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MANUFACTURING PROCESS IMPROVEMENT THROUGH TECHNICAL SOLUTIONS: A CASE STUDY

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ABSTRACT

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The purpose of this exploratory thesis study is to observe a manufacturing process area in its current state and the opportunities to improve the process area by implementing Artificial Intelligence (AI), Machine Learning (ML) and other technical solutions in industrial manufacturing companies. The theoretical baseline is based on process management, process improvement solutions, AI, and ML. The research is centred around studying industry research and case studies with similar issues and goals as the case company. Data collection was conducted through interviews and observing current processes within the case company. The data was analyzed through compiling all the interview data to understand the current issues and determine the goal of the case company and then determine the best solution based on data and research. The empirical section explored how AI and ML can be implemented, managed, and evaluated for optimization in an industrial manufacturing context. Literature insights were compared with the results from my observations in the discussion section. The answer to the research questions, the limitations of the study, and future research questions are covered in the conclusion.

Keywords: Optimization, Artificial Intelligence (AI), Machine Learning (ML), Lead Time, Data Management, Data Processing

TIIVISTELMÄ

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Tämän tutkielman tarkoituksena on tarkkailla valmistusprosessialuetta sen nykytilassa ja mahdollisuuksia parantaa prosessialuetta toteuttamalla tekoäly (AI), koneoppiminen (ML) ja muita teknisiä ratkaisuja teollisuusyrityksissä. Teoreettisesti laskettu lähtötaso perustuu prosessinhallintaan, prosessinparannusratkaisuihin, tekoälyyn ja ML: ään. Tutkimus keskittyy teollisuuden tutkimuksen ja tapaustutkimusten tutkimiseen, joilla on samanlaiset kysymykset ja tavoitteet kuin tapausyhtiöllä. Tiedonkeruu tehtiin haastatteluilla ja havainnoimalla tapausyrityksen nykyisiä prosesseja. Tiedot analysoitiin kokoamalla kaikki haastattelutiedot ajankohtaisten asioiden ymmärtämiseksi ja tapausyrityksen tavoitteen määrittämiseksi ja sitten parhaan ratkaisun perusteella tietojen ja tutkimuksen perusteella. Empiirisessä osassa selvitettiin, kuinka tekoäly ja ML voidaan toteuttaa, hallita ja arvioida optimoinnin kannalta teollisen valmistuksen yhteydessä. Litera-ture Insights -ohjelmaa verrattiin keskusteluosastani tekemieni havaintojen tuloksiin. Vastaus tutkimuskysymyksiin, tutkimuksen rajoitukset ja tulevat tutkimuskysymykset käsitellään johtopäätöksessä.

Avainsanat: Optimointi, tekoäly (AI), koneoppiminen (ML), läpimenoaika, tiedonhallinta, tietojenkäsittely

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1 INTRODUCTION

Broadly speaking, case studies consist of several steps, such as defining the case and finding a solution to address the focus area issues. To accomplish this, research data is gathered from a wide breadth of sources and then analyzed (Yazan, 2015). Additionally, to gain clear and comprehensible research questions and relevant case study design are developed; finally, data collection is conducted to aid the analysis (Baxter & Jack, 2008).

Using this methodology, this thesis studies the impact of bottlenecks in lead time on time-based services in process optimization to increase order fulfilments in the field of the manufacturing industry. In this first section I present a high-level overview of the theoretical baseline. Next, I outline a brief overview of the resulting research questions for the case company's research area. Finally, I conclude with an overview of my thesis methodology.

1.1 Theoretical Baseline and Key Concepts

The theoretical baseline of this thesis is a business process management study, with the target of optimizing the roll covering and re-covering process area through process improvement solutions, Artificial Intelligence (AI), and Machine Learning (ML). Throughout this thesis there are several key concepts discussed. For clarity, the key concepts discussed in this thesis will be explained in general terminology as follows:

- **Artificial Intelligence** (AI) is the engineering and science of making machines intelligent, particularly in an intelligent computer. AI is not confined to methods that are biologically observant but relates to the computer functions tasked with an understanding human intelligence

and building upon that understanding and acquired knowledge (McCarthy, 2004).

- **Data Management** is a framework to manage data entities. Data entities represent common concepts of data functionalities. Data entities are intended to be easily understood by users and can be utilized for integrations into technical solutions such as AI and Machine Learning (ML)(Garg, Erickson, Reynolds-Haertle, & Fehr, 2021).

- **Data Processing** is data manipulation conducted by a computer. This process included converting raw data into machine readable data formats (Britannica, 2021). In terms of the case company, this refers to the processing of data required to run operations on the shop floor.

- **Infor LN** is a software that provides manufacturing companies with ERP capabilities paired with a state-of-the-art design for users. It provides the flexibility for manufactures to integrate software systems and processes that span across the organization (Infor, 2021).

- **Lead Time** is the time passed from the start of a process until the conclusion of the process. In the manufacturing industry lead time is reviewed in pre-processing, processing, and post-processing. Inefficiencies can be determined through comparing results gathered against established benchmarks (Kenton, 2021).

- **Machine Learning** (ML) is the use of statistical learning and optimization methods to enable computers to analyze datasets and identify patterns in the given data. It leverages data mining to locate historical data trends to inform future models (Tamir, 2020). Statistical learning methods are used by ML to identify boundaries, such as decision trees which look at variables one-by-one (Yee & Chu, 2015).

- **Optimization**, in this thesis' manufacturing context, means the goals that are set and timeframes that are established to improve the overall process or processes. There are only two key goals: maximize productions and minimize costs (O'Neill, 2018).

- **Technical Solutions** aim to support relations between customers and suppliers, as well as an organization's internal processes involving the supply chain (IGI Global, 2021).

1.2 Research Questions

1. Manufacturing companies commonly lack the insight to focus their efforts on where technologies, such as AI and ML, can add the most valuable and drive solutions to scale (Brosset et al., 2019). Leveraging capabilities through adopting technological advancements is changing the very nature of the service and products offered to customers (Lenka, Parida, Sjödin & Wincent, 2016). Therefore, the two main questions that need to be answered first are the following: How can lead time on the manufacturing shop floor be improved; and

2. How can operations data from the shop floor be processed for technical solutions?

Lead time likely comes at a time and financial cost to the manufacturing company. Competitors that are rapidly implementing technology to increase production speed and competitor's increased output could threaten the case company's current market share. Supporting research questions that help dive deeper are as follows:

a) Is there sufficient data within the case company; and

b) Is the data at a level of quality and quantity that is useable for implementing a technical solution?

1.3 Methodology

A critical element of manufacturing is being able to reduce and accurately forecast lead time (Sherman, 2019). Hence, the exploratory nature of this research, an iterative approach, was constructed through arranging interviews with the case company's key stakeholders to qualify a designed theoretical framework model. Designing a technical solution starts with understanding the current process, collecting and evaluating the current data, identifying the customer and business needs, and then forming business requirements based on these areas and constructing a complete idea to reduce lead time and bottlenecks in the current process.

This technical solution design flow can be observed throughout this thesis. In section two entitled *Case Company*, the case company is introduced, followed

by the issues to be research and solutioned through this thesis. In section three entitled *Research Framework*, a detailed depiction of the research framework is presented via a brief discussion of the thesis objective and research questions, in addition to the business and technical opportunities, based on theoretical research. Section four entitled *Theoretical Foundations*, establishes where value-add can be achieved through process optimization —which is discussed in terms of the case company and theory from literature reviews. Section five entitled *Analysis Methods* outlines the empirical research and methods, theoretical framework, and data collection and analysis methods. Section six entitled *Results and Discussion*, discusses and describes the key findings of the empirical research from the interviews conducted at different levels of seniority and diverse roles within the case company. In section seven entitled *Conclusion*, the research questions are answered, and future research is considered.

2 CASE COMPANY

In this section, the case company is described from a basic overview perspective to a more detailed description of the issues the case company needs resolved. The current production planning and controlling process is observed and the current flow is understood. Through familarizing with the current processes, the path to digest the causes of bottlenecks and how they can be resolved is better understood.

2.1 Description

The case company for this thesis is a leading manufacturing company in Finland with over 10,000 employees across the globe, operating in the pulp, paper, automation, and energy industries. The operations brought in yearly net sales of over 3 billion euros in 2020. If the case company is able to enhance the quality and availability of machine and lead time data, there is a potential of becoming among the top leaders in smart manufacturing in Europe and further increase their sales in the roll covering and re-covering process area. The case company has twenty-seven manufacturing shops around the world; this study will focus on the manufacturing shop floor in Finland. Roll covering and mechanical services are a large part of daily operations on the Finnish shop floor. The roll covering business has four types of covers — these include rubber, ceramic, composite, and polyurethane (PU). These covers are applied to new (covering) and existing rolls (re-covering). Customers can send their existing rolls in to be re-covered in any of the four coverings or request mechanical servicing on their rolls.

2.2 Problem Areas

It is not possible to predict well in advance which service the customer will select. If roll re-covering is requested, often the customer has a strict turnaround time requirement. Customers may only have one backup roll and if the backup roll breaks while the other roll is in service, their manufacturing will come to a halt; This is where the first issue develops. Another major element to consider is the allocation of grinding machines. Currently, the grinding machines run 24/7 and are often the cause of bottlenecks on the shop floor. When a roll comes in for a re-covering service, no matter which cover is applied, the roll must go through a heat treatment. After the heat treatment the roll is then sent to a grinding machine. Rolls often have to queue for long periods of time to secure a time slot for the heat treatment and grinding machine process. The rolls in queue take up limited space on the shop floor as they wait to be processed. Scheduling for the limited number of grinding machines is challenging since the amount of time an individual roll takes in the grinding process depends on the size of the roll; It takes a certain amount of time per sqm of the roll. The same issue applies to the heat treatment process. The process can take anywhere between twenty to a hundred hours, based on the size of the roll. An equal amount of capacity between the heat treatment and grinding machines is necessary to reduce the bottleneck.

Delfoi is the current system in place to allocate when each roll will go to the appropriate machines. This information is manually entered into Delfoi and is prioritized on a first come first serve bases. Delfoi does not have the capacity to optimize the process, since it relies on manual scheduling by individual employees in the case company. This means the first customer order received will be the request scheduled in the next available slot for the machines needed to complete the order. The ovens and grinding machines are running twenty-four hours on average. It is not highly feasible to change the layout of the floor or add more machines due to a low value add to the operation with high costs and lack of space on the shop floor. In terms of improving optimization around the ovens and grinding machines, it would come down to scheduling. There is a steady flow of data coming in from all shop floors through Delfoi, Infor LN, and other internal management systems, but currently it is not being managed properly, to be utilize in a data based technical solution for process optimization.

2.3 Current Processes

Several types of operations are taking place simultaneously on the case company's shop floor. This is challenging to manage since different types of bottlenecks are constantly occurring. The way these issues are currently solved is with manual human management and planning. However, this does not achieve the optimization results desired by the case company. From a planning point of view, the goal is to reduce the lead time of production. Therefore, how can the case company get to the next level of optimization through AI and ML and other optimizing strategies? The answer is, first start with collecting and analyzing the data in its current state within the case company and then determine the quality and quantity of the data on hand. A technical solution can only be properly planned for and implemented if there is substantial data that is historical, clean, machine readable, and relevant to the issue.

The *enterprise resource planning* process, for shop floor processes, in the case company is handled by an enterprise resource planning (ERP) system called Infor LN, which specializes in the manufacturing industry. A depiction of what a day in production planning often looks like for the case company is as follows (see below Figure 1). Resources in terms of the case company refers to the machines, supplies, and workforce. The first step is *Assessing the Situation*, where the current status is assessed for what resources are available and where they are located. The second step is *Crisis Identification*, an assessment of where immediate action is needed. The third step is *Replanning and Task Allocation*, considering and reconsidering to ensure the most appropriate choice is made. The fourth step is *Updating* the outlook of the plan. This is where any recent changed in the environment or business are considered and the processes is updated accordingly. The fifth step is *Identification* of future problems, e.g., lack of machines or covering material. The sixth step is the relaxations of constrains and problem resolving of future predicted issues. The seventh and final step is planning for the routines to be highly optimal in the predictable events.

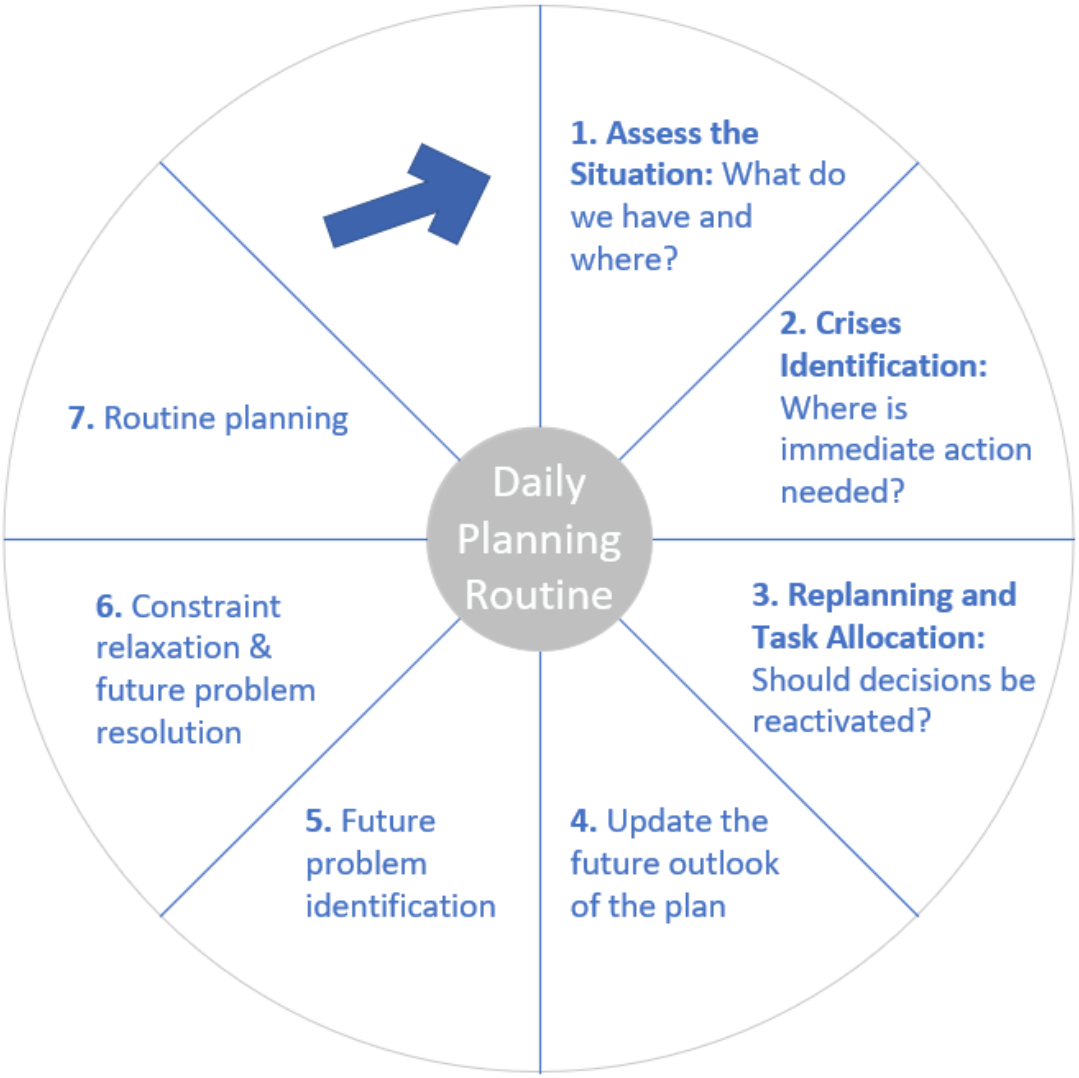

Figure 1. Enterprise Resource Management Process (ERP)

Another current process in the case company is the *production planning* and controlling process. In this process it is about ensuring the right decisions are made to avoid future predictable problems. This includes taking care of problems that are not currently present, while at the same time ensuring not to develop more problems in the prediction process. Figure 2 depicts the production planning process. In this process, the first phase addresses the demand planning, SOP, sales, and operations planning. From there the next phase forms the master production plan. In the final phase, scheduling and execution of shop floor procurement, material, and capacity is laid out.

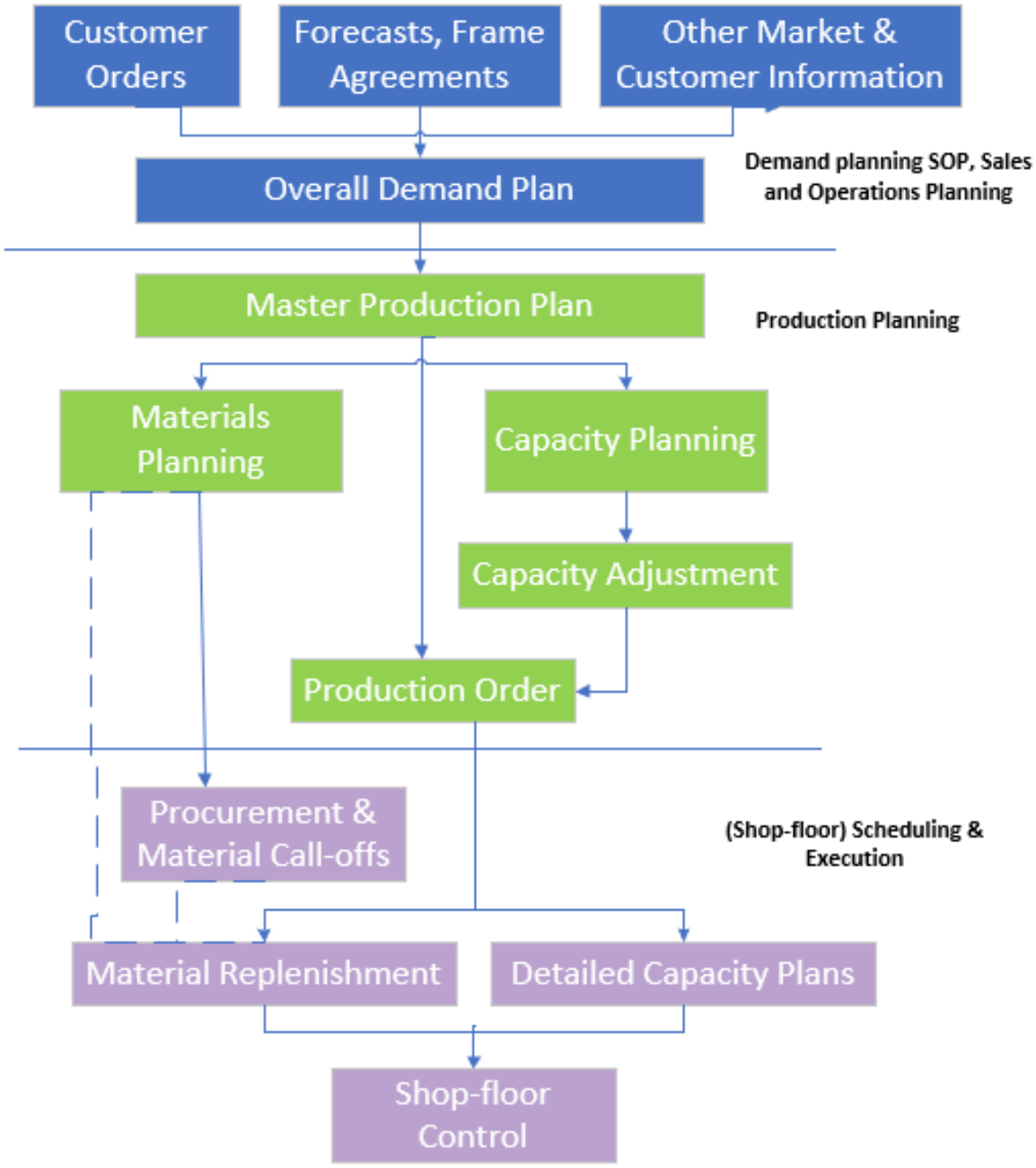

Figure 2. Production Planning Process

The case company's resource and production planning process validate that there are planning processes in place. This proves that even though there are processes in place that show ample planning, the technology elements should be implemented to improve the lead time. In this case, the manual planning in Delfoi and Infor LN would be the targets of enhancement through technical solutioning to reduce lead time in the shop floor planning process.

The case company has substantial process planning in place; however, the process flow issues and bottlenecks on the manufacturing shop floor cannot be addressed optimally with these planning processes alone. The main issues are with time allocation for machines with varying requirements for each roll order and manual shop floor flow planning. Whether a customer sends in an existing roll for re-covering or orders a new roll, both types will go through the same machines on the manufacturing shop floor.

There are several machines on the manufacturing shop floor and a select few machines, this included the ovens and grinding machines, can handle more than one roll at a time. Even if the machine can handle more than one roll at a time, the rolls should be similar sizes as the time in the machine varies based on each sqm of the roll. Depending on the cover type and size of the roll the time required in the grinding machine and oven varies dramatically. There are a lot of elements to be considered when scheduling customer orders. Since the manufacturing shop floor roll order planning is being done manually, on a first come first serve bases, there is a lot of room for errors and inefficiency. Through implementing a technical solution to analysis, the flow of the shop floor and take into account the downtime of machines to maximize the process flow, the case company could see a process with improved process flow and the reduction of bottlenecks. Additionally, material supply is a concern. The four roll cover types require a different mixture of raw materials that have expiry dates. Since these raw materials expire there is a limited supply kept on-site. Once the manufacturing shop floor roll order planning has been optimized and there will be a better idea of how many orders will be requested by customers. Technology solutions, such as AI, should feed off of this data to order the raw supplies based on the predicted manufacturing shop floor capacity and predicted orders. Therefore, increasing their bottom line in processing and reduced waste (Rauniaho-Mitchell, 2020).

3 RESEARCH FRAMEWORK

The first part of this section will briefly discuss the objective and research questions, and the business and technical opportunities, based on theoretical research. Information provided within the case company did not cover all the possible situations for issues, solutions, and strategies and business objectives. As such, literature review is required to fill in the gaps. Figure 3 provides an overview of the research framework designed for this thesis' research.

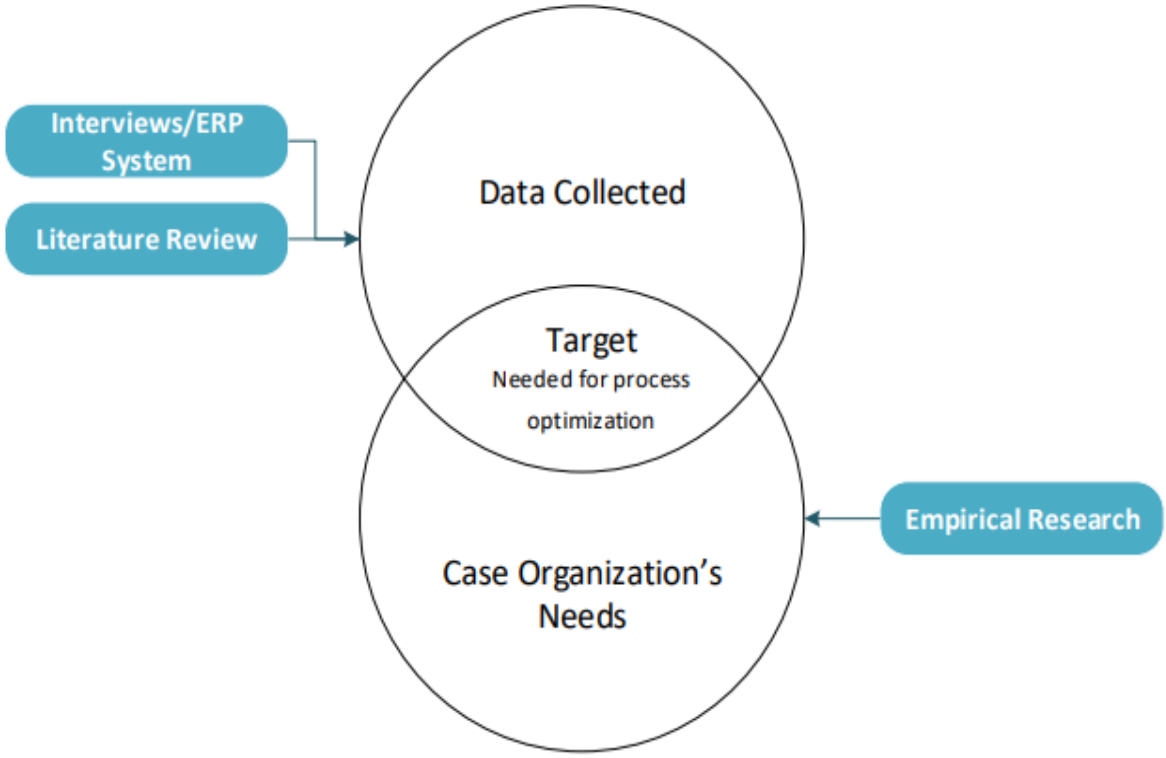

Figure 3. Research Process and Focus

3.1 Objective

The objective of this thesis is to develop an understanding of how lead time can be improved in everyday operations on a manufacturing shop floor through the implementation of a technical solution such as AI or ML. It focuses on the impact time has on the efficiency within the case company. This study's goal is to reveal what is needed and how to implement process optimization through technology on manufacturing shop floors in large companies.

3.2 Research Questions

Initial conversations and interviews from the case company raised the main research issues. These research issues were then formed into two main research questions, based on the manufacturing industry. The two main research questions focused on throughout this thesis are as follows:

1. *How can lead time on the manufacturing floor be improved?*
    a. The answer to this question will identify what kind of processes are needed to successfully implement an IT solution to improve lead time on the manufacturing floor.

2. *How can operations data from the shop floor be processed for technical solutions?*
    a. There is not a substantial amount of prior research on strategies and business objectives in this area. As a result, interviews within the case company, literature reviews, and empirical research, will aid in constructing a method where process flow needs arise. These findings and methods can later be applied to other companies in the manufacturing industry or other similar industries.

There are also two supporting research questions to aid in diving deeper into the details of implementing a technical solution:

a) *Is there sufficient data within the case company?*
    b. To implement a technical solution, such as AI or ML, there must be a large quantity of historical data that is of high quality providing relevant insight.

b) *Is the data at a level of quality and quantity that is useable for implementing a technical solution?*

c. Through interviews and working closely with key stakeholders and employees involved in the manufacturing shop floor management, the current data was collected and assessed.

3.3 Data Collection and Analysis

There are three main categories of interview studies: 1) structured, 2) semi-structured, and 3) unstructured interviews (Qu & Dumay, 2011). For the purpose of this research the unstructured interview process type was chosen. Even though an interview is unstructured and rather causal, it still focuses on a particular theme; in this case the theme was understanding the current process on the manufacturing shop floor, the bottleneck in the current process, and current data status and clarity in the case company (Hannabuss, 1996).

Since the interviews were unstructured, they were not guided by a template of set questions. In this process, the individual situation and context shapes the interview. The interviewer was not given a list of questions to be discussed in advance of the interview. Rather, a basic idea of the interview was framed, and the interview was guided through natural conversation (Qu & Dumay, 2011). There were two basic interview question frameworks: the first was about the current manufacturing shop floor flow and bottlenecks; the second was about data available such as lead time and machine operations time stamps. In depth notes were taken for each interview and then analyzed. Every challenge and idea presented through the interviews were considered to form a technical solution proposal of this thesis. After all viable technical solutions were considered based on the interview findings, an evaluation was conducted.

4 THEORETICAL FOUNDATION

The research questions are addressed through two primary methods: 1) through literature review, and 2) through evidence and data collected from the case company which is presented via a value stream map analyzing lead time. The value stream map was developed based on the case company's current process to understand where bottlenecks are currently occurring. Opportunities for the case company's future optimization options are discussed through literature findings.

The research in this thesis originated from the case company's desire to improve lead time and overall process flow on their manufacturing shop floors—first locally at one shop floor in Central Finland, then across Finland, and eventually to all shop floor sites globally. Since data from interviews within the case company is the main source of information for this research problem the approach is qualitative. There were no experts in AI or ML in the case company, therefore it was necessary to meet with several experts in the manufacturing shop floor process, scheduling, and data management to gather a better understanding around the current process, resources, and available data. Overall, this improved the ability to evaluate and understand the research results thoroughly.

The answer to the first research question —"*How can lead time on the manufacturing floor be improved?*"—provides guidelines to identify what kind of processes are needed to successfully implement an IT solution to reduce overall lead time on the shop floor and improve the process flow. To achieve this, we must analyze how other firms are accomplishing lower lead times compared to the current process in the case company.

The answer to the second research question —"*How can operations data from the shop floor be processed for technical solutions?*"—requires that the case company's data be sufficient and clear enough to design and implemented into

a technical solution. There is not a substantial amount of prior research on strategies and business objectives in this area. As a result, interviews within the case company, literature reviews, and empirical research, aid in constructing a method where process flow needs arise. These findings and methods can later be applied to other companies across the manufacturing industry.

Two supporting research questions have been formulated to determine the current data status in the case company and help draw a conclusion as to whether the case company is ready to start implementing a technical solution in its current state or not. The first supporting research question—"*Is there sufficient data within the case company*"—guided the exploration of the case company's available data. Data found included time stamp data, lead time data, and value stream map process flow data. Lead time data for example provided insight into what machines are sitting idle at any given time. The question also led an inquiry into whether the case company was offering significantly diverging lead times on orders for different customers. Lead time on the manufacturing floor can be improved through process chains mapped through value streams. Value streams can outline pathways to higher levels of productivity, therefore increasing the overall value added in a given period of time (Kuhlang, Edtmayr, & Sihn, 2011). This could help determine if there is a bottleneck in the process flow on the shop floor.

The second supporting research question— *"Is the data at a level of quality and quantity that is useable for implementing a technical solution"*— guides the level of data quality in the case company and the type, quantity, and quality of data necessary for future implementations of AI, ML, or other technical solutions. If the data is sufficient enough it provides insight into whether a technical solution can be explored and, if so, what type of technical solution can be embedded (e.g. AI, ML, or other).

Trying to train an AI system on error strewn data will ultimately lead to poor results. The data criteria for implementing a successful AI system is as follows: the dataset contains patterns that are clear for the model to explore when making predictions and the dataset does not contain accidental patterns, which would result in the model learning biases (Government Digital Service & Office for Artificial Intelligence, 2019).

4.1 Literature Review Findings

4.1.1 Business and Process Improvement Opportunities

Literature review has highlighted that ML and AI have had a major effect, which is continuously growing, in the manufacturing industry; it continues to be an area that more organizations have recently started actively research and implement. The goal of these companies is finding solutions to optimize machine capacity and data usage through automation augmented by AI and ML.

However, continued work is required to grow a better understanding of the potential ML and AI can have on capacity and shop floor optimization in manufacturing organizations. For instance, AI helps with shop floor optimization, data management, and security. Security of data, processes, and overall networking is another factor to consider — this will be discussed more in the *future recommendations* subsection.

Literature review also highlighted how ML ties into AI—Machine learning is a subset of Artificial Intelligence. ML provides the ability, without being programed, to learn and improve experiences automatically (Serokell, 2020). ML is a growing area, especially around production flow and shop floor optimization. Before ML and AI can be implemented though, data requirements must be met within the organization. Through the literature review process, the struggles and bottlenecks that other manufacturing organizations faced in this area served as a roadmap upon which the case company could expand and learn from. From there a tailored roadmap for the case company can be developed outlining solution for organization's needs in shop floor optimization and data utilization and management (Bottou, Curtis, & Nocedal, 2018).

4.1.2 General Optimization Ideas

Literature review on general optimization revealed how a pull system can produce highly effective production environments. Pull systems authorize production, while push systems schedule production (Hopp & Spearman, 2012). The basis for the pull system is where things are requested as needed on the shop floor to avoid excess inventory or work in progress (WIP) (Andrews, 2021). In a pull system WIP is the fundamental cap that limits the total inventory on a production line. If this cap is not present, then the system cannot be classified as

a pull system. Identifying current locations of parts in the line falls under WIP tracking. The implementation of WIP tracking can be automated and detailed through optical scanners. Another option is to implement WIP tracking manually through log entries at specified points in the manufacturing line.

Another idea for general optimization is material flow control (MFC). MFC is a mechanism where you decide what materials move between machines or workstations. MFC allows for smooth shop floor control (Hopp & Spearman, 2012).

4.1.3 AI and ML Optimization Ideas

Investing in AI systems allows manufacturing systems to use human reasoning as a model, but not necessarily the end goal. This provides better services, rather than trying to achieve a perfect replica of human reactions (Marr, 2018).

Reactive machines and limited memory are two current elements of AI that are useful on today's manufacturing shop floors. Reactive machines do not form any memories or look at past event data; therefore, they are purely reactive. This type of AI will ensure the machine will behave the exact same way every time making it very reliable. This can be useful on manufacturing shop floors to autonomize processes that are routine.

Limited memory AI means that machines can look at past event data. A machine can monitor specific objects with this type of AI and monitor them over time. However, at this stage of AI it is still difficult for the machine to learn from past mistakes and make corrections on its own — this is where ML can come into play (Hintze, 2016). For instance, real-time monitoring with AI allows for troubleshooting production bottlenecks, tracking scrap rates, and ensuring customer delivery dates are met. This data can be used to train the ML models of machines on the shop floor. There are unsupervised and supervised ML algorithms that can interpret several production shifts: real-time data within seconds to uncover new processes, workflow patterns, and products (Columbus, 2020).

Both reactive and limited memory AI systems can provide practical solutions for common problems on manufacturing shop floors. For instance, AI can be used to manage machine maintenance. In 2020, it was reported that 29% of manufacturing AI implementations were for machinery maintenance and production assets (Capgemini, 2019). Autonomizing the machine maintenance needs saves downtime in production lines by preventing unexpected breakdowns, therefore increasing production flow. Intelligent maintenance can be broken down into six simple steps: 1) past data is used to train AI of the

machine past failures; 2) plant equipment sensors are constantly collecting data on several operational parameters affecting the performance of the machines; 3) collected data is uploaded to a cloud-based storage platform; 4) the data is analyzed by an AI-based system and makes recommendations while improving the correctness of its predictions; 5) service personal are alerted when the probability of a failure arises, key drivers of the breakdown are identified out of a large number of causes, and the optimal repair time, to minimize production lose, is presented; and 6) data from the failure is fed back to the AI system to improve accuracy for future predictions (Capgemini, 2019).

Another example of AI use can be found in product inspection where AI systems analyze images in real time to inspect quality. This helps the companies stay competitive with compliance of stringent regulatory requirements. AI can be implemented to evaluate the components images from the production line on the shop floor. AI would compare the live image to the data found in the image database and if the order data does not match the final inspection team would be notified (Capgemini, 2019).

Another option is to use ML to improve demand forecasting accuracy (Capgemini, 2019). This reduces the manual labour needed to schedule the machine process flows and can go even further to improve the coordination across sales, account management, finance, supply chain, and the shop floor planning. This reduces forecasting errors, lost sales, and reduces the demand for the planners' workload.

5 ANALYSIS METHODS

This thesis is based on qualitative research. As such, this section explains this theoretical framework and applies it to the case company. To address the quality of research the key elements are reliability and validity.

Two main methods of research have been conducted — a literature review and empirical research. The literature review, or desk research, aspect consisted mostly of collecting and analyzing past research and findings from other studies in the manufacturing industry. Selecting and reviewing the literature is done through understanding the case company's history in terms of the research questions, reviewing other related thesis findings, reviewing industry findings and article in related topics (SIS International Research, 2020).

The empirical, or field, research consisted of interviewing employees from the case company over a 6-month period (see appendix for details) and researching the case company's current manufacturing processes against its end goals (Burgess, 2016). The interviews gave in-depth explanations of the case company's manufacturing process which helped target the research and define the possible benefits of the research conducted in this thesis. Through the interviews, a picture of the current operations was drafted as depicted in a high-level value stream map (VSM) (see Figure 5 below).

To defined value-add from the customer's perspective we can ask, "*Is the customer getting what they really want and what are they willing to pay for the service?*" The impact of the case company's roll processing service goes beyond just the customer placing orders. It includes business owners and stakeholders, of the customer's company, who expect a profit from the services offered. Value added goes beyond the final customer, it must also satisfy the needs of the stakeholder and many customers along the process (Lean Manufacturing Tools, 2013).

Quality is a key element in the value-added time (see Figure 4 below). The end service must deliver exactly what the customer desires, not a compromised service that suits the service company's process (Lean Manufacturing Tools, 2013). If we think in terms of the case company's roll processing service, when a customer orders a re-covering on an existing roll the service provided must be a flawless cover as if the roll were new.

In the case company, processing time is one of the main areas of desired improvement. By reducing the current lead time there is room for more orders, therefore allowing the case company to acquire more of the market share in this service area. The lead time can be calculated by a set period (hours, minutes, etc.) required by the service process to transform the inputs (materials, customers, money, and information) into outputs (services in this case) (Kuhlang, Edtmayr, & Sihn, 2011). Cost is the economical path to complete the service without creating waste. Therefore, shorten the lead time and allowing the case company to sell more rolls results in lowering the production cost for the case company and the service price for the customer (Lean Manufacturing Tools, 2013). This ultimately allows the customer to achieve the desire quality at a desirable price.

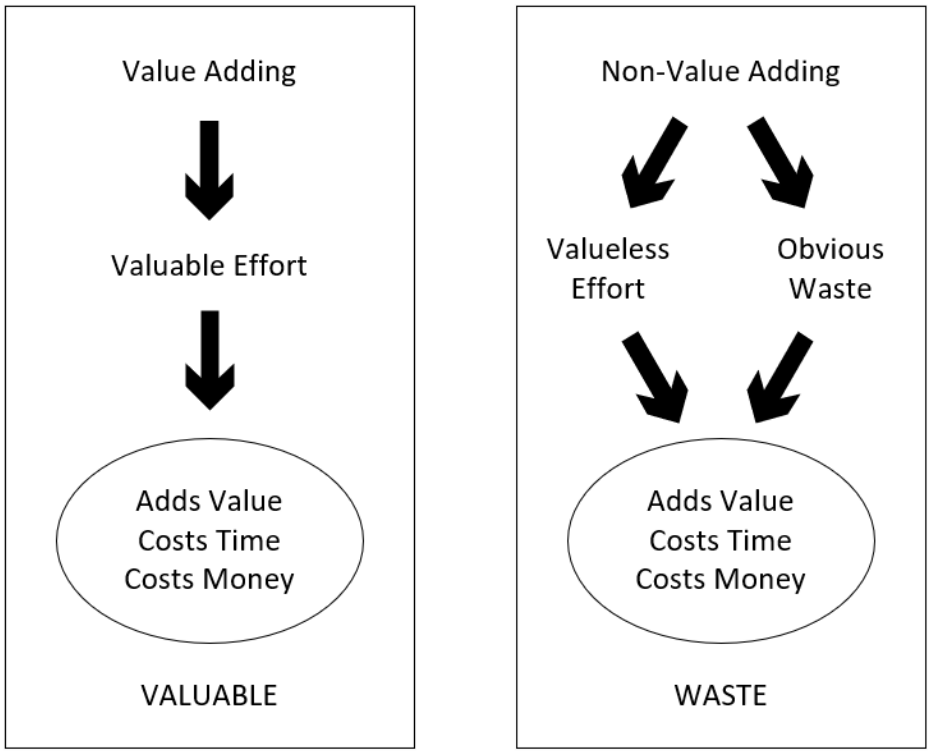

Figure 4. Value Add vs Non-Value Add

To accomplish lower lead times, and higher quality for a lower cost, the bottlenecks at the case company needed to be identified. For this, a VSM (see Figure 5) of the current process was created:

1. Firstly, the company receives the order from the customer, this happens daily. These orders are entered into the Delfoi system and are manually scheduled. Scheduling is manually done base on which order comes in first — a first come first serve bases. This often leads to long wait times for orders.

2. Then the raw materials needed based on the roll re-covering type are determined. Wither order new materials or use the supply stock, if there is enough reserved for re-covering rolls as it is usually used from new rolls. If the raw materials are not available in the stock supply a new order must be made which can add to the wait time. The stock supply cannot hold a significant amount of extra raw materials as they are perishable.
3. The rolls are then held for processing. The holding occurs while the process flow is determined. If the machines needed open, then the process moves ahead, if not then the rolls sit on the floor and wait anywhere between a few hours to several weeks.

4. The old covering is removed from the roll by the grinding machine. The time of this process is different based on the size of the roll. It can be anywhere between twenty to fifty hours per roll.

5. The cover treatment type is then determined and applied. This is where the process time and supplies needed vary drastically between the roll cover type applied.

6. After the cover treatment type is applied it goes into the oven to set. After it is removed from the oven the roll must cool for five hours.

7. The roll is once again sent to the grinding machine. Like stated above, the amount of time this process takes is based on the size of the roll. It can be anywhere between twenty to fifty hours per roll.
8. Finally, the roll is packaged and shipped back to the customer.

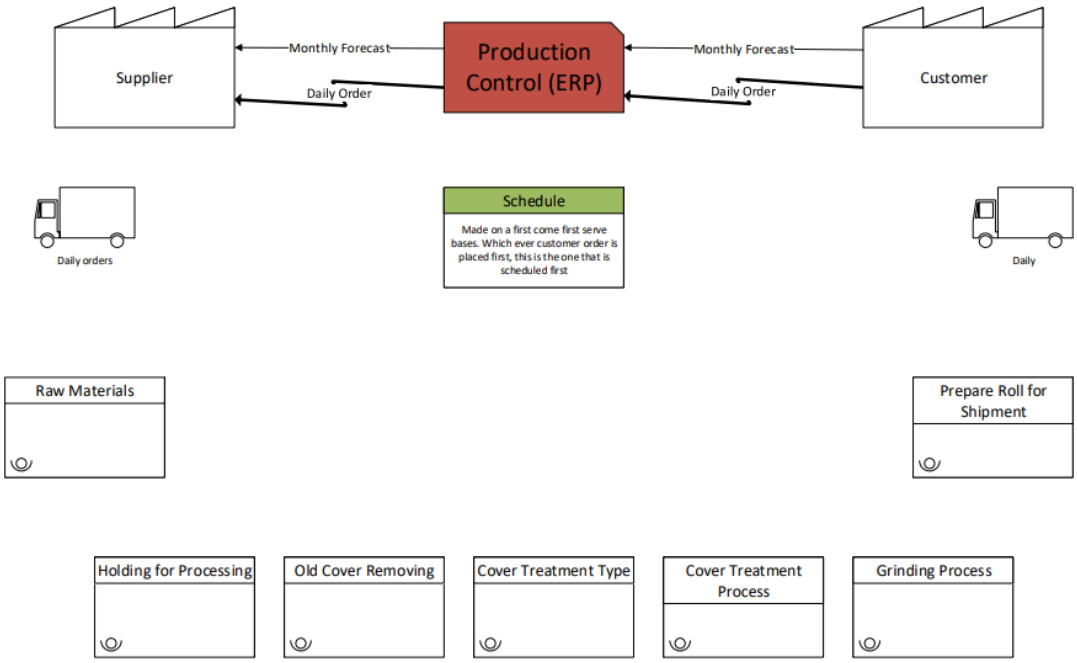

Figure 5. Value Stream Map of Current Order Process

6 RESULTS AND DISCUSSION

This section discusses and describes the key findings of the empirical research from the interviews conducted at different levels of seniority and roles within the case company. The Empirical Conclusions (EC) are general findings made while conducting the empirical research. The results found are linked to the theoretical foundation and earlier literature by going through the primary empirical conclusion in this discussion section. Practical implications are provided by the primary empirical conclusions and existing research.

6.1 Empirical Research Results

6.1.1 Key Stakeholders

The key stakeholder selection process in the case company was executed through interviewing leads in the data management and shop floor areas. Through their interviews additional stakeholders and area specialists (company experts) who were responsible for shop floor process flow and data systems and management were discovered and interviewed. Meetings via Microsoft Teams were arranged and suggestions about participants began to flow in. Discussions were not always straight forward since there was not a clear roadmap or organizational flow chart of who was responsible or had the correct knowledge in terms of data collection and storage location of the data or if the data even existed within the company. Previous knowledge was used to solution and find resources to the best of the interviewees' abilities.

EC 1 All relevant key stakeholders should be selected carefully.

6.1.2 Technical Process Optimization Awareness

The level of awareness of data requirements, storage, and management among the key stakeholders, and other areas of the business, should be considered in further research. However, if the investigator is an expert in AI, ML, or other technical solutions for process optimization on manufacturing shop floors, this kind of evaluation is not necessary. Although there was no issue in the idea of implementing a technical solution, there was an issue with the current state of the data within the case company.

Individual key stakeholders' knowledge about where to find relevant manufacturing process data fluctuated considerably. Some key stakeholders did not have any idea about where particular data was stored, who would know where to find it, or if it was even currently being collected. Often, I was sent through a long trail of referrals, from one person after another to discover that the data did not exist or that it was not sufficient for analysis. The process was highly time consuming. All data should be stored in common systems that are easily accessible to those who are authorized to see the data. It was clear that the data is not organized efficiently since there was no common knowledge of where particular and more specific data can be located without going through a long chain of employees. Additionally, a substantial amount of the data that was available was incomplete and not sufficient to implement an AI or ML solution. For example, machine timestamp data was "stamping out" automatically at the end of day. Therefore, this data was not usable since it does not give an accurate image of when the machine was in use or sitting idle.

EC 2 Lack of knowledge around existing data influences the quality of technical solution ideas by addressing larger concerns than just technical solutions within the case company.

6.1.3 Business Knowledge and Roles

Through the interviews it was clear that the overall knowledge of the business was at a high level in the case company. There is a strong level of historical knowledge that spans over the organizational units and regions within the company. The time individual stakeholders were willing to spend and their personal interest in this study varied. Generally key stakeholders who were higher up in the organization's hierarchy, saw the study as a potential solution in the future to improve business return. Whereas the key stakeholders lower in the hierarchy, who were closely related to manual process optimization on the shop floor, saw this research as an opportunity to reduce

manual labour in planning process flow on the shop floors. Generally, the higher personal level of investment an employee had in the study, the lower they were in the organization's hierarchy. In turn the interviews with the lower-level stakeholders were more creative and solution driven in that there was more problem solving and attempting to solution around the data collection issues experienced. Lower-level stakeholders were involved in more specific functions, where a deep understanding of specific operations was needed. Contrastingly, higher-level roles focused on leading and communication to internal groups to fulfil the business needs.

EC 3 The role of the key stakeholder coincides with the scale of knowledge regarding shop floor processing details.

6.1.4 Technical Solution Candidates

Process flow improvement on shop floors is a potential technical solution, where technical solutions such as AI and ML could be used. There are many possible scenarios where AI and/or ML could be used to make the services more reliable, faster, or more cost efficient. There is no limit to what technical solutions could bring to the table, although it is about which solutions bring the best return based on effort. The understanding of how AI and ML could improve process flow on the shop floor was high, the understanding of the level of data quality was low. Therefore, the focus was on collecting as much data as possible to see if there was sufficient data to implement AI, ML, or another technical solution with the data's current state in the case company.

EC 4 Data quality and quantity must be checked and tested before implementing a technical solution.

EC 5 A lack of useable data will result in an unsuccessful AI, ML, or other data based technical solution.

6.1.5 Technical Solution Opportunities

It was expressed in a few interviews and was apparent through deeper research of the case company, that data management is poor and prevents the implementation of a technical solution to enhance process optimization. The data does not consistently meet data quality requirements. The datasets regarding different detailed processes on the shop floor often have different

owners, leading to a lack of data harmonization. This is a common problem in large companies.

EC 6 Discussing solutions for process optimization on the shop floor presents various challenges and concerns in the possibility of implementing a technical solution surfaced.

Through discussions in the interview process, key stakeholders agreed the overall data collection processes needed to be advanced before implementing a technical solution. One major area of improvement identified was improving the data collection process of machine time stamps, as currently the process has automatic time out and start time trackers set which reduces the reliability of the data.

EC 7 Improved data tracking can lead to data that is ready for a technical solution implementation.

Once the data issues have been resolved, a technical solution could be used to analyze data, such as machine time stamps, to indicate bottlenecks. This would reduce the amount of downtime for machines and increase production flow. The end goal is to reduce the number of rolls sitting on the shop floor waiting to be moved into machines.

EC 8 Technical solution opportunities can be revealed by gaining knowledge around why the data collection is failing and how to improve it.

6.1.6 Technical Solution Value Proposition

The technical solution value proposition outlines the added value that a technical solution such as AI and ML could bring to current shop floor processes. The perfect service or process flow does not exist, therefore there is always room for improvement to make the processes faster, more efficient, and reduce cost. The value-add of a technical solution is to improve shop floor performance optimization. Implementing the value propositions, though, for instance, implementing an AI solution that monitors defects more efficiently than a human can by using high-resolution cameras to catch these defects can create value. A cloud-based data processing framework could be combined with an AI solution to generate automatic responses—all dependent on the data at hand and how it is stored and managed (Hoerig, 2017). The value proposition can be determined in greater detail once the data gaps have been filled. From there the extent of the data can be observed and then applied to technical solutions that fit with the data at hand.

EC 9 To understand how a technical solution brings value, the added value of the data needs to be understood.

6.1.7 Business Needs

The needs of the business were discovered through the desired goals for the outcome of this thesis research. Therefore, the needs can be linked to the technical solution data requirements. Through interviews with key stakeholders the need for improving the roll covering and re-covering processing time was strongly expressed. In turn, improving this area would increase the number of customer order requests processed each year.

EC 10 Business needs describe the desired outcomes and requirements for the technical solution ideas.

6.1.8 Summary of Empirical Conclusions

The analysis above has identified 10 Empirical Conclusions for ease, they are summarized again below.

Empirical conclusions (EC) Table	
Section	***EC***
Key Stakeholders	EC 1 All relevant key stakeholders should be selected carefully
Technical Process Optimization Awareness	EC 2 Lack of knowledge around existing data influences the quality of technical solution ideas by addressing larger concerns than just technical solutions within the case company.
Business Knowledge and Roles	EC 3 The role of the key stakeholder coincides with the scale of knowledge regarding shop floor processing details
Technical Solution Candidates	EC 4 Data quality and quantity must be checked and tested before implementing a technical solution
	EC 5 A lack of useable data will result in an unsuccessful AI, ML, or other data based technical solution
Technical Solution Opportunities	EC 6 Discussing solutions for process optimization on the shop floor presents various challenges and concerns in the possibility of implementing a technical solution surfaced.
	EC 7 Improved data tracking can lead to data that is ready for a technical solution implementation
	EC 8 Technical solution opportunities can be revealed by gaining knowledge around why the data collection is failing and how to improve it.
Technical Solution Value Proposition	EC 9 To understand how a technical solution brings value, the added value of the data needs to be understood.
Business Needs	EC 10 Business needs describe the desired outcomes and requirements for the technical solution ideas.

Table 1. Empirical Conclusions (EC)

6.2 Technical Process Optimization

The ideas for AI and ML, mentioned in the *Research Framework* section, have a set of requirements to make it possible in the real world. As previously mentioned, the current status of the data in the case company is not sufficient to implement a technical solution — insufficient data, data owner fragmentation, and implementation issues are all prevalent in the case company. To successfully implement an AI solution in a manufacturing setting there is no straightforward path. There needs to be a deep understanding of where to apply the technology to achieve the best results. The adoption of AI requires both a cultural shift and the adoption of digital transformation journey. A high dimensionality of data, variability, and uncertainty is when AI-base solutions thrive; building talent to make transitions happen is also a key element (Kommareddy, 2019).

Primarily the availability of quality data is the precursor. It starts with the collection and storage of data from all entities in their manufacturing operations and supply chain. After substantial relevant and clean data is available use cases should be identified and prioritized to make sense of where AI should be deployed — either in a fully automated fashion or with human interactive elements.

The final, very critical decision is whether to develop data science capability using open-source tools in-house or use pre-made ready-to-use commercial solutions (Kommareddy, 2019). This relates to *EC 1 All relevant key stakeholders should be selected carefully. EC 1* coincides with *EC 3 the role of the key stakeholder coincides with the scale of knowledge regarding shop floor processing details.*

The design process starts by defining data requirements. The bottom line of data requirements means gathering the relevant data, in the correct formats and systems, and in the correct quantity (Sundblad, 2018). If sufficient data is available and clean, performance of machines, including their lead time and down time, can be utilized to make better strategic decisions and find bottlenecks in the process flow of the shop floor (Chuprina, 2020). The data selection should be made very carefully at this stage. Clean and a substantial amount of data—usually at least a few years' worth of data which includes information such as machine time stamps—is pertinent to develop and implement a technical solution.

Key stakeholders are imported to understanding the level of knowledge and skills in the case company. As *EC 2* states, there is a *lack of knowledge around existing data influences the quality of technical solution ideas by addressing larger concerns than just technical solutions within the case company.* Therefore, these gaps

must be addressed prior to moving to the planning and implementation phase of a technical solution on the shop floors to improve process optimization. To address the data gaps the collection stage comes first — such as gathering production data from the manufacturing shop floor or a cloud source. The data can be pulled from programmable logic controller (PLC) machines or open platform communications (OPC) servers on the factory network. Production data is collected from quality systems, history, ERP, and other industrial sources collected through automation. Once the data has been collected it can be transformed into useable, machine readable data. Logical attributes are assigned to data through labels and renaming tags. Additionally, streaming production data is corrected and edited. The data is the transmitted securely to the cloud. To optimize bandwidth the data is compressed. Then the data is encrypted for transport and connectivity issues are mitigated (Sight Machine, 2021).

In ML solutions, large volumes of data are necessary to form the learning process by drawing entities, relationships, and clusters. This links to *EC 4 Data quality and quantity must be checked and tested before implementing a technical solution.*

As stated above, the case company does not have the quantity of data nor the quality of data in its current state, which proves *EC 5* and *EC 8*. To further enrich and broaden the correlations made by ML algorithms, data from diverse sources, formats, and business processes is an asset. For a comprehensive learning experience through diverse training data — meaning it is integrated from several sources and concerns diverse business entities, collected at multiple time frames — allows for more success in production and the real-world. When in production, large amounts of data are constantly read by ML algorithms and the model is kept up-to-date and given the ability to grow through diverse data sets (Russom, 2018).

AI and ML based solution could be the use of neural networks. Neural networks allow computer programs to identify common patterns and resolve problems through AI, ML, and deep learning. Artificial neural networks (ANNs) consist of nodes layers, which contains an input layer, one or several hidden layers, and an output layer. All the nodes connect to one another, therefore if the output of a single node is above the threshold that has been specified, the node is activated. The data is then sent to the next layer of the network. If the node does not meet the threshold outlined, it will not be activated, and no data will be sent. The networks rely on data training to improve its accuracy over time (IBM Cloud Education, 2020). In terms of the case company, neural networks can be used in quality assurance, scheduling, and process planning. For scheduling, optimization is achieved through allocating a limited number of

resources to a particular set of tasks — through determining which configurations provide the best solutions, achieved through pattern recognition (Zhang & Huang, 1995).

EC 9 states that there needs to be an *understanding of how a technical solution brings value, the added value of the data needs to be understood.* This ties into the need for comprehensive learning and key stakeholder involvement. Based on data collected and the process optimization issues and goals in the case company a roadmap to implementing the appropriate technical solution should be developed. The best solution for the case company's issue can be determined in great clarity once the data is developed to a useable level. Besides the lack of data quality and quantity, several challenges can occur with implementing technical solutions such as AI and ML — *EC 6 Discussing solutions for process optimization on the shop floor presents various challenges and concerns in the possibility of implementing a technical solution surfaced.* A good understanding of what is entailed to successfully execute technical solutions and create customer and business value among the stakeholders, project managers, architects, and other levels related to the manufacturing shop floor creates a base for project traction. In addition to data issues, performance metrics are pertinent to identify the value metrics, particularly useful for evaluating ML solutions (Kumarl, 2020).

As mentioned in *EC 7, Improved data tracking can lead to data that is ready for a technical solution implementation.* Given the constant need to handle and track data preparation, processing, and access from various teams operating in different offices and geographic locations, the database (DB) and data science (DS) teams, as well as the data protection team, need to coordinate at regular intervals to ensure data scientists have secure access to the correct data set. The DB and DS teams need to cooperate on data collection and update their plans on regular intervals (Kumarl, 2020).

6.3 Business Knowledge and Role

The role of the key stakeholder coincides with the scale of knowledge regarding shop floor processing details. Without knowledge of the current process and bottlenecks, then the business needs are unknown – *EC 10 Business needs describe the desired outcomes and requirements for the technical solution ideas.* If key stakeholders are involved and well aware of the issues within the company, then there is a higher chance of a technical solution gaining traction. In the case company, the key stakeholders are aware of process optimization issues on the manufacturing shop floor, the extent of this knowledge varies base on the role on the key stakeholder. The interviews conducted with key stakeholders showed the need for improving the roll covering and re-covering processing time was a priority within the company. Improving the process flow would potentially increase the number of customer order requests processed each year. Overall, in the case company there is excitement at all levels to implement a technical solution to improve process optimization through the use of a technical solution. The needs of the business were discovered through the desired goals for the outcome of this thesis research. These needs are linked to the technical solution data requirements.

6.4 Limitations

Through the process of this research paper, several key areas within the case company were discovered as inadequate for the original desired outcome to optimize process improvement through a technical solution, such as AI and ML. The main limitations observed that led to roadblocks for further progress of this research paper are insufficient data, fragmented data ownership, issues with current processes in the case company, and implementation issues.

6.4.1 Insufficient Data

Applying revolutionary new technological solutions such as AI and ML for process optimization and business growth is useless without applying the correct techniques for data processing. The data extracted can be in a structured, semi-structured, or unstructured form, because it must be transformed into a usable form for the technical solution to comprehend. However, if the data is

not relevant or complete enough, which is the case in the case company, it cannot be expected that the algorithms will eventually make the data smart and derive value from it (Logic Simplified, 2021).

There are five main steps in the data process: Data Selection, Data Preprocessing, Data Transformation, Data Output, and Data Storage. In the first step of Data Selection all relevant data is collected from available sources that are trustworthy. This step was very difficult in the case company as knowledge of where trustworthy and relevant data could be found was not clear. The data collected was incomplete and, in some cases, lacking trustworthiness. Therefore, it was not possible at the time to move on to the Data Processing step in the case company, or the steps proceeding after that. If sufficient data is collected in the future, the case company must then format the data — increasing the ease for learning models to work effectively with the data. Cleaning and sampling the data then follows. After that the data needs to be transformed through scaling, decomposition, and aggregating raw data. From there the data output is decoded into an understandable format. In the final step, the data should be stored in a central location for future use (Logic Simplified, 2021).

6.4.2 Fragmented Data Ownership

Data ownership in the case company is highly fragmented. Separate departments and teams have different systems and methods of collecting and analysing the data from the shop floor. The focus on what data is important also differs at times. Therefore, when collecting data from within the company it proved to be a timely and confusing process. Since there is no central data storage place the process of collecting the data was timely as it requires going to different teams and departments for the data. The individuals that use the data within the teams did not always know where the original source of data was stored or who was the data owner.

6.4.3 Current Processes

The current processes within the case company are not mature enough for the use of a technical solutions. If current processes are improved upon, such as data ownership, data analysis, and data storage, then there is potential to continue moving towards implementing an AI or ML solution. However, the data must be historical, clean, and formatted for technologies such as AI or ML.

6.4.4 Implementation Issues

The lack of data in the case company does not allow for the implementation of an AI and ML solution at this point. The problem with the level and readiness of the data was not realized in the organization till the process of writing this thesis. Currently, the case company is taking a reactive approach to managing data. The thesis was a specific issue that sparked the need to fix the shop floor data quality within the organization. Between teams the data was inconsistence at times. Data ownership is predominantly fragmented, multiple stakeholders drive the management of the data quality and is measured at a department-by-department level, rather than across the business as a whole. A shift to a more centralized data management strategy will allow for more sophisticated data projects (Mund, 2016).

6.4.5 General Outcomes

As technical solutions in the manufacturing industry become increasingly popular, so does the common knowledge of what works and what does not work. Through observing similar companies in the manufacturing industry, to the case company, that are implementing technical solutions, it is apparent that there is a lot of trial and error. Even with sufficient historical data these solutions can still fail or produce results that were not expected once implemented into a real-world manufacturing setting. Data can also be formatted incorrectly; companies in the industry often face this problem. A common example is that data is originally generated for process monitoring, not for applying machine generated algorithms (Khurana et al., 2020). This is an area to consider in the data collection process of a technical solution implementation. This leads into one of the lessons learned, that data is key. Without historical, relevant, and clean data an AI or ML solution will not work. To get this data you need to have systems in place to track and store the data and a team that is onboard with the implementation and skilled in technical solutioning and data management. Generally, there needs to be a team that is knowledgeable in data engineering, project management, business operations, and analytics to successfully implement a technical solution. There are some constraints around technical and data management knowledge in the case company. There is an opportunity to assign or bring in an external data engineer; a person in charge of collecting and making the relevant data accessible.

Currently there is not enough knowledge of technical solutions such as AI and ML to fully understand all the future potentials in the case company.

Hiring or training a specialized analyst to understand the future direction of where the data is going and can pinpoint data issues, is a potential solution (Mampilli, 2020). Data management can also be improved by creating a central data storage area for the manufacturing team either through a cloud system or central internal data storage area. A major issue is around locating the data. At this one site alone, there are different teams within the manufacturing floor element. When interviewing teams and collecting data it was apparent that between the team data knowledge was not shared and tracking systems varied. The collection process included large amounts of time and effort to find the correct teams and then the correct employee within the team. Individual team members track a particular element of the shop floor process and do not have knowledge of other data that might exists within the company. A central database or cloud store option could eliminate this issue and improve the data collection process. If the data is stored in a central place it will be easier to analyse the data and identify any gaps in the data for technical solution implementations.

7 CONCLUSION

This section concludes the thesis through summarizing the research. There are two parts of this section. The first part answers the research questions that guided the thesis research. The final section gives guidance for future research that builds on the discoveries presented.

7.1 Answer to Research Question

A technical solution, such as AI or ML, is necessary to help improve the process flow in large manufacturing shop floors to keep-up with consumer demand, produce high-quality products and services, and meet time-to-market expectations. In the manufacturing industry, if production falls short of the set goals, traditionally the solution would be to add more machines and operators to the shop floor. This may temporarily solve the issue, through increasing output to reach production goals. Ultimately it will lead to a higher overhead cost — increasing parts usage, capital expenses, utilities, and facilities requirements. Indirect labour costs through the increase in supervisors and administrative personnel on the shop floor must be considered too. A modern solution is to implement control technology on the shop floor, such as AI and ML. These technical solutions create competitive advantages while increasing shop floor productivity (Hoerig, 2017).

It has been clearly determined that a modern solution to implement control technology on the shop floor is the best path for the case company. Specifics that must be defined are data availability, data quality, ability to implement a technical solution with current data, and employee skill sets. The designing process starts by defining the requirements and specifications in co-operation with the consumer's needs, identifying how technical solutions will

be used to improve lead time and optimize the process flow. Before considering which technical solution to implement, you must first collect your data and determine the current state of the data and form a realistic data improvement strategy and timeline. This is key in ensure a successful process improvement project. It is easy to get ahead of yourself in a project and jump straight to the technical solution to improve the manufacturing process flow. However, this behaviour will significantly decrease the success of a technical solution implementation with lasting and desired results. With sufficient data, AI and ML solutions reduce human errors and inefficiencies in shop floor planning. Through automated planning, there is the opportunity to process more orders and increase probability. There is also the ability to track and manage supplies for roll coverings through AI technology.

As mentioned above, in AI and ML implementation, data is key. Also, the capability and knowledge of employees is a crucial asset in implementing these solutions. In terms of the case company there are minimum requirements for the level of data. These requirements include historical data, that is clean and relevant for technical solutions, such as AI and ML, to build algorithms from. Based on the current data in the case company there is potential for this data to be developed into a state that is usable. It involves separate teams working together to store data in a central place and collecting more detailed information, in particular areas of the shop floor process and machine operations. Once the data is sufficient, based on similar cases, a technical solution could easily be implanted in the case company's shop floor processes. Without data that is relevant and a team that has knowledge technical solutions in manufacturing, a technical solution will not be successful.

Though the goal of the case company was to create a sandbox environment for a technical solution to improve their shop floor process optimization. Unfortunately, there is no fully functioning technical solution to address the rather straight forward scheduling and process problem. As repetitively stated throughout this thesis, the case company was not able to reach that level of development desired due to the current state of their data. It is not uncommon for companies to experience AI or ML related implementation issues that contribute strongly to prolonged development periods, as observed through the literature review (Kempf et al., 1990). In this case data and a lack of AI and ML expertise knowledge in the case company led to non-AI and ML related issues.

7.2 Future Research

The case company needs to conduct further research to develop and implement a technical solution on their manufacturing shop floors in the example shop floor in Central Finland and across their global shop floors to improve process optimization. The main future research recommendations are listed below.

7.2.1 Global Impact

From a global perspective of the case company's manufacturing shop floors, the differences across the globe in terms of shop floor processes and data management should be considered in the future. The technological advancements may differ drastically between regions and countries. The shop floors in the twenty-seven countries should be observed. Question such as — what processes they are using to improve process optimization on their shop floors, if any — should be addressed. Also, are the data issues the same for all the shop floors across the globe, if so, what does that mean for data management and the future of technical solutions on shop floors?

7.2.2 Data Security

Data security, such as unauthorized access to company data, is a growing issue that should be addressed urgently. In manufacturing this regards anything accessing machines to capture machine data with suspicious activity or motive. Machines contain programs necessary to their operations; these programs contain critical intellectual property that must be protected. If the data, which is highly confidential, is moved to a cloud storage solution, then it should be ensured it is stored on a private cloud as a public cloud provides minimal security. Policies and governance procedures set by the cloud computing industry should be adhered to, to ensure proper security measures are in place within the case company (Kaufman, 2009).

7.2.3 Lack of Necessary Skills

There are two main areas of necessary skills that need to be researched and developed further — hard skills and soft skills. Both of these skill sets increase the productivity of individuals. Hard skills are classified as teachable skills that can be measured and defined. While soft skills are classified as

intangible and challenging to quantify. They represent behaviours that are learned based on the predispositions of individuals; therefore, they are significantly less measurable (Balcar, 2016).

In terms of the case company, and for other companies in the same industry, an area that should be considered is lack of internal AI and ML skills. Something to consider is if the case company has the internal capability to train their employees in these areas or if it would be more beneficial to hire an external vendor to either implement a solution or train employees (Kuhn & Weinberger, 2005). In terms of AI there are two skill set areas that need to be considered. First, technical capabilities such as algorithms and technical tools. Second, is business knowledge. In terms of the case company on the business side an individual must have knowledge of Infor LN (ERP software for manufacturing) in addition to the technical aspects mentioned above. These two skill set areas should work in tandem together, however in the case company individuals with skills in both areas does not exist. The AI technical skill side can be highly time consuming to train and for individuals to fully grasp. Therefore, the case company should consider in depth training or hiring an external consulting firm.

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APPENDIX

A Case Company Roles of Interviewees

Interviewee Job Title	High-level Role of Interviewees in Relevance to the Thesis
Development Managers	Knowledge around the LN systems and tracking of particular data (confidential).
Global Implementation Owners	Data knowledge regarding time stamps and other related process time data from internal systems.
Shop Floor Managers	Manages the floor and has detailed knowledge of the current flow and processes. Has some limited knowledge of the data available.
Local Shop Floor Coordinators	Schedules roll orders for new and re-coving rolls. Has deep knowledge of shop floor flow of all four roll cover types.
Information Architects	Defines features, phases, and solution requirements and Provides specifications according to which the solution is defined, managed, and delivered.
IT Director	Develop strategy, manage the teams, implement systems, and contribute to product and system development.

B Information Collected from Case Company Interviews

Main Topics of Information Collected
• Analytics of current processes • Shop floor bottlenecks • Current data management systems in the case company • Current systems to track data and shop floor flow • Where current data for machine time stamps and other related data is located • Why the data is not being fully tracked • Why the data is relevant • Why the data is not being fully tracked • Finding more detailed information about current processes and bottleneck • Machine layout on the shop floor • Current overall physical shop floor layout (storage, machines, cooling areas) • Technologies being developed in other areas of the company • Roll covers types and materials needed for each type • Machines needed for which roll covers and the process • Manual tracking process • Information around LN and Delfoi • What data could be helpful in the future • Why a technological solution is important • What the expectations are from a technological solution • Level of knowledge of technological solutioning in the case company • What other shop floors in the company are doing