
Johannesburg

See More from Siphamandla Phenyane

Appendix E: Participant Information Sheet (PIS)

Participant Information Sheet (PIS)

Dear Sir / Madam

My name is Siphamandla Sifiso Phenyane I am a master's student currently pursuing my Master of Management in Digital Business at the University of the Witwatersrand, Johannesburg. My supervisor is Dr Michael Sony. I am conducting a research study about designing an AI-based maintenance framework for the purpose of improving overall equipment effectiveness (OEE). The study title is Designing an AI-based Predictive Maintenance framework to improve OEE for an Automotive Manufacturer in South Africa.

I am inviting you to take part in a questionnaire. If you decide to take part, your participation in this research study will last about 20 minutes. The activity will take place online at your own convenience.

With your permission, I would like to store the results in a private repository. This data will be stored in a database for 1 year and deleted after 1 year. Only the researcher will have access to the data.

During the research activity, I will need to ask for some personal information about you, including your job title, years of experience, qualification, and department.

The questionnaire will be confidential and anonymous. When I share the results of the research study, I will not include your name or anything else that could identify you. With your permission, other researchers may use the data collected from this research study, but your name and any personal information will not be used or passed on.

If you decide to take part in the research study, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the research study. You will not lose any services, benefits or rights you would normally have if you decide not to join. Taking part in the research study will not cost you anything. You will not be paid for being in this research study.

The risks for this research study are no more than what happens in everyday life / some of the questions asked may make you feel frustrated. If this happens, you may stop and continue another time.

This research study will be written up as a research report. The report will be available on the university library website. If you would like to receive a summary of this report, I will be happy to send it to you.

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor on the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours sincerely,
Siphamandla Sifiso Phenyane

Researcher:
Siphamandla Sifiso Phenyane, Wits email, +(27) 63 180 2937

Supervisor:
Dr Michael Sony, Wits email, michael.sony@wits.ac.za

Appendix F: Python code used for OpenSearch data extraction.

```python
class OpenSearchExporter:

    def __init__(self, opensearch_url, auth):
        self.opensearch_url = opensearch_url
        self.auth = auth

    def fetch_data(self, query):
        # Open a CSV file to append data
        with open('fetch_log.csv', 'a', newline='', encoding='utf-8') as file:
            csv_writer = csv.writer(file)

            # Initialize the scroll - sending the initial request
            response = requests.get(
                f"{self.opensearch_url}/_search?scroll=1m",  # 1m is the time each scroll context is kept alive
                auth=self.auth,
                json={"query": query, "size": 10000},  # Fetch up to 5000 documents per scroll batch
                verify=False  # Bypass SSL verification if needed
            )
            response.raise_for_status()
            results = response.json()
            scroll_id = results['_scroll_id']  # Extract scroll_id from the initial response
            all_hits = results['hits']['hits']

            # Log the initial batch fetch
            csv_writer.writerow([len(all_hits), len(all_hits)])  # Write initial fetch count to CSV

            # Extract the base URL from the full URL
            opensearch_base_url = 'https://msb-elk.zarsa.corpintra.net:9200'

            # Start scrolling
            while True:
                response = requests.post(  # Subsequent requests should be POST
                    f"{opensearch_base_url}/_search/scroll",  # Correct endpoint for scrolling
                    auth=self.auth,
                    json={"scroll": "1m", "scroll_id": scroll_id},  # Use the last received scroll_id
                    verify=False
                )
                response.raise_for_status()
                results = response.json()
                scroll_id = results['_scroll_id']  # Update scroll_id
                new_hits = results['hits']['hits']
                all_hits.extend(new_hits)

                # Log each fetch to CSV
                csv_writer.writerow([len(new_hits), len(all_hits)])  # Write fetch counts to CSV

                # Break the loop if no new hits are found
                if not new_hits:
                    break

        # Return the source of all hits
        return [hit['_source'] for hit in all_hits]


    def export_to_csv(self, data, file_name):
        df = pd.DataFrame(data)
        df.to_csv(file_name, index=False)
        print(f"Data exported to {file_name}")
```

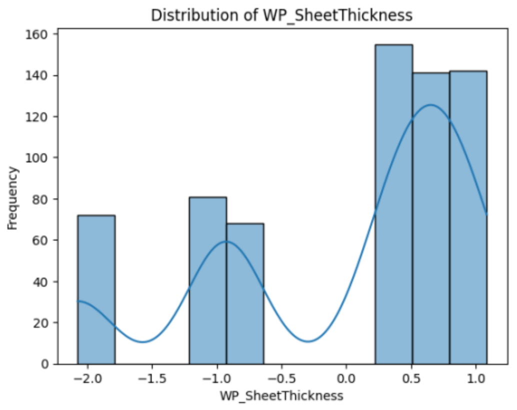
Python

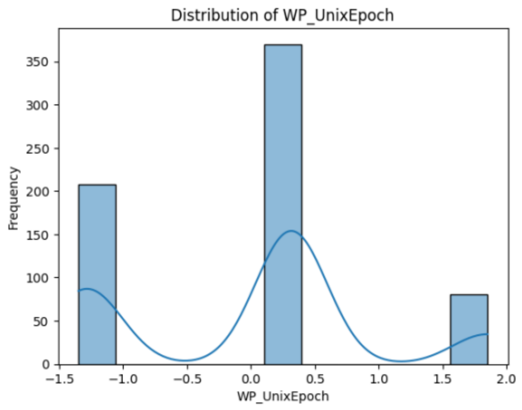
Appendix G: Code snippet for data cleaning

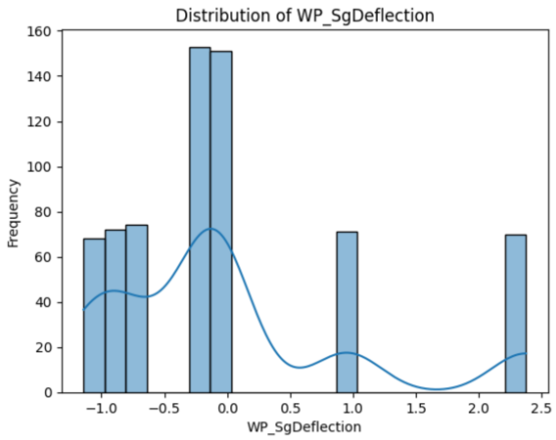
```python
# Define the function to extract OEE values from the 'CW' column
def extract_oee(value):
    try:
        # Parse the string into a dictionary
        value_dict = ast.literal_eval(value)
        # Return the OEE value if it exists
        return value_dict.get('OEE', None)
    except:
        # Return None in case of parsing error
        return None

# Apply the function to extract OEE values
data['OEE'] = data['CW'].apply(extract_oee)

# Convert 'Timestamp' to datetime format and extract the month
data['Timestamp'] = pd.to_datetime(data['Timestamp'])
data['Month'] = data['Timestamp'].dt.to_period('M')

# Remove rows where OEE is None or 0.0 to clean the data
oee_data = data.dropna(subset=['OEE'])
oee_data = oee_data[oee_data['OEE'] != 0.0]

# Group by 'KPIName' and 'Month' and calculate the average OEE
average_oee_per_kpi_month = oee_data.groupby(['KPIName', 'Month'])['OEE'].mean().reset_index()

# Sort the results by OEE in descending order
average_oee_per_kpi_month_sorted = average_oee_per_kpi_month.sort_values(by='OEE', ascending=True)

# Display the results
# data = average_oee_per_kpi_month_sorted.head(20)

# Include only Bodyshop KPIs
data = data[data['Shop'] == 'RB']
data = data[data['PlannedOEE'] <= 100]
data = data[data['OEE'] <= 100]
data = data[data['OEE'] > 0]

## Weekly OEE average per KPIName
print(data.head())
print(data.tail())
data.to_csv("RB_OEE.csv", index=False)
```

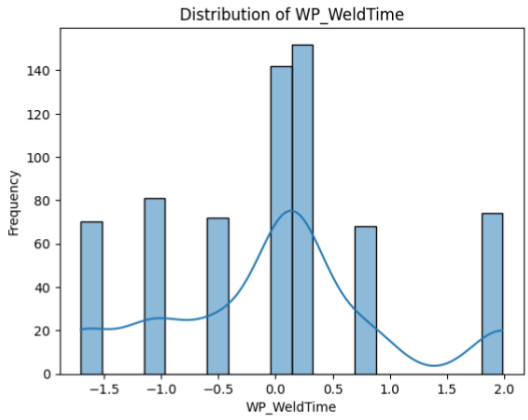
Python

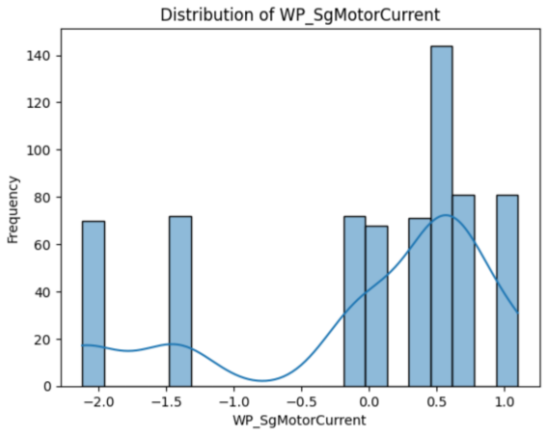
Appendix H: Distributions for selected spot-welding features

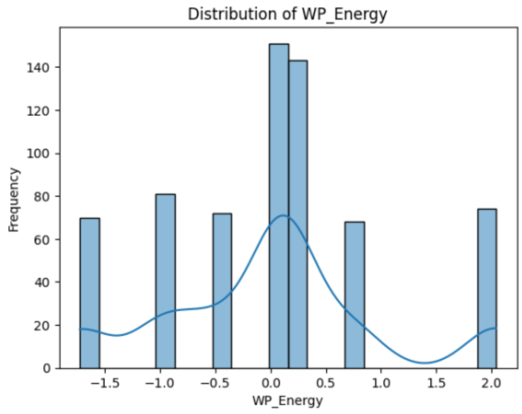












Appendix I: Ethics clearance Wits Business School

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number:	WBS/DB706212/695

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

This certificate is only valid if accompanied by formal permission from the relevant stakeholder(s).

Project title	Designing an AI-based predictive maintenance framework to improve OEI an automotive manufacturer in South Africa
Investigator / Researcher	Mr Siphamandla Phenyane
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonyr and confidentiality.
Issue Date of Certificate	2023/10/17
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

---

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethi Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research an guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

	2023/10/18
Signature	Date:

Appendix J: Ethics clearance Company X

12/19/2023 Private & Confidential

Siphamandla Phenyane
Solutions Architect
Mercedes-Benz South Africa Limited
07 Settlersway, Westbank

Dear

This hereby confirms that Mercedes-Benz South Africa Limited permits the use of internal data for the purpose of completion of your research project towards the study of a Master of Management in Digital Business at the University of the Witwatersrand.

Only data pertaining to the research topic, *"Designing an AI-based Predictive Maintenance framework to improve OEE for an Automotive Manufacturer in South Africa"*, may be used.

Please note that the study should be conducted in a way that does not compromise the name and image of the Company.

This letter must be included in the study documentation, to ensure that this information is not distributed. Details regarding these restrictions should be indicated in the Ethical Clearance Form, and a copy thereof must be sent to Mercedes-Benz South Africa Ltd.

Thank you for your interest.

Yours faithfully
MERCEDES-BENZ SOUTH AFRICA LTD

____

ABEY KGOTLE
EXECUTIVE DIRECTOR HR

Ref. *Research_Approval to Conduct_23.06.2017*
Research Proposal Request Process