University of Agder

How artificial intelligence can be used to improve lean manufacturing and production processes

A case study of Hennig Olsen

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We chose to explore the topic of artificial intelligence in our master thesis because of our interest in innovative technologies. Moreover, the growing prominence of artificial intelligence, particularly through AI chatbots like ChatGPT, caught our attention and sparked our curiosity. We wanted to investigate if artificial intelligence could be applied to our thesis, and as it turned out, it was indeed applicable. Our objective was to examine a nearby production facility that appeared intriguing and had the potential to benefit from this technology. After conducting thorough research, we found it fascinating to explore the integration of artificial intelligence in lean practices.

We would like to extend our sincere gratitude to Hennig Olsen for their invaluable support in making this thesis possible. We are deeply appreciative of Thor Eivind Ruud's willingness to contribute to this project and his invaluable assistance. We would also like to express our heartfelt thanks to our family and friends for their unwavering support. Lastly, we would like to express our gratitude to our supervisor at UiA, Knut Erik Bonnier, for his guidance, extensive knowledge, and valuable advice throughout this semester.

Abstract

The implementation of Lean and Artificial Intelligence has demonstrated a positive correlation across different industries. By integrating AI techniques, the efficiency and effectiveness of Lean processes can be enhanced. The combination of Lean and AI contributes to improved decision-making, increased productivity, and reduced waste. Moreover, AI can identify and rectify process errors, enabling streamlined and more efficient operations.

In 2014, Hennig Olsen initiated the implementation of lean thinking, which yielded mixed results initially. However, they decided to adopt lean principles according to their specific requirements, leading to significantly improved outcomes. With the rapid advancement of technology, Hennig Olsen ventured into experimenting with artificial intelligence, particularly in the realm of vision control, starting in 2019. Subsequently, they have consistently embraced and integrated increasingly advanced technologies to continuously enhance their production lines.

This case study examined the impact of implementing artificial intelligence on the company's performance. The findings revealed that as Hennig Olsen incorporated more artificial intelligence into their production lines, they experienced a significant reduction in customer complaints. However, they continue to face challenges in meeting their overall equipment effectiveness goals. The thesis also identified potential areas for improvement, emphasizing the potential benefits of integrating six sigma processes through AI initiatives. More specifically, implementing predictive maintenance to minimize unexpected downtime and improve OEE emerged as a key opportunity. Leveraging AI to analyze vast amounts of data could also prove advantageous in optimizing cycle time and reducing waste within the organization.

Finally, this report has examined the readiness of Hennig Olsen to further integrate AI tools into their operations. To fully capitalize on the potential benefits of AI and evolve into a comprehensive smart factory, the company needs to invest in additional technologies such as the Internet of Things, big data analytic, and cloud computing. However, a significant hurdle arises from the limitations of their existing machinery, which cannot gather extensive data or establish interconnectivity. Moreover, sourcing qualified personnel proficient in developing these technologies poses a challenge. A more effective strategy, along with support from stakeholders, is necessary to encourage investments in new technologies. This will facilitate the successful implementation of AI technologies and foster improved acceptance of new technology among employees.

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Chapter 1

Introduction

1.1 Background

Lean methodology, originally pioneered by Toyota, has long been regarded as an industry standard for companies worldwide (Womack & Jones, 1997). However, in the present era characterized by increased complexity, there is a growing belief that traditional lean thinking alone may not be sufficient (Perico & Mattioli, 2020). To address this new level of complexity, one potential solution is the transformation into a smart factory by incorporating Artificial Intelligence (AI).

AI's originator, Alan Turing, described AI as: "A computer deserves to be called intelligent if it could deceive a human into believing that it was a human" (Turing, 2009). Since then, artificial intelligence has constantly evolved through technological advancement and development, and the meaning itself still changes. Artificial intelligence is often referred to as technologies that can perform tasks that typically require human intelligence. It has the ability to learn, reason, and make decisions with minimal human intervention (T.-C. T. Chen & Wang, n.d.).

AI has the potential to change the world in significant ways by transforming various aspects of society, from healthcare and education to transportation and manufacturing (Van Wynsberghe, 2021). With its ability to process vast amounts of data, AI can improve decision-making, optimize systems, and automate mundane tasks, leading to increased efficiency and productivity (Sahoo & Lo, 2022; Van Wynsberghe, 2021). Moreover, AI can personalize experiences for individuals, and even help address some of the world's most significant societal challenges, such as climate change (Van Wynsberghe, 2021).

A more advanced manufacturing operation can be accomplished through the use of Industry 4.0 technologies. Because of the market volatility, manufacturing systems are becoming more intelligent, more flexible, and more digital as the global market continues to evolve (Zhong et al., 2017). Smart manufacturing enables manufacturers to maximize the efficiency of existing production capacity as well as developing next generation production capabilities to compete in the digital economy (Rahardjo et al., 2023). Manufacturing industries benefit greatly from Industry 4.0 technologies due to better machines, enhanced communications, improved working conditions, and improved product quality (Jamwal et al., 2021).

The concept of Industry 4.0 often includes the integration of AI technologies as a key component to monitor the health status of industrial components and analyze machine data for fault detection and localization. This optimizes maintenance processes and predicts system degradation and the remaining lifetime of machines to mention some (T.-C. T. Chen & Wang, n.d.; Waltersmann et al., 2021). The integration of AI can also enable connectivity, real-time data exchange, and remote monitoring in manufacturing environments to optimize processes and enhance efficiency (T.-C. T. Chen & Wang, n.d.). The manufacturing industry has to accept that to benefit from the increased data availability high level of support is needed to handle the high dimensional, complexity, and dynamics involved (Wuest et al., 2016).

Although Siemens presented the idea of implementing AI in factories back in 2011, many companies are still struggling to adopt this new technology (Turconi et al., 2022). Despite the growing urgency to implement AI into the factories, there is a lack of understanding of the key challenges and necessary capabilities to ensure success (Sjödin et al., 2018). The limited availability of case studies and best practices further complicates the adoption process. According to a study by Sjödin et al. (2018), there are three main categories of challenges companies face in implementing AI: people, technology, and processes. Staff lacks a common understanding of the new vision, operating AI is complex, and manufacturing companies find it difficult to adapt to new transformations (Sjödin et al., 2018).

Integrating AI to help with continuous improvement has become a current topic in the industry. Combining lean management with AI could gain the company by lower waste and cost, where lean management is not sufficient on its own (Ding et al., 2021). Applying lean principles would also decrease the expenses of integrating AI into the production line (Rahardjo et al., 2023). Organizational performance could also increase with implementing AI, which is named lean digital transformation (Calabrese et al., 2022).

This case study, about Hennig-Olsen, is the Nordic region's oldest ice cream producer. It was established in 1924 by Sven Hennig-Olsen (Olsen, n.d.). Today, Hennig Olsen produces approximately 32 million liters of ice cream at their factory in Hannevika, outside Kristiansand (Olsen, n.d.). Hennig Olsen first introduced lean management in 2014. Since then, it has been a continual search for new opportunities to improve production efficiency. This has brought them to the exploration of AI.

1.2 Problem statement and research question

This study aims to elaborate on the knowledge and research of the usage of AI for Hennig Olsen, and for them to further develop into Industry 4.0. The research conducted is to be discussed together with literature and key findings to get a better understanding of how AI can be used to further improve lean processes in the plant. The problem statement has therefore been defined as:

How artificial intelligence can be used to improve lean manufacturing and production processes?

This case study is delimited to the extent of what AI can do for Hennig Olsen to improve their production methods and thus improve lean. Given the research question, it is pertinent to also provide an analysis of why Hennig Olsen should continue to implement AI in their production methods. The thesis also covers what aspects of the production AI can make improvements, and whether the AI tools they use today have made enough improvements. Lastly, an assessment of their readiness for further implementation of these technologies is also done.

The scope of this thesis is limited to technologies, systems, and production methods that are related to what is pertinent for the production facilities at Hennig Olsen. Economics is also an important part when investing in the technologies discussed, but will not be a part of this thesis.

1.3 Structure of the thesis

This master thesis is structured into six comprehensive chapters. The first chapter serves as an introduction, providing a background and an overview of the research conducted in this paper. Chapter two is a literature review that analyzes and evaluates the existing theoretical concepts and academic research that are relevant to the research questions. This chapter synthesizes the most recent and relevant research in the field and explores the theoretical concepts. Chapter three presents the methodology and research design that are used in this study. This chapter explains how the research was conducted, the research approach, data collection, and analysis techniques. Chapter four describes the results of the research conducted. This chapter provides an in-depth analysis of the data gathered and discusses the findings that emerged from the research. This chapter also includes tables, figures, and diagrams that illustrate the results. Chapter five discusses the empirical data collected against the theory presented earlier in the literature review chapter. Chapter six provides the conclusion to the research conducted. This chapter summarizes the research findings and answers the research questions. Lastly, there is a small paragraph for further work that suggests areas for future research that can extend and enhance the current research.

Chapter 2

Theoretical background

This chapter presents the theoretical foundations that the authors of this paper deemed important for understanding the research presented. Introduction to modern production facilities and what lies behind them. This chapter further provides a general introduction to artificial intelligence and machine learning and how they can be utilized in industrial factories to improve production processes and enhance productivity. The authors also highlight the foundation that must be in place for successful AI implementation in production facilities. Then a segment that delves into the principles of lean manufacturing, which is a widely adopted approach to optimize production processes and reduce waste.

2.1 Artificial Intelligence and Machine Learning

2.1.1 Artificial intelligence

Artificial intelligence (AI) is a technology that is utilized as a simulation of the human brain to solve complex problems (Paturi & Cheruku, 2021). The field of AI encompasses a wide array of sub-fields that span from general topics such as learning and perception to more specific applications such as playing chess, proving mathematical theorems, writing poetry, diagnosing diseases, and driving a car on a busy street. It is an all-encompassing field that has relevance to any intellectual task, making it truly universal (Russell, 2010).

Machine learning, a subset of artificial intelligence, enables machines to learn automatically from past data without explicit programming. The capacity to replicate human intelligence and comprehend every aspect of a given problem through experience makes machine learning an essential process in the field of artificial intelligence (Paturi & Cheruku, 2021; Pham & Afify, 2005). Machine learning offer significant potential to transform the manufacturing industry through the use of increasingly available and user-friendly software tools (Wuest et al., 2016).

The integration of artificial intelligence has enabled more efficient utilization of robots and minimized human intervention in hazardous environments. Additionally, AI facilitates improved maintenance of production lines and early detection of machinery or product malfunctions. AI-based systems possess the ability to autonomously make decisions, optimize processes, automatically respond to production schedule changes and machine malfunctions, replace machine components, and raise alarms for unmanageable situations (Lee et al., 2018). By analyzing real-time data, the inclusion of artificial intelligence algorithms in dynamic optimization can enhance the operational efficiency of the system (Liu et al., 2021).

2.1.2 Advantages and challenges

The advantages of machine learning (ML) in manufacturing have been established, such as its ability to handle huge amounts of complex data. It can also extract implicit relationships within large data sets in a complex and dynamic environment. Machine learning can allow artificial intelligence models to reducing cycle time and scrap, improving resource utilization, and continuous quality improvement. It also offers powerful tools for handling high dimensional problems and data. Additionally, these models can discover formerly unknown knowledge and identify implicit relationships in data sets, and provide the opportunity to learn from dynamic systems and adapt to changing environments automatically (Wuest et al., 2016).

The use of AI applications can aid in production planning by forecasting future demands and configuring production lines that are optimally designed (Waltersmann et al., 2021). It can also help companies with processing sensor data, and the potential to get information from the unstructured data that remains unsolved (Ansari et al., 2021). It can be used to derive patterns from existing data sets and support decision-making, and its goal is to detect patterns or regularities that describe relations (Wuest et al., 2016).

Machine learning requires vast amounts of data to be able to achieve proper learning, and acquisition of this relevant data is a common challenge (Peres et al., 2020). The availability, quality, and composition of data can greatly influence the performance of the ML algorithms (Wuest et al., 2016). It is preferable if the training data is mostly labeled so that the algorithm knows how to categorize it (Peres et al., 2020). High-dimensional data, which may contain irrelevant and redundant information, can also impact performance and therefore pre-processing is sometimes necessary (Wuest et al., 2016).

Missing values in the data can present a challenge for the application of ML algorithms (Wuest et al., 2016). Choosing the right ML technique and algorithm is also a major challenge, as there are many specialized algorithms available and the use of hybrid approaches is becoming more common. This makes it difficult to make a neutral and unbiased assessment of results (Wuest et al., 2016). In practical tasks, attributes may not contain all the necessary information to determine the class of an example, and errors or missing values can limit the achievable accuracy of the learning algorithm (Pham & Afify, 2005).

2.1.3 Success factors for implementation

Stakeholder support, such as from end-users, maintenance, works council, management, and human resources, is vital for implementing AI successfully. It is also critical to have AI competencies and a basic understanding of AI in related departments. At the organizational level, fast development cycles are essential for success. This means putting the AI service into production as soon as possible to improve product quality and stability. It also helps to demonstrate the product's value early on and gain stakeholder support (Kutz et al., 2022).

Technology acceptance is a significant challenge for developing, implementing, and operating AI services. Employees can feel threatened by AI technologies and fear losing their jobs. The collaboration between IT and manufacturing is also challenging and getting access to manufacturing staff is perceived as difficult. Another challenge is the unclear roles and responsibilities that come with introducing new technology into a company (Kutz et al., 2022).

2.2 Industry 4.0

The foundation for utilizing AI in factories is being established by Industry 4.0 (Sahoo & Lo, 2022). The manufacturing industry is currently facing an unprecedented increase in available data, including sensor data, environmental data, and machine tool parameters (Wuest et al., 2016). This phenomenon has been referred to as Industry 4.0, Smart Manufacturing, or Smart Factory (Wuest et al., 2016).

Industry 4.0 was first introduced by Siemens in 2011 (Turconi et al., 2022). This is the latest evolution of industry manufacturing after the beginning of the the first industrial revolution (Turconi et al., 2022). In today's world where the global landscape continuously changes, companies need to adapt to shorter delivery dates, increasing product variability, and high market volatility (Wiendahl et al., 2007). Implementing AI could be a solution for some of these challenges, by adding digital information and communication technologies into production systems (Helmold, 2020).

The main objective of a smart factory system is to continuously share information about stock, problems, and failures in the production line, to improve efficiency and optimize time, product quality, consumption, and development (Turconi et al., 2022). Therefore, smart networks are developed, i.e., intelligent networks based on machines interacting with products and users along the whole value chain; this is the basis of the Smart Factory (Turconi et al., 2022). To be able to operate Industry 4.0 it is a necessity that Big Data Analytic, Internet of Things, and cloud computing are in place (Sahoo & Lo, 2022). Furthermore, human resources that can manage to operate this complex system in Industry 4.0 will be decisive (Jerman et al., 2020).

2.2.1 Big data analytic

To be effective, AI requires large amounts of data to learn from. This is where big data analytic comes in. Big data analytic refers to the process of examining large and complex data sets to uncover hidden patterns, unknown correlations, and other useful information (Demigha, 2020). Big data encompasses data that cannot be effectively processed using traditional applications due to the inherent challenges of capturing, storing, transferring, querying, and updating such vast quantities of data (Demigha, 2020). By analyzing vast amounts of data, companies can gain insights into customer behavior, market trends, and other important factors that can inform decision-making (Demigha, 2020). The need for big data analytic arises from the limitations of traditional data warehouses and relational databases, which struggle to handle the overwhelming influx of unstructured data that characterizes the modern world (Demigha, 2020). It is noteworthy to mention that the advancement of big data technology relies on artificial intelligence, as it incorporates various theories and methods of artificial intelligence in its implementation (Demigha, 2020). The relationship between AI and Big data has evolved into a continuous, cyclical process. They are now permanently interconnected, and their combined utilization is expected to expand significantly in the years to come (Demigha, 2020).

2.2.2 Cloud computing

The primary objective of cloud computing is to ensure the availability of storage and computing capacity that AI relies on to operate effectively (Turconi et al., 2022). This integration enables the simultaneous execution of different computational steps across multiple computers connected to the same network (Turconi et al., 2022). Such distributed processing is essential since a single computer cannot handle the vast amounts of data involved (Turconi et al., 2022). Additionally, investing in a large number of individual computers is not competitive when compared to the flexibility offered by a robust cloud computing system (Turconi et al., 2022).

AI applications heavily rely on large volumes of data, and cloud computing provides secure and scalable storage solutions to meet this requirement (Turconi et al., 2022). By leveraging cloud computing resources, organizations can securely store and access the extensive datasets needed for AI algorithms and models (Turconi et al., 2022). The flexibility and scalability of cloud computing make it an ideal solution to handle the computational demands of AI applications, enabling efficient and effective data analysis and decision-making processes (Turconi et al., 2022).

2.2.3 Internet Of Things

The correlation between big data analytic and cloud computing is a crucial aspect of Industry 4.0 (Turconi et al., 2022). This interconnection relies on the widespread adoption of sensors and network technology, commonly known as the Internet of Things (IoT) (Turconi et al., 2022). These embedded sensors and software play a vital role in gathering and analyzing information across systems. Additionally, sensors and chips can be integrated into manufacturing assemblies to collect and process data pertaining to production processes (Turconi et al., 2022).

One of the notable advantages of IoT is its ability to operate on multiple levels (Turconi et al., 2022). It can simultaneously receive and transmit real-time data while also gathering aggregated data derived from processing and analysis. This capability provides valuable information that is essential for industrial infrastructure and facilitates the seamless integration of all stages within the production chain (Turconi et al., 2022).

2.2.4 Skill Requirement

The path toward implementing a smart factory system remains unclear, as there is currently no agreement on the defining components and their attributes that would facilitate the design and implementation of such a system. The reason for the unclear path is because of the complexity to operate the system. However, the human element is one of the most challenging aspects for transforming into a smart factory (Jerman et al., 2020).

The labor between humans, robots, and other high-tech work increases the complexity, which means the future workforce must be able to manage a higher level of complexity. For that reason, there will be an increased need for cross functional work (Bonekamp & Sure, 2015). It is advisable for organizations to thoroughly assess the proficiency and abilities of their current workforce, particularly in the realm of digital skills, and consistently foster the development of new competencies among their staff (Hecklau et al., 2016).

AI is expected to replace many human-executed tasks across various enterprises. Initially, AI could take over service-related tasks, but as it evolves, it may also replace jobs that require analytical skills (Huang & Rust, 2018). However, as traditional manufacturing industries transition to smart factories, a new set of skills will be necessary. A case study on a Slovenian automaker found that smart factories require individuals with expertise in programming, mechatronics, robotics, data analysis, internet of things, design, maintenance of smart systems, process analysis, and bionics (Jerman et al., 2020).

2.3 AI in manufacturing

The implementation of novel technologies in smart factories has led to various enhancements, and with the necessary requirements in place, artificial intelligence has the potential to revolutionize the entire factory ecosystem. In light of this, there exist numerous opportunities where AI can drive significant improvements for manufacturing companies.

2.3.1 Predictive maintenance

Today the industry is in most cases based on reactive maintenance, which means that the production line will only be maintained when an error occurs to the production line (Achouch et al., 2022). Reactive maintenance faces challenges like difficulties retaining skilled personnel, significant unplanned downtime, and increased costs (de Faria Jr et al., 2015). A preventive maintenance program is aimed at reducing the risk of failure and the number and duration of unscheduled shutdowns, thus reducing the likelihood of failure and extending the equipment's life (Levitt, 2003).

The practice of predictive maintenance (PdM) relies on the collection of pertinent time-series data throughout the operational lifespan of a machine. This data is then analyzed to monitor and track the condition of the underlying infrastructure. The goal of this approach is to identify patterns that can be used to forecast potential failures and take proactive maintenance measures to prevent them. By implementing efficient maintenance practices, businesses can reduce material and energy waste caused by tool and machine wear and tear, while also limiting the replacement of components only when necessary (T.-C. T. Chen & Wang, n.d.; Hafeez et al., 2021; Waltersmann et al., 2021).

Performing predictive maintenance can reduce machine downtime, costs, control, and quality problems (Zonta et al., 2020). Predictive Maintenance uses past data, models, and industry expertise to predict potential equipment failures. It uses statistical or machine learning methods to analyze trends, patterns, and relationships to make maintenance decisions before failures occur and minimize downtime (Lee et al., 2006; Sezer et al., 2018). Maintenance has become crucial for industries as the connections between production processes in complex manufacturing ecosystems have become more complex (Sezer et al., 2018). The Internet of Things, enhances the Predictive Maintenance process. It integrates the IoT with Machine Learning and Big Data Analytic to create a more efficient system for data management (Sezer et al., 2018). It is estimated that maintenance costs represent 15-60% of the total cost of operating all manufacturing facilities (Haarman et al., 2017). With PdM, scheduling actions can be generated based on equipment performance or conditions over time, which makes sense for the industry's future (Wu et al., 2016). Predictive maintenance can only be achieved effectively if the manufacturing process has enough data collected from all parts (Kiangala & Wang, 2018).

2.3.2 Quality control

Today's industry relies a lot on manual inspection. The problem with manual inspection is that it is subject to various factors such as work conditions, operator perception, and performance, which can be affected by fatigue, stress, and motivation levels (Teng et al., 2019). Additionally, visual-based control by a human operator is a subjective method and can be time-consuming, which may not always yield satisfactory corrective results (Chouchene et al., 2020). The use of AI in the industry has brought quality control in the production line, led by the development of computer vision systems that enable the inspection of products. This technology plays a crucial role in ensuring the quality of products as visual detection is a critical aspect of the manufacturing process (Vergara-Villegas et al., 2014).

Machine-based vision systems can identify materials and parts, sort and organize them before assembly, and assist in intelligent manufacturing by accurately identifying mating points or machinery load points. Additionally, these systems can verify that proper assembly has been achieved (Chouchene et al., 2020). Implementing AI-based quality control measures can result in a reduction in assessment time and greater consistency in detecting defects, allowing human resources to be utilized only when necessary. By applying AI to visual inspection processes, organizations can enhance their overall throughput and performance (Chouchene et al., 2020).

There are currently AI-based methods available for detecting defects in the industry. These methods utilize radiography and ultrasonic techniques to examine the specimen's internal structure and integrity (Vishal et al., 2019). In the era of Industry 4.0, advancements in technology have enabled us to envision an assembly domain where quality issues can be identified at an early stage and with greater accuracy. With the help of technology, even the smallest defects, imperceptible to human senses, can now be quickly detected (Chouchene et al., 2020). Visual Machine Inspection is a process of analyzing items on the production line to ensure quality control at regular intervals. Studies have shown that visual machine inspection often reveals previously undetected defects during the production process (Khan, 2021).

2.3.3 Decision-making

In the era of information, decision makers have access to vast amounts of data. Big data refers to data that are not only large in size but also diverse in nature and rapidly changing in velocity, making them challenging for humans to manage using conventional tools and techniques (Elgendy & Elragal, 2014). Empowering the manufacturing sector with autonomous decision-making capabilities is the primary characteristic of the fourth industrial revolution (Sahoo & Lo, 2022). In 2012, General Electric introduced the concept, proposing that the future of manufacturing is reliant on incorporating intelligent equipment, production systems, and decision-making (Evans & Annunziata, 2012).

Machines collaborate by integrating the IoT into the manufacturing system, enabling them to share real-time information. The corresponding system algorithms facilitate informed decision-making throughout the manufacturing process (Sahoo & Lo, 2022). Smart manufacturing is notably impacted by big data analytic, which entails the gathering and examination of extensive data from production units, customer feedback, and product request systems, enabling real-time decision-making (Phuyal et al., 2020). Big data analytic will also hasten the extraction of pertinent information and knowledge from a vast volume of production data, providing support for targeted decision-making (Sahoo & Lo, 2022).

Systems powered by AI possess the ability to make autonomous decisions, self-optimize, automatically respond to production schedule changes and equipment malfunctions, replace machine components automatically, and generate alerts for uncontrollable situations (Lee et al., 2018). Furthermore, AI can make systems manage effortlessly operational processes and make vital decisions concerning factors like security, safety, and productivity efficiency (Sahoo & Lo, 2022). A manufacturing system controlled by deep learning can learn autonomously from vast amounts of data, recognize patterns, and make decisions by extracting knowledge (Sahoo & Lo, 2022). By embracing this framework, enterprises will be propelled towards establishing a culture of data-driven AI decision-making (Sahoo & Lo, 2022).

2.3.4 Sustainability

According to a survey presented by Chui et al. (2022), numerous organizations that have implemented AI are incorporating AI functionalities into their sustainability initiatives, and they are proactively looking for ways to reduce the environmental impact of their AI usage (Chui et al., 2022). Of the participants representing organizations that have embraced AI, 43% assert that their companies are utilizing AI to support their sustainability objectives, while 40% are striving to diminish the environmental impact of their AI utilization by minimizing the energy required to operate and train AI models (Chui et al., 2022). It is indisputable that the manufacturing industry plays a substantial role in global energy consumption, accounting for as much as 50% of the overall usage (Sahoo & Lo, 2022). The majority of waste generated is attributable to substandard products and unused raw materials in the production process. The International Energy Agency reports that energy demands are on the rise (Sahoo & Lo, 2022).

Artificial Intelligence in the production line has the potential to address problems like minimizing the excessive utilization of materials that are environmentally harmful when discarded, streamlining the generation of scrap waste, and rectifying the uneven allocation of energy resources in logistics (Sahoo & Lo, 2022). Employing robots trained by ML enables better precision execution of tasks, resulting in reduced energy consumption. AI, when utilized effectively, aids in identifying quality concerns with products and optimizing inventory levels and resource utilization in the production line (Sahoo & Lo, 2022). Consequently, if manufacturers utilize AI to manufacture top-quality products, the production of manufacturing waste will automatically decrease (Sahoo & Lo, 2022).

2.4 Lean

The following paragraphs present lean philosophies and tools that the authors recognize as important for finding a correlation between AI and Lean.

2.4.1 Lean 4.0

The traditional lean manufacturing philosophy should be used in production to reduce the losses related to people, inventory, time to market, and production space, to obtain a highly reactive demand for customer needs, while producing high-quality products efficiently and cost-effectively (Pavnaskar et al., 2003). By applying different types of lean tools organizations have been able to achieve significant cost and quality advantages, compared to for that continue using traditional manufacturing methods (Turconi et al., 2022). However, it appears that the current methods of value creation are no longer appropriate for meeting the demands of adaptability, productivity, and product customization (Perico & Mattioli, 2020).

One of the fundamental principles in establishing a Lean 4.0 setting is the interconnection of systems and individuals to form smart networks throughout the value chain. Perico and Mattioli (2020) defines Lean 4.0 as an insight into the integration between Lean and Industry 4.0 for manufacturing companies. It is mentioned that AI is the key enabler between them. This is because of enhances the background to streamline the entire process, makes the most current information readily accessible, and supports complex problem solving (Perico & Mattioli, 2020). More specifically it can design a better product that fulfills customer needs and requirements and that improves global production quality. Furthermore, advancing predictive market trending through forecasting analysis to identify what are the relevant manufacturing technologies to meet current or future customer needs (Perico & Mattioli, 2020).

2.4.2 Kaizen

Kaizen is a word combined from two concepts: Kai (change) and Zen (for the better) (Palmer, 2001). However, Kaizen is most likely to be recognized as the Japanese word that means "improvement", and it is often referred to continuous improvement in performance, cost, and quality (Brunet & New, 2003; Singh & Singh, 2009).

It is currently necessary for most manufacturing industries to respond rapidly to changing customer demands. To maintain market share in this global market, industries must continuously improve their manufacturing system processes (Singh & Singh, 2009). To solve these problems the various manufacturing industries need to increase productivity, organizational potential, and incremental improvements by using Kaizen (Singh & Singh, 2009). The potential benefits of Kaizen to industry share several similarities with the advantages highlighted by Sahoo and Lo (2022) of the capabilities of a smart factory.

2.4.3 Lean Six Sigma

Lean Six Sigma is an data driven improvement methodology that improves process performance, leading to better customer satisfaction and bottom-line results and increased shareholder value (Albliwi et al., 2014; Anvari et al., 2020; Laureani & Antony, 2012). It combines the Lean and Six Sigma methodologies, and it has been deployed successfully in many large Western organizations and small- and medium-sized manufacturing and service industries (Albliwi et al., 2014; Laureani & Antony, 2012). Anvari et al. (2020) expresses that Lean six sigma and industry 4.0 mutually benefits from each other.

Lean is a process improvement methodology used to deliver products and services better, faster, and at a lower cost, while Six Sigma is a data-driven improvement methodology that uses statistical analysis to achieve stable and predictable process results by reducing process variation and defects. Lean Six Sigma uses tools from both methodologies to increase speed and accuracy and enhance customer satisfaction and improved bottom-line results. (Laureani & Antony, 2012). However, poor implementation of lean six sigma can render it ineffective, and not all organizations can benefit from it (Albliwi et al., 2014).

The successful implementation of Lean Six Sigma in an organization depends largely on the support and commitment of the management team. This has been confirmed by (Albliwi et al., 2014; Laureani & Antony, 2012). Other critical success factors include having the right organizational culture, linking lean six sigma to business strategy, and having enough resources, and leadership styles to be important (Albliwi et al., 2014; Laureani & Antony, 2012). Lack of management support and resources is a major obstacle to lean six sigma's success in many organizations. Despite these challenges, it is believed that Lean Six Sigma will become a leading quality improvement program in the coming years (Albliwi et al., 2014; Laureani & Antony, 2012).

2.4.4 Overall Equipment Effectiveness

If an organization aims to track and assess its manufacturing progress, as well as identify and address any issues, implementing Overall Equipment Effectiveness (OEE) can prove to be a valuable tool within the framework of lean methodologies (Fleischer et al., 2006). Due to its potential efficacy in assessing manufacturing progress and identifying problems, OEE was selected as the metric of choice in a six-month experimental initiative aimed at monitoring the impact of implementing AI within a candy packaging production line. The OEE improved from 0,42 to 0,82 using this new AI manufacturing system (B. Chen et al., 2017).

Overall equipment effectiveness is a way of measuring types of production losses and identifying areas for improvement (Akter et al., 2016; White, 2012). Most manufacturing industries have adopted overall equipment efficiency as a key performance indicator since it considers three key indicators: availability, quality, and performance (Bonada et al., 2020). Using the equipment effectively is a measure of the overall effectiveness of the equipment (Bonada et al., 2020). There are three key indicators when talking about OEE as a KPI measurement for the manufacturing industry. OEE is also used as a measurement for lean six sigma (Gibbons & Burgess, 2010).

- Availability, percentage of time that equipment can operate (Bonada et al., 2020).
- Quality, percentage of good produced parts (Bonada et al., 2020).
- Performance, percentage of maximum operation speed used (Bonada et al., 2020).

Any occurrences that makes the production line stop are recognized as an availability loss. To achieve 100% in availability the process needs to be operating exactly as the production line is scheduled (Bonada et al., 2020). To get an OEE score of 100% all products need to be produced perfectly, and without any stoppages time (Al Hazza et al., 2021). An OEE score of 85% is recognized as a word class manufacturer. 85% is a benchmark level where most companies should have a suitable goal to archive (Al Hazza et al., 2021). Generally, an OEE score of 85% or above is considered a good score, indicating high levels of efficiency and productivity. Scores below 60% may be considered poor and could suggest that improvements are needed in the manufacturing process (Al Hazza et al., 2021). An OEE score of 40% OEE is considered a very low score. Companies that produce at these levels are looked at as start-up manufacturers with the aim to improve the production line (Al Hazza et al., 2021).

2.4.5 Cycle time

By reducing the cycle time required to manufacture a product, several benefits can be achieved. Firstly, faster deliveries to customers can be made, which enables the provision of more accurate due dates and increases the likelihood of securing orders (Chang et al., 2001). Secondly, reducing cycle times for all products can lower the level of work-in-process in the factory, leading to a more manageable working environment (Little, 2011). Thirdly, shorter cycle times allow the factory to be more responsive to emergency orders. Finally, reducing cycle times can decrease the variability of processing times and product quality issues encountered during production. As a result, shortening the cycle time of a product is a key objective for any manufacturing system, particularly lean manufacturing systems, and there are various methods to achieve this goal (T.-C. T. Chen & Wang, n.d.).

Job scheduling optimization, mathematical programming models, pull production, and lot sizing are among the most common methods to achieve lower cycle times. AI technologies can help in estimating job times and clustering jobs. Mathematical programming models can be used to schedule jobs, and evolutionary computing methods can be applied to search for optimal solutions. Pull production and lot sizing are also popular methods to reduce cycle times, with AI techniques used to determine optimal job sizes (T.-C. T. Chen & Wang, n.d.).

2.5 Summary

Table 2.1. *Summary of the theoretical background*

Topic	Findings	Main sources	Relevance
Artificial intelligence and machine learning	1. Machine learning can offer several benefits in manufacturing, including the ability to handle complex data, reduce cycle time, and improve quality, but it requires vast amounts of relevant data. 2. For successful AI implementation, organizations need stakeholder support, competencies, and fast development cycles, and must address challenges like technology acceptance, employee fear, collaboration, and unclear roles.	Paturi and Cheruku (2021) Wuest et al. (2016) Kutz et al. (2022)	Basic foundation of artificial intelligence and machine learning
Industry 4.0	1. Big Data Analytic is a process of examining large and complex data sets to uncover hidden patterns and correlations to inform decision-making. 2. Cloud computing provides scalable computing capacity and enables simultaneous execution of computational steps across networked computers. 3. Internet of Things enabled by sensors and network technology, allows for real-time data collection, analysis, and aggregation across multiple platforms.	Demigha (2020) Turconi et al. (2022)	Getting the full potential from artificial intelligence in manufacturing
AI in the industry	1. Predictive maintenance uses data analysis to monitor machine condition and forecast failures 2. AI-based quality control enables automated and efficient quality control and reduces manual inspection, enhancing defect detection accuracy. 3. AI can be used for efficient production planning by utilizing forecasting, optimization, and analysis techniques to enhance production line configuration, classify production methods, and leverage untapped data for automated processes in manufacturing.	Sezer et al. (2018) Zonta et al. (2020) Chouchene et al. (2020) Waltersmann et al. (2021) Sahoo and Lo (2022)	Appliance of AI in manufacturing

	4. AI can be used to support sustainability objectives, reducing environmental impact by addressing manufacturing waste through precision execution, quality identification, and optimized resource utilization.	Chui et al. (2022) Sahoo and Lo (2022)	Appliance of AI in manufacturing
Lean principles	1. The integration of Lean principles with Industry 4.0, known as Lean 4.0, leverages AI as a key enabler to streamline processes, improve product design and quality, and facilitate predictive market analysis for meeting customer needs in manufacturing companies. 2. Kaizen, the concept of continuous improvement, enhances efficiency, productivity, competitiveness and improve manufacturing processes. 3. Lean Six Sigma is a data-driven improvement methodology that combines Lean and Six Sigma approaches to enhance process performance, customer satisfaction, and bottom-line results; successful implementation relies on factors like management support, organizational culture, and resource availability.	Perico and Mattioli (2020) Singh and Singh (2009) Sahoo and Lo (2022)	Correlation between AI and lean and what AI can improve
Lean metrics	1. Overall Equipment Effectiveness is a performance measurement tool that helps manufacturers track and assess their production progress, identify areas for improvement, and maximize equipment efficiency within the framework of lean methodologies. 2. Reducing cycle times in manufacturing systems, through methods such as job scheduling optimization, pull production, and lot sizing aided by AI technologies, brings benefits such as faster deliveries, reduced work-in-process, improved responsiveness, and decreased variability and quality issues.	Fleischer et al. (2006) Bonada et al. (2020) Chang et al. (2001) Little (2011)	Metrics artificial intelligence can improve and use to recognize further improvements in manufacturing

Chapter 3

Methodology

This chapter aims to present the methodological approaches made during the research period, including research design, methods and procedures followed during the interviews.

3.1 Research design

Before the study was conducted, determining a research design that is suitable in relation to the research question is important (Johannessen et al., 2010). A research design can be described as a sequence or a model that describes the steps that get us from the question to the answer (Yin, 2018), and is described further down this chapter from the lights of Cassell and Symon (2004).

3.1.1 Choice of method

Multiple techniques can be used to gather data for answering a problem statement. Therefore, it is important for the choices that are made are justified based on what the problem statement is looking to answer. The two main methods are qualitative and quantitative research, although a combination could prove to use fully in some instances (Busch, 2013; Krumsvik, 2014).

Qualitative methods is an inductive approach that aims to capture opinions and experiences from a small, but detailed sample. It can therefore be difficult to quantify. This method is therefore best suited for when the cause of a phenomenon or term is to be researched and when there is limited knowledge about it (Dalland, 2020). An advantage of the qualitative method is that it allows for flexibility and can present answers to a problem accurately, representing the real world. It can therefore provide an opportunity to make new discoveries and adaptations. If new information emerged during an interview, it is possible to take a closer look at it than previously planned and adapts the theory as data was collected (Busch, 2013). From this, new perspectives and results will emerge for the company that can be useful for further development of the thesis (Cassell & Symon, 2004). A downside is that it can be resource-intensive, collect a large amount of information that can be complex, and difficult to draw generalized conclusions from (Dalland, 2020).

Quantitative methods are deductive and provide measurable findings and are suitable for examining a known phenomenon with a clear problem statement (Johannessen et al., 2010). The advantage of quantitative methods is that they benefit from standardizing and structuring information, making it easier to process and generalize the results (Dalland, 2020). Quantitative methods can also be used as a verification method, where the theory could easily be confirmed or disproved through the data collected (Cassell & Symon, 2004). It can, however, lack nuances in that the data and the examiner may decide on relevant factors before the examination starts. Quantitative methods are also more rigid and provide less room for flexibility compared to qualitative methods.

In this study, it was not only desirable to find out what effects AI has made, but also to what extent and in what situations it did make a difference. It was therefore a mixed-method research approach with a focus on both qualitative and quantitative methods that was seen as most eligible for conducting this study, to best achieve the desired results (Yin, 2018). A qualitative method was used to examine the in-depth implementation of AI in Lean management at Henning Olsen. Meanwhile, quantitative data was collected from Hennig Olsen's digital archives and used to see what impact their technology already had made.

The approach followed during this research was to first find out to which extent Henning Olsen had implemented AI tools that contributed to continuous improvement of their production to date. This meant to get an overview of today's use of the technology, and how they used it. Then an analysis of what and how it has made an impact on the production and products. This was done by looking at historical data provided by the company and visits to the factory to get an insight into what impact the technology had. Lastly, a study was done to see what could be improved or if more tools and processes could be improved using AI. An interview with the technical director provided insight into their process and views of the future.

3.1.2 Case study

Yin (2018) explains that a case study looks at a phenomenon that is currently occurring in the real world. Cassell and Symon (2004) explains case studies as a way of doing research where you look closely at a real-life situation in a group or organization, and try to understand how it works by collecting information. This thesis employs a single case study as outlined by both Cassell and Symon (2004) and Yin (2018). Since this thesis examines a single example of a class of phenomenon, the findings might not apply to the broader classes. A case study is useful when the research question requires the exploitation of a phenomenon (Yin, 2018). The factory in question is an ice cream factory, which is a niche and specific industry. And thus a single case study of this factory was chosen, because of the lack of similar factories available which might produce different results and could not be comparable.

From Cassell and Symon (2004) a case study starts with choosing the organization, which in this case was done from our interest, what was available, and what was nearby. The next step is about gaining and maintaining access to the organization and key persons. After the organization was known there was developed a theoretical framework based on what thought to be relevant for the thesis, the framework was evolved as more information was gained to better suit linking the case study to the wider literature (Cassell & Symon, 2004). Further, one should obtain a general overview of the organization through orientation and observation which makes it easier to plan the study and make guides to conduct the interviews (Cassell & Symon, 2004).

When it is time to collect the data, it is important to make a plan and prepare for how to go through with the collection. The data collected has then to be analyzed, examined, and connected to the theoretical framework. The findings must also be verified by the participants to ensure they are correct (Cassell & Symon, 2004). When enough data has been collected and analyzed, the results are to be discussed to understand the phenomenon studied. This is done by generalizing with other studies and literature and connecting it to this study (Cassell & Symon, 2004)

3.2 Acquisition of literature

To obtain specific information about the topic and how Lean and AI have been used in other companies, articles from Google Scholar and Oria were used. There can be an overwhelming amount of articles and information presented on these sites, so using effective keywords and actively using filters was used (Busch, 2013), although it can be a challenge. One thing to determine what was regarded as credible sources was how the study was conducted. If the study had backed their claims through empirical trials it was also considered more credible (Yin, 2018). Other indications of which papers had more credibility were to look at their sources if it was peer-reviewed, and if the paper was cited by many others. Attempts were also made to have multiple sources to back a statement where possible to improve accuracy (Yin, 2018).

AI is a rapidly changing technology and advances all the time, so it was of high importance to have the latest papers to do the research. Also, the theme about kaizen and improvement is not a concrete theme, and contains many different opinions, so efforts were made to present the different perspectives on the same topics to provide insight from multiple dimensions (Busch, 2013).

3.3 Data collection

As previously stated, this study used both qualitative and quantitative methods to collect the data, also known as a triangulation method since multiple methods were used (Busch, 2013). Because parts of the study aimed to answer to what degree AI improved production, quantitative data was requested such as statistics, results, and statistical data (Busch, 2013). This was used to get an overview of how the development has been since implementing the measures.

3.3.1 Quantitative

Information was gathered through document analysis of Hennig Olsen's historical data from their database. Additionally, observations of the company's operations were conducted to gain a better understanding of the implementation of AI and its effects on continuous improvement. Hennig Olsen had stored a lot of valuable data which if analyze can be used to uncover causes of a phenomenon (Johannessen et al., 2010). The quantitative data were processed in Excel to visually represent them in a graph. This was done to make it easier to discuss how the development unfolded by referring to the graph. The theory that was previously obtained was used to find possible connections and explanations for why the graph looked like it did.

3.3.2 Interview

To complement the quantitative data, the technical manager of Hennig Olsen where interviewed to collect qualitative data. The individual, semi-structured interview stood for our primary source of data for this thesis and provided the necessary insights to perform this thesis. According to (Yin, 2018), interviews can provide valuable insights into attitudes, perceptions, explanations, and meanings, which was essential for understanding the impact AI and lean has had on the factory.

It was necessary to interview the technical manager because he was expected to have unique, holistic, and valuable insights into both the processes and technologies related to the operations and improvements of the factory. One could argue that interviewing more people would gain a broader perspective of how the situation at Hennig Olsen. An operator could have personal views and information of how their routines on the floor have changed, but at the same time would the technical director as they have weekly meetings with them about how their week has been. The operators would also most likely have limited knowledge of the technical and holistic aspects of what was going on in the production lines.

What was important in this thesis was to get an understanding of how AI can be used in lean, and what impact it has, which the operators most likely would not be able to answer. Focusing solely on the technical director in combination with historical data was therefore viewed as the best approach to get the understanding needed for this thesis. During the observation tour at the factory, the authors did get a view of how the working condition and tasks of the employees was. More interview objects would also be more time-consuming for the authors and expensive for Hennig Olsen, and would in return not bring useful additions to the findings.

The interview guide where developed with an introduction of general information (Johannessen et al., 2010). The guide was only used as a starting point so that together with follow-up questions should lead to a more open conversation with the interviewee (Cassell & Symon, 2004). The question was developed to avoid the respondent to lean towards a particular answer, but at the same time understandable enough. The interviewee was also given the interview guide in advance so the respondent could prepare before the interview, although it may have influenced their subjectivity. The guide is attached as appendices to this thesis.

The interview was conducted at the end of March 2023 on a video call. The video call provided a similar opportunity to face-to-face interviews, where the face- and body language and tone were still intact, which ended lasting for about 45 minutes. During the interview, it was important to ensure that the questions were formulated in such a way that the respondent stayed on topic, but could still speak freely and openly. Questions were as stated pre-prepared and follow-up questions were asked based on the subject's responses. The interviewee also got the opportunity to speak candidly about what he deemed important, without interference. After the interview, the technical manager did get some follow up questions through mail after the authors have had time to reflect over the data gathered from the interview.

When writing a thesis for UiA, it is mandatory to comply with the NSD guidelines for privacy. This means written consent has to be signed before their response can be used containing that the interview will be recorded, when the files and information will be deleted to mention some. To effectively record the interview, the Diktafon app was utilized which also stored the data according to regulations. Using Open AI's Whisper, the interview was transcribed, and a few corrections were made. This was done for the purpose of easier categorizing and connecting in a table with simplified data and sentences into categories and topics with the other data.

3.3.3 Observation

From Yin (2018), observations can provide useful additions of findings to the topic studied. For example, it can provide a great understanding of how new technology is being utilized in for example factories. Some of the data presented in this report was collected by the authors through their observations during a visit to the Hennig Olsen factory in Kristiansand in March 2023. During the approximately one-hour tour around the production facilities, the technical manager guided the authors and provided explanations of the steps in their processes, done both by artificial intelligence and human operators.

The goal was not to observe how employees performed, but rather learn how the production line works and the techniques, technologies, and steps applied in the process. This was done to make it easier for the authors to write this thesis when the production lines and methods have been observed in real life. It made it easier to decide what kind of theoretical material and method to use and how to shape the research question and thesis in general (Cassell & Symon, 2004). The observers were free to ask questions and form their own opinions on what could be improved in the production lines. Some of the observations were also the basis of some questions that were prepared for the interview.

3.4 Validity and reliability

Validity is how accurately a study measures what is intended and claims to measure (Busch, 2013; Yin, 2018). Reliability refers to the consistency and accuracy of the findings, to minimize errors and biases in the study. This is done by documenting the procedures in a study which makes for easy replication and getting consistent findings (Yin, 2018).

To ensure the validity and reliability of the study, several measures were taken. First, triangulation of data sources was used, with data being collected from multiple sources to ensure that the findings were representative of the overall phenomenon being studied. The quality of data collected during the interviews is dependent on factors such as the clarity of the questions. Open-ended questions were used to maintain objectivity and interview guides were prepared in advance to ensure validity (Johannessen et al., 2010). The interviewee also did get the chance to read through the translated transcript to ensure everything was correct and make corrections if needed which ensured validity

The limited number of interviews conducted and the potential bias of non-participation also weaken both validation and reliability in the fact that it would not be able to capture a diverse range of experiences and perspectives. This also increases the risk of capturing biased findings and not being able to generalize the findings to a broader specter of other similar research (Cassell & Symon, 2004). Respondents has also the tendency to tell the interviewers what he or she thinks they want to hear (Yin, 2018). A structured interview guide could make it easier to keep control of the findings and increase validity (Johannessen et al., 2010).

Henning Olsen provided historical data and evaluation sheets on results since the implementation of their AI tools, which were used to validate their implementation. However, it should be noted that documentation can be biased, and the numbers may have been skewed to present a favorable view of the employee's performance. Qualitative data alone can also quickly become speculation without any basis, and with quantitative data, one can be left with a phenomenon that cannot be explained. In that both Quantitative and qualitative data support each other can strengthen the validity and reliability (Johannessen et al., 2010).

Although lean and continuous improvement contains rules and guidelines on how a company should proceed to increase efficiency, it is primarily a philosophy. It is up to each company to adapt it to their production methods and culture. Because of this, it may be difficult to transfer the direct results from this study as it looks at how this specific company has done it. By the corpses companies with the same type of culture, it is conceivable that the overall results can be generalized as the characteristics of the companies that have made it happen seem to have similar features, such as the company in this case also had.

While touring the factory, high levels of noise were present, and as a precautionary measure, all personnel inside the production facilities were required to wear earplugs for noise protection. Consequently, some parts of the conversation between the consultants and the technical manager were difficult to hear and may have been misinterpreted. But to further increase the reliability, there were multiple observers attending the observation (Yin, 2018).

During the observation, there was no observation guide developed, that could provide for a more efficient and comprehensive tour that went more in-depth than the authors did receive and at the same time improve the reliability. With no observation guide, however, one could argue that the authors did observe the factory with a more open mind.

Even though Hennig Olsen was categorized as a critical business and operated as usual during the covid-19 pandemic, there also may be some variables in their historical data and improvement work that has been influenced due to stricter rules and regulations in the general community

Chapter 4

Results

The presented results in this study comprise a combination of quantitative, qualitative, and observation data all of which have been provided by Hennig Olsen.

4.1 Quantitative

4.1.1 OEE Results

Figure 4.1, 4.3 and 4.5 shows the OEE results from Spann 1 and 2 and Speedline from weeks 9 to 48 in 2022. The grey striped line on the graphs is the OEE goal that was mostly 96% for the Spann 1 lines with a few exceptions. Speedline has more variation on the OEE goal, since it produces a greater variety of different products, while Spann 2 only produces buckets of ice cream. The OEE results are based on availability, quality, and performance, which is shown in 4.2, 4.4 and 4.6. There is a lot of variety of the results that reasons for lack of, waiting on, and bad raw materials, chaining of thanks, products, and other unforeseen events with equipment, employees, and mixture.

Figure 4.1 shows that Hennig Olsen has set an OEE target between 90 and 100 %. However, as the graph shows, the total output never achieved reached the OEE goal.

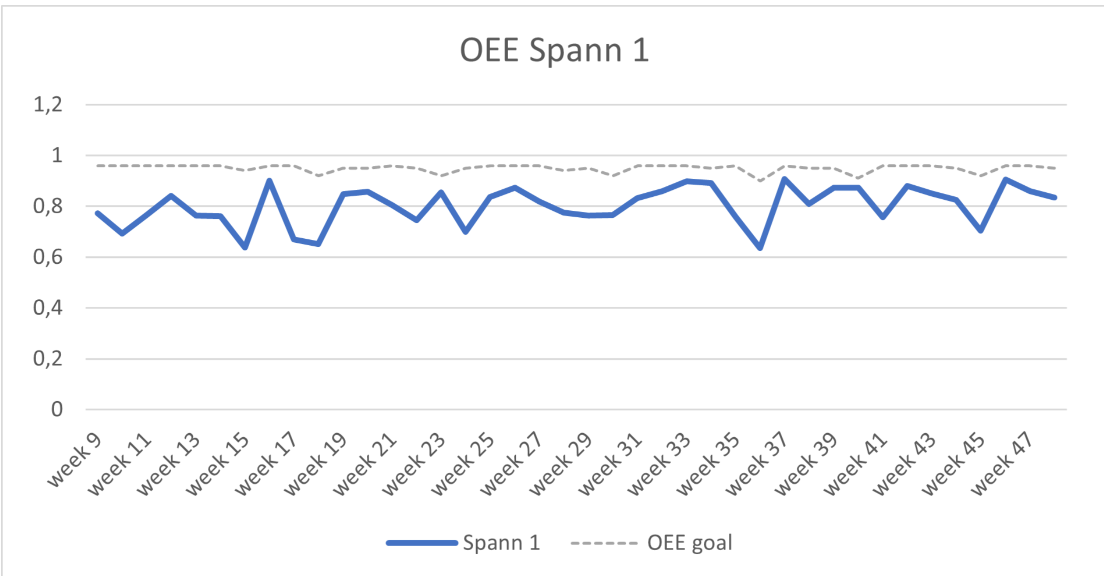

Figure 4.1. *OEE results of Spann 1 from 2022*

Figure 4.2 shows the key performance indicators used to calculate the OEE scores in Spann 1. The parameters show a relativity high output, but the performance factor stands out compared to the other two factors as it is more variable than the others because there was a lot of waiting on the mixtures. Quality and availability have been more or less the same during the time of this data collection.

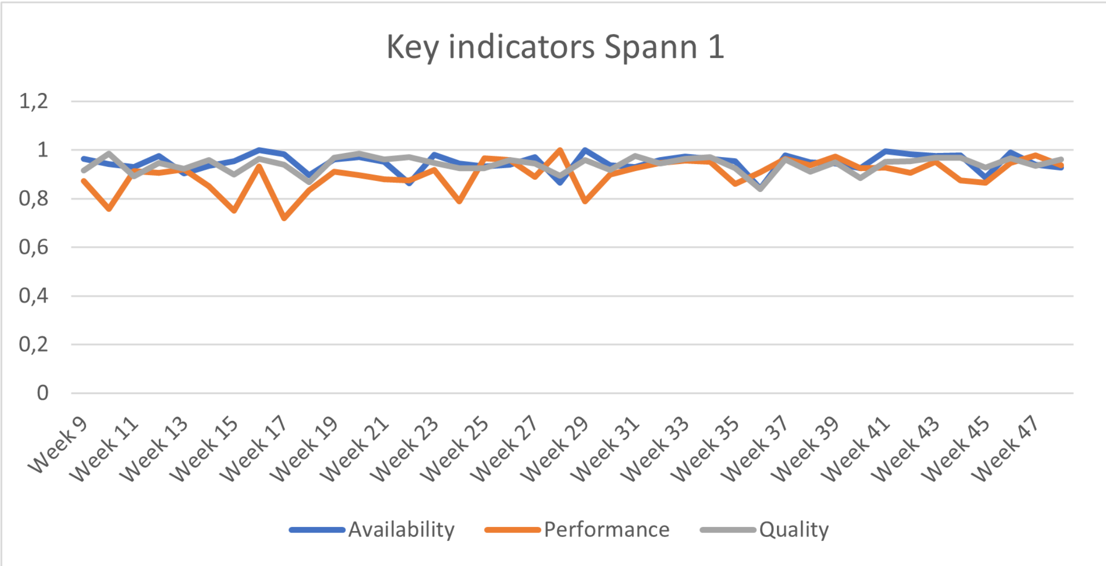

Figure 4.2. *The key indicators to Spann 1, used to calculate OEE for 2022*

Figure 4.3 varies a lot in the output. The lowest output was recorded below 60‘%. The highest data registered exceeded the OEE twice and were close to reaching output higher than the OEE goals multiple times.

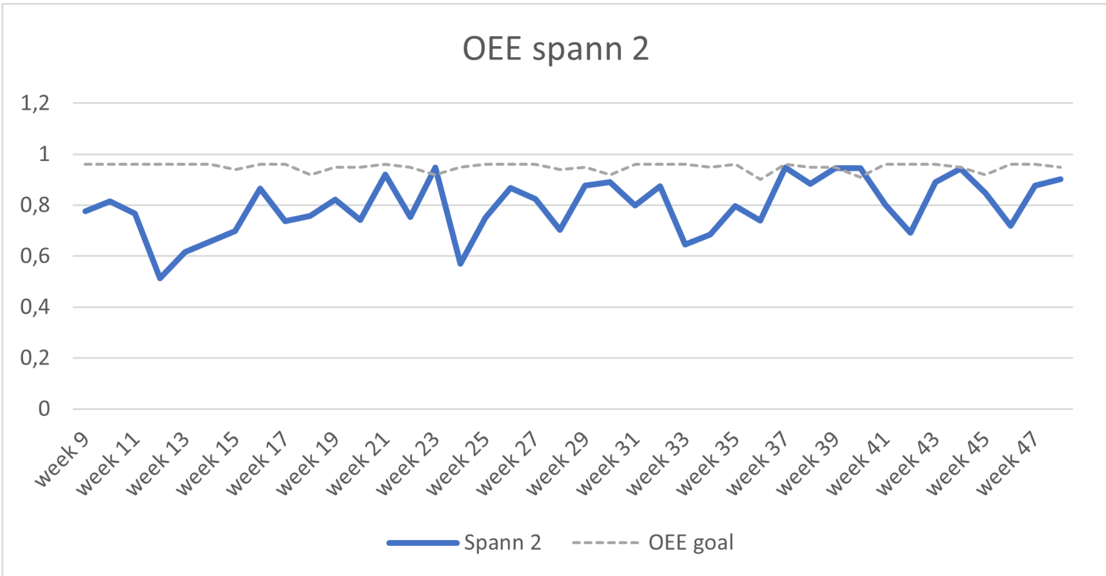

Figure 4.3. *OEE results of Spann 2 from 2022*

In this graph 4.4, performance is the factor that shows the lowest output and was the reason the OEE dropped to 60%. Especially between weeks 12-15 where there is a huge drop because of a lot of time used on waiting on mixtures. Quality and availability are more or less the same, apart from some minor exceptions.

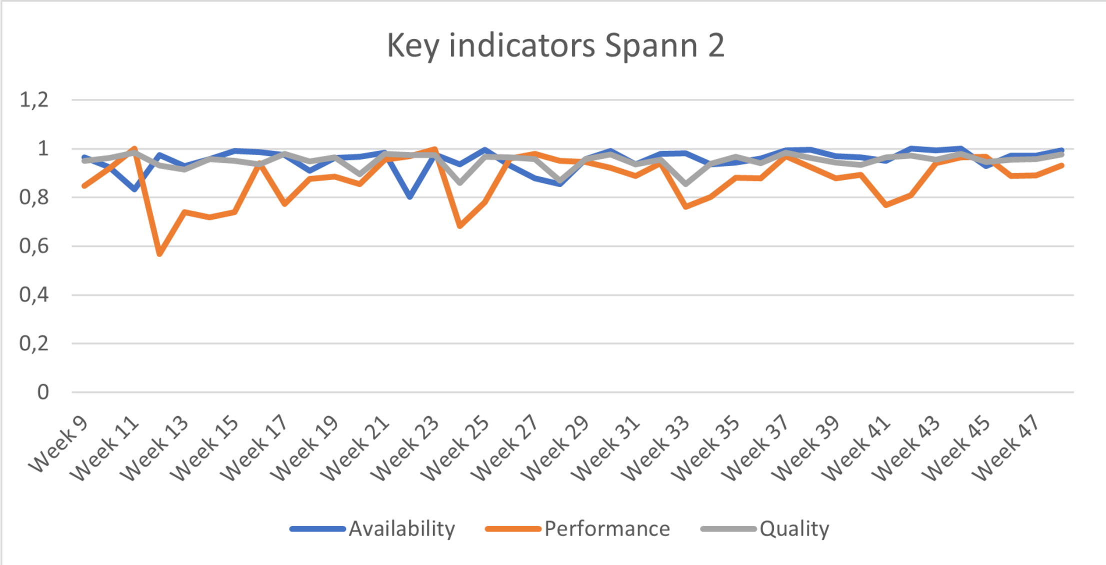

Figure 4.4. *The key indicators to Spann 2, used to calculate OEE for 2022*

Figure 4.5 demonstrates that Speedline's output fell below 60% on multiple occasions while achieving a higher level of OEE once. In 2022, Hennig Olsen's OEE data indicated 49 instances where the Speedline production line recorded a score below 60%, with 21 of these incidents being attributed to electrical or mechanical issues within the production line.

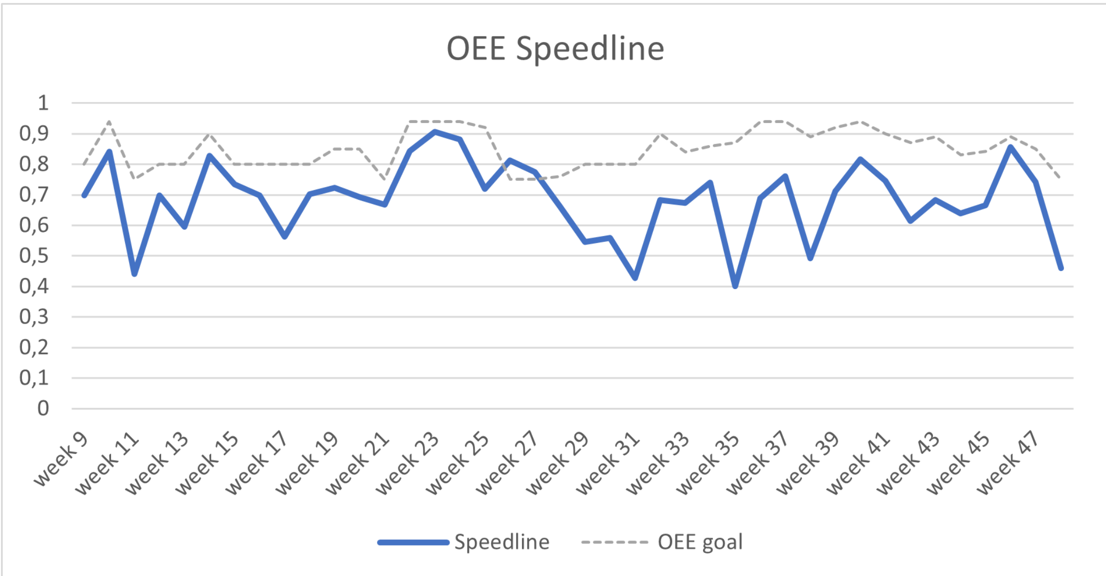

Figure 4.5. *OEE results of Speedline from 2022*

Figure 4.6 is the only graph where the availability factor is close to reaching 60 %. The quality output is close to following the same trend as availability. The performance rate is between 80-100%, except for a few incidents.

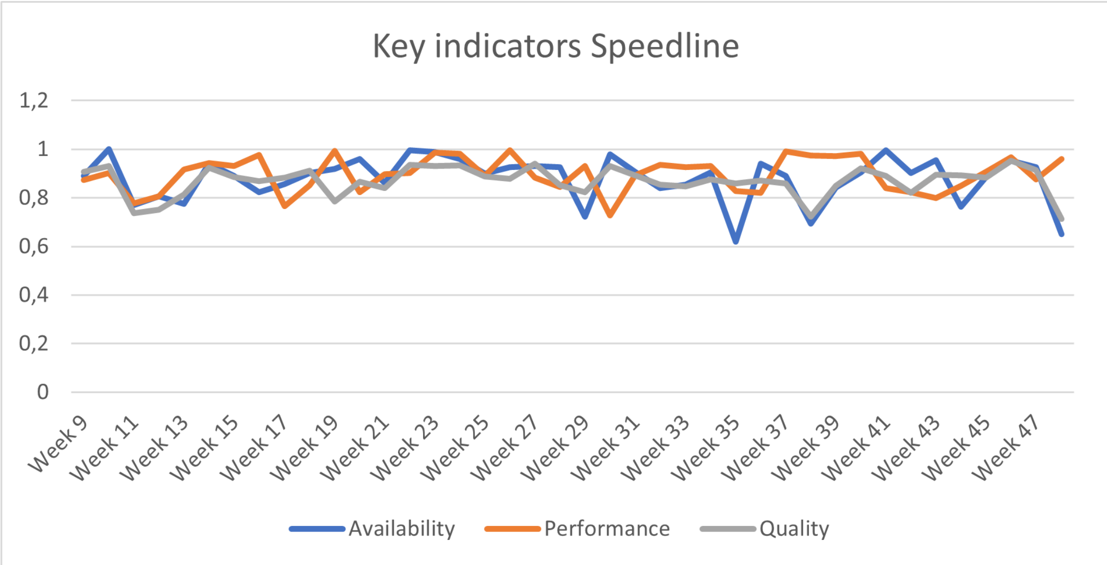

Figure 4.6. *The key indicators to Speedline, used to calculate OEE for 2022*

4.1.2 Downtime

There are a lot of variables that can cause problems in Hennig Olsen's production lines. It is mainly mechanical and electrical problems predictive maintenance can eliminate, and that is what these results show.

Figure 4.7 depicts that mechanical and electrical faults contribute to 10% and 4% of the total faults, respectively, amounting to a combined total of 14%. Hennig Olsen aims to address these downtime instances through the implementation of predictive maintenance practices. The remaining portion of the chart represents line stoppages caused by activities such as cleaning, changing mixtures and products, emergency stops, and scheduled maintenance, among others. The 14% of downtime resulting from mechanical and electrical faults corresponds to a total of 126,500 minutes, which is equivalent to 21 days of production per year. Implementing predictive maintenance has the potential to eliminate this 21-day production downtime and maximize operational efficiency.

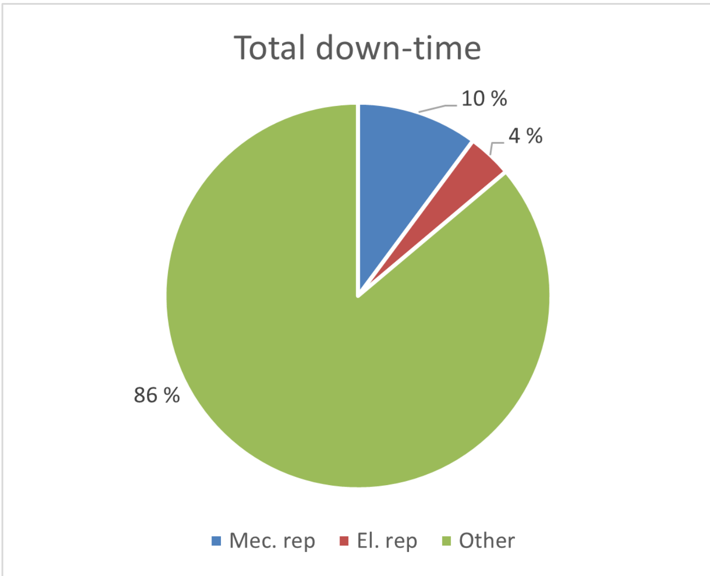

Figure 4.7. *The proportion of electrical and mechanical faults compared to other reasons their production lines have stopped.*

Below are the graphs illustrating the downtime in minutes caused by electrical and mechanical faults in different production lines at Hennig Olsen's factory. The X-axis represents the production lines, while the Y-axis displays the duration of downtime caused by either electrical or mechanical issues. The data presented in both graphs cover the interval between 2019 and 2022.

Figure 4.8 provides a visualization of the downtime resulting from electrical difficulties in different production lines. The Spiral production line demonstrates the least amount of stoppage time, with approximately 250 minutes, which can be attributed to its smaller ice cream production volume. In contrast, the Speedline production line experiences a significant amount of downtime due to electrical issues, accounting for nearly 12,000 minutes. This corresponds to over two full days of downtime within a year. The straightline production line follows with the second-highest downtime, exceeding 7,000 minutes.

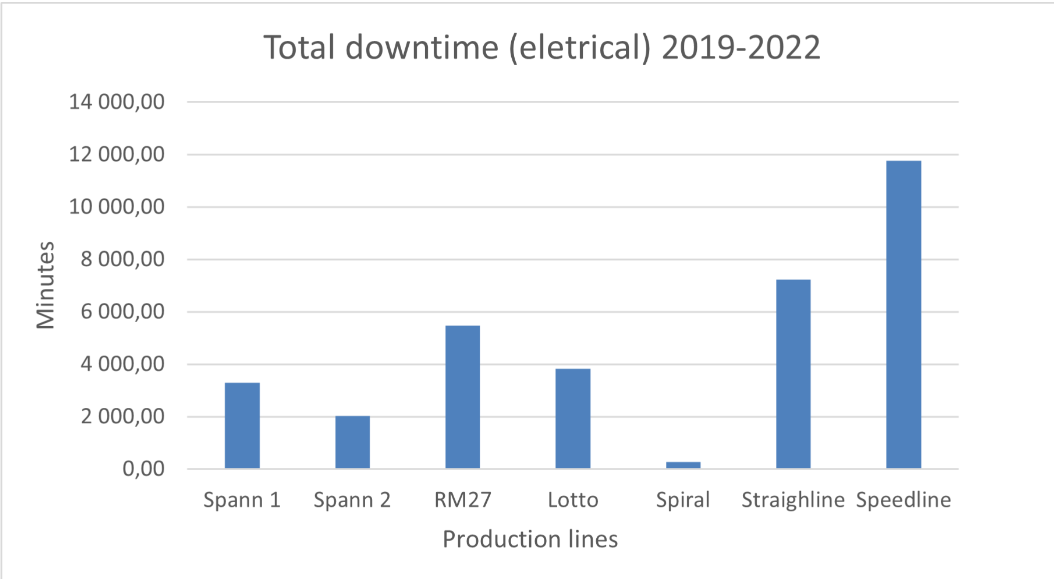

Figure 4.8. *Total downtime in minutes caused by electrical error*

Figure 4.9 provides insights into the average duration of downtime when the production line comes to a halt due to electrical issues. RM27 and Speedline exhibit the highest average downtime, surpassing 80 minutes.

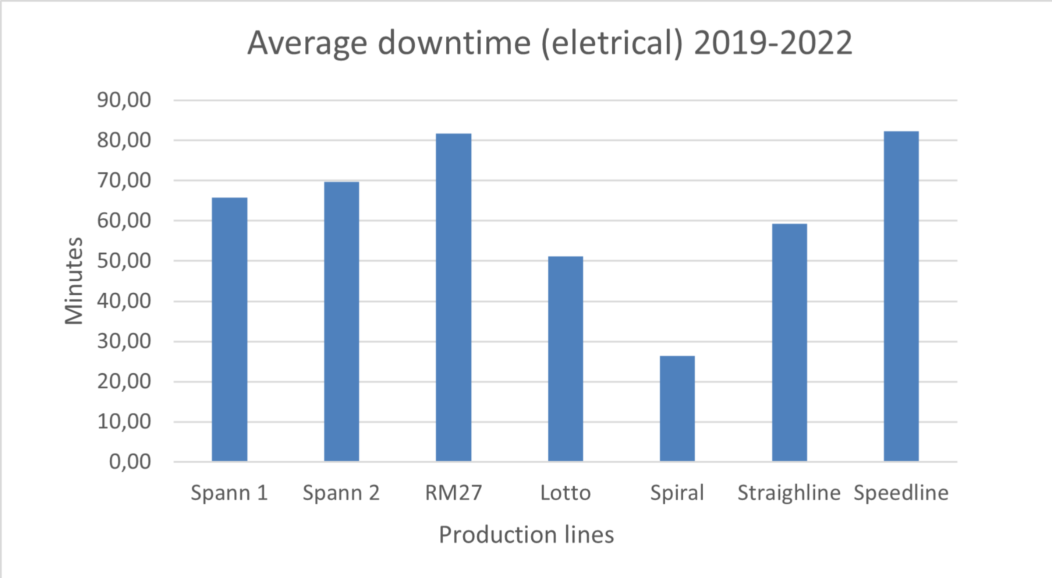

Figure 4.9. *Average downtime in minutes each time a problem caused by an electrical error occurred*

Figure 4.10 highlights that mechanical issues result in a higher amount of downtime compared to electrical problems. Despite this difference, the graphs depicting downtime for both types of issues exhibit a similar pattern. The production lines are ranked similarly, starting with Spiral having the least downtime. However, there is one notable exception when it comes to mechanical issues. In this case, Straightline surpasses Speedline in terms of downtime, accounting for over 26,000 minutes. This represents a significant increase compared to electrical errors. The data translates to a total of four and a half days of downtime.

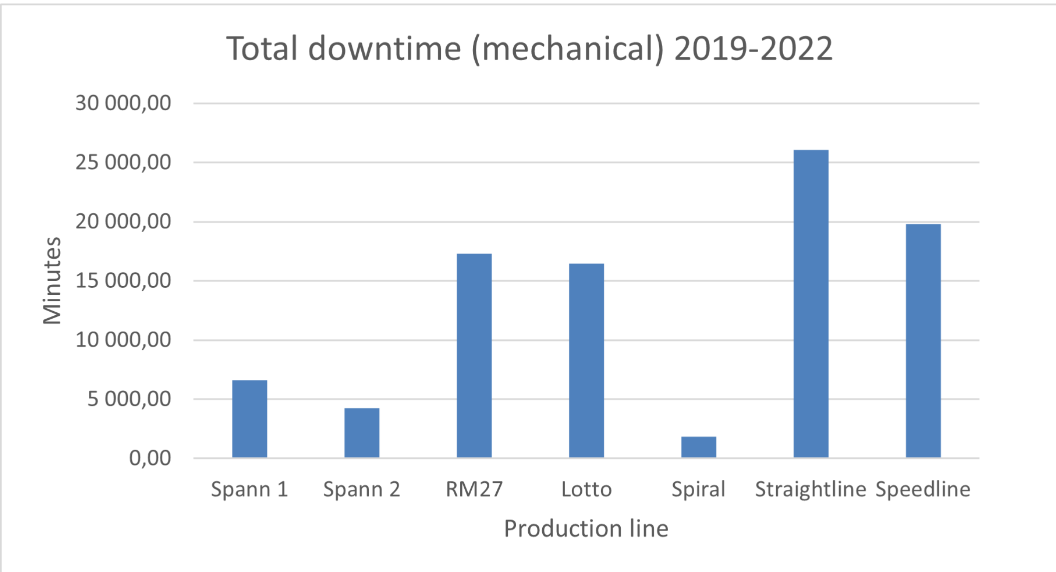

Figure 4.10. *Total downtime in minutes caused by mechanical error*

Figure 4.11 reveals that Speedline experiences the highest average downtime, nearly 80 minutes. On the other hand, Spiral has the lowest average downtime, slightly above 40 minutes.

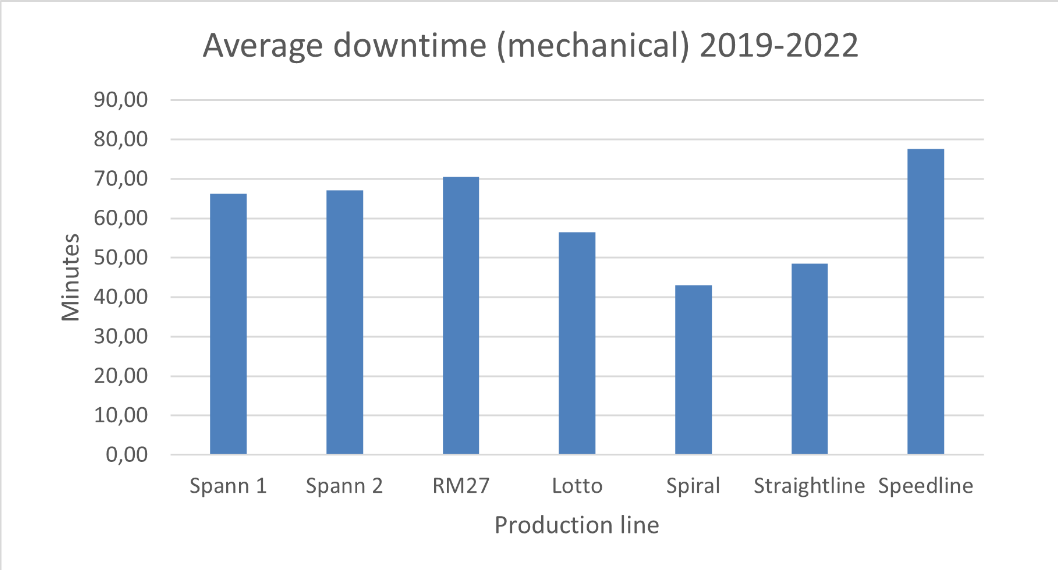

Figure 4.11. *Average downtime in minutes each time a problem caused by a mechanical error occurred*

4.1.3 Quality control

Hennig Olsen has introduced some artificial intelligence in their production lines regarding quality control of their ice cream called Vision. It contains cameras, lasers, and weights to ensure the ice cream has been filled to the right amount, in the right packages, and getting packaged according to regulations. It should be mentioned that they only have implemented Vision to some of their lines and steps. DPAK and FPAK are a distributor and consumer packaging. A list containing which lines and steps Vision is implemented it is provided here:

- Spann, filling machine, box- and lid-control: August 2019.
- Speedline DPAK: November 2019
- Straightline DPAK: Juni 2020
- Lotto DPAK: November 2020
- Spann 1 DPAK: March 2021
- Spann 2 DPAK: Mach 2021
- RM27 DPAK: Mach 2021
- Spann 1 FPAK: Juli 2022
- Spann 2 FPAK: Juli 2022

In figure 4.12, the number of customer complaints Hennig Olsen receives from their distributors and other customers is illustrated. The faults were mainly of bad, or wrong packaging or too little of the product in the packaging, in both consumer and distributor packages. This means that products with faults had bypassed the checks and controls that were implemented at that time and were shipped. The complaints that were acquirable is from August 2020 until December 2022.

Figure 4.12. *numbers of customer complaints*

4.2 Interview

This chapter presents the results found in the interview. All the answers was given from the technical manager of Hennig Olsen.

The technical manager from Hennig Olsen explained that they have experimented with lean since 2014. Since then it has been a variation in the degree to which it has been focused, with an intense start, but declining after some time. After some time they decided that they would try another approach by adapting the lean terms and methods and making it their own. Starting small, then gradually escalating it, unlike when they first tried it on the company as a whole. Now they are up to speed and using many of the traditional lean tools and methods such as different analysis tools, A3, fishbone analysis, and board meetings to reduce waste. The operator is also present explaining how it went, what went wrong, why, and what to do for it not to happen again.

"We don't have to go around believing and thinking about why things happen. Now we actually have good facts, so we can continue to work on the improvement process."

When the respondent was asked about how their understanding of AI was, and how it could be used to improve the production process, it was explained that it varies a lot among the employees, but the interest is increasing. It is today mostly used in quality control, which is a part of their investment in continuous improvement and lean.

They have also tried it on their sales prognosis, to make a production plan, but is still at an early development and is not working properly yet, but is still seeing signs of improvement in accuracy regularly. They have also considered other things, like responding to customer's inquiries and advertisements.

They explain that they collect a lot of data, and would have collected more if it was not for relatively old machinery in some areas, which makes it hard to transmit the data to their database. But in the areas where they collect a lot of data, they struggle to find enough resources to interpret the data, both in software to sort and present it and in people that can make decisions from it.

Their vision systems are used mostly from checking that their packaging is done right and with the right amount of product, both in weight and quantity. If a product has faulty packaging it is thrown out or in some instances, the line has to stop.

"The complaints we receive from our distributors, that there is, for example, a packing missing, or that the packing is damaged, or something like that, those messages have become fewer and fewer."

When the system was first initiated they had quite a few false detections where the system misinterpret what was observed. Some products that were fine were thrown out, and some faulty products were accepted and continued down the line. This resulted in some of the operators getting a bit tired of the new system not working properly.

"We had some challenges with them turning off the camera, because they felt it was extra work and a lot of trouble. As it was."

But after some trial and error, it has become much better as the model had time to learn and become better. Now it is just a part of their everyday work as anything else.

How they began with the idea of developing such a system is that they grew tired of the increasing complaints from their distributors. The team at the technical division came up with the initiative that it may be a wise idea to establish an AI solution to help with this problem and then tried it.

"At Hennig Olsen, we have a fairly flat organizational structure, where you have the opportunity to make such decisions, and start with such change and improvement initiatives, without a very long process to anchor your strategies."

Their automation technicians also get the opportunity to dig into the systems on their own and learn to ensure good solutions. As they began to develop the system they noticed that the interest around the project increased and was requested. They also saw that it could be useful in their work toward continuous improvement. The process continued with getting the right equipment, software, and programmers to develop the system from the bottom.

"Where we missed on the most in that process was the involvement of the operators, that something new is coming."

To also inform the operators what the situation is going to be and what is going to change. Including it is not going to be perfect at the beginning but to reach the goal they all have to collaborate. Another challenge when utilizing these kinds of solutions is to be able to get a hold of qualified personnel. People with specialized knowledge of programming are hard to get by in Norway right now. It is both expensive and a lot of waiting time.

The technical manager explains that the learning curve has been steep, from mostly self-learning. But as more and more production lines have this kind of system, when establishing new systems they are operating at an acceptable level much faster than the first ones.

As a result of this system, the employees have experienced fewer complaints from distributors and customers, which in the end also reached the operators in the production. They can also notice and appreciate the results the changes have had. The system is just a small piece of the bigger picture of Lean and continuous improvement. It is one of many initiatives made to have a better process, efficiency, profitability, and a better environment for the employees.

If something went wrong in their lines, as in the pasteurization process it means the whole factory stops. This is due to it removing dangerous bacteria that could be harmful for humans to consume. Other machinery, including their cooling compressors, fail, resulting in their products not keeping the correct temperature and can therefore be discarded.

When lean first was introduced it was difficult and often met with negativity, and it is important to approach such initiatives thoughtfully and wisely. If Lean is not implemented properly, it may result in employees waiting for the initiative to pass and returning to their old ways. The life cycle is of enthusiasm at the beginning and difficulty in maintaining momentum over time. Changing a company's culture overnight is not feasible and requires a lot of hard work.

The first measure to make the transition easier is to start with one production line and to listen carefully to the operators' needs and desires. It is important to understand what is required for them to perform their job well, and it is not always about adding more staff. There are other factors that must be addressed, and it takes time to establish a new system and way of working. It is not enough to give the operators new tools and expect them to work at once. Regular follow-up meetings should be held to track progress and make adjustments to improve the work environment. The key is not to lose momentum in the change process and to recognize that it takes time to implement the changes successfully. Once a small part of the organization has successfully adopted the new system, it can serve as a model and inspire others to join in. People naturally resist change, so it is important to find ways to encourage and engage employees rather than imposing changes on them.

The most challenging aspect for the company has been getting employees from diverse cultures to speak up and communicate issues or suggest improvements to management, especially for those from cultures where it is not common to speak up to the boss. Communication barriers due to language differences have also been a challenge. Another difficulty has been motivating employees to change their ways of working when the company has been profitable and successful for many years, without a sense of urgency or a burning platform to drive change. However, recent changes in the world, such as the bad weather last summer affecting the profitability, has made it easier to sell the message that the company needs to change in order to remain profitable and retain customers and jobs.

The technical manager misses a sharper focus on technology in the company strategy. To have a clear strategy on how new technology can be utilized in order to increase the profitability of the company. It is a lot of talk about what is new, exciting, and useful, but it is hard to gather and get a structure on all the thoughts into a strategy. The struggle is that it is too many choices and opportunities, and a plan on what to do in both scope and order is missing. The company is thus developing a digitization-strategy, of not only what to do but how, and which tool to utilize in the company in order to get good profitability.

4.2.1 Follow-up questions

In subsequent email exchanges with the technical manager, Hennig Olsen was queried about their familiarity with Big Data, cloud computing, and the Internet of Things. In response, the manager explained that external parties frequently visit Hennig Olsen with offers to analyze their big data and assist in identifying patterns within their process data to identify and resolve errors. However, Hennig Olsen has not yet availed himself of these services.

Regarding cloud computing, Hennig Olsen has not yet adopted it, but they anticipate incorporating it more extensively in the future. However, due to the presence of older equipment in the factory, the implementation of IoT poses challenges. Currently, interconnecting the equipment is deemed impractical, and Hennig Olsen recognizes the need for gradual changes in this aspect in the upcoming years.

When asked about the factors determining the production rate, the technical manager clarified that the production rate primarily adheres to the technical specifications for which it is designed. However, in instances where a product necessitates a different pace than the norm, the decision is made by either the factory manager or the production manager. The production rate is then determined based on considerations such as the complexity of the specific product, the characteristics of the raw materials involved, and the machinery utilized in the production process.

The technical manager clarified that Hennig Olsen currently does not employ AI predictive maintenance. This decision stems from the difficulties encountered in integrating such technology into their existing production lines, which consist of relatively older equipment. Additionally, it was revealed that components in the production line are replaced based on predefined service intervals, irrespective of their excellent operational condition.

The technical manager was asked about his opinion what AI could mean for the employees working at Hennig Olsen. In his response, he suggested that AI could potentially replace some of the jobs that are currently executed by human operators. However, he further stated that the employees that manages to adapt and are curious about the new technology can continue to contribute a lot to Hennig Olsen.

4.3 Observation

During the visit to the Hennig Olsen ice cream factory, a detailed investigation of the production lines was conducted. The focus was to learn how Hennig Olsen utilized various AI methods and lean thinking in their production facilities. Along the tour, there were some notable observations made, that are described in this section.

Throughout the visit to the Hennig Olsen ice cream factory, it was observed that the production floor was highly technological, with most of the production lines fully automated and a lot of quality controls monitoring the production. Despite this, there were still a number of operators present to ensure that the production process ran smoothly and efficiently. One example was that one of the operator's tasks was to ensure that strawberry sauce was accurately filled into the ice cream. This task required high levels of consecration at receptive movements as the correct amount of sauce needed to be added evenly to each ice cream. This was one of multiple stations where operators had to sit and watch a single step in the production, thus the observer did not get enough time to see how long the shifts were.

An observation of a malfunction in the production line was also made, causing products to collect on the floor. The problem seemed to be that something was stuck, and the company's maintenance team worked to resolve the problem and regain production. However, the problem in production resulted in a large quantity of ice cream being discarded, which was an unfortunate waste of valuable resources. There was also the case of multiple other stations that has high amounts of discarded product on the floor that resulted in malfunctions.

During the observation of Hennig Olsen's production facilities, it was noticed that there was a significant amount of ice cream waste on the factory floor. The technical manager stressed the significance of maintaining a reasonable production rate to avoid an overflow of waste. At one station in the production line, there was a full basket of excess waste of ice cream. The reason for the waste was that the production line was too fast for the robot arm to pick up the ice cream. The manager explained that the company's focus on quality and sustainability meant that they prioritize minimizing waste and ensuring that resources are used efficiently over high production rates.

4.4 Summary

Table 4.1. Summary of the key findings from the results

Element	Findings	Method	Relevance
OEE	1. Figures 4.1,4.3 and 4.5 shows the OEE results do not hit their OEE goals for Span 1 and 2, and Speedline. 2. Figures 4.2, 4.4 and 4.6 shows the different key indicators used to calculate the OEE scores. Here it is possible to get an indication on what caused the poor OEE scores.	Quantitative data	Predictive maintenance Quality Control Decision-making
Downtime	1. Figures 4.7-4.11 shows how much downtime the production lines has, compared to other reasons, and each other. 2. Due to old machinery it is difficult to integrate predictive maintenance in existing production lines. 3. Predictive maintenance can only fix electrical and mechanical issues	Interview Quantitative data	Predictive maintenance
AI-Vision	1. Figure 4.12 shows that the number of customer complaints has reduced after the implementation of AI quality control provided in the list. 2. There is still some areas that have humans do the quality control.	Quantitative data Interview	Quality Control
Waste	1. A lot of waste was observed discarded after problems in the production line. 2. They prioritize less waste rather than high production rate.	Observation Interview	Predictive maintenance Quality control Decision-making

Today's technology status	1. Employees has shown signs of not welcoming new technology and changes 2. With the old machinery, it is hard to take advantage of internet of things, big data analytic and cloud computing. 3. The management have learned a lot from previous experiences with implementing AI and other major changes. 4. Lacks clear strategy for technology development.	Interview	Readiness for further development of artificial intelligence

Chapter 5

Discussions

5.1 Findings and analysis

5.1.1 Why is AI the next stage for lean thinking to Hennig Olsen

Hennig Olsen has been applying lean thinking since 2014, using different tools such as board meetings and A3. However, as the company looks to stay competitive in an ever-changing market, it is important to consider how integrating AI can enhance its lean approach. In the interview, the technical manager mentioned that today Hennig Olsen is up to speed in the usage of many traditional lean tools. This strategy could face challenges since there are opinions that the traditional lean tools no longer can adapt to today's complex environment (Perico & Mattioli, 2020). From the interview, it is explained that the goal of applying these traditional lean tools is to reduce waste in the company. It is mentioned in the theory chapter that AI can potentially minimize the excessive use of raw material (Sahoo & Lo, 2022). For that reason, a higher focus on implementing AI in production lines could give higher rewards. Additionally, the OEE score from figures 4.1, 4.3, and 4.5 reveal that Hennig Olsen rarely achieves their OEE goals, though these scores are only from 2022, making it challenging to determine if there has been any improvement in recent years. Given the significant gap in results, it is perhaps time for Hennig Olsen to consider a broader implementation of AI.

One of the most important aspects of lean is customer satisfaction (Albliwi et al., 2014; Anvari et al., 2020; Laureani & Antony, 2012). After implementing AI quality control in 2019, the number of customer complaints has reduced for Hennig Olsen. Figure 4.12 regarding customer complaints, does show the decline which has occurred since April 2021, after AI quality control was implemented. This has allowed Hennig-Olsen to catch any packaging errors early on in the production process before the ice cream is shipped out to retailers. The implementation of AI-vision technology has demonstrated that Hennig Olsen is capable of successfully integrating AI to improve their production line. Therefore, it is reasonable to assume that continuing the implementation of AI can further improve Hennig Olsen's production.

Van Wynsberghe (2021) suggested that one of the greatest achievements of AI is to operate more sustainably. Hennig Olsen is a small part of the manufacturing industry, that represents 50% of all energy consumption worldwide, making it important for them to reduce their carbon footprint (Sahoo & Lo, 2022). According to a McKinsey report, numerous companies have already implemented AI to deal with sustainability issues (Chui et al., 2022). Specifically, 43% of the survey participants are using AI to achieve their sustainability goals (Chui et al., 2022). During a tour of Hennig Olsen's factory, a lot of waste was observed on the production floor, resulting in a loss of raw materials and energy. It is debatable if Hennig Olsen's traditional lean tools have been sufficient for minimizing the waste of energy and raw materials. To send a message to the industry, Hennig Olsen should consider accelerating their adoption of AI in their production lines to improve sustainability, as their current waste products could be better.

5.1.2 How Hennig Olsen can improve their production with AI

As Hennig Olsen remains committed to continuous improvement, there are numerous ways in which AI can prove beneficial. One potential avenue for Hennig Olsen to explore in the future is the adoption of lean six sigma. This data-driven methodology, centered around statistical analysis (Laureani & Antony, 2012), could greatly benefit from AI. One of the key advantages of artificial intelligence is its ability to swiftly analyze vast quantities of data and information, making it a valuable tool in implementing lean six sigma practices. Lean six sigma can be used to monitor their production lines in real-time, identify bottlenecks, and provide suggestions for process improvement (Lee et al., 2006; Paturi & Cheruku, 2021; Sezer et al., 2018). This can lead to more efficient production processes, reduced cycle times, and increased output. Lean Six Sigma focuses on reducing defects and improving quality, and AI can be used to identify the root cause of quality issues (Albliwi et al., 2014; Laureani & Antony, 2012). By combining Lean Six Sigma and AI, Hennig Olsen could quickly identify quality issues, implement corrective actions, and prevent defects from occurring in the future.

Albliwi et al. (2014) and Laureani and Antony (2012) explained that to have a successful implementation of lean six sigma they will depend heavily on management support and commitment, the right organizational culture, linking it to business strategy, having enough resources, and effective leadership styles. The employees also need to understand how to work with AI technology and how to analyze data to identify areas of improvement (Kutz et al., 2022).

From a lean perspective, a stop in the production line is recognized as a loss, because the production line is not producing ice cream, but waste (Bonada et al., 2020; Pavnaskar et al., 2003; Singh & Singh, 2009). Integrating predictive maintenance could potentially fix both losses. Currently, Hennig Olsen doesn't have any AI predictive maintenance in their production lines. As of today, Hennig Olsen does maintenance at service intervals, and by reactive maintenance, where parts are changed in the production line stops unexpected (Achouch et al., 2022). In conversation with the technical manager of Hennig Olsen, he shared that the reason why they are not using AI predictive maintenance is because of the difficulty to integrate predictive maintenance in existing production lines.

A reactive maintenance approach causes a lot of problems regarding unexpected downtime. Between 2019 and 2022, electrical and mechanical errors accounted for a total of 126,500 minutes of downtime. From the interview, the technical manager states that it is these errors that can be solved using predictive maintenance. Figure 4.7 show the faults in the production line related to mechanical and electrical is 14% of the total amount of downtime. When faults are occurring, an in-house technician will first take time to evaluate what the problem is, before actually correcting the problem. This operation takes up valuable time and they are not able to produce ice cream. Figures 4.9 and 4.11 show the average downtime for production lines. Among these lines, Speedline has the highest recorded average downtime, slightly above 80 minutes for electrical and just under 80 minutes for mechanical. This downtime can lead to a significant amount of product waste, which can hurt the company's bottom line (T.-C. T. Chen & Wang, n.d.; Hafeez et al., 2021; Waltersmann et al., 2021).

In an earlier conversation with the technical manager, he revealed that parts in the production line are also changed when the service interval is due, even though the machine works in excellent condition. This approach to maintenance is not only costly but can also result in unnecessary downtime and lost production (Levitt, 2003). From a lean perspective, it is contradictory to discard equipment that is still functional since the core aim is to create improvement (Brunet & New, 2003; Singh & Singh, 2009). Furthermore, this practice is considered unsustainable, especially if the manufacturing industry is actively striving to become more sustainable (Chui et al., 2022). Implementing predictive maintenance can help Hennig Olsen move from a reactive and interval maintenance approach to a proactive one. Where maintenance is performed based on data analysis and machine performance that would reduce machine downtime, costs, control, and quality problems (Zonta et al., 2020).

During the visit to Hennig Olsen's factory, a production line stopped unexpectedly. In only a matter of a few seconds, the production floor was filling up with ice cream waste. When the production stops, the consequences are severe in the form of the waste produced, and unused raw materials. The technical manager also explained that it could be severe complications if their pasteurization process fails, which is critical because it could result that the ice-cream is not safe to consume. Their cooling compressors are also a key component for the products and ingredients holding the right temperature. There are many steps in the production, and many parts that could fail. In the case of Hennig Olsen having issues and downtime with only one of these machines, it is likely going to result in a substantial amount of wasted product (Zonta et al., 2020). This further highlights the need for a more effective maintenance strategy, backed by AI.

The downtime experienced by Hennig Olsen has a significant impact on their OEE score, particularly in terms of the availability factor. Figure 4.6 indicates that the OEE output consistently falls short of the company's goals. During the measured period, Speedline had 49 incidents where the OEE score in figure 4.5 fell below the poor performance baseline of 60% (Al Hazza et al., 2021). Out of these incidents, 21 were caused by either electrical or mechanical issues with the production line. The frequent occurrence of such incidents indicates that production line failures are a part of the declining OEE score. These problems bring an average of 80 minutes of downtime per incident, which substantially reduces the availability factor. Given that an OEE score below 60% is considered poor performance, Hennig Olsen should consider implementing predictive maintenance as a solution to improve their OEE score.

At Hennig Olsen, there were observed cameras, weights, and lasers that were continuously watching over the different steps of the production lines for comprehensive quality control. However, looking at the different key indicators for Spann 1, Spann 2, and Speedline illustrated in figures 4.2, 4.4 and 4.6, there is still room for improvement. The OEE quality scores are all below the goals of Hennig Olsen. Nevertheless, there are multiple times when the quality scores reached the goal, which indicates that there is possible to achieve these high-quality scores. If they follow the kaizen philosophy and continue to develop AI-vision controls it could help achieve these scores more often (Singh & Singh, 2009).

One of the essences of Kaizen is to continue reaching for increased improvement to utilize the full organizational potential (Singh & Singh, 2009). While Hennig-Olsen has implemented AI quality control in their production line, there are still some areas where humans are controlling ice cream production. For example, there is an operator that is responsible for ensuring that the strawberry sauce is added correctly to the ice-cream. The consequence of operating with this method is that the station holds up valuable resources in the form of manpower. In addition, when an operator continuously watches one repetitive step it is easy to make mistakes and for the operator to experience fatigue (Teng et al., 2019). Perico and Mattioli (2020) argues that adopting AI is a way forward for future lean management, and could also improve this step.

One approach to continuous improvement is to reduce cycle time, which offers several significant benefits. These include faster deliveries to customers, a more manageable working environment, and improved responsiveness to orders (Chang et al., 2001; Little, 2011). During the factory visit, the technical manager emphasized that Hennig Olsen prioritizes quality and waste reduction over high production rates. To support these objectives, it is crucial to identify areas that can be improved (Muchiri & Pintelon, 2008), and one effective tool for achieving this is OEE (Gibbons & Burgess, 2010).

Figure 4.6 presents key indicators that form the OEE, and it reveals that there are instances where the graph indicates performance close to full utilization, but the output quality is compromised. This is a critical observation considering the objective is to maximize the number of successfully produced items from the input of raw materials within the shortest possible time. By identifying and addressing these issues, Hennig Olsen can enhance their production processes and optimize their overall efficiency.

Figure 4.5 highlights several weeks where the OEE score falls below the targeted level. In such instances, when the machinery needs to operate at a different speed than its rated capacity due to the complexity of various products, difficult decisions must be made. These decisions need to strike a balance between ensuring efficient machine operation and avoiding a compromise in quality. Given Hennig Olsen's priority of minimizing waste, it becomes crucial to determine the appropriate performance level on the production line. This ensures that the production process maintains optimal efficiency while upholding the desired quality standards.

In the instances the factory or production manager has to make decisions regarding the production rate, they have to rely on information on the complexity of the specific product, the properties of the raw materials, and the machinery used which varies from product to product. Artificial intelligence can thus help analyze this information and help decide the optimal rate to ensure a correlation between performance and quality output instead of the managers having to use valuable time doing this. Additionally, AI could monitor production and provide real-time feedback to ensure optimal rates and make adjustments if necessary (Sahoo & Lo, 2022).

Artificial intelligence requires vast amounts of data to function efficiently (Peres et al., 2020). The question is therefore whether there is enough data available to achieve this efficiency. Hennig Olsen accumulates a considerable amount of data, but their outdated machinery has prevented them from gathering even more. The primary challenge they face is the lack of resources to interpret and effectively utilize the collected information. This is where integrating AI can be beneficial. The older machinery may however hinder the accuracy of the predictions made by AI if it fails to gather sufficient data (Sahoo & Lo, 2022).

5.1.3 Is Hennig Olsen ready to further implement AI?

The current discussion has so far presented arguments on how AI can improve various aspects of their production. Nevertheless, it should be acknowledged that the implementation of such a transformation poses significant challenges due to its inherent complexity (Bonekamp & Sure, 2015). As such, it may be reasonable for Hennig Olsen to consider deferring the development of AI until the organizational infrastructure and readiness align with the requisite technological advancements (Jerman et al., 2020).

Big data analytic, cloud computing, and IoT are valuable components that enhance the capabilities of AI. To establish a comprehensive smart factory, it is necessary to have machinery that can seamlessly interact across the entire supply chain and production line (Sahoo & Lo, 2022; Turconi et al., 2022). However, the technical manager mentioned that the older equipment in Hennig Olsen's factory faces challenges in achieving the required level of interconnection, particularly in terms of the implementation of internet of things. Despite this limitation, Hennig Olsen has successfully integrated AI systems for quality control, gaining valuable experience and establishing a foundation for operating AI-enabled facilities. Therefore, it is advisable for Hennig Olsen to invest in future technologies and technical features that can unlock the full potential of AI, particularly when newer equipment is to be purchased. By leveraging these advancements, Hennig Olsen can further enhance their operations and harness the benefits offered by AI in their production processes.

Hennig Olsen faces challenges in effectively interpreting the vast amount of data they collect and store. They struggle with limited resources, both in terms of software to organize and present the data and skilled personnel capable of making informed decisions based on it. While they have received offers from external parties willing to analyze their data, Hennig Olsen has yet to take advantage of this service. This highlights the potential for outsourcing data analysis tasks. Alternatively, Hennig Olsen could consider implementing artificial intelligence alongside cloud computing and the IoT to create a comprehensive smart factory with big data analytic (Turconi et al., 2022). This integration would enable more efficient analysis of their data, leading to better decision-making processes (Sahoo & Lo, 2022). Additionally, upgrading to more modern machines capable of collecting even larger volumes of data would further enhance the effectiveness of artificial intelligence in their operations (Turconi et al., 2022). By embracing these technological advancements, Hennig Olsen can unlock the full potential of their data and optimize their manufacturing processes.

Cloud computing, which they have not yet utilized, again due to their old machinery that have difficulties to get them all online working together. They have stated that they are going to focus on this in future projects. This implies that the company may not possess the necessary technological infrastructure to support the integration of AI into its production lines today, but in the future when new machines are to be implemented in the factory, Hennig Olsen could greatly benefit from these technologies (Turconi et al., 2022).

Human resources that are capable of effectively utilizing AI is a critical factor that should be in place to be able to manage the complexity of this technological advancement (Bonekamp & Sure, 2015; Jerman et al., 2020). In the interview, the technical manager told the problem is that the particular skills that are required for implementing these systems are very scarce. This could be a challenge for when Hennig Olsen is eventually going to continue to implement more artificial intelligence in their production.

According to the technical manager, there have been mixed reactions whenever the company has attempted to implement new technology and improvement methods. Initially, when the company embraced lean principles in 2014, they faced implementation challenges. Consequently, a shift in approach was required, leading to the adoption of a company culture that emphasizes gradual change. This change in strategy has yielded positive results, as noted by the technical manager. Previous experiences have highlighted the importance of involving operators in the adoption of new technologies, a lesson learned by Hennig Olsen. While the learning curve has been steep, ensuring that individuals adapt to new technologies is crucial for a successful transition to AI within the company (Sjödin et al., 2018).

For successful implementation of AI in an organization, stakeholder support is vital (Kutz et al., 2022). But since the technical manager said that he misses a clear strategy on the usage of technology from the upper hold, there are signs that it might take some convincing to get enough support. The management has also, due to some successful years, not had the urgency to change things because they did not see any reason to do so. The recent summer, however, resulted in poor results compared to previous years. This might change the manager's perception of not having to change because things are not going so well. This also implies that they should consider further development of their production planner to help see patterns in sales and become more efficient. Kutz et al. (2022) suggest that putting the AI services into production quickly can further help gain support and demonstrate value to the stakeholders. And since Hennig Olsen has a flat organizational structure and the opportunity to initiate such projects easily, it might show the stakeholders the value it can bring and gain more support for such projects in the future.

Technology acceptance can thus be a significant challenge due to unclear roles and responsibilities, and difficulty in collaboration between IT and manufacturing (Kutz et al., 2022). As the technical manager explained they have had issues with the employees turning the vision system off due to it not working properly. The manager also admitted that they were bad at communicating with the employees that something new is coming, and what it was going to be like in the beginning. If they in the future can learn from this experience and it could be easier to conduct new AI projects by having everybody on board from the very start. While AI is expected to replace many jobs in today's industries (Huang & Rust, 2018), the technical manager at Hennig Olsen suggested that employees who can adapt to new technologies will remain valuable.

5.2 Summary of discussion

The initial phase of the discussion focused on why AI should be the next step for Hennig Olsen's lean management strategy. The lean tools used today was found to have room for improvements. While the successfully implementation of AI has resulted in fewer complaints, they do not reach their OEE goals. Improvements and expanding their implementation of artificial intelligence could result in reduced waste, minimize the usage of raw materials, better sustainability and improved efficiency.

During the second phase of the discussion, the focus shifted towards how Hennig Olsen could utilize AI to enhance its production efficiency. Due to a significant amount of downtime, it was suggested to implement predictive maintenance. Specifically, Hennig Olsen had experienced 126,500 minutes of downtime caused by electrical and mechanical faults that could potentially be eliminated. AI can also benefit Hennig Olsen's continuous improvement efforts by integrating it with lean six sigma. This would allow for real-time monitoring, identifying bottlenecks, and suggesting process improvements. Although AI-vision had already been implemented in various areas of the production line for quality control, it was proposed to further expand on its usage. Finally, AI decision-making and data analysis was recommended as it can access larger amounts of data to optimize production rates and minimize instances where the OEE score fell below 60%.

The final phase of the discussion focused on whether Hennig Olsen is prepared to implement new technology in the company. Implementing AI could face challenges as there is limitations in their infrastructure, mainly their old production equipment. This makes it hard to utilize big data analytic, internet of things and cloud computing which could make for a optimized use of artificial intelligence. Scarce skills and lack of clear strategy is also a hindrance that has to be addressed. Gradual change and involvement of operators is thus something Hennig Olsen has improved upon and could facilitate future AI projects.

Chapter 6

Conclusions

This conclusion will address how artificial intelligence can be applied to enhance lean manufacturing and production processes. Additionally, it will provide an assessment of why AI is the ideal solution for Hennig Olsen's lean development and whether the company is ready to implement it.

Hennig Olsen ought to expedite its progress towards Industry 4.0. The company has already adopted lean manufacturing methods since 2014, which have yielded significant improvements. However, during a factory tour conducted by the authors of this paper, a considerable amount of waste was observed on the floor, representing a loss of raw materials and unnecessary energy consumption. As the manufacturing industry accounts for nearly 50% of today's energy consumption (Sahoo & Lo, 2022), it is crucial that Hennig Olsen assumes responsibility for more efficient production. This situation highlights that current standards could be improved, and Hennig Olsen should explore new methods to further streamline their lean manufacturing process. Implementing artificial intelligence will be a part of achieving more efficient lean manufacturing, which Hennig Olsen already has experienced through the reduction of customer complaints since the adoption of AI vision control (Perico & Mattioli, 2020).

The application of artificial intelligence in a smart factory setting offers several opportunities for enhancing Hennig Olsen's manufacturing processes. While Hennig Olsen has already implemented AI for quality control purposes in its production lines, there are still areas, where human operators oversee the production. Since human operators are prone to fatigue, Hennig Olsen should continue to further develop its implementation of AI for quality control purposes (Teng et al., 2019).

Predictive maintenance is not yet implemented in any of Hennig Olsen's production lines, although the management is considering it for the future. Recorded data shows that downtime due to electrical and mechanical issues between 2019-2022 amounted to a total of 126,500 minutes, leading to significant non-production time and waste. Therefor, they should include predictive maintenance when the time has come to renew their machinery or expand to more lines. They should also consider accelerating the plans for replacing old machinery to reduce machine downtime, and maintenance costs, and improve quality (Zonta et al., 2020).

Since it only was on rare occasions Hennig Olsen managed to achieve their OEE goals, combined with the several times the OEE went below 60%, which are considered poor results suggests that improvement is needed (Al Hazza et al., 2021). When the production rate is decided by the factory or production manager, a lot of data needs to be assessed in real-time, which Hennig Olsen struggles to find resources for to attain the highest efficiency, not compromising either quality or performance (Elgendy & Elragal, 2014). Hennig Olsen is storing data, but they are lagging in developing the means to evaluate the data coming from production processes. It is recommended that Hennig Olsen undertake significant research in this area to achieve the highest efficiency rate.

In the event that the previously mentioned implementation suggestions are not of interest to Hennig Olsen, there is an alternative approach: Lean Six Sigma. By combining Lean Six Sigma with AI, Hennig Olsen can leverage the advantages of Lean Six Sigma in terms of defect reduction and quality improvement, while utilizing AI to identify the underlying causes of quality issues (Albliwi et al., 2014; Laureani & Antony, 2012). This integration allows for a comprehensive approach to enhancing quality control and process improvement within the organization.

To evaluate if Hennig Olsen is ready to continue to implement AI, both technological and human measures are advised. From a technical perspective, Hennig Olsen currently lacks the modern foundation of big data, IoT, and cloud computing. Which can help to utilize AI more efficiently in the production lines (Demigha, 2020; Turconi et al., 2022). Their old machinery is also a part of the main problem in getting everything to work together with these technological advancements.

While AI may replace many current employees, those who adapt to the new circumstances will prove to be valuable assets for Hennig Olsen, particularly considering the scarcity of artificial intelligence skills. For operating AI efficiently, Hennig Olsen needs human resources that can control these complex systems (Jerman et al., 2020). The technical director stated that it is a challenge for qualified personnel. Hennig Olsen should intensify its search for these skills.

Hennig Olsen has faced challenges in the past when attempting to implement new lean methodologies. This process began with the early lean transformation in 2014. Initially, there were difficulties in adapting to these new methods. However, the breakthrough came when Hennig Olsen personalized the lean theory to fit its own culture. If Hennig Olsen chooses to implement more AI in the company, it is therefore plausible that take a similar, personalized approach to achieve a successful transition. The company should consider the unique needs and characteristics of its organization, employees, and production lines when developing and implementing AI systems. By doing so, Hennig Olsen can overcome potential challenges and ensure a smooth and effective adoption of more AI technology.

6.1 Future research

This paper has discussed the advantages and how to apply artificial intelligence in a production facility in light of lean production and processes, focusing on the technical aspect of production. However, lean manufacturing is also connected with employee engagement, communication, and teamwork. The limitations in this thesis on how in-depth the human side of lean manufacturing has gone into implies that there is needed future research in this area. How these technologies can enhance this aspect of lean manufacturing, such as by improving communication between managers and operators or providing real-time feedback to employees to help them identify areas for improvement.

The AI production planner of Hennig Olsen is also in development, but since they stated it did not work sufficiently yet, it is also a place for further research. Evaluating the effectiveness of this tool alongside other AI tools used in lean manufacturing. Focusing on the accuracy and time savings it could provide.

Since artificial intelligence is a rapidly developing field, there are likely new areas the technology can improve in the future. At the same time, AI is a technology that can be adapted to a very broad specter of usages. Studies of other applications than those covered in this thesis could also be of interest. Future research could explore new applications of AI in lean manufacturing, such as using AI to optimize supply chain management for example. New applications could also be explored through simulations or experiments.

Furthermore, an economic analysis of the impact AI has on profitability could be another point for future research. This could include assessments of the long-term costs and other benefits when adopting AI technologies, and whether the benefits of using AI in lean manufacturing justify the costs it brings to install and operate.

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Appendix A

Interview guide

- Hva er din posisjon, arbeidstittel, hvor lenge har du jobbet her, og hva har du jobbet med?
- kan du gi en kort oversikt over produksjonssiden, hva dere lager, og hvordan flyten går i det?
- Hvilken grad benytter dere Lean i bedriften?
- Kan du nevne noen spesefikke verktøy dere bruker?
- Kan du si noe om hvordan det har påvirket bedriften?
- Hvordan er deres nåværende forståelse av AI, og potensialet for å forbedre produsksjonsprisessen?
- Har dere andre utfordringer eller problemer som dere tenker AI kan være med å løse?
- Om det skjer noen feil i produksjoen, har det store konsekvenser, eller hva er det mest problematiske som kan skje?
- Føler du at du har de viktigste prarmeterne, eller grunnlaget, for å implementere AI-løsninger, for eksempe data tilgjengelighet, maskinvare, teknisk ekspertise?
- Kan du fortelle litt mer om deres AI kvalitetskontroll, hvordan det foregår?
- Har det vært noen forskjell på de forventede resultatene og de reelle resultatene etter implementeringen?
- Har det ført til noen uønskede resultater? Er det noen som har fungert mindre bra eller dårlig?
- Kan du fortelle litt om prosessen dere hadde da dere implementerte forskjellige løsninger? Har dere en klar strategi på hvordan dere gjorde det?
- Så føler du at det er nok kompetanse på dette området? Eller har dere vært på kurs eller liknende?
- Kan du si litt mer om hvordan læringskurven har vært, ved bruken av AI?

- Kan du fortelle litt om noen spesielle utfordringer, eller risikoer dere har hatt med implementeringen?
- Har dere noen strategier om hvordan man minimaliserer de forskjellige risikoene?
- Hvordan vil du beskrive hvordan de ansatte har omstilt seg til å bruke verktøyene?
- Har det vært noen endringer hvordan de ansatte som er på produksjonen har det, motivasjon, redusert kjedelig arbeid? Har det blitt mer engasjert etter dere har begynt AI?
- Har de ansatte vært involvert i den utviklingsprosessen til AI løsningene?
- Har det vært noen ansatte som ikke synes at det har vært noe særlig etter de forskjellige løsningene gått?
- Kan du si noe om de forskjellige tiltakene dere har gjort for å prøve å få overgangen lettere?
- Kan du si noe mer konkret om akkurat hva som har fått mest motgang?
- Er det noe vi ikke har snakket om, men du føler du burde snakke om?