A Comprehensive Evaluation of OEE as a Production Monitoring Tool for a Diverse Manufacturing Environment

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1 Abstract

This thesis examines the effectiveness of Overall Equipment Efficiency (OEE) as a production monitoring tool in diverse manufacturing environments through four case studies. The research evaluates OEE's ability to meet stakeholder needs and provide meaningful insights into production processes. Each case study is conducted in a real-life setting with varied production equipment, highlighting the actual challenges posed by the lack of standardization in OEE implementation and data collection methods.

The findings reveal significant variability in reported OEE numbers, difficulties in accurately determining production states, and the absence of benchmarking mechanisms. While OEE offers insights into potential production losses, the cases fall short of achieving the OEE world-class level that is often considered a production goal. The main reasons behind the challenges in production monitoring are the issues posed by the diverse environment and the lack of universal applicability of OEE as a standardized production evaluation metric.

The study underscores the importance of tailoring the definitions of the factors contributing to OEE and employing accurate data collection methods to enhance the utility of OEE. Additionally, the thesis suggests using complementary key performance indicators and downtime analysis to provide comprehensive insights into machine performance and production efficiency. While OEE has its place in monitoring overall equipment efficiency and the successful inclusion of TPM in a homogeneous production environment, the overall conclusion underscores the need for customized approaches to production monitoring. The KPI customization is essential to address the unique requirements of diverse manufacturing environments and to effectively meet varying production monitoring needs.

2 Abbreviations

Artturi	A maintenance software provided by Aneo
Big data	Structured or semi structured data that can be utilized from data and used for machine learning or predictive modelling
ERP	Enterprise Resource Planning is a software system that integrates and manages core business processes across various functions within an organization
Gema	A production monitoring-system provided by Pinja
IIOT	Industrial internet of things. Same as IoT but for industrial purposes
IMM	Injection molding machine
IOT	Internet of things. IoT describes physical objects (with sensors, software, processing ability) that connect the collected and exchanged data with other devices and systems over communication networks (Internet for example)
KPI	Key performance indicator
MCE	Manufacturing cycle efficiency
OEE	Overall equipment effectiveness
PLC	Programmable Logic Controller
TPM	Total productive maintenance (a maintenance system developed by Toyota)

3 Table of Contents

4 Introduction and purpose

In contemporary manufacturing, achieving optimal competitiveness and efficiency are seen as goals with great importance. Production development tools such as lean manufacturing and Total Productive Maintenance (TPM) are implemented to company strategies in order to minimize wasted resources and streamline operations. Essential to reach production improvement goals is to monitor production efficiency and receive a deeper understanding of the production and underlying problems, different key performance indicators (KPIs) are needed. These KPIs can be accurately formed using data that represents actual production at the equipment level within the plant.

The aphorism “Perhaps what you measure is what you get. More likely, what you measure is all you’ll get. What you don’t (or can’t) measure is lost” by H. Thomas Johnson, an American accounting historian and professor, can be reflected in production monitoring and development. (Guarini, 2023) The quote underscores the need of measuring appropriate things and variables in order to yield accurate results that fulfil their purpose for stakeholders. Conversely, inaccurate data and wrongly collected information does not contribute to its purpose and can result in misguided decision making.

In production development and monitoring, the requirement for informative production analysis necessities reliable data. Collected data gives a base for production monitoring and the collected information can be processed and transformed into different KPIs offering a comprehensive overview of processes and insights into production. The key is to find the right measurement tools and indicators and implement them in a way that aligns with their intended purposes and promotes the successful achievement of end goals.

The statement of H. Thomas Johnson can be further applied to OEE which is often considered as a best practices solution for production evaluation. OEE has a benchmark of 85% which is seen as an indicator of world class production and often also as a production goal. As there is no universally agreed method of applying OEE, the measured results have a risk of potentially being misinterpreted and manipulated resulting in misleading results.

While OEE is generally seen as a versatile KPI the consensus of defining the three different factors are not uniform at all. Software as a Service (SaaS) providers market OEE as a tool for production efficiency monitoring that will boost up production. (Lääts, 2023) Studies have indicated that OEE in its basic form doesn’t always fit the purpose of production monitoring. One of the major limitations of OEE is that it doesn’t consider the planning factor in the production which reflects the actual production to the planned production. (Jean Mathot, 2007)

With these considerations acknowledged, this thesis analyses the production in four distinct case studies comparing the results to commonly accepted OEE metrics. The evaluation takes into account stakeholder needs, assessing the suitability of OEE for each production equipment and compares them to the world class limit of 85%. The study seeks to discern the effect of excluding the planning factor from OEE and if it should be combined with OEE to achieve better suitability to the production monitoring needs.

The purpose of these complicated subjects is to bring nuanced views to the discussion of production monitoring and evaluation in the scope of OEE in a diverse manufacturing environment. The study and results emphasize the importance of data reliability and choosing right KPIs for different purposes.

4.1 Thesis background

This thesis was conducted for a factory in which a varied range of machinery is operated through distinct operations. The production machinery encompasses injection molding, wood processing machines and a CNC cutter for cardboard. These machines are in three separated departments in the factory. Furthermore, the production environment at the company incorporates a mix of manual labour and automated processes to fulfil operational requirements and production needs which adds complexity in the frame of monitoring production with an automated production monitoring system.

The production activities monitoring is initially conducted through physical observations by operators and statistics collected by supervisors. Production metrics and statistics are gathered by workers and recorded by an Enterprise Resource Planning system (ERP) which facilitates the analysis of production trends from extended time periods. However, it is important to acknowledge that the data input to the ERP system is partially manually undertaken, introducing a possibility for unreliability in the data due to the inherent human factor involved in the process. The statistical representation of the production is characterized by a wide generalization which results in challenges to seamlessly correlate actual production dynamics and identify bottlenecks with time specific causes. In addition to the ERP system, a dedicated maintenance system is used to analyse faults and address preventive maintenance initiatives within the factory.

The company adheres to the principles of lean thinking in both production processes and product design with a focus on reducing waste and improving the ergonomics of the workers. The organization has achieved notable reductions in waste across various production operations through continuous improvement, aligning with contemporary trends in modern and smart manufacturing. The evolution is conducted to both social and environmental sustainability. Recognizing the transformative potential of the Industrial Internet of Things (IIoT), underscores the potential that can be reached by development of progressive companies. The incorporation of these technologies into production necessitates the acquisition and utilization of accurately documented production data. This brings questions about the classification and implications of big data in this context. This thesis aims to explore the interplay between these principles and technologies in the context of the company's production environment.

The objective of the case studies is to introduce a tool to provide relevant and useful production data for the company and the diverse need by figuring out how machines are utilized, and which metrics are the best to visualize it. The main goal is to produce precise production data and present it in a format that favours the different stakeholders without causing unnecessary burden to the operators. The results of the study will be analysed to determine if OEE is suitable as a metric for monitoring and evaluation production in the real-life production environment.

4.2 The study environment

The company, a well-established Finnish manufacturer of industrial products, operates in three factories. This thesis was conducted in only one of them where the production was the most diverse to give a holistic insight of production monitoring. In terms of production, the factory manages assembly work, injection molding, and wood manufacturing, while the other facilities focus mainly on metalworking and powder coating.

This industrial manufacturer has a rich history dating back many years. The company has undergone mergers with various companies in the plastic and metal industries over time, with significant mergers occurring in recent years. It has expanded its global presence with subsidiaries and retail partnerships in numerous countries. The mergers and the increasing production demand has led to production and organizational improvements.

Ergonomics and lean principles are fundamental to the manufacturing, retail, and design of the company's products. It is committed to delivering high-quality products that meet customer needs, preferences, and ergonomic standards, which are prioritized in the design of manufacturing processes. The values highlight the needs for purposeful production and equipment monitoring.

As already stated, this thesis will focus on monitoring production and machinery at a factory which utilizes a variety of machines and production methods. In this factory, although many manufacturing operations are still manual, a shift towards automation is noticeable. The project aims to understand the challenges faced by analysing different manufacturing equipment and processes, considering the need for comprehensive production monitoring.

4.3 Research Problem

Accurate and relevant data is needed to gain an overview of production, create a foundation for daily management and to improve and develop processes including manufacturing and other operations. High quality data creates understanding and visual indicators that can be used for knowledge-based management and for development to reach the essential targets and production needs. (Radu, 2023) Production monitoring systems are often sold to the customers as “OEE-systems” to collect data and monitor production with a promise of noticeable improvements in production. For example, Evocon references on their website the findings of “The Productivity and Payback of Employee Engagement” by Chuck Schaeffer, highlighting the high production improvement potential in the OEE metrics (New, 2024).

As demonstrated in the previous paragraphs, the factory where the case study takes place doesn’t currently get accurate and relevant data of the production and the condition of the machinery. All data is collected retroactively and exhibits weak links to actual production activities. While the collected data may serve well its primary intended purpose, the deficiency lies in the absence of data that can effectively be pinpointed into bottlenecks and combined with specific conditions and states with the production equipment. Improving production is challenging and imprecise when the bottlenecks, initial conditions and the overall accuracy of the production status are not known for sure, turning the assessment into educated estimates.

Identifying production losses is challenging without a proper and reliable way of monitoring production. Striving towards lean manufacturing and Industry 4.0 model is consuming investments and constant improvement, requiring a foundation built on numbers and precise data. With aspirations to evolve and streamline production, it is important to constantly improve production-related processes. Achieving performance improvements requires optimization of processes by reducing wasted resources and improving production efficiency. This entails systematically gathering precise and purposeful data from production. By utilizing the insights gained, results can be achieved by improving production and utilization of the machinery.

In the process of developing production equipment related operations, feedback of what has been achieved and how different activities have contributed to them is significant. A widely adopted method of measuring production is the utilization of OEE-systems provided by different software companies. However, implementing an OEE model, or any other production monitoring system, has a risk of measuring incorrect parameters or irrelevant data which doesn’t contribute to production development. Such scenarios do not serve the interests of stakeholders, nor do they align with the purpose for which a production monitoring system was implemented in the first place. It is essential to acknowledge that OEE is just a measuring tool; understanding the potential and possibilities of such a system enables the effective utilization of the results to benefit from the production monitoring efforts.

OEE, which is a widely applicable production measurement tool, can face challenges when adapting to different production types. Its primary limiting factor is combining three separate metrics into one percent without into one percentage without considering the equipment's' actual planned uptime. This can be a significant drawback, as it in some cases may result in oversimplifying the evaluation process and it may not be able to effectively account for the nuances of diverse production. Other challenges associated with OEE include the absence of standardization and the inability to compare actual production with planned production.

The research questions are:

1. Does OEE-metric provide pertinent data meeting stakeholder needs in diverse manufacturing contexts?
2. How does the inclusion of the planning factor in the OEE formula contribute to its effectiveness in assessing equipment performance, especially in cases where machines are not designed to operate continuously?

4.4 Research approach

This thesis utilizes a mixed methods approach that encompasses both qualitative and quantitative research methods within a case study framework. The research collects and analyses a significant amount of numerical data, which is then processed into various metrics to facilitate evaluation focused on the quantification of recurrences and patterns. To ensure accuracy of the collected data, the results are compared to real life events. Stakeholder needs and the appropriateness of OEE as a production KPI are evaluated by analyzing meetings and interviews, comparing the gathered data and metrics to real life events to ensure the specific requirements are met. The conclusions presented in this thesis are drawn by integrating the measured results with manually collected data regarding the operations and production events in real life environment.

Dealing with a high amount of data which contains a lot of information, necessitates quantitative methods to quantify the patterns and underlying factors in the collected information. (Moore, 2007) In this thesis the raw data collected from the production equipment in the different cases is analysed and manipulated with quantitative methods including numerical data analysis, statistical metrics, and trends, monitored with sensor data, time-series analysis and efficiency metrics and benchmarking. Statistical metrics are monitored in an extended period to reduce data distortion due to a too small test period.

In the case study, the data is gathered from the production by using a production monitoring system, which effectively collects and analyses the collected raw data into a meaningful form and presents it to the end users and operators. Some of the information was manipulated in Excel which is much more flexible and versatile in data handling than the software provided by the system integrator. The gathered data and metrics derived from it were examined with a comprehension of real life by time series analysis and operational perspectives to ensure the comprehensive and accurate interpretation of the production environment. The used methods contribute to a thorough data driven understanding of the measurements in the frame of the production environment.

Qualitative research method on the other hand can be described as collecting a lot of meaningful and in-depth data from a small number of instances. The aim in this thesis is to inspect the topic from the viewpoint of the different stakeholders involved in the study in order to see if OEE is a suitable tool for real life production monitoring. The research approach contains interviews with detailed topics with the stakeholders involved in the study. In case studies this kind of qualitative research approach is going to help forming hypotheses and understanding the collected production data. (Angeles, 2016) In depth data collection was conducted to get an understanding on how well the measured information fulfils its purpose and how accurate the measurements really are.

The objective of the thesis is to understand the production and its monitoring as a phenomenon. Stakeholder interviews and ongoing meetings create an understanding of the information and needs encountered in a production environment with diverse types of machines. The purposive data collection sample in this case study contains data collected from four production cells. The data is associated with actual production and evaluated by using various approaches such as TPM and lean which are often associated with OEE and assessed for its suitability for each of the methodologies. (Scott, 2011)

In order to ensure the quality of the collected data, it is crucial to align it with real life situations. (Stevenson University, 2023) The collected raw data and generated metrics, along with their validity underwent analysis through comparison with observations obtained by monitoring equipment operations. The data is systematically sorted, and observations are categorized to align the equipment operations at field level. In this process, raw data undergoes a transformation into reliable conclusions and results which are validated and evaluated for their suitability in the context of production monitoring.

The choice of a case study as a research method for this study is based on its ability to provide an in-depth understanding of production monitoring in a real-world setting, giving the study contextual depth. Examining OEE in a real-life production environment enables data validation and a thorough assessment of stakeholder needs while the appropriateness of the measured metrics can be assessed. This approach integrates both qualitative and quantitative research methods promoting a holistic understanding of research questions, which is seen to fulfil the research methods needed in a mixed method research (Angeles, 2016). By adopting a case study framework, this thesis endeavours to explain the complexity of production monitoring by applying theoretical concepts with practical applications to generate meaningful insights.

OEE is a complex metric with a lack of a universally defined standard. (Ivana Šajdlerová, 2020) Its application varies across different types of equipment, with metrics and data collection methods being machine and application specific. Therefore, a comprehensive understanding of equipment operations, functions and production processes is needed to validate various metrics as suitable production monitoring tools. The use of a case study approach facilitates the analysis of the influence of the three individual OEE components in shaping overall equipment efficiency, particularly from a production-oriented perspective. The thesis investigates whether other factors, such as the planning factor, should be considered when forming figures that present production KPIs. The case study provides a versatile opportunity to comprehensively understand production monitoring applied to real life machinery.

The case study involves analyzing machine operations and validating signals to ensure the accuracy of data reflecting real-life production. Following the establishment of a production monitoring system, diverse metrics are formulated to consider the stakeholder needs and OEE measurement requirements. To understand production monitoring comprehensively, stakeholder needs are assessed, and the effectiveness of metrics and signal data in meeting these requirements is evaluated. The findings are then benchmarked against common methods and industry best practices.

5 Theoretical framework

The aim of this chapter is to provide a theoretical overview of the OEE measuring method, clarifying its principles, calculations, and underlying concepts to facilitate understanding of the results from a production-oriented perspective. As OEE is closely intertwined with various production improvement philosophies, such as lean and TPM, this chapter also introduces these frameworks as means to reduce wasted resources in diverse operations. The objective is to outline contexts where OEE results can be effectively utilized, considering that OEE alone does not directly enhance production or offer a means to justify the implementation of a production monitoring system. Additionally, the chapter deepens into the theoretical foundations that underpin production monitoring, culminating in an exploration of OEE and its variations as key performance indicators in production monitoring.

5.1 Literature background

OEE is a KPI based on the analysis of real-life production and comparing it to an ideal scenario where the machines are available for production 100% of the time, there are no faults or defects, and the machines run at maximum speed. (Roser, 28.6.2023) OEE tracks production losses in three different categories, including quality, performance, and availability losses. The OEE number is generated by multiplying these three factors together and presented as a percentage. Criticism about OEE is targeted on the complexity that lies in the lack of unambiguous definition and lack of factor standardization.

A widely acknowledged issue with OEE is its amalgamation of three distinct performance measurements: availability, quality, and speed. Williamsson criticizes the use of combined measurements as a production indicator, asserting that “availability” lacks proper definition and that even OEE experts do not unanimously agree on the foundations for OEE. (Williamson, 2006) This problem with OEE is also highlighted in an article conducted by ResearchGate, where it was suggested that in many cases, alternative indicators such as Production Equipment Efficiency (PEE) or Total Equipment Effectiveness performance (TEEP) would be necessary to achieve desired production monitoring results. These metrics are derived from OEE to address specific production monitoring needs. (Amrik Sohal, 2010)

According to Seiichi Nakajima, the founder of OEE and TPM, the original purpose of OEE was to analyse machinery availability in conjunction with the implementation of total productive maintenance. (Williamson, 2006) However, OEE is often seen nowadays more as a production goal than as a tool for understanding the production processes. (Ivana Šajdlerová, 2020) Williamson’s perspective on the matter is production oriented, suggesting that the primary function of OEE should be collecting asset performance data, with the OEE percentage serving only as an indicator of individual equipment. Ellis New's perspective on OEE aligns with Nakajima's original concept of using OEE as an improvement metric solely focusing on the performance and losses of a single machine. (Vorne, 2024)

OEE software providers seem to have a differing view from Seiichi Nakajima’s original concept of OEE promising efficiency improvements and comparing machine performance to the world class level. For instance, Pinja, which provided the Gema production monitoring system used to collect data in the case study, asserts that OEE should be compared to the maximum capacity of the equipment. In this approach, all machines are individual entities rather than parts of a larger process, timed by various actions in the factory. Juho Arkkola (Head of Sales at Pinja) even contends that OEE should solely compare production speed to the best cycle time possible (without tooling, or molds etc.), without considering the impact of product specific tools which dictate the maximum actual production speed (Arkkola, 2023) This is misleading in cases where a machine is operated with the maximum speed that a product or tool allows even though the machine could perform more efficiently producing another product.

Another issue that rises when aiming for a high OEE-number, such as the 85% world class treshold, is that if customer demand is low, running equipment over the demand rate results in overproduction, which is a major source of waste in lean manufacturing. (Jean Mathot, 2007) Perumal Puvanasvaran reached the verdict in his research that high OEE numbers resulted in overproduction and increased costs while the demand was low. Puvanasvaran also sees the need to focus on a production line and the overall picture instead of focusing on individual machines. (Puvanasvaran, 2013) This raises the question if a machine should be loaded for all the available time. Williamsson sees the need of adding “scheduled losses” to the OEE number, including scheduled and planned stops such as planned maintenance. These should not affect the OEE number since the machine is not scheduled to be operated during for example planned maintenance breaks. Francis Wauters and Jean Mathot reached the same verdict in “Overall Equipment Effectiveness” adding the planning factor to the OEE number to reduce the impact of planned stops to the metrics. (Waddill, 2024)

Pinja’s OEE guide underscore the meaningfulness of the world class limit of OEE as a factor that should be strived for. (Pinja, 2024) Other OEE system providers have similar perspectives, for example Evocon states that measuring OEE from a machine shows how effectively quality products can be delivered to the customers. (Lääts, 2023) Both companies suggest comparing the OEE efficiency to the 85% “world class limit”, although they mention that the level might be challenging to reach. Williamson criticized the world class limit of OEE due to its diverse definitions and lack of statistical validity as a metric. Another noted concern is that the pursuit of maximizing OEE to meet the 85% threshold may not always be optimal, potentially overlooking individual circumstances and resulting in suboptimal decision-making and over production (Ivana Šajdlerová, 2020).

OEE seems to have its place in the production world despite the criticism about its character. Comprehending OEE necessitates an understanding of data collection and its connection to the production development methods used. (Soliman, 2020) The study emphasizes the importance of understanding the collected data having a proactive management committed to utilizing the information. Although OEE does not provide straightforward answers to complex questions, it holds its position as an industrial measurement. The study performed by Advances in Sciences conducted that OEE functions effectively as a production benchmark. (Soliman, 2020)

5.2 Lean

Lean is often described to reach towards a world-class production system. Despite the definition, lean can be used as a tool for everyday operations and production with the aim of minimizing wasted resources in processes by still creating value to the end customer. Taiichi Ohno is credited as the progenitor of lean, which originated in Japan as Toyota sought to enhance its competitiveness amid industry competition. Many production improvement tools are based on the principles of lean.

Lean can be defined as a multi-step process that starts with defining value for customers. It involves improving the flow of the value stream and implementing the pull principle, where production systems respond directly to customer demand. This approach is stated to respond to actual customer demand and minimize waste in the production. (Vorne, 2023)

The benefits of using the lean methods are improved efficiency and agility as an organization if the theorem is applied properly. (Mflow, 2023) As lean primarily serves as an ideology for enhancing production, KPIs like OEE are commonly employed as benchmarks and metrics to provide quantifiable data on process functionality and effectiveness. The collected data aids in the implementation of lean practices and strategies. (https://www.leanproduction.com, 2020)

Lean serves as a tool for the company undergoing the study, playing a significant role in various aspects of its operations. The factory manufacturing environment and product portfolio are designed according to lean philosophy in order to provide customers with smart solutions. The company provides solutions that go hand in hand with the 5S mindset, also considering safety. The incorporation of the lean philosophy into product design enhances workflow and ergonomics, facilitating waste reduction and promoting waste-free production within the company. (Vasel, 2012)

5.3 Lean as a production development tool

While lean can serve as a comprehensive approach to enhancing efficiency across various processes, this paragraph primarily focuses on its application as a tool for production development and improvement. To facilitate the development of production processes, there must be indicators highlighting necessary changes and assessing whether these changes are leading in the right direction. The ultimate indicator of success in production development can be viewed as the value delivered to the end customer. Defining "value" is essential to determine whether actual value is being created or lost.

When talking about lean and value, the concept of “value streams” rises in the discussion. Value streams can be seen as all the specific actions and steps that are needed for a product (a good, service or a combination of both) to reach its full potential from the beginning of the process to the delivery to the customer or end users. The value stream contains all physical transformation (from raw materials to end products) and all information management, problem-solving, handling, development and design that are involved in the production. (Vorne, 2023)

Lean ideology was originally presented in “The Toyota Way - 14 Management Principles From the World’s Greatest Manufacturer". The idea is based on a production system called TPS utilized by Toyota. TPS is the acronym of Toyota Production System which has its roots in JIT (just in time) thinking. JIT can be seen as a system where every operation gets ready for the next step “just in time”, not too early and not too late to optimize the production. The benefits of the philosophies listed above are less storing and the avoidance of overproduction which results in better workflow and improved production with reduced processing. The other main goal in TPS is ensuring good enough quality of the produced products which results in less wasted resources. (James P. Womack, 2003)

Lean serves as a foundational ideology in modern industries, aiming to enhance production efficiency by optimizing workflow and minimizing resource wastage throughout the processes. Emphasizing quality and streamlined processes, lean methodologies focus on eliminating unnecessary operations and steps. Continuous improvement is integral to lean implementation, with the company's operating models playing a crucial role. (Liker, 2004) Waste, defined as wasted time, resources, space, and operations, must be systematically removed from operations to achieve lean objectives.

The goal of an efficient business model is adding value in the process and shortening the time needed for production. The basic idea in lean is that everything that doesn’t add value to the company or product is waste. Recognizing and removing waste are key elements in improving competitiveness. (James P. Womack, 2003)

5.3.1 Waste in lean

Waste in lean can be divided into three basic components: muda, mura and muri which means waste, unevenness, and overburden (Sixsigma 2023). Waste is defined in “Lean Thinking” by J. Womack as “any human activity which absorbs resources but creates no value”. (James P. Womack, 2003) Although waste can occur outside of human activity, the definition emphasizes the basic concept of unnecessary utilization of resources in production activities.

Taiichi Ohno can be seen as the person who originally identified the seven different original types of waste in lean thinking that are classified as “muda”. (James P. Womack, 2003) Muda (waste) is the most common type of waste and basically means wasted resources. It means an operation that uses resources without adding value to the process or product and is quite easy to detect in a process. (Sixsigma 2023) Different types of muda are waiting, inventory and extra materials, quality defects, over processing, transportation, and unused potential. (Mäenpää, leanthinking.fi, 2023)

Overproduction means producing more products, services or parts that are immediately required by customers. Overproduction leads to excess inventory, storage costs and increased risk of obsolescence. Overproduction can be reduced by gaining understanding about production demand and aligning it with production in a way that avoids unnecessary production.

Waiting can be described as downtime for either workers, equipment, or materials. Typical causes for wait are inefficient scheduling, delays, or bottlenecks in production processes. Waiting (lack in availability) is a factor that affects the overall equipment efficiency.

Inventory and extra materials cause waste by having excess resources compared to what is necessary for immediate production needs. Extra resources tie up capital, storage space and similarly to overproduction, increases the risk of waste and obsolescence.

Quality defects means products and services that do not meet customer requirements and is one of the factors considered when calculating overall equipment efficiency. The result of occurring quality defects can be scrapping or rework. Quality defects lead to additional costs and customer dissatisfaction.

Over-processing entails carrying out unnecessary or excessive work that fails to add value to customers, thereby resulting in wasted time, effort, and resources.

Waste in transportation means unnecessary transfer of handling during the production process including material or product handling, or data between process steps or locations. The result of transportation waste is inefficiencies, delays and increased risk of damage or loss.

Unused potential means underutilization of human or machine resources, skills, or equipment capabilities. Unutilized resources cause a lack of opportunities for improvement and innovation. The third OEE loss, speed, or performance, can be seen as unused potential.

The listed waste categories contain the different factors from OEE, including quality, stops and unused potential (speed). (Mäenpää, leanthinking.fi, 2023)

Lean manufacturing concept “muri” represents a kind of waste that prevents smooth and straightforward operations. It covers situations such as process or department overloading, and the skill or capacity level of employees being exceeded. (Mäenpää, leanthinking.fi, 2023) While muri is not typically regarded as a component of OEE, since overall equipment efficiency mainly centers on equipment utilization and performance metrics, muri-related issues can still contribute to downtime if the machine is unable to operate due to factors such as overloading or exceeding the capabilities of workers.

“Mura” refers to waste resulting from variations in processes, which can stem from imbalances in various aspects such as quality, costs, and process times. These imbalances can lead to inconsistencies and inefficiencies in production, ultimately contributing to mura. (Mäenpää, leanthinking.fi, 2023) Mura can contribute to downtime in OEE due to factors such as fluctuating demand, changes in product specifications, uneven production flow, or variation in equipment performance.

5.4 TPM

TPM (Total Productive Maintenance) is a holistic approach to maintenance which can be seen as a foundation for lean production ideology. The original idea of TPM was created by the Toyota group member Nippondenso to ensure that every production machine could reach the top of their performance and capacity. (Vorne, 2023) The initial target with TPM is to utilize the full capacity in productivity and to make production economically more profitable. (Dennis McCarthy, 2004) Fundamentally, TPM aims to achieve zero downtime caused by breakdowns, defects, and slow running, along with streamlined production. The approach maximizes the operational efficiency of the equipment and helps reaching and utilizing its full potential. (James P. Womack, 2003) TPM is closely aligned with the production improvement principles of lean thinking and is often used together with lean, especially in the field of maintenance. (Vorne, 2023) OEE was developed to monitor TPM and analyse losses, as discussed in detail later in this thesis.

TPM is a reliability and improvement strategy that emphasizes system maintenance throughout the entire lifespan of equipment where TPM is implemented. It serves as a method for achieving development goals by continually enhancing maintenance methodologies. The goal of TPM is to systematically eliminate any losses caused by breakdowns, accidents, and defects until “world class” level is reached. (James P. Womack, 2003) The production losses can be measured with KPIs such as OEE.

TPM focuses on the six losses:

1. Breakdowns
2. Setup/adjustment
3. Idling/ minor stoppages
4. Speed
5. Defects in process and rework
6. Startup losses

The losses observed in TPM mirror those identified in lean practices and OEE assessments. TPM aims to mitigate downtime resulting from underutilized equipment performance, which is a concern that aligns with the goals of lean methodologies. Furthermore, OEE can be used as a tool for monitoring production equipment efficiency to evaluate the fulfilment of TPM.

Within the framework of TPM, the financial aspect is inherent, as production costs directly affect overall process efficiency, and material and labour costs are taken into account to ensure optimal use of resources and cost effectiveness. The delivery aspects emphasized in TPM are parallel to lean, which emphasizes the importance of accurate and efficient product delivery, avoiding wasted resources.

Safety measures are often paramount in TPM implementations, reflecting a commitment to ensuring a safe work environment for all stakeholders and reducing risks to prevent workplace accidents or injuries. Additionally, some organizations focus on environmental sustainability in TPM, aiming to minimize their ecological footprint by reducing pollution, avoiding wasted resources, and aligning production with sustainable development goals. Furthermore, morale is a critical indicator of overall employee satisfaction, motivation, and engagement, promoting a positive work culture that fosters productivity and success.

5.5 OEE

OEE (Overall Equipment Efficiency) is a key performance indicator (KPI) lacking standardized definition, which quantifies the overall productivity of a machine or production cell. It is expressed as a percentage with a maximum value of 100%. Overall equipment efficiency contains quality, availability and performance and combines these three factors together into one value. OEE is possible to monitor in real time and therefore it considered as a powerful effectiveness and utilization tool for daily management, process development and maintenance planning. The OEE-number tells what amount of the production time is being used productively. (Vorne, 2023) The definition of the different factors of OEE varies a lot since it lacks proper definition. This chapter presents OEE in its more traditional approach where only the three key components are taken in account.

TPM takes in account the whole production efficiency which shares the same aspects with OEE. TPM can be monitored using various KPIs within different management and operational frameworks. Seiichi Nakajima is credited with founding both OEE and TPM.

The main issues and characteristics of OEE are presented in the theoretical framework. One of the observations is that OEE is more of a general indicator than an actual production goal. The aim of using OEE is to understand the happening losses in the manufacturing processes to help manufacturing and maintenance to target their resources in more accurate ways. The OEE losses are compared to an ideal situation where a manufacturing process contains no losses. Losses in overall equipment efficiency can be divided into availability, quality, and performance losses. (Kirsty Williamson, 2017) These losses are not standardized but in a “traditional” OEE approach which aligns with TPM, the performance losses can be divided into six causes which are:

1. Equipment failure/ breakdowns
2. Set-up and adjustment
3. Idling and minor stoppages
4. Reduced speed or speed losses
5. Quality defects
6. Rework

Given that OEE functions as a comprehensive measurement tool for overall effectiveness, it includes losses such as equipment failure, setup time, and minor stoppages, all of which are also addressed within TPM and lean methodologies. Quality defects and rework are further classified as "quality defects" within OEE assessments, Equipment failure, set-up time and minor stoppages are classified as a loss in “availability” or “performance”.

In the context of OEE, equipment failure and breakdowns denote any problems causing machine downtime due to malfunctions. Stops that briefly pause production are classified as idling or micro stops. Quality defects within OEE calculations encompass both scrapped parts and those needing rework. Set-up and adjustment operations, essential for machine operation, are subject to debate regarding their inclusion in calculating the OEE number.

5.6 Availability

As previously mentioned, OEE is characterized by a wide range of definitions, lacking consensus on how to define its various aspects. The different interpretations of availability form the OEE number according to the preferences of the system implementer. One definition of availability in the context of OEE is that it can be seen as the ratio of actual uptime to the total scheduled time providing information about the reliability and technical readiness of a system (Lennard Sielaff, 2022). Depending on the definition availability can either be seen as the availability of the full working hours or as availability compared to the planned hours. A third interpretation, a KPI measure for technical availability can be generated, although it is not commonly used as a part of OEE analysis. Technical availability can be described as a measure of how often a production system or machine is operational and ready to perform its intended task within a time frame from the technical point of view.

Availability is a metric measured in the framework of OEE, which covers the time span during which a certain machine is loaded or available for production within a specific time frame. The lack of availability is further defined by subcategories of production losses and downtime causes. (Radu, 2023) These losses typically include all events that prevent the realization of planned production and stops exceeding a predefined threshold. In contrast, short outages are classified as micro stops, which differentiate between major disruptions and smaller breaks in the production timeline. (Sermin Elevli, 2010)

A planning factor is common addition to the availability calculations of OEE even if it lacks standardization. The factor can either define the measuring period or the downtime causes that are considered in the generation of the OEE number. The purpose of a planning factor is to tie the measurements to the actual production.

The planning factor can be utilized when calculating availability:

The planning factor tells if a stop is categorized as planned or unplanned production. The planned stops are not affecting the OEE number while the unplanned stops decrease the availability. Planned events include typically scheduled events such as changeover periods, planned maintenance operations, moving pallets within a production cell, and other instances where production is intentionally stopped. On the other hand, unexpected distributions such as machine malfunction and material shortages cause the machinery to perform unplanned idling or stops. The duration during which the production activity proceeds without unplanned interruption and which considers the cumulative effects of both planned and unplanned events is called runtime or loading time in the context of OEE analysis. (Sermin Elevli, 2010) OEE has some derived versions such as TEEP and PEE. These versions have different variations in defining the factors contributing to the overall equipment effectiveness.

Depending on the definition of OEE, either availability or utilization rate can be used in the calculation of the availability factor. This diversity of definitions is caused by the absence of a standardized approach for integrating the planning factor into the KPIs. As a result, organizations may adopt varying methodologies tailored to their specific operational contexts and still measure OEE.

5.7 Quality

In the context of OEE, the aspect of "quality" pertains to both the quantity of production units achieved and the degree to which these units fulfill predefined quality standards, covering the successful achievement of acceptable quality levels set for manufactured products. In instances where manufactured parts are not meeting the quality standards, corrective actions such as rework is needed. In more severe cases, defects lead to the complete scrapping of produced units, resulting in a reduction in overall productivity. This renders the running time non-profitable due to the presence of unusable production units. The manufacturing time of products that comply with quality standards is defined as the full return time within the scope of the OEE analysis. (Sermin Elevli, 2010)

5.8 Performance and Speed

Speed loss in OEE can also be seen as a performance loss in a production process since the loss of speed is classified as the inability to utilize the complete capacity of the machinery. The speed loss regards slow cycles and small stops. The time after the performance loss is subtracted is called the net run time. (Sermin Elevli, 2010) Like availability, also performance or speed can be defined in multiple ways.

Understanding OEE requires distinguishing between speed and performance. Speed rate is determined by comparing the optimal production speed to the actual production speed. In OEE, speed considers the operational speed of the equipment during production.

The speed rate can be derived into performance by comparing the theoretical production output to the actual production output. This accounts for any speed losses and micro stoppages during the operational process.

OEE does not define whether the speed or performance rate of the machine should be prioritized in the calculation. The choice between these rates can be determined and adjusted based on the preferences of the implementer, the characteristics of the machine, or the specific requirements of production monitoring.

5.9 Calculations

OEE formula multiplies three different components together, yielding a percentage that comprehensively considers all the previously introduced factors. This percentage indicates the overall equipment efficiency, providing a holistic assessment of the equipment's performance.

$$OEE = quality \times availability \times performance.$$

As previously discussed, the OEE number is determined by multiplying quality, availability, and performance into the same equation. While the specific measurements will be customized to suit the requirements of each machine, the fundamental format remains consistent. However, it's crucial to acknowledge that inaccurately assumed total time and unreliable or improperly classified data can significantly distort the results of OEE. (IIoT World, 2023) This highlights the importance of carefully considering these factors during the calculation of the overall equipment efficiency.

A commonly accepted benchmark value for the OEE is 85% which is classified as world class overall equipment efficiency level and is widely considered to be a long-term target for a company that wants to improve its productivity.

The world-class level serves as an indicator of the optimal performance required to achieve production targets and is commonly used as a best practices indicator. It's important to recognize that the OEE value is heavily influenced by factors such as production type, machinery specifications, and the definition of OEE components, leading to significant variations in OEE numbers. Moreover, a high OEE primarily reflects equipment utilization rather than solely indicating manufacturing cycle efficiency (MCE). (Pinja, 2024)

Furthermore, the overall efficiency of production equipment typically falls below the ideal speed, as production rates often align closely with current demand, resulting in lower OEE numbers. Overproduction can lead to increased costs due to the need for additional operations and work force. (Roser, 28.6.2023)

5.10 Variations

OEE, lacking standardization, exhibits diverse variations tailored to meet distinct production monitoring requirements. These variations cover a range of definitions regarding the measurement period and the factors, and their definitions integrated into the metric. Each variation of OEE prioritize different aspects of production efficiency, and the factors involved in it, depending on the specific needs of the manufacturing process or industry sector. Consequently, the amount of flexibility in these variations allows organizations to customize OEE implementation according to their unique operational contexts and objectives, enhancing adaptability and utility across diverse production environments.

A slightly used variation of OEE is TEEP (Total Effective Equipment Performance), extending the concept by considering the full available time rather than just planned production time. It incorporates a fourth factor, utilization, which evaluates management effectiveness in asset utilization. TEEP quantifies production around the clock, emphasizing both equipment effectiveness and management efficiency.

In contrast, Production Equipment Efficiency (PEE), proposed by A. Raouf, introduces weighted factors to OEE, providing better suitability to different production environments. PEE incorporates factors like product support efficiency and operating utility to enhance continuous production monitoring. However, PEE lacks widespread adoption due to its abstract nature and complexity in definitions.

The presence of variations in OEE metrics underscores the absence of standardization and highlights the necessity of adapting case specific definitions. These variations reflect the diverse requirements and operational contexts within different industries, prompting the need for flexible frameworks that can accommodate various production monitoring needs. Consequently, organizations must be prepared to adjust and customize OEE definitions to better align with their specific processes and objectives. This adaptability ensures that OEE remains a relevant and effective tool for assessing equipment performance and overall production efficiency across diverse manufacturing environments.

6 Methods and dataset

To comprehensively gather and understand the significance of collected data and to receive a holistic overview of production, an automated data collection methods was employed and customized according to the specific equipment and stakeholder needs. This tailored approach facilitated the extraction of relevant information from machine operations in a real-life environment where the data collection and KPI generation could be adjusted to fulfil individual equipment requirements and specific stakeholder needs.

The validation of collected data involved comparing gathered information with real-life events, studying signals and electrical schematics from the machines to ensure suitability for production monitoring and to overcome limiting challenges. Furthermore, meetings with machine suppliers and stakeholders were conducted to identify optimal data collection methods aligned with machine-specific needs and best practices.

Weekly stakeholder meetings and organizational collaboration with different departments were pivotal for the purposeful implementation of the production monitoring system, including the generation of KPIs and effective utilization of the collected data. Stakeholder-specific metrics were developed to facilitate meaningful data collection, and data validation spanned across different departments to ensure result reliability and stakeholder need fulfilment. Additionally in the meetings, the importance of the individual factors of OEE was discussed to get a comprehensive understanding about the production and the key performance indicators applied to it.

The production monitoring system generated a large volume of raw data, which was then transferred to the cloud for processing into visual formats that stakeholders could utilize. Both the raw and the processed data got evaluated during the production monitoring system implementation period. Following the validation process, the collected data, KPIs, generated graphs, and downtime reasons were thoroughly analysed and evaluated in collaboration with the different stakeholders. This analysis involved discussing production metrics and goals, examining KPIs, and analysing the collected data to determine which production metrics best suited the needs of various stakeholders.

6.1 Data Collection

To obtain useful data, methods can range from manual observations to fully automated data collection systems. Many machinery manufacturers have their own systems and software designed to automatically collect production data from processes using integrated interfaces and protocols, which then can be used for generating KPIs. Another option is to use universal interfaces like OPC-UA to collect data from machines and process it on external servers. For lighter data collection needs, various measuring tools or loggers can be used to directly read data from signals within the machine, enabling analysis on an external server.

In the case study, data monitoring is conducted using SaaS software from a software supplier, which benefits from the ease and flexibility of data collection options for the customer, since with an external interface or data logging system, data collection can be easily influenced if needed. For a customer with multiple different brand machines, a universal data collection system makes more sense, as it allows for operation and monitoring through a single interface with the downside of a slightly more challenging implementation process.

There are several options available when choosing production monitoring systems. Some software companies specialize in production monitoring products marketed as "OEE software", while many manufacturing equipment suppliers offer their own production monitoring software to collect and track data. In addition, certain machine suppliers may offer retrofit options for data collection interfaces. Despite the widespread use of the OPC-UA interface as a common communication standard, it was deliberately excluded from the case study. Instead, external data collection devices were utilized as versatile and customizable data collection methods for machines lacking built-in interfaces, offering a cost-effective alternative.

The production monitoring data collection process in the case study is a combination of automated and manual methods. The automated component utilizes the Gema by Pinja production monitoring system, while the manual methods involve acknowledgements made by operators. Initial raw production data is gathered using data collection devices made by Moxa. The collected data is transferred into a cloud where it is processed into a visual format and further enriched by machine operators. This refined data is further transformed into graphs and reports for analysis.

The collected raw data is processed by servers that communicate with both the data collection devices and the units used by operators and end users. Operators enrich the data with additional information, while end users evaluate the data using various figures and reports generated by the Gema software to gain insights into production performance and implement improvement strategies.

Data analysis can be performed in the Gema online-based environment, where users have the flexibility to generate customized reports and select specific data collection periods. Additionally, the data can be exported from the software in .xlsx and .pdf formats, allowing for further analysis and manipulation.

The data collection devices used in this process are Moxa ioLogik E1210, which is part of the Moxa E1200-series specialized for industrial digitalization and SaaS solutions. These devices are equipped with 16 signal inputs and are connected to servers for data analysis and visualization.

The integration of the Moxa data collection devices with the production machinery required a comprehensive evaluation of signals to ensure they were suitable for representing machine operations precisely. The processed data is then presented in an online platform accessible to operators and supervisors.
However, a notable limitation arises from the capabilities of the Moxa ioLogik E1210 devices, which can only analyse digital data. To address this limitation, sensors and relays were added to the equipment to provide compatible signals.

Manual data collection supplements the automated process, as operators enrich the collected data by adding reasons for production interruptions and downtime. These acknowledgments enhance the usefulness of the data, enabling the tracing of stops and analysis of underlying reasons. Interviews with operators further contribute to gathering additional insights into production events.

Ensuring the reliability of collected data was a crucial process, necessitating validation over an extended period. This validation process involved comparing raw data to actual machine operations and adjusting production state definitions and signals accordingly.

6.2 Data processing

An automatic and fully independent data collection system can become complex in terms of data collection and usability, emphasizing the importance of efficient data processing. To maintain system simplicity, compromises are often made in terms of the depth of analysis and the amount of additional information operators need to complement the data.

Since none of the machines had useful existing interfaces for data collection, it was necessary to utilize multiple signals and equations to transform machine operations and different operational states into reliable and informative data. The signals collected require a flexible approach to processing in order to transform the data into an usable form for analysis and decision-making. The flexibility allows for the adaptation of data processing methods based on the specific needs and characteristics of the signals obtained from different machines and operational machine states.

The Gema OEE system by Pinja had limitations in how data could be configured. The operational states of the system can be represented effectively using one or multiple signals. These signals provide essential data that, when processed appropriately, enable a comprehensive understanding of the equipment's operational status and efficiency. To address data collection limitations, multiple signals could be combined to represent specific operational states. However, the system's constraint was that only "and" and "or" syntaxes could be used, making data processing challenging and restricting certain measurement methods and signal collections. These limitations caused challenges in ensuring the reliability of processed data.

Since only digital data could be collected, all analog information was out of reach and additional information had to be manually entered into the production monitoring system. Although manual data entry introduces a human factor and the potential for errors, it was chosen to maintain a reasonably user-friendly data collection system. On the other hand, the data collected by operators provided an opportunity to enrich and delve deeper into the reasons behind equipment downtime.

The operations of each machine were analyzed independently, and specific production states were defined to suit the unique data collection needs of each machine. Requirements for each operational state were discussed and evaluated to ensure accurate results. During the evaluation of these states, it became apparent that customized methods and definitions were necessary for each machine to accurately represent the different production states. The collected data underwent a process where individual signals were combined to fulfill various operational state configurations.

Downtime reasons are categorized into two types: categorized and non-categorized. Initially, every stop starts as unclassified, requiring operators to enrich the stop causes by adding specific reasons. Operator actions are necessary to provide insight into the collected data. Automatically collected stops are classified initially as stops without a reason. Operators acknowledge these stops by choosing the correct reason from a list that includes differing stop reasons, such as wait, fault, setting, maintenance.

To monitor the instances when the machines didn’t run, extensive definition work was required, comparing the OEE theorem to the operation of the machine during the defining part of the project. Machine wiring diagrams were examined to identify signals corresponding to different operational states, a topic detailed in later chapters. The primary challenge was finding signals that accurately represent the states, as establishing a clear and unequivocal definition proved difficult. This work was essential to make the processed data to be exploited.

6.3 Challenges faced during data collection

Implementing the Gema data collection system presented various challenges and limitations that needed to be addressed during the integration process. Firstly, the absence of ready-made data interfaces for data collection required the use of external loggers and manual input of information, complicating the process and limiting the scope of data analysis. Given the need for a lightweight data collection system, external data collection devices were selected over heavier methods, despite facing various challenges and limitations in data collection.

One major limitation arose from the definition of machine states in the data collection system, which was constrained by the digital signal data and limited syntax options for defining operational states. The loggers only accepted basic syntaxes such as “and”, “or”, and “not”, making it challenging to effectively combine multiple signals when determining production states. Additionally, the lack of control over the diverse operational state definitions without an admin license hindered flexibility and disrupted the process of defining production parameters.

A significant challenge is related to OEE itself, which lacks standardized measurement methods, affecting production monitoring. Machine-specific production monitoring software may not universally meet the monitoring needs of various machines and brands. Although some software providers offer integration capabilities for diverse equipment manufacturers within their OEE monitoring systems, the absence of standardization poses a risk of implementing potentially biased data collection practices.

Another obstacle was the dependence on external servers for processing collected data, resulting in delays of up to 30-60 seconds in operational state changes. The delay was a challenge for the operators when the downtime reasons needed to be acknowledged resulting in downtime being unacknowledged. Additionally, integrating product information into Gema required an additional module and a license, adding complexity and cost to the system.

Challenges in Gema integration was further compounded by production-related issues, including variations in machine operation methods and the lack of standardized work procedures. The intermittent nature of production, especially for machines like Cases 2-4, made classifying downtime problematic. Operators also faced difficulties in acknowledging premises due to complex definitions. On the other hand, Case 1 had a high level of reliable and automated data collection, ensuring a reliable way of production monitoring which further improved the collected data quality.

Overall, the integration process was characterized by the need for extensive research, complex spatial definitions, and a lack of unanimous production signal definition. Despite these challenges, efforts were made to adapt the system to the unique needs of each machine and improve data collection accuracy, which highlighted the non-standardized character of OEE.

Data collection could have been further improved for example by using other methos, such as OPC-UA, which is is a standardized communication protocol used in industrial automation and control systems to facilitate interoperability and data exchange between different devices and software applications.The use of this method was narrowed outside the scope of this study to retain simplicity and cost efficiency in the project.

The integration of the data collection system was complex and time-consuming, requiring careful consideration of multiple factors. Key challenges included ensuring system compatibility, identifying relevant data sources, processing data effectively, and addressing issues related to data source identification. Some of these challenges are detailed in the individual cases.

However, the validation process was challenging due to the absence of existing interfaces and for the diverse natures of the production machines in the case study. It involved closely monitoring machine operations under various conditions and investigating electrical drawings to identify relevant and usable signals for production monitoring.

Ultimately, it was noted that the reliability of measured data depends on the accuracy of signals representing production states and may be influenced by the human factor introduced during manual data enrichment. Therefore, precise definition and monitoring of production states are crucial to accurately reflect the operational status of production machinery.

7 OEE Case Study

The case study was carried out in an industrial company that implemented an OEE system in 2023. Prior to this, production monitoring relied on manual observations and tracking production statistics retroactively via an ERP system. Although the company had previous experience with an OEE measurement system at another factory, it was primarily used to monitor availability and suffered from outdated technology and measurement inaccuracies. Instead of replicating this less informative system, the company opted to invest in a modern and more versatile production monitoring system, which was subsequently acquired and implemented.

The impetus for implementing a production monitoring system arose from the company's increasing focus on optimizing production processes and streamline operations. Recognizing that machinery represents a significant investment requiring optimal performance, the importance of enhancing production efficiency and continuous improvement became evident. A production monitoring system was selected as a comprehensive measurement system to uncover latent potential within production operations. Ultimately, the decision to implement a production monitoring system was driven by the necessity to maximize operational efficiency and remain competitiveness in the manufacturing environment.

The "Theoretical framework" chapter explores various production development ideologies and evaluates OEE. It becomes evident in the paragraph discussing OEE as a production monitoring method that it serves the role of a measuring tool to monitor production and identify areas of concern. However, it is emphasized that other tools, such as lean and TPM, are necessary for the actual development of production processes. Both theorems are integrated into the company's strategies to drive production improvement and efficiency.

After contacting various production monitoring system suppliers and comparing their products compatibility with the different options over a couple of months, Gema production monitoring system offered by Pinja was selected. This decision was influenced by the company's prior collaboration with Pinja and the alignment of the Gema system with the stakeholder needs. Additionally, Pinja provided various options for data collection, enhancing the system's flexibility, and accommodating future expansion plans.

Data collection methods were evaluated to meet both production equipment requirements and stakeholder expectations. Discussions with the system supplier and company stakeholders led to solutions that addressed the diverse monitoring needs in addition to OEE. As mentioned, the study comprises four production machines analyzed using the chosen production monitoring system. Since none of the machines had suitable existing interfaces, measured signals were defined case by case, and external logger devices were employed for data collection to keep the process straightforward. In the theoretical framework, different approaches to collecting production data are explored and evaluated. The chosen method involved adding sensors and using I/O devices to transmit essential data to a cloud for processing, ensuring simplicity and efficiency in data collection. In addition to the automated data monitoring, the collected data is further enriched manually by the operators.

Following the application of the measuring system, data was collected and analysed. Ensuring the correct correlation between machine operations and the different operational states, the production monitoring system required thorough evaluation and validation to ensure data accuracy and applicability to the stakeholder needs and OEE related design parameters.

The production monitoring system was implemented across four production machines that reflect different machines and diverse types of production to assess the full potential and suitability of OEE for the case study and the company's production. A test period was established to gather and analyse data, with plans to expand measurement to additional machines based on the results if the collected data was meaningful and fulfilled the stakeholder needs. Otherwise, alternative measuring tools and evaluation theories will be explored to effectively measure production.

7.1 Stakeholder needs

As discussed in the previous chapters, to acquire meaningful production information, the collected data must align with its intended purpose. Various stakeholders require tailored KPIs, data, and reports to enhance their operational effectiveness, each focusing on specific variables relevant to their respective functions. To assess the relevance of collected data for various departments, it is crucial to define the actual stakeholder needs. The collected data must then be processed in a manner that ensures easy accessibility, provides informative insights, and fulfills the intended purpose of the measurements. The challenge is to find and define the different operational states, reports and KPIs in order to fulfil the stakeholders' needs. In the case study, the primary stakeholders include the maintenance team, production management and planning teams, and the development team.

The needs were discussed in both individual and general meetings with the different departments and the stakeholder representatives, including operators, forepersons, and the production and factory managers. The requirements and needs to determine the right monitoring needs were analysed by discussing different production development methods and stakeholder specific goals. The needs were discussed and compared with the general production goals and thresholds which each department had for their machine operations. During the discussions in addition to OEE, a set of common key performance indicators was identified, highlighting the necessity to monitor specific data points unique to each machine. The results of the discussion were aligned with the focus on optimizing production and enhancing efficiency. Key development and supervision areas were defined for each machine and department within the case study while exploring suitable monitoring techniques.

Common among stakeholders was the recognition of the significance of machine downtime, underscoring the importance of comprehending the reasons why a machine is not operational. As a result, different states were categorized to enable effective monitoring of machine operations. This categorization facilitated a deeper understanding and filtration of downtime reasons and aided in devising strategies for improvement.

Definition of premises was a long process since stakeholder needs, the different OEE factors, machine operations and the signals had to be found out and defined. These parameters were extensively discussed with the system supplier, responsible for managing the software, servers, and integrations. However, it's important to note that the chosen monitoring system and data collection methods had limitations in gathering production data, which is an essential factor in the study. The limitations necessitated compromises in production monitoring and meeting stakeholder requirements.

7.1.1 Production management

In order to achieve and maintain production targets and world class production standards, continuous improvement in production is essential, necessitating fact-based decision making and management. A production monitoring system and the production data measured can be used to help analyse production, find bottlenecks, and monitor production equipment essential to the production. In daily production management, the availability of easily accessible and reliable information is crucial. This enables production teams to adapt to fluctuations in demand and optimize machinery capacity and resources in real time.

To make production processes more efficient and accurate, measured, and reliable production data is a prerequisite for production planning, management and development. The availability of this information plays a pivotal role in comprehending the dynamics at the factory level and the equipment involved. Adaptation strategies include, for example, matching production plans with known capacity improving machinery usability and efficiency. Relying on the facts related to the actual production equipment is however essential for informed decision-making.

The approach to monitoring machinery in production that preceded the production monitoring system relied heavily on manual data collection methods. Data was collected indirectly through systems such as Jotbar and the ERP system, requiring manual entry by employees. This data was not necessarily directly machine-related but helped outline directions and trends in the usability of machines. This data provided an overview of the data collected over long periods of time, leaving room for human error, and lacking detailed insights into production dynamics. The generalized data made accurately locating production events with the measured data difficult.

For production management, knowing machine availability and utilization rates are crucial to improving operations and understanding how the machinery is being utilized. However, simply knowing these metrics is not enough without understanding the reasons affecting them. Visualization tools are important for easily identifying and correcting undesired inefficiencies, allowing waste reduction and a better understanding of the production processes.

Usability and availability are essential factors in production development and investment decisions. Production can highlight the need for updating machinery if the machinery operations are remarkable causes for machine downtime, leading in decreased production efficiency. Recognizing the importance of usability can promote further improvements in production processes.

The desired workload of certain machines, such as the cardboard cutter in Case 4, is particularly significant and hard to determine because the planning factor plays a key role in the production flow, affecting a large part of production. While increasing machine utilization rates may seem advantageous, finding a balance with the potential risk of overproduction is crucial when focusing solely on the availability. In contrast, underproduction due to disruptions caused for example by machine downtime is another factor to consider. Maximizing the excess potential of machine availability can help reduce these risks effectively.

The implementation of the OEE system highlighted the importance of ensuring user-friendly production monitoring systems. While reporting downtime causes is crucial for gaining production insights, it's essential to minimize the extra workload on workers due to reliance on human acknowledgment. Stakeholders unanimously agreed that the collection of equipment performance data should not disrupt employees' everyday workflow or compromise ergonomics. Additionally, meeting special operational requirements, facilitating easy access to production information, and providing unambiguous definitions of machine production states were key considerations during system implementation. Furthermore, storing production data for future benchmarking was identified as a priority for future changes in production.

Production management needs:

1. Real-time visibility into machine performance
2. Downtime analysis
3. Machine availability
4. Comparison between planned production and actual production
5. Identification of bottlenecks and inefficiencies in machine operation
6. Enhanced decision-making based on measured and accurate data
7. User-friendly HMI and easy access to data
8. Low amount of additional work for operators

7.1.2 Maintenance

The maintenance department at the company is responsible for the maintenance of all machines listed in "Selection of machines". The maintenance department utilize a maintenance software, Artturi by Aneo, which enables operators and maintenance workers to report machinery faults, plan advanced maintenance and track repairs, faults and other maintenance related operations done to the machines. Although Artturi underline various machine and operational features and has already made strides in improving maintenance procedures, its effectiveness in equipment monitoring is inhibited by several limitations. The most significant restriction lies in the reliance on fully manual data entry, which accentuates the human factor in data collection. Furthermore, numerous minor faults frequently go unnoticed as operators promptly resolve them without involving maintenance staff, resulting in these incidents going unreported along with their underlying causes.

Additionally, the full duration of downtime resulting from machine faults remains invisible to the maintenance system, as there is always a delay between the fault occurrence and maintenance intervention. In essence, while a maintenance system excels in managing maintenance tasks, extending asset lifespan, and enhancing preventive maintenance practices, an external production monitoring system is primarily dedicated to comprehensive monitoring and improvement of equipment efficiency.

The production monitoring system utilized in the case study, Gema by Pinja, tracks downtime and categorizes the downtime reasons based on their causes. Maintenance has the need of monitoring downtime caused by breakdowns and preventive maintenance. The collected data should help the maintenance team to identify recurring issues and prioritize maintenance activities accordingly. By understanding the root causes of downtime, underlying issues can be fixed before a full breakdown of the machines occurs. Also, the ratio between preventive and corrective maintenance talks about the success rate of made maintenance actions.

The maintenance team at the factory aims to monitor both major and minor defects in the factory's machinery to address production issues and minimize operational losses. Striving for continuous improvement requires implementing proactive maintenance measures, which necessitate access to accurate and reliable data about when each machine and component should be serviced or changed to prevent unexpected breakdowns. To succeed in this endeavour, accurate data on machine usage and production time analysis is essential. Additionally, access to data on wait, downtime, and production durations is crucial for thorough analysis. Notably, analysing total running times and stroke rates of molds and injection molding machines in Case 1 has proven to be valuable for planning advanced maintenance activities.

A KPI to determine the success of the maintenance is needed in order to get feedback for further improving maintenance and its methods. Maintenance is interested in getting effective work requests to maintenance workers for further improving the maintenance processes. When reaching for continuous improvement, monitoring technical availability was found out to be a powerful tool that suits the needs of the maintenance team. Technical availability tells how big a percentage of the total work time the machines are technically available for production. For improving this percentage, the causes of disturbances must be defined and addressed. The feedback from preventive maintenance and the success of the measures taken on the machines supports making the right decisions at the right time and to perform the right actions while planning future maintenance.

Machine performance data has the potential to supplement information collected from maintenance software. Although consolidating the maintenance and production monitoring systems was considered, it was decided to maintain separate systems for ease of operational use and system integration. However, if necessary, the data from both systems can be manually combined to facilitate analysis and decision-making processes.

Maintenance requirements for production monitoring

1. Accurate tracking of downtime caused by breakdowns and preventive maintenance
2. Identification of recurring issues to prioritize maintenance activities
3. Understanding root causes of downtime to address underlying issues proactively
4. Monitoring the ratio between preventive and corrective maintenance actions to monitor the success rate of maintenance operations
5. Access to reliable data on machine usage and production time analysis
6. Availability of data on wait, downtime, and production times for thorough analysis
7. Analysis of total running times and stroke rates of molds and equipment for planning advanced maintenance activities
8. Implementation of KPIs to evaluate maintenance success and provide feedback for further improvement

7.1.3 Method development

The method development team at the company involves in and leads projects and plans machine acquisitions and has a pivotal role in production development. In contrast to production and maintenance perspectives, method development needs for production monitoring data focuses less on daily monitoring and more on enhancing overall production efficiency and capacity. In order to promote production processes and achieve optimal efficiency, it is necessary to increase production capacity and maximize machine utilization. This requires improving overall production efficiency and accelerating manufacturing speed to increase capacity and performance. KPIs such as OEE provide valuable insights into machine performance and utilization, guiding efforts to optimize production processes and achieve production targets. Additionally, OEE helps assessing the need for investments in new machinery to expand production capacity. The function of method development is to refine production to meet the demands of manufacturing volumes and requirements.

In manufacturing environments, KPIs are useful tools for benchmarking machines and production. By comparing efficiency indicators across different machines, areas of improvement can be recognized helping setting goals and allocate resources better. Moreover, the machine evaluation monitors the advancement of improvement initiatives. Comparing against industry benchmarks provides valuable insights and encourages collaboration in order to find improvement in production. A tool for reliably benchmarking machine performance was observed to be of great interest in development purposes.

When considering investments in new machinery, it's crucial to understand the existing limitations of production processes and the utilization rate of production time. Production performance and downtime analysis provide vital insights into production-related bottlenecks and factors that prevent optimal efficiency and productivity from being reached. Knowing these limiting factors is essential for justifying new investments in machinery based on reliable data. With a comprehensive understanding of production inefficiencies and areas for improvement, investments in new machines can be justified to enhance overall production capacity and efficiency. This data-driven approach ensures that investments are strategically aligned with addressing key bottlenecks and optimizing production processes for long-term success.

Streamlined data entry processes are crucial for the efficient operation of the production monitoring system since reliable and accurate data was seen as an area of concern for the stakeholders in order to generate reliable data. The operational system should feature user-friendly and intuitive interfaces that allow operators to easily enrich the data by acknowledging downtime and adding production information. Moreover, for the system to be effective, end users must have straightforward methods to utilize the collected data. This user-friendliness facilitates reliable and comprehensive data enrichment by enabling operators to efficiently enter and manage data and the other stakeholders to utilize the collected data.

Method development needs:
1. Accurate collected data to support informed decision-making and performance evaluation
2. Generated KPIs should encompass efficiency and usability metrics to assess production performance effectively
3. The operational system must be flexible to accommodate changing production and operational needs
4. Data collection must have a high accuracy and a automation rate
5. The system must be scalable to accommodate potential expansion within the manufacturing environment
6. A user-friendly interface for facilitating easy data entry and utilization

7.2 Selection of machines

The machine selection in this case study reflects the factory production machinery and covers different types of machines that are used in different factory departments. Despite the variety of machines, the production is connected by the common goal to ensure that the machinery efficiently meets the production demand. The machines in the case study were specifically chosen to offer insights into the application of OEE in diverse manufacturing environments where different machines are operated variously. Additionally, the equipment selection was driven by the potential value of the information OEE could provide to stakeholders for further production monitoring expanding.

The chosen equipment comprises an injection molding machine, CNC milling machine, edging machine, and cardboard cutting CNC. Each machine was selected to showcase and provide an overview of the diverse production machinery utilized at the factory. The inclusion of the cardboard cutter was driven by its recent acquisition and the opportunity for valuable data collection it provided. Conversely, the other production equipment selected, which have been in operation for an extended period, allows for insights into machinery that have been used long-term and which are familiar utilization wise for the stakeholders.

In addition to the machines chosen for the case study, the company has eight injection molding machines (IMM) which play a central role in the production of plastic products of diverse sizes. For the case study, the IMM with the highest level of automation was chosen, featuring an automated product packing cell. This selection allows for an in-depth examination of downtime causes and assesses the feasibility of using OEE to monitor an both an entire production cell and a single production machine.

CNC and the edge machine are in the same area of the factory and are used by the same operators. Both machines were selected for the case study to evaluate the applicability and possibilities of OEE for the control and monitoring of an entire production department where the production is linked together. The capacity of both machines has been uncertain for the stakeholders, which was also a reason for adding both machines to the scope of the production monitoring system implementation in order to give insight about the overall equipment efficiency.

7.2.1 Case 1 – IMM With an Automation cell

Injection molding machines (IMM) are modern production machines, which enables continuous mass production of different sized plastic parts with high precision and efficiency. IMMs work by melting plastic pellets and injecting the molten material into mold cavities under high pressure. The material solidifies in the molds and the finished parts are ejected from the mold.

In this case study, the automation cell primarily manufactures bundles of diverse plastic parts. These finished bundles are packed in cardboard boxes or, for internal use, placed directly on pallets with collars. The production cell includes an Engel injection molding machine, two robots, a taper, and a package erecting/closing system. The cell is designed for continuous and independent production.

The plastic product manufacturing and packing cell can operate in either automated or non-automated modes. In the automated mode, the entire cell operates producing and packing the manufactured parts. Conversely, in the non-automated mode, only the IMM operates without the automation cell, dropping the manufactured parts onto a conveyor leading to a storage container.

Operation cycle on automated mode:
1. A case erector erects a cardboard box and moves it into the automation cell
2. The injection molding machine finishes its cycle
3. Parts are picked from the mold and placed on a locator by a linear robot
4. Step 2 is repeated until the stack is full
5. A full stack is picked up by a six-axis robot and bundled together with a plastic band
6. The stack is placed in the box erected in step 1
7. After the box is full, it is closed by a box-closing machine
8. The closed box is picked up by the six-axis robot and placed on a pallet

In the manual mode, only number two is repeated. The finished products are dropped on a conveyer which drops the manufactured parts in a container.

The primary challenge in achieving overall equipment effectiveness stems from the nature of injection molding machine manufacturing. Unlike equipment designed for continuous operation at a fixed speed, an IMM's production speed is dictated by the specific product being manufactured. This speed is constrained by factors such as the product specific mold and the material used, which directly obstruct the equipment from running at maximum machine speed.

Defining the production

When injection molding production starts, the IMM is expected to operate continuously with a constant performance rate until the desired quantity of products is achieved or until production is halted at the end of planned working hours. The operation of the injection molding machine can occur autonomously without automation, or it can be integrated with the entire packing cell.

At the initial stages of production, the injection molding machine is heated to reach the required operating temperature, and operators ensure that the correct materials, colors, and other resources are loaded, along with selecting the appropriate machine programs before starting the machine production. During the initial stages or when transitioning between products, waste pieces are generated due to start-up procedures, material changes, or color adjustments. These initial defect products are typical in injection molding processes. As production stabilizes, the expectation is for the machine to consistently produce defect-free parts under stable processing conditions. Operators manually record the number of defective parts during product changeovers, as there is no IO data available to monitor production defects.

Machine downtimes are classified into seven different production states: undefined stop, waiting, undefined fault, fault, setup, advanced maintenance, and idle. In contrast, production is classified into three categories: production, automation and slow production, the latter covering both slow automated and slow manual production. These classifications are derived from evaluating production and interviewing the operators and production managers.

To address the challenges highlighter by the absence of ready-made interfaces, high implementation costs, and the data collection requirements of OPC-UA and EUROMAP 77, Moxa data collection devices were implemented for data gathering. These devices collect and transmit production data, with the signals obtained by connecting the Moxa devices to the IO cards of the injection molding machine and the automation PLC. Utilizing signals from the automation PLC enabled the collection of automated fault signals, allowing for real-time monitoring and evaluation of system malfunctions.

Tracking production cycle times with Gema requires defining the product to be manufactured in the system, because Moxa devices only collect IO data. Operators are responsible for setting and updating product information in the Gema software. Gema maintains a database of product cycle times copied from the ERP system and compares them to the actual machine cycle times. Production is classified as "slow production" when cycle times exceed pre-defined thresholds. At the same time, Gema calculates production efficiency by comparing actual production volumes with theoretical production volumes.

Machine operational state is classified as "faulty" when production is interrupted due to machine malfunctions or unplanned lack of resources. The waiting time indicates the lack of production due to the machine heating up or the absence of an operator. Regular advanced maintenance is carried out on the machine in order to avoid downtime due to faults.

If a machine remains powered on during production hours but lacks control power, it is categorized as "not in production use." Conversely, the "offline" state occurs when both the control and main power are deactivated.

These states serve as the basis for generating graphs and reports, aiding in the comprehension and utilization of the collected data. Processed into reports, the collected data includes metrics such as quality, production performance, and produced units, tailored to the machine's operational characteristics and stakeholder requirements.

7.2.2 Case 2 – Board cutting CNC

The Board cutting CNC is used to cut different pieces laminated chipboard sheets. The machine is a semi-automatic CNC but needs an operator to switch between different materials and tooling, filling the material storage, making nestings and unloading the finished pieces.

The equipment is a three axis CNC machine specifically designed and used for cutting and shaping planar wood sheets in woodworking applications. The CNC machine is equipped with an automatic pickup system for collecting board sheets and transporting them to the working area, where the sheets are held in place during the cutting process using vacuum. The cutting is made by a spinning spindle that can be equipped with different tooling such as drills, planers, and end mills. The CNC produces shapes on the board sheets according to programmed specifications.

In operation, the CNC machine follows a structured production cycle, typically lasting between 5 to 30 minutes per cycle. During and between the cycles, additional work is done by the operator to ensure that the CNC has sufficient material and that finished products are palletized and transported to their corresponding places in the storage area. The manufacturing process begins with the machine retrieving a sheet and positioning it on the work surface using the automatic pickup system. The board is secured in place with vacuum in order to hold the sheet in place during the cutting operations. The operator loads product-specific chipboards into the machine and defines nested patterns for optimal use of the material. Upon completion, the finished products are automatically transferred by the machine to a conveyor system, which transports them to the designated palletizing area for further handling done by the operator.

In the automated mode, the process begins with the machine retrieving a board sheet and positioning it on the worktable using the automatic pickup system. The operator plays a pivotal role in loading product-specific chipboard sheets into the machine magazine and configuring nesting patterns for optimal material utilization. Additionally, the operator initiates the production cycle by running the programmed instructions and supervises the machine's performance throughout the manufacturing process. Upon completion, the finished products are automatically transferred to a conveyor system, which transports them to the designated unloading area for further handling.

The challenges regarding OEE is the lack of unambiguously defined disturbance signals, the way the machine operates, and the diverse products manufactured in the cell. The CNC is not designed to be run continuously since it needs an operator to do nestings, load boards and empty the unloading conveyor. The production is timed by the operator workload and the recieved work orders.

Defining CNC

In order to start production, the operator needs to fill the material magazine with the right material and nest the desired products to fit the boards while minimizing wasted material. The nesting process must be applied to all the products that are produced, even though some premade programs are available.

A cutting cycle typically takes 15-30 minutes, depending on the nestings and the board material. The CNC production cycle starts by the machine picking up a board blank from the material magazine when the operator starts the program. The sequence of operations proceeds as follows:

1. The operator starts the program
2. The CNC retrieves a blank from the material storage
3. The CNC places the blank on the cutting table
4. Vacuum is activated and keeps the board in place
5. The CNC start its cutting cycle
6. Cutting finishes and the vacuum is deactivated
7. The CNC transfers the pieces to a conveyer
8. Operator cleans the conveyor, shreds the waste pieces and palletizes the boards

In some instances, the machine is operated manually. Manual operation means that the boards are manually handled in the cutting area by the operator. This normally happens when pre used blanks are used as board material.

The machine is in considered to be loaded when it goes through its production cycle. In the absence of previously existing interfaces for data monitoring the production signals are derived from the CNC pick-up movements and vacuum circuits that are used for holding the blanks to the cutting area. The threshold time for the stop acknowledgment is extended to ten minutes, considering short production breaks, the large number of which the stakeholders considered to become a burden for the operators. The delay cleans up the production data but adds a level of inaccuracies when generating the KPIs. The other reason for the expanding of the acknowledgement threshold was to decrease the workload of operators caused by the high number of short stops causing additional workload caused by the manual acknowledgements.

Since fault or stop signals are not available, downtime is determined to occur when no "production" signals are detected within a specified time frame. The downtime reasons can be either setting, malfunction, maintenance or waiting.

The first reason for downtime is categorized as “wait”. Wait time is when the machine is idling due to a variety of factors, such as a lack of necessary resources or operator presence. Waiting contains the cases where the machine is temporarily stopped from operating, waiting either for the replenishment of resources in order to resume production. During the stops the machine remains in standby mode and is ready to continue production when the required conditions are met.

The second most common reason for downtime is categorized as “setting”. Loading blanks, unloading boards, and setting up nestings are classified as "setting" tasks within the operational protocol of the CNC router, contributing to the production processes. These are manual operations done by the operator in order to keep the machine running.

Like in the other cases, the CNC downtime caused by machinery malfunctions are classified as “faults”. Also, preventive maintenance causes downtime for the machine. The maintenance is done either by the operators, maintenance team or the manufacturer service personnel.

7.2.3 Case 3 – Edge Banding Machine

The edge banding machine plays a role in the board manufacturing process, adding an edge to the boards produced by the CNC described in the previous chapter. Unlike the CNC, the edge banding machine operates manually, requiring constant supervision from an operator during manufacturing. The manual tasks involve feeding boards in the machine and palletizing the finished products. Additionally, the operator needs to adjust the machine for the right board thickness and make sure that the machine has all necessary resources.

During edge banding, the machine glues an plastic strip to each product one side at a time. The products are fed into a conveyor system that guides them through the machine where the edge band is attached. After this, the return conveyor brings the edged tabletops back to the operator for further processing. This process continues until all the edges of the products are finished. Upon completion, the finished parts are placed onto pallets by the operator. These pallets are then transported to the storage area for temporary storage until they are ready for further processing or distribution.

The challenges with the edge banding machine are primarily due to the definition of "production". Although the machine can be in "running" mode while the conveyors are operating, the actual loading only takes place when the operator feeds boards onto the conveyor. Thus, the edge bending process itself comprises less than half of the total operating time. In addition, due to the limitations of continuous board feeding, there are production gaps of different lengths between the processed boards. In order to minimize the effect of these micro stops, some delays were necessary to add to the state definitions. Other production stops occur when the operator changes pallets and does other work-related tasks.

Defining Edge Machine

The edge banding machine heats up glue from pellets and uses it to fasten the edge band to the sides of the boards. The boards go through the machine where it is attached and trimmed to fit the board one side at a time. The machine needs an operator to be present during its whole operational time. The operator's tasks are to feed the boards and palletize them, set the machine for the correct board thickness and fill the band magazine with the product specific bands.

The edge banding machine didn't have any pre-made interfaces for data collection. However, it was possible to collect signals from relays and PLC outputs. The production corresponding signals were collected after monitoring the machine operation for an extended period which was a challenging task to accomplish due to the lack of unambiguously definable production states. The "production" state is a combination between multiple signals while there were no signals to indicate the "fault" state which resulted in the same challenges as described in the chapter that handles defining the CNC.

It takes 20-25 seconds for the edge banding machine to finish one edge. The machine needs to have gaps between the boards which prevents continuous processing. The operator feeds a new board into the machine once the edge bander is ready with the previous board. The operator palletizes the finished boards which increases the downtime between production.

Other reasons for downtime come from storing the pallets, picking up new work orders and from heating up the machine. These reasons are classified as "wait". Changing or filling the band into the magazine is classified as "setting".

The machine is maintained by operators, maintenance team and external maintenance workers that are specialized to the edge banding machine. The downtime caused by maintenance is classified as "preventive maintenance" or "fault" similar to the other cases.

7.2.4 Case 4 – Cardboard cutting CNC

The last machine involved in the case study is a cardboard cutter manufactured by Homag. The cutter has an automatic feeding system and magazines. The machine is operated by a computer where the correct cardboard models are selected from a library. After the correct model and dimensions are selected, the machine cuts the cardboard and feeds it out from the machine outlet.

The cardboard cutting machine is utilized to produce packing materials for products within the factory. The operation of the machine is automatic, leaving the operators to do the nestings and unloading the finished products and the waste pieces. The machine features multiple magazines that supply cardboard of various widths and types to the cutting unit. Operators are responsible for maintaining these magazines ensuring uninterrupted production. The operators retrieve the cut cardboard pieces and distribute them to the right departments within the factory.

Like other machines in the case study, the operation of the cardboard cutting CNC is also driven by demand, and operators perform various tasks in addition to operating the machine. The machine performs the cutting process independently, but the operators perform other tasks included in the job description.

Additionally, while the cutting process itself is brief, other tasks such as material handling and machine setup significantly adds to the overall workload and operational efficiency.

Defining cardboard cutter

The cardboard cutter cuts cardboard sheets from a folded cardboard strip according to the operator's demand. The cutting process is quite fast and depends on the number of sheets to be cut and the complexity of the models. The batches the operator produces are usually quite small (normally 5-20 pieces at time), which results in the cutting time being typically shorter than the nesting time. The machine has a lot of downtime caused by the way the machine is operated and the low demand.

The operator nests the pieces to be cut, collects the finished parts, and cleans up the residual cardboard waste. The finished sheets are collected to transport trolleys that are moved to the corresponding places to the production. The operator also loads the cutter's magazines with cardboard and takes care about the tidiness around the machine.

The cardboard cutter had output cards where it was convenient to collect production signals. The cutter has 9 blades from which 8 are for cutting lengthwise and 1 to cut across. The cutters are operated by air cylinders and controlled by PLC outputs. The production signals were collected from the same outputs that control the blades. The machine generates a fault signal that is indicated by an indicator and flashing lights. The fault signal is collected from the acknowledgment button and is automatically shown in Gema as "fault". The operators must acknowledge the fault reasons in order to give the specific reasons.

The cardboard cutter's preventive maintenance consists of cleaning done by the operatros and services made by the maintenance organization. Fault fixing is done either by the maintenance organization or by specialized Homag service team.

8 Results

The results are evaluated individually for the four different cases in order to provide insight over the production monitoring. Since OEE lacks standardization and each case have a unique way to determine production, the results provide deep insight of the different factors that determine overall equipment efficiency. Availability and production are determined in three different ways to show the effect the definition of the key figures have. The quality number was high in all the cases highlighting the meaning how differently the various factors contribute to the OEE number.

Additionally, the production downtime is analysed in a way that helps understanding the production in a diverse production environment. The real-life evaluation analyses OEE to provide insights into production monitoring by comparing the results to actual production events. To give an answer if OEE provides value from the stakeholder point of view, OEE is analysed to show how it can provide in real-life production monitoring compared to different KPIs.

To understand the structure of machine downtime, downtime analysis is done for the equipment. This highlights the fact that the machines operate in diverse ways, with different capacities fulfilling their production needs. The results underscore the importance of accurate and automated data collection methods.

The results show in general the issues that OEE has as a production monitoring KPI by highlighting the importance of determination of the operational states and the effect manual data collection methods and delays between the states and the acknowledgements have.

8.1 Reliability of results

The reliability of the data collected for the production monitoring system, as well as the factors involved in it, are essential for accurate performance evaluation in a manufacturing setting. While OEE serves a role as a metric for assessing total equipment efficiency, challenges arise in standardizing data collection methods and defining the various factors involved.

During the implementation of the Gema production monitoring system, a validation process was undertaken to answer the accuracy and reliability needs for the collected data. This process revealed challenges that highlighted the complexity of OEE, and issues identified in the “Theoretical framework”.

One of the primary challenges encountered in assessing data reliability stems from the lack of standardization and unanimous definitions of OEE. The implementation of the Gema system was tailored to accommodate the unique characteristics of each production machine and the individual stakeholder needs, departing the generated OEE from both classical definitions and those provided by the system supplier. This customization was essential to meet stakeholder requirements and to provide data that was useful for the stakeholders. The OEE data in the results is generated retroactively to give an insight of non-biased overall equipment efficiency monitoring.

In the project implementation phase, the collected data underwent an evaluation process to validate its accuracy and its representation of various production events. This critical assessment was carried out by the method development team with the Gema contact person involving in the integration process. The collected data had some limitations discussed earlier in this thesis.

8.1.1 Availability

In the case study, availability is defined in a couple of distinct ways: firstly, as “utilization rate”, which compares the machine loading time to the full production time available, and secondly, by comparing the machine loading time to the time the specific equipment is in production, wait, or fault states. The latter is referred to as "availability" by the stakeholders since it indicates how well the machine is available for production when the machine is supposed to be running, leaving setting and preventive maintenance outside of the calculations. Depending on the interpretation of OEE, either “availability” or “utilization rate” can be used to generate the OEE number. Additionally, a third definition, technical availability was used to monitor the fault level of the machinery compared on the time the machine was supposed to run. Technical availability shows how much the machine was ready for production compared with the time it was supposed to be loaded.

The production managers individually determined the planned production time for each machine, giving an accurate base to calculate the utilization rate. Despite the possibility to set working hours according to production and machine specific needs, default working hours were established from 6:00 to 23:00 in all cases to accommodate the early arrival of the first workers and the time the factory was closed. The operators have flexible work times, with production typically starting somewhere between 6:00 and 7:00, rising challenges in accurately determining production time for monitoring all operational states generated throughout the entire production process. The measuring period being extended results in decreased utilization rates due to the measuring period being longer than the actual planned production time. Any deviations from the standard hours, such as bank holidays and cancelled production shifts, were promptly adjusted by the production managers in the calendar.

Machine availability was monitored using Gema across all machines, with different states determined individually for each machine. However, challenges arose in classifying the loading time which equivales in Gema as the machine state "production".

For instance, defining loading time in Case 3 was challenging, since the edge bander posed challenges in defining production as it adds value to the product for only a brief period during the production cycle. While the operator feeds boards into the machine, the equipment is loaded only when the board is present in the machine, with the remaining time used for board transportation. Thus, the machine is considered to be "in production" when a board is being worked on, the transportation of boards can also be viewed as part of the machine cycle. On the other hand, the machine can be running without a board inserted in which case it does not do productive work. Similar complexities were discovered during the implementation and validation processes of the other cases.

The complexity discussed led to the inclusion of delays in production signals to prevent numerous microstops between production signals, addressing the challenge of accurately defining loading time and different production states. Similar assumptions were made with the other machines, except for the IMM in Case 1, where production was determined by production cycle times and the fulfilment of the full production cycle.

8.1.2 Quality

Quality monitoring using Gema was limited primarily due to the system inability to collect online quality information, relying instead on manual operator inputs and retrospectively combined data. This limitation decreased the usability and topicality of the data. Gema was only able to monitor quality for the IMM, with rejected or further processing needing products being infrequent. Consequently, OEE data could only be formed retroactively preventing monitoring of the instantaneous quality number.

The incapability of Gema to monitor quality in real-time diminished the accuracy of OEE and the usability of data collection. As Gema could only detect digital data signals, online quality information couldn't be collected due to lack of signals of defect production units. The IMM operators would acknowledge the number of rejected products during mold changes for the next production run, making it challenging to correlate rejected pieces with specific production events, rendering it merely a quality indicator. In other cases, quality was added retroactively to the OEE number outside of the production monitoring software.

The overall low number of rejected parts in all cases reduced the significance of quality as a production KPI despite the retroactive nature of data collection. The production run specific quality data could be found from the ERP system, making it more accessible to stakeholders.

8.1.3 Performance (speed)

The third factor of OEE lacks proper definition but is usually seen either as "performance" or "speed" as discussed in the theoretical framework. In the case study, speed is measured as movement velocity or the time a task takes to be accomplished focusing on the time aspect of an action or process. Performance on other hand is a boarder concept that encompasses various factors beyond just speed. Performance in this case study is defined as a relation between actual production compared to ideal production.

The performance could be monitored in Case 1 and Case 2 where maximum production speed or performance was accessible. The performance monitoring provided information for the stakeholders in the first case and highlighted the need of measuring productivity. The second case underscored the challenges that are faced when addressing maximum machine speed or performance. In the Case 1, cycle times recorded to the ERP system are utilized to evaluate both speed and machine performance in real time.

In case 3 the machine had a constant speed it was operating. Case 4 on the other hand had three alternative speeds that was chosen by the operator during the nesting process. Since best practice or constant production speeds were used, the results assumes that the performance and speed factors were 100% aligning with best practices.

The determination of a machine's top speed is complex, particularly for CNC machines where various factors come into play. Top speed can be measured in terms of spindle speed, feeding speed, or the number of units produced within a specific time frame. However, none of these measures are constant across production due to machine limitations and differentiating products.

One reason why machines often operate at best practice speeds, even if higher production speeds could theoretically be achieved, is based on past experiences. It has been observed that exceeding these best practice speeds can lead to an increase in defective pieces and cause additional wear on the machines, resulting in a higher incidence of machine defects and additional downtime.

8.1.4 Conclusion

In conclusion, the reliability of data collected for production monitoring systems is crucial for accurate performance evaluation in manufacturing settings. Challenges in standardizing data collection methods and defining factors like availability and performance rates underscore the complexity of implementing OEE.

The implementation of the Gema production monitoring system highlighted the need for customization to accommodate diverse machines and stakeholder needs, deviating from classical definitions of OEE. Challenges in determining production states, particularly for machines like the edge bander, emphasized the importance of accurate data classification.

While Gema provided valuable insights, limitations in quality monitoring and the reliance on manual inputs affected the timeliness and accuracy of the collected data and the generated KPIs. Efforts to measure efficiency and productivity varied across cases, with challenges in defining true top speeds and balancing production rates with quality considerations.

Overall, the results underscore the importance of understanding data collection methods and the need for proactive management committed to utilizing information effectively. Despite the challenges faced, OEE remains as a valuable industrial measurement, albeit with room for improvement and refinement in implementation with a reasonable level of reliability despite the data collection challenges.

8.2 Case 1 – IMM + automation cell

The Case 1 had the highest level of automated data collection. Gema received automated availability and performance information from the IMM, while the quality data was inserted to the system retroactively by the operators to form the OEE numbers. Additionally, automatic "fault" signals were derived both from the IMM and the automation cell adding detail and accuracy to the data collection.

Case 1 resemble homogenous production where the production cell that is supposed be constantly loaded during the planned production runs, which adds perspective to the OEE evaluation.

8.2.1 Availability

Case 1 determine equipment loading time by monitoring the cycle signals gathered from the part ejection process. The different machine states classified as loading time are "production", "automated production" and "slow production". The loading time is accurately shown during continuous production, but there are data inaccuracies during machine startups and production changes due to irregular, product specific cycle times.

To understand the practical differences regarding the various definitions of availability, comparison must be done. Availability and utilization rates had quite little deviation indicating that the total comparison times the loading time was compared to was in general similar. On the other hand, the technical availability was high indicating that downtime was mainly caused by other reasons than fault.

The similarity between availability and utilization can be seen in Figure 1 and Figure 2. The similarity is high with an average value of 6% with a remarkable difference only on 12.2.2024.

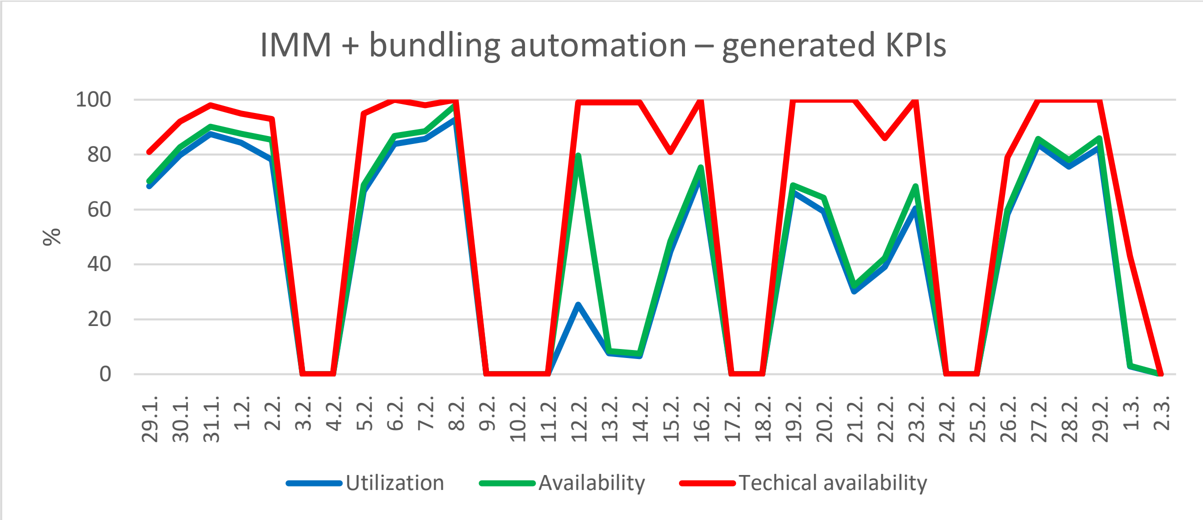


Figure 1 Case 1 – KPIs (5 weeks)

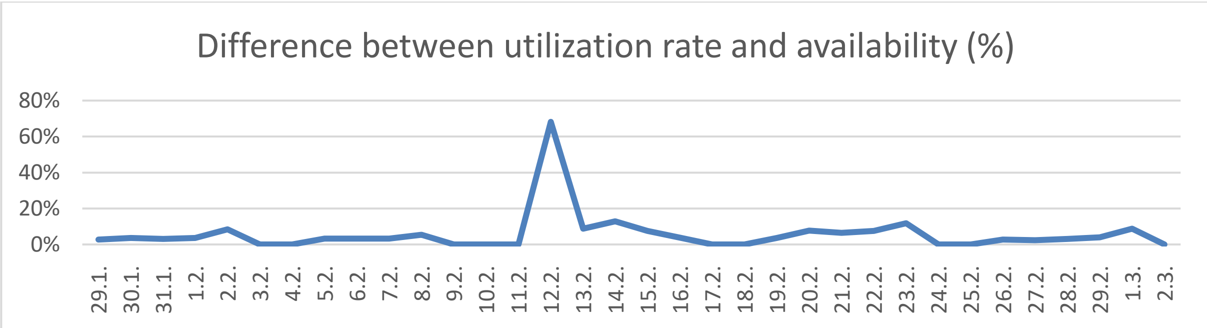


Figure 2 Case 1 – Comprasion between utilization rate and availability. The average similarity was within 6%.

Figure 1 compares utilization, availability, and technical availability over a five-week monitoring period, illustrating production patterns resembling normal operations in the department. The data shows that the technical availability stays the highest since it shows the time machine is not faulty compared with the time it is ready for production. As discussed earlier, the utilization rate and availability show similarity with the expectation of 12.2.2024. Figure 5 illustrates that on a specific day, the IMM underwent preventive maintenance, resulting in a decreasing utilization rate. Preventive maintenance, setting time, and offline are not considered when calculating availability, which explains the differences shown in Figure 2.

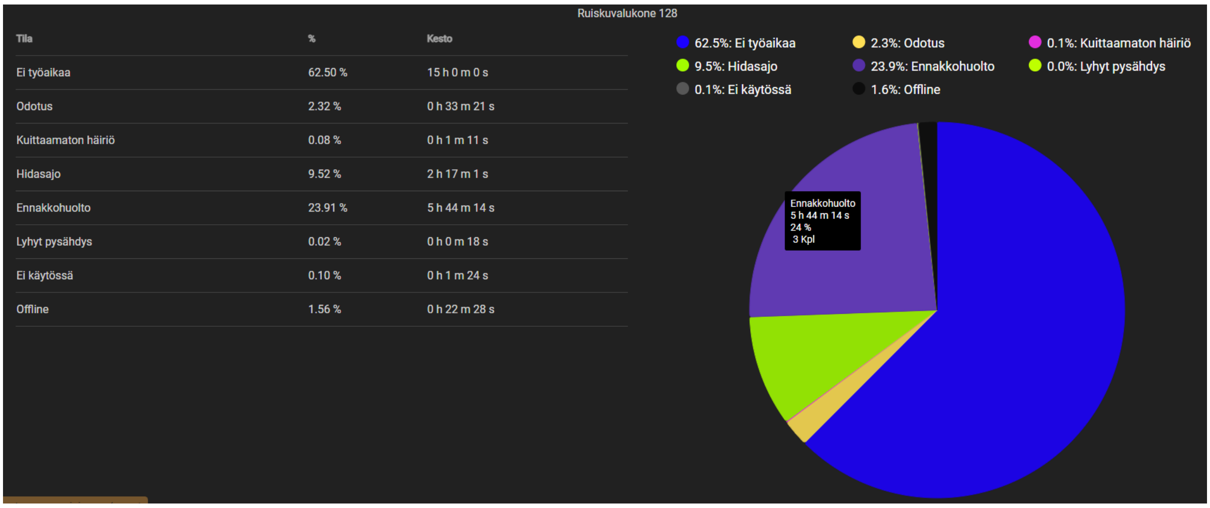


Figure 3 Case 1 production12.2.2024 (View from Gema)

Both availability and utilization appear to be quite low on some occasions, for example on 21.2.2024 (Figure 1) due to low production hours. Figure 5 on the other hand shows that the production hours are adjusted compared to the normal work time (6:00-23:00) which further explains the similarity between availability and utilization rate. The advantage with monitoring two differently defined availabilities is the sensitivity to notice the affect the different downtime reasons have to the KPIs.

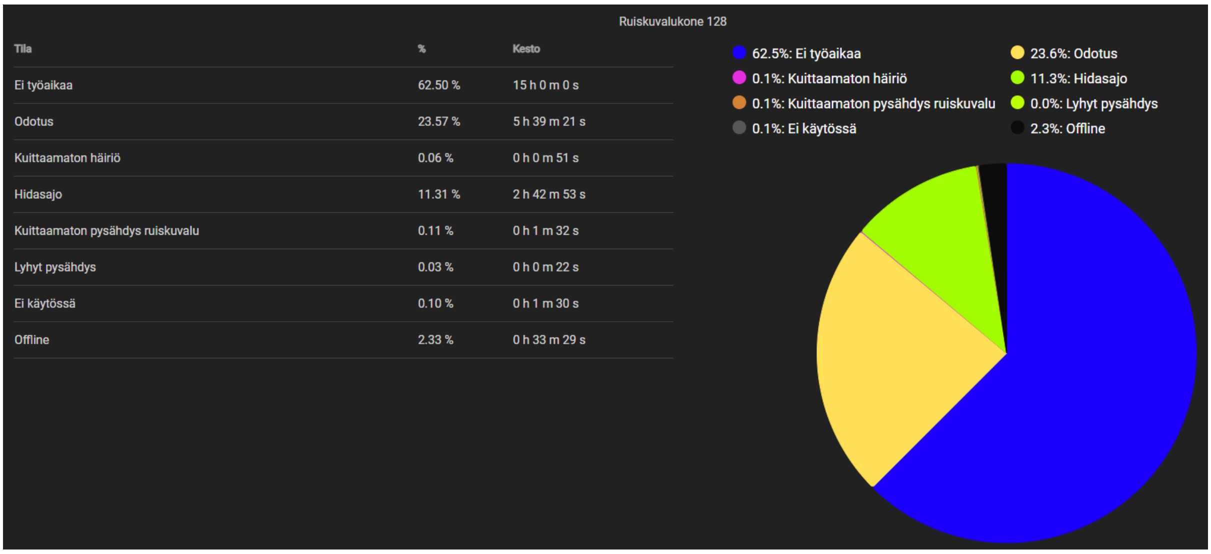


Figure 4 Case 1 production states 21.2.2024 (View from Gema)

Comparing Figure 3 to Figure 4 shows that both days have a similar amount of loading time, even though the KPIs in Figure 1 shows different levels of utilization between the days. The difference highlights the difference that availability and utilization rates have. In Figure 3 can be seen that 23,9% of all time is classified as preventive maintenance while Figure 4 have 23,6% of wait time. Preventive maintenance is considered while calculating utilization rate while it doesn't affect the calculating of availability.

Monitoring availability was considered uninformative by the stakeholders without the comparison with the actual production times and an analysis of downtime. These KPIs were only used to find the production time losses while the production state analysis was used as a tool to understand the downtimes and the reasons behind them.

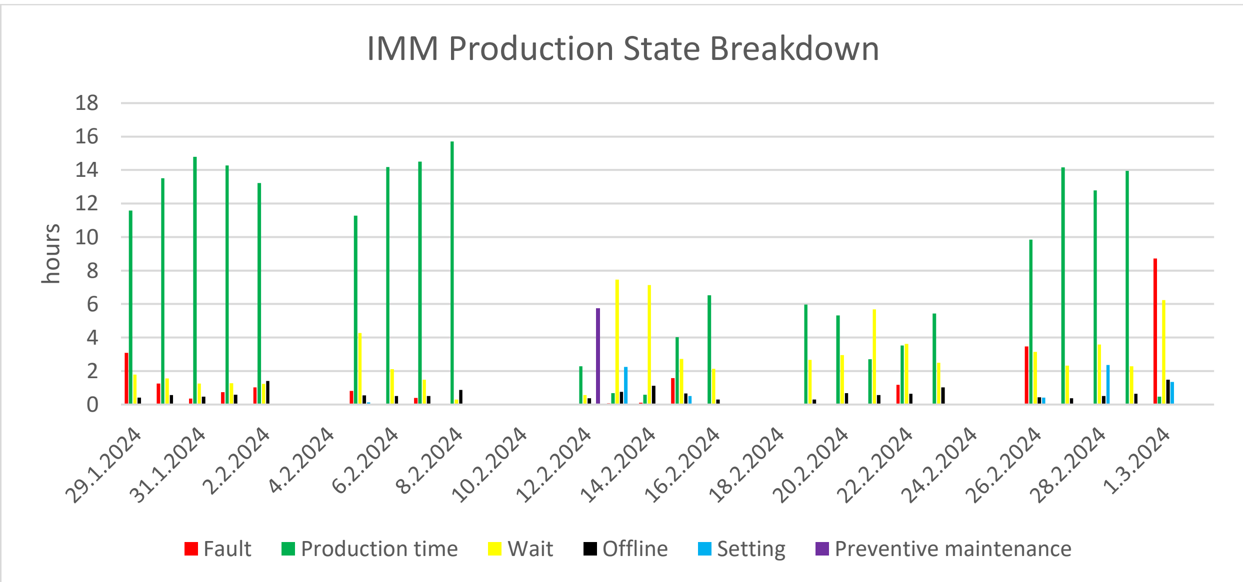


Figure 5 Case 1 Production State Breakdown

The production breakdown shows the production time analysis in a visual form. While availability and utilization rates are high, the production time (visualised in Figure 5) is high compared with the other production states. Similarly, the ratio between production time and the downtimes gives insight to the KPIs and the ways they are formed. It is noteworthy that from 12-24.2, production time was limited to only one shift, as reflected in Figure 1 and Figure 5. Even if the net run times are lower than usual, the change isn't visible in the availability and usability factors since they represent the production trough percentages.

Time	Utilization rate (%)	Availability (%)	Technical availability (%)
1.8.2023	58,1	63,4	82,0
1.9.2023	57,7	64,6	88,0
1.10.2023	56,5	63,3	88,0
1.11.2023	56,4	65,9	91,0
1.12.2023	42,9	52,3	82,0
1.1.2024	66,4	75,1	92,0
1.2.2024	66,0	71,2	96,0
1.3.2024	64,5	68,6	87,0
Standard deviation P	**7,6**	**6,7**	**4,8**
Average (%)	**58,56**	**65,6**	**88,3**

Table 1 Case 1 – the different availabilities over an extended period

The table shows the different definitions of availability over an extended period. The results are similar with those observed during the five-week monitoring period evaluated earlier. An important point to note is that technical availability shows fluctuations indicating downtime caused by faults throughout the monitoring period. Despite meeting production goals, both the utilization rate and availability fall significantly below the world-class levels typically used for evaluating overall equipment effectiveness.

8.2.2 Quality

The IMM produces defect parts during startup and product changes due to production typical issues. In Case 1 the quality monitoring was limited to retroactively gathered data because of reasons described earlier in this thesis. Since the quality was monitored as an average value that the operator updated after the production runs, it's meaningful to monitor the quality data only over an extended period to average the affection of the quality changes during different phases in production. This prevents combining quality losses with the actual production events.

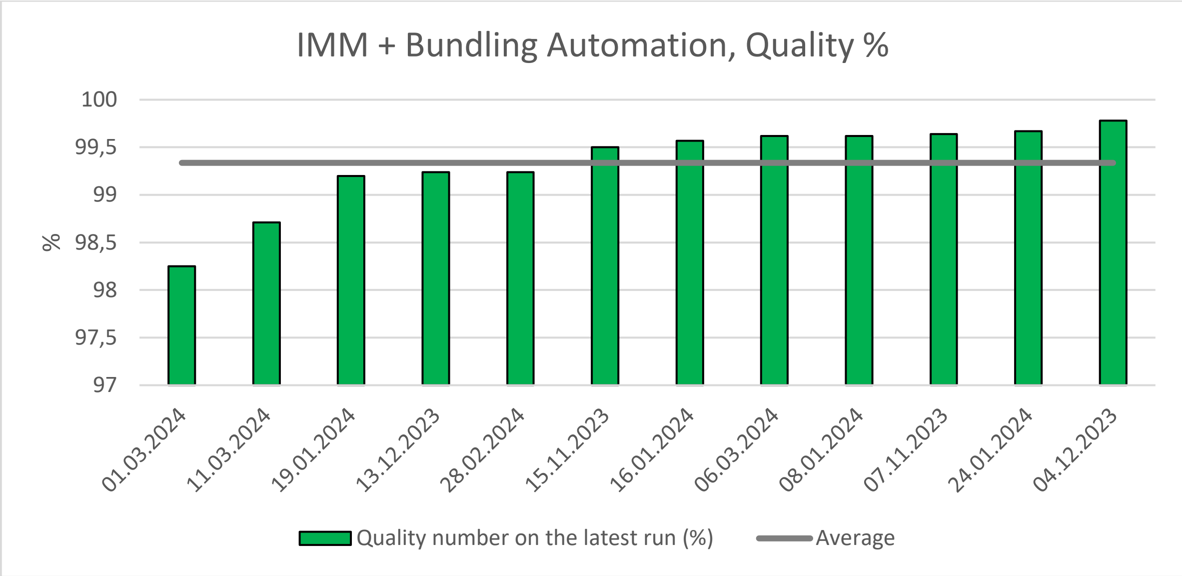


Figure 6 Case 1 production quality-% lowest to highest (1.9.2023-24.3.2024)

The average quality level of the whole monitoring period was 99,5% with the lowest being 98%. The 28.12.2023 result is over 100% and it was caused by human errors which highlights the value of automated data collection. The “accepted product” count is marked as 14088 while the total production quantity was marked to 14000 skewing the rating. The number of 15.02.2024 on the other hand had 15000 both at total number and as the quantity of good parts, which is impossible due to the mandatory number of defect parts during startups. If these numbers are excluded from the figure, the average quality percentage drops to 99,3%, which is still remarkably good considered the high number of startups during the production.

Quality monitoring did not provide any additional value to the stakeholders since the same information was available from the ERP-system. The retroactively updated average values didn’t combine the scrapped parts with specific production events, which was seen as a downside by the stakeholders. The quality data would have been more informative and contributed to the stakeholders needs if the defects in production could have been correlated with specific production events.

8.2.3 Performance

The third factor of OEE is eighter speed or performance depending on the definitions. In Case 1 the production cell the production performance was measured rather than speed since the IMM cycle times are product and material specific. Measuring IMM cycle speed and comparing it to the machine maximum speed would not give any meaningful info about production since the machine is capable to perform remarkably faster cycles than what is needed for manufacturing the plastic products. Additionally, relying only on speed measurements may lead to inaccuracies in performance readings due to variations in production monitored by operational data. Productivity is assessed by calculating the number of units produced within a specific timeframe and comparing this to the theoretical maximum output.

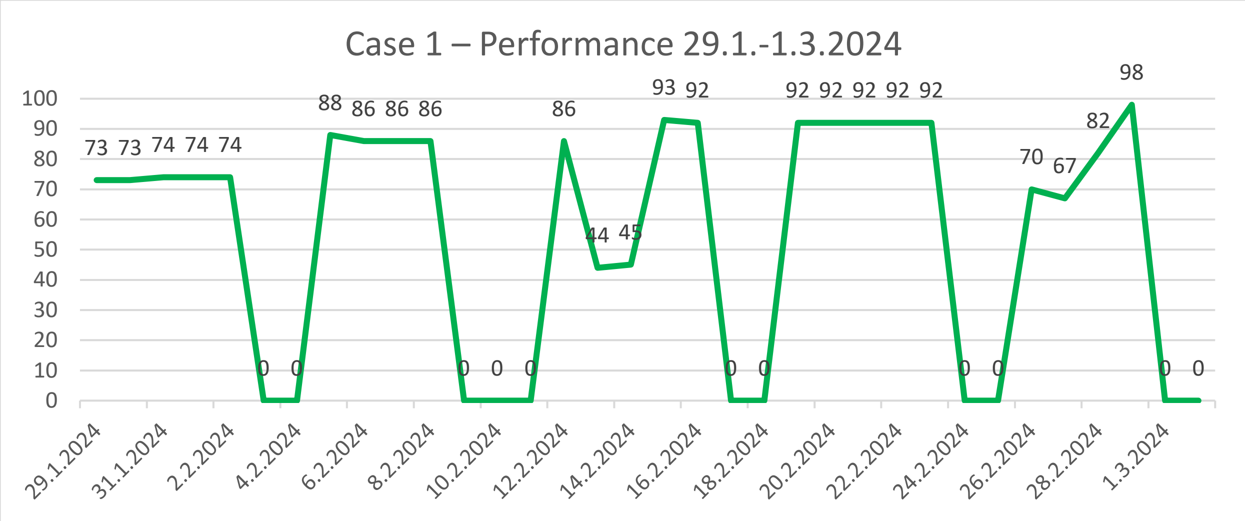


Figure 7 Case 1 – IMM + automation performance

Product changes can be identified from Figure 7, which illustrates production performance over a five-week period. These product changes are reflected in production efficiency, which consistently remained the same within a production run but changed during mold changes. Due to machine-related problems, the production performance on March 1st was changed to 0% because the machine was not in operation for the day. Misleading signals were caused by maintenance operations, resulting in distorted measured data.

Due to human factors and challenges associated with the data collection methods, the data isn't always reliable, especially during startups and product changes. Because different products have different designed cycle times, for the performance factor it is essential that the produced product is changed in Gema simultaneously as it happens in real life. Figure 8 demonstrates an example of data collection errors leading to unusually high performance numbers.

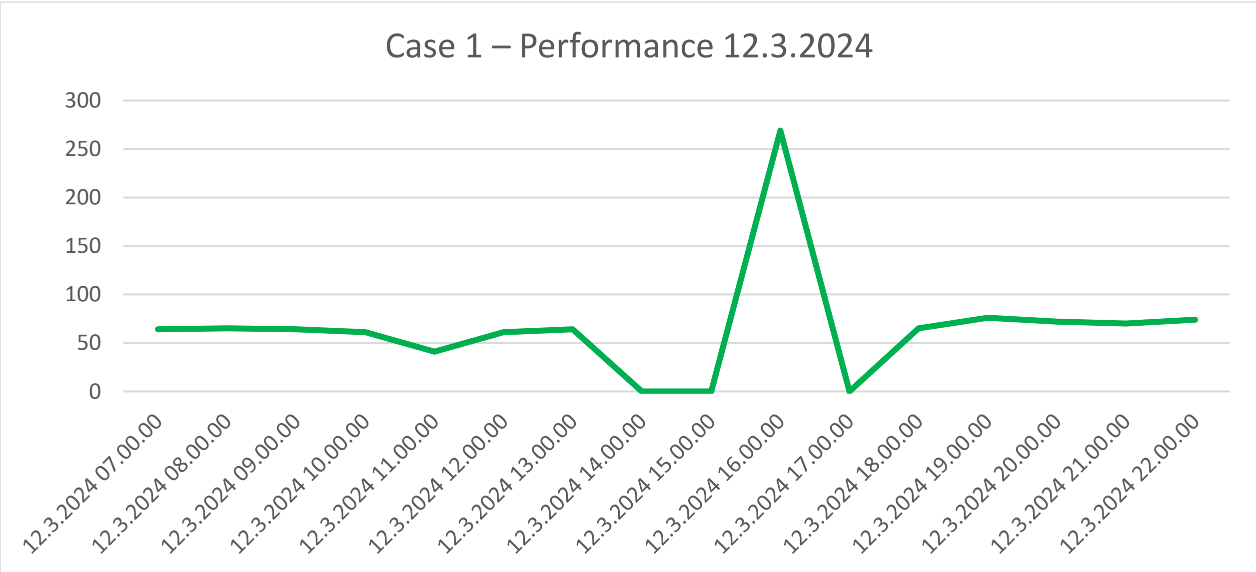


Figure 8 IMM production performance

Figure 9 illustrates that the spike in productivity numbers coincides with a product change. The discrepancy in timing between the product acknowledgment and the signals generated during the mold change is the reason for the performance variation observed.

Koneen nimi	Syy 1	Syy 2	Kommentti	Kuittaaja	Tila	Alkuaika	Lopetusaika	Kesto h:mm:ss	Kesto min	Kesto s
Ruiskuvalukone	Asetus	Muotin vaihto			Asetus	12.3.2024 16.00.41	12.3.2024 18.09.39	2:08:58	128,97	7738
Ruiskuvalukone	Asetus	Muotin vaihto			Asetus	12.3.2024 15.46.15	12.3.2024 15.59.31	0:13:16	13,27	796
Ruiskuvalukone	Asetus	Muotin vaihto			Asetus	12.3.2024 14.29.06	12.3.2024 15.40.55	1:11:48	71,81	4309

Figure 9 Case 1 – products changes 12.3.

During machine startups, additional inaccuracies and faulty signals occur due to the way the production is determined. Since the IMM makes production cycles during the product change and initialization, Gema assumes the received signals as normal machine operations resulting in “production” or “slow production” signals. Figure 10 shows the variety of signals gathered by Gema during a product change. Furthermore, when operators open the protective doors of the IMM, automatic fault signals are also triggered. The multiple signals during mold changes causes challenges in the production monitoring and downtime evaluation. To even up these presented issues causing disturbances in performance evaluation, the metric was monitored as an average during an extended period if production signals were received.

Tila	Alkupäivämäärä ↓	Lopetuspäivämäärä	Kesto
Hidasajo	12.03. 18:09:39	12.03. 18:10:39	00:01:00
Asetus	12.03. 16:00:41	12.03. 18:09:39	02:08:58
Hidasajo	12.03. 15:59:41	12.03. 16:00:41	00:01:00
Lyhyt pysähdys	12.03. 15:59:38	12.03. 15:59:41	00:00:03
Kuittaamaton häiriö	12.03. 15:59:31	12.03. 15:59:38	00:00:06
Asetus	12.03. 15:46:15	12.03. 15:59:31	00:13:16
Hidasajo	12.03. 15:45:15	12.03. 15:46:15	00:01:00
Kuittaamaton pysähdys ruiskuvalu	12.03. 15:41:00	12.03. 15:45:15	00:04:14
Kuittaamaton häiriö	12.03. 15:40:55	12.03. 15:41:00	00:00:05
Asetus	12.03. 14:29:06	12.03. 15:40:55	01:11:48
Kuittaamaton häiriö	12.03. 14:28:35	12.03. 14:29:06	00:00:30
Kuittaamaton pysähdys ruiskuvalu	12.03. 14:24:02	12.03. 14:28:35	00:04:33
Kuitattu häiriö	12.03. 13:44:15	12.03. 14:24:02	00:39:46

Figure 10 Case 1 – Production states during a typical product change

As discussed earlier, the performance level remains consistent throughout a production run, which can be seen in Figure 11 that shows the production during 22.11.2023. The performance spike and drop at the end of the day is caused by the operator performing a product change, leading to errors in the performance numbers. Typical deviations in performance occur primarily only in connection with product changes or by faults caused by the machinery.

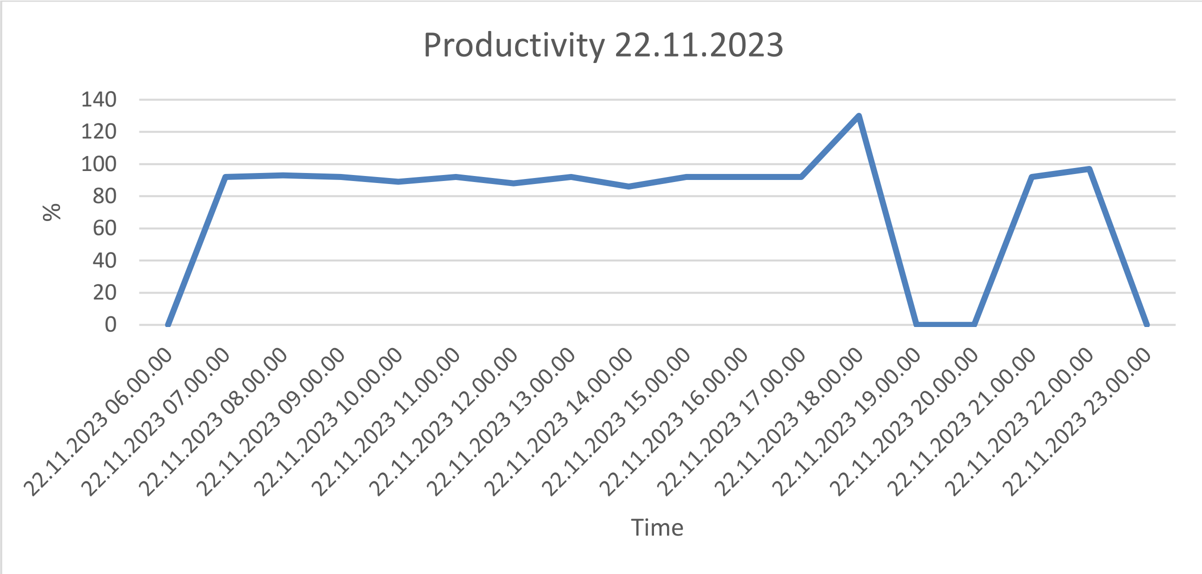


Figure 11 Case 1 – Productivity during 22.11.2023

Monitoring performance over an extended period shows possible underlying issues in the metric. The production averages 80% and has a lot of deviation, which can be seen in Figure 12 where monthly average performance is evaluated. November 2023 highlights instances of measurement errors arising from manual data collection methods, which diminish the credibility of the results. Additionally, the consistently low performance rates during the measuring period highlight a potential area for production improvement that affects OEE and should be considered by the stakeholders.

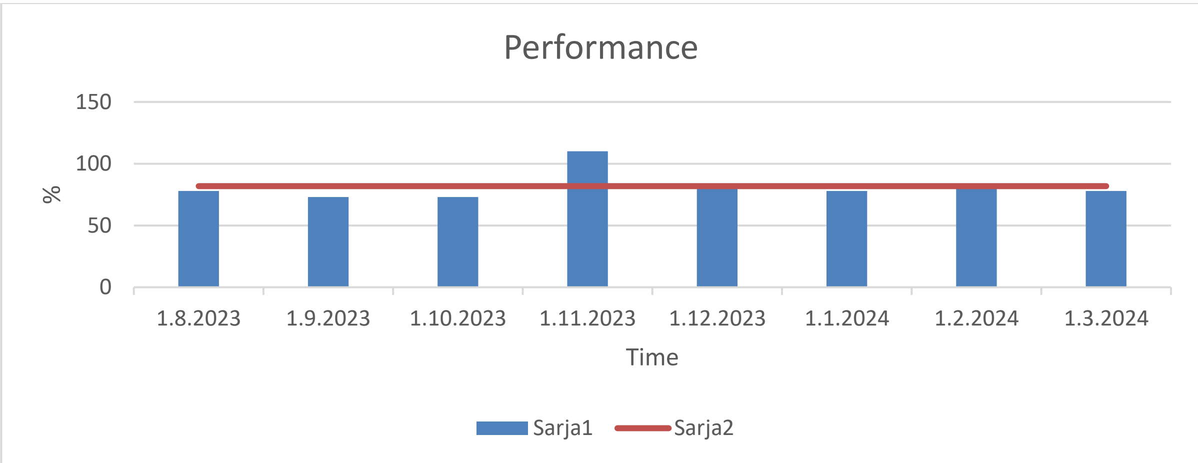


Figure 12 Case 1 – Monthly average performance readings

The variation in the performance explains the challenges and possibilities in production monitoring. In Case 1 the production performance was the OEE factor with second biggest effect on the total score highlighting the importance of performance monitoring.

8.2.4 OEE

Case 1 was the only case where the overall equipment efficiency could be entirely evaluated using the Gema production monitoring system. As mentioned previously, the only factor lacking automated data collection is the quality factor, which had an average number of 99,3% evenly distributed over the total production when creating the KPIs. To gain insight into the various definitions of OEE, the number is calculated by using availability, technical availability, and utilization rate to generate the OEE values. Figure 13 shows the different OEE numbers generated by using different definitions of availability.

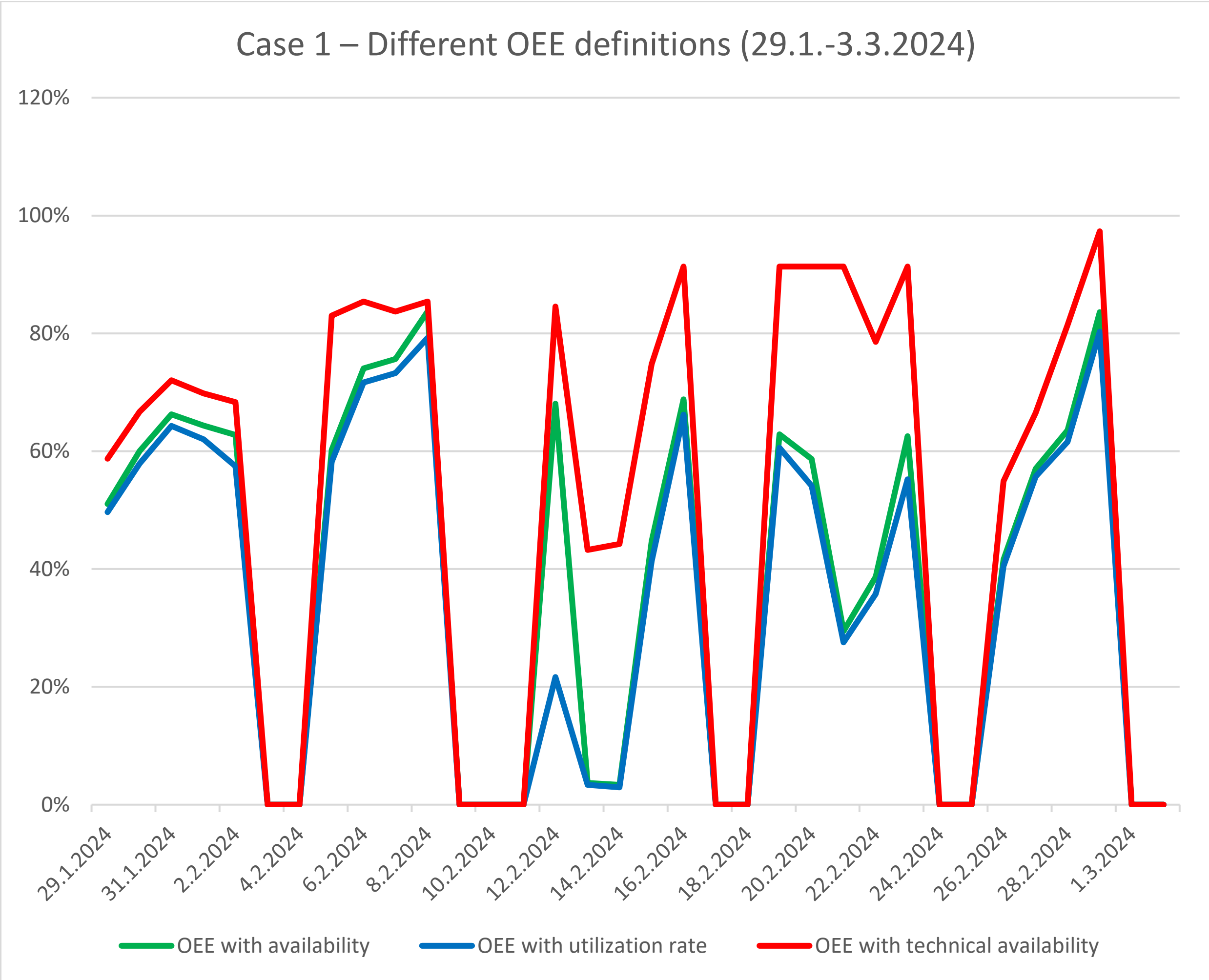


Figure 13 Case 1 – Different OEE definitions

The previous paragraphs explain the distinctions between availability, technical availability, and utilization rates. Given the significant deviation in numbers resulting from the three definitions, it is essential to comprehend these factors to gain insights into production. It is worth noting that the varying OEE values calculated using utilization rate and availability exhibit heavy deviation and do not reach the 85% world-class threshold limit. The deviation added challenges to the data utilization from the stakeholder point of view.

	OEE with availability	OEE with utilization rate	OEE with technical availability
Average	56 %	51 %	76 %
Min	3 %	3 %	43 %
Max	84 %	80 %	97 %

Figure 14 Case 1 – Comparasion of different OEE values 29.1.-1.3.2024

The 5-percentage point difference in the OEE calculated using availability and utilization rate is attributed to the varying time frames against which production is measured. The minimum and maximum values shown in Figure 14 highlight the wide range of OEE numbers, consistently falling below the world-class limit.

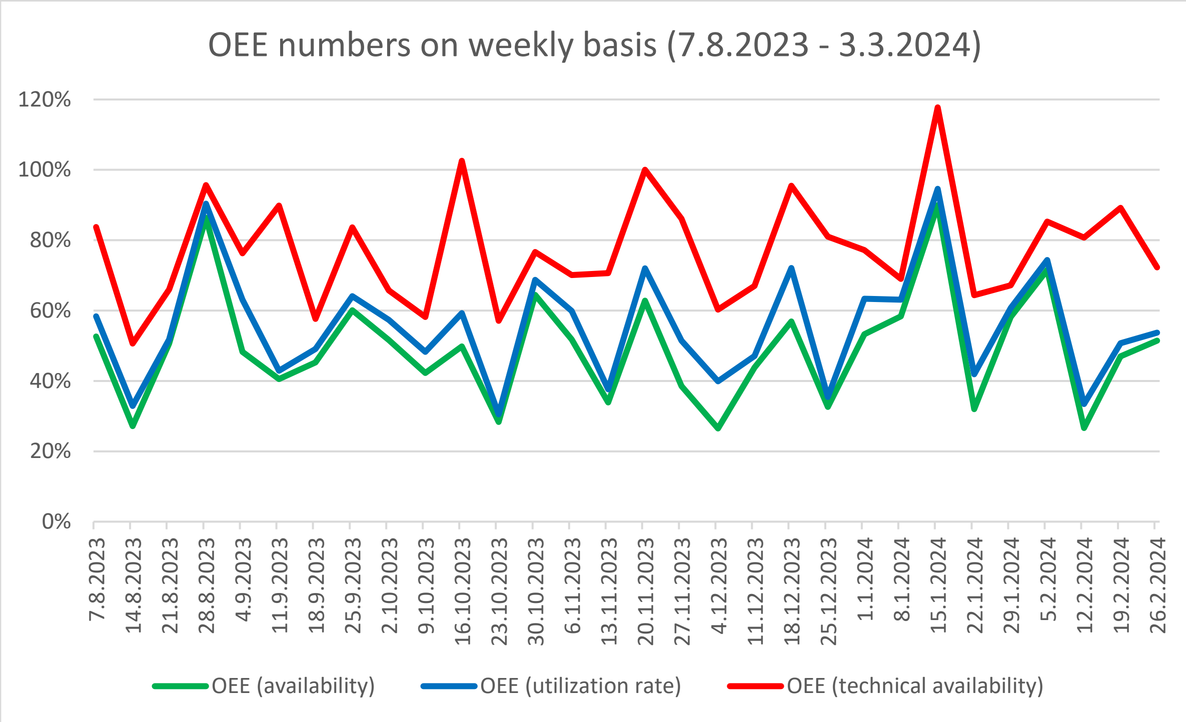


Figure 15 Case 1 weekly OEE

Figure 14 and Figure 15 illustrate significant variability in daily and weekly OEE numbers, respectively, without clear trends or patterns evident from the graphs. This variation can be attributed to various factors, including product-specific parameters and downtimes due to different reasons. Given that OEE comprises three interdependent factors, a deviation in one factor can impact the others which affects the overall equipment effectiveness.

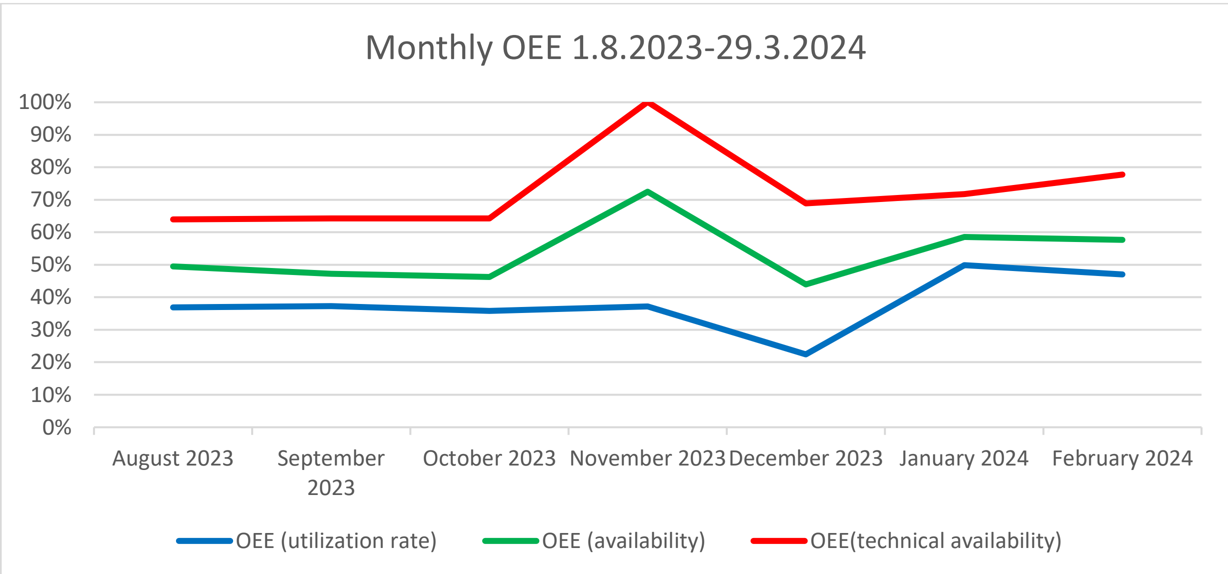


Figure 16 Case 1 – Monthly OEE

Figure 16 illustrates OEE over extended measurement periods, showing stabilized trends over longer measurement periods. However, the repeatability of monthly OEE numbers does not exhibit recognizable patterns, despite a detectable base level for OEE. Without a clear understanding of the factors influencing these KPIs, stakeholders can use the monthly results purely as indicators of overall production effectiveness from an efficiency standpoint, highlighting the importance of comprehending the collected data for meaningful production-KPI integration.

Even if the OEE numbers are low, the IMM fulfilled the designed production demands during the period. And as discussed, the low OEE numbers are not indicating in which factors the issues lie. Since OEE is a general KPI without proper standardizing, understanding the underlying issues requires monitoring and evaluation of the different factors affecting overall equipment efficiency.

Since quality data was not received in real time, the results average out on the production days. The number of scrapped parts is quite constant due to the constant amount of defect parts during startups, which helps with the reliability of the data, which should provide a quite good overview when the OEE is calculated for a full production day or for a longer period. Since the average quality level is high compared with productivity and availability and the utilization rate, the quality factor had a marginal impact on the derived OEE numbers.

8.2.5 Conclusion

In conclusion, Case 1 highlights the complexities and challenges in monitoring production efficiency using the OEE metric, particularly in relation to the different definitions of the availability factor. The equipment in the case utilized unique definitions for different production states with diverse specifications, which resulted in some variations in the KPIs, particularly during startups and mold changes where human intervention was required.

Comparison between availability and utilization rates revealed a close resemblance, with technical availability being consistently higher due to its focus solely on downtime caused by machine breakdowns. However, discrepancies between availability and utilization rates underscored the importance of understanding the definitions and implications of each metric and how they affect the overall equipment efficiency.

Quality monitoring was limited to retroactively gathered data, impacting the timeliness and accuracy of quality assessments, reflecting to the OEE metrics when evaluated over shorter periods. Despite this limitation, average quality percentages remained high, with minor fluctuations, mainly attributed to human error and machine-related issues. In the end, the quality factor had only a small effect on the OEE number due to the other factors being remarkably low in comparison, reducing the significance of the monitoring limitation.

Performance measurements provided valuable insights into production efficiency, particularly in identifying patterns related to machine downtime and product changes. However, challenges in data reliability and collection methods necessitated careful interpretation of productivity spikes and deviations.

Actual OEE evaluation revealed significant variations depending on the definition of "availability factor" used, highlighting the importance of selecting appropriate metrics for accurate performance assessment to fulfil the specific stakeholder needs. Despite fluctuations in weekly and monthly OEE numbers, the IMM production cell consistently met production goals, underscoring the need for comprehensive monitoring of multiple factors to identify underlying issues and optimize production processes.

8.3 Case 2 – Edging machine

The edging machine in Case 2 differed from the other cases from the operational point of view. The production cell faced limitations in collecting detailed production data from the machine, leading to estimations and assumptions about loading time and various production states. Within this setup, only availability and performance were monitored using the Gema production monitoring system. Although quality data was not monitored in real-time, its impact on overall equipment efficiency was marginal because the other OEE factors were significantly lower compared to the high quality of the produced parts.

8.3.1 Availability

The operation principles of the edging machine are explained in Case 3 – Edge Banding Machine. Many different, constantly changing production states were defined for the equipment, resulting in a creation of a high quantity of. To understand the measurements and the creation of OEE, its crucial to understand how the data is evaluated and defined.

To gain insight into the normal machine operations, an evaluation was conducted on 25.3.2024 when the machine ran for a full production day, representing average operating of the machine. Additionally, 28.2.2024 was evaluated due to its high production rates, providing an understanding of the manufacturing capacity and equipment utilization. Through the evaluation of various KPIs and production states over an extended period, a baseline of averages was established to gain a deeper understanding of overall equipment efficiency.

On 25.3.2024, slightly over 900 meters of board was produced, which is slightly higher than the average reading. During the day, technical usability was 95%, availability was 61% and utilization rate 44%. To comprehend the measurement complexity that persisted with the chosen data collection method, over 1400 different production states were observed during the measurement period. Out of these states, 692 were "occupied," indicating the number of times a board was inserted into the machine. Given that each board has 4 sides, the edging process involved 173 boards during the day. Notably, none of the produced parts were defective, resulting in a 100% quality rate.

The progression of the production day can be seen in Figure 17, representing typical operations of the equipment. It's worth to notice how uneven the "Idling" and "Occupied" graphs are due to the operation principles of the machine, resulting loading to be significantly less than the downtime of the machine. The graph that shows produced meters is updated hourly, making it an inaccurate KPI for shorter periods, decreasing the relevance for the stakeholders.

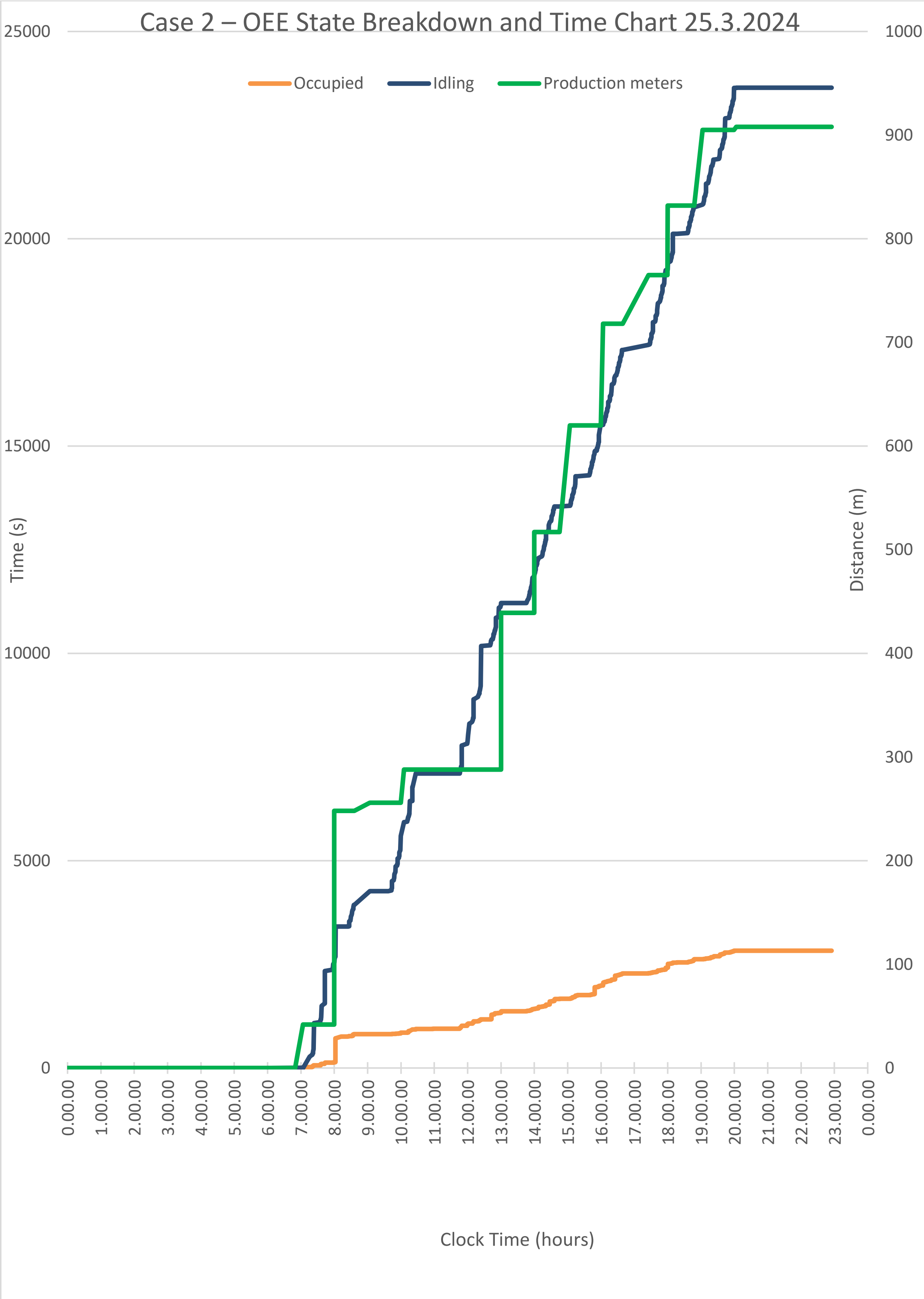


Figure 17 Case 2 – Production progression 25.3.2024

The machine is loaded when it is "occupied", the duration of which is typically low compared to the machine's total working time due to machine specific characteristics. This underscores the unique characteristics and production monitoring needs specific to Case 2. The discrepancy between the idling and "occupied" graphs arises because the actual machine loading time during a production cycle is much shorter than the wait time for products to return on the conveyor. Also, the product handling made by operators adds delays to the feeding process to the machine, which can be seen as a high quantity of micro stops.

The produced meters are measured on hourly basis and has therefore notches in the graph. The figure shows the time difference the machine is in either occupied or idling state, which have a correlation with the meters produced. Even if the loading time of the machine is low, the production goals were constantly met. Another reason for downtime is that the operators have additional tasks that they perform in the side of operating the edge bander.

Figure 18 displays the differently definite availability key performance indicators reflecting the machine's performance on the day of 25.3.2024, which was analysed earlier. The graphs show significant deviations, which are typical for the machine due to order-oriented production and machine operators performing additional work-related tasks.

Figure 19, on the other hand, illustrates the monitoring period with various production states, providing an overview of how different production states influence the formation of KPIs. This underscores the complexity caused by the lack of standardization in OEE. The figure also contributes to understanding the KPIs and their differences shown in Figure 18, emphasizing the importance of selecting purposeful factors for production monitoring needs.

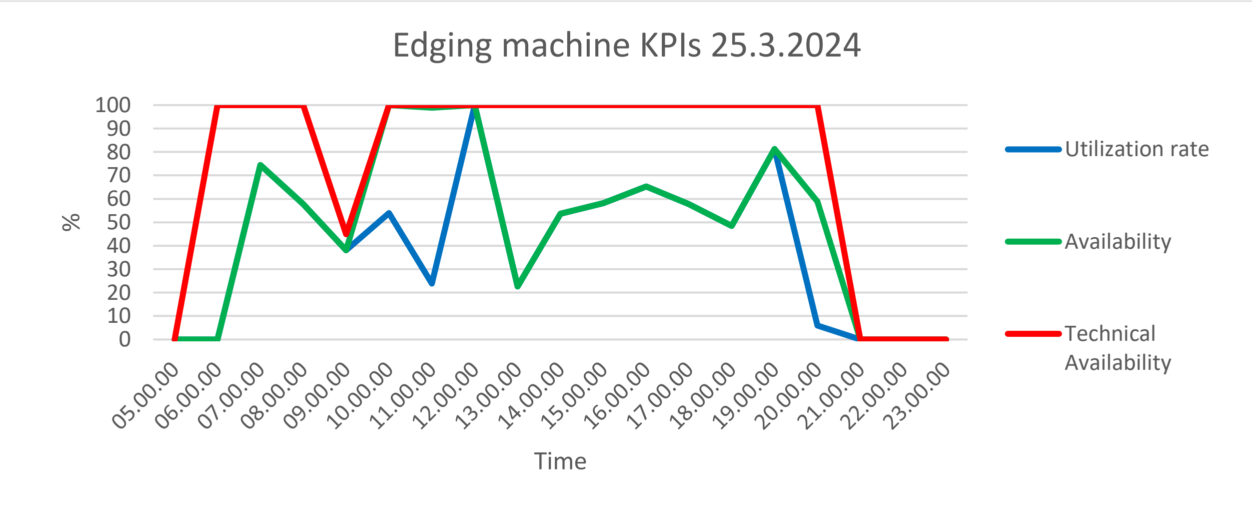


Figure 18 Case 2 – Edging machine operation during 25.3.2024

There are visible differences between utilization rate and availability as can be seen in Figure 18. The differences seem to occur at 10:00-11:00 caused by preventive maintenance, showing a difference in utilization rate and availability in Figure 18 and as a flat "Occupied" line in Figure 17. A similar situation can be identified at 20:00, which is also caused by the occurrence of preventive maintenance which is not considered when calculating availabilities and the utilization rate. As described earlier, the time the machine is in "Preventive maintenance" state is excluded from the time used for calculating machine availability.

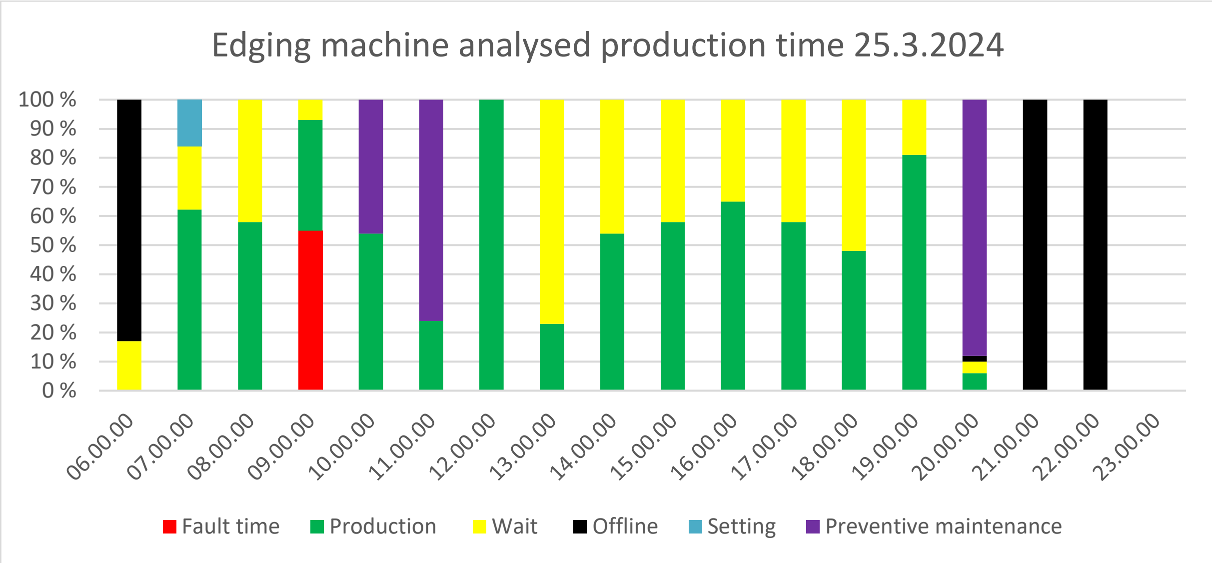


Figure 19 Case 2 – Different production states during 25.3.2024

Analysing the downtime data reveals that Case 2 experienced an exceptionally high number of micro stops, as evidenced by the idling data shown in Figure 17. On the day, the machine had a percentage of micro stops, with 89.7% of the stops lasting shorter than 60 seconds. The idling is primarily caused by the time between feeding the boards, resulting in the machine idling until a new board is fed in. The average distribution of stop lengths and the downtime caused by the micro stops can be seen in Figure 20.

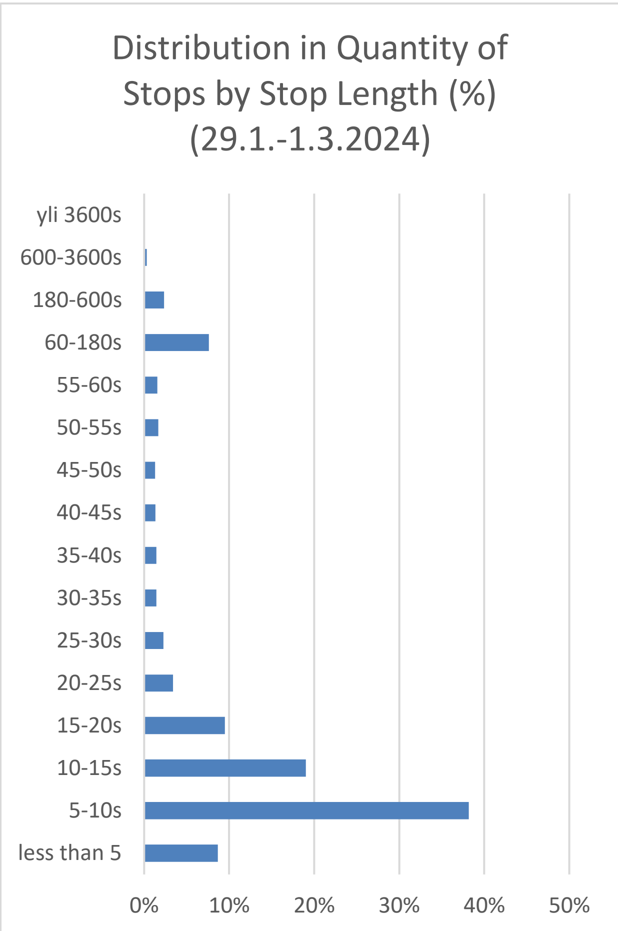


Figure 20 Case 1 – Stop length distribution

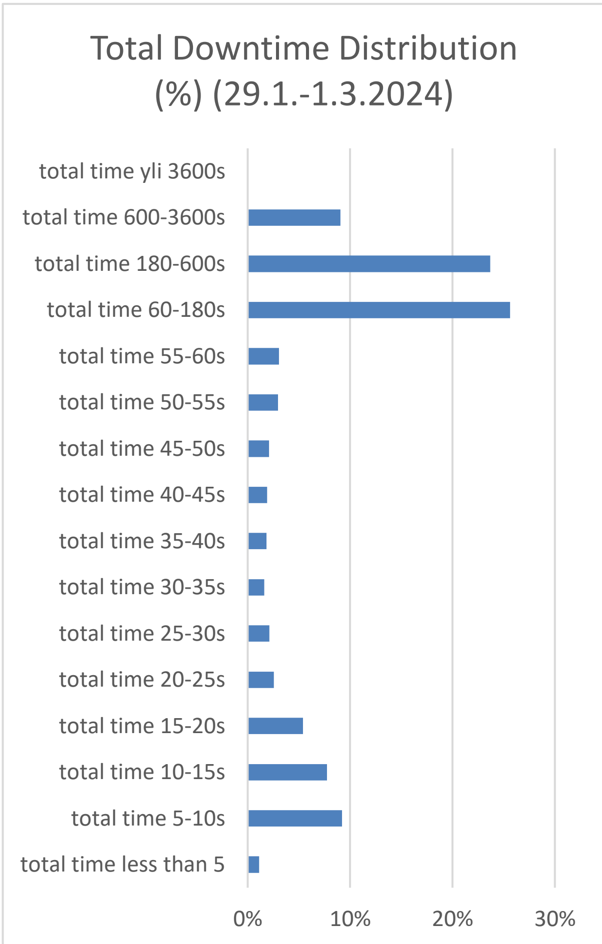


Figure 21 Case 1 – Total Downtime Distribution

Average (29.1-3.1.2024)				
Stop length	0-60 seconds	60-180 secons	180-600seconds	over 600s
Precentage	89,7 %	7,6 %	2,3 %	0,3 %
Average time/day (%)	41,6 %	25,6 %	23,7 %	9,1 %

Figure 22 Downtime analysis

During the evaluation period from 29.1. to 1.3.2024, the average technical availability was 97.02%, availability was 52.65%, and utilization rate was 33.58%. A total of 17,327 meters were edged during this period, averaging 722 meters per day. There were 16,089 "Occupied" signals recorded, corresponding to 4,022 boards, which equates to approximately 168 boards per day on average. These metrics provide a comprehensive overview of the machine's operational performance and production output during the specified timeframe and helps reflecting the number of micro stops with the KPIs shown later in Figure 29.

The downtime analysis reveals that the availability losses discussed earlier are attributed to various lengths of production stops, with the highest number of downtime occurrences being micro stops shorter than a minute. "Production" is considered to happen when either "available" or "occupied" signals are present. Following an “occupied” signal, there is a 60-second delay during which Gema indicates "production". Gema classifies downtime over 60 seconds as "slow production", while downtime exceeding 180 seconds is categorized as "unclassified downtime". Stops lasting over 600 seconds require operator acknowledgment, with only 0.3% of all downtime instances being classified in this way. Although most instances are short production stops, the stops lasting over 60 seconds account for most downtime, covering 58.4% of the total downtime. These findings highlight the ineffectiveness of the production monitoring system in analysing downtime in Case 2, where the number of production stops is significant while the stops are production related.

On average, 90.9% of the total downtime went unacknowledged, with only 0.3% of all instances exceeding the acknowledgment threshold. These unclassified downtime events were automatically classified either as "wait" or "offline", the latter indicating that the production monitoring device was without power, signifying downtime. A higher level of automation in data collection would have facilitated downtime analysis and better met stakeholder needs for production monitoring.

The downtime analysis shows the distribution of different downtime lengths. Figure 21 shows that 27% of downtime is causes by “wait”, which aligns with the assumption that the downtime analysed in the previous graph is caused by the way the machine is operated. Furthermore, the machine is shut down after reaching the daily manufacturing goal, resulting in the machine being "offline" for a quarter of the potential production time. Setting, preventive maintenance, and faults accounted for 14% of the available production time.

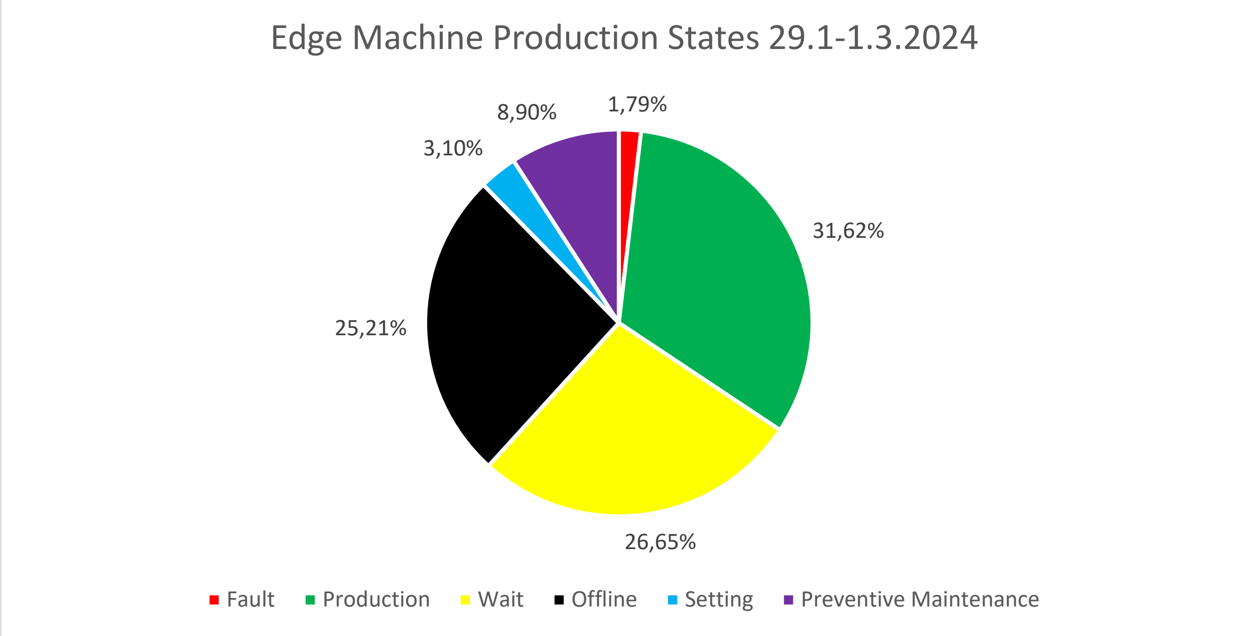


Figure 23 Case 2 – Production states29.1.-1.3.2024

The production days exhibit considerable variability, as demonstrated by comparing the average production from January 29 to March 1, 2024, with February 28, which experienced a significantly higher production volume. Despite the increased output on February 28, the distribution of downtime durations remained consistent, with the difference of showing slightly fewer longer stops and an additional number of micro stops. Notably, February 28, 2024, had a higher frequency of stops lasting less than 180 seconds compared to the average. Additionally, it's worth noting that only 0.4% of stops exceeded 600 seconds, whereas the average during the extended period analyzed earlier was 9.1%.

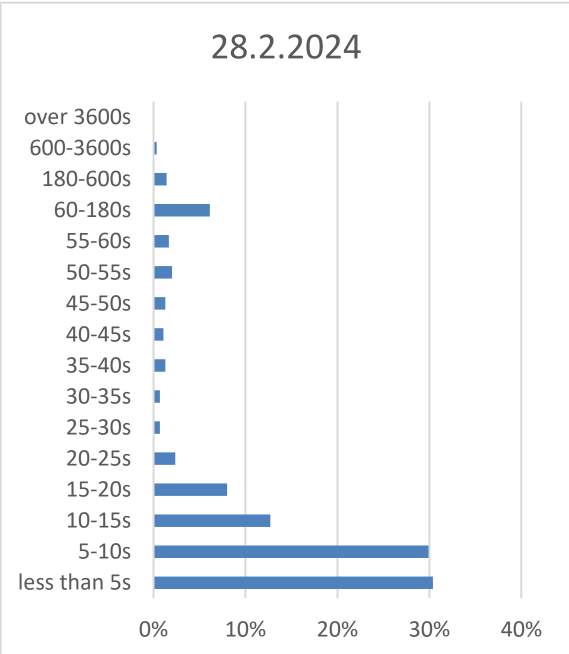


Figure 25 Case 2 – Stop length distribution

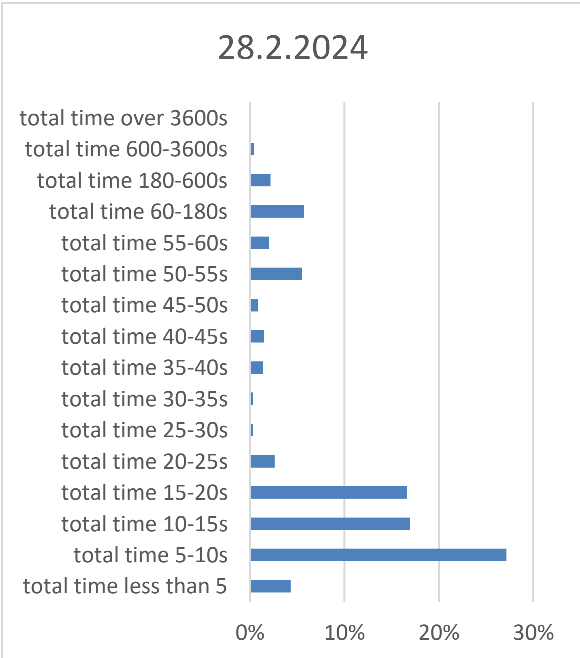


Figure 24 Case 2 – Total downtime distribution

During this exceptionally productive period, the technical availability reached 100%, while the availability and utilization rates were 69.7% and 52.2%, respectively. The edge banding process achieved a high output of 2589 meters, significantly surpassing the average, with a filling rate of 27%. This performance highlights the efficiency and productivity of the edge banding operations during a day where the demand is high. This notable performance also underscores the efficiency and output capacity of the manufacturing operations in the case.

28.2.2024				
Stop length	0-60 seconds	60-180 seconds	180-600seconds	over 600s
Percentage	92,1%	6,1 %	1,4 %	0,4 %
Time/day (%)	79,5 %	5,7 %	2,2 %	0,4 %
Time/day (s)	18422	1331	503	98

Figure 26 Case 2 – Production values 28.2.2024

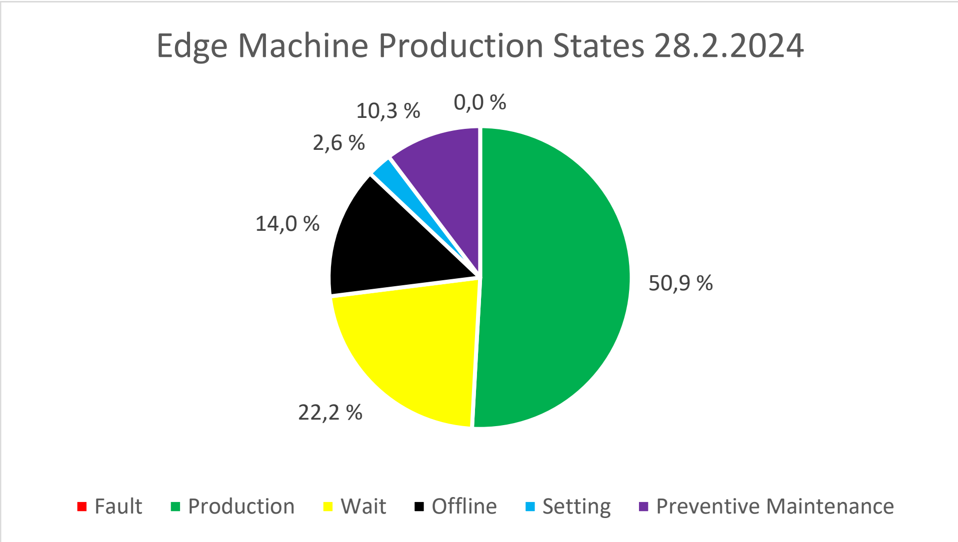


Figure 27 Case 2 – Production states

Additionally, comparing the production state distribution on 28.2.2024 shows that over half of the time was spent loading the machine which is remarkably higher than the average. While the production time increased, the downtime caused by wait, setting and preventive maintenance stayed similar to the average within a small margin. The production time increase can be explained with the decreased amount of "offline" compared with the average.

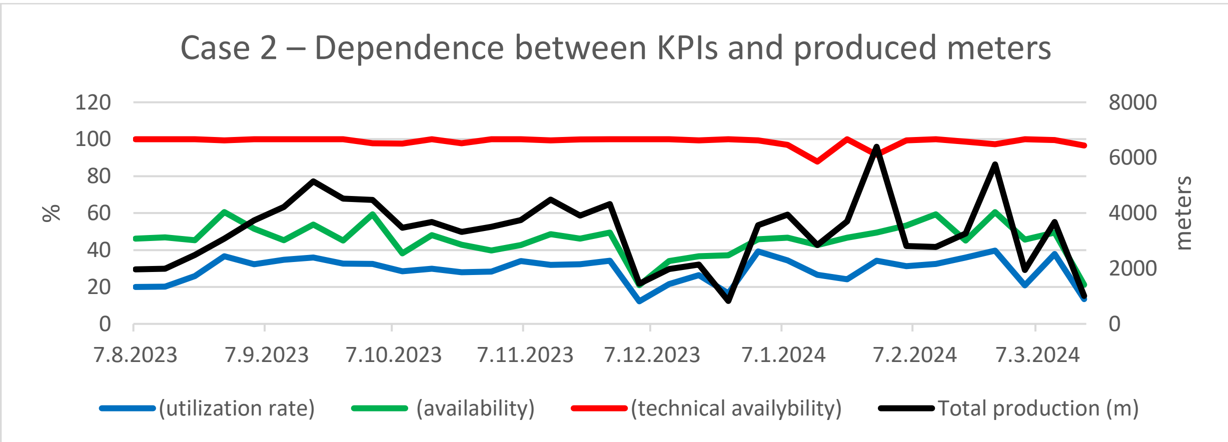


Figure 28 Case 2 – Dependence between KPIs and produced meters

Figure 28 compares produced meters with the different variations of availability to highlight the challenges in production monitoring in diverse environments where the collected production data is limited. The KPIs and produced meters exhibit some dependency, but it is challenging to discern clear patterns in the collected data. The availability and utilization rate graphs mirror to some extent the shape of the produced meters graph, whereas technical availability shows no direct influence on the production output. This underscores the importance of understanding and selecting the appropriate KPIs for specific applications and know the limitations and properties the specific metrics have.

8.3.2 Quality

In Case 2, quality monitoring was not integrated to Gema. The quality percentage can be considered as 100% since only 4 rejected parts were reported to the ERP system between Case 2 and Case 3 during 2023, with the same trend continuing in 2024. In only 6 occasions, downtime caused by parts needing rework was reported to the production monitoring system during the evaluation period. These instances were addressed immediately after the parts came off the production line, causing downtime as operators paused production during the quality repairs. Only one part was scrapped during the monitoring period.

Machine	Reas	Reason 2	Comment	Alkuaika	Sarake1	Duration h:mm
Edge machine	Odotus	Fixing quality defects	väärä lista	19.1.2024 15.00.00		1:17:29
Edge machine	Odotus	Fixing quality defects	erikoistilauksessa kosmeettisiä virheitä, levy lopuksi korvattu toisella	10.10.2023 15.58.22		0:23:47
Edge machine	Odotus	Fixing quality defects	rasvaa radalla	6.9.2023 12.35.04		0:32:12
Edge machine	Odotus	Fixing quality defects	rasvaa radalla	6.9.2023 09.54.56		0:22:49
Edge machine	Odotus	Fixing quality defects	öljyä radalla	4.9.2023 08.49.02		0:28:35
Edge machine	Odotus	Fixing quality defects		29.8.2023 20.28.30		0:39:08
Edge machine	Odotus	Fixing quality defects		29.8.2023 18.53.14		0:17:08

Figure 29 All downtime reasons caused by quality defects trough the measuring history (5 months)

As previously explained in the downtime analysis, stops caused by quality defects and reworked parts is acknowledged if they result in a production stop longer than 10 minutes. Quality reworks typically do not abort production over this threshold, which makes the reasons for the downtime data less credible. Given that availability and utilization rates are low while quality is close to 100%, the unclassified quality defects have a minimal to negligible impact on the overall equipment efficiency.

8.3.3 Performance

In Case 2, both performance and production speed were monitored. The edge banding machine operates at a set speed of 18m/min, which is lower than its maximum operational speed. Previous experience indicates that increasing the production speed leads to quality defects, increases strain on the machine, and requires operators to work at an unnecessarily fast pace. When evaluating overall equipment efficiency, machine maximum operational speed is often used in the evaluation. However, the lack of a specific definition of OEE raises questions about whether the maximum speed refers to the machine's top speed or the maximum production speed, which should be clarified for accurate evaluation. In this Case, best practice speed is being utilized to create OEE metrics.

Increasing the production speed would not significantly impact the OEE number because the average utilization rate is 34% and availability is 53% (during the measurement period of 29.1.-3.1.2024), while production speed was significantly closer to 100%. Also, since the machinery have unused capacity, the stakeholders don’t prioritize improving productivity at the expense of quality degradation. If overall efficiency needs to be improved, the focus is instead on increasing the low availability and utilization rates, as these factors are considerably lower compared to other contributors to the overall equipment efficiency, offering a more feasible path to improving overall efficiency.

Machine performance is evaluated by comparing the actual hourly produced distance to the maximum rate of 1080 meters per hour. The production distance is calculated by multiplying the band speed of 18 meters per minute by the duration of time the machine is in the "production" state. With a two-minute delay before classifying a production stop as downtime, production efficiency serves as a proportional metric, demonstrating the effectiveness of production relative to the maximum achievable output within a specified period. This approach reduces the impact of production typical micro-stops on performance and OEE measurements.

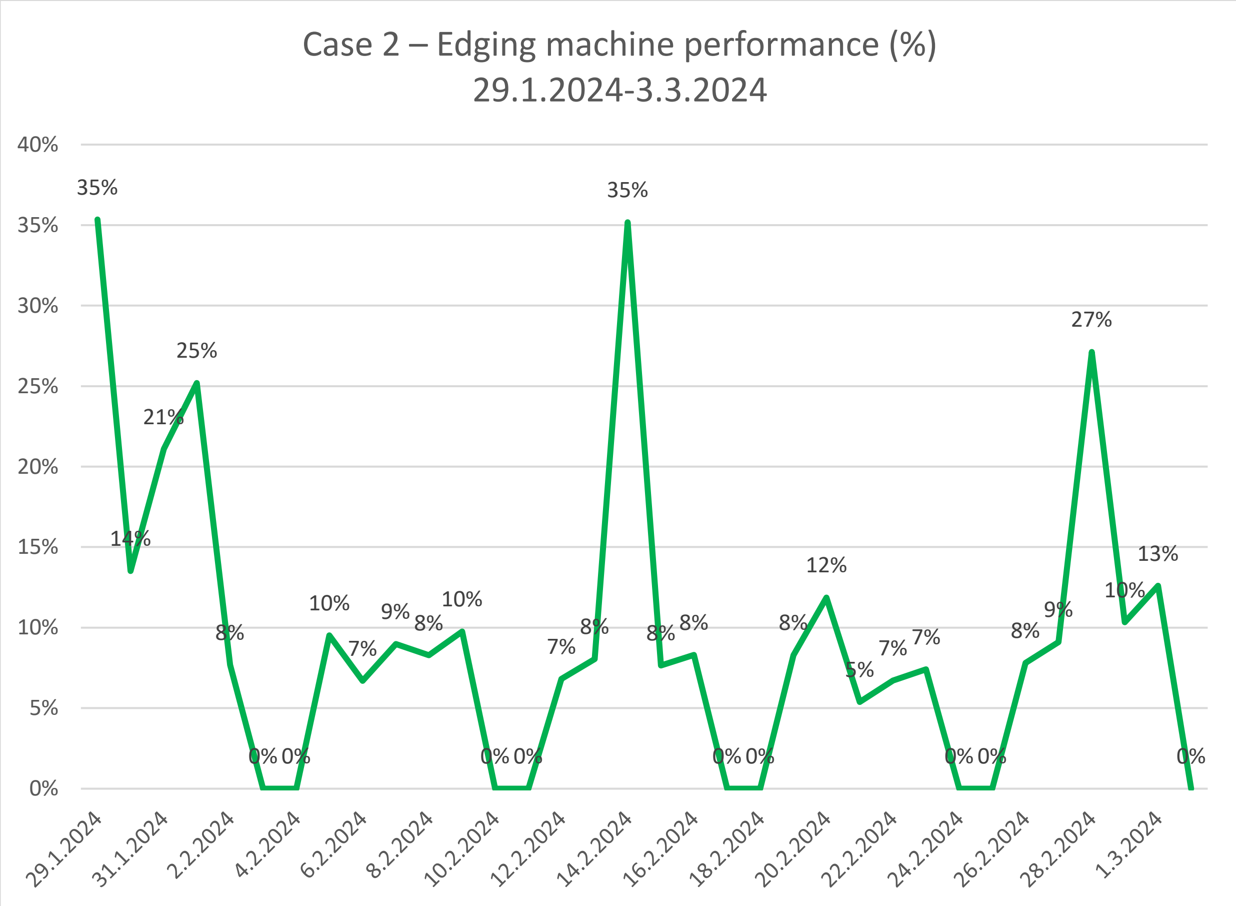


Figure 30 Case 2 – Performance 29.1.-3.3.2024

Figure 31 shows slight dependency between production hours and produced meters. The relationship between these graphs exhibits variation that requires a deeper understanding of the actual production events to receive insight about the actual production. When monitoring performance, it becomes apparent that the produced meters do not directly correlate with the key performance indicators and production time, as depicted in the figure below. Productivity is influenced by the size of the manufactured units, with larger pieces covering more distance with the same number of units. To mitigate the impact of varying product sizes, production should be measured over an extended period to average out these effects.

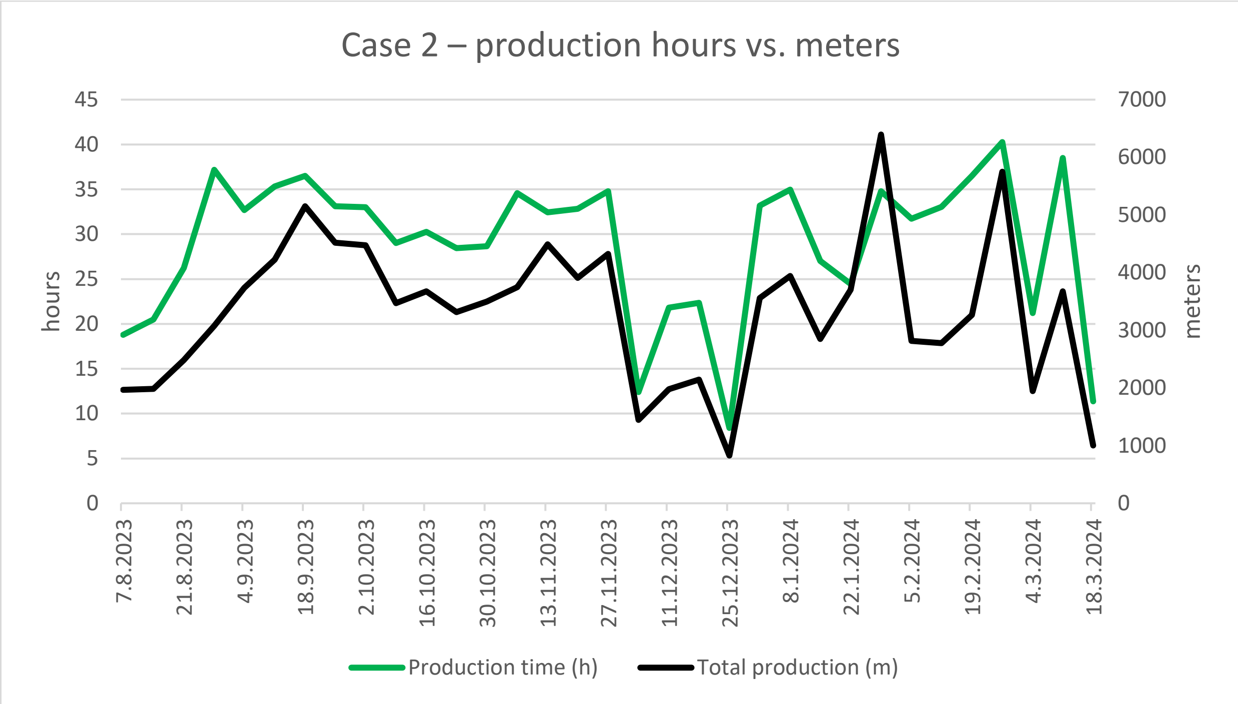


Figure 31 Case 2 – Production hours vs. produced meters

Comparing performance to the produced distance reveals deviations in the graphs in multiple occasions when observed over an extended period. Figure 23 illustrates the weekly produced meters alongside the average production hours over an extended period, highlighting the variability in the metrics on multiple occasions. The figure shows that production time does not consistently affect the produced metrics, regardless of total weekly production.

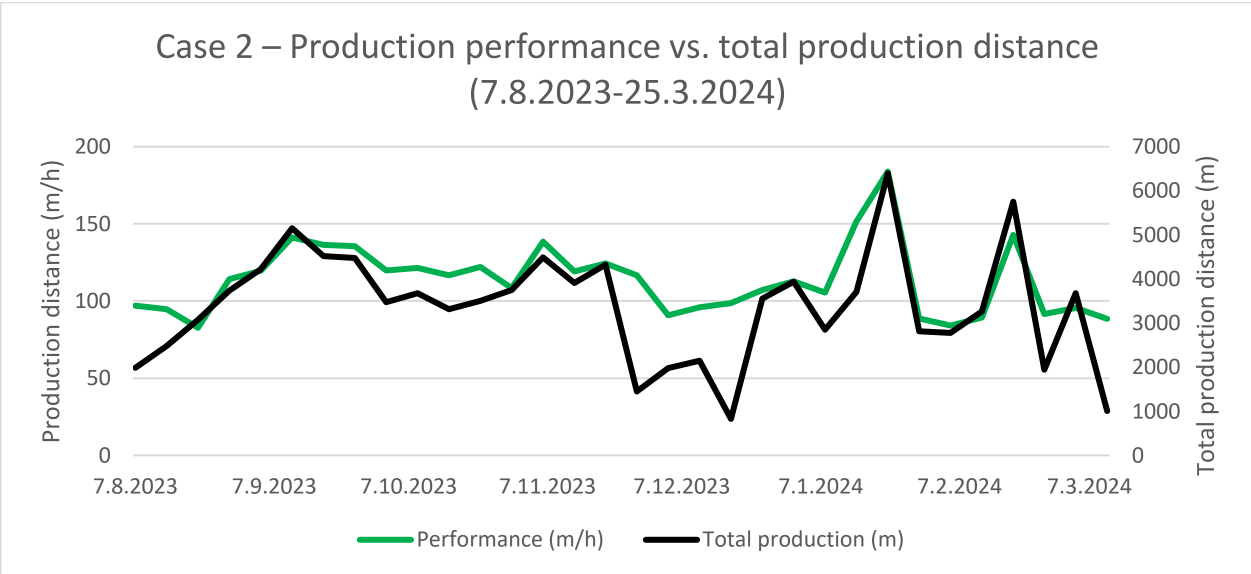


Figure 32 Case 2 – Production performance vs total production distance (7.8.2023-25.3.2024)

When comparing total production distance to performance, it can be seen that the performance is less sensitive than the production hours to the total produced distance while both figures have some notable dependency. Figure 32 shows that the performance and the produced distance are not joined together which makes the productivity monitoring inaccurate and misleading. This is caused by different sized pieces and monitoring inaccuracies which adds a variable that needs to be considered when defining production speed and performance in the context of OEE.

8.3.4 OEE

The individual factors evaluated shows that overall efficiency of the equipment is strongly dependent on the factors used. In Case 2, there are three definitions for availability and two definitions for production performance. Analyzing different combinations provides an overview of the challenges these definitions pose for OEE evaluation and filling the stakeholder needs. These factors have been defined in earlier chapters to provide holistic understanding of the production monitoring.

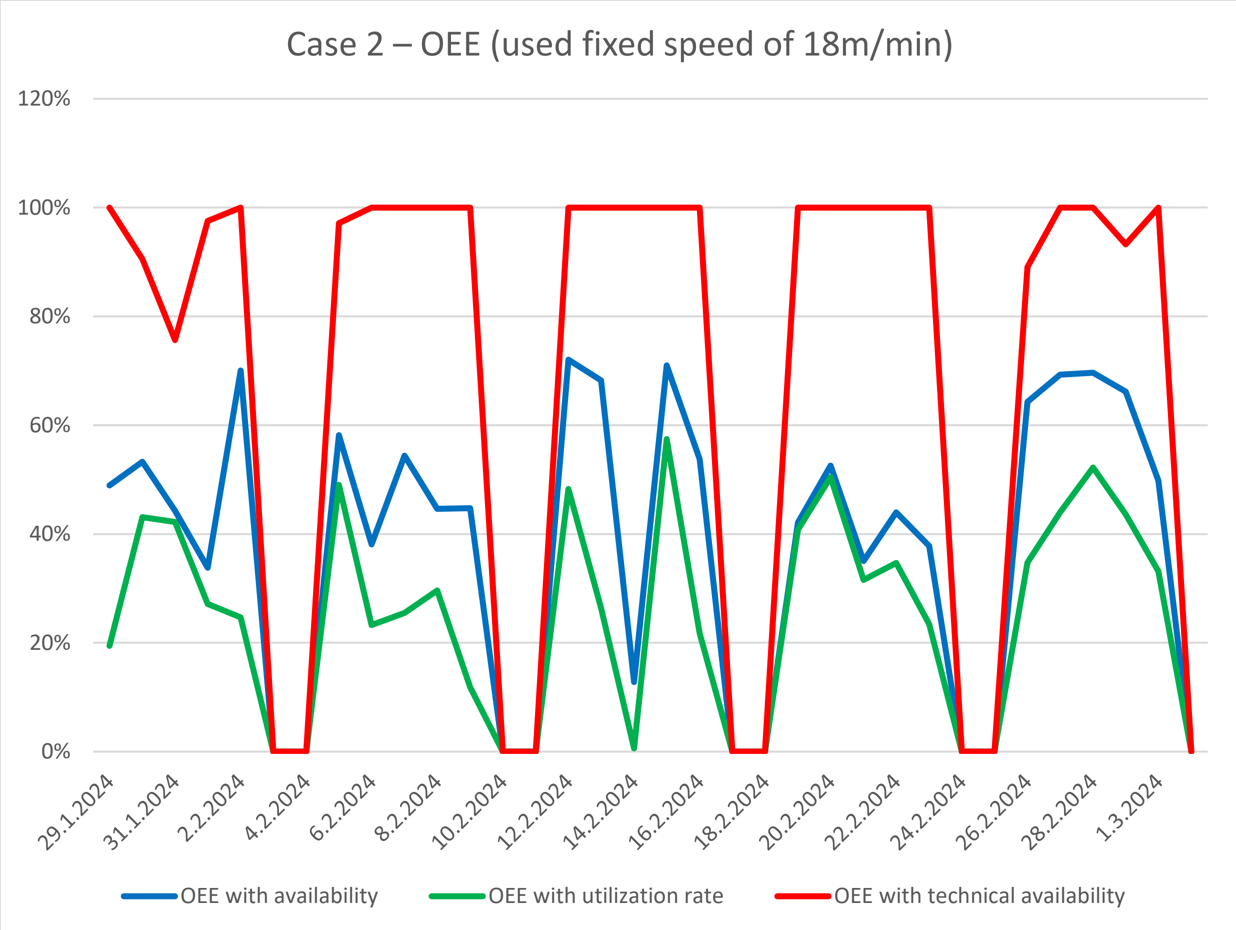


Figure 33 Case 2 – OEE calculated with machine running speed

Figure 33 illustrates significant daily deviations in the overall equipment efficiency in Case 2. The metrics represents the availability factor since the machine operation speed is constant and there are (almost) zero defects. The measured values are low, with technical availability showing a notable difference due to the metric indicating the downtime caused by faults. The OEE numbers calculated using availability and utilization rates differ from each other due to the definitions used for the individual metrics.

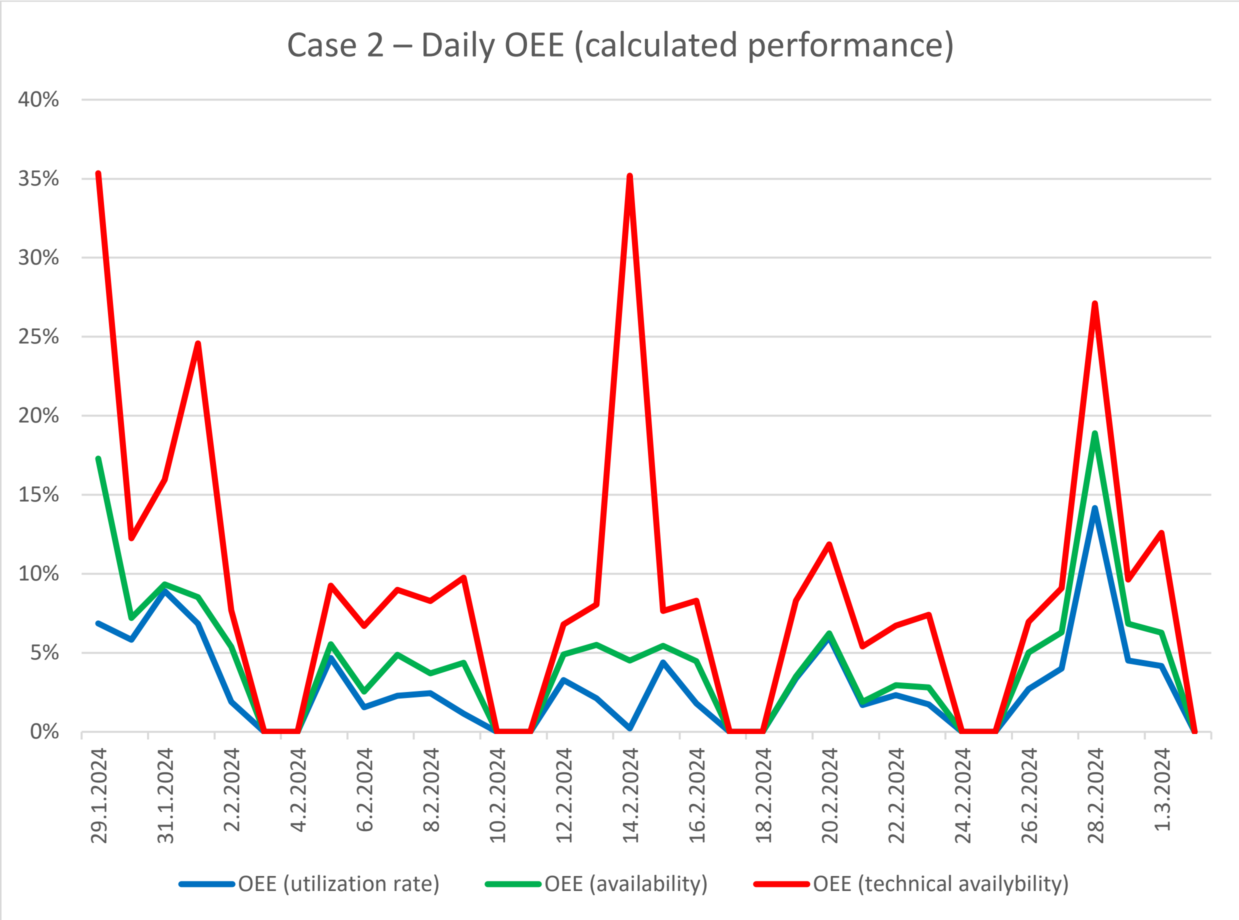


Figure 34 Case 2 – OEE calculated with performance instead of speed

Figure 34, when calculating overall equipment efficiency based on daily performance instead of machine speed, the OEE numbers change significantly. There is a clear discernible interaction between the different components of OEE, and the different definitions showing significant mutual variance highlighting the need of choosing the right parameters for the production monitoring. The figure shows that performance setbacks directly correlate with a reduction in overall equipment efficiency. When machines experience issues that impede their optimal functioning, such as the micro stops discussed earlier, it directly impacts machine availability, thereby diminishing overall equipment effectiveness.

The average values of both performance definitions indicate low overall production efficiency, despite the equipment meeting production goals. Comparing the maximum and minimum values to the averages reveals a significant deviation in the numbers.

The effect availability and performance factors have, result in low overall equipment efficiency, even when the machine is operating at full speed and producing high-quality output. This underscores the inadequacy of using OEE for short-term production monitoring of the edging machine especially with the performance used as an OEE factor.

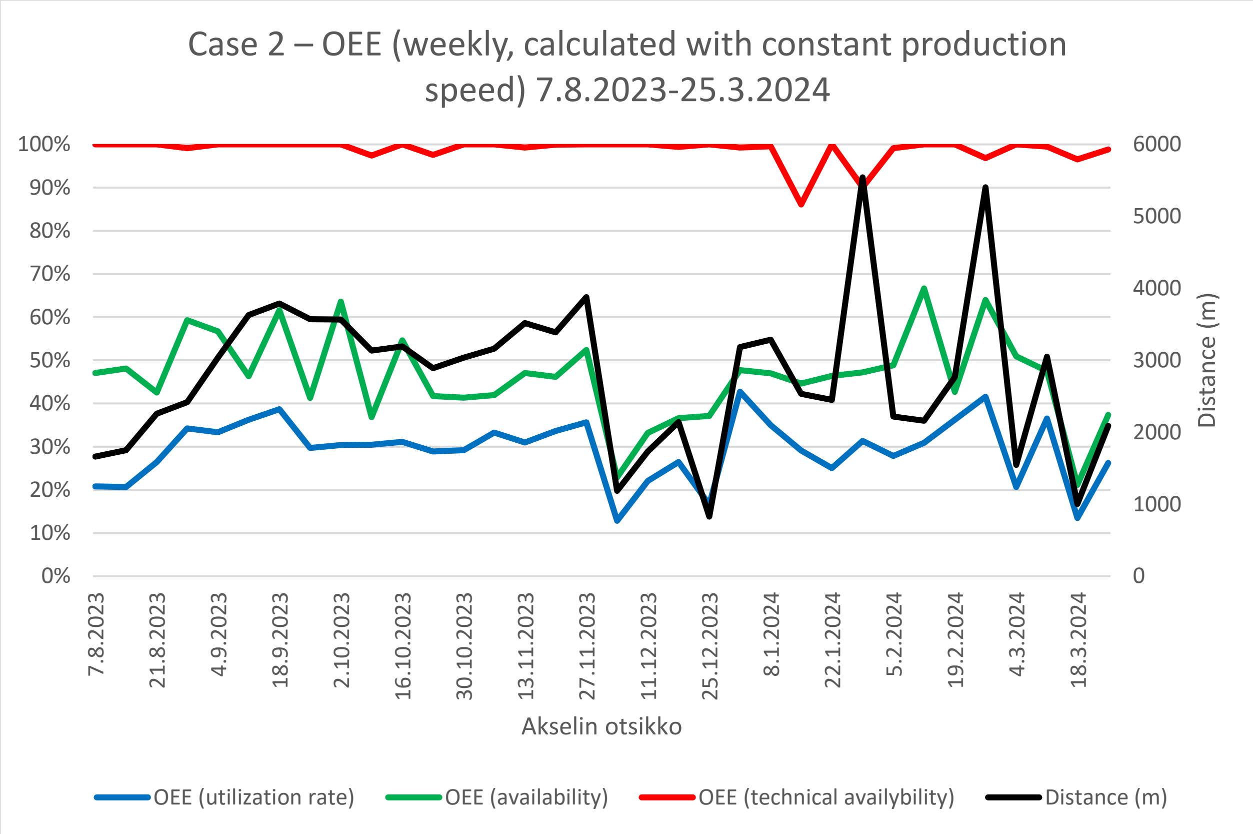


Figure 35 Case 2 – Weekly OEE calculated using constant production speed

The weekly OEE number calculated based on production speed represent machine availability and shows deviation and models that are difficult to distinguish and connect to production events. Even with the longer measurement period, overall equipment efficiency does not appear to correlate with the produced meters, as indicated by the black graph which is like the findings of the previous paragraphs.

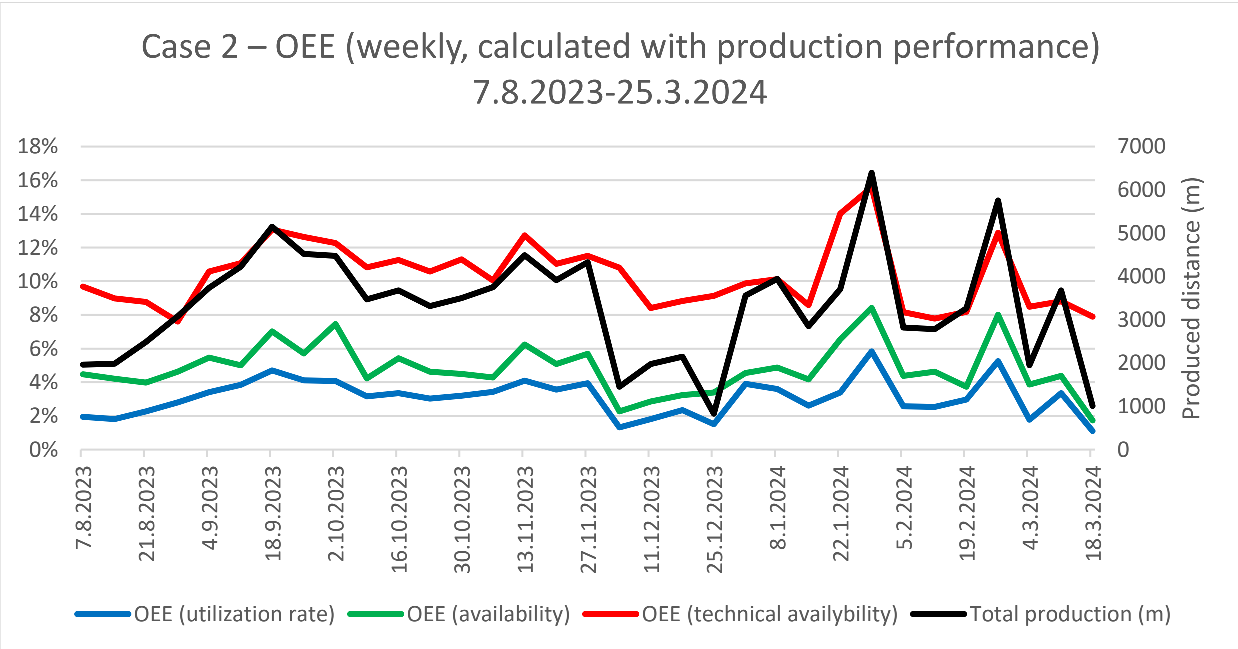


Figure 36 Case 2 – Weekly OEE calculated using weekly performance average

The OEE graphs with different availability definitions align more closely with the produced meters when measured over longer periods, allowing for the averaging out of results as can be seen inFigure 35. The OEE calculated using technical availability varieties compared to other definitions due the different nature of the KPI, whereas the numbers derived from utilization rate and availability show more similarity to each other. Notable differences in graph values, such as those between February 5th and February 19th, 2024, highlight the challenge of understanding the collected data and understanding the factors that causes the differentiation.

Figure 36 illustrates that OEE calculated using machine performance exhibits better correspondence with the produced meters compared to Figure 35 that incorporate constant production speed into the OEE values. The weekly evaluation of OEE appears to mitigate some of the deviations in OEE, making the graphs more accurate for production monitoring.

An issue with OEE noted in Case 2 is that the occurrence of potential quality defects or the need for rework stops production, which decreases availability. Quality issues necessitate interruptions in the production process to address them, leading to downtime and a subsequent decrease in machine availability. This means that quality defects impact the overall efficiency calculations twice skewing the overall equipment efficiency calculations.

The complex relationship between the different factors underscores the importance of focusing on the right metrics and understanding the underlying reasons that affect them. The complexity and lack of standardization highlights the necessity of taking a comprehensive approach to optimizing production processes, ensuring that stakeholders use KPI metrics that fills their specific needs. Additionally, the definitions of operationa states are critical role in this context.

8.3.5 Conclusion

In summary, Case 2 brings out several insights into the challenges and complexities of monitoring production efficiency using the OEE metric. The lack of standardization and the complex methods of defining production states and OEE components add challenges to understanding and selecting the right metrics to fulfill stakeholder needs.

Availability and utilization rates exhibit significant fluctuations due to the machine's complex operational states and irregular operational patterns, characterized by numerous transitions between different production phases. Although technical usability, quality and speed rates may reach high levels, availability, utilization rates and performance remain moderate, reflecting the machine's intermittent operational behavior and room for improvements.

Challenges in determining operational states, contribute to discrepancies between availability and utilization rates. Factors such as preventive maintenance and setting times influence these differences, highlighting the need for accurate data classification and interpretation that suits the production monitoring needs.

Quality monitoring reveals minimal defects and rework instances, indicating high-quality production standards. However, the impact of quality issues on downtime underscores the importance of efficient quality control measures to minimize disruptions. Another notable feature is that quality defects impact OEE in a couple of ways: once by lowering the quality number and again by causing machine downtime causing loss in availability and performance while the operator aborts the production to fix the defects. This multi-impact underscores the significance of addressing quality issues in production processes to optimize overall equipment efficiency.

In general, OEE calculations exhibit significant variability depending on the availability and performance factors included, with the performance losses impacting availability and overall equipment effectiveness. The disparity between OEE values calculated based on production speed versus true performance highlights the complexity of interpreting OEE data in short-term production monitoring scenarios. Overall, Case 2 underscores the importance of comprehensive data analysis and interpretation in understanding production efficiency dynamics and the factors that contributes to the metrics.

8.4 Case 3 – Board Cutting CNC

The edging machine in Case 2 and the board cutting CNC in Case 3 share some operational similarities despite being completely different machines. Both machines are operated within the same department and by the same operators. The board cutting CNC processes boards that are subsequently edged by the edging machine, producing pieces for use in the edging process. This coordinated workflow highlights the interdependency of these machines in the production process.

The production in Case 3 is cyclical and consists of different phases where the machine is idling due setting, material handling and other production related instances. Since the cutter produces products faster than the edging machine can handle, downtime is occasionally necessary to prevent overproduction and ensure efficient workflow coordination between the two machines.

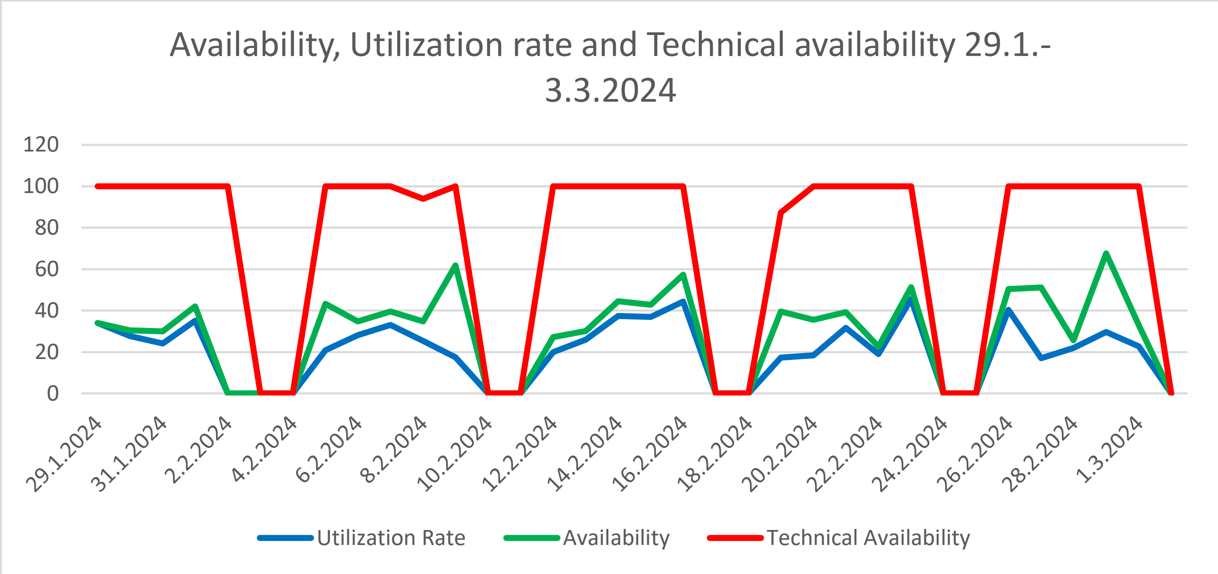
8.4.1 Availability

The availability in Case 3 is difficult to determine unanimously since the machine can be used in a fully automated mode where the manipulator takes care of the loading of the blanks and unloading of the finished pieces and the scrap material. The other operational option is the manual mode where the CNC is typically used for single production runs to utilize otherwise wasted pieces. In the manual mode, the operator takes care of placing the blanks on the cutting table and the unloading of the finished pieces and the scrap material.

The machine is in "production" state when it loads or unloads boards, or when it is actively cutting. To generate production signals, retrofitted pressure sensors was employed to detect manipulator operations due to a lack of premade interfaces. Since spindle speeds and movements could not be easily tracked, cutting was determined to occur when a cutting program was initiated and the vacuum on the machine bed was activated. Delays were deliberately introduced between operations to facilitate data cleanup and ensure that the collected data reflected actual production. Detailed explanations of these data collection methods are provided earlier in this thesis.

The issue with the production determination method is that in manual mode, the vacuum can remain activated even when there are no boards on the cutting table, leading the machine to faulty register the operational state as "production". Despite the measurement inaccuracies, the ratio of manual operation is low compared to the automated mode, which reduces the significance of potential errors.

The average production values between the period of 29.1.-3.3.2024 can be seen in the table below. The availability and utilization rates are low with some deviation and the average production hours are low, highlighting the effect offline and wait have for the availability and utilization rate. The only KPI that reaches higher levels is the technical availability of the machine, due to different definitions used.



The different availability figures shows that the availability and utilization rates variate a lot depending on the day, while technical availability stays close to 100%. This indicates that there are a lot of downtime caused by other reasons than machine failures.

Aika	käyt-töaste	käytet-tävyys	tekninen käy-tettävyys	häiriöt (tunteina)	tuotan-toaika	odo-tus	of-fline	ase-tus	ennakko-huolto
Average	19,8	28,5	73,0	0,1	3,4	5,7	3,2	1,0	0,2
Average (ex-cluding 0)	28,1	40,3	99,2	0,9	4,8	7,7	4,5	1,8	0,9
Min (exclu-ding 0)	16,9	22,6	87,2	0,8	2,9	1,8	1,5	0,2	0,3
Max	45,5	67,6	100,0	1,0	7,7	14,6	12,1	5,1	2,0

The dissimilarity between availability and utilization rates depends on the definition of the KPIs in the same way as in the other cases. Since utilization rate compares productive time to total time while availability compares the production time to the time the machine is either in "production", "wait" or "fault" states. Figure 37 visualizes the proportional amounts that the machine is in different states during the measurement period. "Setting" and "Offline" are not considered when calculating availability which explains the differences in the different KPIs.

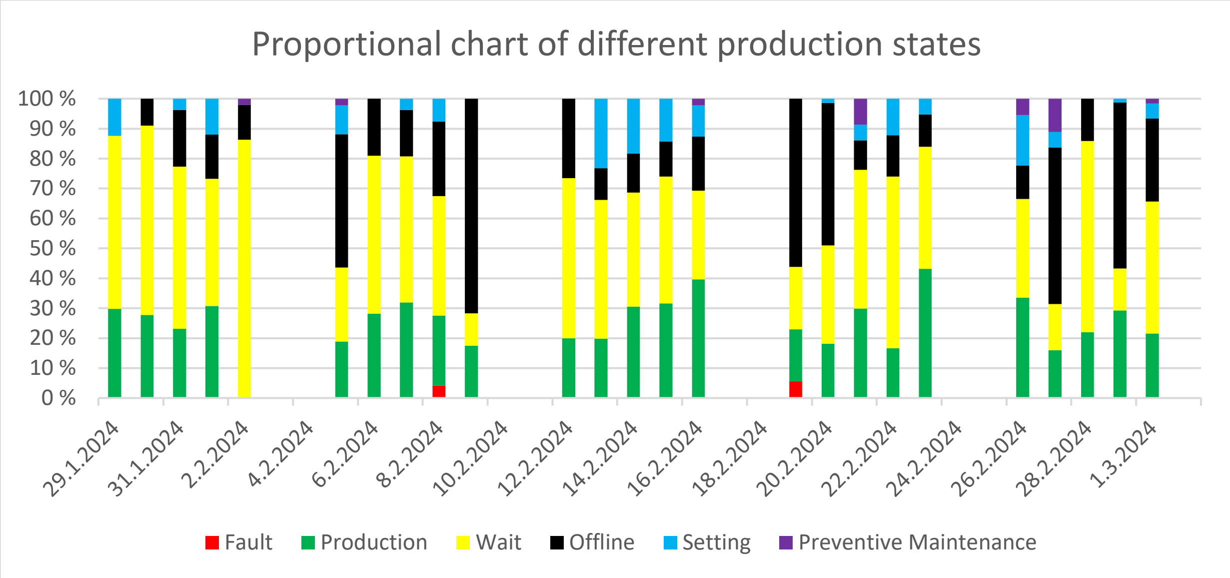


Figure 37 Proportional chart of different states 29.1.-3.3.2024

The actual production times are relatively short compared to the significant amount of "Wait" time, which is the primary reason for downtime. Nearly 99% of the "wait" instances were attributed to "Operator performing other duties." Despite machinery operation being the operator's primary responsibility, operators have additional tasks that often take precedence over continuous machine operation, which has a reducing effect on the utilization rate and machine availability.

The stop length analysis reveals a high frequency of micro stops and illustrates the distribution of downtime durations. Although short stops contribute significantly to downtime, the primary reason for machine downtime is production stops lasting over an hour.

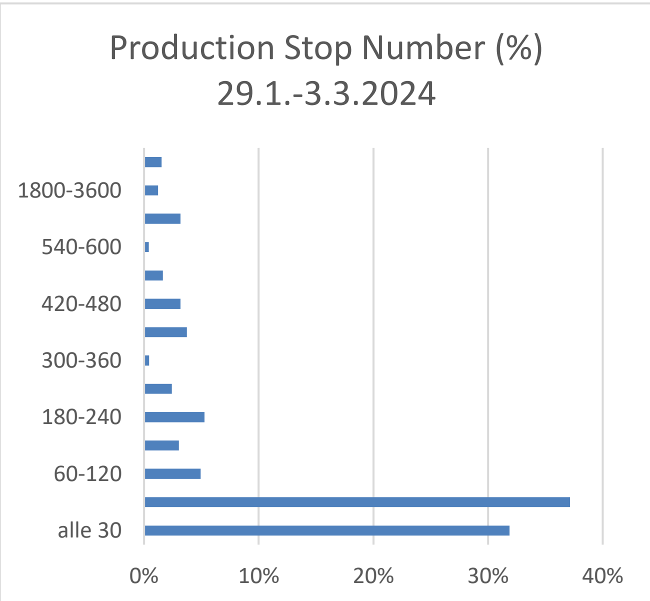


Figure 39 Production stop instances (%)

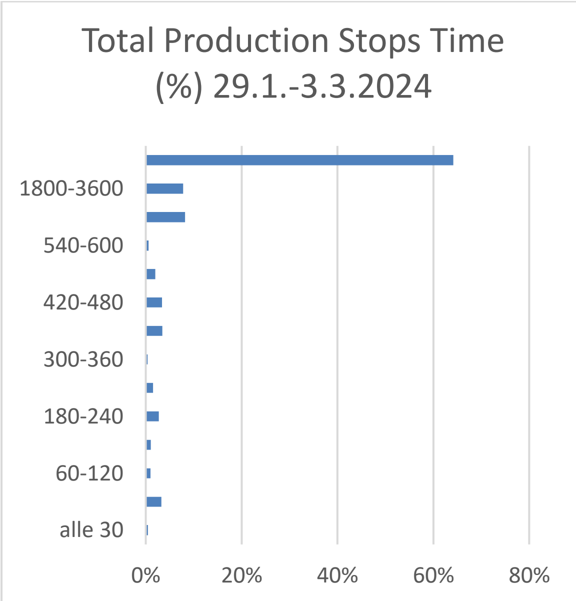


Figure 38 Production stops total lengths (%)

Figure 39 illustrates that most stops are micro stops lasting under 60 seconds. However, due to the acknowledgment threshold of 600 seconds, 94% of stop instances remain unidentified. To clarify the information presented in Gema, delays were added to the operational state definitions to account for short stops between states and to filter out production related micro stops.

Stop type	Instances	Time
Micro stops (0-60s)	69 %	4 %
Unacknowledged stops (0-600s)	94 %	20 %
Over 3600 seconds	2 %	64 %

Figure 40 Production stops analysed

It's noteworthy that only 2% of the stops are longer than 1 hour, even if these stops account for 64% of the total downtime for the production cell. This reflects the challenges that OEE faces in diverse manufacturing environments, where relatively infrequent but prolonged downtime events can significantly impact overall equipment effectiveness. Figure 41 illustrates the reasons for these extended stops caused by "Offline". The most common reason for long downtimes is "Offline," indicating that the machine is not powered. Over the 5-week measuring period, the board cutting CNC was "Offline" for more than 1 hour on 33 occasions, resulting in 91 hours and 48 minutes of downtime. This downtime occurred because the machine was shut down after reaching the daily production goal.

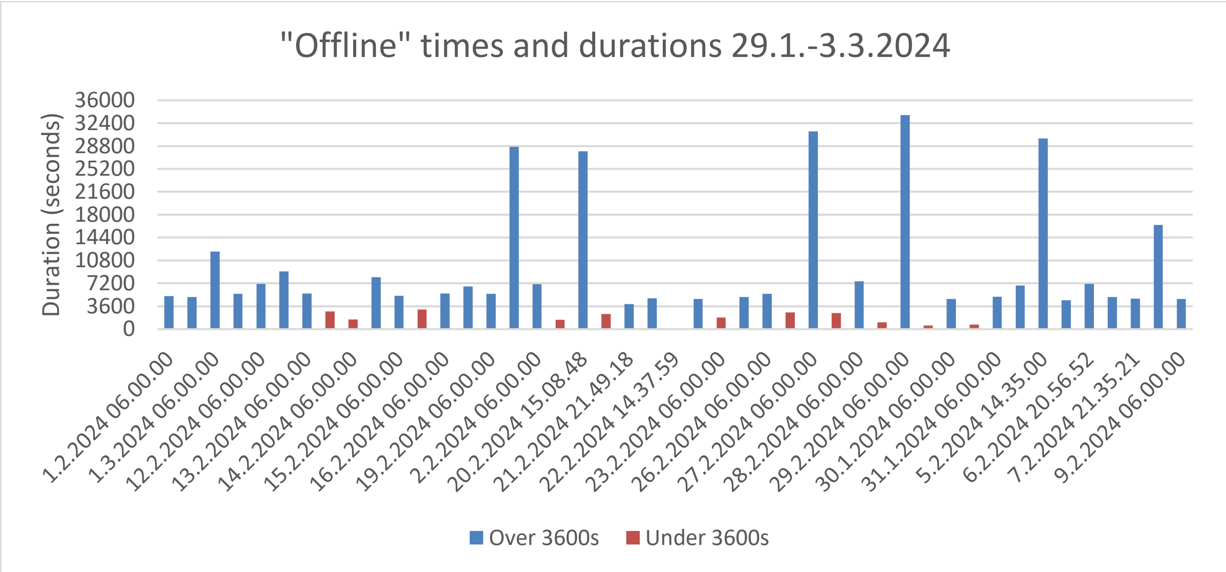


Figure 41 Offline times and durations 29.1.-3.3.2024

As discussed, Figure 41 illustrates the distribution of "Offline" operational states, with stops exceeding one hour highlighted in blue and the shorter ones with red. Downtime analysis reveals that it's common for production days to begin and end with "offline" due to the nature of machine operation. The longer stops shown in the graph are attributed to the machine being operational for only one shift. Typically, the CNC was started after 7:00 when operators had arrived, and other preparations were completed. The time between measurement period start 6:00 and production initiation was classified as downtime caused by "Offline", which skews the downtime measurements and KPI evaluations. The amount of "Offline" is credible since automated data collection methods was utilized in the downtime analysis and data collection.

The second most common downtime reason is "Unacknowledged stop," indicating that operators have not added a reason for the stops, which adds uncertainty about the downtime causes. Upon checking the maintenance system Artturi, it was found that during the evaluation period, only one task required maintenance supervision (on 2.2.2024), indicating credibility also to the downtime distribution. Unacknowledged stops are classified as "Wait" as an assumption. Another reason for the high number of unacknowledged stops is the short acknowledgment threshold, resulting in only 6% of the stop reasons being unacknowledged.

Sarake1	Setting	Preventive Maintenance	Unacknowledged Stops	Wait	Offline
Number of instances	7	3	15	16	33
Time (h/min)	13h12min	4h6min	38h24min	29h19min	91h48min

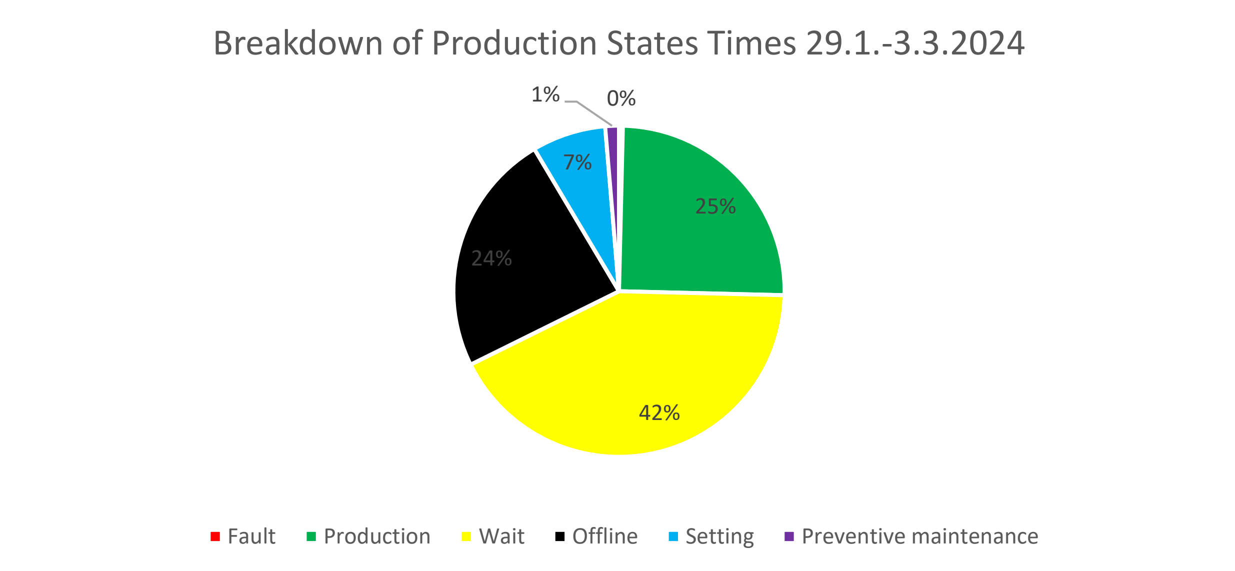


Figure 42 Breakdown of production states 29.1.-3.3.2024

Figure 42 provides a breakdown of different operational states, highlighting the low proportion of actual production time compared to downtime attributed to "offline" and "wait" operational states. Specifically, only 25% of the time is utilized for production, while the board cutting CNC remains offline for 24% of the production time, indicating potential capacity for quicker production fulfilment although the production goals were constantly met.

Setting activities account for 7% of the total time and involve tasks like nesting boards, loading materials, changing tools, and preparing the cutting table. These are essential preparatory steps for production but contribute to overall downtime. The incidence of setting was higher than average in other cases, indicating room for optimization. It is worth noting that the CNC serves as a tool for the operators and is not designed for continuous operation cycles, highlighting the challenges the evaluation of overall equipment efficiency introduces.

No automated fault signals were generated in Case 3, rendering the fault data somewhat implausible due to human involvement in fault acknowledgment. Improved data collection methods could have enhanced the different KPIs and especially technical availability by capturing fault data more accurately and objectively, contributing to downtime analysis.

8.4.2 Quality

Only four parts were rejected in 2023 combined between the edging machine and the CNC board cutter as discussed in Case 2. Therefore, the quality number can be seen as 100%. During the measuring history there were zero downtime acknowledged for quality defects. The threshold for downtime acknowledgement is 10 minutes which isn't sensitive for rework done for the products due to the automated operational characteristics of the machine.

8.4.3 Performance

As discussed earlier, machine performance and speed can be defined in several ways. In Case 3, cutting processes were excluded from speed monitoring due to a lack of useful data and consistent methods for monitoring performance and therefore the operational settings were assumed to follow best practices and is considered to be 100%.

The difficulty of evaluating the CNC machine speed arises from the wide range of produced products and materials used. The cutting speeds and the number of passes can be determined by the operator, who typically use maximum settings that still produce good quality parts. A more accurate method would involve monitoring the actual cutting times of boards and comparing them to a threshold value provided for example by the ERP system. However, this data was not available, and therefore true machine performance could not be measured. Additionally, since the machine performs operations on various products with different design times, average readings cannot effectively monitor performance due to inevitable measuring errors.

8.4.4 OEE

In Case 3, the overall equipment efficiency is heavily influenced by high quality and performance factors, while availability exhibits significant variability and remains low, resulting in OEE figures aligning closely with availability. Figure 43 illustrates notable deviations in OEE numbers due to the variability in the availability factor as discussed in previous chapters.

The graph that presents OEE calculated with technical availability indicates strong machine performance from a technical perspective, meeting production requirements effectively.

Challenges with the individual KPIs have been discussed earlier in this chapter, which adds understanding about the overall equipment efficiency falling short of world-class levels despite consistent production goal achievements. The variation in these graphs complicates evaluation and benchmarking efforts for desired values.

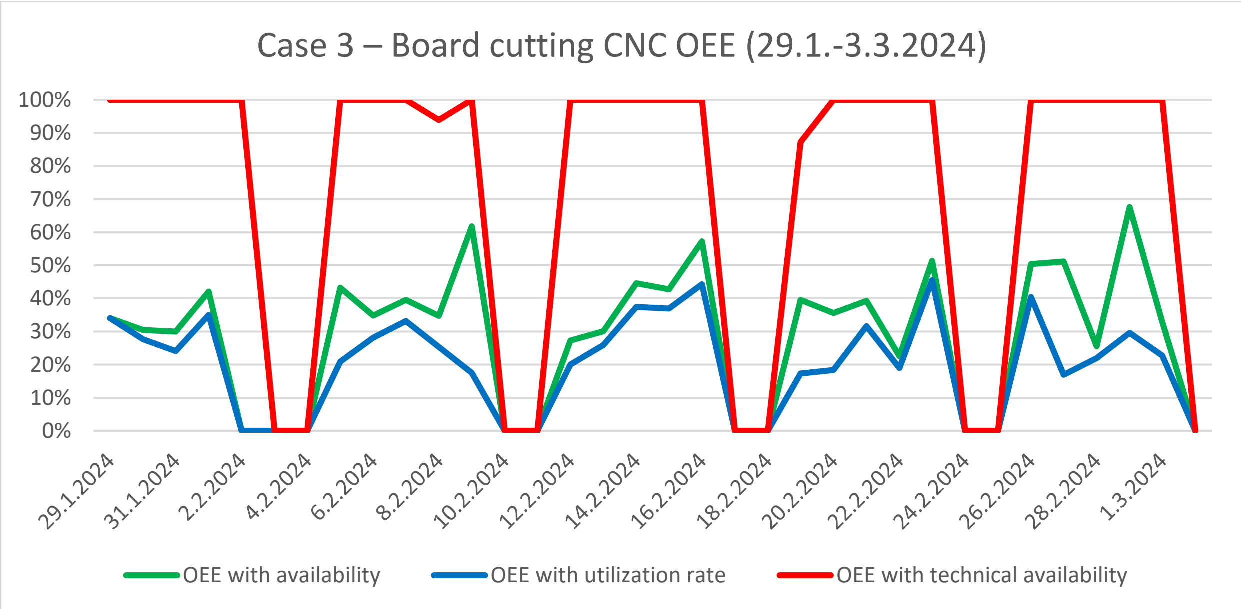


Figure 43 Case 3 – OEE-numbers

The OEE data reveals a pattern where each week experiences a peak in the OEE number on one day, which is a coincidence according to the operators and production management. This variability in production highlights the need to analyze over a longer period to fully understand the underlying factors contributing to these fluctuations.

Sarake1	OEE with availability	OEE with utilization rate	OEE with technical availability
Average	39 %	26 %	99 %
Min	0 %	0 %	87 %
Max	68 %	46 %	100 %

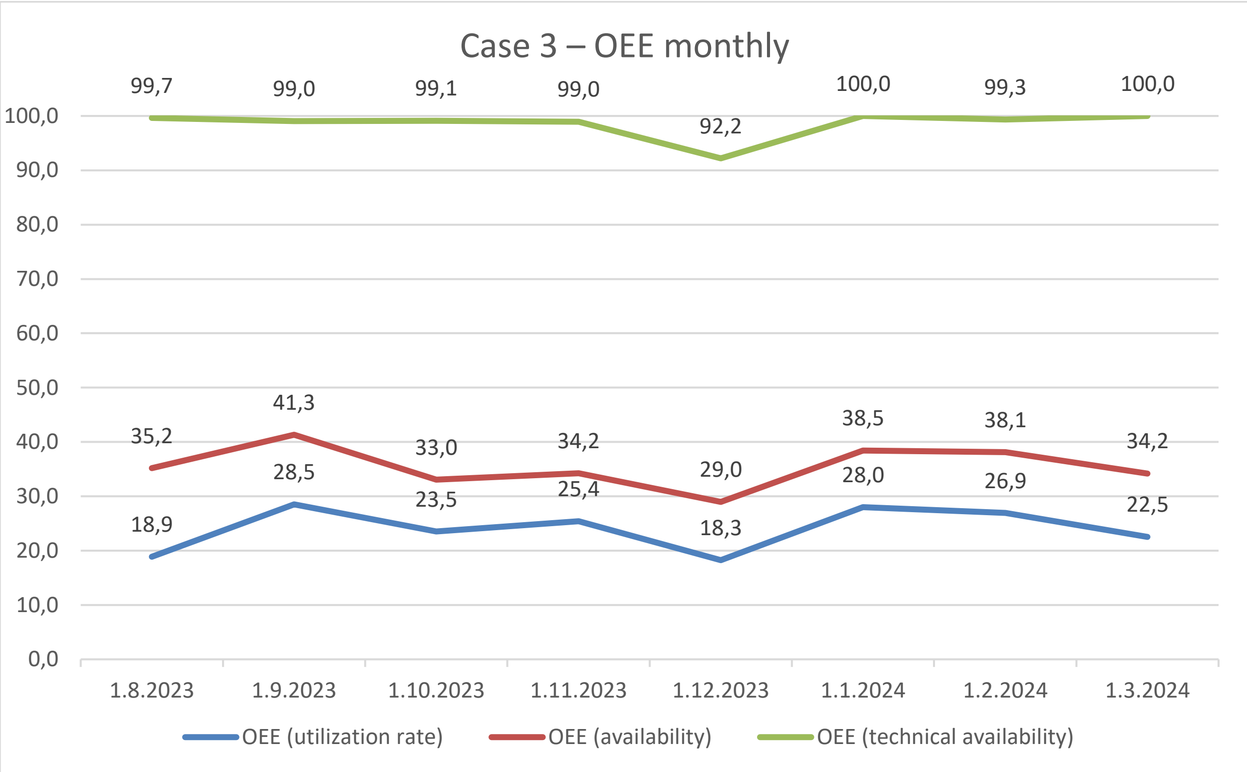


Figure 44 Case 3 – Monthly OEE fluctuations

A monthly analysis of OEE reveals slightly more stable graphs compared to daily figures, indicating consistent production levels over time. However, the similarity in average values between daily and monthly OEE suggests that improvement requires detailed downtime analysis to uncover the factors contributing to low overall equipment efficiency.

Given that availability is the only factor affecting overall equipment efficiency, where OEE equals availability offers limited production insight to stakeholders. A more useful KPI would incorporate variation in other factors beyond availability. Moreover, the variability introduced by order-oriented production makes it challenging to establish benchmarks and evaluate production performance effectively. Choosing the correct measurement period also presents challenges in accurately assessing production efficiency and reflecting it to benchmarks.

8.4.5 Conclusion

In Case 3 the quality and performance metrics within the OEE framework exhibit commendable levels, while availability struggles with inconsistency and variability. This results in OEE figures representing only availability, highlighting the significant impact of the definitions of availability on overall equipment efficiency.

The collected data highlights the challenge of interpreting OEE metrics when availability dominates the equation. Despite consistently meeting production goals, OEE fall short of world-class standards, indicating room for improvement. The presence of peaks in OEE numbers on a weekly basis suggests potential areas of optimization, but a deeper understanding requires analysis over a longer time frame.

Monthly OEE analysis reveals marginally more stable figures, suggesting a degree of consistency in production efficiency. However, achieving improvements demands a thorough downtime analysis to highlight the root causes of low overall equipment efficiency.

The alignment of OEE with only availability, without significant variation in other factors, diminishes the utility of OEE as a performance evaluation tool. Greater variability in factors beyond availability could enhance its effectiveness in providing actionable insights for production evaluation and benchmarking. Further challenges are caused by the downtime distribution and the high level of "offline" during the measurement period. Automated data collection methods and a comparison with planned production would add value to the stakeholders.

In conclusion, Case 3 underscores the importance of addressing availability issues to enhance overall equipment efficiency. While OEE metrics offer valuable insights, their utility is maximized when accompanied by a comprehensive understanding of all contributing factors and their interplay in the production process. The challenges posed by the lack of automated and purposeful data collection methods make it difficult to evaluate overall equipment efficiency in reliable ways and highlights the problems related with downtime analysis.

8.5 Case 4 – Cardboard Cutting CNC

The cardboard cutter in Case 4 is designed to operate below its maximum capacity to accommodate changes in demand. The machine operates in an order-oriented manner with significant variability. Operators use the machine to produce cardboard pieces for production needs on short notice to minimize unnecessary inventory and to streamline production.

8.5.1 Availability

"Production" in Case 4 was determined to occur whenever the machine is performing a cutting operation. During monitoring the operations of the equipment, it was observed that during loading, at least one of the multiple cutting blades was in "down" position. Signals controlling the operation of the blades were collected individually from the I/Os. A small delay was added to mitigate the impact of micro stops within a production run to clarify the operational data and to better represent the utilization of the equipment.

The operators perform various additional tasks such as palletizing, transporting finished pieces, creating nestings, and filling material magazines, which are essential for production but contribute to lower availability of the cutter. It was observed that when availability exceeded 30%, the operators reached their maximum capacity due to the additional workload, despite the machine having unused potential. Due to these constraints, stakeholders did not see value in increasing availability of the machine, as it would require more handling capacity and could lead to overproduction.

The cardboard cutter lacked pre-existing data collection interfaces for desired data collection, requiring production data to be collected through Moxas. Operating at a consistent speed with high-quality output posed similar challenges for evaluating overall equipment efficiency as observed in Case 3 with the difference that the cardboard cutter provided automatic fault signals, which reduced the impact of human factor related challenges in data collection.

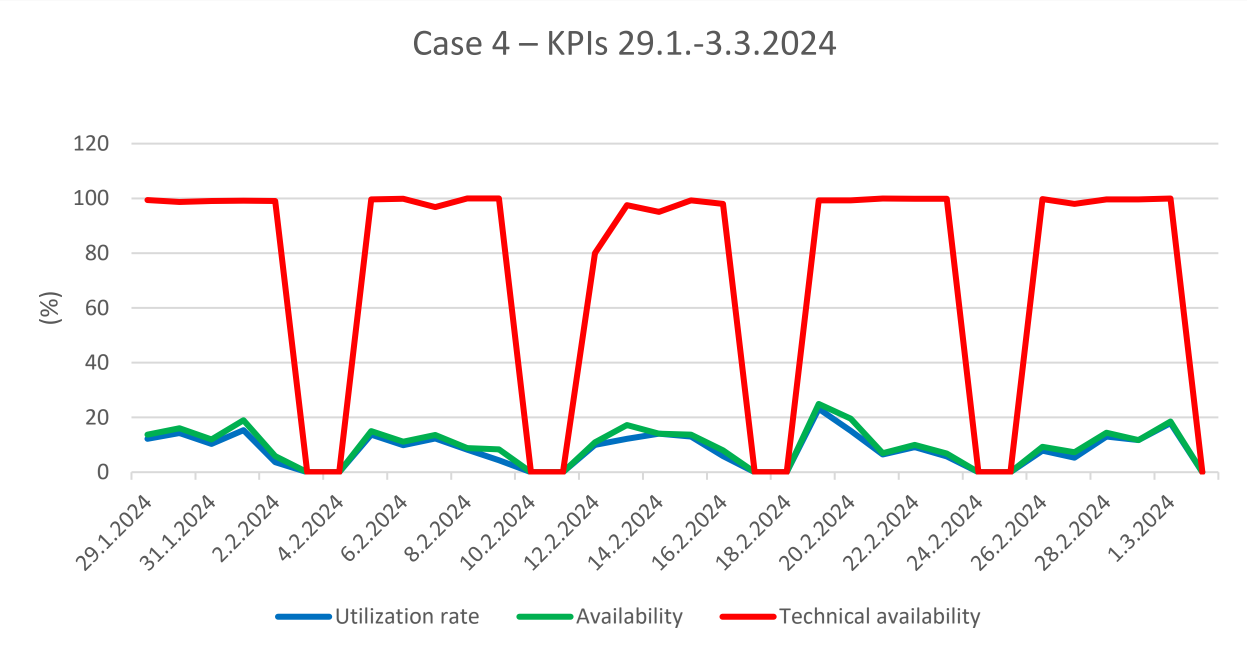


Figure 45 KPIs 29.1.-3.3.2024

Figure 45 demonstrate consistently low utilization and availability rates during the measurement period, both exhibiting considerable variation and mostly staying under 20%. Technical availability remains high, staying close to 100% due to a minimal number of breakdowns. The similarity between availability and utilization rates stems from the machine being powered for most working hours, even when not in operation, aligning the comparing times for both metrics. Deviation in downtime calculations is primarily driven by "offline" and "preventive maintenance," which are not factored into utilization rate calculations. "Wait" accounts for the most significant downtime, while "setting" and "preventive maintenance" have marginal impacts on the KPIs. Figure 47 shows a breakdown of the different production states which confirms the structure of the downtime.

Time	**Utili-zation rate (%)**	**Availa-bility (%)**	**Technical availability (%)**	**Fault (h)**	**Pro-duc-tion (h)**	**Wait (h)**	**Of-fline (h)**	**Set-ting (h)**	**Preven-tive mainte-nance (h)**
Average	8,1	9,3	72,3	0,2	1,3	8,9	1,7	0,1	0,1
Average (ex-cluuding weekends)	11,0	12,7	98,3	0,3	1,8	12,1	2,6	0,4	0,9
Min (ex-cluuding weekends)	3,6	5,9	80,0	0,0	0,6	7,1	0,9	0,1	0,2
Max	23,2	24,9	100,0	3,1	3,9	14,9	8,1	0,7	2,6

Figure 46 KPIs and production states 29.1.-3.3.2024

Figure 46 indicates that the primary reason for the low KPIs is the limited production hours compared to the wait time the machine receives. On average, the machine operates for only 1 hour and 48 minutes per day, with the highest production hours reaching 3 hours and 55 minutes (on 19.2.2024). Despite the machine being powered throughout the day, both the utilization rate and availability remain low and closely aligned. The machine executes rapid production cycles, with the actual loading part of the cardboard manufacturing process being notably brief, which reduces the impact of the low production times. Additionally, the machine spends idle time awaiting new orders, and once the production target for the day is met, operators switch off the machine.

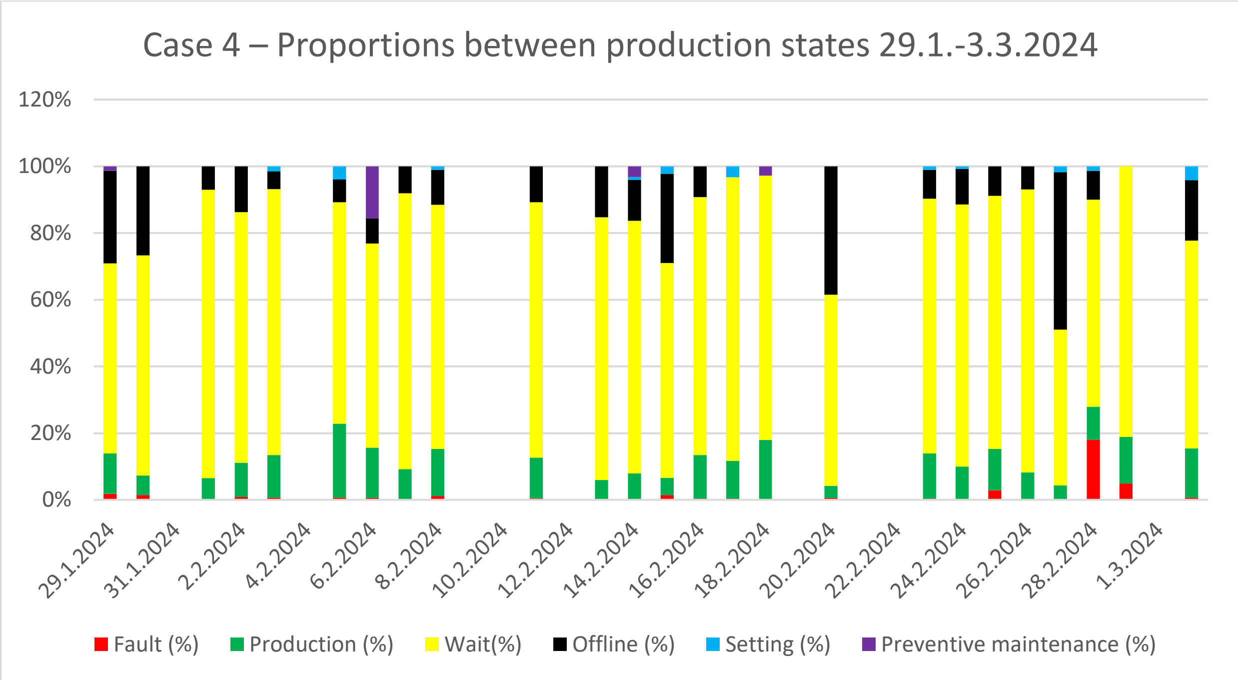


Figure 47 Proportions between different production states (percentages)

Like in cases 2 and 3, a significant downtime reason for the cardboard cutter was "wait". Figure 48 illustrates that 72% of the recorded time is categorized as "wait", while 13% is attributed to "offline". The machine operates for only 11% of its available time highlighting the low utilization of the machine. The daily downtime breakdown is illustrated in Figure 47.

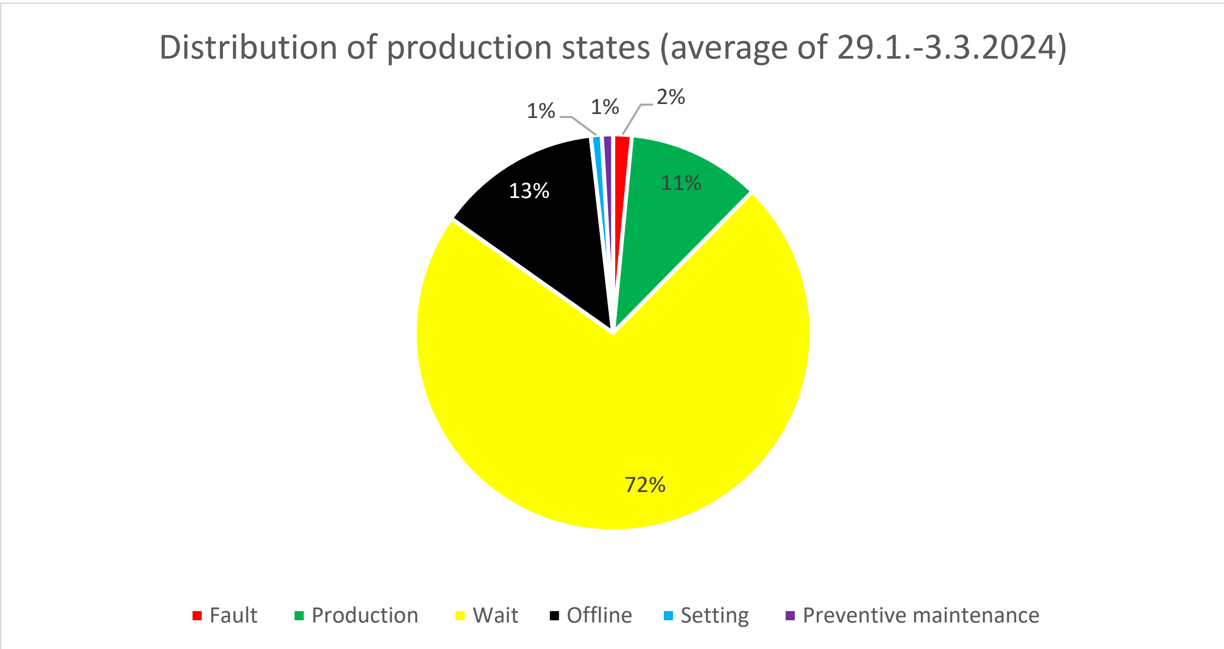


Figure 48 Distribution of production states (29.1.-3.3.2024)

Figure 49 illustrates the downtime reasons that occurred during the production monitoring period. When evaluating downtime reasons, it can be noted that the primary cause of "wait" is operators performing other duties, which leads to a significant amount of downtime. Another reason was operators attending meetings, interrupting normal cutter operation even the significance of the reason was low. Other minor downtime reasons include blockages in the material handling area due to short cardboard pieces getting stuck in the unloading outlet, triggering the automated fault signals. These minor issues contribute to the total downtime relatively little compared to the downtime caused by normal production-related downtime.

Time frame 29.01.2024 - 03.03.2024	**Reason**	**Time (hours)**	**Instances**
	Wait / Operators perform other duties	256 h 23 m 31 s	412
	Fault / Unloading area blocked	4 h 9 m 26 s	19
	Setting / Material loading	3 h 52 m 14 s	12
	Preventive maintenance / Maintenance team	3 h 24 m 4 s	4
	Wait / Meeting	1 h 16 m 58 s	2
	Wait / Unloading area blocked	0 h 45 m 43 s	3
	Fault / Repair	0 h 36 m 50 s	4
	Fault / Adjustment	0 h 26 m 29 s	2
	Preventive maintenance / Cleaning	0 h 15 m 15 s	1

Figure 49 Case 4 – Downtime reasons (29.1.-3.3.2024)

8.5.2 Quality

The machine operates in three different modes: performance, intermediate, and quality, with the first being the fastest and the last the slowest. The operator selects the cutting settings based on the production requirements. Lower speeds are utilized for products that necessitate back-and-forth motions, as operating at higher speeds could result in quality defects. The quality defects, which consists of dimensional errors caused to the cartons, can be avoided by using best practices setting to avoid defects and ensure best possible cutting speed and quality ratio.

Quality monitoring for the cardboard cutter is not conducted using Gema due to the absence of suitable quality signals and data collection interfaces. Instead, potential quality issues are monitored through the ERP system utilized for production control. Evaluating data collected with the ERP system indicates that the cardboard cutter operates with a quality rate close to 100% highlighting the effect the other factors have for the overall equipment efficiency. The infrequent occurrence of quality defects poses minimal problems in production due to the consistently high overall quality level. Additionally, any potential defective parts can be reproduced without significant waste of resources.

8.5.3 Performance

As mentioned above, the cardboard cutter has three cutting modes which performance wise can be classified as slow, intermediate, and fast. The operators use the best practice speed to maintain production quality and ensuring efficient production. Slower production speeds are usually chosen by the operators because they yield slightly better cutting quality without significantly extending cutting time in short production runs. Given that the production speed options are relatively fast meeting production demand and considering the limited total production hours, slower speeds are considered suitable for the purpose. If production capacity limits are reached in the future, production speed could be increased to meet the demand. However, given the small production runs and considerable additional downtime, machine performance is currently not considered a critical factor for overall equipment efficiency.

Like quality monitoring discussed earlier, production speed or performance is not monitored due to the lack of performance signals and production monitoring interfaces. Operators rely on best practice speeds to ensure effective manufacturing of high-quality products. Given the use of best practice speeds and the low availability, performance is assumed Similar to quality monitoring, production speed or performance is not monitored due to insufficient signals. Given the use of best practice speeds and the low availability, performance is assumed to be 100% due to limitations in more accurate measurement methods.

8.5.4 OEE

Like Case 3, the OEE value can be seen equivalent to availability because both production speed and quality were constant and considered to be 100% while the availability had significantly lower numbers. The evaluation of overall equipment effectiveness is slightly limited due to the lack of automated data collection methods and assumptions about the use of best practices. As discussed in earlier chapters evaluating different components of OEE, the definition of single components like production speed can impact overall efficiency significally. However, given the average availability being less than 10%, the potential effect of reduced speed or quality on the OEE score is minimal.

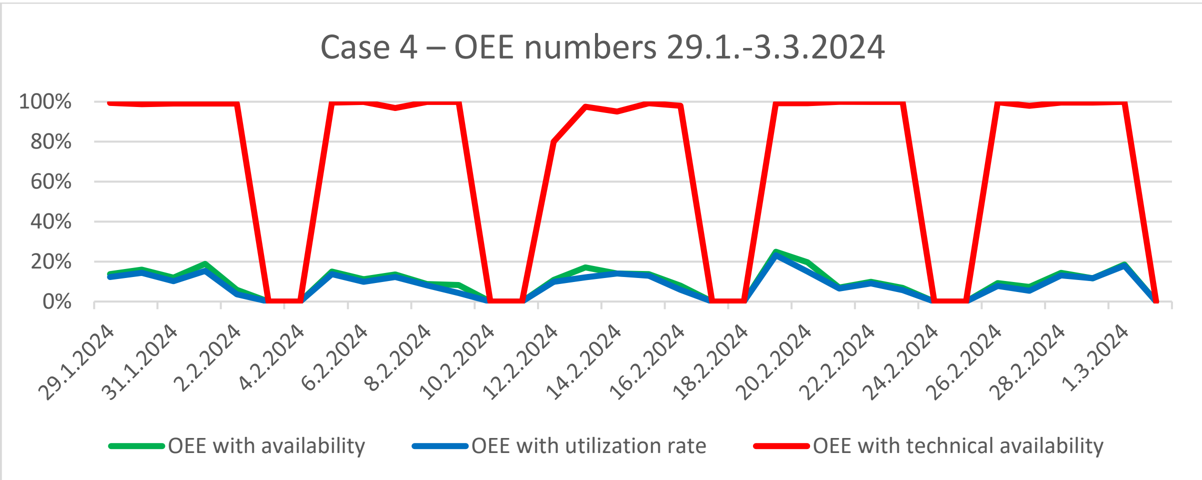


Figure 50 Case 4 – OEE 29.1.-3.3.2024

	OEE with availability	OEE with utilization rate	OEE with technical availability
Average	13 %	12 %	98 %
Min	6 %	4 %	80 %
Max	25 %	23 %	100 %

The different KPIs show similar patterns as observed in other cases, with the difference that the total efficiency of the equipment calculated based on availability and utilization rate differs by only one percentage point, since the machine is powered on for almost the entire production time. Despite the generally low availability, the machine effectively met its production demand. The high OEE figure calculated with technical availability indicates that the machine performed well from a technical standpoint, with minimal quality defects, faults, and speed losses.

The variation in daily OEE numbers makes it challenging to compare results over a short period and identify trends or patterns without a reference for planned production, as shown in Figure 50. The low overall efficiency is due to the way the production machine is utilized where operators use the cardboard cutter more as a production tool rather than a machine that should produce pieces continuously. Despite daily fluctuations in OEE, the figure stabilizes when monitored over a longer period, providing a clearer view of overall efficiency trends.

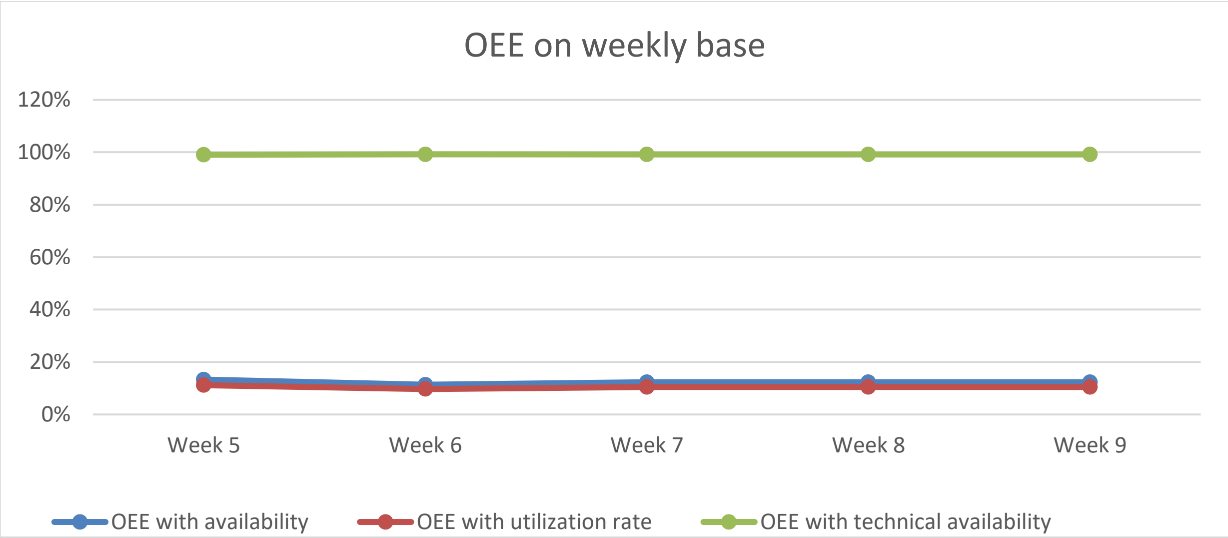


Figure 51 Case 4 – Weekly OEE

Weekly monitoring of OEE helps smoothen out production variations over time resulting in a stable figure over a five-week period. The weekly assessment is close to the average number and shows little variation, providing a stable baseline for overall equipment efficiency monitoring.

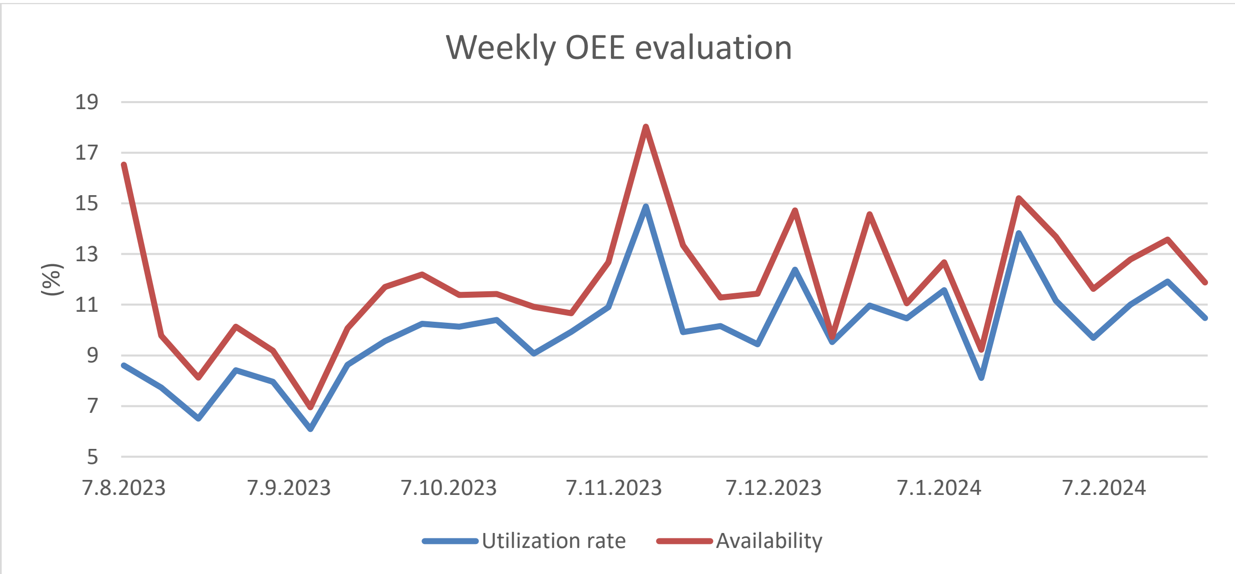


Figure 52 Case 4 – Weekly OEE fluctuation over an extended period

Further analysing availability and utilization rate shows the weekly deviation from an extended period. By evaluating thegraphs in Figure 52, the average on the KPIs seems to be within a relatively small margin although the monitoring over an extended period shows some deviation. Both KPIs follow each other closely reducing the importance of choosing the right values for production monitoring.

	Utilization rate	Availability	Technical availability
average (%)	10	12	97

Figure 53 Average KPIs 7.8.2023-3.3.2024

The average value over the extended period reveals that only a small level of downtime is caused by machine faults, emphasizing the importance of other factors and downtime analysis. To gain deeper insights into the KPIs, a monthly evaluation over a longer period is necessary to better understand the average trends, patterns and fluctuation in the overall equipment efficiency.

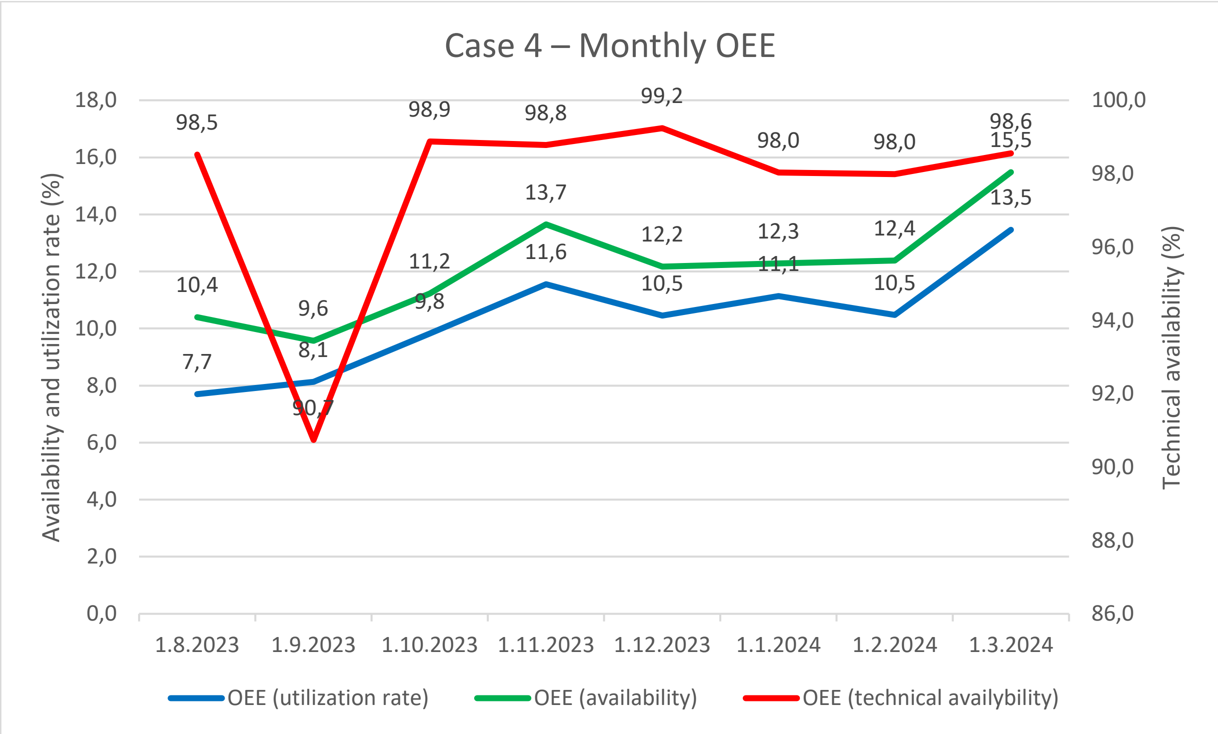


Figure 54 Case 4 – monthly OEE

	OEE (utilization rate)	OEE (availability)	OEE (technical availybility)
average	10,3	12,1	97,6

Analysing Figure 54 reveals that technical availability does not significantly impact the other KPIs on a monthly level, although higher technical availability seems to correspond to lower values in other KPIs and vice versa. Availability and utilization rates tend to closely track each other on monthly monitoring intervals. Monitoring over a longer period helps to smooth out fluctuations, although some variation remains visible. A notable trend is the improved machine runtime over time, which increases the demand for availability, underscoring the potential need for enhanced production monitoring and production optimization in the future.

8.5.6 Conclusion

In Case 4, the cardboard cutting CNC operates in a dynamic environment characterized by order-oriented production and frequent fluctuations in demand. Despite its capability for higher overall equipment efficiency, the machine is intentionally operated below its maximum capacity to accommodate demand fluctuations and to prevent overproduction. Operators utilize the cardboard cutter as a tool to produce finished pieces, emphasizing capacity management aligned with demand. This approach prioritizes operator capacity over equipment capacity in the context of resource utilization.

Availability assessment relies on monitoring cutting operations with signals collected from individual IO outputs controlling cutting blade operations. However, the machine's true capacity is constrained by additional operator tasks, leading to relatively low overall equipment efficiency even if the manufacturing goals are constantly met. Notably, there is a balance between machine capacity and operator workload to avoid overproduction and wasted resources.

There are some limitations regarding the data collection, such as the absence of pre-made interfaces and the difficulty in defining performance and quality, which slightly lowers the credibility of the results. On the other hand, automated fault signals are collected by automated methods adding insight to the downtime analysis. The availability was notably low compared to assumptions about other OEE factors, highlighting the difficulties in using overall equipment efficiency to evaluate production in diverse production environment where the designed production hours are low. Adding a planning factor to the KPIs would bring insight to the stakeholders and tie the results with real life events.

Best practices cutting speed was utilized to balance quality and performance. Given the machine's small production runs and high downtime, performance is not a significant driver of production efficiency. Also, the quality was high in Case 4 reducing the significance of the possible measurement errors.

The OEE analysis reveals similarities with Case 3, where availability plays a significant role in the KPIs due to consistently high quality and production speed. Despite low OEE figures, the machine effectively meets production demands and performs well, as evidenced by high technical availability. Weekly OEE monitoring helps mitigate daily fluctuations, providing a more stable evaluation over extended periods. However, while technical availability remains consistent, the slight deviation with availability and utilization rates highlights the diversity of the production. In Case 4 the similarity between availability and utilization rate reduces the importance of defining production states and signals.

The OEE analysis highlights similar issues with Case 3, where availability significantly impacts KPIs due to consistently high quality and production speeds in comparison with availability. Despite low OEE figures, the machine meets production demands well, with high technical availability indicating good machine performance. The short term OEE monitoring shows fluctuation which stabilizes when extending the monitoring period. The value of overall equipment efficiency evaluation and production monitoring would increase if stakeholders could compare actual production with planned production to gain insight about the machine capacity utilization with a context.

8.6 Summary of Results

The four different cases underscored the complexities and challenges of monitoring production efficiency through overall equipment efficiency evaluation. Each case provided unique insights into the individual characteristic of production monitoring in diverse production environment and the various factors influencing OEE calculations. A common theme across these cases was the critical importance of accurate measurements and reliable monitoring methods for the different components of OEE. Meaningful and accurate data proved to be essential for stakeholders to make informed decisions and optimize manufacturing processes effectively. The data inaccuracies observed in these cases were primarily caused by limitations in production monitoring signals and interfaces. These limitations hindered the collection of accurate and comprehensive data necessary for evaluations of overall equipment efficiency.

The cases from one to three underscore the significance of comprehending the various definitions of the different factors when evaluating availability, especially in the context of diverse manufacturing which involves complex machine-specific production states. In Case 4, the availability definition is not crucial when comparing availability and utilization rate calculations due to the machine's operational approach. Despite facing challenges in accurately defining operational states, all production cells in the case study consistently achieved their production goals, despite fluctuations in production demand.

The study demonstrates the impact of production state definitions on the different factors of OEE, with the difficulties of definition the KPIs and the fluctuations attributed to factors like preventive maintenance, wait and setup times. Despite high-quality standards and efforts to optimize productivity, OEE calculations exhibit variability, emphasizing the need for comprehensive data analysis. The challenges with production definition highlight the critical need for precise definitions and data collection methods to ensure reliable production monitoring and assessment. The study shows that it’s important to understand the produced metrics and what information and data effects on them.

Case 3 and 4 highlight the dominance of availability within the OEE framework, with limited variability in other factors affecting overall equipment efficiency. While consistently meeting production goals, overall equipment efficiency falls short of world-class standards, indicating room for efficiency improvement thorough downtime analysis highlighting the need for finding right production goals.

The case study, and especially the Case 4, illustrates the challenges of balancing machine capacity with operator workload in order-oriented production settings and adjusting production speed to producing only quality products and reduce wear on machine. Despite low OEE figures, the machine effectively meets production demands, with technical availability scores reflecting its capability of improving production hours. The machine was used as a tool for operators and the overall efficiency was not considered to be an issue since increasing in the numbers would have led to overproduction.

Performance evaluation highlighted that the production emphasized prioritizing quality over speed to optimize production efficiency. The challenges in performance monitoring across the different cases yields from the various ways of defining production availability, production speed and performance.

None of the cases reached the world-class OEE level. Availability was the primary limiting factor for each machine, with the most significant impact on the overall equipment efficiency. Production quality was consistently high across all machines, as discussed later in this chapter. An additional quality related issue was noted in Case 2 where the quality defects requiring rework by the operator resulted in production downtime and performance losses being accounted multiple times when calculating overall equipment efficiency.

Overall, the case studies underscore the complexity of monitoring diverse manufacturing equipment, with factors such as operational states, operator interventions, production related downtime, and maintenance activities influencing availability, quality, and performance metrics. Effective OEE analysis requires a comprehensive understanding of these factors and their interactions to identify opportunities for improvement and enhance overall equipment efficiency in manufacturing operations. Also, the lack of planning factor reduces the usability of the collected data since the diverse essence of the production adds challenge to interpret the generated results. The use of a planning factor would benchmark the production to the planned production adding value to the stakeholders.

Overall, the cases underscore the importance of comprehensive data analysis, accurate data collection, and a nuanced understanding of production dynamics in optimizing manufacturing processes and enhancing overall equipment efficiency.

Discussion

This thesis was conducted by four case studies where the results were evaluated with mixed methods. The research took place in a versatile real-life environment with diverse production equipment to give depth for the research. In the study environment, a production monitoring system was implemented to the machines within the scope of this thesis to evaluate OEE as a production monitoring tool in a diverse manufacturing environment. The production monitoring system was implemented and adjusted completely according to specific stakeholder needs and preferences highlighting the lack of standardization and differing definition options when determining the different factors of OEE. After production monitoring system implementation and validation, data was collected and evaluated over an extended period to ensure a comprehensive perspective.

The case studies highlighted the complexity of OEE and the challenges that the lack of standardization have regarding the production monitoring in an accurate way. Especially the lack of unanimous data collection methods and the diverse manufacturing environment caused the OEE data to be hard to understand and utilize by the stakeholders. The high deviation in overall equipment efficiency added challenge in benchmarking the production results and combining the KPI numbers with actual production events. Additionally, the issues regarding the system implementation made it challenging to determine the production states accurately in real time since the data collection was done with IO data collection devices that supported only digital signals, and had a slight delay, supporting only a limited number of syntaxes that could be utilized for production monitoring.

OEE failed to fulfill the most of stakeholder needs and requirements for an effective production evaluation KPI. This was primarily attributed to the significant variability in the reported numbers, challenges encountered in accurately determining production states, and the absence of benchmarking mechanisms for evaluating the results. Particularly, stakeholders seeking insights into production processes and losses found out that OEE did not meet their needs. Moreover, the abstract and misleading nature of OEE, particularly in its availability and performance metrics, compounded the issue due to differing definitions of key performance indicators. In contrast, technical availability, a component not traditionally included in OEE, offered valuable insights to various stakeholders regarding equipment operation. Ultimately, the production monitoring system addressed stakeholder needs by providing detailed and personalized information and downtime analysis.

Despite the production goals being consistently met, none of the cases achieved the OEE world class level of 85%. This discrepancy underscores the challenges that OEE encounters within diverse manufacturing environments since a common way of evaluating OEE is comparing it to the world class level that is often treated as a production goal. However, it's noteworthy that despite falling short of reaching the world class level, OEE did offer some value. Specifically, it proved useful in identifying genuine potential production losses, albeit this aspect held less significance for the stakeholders within the study. The 85% level is misleading particularly for evaluating overall equipment efficiencies on machines that are not supposed to be operated constantly, highlighting the lack of planning factor in OEE.

The variability across different components of OEE presents challenges in both assessment and implementation of the production monitoring, particularly regarding availability variations stemming from planned production stops. The lack of a planning factor adds complexity to result interpretation, requiring stakeholders to discern their relevance. In Case 1, where data collection was widely automated and production was supposed to run continuously, OEE added value to the stakeholders. However, in Cases 2-4, where the production was order-oriented and the machinery included diverse equipment, OEE lacked additional utility. This was particularly evident in Case 4, where the cardboard cutter served purely as an operator tool, resulting in diminished availability and reduced significance of OEE. In cases 2-4, the low availability and high production quality were also recognized as well the fact that the production speed and performance was adjusted to fulfil best practices.

Another issue noticed with OEE was the potential overlap of factors, resulting in efficiency losses being double counted. For instance, in Cases 2 and 3, quality defects led to downtime, which in turn reduced availability, resulting in the same downtime being accounted twice. Similarly in Case 3, due to the way performance was defined, a lack of the performance factor corresponded to a reduction in availability resulting in further losses in overall equipment efficiency.

These findings underscore the importance of tailoring availability definitions to align with specific production, machinery, and stakeholder requirements. Given the lack of consensus in defining overall equipment efficiency, it is crucial to understand the parameters being measured and their implications for production. Moreover, the study emphasized the significance of accurate data collection for monitoring OEE, highlighting the considerable advantages of employing automated data collection methods to minimize human involvement and reduce data inaccuracies. Standardized monitoring methods may not suffice, especially in diverse production environments where customization is necessary for meaningful OEE data.

Ensuring the accuracy and reliability of data is crucial for obtaining meaningful OEE insights that reflect real-life scenarios. The case study highlights the challenges limitations in data collection methods can have that impede the results and the utility of the OEE metric. The absence of real-time monitoring for quality and performance diminishes the informativeness of OEE, particularly in non-automated monitoring setups. Moreover, reliance on digital data signals, along with limited options for configuring production states and user-enriched data, introduces uncertainties such as insensitivity to micro stops and delays resulting in downtime which had a significant effect in Case 3. Another challenge encountered in production monitoring is the inability to acknowledge every stop due to predetermined minimum stop lengths, resulting in skipped acknowledgments during production resulting in a lack of production information. These challenges underscore the importance of accurate and reliable data collection processes.

Since OEE didn't answer stakeholder needs, other KPIs and downtime analysis were found to be more informative than OEE, indicating a need for tailored definitions that align with different needs exists. Overall equipment efficiency is not a universal KPI, as different definitions suit different requirements and production monitoring needs. Despite this, analysing the generated data offers insights into production, especially when using individually tailored KPIs. Evaluating individual machines and comparing the production to case specific goals.

The research highlights the need for customized definitions that suit different production needs and the ability to compare the actual production to the planned production. Furthermore, the challenges in data collection methods, such as the absence of real-time monitoring and the insensitivity to micro stops, emphasized the importance of accurate and reliable data collection processes. Considering these findings, it is evident that while OEE serves as a valuable tool in evaluating machine performance, its effectiveness depends on customization and production analysis to align with specific production requirements and the use of complementary KPIs and downtime analysis for comprehensive production monitoring.

In order to answer the research questions, it is important to understand the complexity of OEE and the contribution diversity of the equipment, manufacturing environment and the data collection methods have when evaluating overall equipment efficiency. The four cases highlight that OEE is more suitable for continuous production where the production is supposed to be operated according to the principles of TPM. The variation of equipment and production makes overall equipment efficiency a general KPI that is difficult to combine to actual production and phenomena at production, raising the need for a planning factor to be added to the evaluation. The issues faced in the production monitoring system implementation and evaluation phase highlighted the need to customize the production monitoring and the KPIs to each stakeholder to answer the diverse production monitoring needs.

The case study highlights and summarize the key points causing challenges in OEE definition. Further research could be done to research the planning factor and its contribution to overall equipment efficiency evaluation. Likewise further development areas could be identified by improving collected data accuracy and to generate reliable data and avoid errors in the process of generating key performance indicators. Especially the acknowledging of short downtime periods would add depth and improve stakeholder utilization of production monitoring in diverse manufacturing environments.

In conclusion, this thesis conducted four case studies to evaluate the effectiveness of OEE as a production monitoring tool in diverse manufacturing environments. The results highlighted the complexity of OEE and the challenges stemming from its lack of standardization, particularly in data collection methods and the various definitions. Despite efforts to implement a production monitoring system tailored to stakeholder needs, OEE fell short of meeting most requirements for effective production evaluation. Issues such as variability in the factors that form the OEE, challenges in accurately determining operational states, and the absence of benchmarking availability to production demand. Although OEE provided some value in identifying the overall effectiveness in the diverse cases, the benefits for the stakeholders remained small. The comparison with the world-class value turned out to be pointless, as the total productivity of the machines was clearly below the threshold value, even though the production needs of the machines were constantly met. These factors highlighted the unsuitability of OEE as a production monitoring KPI in a diverse manufacturing environment.

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