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Data-Driven Decision-Support for Maintenance Operations in Stacking Battery Production

Master's thesis in Production Engineering

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Abstract

In the contemporary landscape of battery production, the integration of data-driven predictive maintenance strategies stands out as a pivotal enhancement to operational efficiency and equipment reliability. This study focuses on the predictive maintenance of the stacking process in lithium-ion battery (LiB) production, a critical phase with a significant impact on total productivity of the organisation, due to frequent downtimes associated with the stacking cutting module. Utilizing a CRISP-DM framework within the mixed methods research methodology , this thesis examines the practical implementation of predictive maintenance by analyzing historical data and conducting qualitative research through workshops and literature review. The research highlights the critical role of data quality and availability in the successful application of machine learning models for enabling predictive maintenance. Key findings suggest that while the potential for data-driven maintenance to improve operational efficiency is substantial, significant challenges remain in data collection, system integration, and aligning technological advancements with organizational goals. This study contributes to the body of knowledge by outlining a structured approach in implementing predictive maintenance in battery manufacturing and providing insights into the technical considerations necessary for leveraging Industry 4.0 technologies effectively. The thesis supports industry practitioners in transitioning towards data-driven decision-support for enabling predictive maintenance models, thereby enhancing the sustainability and competitiveness of battery production facilities.

Keywords: Battery manufacturing, Predictive maintenance, Data-driven approach, Sensor data, Machine learning, Stacking.

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As we conclude our two years at Chalmers University of Technology, we reflect on the journey with gratitude towards our family members, friends, and teachers whose support made these years extraordinary. It is with great anticipation that we look forward to embarking on new adventures. Avancez!

Sourav Uday Jannu & Yadhunandan Mallohalli Jagadish, Gothenburg, June 2024

Declaration of Artificial Intelligence tools Utilization

We, hereby, acknowledge the use of Artificial Intelligence (AI) tools that aided in completion of our thesis study. Tools like Chat-GPT and Perplexity have been used at times to assist in refining and structuring the content for the thesis to ensure it met academic standards. All the AI-generated material was thoroughly reviewed and carefully integrated with the original work to enhance the impact and understanding for the reader. With regard to the thesis research, for brainstorming the ideas, finding relevant articles, and summarising the articles assistance was sought from the AI tools. Also, assistance with respect to methods and procedure for data analysis was outlined using the available tools. Hence, by stating the extent and manner of AI tools utilization, this declaration comes forth with the intention to maintain transparency and uphold the academic integrity. Also, since the utilization of AI tools is being encouraged in the industries, it is only natural that this opportunity assisted us in being accustomed to its utilization.

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

CBD	Condition-based Maintenance
CRISP-DM	Cross-industrial standard process for Data mining
EV	Electric Vehicles
LiB	Lithium-ion Batteries
MMR	Mixed method research
MTTR	Mean Time to Repair
OEE	Overall Equipment Effectiveness
PdM	Predictive Maintenance
TEEP	Total Effective Equipment Performance
TWh	Terawatt-hours

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1

Introduction

This chapter provides the context for the master's thesis. The thesis begins with a problem statement, outlining the key issues to be addressed. It then presents the purpose and aim of the research, followed by three specific research questions that guide the investigation. The limitations of the study are also discussed to clarify the scope and boundaries. Finally, the structure of the thesis is outlined to help readers understand the organization and flow of the content.

1.1 Background

Lithium-ion batteries (LiBs) play a crucial role in the mobility and energy sectors. Despite their significance, the manufacturing of LiB cells is plagued by high production costs, significant process variability, elevated scrap rates, and substantial energy demands (Turetskyy et al., 2021a). Addressing these challenges requires the integration of cutting-edge technologies such as Big Data, the Internet of Things (IoT), and Cyber-Physical Systems (Alcácer & Cruz-Machado, 2019). The adoption of advanced, data-driven systems and high-level sensors in recent years has revolutionized manufacturing. This revolution extends to maintenance tasks, necessitating more predictable and efficient practices, especially in complex production environments like battery manufacturing, where multiple parameters influence the creation of a single product.

The 'Smart Maintenance' as described in Bokrantz (2019), encapsulates how technological advancements and new organizational methods are being incorporated. The evolution of maintenance practices is increasingly driven by data-based approaches that ensure the integrity of components, products, and systems by analytically and prognostically identifying issues that could negatively impact production processes, such as in battery manufacturing. The field of machine learning in predictive maintenance is rapidly expanding, enhancing production standards and organizational profitability (Theissler et al., 2021). Nevertheless, effective implementation of predictive maintenance in the industry demands a thorough examination of all factors from data sources to data quality that influence the outcomes of machine learning algorithms.

Reflecting broader trends in the battery industry, Northvolt, with its gigafactories, is advancing digitalization initiatives and aims to integrate data-driven systems across

its entire battery production process. Currently, Northvolt's practices are setting the groundwork for achieving significant advancements in maintenance. Although the potential for these innovations is widely recognized, efforts towards implementing predictive maintenance are progressing in phases. This thesis contributes to these efforts by focusing on the predictive maintenance of the stacking process in battery production, thereby laying the foundation for future developments in this area.

1.2 Context of study

The research context of this thesis will be at Northvolt in Sweden. As Northvolt is involved with the research project MATTER@SCALE and the project being highly relevant for this thesis, both Northvolt and MATTER@SCALE are presented in this section.

1.2.1 Northvolt

Northvolt AB was founded in 2016 and is the largest battery developer and manufacturer in Sweden specialising in lithium-ion technology (European Investment Bank, 2020). It was founded with the aim of supplying batteries to automotive industry but has eventually grown to producing cells for the purpose of storage systems and other applications. With investments coming from various stakeholders such as BMW Group, Volkswagen Group, Goldman Sachs and others, the company has expanded its presence in multiple countries. In accordance with the European Commission, the company has established Northvolt Ett, its first gigafactory in Skellefteå, Sweden with the intention of producing the batteries that have the least impact on the environment and also enabling sustainability. In these changing times, it also aims to redirect the supply chain from the dominant Asian markets back to Europe increasing transparency, credibility and dependability.

At Northvolt Ett, the manufacturing of LiBs can be categories into three steps; upstream, downstream and formation and ageing. The upstream involves all the process for slurry preparation of electrodes. Followed by, it moves into downstream, encompassing stages until the cells stack is assembled. Finally, it goes to formation and ageing where they undergo performance evaluation. With the growing demand for LiB batteries, the Ett aims for battery output of 16 gigawatt hours (GW) by the end of 2024, for which, it is constantly scaling up its operations and output (Mukherjee & Soderpalm, 2021). To reach these goals, the production at Ett needs to be optimized where maintenance is a key enabler that can be improved by utilizing the data generated to enable data-driven solutions.

1.2.2 MATTER@SCALE

MATTER@SCALE standing for Maintenance of Battery Production at Industrial Scale is an ongoing research co-ordinated by Chalmers University of Technology involving industrial stakeholders. It aims to develop circularity principles regarding the maintenance organisations particularly in battery manufacturing companies.

It's goal is to enable the maintenance organisations in reaching the targets set for Swedish battery industry and also to equip them for scaling up their operations. Along the pathway for reaching its goals, the project identifies four categories of capabilities for industrial maintenance: competence, organization, supplier collaboration, and data analytics (Vinnova, 2023). This thesis is a part of the MATTER@SCALE project and addresses the data analytics aspect of maintenance in battery production.

1.3 Problem description

Northvolt Maintenance acknowledges the importance of predictive maintenance in their future role in battery production. However, requires a clearer understanding of how to integrate these advancements into their organization to minimize downtime and enhance efficiency. Recognizing the complexities and uncertainties inherent in battery production, particularly in the stacking process, aims to incorporate predictive maintenance to optimize productivity.

1.4 Purpose and Aim

Purpose

The primary purpose of the thesis is to gain a deeper comprehension of how a data-driven approach can enhance maintenance strategies and boost efficiency regarding production in the battery manufacturing field.

Aim:

To identify the root causes of downtimes in the stacking process, specifically focusing on the stacking cutting module, which is a contributor to downtime, thereby reducing efficiency of production.

1.5 Research questions

The objective of the thesis can be specified by the following research questions:

1. How can data-driven solutions be effectively implemented in battery stacking production to enhance predictive maintenance outcomes?
2. What are the critical data required to develop robust predictive maintenance models in battery manufacturing?
3. What design considerations are necessary for optimizing the implementation of predictive maintenance in battery manufacturing, specifically in the stacking cutting module?

1.6 Limitations

Due to time constraints, some limitations have been made. The focus level has been only towards the stacking cutting module and not any other component of the stacking machine. Firstly the thesis will only look at one battery plant, namely Northvolt Ett located in Skellefteå, Sweden. This is due to Ett currently being the only operational gigafactory in Sweden. The decision to use this level of abstraction, where we focus on specific machine component ensures the results are as useful as possible for the industry. A broader focus might render the results too general, while a narrower focus could streamline the applicability and value. By limiting the scope, unique characteristics and requirements of the stacking cutting module can be better acknowledged. Furthermore, the technical suggestions and methodology provided for solving the problem is independent to each production facility and machine specific.

1.7 Structure of the thesis

Chapter 1 introduces the rationale for the thesis, covering background, problem statement, purpose, aim, research questions, limitations, and overall structure. Chapter 2 provides a theoretical framework on battery production processes, including cutting and stacking, maintenance, its evolution, predictive maintenance, and smart maintenance aspects. Chapter 3 describes the mixed method reasoning used, outlining the research approach, design, techniques, and procedures. Chapter 4 details the results from the research, such as statistical predictive maintenance analysis, data analysis, workshops, and a secondary literature review, along with further technical development for predictive maintenance implementation. Chapter 5 discusses the implementation of condition-based predictive maintenance in the battery manufacturing industry, addressing research questions and methodological reflections, along with limitations, future work, and ethical, societal, and ecological considerations. Finally, Chapter 6 summarizes the thesis's major outcomes and presents its conclusions.

2

Frame Of Reference

In this chapter the theoretical framework, outline of the battery production process, battery stacking, maintenance policies and the application of a data-driven approach in maintenance will be discussed. Lastly, the literature findings regarding relevant data-driven solutions in the industry will be presented in table 2.1.

2.1 Industrial Production

Historically, humans crafted their methods to refine raw materials into products of added value. The added value for the finished product deemed a profitable venture which paved way for the development of the production domain (Kenton, 2020). In a manufacturing context, production refers to the process of converting raw materials into finished products (Esmaeilian et al., 2016). In other words, it can be stated as a process to convert the inputs into outputs with the involvement of human, material, machine and methods. The industrial processes could be divided into primary and secondary operations. Primary operations are value-adding processes whereas secondary operations are process to support the functioning of primary operations. In order to obtain valuable output, the synergy between these operations is necessary (Porter, 1985).

Over the time, the nature and method for producing products i.e outputs have changed. The customer and industry requirements have constantly driven and aided in the development of products. The evolution of products involves the co- development of production processes. Today, automation has revolutionised the traditional production process by making it more efficient. The new shift also brings in the challenges of displacing human labour and the need for workers to constantly adapt to the advancing environment through constant learning. But nevertheless, the impact of integrating technologies into processes in production outweighs the challenges. By investing in the cutting edge technologies, industries can reach their ultimate potential which is important to stay competitive and relevant in the market (ElMaraghy et al., 2021).

2.2 Overview of Battery Manufacturing

In the present situation, battery production has an important role in supporting the advancement of electric vehicles (EVs) and renewable energy storage systems. The growing ambition towards sustainability and renewable energy has driven the demand for efficient and long lasting batteries. It is particularly automotive industries that depend on the advancement in the battery technology since they are transitioning to e-mobility. Battery performance determines the range and charging times which is directly related to the performance of EVs and thereby having an influence on the customer (Nykvist & Nilsson, 2015). The demand of batteries for EVs crossed 750 gigawatt-hours (GWh) in 2023. This marked a 40% increase compared to an year earlier (IEA, 2024). Also, at the end of the current decade it is projected that the demand for LiB would scale up to around 4.7 terawatt-hours (TWh) (Jakob Fleischmann & van de Rijt, 2023). The forecasts have reiterated the importance of LiB and also signals the significance of robust method for battery production in a sustainable way in order to meet the industrial demands.

The LiBs' manufacturing process is a complex and multi-faceted ordeal involving several sub stages. It is an intricate sequence of operations critically controlled to ensure the utmost performance, safety and reliability. Among manufacturers, the technique employed and equipment used for the battery manufacturing processes differ at each phase since each of them have tailored the practices to meet their own requirements. According to (Lombardo et al., 2022), the whole LiB manufacturing process can be divided into three stages: electrode manufacturing, cell assembly, and cell finishing as shown in figure 2.1. Also, it's important to note that certain process steps, such as those for anode and cathode electrodes, are performed separately to prevent cross-contamination.

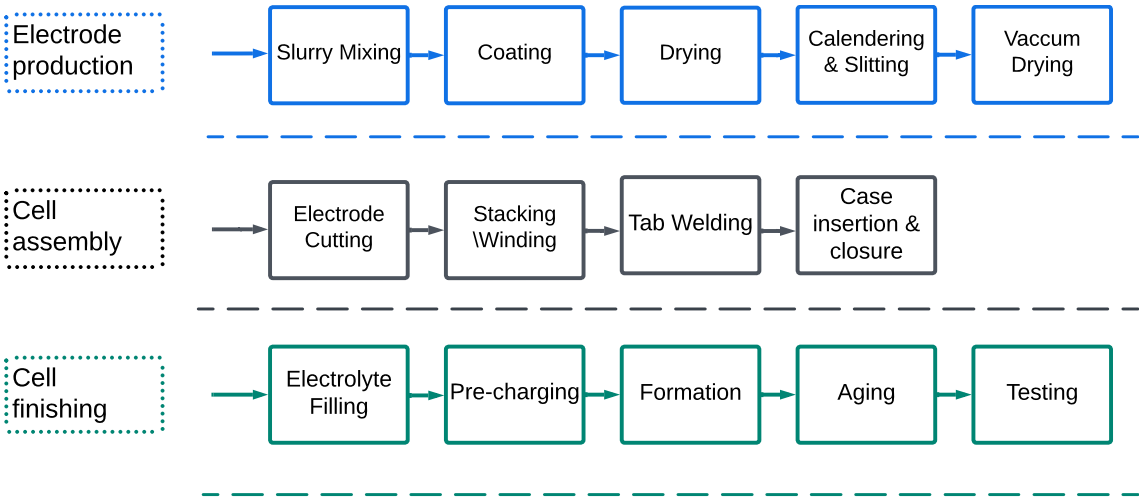

Figure 2.1: Battery manufacturing process

During electrode manufacturing, the electrode rolls for battery are prepared. This phase commences with the preparation of slurry that is consistent and homogenous. The constituents for the slurry include the active materials of electrode, conductive

additives, binders, and solvents (Duffner et al., 2021). The nature and type of constituents depend on the electrode type. Then, the slurry is applied onto metallic current collector utilizing methods such as slot-die coating. The coated electrode web are sent to the drying station to get rid of excessive moisture and remove the solvent (Ahmed et al., 2016). This follows the calendaring where the electrodes are compressed to the desired thickness depending on the desired density. Depending on the type of cell, the electrode is slit accordingly and further vacuum dried to remove moisture and leftover solvent (Lombardo et al., 2022; Brodd & Tagawa, 2002).

After this, the cell assembly stage commences. Here, the slit electrode rolls undergo processes that are meant for further shaping which is also determined by the type of cell. Typically there are three cell types i.e pouch, cylindrical and prismatic. The pouch and cylindrical cells have lower production costs but the prismatic cell have leverage over energy density (Lombardo et al., 2022). The primary focus of this study are prismatic cells, wherein the electrodes undergo notching process where they are further cut leaving the uncoated tabs which constitute the electrical connections for the cell and then wound. After notching, the electrode roll is further cut into individual sheets of dimensions predetermined according to the customer. These shaping processes are carried out through punching or laser cutting. These processed electrodes are then stacked alongside the separator alternatively (i.e cathode, separator and anode) to form cell stack. The uncut electrode tabs are then welded usually using ultrasonic or laser welding (Liu et al., 2021) to the current collectors forming the electrical connections within the cell. Subsequently, the cell stack is enclosed into a protective case housing (Brodd & Tagawa, 2002).

Cell finishing phase starts with filling of electrolyte under a weak vacuum, extremely dry and controlled environment. This process is monitored to control the homogenous distribution of electrolyte (Lombardo et al., 2022) after which it is pre-charged to prevent internal corrosion using pre-charge channels bringing the cell to safe minimal voltage. After this, the cells undergo a critical process called formation where they are charged and discharged cyclically in a controlled manner (Tan et al., 2023a). This process is significant in formation of solid-electrolyte interphase (SEI) which impacts battery performance and life cycle. After formation, the process of aging starts where cells are stored in controlled environments at elevated temperature to identify micro-short circuits and stabilize the SEI layer. Aging requires a devoted storing space and is an indispensable process determining the stability and reliability of cells (Wood, Li, & An, 2019). Finally, the cells undergo tests and evaluations. Once graded based on performance metrics, the ones passing the set standard are supplied to the clients (Lombardo et al., 2022).

2.2.1 Cutting and Stacking Process

Cutting and stacking is one of the crucial processes in lithium-ion battery manufacturing having an impact on the performance of the battery. Once the electrode undergoes notching to remove bare foil and only retaining tabs necessary for electrical connections, they enter the cutting and stacking machine. According to Baumeister and Fleischer (2014), there are several competitive stacking methods.

Popular among them are single sheet stacking, z-folding with one sided coating and z-folding with single sheets.

In the single sheet stacking as shown in figure 2.2, the electrodes and separator sheets are individually cut from the material web and then stacked in a pick and place manner one over the other. Although this process caters to high quality cells, it is complex in nature and resource oriented. In the z-folding process with one-sided coating, electrodes are folded back and forth with an intermediate separator in a zigzag manner. Although this is a continuous process, it has disadvantages in terms of power to weight and energy to weight ratio reducing cells performance. Conversely, as seen in figure 2.3, during z-folding with single sheets, an extensively used industrial method (Kurfer et al., 2012), only the separator is continuously processed, while the pre-cut electrode sheets are inserted between the layers of the folded separator wherein the handling of individual separator sheets is completely avoided.

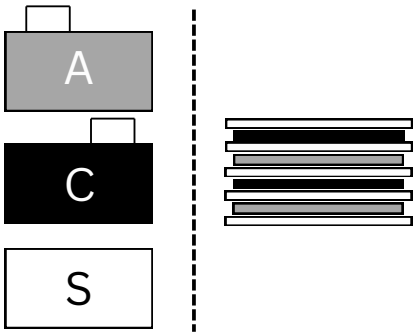

Figure 2.2: Single sheet stacking (Baumeister & Fleischer, 2014)

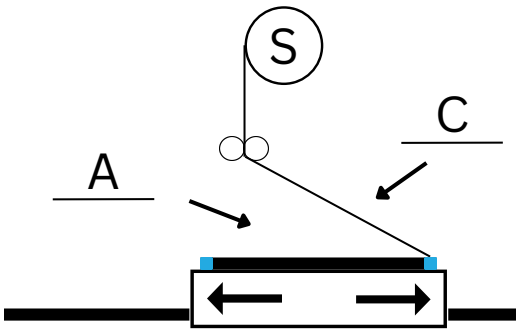

Figure 2.3: z-folding with single sheets (Baumeister & Fleischer, 2014)

The individual functional layers (electrode and separator), which start as separate material webs, need to be combined to create a complete cell stack. This involves sequentially layering the extremely thin and flexible anodes, cathodes, and separators in an alternating pattern. The total number of electrodes layered is determined by the desired cell capacity (Baumeister & Fleischer, 2014).

At Northvolt, both cutting and stacking is carried out by a single equipment that has two channels for cutting electrode rolls (anode and cathode) and a unified stacking area. The cut electrode sheets are checked for quality issues using manual and automatic methods and are conveyed to the stacking section where they are alternatively placed in the separator web and stacked using robot arms.

The primary focus of this study revolves around the cutting of electrode sheets for stacked cell designs, such as prismatic cells, where the notched electrode sheets are further cut into individual pieces of the necessary dimensions. Here, the stacking cutting module is responsible for electrode cutting and it splices the incoming electrode sheets into single sheets of the required dimensions for various types of EV

batteries. The cutting module assembly works on principles comparable with sheet metal cutting dies and houses the blades (upper and lower), a punch plate, guide rods, and a mechanical driver. The punching action reciprocates and is mediated by the servo drive wherein the speed of punching is matched with the conveyor that is feeding the die.

Generally, tool-related problems account for approximately 7% to 20% of machine downtime (Drouillet et al., 2016). Likewise, at Northvolt, the cutting die breakdown is causing disturbances at the production line. Currently, the company practices a scheduled maintenance strategy for the equipment which is established by the supplier. But much before reaching the threshold set by supplier, the cutting die is causing unplanned changeovers and there is a need for improving the maintenance strategy. There is a need to predict the changeover to improve the productivity and reduce the downtime. With the futuristic approach, having the intention of enabling predictive maintenance , this thesis focuses on understanding the failures of cutting dies and uses a data-driven approach to figure out the improvements in maintenance actions.

2.3 Production disturbances

Production disturbances are the undesirable disruptions that deviate the normal functioning of production systems (Frizelle et al., 1998). These disruptions can be caused due to a variety of reasons such as human errors, equipment error, material inaccuracies and others (Bokrantz et al., 2016).

A disturbance consists of a cause and an effect and its timeline can be divided into two phases i.e the latent phase and the manifest phase. The latent phase starts with the occurrence of the fault cause and ends with the onset of the disturbance effect. Following the effect the manifest phase starts that lasts until the resolution of the disturbance. Here, the latent phase refers to a buffer period, preventing immediate noticeable deviations. But soon after the buffer's exhaustion, this phase manifests as a disturbance effect. In a way, the latent phase determines the reaction time available before the disturbance effects are realized (Heil, 2013).

More importantly, these disturbances have a direct negative impact on productivity, efficiency, and overall equipment effectiveness, resulting in production losses and increased operational costs. The disturbances cause a loss in production capacity and according to Ylipää et al. (2017) it is around 50%. More importantly, these can impact the environmentally and socially thereby causing potential worker safety issues. These disturbances cause overall loss in the resources and hence diagnosis is necessary to efficiently manage them. By addressing these issues, an industry can retain efficiency and mitigate risks thereby profiting from the benefits. But even with best efforts, some disturbances are unavoidable implying the significance of maintenance practise to ensure the ongoing functionality (Ito et al., 2021).

2.4 Maintenance

During production, equipment and operations fail due to numerous disturbances. The production is responsible for operations producing the products whereas the maintenance is accountable for ensuring the capacity of the production. It helps to retain and extent the life of equipment thereby assist in preventing asset losses to the industry. With the advancements in industries over the years, maintenance has adapted itself to the changing production environment and transitioned from a supportive operation to an indispensable element of operational efficiency. It can be considered as a parallel organisational function and can be defined as *"The combination of all technical and administrative actions, including supervision actions, intended to retain an item in, or restore it to, a state in which it can perform a required function"* (International Electrotechnical Commission, 2006).

Production system having inadequate maintenance suffer from speed losses, availability and quality issues which causes inefficiencies. According to Al-Najjar and Alsyouf (2004), in the current generation, with the increasing awareness of maintenance and its impact, maintenance has grown significantly due to its influence on various operational areas wherein effective maintenance improves machine availability and enhances product quality. Hence, with its control over both quality and quantity of output, it has an overarching impact on overall organisational performance (Ben-Daya & Duffuaa, 1995).

2.4.1 Evolution of Maintenance

Maintenance has significantly evolved over the decades and now has now become an integral strategic functionality of organisations. Historically, maintenance was reactional meaning it addressed the equipment failures only after they occurred (Dhillon, 2002a).

It was during the early 20th century that the industrial revolution gave way for complex machinery and brought the understanding of productivity in an industrial realm. In the mid-20th century, the concept of planned maintenance emerged that scheduled timely maintenance activities to prevent untimely failure of machinery and equipments. However, this practise doesn't take into consideration about the assessment of condition of equipment rather follows a plan. As the technologies advanced in the industries during the late 20th century, a new approach of targeted maintenance emerged capable of predicting failures ahead of time to plan the corrective actions and thereby reducing unnecessary maintenance tasks and costs (Mobley, 2002).

Comparing with the traditional method, the current generation presents a huge leap that relies on analysis of real time data for monitoring the tools and being able to predict failures accurately thereby enabling prescriptive maintenance to take proactive curative actions (Pintelon & Parodi-Herz, 2008; Ahmad & Kamaruddin, 2012).

Over the years, the maintenance strategies have evolved and likewise, there are several maintenance policies whose classification are varied but according to Susto et al. (2015), the different maintenance policies include:

Corrective Maintenance: Here, the maintenance is carried out only after the breakdown occurs. It follows the approach of Run-to-Failure and is the most basic form of maintenance. It is applicable in instances which are non-critical and where the cost of downtime is low. It lacks any planning resulting in unexpected downtimes. It leads to potential deterioration of equipment health and could also pose safety risks (Dhillon, 2002b).

Preventive Maintenance: Maintenance carried out at regularly at predetermined intervals. It follows the Time-based-Maintenance and aims at preventing unexpected downtime and assists in preserving the life of asset. Mitigates the risks of safety issues but does not asses the exact condition of machinery. It is implemented in sectors of manufacturing, transportation, construction etc (Dhillon, 2002b).

Predictive Maintenance: Maintenance is pro-actively scheduled by predicting the breakdown using real-time data. It employs the data analysis techniques to establish the prognosis of equipment failure by monitoring machinery. It leads to increased availability compared to other maintenance practises but the implementation is time and resource consuming.

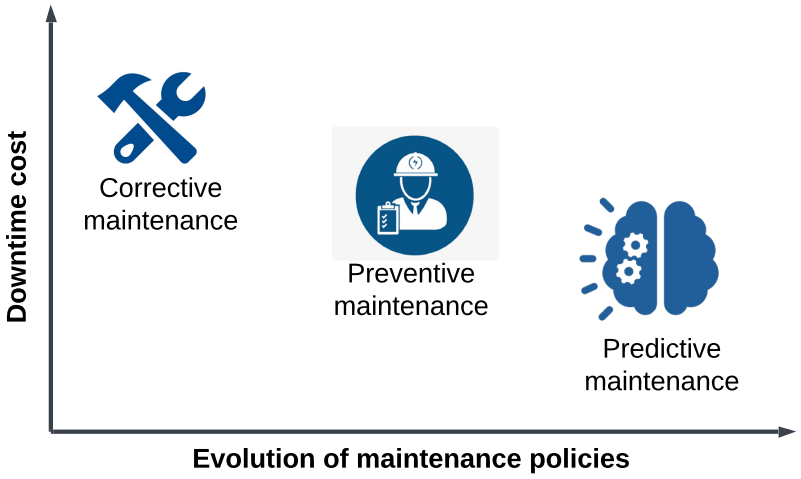

Figure 2.4: Evolution of maintenance

2.4.2 Predictive Maintenance

Predictive maintenance (PdM) utilises data models to predict potential equipment failures, enabling proactive maintenance actions. This assists foresee failure and take proactive curative steps. Some researchers often use it interchangeably with Condition-based Maintenance (CBM), wherein, CBM relies on the real-time condition monitoring systems to asses the equipment condition to guide maintenance decisions (Gouriveau et al., 2016; Mobley, 2002).

Condition-based Maintenance relies on continuous or periodic monitoring of equipment. Using various data collection techniques to obtain data it analyses the data with the help of advanced algorithm, machine learning or artificial intelligence to identify patterns that indicate the degradation limit. Once the monitoring reaches set threshold, it sends an alarm for maintenance actions.

Apparently, PdM is an overarching method focusing on prognostics to predict the breakdown well before it occurs to take proactive steps. Here, the Tool Condition Monitoring (TCM) system plays a vital role by keeping a check on tools' operations and thus assists in upholding productivity and quality. The means of TCM can be divided into two types; direct and indirect measurements. Direct measurement techniques involves assessment at the point of wear providing accurate evaluations. However, they are not without practical limitations. On contrast, indirect measurement methods assess the tool's condition by monitoring signals correlated with tool wear. Each technique has its own merit and demerit and its applicability depends on the user's requirement (Drouillet et al., 2016).

Direct methods are practically less feasible for online monitoring due to the harsh machining environment, such as the presence of coolant and machining. It directly quantifies by determination of the volume of material lost for tool wear using laser, optical sensors and more recently, vision systems enabled by neural networks (Drouillet et al., 2016; Sari et al., 2017). Indirect methods are better equipped for real-time monitoring and are less intrusive. These techniques utilise the sensors with high accuracy that are adept at detecting various wears. It uses sensors for parameters such as cutting force, acoustic emission, motor current, vibration etc.. After obtaining this data, they are processed and combined with algorithms, machine learning or artificial intelligence methods to obtain degradation information. But the challenge is that this method requires repeated validations and iterations during modeling which is time and resource consuming (Y. Zhang, Qi, Wang, & He, 2023).

Predictive maintenance has been successfully implemented across a wide range of industries, including manufacturing, healthcare, automotive, oil and gas, construction etc. Implementing predictive maintenance strategies can lead to a 5% - 10% reduction in overall maintenance costs and it would also enhance equipment uptime by 10-20% in manufacturing settings (Deloitte, 2017).

2.4.3 Digitalization and Smart Maintenance

Over the decades, the landscape of production sector has advanced with the development of technology. With the time, the customer needs have evolved and in order to match the requirements the industries have undergone tremendous transformations. This motive has resulted in four industrial revolutions with the current being Industry 4.0 (Yin et al., 2018). According to Dalmarco et al. (2019), every industrial revolution that occurred corresponds to a unique characteristic and that can be attributed to mechanization, electrification, computerization, and digitalisation respectively in chronological order.

Industry 4.0 is the fourth industrial revolution denoting the emergence of cyber-physical systems, internet based solutions and smart systems. This evolution brings about a transformation in the industry regarding the interconnectivity, energy efficiency, modularity, autonomous capability and other phenomenon. To cope up with these ever advancing production environment, there is a need for parallel advancement in maintenance sector to sustain the production (Kans, 2019). There is an urge for the advancement in the sector and likewise, in context to digitalization, new age concept e.g 'Smart Maintenance' has emerged. It is defined as "*an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies*" (Bokrantz et al., 2020). Bokrantz et al. (2020) has presented Smart maintenance with four dimensions as Data driven decision making, Human capital Resources, Internal integration and External integration :

Data-Driven Decision-Making: It is a pivotal aspect emphasizing the utilization of data to equips decision-making processes. This involves harnessing data from diverse sources such as sensors, condition monitoring systems, and historical event records. It involves leveraging data analytics and employing machine learning algorithms to provide predictive and prescriptive maintenance strategies.

Human Capital Resource: This dimension focuses on enhancing maintenance personnel's competencies in smart technologies, and innovative approaches through knowledge management, training programs, and fostering a culture of continuous learning, particularly in developing analytical and information and communication technology proficiency.

Internal Integration: It put emphasis on robust inter-connections among organisational departments and systems. This is crucial in terms of information exchange over the functional boundaries to enhance the findings and understandings.

External Integration: It underscores the importance of collaboration with external stakeholders. This involves external information flow, strategic partnerships, operational co-ordination etc. The external stakeholders refer to suppliers, customers, service providers and such others (Bokrantz et al., 2020).

It is imperative to recognize the interdependent nature of these core dimensions, necessitating a holistic approach towards enhancing smart maintenance practices. In this thesis, the approach for the dimension of data- driven decision making was focused and worked upon, and in the process, the impact of External Integration was realised and being reflected.

2.4.4 Data-Driven approach for Maintenance

The exploration in information technology has made manufacturing intelligent by making it data-driven. Due to the advancement of computational power and accessibility to large amount of data, data models are getting popular (Ma, Ren, Xiang, & Turk, 2020). The modern systems employed in production constantly monitor and record a range of operational parameters suitable for data models. This data-driven approach leveraging advanced analytics is used to enhance efficiency in the

maintenance domain. Montero Jimenez et al. (2020) has categorized data-driven models into three main types:

Statistical Models: They identify the degradation pattern and are capable of diagnostic and prognostic assessment of the production assets and systems. It is employed by conducting a comparative study between current behaviour of random variables and behaviours showcased by data series. As with other data models, data cleaning is the necessary preliminary task required before analysing the degradation trend. The only pressing need is for the availability of sufficient historical data. Examples include regression analysis, autoregressive models and bayesian models.

Stochastic Models: These are probabilistic models that focus on random variable evolution over time. Stochastic models are built upon stochastic process such as Gaussian process, Markov process, levy process etc. These models are equipped for degradation modelling and estimation of remaining useful life. The challenges involved with these models are that they need mathematical understanding and high computational capability.

Machine Learning Models: These models are built on data using the learning algorithms. Compared to statistical and stochastic models these models have advance capability for interpreting complex relationships within the data. Algorithms can include artificial neural networks, clustering, decision trees, random forests etc. They often require sufficient preliminary data pre-processing phase for reliable output. Although the reasoning behind these models lack comprehensive explanation, they are widely used in predictive analytics (Montero Jimenez et al., 2020). This thesis focuses on developing a machine learning model for predicting the stacking cutting module breakdown employing CRISP-DM methodology.

2.5 CRISP-DM

The Cross-Industry Standard Process for Data Mining, known as the CRISP-DM is an open standard model for carrying out data mining projects (Shearer, 2000). This methodology contains six distinct phases as shown in figure 2.5. It is an iterative method running back and forth between phases improving the overall model through new insights and findings. The different phases are (Saltz, 2021):

1. **Business Understanding**: This phase is the most crucial step which determines the success of the data mining project. It takes into account of the stakeholders and articulates the goals, objectives, and success criteria from a business point of view. Important sub-tasks are determining business objectives, determine data mining goals, producing project plan

2. **Data Understanding**: Involves procuring data from different systems, or from external source. It enables one to acquaint themselves with the data and acquire preliminary understanding of it so as to identify interesting data subsets. Important sub-tasks are collecting, describing and exploring data along with verifying data quality.

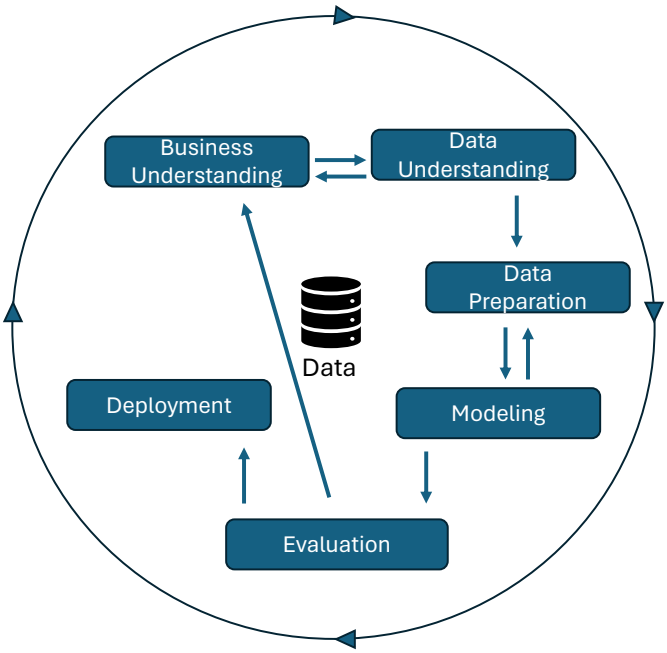

Figure 2.5: CRISP-DM process (Saltz, 2021)

3. **Data Preparation**: This phase encompasses the tasks necessary to create a dataset for building the model. The data undergoes pre-processing steps such as cleaning, eliminating or incorporation of data points etc. to enhance the data quality before being fed for model generation. Quality of the data is crucial since the performance of the model in the modeling phase relies on it. Around 50% to 80% of the project effort goes into this phase (Saltz, 2021). Important sub-tasks are selecting, cleaning, constructing and formatting data

4. **Modeling**: It involves choosing different modeling techniques and applying them. Once the modeling technique is chosen and implemented, the model is tested to analyze its performance, and the test design is generated. The model's parameters are adjusted to enhance its performance and then re-assessed. Important sub-tasks are extracting features, selecting modeling technique, generating test design, building model etc.

5. **Evaluation**: The evaluation process assesses the model's suitability, always mindful of the business context. If the performance falls short, the preceding steps are revisited until a satisfactory model is achieved. This iterative approach persists even when opportunities exist to enhance the current model. Important sub-tasks are evaluating results, reviewing process and possible iterations in improving the model.

6. **Deployment**: This marks the concluding phase, where the model is put into action, translating into real-world applications. The monitoring plans are set as well to inspect the ongoing operation of model. Often, this stage is challenging due to various factors including deployment costs, board consensus,

internal considerations, among others. Important sub-tasks are planning deployment, maintenance, final project review and documentation.

The beginners and professionals in the field of data mining favor CRISP-DM due its simplicity, reliability, and flexibility and based on a recent study, it is the most widely employed model for data mining (Harding et al., 2006). It is also noteworthy that this model is not biased towards industry or technology (Wirth & Hipp, 2000) and is also largely attributable to the fact that it is tool and application neutral (Mariscal et al., 2010).

2.6 Data Quality

Through adoption of digital technologies, the industries are ambitiously striving towards automation. This progress has resulted in the amplification of the amount of data produced. Further, the advancements in data storage systems have brought about effective data management for large amount of data in a cost-efficient manner. With the help of well equipped processing frameworks, the organisations have used this extensive data to gain tactical insights. Likewise, the integration of machine learning further enhances the capability at organisations to obtain data-driven decision-support. This has made data, an important asset for various industries.

These datasets, which can be structured, semi-structured, or unstructured, are characterized by their volume, velocity, and variety. Here, volume pertains to the sheer size of the data; velocity indicates the rapid rate at which data is generated; and variety constitutes the diverse formats of the data. Additionally, data veracity which denotes data quality and data value is an equally crucial aspect of data (Onay & Öztürk, 2018). But due to the expansion of large data architectures, it leads to challenges in maintaining data quality (Xie et al., 2020).

To tackle data quality issues, a framework was suggested by Cai and Zhu (2015), encompassing various dimensions with distinct features: Availability, Usability, Reliability, Relevance and Presentation Quality. Here, Availability denotes the ease at which users can access data signifying accessibility and timeliness of data. Usability dimension refers to the credibility of data in meeting users' needs. Reliability indicates the trustworthiness of data giving information on accuracy, consistency, integrity and completeness. While the Relevance deals with data meeting users' need to provide pertinent information, the Presentation quality refers to the understandability, readability and clarity of data.

Each of the data dimensions have their own implication on data quality. During modeling of predictive analytics, data quality issues pose major problem since they do not represent real time data and lead to predictions which are not reliable. Also another setback is that there are no accepted universal standards for data quality in the realm of big data, leading to challenges in ensuring consistent data quality across various datasets and platforms (Cai & Zhu, 2015).

2.7 Workshop

Workshops within qualitative research are interactive sessions crafted to involve participants in various activities aimed at gathering information, and collaboratively generating new insights. According to Collins Publishers (2022) workshop is defined as "*a period of discussion or practical work on a particular subject in which a group of people share their knowledge or experience*" It is a research approach which researchers and practitioners utilize to address and resolve issues together wherein it forms the culmination of theoretical and practical worlds. It's format can be adjusted to suit various research settings and goals (Krueger & Casey, 2015).

Designing workshop needs several key components to be considered. Importantly, clear objectives have to be established to steer the workshop's focus and outcomes, whether it's understanding participants' knowledge or brainstorming solutions along with selection of a diverse group of participants to enrich discussions and insights. The facilitators are responsible for creating open discussions that are productive. Also, it is crucial for group discussions or hands-on exercises to be engaging to the participants. These elements make sure the effectiveness of workshops in solving the problems (TACSI, 2024; Voltagecontrol, 2023).

Workshops offer researchers an opportunity to recognize and investigate pertinent factors within a specific domain. This method proves especially beneficial in combining the understandings from intricate work and knowledge procedures and also have the potential to unveil factors that may not be readily apparent to either participants or researchers prior to initiating the workshop process (Ørngreen & Levinsen, 2017).

2.8 Related work

The thesis incorporates a multidisciplinary study that spans across various fields. To achieve a comprehensive understanding, an extensive literature review was conducted at the outset and continuously throughout the study to incorporate relevant viewpoints from existing literature. The review encompassed articles pertaining to battery manufacturing, data-driven technologies, machine learning, predictive maintenance, sensor technologies, and other relevant aspects. Selected articles from this review are presented in the table 2.1 below.

Table 2.1: Literature review

Article	Category	Description
Choudhary et al. (2022)	Defect Detection	The paper presents a method for detecting defects in battery electrodes using autonomous visual systems. It leverages machine learning techniques to identify and categorize various types of defects, improving the quality control process in battery manufacturing.
Turetskyy et al. (2021b)	Production Design	This study focuses on the design of battery production processes using multi-output machine learning models. It aims to optimize production parameters to enhance efficiency and reduce costs, contributing to better overall performance of battery manufacturing.
Tan et al. (2023b)	Production Modeling	This research highlights the application of machine learning in modeling battery electrode production processes. It emphasizes the importance of data in optimizing production steps, ultimately leading to higher quality and efficiency in battery manufacturing.
Schmidt et al. (2020)	Manufacturing Impact	The study models the impact of various manufacturing parameters on the production of lithium-ion batteries. It provides insights into how changes in the manufacturing process can affect the final product's performance and reliability.
Overbeck et al. (2023)	Agile Production	This paper proposes optimal line configurations for agile production systems in battery cell manufacturing. Using simulation and digital twins, it evaluates different production scenarios to identify the most efficient setups for various production requirements.
Shin et al. (2018)	PHM Framework	The paper discusses a framework for implementing prognostics and health management (PHM) applications in smart manufacturing systems. It highlights the integration of PHM with IoT and machine learning to enhance maintenance processes.
H. Zhang et al. (2009)	Hybrid PHM	This study presents a hybrid approach to prognostics and health management (PHM) for condition-based maintenance (CBM). It combines physics-of-failure models with data-driven techniques to predict the remaining useful life of equipment.
Solle et al. (2017)	Modeling Approaches	The paper compares data-driven and mechanistic modeling approaches for process operation in chemical engineering. It emphasizes the strengths and weaknesses of each method and suggests scenarios where each approach is most effective.
Sai et al. (2019)	Predictive Maintenance	The research introduces a data-driven framework for predictive maintenance within the Industry 4.0 paradigm. It focuses on leveraging machine learning and IoT technologies to predict equipment failures and optimize maintenance schedules.
W. Zhang et al. (2019)	Predictive Maintenance	This survey paper reviews various data-driven methods for predictive maintenance of industrial equipment. It categorizes the approaches, discusses their advantages and challenges, and provides insights into their application in real-world scenarios.

Article	Category	Description
Atamuradov et al. (2017)	Maintenance PHM	The study explores different prognostics and health management (PHM) strategies for maintenance. It covers methodologies for assessing equipment health, predicting failures, and implementing maintenance actions to improve system reliability and reduce costs.
Turetskyy (2022)	Data Analytics	The paper explores the use of data analytics to optimize battery production systems. It highlights the benefits of using data-driven approaches to enhance the efficiency and effectiveness of production processes in the battery industry.
Schnell et al. (2019)	Data Mining	This study applies data mining techniques to analyze lithium-ion battery cell production. It identifies key quality drivers and process dependencies, aiming to reduce production costs and scrap rates through better quality management and process optimization.
Turetskyy et al. (2020)	Cyber-Physical System	The paper presents a data-driven concept for implementing quality gates in lithium-ion battery cell manufacturing. It emphasizes the use of cyber-physical systems to predict product quality and improve production control.
Stock et al. (2022)	Cycle Life Prediction	This paper introduces a machine learning approach for early classification and prediction of battery cycle life during production. It aims to improve the quality control process by predicting potential failures early in the production cycle.
Taşcı et al. (2023)	RUL Prediction	The study presents methods for predicting the remaining useful lifetime (RUL) of equipment in manufacturing. It combines data-driven techniques with predictive models to enhance maintenance strategies and reduce downtime.
Ruiz-Sarmiento et al. (2020)	Predictive Maintenance	The paper presents a predictive model designed for the maintenance of industrial machinery. It focuses on minimizing downtime and maintenance costs by predicting equipment failures and scheduling timely maintenance actions.
Subramaniyan et al. (2016)	Bottleneck Detection	This study introduces an algorithm for data-driven detection of shifting bottlenecks in manufacturing processes. The algorithm helps in identifying process constraints and optimizing production flow.
Wang et al. (2022)	Big Data Analytics	The research explores the use of big data analytics in intelligent manufacturing systems. It highlights various applications and benefits of big data in enhancing manufacturing efficiency and decision-making processes.
Gökalp et al. (2021)	Data Science Maturity	The paper presents an assessment model for evaluating data science maturity in manufacturing. It provides a framework for organizations to gauge their data capabilities and identify areas for improvement.

3

Methodology

The following chapter describes the research methodology, including mixed method research, research approach, design, techniques and procedure.

3.1 Methodology Overview

This thesis employs a mixed method research (MMR) approach, structured sequentially, commencing with quantitative analysis followed by qualitative analysis as shown in the figure 3.1. The initial phase of the methodology involves a comprehensive quantitative analysis to establish a foundational understanding of the research subject. The quantitative analysis is conducted, guided by CRISP-DM methodology. The quantitative analysis incorporates the first three phases of the CRISP-DM methodology, namely Business Understanding, Data Understanding, and Data Preparation. These phases ensure a systematic and thorough exploration of the research context, data sources, and data preparation processes, which are essential for the subsequent quantitative analysis.

The qualitative analysis further involves conducting a workshop and performing a secondary literature review. The workshop serves as a platform for gathering insights and perspectives from relevant stakeholders, while the secondary literature review provides a comprehensive examination of existing research and theoretical frameworks related to the research topic.

This sequential integration of quantitative and qualitative analyses ensures a robust and comprehensive examination of the research problem, facilitating a nuanced understanding and informed conclusions.

3.2 Mixed Method Research (MMR)

The research methodology employed is the Mixed Method Research methodology, which integrates both quantitative and qualitative methodologies (as depicted in Figure 3.2) to offer a comprehensive examination of complex issues. This approach is particularly beneficial for studies that investigate multiple facets of a problem, allowing for a more nuanced understanding. In the thesis, this is exemplified through the sequential explanatory method (Halcomb & Hickman, 2015). Initially, this method

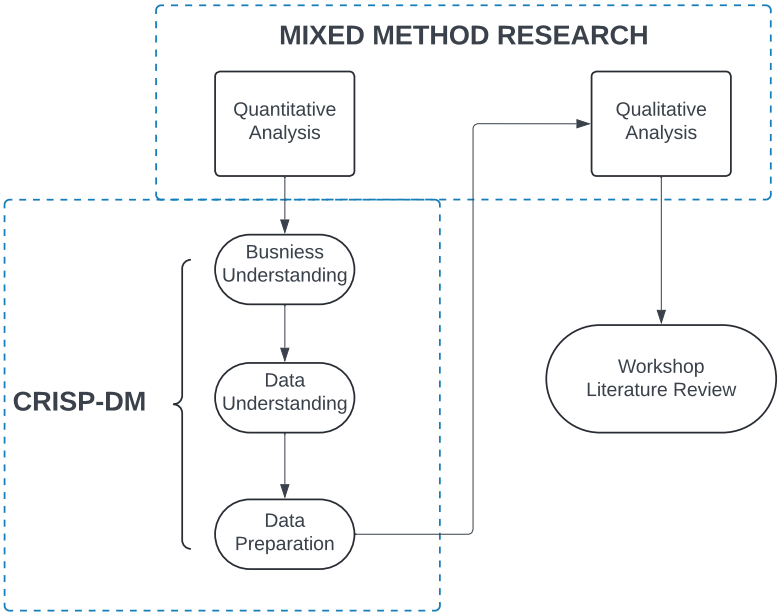

Figure 3.1: Visual presentation of the overview of methodology followed in this thesis

involves a rigorous quantitative analysis to collect and interpret numerical data from the battery production area. This phase is followed by qualitative analysis, thus uncovering subtle insights and meanings that numbers alone cannot reveal (Caruth, 2013).

In the context of battery production support, utilizing mixed methods research proves advantageous as it identifies the appropriate resources and methodologies for a thorough analysis (Halcomb & Hickman, 2015). Quantitative methods are used to measure aspects such as production efficiency, downtimes, and defect categories. On the other hand, qualitative techniques capture the complex experiences and insights of key stakeholders, including maintenance engineers, process engineers, and other practitioners. This dual-layered approach not only provides a comprehensive overview of operational metrics but also offers a deeper understanding of stakeholder dynamics and industrial challenges (Caruth, 2013).

Mixed methods research is particularly effective in exploring both the broad trends and the intricate factors that influence these trends. For instance, while quantitative data might reveal a bottleneck in battery production, qualitative insights from engineers might uncover underlying issues related to machinery maintenance, design complications or process inefficiencies. This combination of methodologies ensures that findings are not only statistically significant but also contextually rich, providing stakeholders with actionable insights that can inform policy and production strategies.

Moreover, mixed methods research allows for a more flexible and iterative approach to problem-solving (Tashakkori & Teddlie, 2010). By continuously integrating and cross-referencing quantitative and qualitative data, researchers can adapt their strategies to emerging findings, leading to more robust and dynamic conclusions (Clark & Ivankova, 2011). This adaptability is crucial in the ever-evolving field of battery production, where technological advancements and market demands constantly reshape operational landscapes.

Figure 3.2: Mixed method research

3.3 Research Design

The research design employs a mixed-method approach, blending quantitative and qualitative analyses to address predictive maintenance challenges in battery manufacturing. Specifically, the focus is on the stacking cutting module of the stacking machine within the context of a gigafactory scale at Northvolt.

Here, the CRISP-DM methodology, a widely recognized framework for data mining projects, has been to guide the research process. This methodology comprises six major phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. Each phase contributes to a comprehensive understanding of predictive maintenance in battery manufacturing.

The quantitative analysis dives into predictive maintenance within battery manufacturing. A systematic dissection of production processes, identification of key factors contributing to downtime, and analysis of data to develop effective maintenance strategies was carried out. The Business Understanding phase ensures alignment with project objectives and requirements, focusing on understanding the battery production process and the stacking machine's stacking cutting module.

In the Data Understanding phase, an in-depth analysis of operational data was conducted, particularly downtime records and Mean Time to Repair (MTTR). This phase involves collecting, describing, exploring, and verifying data quality to gain insights and identify challenges. Subsequently, the Data Preparation phase assimilates and analyzes data from various sources to construct the final dataset for modeling and analysis.

While the Modeling phase typically involves building predictive models, our research focuses more on the initial phases due to significant data quality issues. Conse-

quently, we shift our attention towards qualitative analysis, emphasizing insights gained from earlier stages and refining data collection practices for future research.

Our qualitative analysis component involves a literature review and workshops. The literature review examines existing scholarly articles and industry reports to enhance understanding of the technological landscape and its applicability. Meanwhile, workshops gather input from industry experts and practitioners to determine necessary design modifications for implementing condition-based maintenance effectively.

By integrating quantitative and qualitative approaches, our research aims to provide a holistic understanding of predictive maintenance in battery manufacturing, contributing to improved efficiency and productivity in the industry.

3.4 Research Phases

The research procedure is systematically divided into three major phases as shown in figure 3.3, which are the business analysis, data analysis, and qualitative analysis. Each phase is methodically explained, outlining the assumptions considered and the steps undertaken to ensure a comprehensive examination of the research problem.

Figure 3.3: Visual presentation of the phases followed in this thesis

3.4.1 Business Analysis: Stacking Cutting Module

The initial phase of business analysis involves a thorough examination of the battery production process, with a particular emphasis on the stacking cutting module. This phase is crucial for understanding the operational mechanisms of the stacking machine, its constituent components, and the prescribed maintenance plan for the stacking cutting module.

The stacking cutting module is integral to the battery manufacturing process. The stacking cutting modules are subject to a predetermined punch limit, necessitating preventive maintenance and replacement to ensure continuous and efficient operation. The maintenance process involves meticulous tracking of knife replacements,

which is facilitated by maintenance teams through designated platforms. Concurrently, manufacturing teams monitor maintenance activities using work orders and other relevant tools. Unplanned downtimes due to cutting tool replacements are tracked, as these downtimes impact negatively on Overall Equipment Effectiveness (OEE), a comprehensive metric that evaluates the overall performance of equipment by considering three factors such as availability, performance, and quality rate. Understanding and minimizing the productivity losses are vital for optimizing the performance of the stacking machine.

The classification of downtimes attributable to the stacking cutting machine is examined within the framework of the Total Effective Equipment Performance (TEEP), a key metric in the field of maintenance management and equipment effectiveness. TEEP is in a way, an extension of OEE, involving additional parameter called loading that assess actual total calendar time scheduled for operation while OEE assesses efficiency based on scheduled hours (Metrics, 2013). Hence, TEEP provides a holistic view of equipment effectiveness by quantifying OEE against calendar hours, helping organizations identify opportunities for improvement and optimize maintenance strategies. By analyzing downtime within the context of the Technical Availability component of TEEP, a structured understanding of the rationales behind various downtimes was achieved, enabling more targeted and effective maintenance policies. This approach allows maintenance teams to prioritize interventions based on their impact on overall equipment performance, ultimately enhancing operational efficiency and reducing downtime costs.

3.4.2 Data Analysis

The data analysis phase begins with a meticulous examination of historical data to identify and categorize downtimes associated with the stacking cutting module. This analysis focuses on three key parameters: downtime frequency, duration, and Mean Time to Repair (MTTR). Data from multiple time periods, one year and six months are scrutinized to discern potential trends and patterns.

The analysis aims to identify predominant downtime categories related to the stacking cutting module. A methodical, tiered approach is adopted, progressing through different levels of categorization. Visual aids such as pareto charts and bar charts are employed to effectively illustrate the findings, facilitating a clearer understanding of the data.

A comprehensive categorization of downtime causes across multiple tiers is achieved, which sets the stage for a structured exploration via the 5 WHY analysis. This technique, developed by Sakichi Toyoda, involves asking "why" five times to explore the cause-and-effect relationships underlying a particular problem. The collaborative engagement with maintenance engineers and process experts was pivotal in this phase, as it helps to ascertain the root causes of issues related to the stacking cutting machine.

Building on the insights obtained from the 5 WHY analysis, the focus transitions to

condition-based data analysis i.e servo motor analysis. This phase involves identifying relevant data sets and ensuring their quality, aiming to achieve a more detailed understanding of operational challenges and potential enhancements. The analysis highlighted the necessity for reliable condition-based data sources, leading the thesis to explore the qualitative aspects of the problem statement.

3.4.3 Qualitative Analysis

The qualitative analysis component of the study leverages insights gained from the data analysis phase to enhance the implementation of sensors in the stacking cutting module. This phase involves a comprehensive workshop and an in-depth literature review, integrating feedback from key stakeholders and relevant secondary sources to develop a robust strategy for predictive maintenance.

The workshop serves as a collaborative platform, bringing together stakeholders from the maintenance, manufacturing, and production departments. These participants discuss various aspects crucial to the implementation of sensors in the stacking cutting unit, focusing on practical design modifications and the integration of new technologies. The primary objective is to gather diverse perspectives on optimizing the maintenance strategy for the stacking-cutting machine.

Key topics addressed during the workshop include:

1. **Sensor Applications:** Discussions on the types of sensors (such as force and acoustic sensors) that can be deployed to monitor the condition of the cutting knife module. Stakeholders share their experiences and insights on the efficacy of different sensor technologies in detecting and predicting potential failures.

2. **Data Sources:** Identification of the most relevant data sources that can be harnessed to support predictive maintenance. This includes operational data, sensor data, and maintenance records. The goal is to ensure comprehensive data collection that can provide a holistic view of the equipment's condition.

3. **Data Quality:** Emphasis on the importance of high-quality data for accurate predictive modelling. Stakeholders discuss challenges related to data collection, such as noise, data gaps, and inaccuracies, and propose solutions to enhance data reliability.

In addition to these topics, the workshop explores necessary design changes to the stacking cutting machine that could facilitate better sensor integration and data collection. Stakeholders provide input on mechanical adjustments, sensor placement, and system integration to ensure that the new technologies can be seamlessly incorporated into the existing production setup.

Following the workshop, stakeholders' comments and suggestions are compiled and analyzed, and this feedback is correlated with findings from a detailed literature review. The literature review encompasses existing scholarly articles and industry reports on sensor applications, predictive maintenance frameworks, and data mining

algorithms. It aims to identify best practices and advanced methodologies applicable to the stacking cutting machine context, covering aspects such as the technological landscape, including current sensor technologies used in industrial maintenance, and case studies highlighting successful predictive maintenance deployments and key success factors. By integrating stakeholder feedback with the literature review, the study develops a comprehensive and informed strategy for implementing predictive maintenance in the stacking cutting module. This approach ensures that practical insights from the workshop align with theoretical and empirical evidence from secondary sources, providing a well-rounded perspective on the subject. Overall, the qualitative analysis component enriches the research by offering a multidimensional understanding of the challenges and opportunities associated with predictive maintenance.

4

Results

The results section of this study delves into the detailed analysis of production data, highlighting the key issues causing downtimes. By systematically examining historical data over a significant period and employing a structured methodology, the analysis identifies the primary contributors to production inefficiencies. Likewise, regarding the analysis done, the charts and graphs showcased in this section have been intentionally omitted of their data points in order to comply with the company policy. The following sections provide a comprehensive breakdown of the analysis process and findings.

4.1 Quantitative analysis

Firstly, it started with understanding the battery production process where each step is investigated and understood with a greater emphasis on stacking machine, stacking cutting module. Furthermore, after speaking with maintenance engineers and process engineers a better understanding of the production line maintenance process was gained. Based on this, the research question were defined.

Once the battery production was understood, the operational data which showed data regarding the downtimes caused due to various categories in the stacking process were analyzed, during which a structured approach was followed. Firstly, the three parameters were considered: frequency of downtime, downtime in minutes, and Mean Time to Repair (MTTR).

The frequency of downtime was chosen as it is one of the primary indicators of the reliability of the equipment. A high frequency of downtimes suggests recurrent issues that need addressing, helping to identify patterns or recurring problems that can be mitigated through preventive measures (Nakajima, 1988). Additionally, this metric aids in prioritizing which equipment, processes or categories of downtimes require immediate attention, ensuring that resources are allocated effectively.

Downtime in minutes was considered because it provides a direct measure of the impact each downtime event has on production. This metric is essential for assessing the resource allocation needed to minimize production interruptions (R. Smith & Hawkins, 2004) understanding the duration of downtime helps in implementing

policies to reduce production losses and improve overall efficiency.

Mean Time to Repair (MTTR) was included as it is a crucial measure of the efficiency of the maintenance process. Lower MTTR values indicate quicker recovery times and reduced production loss, serving as a benchmark for maintenance performance against industry standards (Blanchard, 1998). Tracking MTTR also helps in monitoring improvements in maintenance procedures and evaluating the effectiveness of training programs.

By using a combination of these metrics, a comprehensive view of the equipment's performance and maintenance effectiveness was obtained. This holistic approach facilitates a thorough root cause analysis by correlating frequent downtimes with repair times and total downtime, enabling data-driven decision making for maintenance policies and resource allocation (Moubray, 1997). These metrics not only provide valuable insights into the reliability and efficiency of the stacking process but also guide targeted improvements for optimal production performance.

The analysis included around 18 machines, each with two stacking cutting modules, resulting in 36 stacking cutting units under consideration. Using the previously mentioned metrics—frequency of downtime, downtime in minutes, and Mean Time to Repair (MTTR) a top-down approach was followed to map the root causes of downtimes in the stacking cutting station. The data was specifically analyzed to identify downtimes caused by the stacking cutting module section of the stacker, which is the focal point of this analysis. The study spanned two-time frames, 6 months and 1 year, to observe if similar trends persisted over different periods.

In Northvolt, downtime categories are organized into hierarchical tiers to facilitate detailed problem identification. Tier 1 is labeled "Technical Availability," representing the overall operational readiness of the equipment. Tier 2 is named "Unplanned Downtime," which indicates periods when the machinery is unexpectedly non-operational. Tier 3 further breaks down the issues into "Machine" and "Process" downtimes, specifying whether the problems are related to the equipment itself or the operational processes. Finally, Tier 4 dives into specific reasons for downtimes, such as "Tooling Breakdown," "Mechanical Breakdown," "Assembly Adjustment," and "Machine Component Adjustment."

The figure 4.1 provided, illustrates a downtime tree that sorts issues from the broadest category (Technical Availability) down to specific issues (Tooling Breakdown, Mechanical Breakdown, etc.). This detailed categorization allows for a more targeted approach to troubleshooting and resolving downtimes. By mapping downtimes in this manner, the analysis can pinpoint the exact layer where the problem originates, enabling more effective maintenance strategies and reducing the overall downtime.

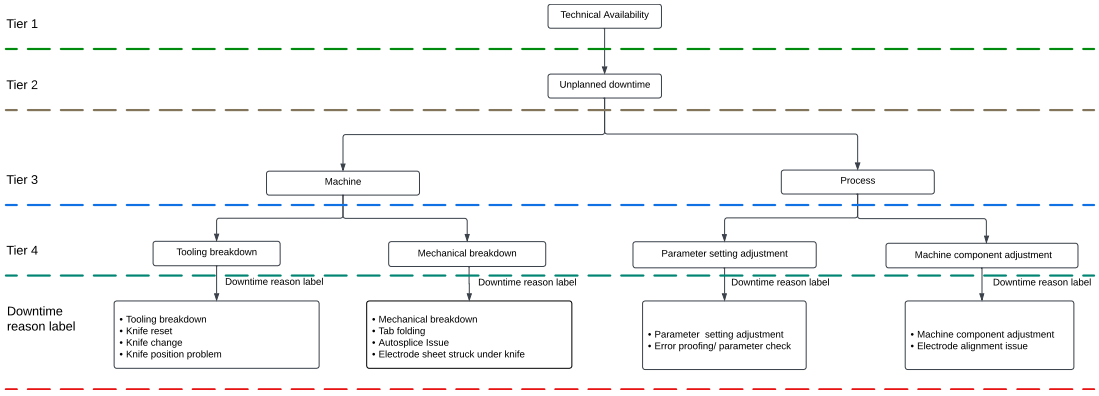

Figure 4.1: Downtime hierarchical chart

The downtime hierarchical chart, supported by this tiered classification, is essential for systematic problem-solving in manufacturing environments. It ensures that all potential causes are considered and that the true root cause is addressed rather than just treating symptoms.

To better understand the root cause of downtimes in the technical availability category, the focus was specifically on issues related to the stacking cutting module. By analyzing data to pinpoint the exact reasons for these downtimes, effective solutions could be identified. More broadly, reducing downtime involves continuously eliminating waste through small improvements, as suggested by Lean-Kaizen principles (Imai, 1986). To thoroughly investigate and address the reasons for downtime, the 5 Whys analysis (Ohno, 1988) was employed, a method that helps dig deep into the core issues causing the downtimes. This comprehensive approach ensured that all aspects of production were considered, avoiding any bias towards a particular aspect of downtime, and emphasized machine-related problems, aiming to find data-driven solutions.

To address the major downtimes, the 5 Whys analysis was used to investigate various data sources, given the absence of sensors directly recording the condition of the knife or other stacking cutting module components. These sensors could have provided a better understanding of unplanned downtimes. Therefore, different data sources related to the stacking cutting module were examined to determine if predictions could be made using operational data. The most relevant source of automation-related data was identified as the servo motor, which drives the stacking cutting module in a linear motion.

The servo motor was chosen because literature studies indicated that data from servo motors could be treated as a data source (Girit, Atakok, & Ersoy, 2020). Components of this data, such as current, voltage, temperature, speed, position, and vibration, can be correlated with downtime data. This correlation helps in understanding the normal and deviated behaviors of the systems, providing high-quality data and a reliable reference for actual working conditions. This, in turn, supports the creation of predictive models, enabling maintenance and production

teams to make better decisions, efficiently use resources, and reduce unplanned downtimes, thereby increasing productivity (Liker, 2004)

The servo motor data is referred to as telemetric data, which is stored in the cloud and can be accessed via the cloud platform, where all automation-related data is stored. During the investigation, it was found that the servo motor successfully records speed and position, though it currently does not capture temperature, current, voltage, or vibration. Further investigation revealed that the servo motor in use is not capable of recording these parameters.

Given the recorded speed and position data, it was decided to proceed with the investigation. Servo motor data was collected for two months, and a new dataset was created by integrating this time-series data with speed and position values with downtime data from another platform, matching the timelines. An additional column labeled "downtime" was added, where downtimes were marked as 0 and uptimes as 1. This created a meaningful dataset for comparing downtimes with motor parameters over time. To prove its predictive capability, the data quality was assessed by checking for correlation with the operational data. Correlation studies were used as tools for this assessment (Eger, Reiff, Brantl, Colledani, & Verl, 2018). Based on the results, it was found that the available data could not provide reliable predictive models. Consequently, the focus shifted to the qualitative aspects of the thesis, including literature reviews, workshops, and interviews to find solutions.

4.1.1 Detailed Analysis and Investigation

In this part, we look into the detailed data analysis and investigation aspect of the thesis where the focus is on the comparison of data and looking into the data quality aspect.

4.1.1.1 Data Analysis

The investigation into the production data revealed that issues related to the stacking cutting module were the most significant in terms of both frequency and total downtime minutes. The graphical representation clearly illustrated this trend, showing that stacking cutting knife-related issues were not only frequent but also resulted in considerable downtime. This category included problems such as mechanical failures, burrs, delamination, and operational errors, which were pervasive and consistently caused significant downtimes. Mechanical breakdowns were identified as a major contributor, often requiring extensive repairs and associated with high Mean Time To Repair (MTTR). Tooling problems, such as blunt knives and knife misalignment, were frequent and led to substantial downtimes. Misalignments or improper assembly settings caused interruptions in the production process, necessitating adjustments that contributed to downtimes. Additionally, general machine malfunctions were significant contributors to downtimes. The high MTTR for issues involving the stacking cutting knife indicated that these problems were not only frequent but also time-consuming to resolve, highlighting the critical need for targeted maintenance and operational improvements in this area.

4.1.1.2 Preliminary Analysis: Tier 3 Category Analysis

Before delving into the Tier 4 analysis, a Tier 3 Pareto chart was examined to provide a broader overview of the issues, which was crucial in identifying the main categories requiring further investigation. The analysis revealed that process issues and machine issues were significant contributors to downtimes. Process issues encompassed a wide range of problems, including operational errors, process inefficiencies, and workflow interruptions, accounting for a large percentage of the problems. Machine issues, including general malfunctions, mechanical, and tooling issues, were also highlighted as major contributors. Together, these categories accounted for approximately 80% of the problems in both downtime and frequency parameters, as shown in figures 4.2 (downtime) and 4.3 (frequency). This finding underscored the importance of focusing on these categories in the subsequent Tier 4 analysis.

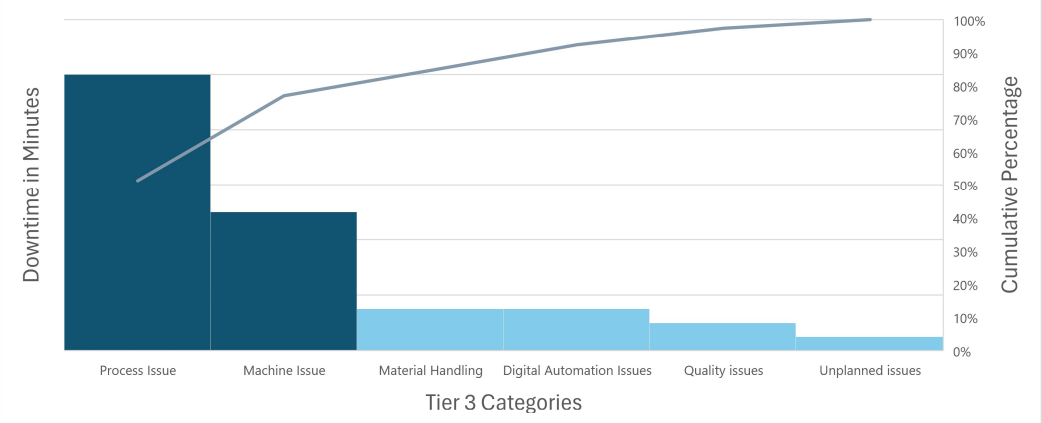

Figure 4.2: Pareto chart for Tier 3 categories downtime in minutes

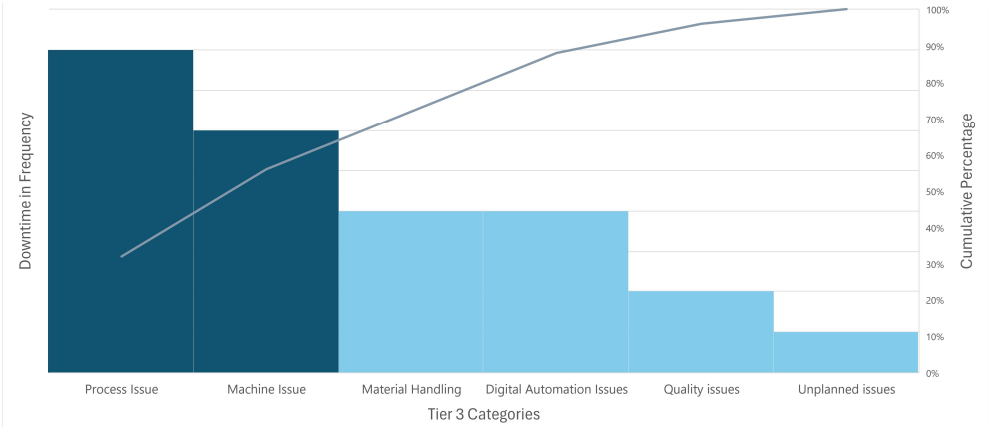

Figure 4.3: Pareto chart for Tier 3 categories downtime in frequency

4.1.1.3 Detailed Analysis: Tier 4 Category Analysis

Based on the Tier 3 category analysis, a significant emphasis was placed on process and machine-related issues. Further examination revealed that issues asso-

ciated with the stacking cutting module, such as mechanical breakdowns, tooling breakdowns, assembly adjustments, and machine-related issues, ranked among the top four reasons for downtime, as depicted in figures 4.4 and 4.5, which compare downtime in minutes and frequency over two time periods of six months and one year. Notably, this trend persisted across both datasets, highlighting its consistency. Conversely, the remaining categories comprised issues such as electrical and automation-related problems. The detailed tier 4 analysis elucidated that a considerable portion of downtimes stemmed from specific issues within each major category. For instance, blade dullness and misalignment emerged as primary causes of tooling breakdowns. Adopting a systematic hierarchical approach, the preliminary Tier 3 analysis guided the focus towards process and machine issues. Subsequently, the Tier 4 analysis delved deeper to pinpoint specific problem areas within these categories. This hierarchical method facilitated a comprehensive understanding of the issues, corroborating consistent trends across analyzed timelines. The analysis underscored the primary sources of downtime linked to the stacking cutting module, emphasizing mechanical and tooling breakdowns, assembly adjustments, and machine-related issues as the most critical categories. These findings provide a clear roadmap for addressing the major causes of downtime, thereby enabling targeted improvements in the production process.

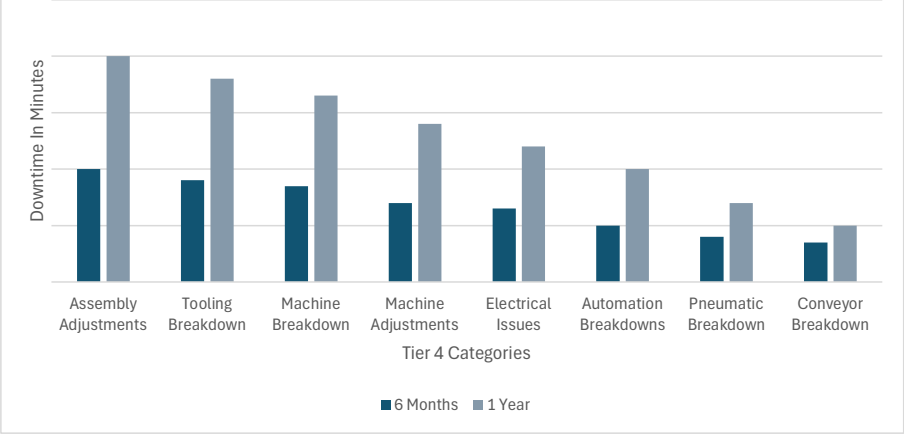

Figure 4.4: Comparing Major Tier 4 Categories (6 Months vs 1 Year) downtime in min

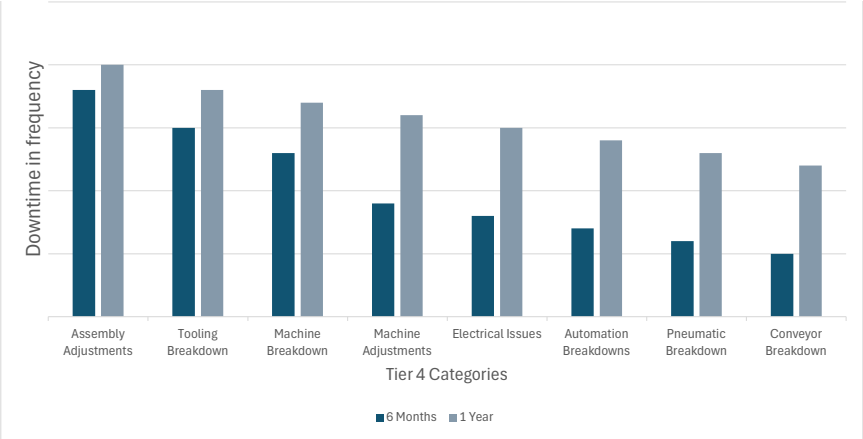

Figure 4.5: Comparing Major Tier 4 Categories (6 Months vs 1 Year) downtime in frequency

4.1.1.4 Root Cause Analysis Using the 5-Why Method

Based on the results of the data analysis, it was determined that categories pertaining to the stacking cutting module significantly contributed to downtimes. However, in order to develop a robust predictive maintenance model, it is essential to identify the appropriate datasets associated with the stacking knife. To address this requirement, the 5 Why analysis tool was employed. This analytical method is effective in uncovering the root causes of problems. Collaborative brainstorming sessions involving maintenance and process engineers were conducted to conduct this analysis, with the aim of delving deeper into the underlying causes of downtimes related to the stacking cutting knife. The focus was primarily on major problem statements such as knife change, knife reset, tab folding sheet stuck under the knife, and machine component adjustment. These issues were prominently featured in the categories of tooling breakdown and mechanical breakdown. Additionally, parameters such as setting adjustments and mechanical component adjustments were considered, although they were primarily associated with operational aspects and did not directly provide information about the condition of the knife or the mold.

Key Findings from the 5-Why Analysis

1. Knife Change:

- **Problem Statement:** The process of changing the knife on the equipment is causing issues.
- **1st Why:** The difficulties in the knife change process are due to problems during the assembly of the tooling.
- **2nd Why:** The assembly of the tooling is problematic because the bolts are

not being tightened properly.

- **3rd Why:** The bolts are not tightened properly because there are no defined limits for the tightening torque, leading to inconsistent tightening.
- **4th Why:** The lack of defined tightening torque limits is compounded by variations in the material specifications received from upstream processes.
- **5th Why:** The variations in material specifications occur because different batches of materials are combined in varying proportions.
- **Root Cause:** The root cause of the knife change issues is the improper assembly of tooling due to undefined tightening torque limits, coupled with variations in material specifications resulting from different proportions of combined materials.

2. Tab Folding:

- **Problem Statement:** The Tab folding issue is causing downtimes in stacking machine.
- **1st Why:** The tab folding issues originate from the previous notching process.
- **2nd Why:** The problems from the notching process occur because the tab guides are set up incorrectly.
- **3rd Why:** The incorrect setup of tab guides causes the stripper plate to encounter the tabs, generating heat.
- **4th Why:** The heat generation and contact between the stripper plate and tabs happen because the sheet alignment is causing improper contact.
- **5th Why:** The alignment issues are a result of the die customization for depth of cut adjustment.
- **Root Cause:**The root cause of the tab folding issues is the incorrect setup of tab guides and alignment problems, which lead to contact and heat generation.

The analysis of encountered downtime issues reveals a spectrum of factors ranging from material inconsistencies and alignment discrepancies to operational problems and modifications in design. It becomes evident that no single component is solely responsible for the downtimes. The investigation underscores two primary factors contributing to these issues: limited data availability and inherent design flaws. Addressing these aspects is crucial for effectively reducing downtime. To accurately determine the root causes of the downtime, the implementation of condition monitoring is essential. This involves closely observing the condition of both the stacking cutting module. By collecting and analyzing condition monitoring data, a reference point can be established to identify performance deviations. Presently, no sensors

directly monitor the stacking cutting module condition; the closest real-time data available is from the servo motor. Therefore, analyzing the servo motor's performance was considered in the subsequent steps of research.

Research findings suggest that servo motor analysis can offer valuable insights for modeling and evaluation purposes (Girit et al., 2020). However, the current setup of our motors records only speed and position, whereas comprehensive studies typically incorporate additional parameters such as current, voltage, vibration, and temperature data from servo motors. In response to this limitation, we devised a time series analysis approach. This involved compiling a dataset comprising timestamps of motor parameters (i.e., speed and position) alongside operational data indicating downtimes (coded as 0) and uptimes (coded as 1), as depicted in Figure 4.6. Preprocessing steps, including removal of missing values and imputation of mean values, were applied to ensure data integrity. While this process primarily served as part of the data preparation phase, it was instrumental in examining the correlation between servo motor data and operational data.

Downtime Data		Telemetric data			
Downtime reason	Anode Cutting Knife reset				Downtime/Uptime
Stared at Time	13-03-2024 20:47		X_AxisPositionPV-1mAVG	X_MotorSpeedPV-1mAVG	(0 = Downtime , 1 = Uptime)
Ended at Time	13-03-2024 20:54	2024-03-13T20:47:00	6866645	-0.000404719	0
		2024-03-13T20:48:00	6866645	-0.000129341	0
		2024-03-13T20:49:00	6866645	8.754E-05	0
		2024-03-13T20:50:00	6866645	-7.34205E-05	0
		2024-03-13T20:51:00	6866645	-5.39084E-05	0
		2024-03-13T20:52:00	6866645	0.000114648	0
		2024-03-13T20:53:00	6866645	-0.000132986	0
		2024-03-13T20:54:00	6866645	5.84717E-05	0
		2024-03-13T20:55:00	6866645	-6.36501E-05	1
		2024-03-13T20:56:00	6866645	7.56482E-05	1
		2024-03-13T20:57:00	6875601	252.77713	1
		2024-03-13T20:58:00	6895520.5	379.82578	1
		2024-03-13T20:59:00	6923210.5	568.23004	1
		2024-03-13T21:00:00	6949492.5	344.56543	1
		2024-03-13T21:01:00	6970998.5	398.94894	1
		2024-03-13T21:02:00	6989614	297.2321	1
		2024-03-13T21:03:00	7011462.5	386.9938	1
		2024-03-13T21:04:00	7035348.5	381.1478	1

Figure 4.6: Data preparation

For this purpose, data from the servo motor, spanning two months, was analyzed. Preliminary tests on this dataset aimed to assess the data quality. The correlation coefficients between speed and downtime and between position and downtime were found to be 0.06 and 0.05, respectively as shown in figure 4.8 & 4.7. These results indicate a very weak relationship and suggest that speed and position are not strong predictors of downtime. The heat maps generated also support this conclusion, underscoring the inadequacy of these variables for predicting uptime/downtime statuses effectively. Given the weak correlation of the data obtained from the existing variables, it was unworthy to proceed ahead with modelling. Hence, the focus was shifted towards qualitative analysis.

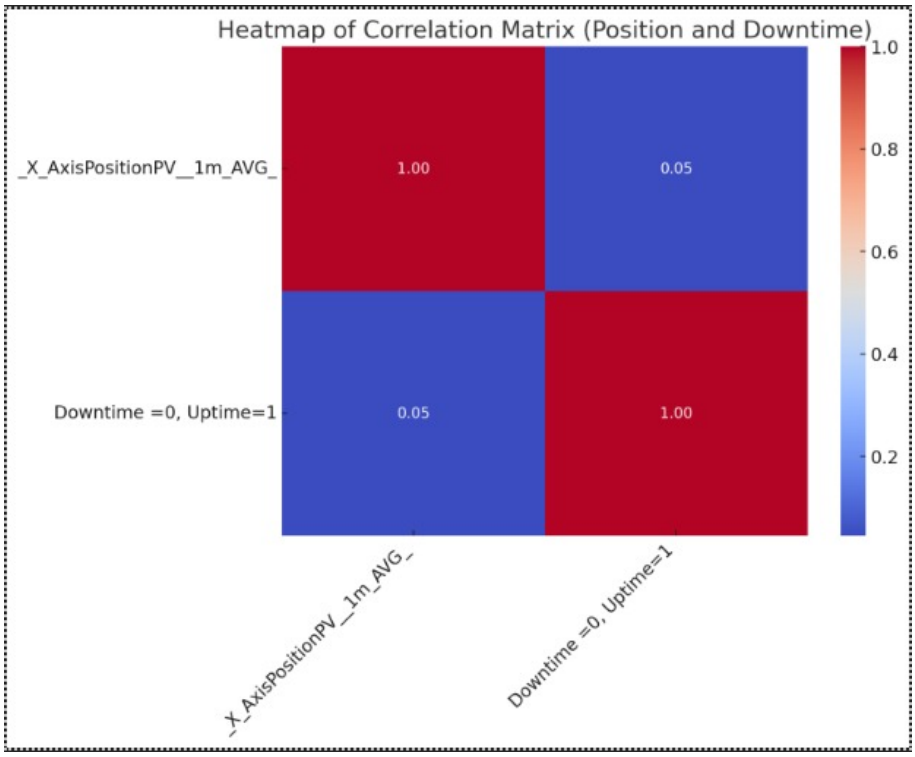

Figure 4.7: Correlation matrix (position and downtime)

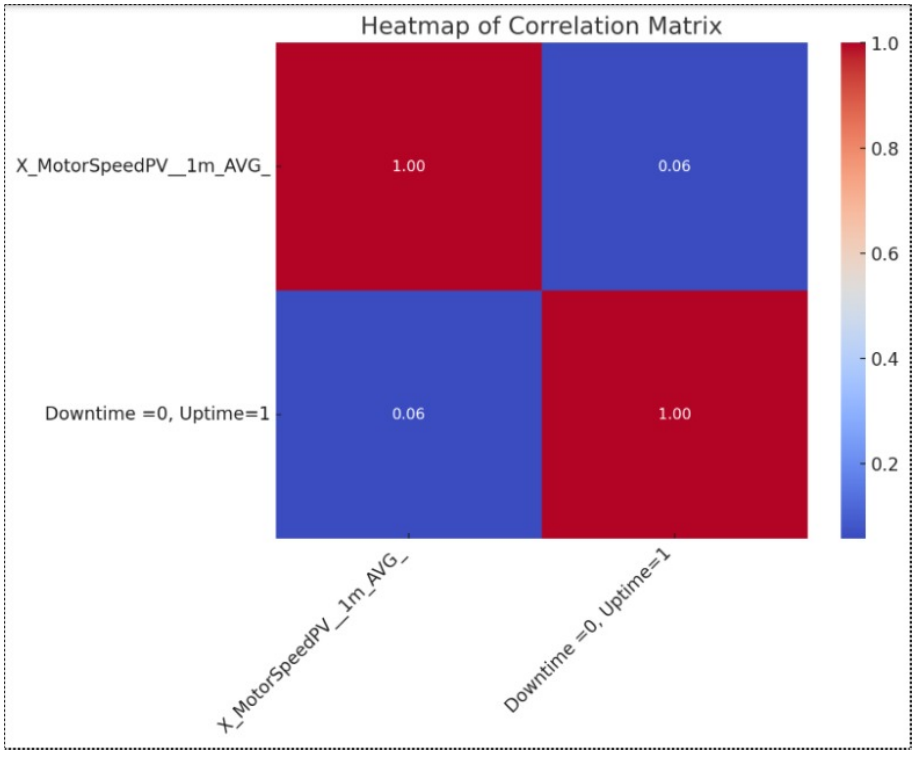

Figure 4.8: Correlation matrix (speed and downtime)

4.2 Qualitative analysis

The results obtained pointed in the direction of lack of relevant data for enabling a machine learning model. So, in order to fulfil this requirement, a qualitative approach in terms of literature review and workshop were conducted to assist in establishment of the steps required to reach the PdM level of maturity. This approach helped us understand the necessary frameworks and prerequisites for data quality that are essential to implement robust machine learning algorithms capable of developing an effective predictive model. The literature review was extensively carried out to get an overview regarding the latest advancements that has the potential to be implemented in battery manufacturing and further to the literature review, a workshop was conducted, as detailed in section 4.2.2, which provided valuable insights from industry experts. This interaction was instrumental in shaping the findings and aligning them with industry standards and expectations. The insights gathered from the workshop emphasized the importance of integrating comprehensive sensor technology and enhancing data collection techniques to facilitate more accurate and predictive analytics.

4.2.1 Literature Review

With regard to the literature review, sensors technology which can capture the contextual data that could interpret the breakdowns was investigated upon. Following are the summary of some of the articles that discuss in detail about the different methods and sensors that can be employed for improving the maintenance.

Klingenberg and de Boer (2008) discusses about punching/blanking and examines force-displacement graphs during the blanking operation. Experimental measurements reveal that the work done up to the maximum blanking force and the punch penetration at maximum force can serve as indicators of tool wear. Additionally, the analysis includes a study of the change in punch tip radius and work done. The paper acknowledges that relying solely on blanking force as an indicator of tool wear is inadequate due to variations in material properties and other parameters. To address this limitation, the paper explores the use of artificial neural network (ANN) models and compares them to expert systems. It proposes a hybrid approach that combines neural network and rule-based expert system methodologies to better interpret force-displacement data and its correlation with tool wear.

In the case study of Kolhatkar and Pandey (2023), a set of high-speed progressive tooling components was selected from a sample of 240. Punching was identified as the critical element causing production stoppages due to punch wear, burr formation, and punch breakage. A 6000 lb capacity Toledo load cell, synchronized with the press crank angle, captured the load signature during punching. Any variation beyond $\pm 5\%$ of the peak load triggered a machine stoppage. The load value was monitored and correlated with punch wear and burr formation on components measured every 50,000 strokes. The limiting condition was either the pierced hole dimension out of tolerance or burr height exceeding 0.06 mm of material thickness. After monitoring 4 production cycles followed by maintenance, the load value

consistently reached 0.352-0.361 tons. Punch wear and load signature drift were analyzed, setting the PdM trigger threshold at 0.358 tons, reducing maintenance cycle frequency comparatively.

According to Y. Zhang et al. (2023), a new deep learning model to identify the wear status of cutting tools based on force signal data is proposed. It utilizes techniques like continuous wavelet transform (CWT), short-time Fourier transform (STFT), and gramian angular summation field (GASF) to convert the one-dimensional force signal into a two-dimensional image representation. This image representation of the force signal is then fed into a convolutional neural network (CNN) model with a multiscale feature pyramid designed to effectively extract spatial features from the force signal images and classify the tool wear condition. To address interpretability, a hybrid architecture combining CNN with expert systems or rule-based methods is proposed, leveraging both methodologies for robust tool wear monitoring.

Lara de Leon et al. (2024) conducted a thorough examination and analysis of methods employed in monitoring the condition of cutting tools within metalworking processes, with a specific focus on literature published from 2012 to 2022. It addressed the significance of tool condition monitoring in mitigating downtime, enhancing product quality, and reducing costs related to tool wear and malfunctions. The paper underscored the common signals utilized by researchers and scientists for monitoring tool conditions, pointing it out to be tool cutting force (27%), vibration of the cutting tool and workpiece (21%) , and acoustic signal (10%) (2012 -2022 publications). Moreover, it recognized the pivotal role of machine learning and other statistical techniques in assessing the wear of cutting tools.

Machine vision systems automate quality control in sheet metal tooling by capturing detailed geometrical data of parts. They function through three stages: image acquisition, processing, and interpretation. Cameras capture images of the part, which are then processed to create a 3D geometry. This facilitates actions like removing defective parts. While they offer accuracy and rapid measurement, their setup cost is a significant drawback (Altan & Tekkaya, 2012).

With regard to predictive maintenance being implemented in cutting and stacking operation of battery manufacturing process there is little to no literature studies or researches. This points out to the research gap that is to be filled in through collaborative research between academicians and battery manufacturing industries. The literature found is therefore synthesized towards sheet metal cutting and other cutting operation related domains. These sources point out to the advancements that has the potential to be implemented in battery manufacturing.

4.2.2 Results from the Workshop

The workshop focused on exploring potential improvements in data quality for stacking cutting machines, particularly regarding the condition monitoring of cutting knives. Participants emphasized the importance of identifying the root cause of operational issues before implementing sensor solutions. It was noted that a significant

challenge lies in distinguishing between problems caused by the cutting knife and those arising from bearing issues.

Several potential solutions were discussed. One suggestion was the implementation of force sensors to measure the cutting force, as an increase in required energy could indicate a dull knife. However, it was also noted that higher loads might more commonly point to bearing issues rather than knife condition. Therefore, there was a consensus on the need for comprehensive monitoring that includes both load and acoustic sensors to capture a broad spectrum of data.

The workshop identified specific data requirements crucial for correlating machine downtime with the condition of the cutting knife. Currently, the data being collected includes downtime, servo motor position, and speed, but lacks direct indicators of knife condition. It was suggested that additional data points, such as torque from servo motors, could provide valuable insights into spring preload and bearing conditions. This data would be instrumental in developing a more accurate predictive maintenance model.

In terms of practical implementation, it was recognized that any new solutions need to be tested in a controlled environment before full-scale deployment. There were discussions about the feasibility of conducting these tests in lab settings versus production environments, highlighting the potential risks and benefits of each approach.

Furthermore, the workshop addressed the need for design improvements to facilitate easier access to the knives for cleaning and maintenance, which would significantly reduce downtime. Ideas included mechanical solutions to automatically clean the knife by wiping or blowing dust off, as well as using special coatings on the blades to minimize dust accumulation and cleaning frequency.

Overall, the workshop concluded that a multifaceted approach combining sensor technology, improved data collection, and design modifications is necessary to enhance the performance and reliability of stacking cutting machines. This approach will require careful experimentation and validation to ensure that the proposed solutions effectively address the identified challenges without introducing new issues.

4.2.3 Empirical and literature findings

The workshop on stacking cutting machines emphasized implementing force sensors to measure cutting force, noting increased energy could indicate a dull knife, but higher loads might also signal bearing issues. This aligns with literature where force signals dominate tool condition monitoring at 27.4% (Lara de Leon et al., 2024) and are effectively used in neural networks (L. Zhang, Kim, & Nguyen, 2021). Force sensors are less affected by noise and the force-displacement graphs are used to detect tool wear, (Klingenberg & de Boer, 2008). The workshop also recommended acoustic sensors for comprehensive monitoring, supported by literature noting their 10.2% usage in TCM (Lara de Leon et al., 2024) and their utility in detecting punch breakage and lubrication issues. Data requirements highlighted by the workshop

included torque from servo motors to correlate machine downtime with knife condition, paralleling findings on tonnage/cutting force signals' importance in sheet metal work (Sari et al., 2017). Further, correlations between load signatures and punch wear was used to reduce the frequency of maintenance cycle (Kolhatkar & Pandey, 2023). Practical implementation discussions from the workshop, emphasizing controlled environment testing, mirror literature's iterative approaches Klingenberg and de Boer (2008). Additionally, design improvements for easier maintenance suggested by the workshop are indirectly supported by literature advocating for comprehensive and maintainable monitoring solutions. Visual sensors were also discussed for their high accuracy in providing geometrical information despite being expensive (Altan & Tekkaya, 2012). Both sources converge on the necessity of a multifaceted approach combining sensor technology, detailed data collection, and practical design changes to enhance cutting machine performance and reliability.

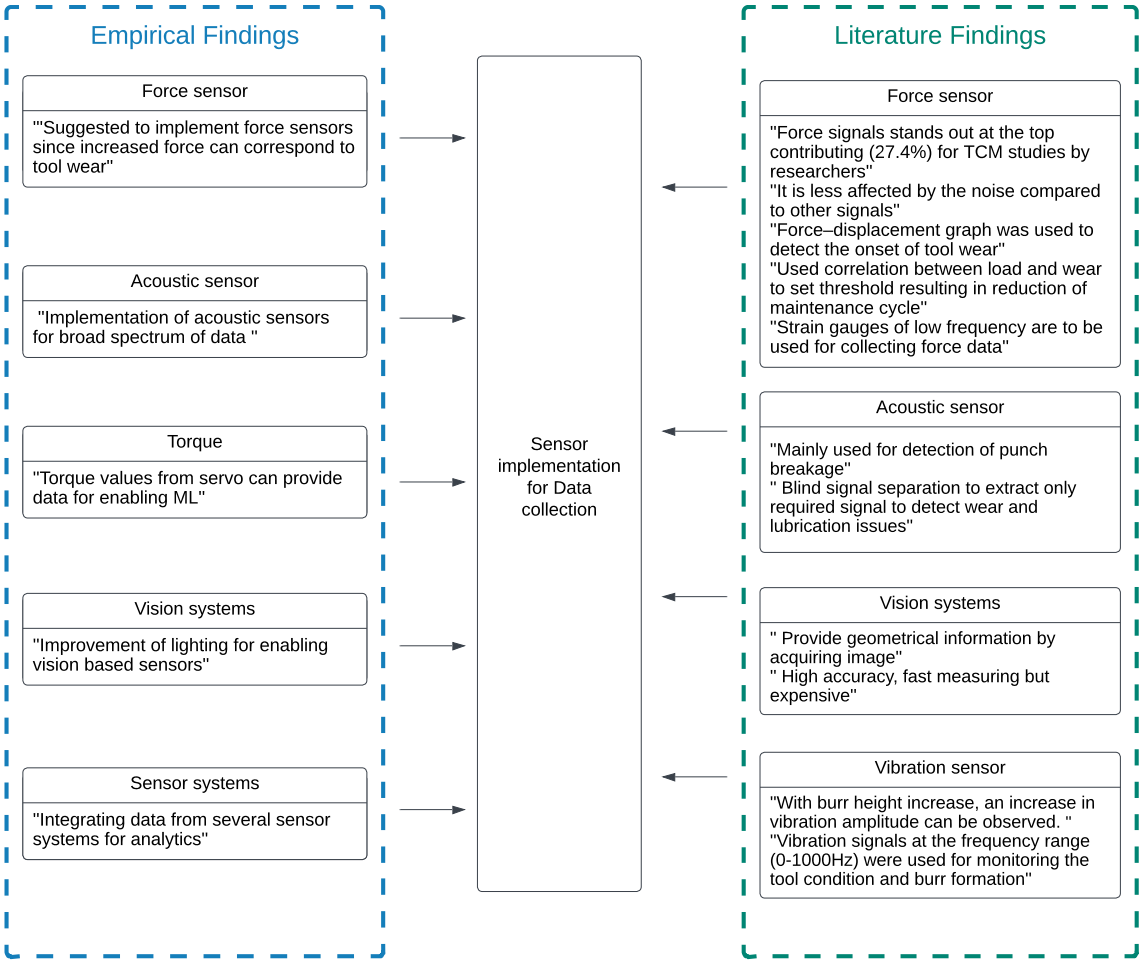

Figure 4.9: Empirical and literature findings

5

Discussion

This chapter explores the implementation of Predictive Maintenance in lithium-ion battery production, with a focus on the stacking process. It examines the methodologies, impacts, and complexities of advanced maintenance technologies. The discussion addresses the research questions, methodological considerations, study limitations, and future research directions, while considering ethical, societal, and ecological implications.

5.1 Implementing Predictive Maintenance in the Stacking Process of Battery Production

Predictive maintenance is a vital technology in the modern production industry, significantly contributing to cost reduction, efficiency enhancement, and increased safety in manufacturing. For industries to transition effectively into predictive maintenance, a step-by-step approach is essential: moving from preventive maintenance to condition-based maintenance by implementing the right sensors, validating sensor data, and finally advancing towards predictive maintenance as illustrated in Figure 5.1. This approach to maintenance is instrumental in creating sustainable systems. Predictive maintenance relies on several components, including sensors, data preprocessing, AI algorithms, decision-making modules, communication and integration, and user interface and reporting. For predictive maintenance to be effective, it is crucial that all these components function seamlessly together.

In this thesis, the focus is primarily on the sensor and data preprocessing aspects, which are pivotal because without accurate sensor data, deploying effective machine learning models is not feasible. The implementation of predictive maintenance follows a structured progression: moving from preventive maintenance to condition-based maintenance, and finally transitioning to predictive maintenance. The condition-based maintenance of the stacking cutting module was investigated through two approaches: operational data analysis and sensor data analysis. The statistical analysis of the operational data revealed that the correlation between the variables was insignificant, suggesting that proceeding with predictive modeling would likely result in unreliable predictions due to weak underlying relationships within the data. This finding underscores the necessity of robust sensor data for

effective predictive maintenance.

The stacking cutting unit currently lacks specific sensors, with the closest sensor being the servo drive, which does not capture current or voltage data that could be valuable for monitoring cutting performance. The absence of these specific sensor data points presents an opportunity to enhance the predictive maintenance model. Literature and workshop findings suggest that implementing sensors such as acoustic and force sensors could establish a solid data foundation, essential for advancing predictive maintenance efforts.

The necessity for advanced predictive maintenance frameworks in battery manufacturing, especially in processes like the stacking cutting operation, is becoming increasingly apparent as the industry aims to enhance efficiency and minimize downtimes. While predictive maintenance is well-established in other sectors, the battery manufacturing industry is only beginning to explore its potential applications. This thesis contributes to this nascent field by examining the critical elements required for effective predictive maintenance systems: data availability, types, and quality.

Implementing predictive maintenance in battery manufacturing involves several practical challenges and strategic considerations. Golightly (2021) highlights the role of suppliers and cross-organizational factors in deploying predictive maintenance solutions. Traditionally, large infrastructure operators owned, operated, maintained, and even manufactured their assets. However, with the advent of extensive data, these roles are increasingly distributed across different organizations. Some suppliers produce products, while others offer services such as data analysis, visualization tools, or condition monitoring solutions, resulting in complex supply chains delivering predictive maintenance solutions.

The distributed nature of condition monitoring supply chains complicates the establishment of a business case, especially regarding the application of standards or common data frameworks to support data exchange. Concerns about trust and access to performance data across the supply chain are significant. However, effective implementation of predictive maintenance can yield substantial benefits for various stakeholders within the supply chain.

To advance predictive maintenance in the stacking cutting unit, a Design of Experiments (DOE) approach can be employed to examine the condition of the knife and other components. By analyzing this data, the root causes of unplanned downtimes can be identified. Subsequently, appropriate sensor implementations can be carried out. Collecting relevant data from statistical, operational, and condition-based sources will then enable effective predictive modeling and the selection of suitable machine learning algorithms. This structured approach can facilitate the successful implementation of predictive maintenance, providing a roadmap for researchers and practitioners to address unplanned downtimes through data-driven solutions.

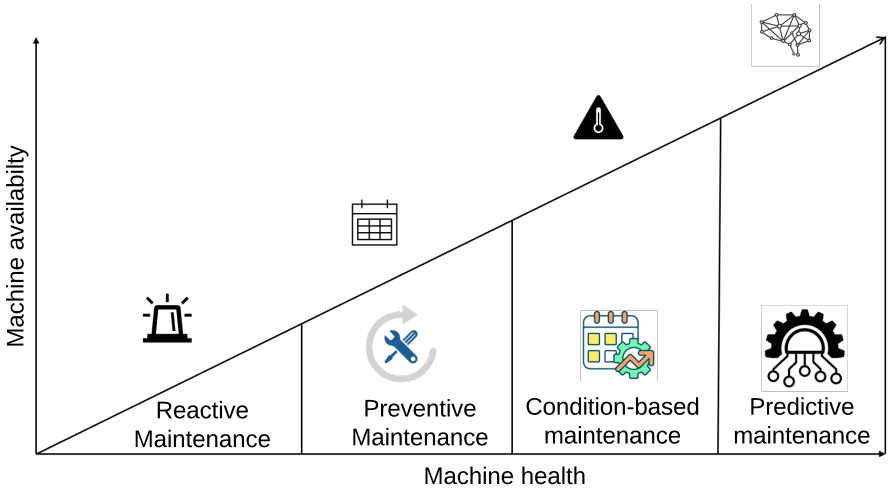

Figure 5.1: Transition towards predictive maintenance

5.2 Research Questions

R.Q.1 How can data-driven sollutions be effectively implemented in battery stacking production to enhance predictive maintenance outcomes?

Implementing data-driven frameworks in battery stacking production involves several steps. Firstly, it is crucial to establish a robust data collection infrastructure. This requires the deployment of appropriate sensors, such as acoustic and force sensors, to monitor critical parameters of the stacking-cutting process (L. Zhang et al., 2021). The collected data must then be preprocessed to ensure its quality and relevance. This involves filtering out noise, handling missing values, and normalizing the data (A. Smith & Jones, 2019). Once the data is prepared, machine learning algorithms can be applied to develop predictive maintenance models. These models need to be trained on historical data to recognize patterns indicative of potential failures. The decision-making module is then used to generate actionable insights from the predictive models, enabling timely maintenance interventions (Chen & Wang, 2018). Integration and communication are essential for the seamless operation of predictive maintenance systems. Data must be exchanged between different components of the system in real-time, and maintenance decisions should be communicated effectively to the relevant personnel (Garcia et al., 2017). A user-friendly interface is also necessary to facilitate easy interpretation of the maintenance recommendations and reporting (Davis & Thomas, 2016). Effective implementation of data-driven frameworks requires collaboration among various stakeholders, including sensor manufacturers, data scientists, and maintenance engineers (Brown et al., 2022). Establishing common data standards and frameworks can also support data exchange and interoperability across different systems and organizations.

R.Q 2. What are the critical data required to develop robust predictive maintenance models in battery manufacturing?

Developing robust predictive maintenance models in battery manufacturing necessitates several critical data types:

1. **Operational Data:** This includes data on the performance and utilization of the stacking cutting unit, such as production rates, downtime occurrences, and operational conditions. These metrics help identify patterns related to machine performance and potential failure modes. According to Lee et al. (2014), operational data is fundamental for understanding and predicting equipment behaviour in manufacturing settings.

2. **Sensor Data:** High-quality sensor data is essential for monitoring the physical and operational state of the equipment. Relevant sensors include acoustic sensors for detecting abnormal sounds, force sensors for measuring the cutting force, and vibration sensors for monitoring mechanical vibrations. This data provides real-time insights into the condition of the equipment. As noted by Jardine, Lin, and Banjevic (2006), sensor data is critical for condition-based maintenance and early fault detection.

3. **Maintenance Data:** Historical maintenance records, including details of past failures, repairs, and replacements, are critical for training predictive models. This data helps identify common failure modes and the effectiveness of different maintenance strategies. Maintenance data serves as a historical reference that aids in predicting future failures, as highlighted by (Mobley, 2002).

4. **Environmental Data:** Information on the operating environment, such as temperature, humidity, and air quality, can influence the performance and longevity of the equipment. Incorporating environmental data helps create more accurate predictive models by accounting for external factors affecting the equipment. Environmental factors are known to impact equipment reliability and should be integrated into predictive models.

5. **Production Quality Data:** Data on the quality of the produced batteries, such as defect rates and quality control metrics, can indicate the effectiveness of the stacking process and potential issues with the equipment. Quality data is essential for linking equipment performance with product outcomes, as supported by research from Montgomery (2009).

The predictive maintenance framework depicted in Figure 5.2 emphasizes the importance of various data inputs, including operational and sensor data, in developing reliable predictive maintenance models. These models are indispensable tools for maintenance and engineering teams, aiding in proactive planning and task execution on the shop floor. By integrating diverse data types, such as historical performance metrics and real-time sensor readings, comprehensive predictive maintenance models can be constructed. These models enable accurate anticipation of equipment failures and optimization of maintenance schedules, thereby enhancing the efficiency and dependability of battery manufacturing processes. It is crucial to underscore the significance of data quality assurance in this process, as it plays a pivotal role in

fostering the development of robust machine learning models capable of providing precise and actionable insights for predictive maintenance.

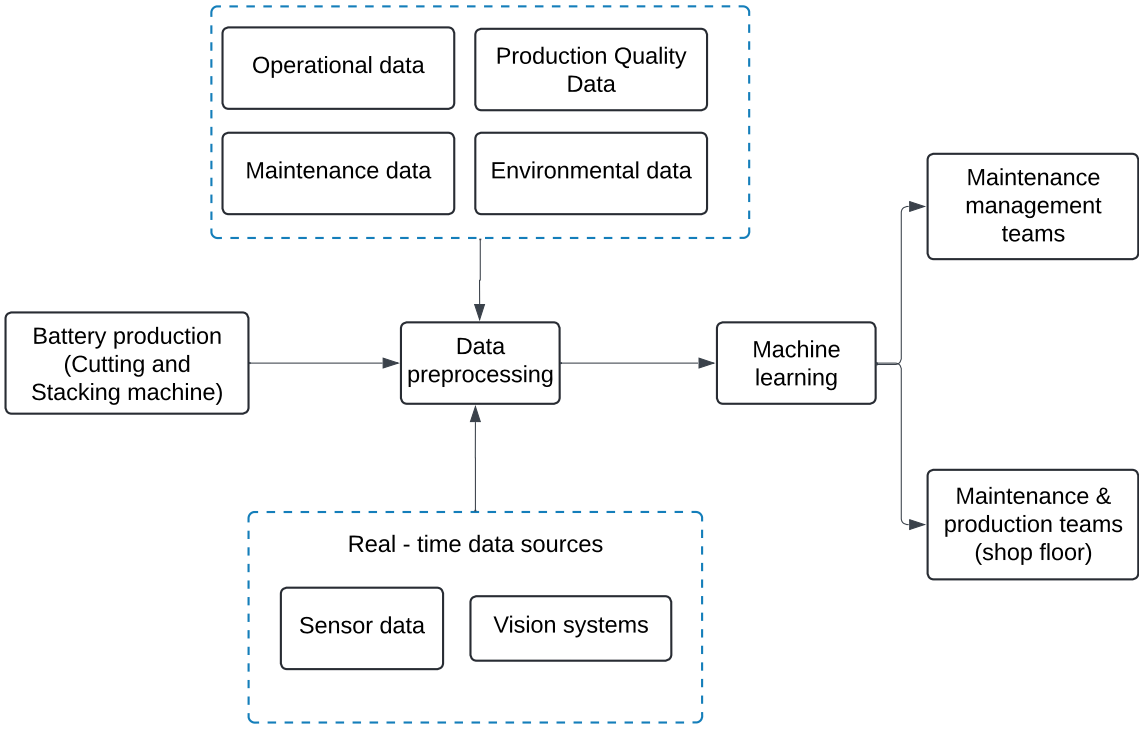

Figure 5.2: General framework for PdM

R.Q.3. What design considerations are necessary for optimizing the implementation of predictive maintenance in battery manufacturing, specifically in the stacking cutting unit?

Optimizing the implementation of predictive maintenance in the stacking cutting unit involves several critical design considerations that must be meticulously addressed to ensure effectiveness and efficiency. First and foremost, sensor placement and selection play a pivotal role. It is essential to choose the right sensors that can monitor critical parameters such as cutting force, vibration, and acoustic signals (Bogue, 2013). Proper placement of these sensors is equally important to ensure that they capture relevant data without interference or noise, leading to more accurate and reliable predictive maintenance models.

Another crucial aspect is data integration and communication. The predictive maintenance system must seamlessly integrate with existing manufacturing systems, necessitating a robust communication infrastructure that facilitates real-time data exchange between sensors, data processing units, and decision-making modules (Lee, 2020). Utilizing standardized data formats and protocols can significantly enhance interoperability and data sharing, making the system more efficient and easier to manage.

Scalability and flexibility are also key design considerations. The system should be

scalable to accommodate future expansions and flexible enough to adapt to changes in the manufacturing process. This includes the capability to add new sensors, incorporate additional data sources, and update predictive models (Bengio, Courville, & Vincent, 2013) as new data becomes available, ensuring the system remains relevant and effective over time .

A user-friendly interface is essential for the effective implementation of predictive maintenance systems. Maintenance personnel must be able to easily access and interpret the recommendations provided by the system (Theissler et al., 2021). Therefore, the system should offer clear and actionable insights along with detailed reports on equipment health and maintenance needs. An intuitive interface can greatly enhance user engagement and adherence to maintenance protocols.

Finally, successful implementation requires collaboration among various stakeholders, including engineers, data scientists, and maintenance personnel. Providing adequate training and support to the maintenance team is crucial for the effective use of the predictive maintenance system. Engaging stakeholders in the design and implementation process helps ensure that the system meets their needs and expectations, fostering a collaborative environment that enhances overall system effectiveness.

Finally, optimizing predictive maintenance in the stacking-cutting module requires careful consideration of sensor placement and selection, data integration and communication, scalability and flexibility, user interface design, data security and privacy, and stakeholder collaboration and training. Addressing these considerations with planning and execution can lead to significant improvements in maintenance efficiency and equipment reliability.

5.3 Future Research Directions

Future research in predictive maintenance should prioritize several critical areas to enhance the robustness and scalability of the models. Firstly, detailed monitoring of individual machinery components is crucial for obtaining high-quality data sets. This granular data allows for more precise and reliable predictions, improving the effectiveness of maintenance strategies. Additionally, integrating multiple systems, such as combining different types of sensors and data sources, can significantly enhance predictive capabilities. This integration provides a holistic view of the machinery's health and performance, allowing for more comprehensive and accurate predictions.

Furthermore, the design phase of machinery should incorporate considerations for sensor placement and functionality. Ensuring that sensors can monitor both process parameters and individual components from the outset enables effective condition-based monitoring throughout the machinery's lifecycle. This proactive approach can identify potential issues before they become critical.

Utilizing root cause analysis and Design of Experiments (DOE) methodologies is also vital. These techniques help identify the underlying causes of equipment failures and

determine the most effective maintenance strategies. By systematically testing and analyzing different variables, researchers can optimize maintenance processes and implement improvements that are both targeted and efficient.

Precise data labeling is another critical area of focus. Data should be labeled based on the specific root causes of problems rather than using generic labels. This precision facilitates more effective data preprocessing, which in turn leads to more accurate and actionable insights. Accurate labeling ensures that the models can learn from the data more effectively, improving their predictive performance.

Expanding research to include these areas and conducting pilot studies in multiple production facilities will validate the effectiveness of the proposed models and design changes. This broader approach will enhance the generalizability of the findings, providing a deeper understanding of the challenges and opportunities in scaling predictive maintenance across different industrial contexts. By addressing these areas, future research can push the boundaries of predictive maintenance, making it more reliable, efficient, and widely applicable.

5.4 Ethical, Social, and Ecological Considerations

While dealing with the data-driven solutions, it is important to consider the ethical, social and ecological implications to ensure that these new age approaches are not only effective but also responsible and sustainable. Addressing these issues mitigate the unintended risks and consequences.

First of all, the shift towards more automated and data-driven maintenance systems raises several ethical concerns regarding data privacy and security. Also, the opaque nature of complex algorithms undermine the trust and accountability. To ensure ethical compatibility, robust data frameworks, data protection regulations, accountability mechanisms, transparency and anonymization techniques are vital.

The automation of maintenance tasks can impact employment and requires careful management of workforce transitions. Also, to efficiently utilise the emerging technologies, there is the need of constantly upgrading oneself with the necessary skills from time to time. To mitigate these adverse effects, the development of data-driven solutions must involve diverse stakeholders to ensure that comprehensive inputs and perspectives are taken into consideration before implementation.

Additionally, the collection, storage and processing of large volumes of data can have significant environmental impacts regarding energy consumption and emissions. Adopting sustainable data practices, such as energy-efficient computing and responsible data management is crucial for minimizing the ecological footprint of data-driven solutions.

6

Conclusion

This thesis has explored the complexities of implementing Predictive Maintenance (PdM) within the battery production industry, specifically focusing on the stacking process in lithium-ion battery manufacturing. Advanced maintenance frameworks are crucial for enhancing efficiency and reducing downtimes in this rapidly evolving sector. PdM marks a significant departure from traditional maintenance strategies by using data and advanced analytics to predict and prevent equipment failures. In battery manufacturing, where precision and reliability are critical, PdM offers a promising approach to improving operational efficiency and minimizing unexpected downtimes.

The accurate collection and monitoring of operational data are vital for PdM. In the stacking process of lithium-ion batteries, variables such as force, voltage, and other operational parameters provide insights into the machinery's condition and help identify potential issues before they cause significant production stoppages. This proactive approach not only ensures continuous production but also extends equipment lifespan by preventing severe damage.

However, implementing PdM in battery manufacturing presents challenges, particularly the current lack of suitable sensor data, which hampers the effective application of predictive models. Many existing machines lack the necessary sensors to capture high-quality data relevant to PdM. This gap necessitates design modifications in stacking machines to enhance data collection and facilitate condition monitoring. Integrating PdM into existing manufacturing processes requires strategic planning and collaboration with suppliers, as the roles of suppliers and cross-organizational factors are crucial in deploying PdM solutions.

Another practical challenge is ensuring the quality and relevance of the data collected. Without high-quality, relevant data, the application of predictive maintenance models cannot proceed effectively. A strategic approach to sensor integration and data collection is essential, ensuring that the captured data supports robust predictive analyses and enhances the accuracy of maintenance predictions.

The necessity for advanced predictive maintenance solutions in battery manufacturing, especially in processes like the stacking cutting operation, is becoming increasingly apparent as the industry aims to enhance efficiency and minimize downtimes.

While predictive maintenance is well-established in other sectors, the battery manufacturing industry is only beginning to explore its potential applications. This thesis contributes to this nascent field by examining the critical elements required for effective predictive maintenance systems: data availability, types, and quality. Implementing predictive maintenance in battery manufacturing involves several practical challenges and strategic considerations. The distributed nature of condition monitoring supply chains complicates the establishment of a business case, especially regarding the application of standards or common data frameworks to support data exchange. Concerns about trust and access to performance data across the supply chain are significant. However, effective implementation of predictive maintenance can yield substantial benefits for various stakeholders within the supply chain.

To enhance predictive maintenance in the stacking cutting unit, a systematic approach can be adopted to analyze the condition of the stacking cutting module and other components. Our travel to Skelleftea and close observation of the battery manufacturing process helped us understand the system better and plan more effectively. This hands-on experience provided a clear picture of the problem and guided us in the right direction. Through comprehensive data analysis, the root causes of unplanned downtimes can be effectively identified. This analysis will inform the implementation of suitable sensors to collect relevant data from various sources, including statistical, operational, and condition-based data. By leveraging this diverse dataset, robust predictive models can be developed, supported by the selection of appropriate machine learning algorithms. This methodical approach provides a clear pathway for researchers and practitioners to mitigate unplanned downtimes through predictive, data-driven solutions.

References

Ahmad, R., & Kamaruddin, S. (2012). An overview of time-based and condition-based maintenance in industrial application. *Computers Industrial Engineering*, *63*(1), 135-149. Retrieved from https://www.sciencedirect.com/science/article/pii/S0360835212000484 doi: https://doi.org/10.1016/j.cie.2012.02.002

Ahmed, S., Nelson, P. A., Gallagher, K. G., & Dees, D. W. (2016). Energy impact of cathode drying and solvent recovery during lithium-ion battery manufacturing. *Journal of Power Sources*, *322*, 169-178. Retrieved from https://www.sciencedirect.com/science/article/pii/S037877531630475X doi: https://doi.org/10.1016/j.jpowsour.2016.04.102

Alcácer, V., & Cruz-Machado, V. (2019). Scanning the industry 4.0: A literature review on technologies for manufacturing systems. *Engineering Science and Technology, an International Journal*, *22*(3), 899-919. Retrieved from https://www.sciencedirect.com/science/article/pii/S2215098618317750 doi: https://doi.org/10.1016/j.jestch.2019.01.006

Al-Najjar, B., & Alsyouf, I. (2004). Enhancing a company's profitability and competitiveness using integrated vibration-based maintenance: A case study. *European Journal of Operational Research*, *157*(3), 643-657. Retrieved from https://www.sciencedirect.com/science/article/pii/S0377221703002583 doi: https://doi.org/10.1016/S0377-2217(03)00258-3

Altan, T., & Tekkaya, A. E. (2012). *Sheet metal forming: processes and applications*. ASM international.

Atamu-radov, V., Medjaher, K., Dersin, P., Lamoureux, B., & Zerhouni, N. (2017). Prognostics and health management for maintenance practitioners-review, implementation and tools evaluation. *International Journal of Prognostics and Health Management*, *8*(3), 1–31.

Baumeister, M., & Fleischer, J. (2014). Integrated cut and place module for high productive manufacturing of lithium-ion cells. *CIRP Annals*, *63*(1), 5-8. Retrieved from https://www.sciencedirect.com/science/article/pii/S0007850614000663 doi: https://doi.org/10.1016/j.cirp.2014.03.063

Ben-Daya, M., & Duffuaa, S. O. (1995). Maintenance and quality: the missing link. *Journal of Quality in Maintenance Engineering*, *1*(1), 20–26. Retrieved from https://doi.org/10.1108/13552519510083110 doi: 10.1108/13552519510083110

Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review

and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *35*(8), 1798–1828. doi: 10.1109/tpami.2013.50

Blanchard, B. S. (1998). *Logistics engineering and management*. Prentice Hall.

Bogue, R. (2013). Sensors for condition monitoring: a review of technologies and applications. *Sensor Review*, *33*(4), 295–299. doi: 10.1108/sr-05-2013-675

Bokrantz, J. (2019). Smart maintenance. Retrieved from `https://research.chalmers.se/publication/512579/file/512579_Fulltext.pdf`

Bokrantz, J., Skoogh, A., Berlin, C., Wuest, T., & Stahre, J. (2020). Smart maintenance: an empirically grounded conceptualization. *International Journal of Production Economics*, *223*, 107534. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0925527319303615` doi: https://doi.org/10.1016/j.ijpe.2019.107534

Bokrantz, J., Skoogh, A., Ylipää, T., & Stahre, J. (2016). Handling of production disturbances in the manufacturing industry. *Journal of Manufacturing Technology Management*, *27*(8), 1054–1075.

Brodd, R. J., & Tagawa, K. (2002). Lithium-ion cell production processes. In *Advances in lithium-ion batteries* (pp. 267–288). Springer.

Brown, J., Green, P., & White, S. (2022). Collaborative approaches in industrial maintenance. *Journal of Industrial Technology*, *34*(2), 45-60.

Cai, L., & Zhu, Y. (2015). The challenges of data quality and data quality assessment in the big data era. *Data science journal*, *14*, 2–2.

Caruth, G. D. (2013). Demystifying mixed methods research design: A review of the literature. *Online Submission*, *3*(2), 112–122. Retrieved from `https://eric.ed.gov/?id=ED544121`

Chen, R., & Wang, Q. (2018). Predictive maintenance using machine learning: A review. *Maintenance and Reliability*, *19*(4), 556-565.

Choudh-ary, N., Clever, H., Ludwigs, R., Rath, M., Gannouni, A., Schmetz, A., ... others (2022). Autonomous visual detection of defects from battery electrode manufacturing. *Advanced Intelligent Systems*, *4*(12), 2200142.

Clark, V. L. P., & Ivankova, N. V. (2011). *Mixed methods research: A guide to the field*. SAGE Publications.

Collins Publishers (Ed.). (2022). *Collins english dictionary* (13th ed.). London: HarperCollins.

Dalmarco, G., Ramalho, F. R., Barros, A. C., & Soares, A. L. (2019). Providing industry 4.0 technologies: The case of a production technology cluster. *The journal of high technology management research*, *30*(2), 100355.

Davis, T., & Thomas, L. (2016). Designing user-friendly maintenance interfaces. *Human-Computer Interaction Journal*, *11*(3), 245-260.

Deloitte. (2017). *Predictive maintenance: Taking pro-active measures based on advanced data analytics to predict and avoid machine failure.* `https://www2.deloitte.com/content/dam/Deloitte/de/Documents/deloitte-analytics/Deloitte_Predictive-Maintenance_PositionPaper.pdf`. (Analytics Institute)

Dhillon, B. S. (2002a). *Engineering maintenance: a modern approach*. cRc press. Retrieved from `https://www.taylorfrancis.com/books/mono/10.1201/9781420031843/engineering-maintenance-dhillon`

Dhillon, B. S. (2002b). *Engineering maintenance: a modern approach*. cRc press.

Drouillet, C., Karandikar, J., Nath, C., Journeaux, A.-C., El Mansori, M., & Kurfess, T. (2016). Tool life predictions in milling using spindle power with the neural network technique. *Journal of Manufacturing Processes*, *22*, 161-168. Retrieved from https://www.sciencedirect.com/science/article/pii/S1526612516300123 doi: https://doi.org/10.1016/j.jmapro.2016.03.010

Duffner, F., Kronemeyer, N., Tübke, J., Leker, J., Winter, M., & Schmuch, R. (2021). Post-lithium-ion battery cell production and its compatibility with lithium-ion cell production infrastructure. *Nature Energy*, *6*(2), 123–134. Retrieved from https://doi.org/10.1038/s41560-020-00748-8 doi: 10.1038/s41560-020-00748-8

Eger, F., Reiff, C., Brantl, B., Colledani, M., & Verl, A. (2018). Correlation analysis methods in multi-stage production systems for reaching zero-defect manufacturing. *Procedia CIRP*, *72*, 635–640. doi: 10.1016/j.procir.2018.03.163

ElMaraghy, H., Monostori, L., Schuh, G., & ElMaraghy, W. (2021). Evolution and future of manufacturing systems. *CIRP Annals*, *70*(2), 635–658.

Esmaeilian, B., Behdad, S., & Wang, B. (2016). The evolution and future of manufacturing: A review. *Journal of manufacturing systems*, *39*, 79–100.

European Investment Bank. (2020). *Swedish company gives jolt of energy for electric car battery tech.* https://www.eib.org/en/stories/electric-car-battery-tech. (Retrieved 19 August 2020)

Frizelle, G., McFarlane, D., & Bongaerts, L. (1998). Disturbance measurement in manufacturing production systems. *Proceedings of the ASI, June, Bremen*.

Garcia, M., Li, X., & Patel, K. (2017). Real-time data integration in industrial systems. *International Journal of Data Integration*, *22*(1), 34-50.

Girit, O., Atakok, G., & Ersoy, S. (2020). Data analysis for predictive maintenance of servo motors. *Shock and Vibration*, *2020*, 1–10. doi: 10.1155/2020/8826802

Gökalp, M. O., Gökalp, E., Kayabay, K., Koçyiğit, A., & Eren, P. E. (2021). Data-driven manufacturing: An assessment model for data science maturity. *Journal of Manufacturing Systems*, *60*, 527–546.

Gouriveau, R., Medjaher, K., & Zerhouni, N. (2016). *From prognostics and health systems management to predictive maintenance 1: Monitoring and prognostics*. John Wiley & Sons.

Halcomb, E. J., & Hickman, L. (2015). Mixed methods research.

Harding, J. A., Shahbaz, M., Srinivas, & Kusiak, A. (2006). Data mining in manufacturing: a review.

Heil, M. (2013). *Disruption of operational processes*. Springer-Verlag.

IEA. (2024). *Global ev outlook 2024.* Paris: IEA. Retrieved from https://www.iea.org/reports/global-ev-outlook-2024 (Licence: CC BY 4.0)

Imai, M. (1986). *Kaizen (ky'zen), the key to japan's competitive success*. Random House Business Division.

International Electrotechnical Commission. (2006). *International electrotechnical vocabulary.* Available at http://std.iec.ch/iev/iev.nsf. (IEV 191-07-01 Accessed: 08-05-2024)

Ito, A., Ylipää, T., Skoogh, A., & Gullander, P. (2021). Production disturbances

handling: where are we and where are we heading. In *2nd south american conference on industrial engineering and operations management, ieom* (Vol. 5, pp. 12–23).

Jakob Fleischmann, E. H. D. I. S. J. M. L. P. S. L. T., Mikael Hanicke, & van de Rijt, A. (2023). *Battery 2030: Resilient, sustainable, and circular.* https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/battery-2030-resilient-sustainable-and-circular. (Archived in the Library of Congress Web Archives at www.loc.gov)

Kans, M. (2019, 05). Maintenance in the digital era -an interview study of challenges and opportunities within the swedish maintenance ecosystem..

Kenton, W. (2020). Manufacturing. Retrieved from `https://web.archive.org/web/20201117184723/https://www.investopedia.com/terms/m/manufacturing.asp`

Klingenberg, W., & de Boer, T. (2008). Condition-based maintenance in punching/blanking of sheet metal. *International Journal of Machine Tools and Manufacture*, *48*(5), 589-598. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0890695507001526` (Advances in Sheet Metal Forming Applications) doi: https://doi.org/10.1016/j.ijmachtools.2007.08.013

Kolhatkar, A., & Pandey, A. (2023). Predictive maintenance methodology in sheet metal progressive tooling: a case study. *International Journal of System Assurance Engineering and Management*, *14*(4), 980–989. Retrieved from `https://doi.org/10.1007/s13198-021-01564-3` doi: 10.1007/s13198-021-01564-3

Krueger, R. A., & Casey, M. A. (2015). *Focus groups: A practical guide for applied research.* Sage.

Kurfer, J., Westermeier, M., Tammer, C., & Reinhart, G. (2012). Production of large-area lithium-ion cells – preconditioning, cell stacking and quality assurance. *CIRP Annals*, *61*(1), 1-4. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0007850612001035` doi: https://doi.org/10.1016/j.cirp.2012.03.101

Lara de Leon, M. A., Kolarik, J., Byrtus, R., Koziorek, J., Zmij, P., & Martinek, R. (2024, 01 01). Tool condition monitoring methods applicable in the metalworking process. *Archives of Computational Methods in Engineering*, *31*(1), 221–242. Retrieved from `https://doi.org/10.1007/s11831-023-09979-w` doi: 10.1007/s11831-023-09979-w

Lee, J. (2020). Historical data in predictive maintenance. *Journal of Maintenance Engineering*, *29*(1), 12-28.

Liker, J. K. (2004). *The toyota way: 14 management principles from the world's greatest manufacturer.* McGraw-Hill.

Liu, Y., Zhang, R., Wang, J., & Wang, Y. (2021). Current and future lithium-ion battery manufacturing. *IScience*, *24*(4).

Lombardo, T., Duquesnoy, M., El-Bouysidy, H., Årén, F., Gallo-Bueno, A., Jørgensen, P. B., ... Franco, A. A. (2022). Artificial intelligence applied to battery research: Hype or reality? *Chemical Reviews*, *122*(12), 10899-10969. Retrieved from `https://doi.org/10.1021/acs.chemrev.1c00108` (PMID: 34529918) doi: 10.1021/acs.chemrev.1c00108

Ma, Z., Ren, Y., Xiang, X., & Turk, Z. (2020). Data-driven decision-making for

equipment maintenance. *Automation in Construction*, *112*, 103103.

Mariscal, G., Marban, O., & Fernandez, C. (2010). A survey of data mining and knowledge discovery process models and methodologies. *The Knowledge Engineering Review*, *25*(2), 137–166.

Metrics, C. (2013). *Oee - a general discussion with calculation methods.* https://www.example.com/path/to/pdf. (Archived from the original (PDF) on 27 September 2013. Retrieved 23 September 2013)

Mobley, R. K. (2002). *An introduction to predictive maintenance*. Elsevier. Retrieved from https://books.google.se/books?hl=en&lr=&id=SjqXzxpAzSQC&oi=fnd&pg=PP1&dq=%5CMobley,+R.+K.+(2002).+An+Introduction+to+Predictive+Maintenance.+Elsevier.&ots=iHpRLELign&sig=AtTBTNG-DYyoeOIzHHBztQ_wSqk&redir_esc=y#v=onepage&q&f=false

Montero Jimenez, J. J., Schwartz, S., Vingerhoeds, R., Grabot, B., & Salaün, M. (2020). Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics. *Journal of Manufacturing Systems*, *56*, 539-557. Retrieved from https://www.sciencedirect.com/science/article/pii/S0278612520301187 doi: https://doi.org/10.1016/j.jmsy.2020.07.008

Moubray, J. (1997). *Reliability-centered maintenance*. Industrial Press Inc.

Mukherjee, S., & Soderpalm, H. (2021). Northvolt battery plant sparks into life, a first for europe. *Reuters*. (Retrieved 30 December 2021)

Nakajima, S. (1988). *Introduction to total productive maintenance (tpm)*. Productivity Press.

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature climate change*, *5*(4), 329–332. Retrieved from https://www.nature.com/articles/nclimate2564

Ohno, T. (1988). *Toyota production system: Beyond large-scale production*. Productivity Press.

Onay, C., & Öztürk, E. (2018). A review of credit scoring research in the age of big data. *Journal of Financial Regulation and Compliance*, *26*(3), 382–405.

Ørngreen, R., & Levinsen, K. T. (2017). Workshops as a research methodology. *Electronic Journal of E-learning*, *15*(1), 70–81.

Overbeck, L., Voigtländer, S., & Lanza, G. (2023). Optimal line configurations for agile production systems for battery cell manufacturing. *Procedia CIRP*, *118*, 976–981.

Pintelon, L., & Parodi-Herz, A. (2008). Maintenance: An evolutionary perspective. In *Complex system maintenance handbook* (pp. 21–48). London: Springer London. Retrieved from https://doi.org/10.1007/978-1-84800-011-7_2 doi: 10.1007/978-1-84800-011-7_2

Porter, M. (1985). *Competitive advantage.* New York: The Free Press.

Ruiz-Sarmiento, J.-R., Monroy, J., Moreno, F.-A., Galindo, C., Bonelo, J.-M., & Gonzalez-Jimenez, J. (2020). A predictive model for the maintenance of industrial machinery in the context of industry 4.0. *Engineering Applications of Artificial Intelligence*, *87*, 103289.

Sai, V. C., Shcherbakov, M. V., & Tran, V. P. (2019). Data-driven framework for predictive maintenance in industry 4.0 concept. In *Creativity in intelli-*

gent technologies and data science: Third conference, cit&ds 2019, volgograd, russia, september 16–19, 2019, proceedings, part i 3 (pp. 344–358).

Saltz, J. S. (2021). Crisp-dm for data science: Strengths, weaknesses and potential next steps. In *2021 ieee international conference on big data (big data)* (p. 2337-2344). doi: 10.1109/BigData52589.2021.9671634

Sari, D. Y., Wu, T.-L., & Lin, B.-T. (2017). Preliminary study for online monitoring during the punching process. *The International Journal of Advanced Manufacturing Technology*, *88*(5), 2275–2285. Retrieved from `https://doi.org/10.1007/s00170-016-8956-y` doi: 10.1007/s00170-016-8956-y

Schmidt, O., Thomitzek, M., Röder, F., Thiede, S., Herrmann, C., & Krewer, U. (2020). Modeling the impact of manufacturing uncertainties on lithium-ion batteries. *Journal of The Electrochemical Society*, *167*(6), 060501.

Schnell, J., Nentwich, C., Endres, F., Kollenda, A., Distel, F., Knoche, T., & Reinhart, G. (2019). Data mining in lithium-ion battery cell production. *Journal of Power Sources*, *413*, 360–366.

Shearer, C. (2000). The crisp-dm model: the new blueprint for data mining. *Journal of data warehousing*, *5*(4), 13–22.

Shin, I., Lee, J., Lee, J. Y., Jung, K., Kwon, D., Youn, B. D., ... Choi, J.-H. (2018). A framework for prognostics and health management applications toward smart manufacturing systems. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *5*, 535–554.

Smith, A., & Jones, B. (2019). Data preprocessing techniques in machine learning. *Journal of Data Science*, *13*(2), 123-145.

Smith, R., & Hawkins, B. (2004). *Lean maintenance: Reduce costs, improve quality, and increase market share*. Butterworth-Heinemann.

Solle, D., Hitzmann, B., Herwig, C., Pereira Remelhe, M., Ulonska, S., Wuerth, L., ... Steckenreiter, T. (2017). Between the poles of data-driven and mechanistic modeling for process operation. *Chemie Ingenieur Technik*, *89*(5), 542–561.

Stock, S., Pohlmann, S., Günter, F. J., Hille, L., Hagemeister, J., & Reinhart, G. (2022). Early quality classification and prediction of battery cycle life in production using machine learning. *Journal of Energy Storage*, *50*, 104144.

Subrama-niyan, M., Skoogh, A., Gopalakrishnan, M., Salomonsson, H., Hanna, A., & Lämkull, D. (2016). An algorithm for data-driven shifting bottleneck detection. *Cogent Engineering*, *3*(1), 1239516.

Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Transactions on Industrial Informatics*, *11*(3), 812-820. doi: 10.1109/TII.2014.2349359

TACSI. (2024). How to facilitate meaningful and productive conversations. Retrieved from `https://www.tacsi.org.au/news-ideas/how-to-facilitate-meaningful-and-productive-conversations` (Accessed: 2024-05-27)

Tan, C., Ardanese, R., Huemiller, E., Cai, W., Yang, H., Bracey, J., & Pozzato, G. (2023a). Data-driven battery electrode production process modeling enabled by machine learning. *Journal of Materials Processing Technology*, *316*, 117967. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0924013623001127` doi: https://doi.org/10.1016/

j.jmatprotec.2023.117967

Tan, C., Ardanese, R., Huemiller, E., Cai, W., Yang, H., Bracey, J., & Pozzato, G. (2023b). Data-driven battery electrode production process modeling enabled by machine learning. *Journal of Materials Processing Technology*, *316*, 117967.

Taşcı, B., Omar, A., & Ayvaz, S. (2023). Remaining useful lifetime prediction for predictive maintenance in manufacturing. *Computers & Industrial Engineering*, *184*, 109566.

Tashakkori, A., & Teddlie, C. (2010). *Sage handbook of mixed methods in social behavioral research*. SAGE Publications.

Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliability Engineering System Safety*, *215*, 107864. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0951832021003835` doi: https://doi.org/10.1016/j.ress.2021.107864

Turetskyy, A. (2022). *Data analytics in battery production systems* (Unpublished doctoral dissertation). Dissertation, Braunschweig, Technische Universität Braunschweig, 2022.

Turetskyy, A., Wessel, J., Herrmann, C., & Thiede, S. (2020). Data-driven cyber-physical system for quality gates in lithium-ion battery cell manufacturing. *Procedia CIRP*, *93*, 168–173.

Turetskyy, A., Wessel, J., Herrmann, C., & Thiede, S. (2021a). Battery production design using multi-output machine learning models. *Energy Storage Materials*, *38*, 93-112. Retrieved from `https://www.sciencedirect.com/science/article/pii/S2405829721001008` doi: https://doi.org/10.1016/j.ensm.2021.03.002

Turetskyy, A., Wessel, J., Herrmann, C., & Thiede, S. (2021b). Battery production design using multi-output machine learning models. *Energy Storage Materials*, *38*, 93–112.

Vinnova. (2023). *Matterscale - maintenance of battery production at industrial scale.* (Accessed: 31 May 2024)

Voltagecontrol. (2023). How to facilitate a workshop. Retrieved from `https://voltagecontrol.com/blog/how-to-facilitate-a-workshop/` (Accessed: 2024-05-27)

Wang, J., Xu, C., Zhang, J., & Zhong, R. (2022). Big data analytics for intelligent manufacturing systems: A review. *Journal of Manufacturing Systems*, *62*, 738–752.

Wirth, R., & Hipp, J. (2000). Crisp-dm: Towards a standard process model for data mining. In *Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining* (Vol. 1, pp. 29–39).

Wood, D. L., Li, J., & An, S. J. (2019). Formation challenges of lithium-ion battery manufacturing. *Joule*, *3*(12), 2884-2888. Retrieved from `https://www.sciencedirect.com/science/article/pii/S254243511930532X` doi: https://doi.org/10.1016/j.joule.2019.11.002

Xie, H., Hu, X., Peng, Z., Jiang, J., Wen, B., & Yang, Q. (2020). Energy system time series data quality maintenance system based on data mining technology.

In *2020 ieee 4th conference on energy internet and energy system integration (ei2)* (pp. 3096–3100).

Yin, Y., Stecke, K. E., & Li, D. (2018). The evolution of production systems from industry 2.0 through industry 4.0. *International Journal of Production Research*, *56*(1-2), 848–861.

Ylipää, T., Skoogh, A., Bokrantz, J., & Gopalakrishnan, M. (2017). Identification of maintenance improvement potential using oee assessment. *International Journal of Productivity and Performance Management*, *66*(1), 126–143.

Zhang, H., Kang, R., & Pecht, M. (2009). A hybrid prognostics and health management approach for condition-based maintenance. In *2009 ieee international conference on industrial engineering and engineering management* (pp. 1165–1169).

Zhang, L., Kim, H., & Nguyen, T. (2021). Sensor deployment strategies for battery stacking processes. *Sensors and Actuators*, *17*(3), 213-220.

Zhang, W., Yang, D., & Wang, H. (2019). Data-driven methods for predictive maintenance of industrial equipment: A survey. *IEEE systems journal*, *13*(3), 2213–2227.

Zhang, Y., Qi, X., Wang, T., & He, Y. (2023). Tool wear condition monitoring method based on deep learning with force signals. *Sensors*, *23*(10). Retrieved from `https://www.mdpi.com/1424-8220/23/10/4595` doi: 10.3390/s23104595

A

Appendix A

A.1 Workshop Discussion

Topic: Sensor Implementation

Objective: To identify potential enhancements of additions to sensor setups

Discussion Points:
1. What types of new sensors could be integrated?
2. How can sensor placement be optimized for better data accuracy?
3. Are there technologies or methods that can enhance existing sensor data collections?

Topic: Design Improvements

Objective: To discuss design changes that could facilitate better maintenance and data collections

Discussion Points:

1. What design modifications can improve accessibility for maintenance?
2. How can the design support more comprehensive data collection?

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