Master's thesis

NTNU
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Application of Production Feedback Data in Tactical Production Planning; Concept and Method

Master's thesis in Engineering and ICT
Supervisor: Anita Romsdal
Co-supervisor: Mina Rahmani
June 2023

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Preface

This master thesis concludes my master's degree in Engineering and ICT at the Department of Mechanical and Industrial Engineering at the Norwegian University of Science and Technology.

First and foremost, I would like to thank my supervisor, Anita Romsdal, and co-supervisor, Mina Rahmani, for their invaluable guidance and feedback throughout my entire final year in Trondheim. I am also grateful for the opportunity to contribute to the two APMS papers, which was a valuable and rewarding experience.

I would like to thank Brynild for the cooperation and insight into their company. In particular, I extend my thanks to Martin Oskarsson and Mathias Holm for taking the time to answer my many questions through e-mails and meetings.

I want to thank my family, in particular my mother, and Anne for their unwavering support, encouragement, and motivation throughout the formulation of this thesis. Finally, thanks to my fellow students and friends.

Øyvind Anders Myrset Syversen
Trondheim, June 2023

Abstract

High-quality production plans are essential for any manufacturing company. To construct accurate production plans, reliable and accurate planning data is necessary. Production Planning and Control (PPC) consists of three levels: strategic, tactical, and operational. An important type of planning data for tactical planning is called master data. Traditionally, master data are set as static values that are rarely updated. Industry 4.0 has enabled the collection of data from a variety of sources related to production, including production feedback data that provide information about the situation on the shop floor. This also introduces opportunities for the application of this type of data in PPC. This principle of making PPC more data-driven is called smart PPC.

The primary objective of this study is to examine how production feedback data can be applied in production planning in order to increase planning quality. The research strategy employed in this study is based on design science and abductive reasoning. These approaches are based on a real-life observation, or a field problem, and aim to develop solution designs that introduce new or add to existing theories. The field problem in this thesis was that the case company captured production feedback data but did not know how to utilize it.

The study used three research methods to address the primary objective and field problem: literature study, concept development, and case study of the Norwegian manufacturing company Brynild.

The literature study is used to define the relevant theoretical aspects and create a theoretical base for the development of the concept. The theoretical findings can be divided into three main parts: PPC, Industry 4.0, and smart PPC. It showed that there was a research gap in the field of applying production feedback data in PPC beyond the strictly theoretical. In addition, it showed that there are often discrepancies between master data and the current conditions on the shop floor. Planning quality is highly reliant on accurate and reliable planning data, thus inaccurate master data negatively affects planning quality. To improve planning quality, there is potential in applying production feedback data to set accurate master data values and thus improve this representation.

The concept developed in the study describes how production feedback data can be linked to specific master data used for tactical planning. The concept also proposes that some master data values should be set dynamically based on information from production feedback data. In addition, the concept illustrates further how production feedback data can be applied in tactical planning. To support the concept, a step-by-step method is presented for how companies can implement the concept in their operations. This method consists of four steps: mapping, analysis, design, and implementation.

The method was then used in the case study to illustrate the concept through a practical example. The case study showed that Brynild only collected production feedback data from one of the production steps, which implied that quantitative analysis of the data was not feasible. The application of the concept in Brynild was therefore carried out qualitatively. This meant that the case study included a review of the method with advice on how Brynild themselves can prepare to introduce the concept instead of contributing empirical results that confirmed or contradicted the purpose of the concept. Through the case study, it emerged that the implementation step should have included a risk analysis and that the implementation plan should have specified an incubation period where data is collected.

This study provides three primary contributions to theory: 1) an overview of links between production feedback data and master data for tactical planning; 2) a concept for applying production feedback data in tactical planning; and 3) a method for applying production feedback data in tactical planning. It also contributes to practice by providing practical recommendations and guidance for implementing a specific smart PPC solution in companies.

Sammendrag

Produksjonsplaner av høy kvalitet er viktig for envher produksjonsbedrift. For å konstruere nøyaktige produksjonsplaner er det nødvendig å ha pålitelige og nøyaktige planleggingsdata. Produksjonsplanlegging og kontroll (PPC) består av tre nivåer, strategisk, taktisk, og operasjonelt. En viktig type planleggingsdata for taktisk planlegging er kalt masterdata. Tradisjonelt sett er masterdata statiske verdier som oppdateres sjeldent. Industri 4.0 har muliggjort innhenting av data fra en rekke forskjellige kilder relatert til produksjon, inkludert data fra produksjonssystemer som gir informasjon om situasjonen på produksjonsgulvet. I tillegg introdusererer dette muligheter for applisering av denne typen data i PPC. Dette prinsppet om å gjøre PPC mer datadrevet er kalt smart PPC.

Hovedmålet med denne studien er å undersøke hvordan tilbakemeldingsdata fra produksjon kan appliseres i taktisk produksjonsplanlegging for å forbedre planleggingskvalitet. Forskningsstrategien som brukes i denne studien er basert på designvitenskap og abduktivt resonnement. Fundamentet til disse er en observasjon i virkeligheten, et feltproblem, og de har som formål å utvikle et løsningsdesign for å introdusere nye, eller tilføye til eksisterende teorier. Feltproblemet i denne oppgaven var at casebedriften innhentet tilbakemeldingsdata fra produksjon, men de visste ikke hvordan de skulle utnytte dem.

Studien benyttet seg av tre forskningsmetoder for å addressere hodvedmålet og feltproblemet: literaturstudie, konseuptvikling og case-studie av den norske produksjonsbedriften Brynild AS.

Literatustudien brukes til å definere de relevante teoretiske aspektene og skape en teoretisk base for utviklingen av konseptet. De teoretiske funnene kan deles inn i tre hoveddeler: PPC, industri 4.0 og smart PPC. Den viste at det var et behov for forskning på feltet for applisering av tilbakemeldingsdata fra produksjon i PPC, utover det rent teoretiske. I tillegg viste den at masterdata ofte ikke samsvarer med situasjonen i virkeligheten. Siden planleggingskvalitet er sterkt avhengig av nøyaktige planleggingsdata, så vil unøyaktige masterdata negativt påvirke planleggingskvaliteten. For å forbedre planleggingskvaliteten er det et potensiale ved å applisere tilbakemeldingsdata fra produksjon for å sette nøyaktige masterdata verdier, og dermed forbedre denne representasjonen.

Konseptet som ble utviklet i studien beskriver hvordan tilbakemeldingsdata fra produksjon kan linkes til spesifikke masterdata brukt for taktisk planlegging. Konseptet foreslår også at noen masterdata verdier bør kunne settes dynamisk basert på informasjon fra tilbakemeldingsdataen fra produksjon. I tillegg så illustrerer konseptet videre hvordan tilbakemeldingsdata kan appliseres i taktisk planlegging. Til slutt presenteres en trinnvis metode for hvordan bedrifter kan implementere konseptet i sine operasjoner. Denne metoden består av de fire trinnene kartlegging, analyse, design, og implementering.

Metoden ble så benyttet i case-studien for å illustrere konseptet i gjennom et praktisk eksempel. Case-studien viste at Brynild kun innhentet tilbakemeldingsdata fra produksjon fra ett av produksjonsstegene, noe som medførte at kvantitativ analyse av dataen ikke var mulig å gjennomføre. Appliseringen av konseptet i Brynild ble dermed gjennomført

kvalitativt. Dette medførte at case-studien inkluderte en gjennomgang av metoden med råd for hvordan Brynild kan tilrette seg for å introdusere konseptet, i stedet for at det bidro med empiriske resultater som bekreftet eller motsa formålet med konseptet. Gjennom arbeidet med case-studien kom det fram at implementeringstrinnet burde inkludert en risikoanalyse og at implementeringsplanen burde spesifisert en inkubasjonsperiode hvor data blir samlet.

Denne studien gir tre primære bidrag til teorien: 1) en oversikt over linker mellom tilbakemeldingsdata fra produksjon og masterdata for taktisk planlegging, 2) et konsept for applikasjon av tilbakemeldingsdata for produksjon i taktisk planlegging, og 3) en metode for applikasjon av konseptet i bedrifter. Studien bidrar også til praksis gjennom å tilby praktisk anbefaling og veiledning for hvordan en spesifikk smart PPC løsning kan implementeres i bedrifter.

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Acronyms

AI Artificial Intelligence

APS Advanced Planning and Scheduling

BDA Big Data Analysis

BOM Bill of Materials

CPS Cyber-Physical Systems

CRP Capacity Requirements Planning

DPAK Distribution Packs

ERP Enterprise Resource Planning

HMI Human-Machine Interface

IoT Internet of Things

MES Manufacturing Execution System

ML Machine Learning

MPS Master Production Schedule

MTO Make-to-order

MTS Make-to-stock

MRP Materials Requirements Planning

OEE Overall Equipment Efficiency

PFD Production Feedback Data

PLC Programmable Logic Controller

PPC Production Planning and Control

PSS Purchasing/Supplier System

SCADA Supervisory Control And Data Acquisition

SFC Shop-Floor Control

SKU Stock-Keeping Unit

SME Small and Medium-sized Enterprise

S&OP Sales and Operations Planning

WIP Work-in-Process

1 Introduction

1.1 Background

Today's manufacturing markets are categorized by uncertain business environments and customer requirements. Effectively adapting to such changes is a key success factor for any manufacturing company (Jacobs et al. 2011). Hence, there is an urgent need for responsive PPC with the ability to address these uncertainties (Saad et al. 2021). PPC is the group of systems, procedures, and decisions that combine the different aspects of supply and demand together, and it includes the decisions on when and what to produce, buy, and sell, and in which quantities (Bonney 2000; Slack et al. 2013). PPC consists of large and complex processes and is traditionally based on hierarchical approaches described in three levels of detail, operational (short-term), tactical (medium-term), and strategic (long-term) (Arica and Powell 2014; Vollmann et al. 2005).

Production planning can be described as a process of transforming a set of input parameters, which is based on planning data, into a desired set of outputs (Bonney 2000). These input parameters represent the logical foundation of production planning, and thus, the success of PPC and the quality of the production plans depend on having reliable and accurate planning data and parameters (Hees and Reinhart 2015; Van Nieuwenhuyse et al. 2011). For tactical planning, the input parameters typically consist of static master data often set in the Enterprise Resource Planning (ERP) system of the company and dynamic data, such as customer orders (Vollmann et al. 2005).

Through the introduction of Industry 4.0, a term coined for the recent advances in digital technologies in industrial production (OECD 2017), global production is currently undergoing a significant transformation through digitization (Saad et al. 2021). This emerging digitization has facilitated large-scale data collection from a vast range of sources and provided newfound opportunities for applying this data in production. This application of data has introduced opportunities for more data-driven PPC, named smart PPC (Oluyisola 2021). Smart PPC not only provides support for human decision-making but also aims to automate PPC tasks to facilitate a more integrated, dynamic, and real-time PPC (Rahmani, Romsdal, Sgarbossa et al. 2022).

One specific source of data that has seen an emergence is the shop floor and its production processes (Schäfers et al. 2019). The data is captured from sensory systems on the production machines and can for example provide information about the status of production jobs, the utilization of resources, set-up times, and waste (Schuh, Thomas et al. 2014). This type of data is referred to as production feedback data.

A problem with traditional production planning is deviations between the planned situations and the real-life situations on the shop floor (Kurbel 2016). By analyzing production feedback data, up-to-date information on the current situation on the shop floor can be obtained and used to formalize production plans in order to minimize these deviations. The purpose of this thesis is to investigate the application of production feedback data in tactical production planning and its potential to improve planning quality.

1.2 Research Objectives and Research Questions

The primary objective of this study is to examine how production feedback data can be applied in production planning in order to increase planning quality. In order to achieve the primary objective, three secondary objectives were defined to guide the research, as follows:

1. Identify links between production feedback data and master data used for planning
2. Develop a concept for the application of production feedback data in tactical production planning.
3. Provide a method for companies to integrate the concept into their operations.

In order to achieve the primary objective, the following two research questions have been formulated:

RQ1: Which production feedback data is relevant for improving the accuracy of master data used in tactical production planning?

This research question aims to explore the potential links between the planning data, i.e. master data in the scope of this thesis, and the real-life situation on the shop floor which is captured through production feedback data. In order to address this question, the literature study is utilized to obtain insight into the existing research in the field of PPC and the use of production feedback data. The concept is used to establish links between production feedback data and master data, while the case study is used to illustrate which production feedback data can and should be captured.

RQ2: How can production feedback data be applied in tactical production planning?

Having established the connection between production feedback data and tactical production planning, this research question aims to further develop the understanding of the specific ways in which production feedback data can be utilized for tactical planning purposes. In order to answer this question, it is addressed in two ways: 1) through the concept and 2) through the method for applying the concept in companies. The concept provides an illustration of how production feedback data can be applied in tactical planning, which is then applied in the case study through an illustrative example of how the concept could be implemented in a real-world setting, specifically within the case company. The concept is based on theoretical knowledge and findings from the literature study.

1.3 Research Scope

The research scope is confined to investigating methods of improving planning quality through new smart PPC applications. Particularly, the scope is further limited to tactical, or medium-term, production planning, which includes two primary activities, namely MRP and CRP. The focus is on methods for enhancing the accuracy of the master data used at this planning level through the utilization of production feedback data. Furthermore, the scope is confined to production environments of mass production and standard products, with fixed processing steps and routings, i.e. that the sequence of processing operations is predetermined and static for every product.

1.4 Thesis Structure and Research Outline

Table 1: Thesis Structure

Section 1 **Introduction**	Presents the background and motivation for the research, along with the scope, objectives, and research questions of the study. Additionally, this section provides an overview of the structure of the thesis.
Section 2 **Research Methodology**	Describes the two concepts that guided the research strategy, how the literature and case study was conducted, and how the concept was developed.
Section 3 **Theoretical Background**	Describes the relevant theoretical aspects of the thesis. The three main parts are PPC, Industry 4.0, and Smart PPC. Finally, challenges and opportunities regarding the theory are presented.
Section 4 **Concept for Application of Production Feedback Data**	Presents a concept for applying production feedback data to tactical production planning. The concept includes two conceptual models that demonstrate how production feedback data can be linked to tactical planning, illustration of how production feedback data can be applied in tactical planning and outlines a method for companies to integrate production feedback data into their tactical planning processes.
Section 5 **Case Study: Brynild**	Includes an introduction to Brynild AS, a description of the PPC processes and data capture capabilities of the company, and an analysis of the current situation. Additionally, the concept is applied to the company following the proposed four-step method.
Section 6 **Discussion**	Interprets and evaluates the main findings from the research in relation to the research questions and objectives.
Section 7 **Conclusion**	Presents the main conclusions from the research, the contributions of the thesis, its limitations, and suggestions for future research.

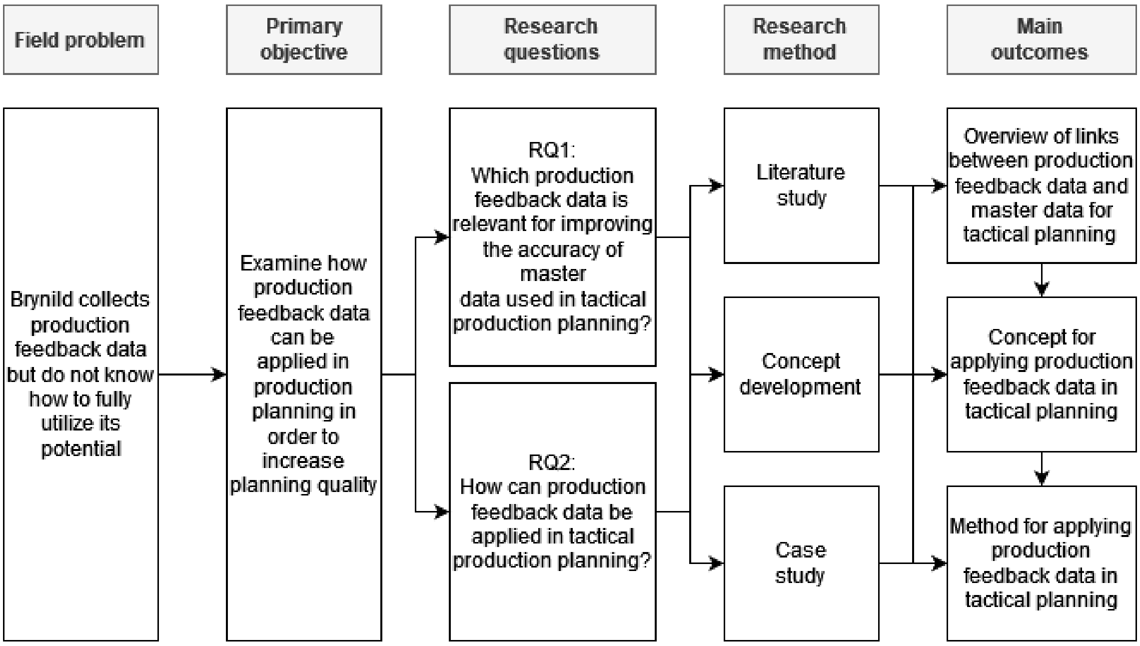

Figure 1: Research outline

2 Research Methodology

The research methodology in this master's thesis comprised three main research methods: literature study, concept development, and case study. Before these are presented, the concepts which guided the research strategy are outlined. These concepts are design science and abductive reasoning.

2.1 Research Strategy

The goal of design science is to develop knowledge to solve field problems through the creation of new systems or the improvement of existing ones (Denyer et al. 2008; Van Aken and Romme 2009). Denyer et al. (2008) characterized design science by:

- Research questions that are driven by an interest in field problems.
- An emphasis on generating prescriptive knowledge that can inform interventions and systems to produce desired outcomes and solve field problems.
- The justification of research products is primarily based on their pragmatic validity, i.e., whether the actions informed by this knowledge produce the intended outcomes.

Design science research studies typically consist of one or more cycles of research moving between exploration and explanation (Romsdal 2014). Figure 2 shows how design science is connected with the environment and the knowledge base with three types of research cycles.

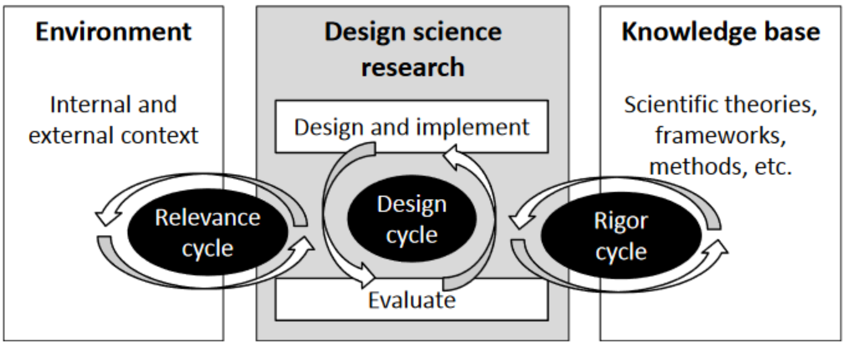

Figure 2: Design science research cycles (Romsdal 2014)

The relevance cycle initiates the research by providing the requirements, i.e. the field problems, while the design science research output is returned to the environment for evaluation in the real-life context. The rigor cycle provides past knowledge to the study, and the outputs from the design science research generate additions to the knowledge base. The design cycle is the core of the design study and generates and evaluates design alternatives until a satisfactory design is achieved (Romsdal 2014). There are generally five stages of design science which aim to: 1) frame a field problem, 2) develop an initial solution design, 3) refine the initial solution design to solve the problem, 4) develop a substantive theory to establish theoretical relevance, and 5) develop a formal theory to strengthen theoretical and statistical generalizability (Holmström et al. 2009; Van Aken and Romme 2009).

Abductive reasoning, or systematic combining, is a research approach that is characterized by a continuous movement between an empirical world and a model world, i.e. empirical observations and theory (Dubois and Gadde 2002). Abductive reasoning focuses on refining existing theories rather than creating new ones. This involves successively modifying original frameworks based on unanticipated empirical findings and theoretical insights gained during the process (Dubois and Gadde 2002). The process allows the evolution of theoretical framework, empirical fieldwork, and case analysis simultaneously. Abductive research starts with a real-life observation and leads to a creative iterative process of "theory matching" in an attempt to find a new matching framework or to extend the theory used prior to this observation (Kovács and Spens 2005). The process is shown in Figure 3.

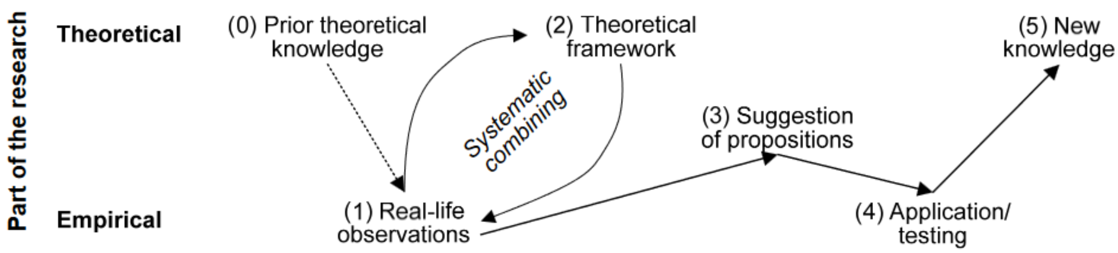

Figure 3: The abductive research process (Romsdal 2014)

Utilizing abductive reasoning in design science research can be very useful, particularly in the development of the initial solution design (Holmström et al. 2009). Furthermore, it can be helpful in the other stages as it facilitates linking the study with the environment and the knowledge base (Romsdal 2014).

The research in this study started with an observation in the case company - the field problem. The next step was formulating the primary objective of the study. To address the primary objective, the knowledge base was studied for existing research on the topic, before continuing the design science cycles and creating a concept draft based on existing theories. This was further refined through the design cycle, while continuously moving between empirical observations and theory according to abductive reasoning. The proposed concept, presented in Section 4, was then illustratively applied to the case company to provide suggestions for how it can be applied in practice. The case study in turn led to refinement of the method.

2.2 Literature study

In order to gain a comprehensive understanding of the relevant theoretical concepts and themes of the thesis, a structured literature study was conducted. Karlsson (2016) highlights three key reasons which emphasize the importance of conducting a thorough literature study. First, reviewing the literature on relevant topics helps identify current knowledge and potential research gaps. This ensures that the chosen research topic is viable and that the thesis has the potential to contribute to existing knowledge. Second, the literature review can inform and inspire the research by suggesting relevant topics, concepts, or methods to employ. Finally, conducting a literature study helps develop the researcher's skills and expertise in their field of study.

The research conducted in this thesis is a continuation of a specialization project (Syversen 2022). Hence, parts of the literature study in Sections 3.1, 3.2, and 3.3 is based on the work performed in that project.

The literature study was initiated with an exploratory research phase where academic databases were searched for information on the relevant theoretical aspects. Thereafter, refined searches were performed and articles were studied in detail. The databases used for this included Scopus, Google Scholar, Web of Science, and Science Direct. In order to continuously improve the theoretical foundation of this thesis throughout its formulation, an iterative approach was employed according to design science and abductive reasoning. This involved systematically revising and reviewing relevant research topics to ensure that new articles and developments were taken into account as new empirical observations emerged, and new iterations of the concept were made. Throughout the study, potential limitations and opportunities were identified, allowing for further refinement of the research topics. To identify additional relevant literature, a backward snowballing approach was used, which involves reviewing the reference lists of highly relevant articles to find other suitable sources (Jalali and Wohlin 2012). Some scientific literature was also provided by senior researchers familiar with the topics of the thesis.

A selection of prevalent search words used throughout the literature study is presented in Table 2. The resulting search strings could consist of one or several main and secondary search words. The goal was to use a combination of generalized and precise search strings to acquire a comprehensive understanding of the three main theoretical perspectives discussed in Section 3, while also facilitating searches on the more detailed topics within the scope of the study. The articles returned from the search strings were initially screened for relevance, with non-relevant articles being disregarded and potentially relevant papers being stored for further review. After this initial screening, the abstracts of the remaining articles were reviewed before the full text was examined to acquire a complete overview. The articles were then classified by their respective research topics. If particularly relevant sections were identified, a backward snowballing approach was applied.

Table 2: Search strings used for the literature study

Topic	Primary search words	Secondary search words
Production planning and control	• PPC • Information systems • ERP • Master data • Planning quality • Data quality • Real-time events	• Applications • Characteristics • Estimation • Handling • Issues • Uses • Manual/experience-based planning • Automated planning
Industry 4.0	• Industry 4.0 • Smart manufacturing • Production feedback data	• Applications • Technologies • Collection • Uses
Smart PPC	• Smart PPC	• Applications • Characteristics • Technologies • Implementation

2.3 Concept Development

The concept development was a collaborative effort between the author, the supervisors, and other senior researchers and industry experts. The concept was developed through a series of workshops and discussions, and it has also been published in Rahmani, Syversen et al. (forthcoming). While the supervisors and other researchers were involved in the conceptualization of the master study, the development of the core concept, and the execution of the case study, the author was the main researcher and made all the main decisions regarding the study. Additionally, the author performed the literature study, developed interview guides, conducted and documented the interviews, validated the case data with the company, analyzed the case data, elaborated the concept, expanded the case study, and designed the proposed solution in Section 5.4.

The concept builds upon existing concepts and frameworks, as well as extensive experience of the co-contributors working on PPC challenges in collaboration with companies from diverse production environments and industrial sectors. As previously stated, the research was based on a real-life observation in the case company; Brynild collects production feedback data from the nut packing lines, but they do not know how to fully utilize the potential. Continuing with abductive reasoning, a meticulous study of the literature indicated that there is largely unexplored potential for applying production feedback data to improve production planning. This potential is facilitated by advancements in recent technologies related to the introduction of Industry 4.0, as well as the emerging concept of smart PPC. After several loops of the design science cycles and systematic combining of the real-life observations and existing theoretical frameworks on the topic, a final iteration of the concept was proposed: production feedback data could improve the master data used for tactical production planning through the feedback loops shown in recent hierarchical PPC frameworks. After the general concept had been derived, the following steps were pursued to support the validity of the concept with examples of master data and production feedback data:

1. A comprehensive list of master data was compiled from the literature.
2. The master data with links to the situation on the shop floor was identified.
   (a) Exclusion criteria: Master data with no discernible connection to planning or that was unrelated to production and the production line was removed.
3. Production feedback data relevant to the master data identified in step 2 was identified.

The concept includes two conceptual models for applying production feedback data. Conceptual modeling is a process in which a representation of selected phenomena within a specific domain is constructed (Wand and Weber 2002), and the models are often graphical representations of the relationship between entities or processes (Davies et al. 2006).

2.4 Case Study

A single case study of Brynild was conducted. In addition to providing the initial field problem this research aimed to solve, the case study supports the theoretical foundation with the context of a real-world example in a relevant company and industry. A case study is a commonly used, qualitative research method that involves an in-depth examination of a social unit (Kothari 2009). In the field of operations management, case studies have consistently demonstrated their effectiveness as a research method, and they can be used for research purposes such as exploration and theory building, testing, and elaboration (Karlsson 2016; Ketokivi and Choi 2014). It is considered especially powerful in the generation of new theories (Boer et al. 2015). To enhance credibility and contribute to theory development, it is important to establish links between case study findings and existing theoretical knowledge (Eisenhardt 1989). This is also supported by design science and abductive reasoning.

The case company is a Norwegian confectionery and nuts manufacturer. It is a Small and Medium-sized Enterprise (SME) actively involved in collaborating with researchers to find innovative solutions. They have installed infrastructure for capturing production feedback data on their nut packing lines, and have collected data for approximately two years. This was the basis of the initial field problem this research aimed to solve; Brynild have good procedures in place for collecting production feedback data, but they do not know how to fully utilize its potential.

The original purpose of the case study was to perform a quantitative analysis of production feedback data in the application of the concept in Section 5.4, the final part of the case study. This could provide empirical findings to support, or reject, the proposed concept in relation to the imposed effects on planning quality. However, Brynild does not capture the necessary data for the analysis. To provide meaningful insight into the effects of applying protection feedback data in tactical production planning, the analysis would require data from all steps or, at a minimum, data from the beginning of processing in addition to their current data. Thus, the case study is instead illustrative and conducted using a qualitative approach providing suggestions for how the application of the concept *could* be included in the company's operations if the required data was available.

After being presented with the initial field problem, the first phase of the case study involved obtaining a general understanding of the company and its operations. This was primarily achieved by reviewing previous case studies conducted by other master's students at the Department of Industrial and Mechanical Engineering at NTNU, information collected by the co-supervisor Mina Rahmani, and public available information on their websites.

Qualitative Data Collection

The next phase of the case study involved qualitative data collection. The data was collected through e-mail correspondences, semi-structured interviews, workshops, and physical visits at Brynild's facilities in Fredrikstad. Parts of the qualitative data collection was conducted in the specialization project Syversen (2022). Thus, the sections presenting information gathered from this phase of the case study, specifically Sections 5.1, 5.2, 5.3.2, and 5.3.3 are also based on information collected in that project.

The company representatives involved in this phase were mainly nut production planner Martin Oskarsson and supply chain director Mathias Holm. As a result of the qualitative data collection the nut production, its related functions, and other relevant research topics could be thoroughly mapped. The following table shows a summary of the main interactions with the company.

Table 3: List of main events related to the quantitative data collections

Actor(s)	**Details**	**Topic**
Supply Chain Director Mathias Holm	Digital meeting Duration: 60 minutes Date: 14/10/2022	Introduction to the project and food manufacturing, direction of the thesis
Supply Chain Director Mathias Holm Production Planner Eirik Johannes Blå	Factory tour and semi-structured interview Duration: 4 hours Date: 21/10/2022	Guided tour of the factory, questions related to Brynild's nut production and PPC
Supply Chain Director Mathias Holm Haris Jasarevic	Semi-structured interview Duration: 120 minutes Date: 22/10/2022	Questions related to the nut production planning and the data they capture from the nut packing lines
Production Planner Martin Oskarsson	Semi-structured interview Duration: 60 minutes Date: 31/10/2022	Questions related to the nut production planning and control
Production Planner Martin Oskarsson	Semi-structured interview Duration: 70 minutes Date: 09/02/2023	Questions related to the nut production processes and planning
Production Planner Martin Oskarsson	Semi-structured interview Duration: 45 minutes Date: 23/02/2023	Questions related to the ERP system and data they use for planning
Supply Chain Director Mathias Holm Automation Engineer Richard Skibenes Haris Jasarevic Representatives from: Hansa Borg BI Buillders Dynamic Engineering	Workshop Duration: 6 hours Date: 01/03/2023	Workshop about the digitalization of factory systems and related topics
Production Planner Martin Oskarsson	Semi-structured interview Duration: 55 minutes Date: 02/03/2023	Continuation to questions about the ERP systems, planning data and operations in the nut factory
Production Planner Martin Oskarsson	Semi-structured interview Duration: 120 minutes Date: 26/03/2023	Questions about real-time events handling in nut production

Quantitative data

Quantitative data were also provided by Brynild to support the qualitative data collection. Both Excel sheets used for production planning and a production feedback data set from the HDG1 packing line were provided. The planning documents were used to gain further insight into how the manual, experience-based planning for nut products is conducted with the support of spreadsheet solutions. The data provided was production feedback data which Brynild currently utilizes for Overall Equipment Efficiency (OEE) calculations. This was used as support for the formulation of the concepts presented in Section 4.

Table 4: Documents and data sets provided by Brynild

Filename	**Description**
kopiProduksjonsbehov nøtter uke 4422-1723	Copy of the general production plans for 26 weeks. Master data is used for constructing the plan
kopiuke_45	Copy of a day-by-day, detailed production plan for one week. Includes what products to be be produced in which shifts, for each packing line
OEE Data from HDG1	production feedback data. One record of data for each run period of the HDG1 nut packing line. Includes start and stop timestamps, pause and stop times, speed, quality, downtime, OEE, etc.

3 Theoretical Background

This section provides an overview of the theoretical foundation established through the literature study. It is organized into three main parts: Production Planning and Control (3.1), Industry 4.0 (3.2), and Smart Production Planning and Control (3.3). The section concludes with a summary of research opportunities provided by the literature study.

3.1 Production Planning and Control

3.1.1 Introduction to PPC

PPC encompasses the activities aimed at balancing the capabilities of operational resources with market demands. It involves the implementation of systems, procedures, and decisions that align various aspects of supply and demand together (Slack et al. 2013). It includes the decisions of when and what to produce, buy and sell, and in which quantities (Bonney 2000). Hierarchical frameworks are commonly used to describe and visualize PPC's many aspects at different levels of detail and time horizons (Oluyisola 2021). One of the most popular PPC frameworks is introduced by Vollmann et al. (2005), and it includes three levels of details; short-term (operational), medium-term (tactical), and long-term (strategic). This framework is used as a foundational element for many of the planning and ERP systems presently used for production (Oluyisola 2021). However, in real-life production systems, several feedback loops are experienced, which this framework does not consider. To obtain a more holistic and realistic depiction of the PPC system, Oluyisola, Sgarbossa et al. (2020) adapted the framework from Vollmann et al. (2005), building upon the works of Garetti and Taisch (1999) and Bonney (2000). This framework is illustrated in Figure 4

The purpose of the long-term, strategic level is to establish a broad and aggregated view of production operations. Sales and Operations Planning (S&OP) combines the plans and data from sales and marketing with the production resources the company has available (Jacobs et al. 2011). It is cross-functional in nature, with functions such as sales and marketing and senior management involved together with the operational functions (Chapman et al. 2017). The inputs for S&OP are demand data regarding volumes per product family and in some cases, metadata regarding forecast accuracy, received from demand management, and future available aggregate capacity received from resource planning (Oluyisola 2021). The S&OP provides the foundation from which Master Production Schedule (MPS) is produced. The role of the MPS is to convert the disaggregated plan from S&OP into a defined production and purchasing plan for the specific product levels (Jacobs et al. 2011). Rough-cut capacity planning analyses the MPS to discover potential capacity problems and whether critical resources are available to support the MPS (Chapman et al. 2017; Jacobs et al. 2011). The output from the strategic level is the input for the detailed material planning at the tactical level (Oluyisola, Sgarbossa et al. 2020).

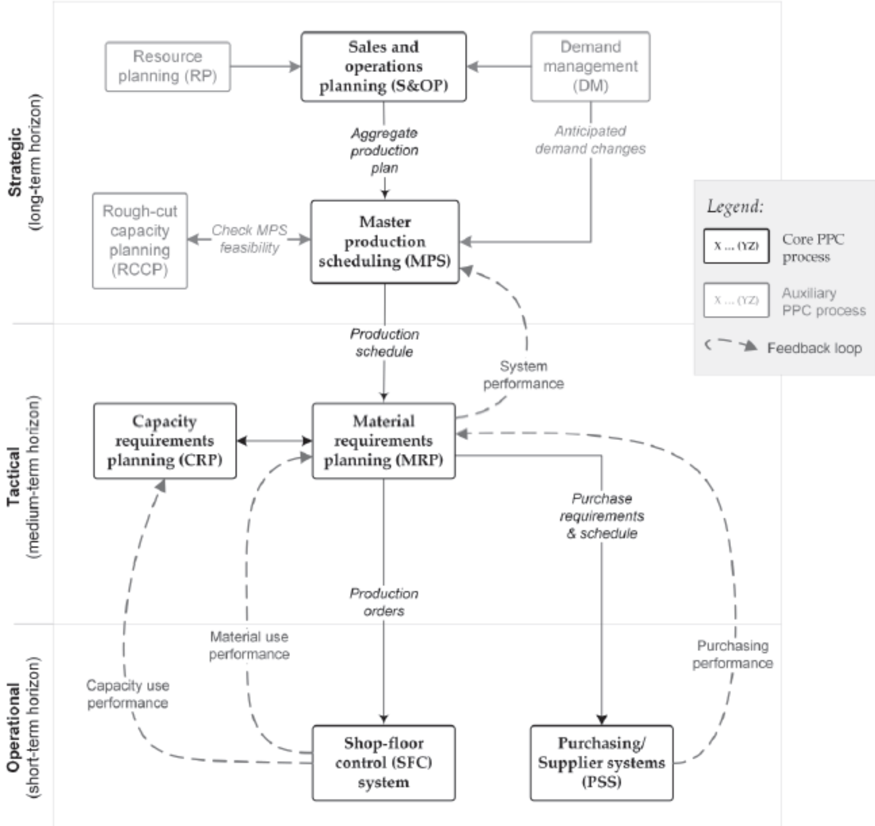

Figure 4: Production Planning and Control System (Oluyisola, Sgarbossa et al. 2020)

The tactical level considers a shorter timespan than the strategic level and emphasizes a higher level of detail and accuracy than the long-term level. At this level, the MPS records are combined together with inventory and Bill of Materials (BOM) data to be used as calculations for Materials Requirements Planning (MRP) (Jacobs et al. 2011). MRP produces a set of raw material and component requirements, together with a suggested replenishment order for materials (Jacobs et al. 2011; Oluyisola, Sgarbossa et al. 2020). To produce the final outputs, a net requirement calculation has to be performed. The MRP logic consists of three iterative steps: netting against available inventory, planned order calculation, and BOM explosion for gross requirement calculations of components (Higgins et al. 1996). MRP's main goal is to decide what to order, in what quantities, and at what time, both from purchasing and manufacturing (Oluyisola, Sgarbossa et al. 2020). Together with MRP, the tactical level also consists of Capacity Requirements Planning (CRP). CRP is directly linked with the MRP and it considers the data from the MRP, open orders, routings, and work centers as its inputs, with a goal of checking that the required capacity is available (Chapman et al. 2017). CRP and MRP produce capacity- and material plans of a significantly higher level of detail and a shorter time horizon than the ones produced on the strategic level. At this level, planning data typically consists of static master data, which can be set in the company's ERP system or defined elsewhere. This includes information such as BOM and processing identification numbers This is combined with dynamic data, such as scheduled receipts and inventory information. The final outputs from the tactical level are the production plans and replenishment orders, which are also continually revised to ensure their accuracy is maintained (Oluyisola, Sgarbossa et al. 2020). Figure 5 shows a detailed view of the MRP process. The figure shows how the net requirement calculation derives from both static and dynamic information; MPS is combined with dynamic information regarding scheduled receipts, inventory status, and Work-in-Process (WIP), together with static master data.

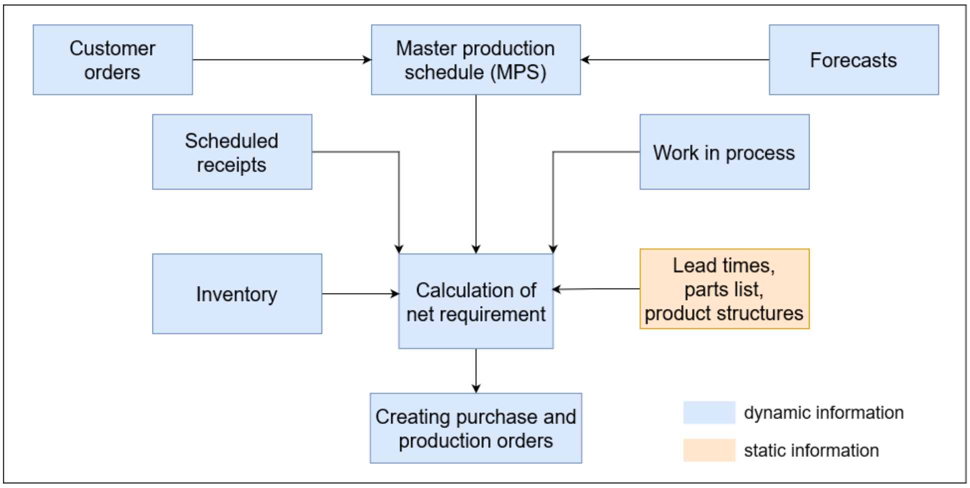

Figure 5: The Material Requirements Planning process, based on (J. O. Strandhagen et al. 2021)

The final operational level considers the daily operations and controls needed on the shop floor and for purchasing and suppliers. The two systems on this level are thus called the Shop-Floor Control (SFC) system and Purchasing/Supplier System (PSS). The SFC system handles detailed scheduling and execution of production orders, and coordination of the manufacturing processes, while the PSS issues purchasing schedules for the required materials to execute daily operations (Oluyisola, Sgarbossa et al. 2020). At this level, the documents usually consist of component-level purchase orders and work center-specific work orders or job lists (Oluyisola, Sgarbossa et al. 2020). At the operational level, the production operations and suppliers are also controlled, measured, and evaluated in terms of their effectiveness (Oluyisola, Sgarbossa et al. 2020).

There is no definitive division between *planning* and *control*, neither in theory nor in practice, and while they can be considered separate activities, they are still closely related (Slack et al. 2013). Slack et al. (2013) furthermore explains that there are some distinguishing features of each that can help differentiate the two. Planning, by nature, is characterized by uncertainty as it is simply a formalization of what one *intends* to happen at some point in the future - and the future is inherently uncertain. It is also defined as the decisions made on how to use current resources, determine what resources are needed, and acquire new resources (Sanders 2017). Due to the uncertainty and lack of definitive information about the future, planning is forecast-driven, and planning is therefore a process of choosing the right actions based on forecasts (Sanders 2017). Control, on the other hand, is a means of managing the potential deviations from the original plan. This may involve revising short-term plans, reallocating resources, or performing unscheduled maintenance on equipment Slack et al. (2013). In general, the importance of control in PPC increases as the time of events approaches (Slack et al. 2013), shown in Figure 6.

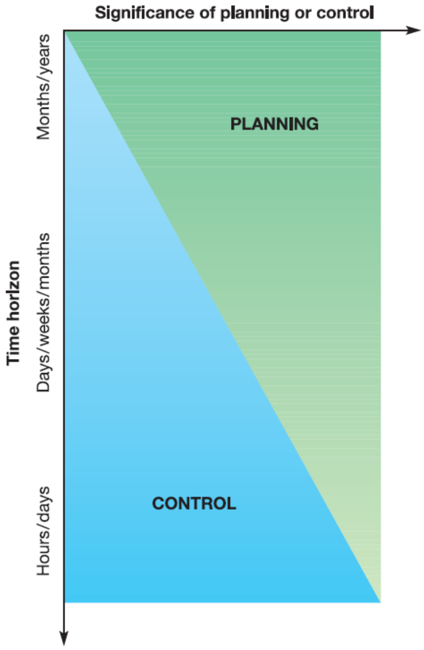

Figure 6: The balance between planning and control activities (Slack et al. 2013)

Kurbel (2016) claims that shortcomings from traditional PPC are due to two main challenges. The first challenge is that the planning of material quantities, capacity loads, and manufacturing dates is performed in separate steps, and there is therefore no innate guarantee that the required number of materials are ready by the due date. This can lead to increased inventory holding costs or cause order deadlines to be missed, leading to manufacturing disruptions and customer dissatisfaction. The second challenge is related to the lack of correspondence between the planned situation and the real-life situation on the shop floor due to production plans not being up-to-date. These discrepancies can be caused by a number of reasons: inaccurate planning assumptions, unforeseen problems occurring such as machine breakdowns, supplier shortages or operator illness, and lack of actual data to update the production plans.

Many of the PPC decisions in today's modern manufacturing environment are still highly reliant on experts' experience (Rahmani, Romsdal, Sgarbossa et al. 2022), and the tasks are often performed manually with the support of spreadsheet solutions (Man and J. O. Strandhagen 2018). This has some particular limitations, especially for tasks such as inventory minimization, factory utilization, and lateness minimization, due to human planners' limited cognitive capabilities to handle tasks with high mathematical complexity (Man and J. O. Strandhagen 2018). Investigating how technological advancements can affect planning decisions is thus crucial, particularly with regard to the balance between manual, experience-based planning, and automated planning (Man, J. W. Strandhagen et al. 2020).

3.1.2 Information Systems and Master Data

While many PPC tasks are performed manually, managing the different levels, activities, and processes of PPC captured in Figure 4 requires information systems that are able to integrate and coordinate the individual components to provide support for cross-functional information sharing (Sagegg and Alfnes 2020). This is commonly achieved through the use of Enterprise Resource Planning (ERP) systems with the support of spreadsheet solutions (Chapman et al. 2017; Man and J. O. Strandhagen 2018). An ERP system contains a database with a collection of pre-built applications that collaborate to support fundamental business activities within an organization. The ERP system is often regarded as the foundation of a company's business software portfolio and frequently works in conjunction with other business software to benefit users and other actors. The integrated database allows for easy access to information and a one-time data entry (Sagegg and Alfnes 2020). There are some fundamental weaknesses in ERP systems. ERP systems are typically difficult to manage and lack the ability to support the real-time decision-making that is required in today's manufacturing (Oluyisola, Bhalla et al. 2022). The systems use system parameters - master data - which do not consider the uncertainties of real-life factors such as unavailability of supply and variations in the shop floor (Koh et al. 2006). Additionally, they are often only able to provide support for initial planning due to the lack of tools that can help update and analyze the proposed plans (Man and J. O. Strandhagen 2018).

To help address some of these limitations and provide more information system tools for PPC, additional software solutions such as Manufacturing Execution System (MES) or Advanced Planning and Scheduling (APS) systems have been developed during the past 20 years (Oluyisola, Bhalla et al. 2022; Öztürk and Ornek 2014).MES are software solutions that directly support the operations on the production floor such as production scheduling, production data collection, production performance analysis, and work center sequencing and optimization (Sagegg and Alfnes 2020). APS on the other hand is more directly involved in the planning process and related tasks. The *APICS Dictionary* describes APS as any computer program that uses advanced mathematical algorithms or logic to perform optimization or simulation on finite capacity scheduling, sourcing, capital planning, resource planning, forecasting, demand management, and others (Blackstone 2013). The systems create a model of the physical planning problem, include an engine that can evaluate different scenarios and consequences of planning actions, and finally visualize the planning results in a user interface (Wiers and Kok 2017). APS has several benefits, including real-time decision-making support. However, there are many challenges regarding how they can be integrated with ERP systems and general implementation, which makes their benefits hard to achieve in practice (Lupeikiene et al. 2014).MES and APS are also described as often being too simplistic and rigid, and even though they can support some levels of real-time decision-making support, they are still limited in their ability to adjust to real-time data (Rahmani, Romsdal, Sgarbossa et al. 2022). They are also often costly and require that employees with specialized competence (Oluyisola 2021).

There are three main data categories for data used by ERP systems; master data, business records, and system-generated transactions (Sagegg and Alfnes 2020). The three categories are all related - the master data is used to create business records, and both of them are further required to create system-generated transactions. But while both the business records and transactions are created through business operations, master data on the other hand is the foundation that identifies and describes all the different business objects (Sagegg and Alfnes 2020). Master data is typically created once, used many times, and is seldom updated or changed (Knolmayer and Röthlin 2006). Due to this static characteristic, the master data used for planning purposes might not accurately represent the current conditions on the shop floor, which might negatively impact the quality of the production planning (Geiger and Reinhart 2016).

There are many different interpretations in the literature of what specific data is included in master data for planning. To exemplify, Sagegg and Alfnes (2020) considers four basic types of data components for master planning in an ERP system, of which two are master data. They are called master data in the form of planning parameters and master data on work centers, respectively. Master data in the form of planning parameters dictate the formulation of master plans and are typically item-specific. These include planning methods, lead times, safety stock levels, planning time fences, and optimal order sizes. Master data on work centers consists of master data on production resources; machines, workers, or even other ERP applications. Capacity calculations of work centers are the primary value, and they provide future load and availability overviews. It defines capacity restraints in production. Master planning also accounts for the BOM of products and thus also considers all the different sub-components or intermediates in production planning. A more in-depth, compiled list of typical master data from scientific and ERP literature is presented in Table 7 in section 4.2.

3.1.3 Planning Quality

One of the primary goals of PPC is to develop a reliable production plan that closely aligns with the actual implementation on the shop floor (Lingitz and Sihn 2020). The term planning quality is frequently used in the industry and literature to gauge the effectiveness of production planning (Lingitz and Sihn 2020). High planning quality is defined by Lingitz and Sihn (2020) as production plans with no deviations or deviations within an acceptable range between the pre-established production plan and the actual execution on the shop floor. These deviations may arise from uncertainties such as inaccurate or incomplete planning data, unforeseeable external events, or inadequate planning and control systems (Lingitz and Sihn 2020). This suggests that planning quality is closely linked to one of the two main challenges to traditional production planning described in Section 3.1. Lucht et al. (2021) also introduced two evaluation parameters to measure the overall performance of production plans: “planning accuracy” and “plan stability”. Planning accuracy refers to the degree of congruence between a planned event and its actual realization, while plan stability measures consistency, early anticipation of future changes, and triggers for additional planning iterations.

The input parameters used for production planning, which are based on planning data, represent the logical foundation of production planning, and thus setting realistic PPC parameters is one of the greatest challenges in PPC (Van Nieuwenhuyse et al. 2011). Wiendahl et al. (2005) explains this by describing errors in planning parameters as one of the eight main “stumbling blocks” of PPC. The parameter errors are divided into two types; *inconsistent* and *unrealistic* parameters (Wiendahl et al. 2005). Inconsistent parameters refer to the event of a discrepancy of parameter values between the different levels of PPC, such as the operational and tactical levels. Unrealistic parameters are those that do not reflect the reality of production (Wiendahl et al. 2005). The accuracy of some of the parameters can be determined by measuring deviations between the actual values measured in production with the ones used in planning (Wiendahl et al. 2005). For this to be achievable, the ability to capture and apply data from the production lines is required.

Continuous updating of plans that can no longer be adhered to due to disruptions or other events can help increase the quality of the plans and counteract the uncertainties of initial production plans. However, this can have some negative impacts on production by creating confusion on the shop floor, adding additional organizational costs due to additional effort needed for planning, and affecting the capacity utilization (Lucht et al. 2021). Therefore, the goal should always be to strive for the highest possible accuracy of plans at every level.

The planning quality is also influenced by the humans involved due to the cognitive strengths and weaknesses they possess (Man and J. O. Strandhagen 2018). The capabilities of human planners are somewhat limited when it comes to complex tasks, as mentioned in Section 3.1. This can impose negative effects on the planning quality, especially if the planner is inadequate at translating the real-life capabilities of the company into production plans.

The quality of the planning processes, and thus also the success of PPC, is highly dependent on the quality of the planning data used, such as the master data (Hees and Reinhart 2015; Jakubiak 2021). As previously mentioned, the static nature of the master data might cause negative effects on the quality due to discrepancies between the situation on the shop floor and the data (Geiger and Reinhart 2016). In their study, (Hees and Reinhart 2015) cites a survey performed by Schuh, Westkämper et al. (2006) which illustrates that planning systems of machine and plant engineering companies suffer from low quality, inaccuracy, and low range in planning data, which directly resulted in a negative influence on the performance of production planning. Further, a study of a medium-sized mechanical engineering enterprise performed by Schuh, Potente et al. (2013), found that deviations between production plans and the actual execution on the shop floor can increase up to 75% if the production planning was performed just three days ahead. This illustrates the importance of companies having updated planning data available; companies should be able to swiftly adapt their production plans to the current situation on the shop floor to avoid consequences such as higher inventory, longer lead times, or low adherence to promised delivery dates (Schuh, Thomas et al. 2014).

Lindström et al. (2023) performed a recent study where the authors mapped different data quality issues which could impose a negative effect on PPC. These data quality issues were visualized in a cause-and-effect diagram, shown in Figure 7.

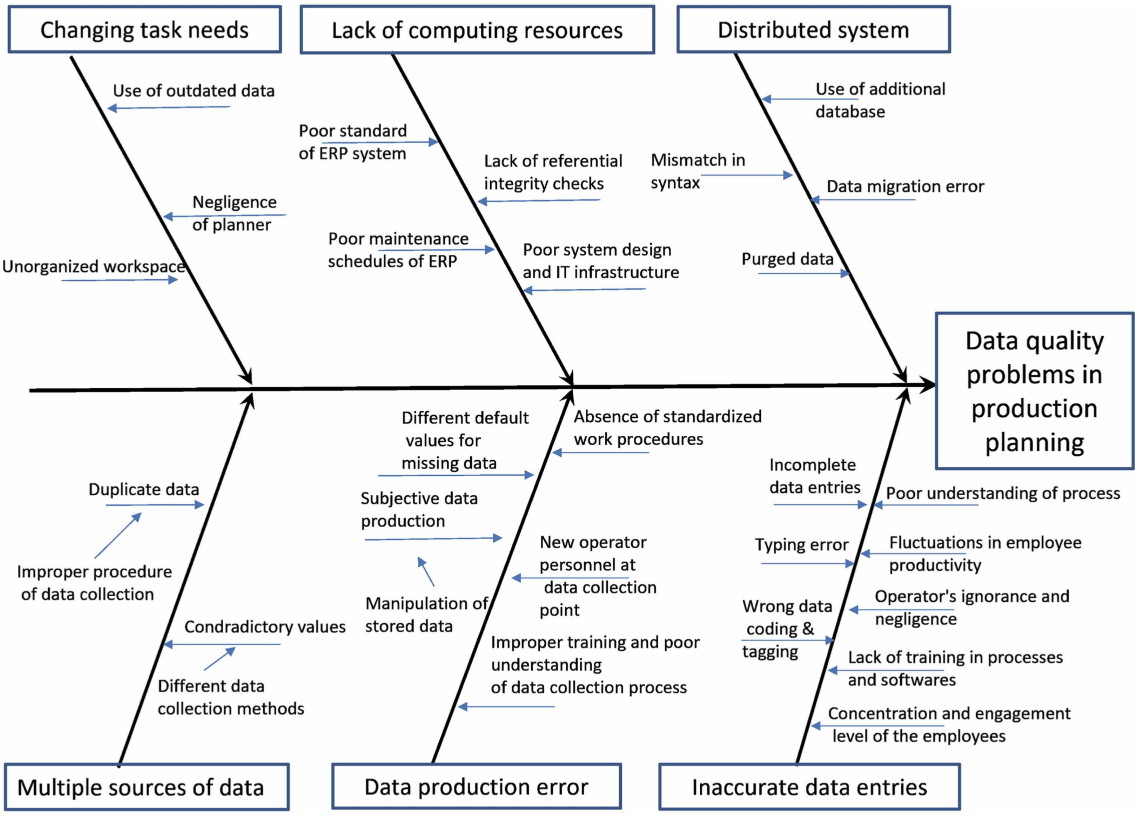

Figure 7: Cause-and-effect diagram showing data quality problems related to sources (Lindström et al. 2023)

The diagram shows that errors from the production planners or other users could impose several prevalent data quality issues in production planning: negligence can cause changing task needs, inexperience can cause data production errors, and ignorance, inexperience, or inattention of the users can cause inaccurate data entries (Lindström et al. 2023). Human errors can also lead to inconsistencies in production feedback data through inaccurate or entirely missing manual feedback (Schuh, Thomas et al. 2014).

3.2 Industry 4.0

Industry 4.0, which originated in Germany in 2011, refers to the fourth industrial revolution. This technological paradigm shift involves the integration of the Internet of Things (IoT), Internet of Services, and Cyber-Physical Systems (CPS) into manufacturing processes (Cañas et al. 2022). The focus of Industry 4.0 is on the development of intelligent procedures and production processes, using technology to address the challenges of rapid product development, flexible production, and complex environments in modern manufacturing (Brettel et al. 2014).

Nosalska et al. (2019) defines Industry 4.0 as "*... a concept of technological and organizational changes along integrated value chains and the development of new business models that are driven by customer needs and the requirements of mass customization and enabled by new technologies, connectivity and the integration of information technology.*" They introduced a framework for defining Industry 4.0, where they distinguish two integral factor groups of Industry 4.0; technology and business. The technological factor group consists of CPS, smart factory, and IoT. Nosalska et al. (2019) argues that the smart factory is the most prominent factor, as they are the physical implementations of Industry 4.0 in the real world. Smart factories are based on intelligent CPS that can "*make autonomous decisions and communicate with each other in real time*", while IoT is described as being an enabler of an interconnected and smart system (Hermann et al. 2016). The business factors include value chain integration, new business models, smart product, and customer position. The most important aspect related to this factor group relates to changes in value chains that are introduced by the exchange of data and communication (Nosalska et al. 2019). To summarize, Industry 4.0 technology serves as an enabler for more interconnected and modern manufacturing, and by connecting people, things, and data, there will be an emergence of new ways of organizing and executing industrial processes (Hermann et al. 2016).

3.2.1 Smart Manufacturing with Industry 4.0

The industry 4.0 revolution has presented the manufacturing industry with opportunities to improve how they operate by creating real-time connections between resources, services, and humans through the application of smart technologies such as IoT, Big Data Analysis (BDA), Artificial Intelligence (AI) and Machine Learning (ML), and CPS (Oluyisola 2021; Rahmani, Romsdal, Sgarbossa et al. 2022; Stock et al. 2018; Zheng et al. 2018). The implementation of Industry 4.0 technologies has become widespread in the manufacturing industry. This can be described as making the manufacturing industry smart (Zheng et al. 2018) and can help address difficulties regarding current demands the manufacturing industry experiences such as improved quality, reduced time to market, and increasingly customized requirements (Zhang et al. 2015).Zheng et al. (2018) developed a conceptual framework of Industry 4.0 smart manufacturing systems, presented in Figure 8. This framework illustrates the common features of Industry 4.0 and potential measures that can be implemented to facilitate a data-driven manufacturing process.

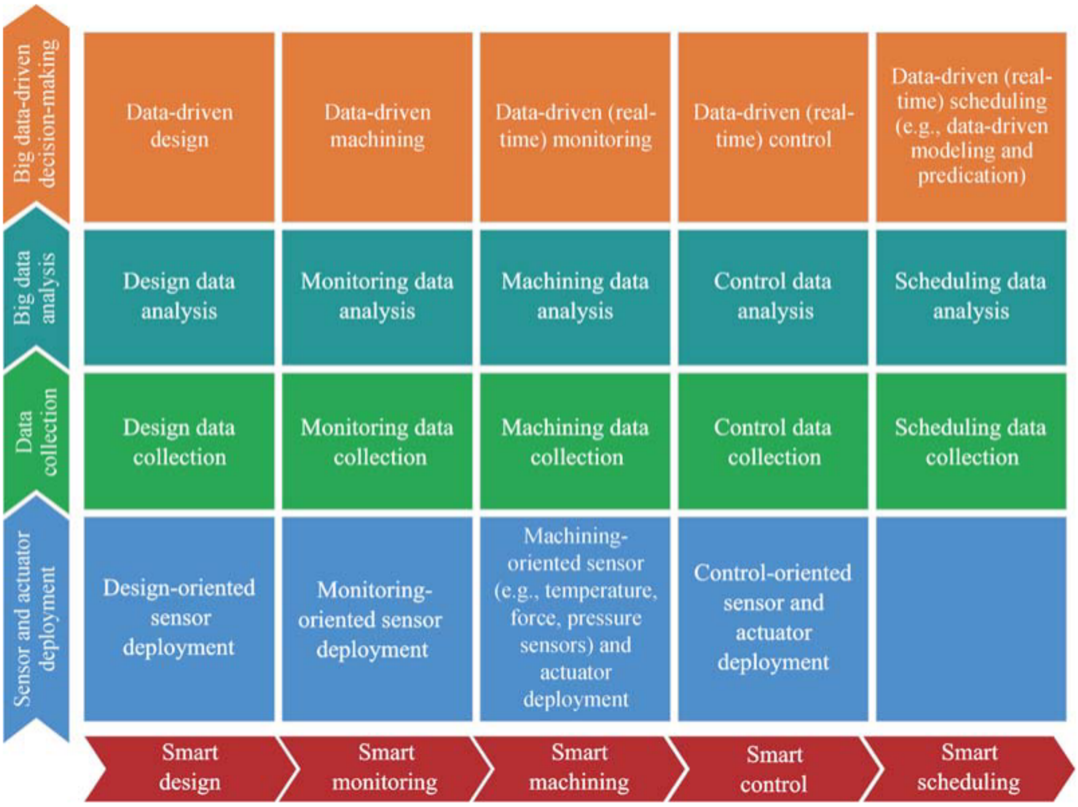

Figure 8: Conceptual Framework of Industry 4.0
Smart Manufacturing Systems (Zheng et al. 2018)

3.2.2 Data Capture from Production

Smart technologies and Industry 4.0 has facilitated the capturing of real-time, updated data from production processes. This type of data is called production feedback data and includes information about the current status of active production jobs, the workstations being used, and the duration of set-up and processing for each process step (Schuh, Thomas et al. 2014). It can also represent information about process times, location data, inventory data, production volumes, and more (Busert and Fay 2018). The data can either be gathered autonomously via sensors through systems such as MES and Production Data Acquisition systems, or it can be gathered through manual reporting from staff on the shop floor (Reuter and Brambring 2016).

ISA95 is an international standard from the International Society of Automation for enterprise-control system integration (ISA 2005). It includes the Automation Pyramid, visualized in Figure 9, which is a hierarchical model that shows the information exchange in five levels. The top level involves business planning and logistics managed by an ERP system. The next level controls manufacturing operations through a MES. The monitoring and supervision level uses Human-Machine Interface (HMI) or Supervisory Control And Data Acquisition (SCADA) systems. Equipment is controlled by the sensing and manipulating level using a Programmable Logic Controller (PLC). Finally, the last level uses sensory and signaling systems to capture data from the shop floor (Åkerman 2018).

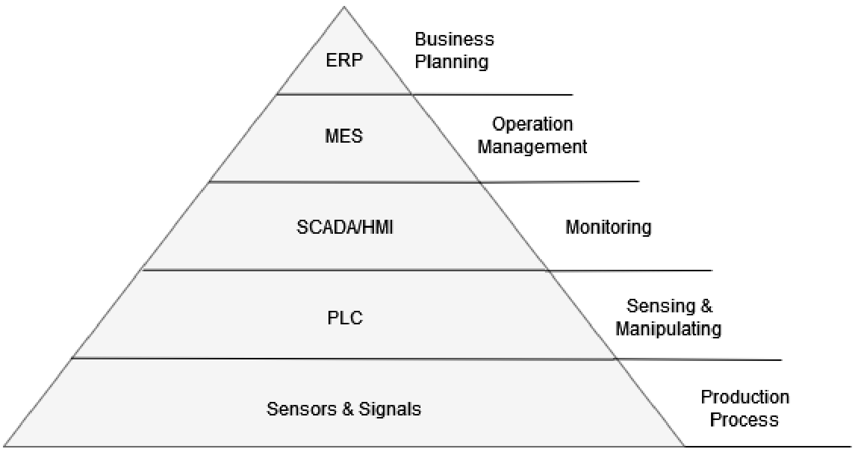

Figure 9: Automation Pyramid (adapted from ISA (2005))

Production feedback data can be used for multiple purposes, including ones shown in Figure 8. For instance, smart monitoring of production is an important aspect of industry 4.0 manufacturing systems (Janak and Hadas 2015). By placing sensors on manufacturing equipment smart monitoring can support operation, maintenance, and scheduling by providing and analyzing production feedback data in real-time, for example, about equipment efficiency, temperature, speed, and breakdowns (Zheng et al. 2018). A typical example of the use of production feedback data for smart monitoring is OEE calculations. OEE is a quantitative metric for measuring the productivity of individual production equipment in manufacturing facilities (Muchiri and Pintelon 2008). OEE typically identifies losses in three aspects of manufacturing; quality, performance, and availability, and the aggregated metric is calculated as a function of these. The losses consume resources but are not value-adding, therefore companies want to minimize these losses and consequently maximize the OEE (Muchiri and Pintelon 2008). Nakajima (1988), who originally introduced the term OEE in 1988, stated that there are six major losses that should be eliminated to increase OEE, shown in Table 5.

Table 5: The six losses of OEE (Nakajima 1988)

Aspect of manufacturing	**Type of loss**
Downtime	• Breakdown losses • Set-up and adjustment losses
Speed (productivity)	• Idling and minor stoppage losses • Reduced speed losses
Quality	• Quality defects and rework losses • Reduced yield losses

Similarly, data-capturing from production lines can be used for smart machining. Machinery with sensors can enable synchronized machining processes by sending real-time data to a cloud-based central system and in-process quality control through self-optimization control systems. (Park and Tran 2014; Zheng et al. 2018; Zhong et al. 2013). For smart production control, CPS can be implemented to achieve adaptive and high-resolution control systems (Stich et al. 2015). Smart scheduling mainly utilizes advanced models and algorithms, often based on ML to analyze production feedback data captured by sensors on the shop floor (Zheng et al. 2018). ML can in short be explained as a computational process that improves itself through experience, and it is a very powerful tool for many application areas, such as pattern recognition (Bishop and Nasrabadi 2006; Jordan and Mitchell 2015). A ML algorithm optimizes itself so that it can not only produce the desired result when given training inputs but it can also generalize to produce the desired result from new, unseen data (El Naqa and Murphy 2015). A drawback with ML analysis is that it requires a large amount of data and high computing resources to process the collected data and convert it to meaningful information (Adi et al. 2020). An example of analysis that can be used for smart scheduling is time series analysis, which aims to understand the mechanism behind an observed series over time and to predict its future values based on its history and related factors (Cryer and Kellet 1991).

An important remark is that the data that can be captured from production lines do not bring any added value on its own; it is with the use of domain-specific knowledge and algorithms that useful information can be extracted (Lingitz, Gallina et al. 2018). And for the data to be useful for operational applications such as PPC, it is essential that the data be reliable, therefore it is necessary to perform quality assessments of the data captured before they are used (Busert and Fay 2018).

3.3 Smart Production Planning and Control

3.3.1 Introduction to Smart PPC

Implementing industry 4.0 technologies into production systems facilitates large-scale data collection from a variety of sources (Rahmani, Romsdal, Sgarbossa et al. 2022). This data can not only assist human decision-making but also enable the automation of planning and control tasks for dynamic and real-time PPC (Rahmani, Romsdal, Sgarbossa et al. 2022). This concept of integrating industry 4.0 technologies with PPC is an emerging concept, which has been aptly named smart PPC. Oluyisola (2021) defines smart PPC as: "*The integration of emerging technologies and capabilities in the industry 4.0 framework with PPC processes to improve the performance of the production system by enabling real-time, data-driven decision-making and continuous learning with input from a more diverse range of sources.*" A systematic literature review was conducted by Bueno et al. (2020) to determine the core Industry 4.0 technologies that support smart PPC. The studies they analyzed that addressed standard planning activities involved the implementation of real-time data collection through IoT, BDA and AI, CPS, and cloud-based manufacturing.

Smart PPC incorporates the three levels from the hierarchical PPC frameworks with the intention of intelligently managing all key processes using data from multiple sources while allowing for human intervention (Oluyisola, Sgarbossa et al. 2020). A mechanism for continuous feedback from the production system should also be incorporated to effectively address any events that may occur (Oluyisola, Sgarbossa et al. 2020).

Smart PPC should, in general, perform better since it will use a huge variety of endogenous data from the production system and external data from its environment (Oluyisola, Sgarbossa et al. 2020), and should thus not exclusively be reliant on the capabilities of the human planner. There remain, however, several challenges to be solved for practitioners in the transition towards smart PPC: 1) the difficulty of agreeing on the value of data, 2) deciding which data to use and share, 3) the cost of technology, 4) the required infrastructure, and 5) the resistance to moving from conventional enterprise systems (Rahmani, Romsdal, Sgarbossa et al. 2022).

Through literature, Rahmani, Romsdal, Sgarbossa et al. (2022) categorized smart PPC into four main elements; real-time data management, dynamic production planning and re-planning, autonomous production (execution) control, and continuous learning. These are briefly explained below.

Real-time Data Management
A real-time data management system tracks, collects, analyzes, and protects data from both intrinsic sources, such as inventory movement and production lines, and extrinsic sources, such as suppliers, in real-time (Saad et al. 2021). For effective use in PPC, real-time technologies must be deployed to relevant objects for data collection. By integrating real-time data into business processes, companies can implement adaptive and responsive planning, scheduling, and execution systems (Arica and Powell 2014). Capabilities to handle the real-time data effectively is a requirement for this to be feasible (Arica and Powell 2014).

Dynamic Production Planning and Re-planning
A dynamic production planning system can quickly respond to unplanned events or changes in production processes (Rahmani, Romsdal, Sgarbossa et al. 2022), allowing companies to adapt to rapid changes in the business environment and customer requirements (Saad et al. 2021). This requires participation from both internal and external parties in the production planning phase, as well as access to real-time data (Saad et al. 2021). Real-time, production feedback data can be used in several ways for dynamic re-planning. For example, real-time events data from the shopfloor can enable model-based scheduling and re-scheduling, and other production feedback data can support dynamic adjustments of planning parameters such as master data. A recent study by Rahmani, Romsdal, Syversen et al. (forthcoming) investigated the relationship between the performance of a production schedule and the accuracy of master data through analysis of production feedback data. Findings from this study indicated that even small deviations in master data accuracy had an impact on the makespan, i.e. the time of a job from start to finish. Advanced models and algorithms are often used to analyze data captured by sensors for real-time re-scheduling (Zheng et al. 2018), and distributed "smart" models utilizing a hierarchical interactive architecture have also been found to be effective for reliable real-time scheduling (Marzband et al. 2016). This suggests a synergy between Smart Manufacturing and Smart PPC, where data generated from Smart Manufacturing can be applied to PPC tasks such as production planning.

Autonomous Production Control
Autonomous production control systems are characterized by decentralized and digitized production control. This means that objects such as machines, pallets, and conveyors can process information and make decisions on their own, without the need for human intervention (Martins et al. 2020). The aim of this approach is to enhance the performance of production systems by allowing individual components to rapidly adapt to changing conditions (Saad et al. 2021). To achieve this, objects must be able to communicate and collaborate with each other in real-time (Pereira and Romero 2017). Additionally, the system must be capable of self-optimization through continuously analyzing the situation and adjusting job assignments to machines as needed (Köchling et al. 2016).

Continuous Learning
Continuous learning involves capturing and converting tacit knowledge and experience from individuals involved in PPC tasks into data that can be used in the production system (Bresler et al. 2020; Oluyisola 2021). Tacit knowledge is a form of implicit knowledge that is relied upon for learning and is invoked in a wide range of intellectual inquiries, including traditional academic subjects and investigations into the nature and transmission of skills and expertise (Gascoigne and Thornton 2014). Many companies have invested heavily in new technologies to automate production processes. However, decisions regarding PPC are still largely based on experience (Bresler et al. 2020; Rahmani, Romsdal, Sgarbossa et al. 2022). Digitizing the processing and relaying of knowledge can improve decision-making in PPC (Rahmani, Romsdal, Sgarbossa et al. 2022).

3.3.2 Assessing the Need for Smart PPC

While Industry 4.0 and Smart PPC provide opportunities to implement new technologies, these are not guaranteed to provide operational improvements regardless of company-specific characteristics and how the technologies are implemented. There are indications from studies that many companies struggle in their efforts to become more data-driven and implement smart operations (Bean and Davenport 2019; Oluyisola 2021). Therefore, the limitations of each technology and the characteristics of the production system and planning environment must thus be taken into account when selecting and implementing smart technologies for a smart PPC system (Oluyisola 2021).

Rahmani, Romsdal, Sgarbossa et al. (2022) provided a framework to assess the need for smart PPC based on a company's planning environment characteristics. The planning environment characteristics assist in determining the PPC contexts where smart PPC is most beneficial by providing an understanding of the setting in which PPC is conducted (Romsdal et al. 2021). Planning environment characteristics can be categorized into three main categories; product, demand, and manufacturing process (Jonsson and Mattsson 2003), and they provide an understanding of the environment in which a company performs its PPC tasks. In the framework, variables from the three main categories of planning environments are linked with the need for smart PPC, where the "need" is understood as the expected degree smart PPC improves PPC performance. The framework has a scale assigned for each variable, where if a company has the variable at its most challenging setting, this is associated with a high need for smart PPC. The scale is from one to three stars (*) for each variable indicating the importance of smart PPC for each; one star means that no considerable PPC improvements are expected, whereas three stars indicate that the variable is currently at its least favorable, and thus has high expected benefit from smart PPC. A table with all the variables, their definition, and how the scale is defined per variable is shown in Table 6.

Analyzing a company's planning environment characteristics and their relationship to smart PPC can provide insight into the potential benefits of revising the company's PPC operations. This can help assess the importance of introducing smart PPC and its expected impact on efficiency and responsiveness. The framework can also assist in identifying appropriate PPC methods and making informed design decisions related to the supply chain (Rahmani, Romsdal, Sgarbossa et al. 2022).

Table 6: Framework linking planning environment characteristics with the need for smart PPC (Rahmani, Romsdal, Sgarbossa et al. 2022)

Category	**Variable**	**Definition**	**Need for smart PPC**		
			*	**	***
Product	Product complexity	Number of levels in the BOM, number of items on each level, and interrelatedness of product components	Low	Medium	High
	Product variety	Number of product variants	Low	Medium	High
	Product life cycle	Stage and length of a product's life cycle from launch to termination	Long	Medium	Short
	Product volume and variability	Volume related to market demand and variability of volume	Low	Medium	High
Market	Delivery lead time	The time window between the placement of customer order until its delivery to the customer	Long	Medium	Short
	Delivery lead time variability	Predictability and stability of demand	Low	Medium	High
	Demand variability	Predictability and stability of demand	Low	Medium	High
	Ability to keep inventory	Perishability of raw materials, intermediates, and finished goods inventories	High	Medium	Low
Process	Process lead time	The time between starting and terminating a process	Short	Medium	Long
	Process flexibility	Ability to change product volume and produce different types of products	High	Medium	Low
	Process complexity	Number of processes and interrelatedness of processes	Low	Medium	High
	Supply variability	Predictability and stability of supply	Low	Medium	High

3.3.3 Implementation of a Smart PPC System

By analyzing a company's planning environment characteristics and their relationship to smart PPC, it is possible to gain a better understanding of whether the company characteristics synergize with smart PPC solutions. While identifying the potential benefits of introducing smart PPC is a crucial first step, it is not sufficient for successful implementation. To effectively implement a smart PPC system, it is also important to design and develop the smart PPC in a careful manner. In this regard, Oluyisola (2021) proposed a set of principles and considerations that should be considered:

- The design of a smart PPC system should consider the characteristics of the planning environment. This highlights a common problem: expensive systems that require managers to alter production systems to fit the PPC system, rather than the PPC system being designed to integrate with the existing production system.
- The architecture of the PPC system should be both scalable and flexible, allowing it to adapt to changes in production system parameters, which may not be accurately predictable or controllable in advance. Such parameters may include demand volumes, demand patterns, and product portfolios.
- The implementation plan for a smart PPC system should include an incubation period during which data can be collected for analysis or for training machine learning models if such data is not already available. This would also provide an opportunity to test the accuracy of machine learning models and account for estimation errors in PPC activities.

Despite the potential benefits of implementing new technologies, there remain economic risks associated with making significant changes to operational processes. Adopting an incremental approach to the implementation of new technologies can mitigate investment risks and facilitate the gradual transition of the company towards a smart system (Schuh, Anderl et al. 2017). This is particularly relevant for small and medium-sized enterprises with limited research and development budgets (Oluyisola 2021).

3.4 Research Opportunities

The presentation of the theoretical background highlights some challenges and opportunities related to smart PPC and new application areas. Planning quality is directly affected by the accuracy of the master data used. Master data is updated infrequently, which can lead to discrepancies between the actual situation on the shop floor and the master data.

Industry 4.0 has facilitated large-scale data collection from various sources, and opportunities have emerged for companies to revamp and optimize operations through the introduction of new technologies. Smart technologies can collect production feedback data and can allow for the data to be processed and applied in real-time. Most studies that address the use of production feedback data for PPC are typically on a conceptual level or apply the data for control or scheduling purposes, but there is an untapped potential for applying production feedback data in tactical production planning.

The addition of smart PPC systems has been the subject of extensive research in recent years. However, studies have indicated that companies face challenges in adopting new technologies and smart operations. While the potential benefits of utilizing data from digitalized production systems for smart PPC purposes are promoted in academia, actual adoption by the industry remains limited. There is also a lack of empirical research demonstrating the improvements that can be achieved through the use of smart PPC.

There is thus an opportunity for more research in the field of applying production feedback data in tactical production planning as a smart PPC solution. Production feedback data can provide accurate information on the same aspects that some master data represents. Analyzing production feedback data and incorporating this into master data can provide a better representation of the real-life situation on the shop floor. The accuracy of the master data will therefore increase accordingly. In cases where the situation on the shop floor varies over time or with other factors that can be captured by production feedback data, some master data should be dynamically determined to ensure that it remains up-to-date and accurate.

4 Concept for the Application of Production Feedback Data in Tactical Production Planning

In this section, the concept for the application of production feedback data is developed and presented. The concept is developed from existing theories introduced in Section 3 and its purpose is to improve the quality of production plans by providing a better representation of the situation on the shop floor in tactical production plans.

4.1 Introduction to Concept

As mentioned in Section 3.1, Oluyisola, Sgarbossa et al. (2020) adapted the established PPC framework of Vollmann et al. (2005) and introduced feedback loops to better capture the real-life situation witnessed in production systems. As the feedback loops are particularly prevalent and significant in real-life situations between the operational and tactical levels (Bonney 2000), the framework from Oluyisola, Sgarbossa et al. (2020) has a particularly detailed focus on these levels. The purpose of this framework, shown in Figure 4 was to research the potential of improving the performance of the production system performance through the application of dynamic data gathered directly from the production system. In this framework, the lower-level planning processes are merely conceptually linked with the higher levels through feedback loops on performance. In particular, there are feedback loops on the system, capacity use, material use, and purchasing performance. However, the framework does not define *what* type of data would be relevant, nor does it depict *how* the data from the lower levels can be applied in higher-level processes. This lack of specification from this and the other established PPC frameworks in literature and academia inspired the work in this section, which resulted in the formulation of a concept, introduced later.

The literature study revealed two key matters regarding the application of master data used for planning, including for the tactical production level i.e. the MRP and CRP processes: 1) the quality of the production planning is highly dependent on the master data used, and 2) since the master data used in planning is typically static, there are possibly large deviations between the current state of the shop floor and the planning process. To better reflect the real-life situation and thus potentially improve the quality of the material and capacity planning, production feedback data could be utilized.

Hence, it is proposed that production feedback data could be utilized to analyze and update the master data to facilitate a more accurate representation of the real-life situation, thereby potentially enhancing the quality of MRP and CRP. To illustrate this, the framework of (Oluyisola, Sgarbossa et al. 2020) is adapted and expanded to demonstrate how such data should be fed into master data rather than directly into the tactical-level planning processes. This approach better reflects the necessity for processing, aggregating, and analyzing production feedback data prior to its utilization in tactical planning processes. The proposed concept is shown in Figure 10

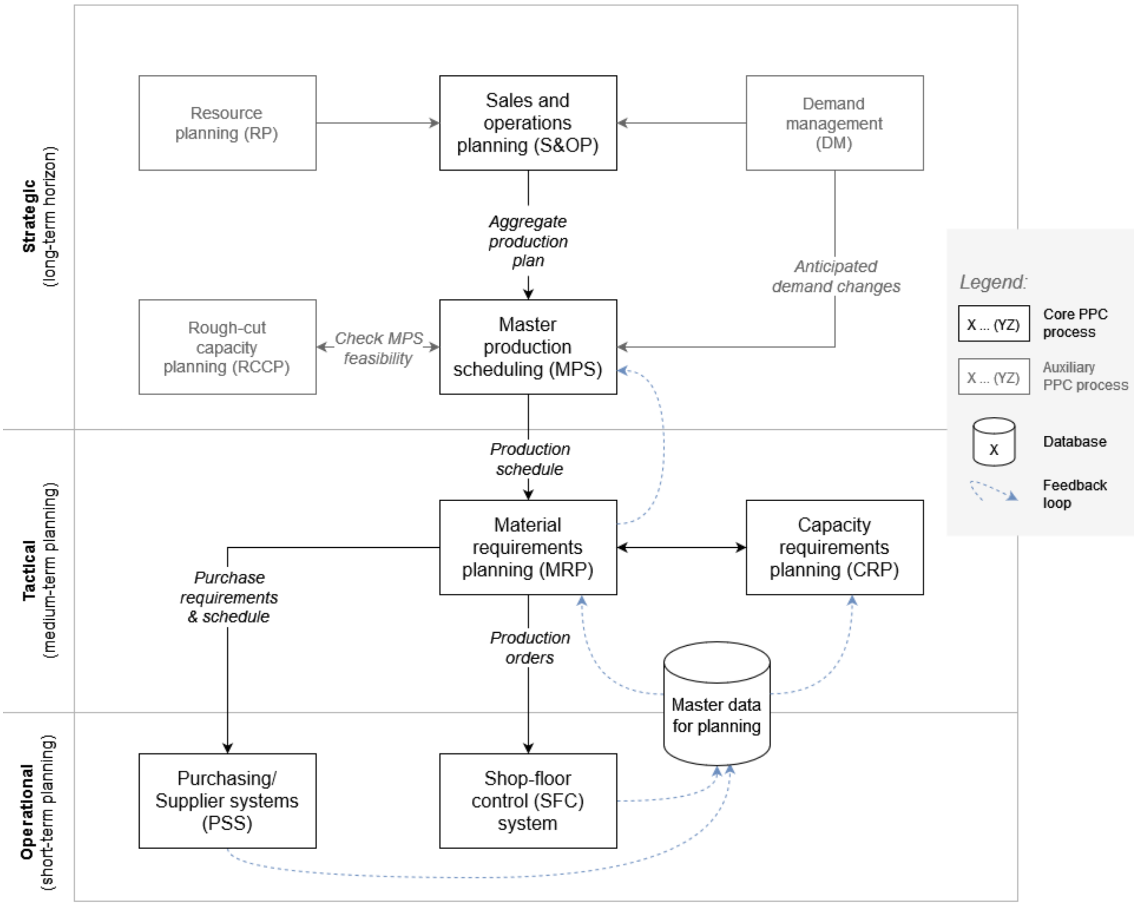

Figure 10: Conceptual model for the application of production feedback data in tactical production planning (based on Oluyisola, Sgarbossa et al. (2020))

In the conceptual model, the feedback from the SFC and PSS is fed into the master data used for the tactical planning processes instead of directly into the processes as performance loops. By taking production feedback data into account when determining the values of the master data, the accuracy of master data can be increased, leading to a better representation of the shop floor's state in tactical planning processes. This is further elaborated below.

4.2 Linking Production Feedback Data to Master Data

The conceptual model in Figure 10 illustrated how production feedback data can be fed into master data for the tactical planning level through feedback loops. The production feedback data increases the data foundation used for assessing the master data values, so the decision-makers are provided with planning data of increased accuracy. As highlighted in section 3.4, some master data should be dynamic if analysis of the production feedback data indicates that the values change over time or with other measurable factors. Therefore, it is suggested that companies conduct an analysis of production feedback data to ascertain which elements of master data should remain static and which should be dynamically determined. For the master data which is deemed static, the production feedback data can be used to validate or optimize the values.

To reflect this, a new conceptual model was created. The model, shown in Figure 11 was adapted from Figure 5, to show at a higher level of detail how production feedback data can be incorporated into the MRP process. The original model included static information lead times, parts lists, and product structures. This complies with the definition of master data and is thus interpreted as such. For the new conceptual model, the two master data components represent the incorporation of production feedback data in the decision-making process: 1) to validate the accuracy of static master data, and 2) to dynamically determine variable master data. Both the static and dynamic master data are then employed in the computation of net requirements.

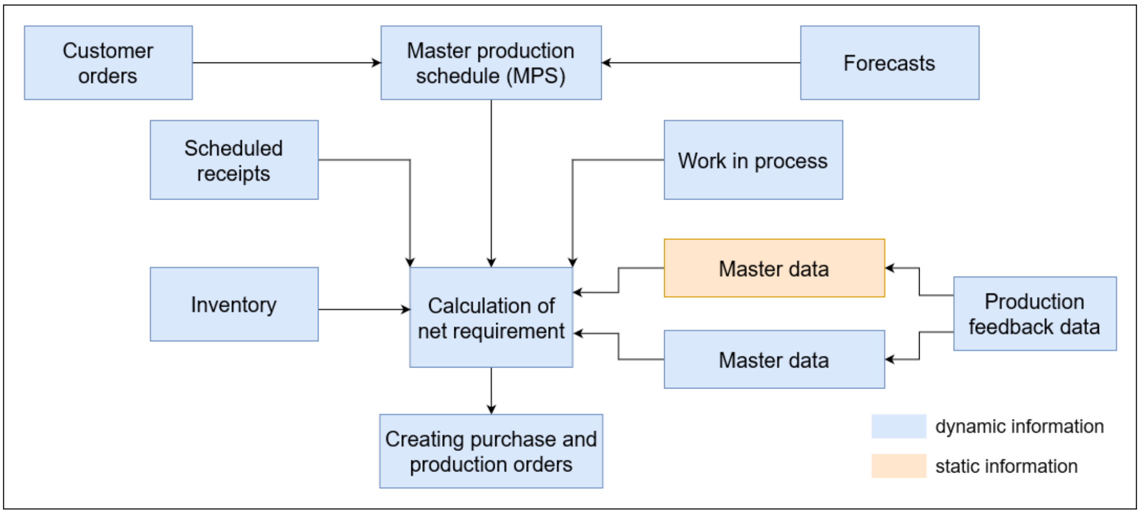

Figure 11: Conceptual model for the application of production feedback data into MRP (based on J. O. Strandhagen et al. (2021))

This conceptual model challenges the traditional view of master data as static values that are set once and seldom changed thereafter. By instead allowing certain master data to be dynamic, production plans can better reflect the situation on the shop floor and thus have increased accuracy.

An example to illustrate how master data can be analyzed through production feedback data and differentiated between static and dynamic follows. Consider the BOM's quantity coefficient; the required quantity of an intermediate or sub-component to produce a finished product (Kurbel 2016). If historical feedback data indicates that the quantity remains constant over time, across different batch sizes and machines, it can be designated as a static parameter in the master data. Conversely, if the data reveals variability in the quantity, it may be advantageous for planners to dynamically determine its value using real-time data from the production line, and incorporate it as an input for the planning process for the upcoming period.

A list of prevalent master data from scientific and ERP literature, primarily from Jakubiak (2021), Kurbel (2016), and Sagegg and Alfnes (2020), was compiled. The master data, shown in Table 7, is separated into five main categories: part or component, product structure, production line or work center, routings, and operating facility. The part or component master data refers to attributes of all parts of the end product, including all sub-components needed and the end product itself (Kurbel 2016). Product master data show which parts make up a product and the relationship between them (Kurbel 2016). Resource data considers the tools and machines used to produce parts where data can be generated and captured (Kurbel 2016). Routings refer to the list of operations required for the manufacturing of a produced part (Kurbel 2016). Finally, operating facility master data provides insights into the manufacturing facilities and other workplaces (Kurbel 2016). There are also some other noteworthy definitions: *scrap rate* is an expression for the percentage of units that are scrapped after or during production due to defects or other quality issues (Chiu et al. 2007). The scrap rate is identified per material, product, and resource. *Processing time* refers to the duration needed to manufacture a product, whereas *changeover time* denotes the time necessary to prepare a resource for transitioning from the completion of a previous batch to the commencement of a new one (Mali and Inamdar 2012).

Table 7: Combined list of master data from the literature (based on Jakubiak (2021), Kurbel (2016), and Sagegg and Alfnes (2020)).

Category	**Master data for planning**	
1. Part or component	• Part type, name, number, and description • Physical characteristics data • Quality characteristics data • Replenishment time data • Basic information including variant code, basic material, drawing number, form identification	• Scrap factor data - part: 1) quantity dependent 2) setup dependent • Organizational data • Validity data
2. Product	• BOM and where-used lists • Quantity coefficient • Structure type data • Information regarding the parts, including upper and lower-part ID and variant code	• Scrap factor data - product • Organizational data • Validity data
3. Resource	• Operation number and description • Necessary operator skills data • Operation times data including: 1) Processing time per unit 2) Setup time 3) Required factors in lead time reduction	• Capacity • Average scrap rate production line • Organizational data • Validity data
4. Routings	• Routing type and number • Parts data, including the part that routing refers to and processed parts in the operations of the routing	• Organizational data • Validity data • Drawing reference data
5. Operating facility	• Operating facility number, location, name, and/or description • Cost center and machine cost rate • Technical data • Capacity	• Worker data • Usage/performance rates • Average setup time • Maintenance data • Organizational data

After having compiled a general list of master data, it was subsequently studied to identify the most relevant master data for tactical planning, i.e. MRP and CRP. Two main exclusion criteria were established: 1) master data without a clear link to tactical planning, and 2) master data without a clear link to production operations. Additionally, master data related to routings were excluded as the scope of the research was confined to fixed routings, though this master data could be relevant in some other production environments. Operating facility data were also excluded because the data is of too high a level to be relevant for tactical planning.

Next, the list of master data relevant to tactical planning was used as inspiration to identify production feedback data that could be linked to each of the master data types. For each master data type, relevant production feedback data were identified and formulas were developed to calculate the master data based on the production feedback data. Examples of application areas were also identified. The result is presented in Table 8.

Table 8: Overview of master data for tactical planning with relevant production feedback data

Category	**Master data for planning**	**Relevant production feedback data**	**Formulas and examples of application in tactical planning**
Part or component	Scrap rate per part	- Number of parts consumed per batch - Number of scrapped parts per batch	- Formula: number of scrapped parts / number of parts consumed - Used in calculation of net requirement for parts
Product	Quantity coefficient per product	- Number of input units or amount of raw materials consumed per batch - Number of units produced per batch	- Formula: number of input units / number of units producted - Used to determine the number of parts or input units in the BOM
	Scrap rate per product	- Number of units producted per batch - Number of scrapped units per batch	- Formula: number of scrapped units / number of units produced - Used in calculation of gross requirement for units
Resource	Processing time per unit	- Start and end time per batch (i.e. production run) - Number of units produced per batch - Start and end times of stops (within batch)	- Formula: batch time ((end time - start time) - total stop time (end time - start time, per stop)) / number of produced units - Used in tactical planning
	Changeover time per resource	- End time of previous batch and start time of next batch	- Formula: sum of time for activities between batches - Used in CRP and scheduling
	Scrap rate per resource	- Number of units produced per resource - Number of scrapped units per resource	- Formula: number of scrapped units per resource / number of units produced per resource - Used in calculation of CRP and scheduling

The first column lists the categories of master data, including parts or components, products, and resources. The second column lists the specific master data for planning that can be improved using production feedback data. The third column provides examples of relevant production feedback data that can be used to improve the accuracy of the master data. The fourth column presents formulas and examples of how this production feedback data can be applied in tactical planning processes.

For example, the first row shows that an accurate scrap rate per part value can be found through production feedback data on the number of parts consumed and parts scrapped per batch. The formula for calculating the scrap rate is provided, and it can be used in the calculation of net requirements for parts. Similarly, other rows show how production feedback data on input units, scrapped units, processing times, changeover times, and other factors can be used to improve the accuracy of other master data for planning.

A key note is that the overview of master data does not contain capacity, despite it being a key parameter used in production planning. This is because the capacity, in practice, is determined by a combination of the company's subjective decisions, such as the length and number of shifts each day and the number of employees, rather than being an objective value that can be captured directly from the production system.

4.3 Method for Application of Concept

The final contribution of this section is a proposed step-by-step method for the application of the introduced concept for companies. A method is a goal-oriented and systematic approach to resolving theoretical and practical challenges. This means that it provides rules and instructions for achieving goals or solving problems through a structured process (Braun et al. 2005). A method is considered valuable support for improving business processes as it provides directions, rules, and structured developing activities that are useful for the act of improvement (Zellner 2011).

The method took inspiration from the control method methodology (Alfnes and J. O. Strandhagen 2000). There are four main steps in the proposed method: mapping, analysis, design, and implementation. The steps are designed to be carried out cyclically or in parallel instead of in a strict, linear sequence. This approach enables ongoing feedback and refinement during the implementation of the concept, and for example, allows findings from later stages to inform and support additional data collection and analysis in earlier stages. A prerequisite for the successful implementation of the method is cross-functional involvement and collaboration in the company, including production managers and planners, IT, shop floor operators, forecasting, etc. The steps are described below with regard to objectives, general activities, and the desired outcomes of each.

Step 1 - Mapping
The objective of step 1 is to map and collect data to construct a systematic representation and thus develop a comprehensive understanding of the company's production processes, ongoing operations, and planning and control mechanisms. This also includes obtaining a detailed overview of the company's inherent data collection and its capabilities. The

mapping should identify production data that is presently being collected, as well as the methods, sources, and frequency of data collection. The company should also compile a list of production data that are not currently being collected but could be beneficial for improving master data. In conjunction with the mapping of production data, a complete list of the master data utilized for planning should be established.

Step 2 - Analysis
The objective of the analysis phase is to analyze the data collected in step 1. In this step, the company should: 1) identify which production data is relevant to use as feedback into master data for tactical planning, and 2) determine which master data for planning should be static and which should be dynamic. The lists of master data for planning and production feedback data from the first step serve as the foundation for the analyses. First, master data lacking a clear link to production planning should be excluded. Then, for each type of master data, relevant production feedback data should be identified and links should be established (e.g. Table 8). The result is a list of the links between master data and production feedback data. After the relevant production feedback data with links to master data has been identified, it should be ascertained whether each master data value should be static or dynamically determined in each planning cycle. For this, historical production data should be analyzed to establish if or how the data fluctuates over time and whether it is random or can be accurately predicted. Data that does not appear to fluctuate over time can be classified as static parameters in the master data, and the analyses can be employed to validate the values used, for example, in the ERP system. Data that is found to vary over time should be classified as dynamic parameters, where historical production feedback data is analyzed to accurately determine values in each planning cycle.

Step 3 - Design
The objective for this phase is to determine, standardize, and describe how production feedback data should be implemented in production planning in the future. This includes defining what production feedback data to collect, how often and from where it should be collected, and how it should be processed. Moreover, production planners and other stakeholders involved with the production feedback data should be provided with documentation and user guides on how to use this data in planning. This includes instructions on how often static master data should be analyzed or validated, the analyses required to classify static or dynamic input parameters in each planning process, and the thresholds that necessitate a reevaluation of the classification of the planning parameters. Additionally, it should be established how the production feedback data should be cleaned, and, if needed, how it should be combined with other data prior to its use for planning.

Step 4 - Implementation
The final step of the method is the implementation of the solution designed in step 3. To ensure a successful implementation, an implementation plan should be created. The implementation step should involve the staff directly associated with the designed solution, such as production managers and planners, shop floor operators, and IT staff. In addition to these, other stakeholders may also be involved. For example, senior management may need to provide support and resources for the implementation, while external

consultants or vendors may be utilized for additional expertise or technical assistance for the installation of production feedback data capturing systems or data management. An implementation plan should be created. The new solution should be implemented into the company's planning processes, the company's ERP system, and other information systems or tools used by the production planners. Overall, a successful implementation will require careful planning, effective communication and collaboration among stakeholders, and a commitment to continuous improvement as the solution is integrated into the company's operations.

Summary of Method

The four steps are all important for effectively implementing the concept in a company. Step 1 helps the company gain a comprehensive understanding of its internal processes and data collection capabilities. This step involves identifying what data is currently being collected and what additional data could be collected and also used for planning purposes. Step 2 provides insight into the relationship between the situation on the shop floor and the master data, and whether the master data are set optimally. It involves analyzing the collected data to determine which production data is relevant for planning and whether master data should be static or dynamic. This step is important for establishing links between production feedback data and master data and for determining accurate and representative master data values. Step 3 provides guidelines on how production feedback data should be implemented in production planning through standardized procedures. This includes defining what data to collect, how often it should be collected, and how it should be processed. This step helps ensure that production planners and other stakeholders have the necessary documentation to start using production feedback data in planning. Finally, Step 4 involves the actual implementation of the solution. This step requires careful planning, effective communication and collaboration among stakeholders, and a commitment to continuous improvement as the solution is integrated into the company's operations. This step is very important to ensure that the solution is effectively integrated into the company's operations.

These steps provide a comprehensive and structured approach to including production feedback data in tactical planning. The method helps ensure that the solution is based on a thorough understanding of the company's operations and that it is tailored to its specific needs. This will increase the likelihood of successful implementation and thus also the potential for improving planning quality.

5 Case Study: Brynild AS

The case study is presented in this section. First, a general introduction to the company is given, before descriptions of its production processes, PPC, and data capture capabilities are presented. Thereafter, an analysis of their planning environment characteristics, PPC, and their data capture is conducted. The section is finalized with illustrative implementation of the method in 4.3, providing suggestions for how Brynild can implement the concept of applying production feedback data in their tactical planning in the future.

5.1 Introduction to Brynild

Brynild is a family-owned confectionery manufacturer based in Norway. The company produces a range of products, including nuts, sugar confectionery, pastilles, and chocolate, which are sold under several different brands, including Den Lille Nøttefabrikken, St. Michael, Brynild, Dent, and Minde Sjokolade.

The company's headquarters and primary production facilities are located in Fredrikstad, Norway, where they have been since the consolidation of seven distributed production facilities into a single centralized location in 2010. In 2021, Brynild also acquired a smaller factory in Årjäng, Sweden. The company employs approximately 230 people and generates annual revenue of around NOK900 million.

Brynild's primary market is Norway, where approximately 90% of its products are sold. The remaining 10% are sold to other Nordic countries. After production at the Fredrikstad facilities, Brynild's products are transported by truck to a finished goods warehouse in Vestby, which is owned by a third-party company. From there, the products are distributed to Brynild's customers, all of which are large Norwegian wholesalers who supply one or more retail chains. In total, Brynild's products are sold to consumers at approximately 6000 sales points, the majority of which are grocery stores.

5.1.1 Market

Norwegian wholesalers impose strict requirements for delivery times and service levels on their suppliers, typically demanding a service level of 98% and delivery lead times of just two to three days. Given the production and logistics lead times involved, it is essential for Brynild to maintain sufficiently high finished goods inventories to meet order requirements. Brynild categorizes its market into four types: new product introductions, regular demand, campaign demand, and seasonal demand:

New Product Introductions For new product introductions, sales must be anticipated in advance. When a new product is introduced to the market, expected demand is forecasted based on previous experience with similar product introductions. A safety stock of approximately two months' supply is maintained to ensure that the supply chain is saturated with the new product.

Regular Demand Regular demand is forecasted using a module in Brynild's ERP system called SAP APO. This module takes into account historical data and other available information to generate a monthly forecast for each Stock-Keeping Unit (SKU), i.e. each product variant.

Campaign Demand Campaign demand arises from product-specific promotional campaigns agreed upon between Brynild and retail chains. These campaigns have a delivery lead time of four to six weeks.

Seasonal Demand There is seasonal demand for uniquely seasonal products and selected regular products increases during Halloween, Christmas, Easter, and summer seasons. This demand is planned four months in advance, alongside regular demand, and is based on historical data. Production of seasonal products begins three to four months before the season to accommodate the significant increase in demand during these periods.

5.1.2 Production Processes

Brynild operates separate production lines and machines for each of its three main product categories: nuts, sugar confectionery, and chocolate. Some products may move between the chocolate and nuts sections for coating purposes, or from sugar confectionery to chocolate. However, no other types of products are allowed into the sugar confectionery section due to concerns about allergen contamination.

There are a total of 25 production lines across the three main product categories, with approximately half of the machines dedicated to processing and the other half to packaging. The production machines generally have high setup times, and the majority of material flow is handled manually. Brynild is currently focused on automating more of its material handling processes and has acquired several collaborative robots and automated guided vehicles to reduce the amount of manual labor required. The production and packaging processes for nuts are described in greater detail in the following parts.

Characteristics of the Nut Production

There are approximately 200 different inputs, i.e. raw materials and packaging materials, and 80 different variants of finished products in nut production. Nuts are characterized by high raw material costs and moderately high perishability. Nut production is mainly organized into four main integrated process steps: separating, cooking (frying or dry roasting), mixing, and packaging. There are no *mandatory* buffer zones between the intermediates, meaning the intermediates could go directly from one step to the next. However, this is not necessarily the case, and intermediates may be stored on the shop floor while waiting for the next process to be ready. All finished intermediates should be packaged on the same day, but they may be stored for up to four days before packaging if needed. Generally, this gives a process lead time for nuts of approximately one to four days until they are ready to be shipped to the finished goods warehouse.

The first three steps are briefly described below, while the packaging is explained in more detail subsequently. The process is also visualized in Figure 12:

Separating The first process is to separate the nuts from potential foreign objects. This process is performed in a vibration separator machine. There are two vibration separators, one of which is allocated to chili nuts.

Frying After the nuts are clean, they can proceed to be fried. There are three machines for frying nuts with variable drum sizes and capacities, one of which is allocated specifically for chili nuts. The chili nuts are first manually coated in flour and water and then fried before spices are added. The largest of the two remaining machines has approximately twice the capacity of the smaller one, and peanuts are only fried in this due to quicker contamination of the frying oil from peanuts compared to other nut types. This allows for higher utilization of the smaller fryer. All nuts are fried in vegetable oil, and salt may be added to non-chili nuts during this step. The coating of chili nuts is the only manual step in this process. There is one active operator for each of the fryers in use.

Dry Roasting Nuts may be dry roasted instead of fried. Dry roasting is performed for unsalted nuts. There is one machine and one operator for the dry roasting process.

Mixing The mixing process is used for nut products which consist of several different intermediates such as salted or unsalted nuts, fruits, and chocolate-coated nuts. There are up to three operators for the mixing process; some intermediates, such as raisins, come in cartons. These cartons have to be manually opened by an operator and then the raisins have to be fed through a special machine which ensures that the intermediates do not stick together. In addition, one operator is always required for the mixing process itself.

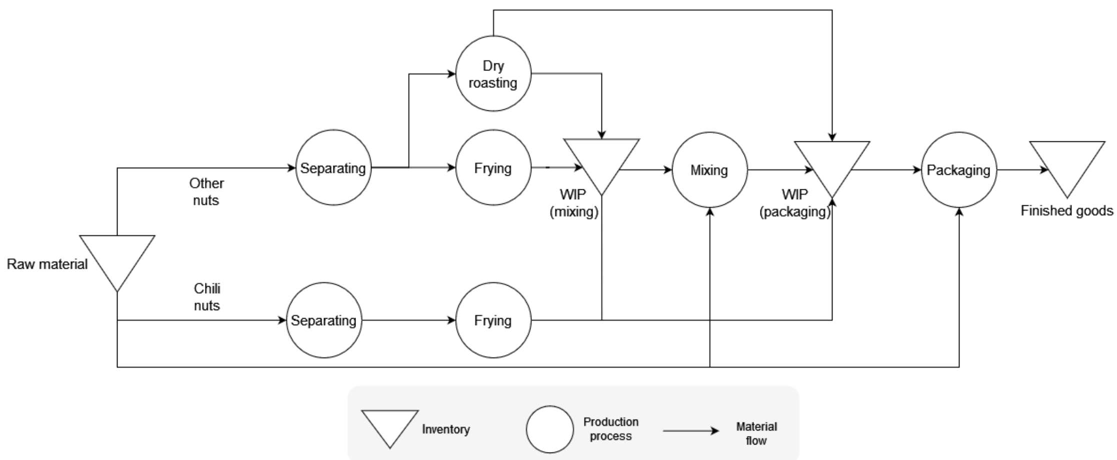

Figure 12: Production process

Characteristics of the Nuts Packaging

The packaging process is of particular interest, as it is where the current infrastructure for capturing production feedback data is installed. Additionally, the production planner initially plans for the output from the packaging line and then backtracks the plans through the processing stage to ensure that the correct output is achieved at each stage of production.

After nuts have undergone the relevant processing steps, they are prepared for packaging and stored as WIP. For a few specific SKU, the products are not processed before being packaged. The nut packaging station comprises five different packaging lines, each designed for a specific type of primary packaging: Bosch, HDG1, Duplex, Beger, and Løsvekt. A table showing these five packaging lines and their corresponding primary packaging types is presented in Table 9.

There are four primary packaging types in general: pillow bags, zipper bags, boxes, and beakers with lids. Boxes are used for pick-and-mix products, whose contents are removed from their primary packaging in stores and placed on specialized shelves or counters where customers can select the products and quantities they want. The remaining three primary packaging types are also consumer units. Pillow bags and boxes are available in several sizes. All nut bags are flushed for oxygen and filled with nitrogen to extend their shelf life, as oxidation significantly reduces the shelf life of nut products. The interior of the nut bags is also laminated with a special coating to ensure that they are completely airtight.

Table 9: Table of packaging lines with corresponding packaging types (Syversen 2022)

Nut packaging line	**Type of primary packaging**
Bosch	Small pillow bags
Duplex	Small and medium-sized zipper bags
HDG1	Medium and large sized zipper bags
Løsvekt	2,5 kg boxes with pick and mix
Beger	Plastic beakers with lid

The nut packaging process proceeds as follows. Final intermediates are first weighed and packaged in primary packaging before undergoing quality control to ensure that the products meet the required standards. Quality control is performed automatically and includes checks of the weight of the primary packaging units and an X-ray scan for foreign objects. Units that fail quality control are removed from the line, while the nuts contained are later returned into circulation to reduce waste.

After passing quality control, the products are sent through a box maker, where they are packed into boxes, their secondary packaging units, which serve as the final distribution packs. These boxes are standardized in size to ensure that they can be stacked on pallets. Boxes containing pick-and-mix products are not further packaged but proceed directly to palletizing. Finally, the pallets are wrapped in plastic and prepared for shipment to the finished goods warehouse. An image of a nut packaging line with its various machines is shown in Figure 13.

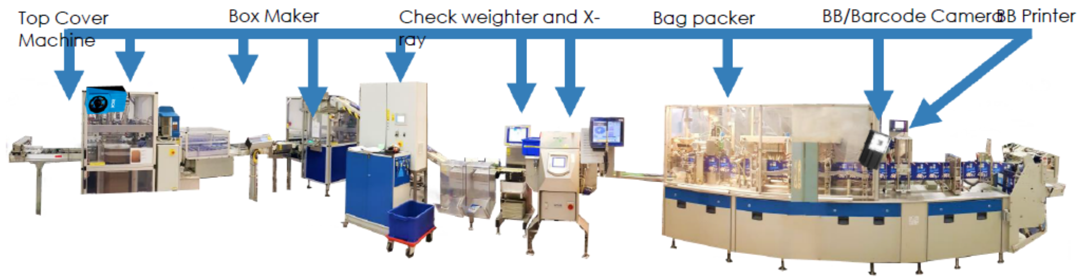

Figure 13: Image of a nut packaging line
Image provided by Brynild

5.2 Production Planning and Control and Data Capture in Brynild

5.2.1 Production Planning and Control

Brynild primarily uses a make-to-stock approach for its standard products, as maintaining an inventory buffer is typically necessary to achieve the desired service level. For promotional campaigns, a make-to-order approach is used. Nut production planning is performed by a single production planner, who creates the production plans manually using Excel and with some support from the company's SAP ERP system. The production planner's primary responsibilities include developing weekly production plans and monitoring progress against these plans. The weekly production plans include the amount to be produced per shift. Planning is primarily performed in cyclic iterations, with some planning activities occurring on specific weekdays and others being performed continuously.

Planning Activities

The foundation of Brynild's planning process is demand forecasting, which is performed using the APO module in the company's ERP system. This is an automated process that uses data from the previous 12 months to generate forecasts for up to 12 months ahead. The initial monthly forecasts are then split into weekly forecasts by the ERP system. The nut production planner considers forecasts for up to 26 weeks ahead when planning production. The planner manually adjusts the weekly forecasts to account for planned new product launches, campaigns, seasonal products, and confirmed orders. The resulting output is an MPS that specifies weekly production orders in terms of the number of distribution packs (DPAKs) for all SKU for the next 26 weeks.

In conjunction with the MPS, the production planner also performs continuous rough-cut capacity planning to smooth production over the coming weeks. There are generally nine shifts available each week for processing all nuts except chili nuts, which have seven shifts available due to the need for more frequent replacement of the frying oil due to more contamination. The production planner plans for only these shifts for nut production to avoid overestimating weekly capacity, but extra night shifts can be added if necessary to meet demand. Capacity is calculated based on an estimate of the average output per shift per SKU, determined through trial and error. The total output can vary significantly between operators and from shift to shift, so the average is considered sufficiently accurate for planning purposes. As of today, Brynild rarely experiences capacity-related issues, and there are no particular capacity bottlenecks in the nut factory that must be accounted for, however, the chocolate coating station located in the chocolate production section can be a bottleneck in infrequent cases.

Brynild has a set safety stock for all SKUs, and the MPS is continuously updated to ensure that the stock levels exceed the set safety stock. The values for safety stock are established manually for each individual SKU. SKUs that are strictly produced by make-to-order do not have a set safety stock.

The MPS is of higher levels of detail the closer they get to the present day. According to the production planner, the plans are generally detailed for the first four weeks, and then the level of precision is gradually decreased. He typically plans for about 10 weeks ahead, while the later week's inputs are an estimate to make sure that they do not run into capacity issues that require capacity leveling. The later weeks may, for instance, also be considered for capacity leveling due to production stopping for three weeks in the summer.

The weekly production schedule is the plan with the highest level of detail. This is constructed manually for the following week and is finalized every Wednesday. These schedules specify the shifts and packaging lines for each SKU, with one SKU assigned to each shift per line. The schedules are updated as needed to account for any disruptions that may arise. Disruptions that require re-planning are typically caused by processing failures that affect the quality or quantity of products produced. Material shortages are rare, as these are generally well-managed earlier in the MPS process.

After finalizing the weekly production schedule, the planner prints and sends the daily production orders to the factory floor. At the end of each shift, digital shift reports are submitted from each packaging line to the factory system, i.e. Brynild's MES. These reports are generally not used for further planning unless significant anomalies are detected. The production planner's final responsibility is to manage raw material requirements and stock levels. Raw material requirements for weekly production orders are obtained from the company's ERP system and forwarded to the purchasing department as needed. An overview of the planning activities and their associated planning horizons is presented in Table 10.

Table 10: Table including all the planning activities for the nut production planner

Planning activity	**Planning Horizon**	**When**	**Manual/ ERP**
Master production scheduling	26 weeks	Continually	ERP/manual
Rough-cut capacity planning	10 weeks	Continually	Manual
Weekly production schedule	1 day - 1 week	Every Wednesday	Manual
Production re-planning	1 week	When required	Manual
Daily production order	1 day	Daily	Manual
Daily shift report	1 day	Each shift	Manual
Raw material requirements	1 Day	Continually	Manually

The production planner is also responsible for monitoring the effectiveness and performance of the production schedule. However, it is noteworthy that there are no established procedures for verifying the accuracy of initial production plans in relation to actual output. This verification could be accomplished by analyzing data from daily plans and computing an estimated margin of error. The production planner for nuts believes that, in general, the plans are fairly accurate, but that their accuracy may be somewhat reduced for chili nuts.

An observation related to these PPC activities is that Brynild does not specifically classify any of their activities specifically as MRP and CRP. This does not mean that they do not perform tactical planning, however. The tactical planning is rather performed through the MPS and the weekly production scheduling.

Planning Data

There are set-up and changeover times for both processing and packaging machines. Machines must be washed between the production of products that contain salt, those that do not, and chili nuts. Theoretically, the most efficient scheduling approach would be to produce unsalted, salted, and chili-coated nuts in that order. However, this may not always be possible due to factors such as demand or inventory levels. While the changeover matrix used is not complex, minimizing the total number of changeovers is an important consideration. Machine set-up times are approximately 30 minutes, while changeover times are around four hours in total.

Another significant factor in nut production planning is the shelf life of products. Production output must be leveled according to demand to ensure that there are at least 100 days remaining until the expiry date for each product type. This is achieved by assigning specific weights to product types based on their overall shelf life. For one packaging line, HDG1, no weights are assigned to products due to their similar shelf lives. The BOM must also be taken into account, as sufficient quantities of each intermediate must be available for the mixing process. In addition, processing speed is considered when planning production. Processing speeds, or the capacity per shift, are set as product-specific constants and rarely change. These speeds have been estimated based on average production output and efficiency on specific lines. Some products have penalized production outputs to account for additional changeover times that may be required. The production planner stated that machine speeds are not changed lightly due to the coordination required with operators.

Since the planning process is conducted manually, the majority of the master data used for constructing the weekly production schedule and the MPS are set in Excel and not in the ERP system. The function, however, is similar to how it would function in an ERP system. The master data in the ERP system is primarily used for forecasting and capacity leveling for the later weeks in the MPS. In addition, some of the master data in the ERP system are merely approximate values, since they are just used for forecasting and general capacity leveling in the future.

5.2.2 Data Capture

Production feedback data is continuously captured from sensory systems installed on all five nut packaging lines and forwarded to their MES. This system for capturing production feedback data has been operational for the past two years, although some packaging lines had the systems installed at a later date. As a result, the system has already processed and stored a substantial amount of data. All the production feedback data is stored in SQL databases.

Each packaging line is equipped with an operator panel HMI, allowing operators to select the products to be packaged during each shift. The MES retrieves all relevant product data, which is then stored alongside the data acquired from the sensory systems. This enables a detailed analysis of how different product types behave on the packaging line. The system captures operational data such as machine speed, alarm types, operator events, and breaks. The MES is also connected to Brynild's ERP system and a web application for data visualization. An overview of the data acquisition system is depicted in Figure Figure 14.

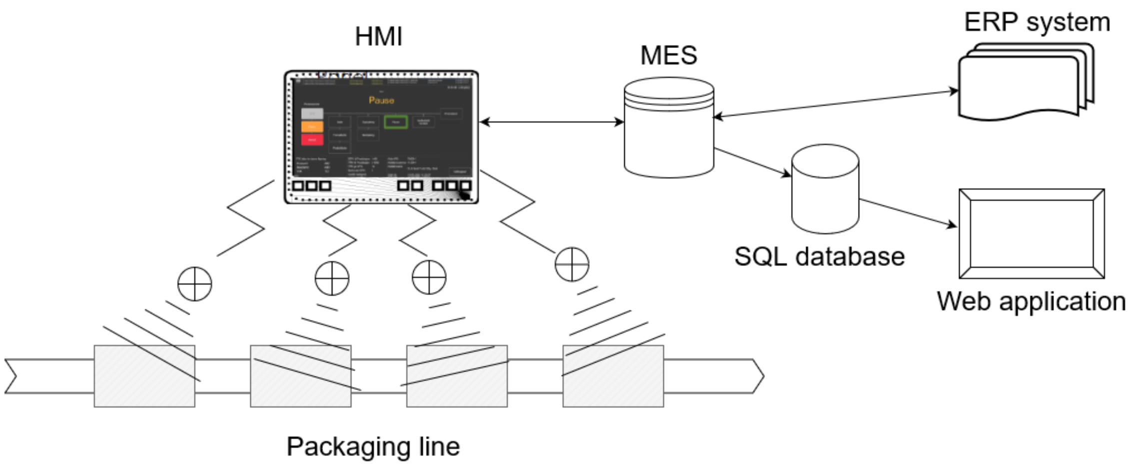

Figure 14: Visualization of the data capturing system
Adapted from Brynild

5.2.3 Current Applications of Data

The data acquired by the system is currently utilized for advanced OEE calculations and alarm classifications during the packaging process. These calculations take into account the operational data from each machine on the packaging lines, and the parameters used in the calculations can be adjusted at any time. This allows for fine-tuning of the measures to produce precise and representative OEE values. For example, breaks are currently factored into the OEE calculations as a negative value, whereas they were not previously considered. The OEE values are also differentiated by individual products, allowing for a more detailed analysis that takes into account the different packaging lines and products. This information is visualized through easily interpretable statistics in the web application. The equations used for their OEE calculations are:

$$OEE = \frac{Actual\, production}{Maximum\, possible\, production} = Availability \cdot Speed \cdot Quality$$

$$\frac{Productive\, time}{Batch\, time} = Availability$$

$$\frac{Amount\, produced}{Productive\, time} = Average\, speed,$$

$$\frac{Average\, speed}{Set\, speed} = Speed$$

$$1 - \frac{Waste}{Amount\, produced} = Quality$$

The web application also generates comprehensive shift reports, which provide detailed information about the data captured on the packaging line during each shift. These reports include information about the difference between the actual and preset packaging speeds, alarms, and breakdowns, as well as data about the physical inputs, outputs, and general properties of the packaging shifts.

5.3 Analysis of Current Situation

A qualitative analysis of Brynild's PPC was conducted. The analysis was performed with the intention of identifying the potential for improving their PPC operations through smart PPC, challenges regarding their current operations, and other uses for the production feedback data they collect.

5.3.1 Planning Environment Characteristics

To evaluate and categorize the PPC, the framework from Rahmani, Romsdal, Sgarbossa et al. (2022) was applied. This provides a structured overview of the operational characteristics and an assessment of the need for smart PPC solutions. The result is shown Table 11 and explained below.

For the product category, there are over 200 different inputs and packaging types and over 80 different variants of finished products. Hence, both the product complexity and product variety variables can be classified as high. Regarding the product life cycle, most standard products experience a long life cycle over several years or decades. But Brynild also introduces a lot of new products to the market, many of which have very short life cycles. Therefore the overall product life cycle can be characterized as medium length. Lastly, product volumes and variability is high due to mass production and high variety in product volume from seasonal demand and promotional campaigns.

Table 11: Brynild's planning environment characteristics with needs for smart PPC

Category	**Variable**	**Characteristics**	**Need for smart PPC**		
			*	**	***
Product	Product complexity	High number of inputs and finished products	Low	Medium	**High**
	Product variety	High variety of products and packaging types	Low	Medium	**High**
	Product life cycle	Long life cycle for most standard products, short for many new product introductions	Long	**Medium**	Short
	Product volume and variability	High product volumes and volume variability	Low	Medium	**High**
Market	Delivery lead time	Two to three days delivery of products	Long	Medium	**Short**
	Delivery lead time variability	Low variability in the delivery lead time	**Low**	Medium	High
	Demand variability	High degree of seasonality and many promotional activities gives high variability in demand.	Low	Medium	**High**
	Ability to keep inventory	Moderately high perishability of raw materials and intermediates.	High	Medium	**Low**
Process	Process lead time	Medium process lead time	Short	**Medium**	Long
	Process flexibility	Limited capacity and fixed process steps	High	**Medium**	Low
	Process complexity	Four main, integrated processing steps. Medium number of different routings.	Low	**Medium**	High
	Supply variability	There can be some variability with the supply of nut products.	Low	**Medium**	High

For the market category, delivery lead time can be classified as short due to their customers demanding a delivery lead time of two to three days. The variability of this lead time is thus also low. Demand variability is high also due to the high degree of seasonality of many promotional campaigns. Nuts have, like many other food products, high perishability compared to other product categories. Thus, the ability to keep inventory is low.

For the process category, the process lead time is between one and four days, which can be classified as medium. There are rarely capacity-related issues, but the processing steps and routings are fixed, hence the process flexibility is classified as medium. The process complexity is medium due to a medium number of different routings between four main, integrated processing steps. Finally, the supply variability is also classified as medium due to some variability from nut suppliers.

The assessment shows that many of the characteristics of the nut production correspond with a high need for smart PPC; seven variables are in the least favorable setting, four in the medium setting, and the final variable is currently in the most favorable setting. If scores are assigned from one to three for each variable where one is given for variables with the most favorable setting, two for medium, and three for the least favorable setting, the nut production planning environment scores a cumulative 29 out of a maximum of 36. This indicates that Brynild may gain significantly from implementing smart PPC solutions.

5.3.2 Analysis of the PPC

Based on the literature study it is evident that the quality of production plans is important, and that it is highly reliant on the quality of master data. Currently, Brynild does not experience any capacity-related restrictions related to the production of nuts. This allows their current simple, manual approach to production planning. The master data utilized for production planning is static, with defined values that remain constant between shifts or weeks. The values are established through trial and error without validation of their accuracy. Furthermore, the planning is performed mostly periodically while their demand is continuous. As a result, the PPC does not accurately reflect the current situation of the shop floor. While these characteristics simplify the planning processes, they also impede the overall accuracy and do not allow for any optimizations of nut production planning as it currently is performed. And given the high cost of nuts as raw materials and strict service-level requirements, Brynild is, as of now, also reliant on accurate production plans to minimize waste and thus reduce overall production costs, and reach customer requirements.

In case of potential future needs for increased capacity, the inaccuracy of the production planning process may represent a bottleneck, inhibiting the full utilization of the production line capacity. As such, methods for optimizing planning procedures are appropriate, and alongside the planning environment characteristics indicate that Brynild should continue exploring options regarding smart PPC.

5.3.3 Opportunities From the Data Capture

Brynild is successfully utilizing some of the data they are capturing in their daily operations through the OEE calculations. These calculations provide insight into the effectiveness of the packaging machines, offering opportunities for future optimization on the packaging lines. However, as acknowledged by Brynild themselves, they are not currently realizing the full potential of the data they are capturing. Additionally, the large amounts of data they have collected over the past two years remain largely unused.

The data collection is currently limited to the nut packaging lines, which means that data-driven optimization of other processing steps is not achievable as is. By implementing data capture infrastructure across all processing stages, Brynild could conduct analyses and optimizations of material flow and get a similar overview of the efficiency and utilization of all the processes through OEE calculations.

One potential application for production feedback data that has been proposed is the utilization of data for improved machine alarm classification. By analyzing factors such as the machine on which the alarm occurred, the error code, and the product being packaged at the time, it may be possible to determine the underlying causes of alarms. This could increase the uptime of Brynild's packaging lines by reducing the frequency of stops and minimizing disruptions to operations. Another potential application is the use of production feedback data for preventative maintenance, which Brynild is currently collecting data to improve through machine learning.

Finally, there is the opportunity of using the production feedback data to improve the accuracy of production planning through master data. The data can be used to classify master data, or used to validate or optimize the static values according to the introduced concept. This is explored further in the next section.

5.4 Proposals for the Application of Production Feedback Data in Tactical Production Planning in Brynild

Following is a proposed design for the application of the concept presented in Section 4 for Brynild. This design follows the four-step method, and aims to address three primary challenges identified in the analysis of the case company: 1) the usage of simple planning procedures, 2) the inability to fully utilize the production feedback data currently being collected, and, 3) they only capture data from the nut packaging line, which does not present a realistic depiction of the situation on the shop floor. The goal is to illustrate how Brynild can start incrementally adopting smart PPC solutions to support their challenging planning environment characteristics.

5.4.1 Step 1 - Mapping

Objective: map and collect data to construct a systematic representation and thus develop a comprehensive understanding of Brynild's production processes, ongoing operations, and PPC mechanisms.

Summary of Findings
The findings presented in Section 5 thus far are the results of the preliminary mapping of Brynild. Below is a summary of some key observations:

- Separating, cooking, mixing, and packaging are the four main production processing steps.
- Production feedback data is only captured in the packaging step.
- There is one production planner responsible for planning, and the planning can be categorized as manual and experience-based. The planner uses Excel to construct the production plans with some support from the ERP system.
- Brynild does not perform MRP & CRP specifically, the tactical planning is a combination of the weekly production schedule and the nearest weeks in the MPS.
- The way Brynild currently performs PPC can only work because they have excess capacity.
- The master data is set through trial and error, and there are master data set in both Excel and the ERP system.
- There are no established procedures to verify the accuracy of production plans.

Table 12: Master data for planning

Excel	ERP
• Safety stock • Changeover times • Processing speed (capacity per shift) • BOM	• Takt time • Production time • Batch size

Production Feedback Data
The production feedback data records Brynild currently collects and utilizes for OEE calculations are collected every time the packing machine starts and stops, meaning there is generally one record of data per batch. These records include the following variables: **report id**, **oee**, **availability**, **speed**, **quality**, **waste**, **startUnix**, **endUnix**, **date**, **start time batch**, **stop time batch**, **total duration**, **time for breaks**, **time for stops**, **article number**, **article name**, **article weight**, **amount produced**, and **input volume (in weight)**.

Table 8 in Section 4 presented master data for planning and linked each to examples of relevant production feedback data. These production feedback data are thus used as a basis for the suggested master data for Brynild to collect. By comparing this list to the list of production feedback data variables above, it is apparent that the types of data Brynild is collecting are relevant for the application in tactical production planning. However, since the four main production processes are considered integrated, they each have to be considered in unison when constructing the production plans. Since the data is only collected from the nut packaging line, analyses of the current data are not sufficient to provide a holistic depiction of the situation on the shop floor. Therefore, Brynild will have to install additional sensory systems and start collecting more data before the concept of applying production feedback data in tactical production planning can be fully utilized.

Master data
With an overview of the relevant operations and production feedback data established, the final part of the mapping step is compiling a list of master data used for production planning. As previously mentioned, Brynild has master data both in Excel and in the ERP system. The master data in Excel is primarily used for constructing the MPS and weekly production schedules. There are specific master data for each SKU. A selection of master data used for planning purposes is presented in Table 12.

To supplement these, Brynild could consider incorporating master data such as scrap rates and quantity coefficients into their planning process, as they are collecting the required data for making such calculations.

5.4.2 Step 2 - Analysis

Objective: analyze the data collected in step 1 and: 1) identify which production data is relevant to use as feedback into master data for planning, and 2) provide examples of how to determine which master data should be static and which should be dynamic.

Brynild does not currently collect the necessary data to perform the desired data analysis for this study. This step will therefore only focus on outlining the steps required to perform such an analysis. It will provide examples of how production feedback data can be analyzed and utilized to determine which master data should be dynamic and which should be static.

Relevant Production Feedback Data

In order to determine which production feedback data Brynild captures that can be analyzed to determine master data values, Table 8 from Section 4.2, which presents links between typical master data and production feedback data, is used as a reference. Any production feedback data that is not represented in this table is excluded from consideration. This leaves **start time batch, stop time batch, total duration, time for breaks, time for stops, amount produced,** and **input volume (in weight)** as the relevant production feedback data from this data set.

Determining Static or Dynamic Master Data

The process of determining if master data should be classified as static or dynamic can involve analyzing historical production data through time series analysis and investigating whether the values change over time. If production feedback data that is linked to a specific master data remains relatively constant over time, the master data should be classified as static. However, if the production feedback data varies over time or in response to other factors, the master data should be considered dynamic. The variations have to be predictable and patterns need to be discovered through analysis of the production feedback data, or through other available data such as which operator was responsible for each batch. As mentioned in Section 3.2.2, ML can be a powerful tool for such pattern recognition, and it can also be useful for finding correlations between master data and different production feedback data. However, ML requires large amounts of data to train on. Therefore, Brynild can not properly apply ML unless data has been captured over a longer period of time.

To illustrate how master data can be determined as static or dynamic in Brynild, the example from Section 4.2 regarding the quantity coefficient of the BOM can be continued. Suppose Brynild is producing a nut product consisting of a single nut raw material which is processed in several steps. The final product should consist of 100 nuts. If analysis of the production feedback data on the raw material input volume and the number of finished products produced per batch show that the resulting quantity coefficient is mostly constant, with small and few variations between different batch sizes and machines, the master data should be classified as static. The predominant value should then be set as the master data value to ensure accurate planning. This is visualized in Figure 15. This shows an example of this analysis showing a possible time series over a period of 80 batches. Most of the values are approximately 111, i.e. there needs to be an input of 111 nut raw material units to produce an output of 100, the required number of nuts per one finished product. The variations are generally small, with very few larger deviations. In this case, the master data quantity coefficient value could be set to 111, ensuring that the master data is accurate and facilitating high planning quality.

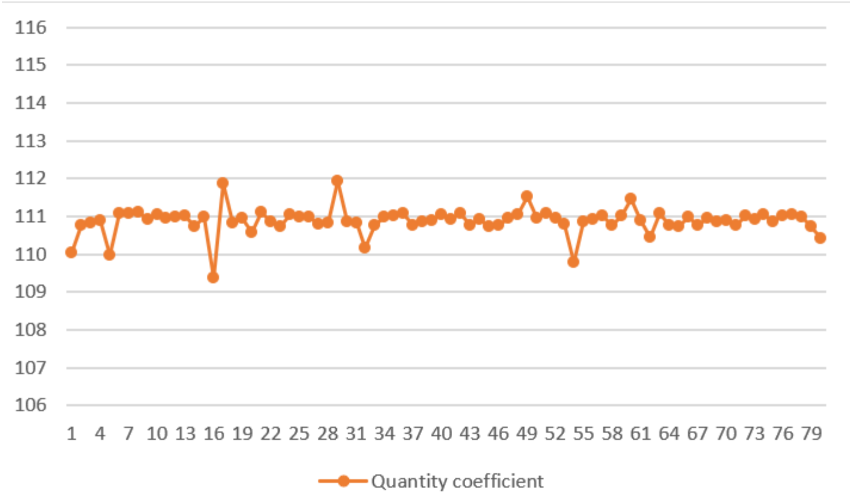

Figure 15: Example of a time series analysis indicating a static quantity coefficient

An analysis of the same production feedback data as the example above could also show a large variation in the quantity coefficient over time. This can indicate that the master data should be dynamic. Further analysis is then required to determine which factors on the shop floor, if measurable, lead to the variations. The master data would have to be analyzed in relation to other production feedback data to find correlations. If a pattern is found, then production feedback data can be analyzed in real-time for each planning cycle to dynamically determine the optimal value of the quantity coefficient. If no pattern is found, an estimated value will have to suffice. An example analysis of this, showing a potential dynamic quantity coefficient, is shown in Figure 16. In this figure, the quantity coefficient varies between 109 and 115. Given the high cost of raw nut materials, such significant variations in the quantity coefficient could result in large deviations in the production plans from the actual situation when using an average value for planning, which leads to substantial expenses over time. As such, it is crucial to ensure the accuracy of the master data to mitigate these costs.

For master data determined to be static, other analyses may be required to validate or optimize the values. For instance, suppose the initial analysis indicates that the processing speed master data should be static. In Brynild, the processing speed is expressed in terms of the amount produced per batch. The objective of this analysis is to identify the optimal processing time per unit that maximizes total production output by balancing the trade-off between increased waste at higher speeds and reduced base output at lower speeds.

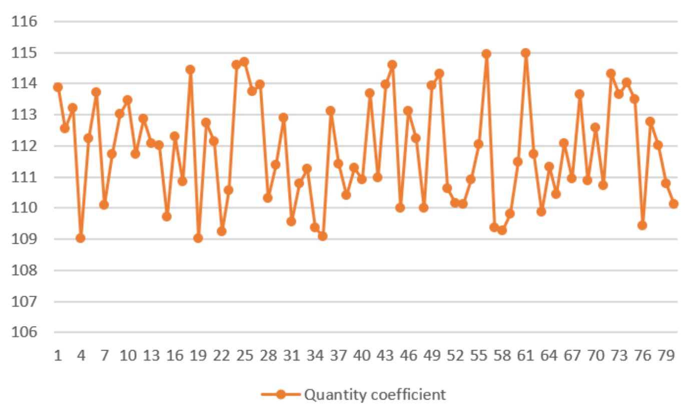

Figure 16: Example of a time series analysis indicating a dynamic quantity coefficient

5.4.3 Step 3 - Design

Objective: determine, standardize, and describe how production feedback data should be implemented in production planning in the future.

Implementing a new production planning system at Brynild may be disruptive to current operations if the system is not designed and developed carefully (Oluyisola 2021). The literature study also found that many companies generally struggle in the implementation of smart PPC. As such, it is important to carefully design the new system with consideration for the principles of implementing a smart PPC system, as outlined in Oluyisola (2021). To summarize, the system should be designed to integrate with the existing production system and the system should be scalable and flexible.

Data Capture

Brynild will have to install additional sensory systems to enable the required analysis for the application of feedback data into production planning. A recommendation is to install similar sensory systems as they already have on the packaging lines, as this will simplify integration with the existing systems and provide opportunities for standardization of the data. It is also recommended to maintain the practice of collecting one data record per batch, as this facilitates the acquisition of the necessary feedback data for analysis as mentioned.

There are several options available for Brynild to consider regarding the capture of data. One approach involves collecting data solely from essential data capture points. These points are defined as those without which no meaningful analysis can be conducted. Two such essential points exist in the processing: at the beginning of separation and at the ending of packaging, i.e. at the start and end of the processing. Analysis of production feedback data from these points can be utilized for the determination of static and dynamic master data about total processing time and the scrap rate per product. An alternative approach involves capturing data from the beginning and end of each processing step which can allow for analysis that gives a holistic depiction of the situation in each processing step. These secondary data capture points can collect data that allows for the analysis of additional master data regarding the processing time and scrap rate per resource, in addition to providing valuable information on the distribution of non-value and value-added time in the production process. There could also be added feedback points at the beginning of each set-up or changeover of the machines to facilitate optimizations of changeover time master data.

Figure 17 shows the possible data capture points from the four processing steps. The figure presents a simplified version of the processing stages and data capture for enhanced clarity. In practice, the system would require data capture from each processing machine, including six machines for separating, cooking, and mixing and five packaging lines capturing production feedback data. The system would initially collect data from the sensors on the data capture points to the HMI before transmitting it to the MES and then to the SQL database before processing and integration into the master data.

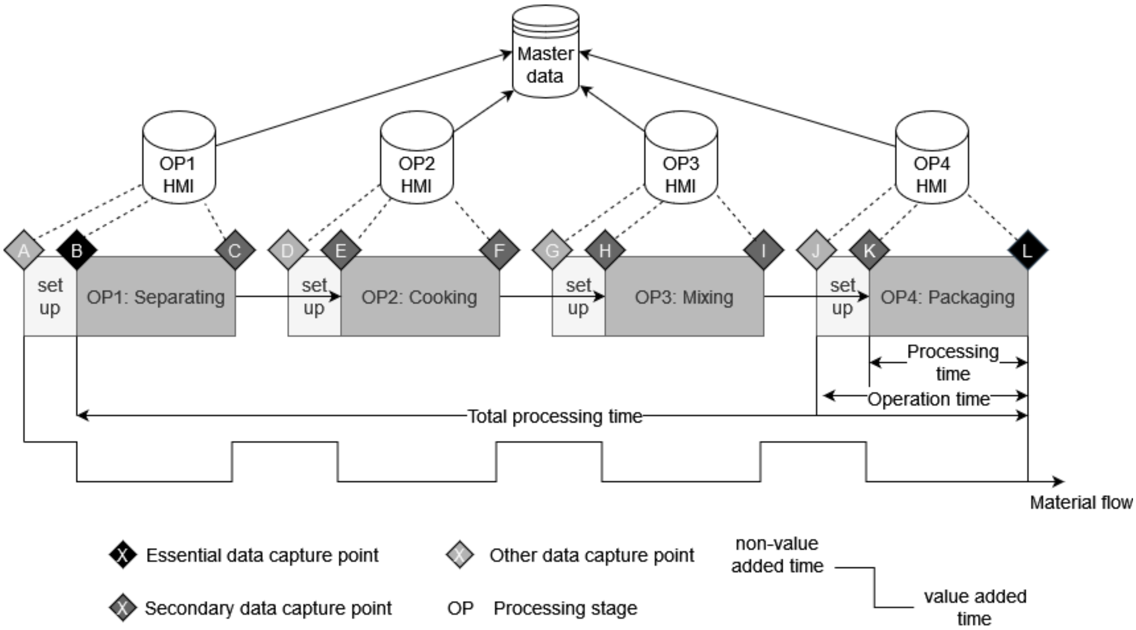

Figure 17: Examples of data capture points

The first method of data capture offers a simplified approach that yields significant information about the process through the analysis of production feedback data. This approach has the benefits of lower financial and resource-related investment costs and ease of implementation in tactical planning. However, it has the disadvantage of providing limited data, as it does not provide information about individual processes or the distribution of non-value-added and value-added time in production. As such, it is recommended to install additional data capture points at each processing step, as well as at the start of each set-up. This would facilitate the optimization of a greater amount of master data and provide opportunities for larger improvements in planning quality. In addition, the data can be useful outside of merely using it to improve the master data. For example, the inclusion of more data capture points would enable calculations of OEE for the other processing steps, providing a more comprehensive insight into the production processes.

Regardless of the chosen approach, it is essential for the system to maintain records of the various product batches throughout the production process to allow for analysis of the entire process. For instance, consider two products that utilize the same raw material but require different processing steps. To optimize production efficiency and meet production goals, the planner may want both products to begin processing in the separating process simultaneously. In this scenario, the system must be capable of recording the allocation of raw materials to each SKU and tracking the intermediates throughout the production process until packaging is complete.

Data Preparation

Once the approach for data collection has been determined, it is necessary to establish procedures for validating, preparing, and processing the data for analysis. The current approach for preparing data can serve as a foundation for developing procedures for handling the newly collected data. The current data is stored in SQL databases, which can be expanded to include the new data. The OEE data is processed and data types are combined more than what is required for the new data. For instance, the "Speed" data is calculated from the amount produced, productive time, and the set speed of the machines. Disaggregated values would be sufficient for the application of production feedback data in production planning. The data would require cleaning through the removal of outliers related to measurement or processing errors, such as records that are just a few seconds or where nothing was produced. This is because they do not represent an actual situation on the processing machine and they can thus distort the analysis.

Instructions on how to utilize the production feedback data in planning

With procedures for capturing and preparing data established, the final part of this step includes providing suggested measures, or instructions, for the production planner and other relevant employees to enable the inclusion of production feedback data in production planning. This part is also based on the analysis performed in step 2.

1. **How often to analyze or validate master data**

   The dynamic master data should be updated for each planning cycle. In Brynild's case, the weekly production schedule is finalized every Wednesday. Thus, the analysis should be performed and concluded so the production planner has time to incorporate the new master data values in the schedules. In the case of the MPS, which is updated continuously, it should suffice with weekly updating of the master data as well due to the lower accuracy of the plans. Additionally, the data should be analyzed and updated in response to large events or disruptions.

   The static master values should be validated periodically, but it should not be necessary to evaluate them at the same frequency as the dynamic values. A suggestion could be to perform validation at the beginning of every month to ensure that the values do not deviate too far from reality and thus negatively affect the planning quality for long periods of time.

2. **The analyses required to classify the master data**
   Adding production feedback data in the tactical planning of Brynild will require a range of different algorithms and methods for analysis. In this proposed design, only time series analysis and general ML have been briefly discussed. Time series can be performed with and without the use of ML, and ML is a broad term including many different methods and algorithms. Thus, more research and examinations of the data are required to provide a full assessment of what is needed to analyze all the different data.

3. **The thresholds that require a reevaluation of the classification of the master data**
   The production processes and operations in Brynild are likely to change with time. Thus, the classifications of static and dynamic master data are not meant to be static themselves. Therefore, thresholds should be established that trigger reevaluation. Master data that was previously static may have larger variations over time due to changes in, for example, machinery and equipment, raw material quality, or product specifications. The opposite is true for dynamic master data. As variations in the master data will change the resulting production plans to a varying degree, the thresholds will have to be individual per master data and set on a basis of cost-benefit. Brynild should also determine whether the static master data should be continuously monitored, or if analysis at regular intervals suffice.

Figure 18 illustrates the process of data analysis in Brynild as a data pipeline. The pipeline starts with raw data sets, which are then validated and prepared for analysis. After the analysis through time series, machine learning or other methods is complete, the results are deployed and the relevant master data values are updated. These master data values now serve as the new foundation for tactical production planning.

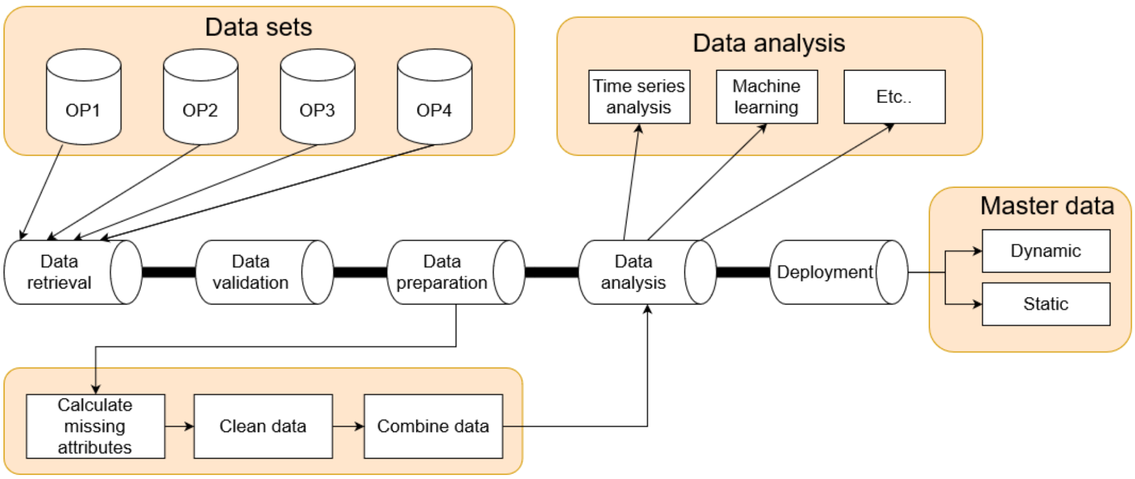

Figure 18: Pipeline for data analysis

5.4.4 Step 4 - Implementation

Objective: provide suggestions for how the solution designed in previous steps can be implemented.

After the first three steps have been conducted, Brynild can move toward the implementation of the designed system. While the implementation of a new production planning system at Brynild has the potential to disrupt current operations if not carefully planned and prepared for, the design of the concept should enable a smooth transition without interrupting ongoing operations. Inherently, the analysis and updating of most master data values should not result in disruptions either.

Implementation plan

A concise implementation plan should be created with expected time frames for milestones. The plan should encapsulate the installation of the data capture systems, the beginning of the data capture, the preparation of data, the establishment of procedures for analyzing the data, and the necessary steps to include the production feedback data in production planning. An implementation plan should also include an incubation period where data can be collected and ML models can be trained (Oluyisola 2021). In this period, the data can be used for OEE calculations of the other processing steps, which Brynild already has established procedures for. OEE calculations would require the addition of data capture points from the beginning and end of each processing step.

Risk assessment

While not included in the original method, Brynild should perform a risk assessment during the implementation step. There are risks associated with making changes to operations, and Brynild as a SME does have a limited research and development budget. Hence, it it is crucial for the company that the implementation is not disruptive to their current planning and control operations. Some risks are mitigated since Brynild is already familiar with the installation of data capture systems and the application of the data. If the application of production feedback data in their production planning were to be unsuccessful, the newly installed systems would still provide valuable data for monitoring their production.

Who should be involved

During the implementation phase of the concept, it is important to involve key personnel from different functions to ensure that the implementation is successful. This includes the nut production planner, the shop floor operators, production managers, and staff responsible for the data infrastructure and capture processes. There should also be a representative from senior management overseeing the implementation. Staff who were involved in previous data capture installations can provide valuable support during the start-up phase of the data and its preparation. Brynild might also have to hire external consultants for support with the data handling and analysis, and will likely require external vendors to support the setup of data capture systems.

6 Discussion

The primary objective of this thesis was to examine how production feedback data can be applied in production planning in order to increase planning quality. This was addressed through the answers to two research questions, in which findings from the literature study and case study are discussed in the following, in relation to the proposed concept. To finalize the discussion, the main limitations of this research and suggestions for future research are presented.

6.1 Research Question 1

RQ1: Which production feedback data is relevant for improving the accuracy of master data used in tactical planning?

This study has identified relevant production feedback data for tactical production planning. This has been compiled in a format easily communicable to manufacturers and is shown in Table 8, as presented in 4.2. This includes an overview of links to relevant master data within the scope of this thesis and was constructed as a part of the concept introduced in this study. A prerequisite for generating the list of relevant production feedback data was to compile a comprehensive list of master data from scientific and ERP literature (Table 7), and study this data. Then, links between the master data and production feedback data could be established based on the characteristics of the master data and how they relate to the situation on the shop floor.

Findings from the literature study did not provide specific examples of relevant production feedback data in the context of applying data for tactical production planning purposes. However, the insights from the literature study and case study had applications beyond directly presenting the answers to the research question. Findings from the literature study in Section 3.2.2 showed that production feedback data typically could include information about the status of production jobs, the workstations, set-up and processing status, in addition to location, production volume, and inventory information (Busert and Fay 2018; Schuh, Thomas et al. 2014). These findings coupled with Table 7 served as the theoretical foundation which allowed the list of relevant production feedback data to be derived from the study of master data. The literature study also identified a number of articles addressing the use of production feedback data for PPC (Reuter and Brambring 2016; Schäfers et al. 2019; Schuh, Thomas et al. 2014), indicating a potential for the application of production feedback data in tactical planning.

The case study illustrated how companies collect and apply production feedback data, such as through OEE calculations for monitoring production resources. Brynild collects a range of production feedback data that they use for this purpose, shown in Section 5.4.1. The production feedback data collected by Brynild provides information about the status of production jobs, set-up and processing status, and production volumes, and thus corresponds with the types of data presented in the literature study. The case study also contributed to understanding difficulties regarding the application of production feedback for the purpose stated in this thesis. To enable the analysis of production feedback data to improve the accuracy of master data, companies must collect data from multiple capture points to obtain sufficient information from the entire production process, from raw materials to packaging. For example, it is insufficient to only analyze data from one specific processing step when determining the quantity coefficient of a product because the coefficient considers the total number of raw materials required to produce a single product.

Table 8 shows production feedback data linked to different master data used for tactical planning. The master data is divided into three main categories, namely part or component, product, and resource. The master data are all characterized by being related to the situation on the shop floor processing, which is the enabling factor that allows assessments of their values through information gathered from the shop floor, i.e. the linked production feedback data. Establishing the master data values based on production feedback data should enable the increase of accuracy and reliability of the master data, as they are based on an accurate representation of the current conditions of the shop floor (Geiger and Reinhart 2016).

Increased master data accuracy should contribute to increased planning quality (Hees and Reinhart 2015), and provide improvements for several aspects of tactical production planning. Increasing the accuracy of master data in the part or component category can improve net requirement calculations through accurate information on the ratio of defective parts, thus improving the quality of MRP. For the product category, increased master data accuracy can improve the precision of the BOM, which can help planning by better representing the time and resources required to produce each product. It can also help with gross requirement calculation. Improved accuracy of resource master data can be beneficial by increasing the quality of the CRP.

By specifying an overview of relevant production feedback data that can be used for improving the accuracy of master data, a foundation has been established for the application of such data in tactical planning. This is addressed further in the next section.

6.2 Research Question 2

RQ2: How can production feedback data be applied in tactical production planning?

The second research question is relevant to any manufacturer. Despite the amount of literature on the topics of smart PPC and production feedback data, a lack of practical guidance and concrete solutions were revealed for the application in tactical production planning. Consequently, a significant portion of this study was dedicated to developing a concept for applying production feedback data in tactical production planning, and further, a method for manufacturers to follow to implement the concept in practice.

6.2.1 The Concept for Applying Production Feedback in Tactical Production Planning

In answering this research question, it is important to consider some of the limitations of existing hierarchical PPC frameworks, such as the one by Oluyisola (2021). These frameworks only conceptually link the lower planning levels with the higher planning levels through feedback loops on performance, without specifying what type of data is relevant and how this information can be applied in the higher-level processes.

The new conceptual model for hierarchical PPC frameworks in Section 4.1, shown in Figure 10, responds to the lack of specification in previous PPC frameworks by establishing the feedback loops from the operational to the tactical level as production feedback data from the shop floor, which this study then posits can be analyzed and fed into master data for the tactical planning processes. Further, the concept suggests that master data should both be static and dynamic, instead of the traditional view of master data as something static that is created once and rarely changed thereafter. Figure 11 shows how both static and dynamic master data can be incorporated in the MRP process. Thus, production feedback data in tactical production planning can have two primary application areas: 1) to validate and monitor static master data, and 2) to dynamically determine variable master data.

Incorporating production feedback data into tactical production planning and allowing master data to be dynamic rather than just static should offer several advantages over traditional approaches to tactical production planning. The utilization of production feedback data expands the data foundation used for planning and ensures that the master data is based on current and realistic information which accurately represents the situation in the company. This addresses one of the main challenges of traditional PPC introduced by Kurbel (2016). This challenge is related to the lack of correspondence between the real-life situation on the shop floor and the planned situation, and improving this can help enhance plan stability. In addition, validating the accuracy of master data through the use of production feedback data ensures that the planning is based on accurate and reliable data, contributing to increased planning quality and ensuring the overall success of PPC (Hees and Reinhart 2015). Lastly, by reducing the reliance on humans in order to establish the data foundation used for planning, several of the prevalent data quality issues experienced in PPC highlighted by Lindström et al. (2023) can be reduced.

6.2.2 The Method for Applying the Concept in Companies

Having established conceptually how production feedback data can be applied in tactical production planning, the method for applying the concept in companies contributes further to the answer to this research question. A method provides valuable support for improving business processes through a structured process (Braun et al. 2005; Zellner 2011). The method consists of four main steps: 1 - mapping, 2 - analysis, 3 - design, and 4 - implementation. The steps are discussed below in relation to the literature study and the illustrative application in Brynild in the case study.

Mapping focuses on developing a comprehensive understanding of the current production processes, PPC, and data collection capabilities of the company. This step highlights the importance of analyzing the current situation and data before further steps are carried out. The mapping of the case company highlighted some differences between how companies conduct PPC and the way it is presented in the literature. Brynild does not perform the traditional tactical production planning processes MRP and CRP, but the tactical planning is rather a combination between the weekly production scheduling and MPS. They also do not solely rely on master data from the ERP system for planning, they also have master data set manually in Excel. The case study also confirms some other findings from the literature study that production is often carried out manually with the support of spreadsheet solutions and that the decisions regarding PPC are highly reliant on expert experience (Man and J. O. Strandhagen 2018; Rahmani, Romsdal, Sgarbossa et al. 2022). Additionally, the case study demonstrated that master data is rarely updated and may be based on estimated values without verification of their accuracy. Lastly, the case study provided valuable insight that companies that are collecting production feedback data may not collect sufficient data to apply the concept without adding more infrastructure for capturing data. This does, however, not mean that the application of the concept is infeasible for Brynild and companies in similar situations. Rather, it means that more extensive initial preparations will likely have to be conducted before applying the concept further for many companies. This emphasizes the importance of thorough mapping as a prerequisite for implementing smart PPC solutions further.

In the next step, analysis, the data collected through the preceding mapping is analyzed. Analyzing the production feedback data is required to validate the accuracy of static master data in the company, and to determine accurate dynamic master data values in each planning cycle. Due to the lack of quantitative analysis in the application of the concept in Brynild, the case study is largely inconclusive for empirically assessing the effectiveness of this step. The literature study, however, presents a recent study by Rahmani, Romsdal, Syversen et al. (forthcoming) that illustrates that even small deviations in master data accuracy have an effect on production schedules. Tactical production planning is performed at a higher level in the hierarchical PPC frameworks, with its outputs having a direct impact on the production schedules. Thus, it can be assumed that the same effect is prevalent in tactical planning as well, highlighting the importance of conducting a thorough analysis of the master data to improve its accuracy.

When data has been analyzed and static and dynamic master data has been determined, the next step consists of designing the system for applying production feedback data in the tactical planning of the company. Findings from the literature study suggested that it is essential that the system is designed to integrate with existing production systems and that the system is scalable and flexible (Oluyisola 2021). As was highlighted in the mapping, Brynild does not collect data from sufficient data collection points. If more data-capturing points are required, carefully deciding where these should be is a pivotal decision to make during the design phase. Adding more data capture points increases the data foundation and allows for more use cases of the data, also outside of the application for tactical production planning. These benefits have to be weighed against the additional cost of installing more data-capturing infrastructure and more complex data management and analysis as a consequence of more data.

The final step of the method involves implementing the designed system. It is crucial to be meticulous during this step to ensure that the company can successfully integrate and apply the concept within its operations. A finding from the literature study suggests that an incubation period should be included in the implementation plan of a smart PPC system. During this incubation period, data can be collected and ML models can be trained (Oluyisola 2021). The proposed implementation step did not specify this as a part of the implementation plan, although it should have been addressed. Numerous data analysis techniques, such as ML, require substantial amounts of data before meaningful analysis can be conducted. In addition, during the case study, it was discovered that the method for applying the concept did not specify that the risks associated with the implementation should be assessed. The introduction of a new procedure for conducting tactical planning is a significant change to the overall planning operations of a company, and there are thus associated risks with the implementation of the system (Schuh, Anderl et al. 2017). Therefore, a risk assessment should be performed to identify potential challenges, risks, and the potential economic impact of successful or failed implementation. While a risk assessment should be performed regardless of company size or budget, it will be particularly important for SME's due to their limited budget and capabilities for research and development. The implementation step is thus expanded to encompass these elements to provide more holistic guidance and direction for companies in the application of the concept in accordance with design science and abductive reasoning.

A finding from the literature state that many companies struggle in the implementation of smart PPC technologies (Bean and Davenport 2019; Oluyisola 2021). This finding highlights the importance of providing guidance and practical approaches to support companies in their efforts to implement these solutions and realize their benefits. By offering clear and actionable advice through the method, companies may be better equipped to implement the concept of applying production feedback data in their tactical production planning and thus benefit from increased planning quality.

6.3 Limitations

This study was conducted by means of a qualitative concept development phase with an illustrative proposal for the application of the concept in the Brynild. Thus, the most prominent limitation of this study is the absence of a quantitative analysis of data to demonstrate the effects of implementing the proposed concept in real-world companies. This limitation was due to Brynild not having the required data for analysis. As a result, the study was unable to provide empirical evidence to support, or reject the concept.

Another limitation is that the list of master data for planning linked to relevant production feedback data Table 8 is not exhaustive. The data will vary depending on company-specific characteristics of the data capture, and operations.

The concept was specifically tailored for a mass production environment with fixed process steps and routings. As such, the production feedback data presented does not fully encapsulate the characteristics of other production environments.

The idea of dynamically determining master data values has not yet been implemented in practice. Thus, the feasibility of dynamically adjusting master data in ERP and other planning tools has yet to be determined. Additionally, the impact of using dynamic master data values on coordination with shop floor operators and production logistics has not been studied.

6.4 Suggestions for Future Research

The case study's application of the concept lacked empirical analysis. As a result, future research should be conducted with a focus on fully exploring the concept's potential through the addition of data analysis. There are several assessments that can be made. Firstly, comparing the results of using approximate master data with accurate master data values validated through the analysis of production feedback data for tactical production planning. The effect of including dynamic master data should be investigated, studying how it would affect production operations. This will provide a more comprehensive understanding of the concept's capabilities and limitations and will help to identify areas for further development and improvement. The concept should also be applied and tested in various production environments.

7 Conclusion

This thesis has examined how production feedback data can be applied in tactical production planning in order to increase planning quality. It was found that production feedback data is relevant for providing information about the situation on the shop floor and that this should be considered in tactical planning to ensure that the plans represent the real-life situation, increasing planning quality. The first research question considered which production feedback data is relevant for improving the accuracy of master data used in tactical production planning, and the second research question considered how production feedback data can be applied in tactical production planning.

An overview was established that links relevant production feedback data with master data used for planning. The accuracy of the master data can thus be increased by better representing the situation on the shop floor. This overview includes specific examples of production feedback data that are applicable in the context of tactical production planning, thereby addressing the first research question.

Production feedback data can be applied in tactical production planning through master data for planning. A concept was developed, which included a conceptual model showing how the operational and tactical planning levels can be linked by applying production feedback data in the master data used for the tactical planning level. The concept also challenges the traditional view of master data as inherently static and proposes that some master data should be dynamically determined to better represent the actual situation on the shop floor. This is illustrated in a second conceptual model, where production feedback data is applied to both static and dynamic master data of the MRP for net requirement calculations. This concept provides a partial answer to the second research question.

In addition, a method for applying the concept in practice was developed. Companies can follow the proposed method to implement the use of production feedback data in their tactical planning. The method, consisting of four main steps, recommends that companies should start with mapping their production and planning operations before production feedback data is analyzed and static and dynamic master data is assessed. After this, the company can design the overall system for how production feedback data should be included in their tactical production planning in the future. The final step includes the implementation of the designed solution. It was found that this step did not highlight the importance of conducting a risk assessment, nor did it specify the need of including an incubation period in the implementation plan. The implementation step is thus suggested to be expanded to encompass these elements. The extension of the method based on empirical observations is an example of the practical application of design science and abductive reasoning used in the study. The method and its application through the case study provide the second part of the answer to the second research question.

Overall, the study provides three main contributions to the theory. The first contribution is the overview specifying links between production feedback data and master data for tactical planning. The second contribution is the two conceptual models demonstrating how production feedback data can be applied in tactical production planning. Lastly is the method for using production feedback data in tactical master planning for companies.

This study thus also provides valuable contributions to practice. Many companies face challenges in applying smart PPC and becoming more data-driven. While the tools and theories exist, there is a lack of detailed recommendations and guidance for companies to effectively implement these systems. The stepwise method provided in this study provides helpful guidance in order to attain smarter operations, increase planning quality, and attain a responsive PPC system able to respond to the variations of today's manufacturing markets.

Further research should be conducted to address the illustrative nature of this thesis. Quantitative analysis should be performed on production feedback data in order to test the master data values, and how it can affect the accuracy of tactical production planning.

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