Doctoral theses at NTNU, 2021:202

Olumide Emmanuel Oluyisola

Towards Smart Production Planning and Control

Frameworks and case studies investigating the enhancement of production planning and control using internet-of-things, data analytics and machine learning

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
Faculty of Engineering
Department of Mechanical and Industrial Engineering

NTNU
Norwegian University of Science and Technology

Olumide Emmanuel Oluyisola

Towards Smart Production Planning and Control

Frameworks and case studies investigating the enhancement of production planning and control using internet-of-things, data analytics and machine learning

Thesis for the Degree of Philosophiae Doctor

Trondheim, June 2021

Norwegian University of Science and Technology
Faculty of Engineering
Department of Mechanical and Industrial Engineering

NTNU
Norwegian University of
Science and Technology

NTNU
Norwegian University of Science and Technology

Thesis for the Degree of Philosophiae Doctor

Faculty of Engineering
Department of Mechanical and Industrial Engineering

ISBN 978-82-326-5860-2 (printed ver.)
ISBN 978-82-326-6785-7 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (online ver.)

Doctoral theses at NTNU, 2021:202

Printed by NTNU Grafisk senter

Dissertation submitted:	Spring 2021
PhD supervisor:	Professor Jan Ola Strandhagen Norwegian University of Science and Technology
PhD co-supervisors:	Professor Fabio Sgarbossa Norwegian University of Science and Technology Associate Professor Marco G. Semini Norwegian University of Science and Technology
Dissertation Committee:	Professor Samuel Fosso Wamba Toulouse Business School Professor Pamela Danese University of Padova Associate Professor Yiliu Liu (Administrator) Norwegian University of Science and Technology

Acknowledgements

“*It takes a village to raise a child*.” --- an African proverb.

This PhD thesis is the culmination of my almost eight years journey so far in Norway. It has been a humbling mixture of cruises and bumpy rides, of coffee times and skiing, of seminars and ‘long’ presentations, and of exciting times meeting many amazing people. I count myself fortunate, having had so many helpers along the way. While the impact of a few has been monumental, I am grateful for all. And while it is impossible to mention everyone, I will try.

Before coming to Norway, I was fortunate to have supervisors who cared to share not only their skills, knowledge and experience, but also through their daily decisions and discussions showed me the promise of a high-performing organization – enough to ignite my interest – during my time at Oando Plc. So, to Seyi Adeleye, Kayode Boladale, Bambo Ibidapo-Obe, Alex Irune, and Ima Ofulue, thank you all for what has turned out to be a solid foundation.

When I arrived in Norway almost eight years ago for my MSc in Global Production Management, I remember shivering on my way to the student village within an hour of my arrival. But things soon changed after meeting my MSc coordinator and master thesis supervisor Erlend Alfnes. You helped make what could otherwise have been a tortuous experience into one of the most exciting times I have known. Thank you for being not just my professor, but an invaluable guide in a new country I have learnt to love and now call home.

At the risk of sounding like a broken record, I will again state how fortunate I feel I am for my supervisor and research-group leader Jan Ola Strandhagen. A globally recognized leader in the field of industrial logistics, your insights and discussions over the years have helped formed the kind of researcher I have become. Thank you. And I remain grateful that you gave me the chance while I was a ‘somewhat inexperienced’ master student looking for part-time work during the final year of my MSc studies. You would go on to trust me with more responsibilities, lecturing opportunities, helping me to learn when mistakes were made, trusting me even at personal level, and for all the life, culture and geography lessons you shared with me during those memorable trips both within Norway and abroad.

To my co-supervisors Fabio Sgarbossa and Marco Semini: thank you Marco for all the work during the early stages and Fabio during the second half of the PhD. I am especially thankful for how you paired perfectly with Ola in the supervision of this PhD. Thank you for showing me that limitations are just obstacles waiting to be cleared, and for the brainstorming sessions. And I am grateful for your encouragement at the toughest periods of this PhD journey.

I also wish to express my profound gratitude the participating companies in the Manufacturing Network 4.0 and the DigiMat projects. I particularly appreciate the time and efforts of Marius Nordheim, Roald Boge, Hans Mogstad, and Sigmund Aandstad at Pipelife; Erlend Gjønnes and Gjermund Kambestad at Orkel; and Mathias Holm, Eirik Blå and Martin

Oskarsson at Brynild. And to our friends at Molde, members of the ManuNet4.0 Steering committee especially Ottar Ohren, Bjørn Jæger, and Lise Halse, and the Møreforsking crew especially Kristina Kjersem and Mikhail Shlopak, thank you.

During this PhD study, I have had the best colleagues one could hope in the Production Management research group: Anita, Pavan, Lukas, Philipp, Kasper, Tara, Natasha, Maria, Gabriele, Sven, Maggie, Hans de Man, Giuseppe, Aili, Jo, Logan, Swapnil, Natalia S, Marco, Mirco, Vivek, Mina, Giulio. Thank you all for the adventure and the lovely memories.

Eli Meistad, you were like a mother to us PhD candidates. I remember how patiently assisted me during the sometimes confusing and knotty visa related issues at the start and through the course of this PhD study. Tusen takk! And to Kari, Gabriela, and Monica, mange mange takk!

The PhD life can be dreary without good friends and here I will name a few who have contributed towards this PhD journey in one way or another: Ruben Ravnå, Siss Frivik, Ugochukwu & Chioma Aronu, Frida Mrope, Bayo & Julya Ajulo, Esperance & Vanessa Sinaniranye, Gerthory & Chantal Toussaint, King Bright & Patricia Sarpong, Nick & Alvine Agofack, May-Ann Sustraido, Khadidia & Yasmina, Pedro Filho, Soma Das, Velin Georgiev, Dipo Olaitan, Solomon Taiwo, Fenfen Liu, Jie Zhang, Simone Mitta, Petra McLeod, Joseph Adeniyi, Bose Dele-Ijagbulu, Oluwamayowa Egbaiyelo, and Temitope Adesemoye. I am grateful for your generosity and I feel lucky to have you as friends.

To the 'three wise men' Samuel Fosso Wamba, Rameshwar Dubey, and Cyril Foropon, it will not be an exaggeration to say that you saved this PhD. For sharing an evening with Jonathan Walker and I, an evening filled with insights and ideas in the old town area of beautiful Berlin, and for showing me how to excel as an operations management researcher, especially at a low point in this PhD, I am grateful. You have been great role models in this adventure. And my gratitude also goes to Cecilia Haskins for the many guidance sessions during this period.

My mother, Aderiike, thank you for not giving up, and for teaching me fortitude and hope. And to my siblings, Olufemi & Blessing, Abiodun & Temitope, Oyewole & Olabisi, and Oluwole, Babajide, Tolulope, and to Uncle Lekan & Olori, Baba-Jide, Mama-Jide, the Akinjoles, the Bajomos, the Sodipos, the Fajimis, and the Buraimohs, thank you for all your support and encouragement. A special 'thank you' to Olwasegun, Adenike, Modupeoluwa, and Anjolaoluwa for being available when I call, and to the Ibikunoluwas, the Odubanjos, Taiye & Kennie for being excellent hosts.

And finally, Surat Temitope and Maya Olumurewa, thank you for your excellent 'layman' proofreading service, for cheering me on all the way, for your patience, for your love, and for believing in me. Words fail me! Tusen hjertelig takk!

Trondhiem, 24.June.2021

Olumide Emmanuel Oluyisola

"The great aim of education is not knowledge but action."

- - -

HERBERT SPENCER

Summary

To be competitive in the era of industry 4.0, manufacturing firms must leverage emerging digitalization technologies to improve their operational efficiencies and customer value offerings. Digitalization technologies such as internet of things, Big-data analytics and machine learning present new opportunities in production management by enabling real-time control of operations and more frequent replanning of production to reflect the live situation within factories and in supply chains. These technologies can also enable intelligent data-driven decision making, and the capturing of operator or manager decision making patterns and experience. With these new capabilities, manufacturing firms can improve their competitiveness sustainably (Iansiti and Lakhani, 2014, Strandhagen et al., 2017).

Manufacturing managers desire clear guidelines and theory to support their digitalization initiatives. A key problem being witnessed is that the use-cases, benefits, and business value of many of these technologies are not always clear for many manufacturing firms. For example, machine learning could work in predicting production line breakdowns and assist in scheduling on-time product deliveries and maintenance activities in a process production company. But the same technology meanwhile offers more value in making, say, an intelligent product for an engine or tractor producer. The question of "strategic fit" arises, highlighting the need for methods, tools, and conceptual frameworks that takes the contingencies of a firm's value-chain into account (Oluyisola et al., 2020).

Although it is possible to take a piecemeal approach to the digitalization of production systems, not using a systemic approach can lead to suboptimization and lower overall value. One good systematic strategy is to approach digitalization through production planning and control (PPC). PPC is the core production management responsibility, and it encompasses decision-making processes and policies about planning (estimating, routing, scheduling, and resource loading) and control (dispatching, expediting, inspection, evaluating, and corrective action) of production processes and resources to produce products that meet market needs in a sustainable and profitable way (Slack et al., 2013). For every manufacturing firm, these PPC decisions and policies are influenced by the market-, product-, and process-related attributes (also referred to as planning- or PPC-environment's attributes) of the firm (Jonsson and Mattsson, 2003). Also, extant research suggests that PPC-environment's attributes affect the efficacy of PPC (Jonsson and Mattsson, 2003, Hong et al., 2010).

This study posits that in a similar manner, such PPC-environment's attributes will be influential when manufacturing firms adopt digitalization in their production systems. In addition, some studies have shown that there is variation in the level of implementation

required to see benefits in production operations. For example, it has been shown that it is sufficient to have real-time data in some inputs such as inventory even if other inputs such as demand data is provided at the end of each business day (Wolfsgruber and Lichtenegger, 2016), suggesting that there are nuances that must be tailored for each use-case, technology and production system. For the preceding reasons about the need for a system view and the potentially moderating effects of the PPC-environment's attributes, this PhD study takes a PPC perspective in investigating this topic and introduces the construct termed 'smart PPC' to describe the objective.

Although several conceptual studies on smart manufacturing have been published, mainly focusing on production systems' configuration and features, very few empirical in-depth case studies have been reported in the literature that specifically focus on the management processes of such systems (Moeuf et al., 2018, Machado et al., 2020). Additionally, only a few of these studies address the importance of PPC in achieving the vision of smart manufacturing (Ren et al., 2015, Moeuf et al., 2018, Sun et al., 2020). This is a missed opportunity, as the PPC process is analogous to a brain for the production system and is the most critical "smartness" element of a smart factory. For this study, **smart PPC** is **defined** 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.*

In addition to the absence of frameworks to guide the choice of a fitting smart PPC strategy and use-cases, there are also gaps of architectural designs, and about how to translate the system requirements and attributes to the lower level design elements – of data structures, of class definitions, of system entity-relationships, of matching algorithms, etc. – in a way that supports the development of smart PPC solutions which fit the near- and long-term requirements of a production system (Kusiak, 2017, Reuter et al., 2017). This is particularly important for smaller firms who have more restrictive research and development budgets, and for big firms at times of global economic crises. Consequently, to address this challenges and gaps in the literature, this PhD **research aim**ed to

> *identify the PPC challenges that are amenable to smart technologies, to identify the elements that a smart PPC system might have, and to determine what constraints the planning environment attributes impose on the design and development of smart PPC.*

This research aim had both theoretical and industrial components as is common in production management research. The research aims were then deconstructed into four targeted **research questions** (RQs) namely:

RQ1: *What are the planning and control challenges in production systems that are amenable to smart PPC?*

RQ2: *What are the elements of a smart PPC system?*

RQ3: *What constraints do the planning environment attributes impose on the design and development of a smart PPC system?*

RQ4: *How can the smart PPC be achieved in practice?*

The **research design** used to address the RQs was as follows. Because many firms were just beginning to try out digitalization technologies at the time this PhD started, preliminary field studies were carried out in three case studies to gain a general appreciation of the nature and scale of the industrial challenges. These sought to address RQ1. The preliminary findings were presented at international scientific conferences and were later used to develop the interview questionnaire that was used to collect data for RQs 1, 2, and 3 in a more structured process in a four-unit multi-case study.

The first three RQs aim primarily to develop new theory even though they also offer industrial value for production managers. After the preliminary round, the three RQs were investigated concurrently. Cases were selected across four types of industries namely food, plastics, propulsion systems, and agricultural machinery. Qualitative data analysis methods such as "*pattern matching, explanation building, and addressing rival explanations*" (Yin, 2013) were used in analysing the data and developing the theory. The aim in RQ4 was to take this research beyond theory by developing a practical guide that can be used to develop smart PPC solutions, so that they fit with the current characteristics and the future requirements of production systems. Because this RQ involved the development of an artefact, the design science methodology was used.

The **findings** of this study can be summarized as follows:

- PPC issues in process manufacturing are more amenable to digitalisation technologies that enhance the PPC processes. Discrete manufacturing are more amenable to smart product strategies.
- The key elements of a smart PPC solution consists of IoT, data analytics, and machine learning. But these can be extended to plan and control other more 'physical' (such as autonomous guided vehicles) or cyber-physical production system technologies.
- In general, the more customizable a product is, the lower the potential for smart PPC for its production system. And as these technologies become more mature, this rule will likely still hold true, although it might shift to a new frontier.

- The intensity of competition in a firm’s industry can influence its need for, and its adoption of smart PPC. Companies in highly competitive industries, which are not market leaders are more likely to rush into digitalisation and in doing so, fail to achieve the fit that is necessary for success.

The key **contributions to theory** can be summarized as follows. The findings suggest a relationship exists between the PPC environment attributes and the digitalization strategy. This establishes a basis for introducing these attributes as factors in future smart PPC research, although further tests are required. Furthermore, by demonstrating the use of the structural contingency theory for this research area, this study demonstrates how more traditional management theories can be applied as both the industry and academia demand more grounded theories to explain the digitalization phenomenon in manufacturing and more specifically as this applies to PPC within the smart manufacturing context.

This study further makes several **contributions to production management practice**. The proposed conceptual model shows how a transition to smart manufacturing can be achieved by following a development pathway from connected, to analytic and finally to intelligent operations. The matrix of use-cases can provide ideas for reference starting points for production managers attempting digitalization.

In addition, this study found that industry 4.0 implementations need not only integrate adequately with an organization’s existing processes and systems, but also with its PPC environment’s attributes. From the literature search, this study is the first to establish this link and provide a strategic framework which shows this relationship. Lastly, this study presents a five-step method for designing and developing smart PPC systems. The method emphasizes the influence of contextual fit in the selection of algorithms, design for scalability, and the flexibility of the designed system to address future demands so that the resulting PPC system fits with the targeted PPC-environment’s attributes.

The research design adopted for this study is beset by a few notable **limitations**, top among which is the small number of cases – a factor that limits the generalizability of the findings. Despite this sample size limitation, this PhD study manages to establish a basis for future research into the application of structural contingency theory in developing smart PPC for sustainably competitive production operations.

Overall, this PhD contributes new knowledge to the emerging production management domain of smart PPC. The developed artefacts – models, framework, and method – provide new decision-making tools for managers who must make important strategic and operational decisions regarding the digitalisation of their production systems.

Sammendrag

For å være konkurransedyktige i dagens "industri 4.0" æra må produsenter utnytte nye digitale teknologier for å sikre effektiv drift og skape god verdi for kundene. Digitale teknologier som tingenes internett, stordataanalyser og maskinlæring gir nye muligheter innen produksjonsledelse. Teknologiene muliggjør sanntidsstyring og hyppigere replanlegging av produksjonen slik at man kan hensynta den faktiske situasjonen i produksjonen og i verdikjedene. Disse teknologiene kan også muliggjøre intelligent, datadrevet beslutningstaking og fangst av beslutningsmønstre og erfaring fra operatører og ledere. Gjennom disse nye mulighetene kan produsenter styrke sin konkurranseevne på en bærekraftig måte (Iansiti and Lakhani, 2014, Strandhagen et al., 2017).

Produksjonsledere ønsker å ha klare retningslinjer og teorier til å støtte seg i beslutninger rundt digitaliseringsinitiativer. Man ser imidlertid i mange tilfeller at fordelene og forretningsverdien av disse nye teknologiene ikke er helt forstått av produsenter. For eksempel kan maskinlæring brukes i en produksjonsbedrift til å forutsi driftsstans i produksjonslinjer og å støtte både produksjons- og vedlikeholdsplanlegging for å sikre at produkter leveres til rett tid. Samtidig kan den samme teknologien skape mer verdi i form av et intelligent produkt for en motor- eller en traktorprodusent. Spørsmålet om hvilke løsninger som passer i hvilke situasjoner er derfor aktuelt og fremhever behovet for metoder, verktøy og konseptuelle rammeverk som tar hensyn til omstendighetene i bedriftens verdikjede (Oluyisola et al., 2020).

Selv om det er mulig å ta en stegvis tilnærming til digitalisering i produksjonssystemer, kan det å unnlate å bruke en systemisk tilnærming lede til en suboptimalisering og lavere totalverdi. En god systematisk og strategisk tilnærming til digitalisering finnes gjennom produksjonsplanlegging og -styring, på engelsk production planning and control (PPC). PPC er hovedansvaret til produksjonsledere og involverer beslutningsprosesser og prinsipper om planlegging (estimering, ruting, tidsplanlegging og ressursbelastning) og styring (utsendelse, ekspedering, inspeksjon, evaluering og korrigerende tiltak) av produksjonsprosesser og ressurser for å produsere produkter som oppfyller markedets behov på en bærekraftig og lønnsom måte (Slack et al., 2013). For alle produsenter påvirkes disse PPC-beslutningene og prinsippene av egenskaper ved bedriftens marked, produkter og prosesser (også omtalt som egenskapene ved planleggingen eller PPC-miljøet) (Jonsson and Mattsson, 2003). Tidligere forskning viser også at PPC-miljøets egenskaper påvirker effektiviteten av PPC ((Jonsson and Mattsson, 2003; Hong et al., 2010).

Denne studien fastslår på en lignende måte at PPC-miljøets egenskaper er viktige når produsenter skal ta i bruk digitalisering i sine produksjonssystemer. I tillegg viser flere studier at det er variasjon i hvilket implementeringsnivå som trengs for å se forbedringer i driften i produksjonen. For eksempel har studier vist at det er tilstrekkelig å ha sanntidsdata for noen faktorer, som for eksempel lagerbeholdninger, mens andre faktorer, som for eksempel etterspørselsdata, kun oppdateres på slutten av dagen (Wolfsgruber and Lichtenegger, 2016). Dette tyder på at det er nyanser som må skreddersys for hvert enkelt tilfelle, teknologi og produksjonssystem. Det beskrevne behovet for et systemperspektiv og de potensielt modererende effektene av PPC-miljøets egenskaper danner bakteppet for denne doktorgradsstudien – hvor et PPC-perspektiv brukes for å undersøke temaet og begrepet "smart PPC" introduseres for å beskrive målet.

Selv om det er publisert flere konseptuelle studier om smart produksjon, fokuserer disse hovedsakelig på produksjonssystemers konfigurasjon og kjennetegn. Litteraturen rapporterer veldig få detaljerte empiriske casestudier med fokus på styringsprosessene i slike systemer (Moeuf et al., 2018, Machado et al., 2020). I tillegg er det bare noen av disse studiene som adresserer viktigheten av PPC for å oppnå visjonen om smart produksjon (Ren et al., 2015, Moeuf et al., 2018, Sun et al., 2020). Dette er en tapt mulighet siden PPC-prosessen kan sammenlignes med hjernen i et produksjonssystem og således er den mest kritiske faktoren for «smarthet» i en smart fabrikk. I denne studien er **smart PPC definert** som:

> *integreringen av nye teknologier og muligheter i industri 4.0-rammeverket, hvor PPC-prosesser forbedrer ytelsen til produksjonssystemet ved å muliggjøre sanntids, datadrevet beslutningstaking og kontinuerlig læring med input fra et større utvalg av kilder.*

I tillegg til å velge en passende smart strategi og brukercase, er det også et potensial knyttet til arkitektonisk design og hvordan en skal oversette systemkrav og egenskaper til lavere nivå av designelementer – for eksempel datastrukturer, klassedefinisjoner, relasjoner mellom enheter i systemet og matchende algoritmer – for å støtte utviklingen av løsninger for smart PPC som er tilpasset kravene i et produksjonssystem på kort og lang sikt (Kusiak, 2017, Reuter et al., 2017). Dette er spesielt viktig for små selskap som har begrenset budsjett til forsking og utvikling, og for store selskap i tider med globale økonomiske kriser. Som en konsekvens av dette var **målet for denne doktorgradsstudien** å adressere disse utfordringene og forskningsgapene gjennom:

> *å identifisere PPC-utfordringer som er mottakelig for smarte teknologier, å identifisere elementene i et smart PPC-system og å fastslå hvilke egenskaper ved et planleggingsmiljø som innvirker på designet og utviklingen av smart PPC.*

Forskningen hadde både teoretiske og industrielle komponenter, noe som er vanlig i forskningen innenfor produksjonsledelse. De overordnede forskningsmålene ble delt inn i **fire forskningsspørsmål** (RQs):

RQ1: Hvilke planleggings- og styringsutfordringer i produksjonssystemer er mottakelige for smarte PPC-systemer?

RQ2: Hva er elementene i et smart PPC-system?

RQ3: Hvordan begrenser egenskapene ved planleggingsmiljøet design og utvikling av et smart PPC-system?

RQ4: Hvordan kan smart PPC oppnås i praksis?

Forskningsdesignet som ble brukt til å adressere forskningsspørsmålene var følgende. Ettersom mange bedrifter var helt i startfasen med å benytte digitale teknologier da doktorgradsstudien startet, ble det gjennomført innledende feltstudier gjennom tre casestudier for å få en generell forståelse av arten og omfanget av de industrielle utfordringene. Dette tok sikte på å besvare RQ1. De innledende funnene ble presentert på internasjonale vitenskapelige konferanser og senere brukt til å utvikle spørreskjema for intervjuer som ble brukt for å samle data for RQ 1, 2 og 3 i en strukturert prosess gjennom en casestudie med fire enheter.

De tre første RQ-ene hadde som mål å utvikle ny teori, selv om de også har industriell verdi for produksjonsledere. Etter den innledende runden ble derfor de tre RQ-ene undersøkt i parallell. Casene ble valgt fra fire forskjellig sektorer; næringsmiddel, plast, fremdriftssystemer og landbruksmaskiner. Kvalitative dataanalysemetoder som "*mønstermatching, forklaringsbygging og adressering av konkurrerende forklaringer*" (Yin, 2013) ble brukt til dataanalyse og teoriutvikling. Målet for RQ4 var å bruke teorien for å utvikle en praktisk veileder som kan brukes for å utvikle løsninger for smart PPC – på en måte som tar hensyn til dagens karakteristika og framtidige behov i produksjonssystemet. Ettersom RQ4 involverte utvikling av et artefakt, ble design science brukt som metodikk.

Funnene fra denne studien kan oppsummeres som følger:

- PPC-utfordringer i prosessproduksjon er mer mottagelige for digitaliseringsteknologier som forbedrer PPC-prosessene. Stykkproduksjon er mer mottakelig for smarte produktstrategier.
- Nøkkelelementene i en smart PPC-løsning består av tingenes internett, dataanalyse og maskinlæring. Disse kan imidlertid utvides til å planlegge og styre mer 'fysiske' elementer (for eksempel førerløse trucker) eller teknologier for cyber-fysiske produksjonssystemer.

- Generelt vil det være slik at jo mer et produkt kan skreddersys, jo lavere er potensialet for bruken av smart PPC i produksjonssystemet. Etter hvert som disse teknologiene modnes, vil denne regelen fortsatt holde, selv om den kan endres i en ny retning.
- Graden av konkurranse i en bransje kan påvirke behovet for og bruken av smart PPC. Bedrifter i svært konkurranseutsatte bransjer, som ikke er markedsledere, har større tilbøyelighet til å forhaste seg i digitalisering og disse kan dermed risikere å ikke sørge for tilpasningen som er nødvendig for å lykkes.

Hovedbidragene til teorien oppsummeres som følger. Funnene tyder på at det er en sammenheng mellom egenskapene i PPC-miljøet og digitaliseringsstrategien. Dette gir et grunnlag for å inkludere disse egenskapene som faktorer i fremtidig forskning på smart PPC, selv om ytterlige undersøkelser er nødvendig. Videre, ved å demonstrere bruken av strukturell betingelsesteori på dette forskingsområdet, viser denne studien hvordan mer tradisjonelle ledelsesteorier kan bli brukt. Både industrien og akademia etterspør mer databasert teoriutvikling for å forklare digitaliseringsfenomenet i produksjon generelt, og mer spesifikt hvordan dette kan brukes i PPC innenfor smart produksjon.

Denne studien gir videre flere **bidrag til praksis innenfor produksjonsledelse**. Den foreslåtte konseptuelle modellen viser hvordan en overgang til smart produksjon kan oppnås ved å følge en utviklingsprosess fra tilkoblet, via analytisk og til slutt til intelligent drift. Matrisen av bruker-case kan gi ideer og referansepunkter for produksjonsledere som prøver ut digitalisering. I tillegg fant studien at implementeringer av industri 4.0 ikke bare trenger å integreres tilstrekkelig med en organisasjons eksisterende prosesser og systemer, men også med egenskapene ved bedriftens PPC-miljø. Litteratursøket viste er denne studien er den første som etablerer denne linken og gir et strategisk rammeverk som viser dette forholdet. Til slutt presenterer denne studien en fem-trinns metode for å designe og utvikle smarte PPC-systemer. Metoden fremhever viktigheten av kontekstuell tilpasning i valget av algoritmer, design for skalerbarhet og fleksibiliteten til det utviklende systemet for å adressere fremtidige krav slik at PPC- systemet passer med egenskapene til det gitte PPC-miljøet.

Studiens forskningsdesign er preget av noen **begrensinger** og viktigst av disse er det lave antall case - noe som begrenser muligheten til å generalisere fra funnene. Til tross for svakheten ved det begrensede utvalget, etablerer studien et grunnlag for fremtidig forskning innen anvendelsen av strukturell betingelsesteori ved å utvikle smart PPC for bærekraftig og konkurransedyktig produksjon. Samlet sett bidrar denne studien med ny kunnskap til det framvoksende domenet av smart PPC innenfor produksjonsledelse. De utviklede resultatene gir ledere nye verktøy for beslutningsstøtte rundt viktige strategiske og operasjonelle beslutninger knyttet til digitaliseringen av sine produksjonssystem.

Table of Contents

List of Figures

List of Tables

Abbreviations

AI – artificial intelligence

BDA – big data analytics

CRP – capacity requirements planning

DM – demand management

ETO – engineer-to-order

IoT – internet-of-things

ML – machine learning

MPS – master production scheduling

MRP – materials requirements planning

MRPII – manufacturing resource planning

MTO – made-to-order

MTS – made-to-stock

OM – operations management

PPC – production planning and control

PSS – purchasing/supplier systems

RFID – radio-frequency identification

RCCP – rough-cut capacity planning

RP – resource planning

SFC – shopfloor control

SOP – sales and operations planning

1

Introduction

This chapter begins with a description of the significance of production planning and control (PPC), a description of the research problem and industry motivation, followed by research gaps and objective, and concludes with an outline of the thesis.

1.1 The Significance of Production Planning and Control (PPC) in Manufacturing

Manufacturing industries have been the source of much of the development in the developed world and remain vital to the long-term sustainability of their economies. Generally, a manufacturing enterprise is organized as a coupling of transportation, transformation, and storage of materials and (human, financial, and intellectual) capital to create products and services for final consumers (Vollmann et al., 2005). These activities are either carried out alone or in collaboration with partners in a supply chain who sometimes have divergent interests and goals. Each member of that supply chain may be situated in the same city or country or be globally dispersed and subject to different regulatory, political, legal, socio-economic, technological, and local market constraints.

Depending on the way products are created, manufacturing enterprises are often categorized as being either process, discrete or semi-process. In process manufacturing, raw materials (often commodities such as petroleum, aluminium ores or milk) are transformed into final products that cannot be disassembled and are indistinguishable from one another. In discrete manufacturing, components are transformed into discrete products, such as shelves or cars. However, in practice the distinction is not always clear-cut, and most production operations have some elements of both types in their operations, which is why some production operations are referred to as semi-process manufacturing. Nevertheless, all types of production involve (albeit to varying degrees) the sourcing and storage of raw materials, transformation of those materials, work-in-process, storage of finished goods, and transportation to various points of consumption either directly or through a supply chain.

Furthermore, the various elements within the company's environment are in constant flux. Consumer demand and quality expectations are increasingly uncertain, distributors' and retailers' demand can be spasmodic (compounded by the bullwhip effect), supply disruptions are increasing due to geopolitical and regulatory disruptions, and the threat of new entrants using rapidly developing digitalization technologies remains critical. These and similar challenges place enormous demands on the management function and the processes used in managing these elements. These processes are together referred to as *production* (or manufacturing) *planning and control* (PPC) (Arnold et al., 2011).

The use of the terms *planning* and *control* span project, production, and service operations. However, while there are commonalities across these three domains – that is, the goal is to manage resources so that the operation is delivered on time, on budget and at the stated quality and with the expected attributes – PPC has the distinguishing feature in that for production operations, it is possible to create and store value in anticipation of expected demand. Therefore, within production, the terms *planning* and *control* more precisely encompasses the set of activities listed under the 'production planning' and 'production control' groups in Figure 1.1.

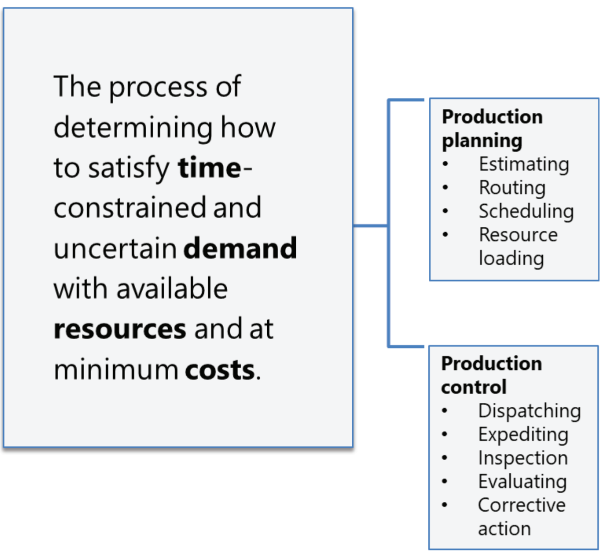


Figure 1.1: A definition for production planning and control

Scheduling concerns *when to do things*; loading concerns *how much to do*; sequencing concerns *in what order to do things*; and monitoring and control is concerned with "*whether or not activities are going to plan and corrective actions needed to bring activities within plan*" (Slack et al., 2013).

Supplementary activities involve the acquisition of information from customers on product needs and the provision (to customers) of information on delivery dates and product status (Vollmann et al., 2005). In practice, this may extend beyond the individual firm to include the coordination of suppliers and key customers in the so-called "extended enterprise" (Jacobs et al., 2011).

The idea of the extended enterprise emerged from period when economies-of-scale and specialized factory theories dominated the research space – a consequence of the seminal work on *focused factories* by Skinner (1974). Since then, it is less common to find a firm producing alone, every input needed for its final products. Nowadays, manufacturing firms collaborate with members of their supply chain, with the aim to produce products and services to customers in the required quantity and quality, and to deliver at the right time and place. Thus, the success of a firm relative to its competitors is no longer only dependent on its ability to organize its operations efficiently and effectively. Rather, it must coordinate its entire value chain to deliver the greatest value to the market compared to its competitors. In other words, the characteristics of a firm's value chain – otherwise referred to as production network or supply chain, as explained in Rudberg and Olhager (2003) – assumes a pivotal role in determining whether or not it will be competitive in the new industrial era. The firm must, therefore, plan and control its use of resources in sync with other members of its supply chain (Arnold et al., 2011).

1.2 Industry Problem and Motivation

The trend towards the digitalization of products and processes – including both production technology and the planning and control processes – presents a disruption to the old way of managing operations (Iansiti and Lakhani, 2014), and major disruptions in production competitiveness are expected in the coming decades (Porter and Heppelmann, 2014). Conventional methods for managing the PPC processes include the use of enterprise planning (ERP) systems, manufacturing execution system (MES) and advanced planning and scheduling (APS) systems. These systems have served industries for decades and are still commonplace as they have enabled organizations to wield greater and more effective control over their operations (Hanseth et al., 2001). However, they are deemed too inflexible or inadequate to meet the needs of current production environments (de Man and Strandhagen, 2018, Kirikova, 2019).

To be competitive in this new era of digitalization and the pursuit of industry 4.0, the firm, through its value-chain, must leverage emerging technologies to improve its planning and control activities in the short-, medium and long-term. But as Porter and Heppelmann (2014) pointed out, some of the changes will be undesirable, such as how increasing information could potentially increase price competition. Yet, some of the changes are desirable, such as the development of new business models, enabled by emerging technologies such as sensors and machine learning, which will generate new revenues by creating additional customer value.

And now, after the initial buzz in the past half-decade, production managers desire clear guidelines to support their digitalization initiatives. A key problem being witnessed is that while several technologies exist each with its expected business value, the benefits and business value of several remain unclear. The question of "strategic fit" arises, raising the prospect for methods, tools, and conceptual frameworks that takes the contingencies of a firm's value-chain into account. Moreover, previous studies have shown that the production planning environment attributes tend to affect the efficacy of methods used to manage operations, and should therefore, be considered when reconfiguring value-chains and the underlying business models with digitalization (Jonsson and Mattsson, 2003, Hong et al., 2010).

In addition, while it is currently widely believed that real-time data of the PPC inputs will lead to better performance, for example, as argued in Strandhagen et al. (2017), this may not always be the case. For example, Wolfsgruber and Lichtenegger (2016), after a simulation study argued that it is sufficient to have real-time data in some inputs such as inventory even if other inputs such as demand data is provided at the end of each business day. In order words, the nuances of each technology must be examined if acclaimed performance improvements are to be achieved. One can therefore surmise that the contingent factors of each case, in addition to the nuances of each technology represent key issues that must be evaluated when introducing emerging digitalization technologies into the production system.

The foregoing arguing presents the risk and opportunity before manufacturers. If they do not leverage these new technologies effectively in their production systems (especially the planning and control systems), and if competitors do, they may witness an erosion of their competitiveness. However, if they are successful, business opportunities will expand and contribute to sustainable contributions to economic growth, averting this risk and thus positioning successful firms in the vanguard of cutting-edge production performance (Dreyer et al., 2010).

1.3 Research Gaps and Objective

The emerging challenges described in the previous section have led to a strong research interest in both the academia and industry, raising an important question: how will digitalization influence production operations? A natural question that follows is: how can production operations become more competitive by leveraging these technologies? In this research project, these questions have been investigated from an operations management perspective as in Rudberg and Olhager (2003), with a focus on the production planning and control which is the primary responsibility of production managers.

One of the key elements in operations management research is the fit of the PPC system with the production system, as the level of fit often decides the efficiency, profitability, and long-term viability of a production enterprise. PPC managers must deal with several additional challenges such as swings in regulatory policies, climate change and other global phenomena all of which appear to put the world in a state of near-perpetual turbulence. In order to deal with the increased complexity and new market demands, production managers continually attempt to improve product and process flexibility, often leading to an increase in the depth of bill-of-materials and greater variation in production routings (Vollmann et al., 2005). This causes PPC to be even more challenging and the consequence is that a significant proportion of production lead time is still wasted as queueing or waiting time and many orders are delayed or produced to early with many weeks waiting in storage (Tony Arnold et al., 2012).

Furthermore, recent developments in digitalization systems particularly with the emergence of the internet-of-things – often represented by the concept of industry 4.0 – highlights the potential to transform all stages in the product lifecycle (from design, sourcing, manufacturing, to distribution, consumption, and recycling). This, it has been said, can be achieved by enabling real-time planning and control of the factory and supply chain operations (Strandhagen et al., 2017, Fatorachian and Kazemi, 2020). To support real-time planning and control, new and more extensive data must be collected and processed from the production system and the supply chain (Reuter et al., 2017). But more importantly, this data must useable either in its raw form – something that rarely occurs – or after much data preprocessing (Kusiak, 2017).

While several conceptual studies on smart manufacturing have been published, mainly focusing on production systems' configuration and features, very few empirical in-depth case studies have been reported in the literature that specifically focus on the management processes of such systems (Moeuf et al., 2018, Machado et al., 2020). Additionally, only a few of these studies address the importance of production planning and control in achieving the vision of smart manufacturing (Ren et al., 2015, Moeuf et al., 2018, Sun et al., 2020). This is a missed opportunity, as the PPC process is analogous to a brain for the production system and is the most critical “smartness” element of a smart factory. Furthermore, addressing the issue from the perspective of PPC enables firms to gradually advance in a holistic manner towards smart and sustainable manufacturing. This will require making PPC ‘smarter’ (thus the term ‘smart PPC’) using these emerging technologies to address the practical challenges of PPC while at the same time recognizing the constraints that each production system and its environment place on the use of digitalization technologies.

For this thesis, the Smart PPC construct is defined 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 while input from a more diverse range of sources.*

If implemented successfully, smart PPC should enable the use of real-time demand and production system data, i.e., reduce uncertainty from forecasts. It should also allow PPC to be dynamic, thus using frequent updates, and be reactive to real-time data. It should also use an expanded set of data input sources from the production system’s environment. It should enable accurate prediction of short-term requirements and support increased flexibility. It should also be able to capture and use the experience of the operators and managers in the production system (Oluyisola et al., 2020, Bresler et al., 2020). Nevertheless, these goals have proved challenging to achieve in practice (Reuter et al., 2017, Oluyisola et al., 2020) and there are “too few … studies” that investigate how the production system’s environment factors could affect the enhancements of PPC with industry 4.0 (Bueno et al., 2020).

Consequently, this study addresses how smart PPC can be achieved in practice, and the sustainability implications of such a system. If these goals can be achieved, it will lead to more precise planning processes, a reduction or elimination of waste, and ultimately to improved competitiveness. Therefore, this thesis has the following **research objective**:

> to identify the PPC challenges that are amenable to smart technologies, to identify the elements that such smart PPC should contain, and to determine what constraints the planning environment attributes impose on the design and development of smart PPC.

In this context, design refers to the architectural design rather than a user-interface or graphical design. This is about the structure and elements of the smart PPC system, and about how to translate the system requirements and attributes to the lower level elements – of data structures, of class definitions, of entity-relationship diagrams, of matching appropriate algorithms, etc. – in a way that supports the development of smart PPC systems that fit the near- and long- term requirements of a production system (Kusiak, 2017, Reuter et al., 2017). This is particularly important for smaller production companies who have more restrictive research and development budgets, and now for big industry leading companies at times of global economic crises. And these categories of firms are more there is no systematic, holistic design and development guide for the design and development of a smart PPC system.

1.4 Thesis Outline

The remaining sections of this thesis are structured as follows. The theoretical background highlighting the relevant extant literature for the entire study is presented in chapter 2. This chapter begins with brief history of PPC, then explores PPC theory, followed by a review of emerging digitalization technologies, design and development considerations, and the argument for contingency theory as an appropriate theoretical lens to view the development of smart PPC. Chapter 3 begins with the research questions which are formed by breaking down the research objective into four research questions RQ1, 2, 3 and 4. The rest of the chapter then details the research design adopted for this study and highlights the relevance of the chosen data collection methods and artefact development approaches. The artefacts developed include conceptual frameworks and a method for developing smart PPC.

The study findings are presented, analyzed, and discussed in chapters 4 to 7. In chapter 4 (addressing RQ1), a description is given of the six case companies that provided empirical data for this study. The cases are described according to their market (supply and demand), product, and process attributes and their practical PPC challenges in PPC. In Chapter 5 (addressing RQ2), a conceptual framework for smart PPC is developed using the literature and the insights from the case studies. A table of use-cases is also provided. In Chapter 6 (addressing RQ3), by using the structural contingency theory, an evaluation is made of the constraints imposed by the planning environment attributes on the fit of emerging digitalization technologies within case companies. From the insights garnered from this evaluation, and the literature, a smart PPC strategy matrix is then developed. Chapter 7 (addressing RQ4) presents a method for developing smart PPC and demonstrates the use of this method with a case study. The final chapter (8) summarizes the findings, conclusions, limitations, and potential future research.

2

Theoretical Background

This chapter presents the theoretical background highlighting relevant extant literature for the entire study. It begins with brief history of PPC, then explores PPC theory, followed by a review of emerging digitalization technologies, and the argument for contingency theory as an appropriate theoretical lens to view the development of smart PPC. It concludes with a research framework which highlights the three key topics that guided this study.

2.1 History of Modern PPC

The history of modern planning and control can be traced to the publication of Frederick W Taylor's revolutionary work (Taylor, 1911): "The Principles of Scientific Management" which came about in reaction to calls for ways to reduce industrial inefficiency at the turn of the 20th century (Wilson, 2016). Scientific management was later defined by Hoxie (1911) as "*a system devised by industrial engineers for the purpose of serving the common interests of employers, workmen and society at large through the elimination of avoidable wastes, the general improvement of the processes and methods of production, and the just and scientific distribution of the product*" (Taneja et al., 2011). The principles espoused in the book such as standardization, task-delineation, the concept of piece-work, the use of scientific methods rather than the rule of thumb in reducing inefficiency laid the foundation for the systematic methods that evolved in the decades that followed (Wilson, 2016).

Materials requirements planning (MRP) was developed in the USA in the early 1960s and was widely implemented during the 1970s (Browne et al., 1988). Higgins et al. (1996) suggest that MRP thinking has revolutionized PPC. Applications of MRP were built around a bill of material processor (BOMP) which converted the aggregated plan of production for a parent item into a discrete plan of production or purchasing for individual component items contained within the BOM. MRP logic can be summarized as an iteration of three consecutive steps (Higgins et al., 1996): netting against available inventory; calculation of planned orders; and bill of materials explosion to calculate gross requirements for dependent items. The main objective of MRP is to determine what and how much to order (both purchase orders and production orders), and when. The input to this is the master production schedule (MPS). As the MRP calculation process makes no consideration of available capacity, a separate capacity requirement plan (CRP) must also be created, and this was integrated into closed-loop MRP system developed in the 1970s.

In the 1980s, the three separate modules – MRP, MPS and CRP – were combined to make a single system, termed manufacturing resource planning (MRPII). This also included the sales and operations planning (SOP) function and rough-cut capacity planning (RCCP). The MRPII systems also allowed integration with a company's financial management system. Thus, it became possible to have an integrated, holistic operations system, which enabled the checking of operation plans vice-a-vice available resources. The system also allowed visibility into the financial implications of the operations and how to take corrective actions (Ptak, 2004). Much of the PPC system in Figure 1 is represented in the MRPII concept. Nowadays, it is common to find the PPC system built-in to enterprise resource planning (ERP) systems. An in addition to enabling planning and control with the plant, ERP systems can be extended to support the coordination of activities beyond the internal factory operations, and across the supply chain (Tarantilis et al., 2008, Oluyisola et al., 2015)

To capture all its elements, PPC is often described using hierarchical frameworks which presents the various elements of the PPC process at varying levels of detail and time horizon. This hierarchy supports the 'drilling down' approach that business managers seek when making decisions about their production systems. One notable PPC framework shown Figure 2.1, by Vollmann et al. (2005), is the basis for most enterprise planning systems in production today. The framework describes the strategic (long-term), tactical (medium-term) and operational (short-term) stages as the common levels of planning that exists within a typical enterprise resource planning (ERP) system regardless of the type of industry in question. And while it has faced some criticism for not capturing the several feedback loops that are witnessed in real life production systems, it remains popular due to its comprehensiveness and its built-in optimization capabilities (Leitão, 2009).

Meanwhile, other PPC frameworks such as Bonney (2000) highlight the importance of the feedback loops as shown in Figure 2.2. Also, these loops are more frequent and more important in the later tactical and operational stages of PPC. Regardless of whether the system in question is built on a hierarchical framework, PPC systems have become colossal systems which are hard to implement and maintain, and which are unwieldy and difficult to adapt to the needs of today's production environment (Leitão, 2009, Ansari et al., 2019).

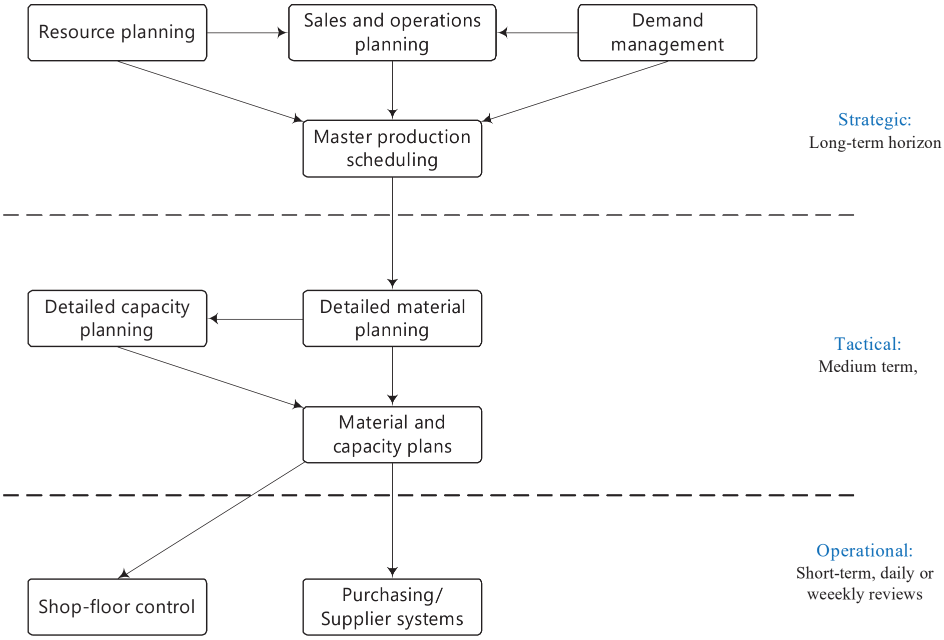


Figure 2.1: The PPC framework (*Source*: Vollmann et al. (2005))

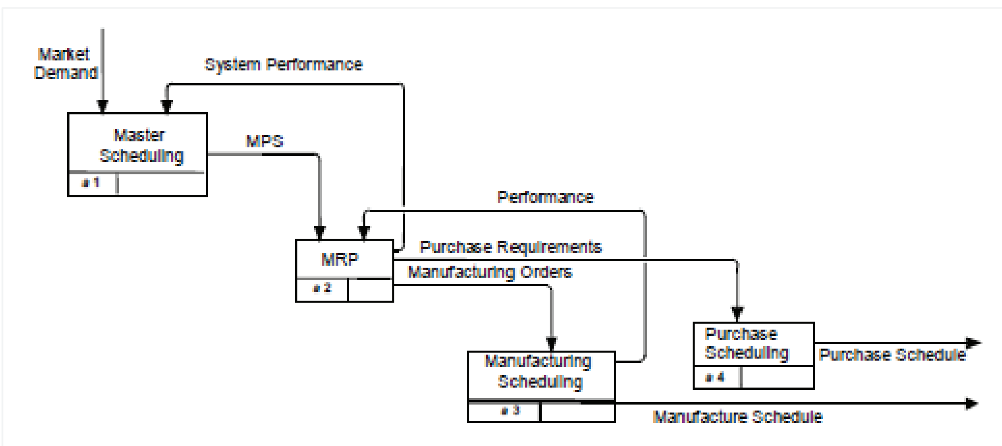


Figure 2.2: Iterative process of PPC (*Source*: Bonney (2000))

Taking these loops into consideration, an adaptation of the three-domains framework into a holistic PPC framework has been proposed as depicted in Figure 2.3 below (Oluyisola et al., 2020).

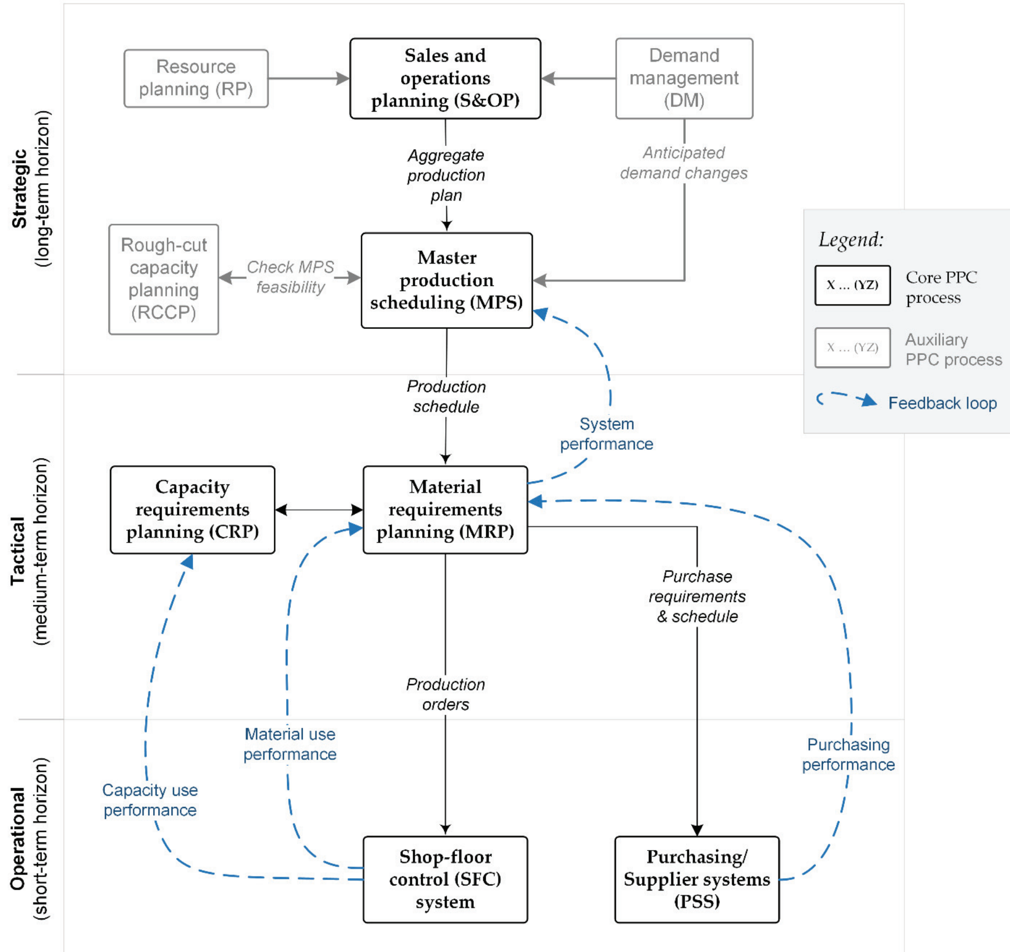


Figure 2.3: The PPC system domains and processes (Source: Oluyisola et al. (2020))

The strategic level takes a long-term view, aggregated view of production operations. The process starts with sales and operations planning (S&OP) which aims to balance overall demand with the available capacity. It receives demand data (volumes per product family per planning period) and in some cases meta data (such as forecast uncertainty) as input from demand management (DM) and future available aggregate capacity as input from resource planning (RP). The aggregated plan generated at that level is thereafter disaggregated from product family into individual products. Since it is aggregated and with a relatively larger time horizon than others, it is not often accurate. The relevant data for this stage typically includes demand forecast data which can be computed from historical demand data or estimated from experience by the sales and marketing team or some combination of the two

(Vollmann et al., 2005). The primary output is the master production scheduling (MPS) which is the purchasing and production plan at individual product level by time, typically weeks. Its output is the input of the detailed material planning at the tactical stage.

At the tactical level, the MPS records are combined with bill of materials data and inventory data to calculate the components' and parts' requirements, and make recommendations to release replenishment orders for materials, a process called materials requirements planning (MRP). Based on the production system's capabilities and manufacturing lead times thanks to the capacity requirements planning (CRP) process, it is possible to release detailed material and capacity plans with shorter time horizon (typically weekly). These plans are revised frequently, and the output of this stage is production plans and replenishment orders for materials; it is the input for the operational stage.

Finally, at the operational level, the concern is about how to execute the production order using the materials and capacity plans from the MRP and CRP. The processes entail day by day, shift by shift detailed scheduling and coordinating of the actual manufacturing processes (shop floor control, SFC), and issuing purchasing schedules to the purchasing function or supplier systems (PSS) for the supply of materials needed to execute daily operations (Vollmann et al., 2005, Bonney, 2000). The documents at this level are typically purchasing orders at component level and work orders/job lists at work centers. This stage also involves the control, measure, and evaluation of the effectiveness of production operations and suppliers. All these processes are not without challenges, and a discussion of those challenges follows in the next section.

2.2 PPC Challenges and the Limitations of Enterprise Planning Systems

One key limitation of PPC at the strategic level is that it implicitly assumes that the effect of extraneous factors such as weather or industrial policy changes, global economic downturns and other disruptions average out from year to year. This often leads to the use – by planners and operators – of excessive capacity buffers and safety stock in the production system. Furthermore, since the data is aggregated, the quality often varies depending on how data-driven the company is. Challenges include quality of data in the long term (as the business environment continues to change), frequency of update, etc. In this case, having real-time data does not necessarily lead to any advantage provided the data is accurate. Perhaps more important is the span of the data, in which case 'longer is better' to enable various simulation scenarios.

Managers of production systems often must make resource planning and flexibility related investment decisions based mainly on uncertain forecast data (Vollmann et al., 2005). Therefore, the S&OP process needs to overcome variations in historical demand, uncertainties in demand forecasts, and unavailability of demand data. Similarly, the MPS process needs to handle issues related to data integrity and completeness, estimation of product-level demand, inventory variability leading to difficulty in estimating available-to-promise, rescheduling frequency periodic scheduling while events alter production system, and a lack of feedback on the accuracy of resource planning.

At the tactical level, the challenges of traditional PPC include planning complexity due to data integrity concerns, product mix exacerbated by increasing product customization needs, estimation of production volumes, control principles that minimizes work-in-process inventory, etc. (Vollmann et al., 2005). Thus, the MRP process must deal with issues regarding the updatedness of bill-of-materials with respect to components and levels; inventory data accuracy – what is produced and exact storage location; and lot-size determination and revision policy. And the CRP process must handle the updatedness of process routes/charts and recipes; accuracy and integrity of production instructions; process variability; variability in resources capabilities and capacity; and continually monitor the size of buffers (Garetti and Taisch, 1999). Production managers deal with all these challenges using leveling and lot-sizing techniques within the constraints of the planning solution that the company employs. They must also deal with the limitation that the production planning process is run periodically while the demand situation is continuously changing. They must also manage the contrast between the objectives of long-term planning versus short-term scheduling – that is, leveling versus the minimization of earliness/tardiness and non-execution (Sánchez-Herrera et al., 2019).

As explained earlier in section 2.1, at the operational (short-term) level, the status of the production system is changing in real-time and the agility and precision of the PPC system in adapting to the changing production environment is critical. However, the reality in most factories is that it is challenging to track and accurately predict work-in-process inventory and resource status, and the system is continuously being disrupted by rush-jobs and unplanned machine breakdowns or large changeover and set-up times (Oluyisola et al., 2018b, Strandhagen et al., 2017). Specifically, the PO process is challenged by the reliability of supplier quality and timeliness accuracy (Oluyisola et al., 2018a). Furthermore, SFC processes and systems handle collection of operations data in real-time, job tracking on the shopfloor, resource performance tracking, and estimating and updating production schedule after rush jobs. Yet, a significant proportion of production lead time continues to be wasted in the form of queueing or waiting time (Tony Arnold et al., 2012). Moreover, the manufacturing technologies are increasingly becoming sophisticated and the SFC systems are required to handle a disparate set of data types and sources.

Overall, a few underlying challenges commonly affect the strategic, tactical, and operational levels of the PPC system. Promotions and campaigns which are becoming commonplace can significantly disrupt supply chains. In addition, the quality and completeness (w.r.t. the span or breadth) of data sources used is a common challenge affecting resource efficiency and demand fulfilment (Gustavsson and Wänström, 2009). These become even more important as systems become increasingly computerized and automated. Amongst many others, some of the key challenges PPC systems are currently required to manage can thus be summarized as follows:

- The goals of product and process flexibility in response to new market demands leads to a more challenging management of material flows (Vollmann et al., 2005).
- A significant portion of production lead time is still wasted as queueing or waiting time (Tony Arnold et al., 2012).
- The depth of bill-of-materials continue to increase and there is more variation in production routing as product complexity increases.
- Frequency of planning periodic while demand is continuous.
- The objectives of planning versus scheduling i.e., leveling versus the minimization of earliness/tardiness and non-execution (Sánchez-Herrera et al., 2019).

The PPC system is tasked with managing the production system with due consideration for challenges, and ultimately, with managing the uncertainty in production systems, either through methods that try to stabilize the system, common with lean approaches (Oluyisola et al., 2016), or through predicting and reacting effectively and speedily to events and changes-in-state of the production system. The latter requires few or frequent rescheduling depending on the kind of operation and the stability of the production environment (Vieira et al., 2003). In achieving these goals, various scheduling logics and planning methods have been developed at different levels of detail and time (hierarchical systems) and at different domains. This diversity of topics and issues have led to different streams of research.

One stream of research has focused on investigating the effectiveness of enterprise resource planning (ERP) systems for PPC in different industrial environments, e.g., in dynamic market environments (Tenhiälä and Helkiö, 2015), in make-to-order (MTO) production environments (Aslan et al., 2012, Aslan et al., 2015), in small and medium enterprises (Ahmad and Cuenca, 2013), etc. The research within this stream has often been triggered by perceived limitations and inadequacies of ERP systems in supporting manufacturing planning and control activities. A frequently mentioned limitation of ERP systems is that it generates unrealistic or infeasible production schedules due to the use of infinite capacity scheduling (Steger-Jensen et al., 2011, Arica and Powell, 2014). Meanwhile, these limitations of ERP systems have paved way for the second research stream, which concerns auxiliary planning and control systems such as MES and APS. Consequently, the infeasibility of production schedules generated by ERP systems and the inability to tightly control operations have led to some large manufacturers using APS systems for planning and MES for production control respectively (Saenz de Ugarte et al., 2009, Steger-Jensen et al., 2011).

While MES and APS systems can address some limitations of ERP systems, these planning and control systems are known to also have their own limitations. The processes within these systems have remained simplistic and too rigid, which limits the factors that can be considered within production planning and control decisions. Adjustment to schedules based on real-time or near-real-time data is infeasible and commonly avoided by production planners. It is also expensive to integrate additional software (called 'add-ons') with the large, monolithic systems, often making it difficult to adapt to changing business needs and leading many manufacturing managers and planners to build simpler, easier to manage, but disparate tools outside their PPC systems (Shaikh et al., 2011, Carvalho et al., 2014).

Consequently, another stream of research has looked at the development of complementary decision support systems for addressing some of the challenges being faced by companies implementing ERP, APS and MES systems. Indeed, it is commonly reported that planners and supervisors, in many instances, tend to prefer simpler and more flexible tools and are more likely to avoid more complex, albeit theoretically performance-improved methods for addressing many of the production planning and control needs (Tenhiälä, 2011, de Man and Strandhagen, 2018). Therefore, while enterprise planning systems inhibited high efficiency for PPC processes by being unwieldy and not including additional real-time system data, flexible approaches have been limited in that they are often very manual, dependent on the availability of specific people and also not holistic (Oluyisola et al., 2020).

2.3 Towards smart PPC in the era of Industry 4.0

The temporal proximity or 'real-time' needs of PPC is a major uphill climb for conventional enterprise systems such as the ERP, manufacturing execution system (MES), or advanced planning and scheduling (APS) systems. Moreover, another critical limitation of these systems is that deviations are common between information in these enterprise systems and the reality on the shop floor and across the supply chain (Schuh et al., 2014). Furthermore, these enterprise systems are commonly configured to collect data from a narrow range of sources in the production system typically from production lines and perhaps warehouse inventories. However, in many production systems and value chains, several more factors influence performance. For example, in the food and beverages industry, the weather affects not only the production but also the distribution and consumption rates of numerous products. Being able to capture and use data from a broad range of sources presents an opportunity for better PPC performance in the current era. These limitations can be addressed by Industry 4.0.

Industry 4.0 envisages a state of manufacturing in which the product's end-to-end lifecycle stages are integrated, the production systems and internal functional units are networked (vertical integration), and the external value creation network is integrated (horizontal integration) (Stock and Seliger, 2016, Stock et al., 2018, Machado et al., 2020). This vision is enabled by the recent advances in technologies including cyber-physical systems, internet of things (IoT), big data analytics (BDA), machine learning (ML), augmented reality, cloud and edge computing, and additive manufacturing (Machado et al., 2020, Hermann et al., 2016b). Therefore, with all things connected, data generated from these integrated systems with the plant and across the value chain will enable real-time control (and, consequently, dynamic re-planning and rescheduling) of the factory and supply chain (Strandhagen et al., 2017, Ivanov et al., 2019). IoT, BDA and ML connected to and run via the cloud can address these temporal proximity needs of a smart and sustainable production value chain (Iansiti and Lakhani, 2014). This specific collection of emerging technologies are at the cutting edge in the development of information systems (IS), having seen tremendous investments in research and development in the previous decade partially due to the significant reduction in the costs of computation power and data storage (Iansiti and Lakhani, 2014). The cost reductions have been possible due to the reducing cost of hardware and the economies-of-scale achieved in cloud computing (Bean and Davenport, 2019).

Another key tenet of industry 4.0 is that production systems will be sentient and autonomous (Iansiti and Lakhani, 2014). This will enable the development of real-time planning and control of the plant and supply chain operations thereby minimizing wastes in the system as every product will be produced as close as possible to when it is required by a customer (Strandhagen et al., 2017). In addition, the ability of BDA and ML tools and technologies to manage data with ordinarily challenging diversity (or variety) is an opportunity. Since computerization of the planning process is, by itself, not new, and enterprise systems and spreadsheet solutions have been used for decades, many production managers find it challenging to step into this new way of using data and ICT (Reynolds, 2015).

In addition, digital technologies have the potential to improve social and environmental sustainability when developed into organizational capabilities (Veile et al., 2019). In a recent study, Dubey et al. (2019) found that BDA improves sustainability performance among Indian firms, consistent with previous studies. However, they also found that the primary driver for its adoption was its expected economic impact rather than any social or environmental benefit. This latter point further highlights previous findings which reveal how economics drives most transformational efforts including those publicized as sustainability programmes (Galpin et al., 2015). Meanwhile in another similar survey-based study in Brazil, Dalenogare et al. (2018) found that the maturity of certain digitalization technologies within the local context can lead to different expectations in their contributions to operational and sustainability performance. In their study, they found a strong positive correlation between the use of sensor technologies and the resulting big data with operational performance (agreeing with (Dubey et al., 2019)), but failed to find a significant relationship between industry 4.0 and sustainability. They also found, contrary to popular belief, that not all technologies are expected to lead to operational performance improvements.

However, more recently, studies are beginning to reveal that numerous companies are struggling in their efforts to become more data-driven and attain smart operations (Bean and Davenport, 2019). The realities of the adoption and use of BDA, ML, cloud computing, and related smart technologies have been much more challenging than anticipated. From anecdotal evidence with industry partners, and as the extant literature shows, certain projects are likely to succeed while others are more likely to fail depending on the structure of the supply chain, the characteristics of the production system, and the products attributes. In other words, there is the question of contextual 'fit' with the planning environment factors in terms of whether a company that applies these technologies in production operations will succeed or fail (Müller et al., 2018, Veile et al., 2019). Therefore, the selection and implementation of smart technologies towards a smart PPC system requires a consideration for the constraints of each technology and the characteristics of the production system.

2.4 Constraints, enablers, and the Structural Contingency Theory

From the foregoing, it is therefore evident that it is not sufficient for a manufacturing firm to select a technology and apply it and expect great results without due consideration for the intra- and inter- organizational factors that play a role in this regard (Schuh et al., 2017). Intra-organizational factors are those that define the working principles and the control of processes within an organization. Examples of such factors include the production process, products attributes, and human resource management systems. Inter-organizational factors, such as the pressures from supply chain partners and the intensity of competition in an industry, can constrain or enable a company's adoption of industry 4.0 technologies for PPC to enable a better synchronization of planning efforts within the supply chain (Banker et al., 2006, Wamba et al., 2015). While these factors can be expected to play a role in the fit of these technologies with the production system, the extent and the nature of this influence is unknown.

In a related study focused on the extended enterprise view, Ngai et al. (2008b) identified cultural issues, functionality requirements and legacy IT infrastructure, organizational and people-related challenges, technical support and training of relevant personnel as the critical success factors for successful ERP implementations (Ngai et al., 2008b). Koh et al. (2011) extended those ideas and identified barriers, drivers, and critical success factors for enterprise-wide ERP (ERPII) implementation across supply chains. They observed that while vendors and suppliers tout real-time information, better decision making power, and efficiencies in operations as the key drivers for ERPII implementation, users and customers are more concerned with how ERPII can provide new simpler and shorter ways for value creation, core competency integration, customer demand responsiveness, and improved product innovation or customization. They further identified barriers such as organizational inertia, resistance to change by employees, cost, gap between the theory and practice of the extended enterprise, disparate data standards and data inaccuracy as important factors. In addition, organizational structure and the learning culture have also been identified as critical factors (Schuh et al., 2017).

More recently, de Sousa Jabbour et al. (2018) extended the concepts related to critical success factors into research on how industry 4.0 can enhance environmental sustainability in manufacturing. They selected 11 non-technical factors including management leadership, strategic alignment, training and capacity building, empowerment to be innovative and discover new uses, national and regional differences, and organizational culture. However, the presence of other studies with conflicting results indicates that the influence of organization culture on the sustainability performance of firms implementing digitalization and industry 4.0 remains unclear (Dubey et al., 2019). Arguably, the influence of these internal and external factors varies based on the context that each production manager must consider when planning his/her production operations. Considering all these factors, the production enterprise is only likely to achieve the expected performance benefits of industry 4.0 if the technologies are configured and implemented in a manner that fits with the characteristics of its production system. Furthermore, certain industries (such as the engineering and equipment production industries) expect a long-term strategic benefit and are willing to pursue industry 4.0 regardless of possible challenges or implementation risks (Müller et al., 2018).

An appropriate foundational theory for addressing these kind of research problems is the structural contingency theory, which argues that organizational processes must align with the organization's environment (Sousa and Voss, 2008). The seminal work by Venkatraman (1989) laid a foundation the general application of contingency theory in management research. In that paper, the author took concept of fit (other conceptual term used for contingency theory) beyond general theoretical discussions and empirical explanations and operationalized it within strategic management research. Venkatraman (1989) further sought to address the "*many testing issues that are central to linking concepts with empirical tests*" [p. 424] and in doing so, identified six perspectives of fit based on two dimensions: the chosen degree of specificity of the theoretical relationship, and whether to anchor the test of fit to an assessable criterion (such as effectiveness or financial performance) or to not use any such criterion.

Along the criterion-anchoring dimension, the three criterion-specific fit forms are 'fit as profile deviation,' 'fit as mediation', and 'fit as moderation' while the three criterion-free fit forms are 'fit as gestalts,' 'fit as covariation,' and 'fit as matching' – with both groups listed in increasing order of specificity of the theoretical relationship. A recent systematic literature review of studies in supply chain integration by Danese et al. (2020) indicates that studies that use contingency theory as a supporting theory tend to adopt the fit as moderation perspective. While no such review has yet been carried for smart manufacturing, similarity of the smart PPC objective to the concept of supply chain integration suggests that inferences can be drawn from the Danese et al. (2020) review. The fit-as-moderation perspective, according to Venkatraman (1989), presumes the relationship between a predictor (for example, choice and use of smart technologies) and the assessable criterion (for example, improved PPC effectiveness) depends on a third set of relationship-influencing variables (for example, market or product attributes).

In one applied example, Hicks et al. (2001) applied the structural contingency theory to explain the characterization of different engineer-to-order (ETO) archetypes in accordance with how ETO companies reorganize their internal and external supply chains to remain competitive in the face of changes in their production environments. Another more closely related example is in Wamba and Chatfield (2009), where the authors build upon an earlier framework by Venkatraman (1994) and other diverse extant literature to develop a contingency model that can be used to assess the potential value of RFID implementation projects within logistics and manufacturing supply chains. The developed contingency model used "*environmental upheaval; leadership, second-order organizational learning, resources* *commitment, and organizational transformation*" as the contingent factors. Furthermore, by using a longitudinal case study to illustrate the application of the contingency model, Wamba and Chatfield (2009) demonstrates the usefulness of this approach to develop and test new theory to guide the context-driven application of information technologies (in their case, RFID) in logistics and manufacturing environments.

Drawing from the foregoing examples, this thesis takes the assumption that the success of relevant digitalization technologies in enhancing PPC to achieve smart PPC can similarly be amenable to contingency theory. In this case however, the contingent factors being test are the market, product, and production attributes. Regarding the technologies, some (e.g., data analytics) tend to have a wider application domain than others (e.g., sensors and machine learning). Therefore, to derive value from these technologies, several contextual (or contingent) factors must be considered because what works in one industry may lead to poor results in another – as examples of sensor-integration investigations in the plastic pipes production and supply chain as shown (Oluyisola et al., 2018b, Høyer et al., 2019). Similarly, the structural contingency theory can also be used to explain for the influence of the supply chain and industry context (Sousa and Voss, 2008, Hicks et al., 2001).

2.5 State-of-the-art on Smart PPC Development

The adoption of smart technologies has seen tremendous increase in recent decades due to increased availability and affordability of computing power (Guha and Kumar, 2018). Generally, there are two ways in which companies adopt a technology: either a company (or its leadership) is pushed by its industry peers in the form of a market trend, or a business need leads to a search for a technology solution (Beckman and Rosenfield, 2008). In either case, the technology's potential value is fully harnessed only when there is a fit between the requirements and application of the technology, and the firm's strategy, processes – both production and support – and its planning environment (Bharadwaj, 2000, Buer et al., 2020). With the enormous hype that came with Industry 4.0, technology push has been the driver for most of its recent research and applications thus far.

Within the last two decades, there has been huge interest in research exploring the use of smart technologies to improve the performance of production systems and these studies can be grouped into three categories. The first group consists of studies where smart technologies are used individually. For instance, there are studies on the use of radio frequency identification (RFID) or other IoT technologies for tracking of materials and goods within a production system to provide data for evaluation and optimization of material flows and layouts (Lee and Özer, 2007, Ngai et al., 2008a). An example is Zhong et al. (2013) who used RFID in a mass-customization production environment to track and trace items on the shop floor, collecting real-time production data to identify and control shop floor disturbances through an MES. In another example, Ngai et al. (2007) report on a case study on the development of an RFID-based traceability system for tracing repairable items in aircraft maintenance operations.

The second group are those that build upon the use IoT technology and other tracking and tracing technology, adding the power of cloud computing to these solutions. This addition typically enables the management of several thousands more IoT sensors thereby allowing for a more nuanced tracking of materials and resources on the shopfloor and in the wider supply-chain. The concept of digital twin falls within this category of research and application especially when applied to a factory or individual machines in the factory. For example, Qu et al. (2016) develop a concept and system for IoT-based dynamic logistics control with cloud manufacturing and demonstrate their approach within a paint-production company in China which uses the make-to-order strategy. The solution concept offers real-time tracking and dynamic re-planning based on changes to the state of the system. In another example, Tao et al. (2018), in their conceptual study on data-driven smart production discusses the distribution and tracking of materials, and the integration of data from the production process into production plans using an example in wafer production. The paper raises several points that can be useful in the design of smart PPC systems (such as the integration of digital twins and IoT technologies such as edge gateways and edge computing) but does not address this explicitly. In a related study, Sun et al. (2020) propose a visual analytics approach to production planning, to address the need for solutions that will enable a quick response to sudden changes in the operations and market environment, and with the ability to handle the deluge of data in emerging industry 4.0 production systems.

The third group is newly emerging, with the recent interest in advanced analytics tools and artificial intelligence and its derivatives/subsets – i.e., machine learning and deep learning (Bueno et al., 2020, Cadavid et al., 2020). The interest in using machine learning in PPC by itself is not entirely new. Garetti and Taisch (1999) long ago investigated the application of machine learning in production scheduling problems. However, as with several studies of its type, their approach to the use of machine learning to improve production through smart PPC suffers from the solution linearity problem (Cadavid et al., 2020). The solution linearity problem is the issue that most of these studies are linear from data cleaning, to data exploration, and so on until insights generation and retraining, typically carried out through desktop operations. However, for production scenarios where scalability and autonomous system operation is desirable, these linear solutions are inadequate and will require continuous, often expensive human expert management to use in production, thus the need for a self-sustaining solution.

These studies have raised, although indirectly, some pertinent issues as regards the design and development of smart PPC systems. Bueno et al. (2020) identify several gaps and suggestions for future research in the smart PPC research domain, a few of which are notable with regards to the design and development of smart PPC systems. First, (on p.15), they highlight a scarcity in extant literature regarding the question of fit of industry 4.0 solutions and the integration of PPC in different environments. This question determines whether a solution, even if well executed, will deliver any real and lasting value to a production operation. In addition, they emphasize on the need for research within development of intelligent decision support systems, frameworks and architectures that can advance smart PPC. In this regard, there is the need to determine the types of data to collect and use, the types of sensors to use and where in the production system to deploy them.

2.6 Considerations for the Design and Development of Smart PPC

Concerning the application of smart technologies for PPC processes, the common cases reported in the literature can be categorized according to whether they address the strategic or long-term, tactical, or medium-term, and operational or short-term scope within the PPC domain. The strategic use cases remain scarce in the literature (Bueno et al., 2020). This could be due to the immaturity of the emerging technologies to handle such broad data types and sources that typically feed into the strategic process, currently typified by use of managerial judgement who are able to also include those data sources that are difficult – but not impossible – to codify or assign a numerical value to. Meanwhile the tactical and operational PPC domains have seen increasing use of data with big data and machine learning for decision-making especially because of greater automation in operations processes. Furthermore, the distinction in the application of emerging technologies at the tactical and operational levels is not always clear, and use cases often overlap. Examples of use cases include real-time visualization and scenarios' simulations (Sun et al., 2020), product quality control, and integrated production-maintenance scheduling (Biondi et al., 2017).

When using machine learning, the choice of appropriate algorithms and the system features to be used in training models can both be critical factors on project outcomes because different algorithms fit or perform better depending on the use case, features' data quality and data architecture, and system architecture (O'Mahony et al., 2008, Pineda-Jaramillo, 2019). As noted by James et al. (2013), "on a particular data set, one method may work best, but some other method may work better on a similar but different data set" [p. 29]. Therefore, it is crucial to find a fitting method to fit the use-case when using ML. An overview of machine learning algorithms in PPC use-cases and some architecture considerations follows.

2.6.1 Choosing an Appropriate Machine Learning Algorithm

As there are several ML tools and algorithms in the public domain currently, it can be a daunting task in finding one appropriate for a PPC use case. Within each of the three general categories of machine learning – that is, supervised, unsupervised, and reinforcement – new and more efficient algorithms and hybrids are being created continually, encouraged by the deluge of data, geometric reduction in computing cost that cloud computing brought about in the last decade, and advances in algorithm development and transference across multiple domains (Risi and Togelius, 2020, Cadavid et al., 2020).

Supervised learning concerns the approximation of a function based on a given set of input-output pairs. In this learning paradigm, the learning algorithm is provided (training) data which provides both, input values and output values, and the algorithm approximates the function that relates the inputs to the outputs. The approximated function can then be used to predict the outputs, given a set of inputs from outside the training set. The second machine learning paradigm, i.e., unsupervised learning is more exploratory in nature. Unlike supervised learning, there is no requirement for predefined input-output relationships in the training data that is used in unsupervised learning. Instead, the learning algorithm explores the data to find patterns and structures in the dataset, revealing which data-elements can be used as predictors of other elements. The third paradigm, i.e., reinforcement learning involves the use of iterative trial-and-error logic to train an algorithm to generate responses to inputs, that are expected to yield the highest reward (Monostori et al., 1996). Some use cases for the different machine learning types are presented in the following paragraphs and a summary Table 2.1 below.

Examples of supervised in the literature include Gyulai et al. (2014) who report on a case where supervised learning is used in optimizing the allocation of different products to two types of assembly lines, namely, reconfigurable and dedicated assembly lines. They use a random forest algorithm for predicting production costs for given order volumes and resource pools. In subsequent work, the authors use multivariate linear regression for predicting capacity requirements for future production scenarios on a flexible assembly line based on data from the MES (Gyulai et al., 2015). Heger et al. (2016) use Gaussian process regression for estimating the effect of different parameter settings on dispatching rules for scheduling. Examples of the use of unsupervised learning includes Pillania and Khan (2008) who applied k-means cluster analysis for categorizing firms in a supply chain according to each firms agility. Huang et al. (2019) propose the use of deep neural network for predicting future bottlenecks in a flexible manufacturing system, which is a use case for unsupervised learning. In another example, Shiue et al. (2012) propose the use of self-organizing maps for selection of scheduling rules in semiconductor wafer fabrication.

Table 2.1: Analytics and ML algorithms applied to PPC use cases

	Strategic	Tactical	Operational
Supervised [linear and non-linear regression, support vector machine, k-nearest neighbors, linear discriminant analysis]	Multi-scenario prediction of production costs of production lines (1) – *Random forests*	Predicting capacity requirements (2) – *Multi-variate linear regression*	Dynamic selection of suitable dispatching rule (3) - *Gaussian process regression*
Unsupervised [principal component analysis (PCA), k-means, self-organizing maps]	Vendor selection (4) – *PCA*; Strategic sourcing (5) – *k-means*	Prediction of future production bottlenecks (6) – *Levenberg–Marquardt;*	Real-time shop floor control and selection of scheduling rules (7) – *Self-organizing map*
Reinforcement [Q-learning, Monte Carlo, SARSA, Relational]	Joint pricing and lead-time decisions (8) – *Q-learning*	Line balancing/ resource levelling under uncertain demand (9) – *Monte Carlo*	Adaptive scheduling in multi-site production (10) – *SARSA*; and Real-time rescheduling (11) – *Relational RL*

Key: *1 - Gyulai et al. (2014); 2 - Gyulai et al. (2015); 3 - Heger et al. (2016); 4 - Petroni and Braglia (2000); 5 - Pillania and Khan (2008); 6 - Huang et al. (2019); 7 – Shiue et al. (2012); 8 - Li et al. (2012); 9 - Tuncel et al. (2014); 10 - Aissani et al. (2012); 11 - Palombarini and Martínez (2012).*

Reinforcement learning, despite its huge potential for production systems, has only seen limited interest in PPC applications. This could be due the limitations in the early years of its development. For example, according to Dean et al. (1993) [*p*. 67], reinforcement learning as used conventionally creates a temporal assignment problem – in which feedbacks to the planning controller is intermittent and delayed. However, recent advances in the development of RL algorithms have addressed this, and other challenges as witnessed by some of the research on the topic in the last two decades. One example is the type of reinforcement learning called inverse reinforcement learning (IRL). According to Ng and Russell (2000), IRL may be useful when an agent is learning a "skilled behaviour," such as the planning optimal scheduling process, and for which the reward function being optimized is determined by “a natural system”, such as a production system.

Li et al. (2012) propose the use of Q-learning algorithm-based reinforcement learning for joint pricing and lead time decisions in a make-to-order system, where the decision problem is modelled as a semi-Markov decision problem. Tuncel et al. (2014) propose a Monte Carlo reinforcement learning algorithm for line balancing in disassembly operations under uncertain demand. Aissani et al. (2012) use a multi-agent based SARSA (state-action-reward-state-action) algorithm for production and distribution scheduling in a multi-site production network of a clothing company. Palombarini and Martínez (2012) use relational reinforcement learning for real-time (re)scheduling of extrusion operations in a secondary case study, i.e., the problem formulation is taken from literature. Lin et al. (2019) demonstrated an adaptation of the deep-Q network using an edge computing framework with multiple dispatching rules to demonstrate improved simulation results for job shop scheduling problems compared to methods using singular dispatching rules.

Despite all these developments, some important gaps remain in the smart manufacturing literature. One of this is how to manage data acquisition and integration, data exploration, and a process to continually update and retrain ML models during use. This absence of a complete (or “circular”) workflow leads to changes to the system going undetected over time, a phenomenon known as concept drift. This is a major shortcoming of extant data analytics and machine learning research in general, and especially with regards to application within the PPC domain (Hammami et al., 2017, Cadavid et al., 2020).

2.6.2 Data architecture considerations

The data architecture describes the design, structure and control of the data generating and collection elements. As data is the foundation for smart manufacturing and related concepts including smart PPC, the data architecture plays a vital role in the implementation and long-term viability and flexibility (to adjust to change) for any such system. For convenience and for hierarchical analysis, data from the production system should be amenable to grouping according the familial associations. This can be achieved using classes and objects belonging to those classes, in fitting with the object-oriented architecture. The objects that are members of the same class with similar attributes such as usage area, etc. For example, a ‘Sugarproducts’ class can have members such as ‘Orangemix’, ‘Gingercandy’ (both random names) which comprise that class. The machines can also be grouped into classes for instance the ‘Driers’ class could comprise all the driers in a factory’s production line.

Furthermore, data quality played a key role in the value companies were able to derive from enterprise planning systems like ERP and MES systems before the emergence of smart PPC systems (Gustavsson and Wänström, 2009). The importance of data quality is now more crucial because of the data intensiveness of smart PPC systems which use data from a wide range of sources including from within the plant, (potentially) from other partner systems, and from the production system's environment (Oluyisola et al., 2020). And while current enterprise systems collect sales transaction data from external customers and transactions generated directly from operations such as materials consumption in warehouses and factory floor production data (Koh et al., 2011, Mantravadi et al., 2019), the capacity to derive value from the abundant data in real-life environments has been a challenge (Kusiak, 2017).

Furthermore, there are different types of data available to any PPC system. Based on the temporal proximity of the data generation and collection processes, they can be classified as being either batch data, where data is collected and updated periodically, or stream data, where data is being generated, collected, and potentially analyzed in real-time. In production environments, many data processing systems implements some kind of runner using the Apache Beam model (Li et al., 2018). Most of data from the factory's environment and some of the machines in the production lines are time-series, stream data. An example of the time-series data snippet from an IoT device on a production machine in the JavaScript Object Notation (JSON) format is as shown in Figure 2.4 below. But there are also batch data which are seldom revised, for example the setup cost, and are input to the PPC processes.


```
Telemetry data: {"vibration":-2.05}Telemetry sent 20:05
Log data: {"vibration":-2.05,"packages":18,"speed":"slow","temp":60.5}
Log data sent

Telemetry data: {"vibration":2.91} Telemetry sent 20:05
Log data: {"vibration":2.91,"packages":20,"speed":"slow","temp":60.67}
Log data sent
```


Figure 2.4: Example of the telemetry data generated by an IoT sensor on a production line

2.6.3 Systems architecture considerations

The architecture of an information system (IS) can be defined as a collection of artefacts, namely a definition of constituent components of the IS, a specification of the properties of those components, and a description of the relationship among those components and their interactions during operation (Goepp et al., 2006, Bass et al., 2013). The use of the term 'design' in this context generally refers to the creation of the architecture of the smart PPC system. Because smart PPC systems are information systems, their developers must follow similar principles used for design similar ISs. This design must be made early in the overall development process, and in a way that allows for enough detail so that it provides sufficient guidance for developers, while at the same time allowing some freedom for the developers to make decisions during the actual development stage (Bass et al., 2013).

Within the broader Industry 4.0 research domain, generic architectural models have been proposed for the industry 4.0 production system and these can provide inspiration for the smart PPC solutions designers and architects. Common examples include the Reference Architecture Model for Industrie 4.0 (RAMI 4.0), the Industrial Internet Reference Architecture (IIRA) and the internet-of-things reference architectures (IoT RA) standard in the ISO/IEC 30141:2018 (Standardization, 2018). Nevertheless, these models can only serve as reference due to their generic nature and the fact that they do not cater for the context each production manager must address.

Typically, enterprise planning systems are designed as hierarchical control systems using a monolithic architecture (Themistocleous et al., 2005). This means that the system is built on a single, large, high-powered computer hardware. Such an architecture has several benefits, not least its speed due to its low natural latency, its limited need to manage integrations with several units, and that there is only a single hardware device to be managed instead of potentially several. And this was important for many decades before the advent of cloud computing since companies had to create a physical datacenter with server hardware and all the attendant management requirements. But this architecture also has several shortcomings. For example, its limited flexibility to add new tools and functionalities. This is because add-on functions need to be upgraded every time the main server itself received an upgrade from the ERP supplier who is typically a very large software vendor and whose upgrades are designed for general needs, and not for the specific needs of each customer. It is more costly to start-up, manage and run with a savings of up to 50% in terms of total cost of ownership (Mattison and Raj, 2012). This contrasts with the emerging smart technologies which are changing so fast, that there is an intrinsic need to design for flexibility and frequent changes.

These design considerations are addressed by the modular-by-design microservices architecture instead of a monolithic architecture. The microservices architecture presents a considerable benefit for several reasons: it can scale easily, and it is highly adaptable. It has been reported that self-adapting and self-optimizing multi-agent distributed production control systems have been demonstrated to perform better during transitions when used in job-shop environments where hierarchical systems are too rigid to adjust to the flexibility requirements of such environments (Ma et al., 2020). Thus, developers of smart PPC systems have a better chance at success if they employ a microservices architecture.

Furthermore, most research on the use of ML in PPC suffer from workflow-design linearity in addition to being based on artificial or historic, sampled data (Cadavid et al., 2020). While these conditions make testing specific models for confined problems easy, they are not feasible in real-life industrial practice. The challenge with linear design is that to use it in practice, a human operator needs to administer the intelligence creation process of the system, as seem in reported case literature, for example, Garetti and Taisch (1999) and Brintrup et al. (2019). In real-life industrial scenarios however, the smart PPC system should be able to collect data, clean it, prepare it for analysis, retrain its models, and offer refreshed insights without human intervention potentially self-adjusting its control parameters (Oluyisola et al., 2020, Rojas and Garcia, 2020). It should address the risk of concept drift, for instance by using adaptive time windows (Bifet and Gavalda, 2007). This could be achieved using data processing pipelines and monitoring scripts connected to a version control system for managing model versioning, a concept referred to as MLOps – that is, machine learning operations, which is a derivation of DevOps for ML.

To summarize, there are two main perspectives in the literature through which topics related to smart PPC have been viewed. First, in the puristic production and operations management perspective, ICTs are viewed as add-ons or auxiliaries that can enable or improve information flow but are usually considered exogenous (Slack et al., 2013). A contrasting view is that of information systems-centered research within the context of manufacturing, that considers ICTs as an integral variable and focuses on opportunities for performance improvements by employing ICTs – for example, Huang (2017). In the smart PPC development method proposed in chapter 7 of this thesis, an attempt is made at using a more balanced, multi-disciplinary view. In the example case study in the same chapter, material flow is controlled and monitored with ICT-enabled information flow, thus making ICTs integral components of the industrial system. Smart technologies or advanced ICTs are thus viewed as intrinsic elements of the smart production system as opposed to being add-ons.

2.7 Proposed Research Framework

From the foregoing literature review, a research framework is presented in Figure 2.5 highlighting the key elements from the literature that provides a foundation for the following chapters of this thesis. As shown in the figure, the PPC processes and the PPC environment variables are the foundation that smart technologies are then fused with to achieve smart PPC.

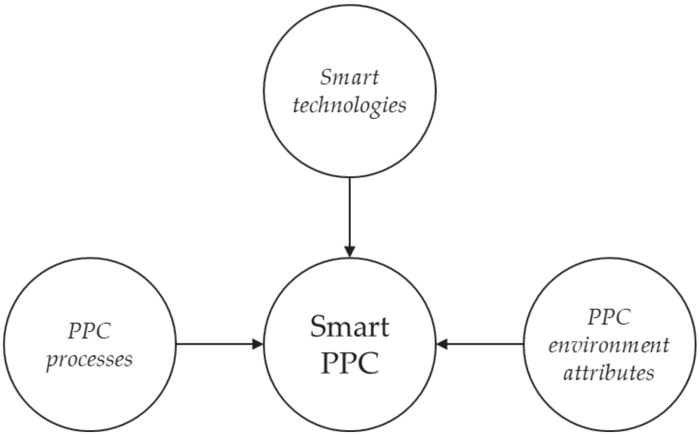


Figure 2.5: A preliminary research framework

The moderating PPC environment attributes grouped into market, product and process categories can be further measured in terms of:

- *market attributes*: demand uncertainty, customer order decoupling point (CODP), delivery variability, input supply uncertainty, few vs many suppliers;
- *product attributes*: variety, complexity, shelf-life, electronic-intensity for function or control, volume-to-cost ratio, unit cost, customization, final product or input;
- *process attributes*: production lead time, batch size, manual vs automated process, chemical vs physical process, process tolerance specificity, cost of capacity.

The PPC processes from aggregate planning to shopfloor control are shown in Figure 2.3 and described in section 2.1, and the relationship between PPC environment attributes and PPC processes has been established. For instance, it is known that managers of production systems that have a lot of process uncertainty are more likely to use spreadsheets for the planning activities and depending on how big the company is, are likely to use MRP systems for inventory control (Jonsson and Mattsson, 2003). And with the advent smart manufacturing and the recent push towards digitalization, there is a need for more insights about the relationship of these attributes with smart technologies being introduced into manufacturing systems to make the PPC system and its constituent processes smarter. The hypothesis here is that PPC environment attributes moderate the fit of smart technologies with PPC processes towards smart PPC systems. PPC processes are used to coordinate the activities in production systems which have codifiable attributes and these attributes determine what kind of smart technology will fit with the PPC processes in a production system. Having established the foundation for smart PPC, and the potential practical benefits, a research design for this to address this budding area of research is presented in the next chapter.

3

Research Design

This chapter details the research design adopted for this study and highlights the relevance of the chosen data collection methods and artefact development approaches. It concludes with a discussion of steps taken to ensure research quality.

At a very basic level, a PhD study aims to equip the candidate to be able to independently carry out research in his/her field later in his/her career (Phillips and Pugh, 2010). For these reasons, this PhD project was approached in a way to maximize both its practical and instructional value. According to Matthews and Ross (2010) learning how to do a reliable, valid and generalizable research through a defined methodology is a crucially important part of research education. However, meeting these criteria for operation management (OM) research can be more challenging that, say, research in the humanities or in the pure sciences. OM research is said to be either (a) semi-theoretical, because the aim is "*not to create theory, but to create scientific knowledge*" (Handfield and Melnyk, 1998) about empirical observations, or (b) pragmatic, because it attempts to solve practical OM problems that operations managers grapple with (Meredith, 2001, Holmström et al., 2009). Both types of OM research serve their purpose since OM research is a field that is expected to solve practical problems and the theory is needed to explain the empirical evidences. Consequently, research approaches in OM have had to take both facets into account as explained in the following section.

3.1 OM research approaches and case selection

As a result of these requirements of OM research, seven research approaches have been developed or adapted (from other fields) for developing scientific knowledge within OM over the years, and each of these approaches have their strengths and weaknesses. They are surveys, case research, longitudinal field studies, action research, clinical management research, design science, modeling and simulation (Flynn et al., 1990, Meredith, 1998, Karlsson, 2009, Holmström et al., 2009). Some of the methods are better suited for empirical research (e.g., surveys and case research), and are common approaches for studies investigating contingent factors. For exploratory research, case research, action research and design science provide the necessary flexibility and controls in charting a path, helping with the mapping of variables, and developing new artefacts within emerging research fields (Handfield and Melnyk, 1998).

Consequently, since this study addresses an emerging problem area, much of the research in this field are still of the exploratory nature. At this early phase in its development, research activities will aim to *discover* i.e., uncover areas research and theory development; to *describe* the territory; to *map* the key variables and identify the critical themes, patterns and categories; and improve the maps by *identifying the relationships* between variables and an explanation of these relationships (Handfield and Melnyk, 1998). It has also been established that if the objective is to gain in-depth understanding of a phenomena, the case study approach is a feasible and adequate research methodology (Karlsson, 2009).

Therefore, this study started with exploratory case studies to discover areas for research and then followed by case studies explored the territory identifying the challenges companies were having with their PPC processes and in their attempts at using digitalization to improve those processes. Thereafter, the study moved towards identifying the relationships between the variables and identifying the 'why' that explains these relationships. Cases were chosen across different industries to allow contrasting or attribute comparisons. The principles for case research in Yin (2013) guided the selection of cases and in addition, the guidelines by Handfield and Melnyk (1998) were used as a methodological guide throughout the project for data sampling, the choice of data collection methods, and subsequent data analysis.

3.2 Data collection and analysis methods

Recall from chapter 1 that the objective of this PhD study was:

> to identify the PPC challenges that are amenable to smart technologies, to identify the elements that such smart PPC should contain, and to determine what constraints the planning environment attributes impose on the design and development of smart PPC.

And as noted earlier in chapter 1, achieving the objectives will require an evaluation of already established PPC processes and systems and how their attributes can affect the firms' ability to fully leverage new technologies. Case study research seem appropriate for this requirement to achieve sufficient depth. A large sample survey would have proved inadequate at this stage without first understanding and clearly defining the important constructs of the study

(Malhotra et al., 2017). But first, it was necessary to identify and itemize challenges in PPC observes in the cases. Due to the technical and complex nature of this subject, it is important to collect case data from those with day-to-day experience with the PPC processes to ensure reliability (Tenhiälä, 2011). Thus, the following questions was specified:

RQ1: *What are the planning and control challenges in production systems that are amenable to smart PPC?*

To address this research question, data was collected during visits to the case companies. A narrative interview approach was used to allow the production planners and managers to discuss their PPC challenges openly, followed by discussions about which of the itemized challenges are could potentially be solved digitalization technologies. This preliminary data was presented and published at three international conferences. This was followed by a formalization of research questions which premised the subsequent case data collection and literature review. A final data collection round was thereafter carried out using an interview guide. And the following questions where subsequently specified:

RQ2: *What are the elements of a smart PPC system?*

RQ3: *What constraints do the planning environment attributes impose on the design and development of a smart PPC system?*

These two questions RQ2 and RQ3 are tightly linked. In addressing both questions, a literature review was necessary to establish the state of the art on the subject and to identify the gaps in the literature. This was necessary so that the artefacts and frameworks that may arise from this study can be guaranteed to not only address industry needs but to also address some of the documented gaps in the literature.

Moreover, it has been shown that the process during which a PhD candidate conducts a literature study helps the candidate to gain authority and later, legitimacy for his/her research. During this process, the candidate is also able to determine if the chosen research areas are feasible and are of interest to the scientific community (Karlsson, 2010). The aim of the literature was to gain increased understanding about the coverage of the topics and issues in the extant literature and to verify the research gaps before proceeding to collect data and carry out the research work. Literature analysis can also be a key component in the development of theory – as in this case. Notable publication databases (CiteSeerX, ACM, AISeL, EBSCOhost, Emerald Insight as in Hermann et al. (2016a)) were used and these were complemented with Google Scholar.

Using the findings from the literature, and from the preliminary case studies, an interview protocol was developed (Appendix 1) and administered in a multi-case study. The empirical data was analysed using a pattern analysis to develop a framework and strategic matrix. The case study approach was applied as described in Yin (2009), and Voss et al. (2002). A use-case matrix was also generated through brainstorming with experts from the industry and senior OM researchers. The brainstorming sessions took place during the early phases of the project with supervisors to determine the project scope and approach (approximately) every two weeks throughout the project duration.

While the developed frameworks and theory have both scientific and industrial value, this study wanted to extend the findings in the previous three RQs into a more practical guideline for manufacturing firms facing these issues. Having developed a concept for smart PPC in Oluyisola et al. (2020), that paper and other notable publications on the subject (Bueno et al., 2020, Cadavid et al., 2020) of smart PPC highlighted the gap in the literature for a guide and systematic method to aid the practical implementation of smart PPC, especially in small and medium sized companies with tighter budgets and also for big firms at times of global economic crises. Therefore, in the final phase of this PhD, and still in line with the research aim, the following question was specified:

RQ4: *How can the smart PPC be achieved in practice?*

In other words, how should a smart PPC system be designed and developed so that it fits with the current characteristics and the future requirements of the production system?

Currently, there is no systematic, holistic design and development guide for the design and development of a smart PPC system. This thesis (in chapter 7) presents an attempt to address these gaps by discussing the design principles for smart PPC solutions and demonstrating (with a case illustration from a semi-process industry) the use of a five-step method for designing and developing smart PPC solutions. The method details how to capture the PPC-environment's attributes in the design and development process.

Although the method was demonstrated using a case study, the actual development of the method followed a design science approach. Design science, as an active problem solving research method, is useful when a researcher aims to develop an artefact (Holmström et al., 2009). The case study used in illustrating this method in chapter 7 was selected because it offers a production environment amenable to smart process strategy (see Figure 6.1) (Tenhiälä, 2011, Oluyisola et al., 2020). In addition, the case used to illustrate the method had been studied for almost two years a sufficient level of understanding of the processes had been gained by the PhD candidate (Voss, 2009). Figure 3.1 below gives an overview of the research design and the results which follow in the chapters 4-7 of this thesis.

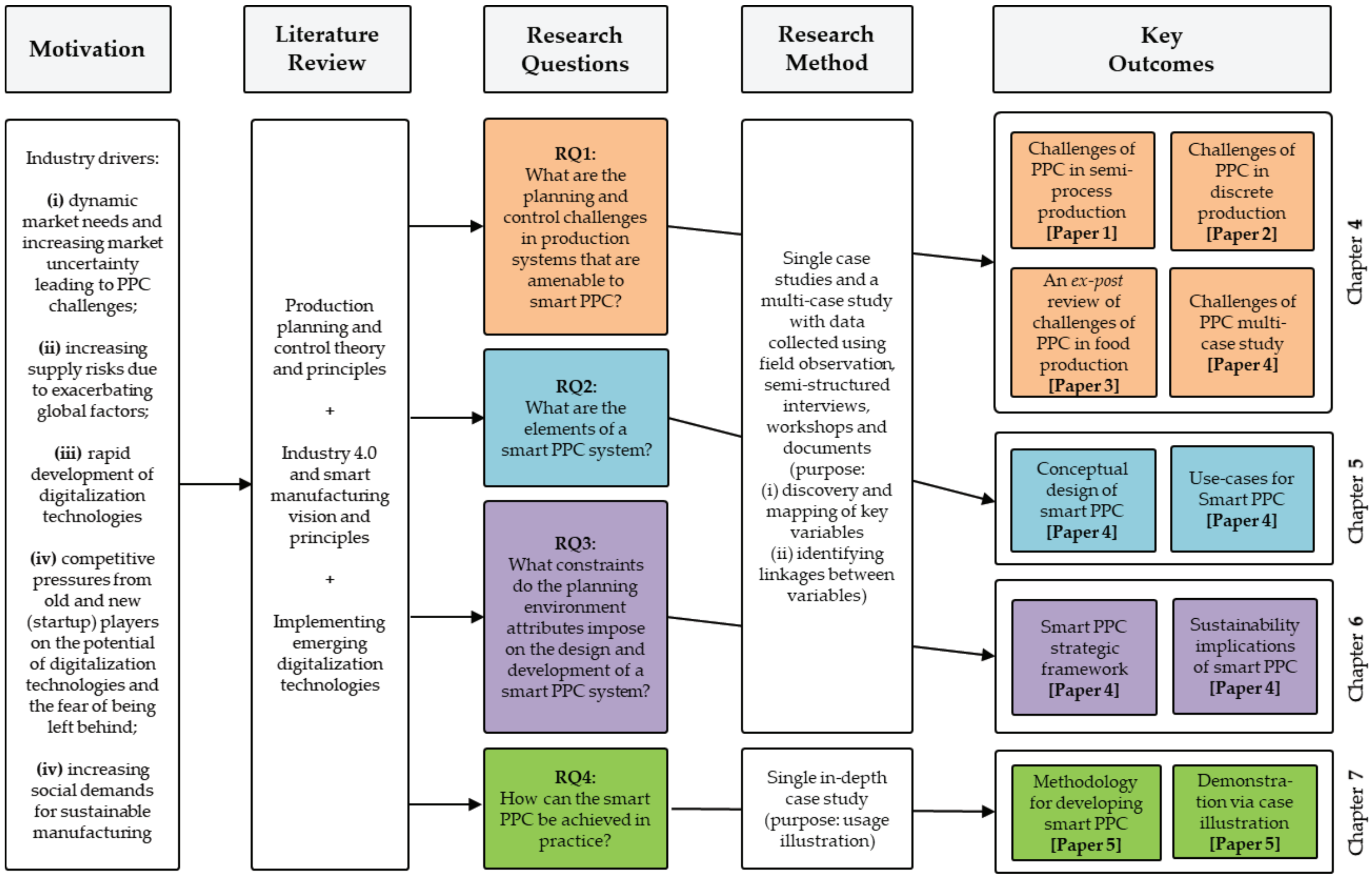


Figure 3.1: The Research Design and Results Overview

3.3 Research Quality

All the methods being considered for use in this project have limitations which must be considered for effective application. For example, case studies have limitations in their nature due to the constructivism approach and difficulties in generalization of the theories from specific cases (Creswell, 2013, Karlsson, 2010). The case study in this research faces this limitation and as such, questions about scientific rigour must be addressed (Eisenhardt and Graebner, 2007, Boyer et al., 2005). Nevertheless, by using several data sources to investigate the same questions, it is possible to triangulate the results and improve the validity of case research findings (Lewis, 1998). More generally, case research needs to pass four quality tests (Yin, 2013).

3.3.1 Construct Validity

Construct validity is the requirement that the correct operational measures for the concepts being studied are defined *a-priori* and not open to selective and subjective interpretation by the investigator during data collection and analysis (Voss, 2009, Yin, 2013) To this end, Yin (2013) further described three tactics that be adopted in case research to improve construct validity: during data collection, to use multiple sources, to establish a chain of evidence, and thirdly, to have key informants review the case report.

In this PhD study, all three tactics where adopted to ensure construct validity. Historical production plans, historical production reports, interviews, direct observation, and other external reports were sourced during the data collection for the four research questions. Furthermore, an established chain of evidence was used in addressing the second research question which is explanatory in nature. Finally, key informants reviewed the preliminary case reports at various stages of the research both before and after the data analysis.

3.3.2 Internal Validity

Internal validity has received a lot more attention in quantitative research and explanatory case studies. It addresses the question of whether a researcher's conclusion that "*x* causes *y*" is accurate, and not that another unknown factor z is the causative factor (Voss, 2009). However, due to the 'inferential' nature of case research (that is, by using interview and documentary evidence, a researcher infers that the property or outcome being studied was caused by an earlier event), case researchers must anticipate this and have it in mind at the inception (Voss, 2009, Yin, 2013). The question of internal validity does not arise for the descriptive and explorative parts of this project, that is, the first research question. Instead, it applies to the second research question in which there was an attempt to explain how and why smart PPC can be achieved in different kinds of PPC environments. For this case, tactics such as "*pattern matching*, *explanation building* and *addressing rival explanations*" were used to enhance internal validity (Yin, 2013).

3.3.3 External Validity

One of the main goals of research is that findings made in one study can be applied in other cases where applicable conditions are met, that is, that the findings are generalizable (Matthews and Ross, 2010). This is an important weakness for case research in particular because of the often-limited sample size and the risk of bias in such studies. However, Yin (2013) proposed two tactics to address this weaknesses: (a) that theory should be used to strengthen research involving single case studies; and (b) to design multiple-case studies with a replication logic.

This PhD project followed these proposals. Following the preliminary studies and the subsequent literature review, an evaluation of theories relevant to (or that have been tested) in OM research was done (Ketchen Jr. and Hult, 2007, Sousa and Voss, 2008). The structural contingency theory was identified as providing the best lens through which the case study could be conducted. Furthermore, the first, second and third research questions were addressed with a multiple-case study design with a replication logic – replication of cases covering process and discrete production systems. While an exhaustive large-sample size survey might be needed to achieve full generalizability, the tactics deployed helps to enhance the external validity of this study.

3.3.4 Reliability

The goal of a reliability test of research quality is to minimize biases and eliminate errors that the researcher(s) could have unwittingly introduced during the study. For case research, this implies that it should be possible for another researcher to carry out the same 'case' study again and arrive at the same conclusions (Yin, 2013). Tactics to address the reliability requirement include the use of case study protocol and database, thereby ensuring that every step can be documented and be auditable. In this regard, an interview protocol with a detailed questionnaire was developed for this study to address the first, second, and third research questions, and to provide insights into how the fourth research question could be answered. The questionnaire was applied to the first four cases companies where data was collected for answering RQs 1, 2 and 3. Case companies 5 (Tine) and 6 (PowerMac) were added to check the validity of findings at the preliminary stage while RQ1 was being investigated.

4

Description and Analysis of Case Studies and PPC Challenges

What are the planning and control challenges in production systems that are amenable to smart PPC? This chapter presents the descriptions of the six case companies, their PPC processes, and an analysis of their PPC challenges. The cases are described according to their market (supply and demand), product, production-process attributes. A pattern analysis of the PPC challenges wraps up the chapter.

4.1 Brynild: PPC Environment Attributes and System

Brynild is a food company which produces nuts, sweets (including pastilles) and chocolate from its factory situated in Norway. The company also distributes some non-food products for an international brand within Norway, leveraging its supply chain in the Norwegian market. The company manages its product development, purchasing, production, supply chain logistics, sales, and marketing along with its partners.

4.1.1 Demand and supply attributes

Brynild sells its products through the supermarket chains (‘*dagligvarehandel*’ in Norwegian) and the petrol stations’ mini-mart chains. It supplies its products to an industry that altogether is valued at NOK 180 billion. In the business year 2018 and 2019, Brynild reported a turnover of NOK 750 million (USD 81 million) across its three product categories. An overview of the market size and share by product category (as at 2019) is summarized in Table 4.1.

These products are of the kind that are impulsively purchased, typically when customers are at the cashier stands in supermarkets. Demand is seasonal, rising during holiday periods. Also, because several competitors are trying to get a good share of this seasonal demand, there are often several simultaneous promotional sales campaigns being held concurrently by several competitors. There is high competition and manufacturers aim to achieve economies-of-scale. Demand is also influenced by swings in national moods about social issues such as obesity, creating additional uncertainty in demand.

Table 4.1: Product categories and market share (for 2019)

Product category	Industry size (m NOK)	Market share
Confectionery Pastilles Vane; pastilles Oil; Drasje; Losvekt; Pick & mix, SugarChoco	3 050[1]	14%
Nuts Nøtte Fabrikken, St. Michaels Cashew, Chip nuts and more	1 300	32%
Chocolate: Chocolate mix; Losvekt CoatedChoco; CoatedChoco mix in nuts; SugarChoco mix, and more	6 000	3%

4.1.2 Products' attributes

A list of some of Byrnild's product families is given in Table 4.1 and a few of the product examples are shown in Figure 4.1 below. The company has a small R&D department which is tasked with developing and testing new products. After a new product is approved, the tier-two supplier inputs and processes must be certified for quality and safety. The food industry is highly regulated due to potential safety risks to the consuming public. Currently, Brynild has both the British Retail Consortium and the Det Norske Veritas (DNV) for its processes and supply chain. The company manufactures products under seven brand names.

Figure 4.1: Examples of Brynild's products

Under the confectionery category, which is the focus of this study, Brynild produces over 40 SKUs within 19 product families. The shelf-lives of these products vary from few weeks to several months even though some of these products share some production stations such as cooking and drying for their production. The products are made available to customers in two forms – in small plastic and paper resealable wraps, and in large drums where customers can dish their desirable quantities at the supermarkets. A typical product could cost about 5 Euros

[1] *Source*: Statista.com (sourced on 05.Jun.2020)

in the supermarket and the demand is somewhat stratified with high demand for confectionery products among kids while other products are purchased more by adults.

4.1.3 Production process attributes

The factory at Fredrikstad is divided into three sections, each for confectionery, chocolate, and nuts-based products. Due to regulatory requirements about the transference of allergens, the movement of people and materials across sections is tightly controlled. Most importantly, nuts-based products cannot be transported to the other sections of the factory handling products that will not have nut-allergen warnings on their packaging. A diagram showing an overview of the confectionery production processes from raw materials to the finished goods storage warehouse is shown in Figure 4.2 below.

Raw materials include sugar, flour, and formulation ingredients that give the products that unique properties and tastes. Cooking is done in boilers, with one boiler serving each production line. After cooking, the material flows to the molding station which houses a fast molding machine with trays. These trays must be retrieved and manually stacked into racks in preparation for drying. The filled racks are then taken to the drying ovens and once each batch is completed and loading into an oven, the oven is closed, and the drying settings and duration set based on predetermined values that are also stored in Microsoft Excel Spreadsheets.

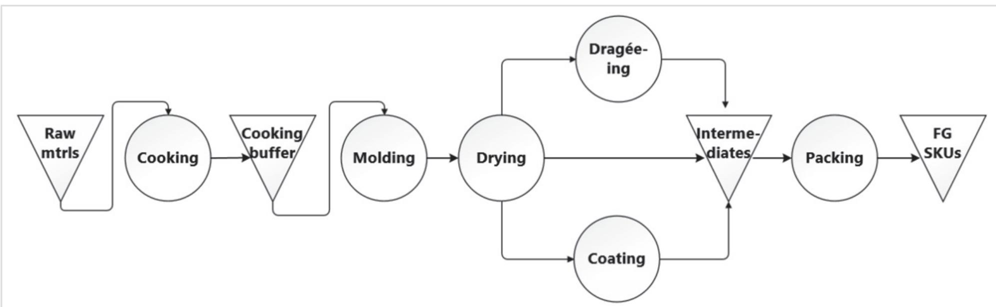


Figure 4.2: The confectionery production process

The output from the drying stage then proceeds to ordinary coating process or to drasje-ing which is also a kind of coating with a unique product surface area feel. They also sometimes go directly to storage for intermediates as show in Figure 4.2. Intermediates are stored in inverted conical drums which are then transported to the packaging station within the factory. The packaging line are limited by product constraints and packaging types. For example, confectionery products cannot be packed in the lines for nuts even if these are free because of the regulation regarding allergens. This is an important factor that the planners must consider during planning. The company's current strategy regarding the choice of production technology is to increase automation and to move towards more flexibility manufacturing systems, that is, machines that can process several different products.

4.1.4 Production planning and control

The operations management team holds the sales and operations planning meeting to discuss the aggregate production plan ('*hovedplan*') using the demand forecast and the firmed customer orders to plan production for the short-term. The hoved plan is an aggregation of all planned orders for all intermediates. Using the hoved plan as reference, rough-cut capacity planning is done on a weekly basis on Mondays. The main goals for rough-cut capacity planning is production smoothing in the "hoved-plan" for the next 4 to 5 weeks and incorporating seasonal demand that lies further into the future. The detailed production schedule is then made by the production planner who is also responsible for monitoring its execution. The schedule is converted into production orders for the shopfloor. The production orders are generated within the enterprise resource planning system SAP/R3 using the master production scheduling function. The planners consider the following factors during the process:

- Promotions in Xmas, Easter, and other periods that Brynild's on partners' marketing teams dictate – products and process flexibility.
- Input materials delicate and must be kept at narrow environmental limits.
- High set-up time in the production process and finished goods and WIP inventory.
- Packaging lines independent, and intermediates need to be transported for packaging.
- Schedules are made at the end of each week for the next week based on firmed customer orders and MPS values.
- Combination of processes with varying throughputs and levels of automation.

The **detailed production planning** process is as follows. Brynild runs two or three production shifts each day and the planned batch size of each intermediates' production is the amount that can be produced within one shift. This is done for practical reasons and to avoid changeover and setup times in the middle of a shift. The different changeover times between production of intermediates is considered when making the schedules. It is common to schedule long changeover products for the last shift of the day so that the changeover period occurs overnight. This allows for extensive cleaning (e.g. cleaning with water, which requires drying afterwards), at the end of the second shift. The main consideration here is that the line can dry after such cleaning.

Furthermore, intermediates are scheduled to be produced consecutively if they are used in the same SKU. The drying process is pacemaker and it limits the pace of the production line and is therefore a key consideration when making production plans. The eventual production plan is also used to estimate the number of required operators for shift. This is achieved by converting the workload into operator-hours. Many spreadsheets with planning input data such as changeover times between the SKUs, drying rates, input proportions and material estimates are managed by the production planners. After completing the production activities planned for each shift, a paper-based shift report is completed, and the SAP system is updated with the actual (as supposed to the planned) dates and amounts.

4.2 Pipelife: PPC Environment Attributes and System

Pipelife is a large producer of plastic pipe systems and is a member of one of Europe's leading conglomerates in the market for plastic pipes and associated parts. The company has factories in Norway, and trading operations in Sweden, Norway, Finland, and the Baltic States; it is a market leader in the supply of plastic pipe systems in Scandinavia. Pipelife's strategic direction for the near-term will give an even stronger focus on innovation and sustainability.

4.2.1 Demand and supply attributes

Pipelife's products have been used in water, sewage, cable protection, electrical installations, and gas. A considerable share of the production is exported, particularly large dimensioned polyethylene (PE) pipes which is tugged to customers all over the world. However, the competition is stiff, and even though the middlemen in this industry (distributors) are large, the bulk of the customers are small and medium enterprises who are often price sensitive. Input feed and other materials for the production process are sourced from upstream chemical manufacturers, and smaller plastic manufacturers in Norway and abroad. Manufactured products are stored in inventory facilities located at the factory from where distributors are then supplied when orders are placed to the sales team. Demand is seasonal rising in the warmer months of the year when building and construction companies are most active and dipping in the winter and colder months. The products can be bought in small quantities (costing less than a 100 Euros) from large tools' stores or directly from Pipelife.

4.2.2 Products' attributes

Pipelife manufactures and markets a wide range of high-quality pipe systems, providing tailor-made solutions for municipal infrastructure as well as for the industrial and house-building sectors. In addition, PE pipes, polyvinylchloride (PVC) pipes, and plastic-protected cables are produced to stock in several colour variants. There is also a section for customized solutions, mainly drainage solutions such as manholes and curved pipes with precise angular dimensions. In recent times, the company has been researching the potentials for smart pipes and systems which can reduce waste, safeguard water quality, and improve sustainability by using sensors and digital monitoring solutions. Some examples of Pipelife's current range of products are given in the figure below.

Figure 4.3: Examples of Pipelife's products

4.2.3 Production process attributes

The main products, PE, and PVC pipes are produced using injection moulding and blow forming. The PVC pipes are produced in similar production lines, and the processes are fully automated from feeding the raw materials into the mixing chamber and then dosing this mix into the moulding lines. For a few of the production lines, particularly those producing the smaller units, the packaging at the end of the lines is also fully automated. In the customized products department where products require significant amount of manual work to meeting specific customer design and engineering requirements (for example, manholes or pipeline elbows), the processes can include cutting, milling, grinding, and welding high-strength section of large PE pipes.

4.2.4 Production planning and control

There is no production planner title at Pipelife, but the function of production planning is jointly managed by the production manager and the supply chain manager. The sections in the factory have different control principles, with the PE, PVC, and plastic-protected cables mostly produced to inventory (except for cases where property developers or municipality projects place a large order). In general, production is made according to the demand forecasts and sometimes to meet specific customer orders for large projects. In additional, the company builds up inventory towards the high demand seasons. ERP software are used for production planning and inventory control while and MES software is used for production control.

4.3 Brunvoll: PPC Environment Attributes and System

Brunvoll is a global supplier of heavy-duty propulsion, positioning, and maneuvering systems to shipping yards and marine companies with a turnover of 1000 million NOK (130 million USD) in 2014. The company has a subsidiary in Germany and manufactures thrusters that are used in maneuvering large maritime vessels and smaller boats.

4.3.1 Demand and supply attributes

Demand for thrusters is complimentary with the demand for ships and both demands swing with the trends in global economy. The customers are large shipping companies and shipyards who individually can produce tens of large ships per year or hundreds of smaller yachts and ships. Brunvoll designs and produces all its products in-house to customer specifications, taking full responsibility for the delivered system. A few components are outsourced from nearby, tightly integrated suppliers. Demand is global but concentrated around ship-production hubs such as South-Korea/China and Eastern Europe.

4.3.2 Products' attributes

Brunvoll offers electric, hybrid and diesel drive systems and provides service and support for the entire lifetime of the supplied system. An example is shown in Figure 4.4 below.

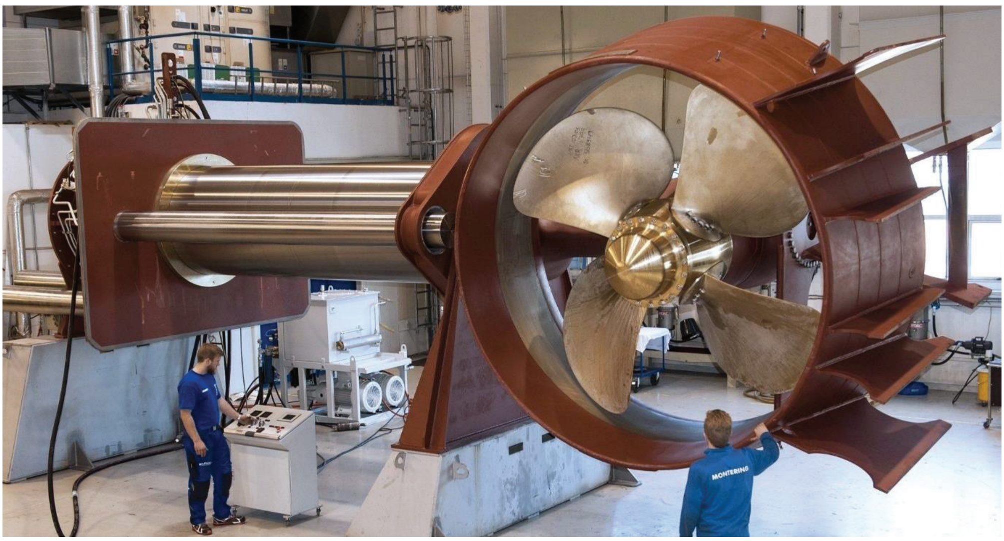


Figure 4.4: Example product - the Azimuth thruster

In general, product complexity is relatively high; demand varies highly and is relatively low in comparison with, for example, an automobile engine production plant. Product variety is also high and typically require considerable engineering time and competence, due to the degree of customization accepted from customers. In addition, products have a very deep and wide product structure vis-à-vis the bill of materials (BOM). The company also manufactures a few small standardized thrusters.

4.3.3 Production process attributes

Raw materials are purchased using estimates from order backlog received from suppliers and kept in inventory. The purchased raw materials (e.g., sheet metal) are taken to the machining department based on the manufacturing BOM for released production orders. The welding and final assembly for most customer orders are difficult to plan due to the significant variation in the throughput time. For the complete product from order confirmation to delivery, the throughput time can be a few weeks for smaller, more common systems and months for the more complex products.

4.3.4 Production planning and control

The sales team and production planner coordinate the customer ordering and delivery date setting process. The planner estimates a feasible delivery date by performing MRP and CRP calculations using dummy bill-of-materials (BOMs) and routings that are derived from historical completed orders. The planner is responsible for identifying (from experience) which BOM and routings are most like the new customer order. When order details (price, delivery date, *etc*.) have been agreed with the customer, the order is scheduled for production. Currently, production planning is performed using the M3 ERP system while spreadsheets are used less and less. The planning principle used is the backward planning, which starts estimating backwards from the planned due date. A key company objective is to maximize output while maintaining the current cost levels—that is, to maximize throughput without increasing overtime cost or additional cost due to subcontracting. An add-on application shows machine loading and allows the planners to adjust due dates to avoid overloading.

Most of Brunvoll products are made-to-order and most of the components are made-to-order or purchased when a customer is confirmed. However, some commonly used items are kept in inventory. Due to the variability in the welding and final assembly processes, production planning emphasizes machine capacity availability. Although equipped with an untested finite capacity option, Brunvoll, like several other companies in this industry, rarely uses this functionality. One reason in this case is the lack of experience with the functionality and the concern of the production planners that operations could be disrupted with unpredictable consequences if this functionality is used; therefore, the company uses the default setting.

4.4 Orkel: PPC Environment Attributes and System

From its current headquarters in the Trøndelag region of Norway, Orkel AS started operation in 1949 making small, detachable tools for its local farming community. The company continued to expand its capabilities and in 1986, produced the world's first chopping baler with a coupled forage harvester. Further innovations in product development followed with the production of the integrated baler machine in 1987, and the world's first compactor in 2002. With the emergence of digitalization, the company ventured into the development of precision farming solutions in 2014.

4.4.1 Demand and supply attributes

Up to 20% increase in milk production has been found when cows consume forage stored in the form of bales compared to those consuming forage stored in silos. The effect of this improvement in agricultural milk production has led to increasing demand for bale production machines – a form of combine harvesters. In addition, the ease of transportation of bales compared to forage stored in silos has made spurred the demand for these products, including also in other industries such as for industrial waste management machines. This new application area is gaining increasing attention due to the improved ease of transportation and handling after compacting into bales wrapped in plastic foil.

4.4.2 Products' attributes

An example product is shown in Figure 4.5. Orkel manufactures agricultural and industrial compactors (also referred to as baling machines).

Figure 4.5: Product example - the MP2000-X baling machine

The company manufactures several variants of these compactors, broadly classified into three (3) product families in addition to several accessories – Dens-X (including the HI-X Evo and HI-X), MP series (the MP2000-X) and the MC series (MC 1000 and MC 850).. The industrial compactors are of the Dens-X family while the agricultural compactors are three product families. The compactors make bales of three diameters namely, 115 cm, 100 cm and 85 cm with the Dens-X being the newest product family with the highest capacity. The compactors and the accessories are used for compacting, baling, and wrapping maize silage and other forages. In recent times, more digital capabilities are being built into the products to make improve the performance and avoid breakdowns through condition-based maintenance and other data-driven methods.

4.4.3 Production process attributes

The production facility is organized in a functional layout as shown in the figure below. There are several workstations within the various departments – 10 welding stations, and 15 assembly stations. Other components and panels are products in other departments and brought to the assemble department. Some of the welding process has been automated and the company embraces several lean production tools and methods.

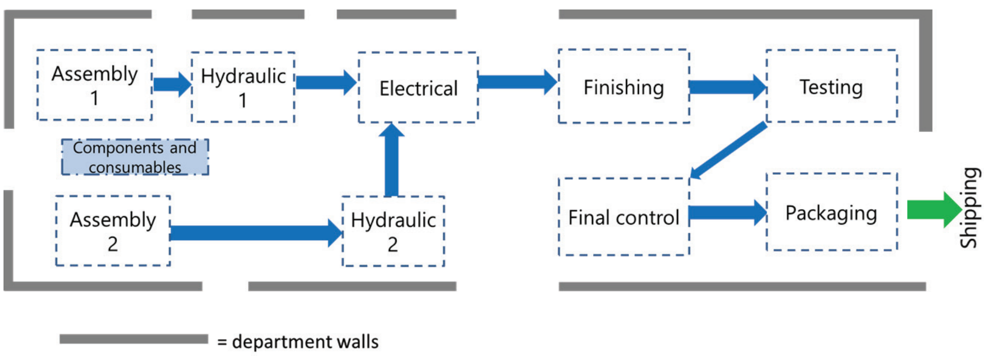


Figure 4.6: Material flow at the assembly line

4.4.4 Production planning and control

Orkel AS uses an MRP system – Visma Business for tracking the purchase and consumption of materials from inventory, but not for production planning. Instead, customized spreadsheet templates are used for planning since this provides flexibility and a good pictorial overview of the work-in-process and the backlog of orders. At periodic planning meetings, all delays and weekly workplans are discussed and aligned. There is a seasonally high demand at the beginning of the harvesting season.

When orders are received and agreed with a customer, the planning spreadsheet is updated with predetermined work estimates for the order. In the example in Figure 4.7, two product orders are indicated where orange represents product type-1 and the yellow represents product type-2. Each coloured cell has a number representing the estimated number of operators required for the operation at the date given in the date row on the top of the table. The first top row of the template indicates the current estimated manning requirements.

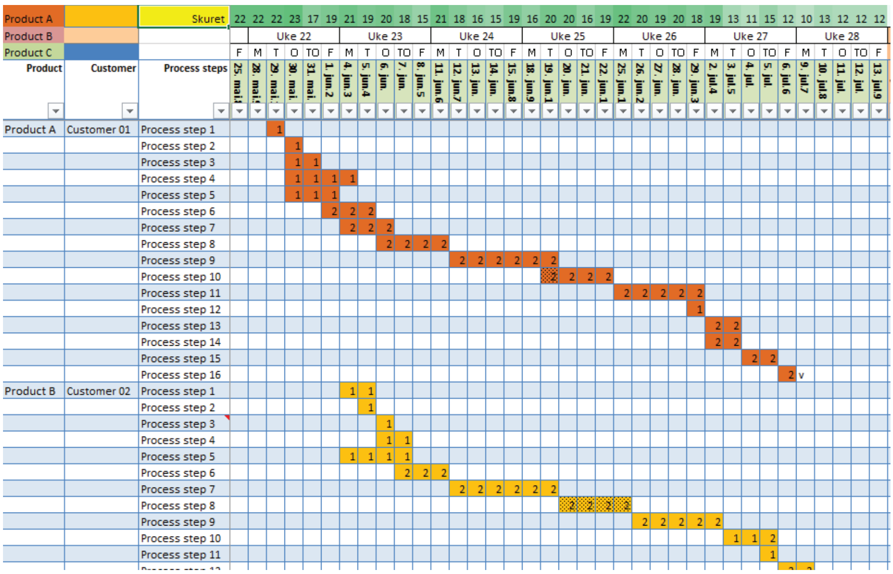


Figure 4.7: Snippet of planning template for capacity planning

4.5 Tine: PPC Environment Attributes and System

Tine SA is Norway's largest producer, distributor, and exporter of dairy products with 11,400 owners and 9,000 cooperative farmers. A major input into Tine's products is fresh milk which is collected by milk trucks from several farms across Norway.

4.5.1 Demand and supply attributes

The products are primarily sold through all grocery retail stores, local convenience stores and kiosks. Domestically, the company faces some competition in most product categories. Promotions and other sales campaigns are common. The company is successful internationally as well. Demand uncertainty is high because there is a large variation in periodic demand, the promotional activity is high and increasing, and the presence of the bullwhip effect is high. Despite the high perishability, the demand is still met from the finished goods inventory for most of the products. Because of the aforementioned factors, the fresh food supply chain can be considered as one of the most challenging and therefore requires a very capable PPC system. Tine has a strong brand recognition and competitors typically compete with lower prices as expected with most products in this commodity-based industry. There is a trend towards more sustainable production and Tine continues to innovate in this direction.

4.5.2 Products' attributes

Tine Products include dairy-based products with shelf lives ranging from 11 to 91 days. This include short shelf-life products such as fresh milk and various kinds of flavored milk products. It also includes yoghurts, butter, cream, cheese, sour cream and deserts, bars, juice, and fruit drinks with shelf lives going more than a few months. Many of the products require strict environmental controls to meet regulatory requirements. Storage and transport temperatures must be kept within specified limits to preserve the shelf-life of the products. During the collection of raw materials, the processing, intermediate storage, shipment and retailing for milk, creams, and some cheese, require lower-than-ambience temperatures and tight controls to forestall biological contamination.

Figure 4.8: Examples of Tine's products

4.5.3 Production process attributes

Tine has two different types of supply chains: direct distribution to retailers and distribution through wholesalers. The process is a 'make-to-stock' and 'one-to-many' type of operation, i.e., the type where one raw material – milk – is processed into many products. Tine (as well as its competitors) must meet a high service-level requirement. The company produces from

31 dairies, two central warehouses and two distribution terminals. Production is done in batches with a high level of process automation. Tine's factories are also located in multiple regions within Norway.

4.5.4 Production Planning and Control

The supermarket chains require frequent deliveries with very short response times when orders are placed. This is partially due to the high perishability of many of the products. The challenges are increasing as there are more product variants and more demand uncertainty. The consequence is an even lower predictability. Furthermore, because weather patterns greatly affect demand at the supermarkets, PPC needs to be able to take all these into account when forecasting demand. Food producers (including Tine) often bear the cost of unsold items and discounts when expiry dates approach and they therefore tend to invest heavily in forecasting tools in addition to the use of ERP systems for production planning in the factories.

4.6 PowerMac: PPC Environment Attributes and System

PowerMac is a global manufacturing firm which produces low- and medium-voltage power and automation systems for the marine industry. The products are designed to deliver automated and energy efficient power management for passenger, off-shore, and other special-purpose vessels. The company has its headquarters in Scandinavia but has service offices and factories on every continent. PowerMac produces electronic and electro-mechanical within six general application areas namely, deck machinery, pumping of water and other liquids, propulsion systems, security and safety systems, electric power systems, and products that provide 'comfort on board'. The company is organized around six main manufacturing hubs – one each in Norway, Sweden, Finland, USA, China, and Singapore. The China plant, which produces propulsion systems, was the focus of this case study.

4.6.1 Demand and supply attributes

Demand for PowerMac's products are often subject to volatile global economic events due to the nature of the industry. The products are used in marine vessels (namely, ships, offshore oil rigs) which are typically expensive, owned by few international firms and operated in multiple countries concurrently. However, the trend in the last two decades whereby an increasing share of the worlds marine vessel production was moved to Asia (first South Korea, but increasingly, China) led to the establishment of this factory over a decade ago. Most components and materials are sourced from local suppliers while a few components are procured from Europe.

4.6.2 Products' attributes

PowerMac produces various types of Power and propulsion systems including electronic relays and controls, explosion protective components and systems, circuit breakers, current and voltage sensors, fuse gear, soft starter, pilot devices, motor controllers uninterrupted power supply (UPS) systems, and emergency lighting solutions. The China plant produces two types of rudderless and gearless thrusters and offers some customization to customer engineering requirements. The products are complex and electromechanical, with each unit having hundreds of components.

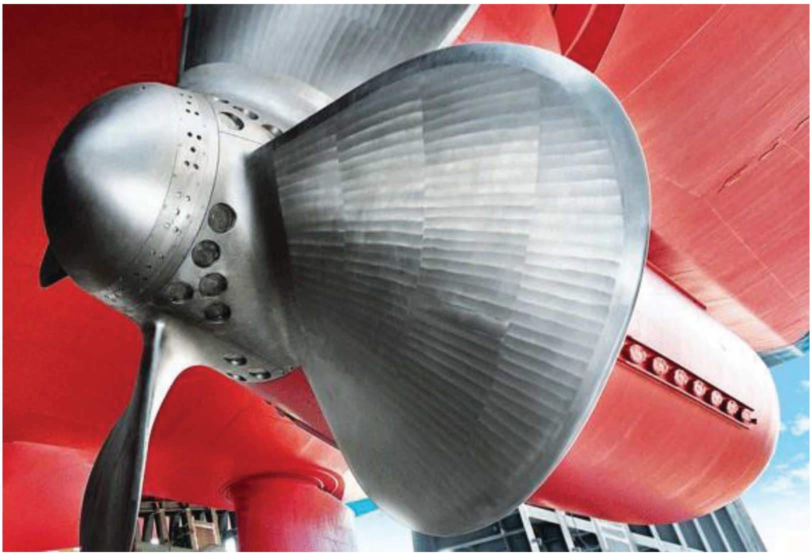


Figure 4.9: An example of PowerMac's products

4.6.3 Production process and Supply chain attributes

Complex engineer-to-order products typically require an engineering design phase in their production. For PowerMac, the engineering design process is handled in-house except for these products. The products are assembled from components and subassemblies supplied by suppliers. The China production facility uses many suppliers although a few of them have well established longer-term relationship with the plant. Notably, four suppliers have been identified as being most vital by the volume of products they supply.

4.6.4 Production and supply chain planning and control

PowerMac ASA is run as an engineer-to-order operation with a fully project-based control of production. After a sales contract is agreed with the customer, the sales team hands-over the customer order to the project team. The process involves engineering, purchasing of components and materials, assembly, installation, and commissioning. The process is managed with both an ERP system and add-ons that complement the functions that the system does not adequately address such as customer management. The on-time delivery (OTD) measure is a key performance measure for the company. In this case, delivering too early as well as later deliveries are undesirable.

4.7 PPC Challenges at Case Companies

4.7.1 PPC challenges at Brynild

The constraints imposed by the production environment's attributes described above creates some challenges for PPC at Brynild. Furthermore, in view of its sometimes competing KPIs and the perceived shortcomings of the ERP system, compromises must be made when setting PPC policies to improve the performance of the production system. The production planning data is currently maintained manually in SAP and is not updated automatically. These means that until the plans are updated manually, they do not account for the most frequent updates to the planning environment such as if a new input raw material consistently leads to overproduction using the out-of-date values.

Secondly, some of the constraints set upon the system to maximize the use of employee time creates flexibility issues for the planners. For example, the typical two-shift per day system with a planning policy to try to fit production into each of these two shifts leads to a situation in which planners aim to produce each batch in quantities that match the duration of a shift for the set-up, production and post-production cleaning activities. While this may seem innocuous, it can be a major planning efficiency delimiter because this policy does not allow enough flexibility regarding lot sizes and it places an additional burden on the planners when planning the sequence of batches. Furthermore, as the production demand increases due to increasing market demand since the pandemic began, the need to increase the effectiveness of this planning process is further highlighted. There is an option to use three shifts instead of two, but in the case, the drying and the packaging sections again place a limit on this option and must be addressed before this three-shifts option can be fully utilized.

All these challenges combine with the market (demand and supply) constraints to lead to the following consequences:

- Queues/waiting and poor asset utilization due to suboptimal material flow
- High WIP inventory due to the combination of processes with varying throughputs and levels of automation

- Resource constraints and capacity underutilization due to the fixed process layouts
- Large swings in resource requirements due to the current heuristics-based planning approach and planning of the bottleneck process (drying)
- Long production lead time due to large batch-sizes and high set-up times
- High demand variation due to frequent and sometimes uncoordinated promotions by supply chain actors
- Large number of products (46) from the confectionery business alone leading to high finished goods inventory
- In addition to the large number of products (52 primary input materials), there are also many product routings which leads to a high combinatorial scheduling problem.

Two primary problem groups can therefore be identified – one, a short-term scheduling solution that takes all these constraints into account, and a precision planning support system that reduces the need for using gut feel in estimating the expected yield in planning. Additionally, there is also a long term- planning problem in which a solution that provides more flexibility than that offered by the current Microsoft Excel and SAP R3 ERP system.

4.7.2 PPC challenges at Pipelife

The challenges associated with PPC at Pipelife centre around tracking and tracing materials and components in the factory, inaccurate inventory levels in the input materials' warehouses, and suboptimal material flow in certain sections of the factory. Occasionally, the storage location of consumables can be haphazard since the factory has several storage facilities within the factory area and operators occasionally forget to move pallets of consumables to the designated locations.

Furthermore, since materials are purchased based on inventory levels in the ERP system, it is important – even critical – for the numbers in the system to be accurate. However, there is the issue that inventory levels of some input components and consumables do not match what is on the ERP system. For example, plastic pipe covers/sealants (which will fall into class 'C' in the ABC inventory classification) are often culprits. This is due to outdated product data and BOM data on the ERP system; difficult for operators to update the materials register when materials are consumed; and losses during the movement of products from the factory to other locations. It also happens that drawn-down pallets are occasionally returned to the warehouse after a batch is produced, and the ERP record still appears as having a full pallet instead of the reduced actual quantities, since the measurement system counts pallets and not a measure of the contents. The pallet count is only reduced when a full pallet is emptied, and individual consumption is not recorded due to the inconvenience such detail would require.

4.7.3 PPC challenges at Brunvoll

Complex, highly customizable production causes uncertainties in the production, so much so that planning then relies on the shift planning with large planning buffers. In addition, material planning is order-driven and not forecast based due to the high holding cost of input materials and components. Demand exhibits large swings due to the increasing chaotic global economy which affects customers, making forecasting problematic. The use of dummy BOMs and routings is another source of variation in delivery precision. And unfortunately, the experience is carried by the production planners and is not available in a computer-useable format. When a planner leaves the company, the planner carries that experience with her/him, and new planners must learn and acquire this experience afresh.

Furthermore, due to the high design and engineering content for every customer order, the PPC system is unable to plan for this part of the lead time and must use estimates, the consequence of which is a lower delivery precision. These non-physical production activities need to be captured and integrated into the production planning process to improve PPC performance. The consequence of all these challenges and the current PPC system is that orders are consistently late which is why the planners always use a three weeks buffer for the production plans.

4.7.4 PPC challenges at Orkel

While some common components of the three product families are kept in inventory, the cutting and welding of customizable parts and the main assembly starts main assembly starts after a customer order has been confirmed. This creates a need for speed to be competitive. However, there is much uncertainty in the assembly process, most of which are identified at the final steps of testing and control. This leads to delays when major corrections need to be made. A process-variance analysis of the assembly process data for one product family for the year 2019 was carried out. The analysis showed a high amount of variation at two workstations namely, preparation and testing. As this are not core processes, but rather quality assurance process steps, it could imply that Furthermore, the existing layout imposes two lines on the assembly process up until the electrical workstation. After this station, there is a single flow line and the variation per order and workload across workstations create waiting and delays in the assemble line.

4.7.5 PPC challenges at Tine

Tine runs a challenging supply chain. The short shelf-life of most of the products means that speed to the shelves and transport conditions are given lots of attention. Ideally, due to the sometimes-varying cooling conditions on the path to the shelf, leading to earlier spoilage, it’s also desirable to monitor temperatures throughout the product's life till it is purchased. Tine, as well as its competitors, face this challenge. Furthermore, there is also the potential to analyse material flow paths in a bid to reduce transportation wastes. And all the generated information could be shared with SC partners to improve the overall supply chain surplus. However, there was little information sharing with SC partners for 'strategic reasons' leading to suboptimal inventory planning strategies by the SC partners. These are some of the reasons why the company invested in RFID technology. The pilot project tested the use of RFID to improve control through better tracking and tracing. However, the project had to be abandoned after two years as it did not achieve all the expected benefits.

4.7.6 PPC Challenges at PowerMac

The main PPC challenge for PowerMac stem from its dependence on suppliers for all the components it uses in each of its products. As a result of this dependence, it often suffers delays in the supply of components and subassemblies needed to fulfil its customer orders.

Poor delivery performance by these suppliers to PowerMac disrupts its production plans in two ways. First, since the production planning at PowerMac is scheduled based on the available production slots and delivery dates promised to the customer, delivering earlier than agreed is generally disadvantageous. This due to increased inventory levels and capital tie-downs. Secondly, late deliveries from suppliers is also crucial because such delays lead to production stoppages, waiting, overtime work, risk of high penalty and reputational damage from the shipyards. These then lead to increased costs in project execution and reduced profitability. To manage its own consequent order fulfillment process variability, which is relatively high, PowerMac uses internal buffers. The causes for high delivery-time by the four main suppliers are summarized in Table 4.2 below.

It was also found that the most significant causes for delays were poor communication and coordination at Supplier A, process inefficiency at Supplier B, lack of process standardization at Supplier C, and a long transport distance in addition to inflexibility in the order-fulfilment process at Supplier D. The lack of transparency in suppliers' order fulfillment process made it difficult for PowerMac to coordinate and manage suppliers. Very often, problems are discovered much later in the production process. As a result, it is highly problematic to trace the sequence of events that led to the issue precisely, and thus develop solutions to avoid such issues in the future. This is especially true with supplier A and B, who produce long lead-time components.

Table 4.2: Summary of PPC challenges relating to four PowerMac's SC partner

	Supplier A	Supplier B	Supplier C	Supplier D
Primary source of untimely delivery	Poor coordination between design departments of PowerMac and Supplier A	Defective output from the casting process	Lack of process standardization	Long transport time; and inflexibility in order fulfilment process;
Where/ when does it happen?	Design phase, due to need for customer and 3rd party approval	Casting process facility	Entire operation relating to this supply chain	Rush orders
Other observations	Poor inventory control leading to missing parts	Poor coordination within two facilities; high inventory	Need to have large time buffers for delivery of orders	Poor inventory control, and use of large buffers

4.8 Insights from Cases and Potentials for Digitalisation

A summary of the PPC environment attributes and challenges are given in Table 4.3 below. It is common to see issues about inventory management for the semi-process, MTS case-studies and issues about delivery precision for discrete, MTO manufacturers. This is likely because of market engagement strategies in the two companies. However, some of the challenges observed in the cases have been unique.

For example, at Brynild, one of the current PPC challenges is the result of a history of planning policy compromises to achieve stable operation. Instead of planning each production batch to fit a shift as it currently done, planning for smaller batch sizes might lead to improvements in flexibility, inventory levels, and other KPIs. However, changing this policy might reduce the efficiency and stability required in operator shift-planning. This problem is not one that digitalization can easily solve without causing much operator dissatisfaction especially while the issue of process uncertainty at the drying section persists. On the contrary, the challenge relating to process uncertainty is more amenable to solutions using emerging digitalization technologies since process data is often available of can be collected with increasingly abundant sensors. Furthermore, the type of data in process or semi-process production is often time-series data for which many simple and advanced data analytics and machine learning algorithms have been developed and published.

For PowerMac, one reason for its challenges is that process times are not measured at the suppliers, making it very difficult to trace the sources of process variability. Therefore, one key outcome of this study was the proposal that PowerMac and its suppliers begin to monitor actual process times or order fulfillment times, especially for orders involving long lead-time items. Another suggestion is to introduce delivery-time windows (or period) in purchase orders, thus allowing suppliers more flexibility in planning their own production to accommodate other operational constraints. In cultures where there is punishment for revealing issues, a management policy that rewards openness – maybe in the form of a continuous improvement programme – will lead to improvements.

For Tine, the cost of implementing a material tracking technology and the relative benefits for the organization turned out to be the most critical for the choice of a solution to solving their production and inventory control problems with RFID. This is important especially because there was a perception by Tine that the wholesalers had more to gain than Tine from the RFID project. However, the cost had to be borne by Tine. Thus, the RFID project was discontinued although both Tine and the supermarket chain involved in the pilot project indicated interest in pursuing similar improvements projects in the future.

Therefore, the preceding discussion highlights some of the considerations that must be made in developing a smart PPC solution. The commonality of scheduling-related problems that lead companies to keep larger-than-ideal inventories and the challenges with tighter control of production processes are areas where digitalization technologies could be applied. Technologies like the Internet-of-Things, data analytics, and potentially machine could lead to improved calculations and scheduling. Meanwhile, for the make-to-order cases, delivery precision issues and common capacity calculation problems appear to be challenges that can be ameliorated at the least with improved coordination among stakeholders and streamlined processes.

Table 4.3: Summary of environment attributes and PPC challenges

	Brynild	**Tine**	**Pipelife**	**Brunvoll**	**PowerMac**	**Orkel**
Type	Semi-process	Semi-process	Semi-process	Discrete	Discrete	Discrete
CODP	Make-to-stock	Make-to-stock	Make-to-stock	Make-to-order	Make-to-order	Make-to-order
Demand and supply attributes	Supplies products to few large grocery chains through a distribution WH; at point of sale, does not have direct access to customers	Supplies products to grocery chains from distribution centers; has no direct access to customers	Supplies products to contractors at project locations and to wholesalers at WHs; has direct access to few large customers only	Supplies products to builders of ships; keeps some components in inventory; has direct access to few large customers	Supplies products to builders of ships and boats; has few suppliers; has direct access to few large customers	Supplies products to medium-sized farmers; builds from stocked components after firming orders; has direct access to global customer
Product attributes	Nuts, sweets, and chocolates with short shelf life	Fresh foods with relatively very short shelf	Plastic (PE and PVC) pipes with long shelf life	Propulsion systems with long shelf life	Propulsion and power systems with long shelf life	Large, complex bailing machines with some customization
Production process attributes	Batch production; high automation in production lines	Batch production, high automation in production lines	Batch production, high automation in production lines	Dominant player in its SC; produces most components in-house	Dominant player in SC; outsourced production of components	Outsources production of some components, final assemble in-house
PPC	Spreadsheet for CRP; ERP for MRP and inventory control	ERP and APS systems for planning and inventory control	ERP for planning and for inventory control; MES for shopfloor control	Spreadsheet for planning and ERP for inventory control	Spreadsheet for planning and ERP for inventory control	Spreadsheet for planning and ERP for inventory control
Key PPC challenges	Planning precision uncertainty due to factory environment; high-combinatorial scheduling problem	Tracking of materials within the production line and supply chain (SC)	Poor tracking of key consumables; high holding inventory in preparation for high demand season	Low precision in CRP leading to large buffers in promised delivery dates	Variation in delivery precision by component suppliers leading to poor delivery precision	MRP inefficiencies in final assembly; large CRP buffers to compensate for high variability in assembly lead time

5

Conceptual Model and Use-case Matrix for Smart PPC

What are the elements of a smart PPC system? In this chapter, a conceptual model of smart PPC is developed from the literature and case data. A use-case matrix concludes the chapter.

5.1 The Smart PPC Concept

Smart PPC focuses on the 'brain' of production operations and aims to intelligently plan and control current industrial assets and materials as well as future, more adaptive production systems. A Smart PPC system should employ emerging technologies to: enable the reduction of forecast uncertainty by using real-time demand and production system data; offer dynamic re-planning in the sense that it enables frequently updating and the ability to re-plan when there are new developments in the production system; capture the influence of an expanded set of factors including telemetry factors especially for the process and semi-process industries; to capture the experience of the operators or the production planners over time; and predict short-term system parameter values and enable increase agility (Strandhagen et al., 2017, Oluyisola et al., 2020, Bueno et al., 2020).

This section presents the developed smart PPC concept and a description of its elements i.e., addressing RQ1. As firms digitalize their production operations in the move towards industry 4.0, they progress in stages. Schuh et al. (2017) identified six progressive stages that an operation on the path towards smart manufacturing should follow. These are computerization, connectivity, visibility, transparency, predictive capacity, and adaptability. To simplify, the six stages were re-classified into three namely: connected, transparent, and intelligent. These three stages, shown in Figure 5.1, relate easily to production systems' managers who seek better tools to improve their ability to respond quickly and accurately to changes in the business environment. A description of the theory behind each stage, the conceptual model, and a table of potential use-cases for smart PPC follows.

5.1.1 Connected

Computerization of PPC processes is, by itself, not new. ERP systems and spreadsheets have been used for decades and almost every production system today is planned and controlled to some degree by either of these technologies. Moreover, the use of spreadsheets does not appear to be waning even with the advances in ERP systems and other planning solutions, probably due to the flexibility and ease of use that spreadsheet solutions afford most production planners (Klaus et al., 2000, de Man and Strandhagen, 2018). In addition, the production processes nowadays tend to have more electronic components and programable logic controllers (PLC), thus allowing for more automation of the production processes. Increasing computerization means that all elements in a production system have a digital life and can therefore be connected to a digital industrial network in the smart factory.

On the contrary, connectivity is only just becoming widespread in this decade of digitalization and industry 4.0 as sensors and networking infrastructure gradually become ubiquitous and more affordable (Iansiti and Lakhani, 2014). This sensing will be achieved using auto-identification and telemetry data collection sensor technologies such as radio frequency identification (RFID) technology, beacons and IoT devices (Liao et al., 2017). Furthermore, since the move from the internet protocol version 4 (IPv4) to the new internet protocol version 6 (IPv6) standard which theoretically can allow up to 3.4*10E38 internet addresses, it is now possible to connect things that hitherto would have been too complicated or expensive to connect to the internet (Schuh et al., 2017, Davies, 2012). Therefore, with increasing ease to connect ‘things’ to networks, everything can be connected, traced, tracked, measured, and improved and all the data generated by the action or movement of things can then be used to improve the way systems are designed, the way processes and operations are planned and managed. This implies that tracking and tracing items within a factory becomes much easier. IoT connected sensors can, through IoT edge devices, interact with the physical production system sending location and state and compute request and receiving data and instructions from services hosted on cloud infrastructure. IoT Edge devices are more suited when there is need for quick reaction (e.g., action to prevent a crane from collapsing if the sensor data already detects that might happen, or action to prevent an automated tractor from colliding with an approaching operator) especially when there is higher-than-acceptable device to cloud data transfer latency, and when bandwidth could be a challenge (e.g., on offshore platforms what use satellite internet connection and have several functions demanding the available bandwidth) (Chen et al., 2018).

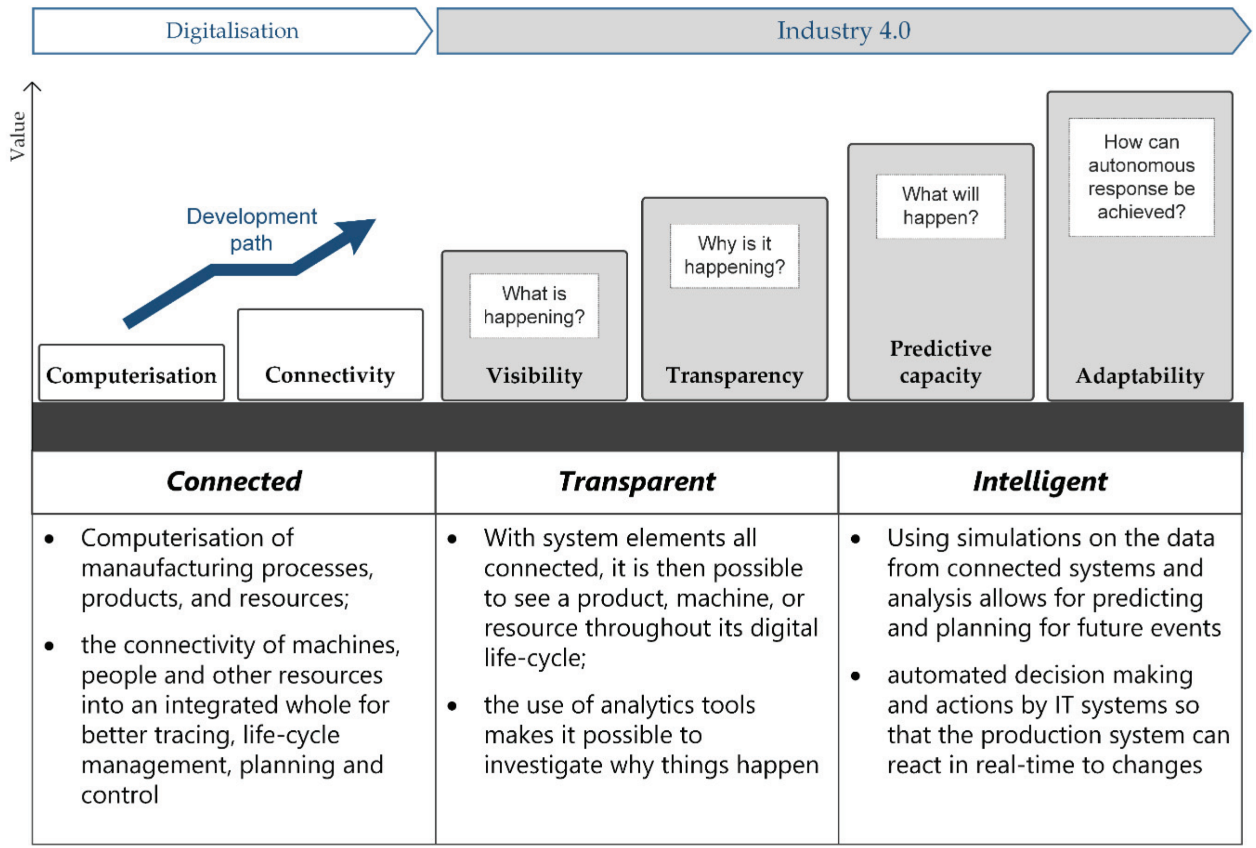


Figure 5.1: The development path for smart production systems (*Source*: Oluyisola et al. (2020); *originally adapted from* Schuh et al. (2017))

Consequently, real-time planning and control of the production system and supply chain becomes possible. Examples abound especially in the retail industry, which gained popularity in the past two decades due to the performance improvement achieved in inventory management and distribution logistics (Kärkkäinen, 2003, Ustundag and Tanyas, 2009). The same principles are now being applied in job shops, and production lines and warehouses at equipment manufacturers (Huang et al., 2019, Oluyisola et al., 2018b). Thus, computerization and connection enable smart PPC by making enabling the determination of the exact location of products, routes travelled in the factory, status of machines and other resources, frequency of use, idle times and non-value-added time, etc. all information which can then be processed with data analytics solutions to gain insights into the state of the system, why the system is performing that way, and the performance of the PPC processes managing that production system

5.1.2 Transparent

When 'things' are computerized and connected, it is possible to make a digital model of not only individual machines or factories, but also components and final products moving through the production processes, i.e., a digital shadow of the entire system and all its elements (Schuh et al., 2017, Park et al., 2019). The digital shadow represents a digital state map of the production system and accepts data from the connected elements of that system to present in a form, typically visual, that production managers and planners can use to plan future states and operations of the system. A digital twin meanwhile goes a step further and in addition to accepting data can send action instructions to the production system (Kritzinger et al., 2018). The data can be collected from within the factory or on a truck transporting raw-materials or other critical components or from the sensor-enabled pallets at the customer warehouses. It then becomes possible for a production planner to analyze the data to determine the sources and root-causes of logistical problems at the strategic, operational and tactical levels using dashboards with real-time KPIs collected from integrated enterprise and IoT systems (Kuo and Kusiak, 2019, Schuh et al., 2017).

Regardless of the type used, or even in cases where no digital shadow or twin is used but that KPI data specific to the production system are sent to a database for processing and analysis, there is a tendency for this data to be enormous and of high-dimensionality if they are collected from several IoT sensors in a typical production system. This situation presents an opportunity and a challenge. First, the abundance and breadth of data possible allows for higher precision of simulation models of production systems (Kuo and Kusiak, 2019). However, it also creates a case in which standard data processing technologies are not capable to derive insights from such (big) data. As such, new emerging technologies and methods for big data analytics such as MapReduce and Hadoop would be required to derive value from all the data being generated (Ren et al., 2015). And even when the data processing challenge is overcome, there is also the causality problem which requires an understanding of the underlying engineering principles and business context to translate data correctly (e.g., translating sensor measure depth in a raw material silo into estimated volume of weight of materials in the silos) and to establish cause and effect relationships from the data being generated by the system and the production and logistic KPIs of interest (Schuh et al., 2017).

Hence, when used appropriately, big data analytics enable transparency of process performance, critical materials and critical paths, estimate delays per supplier, process material yield, and other factors affecting the behavior and output of the system (Dubey et al., 2019, Strandhagen et al., 2017, Kuo and Kusiak, 2019, Wamba et al., 2015). However, it still requires a production planner who is highly skilled in production planning and data analytics methods to take an active look at the data, process and analyze the it, and make decisions. With the increasing research and wide application of ML and artificial intelligence, there is potential for a machine intelligent, self-optimizing PPC system which can handle all the relevant processes, process all data and interact with planners from time to time as may be determine by the production managers.

5.1.3 Intelligent

An intelligent system should be able to combine data from several sources about itself and its environment to learn and autonomously predict events which may influence its performance regarding set goals. In production, that implies being able to predict production delays, supplier delays, reduction in demand, etc. to avert a performance failure. Recent industrial interests in ML has led to significant advances which make these technologies and methods more feasible now for PPC than, say, a decade ago. Research into the use of AI approaches to planning and scheduling production systems have been going on since the 1980s, although those were of the form of expert systems and knowledge-based systems (Kusiak, 1987). However, it is the interest of companies like Google, Facebook and Amazon with vast compute and human resources have extended the capabilities and possible use-cases of ML and have also extended neural networks (a type of ML method) to new depths (i.e., deep learning) with advanced techniques and applications.

There are three types of ML namely supervised, unsupervised, and reinforcement learning and all three types have been explored in PPC research, although limited empirical case studies have been reported. Supervised learning techniques have been applied in (Monostori et al., 1996). ML has also been applied for planning and control in the extended enterprise for predicting supply disruptions (Brintrup et al., 2019). Reinforcement learning applications has been experimented on for real-time scheduling (Shiue et al., 2018). Other noteworthy empirical studies of ML use in PPC have been published. Using case studies, Garetti and Taisch (1999) explored the use of artificial neural network (ANN) for the selection of a production control strategy at a manufacturer of valves, and as a decision support system for plant parameter definition at the paintshop of a wagon manufacturer, highlighting each method's pros and cons or each method and the implementation challenges. Except for a few cases such as these, many of the ANN research output at that time lacked real-life application (Corsten, 1996).

Furthermore, these cases have been applied to static, one-off PPC problems while research looking at the dynamic case of real-time learning PPC system has been rare. In the past decade however, deep learning has received enormous attention from the software industry and has witnessed significant application in industries outside of manufacturing. Prior to that, several studies investigating the use of ML methods to address different subsets of the PPC system where published. For example, Hruschka (1993) used the marketing variables (current and one-month lagging advertising budget, and the retail price), together with an exogenous variable (average monthly temperature) to predict sales for an Austrian consumer brand. However, the author highlighted how computer processing power was a challenge due to the limitations of the approach at that time (i.e., the low learning speeds of ANNs).

In today's production environments, an autonomous solution can be built using robotic process automation (RPA) with event-driven or scheduled applications and data pipelines for connected system of applications. According to Wróblewska et al. (2018), RPA allows for continuous upgrade of solution modules and therefore allows for continuous learning. Thus, smart systems can be preprogrammed so that they can not only run independently, but also learn and improve without human interventions. Nevertheless, the case study in (Wróblewska et al., 2018) (and most in the RPA literature) was within the financial services and document management application. It is noted that there is limited application in production management, and more so in PPC despite the potential benefits.

5.2 Use-cases Matrix for Smart PPC

The smart PPC system should incorporate the different levels of the PPC domains and intelligently manage all the key processes using data from diverse sources and allow human intervention. It should also provide a mechanism for continuous feedback from the production system to handle events that occur, the way a fully human-managed PPC system would work.

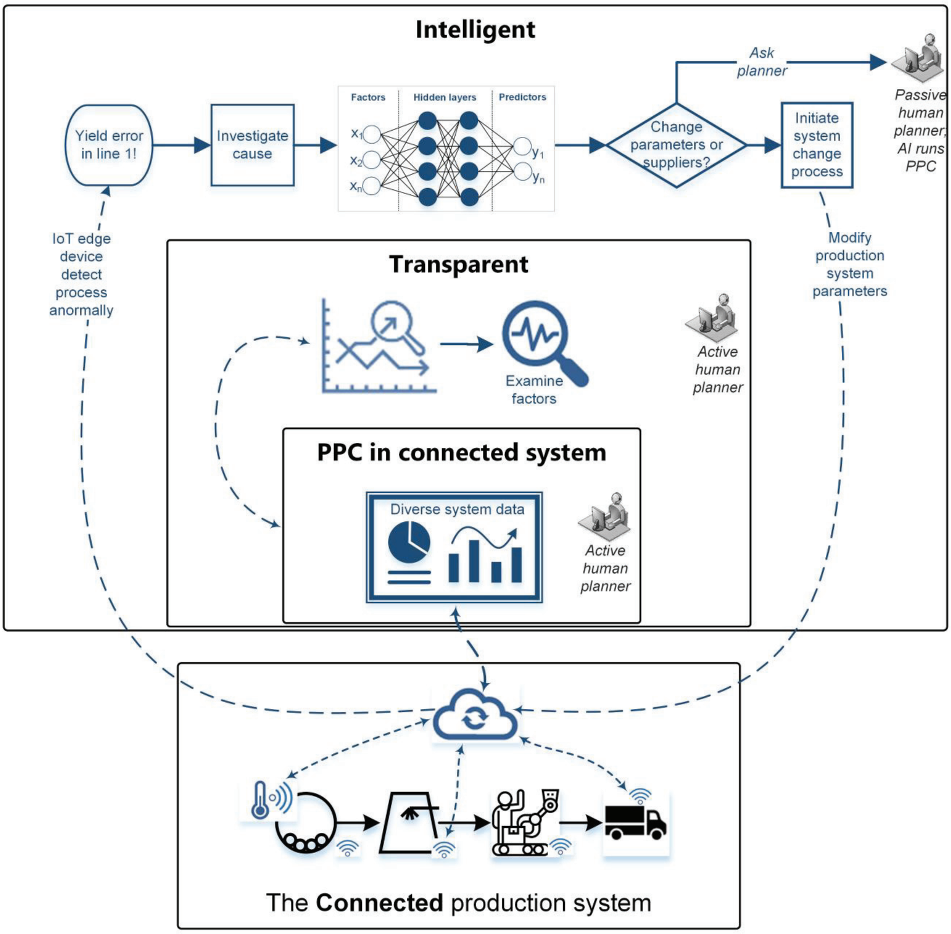


Figure 5.2: Conceptual diagram of smart PPC for a connected production system

In general, smart PPC should perform better since it will be using a vast array of endogenous data from the production system and exogenous data its environment. And for some industries, the opportunity may be greater to incorporate more data into the production planning and control processes. Furthermore, when viewed in terms of PPC challenges, several use-cases can be identified at each of the three stages leading to a Smart-PPC system as the following table shows. The table was developed from the literature and brainstorming with senior researchers in field operations management with extensive research experience industrial logistics and supply chain management.

Table 5.1: A table of use-cases for an incremental adoption of smart PPC

	Challenges in PPC levels	***Connected use-cases*** *(with IoT)*	***Transparent use-cases*** *(with BDA)*	***Intelligent use-cases*** *(with ML)*
	Strategic			
S&OP:	*1. Variable in historical demand* *2. Uncertainty in forecast demand* *3. Unavailability in demand data* *4. Investment assessment for green and brown field resource capacity*	Real-time POS data Real-time GIT data	Demand summary Visibility in production resource performance patterns	Demand patterns detection Identify emerging customer groups Balance inventory and service levels
MPS:	*1. Data integrity and completeness* *2. Estimation of product-level demand* *3. Inventory variability leading to difficulty in estimating available-to-promise* *4. Rescheduling frequency periodic scheduling, while change events continuous* *5. Feedback on accuracy of resource planning*	Identify material locations in real-time	Visibility of system performance for various product mix	Continuous lot-size optimization Multi-sourcing of data with error-detection mechanisms Multi-horizon scheduling and planning with KPIs
	Tactical			
MRP:	*1. Data integrity* *2. Bill-of-materials updatedness w.r.t. components and levels* *3. Inventory data accuracy – what is produced and exact storage location* *4. Lot-size determination and revision policy*	Connected materials are easier to track and trace	Enables transparency into the consumption of materials	Continuous lot-size optimization Intelligent planning of inventory control policy
CRP:	*1. Process routes/charts updatedness w.r.t. updates to processes and recipes* *2. Data accuracy and integrity* *3. Process variability* *4. Variability in the capabilities and capacity of resources*	Capturing the behavior of production assets	Enables robust lifecycle assessment of assets and precise capacity planning	Predicts when capacity may fall below required to meet production plans
	Operational			
PSS:	*1. Reliability of supplier quality* *2. Supplier quantity and timeliness accuracy*	Traceability of supplied parts lifecycle	Visibility intro supplier performance	Real-time delivery estimation and stakeholder engagement
SFC:	*1. Collect operations data in real-time* *2. Job tracking on the shopfloor* *3. Resource performance tracking* *4. Estimating and updating production schedule after rush jobs*	Connected "things" – parts, finished goods, machines,	Visual control for jobs and resource performance tracking in real-time	Real-time resource allocation ML for production control

6

The influence of Planning Environment Attributes on Smart PPC

What constraints do the planning environment attributes impose on the design and development of a smart PPC system? In this chapter, this question is answered by using the structural contingency theory, with empirical data collected from four case studies. Data is collected using an interview protocol, semi-structured interviews, and field investigations. From the insights garnered from this evaluation, and the literature, a smart PPC strategy framework is then proposed.

6.1 Smart PPC Projects at Case Companies

Despite all the noise and marketing, many companies are struggling in their efforts to become more data-driven and attain smart operations (Bean and Davenport, 2019). The realities of the adoption and use of data analytics, machine learning tools, cloud computing, and related smart technologies have been much more challenging than many anticipated. From anecdotal evidence with industry partners, and as the extant literature shows, some projects are likely to succeed while others are more likely to fail depending on the structure of the supply chain, the attributes of the production system, and the kind of products being considered. In order words, there is the question of "fit" regarding whether a project applying these technologies in production operations with succeed or fail.

In this chapter, the ideas explored previously, i.e., about the challenges and limitations of smart technologies in the planning and controlling of production operations, are extended to several cases. The aim is to understand if and how the market, products, and process attributes affect the kind of opportunities pursued, the challenges faced, and the successes achieved.

6.1.1 Smart PPC related projects at Brynild

Brynild has implemented several automation projects in the past few years such as using robots in packaging and palletizing, using visual control and dashboards, etc. One such dashboard projects on the production lines provides direct access to data from the production line, thereby providing the planner real-time access into the status of the processes.

The company is also investigating laser technology to measure the weights of products at the storage for intermediates, something that is not currently being measured. This will enable the measurement of the production at this intermediate stage and therefore it will allow more precise determination of the performance of the earlier processes before the products are weighed at the packaging line. Such data can then be integrated with other data sources to enrich big data analytics and machine learning improvement projects.

The company is currently implementing a digital system which collects data from its production line and sends it to a data warehouse where big data analytics (BDA) tools can be used to harness this data and generate meaningful insights. Despite these efforts, Brynild struggles with its development of BDA and potential use of machine learning (ML). There may be several reasons for this, one of which is the complexity of the existing ERP system. The sheer cost of modifications and upgrades was highlighted as a major hinderance regarding the move to the use of smarter PPC with data analytics and ML. However, new cloud solutions such as Microsoft Azure and Google Cloud solutions offer a means to overcome such challenges.

6.1.2 Smart PPC related projects at Pipelife

Pipelife is involved in projects to improve material flow within the factory and the production efficiency of the operation. At the operational level, these include a pilot project investigating the use of autonomous guided vehicles (AGVs), and an investigation and pilot of ML for an autonomous error detection and classification in the PVC production lines. The company has also investigated the use of RFID for material control in the shop floor and warehouses. In addition, Pipelife is also involved in a collaboration project for a digital platform solution for the industry which will enable closer interaction with the final customers and create new product configuration discoveries.

6.1.3 Smart PPC related projects at Brunvoll

There is the smart welding project which aim to use robots to improve the quality, speed, and cost performance of the welding process. There is also a plan to develop a RCCP spreadsheet for the planners and the sales team to be able to quickly check available-to-promise (ATP) capacity before confirming a new customer order. A condition monitoring service if also offered to customers. Finally, there is a new plasma and water cutting machine with an integrated software for managing the production process and inventory of steel plates.

6.1.4 Smart PPC related projects at Orkel

Orkel ventured into the development of precision farming solutions in 2014 and is increasing the digital capability of its products to improve product lifecycle. The company is attempting to utilize machine learning to generate intelligent insights about the use of the product and the health of its components by harnessing the data generated from integrated sensors. Other ongoing initiatives include kit-based material control for the assemble process, a research project to develop a decision support tool for selecting geography-oriented marketing, and a method for sharing plans and forecasts in Orkel's value chain using new ICT technologies.

6.2 Cross-case Analysis: Constraints and enablers on the path towards Smart PPC

Following the analysis, this section reflects on findings from the cases by analyzing the cross-case observations in the following sections. Thereafter, these findings are discussed within the backdrop of the literature presented earlier. The discussion is structured as follows: First, a discussion is presented about how planning environment attributes and supply chain structure, and extant enterprise planning systems, enable or inhibit smart PPC as seen from the cases studies – in section 6.2. Thereafter, a discussion of the sustainability implications of smart PPC (RQ3) follows and an attempt is made to explain why the case data revealed little explicit influence of sustainability KPIs on current PPC processes in the observed cases. This section is concluded with a brief discussion of some managerial implications of these findings (section 6.3). A comparison of the case companies is presented in Table 6.1.

6.2.1 The influence of planning environment attributes

While there are commonalities among the case companies, such as the tendency of production planners and managers to use simpler tools such as spreadsheets – for planning or scenario analysis – a common theme was the lack of KPIs for sustainability in the PPC planning process. Recall from section 2.7 that the moderating PPC environment attributes grouped into market, product and process categories can be further measured in terms of *market attributes*, *product* attributes, and *process* attributes. For the four cases, the semi-process operations differ from the discrete manufacturing operations for some of the attributes and some other attributes show no specific patterns. For example, demand uncertainty is higher for Brynild and Pipelife (MTS environments) relative to Brunvoll and Orkel (MTO environments). On the other hand, product variety and the relative level of supply uncertainty for inputs does not indicate any pattern in the sampled cases and may not explain patterns in smart PPC projects.

Table 6.1: Cross-case comparison of smart-PPC-related projects

		Brynild	Pipelife	Brunvoll	Orkel
	Classification	Semi-process	Semi-process	Discrete	Discrete
Market attributes	*Demand uncertainty*	High	High	Low	Low
	Market competition	National; high	Global; medium	Global; medium	Global; medium
	CODP	MTS[2]	MTS/MTO[2]	MTO	MTO
	Typical finished goods inventory	High	High	Low	-
	Input supply uncertainty	Medium	Low	Low	Medium
	Few vs many suppliers	Medium	Few	Many	Many
Product attributes	*Variety*	Medium	Low	Medium	Low
	Customization	-	Low	Medium	Medium
	Complexity	Low	Low	High	High
	Shelf life	Low	High	High	High
	Electronic	-	-	Medium	Medium
	Volume-to-cost ratio	Medium	High	Low	Low
	Unit cost	Very low	Low	High	High
	Final product or input	Final product	Input	Input	Final product
Process attributes	*Lead time*	Days	Days	Weeks	Weeks
	Batch size	> 1000s	>100	1 or few	1 or few
	Process automation	Medium	High	Low	Low
	Process type	Repetitive	Repetitive	Job shop	Job shop
	Process tolerance specificity requirement	Medium	High	High	Medium
	Cost of capacity expansion	Medium	High	Low	Low
	Planning and shopfloor control	ERP + Spreadsheet	ERP + MES	Spreadsheet	Spreadsheet + custom add-ons
	Inventory control	ERP	ERP	ERP	ERP
	Key PPC challenges	Planning precision uncertainty due to factory environment; high-combinatorial scheduling problem	Poor tracking of key consumables; high holding inventory in preparation for high demand season	Variation in delivery precision by component suppliers leading to poor delivery precision	MRP inefficiencies in final assembly; large CRP buffers to compensate for high variability in assembly lead time
	Connected PPC projects[1]	Give planners remote access to operator dashboard on the shopfloor	RFID for the connected factory Sensor-in-pipe technology	Sensors for collecting usage data	Connect with the SFC systems; product sending data to cloud

	Brynild	Pipelife	Brunvoll	Orkel
Transparent PPC projects[1]	New dashboard for planning and scheduling	Dashboard for production lines	RCCP[2] tool to support sales process	Upgrade of planning tool for resource specificity
Intelligent PPC projects[1]	ML for more process control and higher planning precision	ML for quality control in lines	ML for quality control in the welding process and product CM[3]	ML for processing product use data and predicting service needs
Sustainability consideration in PPC process	Not considered explicitly, except at the strategic level	Yes, as a measure of the quantity sent to recycling.	Not considered explicitly, except at the strategic level	Not considered explicitly, except at the strategic level

[1] *Smart planning projects* include both recently deployed within the past three years or currently being developed or piloted. [2] MTS = Make-to-stock; MTO = Make-to-order; RCCP = rough cut capacity planning. [3] Condition monitoring

The general pattern of smart PPC technology projects however followed the pattern. For connected PPC, the two MTS cases have pursued or are pursuing the use of sensors to establish new connections to the data being generated by the production processes. In addition, Pipelife, the plastic pipe manufacturer, is also investigating a sensor-in-pipe technology although this remains challenging. On the other hand, the MTO cases are both pursuing solutions to connect their products to a data store where that data can later be harnessed for insights. However, Orkel also has process related connected PPC projects. There are several plausible explanations for this. One is that because Orkel produces a final product and not an input component, the user (final customer) experience is a more visible issue for them to address.

For transparent PPC, all four cases had projects which aim to improve the visibility (what is happening) and transparency (why it is happening) of their planning and control processes. In all cases, managers express the need for dashboard solutions that can offer insights and support scenario analysis. While most of these projects are considering the use of spreadsheet-based solutions, one of them uses more open-source software libraries. This case particularly had a starting focus of using machine learning for inspecting product quality before the products proceed to finished goods storage and down the supply chain.

For intelligent PPC, a pattern can be observed for the four cases, but not according to the MTS/MTO distinction. The first three cases Brynild, Pipelife, and Brunvoll are investigating or testing the use of machine learning together with other technologies in their production line. In the fourth case, the use of machine learning is being investigated to make the product smarter, processing data collected from sensors on each product. It can be observed that the MTS cases are trying to use this technology to improve the control of their production processes. On the other hand, the application is split for the two MTO cases. While both Brunvoll and Orkel which produce products with some assembled and some engineered components are attempting to make their products more intelligent for the final user, only Brunvoll is testing this ML in one of its production processes to improve the quality of the machined component and the overall performance of the product in service – so far with little practical success. The observations from the cross-case analysis from the technology point-of-view can be summarized in the following propositions.

Proposition 1: *The fit of application of 'connected' and 'intelligent' technologies for smart PPC depends on the PPC environment attributes of a company. In particular:*

> **Proposition 1a:** *For 'connected' and 'intelligent' technologies, process MTS-type companies and companies with simple, non-electromechanical products tend to achieve a better fit by using these technologies for their production processes.*
>
> **Proposition 1b:** *For 'connected' and 'intelligent' technologies, MTO-type companies or companies with complex products tend to achieve better fit by applying these technologies to their products.*
>
> **Proposition 1c:** *For 'transparent' technologies, all types of companies benefit by applying these technologies to improve their overall PPC performance.*

In this regard, it was observed from the case data that process-based companies are more likely to benefit from (and therefore, should follow) a smart process strategy, with smart PPC as the driver. For MTO companies, it was found that the path to smart control is towards smart products with simplified PPC processes what will continue to allow human control for the needed flexibility. In addition, previous studies have shown that in some industrial sectors such as steel, chemical and plastics and SMEs in general pursue industry 4.0 primarily for operational benefits, while large companies tend to seek long-term strategic benefits from industry 4.0 technologies (Müller et al., 2018). As PPC processes contribute more towards operational performance, one would expect similar results. From the case studies, the reasons for this becomes apparent. Brunvoll, which is the largest of all four case companies for instance, is a global market leader in its industry and the industry has a high barrier of entry where the each product is typically very expensive and highly customized and the products are critical components of the ships they are installed on. In addition to some projects to automate some of the production processes like welding – a very difficult task to automate for MTO production – Brunvoll has focused mostly on innovative technologies that enhance the products by increasing their digital content and making them connected. The same holds true for Orkel.

For Brynild and Pipelife, the products are standardized, have no digital element are more difficult to digitize (even though pallets can be), and are more produced from raw materials which are chemically transformed in semi- or fully automated production lines. These companies (Brynild and Pipelife) are more inclined to pursue a smart process strategy (to achieve smart PPC) rather than smart products due to the process-oriented attributes as illustrated in Figure 6.1 below. The illustration is presented within the context of the product-process matrix by Hayes and Wheelwright (1979). This can be explained by the fact that these two environments have different kinds of PPC challenges and data generation processes. Process manufacturing tends to have more automated production lines already generating data and little product complexity meaning that process data is also consistent and repeatable, enabling smart PPC. The same reason also allows more granularity in the data for analysis and in a format amenable to machine-intelligence.

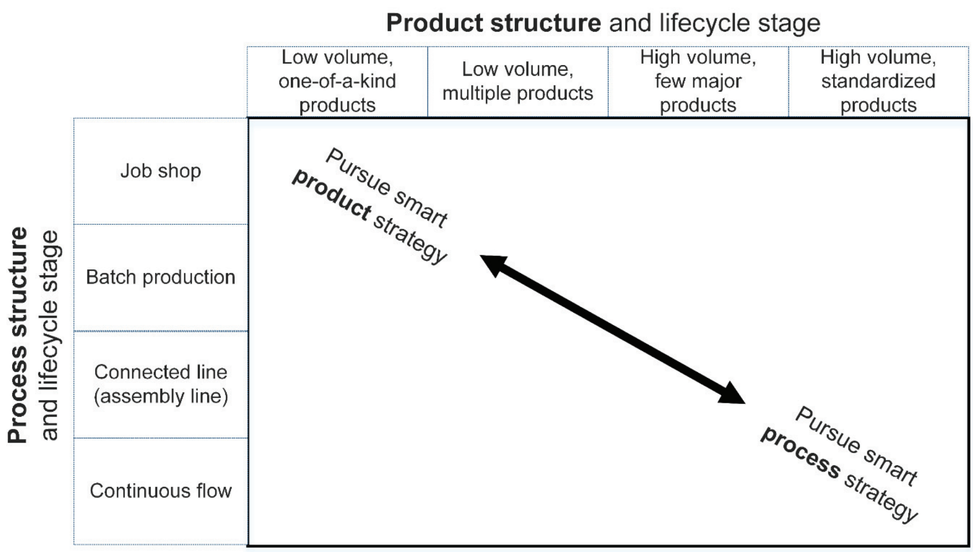


Figure 6.1: Product-process framework for smart PPC (*Adapted from* Hayes and Wheelwright (1979))

In addition, process manufacturing, as seen in companies Brynild and Pipelife, is more amenable to exogeneous telemetry factors which can play a greater role in final production output especially when the production is not sufficiently isolated from its environment. Meanwhile, complex products producers with job shop layouts are more focused on balancing workloads and planning human operator requirements due to the high labour content. Furthermore, complex products manufacturers tend to have functional layouts and require much more manual or operator activity. This implies that the former is more likely to generate data in a consistent, repeatable format while the latter is less likely. The same reason also allows more granularity in the data for analysis and in a format amenable to machine-intelligence. Therefore, the following proposition can be made:

Proposition 2: *Companies that are naturally rich in data (e.g. those who used previous data-intensive methods in the past) are more likely to pursue new smart PPC technologies which are data-driven than they are likely to pursue other smart PPC technologies.*

Finally, there is evidence to support the observation by Veile et al. (2019) about industry 4.0 projects' success/failure in terms of horizontal integration. For instance, Brunvoll, which is more powerful relative to other members of its supply chain seemed to dictate the pace of industry 4.0 related innovation within its supply chain. Also, the intensely competitive industries tend to see more innovations, etc. In this case, this study found that Brynild, which has a relatively small market share in a highly competitive food industry is more eager to pursue innovations within that foster horizontal integration to the extent possible with its supply chain partners and has encouraged joint research projects with its major customers which are the retail conglomerates.

6.2.2 The influence of extant enterprise and data systems influence smart PPC

As it has been reiterated earlier in this thesis, PPC is a function ordinarily performed with ERP systems. But a new system which will take enhance PPC by taking advantage of emerging smart technologies namely IoT, BDA and ML is presented. Therefore, this study could have also been carried out, perhaps, as an investigation of the extended capabilities of enterprise systems. Indeed, many authors consider ERP systems as the foundation for smart production operations (Haddara and Elragal, 2015) and this same perspective was observed in some of the case companies. But these companies also seem to be averse to having their transition to smarter PPC tied to their ERP systems. For example, the Supply chain director at Brynild complained about his company's needs to upgrade to the latest version of the ERP system being used at the company while at the same time concerned about the how expensive the offers from IT vendors have been for implementing some of the upgrades management desires to have if they tried to extend the extant SAP R/3 especially considering that SAP S/4HANA (latest edition) has suitable and useful data analytics and BI functionalities.

Furthermore, while the current ERP (and other enterprise) system(s) technology has led to better business processes and financial planning (Reynolds, 2015), its value as a complete production management solution remains limited in practice. One reason for this is the high cost of regularly upgrading to the latest versions with up-to-date functionalities. This is somewhat linked to the issue of customization and its implications for buggy integration with future upgrades and security updates of the core ERP system. The other reason is the complexity of most ERP installations which leads to many companies using their ERP systems for MPS, MPR, and inventory control, but not the detailed day-to-day or shift-to-shift scheduling, a function now reserved for spreadsheets such as Microsoft Excel. Therefore, to get smarter systems, managers investigating any or all the triad of smart PPC technologies take the path of developing new cloud-based solutions which then connects to the company's ERP database through a data warehousing solution.

In addition, the form, quality of the extant data generating enterprise systems are also very important and the ability to handle different formats can be a critical factor in determining success (Wamba et al., 2015, Gustavsson and Wänström, 2009). There are two types of data that production systems generate namely, stream and batch and these data types require different types of processing for insights to be derived from them. While it would be expected that a company which has enhanced processes and updated, standardized enterprise solutions are more likely to have the foundation to advance faster into smart PPC, no evidence was found for that within the case companies. In fact, the company that was most keen on smart PPC was one which was using an older, non-agile ERP solution i.e., Brynild. However, both Brynild and Pipelife had a significant amount of automation and process sensors which can easily be reconfigured and connected through the ethernet for a smart PPC solution using the streaming data from the PLCs of the machines in the production line. On the other hand, Brunvoll and Orkel pursued solutions that can enhance their capacity planning processes which they both had (from management's point of view) as their most critical performance challenges. In addition to extant data sources, Brynild also sees potential in using exogenous data and historical data in improving the precision of its production planning process. However, the quality of historical data records which such a smart PPC system would need is in a form that cannot be used without arduous pre-processing. This data quality problem was more prevalent than anticipated, consistent with Bean and Davenport (2019). Thus, the relationship between process type, level of automation and smart PPC can be summarized in the following proposition:

Proposition 3: *Companies with automated production lines or chemical production processes are likely to benefit more by pursuing a smart PPC strategy focused on increasing process efficiency, while companies with more manual/operator-driven processes or physical production processes are likely to benefit more by pursuing a smart PPC strategy focused on capacity optimization.*

6.3 Sustainability and Practical Implications

Studies have shown (for example, in the automotive industry (Müller et al., 2018)) that anticipated operational and strategic gains are the primary drivers of industry 4.0 solutions, despite some of its core sustainability benefits. In this regard, this study's findings align with the results of previous studies as all the case companies in this study, except one (Pipelife), had no any explicit sustainability measures or factors driving the PPC process, even though in all but one of the cases, planners were aware of the companies' sustainability goals and internal KPIs. The reasons for this are unclear, but it could be because of the following.

First, the level of societal consciousness about sustainability is very high in Norway and it will be hard to find a company which does not have 'sustainability' somewhere in its mission, vision, or core value statements. Furthermore, all the companies in this study have had lean improvement programs at some point in the past decade and demonstrate all the visible elements of lean in their factories. Coupled with the high level of decision making allowed in Norwegian factories, it seems that the responsibility for sustainability has been given to operators on the shop floors in line in with a bottom-up approach. Although this has good benefits, it limits the true sustainability performance to only the broad measures such as carbon footprint, missing the opportunity to have a truly robust sustainability strategy. Smart PPC will address this, e.g., by enabling explicitly integration of environmental and social KPIs with the financial. Smart PPC can allow sustainability KPIs to be included in the performance parameters of the system, thereby enabling these companies to actively and comprehensive act on their overarching sustainability goals. But it will require new competences and training from operators and production planners, and it may also lead to stress and overextension as observed by Birkel et al. (2019).

Secondly, it has also been reported in the literature that managers will sometimes invest in a new fad (e.g., blockchain) or new technology (e.g., cloud computing, a critical enabler of data analytics and BI) due to the fear-of-missing-out. A study of small and medium enterprises (SMEs) in Malaysia which found that the likelihood that an SME adopts cloud computing increases when competitors are already using the same technology (Hassan, 2020). But the key question is one about organizational and technological fit, about products and production processes, about market and PPC processes and how these issues can influence the use of any new technology in general and data analytics and ML tools in smart PPC specifically. Ultimately, the greatest value is obtained when managers pursue the smart product or process direction that is fitting for their type of company.

In general, managers of companies producing complex, high variety low volume product are more likely to derive most value from pursuing a smart product strategy while those with standard, non-electronic products in mass production environments are more likely to derive more value from a smart process strategy. In the latter case, a smart PPC solution has great potential and can drive an efficient, autonomous learning production system while tangibly addressing the sustainability goals.

7

A Method for Designing and Developing a Smart PPC System

How can the smart PPC be achieved in practice? To address this question, a method is developed from the literature for the design and development of smart PPC. The method is then illustrated using a case study.

There have been increasing research interest in testing or demonstrating aspects some of the tools and listed use-cases of smart PPC partly due to the early stage in its development such as in (Brintrup et al., 2019). Among those studies, few present the design and architecture of sample solutions using either hypothetical scenarios or empirical data (Sun et al., 2020). But most do not emphasize or address the need for a generic development method, and those that attempt to address this gap so far have not been focused on smart PPC – for example Huang (2017). And even more important, the few that do take a far too broad approach, addressing concepts such as industry 4.0 (Chen et al., 1997, Hermann et al., 2019). A method, however, is needed to both to improve success rates and to streamline the process of creating a system.

Brinkkemper (1996) defines a *method* as: "*an approach to perform a systems development project, based on a specific way of thinking, consisting of directions and rules, structured in a systematic way in development activities with corresponding development products*." The discipline of creating methods (also known as methods or methodology engineering) has links with other research areas such as project management and software engineering – fields where design science has seen increasing application (Peffers et al., 2007, Baskerville, 2008, March and Storey, 2008). The development of the method presented here followed the design science approach.

7.1 The Method

Having already established the need for a systematic method and guide for developing smart PPC solutions, the key steps that such a project could follow and the elements that should be considered are presented in this chapter. Here, the presented 'steps' suggests 'sequence'.

However, as it will be explained in the case study, the process does not have to be linear. In practice, it is often necessary to revisit preceding steps while at another as the requirements become clearer to the stakeholders of the project. The following steps can be followed in developing a smart PPC solution:

Step 1. Preliminary study: determine objectives and priorities in fitting with the PPC-environment's attributes.

Step 2. Specify system requirements: validate the operation's problem and identify performance indicators.

Step 3. Identify data sources and select relevant analytics and machine learning algorithms that fits the problem.

Step 4. Design system and data architecture with consideration for integration with extant systems and IoT telemetry.

Step 5. Implement with considerations for software development methodologies, continuous innovation, and long-term adaptability.

Step 1: Preliminary study: determine objectives and priorities in fitting with the PPC-environment's attributes

The immediate goals of the smart PPC solution must be determined ex ante. The process of getting to this could be either from the problem or from a perceived market opportunity. Furthermore, these objectives and priorities must be weighed with the constraints imposed by the planning environment attributes of the operation. However, it is a common occurrence for there to be a need to make tradeoffs over which elements of the solution requirements to prioritize in the short and long term. For instance, a firm in the process industry which produces, say, industrial paint, may see several opportunities and use cases for digitalizing its operations and PPC processes. Easily, managers could be interested in digitalizing the production line with IoT sensors that will collect various kinds of data about the production processes and send these data to the cloud for analytics and predictions, or on an edge device for real-time response. Another use case could involve attaching sensors to the packaging containers (which may be a bucket) or pallet, enabling a full tracking and tracing of the inventory coming out of the production line; yet another could involve the tracking of weather or climate factors and how this affect demand or sales at the stores; and so on.

Now, if this were a large multinational with millions of euros in research and development budget, then the company could start with and run multiple projects simultaneously, bearing in mind that results will be mixed. However, for a smaller company with a tighter budget, it will be critical to prioritize, focusing only on projects with a high expected return be it financial or digital competence gains for the company. In the example, following the argument that a process strategy is has great potential in this type of production environment, and the budget-constrained producer will prioritize those projects that lead to a smart process, for instance digitalizing the production line with IoT sensors capturing parameters that affect the yield of the operations. This could also be combined with other telemetry data from the production line's immediate environment.

Step 2: Specify system requirements: validate the operations' problems and identify performance indicators

The objectives are typically the prerogative of the company's management team and often represent their interpretation of the problems that must be addressed from a top-down view of the operation. However, a lot of the data driven decisions and insights affect or are affected by junior managers and operators on the factory floor. Therefore, there is a need to validate the objectives of the solution from the perspectives of persons directly interacting with the production system.

One way to achieve this is to formalize the requirements using user stories. User stories are described in the format "As an [role/persona], I want to [action] so that [why]." Each user story should have a clear, descriptive title. For example, a user story could go as follows: "As a production planner, I want to be able to upload productions orders for the next two weeks into the solution with approved production orders from the ERP system so that I do not have to copy this manually." User stories should be independent, negotiable, value-focused, estimable, small, and testable. Later during implementation, production managers and the system developers will determine how to prioritize the user stories for development. In addition, there should be flexibility in terms of which elements of the system remain on the list of functionalities to be developed, while allowing for future adjustments (Pressman and Maxim, 2015).

In addition, performance indicators (PIs) are needed to monitor both the quality of analysis and predictions being generated by the smart PPC system and of the reliability of the system. The PIs relating to the quality of the results can include the standard deviation and errors for individual predictions determined through random spot measurements. Those relating to the performance of the smart PPC system can include prediction lag, simulation request processing time, and general indicators like availability/downtime hours and the like. While PIs relating to the quality of the analysis and predictions will be context specific, most of the system PIs are generic and common to service-oriented, cloud-based ICT systems.

Step 3: Identify data sources and select relevant analytics and machine learning algorithms that fits the problem

The user stories give an indication of the services that primary users – production planners and operations managers – require the smart PPC system to fulfill. After identifying these services, the next step is to determine the relevant data sources from the production system and identify the appropriate analytics tools and machine learning algorithms that works best for the kind of insight or prediction required. This determination and identification can be done by a small technical team involving a machine learning engineer or data scientist with a good understanding of not just the technical problem but also the business problem.

In many manufacturing use-cases, pilot projects could start with simpler ML algorithms such as Gaussian linear regression and logistic regression (supervised), and with PCA and k-means clustering (unsupervised) with an acceptable level of success. However, after the pilot phase of such projects – that is, during the real-life implementation – there will be a need to improve the performance of the solution and which can be achieved using hybrid models which combine multiple features of the basic algorithms. For example, when the use case involves sparse data inputs and an extensive feature list, the hybrid algorithm called the DNNCombinedLinearRegression can be used in place of the common supervised learning to combine the strengths of neural networks (generalization) and linear regression models (memorization of feature interactions) (Cheng et al., 2016).

Step 4: Design system and data architecture with consideration for integration with extant systems and IoT technology

Many large manufacturing organizations, in addition to having an ERP system also have full-fledged solutions for the control of production operations on the factory floor – the MES. Some MES systems have basic analytics capabilities built in such as statistical process control charts that allows process-tracking, and most collect time-series stream data from the discrete units of production lines to which they are connected. Alone, using the MES for production control misses the opportunity that a holistic, connected smart system affords. Therefore, the system architecture should cater for the introduction of IoT sensors to the factory even for factories are already automated. The MES and ERP systems provide a good starting point for developing smart PPC solutions. The data from these systems and other factory IT systems might however require extensive transformations before they can be used in combination with newly installed IoT technology in the smart factory.

In general, modular smart PPC solution design would perform better than a monolithic solution since it will allow for future improvements within each module independent of others and will also ensures that failure in one service does not break the entire system. Furthermore, when the solution is built on a service architecture from the onset, the it is easier to add more modules in the future and to update individual modules that are already in use. This is achieved by designing the modules as services and building application programming interfaces (APIs) to manage interaction among services. The data processing, model development, and prediction processes can be carried out without manual human interaction by automating the data preparation and prediction processes using ML pipelines.

Moreover, in cases where an active control (rather than just a monitoring) of the production process is required, it is advisable to have the trained machine learning model interacting with the production machines and processes on the "edge" without the need to send to the cloud and send instructions back to the plant. However, because the real-time data processing occurs at the edge, this creates a challenge due to the limited processing power at the edge and need for continuously monitoring the performance of the model to avert model drift. Furthermore, edge devices may lose their connection to the cloud and thus the solution must cater for offline operations. Otherwise, where there is no need for any serious computing at the edge, it suffices to send all data generated from the production system to the cloud.

Step 5: Implement with considerations for development methodologies, continuous innovation, and long-term adaptability

Regarding the implementations of smart PPC solutions, there are at least four key considerations: whether to develop in-house, which development methodology to adopt, whether to choose managed-cloud services or to use fully open source technologies, and how to foster continuous innovation. It is possible to develop in-house or to establish joint development teams with partners service providers for small scale functionalities and outsource the major development to established firms if the firm does not have the competence to execute the complete development in-house. Moreover, the development of the solution will often involve the choice of building almost from scratch with the use of open source technologies, or if faster deployment is desired, the use of any one or a combination of the several managed-cloud services for a faster development process, while allowing for 'agile' development.

Non-agile methodologies will be insufficient in this area because as they are not flexible enough to support the 'continuous innovation' needed for such a system. Continuous innovation in this sense relates to how the established infrastructure and development processes eliminates tedious manual processes for making changes and improvements to working system, and allow a seamless, continuous integration, testing, and deployment of those changes without any downtime. Because many of these technologies being used in smart PPC systems are experiencing constant, fast-paced advancements, the success of any smart PPC solution requires that there is a smooth and simple process in place for its continuous improvement. Alignment or integration of the workflows/processes of the both the machine learning and information technology developers will streamline continuous innovation and refinement of models as new data becomes available from the production system being measured.

For information systems' developers, the concept of DevOps has arisen as a preferred way to manage the continuous version-controlled, code development cycle – write, test, build, deploy. While machine learning engineers and data scientists take the experimentation, model creation, testing, operations, and maintenance. By integrating these two workflows – to have what is now referred to as DevOps for machine learning (MLOps) – productivity can be improved significantly, allowing machine learning engineers and data scientists to focus on the model performance. One way to achieve this is to use infrastructure-as-code and process automation in managing the system's improvements and the revisions' process in autonomous mode. Process automation could be achieved using bash or python scripts, or through robotic process automation software that allows automation using drag-and-drop tools which a trained production planner can manage, thus reducing development costs.

7.2 Case Illustration – Smart PPC Design at Brynild

Using the Brynild case, the method described above is illustrated below.

7.2.1 Determine objectives & priorities in fitting with PPC-environment's attributes

Candy production at Brynild is serviced by two production lines. The production process for the candy products is as shown in the Figure 7.1 below.

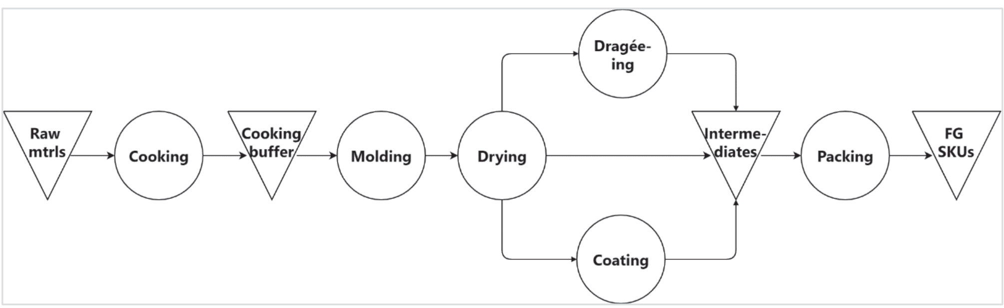


Figure 7.1: The candy production process at Brynild

The operations at the candy section falls into the semi-process class. Raw materials are fed into the cooking drums in amounts determined by the recipe for the batch to be produced. When the cooking process is completed, the output is temporarily stored in a cooking buffer before molding, using mold trays with the shapes of the sweets engraved. The trays are thereafter arranged in racks which are loaded into one of the seven drying chambers in the drying section of the factory. The production data currently used in the production planning process includes the estimated lead time for all processes, stock levels of the different stock keeping units (SKUs) in the finished goods warehouse, recipes (which also provide a bill of materials). The maximum batch size the line can produce for each product is pre-calculated based on the capacity of the production processes.

The challenges of this current PPC system can be described in three categories namely, market (demand and supply) related, product related, and process related. First, market related demand related challenges stem from the high competitiveness of the industry and the fickle nature of human taste preferences. A popular product can sometimes loose its spark with consumers or get overshadowed by new trending products. For this reason, the confectionery industry witnesses a lot of promotions and discount sales to drive and sustain demand.

Secondly, the product related challenges are minimal in this case because the products are neither complex nor have any deep bill-of-materials which could have required extensive materials requirements planning tools. Furthermore, the simplicity of products made by this case company (packed sweets) and the price per unit implies that the product itself will not benefit from a smart product strategy. Rather, a smart process strategy will be for fitting for this type of case (Oluyisola et al., 2020). Such process approach must be able to track the remaining life for any product or batch in the finished goods storage and in the various warehouse within the company's value chain and must also be able to trace its journey through the value (Høyer et al., 2019).

Thirdly, the process related challenges are generally due to the nature of the materials being processed and the level of maturity of the process technologies. Currently, there is a long set-up and changeover time due to the need to wash the machines and equipment producing every new batch. This is also required to meet regulatory requirements for cleanliness and food safety. There is also a yield uncertainty that planners currently must guess when issuing production orders and this causes additional variability in the production system. Also related to the process is the operator-planning related challenges relate to how labour is planned in the company. Over several years, the company has developed a practice of planning batch sizes that can be completed within a production shift. This is a suboptimal constraint on the planning process. Therefore, with the attributes of this production environment, this company's approach to smart manufacturing should take a smart process strategy, rather than a smart product strategy since the product is simple and the unit price is very small.

7.2.2 Specify system requirements: problems and performance indicators.

Problem investigation

Brynild faces one immediate challenge: finding an optimal production schedule and managing the scheduling process to minimize variation. Thus, the production planning problem for this case comprises two main elements, namely: the optimal plan, P, which maximizes throughput through the bottleneck drying process and assumes no yield variation (that is, $Y_k = 1$); and the estimation of a yield uncertainty factor, k, to improve the accuracy of production plans. Currently, planners must guess the what the yield will be and add some buffer to the amount that is produced so that at least the final production output for each batch exceeds the planned amount required to meet order forecasts. This leads to overproduction, and it particularly expensive for products which serve as inputs into 'mix'-type products. The mix-type products are made by combining three to five different types of products into one assortment.

The planning problem can be formalized as follows: given a set of firmed customer orders, OC, and Master Production Scheduling or MPS orders (MPS orders are those generated by SAP using the MRPII principle), OM, each order $\boldsymbol{oc} \in$ OC and $\boldsymbol{om} \in$ OM characterized by: its drying i.e., throughput time $\mathbf{TH_{oc}}$ or $\mathbf{TH_{om}}$, its due date $\mathbf{dd_{oc}}$ or $\mathbf{dd_{om}}$, its volume $\mathbf{v_{oc}}$ or $\mathbf{v_{om}}$ and given a set of drying sections or rooms R, each room $\boldsymbol{r} \in$ R characterized by its capacity, $\mathbf{k_r}$, and given a set of packaging lines L, each room $\boldsymbol{l} \in$ L characterized by its capacity, $\mathbf{k_l}$, find the schedule allocation of orders $\boldsymbol{oc}$ and $\boldsymbol{om}$ that maximizes the number of completed orders at the two stages drying and packaging.

Furthermore, the planning problem can also be viewed as a multi-stage or multi-echelon scheduling problem for which although the drying stage, which is used for all products from the production line, is not always the bottleneck. This is because the average speed of the packaging machines is low enough that they can cause delays if poorly scheduled and depending on the product. This is partly because there are several packaging lines with varying speeds and no single product has a dedicated packaging machine. After production schedule is made, the plan must be adjusted for reality by estimating a yield uncertainty factor. This yield uncertainty is a factor of environmental parameters such as humidity and temperature.

Requirements specification

The requirements, shown in Table 7.1, were gathered from the production managers and planners of Brynild during this research-based improvement project towards smart manufacturing. An overview of the solution concept is presented in Figure 7.2 below. KPI result data going into recommender system will include actual production performance (lateness, earliness, on-time, etc.), specific operator working the process (this shows how specific operators affect performance), etc. The newly added elements of this smart PPC system are described in section 4.3. A description of each step in Figure 7.2 is provided in Table 7.2.

Table 7.1: Brynild's requirements for the smart PPC solution

Purpose:	
"We want a tool that helps the planner schedule production more efficiently." – Senior Manager.	
More precisely, the system shall provide decision support capabilities to the production planner especially regarding the short and medium-term planning.	
Functional requirements:	
Schedule options	• The solution should generate the optimal production when the planned orders for the short-term planning period (next two weeks) is provided.
Integration with ERP system	• The production planner will be able to upload the details of the new orders to the next planning period.
Dynamic rescheduling	• The solution should allow dynamic rescheduling when the attributes of production system changes for example, if an order is delayed or if there is machine breakdown
Using telemetry factors	• The solution should capture the effects of external factors that influence the production yield, to ensure for a more precise planning process
Capture planner experience	• The planning system should capture the practical experience of the planners with the production system which cannot be expressed in planning input parameter values.
Non-functional requirements:	
Ease of use	• The tool should be easy to use for non-advanced computer user, that is, anyone with experience using spreadsheet solutions like Microsoft Excel.
Layout	• The layout should be designed in such a way that important values are easy to read.

Performance indicators

It is important to have predetermined how the performance of the system will be measured. In the selection of performance measures or indicators for this case, there are two categories namely, operations reliability and services quality. The operations reliability measure has to do with how the software system is designed, architected, and developed. It is measured by reliability measures such as up-time (a maximizing measure) or downtime (a minimizing measure), percent failed schedule requests from the user interface and waiting time between schedule launch and results presentation on the dashboard. The services quality refers to the quality of the results, estimates and recommendations offered by the smart PPC solution. Measures include the amount of deviation of the estimated yield from the actual yield, the average performance of the recommended schedule logic over period.

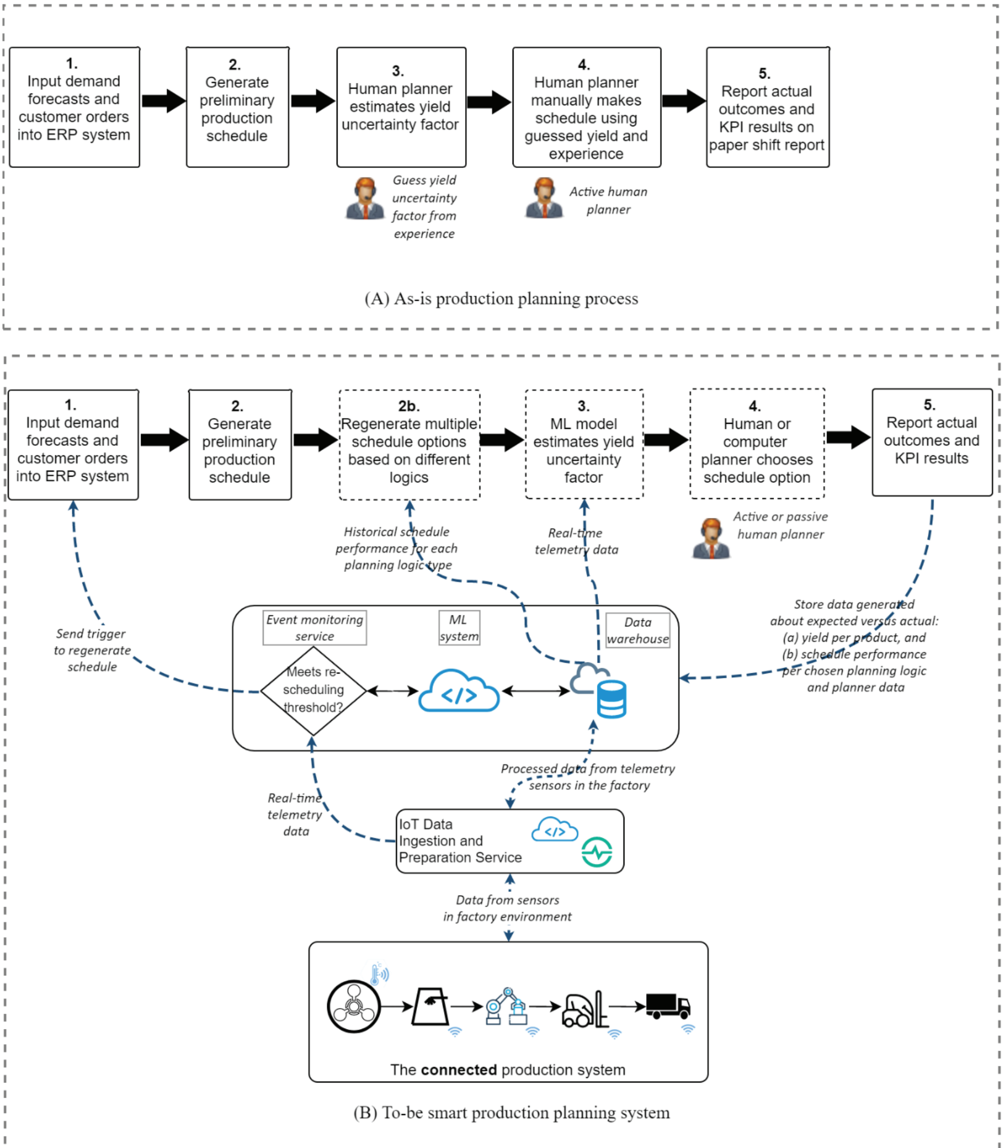


Figure 7.2: Conceptual overview of the as-is compared to the to-be smart PPC solution

Table 7.2: Comparison of the as-is and to-be processes (reference to Figure 7.3)

As-is planning process	To-be planning process
1. *Input demand forecasts and customer orders into ERP system.* Based on the demand forecasts and firmed customer orders provided by the marketing team, the master scheduling processes in the ERP is initiated periodically. The schedule comprises a list of production orders to be executed on the production floor with due dates, quantity or amount to be produced.	1. *Input demand forecasts and customer orders into ERP system*. Same as in the as-is system except that a new plan can be triggered if the changes to the system is significant enough that it reaches the threshold set for a parameter of the factory. For example, if the yield is estimated to be significantly low for the current orders, then it can trigger a new batch or bring forward a batch originally scheduled for a later production date.
2. *Generate preliminary production schedule.* From this ordered list of production orders, the production planners then manually allocated the orders to production shifts based on several constraints including capacity at the drying stage, planned repairs, and shift planning.	2. *Generate preliminary production schedule.* Same process as in the as-is process 2b. *Regenerate multiple schedule options based on different planning logics.* Unlike in the as-is situation, the to-be state will allow the generation of multiple schedules. In the pilot phase, two methods or 'logics' (x and y) will be implemented with the option to add others later as additional features. The modular design and cloud infrastructure allow this, taking advantage of either autoscaling or the use of serverless computing services such as Cloud Functions.
3. *The production planner estimates the yield based on their experience.* A record of this yield is stored in a spreadsheet and updated periodically every second year (see Appendix 2). NB: - In real time, the planners adjust the yield uncertainty factor upwards or downwards based on what their expectations by considering environmental factors and preceding yields.	3. *Yield uncertainty factor estimate generated by ML model.* The trained machine learning model estimates the yield uncertainty for each production order so that the schedule options from Task 2b then reflects the realistic estimate.
4. *Adjust schedule with yield estimates and other constraints.* The orders are adjusted to reflect this yield uncertainty factor and other constraints such as machine breakdowns and drying stage requirements.	4. *Human or computer planner chooses schedule option*. If a human planner is involved, the planner can then choose the adjusted schedule option based on his or her preference. These choices will be recorded and over time, will capture the intrinsic experience of the planner by capturing his/her schedule choices for different scenarios over time, and this data can then be used as input to improve the performance of the computer planner. And if a computer planner is involved, it will use historical data and rank the different options.
5. *Report actual production outcomes in shift reports.* After the production is completed, the paper-based end-of-shift report is filled. The ERP system is also updated to indicate that the order has been produced. However, the details in the shift report (for example, input mass, output mass, etc.) are not digitally stored to allow data-based improvements in the future.	5. *Report actual outcomes and KPI results.* After production is complete, the production data is digitally recorded, and the data is stored in the data warehouse which will serve the ML programs and over time, will lead to an improvement in the accuracy of the yield estimate predictions and scheduling logic selection.[1]

[1]*This measurement and reporting are key to future improvements and will be managed by a strict company policy requiring the operators to take necessary measurements in the absence of an automatic measurement system which can be later integrated.*

7.2.3 Identify relevant tools and algorithms

There are two choices to be made regarding the two applications of machine learning within this Brynild case: one for estimating the yield and the other for recommending which schedule logic alternative will perform best for each planning scenario. The yield estimation (or prediction) can be hypothesized to be the dependent variable of a linear or non-linear system. As such, a simple linear regression model is a good start for this use case. Once the system is built and in place, other variants of the linear regression can be tested in a development environment to see how much improvement in performance is possible. Examples of those are models combining basic models with more performant neural networks such as the wide and deep `DNNCombinedLinearRegression` algorithm or similar. This model will be fitting for this purpose due to the potential sparseness of the features. The data fields that will be used in the model are shown (without telemetry) in the class diagram in Appendix 3 and a detailed list (with telemetry) is provided in the table in Appendix 4. Meanwhile, the subsystem for recommending which planning logic option to choose appears amenable to inverse reinforcement learning.

7.2.4 Solution architecture –data and systems architecture design

While ML academic projects on ML in PPC tend to use linear development processes, live production projects require the use of recyclable, reproducible machine learning pipelines which can be automated. For this case study, an illustrative system architecture for the yield estimator use-case is presented in Figure 7.3 below. The assumption of a one week "fixed" planning window is made in line with current practices by the production planners, during which the list of orders to be processed is assumed to be deterministic – except if a major disruption or urgent firmed customer order is received. However, during this one-week period, the forecasts for some of model feature variables (for example, environmental data) are only precise for two days into the future at any given point. Therefore, there will be a need for re-scheduling at least once every two days to take advantage of the trained model. In the future, when a lengthy historical data has been gathered, it will be possible to train the model using only the historical data without the need to use the weather forecast data whose accuracy diminishes materially beyond a 48-hours from the reference point.

7.2.5 Implementation considerations and performance assessment

This use-case is illustrated using open source technologies for the sake of demonstration. However, for production, the company might be better served by using managed services on any of the major cloud platforms. One could start with a small pilot to test an idea, or go big, with a large-scale project and iterate on improvements. The latter approach can lead to faster business impact. There are also pilot versus real-life production implementation considerations. The nature of this production planning is such as that the properties of the system of interest changes frequently relative to the target precision of prediction results. Furthermore, as the data scientist and the developers working on this project will need close collaboration, and there is a requirement to be able to scale the solution to address other PPC use cases as the companies gains organizational competence with PPC. These factors strengthen the need for MLOps.

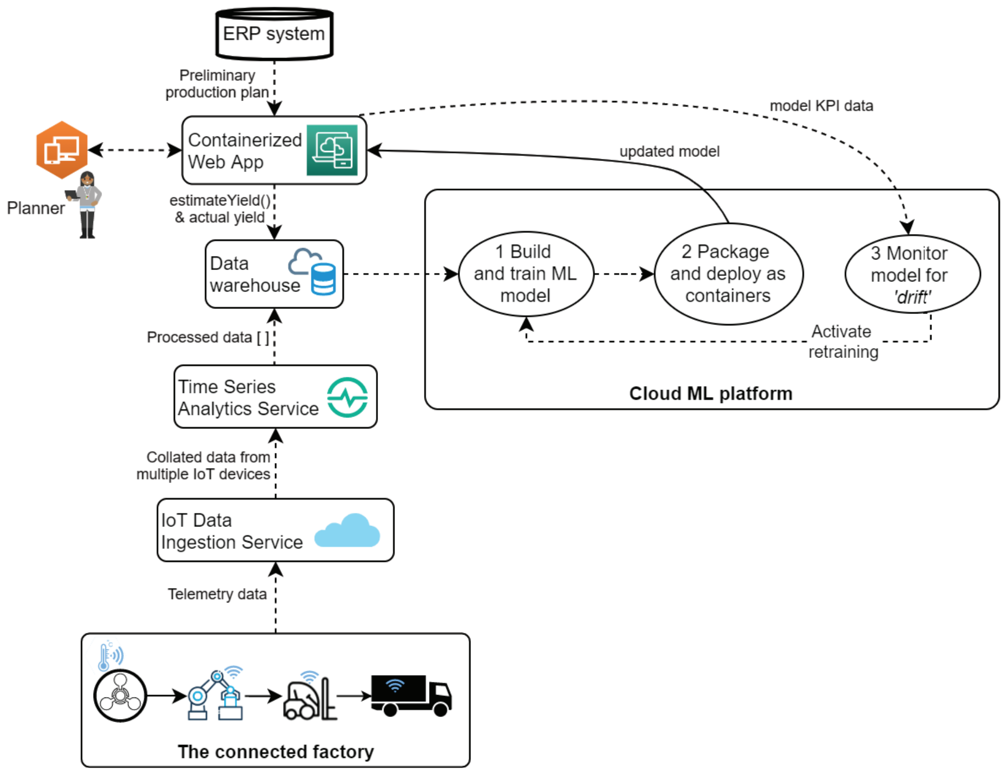


Figure 7.3: An example smart PPC solution architecture for the yield estimator use-case

7.3 Implications for Practice

In the preceding sections, a method for designing and developing smart PPC systems is described and the application of this method is illustrated through a case study. In this section, the application of the method within the case is reviewed, followed by a discussion of the insights gained from the case study and the implications for research and practice.

The objectives and priorities identified in the first step of the method were used as basis for formalizing the problem and specifying the requirements and relevant performance indicators. This step helped refine the requirements that were put forth by production managers and planners, who are the intended beneficiaries of the smart PPC system. These requirements included having multiple schedule logic options, integration with existing ERP system, dynamic rescheduling or more frequent scheduling updates, yield estimation using telemetry factors and capturing the experience of managers. While these were the functional requirements for the PPC system, non-functional requirements such as ease of use and readability of the user-interface layout were also identified although the latter non-functional requirements were not the subject of this case study. Consequently, operations reliability and services quality were deemed as the relevant performance measures for the smart PPC solution design.

Of interest in this case study was the problem of yield of estimation at the drying station. This was important in this case because the yield, which affects the precision of the entire planning process, is highly influenced by exogenous factors, e.g., temperature, humidity, etc., factors which can be modelled and predicted using analytics and ML tools. This again reemphasizes the importance of fitting smart technologies to production systems according to fit as pointed out in (Oluyisola et al., 2020). By the same principle, a smart product strategy would not be beneficial in this case company. In addition, the formalized problem and specified requirements were used to identify candidate tools and algorithms to address the problem and fulfill the requirements. For this case study, this selection of tools and algorithms was based on extant literature on smart PPC (reviewed in section 2.3.1). While this was lightly covered in this thesis, this as an area that future research needs to address for the ML value in PPC to be realizable.

The final step in the method focuses on continuous innovation and/or development, i.e., the system should be adaptable when weaknesses are identified during use or as opportunities for utilization of better or more mature technologies become available. The performance of the current, as-is process is compared with the improvements that can be achieved by the proposed smart PPC (when fully operational) in Table 7.3 below. These are measured against the general goals of the smart PPC system established in the literature. By reason of the capacity, consistency, and flexibility that the smart PPC system affords, as the case illustration highlights, the improvements are such that the manufacturing firm will be able to anticipate and react more precisely to changes in the production environment.

Table 7.3: A comparison of as-is and to-be PPC systems

Smart PPC Goals	Current state performance	Proposed Smart PPC performance
1. Be dynamic, by using real-time demand and production system data thereby reducing variability due to forecasts	Not dynamic, and uses planning data some of which (e.g., the yield estimate) are updated only once per year or less frequently	Use near real-time data from the production system and its environment to monitor and ensure planning and control processes are reflective of the actual system data
2. Use an expanded set of factors and data sources including system telemetry data	Uses only order due dates and planners guess of what other factors could affect the plan	Uses telemetry from within the production process and from the system environment and can determine correlations with yield
3. By using historical and real-time production system and demand data, be able to accurately predict factors and events and thereby also support increased flexibility	Historical data currently inadequate or unusable for advanced analytics due to inconsistencies and poor records	The system is designed to allow real-time control or human planner control of the production system using data from the IoT sensors
4. To capture and use the experience of the operators and planners currently managing the production system	If planner retires, he goes with all his experience and a new planner gets to re-learn the same mistakes	The system keeps records of decision patterns and success ratios of different planning logics, providing a log and summary of the planner's experience

The general implications of having a method such as the one presented in this thesis are significant for research and practice. By having a method which starts with the determination of fit according to the planning and control environment attributes, it will be possible to streamline smart PPC projects and increase their chances of success. Based on the PPC environment characteristics, it was possible to determine early in the process that the case company would benefit more from a smart process strategy rather than a smart product strategy. And while the issues of interest in the case study are primarily operational, the method itself is not constrained vis-à-vis the application context or decision levels and can be applied for projects pursuing strategic and tactical decision support.

Furthermore, due to the current rate of innovation within the disciplines of big-data analytics and machine learning, the availability of tools and algorithms for a given set of problems is constrained by the state of art at any point of time and may change as time progresses. Therefore, this step of the method could be reviewed after an interval, which should be decided during the initial or pilot implementation. The next step in the method concerns architectural considerations for the implementation of the solution. This step not only considers the architectural design for the proposed solution itself, but also considers the integration of the solution with the existing enterprise systems, thus re-emphasizing the focus of the method on ensuring fit of the smart PPC system with the planning environment. Furthermore, while designing the data architecture in this step, due consideration must be given to future scenarios, such that the developed system is scalable and amenable to future operational demands.

Additionally, as Cadavid et al. (2020) highlight in a recent review paper, there is a need to address the linearity limitations of extant research on ML-enhanced PPC and also a need to link tools, techniques and activities for industry get real benefits from research on the subject. The architectural considerations prescribed in this method addresses this key issue and should be a major consideration for future applied research on the subject. This cannot be overemphasized considering how small and medium sized manufacturing firms must grapple with the uncertainties of a pandemic-battered global economy and the post-pandemic global market.

Additionally, anecdotal evidence with manufacturing firms in the Scandinavia region shows that while increasing automation and digitalization has led to the creation of massive volumes of big data in production systems, a lot of the data is neither used nor is useful. The reasons vary for each case, but a recurring theme is that the data architectures are often designed primarily as a logging system for use in maintenance activities and many manufacturing firms still are yet to fully adoption an IoT strategy. All these factors then make it more challenging to derive value using analytics or machine learning to build intelligence into these production environments.

From the foregoing, the several considerations to be made when developing a smart PPC solution include the planning environment challenges which are often relatively consistent in the long-term, and the technology-related challenges which are related to the fast-paced evolution. And due to the significant uncertainty involved in the innovation process, and the high risk of project failure, the selection of use cases cannot be done randomly or based sole on what is trending with competitors. Indeed, while over 60 percent of IT projects fail outrightly or when defined by one of the performance metrics of timeliness, cost or quality (Mark, 2016), anecdotal evidence suggests that this may be even worse for projects involving emerging technologies. In one example, a major distribution and logistics center recently had an innovation project where it tried to deploy autonomous robots with machine learning capabilities in one its warehouses. The project failed both technologically and operationally, and the company did not share information about this failure publicly potentially because it does not help the company's brand posture as a technology savvy organization.

It can therefore be assumed that there is a greater likelihood or perhaps a tendency for companies to want to report only successful digitalization projects. This may, over time, lead to a 'survivorship bias', as researchers would only have cases of successful projects to extract knowledge from, while losing access to the valuable knowledge that could be extracted from the failed implementations. Furthermore, this creates a lacuna because while there may be 'local learning' within each company, there is a global loss due to several companies repeating pilot projects that many others previously tried and failed at. Therefore, a systematic method of the type proposed in this study can help reduce the risk of smart PPC project failure and can reduce the variation amongst several subsequent smart PPC projects, thus enabling easier shared learning.

8

Conclusion

In this chapter, conclusions are drawn from the study findings and discussions. Limitations of this study are described, and potential future research ideas are discussed.

8.1 Summary of Contributions to Theory

An important gap in extant research within industry 4.0, its technologies and their implication for PPC was the lack empirical studies investigating the constraints imposed by the production system's environmental attributes (Bueno et al., 2020). In this thesis, an attempt was made to bridge this gap by delving deep into the processes and operations of six case companies covering four different types of manufacturing industries and spanning both MTS and MTO production environments. The first four case companies described in chapter 4 formed the core of the empirical data source and cases 5 (Tine) and 6 (PowerMac) were only added to check the validity of the findings at the preliminary stages.

In answering the need for a systematic, low-risk adoption of industry 4.0 and its technologies, this thesis posed four guiding research questions, namely, to identify and describe the challenges of PPC amenable to digitalization, to identify the elements of a potential smart PPC solution, to determine and evaluate the constraints and enablers of successfully implementing such a system through a contingency theory lens, and to develop a guideline for implementation in resource-constrained companies. Several artefacts were developed and proposed in this regard including an incremental, conceptual model for development of smart PPC, and some of the artefacts were exemplified in the case studies and have been published in peer-review journals.

The key **contributions to theory** can be summarized as follows. The findings suggest a relationship exists between the PPC environment attributes and the digitalization strategy. This establishes a basis for introducing these attributes as factors in future smart PPC research, although further tests are required. From the literature search, this study is the first to establish this link and provide a strategic framework which shows this relationship. Furthermore, by demonstrating the use of the structural contingency theory for this research area, this study demonstrates how more traditional management theories can be applied as both the industry and academia demand more grounded theories to explain the digitalization phenomenon in manufacturing and more specifically as this applies to PPC within the smart manufacturing context.

This study further found that industry 4.0 implementations need not only integrate adequately with an organization's existing processes and systems, but also with its planning environment. In other words, the planning environment variables – product, production process, and market (i.e., supply and demand processes) – should dictate how industry 4.0 is approached, and consequently, each firm's implementation of smart PPC. Also, the intensity of competition in a firm's industry can influence its need for, and adoption of, smart PPC solution. Companies in highly competitive industries, which are not market leaders are more likely to join the smart 'bandwagon' and in doing so, fail to achieve the fit that is necessary for implementation success.

The presented five-step method for designing and developing smart PPC systems emphasizes the influence of contextual fit in the selection of algorithms, design for scalability, and the flexibility of the designed system to address future demands so that the resulting PPC system fits with the targeted PPC-environment's attributes. The method seeks to harmonize the emerging interest and could help standardize future studies that test the introduction of digitalization technologies in production and logistics systems. By extending the principles of method engineering to smart PPC and illustrating the use of the design science approach in this research, this study increases the likelihood that future research developments in the field have a common basis and not only present results – which are important – but also further guidance on practical implementation, contributing to towards the design area of smart manufacturing (Hermann et al., 2019).

8.2 Summary of Contributions to Practice

This study further makes several **contributions to production and operations management practice**. The proposed conceptual model shows how a transition to smart manufacturing can be achieved by following a development pathway from connected, to analytic and finally to intelligent operations. The matrix of use-cases can provide ideas for reference starting points for production managers by struggling with digitalization. Together, the proposed conceptual model and matrix of use-cases can serve as a reference for production managers and other decision makers struggling in efforts to make their production systems more data-driven and intelligent. And while technologies such as data analytics and BI methods are not new in PPC research, the combination with IoT and the incremental implementation smart PPC approach reduces the risk and allows for a natural maturation to smart manufacturing, both essential indicators for SMEs and companies with limited innovation R&D budgets.

In addition, this study presents the argument that even though the industry currently has no explicit sustainability KPIs guiding the PPC processes, this can be ameliorated in a smart PPC system. This last point is double-edged. On the one hand, one can build environmental KPIs into an smart PPC solution to reduce the waste and other deleterious effects of production operations, while on the other, a mature smart PPC solution might lead to a reduction in the need for human planners where one planner could end up comfortably handling an operation hitherto managed by several planners.

Lastly, the question of how a smart PPC system should be designed and developed for an environment has been addressed in the form of a proposed five-step method. The steps of the method have been formulated and structured with the consideration that the resulting PPC system should fit the characteristics of the environment in question. The importance of contextual fit in algorithm selection, solution scalability and amenability of the smart PPC system to address future demands were also discussed. In summary, the principles and considerations that guide the design in a smart PPC system are as follows:

- The design of the smart PPC system should fit the characteristics of planning environment. This highlights an issue that has been observed in numerous ERP and APS implementation case studies – expensive monolithic systems forcing managers to modify the production system to fit an inflexible PPC system. The proposed method can guide the design and development of such a fitting smart PPC system.
- The design and architecture of the PPC system should be scalable and amenable to variations in future demand volumes, demand patterns, product portfolios, number of users, etc. Since these parameters cannot be controlled or accurately predicted in advance, it is important to have provisions in the architecture to adapt as these parameters change during drift.
- The implementation plan of a smart PPC system should also include a period of ‘incubation’ where data can be collected to train the ML models if the data is not already available. Simultaneously, the models can be tested for accuracy, such that the estimation errors can be accounted for in the planning activities.

8.3 Project and Study Limitations

Considering how limited the sample size for this study is, no bold claims can be made about the generalizability of its findings. This study has explored the questions of interest within four (although starting with six) case companies all based in Norway, albeit with varied company sizes, reach, market positions, and industry structures. Therefore, the location of these companies (being based in Norway) could have influenced these findings as supposed to, say, being situated in Germany which has a much diverse and extensive industrial economy or even neighbouring Sweden with a larger industrial base. Furthermore, it can also be expected that the intensity of promotion of smart operations will be greater in industries which are of national strategic importance such as the oil and gas servicing industries for Norway or the automotive manufacturing industry in Germany. Therefore, the findings may be skewed in the sense that it may not reflect the current level of activity on the topic nationally, for example.

In addition, the technologies in question are evolving and these case companies have been studied only for a short period of time while the future development paths of these technologies or the industry 4.0 vision are unknown. This study also did not capture the effect of popular improvement concepts like lean as factors in the case studies, even though there may be an association with industry 4.0. This was not without thought, as the level of lean maturity varied in terms of application in all the case companies although all four companies had mature lean programmes with signs of visual control evident in their factories. Nevertheless, since the aim of this study was to explore a relatively young research area, the research design is deemed adequate for the stated objectives based on the guidelines in Eisenhardt (1989).

8.4 Future Research

Following the approach in Dennis and Meredith (2000), and in tandem with antecedents in this research domain, for example, as in Feldmann et al. (2009), a future large scale empirical study may extend these findings, taking into account the market, product and process attributes such as firm size, industry type (process versus discrete), product types (complexity, etc.), level of internationalization/globalization of production-network or supply chain, and role within each firm's major network, customer engagement strategy (MTS, ATO, MTO), extant dominant planning and control principle in the case, and the extent of use of information technology to aid these processes, description of level in the five-stage framework, use cases planned, piloted or in use; and expected results versus planned results; constraints and challenges during development and use. This could build upon the findings presented in this thesis and previous studies by Wamba and Chatfield (2009) and Tenhiälä (2011) and more recent studies by Strandhagen et al. (2017) and Oluyisola et al. (2020) to further extend the interrelated research domains of logistics 4.0, smart PPC and the much broader smart manufacturing research field.

Another potential future research direction could explore the link between smart PPC and potential future improvements in production. At the basic level, future research might seek to determine how to address the current challenges with the seamless, real-time integration of data sources from disparate systems with the factory and supply chain. At an higher level, future studies that test the various use-cases individually and in combinations in different market, product, and process configurations would be desirable to provide additional evidence as to the quantifiable effects of these technology interventions to the PPC processes in manufacturing and supply chain environments. In this regard, relevant theoretical support can be found in systems theory such as in Fatorachian and Kazemi (2020).

In the light of the extended enterprise perspective which organizations now adopt to be able to effectively compete globally, future research could also benefit by investigations into how supply chain characteristics can influence the choice and investments of the smart technologies within supply chains. Particularly for technologies that can enhance the level of supply chain integration or coordination and performance, such as the use of sensor technologies to enhance track and trace of material flow through the supply chain, it will be interesting to researchers and practitioners to know how, say, power relationships with supply chains influence whether a firm can choose its own path or invest in complementary digitalization technologies due to pressure from dominant supply chain partners.

Future research could extend this study with the aim to further rigorously test to what extent the insights raised in this study are generalizable. A follow-up large scale national or international survey can address several of the limitations highlighted above. For instance, while this study showed that process and semi-process MTS producers are likely to favour a smart process strategy much more than complex products MTO producers. Studies might also delve deeper into investigating what other factors – in addition to extensive process automation and the low or non-existent digital component of products – influence this choice and how these factors can be addressed by the producers of complex products. From the organizational and human resources perspective, the skills and capabilities of production planners and systems developers will be a critical success factor for achieving a smart PPC and studies showing what skills sets and how to institutionalize that knowledge will be valuable insights for industry.

From a practical implementation perspective, longitudinal studies evaluating actual performance improvements achievable in practice when using a fully developed smart PPC system will reveal how much of an effect a smart PPC system can contribute towards improved operational performance and sustainable production in the factories of the future. Implementing the developed method requires experience and judgement to ensure that the relevant contingent factors have been considered in assessing the fit of objectives and priorities with the planning environment attributes. A framework of contextual variables could provide an exhaustive reference and reduce the requirements for experience in implementing the method effectively and should be addressed by future research. In future studies, this method could also be tested in other types of production environments and industry sectors to assess its weaknesses and improve its robustness and generalizability.

References

AHMAD, M. M. & CUENCA, R. P. 2013. Critical success factors for ERP implementation in SMEs. *Robotics and computer-integrated manufacturing,* 29**,** 104-111.

AISSANI, N., BEKRAR, A., TRENTESAUX, D. & BELDJILALI, B. 2012. Dynamic scheduling for multi-site companies: A decisional approach based on reinforcement multi-agent learning. *Journal of Intelligent Manufacturing,* 23**,** 2513-2529.

ANSARI, F., GLAWAR, R. & NEMETH, T. 2019. PriMa: a prescriptive maintenance model for cyber-physical production systems. *International Journal of Computer Integrated Manufacturing,* 32**,** 482-503.

ARICA, E. & POWELL, D. J. 2014. A framework for ICT-enabled real-time production planning and control. *Advances in Manufacturing,* 2**,** 158-164.

ARNOLD, J. T., CHAPMAN, S. N. & CLIVE, L. M. 2011. *Introduction to materials management*, Pearson Higher Ed.

ASLAN, B., STEVENSON, M. & HENDRY, L. C. 2012. Enterprise Resource Planning systems: An assessment of applicability to Make-To-Order companies. *Computers in Industry,* 63**,** 692-705.

ASLAN, B., STEVENSON, M. & HENDRY, L. C. 2015. The applicability and impact of Enterprise Resource Planning (ERP) systems: Results from a mixed method study on Make-To-Order (MTO) companies. *Computers in Industry,* 70**,** 127-143.

BANKER, R. D., BARDHAN, I. R., CHANG, H. & LIN, S. 2006. Plant information systems, manufacturing capabilities, and plant performance. *MIS quarterly***,** 315-337.

BASKERVILLE, R. 2008. What design science is not. *European Journal of Information Systems,* 17**,** 441-443.

BASS, L., CLEMENTS, P. & KAZMAN, R. 2013. *Software architecture in practice*, Addison-Wesley Professional.

BEAN, R. & DAVENPORT, T. 2019. Companies are failing in their efforts to become data-driven. *Harvard Business Review. Retrieved from https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven*.

BECKMAN, S. L. & ROSENFIELD, D. B. 2008. *Operations strategy: competing in the 21st century*, McGraw-Hill/Irwin.

BHARADWAJ, A. S. 2000. A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS quarterly***,** 169-196.

BIFET, A. & GAVALDA, R. Learning from time-changing data with adaptive windowing. Proceedings of the 2007 SIAM international conference on data mining, 2007. SIAM, 443-448.

BIONDI, M., SAND, G. & HARJUNKOSKI, I. 2017. Optimization of multipurpose process plant operations: A multi-time-scale maintenance and production scheduling approach. *Computers & Chemical Engineering,* 99**,** 325-339.

BIRKEL, H. S., VEILE, J. W., MÜLLER, J. M., HARTMANN, E. & VOIGT, K.-I. 2019. Development of a risk framework for Industry 4.0 in the context of sustainability for established manufacturers. *Sustainability,* 11**,** 384.

BONNEY, M. 2000. Reflections on production planning and control (PPC). *Gestão & produção,* 7**,** 181-207.

BOYER, K. K., SWINK, M. & ROSENZWEIG, E. D. 2005. Operations strategy research in the POMS journal. *Production and Operations Management,* 14**,** 442-449.

BRESLER, M., ROMSDAL, A., STRANDHAGEN, J. O. & OLUYISOLA, O. E. Principles and Research Agenda for Sustainable, Data-Driven Food Production Planning and Control. IFIP International Conference on Advances in Production Management Systems, 2020. Springer, 634-641.

BRINKKEMPER, S. 1996. Method engineering: engineering of information systems development methods and tools. *Information and software technology,* 38**,** 275-280.

BRINTRUP, A., PAK, J., RATINEY, D., PEARCE, T., WICHMANN, P., WOODALL, P. & MCFARLANE, D. 2019. Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. *International Journal of Production Research***,** 1-12.

BROWNE, J., HARHEN, J. & SHIVNAN, J. 1988. *Production Management Systems,* New York, Addison-Wesley.

BUENO, A. F., GODINHO FILHO, M. & FRANK, A. G. 2020. Smart Production Planning and Control in the Industry 4.0 context: A systematic literature review. *Computers & Industrial Engineering***,** 106774.

BUER, S.-V., SEMINI, M., STRANDHAGEN, J. O. & SGARBOSSA, F. 2020. The complementary effect of lean manufacturing and digitalisation on operational performance. *International Journal of Production Research***,** 1-17.

CADAVID, J. P. U., LAMOURI, S., GRABOT, B., PELLERIN, R. & FORTIN, A. 2020. Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. *Journal of Intelligent Manufacturing***,** 1-28.

CARVALHO, A. N., SCAVARDA, L. F. & LUSTOSA, L. J. 2014. Implementing finite capacity production scheduling: lessons from a practical case. *International Journal of Production Research,* 52**,** 1-16.

CHEN, B., WAN, J., CELESTI, A., LI, D., ABBAS, H. & ZHANG, Q. 2018. Edge computing in IoT-based manufacturing. *IEEE Communications Magazine,* 56**,** 103-109.

CHEN, D., VALLESPIR, B. & DOUMEINGTS, G. 1997. GRAI integrated methodology and its mapping onto generic enterprise reference architecture and methodology. *Computers in Industry,* 33**,** 387-394.

CHENG, H.-T., KOC, L., HARMSEN, J., SHAKED, T., CHANDRA, T., ARADHYE, H., ANDERSON, G., CORRADO, G., CHAI, W. & ISPIR, M. Wide & deep learning for recommender systems. Proceedings of the 1st workshop on deep learning for recommender systems, 2016. 7-10.

CORSTEN, H. 1996. Artificial neural networks for supporting production planning and control. *Technovation,* 16**,** 67-93.

CRESWELL, J. W. 2013. *Research design: Qualitative, quantitative, and mixed methods approaches*, Sage publications.

DALENOGARE, L. S., BENITEZ, G. B., AYALA, N. F. & FRANK, A. G. 2018. The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics,* 204**,** 383-394.

DANESE, P., MOLINARO, M. & ROMANO, P. 2020. Investigating fit in supply chain integration: A systematic literature review on context, practices, performance links. *Journal of Purchasing and Supply Management,* 26**,** 100634.

DAVIES, J. 2012. *Understanding IPv6: Understanding IPv6 _p3*, Pearson Education.

DE MAN, J. C. & STRANDHAGEN, J. O. 2018. Spreadsheet application still dominates enterprise resource planning and advanced planning systems. *IFAC-PapersOnLine,* 51**,** 1224-1229.

DE SOUSA JABBOUR, A. B. L., JABBOUR, C. J. C., FOROPON, C. & GODINHO FILHO, M. 2018. When titans meet–Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change,* 132**,** 18-25.

DEAN, T., BASYE, K. E. N. & SHEWCHUK, J. 1993. CHAPTER 3 - Reinforcement Learning for Planning and Control. *In:* MINTON, S. (ed.) *Machine Learning Methods for Planning.* Morgan Kaufmann.

DENNIS, D. R. & MEREDITH, J. R. 2000. An analysis of process industry production and inventory management systems. *Journal of Operations Management,* 18**,** 683-699.

DREYER, H. C., STRANDHAGEN, J. O., ROMSDAL, A. & HOFF, A. 2010. Principles for real-time, integrated supply chain control: An example from distribution of pharmaceuticals.

DUBEY, R., GUNASEKARAN, A., CHILDE, S. J., PAPADOPOULOS, T., LUO, Z., WAMBA, S. F. & ROUBAUD, D. 2019. Can big data and predictive analytics improve social and environmental sustainability? *Technological Forecasting and Social Change,* 144**,** 534-545.

EISENHARDT, K. M. 1989. Building Theories from Case Study Research. *Academy of Management: The Academy of Management Review,* 14**,** 532-549.

EISENHARDT, K. M. & GRAEBNER, M. E. 2007. Theory building from cases: opportunities and challenges. *Academy of management journal,* 50**,** 25-32.

FATORACHIAN, H. & KAZEMI, H. 2020. Impact of Industry 4.0 on supply chain performance. *Production Planning & Control***,** 1-19.

FELDMANN, A., OLHAGER, J. & PERSSON, F. 2009. Designing and managing manufacturing networks–a survey of Swedish plants. *Production Planning and Control,* 20**,** 101-112.

FLYNN, B. B., SAKAKIBARA, S., SCHROEDER, R. G., BATES, K. A. & FLYNN, E. J. 1990. Empirical research methods in operations management. *Journal of Operations Management,* 9**,** 250-284.

GALPIN, T., WHITTTINGTON, J. L. & BELL, G. 2015. Is your sustainability strategy sustainable? Creating a culture of sustainability. *Corporate Governance*.

GARETTI, M. & TAISCH, M. 1999. Neural networks in production planning and control. *Production Planning & Control,* 10**,** 324-339.

GOEPP, V., KIEFER, F. & GEISKOPF, F. 2006. Design of information system architectures using a key-problem framework. *Computers in Industry,* 57**,** 189-200.

GUHA, S. & KUMAR, S. 2018. Emergence of big data research in operations management, information systems, and healthcare: Past contributions and future roadmap. *Production and Operations Management,* 27**,** 1724-1735.

GUSTAVSSON, M. & WÄNSTRÖM, C. 2009. Assessing information quality in manufacturing planning and control processes. *International Journal of Quality & Reliability Management*.

GYULAI, D., KÁDÁR, B. & MONOSOTORI, L. 2015. Robust production planning and capacity control for flexible assembly lines. *IFAC-PapersOnLine,* 48**,** 2312-2317.

GYULAI, D., KÁDÁR, B. & MONOSTORI, L. 2014. Capacity planning and resource allocation in assembly systems consisting of dedicated and reconfigurable lines. *Procedia Cirp,* 25**,** 185-191.

HADDARA, M. & ELRAGAL, A. 2015. The Readiness of ERP Systems for the Factory of the Future. *Procedia Computer Science,* 64**,** 721-728.

HAMMAMI, Z., MOUELHI, W. & SAID, L. B. 2017. On-line self-adaptive framework for tailoring a neural-agent learning model addressing dynamic real-time scheduling problems. *Journal of Manufacturing Systems,* 45**,** 97-108.

HANDFIELD, R. B. & MELNYK, S. A. 1998. The scientific theory-building process: a primer using the case of TQM. *Journal of operations management,* 16**,** 321-339.

HANSETH, O., CIBORRA, C. U. & BRAA, K. 2001. The control devolution: ERP and the side effects of globalization. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems,* 32**,** 34-46.

HASSAN, H. 2020. Factors influencing cloud computing adoption in small and medium enterprises. *Journal of Information and Communication Technology,* 16**,** 21-41.

HAYES, R. H. & WHEELWRIGHT, S. C. 1979. Link manufacturing process and product life cycles. *Harvard business review,* 57**,** 133-140.

HEGER, J., BRANKE, J., HILDEBRANDT, T. & SCHOLZ-REITER, B. 2016. Dynamic adjustment of dispatching rule parameters in flow shops with sequence-dependent set-up times. *International Journal of Production Research,* 54**,** 6812-6824.

HERMANN, M., BÜCKER, I. & OTTO, B. 2019. Industrie 4.0 process transformation: findings from a case study in automotive logistics. *Journal of Manufacturing Technology Management*.

HERMANN, M., PENTEK, T. & OTTO, B. Design principles for industrie 4.0 scenarios. System Sciences (HICSS), 2016 49th Hawaii International Conference on, 2016a. IEEE, 3928-3937.

HERMANN, M., PENTEK, T. & OTTO, B. Design principles for industrie 4.0 scenarios. 2016 49th Hawaii international conference on system sciences (HICSS), 2016b. IEEE, 3928-3937.

HICKS, C., MCGOVERN, T. & EARL, C. F. 2001. A typology of UK engineer-to-order companies. *Int. J. Logis. Res. and Appl,* 4**,** 43-56.

HIGGINS, P., LE ROY, P. & TIERNEY, L. 1996. *Manufacturing Planning and Control Beyond MRP II,* London, Chapman and Hall.

HOLMSTRÖM, J., KETOKIVI, M. & HAMERI, A. P. 2009. Bridging practice and theory: a design science approach. *Decision Sciences,* 40**,** 65-87.

HONG, P. C., DOBRZYKOWSKI, D. D. & VONDEREMBSE, M. A. 2010. Integration of supply chain IT and lean practices for mass customization: Benchmarking of product and service focused manufacturers. *Benchmarking,* 17**,** 561-592.

HOXIE, H. F. 1911. Organized labor and industrial efficiency. *American Review of Reviews,* 44**,** 482-483.

HRUSCHKA, H. 1993. Determining market response functions by neural network modeling: a comparison to econometric techniques. *European Journal of Operational Research,* 66**,** 27-35.

HUANG, B., WANG, W., REN, S., ZHONG, R. Y. & JIANG, J. 2019. A proactive task dispatching method based on future bottleneck prediction for the smart factory. *International Journal of Computer Integrated Manufacturing,* 32**,** 278-293.

HUANG, Y. 2017. Information architecture for effective Workload Control: an insight from a successful implementation. *Production Planning & Control,* 28**,** 351-366.

HØYER, M. R., OLUYISOLA, O. E., STRANDHAGEN, J. O. & SEMINI, M. G. 2019. Exploring the challenges with applying tracking and tracing technology in the dairy industry. *IFAC-PapersOnLine,* 52**,** 1727-1732.

IANSITI, M. & LAKHANI, K. R. 2014. Digital ubiquity: How connections, sensors, and data are revolutionizing business. *Harvard Business Review,* 92, 19.

IVANOV, D., TSIPOULANIDIS, A. & SCHÖNBERGER, J. 2019. Digital Supply Chain, Smart Operations and Industry 4.0. *Global Supply Chain and Operations Management.* Springer.

JACOBS, F. R., BERRY, W. L., WHYBARK, D. C. & VOLLMANN, T. E. 2011. *Manufacturing Planning and Control for Supply Chain Management: APICS/CPM Certification Edition,* USA, McGraw-Hill.

JAMES, G., WITTEN, D., HASTIE, T. & TIBSHIRANI, R. 2013. *An introduction to statistical learning*, Springer.

JONSSON, P. & MATTSSON, S. A. 2003. The implications of fit between planning environments and manufacturing planning and control methods. *International Journal of Operations & Production Management,* 23, 872-900.

KARLSSON, C. 2009. Researching operations management. *In:* KARLSSON, C. (ed.) *Researching Operations Management.* New York: Routledge.

KARLSSON, C. 2010. *Researching operations management*, Routledge.

KETCHEN JR., D. J. & HULT, G. T. M. 2007. Bridging organization theory and supply chain management: The case of best value supply chains. *Journal of Operations Management,* 25, 573-580.

KIRIKOVA, M. 2019. Challenges in enterprise and information systems modeling in the contexts of socio cyber physical systems. *Lecture Notes in Business Information Processing.*

KLAUS, H., ROSEMANN, M. & GABLE, G. G. 2000. What is ERP? *Information systems frontiers,* 2, 141-162.

KOH, S. L., GUNASEKARAN, A. & GOODMAN, T. 2011. Drivers, barriers and critical success factors for ERPII implementation in supply chains: A critical analysis. *The Journal of Strategic Information Systems,* 20, 385-402.

KONUR, S., LAN, Y., THAKKER, D., MORKYANI, G., POLOVINA, N. & SHARP, J. 2021. Towards design and implementation of Industry 4.0 for food manufacturing. *Neural Computing and Applications*.

KRITZINGER, W., KARNER, M., TRAAR, G., HENJES, J. & SIHN, W. 2018. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine,* 51, 1016-1022.

KUO, Y.-H. & KUSIAK, A. 2019. From data to big data in production research: the past and future trends. *International Journal of Production Research,* 57, 4828-4853.

KUSIAK, A. 1987. Artificial intelligence and operations research in flexible manufacturing systems. *INFOR: Information Systems and Operational Research,* 25, 2-12.

KUSIAK, A. 2017. Smart manufacturing must embrace big data. *Nature,* 544, 23-25.

KÄRKKÄINEN, M. 2003. Increasing efficiency in the supply chain for short shelf life goods using RFID tagging. *International Journal of Retail & Distribution Management,* 31, 529-536.

LEE, H. & ÖZER, Ö. 2007. Unlocking the value of RFID. *Production and operations management,* 16, 40-64.

LEITÃO, P. 2009. Agent-based distributed manufacturing control: A state-of-the-art survey. *Engineering Applications of Artificial Intelligence,* 22, 979-991.

LEWIS, M. W. 1998. Iterative triangulation: a theory development process using existing case studies. *Journal of Operations Management,* 16, 455-469.

LI, S., GERVER, P., MACMILLAN, J., DEBRUNNER, D., MARSHALL, W. & WU, K.-L. 2018. Challenges and experiences in building an efficient apache beam runner for IBM streams. *Proceedings of the VLDB Endowment,* 11**,** 1742-1754.

LI, X., WANG, J. & SAWHNEY, R. 2012. Reinforcement learning for joint pricing, lead-time and scheduling decisions in make-to-order systems. *European Journal of Operational Research,* 221**,** 99-109.

LIAO, Y. X., DESCHAMPS, F., LOURES, E. D. R. & RAMOS, L. F. P. 2017. Past, present and future of Industry 4.0-a systematic literature review and research agenda proposal. *International Journal of Production Research,* 55**,** 3609-3629.

LIN, C. C., DENG, D. J., CHIH, Y. L. & CHIU, H. T. 2019. Smart Manufacturing Scheduling with Edge Computing Using Multiclass Deep Q Network. *IEEE Transactions on Industrial Informatics,* 15**,** 4276-4284.

MA, A., FRANTZÉN, M., SNIDER, C. & NASSEHI, A. 2020. Anarchic manufacturing: Distributed control for product transition. *Journal of Manufacturing Systems,* 56**,** 1-10.

MACHADO, C. G., WINROTH, M. P. & RIBEIRO DA SILVA, E. H. D. 2020. Sustainable manufacturing in Industry 4.0: an emerging research agenda. *International Journal of Production Research,* 58**,** 1462-1484.

MALHOTRA, N. K., NUNAN, D. & BIRKS, D. F. 2017. *Marketing research: An applied approach*, Pearson Education Limited.

MANTRAVADI, S., LI, C. & MØLLER, C. Multi-agent Manufacturing Execution System (MES): Concept, architecture & ML algorithm for a smart factory case. ICEIS 2019 - Proceedings of the 21st International Conference on Enterprise Information Systems, 2019. 465-470.

MARCH, S. T. & STOREY, V. C. 2008. Design science in the information systems discipline: an introduction to the special issue on design science research. *MIS quarterly***,** 725-730.

MARK, A. PMI's Pulse of the Profession: The High Cost of Low Performance. How will you improve business results. Project Management Institute, 2016.

MATTHEWS, B. & ROSS, L. 2010. *Research methods: a practical guide for the social sciences,* New York, NY, Pearson Longman.

MATTISON, J. B. & RAJ, S. 2012. Key questions every IT and business executive should ask about cloud computing and ERP. *Accenture White Paper*.

MEREDITH, J. 1998. Building Operations Management Theory through Case and Field Research. *Journal of Operations Management,* 16**,** 441-454.

MEREDITH, J. R. 2001. Hopes for the future of operations management. *Journal of Operations Management,* 19**,** 397-402.

MOEUF, A., PELLERIN, R., LAMOURI, S., TAMAYO-GIRALDO, S. & BARBARAY, R. 2018. The industrial management of SMEs in the era of Industry 4.0. *International Journal of Production Research,* 56**,** 1118-1136.

MONOSTORI, L., MÁRKUS, A., VAN BRUSSEL, H. & WESTKÄMPFER, E. 1996. Machine learning approaches to manufacturing. *CIRP annals,* 45**,** 675-712.

MÜLLER, J. M., KIEL, D. & VOIGT, K.-I. 2018. What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability,* 10**,** 247.

NG, A. Y. & RUSSELL, S. J. Algorithms for inverse reinforcement learning. Icml, 2000. 2.

NGAI, E., CHENG, T., LAI, K. H., CHAI, P., CHOI, Y. & SIN, R. 2007. Development of an RFID-based traceability system: Experiences and lessons learned from an aircraft engineering company. *Production and operations management,* 16**,** 554-568.

NGAI, E., MOON, K. K., RIGGINS, F. J. & CANDACE, Y. Y. 2008a. RFID research: An academic literature review (1995–2005) and future research directions. *International Journal of Production Economics,* 112**,** 510-520.

NGAI, E. W. T., LAW, C. C. H. & WAT, F. K. T. 2008b. Examining the critical success factors in the adoption of enterprise resource planning. *Computers in Industry,* 59**,** 548-564.

O'MAHONY, E., HEBRARD, E., HOLLAND, A., NUGENT, C. & O'SULLIVAN, B. Using case-based reasoning in an algorithm portfolio for constraint solving. Irish conference on artificial intelligence and cognitive science, 2008. 210-216.

OLUYISOLA, O. E., ALFNES, E., GRAN, E., THOMASSEN, M. K. & YU, Q. 2016. Takt-time control in high-variety/low-volume production. *In:* DREYER, H. C. & T., N. (eds.) *23rd European Operations Management Association Conference: Interactions.* Trondheim, Norway.

OLUYISOLA, O. E., SALMI, T. E. & STRANDHAGEN, J. O. 2018a. Causes of delivery-time variance in maritime-equipment manufacturing supply-chains: an empirical study. *IFIP International Conference on Advances in Production Management Systems.* Springer.

OLUYISOLA, O. E., SGARBOSSA, F. & STRANDHAGEN, J. O. 2020. Smart Production Planning and Control: Concept, Use-Cases and Sustainability Implications. *Sustainability,* 12**,** 3791.

OLUYISOLA, O. E., SRIRAM, P. K. & ALFNES, E. 2015. Materials management in engineer-to-order production environments. *In:* REINER, G. (ed.) *22nd International Annual EurOMA Conference: Operations Management for Sustainable Competitiveness.* Neuchâtel, Switzerland.

OLUYISOLA, O. E., STRANDHAGEN, J. W. & BUER, S.-V. 2018b. RFId technology in the manufacture of customized drainage and piping systems: a case study. *IFAC-PapersOnLine,* 51**,** 364-369.

PALOMBARINI, J. & MARTÍNEZ, E. 2012. SmartGantt–An intelligent system for real time rescheduling based on relational reinforcement learning. *Expert Systems with Applications,* 39**,** 10251-10268.

PARK, K. T., NAM, Y. W., LEE, H. S., IM, S. J., NOH, S. D., SON, J. Y. & KIM, H. 2019. Design and implementation of a digital twin application for a connected micro smart factory. *International Journal of Computer Integrated Manufacturing,* 32**,** 596-614.

PEFFERS, K., TUUNANEN, T., ROTHENBERGER, M. A. & CHATTERJEE, S. 2007. A design science research methodology for information systems research. *Journal of management information systems,* 24**,** 45-77.

PETRONI, A. & BRAGLIA, M. 2000. Vendor selection using principal component analysis. *Journal of supply chain management,* 36**,** 63-69.

PHILLIPS, E. & PUGH, D. 2010. *How to get a PhD: A handbook for students and their supervisors*, McGraw-Hill Education (UK).

PILLANIA, R. K. & KHAN, A. 2008. Strategic sourcing for supply chain agility and firms' performance. *Management Decision*.

PINEDA-JARAMILLO, J. D. 2019. A review of Machine Learning (ML) algorithms used for modeling travel mode choice. *Dyna,* 86**,** 32-41.

PORTER, M. E. & HEPPELMANN, J. E. 2014. How smart, connected products are transforming competition. *Harvard business review,* 92**,** 64-88.

PRESSMAN, R. S. & MAXIM, B. 2015. *Software Engineering: A Practitioner's Approach*, Mc Graw-Hill Education.

PTAK, C. A. 2004. *ERP: tools, techniques, and applications for integrating the supply chain,* Boca Raton, FL., St Lucie Press.

QU, T., LEI, S., WANG, Z., NIE, D., CHEN, X. & HUANG, G. Q. 2016. IoT-based real-time production logistics synchronization system under smart cloud manufacturing. *The International Journal of Advanced Manufacturing Technology,* 84**,** 147-164.

REN, L., ZHANG, L., TAO, F., ZHAO, C., CHAI, X. & ZHAO, X. 2015. Cloud manufacturing: from concept to practice. *Enterprise Information Systems,* 9**,** 186-209.

REUTER, C., BRAMBRING, F., HEMPEL, T. & KOPP, P. 2017. Benefit oriented production data acquisition for the production planning and control. *Procedia CIRP,* 61**,** 487-492.

REYNOLDS, G. 2015. *Information technology for managers*, Nelson Education.

RISI, S. & TOGELIUS, J. 2020. Increasing generality in machine learning through procedural content generation. *Nature Machine Intelligence***,** 1-9.

ROJAS, R. A. & GARCIA, M. A. R. 2020. Implementation of Industrial Internet of Things and Cyber-Physical Systems in SMEs for Distributed and Service-Oriented Control. *Industry 4.0 for SMEs.* Palgrave Macmillan, Cham.

RUDBERG, M. & OLHAGER, J. 2003. Manufacturing networks and supply chains: an operations strategy perspective. *Omega,* 31**,** 29-39.

SAENZ DE UGARTE, B., HAJJI, A., PELLERIN, R. & ARTIBA, A. 2009. Development and integration of a reactive real-time decision support system in the aluminum industry. *Engineering Applications of Artificial Intelligence,* 22**,** 897-905.

SÁNCHEZ-HERRERA, S., MONTOYA-TORRES, J. R. & SOLANO-CHARRIS, E. L. 2019. Flow shop scheduling problem with position-dependent processing times. *Computers & Operations Research,* 111**,** 325-345.

SCHUH, G., ANDERL, R., GAUSEMEIER, J., TEN HOMPEL, M. & WAHLSTER, W. 2017. Industrie 4.0 Maturity Index. *Managing the Digital Transformation of Companies (acatech STUDY) Herbert Utz Verlag, Munich*.

SCHUH, G., POTENTE, T. & HAUPTVOGEL, A. 2014. Methodology for the Evaluation of Forecast Reliability of Production Planning Systems. *Procedia CIRP,* 17**,** 469-474.

SHAIKH, N., PRABHU, V., ABRIL, D., SÁNCHEZ, D., ARIAS, J., RODRÍGUEZ, E. & RIAÑO, G. 2011. Kimberly-Clark Latin America builds an optimization-based system for machine scheduling. *Interfaces,* 41**,** 455-465.

SHIUE, Y.-R., GUH, R.-S. & TSENG, T.-Y. 2012. Study on shop floor control system in semiconductor fabrication by self-organizing map-based intelligent multi-controller. *Computers & Industrial Engineering,* 62**,** 1119-1129.

SHIUE, Y. R., LEE, K. C. & SU, C. T. 2018. Real-time scheduling for a smart factory using a reinforcement learning approach. *Computers and Industrial Engineering,* 125**,** 604-614.

SKINNER, W. 1974. *The focused factory*, Harvard Business Review Brighton, MA.

SLACK, N., BRANDON-JONES, A. & JOHNSTON, R. 2013. *Operations management*, Pearson.

SOUSA, R. & VOSS, C. A. 2008. Contingency research in operations management practices. *Journal of Operations Management,* 26**,** 697-713.

STANDARDIZATION, I. O. F. 2018. Internet of Things (loT) — Reference Architecture. *Information technology (IT) in general.*

STEGER-JENSEN, K., HVOLBY, H. H., NIELSEN, P. & NIELSEN, I. 2011. Advanced planning and scheduling technology. *Production Planning & Control,* 22**,** 800-808.

STOCK, T., OBENAUS, M., KUNZ, S. & KOHL, H. 2018. Industry 4.0 as enabler for a sustainable development: A qualitative assessment of its ecological and social potential. *Process Safety and Environmental Protection,* 118**,** 254-267.

STOCK, T. & SELIGER, G. 2016. Opportunities of sustainable manufacturing in industry 4.0. *Procedia Cirp,* 40, 536-541.

STRANDHAGEN, J. O., VALLANDINGHAM, L. R., FRAGAPANE, G., STRANDHAGEN, J. W., STANGELAND, A. B. H. & SHARMA, N. 2017. Logistics 4.0 and emerging sustainable business models. *Advances in Manufacturing,* 5, 359-369.

SUN, D., HUANG, R., CHEN, Y., WANG, Y., ZENG, J., YUAN, M., PONG, T. C. & QU, H. 2020. PlanningVis: A Visual Analytics Approach to Production Planning in Smart Factories. *IEEE Transactions on Visualization and Computer Graphics,* 26, 579-589.

TANEJA, S., PRYOR, M. G. & TOOMBS, L. A. 2011. Frederick W. Taylor's scientific management principles: Relevance and validity. *Journal of Applied Management and Entrepreneurship,* 16, 60.

TAO, F., QI, Q., LIU, A. & KUSIAK, A. 2018. Data-driven smart manufacturing. *Journal of Manufacturing Systems,* 48, 157-169.

TARANTILIS, C. D., KIRANOUDIS, C. T. & THEODORAKOPOULOS, N. D. 2008. A Web-based ERP system for business services and supply chain management: Application to real-world process scheduling. *European Journal of Operational Research,* 187, 1310-1326.

TAYLOR, F. W. 1911. The principles of scientific management. *New York,* 202.

TENHIÄLÄ, A. 2011. Contingency theory of capacity planning: The link between process types and planning methods. *Journal of Operations Management,* 29, 65-77.

TENHIÄLÄ, A. & HELKIÖ, P. 2015. Performance effects of using an ERP system for manufacturing planning and control under dynamic market requirements. *Journal of Operations Management,* 36, 147-164.

THEMISTOCLEOUS, M., ROSEMAN, M., LOOS, P. & MØLLER, C. 2005. ERP II: a conceptual framework for next-generation enterprise systems? *Journal of Enterprise Information Management*.

TONY ARNOLD, J., CHAPMAN, S. N. & CLIVE, L. 2012. Introduction to materials management. *Prentice Hall*.

TUNCEL, E., ZEID, A. & KAMARTHI, S. 2014. Solving large scale disassembly line balancing problem with uncertainty using reinforcement learning. *Journal of Intelligent Manufacturing,* 25, 647-659.

USTUNDAG, A. & TANYAS, M. 2009. The impacts of RFID technology on supply chain costs. *Transportation Research Part E* 45, 29-38

VEILE, J. W., KIEL, D., MÜLLER, J. M. & VOIGT, K.-I. 2019. Lessons learned from Industry 4.0 implementation in the German manufacturing industry. *Journal of Manufacturing Technology Management*.

VENKATRAMAN, N. 1989. The concept of fit in strategy research: Toward verbal and statistical correspondence. *Academy of management review,* 14, 423-444.

VENKATRAMAN, N. 1994. IT-enabled business transformation: from automation to business scope redefinition. *Sloan management review,* 35, 73-73.

VIEIRA, G. E., HERRMANN, J. W. & LIN, E. 2003. Rescheduling manufacturing systems: a framework of strategies, policies, and methods. *Journal of Scheduling,* 6, 39-62.

VOLLMANN, T. E., BERRY, W. L., WHYBARK, D. C. & JACOBS, F. R. 2005. *Manufacturing Planning and Control for Supply Chain Management,* New York, McGraw-Hill.

VOSS, C. 2009. Case Research in Operations Management. *In:* CHRISTER, K. (ed.) *Researching Operations Management.* New York: Routledge.

VOSS, C. A., TSIKRIKTSIS, N. & FROHLICH, M. 2002. Case Research in Operations Management. *International Journal of Operations & Production Management,* 22**,** 195-210.

WAMBA, S. F., AKTER, S., EDWARDS, A., CHOPIN, G. & GNANZOU, D. 2015. How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics,* 165**,** 234-246.

WAMBA, S. F. & CHATFIELD, A. T. 2009. A contingency model for creating value from RFID supply chain network projects in logistics and manufacturing environments. *European Journal of Information Systems,* 18**,** 615-636.

WILSON, J. M. 2016. The origin of material requirements planning in Frederick W. Taylor's planning office. *International Journal of Production Research,* 54**,** 1535-1553.

WOLFSGRUBER, C. & LICHTENEGGER, G. 2016. Optimal Configuration in Production Planning and Control. *BHM Berg- und Hüttenmännische Monatshefte,* 161**,** 221-224.

WRÓBLEWSKA, A., STANISŁAWEK, T., PRUS-ZAJĄCZKOWSKI, B. & GARNCAREK, Ł. 2018. Robotic process automation of unstructured data with machine learning. *Annals of Computer Science and Information Systems,* 16**,** 9-16.

YIN, R. K. 2009. *Case study research: design and methods,* Thousand Oaks, California, Sage Publications.

YIN, R. K. 2013. *Case study research: design and methods,* Los Angeles, Calif., SAGE.

ZHONG, R. Y., DAI, Q., QU, T., HU, G. & HUANG, G. Q. 2013. RFID-enabled real-time manufacturing execution system for mass-customization production. *Robotics and Computer-Integrated Manufacturing,* 29**,** 283-292.

Appendices

Appendix 1: Interview guide for multi-case study

Research title: "Smart production planning and control: constraints, enablers, and key factors"

Date: XX.YYY.2020

1 Research objective in descriptive form:

To determining the enablers, constraints and key factors that influence the fit of smart PPC solutions to the PPC environment (as determined by the market, product, and process dimensions) where such solutions are applied.

2 Important information and interview plan

- Purpose of the study
- Confidentiality and anonymity
- Use of tape recorder, transcription, and possibility to review
- Format: Semi-structured interview – please feel free to talk freely
    - I will present open ended questions which the interviewees are asked to elaborate on
- Publication considerations
- Privacy declaration

3 Interviewee data:

Name:
E-mail address:
Position:
No. of years in the company:
No. of years in the production planner role:
Any other important information:

1. About the PPC environment variables: demand and supply characteristics, product attributes, and production system:

a. Describe the demand characteristics of your market

b. Describe the supply characteristics of your market

c. Describe your products' attributes in terms of

i. Bill of materials levels
ii. Level of digital/electronic functions
iii. Shelf-life
iv. Number of process routes (no. of production lines could be an indicator)

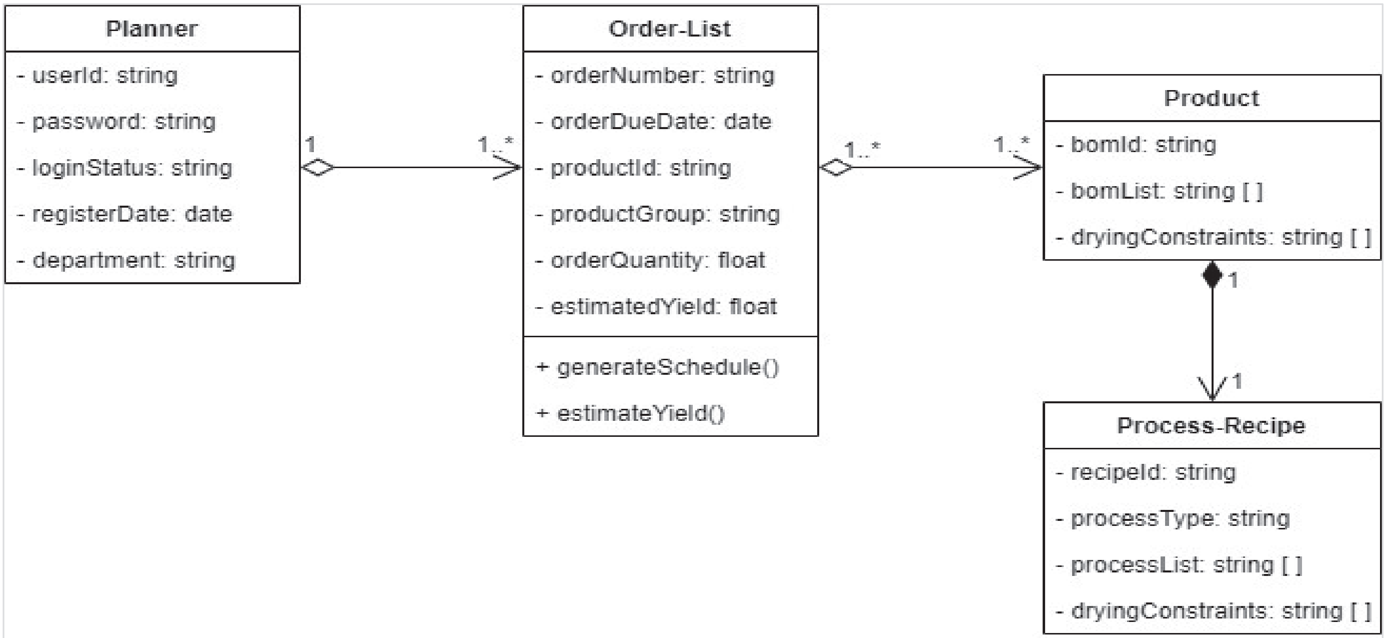
d. Describe your production system in terms of i. layout ii. level of automation iii. level of product customization iv. intensity of operator input
2. Planning and control process and system: process, inputs, outputs, technologies, key stakeholders, current challenges a. Describe the planning process from beginning to the end, step-by-step. b. Level of standardization: i. To what extent is the planning process standardized? What decisions is a planner allowed to use his discretion for? c. Highlight the following for the planning process: i. Frequency of production planning meeting ii. General planning accuracy and how much planning buffer is usual iii. Planning horizon iv. Detailed scheduling horizon v. Frequency of re-scheduling d. PPC process data: i. Describe the input and output data for every step of the planning process Every Monday, the forecast is review ii. What are the sources of these data and in what format is it? iii. Are these data used for improvement of the planning process? e. Describe (if any) the technology used for each step of the process (Excel, paper, SAP modules, *etc*.)
3. History of use of data-driven decision-making: a. Data-driven methods in planning and controlling operations. This is with regards to not just having data from automated production lines, but do you use this data in planning and scheduling or is it used mostly for quality control? b. Does your company use any of the following: i. General business KPIs ii. KPIs for PPC process performance iii. Lean manufacturing elements a. 5S, Visual control, SMED, Kanban, Heijunka, b. Just-in-time iv. Data-intensive improvement methodologies such as statistical process control (SPC), six-sigma, *etc*.

4. Digitalization approach and projects in general a. Has your company completed any digitalization initiative/project in the last 3 years? i. If yes, how many? ii. Which technologies and which use-cases? iii. What was the expected business or operations outcome? iv. Which projects failed, and succeeded? v. What challenges did you face during the implementation and use? b. Is your company currently working on any digitalization project? vi. If yes, how many? vii. Which technologies and which use-cases? viii. What was the expected business or operations outcome? ix. What challenges are you facing with the development, implementation, and use? c. Is your company planning any future (within the next 1-3 years) digitalization project? x. If yes, how many? xi. Which technologies and which use-cases? xii. What is the expected business or operations outcome?
5. Smart PPC decision making projects a. In addition to the initiatives/projects mentioned above, are there any others that perhaps where smaller, but addressed or affected the PPC process directly or indirectly? b. Palettizing which automatically updates the number of pallets produced.
6. What is your opinion on potential of smart technologies in improving the PPC process? (process, inputs, challenges eliminated) a. Which elements of your planning process and system can be enhanced using smart technologies? b. What do you think are possible limitations of having smart PPC?
7. How does this contribute to your sustainability goals? a. Do you have specific sustainability goals for the year? If yes, what are they? b. Do you currently have KPIs related to sustainability goals? c. How do the company's sustainability goals affect your PPC processes and activities? d. Do planners use sustainability parameters when driving the PPC process?

Appendix 2: A manually updated yield estimate spreadsheet

	A	B	C	D
1	**Yield for molded products**		Dok.nr:	****
2	((based on weight into process kitchen and weight of finished product based on foundry with possible candering)			
3				
4	**Article no.**	**Product**	**Yield %**	
5	658944	OrangeCandy	0,84	
6	653448	StrawberryWhite	0,84	
7	843675	Stone	0,68	
8	584876	Stone Special	0,74	
9	651136	Lancert (canderized)	1,00	
10	344455	Red tree, canderized	0,90	
11	347277	Fruitie Flops XL, canderized	0,78	
12	345994	Barits with toppings, canderized	0,92	
13	346991	Baby Cant (canderized)	0,76	
14	341469	Gretter (canderized)	0,75	
15	352289	Liquorice balls, canderized	0,85	
16	341376	Liquorice balls	0,73	
17	351132	Blue buttons (canderized)	0,85	
18	346423	Blue berries, salted berries	0,84	
19	352873	Blue lines skitesse		
20	351640	Blue Sweets	0,90	
21	352870	Liquorice crates		
22	351899	Particle skits		
23				
24	Change log:			
25	22.03.2016 Planner1	Removed old products. NB! Lots of mistakes. The lists must be coordinated. Not right now. Added Blue Sweets.		
26	23.09.2014 Planner3	Changed Yield on Licorice balls, Lancert, Stones, Blue berries and salted berries		
27	05.05.2014 Planner2	Has gone through yield% to Fruitie Flops, liquorice balls, Blue Sweets, Stone, Baby cant, and changed according to new calculation.		
28	03.04.2014 Planner1	Removed old products.		
29	03.04.2014 Planner2	Posted the news until 01.05.14. Liqoorice balls, Fruitie Flops, Blue Sweets, StrawberryWhite.		
30	11.04.2013 Planner2	Barits with toppings changed from 0,86 to 0,92		
31	11.04.2013 Planner2	Stone Special changed from 0,81 to 0,74		

Appendix 3: A Class diagram illustrating modelling variables for the machine learning model



Appendix 4: Data table illustrating modelling variables for the machine learning model

Category	Field-Id	Data type	Comment
Planner	userId	string	
	department	string	
Order-List	orderNumber	string	
	orderDueDate.year	string	
	orderDueDate.month	string	
	orderDueDate.day	string	
	orderDueDate.dayOfWeek	string	
	productId	string	
	productGroup	string	
	orderQuantity	float	
	actualYield	float	
	estimatedYield	float	Value to be predicted
Product	bomId	string	
	bomList	string []	
	dryingConstraints	string []	
Process-recipe	recipeId	string	
	processType	string	
	processList	string []	
	dryingConstraints	string []	
Telemetry from processes and environment	processTelemetry.temp.sd	float	
	processTelemetry.temp.mean	float	
	processTelemetry.humidity.sd	float	
	processTelemetry.humidity.mean	float	
	ovenTelemetry.temp.sd	float	
	ovenTelemetry.temp.mean	float	
	ovenTelemetry.humidity.sd	float	
	ovenTelemetry.humidity.mean	float	
	envTelemetry.temp.sd	float	
	envTelemetry.temp.mean	float	
	envTelemetry.humidity.sd	float	
	processTelemetry.humidity.mean	float	

Appended Papers #1-5

Paper 1

***Citation*:** Oluyisola, O. E., Strandhagen, J. W., & Buer, S. V. (2018). RFId technology in the manufacture of customized drainage and piping systems: a case study. *IFAC-PapersOnLine*, 51(11), 364-369.

***Type*:** Article

***Status*:** Published

Role *of PhD candidate and declaration of authorship*: Oluyisola conceptualized and wrote the first draft. Strandhagen and Buer contributed to the revision process. Oluyisola presented the findings at the INCOM2018 conference in Berlin

Paper 2

***Citation*:** Oluyisola, O. E., Salmi, T. E., & Strandhagen, J. O. (2018). Causes of delivery-time variance in maritime-equipment manufacturing supply-chains: an empirical study. In *IFIP International Conference on Advances in Production Management Systems* (pp. 415-421). Springer, Cham.

***Type*:** Book chapter

***Status*:** Published

Role *of PhD candidate and declaration of authorship*: Oluyisola conceptualized and wrote the paper from the results of the research project carried out by Salmi under supervision by Oluyisola and Strandhagen. Strandhagen presented the findings at the APMS 2018 conference at Seoul

Paper 3

***Citation*:** Høyer, M. R., Oluyisola, O. E., Strandhagen, J. O., & Semini, M. G. (2019). Exploring the challenges with applying tracking and tracing technology in the dairy industry. *IFAC-PapersOnLine*, 52(13), 1727-1732.

***Type*:** Article

***Status*:** Published

Role *of PhD candidate and declaration of authorship*: Høyer and Oluyisola conceptualized and co-wrote the paper from the results of the research project carried out by Madeleine under supervision by Oluyisola, Semini, and Strandhagen. Oluyisola presented the paper at the MIM2019 international conference in Berlin

Paper 4

Citation**:** Oluyisola, O. E., Sgarbossa, F., & Strandhagen, J. O. (2020). Smart Production Planning and Control: Concept, Use-Cases and Sustainability Implications. *Sustainability*, 12(9), 3791.

Type**:** Article

Status**:** Published

Role *of PhD candidate and declaration of authorship*: Oluyisola, Sgarbossa and Strandhagen conceptualized the paper; Oluyisola conducted the research work and collected the data; Oluyisola wrote the first version of the article with supervision by Sgarbossa and Strandhagen; all authors contributed during the revision process.

Paper 5

Citation**:** Oluyisola, O. E., Bhalla, S., Sgarbossa, F., & Strandhagen, J. O. (2021). Designing and Developing Smart Production Planning and Control Systems in the Industry 4.0 Era: A Methodology and Case Study. *Journal of Intelligent Manufacturing*.

Type: Article

Status**:** Resubmitted after reviewers' feedback and revision, currently under review

Role *of PhD candidate and declaration of authorship*: Oluyisola, Sgarbossa and Strandhagen conceptualized the paper; Oluyisola conducted the research work and collected the data; Oluyisola and Bhalla wrote the first version of the article with supervision by Sgarbossa and Strandhagen; all authors contributed during the revision process.

Paper 1

Oluyisola, O. E., Strandhagen, J. W., & Buer, S. V. (2018). RFId technology in the manufacture of customized drainage and piping systems: A case study. *IFAC-PapersOnLine*, 51(11), 364-369.

This is an accepted manuscript of the article published in IFAC-PapersOnLine. The final authenticated version is available online at:
https://doi.org/10.1016/j.ifacol.2018.08.320

RFId technology in the manufacture of customized drainage and piping systems: a case study

Olumide E. Oluyisola*. Jo W. Strandhagen. Sven-Vegard Buer*****

Department of Mechanical and Industrial Engineering,
Norwegian University of Science and Technology (NTNU), Trondheim, Norway
** (Tel: +47-47167686; e-mail: olumide.e.oluyisola@ntnu.no)*
*** (e-mail: jo.w.strandhagen@ntnu.no) *** (e-mail: sven.v.buer@ntnu.no)*

Abstract: While Radio Frequency Identification (or RFId) technology has gained significant traction in the downstream operations and industries like retail, adoption upstream of the value-chain has been much slower. Few reported cases of implementations in job-shops exists today for several reasons, key among which is the relative cost of the technology and uncertainties regarding the expected results. In this paper, we present the insights from the evaluation and pre-implementation stage of a project to implement RFId technology in the customized products' department of a large process manufacturing company in Europe. The case company is an innovation leader in the European pipe and drainage systems' manufacturing industry. Preliminary findings indicate the need to align RFId implementation with strategic goals to minimize the risk associated with the implementation and increase the chance of success.

Keywords: RFId and ubiquitous manufacturing, production activity control, manufacturing plant control, logistics in manufacturing, intelligent manufacturing systems

1. INTRODUCTION

1.1 RFId adoption for manufacturing operations

RFId technology enables the tracking of the movement of objects (materials, machines, operators, etc.) (Brintrup et al., 2010) usually through a well-defined system. In manufacturing supply chains and shopfloors, RFId technology has been reported to enable significant improvement in the coordination of work-in-process within and across factories (Qu et al., 2012). Earlier, Huang et al. (2008) proposed that by combining RFId (or, in general, any auto-ID) technology with the Internet of things (IoT) in manufacturing systems – using the RFId tags with unique, internet-recognizable identities – it is possible to capture manufacturing data in real-time and improve the planning, scheduling and control of manufacturing operations.

However, while similar-function technologies like bar-codes have been widely tested and adopted within industries and across their supply chains, others, such as the RFId technology has only seen relatively limited adoption (Li et al., 2012). Despite several potential benefits, however, barcode technology has several shortcomings when used in a job-shop. Apart from requiring line of sight, close-distance data reading – which is prone to error – it is also slower and requires conscious effort by operators, or pre-design if it is to be built into robotic manufacturing systems. On the contrary, RFID technology allows the simultaneous reading of multiple tags, and does not require items to be along the line of site of the scanner (Yu et al., 2016).

Despite the surge in popularity within the past two decades, the cost of implementing RFId for manufacturing is still rather high. For instance, in comparison with the barcode technology, the cost of implementing RFID is exorbitant for most type of work-in-process materials (Brintrup et al., 2010). Until recently, the implication has been that it was infeasible to justify the investment, except for large-scale applications. But with recent advances in the development of RFId system components notably, that tags are becoming cheaper and more accurate, and that readers increasing in range (Yu et al., 2016), the financial viability should increase.

Furthermore, it is difficult to standardize procedures from previous implementation projects to increase the likelihood of success of subsequent implementations. The reasons for this are not far-fetched: to match the fact that every factory and supply chain is unique, designs and implementations of RFId technology solutions for factories are bespoke. Consequently, an implementation of RFId faces almost equal chance of success today as it would have faced if implemented half a decade earlier. While issues relating to the development of RFId technology are no longer has critical, the issues about managing the information flows between parts of the factory, the enterprise and the supply chain, and the users' interaction with the technology remains important (Spekman and Sweeney 2006).

From the foregoing, in addition to the recent drive towards mass-customization via the digitalization of products, manufacturing systems and supply chains – and the significant role auto-ID technologies have in those systems – there is an urgent need for an assessment of the barriers to success in adopting RFId technology (Brettel et al., 2014). Thus, one expects that the customized nature of job-shop manufacturing environment can also serve as a good environment to investigate the limitations of RFId regarding the mass-customization goals of the factory of the future. Our case study in this paper provides such a context.

1.2 The context: customized drainage systems unit production in a continuous flow production environment

The case company within which this study was carried-out manufactures and markets a wide range of pipe systems, including tailor-made solutions for municipal infrastructure as well as for the industrial and house-building sectors. The company operates predominantly in Northern Europe, and has production and trading operations in Sweden, Norway, Finland and the Baltic States. It is a major producer and supplier of plastic pipe systems, also exporting a considerable share of its production. An example of an important export product for the company is the large dimensioned polyethylene (PE) family of pipes, which it has developed a with unique design concept that is popular in Europe.

The company operates two factories: the first is situated along the south-western coast of Norway, where PE pipes are manufactured, and the other is in the midlands of Norway. Large dimension pipes of long lengths are produced at the coastal factory. The plant employs approximately 50 people. The midland factory, which also serves as the national headquarters, employs around 130 people. At this factory, underground pipes and parts made of PVC and polypropylene intended for the transfer of wastewater are manufactured. In addition, pipes for gas and water distribution, sewage systems, cable protection and electrical installations are also manufactured at this factory.

In addition to the regular pipe manufacturing, the company's 'handmade' department produces customized, drainage junctions and other system components. Therefore, in addition to the more common plastic forming processes of extrusion, injection- and blow- moulding common to this industry, this department can also cut, mill, grind and weld high-strength large plastic pipe sections. The unit of analysis in this study – the handmade department – is the focus of RFId technology deployment at the case company. This department has several characteristics in common with many other high-variety, low-volume production environments. However, the products in this case are non-mechanical, with simple bill-of-materials, and are generally non-reusable, as is often the case with the mechanical components or sub-systems.

The business need according to the company is to increase the traceability of materials through the shopfloor and across the value-chain in order to reduce throughput time for WIP materials, and thereby improve efficiency and delivery precision. Management wanted to leverage sensor-based technologies – both new and matured – to meet this need. It aligns with the company's objective to remain a leader in product and process innovation. The aim of this paper, therefore, is to highlight the challenges and issues identified during the evaluation and pre-implementation phase. To do this systematically, we used the control model framework to evaluate the important factors vital for RFId implementation success. The paper also covers a brief discussion of the use of this framework and its strengths that make it fitting for use for similar RFId projects.

2. LITERATURE REVIEW

Within the RFId literature, there is little or no mention about the application of RFId technology for customized production in the pipe manufacturing industry. While there are cases about the application in the pipe manufacturing industry itself (Song et al., 2006), the requirements for customized manufacturing operations are more nuanced and will require an approach similar to that adopted in the customized equipment manufacturing environments. A description of this type of environment and the literature on RFId applications follow.

2.1 Characteristics of production environments

Several taxonomies and frameworks have been proffered for the classification the manufacturing systems. Besides the two-dimensional framework by Wikner and Rudberg (2005), most frameworks use a seeming linear comparison based on how much the activities upstream the product development and delivery process are similar (Olhager, 2003). In the latter category, there are four common classes namely: make-to-stock (MTS), assemble-to-order (ATO), make-to-order (MTO), and engineer-to-order (ETO). For example, a car manufacturing operation is typically classified as an ATO operation. In this framework, a pipe manufacturing company will be classified as a MTS operation, whereas a drainage systems producer can be classified as either an MTO or ETO operation. Material management in MTO or ATO manufacturing operations are different from conventional make-to-stock operations in that there are often low volumes, higher product complexity, and large variations from one order to the next. The release and movement of materials through the shopfloor can be controlled either manually or with the use of several trace and track technologies like barcode and auto-ID technologies like the RFId technology.

The challenge, thus, is to align the production system with the fast-changing needs of the market to remain competitive (Beckman and Rosenfield, 2008, Miltenburg, 2005). Therein lies the challenge for manufacturing managers. One of the ways to improve the ability of the manufacturing operation to meet the needs of the fast-changing market is traceability – knowing where every important element of the system is per time, and having the historical data of the path taken by the component or the processes which the component has visited at any time (Spekman and Sweeney 2006). Furthermore, in a job-shop production environment, because components are not pushed through a line, there is often many work-in-process materials in and around the shopfloor. This situation could be further worsened when the shopfloor is served by a WIP storage facility, another reason for the high cycle time variation in job-shops (Hopp and Spearman, 2011).

The choice of the order fulfilment process chosen for a manufacturing operation often varies according to the type of production environment. Many variants of the order fulfilment process for ETO production environments have been documented in the literature, such as in Brière-Côté et al. (2010). Notably, Hameri and Nihtilä (1998) presented a comprehensive characterization of the process. They divided the order fulfilment activities in an ETO company into four stages/phases, namely: concept development, design, manufacturing, and operations (after-sales). Each of these order-fulfilment process phases influence operations on the job-shop directly and can disrupt the material flow. In addition, an important area of concern in most companies is the interface between design phase and the manufacturing phase. In addition, each customer order often requires a unique production process and routing (Gosling and Naim, 2009), the implications for material management cannot be predetermined accurately. To deal with this complication, the experience of the material management personnel and the ability of the engineering team to adequately forecast materials requirements – both human factors – are crucial (MacCarthy and Wilson, 2003).

2.2 Tracing and tracking technologies for manufacturing operations

The use of tracing and tracking technologies to provide material visibility in the manufacturing systems is nothing new. For a truly traceable system, it will be possible for the production operation, for example, to simulate the impact of changing a customer order or a disruption in supply (Lockamy, 1994, Bechini et al., 2007). This is one of the drivers for the increasing adoption of the RFId technology solutions in the retail industry and automobile assembly industry (Curtin et al., 2007). In the automobile industry for instance, it will be possible to determine before shipment that all the parts in the bill-of-materials is in a vehicle when it drives through a reader gate using an RFID solution that is integrated with the manufacturing execution system (MES) or the ERP system.

Whereas all these hypothetical applications seem feasible, it has been difficult to implement them in practice. Indeed, the research into RFId applications typically take the form of either mathematical (analytical) studies or small scale, pilot studies (empirical). While the mathematical studies have centered on the accuracy of the technology in real cases, the case studies have been mostly exploratory studies documenting implementation of the technology by case companies. Moreover, little, if any, studies have addressed how the installation of RFId technology influence the flexibility of the manufacturing operation.

While the two main methods dominate the literature on RFId research, there have also been some survey-based studies. A notable example is Vijayaraman and Osyk (2006) who conducted a survey of a warehousing council members working in manufacturing firms in the USA. The authors found that why several of the respondents where either already implementing RFId or were considering a significant investment in the technology in the near term, uncertainty of the expected results persisted. Specifically, the potential of the technology to result in a reduction in operating costs – of an amount which is at least as much as it costs to implement and use the technology – was highlighted, validating the concern raised in Niemeyer et al. (2003). As a testament to the perceived maturity of the technology then, the authors highlighted the need to replicate the study in the future when the technology matures. Niemeyer et al. (2003) also found that in the warehouse industry, companies already implementing RFId were less optimistic about its potential for cost reduction than companies that were just about to implement the technology.

The literature is replete with several document cases from various industries highlighting the opportunities and challenges for implementing RFId technology in the warehouse and within the shopfloor (Spekman and Sweeney 2006, Pero and Rossi, 2014). While the retail and distribution industries have seen increasing application, applications for job-shop operations remain limited (Huang et al., 2008). This may be because of the high level of flux required in production systems utilizing job shops layout.

2.3 Integrating RFID technologies with other ICT systems in manufacturing

Manufacturing systems are slow to change by nature (Miltenburg, 2005), partly because of the inherent pursuit of stability. Facilities once purchased, often are difficult to change; process technologies are generally expensive and require some learning time before acceptable levels of efficiency are attained; and supplier development takes time. Therefore, managers adopt various control methods and technologies to manage their manufacturing operations. In addition to internal factors like organizational capabilities, the choice of production system is often dictated by external factors such as the customer or market requirements, and the available production system technologies such as process and information technologies (Miltenburg, 2005).

Therefore, beyond the factory floor, production and sales managers must collaborate to deliver products to the customers within the required quality and delivery-time limits. To this end, companies deploy enterprise systems software such as ERP and customer requirements management (CRM) systems to manage the order delivery process. It is possible to design an RFId solution that automatically updates and feeds data into the ERP solution (Spekman and Sweeney 2006). Whereas barcode technology can also be used this way, RFId does it seamlessly and can achieve significantly better results in terms of the reliability and timeliness of the operational data (Durugbo et al., 2014, Pei et al., 2017).

3. RESEARCH DESIGN

3.1 Methodology and governing framework

The selection of the case was a matter of convenience. The authors and the case company are partners in a research project, Manufacturing Networks 4.0. In this case, the company's management had decided to explore the potentials of RFID technology to improve the operational effectiveness of the handmade department in the company's factory. To ensure an adequate basis for the engagement with the case company, the authors began this study with a look at the unique characteristics of the handmade department. The authors used the control model framework proposed by Strandhagen et al. (2013) for the evaluation of the production system. The purpose of this holistic evaluation (see fig. 1) is to ensure that the eventual solution is not only technically feasible, but also acceptable to the workers.

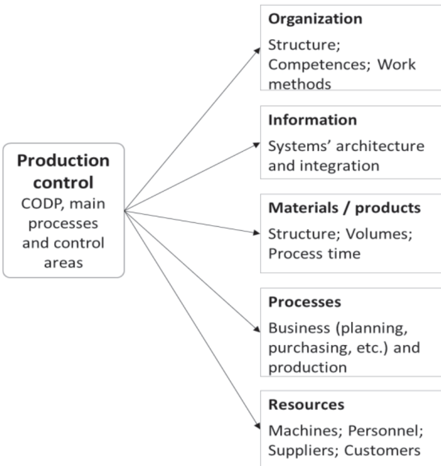


Fig. 1. The control model framework for improving manufacturing operations. *Adapted from*: Strandhagen et al. (2013) .

The control model framework evolved over several years, in the attempt to systematically and pictorially describe a production system, while capturing factors such as the organization, information, materials, processes and resources that interact within that system (Slack et al., 2010, Strandhagen et al., 2013). The underlying premise can be traced to the strategic fit theory by Fisher (1997) and contingency theory. Essentially, the decisions regarding influencing factors should be such that ensures an alignment of those factors and the main production control methods deployed. The factors include: the choice of organizational capabilities and structure, work methods; the systems architecture and their integration of information technologies; the product attributes such as structure, volumes and processing times; the business and production processes; and the network of production resources namely, machines personnel and suppliers. All these factors must be aligned, and considered when decisions are made that could affect the production system.

Using anecdotal evidence, parallels were drawn in terms of the fit of the RFId technology characteristics, challenges and solution approaches within the fields of complex systems, integrated operations and material management. We identified systems theory as the underlying principle and this paved the way for development of more robust solutions in these fields. It is on this basis that the framework was developed and illustrated in the handmade department, which is also the unit of analysis. We use one case company because it fits the exploratory nature of this study (Voss, 2009), even though findings cannot be generalized due to the small sample size (Yin, 2009, Matthews and Ross, 2010).

3.2 Data collection and analysis

The case data was collected using primary and secondary data collection sources. The authors combined workshops, multiple guided tours of the job-shop and secondary data sources like online product configurators and published company documents (Matthews and Ross, 2010, Voss, 2009) to achieve the benefits of triangulation and to improve the accuracy of judgement and discussion (Flynn et al., 1990, Yin, 2009). Two elicitation workshops were held within a three months' period to collect information about the business drivers for the project, the challenges that the management hopes to solve by implementing this technology, and the issues that currently exists in our unit of analysis.

Workshops focused on the current material flow control principles, constraining factors, identified challenges and improvement initiatives currently being implemented or planned for the department. In addition to the minutes of the meeting, each of the authors took notes from the workshops. The authors then shared and synchronized their notes to build up a case database for all of the captured information. Thereafter, the authors discussed the notes with the key stakeholders who attended the workshop – including the supply chain manager and the production manager for the handmade department – for verification and/or correction. For the subsequent clarification of noted points, the authors used follow-up emails and phone calls. The information collected in the case database was used as foundation for addressing the research issues outline in Section 1.

4. PRELIMINARY CASE INSIGHTS

When the management team considered decision to implement RFId technology, they assumed that the technology would help to address concerns about the location of materials, tracking of the travelled paths and overall improvement in the operations and inventory management processes for this department. The decision was made based on the business and technology experience of the management team. Our research team was brought in to guide both the preparation and the implementation processes. Using the control model framework, we performed an assessment of the case, with an emphasis on the material and information flows within the department and across several storage points. As most of the RFId readers are fixed, it is generally desirable to limit changes to the layout after the technology has been implemented. Thus, it is necessary to optimize the flow of materials and information before implementing such a solution.

The control model framework mentions five categories of factors that must be evaluated. The *organization* and *resources* categories relate to structure, competences, work methods, machines, personnel, suppliers and customers. The complexity of the customization involved in the operation requires highly skilled technicians. In this case, the company has highly skilled workers with high process and information technology capabilities. The department uses very little automation because of the customization of every product coming through the department.

The other three categories in the control model framework are material/product, information and processes and these are often the key factors that directly influence the use of a fixed solution system like RFId technology. A preliminary evaluation – using data gathered in reports from previous projects, several factory tours, and two workshops – revealed several logistical challenges, which must be addressed before an RFId solution should be implemented:

a) *Incorrect product structure and registration of material requisitions, which leads to inaccurate inventory register in the ERP system*. Since material purchasing is based on inventory levels in the IT system (ERP), a mismatch between the levels in the ERP system with actual inventory levels can cause avoidable disruptions in production plans and delivery precision. For instance, it was discovered that used pallets (pallets with boxes of components, where the boxes have been unsealed) were sometimes returned to storage after use, and erroneously counted as a full pallet.

b) *Tracking and tracing products locations*: Several items can have different storage locations, and it is sometimes unclear where WIP items are located within the plant. In addition, excess materials are placed *ad hoc* at different locations around the department and are sometimes missed when inventory is being counted.

c) *The flow of material and information is less optimal in the handmade department compared to the rest of the plant*: The department is characterized by recurring flows and multiple products/projects are being processed simultaneously, leading to a proliferation of work-in-process and longer than necessary lead-time.

The described challenges affect the performance of purchasing, inbound logistics and production functions at the department today and are currently being addressed through changes to the processes and better control.

In addition to addressing these problems, the management of also wanted an investigation of the opportunities of applying RFID technology further downstream of products value chain. Currently, it is expected that integrating an RFID solution with the company's customers can further increase the logistics performance of all the members of the value chain – the case company, its suppliers, and customers. Furthermore, a number of ongoing and planned projects in the department would potential alter the layout and material flow in the department. Such alteration, if they were to happen after deploying the RFId solution, would have limited the flexibility in changes to the layout of the department, or in a worst case, required an alteration of the RFId solution.

From the cases documented in the literature, together with our experience so far with this project at the case company, it is observed that the perceived risk (or otherwise, the difficulty) associated with RFId technology adoption is higher for operations that do not follow a steady, continuous path compared to those production environments that do. For example, the literature is rife with implementation studies within the retail industry, but cases for customized production are rare. Furthermore, in this case-study, the amount of uncertainty and process variation that is associated with every customer order has been a recurring factor in our evaluation, and this has been a disincentive, or at least a cause for caution, in going through to the actual implementation phase.

Finally, the perennial question about the appropriate level to apply the tags – at pallet level or for individual items – was also evident in this case. Although item-level RFId application remains elusive in general, the predisposition of the industry to batching of materials has enabled increasing adoption whenever that is possible. In this case, it seems feasible to append an RFId tag to the biggest part of a product. For welded or joined accessories, it is also possible to append an RFId tag when they are not consumables. However, for consumables – components like caps – which are important, even though of little financial value, the only viable option might be to use RFId tags at the pallet level in combination with other methods to track box volume. One possibility is also to use active RFId tags, which will allow update of the volume levels every time workers take items from pallets. Overall, is appears feasible to go to the next phase of technical design, detailing the exact locations and configurations of the readers and antenna in the department and storage locations.

5. CONCLUSIONS AND FUTURE RESEARCH

This study highlights a framework for, and challenges of, RFId technology applications in the customized-production department in a process manufacturing industry. We observe that the challenges of implementing an RFId solution in operations increases with the amount of transformation carried in the operation. Furthermore, strategic changes to operations have significant implication for the usefulness and the ability of the solution to deliver the expected operational improvements.

While the adoption of RFId continues in several industries, implementations projects that are not well aligned to the operations strategy of the company, especially regarding expected changes in manufacturing system, will lead to the worst results. Changes after implementation, say, to process machinery or the addition of a new warehouse are examples of strategic initiatives that can materially alter the layout and flow of materials and other items in a manufacturing system. In this case, we discovered late in the project (during our evaluation) that a new, improved machine at the welding workstation was to be installed in the next quarter. This would have implications for the flow and speed of materials in the job-shop and might necessitate a change to the layout of the department. This was not initially considered in the early phase of the project, and could have either severely constrained the ability to make the necessary changes to the layout of job-shop, or rendered the implementation a waste. To increase the likelihood of success, a thorough evaluation of strategic fit is necessary. A framework similar to the one shown in figure 1 can be used alone or in combination with others such the one in Ren et al. (2011).

As with most case-based research, contextual factors could have significant influence on the case illustration, with the implication that findings might be non-generalizable. Nevertheless, the exploratory nature of the study and the fact that this project is rather innovative justifies the sample size. With a single case study, it is the authors' opinion that the findings are insufficient to allow for generalization. Future studies might examine how the evaluation method affects the results of the implementation. With the current trends about digitalization and industry 4.0, future studies could investigate how technologies such as automated intelligent vehicles, computer vision, and machine learning, used with RFId technology can enhance manufacturing operations.

ACKNOWLEDGEMENT

The Research Council of Norway and industrial partners of the 'Manufacturing Network 4.0' project provided funding for this project.

REFERENCES

Bechini, A., Cimino, M. G. C. A., Marcelloni, F. & Tomasi, A. 2007. Patterns and technologies for enabling supply chain traceability through collabrotive e-business. *Information and software technology*.

Beckman, S. L. & Rosenfield, D. B. 2008. *Operations Strategy, Competing in the 21st Century,* New York, McGraw-Hill.

Brettel, M., Friederichsen, N., Keller, M. & Rosenberg, M. 2014. How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 Perspective. *International Journal of Mechanical, Industrial Science and Engineering,* 8**,** 37-44.

Brière-Côté, A., Rivest, L. & Desrochers, A. 2010. Adaptive generic product structure modelling for design reuse in engineer-to-order products. *Computers in Industry,* 61**,** 53-65.

Brintrup, A., Ranasinghe, D. & Mcfarlane, D. 2010. RFID opportunity analysis for leaner manufacturing. *International Journal of Production Research,* 48**,** 2745-2764.

Curtin, J., Kauffman, R. J. & Riggins, F. J. 2007. Making the 'MOST'out of RFID technology: a research agenda for the study of the adoption, usage and impact of RFID. Springer.

Durugbo, C., Tiwari, A. & Alcock, J. R. 2014. Managing integrated information flow for delivery reliability. *Industrial Management + Data Systems,* 114**,** 628-651.

Fisher, M. L. 1997. What is the right supply chain for your product? *Harvard Business Review,* 75**,** 105-116.

Flynn, B. B., Sakakibara, S., Schroeder, R. G., Bates, K. A. & Flynn, E. J. 1990. Empirical research methods in operations management. *Journal of Operations Management,* 9**,** 250-284.

Gosling, J. & Naim, M. M. 2009. Engineer-to-order supply chain management: A literature review and research agenda. *International Journal of Production Economics,* 122**,** 741-754.

Hameri, A.-P. & Nihtilä, J. 1998. Product data management—exploratory study on state-of-the-art in one-of-a-kind industry. *Computers in Industry,* 35**,** 195-206.

Hopp, W. J. & Spearman, M. L. 2011. *Factory physics*, Waveland Press.

Huang, G. Q., Zhang, Y. & Jiang, P. 2008. RFID-based wireless manufacturing for real-time management of job shop WIP inventories. *The International Journal of Advanced Manufacturing Technology,* 36**,** 752-764.

Li, H. N., Sun, S. D. & Zhang, Y. F. 2012. Using Auto-ID Technologies to Implement Real-Time Manufacturing Resources Tracking and Tracing. *Applied Mechanics and Materials,* 121**,** 1574-1578.

Lockamy, A., Iii 1994. A delivery performance measurement system framework for improved customer responsiveness. *Production and Inventory Management Journal,* 35**,** 17.

Maccarthy, B. L. & Wilson, J. R. 2003. *Human performance in planning and scheduling*, CRC Press.

Matthews, B. & Ross, L. 2010. *Research methods: a practical guide for the social sciences,* New York, NY, Pearson Longman.

Miltenburg, J. 2005. *Manufacturing strategy: how to formulate and implement a winning plan*, Productivity Pr.

Niemeyer, A., Pak, M. H. & Ramaswamy, S. E. 2003. Smart tags for your supply chain. *The McKinsey Quarterly,* 4**,** 6-8.

Olhager, J. 2003. Strategic positioning of the order penetration point. *International Journal of Production Economics,* 85**,** 319-329.

Pei, F. Q., Tong, Y. F., He, F. & Li, D. B. 2017. Research on design of the smart factory for forging enterprise in the industry 4.0 environment. *Mechanika,* 23**,** 146-152.

Pero, M. & Rossi, T. 2014. RFID technology for increasing visibility in ETO supply chains: A case study. *Production Planning and Control,* 25**,** 892-901.

Qu, T., Yang, H., Huang, G. Q., Zhang, Y., Luo, H. & Qin, W. 2012. A case of implementing RFID-based real-time shop-floor material management for household electrical appliance manufacturers. *Journal of Intelligent Manufacturing*, 1-14.

Ren, Z., Anumba, C. J. & Tah, J. 2011. RFID-facilitated construction materials management (RFID-CMM) – A case study of water-supply project. *Advanced Engineering Informatics,* 25**,** 198-207.

Slack, N., Chambers, S. & Johnston, R. 2010. *Operations management*, Pearson Education.

Song, J., Haas, C. T., Caldas, C., Ergen, E. & Akinci, B. 2006. Automating the task of tracking the delivery and receipt of fabricated pipe spools in industrial projects. *Automation in Construction,* 15**,** 166-177.

Spekman, R. E. & Sweeney , P. J. 2006. RFID: from concept to implementation *International Journal of Physical Distribution & Logistics Management,* 36, No. 10, 736-754.

Strandhagen, J., Dreyer, H. C. & Romsdal, A. 2013. Control Model for Intelligent and Demand-Driven Supply Chains. *Industrial Engineering: Concepts, Methodologies, Tools, and Applications.* IGI Global.

Vijayaraman, B. & Osyk, B. A. 2006. An empirical study of RFID implementation in the warehousing industry. *The International Journal of Logistics Management,* 17**,** 6-20.

Voss, C. 2009. Case Research in Operations Management. *In:* Christer, K. (ed.) *Researching Operations Management.* New York: Routledge.

Wikner, J. & Rudberg, M. 2005. Integrating production and engineering perspectives on the customer order decoupling point. *International Journal of Operations & Production Management,* 25**,** 623-641.

Yin, R. K. 2009. *Case study research: design and methods,* Thousand Oaks, California, Sage Publications.

Yu, Q., Sriram, P. K., Alfnes, E. & Strandhagen, J. O. RFID Integration for Material Management Considering Engineering Changes in ETO Industry. IFIP International Conference on Advances in Production Management Systems, 2016. Springer, 501-508.

Paper 2

Oluyisola, O. E., Salmi, T. E., & Strandhagen, J. O. (2018). Causes of delivery-time variance in maritime-equipment manufacturing supply-chains: an empirical study. In *IFIP International Conference on Advances in Production Management Systems* (pp. 415-421). Springer, Cham.

This is an accepted manuscript of the article published in IFIP International Conference on Advances in Production Management. The final authenticated version is available online at: https://doi.org/10.1007/978-3-319-99704-9_51

Causes of delivery-time variance in maritime-equipment manufacturing supply-chains: an empirical study

Olumide E. Oluyisola, Tuomo E. Salmi, and Jan O. Strandhagen

NTNU – Norwegian University of Science and Technology,
Department of Mechanical and Industrial Engineering, Trondheim, Norway
olumide.e.oluyisola@ntnu.no; tesalmi@stud.ntnu.no;
ola.strandhagen@ntnu.no;

Abstract. The overall performance of manufacturing companies has become increasingly dependent on their ability to coordinate a network of suppliers effectively. For manufacturers of customized equipment, it is even more important to coordinate several such network relationships concurrently to achieve service level objectives while minimizing inventory- and quality-related costs. In this paper, we investigate the causes of delivery variance in an engineer-to-order supply chain. Using four case companies within the global supply chain of a customized maritime-equipment manufacturer, we discuss these causes of delivery-time variance and suggestions for managing them.

Keywords: performance management, supplier development, global manufacturing network.

1 Introduction

The overall performance of manufacturing companies – and especially, the 'on-time' delivery of products to customers – is increasingly dependent on their ability to coordinate a network of suppliers effectively. For manufacturers of customized equipment such as thruster systems in large ships, purchased components and sub-assemblies can represent up to eighty percent of the total contract value [1, 2]. Hence, manufacturers of complex, customized-equipment (commonly referred to as engineer-to-order or ETO manufacturing) often need to coordinate several such networks of suppliers concurrently to deliver products on time, at minimum cost and at the right quality [2]. Consequently, the delivery performance of suppliers plays a vital role in the overall delivery performance of ETO manufacturers [1, 2].

Supplier delivery performance is often measured using two performance indicators: *delivery lead-time,* which is an indication of how soon an order can be fulfilled; and *delivery reliability,* an indication of the variance or the deviation from the expected or promised 'delivery window' [3]. All deliveries outside the expected delivery window are considered as not being delivered on-time, since they always lead to additional costs [4] in the form inventory handling costs or disruptions to planned allocation of manufacturing resources. It could also be in the form of penalties from the end-customer for late delivery.

This paper presents empirical findings [section 4] from an investigation of the causes of demand variance in a ship building supply chain. The study comprises four suppliers and a focal company, which manufactures several critical subsystems for ship builders in Asia and Europe. The management of focal company in this study identified long delivery lead-time and high delivery variability as key issues hampering the competitiveness of its Asian operations, which is the target of this study. Thus, this study was commissioned to investigate the factors affecting the delivery performance of the four tier-2 suppliers – tier-2 because the focal company is itself a 'tier-1' supplier for ship builders. One important objective of the study, therefore, was to enable management adequately price the cost of this variance into supply chain transactions and to serve as a motivation for improvements by its members. To address this objective, we briefly considered the theoretical background [section 2] for supply performance in ETO supply chains. Thereafter, a description of the data collection methodology and a case description follows [section 3]. The findings are presented in a structured format [section 4], and discussed in final section.

2 Theoretical background

2.1 Market and supply characteristics of ETO supply chains

A central challenge in ETO markets is high demand fluctuation, which is generally higher than that witnessed in, say, mass production cases, and is almost impossible to forecast [1, 2, 5]. This condition creates a big challenge for manufacturers and at the same time, a business opportunity for companies that are able to deliver in short lead time and within the promised delivery window [6]. In addition to delivery performance, other sources of competitiveness are: design or engineering competences, price and responsiveness [1]. High degree of responsiveness is particularly important in the tendering phase. Caron and Fiore [7] and Gosling and Naim [8] have also identified flexibility in the order fulfillment process as a crucial for order-winning by ETO companies. Surveys [9] have further revealed that seventy percent of project-based cost overruns are due to delivery untimeliness, and that on-time delivery is a good indicator for projects that want to achieve minimize such costs.

Because of such demand characteristics, combined with the fact that each produced unit is a large proportion of the production capacity, a major source of risk for ETO companies is, therefore, that supplier relationships can vary significantly [1, 6]. One reason for this variation is the demand uncertainty, which limits cooperative long-term supply chain relations [1]. To cope with this uncertainty, a large portion of production is outsourced – sometimes up to eighty percent [1, 2]. In order to reduce supply uncertainty many ETO companies use multi-sourcing [6] which is characterized by mutual mistrust and "win-lose" transactions [1]. Furthermore, ETO companies recognize that there are benefits in developing suppliers for long-term collaboration [1]. For those long-term collaborations, the delivery variance must be minimized and eradicated completely where possible.

2.2 Causes of delivery variance in supply chains

The difficulty in controlling ETO delivery timeliness arises from the poor coordination of the interface between engineering and production, and especially in coordinating multiple organizations, not coordination in single organization [10]. Furthermore, the trend of outsourcing production to low-labour cost countries and retaining engineering as a core expertise has resulted in an even larger gap between engineering and production leading to more delays in delivery. Several other causes have been documented in the literature [10, 11] namely:

a. procurement phase delayed due to missing designs and poor quality of documentation;
b. high number of quality problems at the supplier; information flow not integrated between supplier and buyer;
c. poor visibility of business processes by decision makers and workers;
d. excessive optimism in business partner's skills;
e. poor delivery documentation;
f. long-lead times, which increases the chance of occurrence of unpredicted events (e.g. strikes, new trade regulations etc.); and
g. changes in technical requirements after production starts.

Some of causes originate from process and product uncertainty, while others originate from the people-related and organizational factors.

2.3 Management of delivery variance in supply chains

According to Guiffrida and Jaber [12], supply chain managers can use delivery-variance reduction in order to improve delivery performance in a similar way that quality managers historically used the reduction of process variation to improve product quality. In their model, the delivery variance (v) is traded-off against investment in continuous improvement of on-time delivery (cost). Defining the variables G(v), total cost supplier untimeliness; Y(v), the expected cost (penalty) of untimely delivery; C(v), investment cost for delivery variance reduction; and v, delivery variance, Guiffrida and Jaber [12] obtained the following:

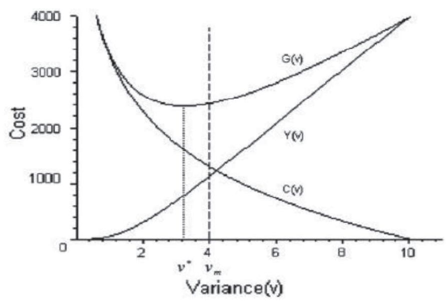


Figure 1: Optimal delivery variance model [12]

The model suggests that there is a variance level, v^*, at which total cost of untimeliness is minimized. This indicates that a trade-off must be regarding (a) how much to invest in efforts to reduce the cost of untimely delivery and (b) how much penalty is expected due to untimely delivery. Several ways to control this variance have been reported namely: the supplier gaining tighter control over process flow times; enhanced coordination of freight transport; more efficient material handling of outbound stock by the supplier and inbound stock by the buyer; and improved communications between both parties [12, 13].

3 Methodology and case description

3.1 Data collection method

This paper uses a case study design with five units of analysis – the four tier-2 suppliers, serving a common customer which will be referred to as Company S – not real name. Company S is a customized-equipment manufacturer serving the ship building industry. Data is collected using semi-formal interviews based on an interview guide, in addition to factory tours at Company S and the four tier-2 suppliers. The interviews were conducted with the supply chain management staff of Company S by the second author using an interview guide, with follow-up phone calls and meetings with the four suppliers for clarification and verification.

The objective of the interview was to identify the critical processes and procedures that contribute to poor supplier delivery performance at the four tier-2 suppliers. The interview guide was designed to elicit the causes for poor delivery performance, the implications of poor supplier delivery performance, and the current supplier delivery performance practices. Followed-up meetings aimed to elicit managers' recommendations about how the delivery performance could be improved.

3.2 Case selection and description

The four suppliers operate in China and Europe, while Company S has its headquarters in Europe and a production subsidiary in China. Out of several suppliers, these four suppliers (of Company S) were selected based on following criteria:

a. The supplier has underperformed the expectations and targets set by Company S during the past two or more years;
b. The suppliers deliver different kind of components which have a significant impact on the operational performance of Company S.

Supplier A is a European company producing slip ring units, which are one of the most critical outsourced subassemblies in Company S products. Design and production of main components are carried out in Europe, after which those components are shipped to China for other production activities. Customers, such as Company S, place orders through the main office in Europe.

Supplier B manufactures larger casted main components for Company S. The production process has two phases – casting and machining. These phases are carried out in separate sections within the same plant in China and shipped to Company S. The components are partly made-to-stock in the casting phase and made-to-order in the machining phase.

Supplier C is responsible for machining several key components. For this study, three most valuable components are considered. Supplier C ships components directly to Company S after the production. All components are made-to-order.

S**upplier D** delivers numerous types of hydraulic systems components such as hoses, couplings and connectors from its facilities in Northern Europe from where all orders are fulfilled and shipped to Company S in China. The hoses are made-to-order while the rest of the components are standard and directly shipped from the stock.

4 Causes of delivery-time variance

In this section, the causes for high delivery-time by the case suppliers are presented - see table 1. Poor delivery performance by these suppliers to Company S typically disrupts its production plans in two ways. Firstly, since the production planning at Company S is scheduled based on the available production slots and delivery dates promised to the customer, delivering earlier than agreed is generally disadvantageous. This due to increased inventory levels and capital tie-downs.

Table 1. Summary of observations at the case companies

	Supplier A	**Supplier B**	**Supplier C**	**Supplier D**
Primary source of untimely delivery	Poor coordination between design departments of Co. S and Sup-A	Defective output from the casting process	Lack of process standardization	Long transport time; inflexibility in order fulfilment process;
Where/ when does it happen?	Design phase, due to need for customer and 3rd party approval	Casting process facility	Entire operation relating to this supply chain	Rush orders
Other observations	Internal planning and control problems leading to missing parts	Poor coordination within the two sites; high inventory after casting process	Need to have large time buffers for delivery of orders	Internal planning and control, leading use of large buffers

Meanwhile, the second issue – of late deliveries from supplier – is adjudged by Company S to be of greater criticality. Such delays lead to production stoppages, waiting, overtime work, risk of high penalty and reputational damage from the shipyards. These then lead to increased costs in project execution and reduced profitability. To manage its own consequent order fulfillment process variability, which is relatively high, Company S uses internal buffers.

5 Discussion and Conclusions

The purpose of this paper was to investigate the causes of delivery variance in a global, engineer-to-order maritime-equipment supply chain. Furthermore, we wanted to observe how those causes are managed in an empirical setting – the focal company of this study and four of its main suppliers. We found that the most significant causes for delays were poor communication and coordination at Supplier A, process inefficiency at Supplier B, lack of process standardization at Supplier C, and a long transport distance in addition to inflexibility in the order-fulfilment process at Supplier D. The lack of transparency in suppliers' order fulfillment process made it difficult for Company S to coordinate and manage suppliers. Very often, problems are discovered much later in the production process. As a result, it is highly problematic to trace the sequence of events that led to the issue precisely, and thus develop solutions to avoid such issues in the future. This is especially true with supplier A and B, who produce long lead-time components.

One reason for this is that process times are not measured at the suppliers, making it very difficult to trace the sources of process variability. Therefore, one key outcome of this study was the proposal that Company S and its suppliers begin to monitor actual process times or order fulfillment times, especially for orders involving long lead-time items. Another suggestion is to introduce delivery-time windows (or period) in purchase orders, thus allowing suppliers more flexibility in planning their own production to accommodate other operational constraints. In cultures where there is punishment for revealing issues, a management policy that rewards openness – maybe in the form of a continuous improvement programme – will lead to improvements.

Culture also plays a role – both within the focal company and at the suppliers. We observed that workers at the suppliers were afraid of being caught to have made mistakes, and for issues to be traced back to them. For the same reason, supplier development is also difficult because the local supply chain team (i.e., in Asia as opposed to Europe-based headquarters) of the focal company prefers that problems are not traceable. This way, those knotty issues can easily be ascribed (and this is often the case) to the differences between the European and Asian business environment.

Future research will extend the preliminary findings of this study by investigating how the use of penalties and rewards will work in this setting. In the next phase of this study, the use of a systematically determined penalty for untimely delivery from suppliers will be explored within this supply chain, as this is currently not in use. The penalty can be based on a revised and agreed delivery-time window, so that suppliers know the customer requirements, and are motivated to improve delivery-time performance. In the same vein, manufacturers such as Company S could also explore the possibility of rewarding suppliers who consistently exceed the performance targets either by publicizing this or by awarding a rank score which will influence future contract awards.

References

1. McGovern, T., C. Hicks, and C.F. Earl, *Modelling supply chain management processes in engineer-to-order companies.* International Journal of Logistics: Research and Applications, 1999. **2**(2): p. 147-159.
2. Mello, M.H. and J.O. Strandhagen, *Supply chain management in the shipbuilding industry: challenges and perspectives.* Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 2011. **225**(3): p. 261-270.
3. Milgate, M., *Supply chain complexity and delivery performance: an international exploratory study.* Supply Chain Management: An International Journal, 2001. **6**(3): p. 106-118.
4. Gunasekaran, A., C. Patel, and E. Tirtiroglu, *Performance measures and metrics in a supply chain environment.* International journal of operations & production Management, 2001. **21**(1/2): p. 71-87.
5. Bertrand, J. and D. Muntslag, *Production control in engineer-to-order firms.* International Journal of Production Economics, 1993. **30**: p. 3-22.
6. Hicks, C., T. McGovern, and C.F. Earl, *Supply chain management: A strategic issue in engineer to order manufacturing.* International Journal of Production Economics, 2000. **65**(2): p. 179-190.
7. Caron, F. and A. Fiore, *'Engineer to order'companies: how to integrate manufacturing and innovative processes.* International Journal of Project Management, 1995. **13**(5): p. 313-319.
8. Gosling, J. and M.M. Naim, *Engineer-to-order supply chain management: A literature review and research agenda.* International Journal of Production Economics, 2009. **122**(2): p. 741-754.
9. Assaf, S.A. and S. Al-Hejji, *Causes of delay in large construction projects.* International journal of project management, 2006. **24**(4): p. 349-357.
10. Mello, M.H., J.O. Strandhagen, and E. Alfnes, *The role of coordination in avoiding project delays in an engineer-to-order supply chain.* Journal of Manufacturing Technology Management, 2015. **26**(3): p. 429-454.
11. Zorzini, M., D. Corti, and A. Pozzetti, *Due date (DD) quotation and capacity planning in make-to-order companies: Results from an empirical analysis.* International Journal of Production Economics, 2008. **112**(2): p. 919-933.
12. Guiffrida, A.L. and M.Y. Jaber, *Managerial and economic impacts of reducing delivery variance in the supply chain.* Applied mathematical modelling, 2008. **32**(10): p. 2149-2161.
13. Guiffrida, A.L. and R. Nagi, *Economics of managerial neglect in supply chain delivery performance.* The Engineering Economist, 2006. **51**(1): p. 1-17.

Paper 3

Høyer, M. R., Oluyisola, O. E., Strandhagen, J. O., & Semini, M. G. (2019). Exploring the challenges with applying tracking and tracing technology in the dairy industry. *IFAC-PapersOnLine*, 52(13), 1727-1732.

This is an accepted manuscript of an article published in IFAC-PapersOnLine. The final authenticated version is available online at:
https://doi.org/10.1016/j.ifacol.2019.11.450

Exploring the challenges with applying tracking and tracing technology in the dairy industry

Madeleine R. Høyer*. Olumide E. Oluyisola. Jan O. Strandhagen***. Marco G. Semini******

Department of Mechanical and Industrial Engineering,
Norwegian University of Science and Technology, Trondheim, Norway.
** (Tel: +47 45915223; e-mail: madelerh@stud.ntnu.no) **(email: olumide.e.oluyisola@ntnu.no)*
****(email: ola.strandhagen@ntnu.no) **** (email: marco.semini@ntnu.no)*

Abstract: The purpose of this research is to identify the various challenges encountered when using tracking and tracing technology in the dairy industry. Based on a systematic literature review, the challenges are reviewed from the supply chain perspective. The findings are then discussed within the context of a large dairy manufacturer that implemented RFID within its supply chain. The paper distinguishes between three different types of challenges regarding tracking and tracing technology: *strategic*, *technical* and *convenience* challenges, and are further categorized as either adoption barriers or implementation barriers. This study also finds that the technical requirements for implementing tracking and tracing technology pose the least difficulty, while organisational change and cyber-security risks are more critical.

Keywords: RFId and ubiquitous manufacturing, logistics in manufacturing, intelligent manufacturing systems, manufacturing plant control

1. INTRODUCTION

Recent trends in technology development offers much promise for addressing the several challenges facing manufacturers in today's dynamic business environment. To cope effectively with ever-changing customer requirements, managers are looking into technology solutions, such as tracking and tracing technologies, to improve planning and control and performance (Kache and Seuring. 2017). This increased productivity will have a significant implication for successful operations management on a factory level but also across entire supply chains (Kehoe & Boughton, 2001). More importantly, it will result in an improved service level and customer satisfaction. This is crucial in such a competitive market as it "increases the customer's confidence, strengthens the brand integrity and increases the customer loyalty" (Costa, 2013).

In the last two decades, tracing and tracking technologies have gained attention as potential enablers for improved supply chain integration, planning and control, and therefore better overall supply chain surplus (Strandhagen et al, 2016; Oluyisola et al, 2018). This has spurred research to increase the understanding of the conditions that facilitate the digitalisation of supply-chains and production systems in the recent times. It is also valuable to understand the role of digitalization in performance improvement and in raising the awareness of the risks, challenges and threats for the companies faced with digitalisation. For instance, there is a growth in available information collected from technologies like tracking and tracing systems and customer collected data. Such data has the potential to create several opportunities like improving forecasts and basing production plans on more accurate customer demand.

Kache and Seuring (2017) noted how the research on the consequences of the lack of updated and "right" supply chain information is limited. Moreover, the need to integrate with existing systems and questions about whether to tag at item level or at package level remains challenging (Kache & Seuring, 2017). Perhaps, this is one reason why adoption has been most prominent in some segments of the retail industry where finished goods items are sold mostly piece-by-piece. Within the factory, adoption is even more limited if judged by the dearth of empirical data in the literature. Therefore, there is a need to shed more light onto the challenges facing the adoption and use of tracking and tracing technologies in other industrial settings, if the potential benefits are to be fully actualised. The paper aims to fill this research gap through a case study of a large producer, and more specifically addressing the manufacturer's perspective.

1.2 Research objective, questions and scope

The paper will investigate the existing challenges and barriers for applying tracking and tracing technology in a cold supply chain in dairy producer operations. These tracking and tracing solutions suited in the dairy industry are intended to improve the accuracy and the efficiency of the planning and control in a complex supply chain whose objective is to remain competitive within the paradigm shift which is currently moving towards a more digital world, frequently referred to as Industry 4.0.

Operational decisions-making is particularly difficult in the dairy industry as they need to address several uncertainties such as high perishability, a large variation in lead times, short delivery times, seasonality and both varying raw material availability and demand. With these characteristics this industry can be considered as one of the most complex and challenging supply chains. There is a plethora of information available supporting the statement that tracking and tracing technology is an enabler of supply chain visibility which can enable more informed planning and control. The purpose of this paper is to increase awareness of the potential challenges that may arise from these technologies.

There is an increasing importance and expectation of monitoring food in the food industry, due to reasons related to both quality and safety. The food industry is exposed to a myriad of devices, sensors and instruments that continuously analyse, monitor and control parameters such as temperature, bacterial levels, pH-levels and contamination levels. These technologies are frequently found on the factory site and it can be less challenging to control these aspects that occur inhouse. Usually, the factory has a clear understanding of these characteristics. Once the consumable products leave the factory premises it will be more difficult to monitor and control. Nonetheless, the products are a lot more vulnerable as they are exposed to more radical and unpredictable changes in the external environments which can have a major influence on the quality of the product. Simultaneously, the products will be impacted by issues related to operations and logistics. Consequently, researching tracking and tracing technologies instead of other possible technologies is very attractive for this industry as they would be able to control and provide the supply chain with information on the current status and performance of the process.

2. RESEARCH DESIGN

A systematic literature review has been carried out in Emerald Insight and Science Direct, and the articles were to be dated no later than between 1998-2018. A further condition was that the articles found in Emerald Insight should come from leading journals as this would increase the validity of the project. Science Direct had articles coming from different journals than Emerald Insight and many of these journals were not regarded as leading. Nonetheless, the contents appeared relevant and therefore the criteria for the background of the journals did no longer aadoptionpply.

The pool of selected keywords were based on a preliminary search. A boolean advanced search was generated separately for both Emeral Insight and Science Direct because each database had different constraints in their search engines. The first boolean search in Emeral Insight involved three blocks and "anywhere", however this resulted in 48 567. After several modifications such as changing the combinations of keywords and extending the search to four blocks resulted in 67 hits after having applied the constraints mentioned above. The same process was repeated for Science Direct, however here two blocks were appropriate for searching in the body of the article and three blocks were tailored towards keywords to be found in the title, abstract or list of keywords. This resulted in 42 articles. The keywords used to retrieve relevant papers were the following: planning, control, forecasting, food industry, make to stock, RFID, traceability, tracking technology, Industry 4.0, challenges and constraints. These words were combined slightly differetly across the various levels in the two databases.

In addition to the literature study, a semi-structured interview was carried out with the Logistics Project Manager at the case company. The purpose of the case study is to complement findings from the literature study, deemed necessary because of the limited studies on these challenges – from a manufacturer's perspective.

3. LITERATURE STUDY

3.1 Findings from literature study

Initially, the literature review resulted in 67 articles from Emerald Insight and 42 articles from Science Direct. Reading through the titles and the abstracts and assessing their relevance reduced this number to 30 articles and 6 articles, respectively. After thoroughly reading through all the 36 articles, the final selection was filtered down to 33. The inclusion and exclusion criteria were based on papers having to include either food industry or cold supply chains, and it was imperative that the papers addressed tracking and tracing technology with the respective challenges. These 33 papers provided relevant information on existing technologies and the challenges when implemeting tracking and tracing technology in the cold supply chain, summarized in table 1, and the following sections will address these findings more specifically.

3.2 Existing technologies

Different traceability systems will have different capabilities and functions, some span across the entire chain, from farmer to retailer, while other solutions are bounded to one specific area. The level of information detail these technologies capture will vary. The following technologies were found during the literature study and were considered as being popular for tracking and tracing.

3.2.1 Barcodes

Barcodes and barcode scanners are a well-established technology for identifying products and they will only identify product types instead of unique items. Barcode technology can often be considered as a simpler form for tracing, nonetheless this is often preferred in industry as it is easier to implement, and it is a cheaper solution while still capturing data to the level of detail and accuracy which is required.

3.2.2 RFID

Radio frequency identification (RFID) technology is a compact technology which consists of two components: an antenna and the chip which contains the electronic product code. Real-time information can be traced continuously throughout the entire chain. With the emergence of RFID technology, research has proven that the handling of inventory and inventory management has improved (Lao et al., 2012), especially in the food industry, as it provides real-time inventory data and hence gives a clearer visibility of stock levels. Adopting RFID technology will also lead to a reduction in human errors originally caused by manual data input. The significant benefits will be particularly experienced by the distributor and the retailer.

3.2.3 Intelligent packaging systems and TTIs

These packaging systems equipped with time-temperature indicators (TTI's) can sense the environment and based on stimuli can detect, sense, record, trace and communicate. These functions assist decision making regarding shelf life, quality, they are capable of warning when deviations occur, and they will support material and information flow (Yam et al., 2005, p.2).

Table 1. RFID challenges from the literature.

Challenges	References
Strategic challenges	
Cost of implementing	Juan Ding et al. (2014); Kumari et al. (2015); Thiesse & Buckel (2015); Li et al. (2017)
Low awareness of benefits	Auramo et al. (2002)
Information sharing	Aramyan et al. (2007); Nakandala et al. (2017); Chaudhurri (2018) ; Morgan et al. (2018)
Coordination, collaboration and trust	Robson & Rawnsley (2001); Aramyan et al. (2007); Matopoulos (2007); Juan Ding et al. (2014); Anastasiadis & Poole (2015); Soosay & Hyland (2015); Jie & Gengatheran (2018); Morgan et al. (2018)
Entrenched business practices	Faisal (2015)
Technical challenges	
Collisions	Kumari et al. (2015)
Environmental interference	Kumari et al. (2015)
Suboptimal reading	Thiesse & Buckel (2015); Kumari et al. (2015)
Data collection	Zhong et al. (2017); Kumari et al. (2015) ; Chaudhurri (2018)
Convenience challenges	
Waste and recycling of RFID tags	Chaudhurri (2018)
Lack of professional skills	Faisal (2015); Chaudhurri (2018)
Security and privacy	Kumari et al. (2015); Li et al. (2017); Chaudhurri (2018)
Regulations and standards	Kumari et al. (2015); Nakandala et al. (2017); Stranieri & Banterle (2017)
Data uniformity and standardisation	Chaudhurri (2018)

3.3 Challenges with tracking and tracing technology

The challenges with tracking and tracing technology encountered during the literature study can be categorised as strategic challenges, technical challenges and convenience challenges (Vermesan & Friess, 2014) and each of these three challenges have various aspects that will now be discussed in more detail.

3.3.1 Strategic challenges

Cost of implementing. High deployment costs remain one of the greatest constraints to applying certain tracking and tracing technology, like RFID. However, it is believed that cost will become a less significant barrier with the expected advances in semiconductor fabrication techniques required to produce some of the components. If this proves to be correct, technologies such as RFID may become a more competitive choice in the future (Kumari et al., 2015).

*Low awareness of benefits and lack of incentive*s. It is believed that there is a lack of incentives for adopting the technologies. There is also a risk in believing in additional benefits when applying new technology to old processes. These can be incompatible with each other and can lead to increased costs and inefficiency.

Information sharing. Information sharing, hence increased transparency and supply chain integration can have a significant positive impact on the entire supply chain by improving planning, production and delivery performance (Zhou, 2007). The quality and the availability of the information shared is critical and will be influenced by accuracy, timeliness, credibility, uncertainties and inter-organizational relationships. Before investing in transparency, there should be an analysis on which situations would benefit from it and where transparency would not be worthwhile (Morgan et al., 2018). With the rise of big data, it will be necessary to ensure that the masses of data are made interpretable and timely for all the partners (Morgan et al., 2018). Information sharing is not achieved appropriately in cold supply chains because temperatures are recorded but are not transmitted. When temperature data is collected it is only used at the destination to determine whether the freight is accepted (White & Cheong, 2012).

Coordination, collaboration and trust. A major incentive for coordination and collaboration is the opportunity of having access to more competencies (Anastasiadis & Poole, 2015). A supply chain can potentially comprise of several partners and there is always a risk of diverging and misaligned interests which can affect the quality of the information which is shared. The strategic value of some information can inhibit the free exchange of information (Aramyan et al., 2007). There is a tendency of associating the act of information sharing with the loss of power and dependency (Soosay & Hyland, 2015). This will be counterproductive when working towards building trust and this can be detrimental to the supply chain's efficiency (Feldmann & Müller, 2003). As a result, trust can easily be an obstruction and will limit both the depth and the width of the collaboration.

Entrenched business practices. Managers can be reluctant to change and commitment and not having all the key participants on board can lead to the technology not being implemented at all. Reasons can be due to high one-off investments.

3.3.2 Technical challenges

Collisions. A risk with technology requiring tags is the possibility of several tags being energised simultaneously when they receive the reader's signal. As a result, the various tags will transmit their response to the reader. The signals may superimpose which will then lead to a collision between the signals and will influence the data quality.

Environmental interference. Environmental factors and high-water-contents materials affect the performance of the tracing technologies (Kumari et al., 2015). These features are critical in food supply chains where foods are often characterised by possessing high contents of water, are exposed to extreme temperatures and have dielectric properties that can interfere with the signals.

Suboptimal reading. A misconception is that technology allows for an error-free detection of products. Faulty readings will directly impact the quality of the collected data (Ruiz-Garcia & Lunadei, 2011) and will for example affect the inventory control as there will be a discrepancy between the reality and the collected data (Thiesse & Buckel, 2015). A further factor that must be considered which is especially relevant in the food industry is that tracking and tracing technology usually traces and monitors the packaging that the food is contained in rather than the product itself. Therefore, there isn't necessarily a one-to-one correlation between the parameters measured on the packaging of the product and the actual parameters of the product itself.

Data collection. Not having an approachable data collection method will confine the data-based analytics and will directly impact the quality of the information and lead to unreasonable assumptions and decision making (Zhong et al., 2017). A reason for this is that the industry is lagging compared to the research which has been done on the digitalisation of supply chains. The reality is that manual and paper-based operations are still common practices, the collected data is unstructured, and the masses of data which are generated are difficult to handle as the current collection systems are limited and unable to cope with large quantities of data.

3.4.1 Convenience challenges

Waste and recycling. Ruiz-Garcia and Lunadei (2011) express that a setback with choosing certain tracing technologies concerns the handling of the end of life of the technology. A disadvantage of RFID is the recycling of the tags.

Lack of professional skills. Lack of professional skills, potentially due to insufficient or poor training of the employees in using the tracking and tracing technology, limits its potential in the supply chain (Ruiz-Garcia & Lunadei, 2011). Human error can lead to inaccurate data collection and poor data interpretation leads to poor decision making.

Privacy and Security. Privacy issues restrain the companies from taking advantage of the opportunities with tracing technologies. Consequences are counterfeited barcodes, hacking, industrial espionage, unwanted customer tracking, virus attacks and malicious intentions.

Regulations and standards. With growing transparency, there is an increasing need for regulations and traceability standards, and several standards currently coexist (Kumari et al., 2015). The lack of standards will lead to system incompatibilities making it more complicated to share information.

Data uniformity and standardisation. The process of collecting and transferring data varies between supply chain partners. This disparity makes it harder to collaborate and leads to a greater incompatibility

4. INSIGHT FROM A CASE STUDY

4.1 Brief description from case

The case company is a large Norwegian dairy product cooperative which offers a wide range of products. The products are primarily sold through all grocery retail stores, local convenience stores and kiosks. Domestically, the company face little to no competition. The company is successful internationally as well. The company makes to stock and has two different types of supply chains: direct distribution to retailers and distribution through wholesalers. The market requirements are frequent deliveries with very short response times. This is partially due to the high perishability of many of the products. The demand uncertainty is increasing because there is a large variation in periodic demand, the promotional activity is high and increasing, and the presence of the bullwhip effect is high. Despite the high perishability, the demand is still met from the finished goods inventory. The supply chain can be considered as one of the most challenging and complex supply chains in Norway. The challenges are increasing as there are more product variants and more demand uncertainty. The consequence is an even lower predictability.

4.2 The challenges from the manufacturer's perspective

Some of the points within each category of challenges will be relevant for certain specific technologies, whereas others will be applicable to a greater variety of tracking and tracing technologies. The case company experiences that their greatest challenge is strategic and weight this as the most decisive aspect when it comes to concluding whether they should implement RFID in their manufacturing. It is stressed that cost and low awareness of benefits are the primary deciding factors for adopting the technology.

From the case interview, it was expressed that the wholesaler would benefit from greater advantages when using tracking and tracing technology than the manufacturer. However, it would be the manufacturer that would have to take the costs. Prater and Frazier (2005) created a framework explaining the different barriers in applying technology and they distinguished between adoption barriers and implementations barriers from a management perspective. For the purpose of this study the definitions have been slightly modified but the essence remains. Adoption barriers are defined as barriers that arise due to the lack of incentives and motivation, whereas implementation barriers are defined as barriers that impact the feasibility of implementing the technology in practice.

It can be concluded that in the case of using RFID technology, the adoption barriers are greater and are more significant than the implementation barriers. Physically implementing RFID is not complicated as many companies have achieved it successfully, however the greatest hinderances arise due to the failure of achieving promised benefits at high deployment costs.

4.3 Impact of the challenges on the manufacturer's performance

It is important to understand how the challenges discussed so far will influence the manufacturer's overall operational performance if they are not managed adequately. Strategic challenges and technical challenges will have a direct implication on the manufacturer's performance and abilities to plan and execute their production. Certain aspects of convenience challenges, such as lack of professional skills, can also influence the performance.

4.3.1 Impacts due to strategic challenges

The ability to share information amongst supply chain partners and the ability to successfully coordinate and collaborate will have direct consequences on the overall operational performance such as longer lead times, higher costs throughout the supply chain and inaccurate information sharing. A possible reason that strategic challenges are weighted as more important by the case copmpany may be because the implications were more immediate during the pilot project.

4.3.2 Impacts due to technical challenges

Essentially, technical challenges can imply poor data quality. Poor data quality means that incorrect data is used for decision making and planning, there will be a poorer visibility throughout the chain and invisible costs may be more difficult to uncover. Poor data quality data can lead to wrong inventory levels and give incorrect information on the location of the products, resulting in a skewed representation of the reality. This inaccurate image makes it more complex to uncover invisible costs and this will complicate the process of improving the manufacturer's operational performance.

4.3.3 Impacts due to convenience challenges

Most of the points that fall under the category of convenience challenges do not directly impact the operational performance. Nonetheless, that does not mean that their importance must be ignored. One aspect that can influence the operational performance is the lack of professional skills because it can lead to human errors. Human errors can impact the accuracy and the efficiency of the production. Humans may slow down production or make incorrect decisions or do wrong actions during their workday. Often it is the humans themselves who need to report these faults and it is likely that not all faults caused by human error are in fact reported as human error. Since not all of these faults are documented it can be difficult to identify them and improve the performance.

4.3.4 Collective impact of challenges on operational performance

Combining the impacts from all the challenges, it can be concluded that this will overall lead to both poor external and internal attributes. Poor external attributes include reduced delivery reliability, responsiveness and flexibility, while poor internal attributes include higher costs and reduced assets management efficiency (Dweekat et al., 2017). Each of the challenges will contribute to the external and the internal attributes in different ways, however the final consequences and impacts on the supply chain management will be the same. Managing all the three challenges correctly will maintain the costs low, and the assets management efficiency, the delivery reliability, the responsiveness and the flexibility will be high. Achieving this successfully will result in a competitive and sustainable supply chain and all the decisions must be made keeping these in the core, as illustrated in figure 1.

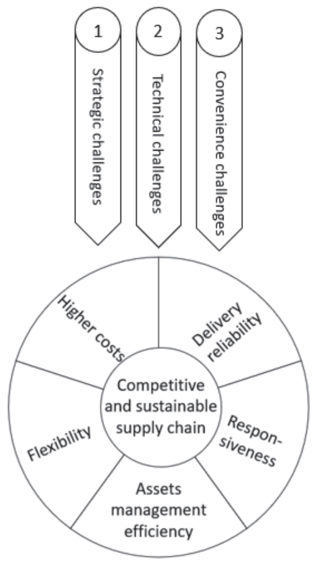


Figure 1. Framework illustrating how the three categories of challenges will impact the internal and external attributes and hence the overall supply chain performance.

5. CONCLUSIONS

There is no doubt that tracking and tracing technology leads to more real and representative data, and hence improves and facilitates decision making. Traceability eases control by product monitoring and continuous process verification. The dairy industry is already a complex and challenging supply chain and if the trends continue the complexities are envisioned to increase due to increased competition and higher customer expectations. Complex, dynamic and unpredictable supply chains need to be resilient and having the competence of capturing, extracting and using high quality data and information will enhance the supply chain resilience (Leat & Revoredo-Giha, 2013).

Several challenges impede the application of tracking and tracing technology, especially from a manufacturer's perspective. Investigating these technologies shows that the strategic, technical and convenience challenges can be categorised as either adoption barriers or implementation barriers. Although these challenges vary amongst companies and different tracking and tracing solutions, the governing challenges tend to be deployment costs and lack of benefits. These reasons are particularly directed towards RFID technology and have led to manufacturers discontinuing RFID pilot projects.

This study concludes that physically implementing tracking and tracing technology does not tend to pose major difficulties, instead it appears to be aspects concerning organisational issues and security. Furthermore, being unable to manage these challenges successfully will have a direct implication on external and internal operational attributes. These attributes are essential to satisfy as they lie in the core of having a competitive and sustainable supply chain. Although the case company discontinued the RFID technology pilot project, both this manufacturer and others remain interested in exploring other solutions that will assist operational decision making.

If the current technological advancements continue, there will be an immense growth in connectivity, information sharing and transparency both internally within organisations and externally amongst supply chain partners. To facilitate the transition from the traditional supply chains we know today towards the connected and digital world which is forecasted it is essential to acknowledge the existing challenges and address them adequately. Therefore, future research should explore how these challenges can be overcome and in which cases and industries the discussed challenges are most predominant.

REFERENCES

Anastasiadis, F., & Poole, N. (2015). Emergent supply chains in the agrifood sector: Insights from a whole chain approach. Supply Chain Management: An International Journal, 20(4), 353368.

Aramyan, L., Oude Lansink, A., Van Der Vorst, J., & Van Kooten, O. (2007). Performance measurement in agri-food supply chains: A case study. Supply Chain Management: An International Journal, 12(4), 304-315

Chopra S., Meindl P., 2016, Supply Chain Management: Strategy, Planning and Operations, 6th edn, Pearson Education Limited, England.

Costa, C., Antonucci, F., Pallottino, F., Aguzzi, J., Sarriá, D., & Menesatti, P. (2013). A Review on Agri-food Supply Chain Traceability by Means of RFID Technology. Food and Bioprocess Technology, 6(2), 353-366

Dweekat, A., Hwang, G., & Park, J. (2017). A supply chain performance measurement approach using the internet of things. Industrial Management & Data Systems, 117(2), 267-286.

Feldmann, M. and Müller, S. (2003), "An incentive scheme for true information providing in supply chains", OMEGA, Vol. 31 No. 2, pp. 63-73

Kache F., Seuring S. (2017) "Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management", International Journal of Operations & Production Management, Vol. 37 Issue: 1, pp.10-36

Kehoe, D. & Boughton, N., 2001. Internet based supply chain management. International Journal of Operations & Production Management, 21(4), pp.516–525.

Kumari, Narsaiah, Grewal & Anurag. (2015) "Application of RFID in agri-food sector". Trends in Food Science & Technology, 43(2), 144-161.

Lao, S., Choy, K., Ho, G., & Yam, R. (2012). An RFRS that combines RFID and CBR technologies. Industrial Management & Data Systems, 112(3), 385-404.

Leat, P., & Revoredo-Giha, C. (2013). Risk and resilience in agri-food supply chains: The case of the ASDA PorkLink supply chain in Scotland. Supply Chain Management: An International Journal, 18(2), 219-231.

Mirosa, M. & Lawson, R., 2012. Revealing the lifestyles of local food consumers. *British Food Journal*, 114(6), pp.816–825.

Mc Carthy, Uysal, Badia-Melis, Mercier, O'Donnell, & Ktenioudaki. (2018). Global food security – Issues, challenges and technological solutions. Trends in Food Science & Technology, 77, 11-20

Morgan, T., Richey Jr, R., & Ellinger, A. (2018). Supplier transparency: Scale development and validation. The International Journal of Logistics Management,29(3), 959-984.

Ruiz-Garcia, L. and Lunadei, L. (2011), "The role of RFID in agriculture: applications, limitations and challenges", Computers and Electronics in Agriculture, Vol. 79 Nos 1-2, pp. 42-50.

Soosay, C., & Hyland, P. (2015). A decade of supply chain collaboration and directions for future research. Supply Chain Management: An International Journal,20(6), 613-630.

Thiesse, & Buckel. (2015). A comparison of RFID-based shelf replenishment policies in retail stores under suboptimal read rates. International Journal of Production Economics, 159, 126-136.

Vermesan, O. and Friess, P. (2014), Internet of Things – From Research and Innovation to Market Deployment, River Publishers, Aalborg

White, C.C. and Cheong, T. (2012), "In-transit perishable product inspection", Transportation Research Part E: Logistics and Transportation Review, Vol. 48 No. 1, pp. 310-330.

Yam, K.L., Takhistov, P.T. and Miltz, J. (2005), "Intelligent packaging: concepts and applications", Journal of Food Science, Vol. 70 No. 1, pp. 1-10.

Zhong, R., Xu, X., & Wang, L. (2017). Food supply chain management: Systems, implementations, and future research. Industrial Management & Data Systems, 117(9), 2085-2114

Zhou, H. (2007), "Supply chain practice and information sharing", Journal of Operations Management, Vol. 25 No. 6, pp. 1348-1365.

Paper 4

Oluyisola, O. E., Sgarbossa, F., & Strandhagen, J. O. (2020).
Smart production planning and control: concept, use-cases and sustainability implications. *Sustainability*, 12(9), 3791.

This is the published version of the article in the Open Access journal Sustainability (MDPI-Switzerland) which is also available online at:
https://doi.org/10.3390/su12093791

sustainability

MDPI

Article

Smart Production Planning and Control: Concept, Use-Cases and Sustainability Implications

Olumide Emmanuel Oluyisola *, Fabio Sgarbossa and Jan Ola Strandhagen

Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, 7491 Trondheim, Norway; fabio.sgarbossa@ntnu.no (F.S.); ola.strandhagen@ntnu.no (J.O.S.)

* Correspondence: olumide.e.oluyisola@ntnu.no; Tel.: +47-471-676-86

Received: 10 April 2020; Accepted: 5 May 2020; Published: 7 May 2020

Abstract: Many companies are struggling to manage their production systems due to increasing market uncertainty. While emerging 'smart' technologies such as the internet of things, machine learning, and cloud computing have been touted as having the potential to transform production management, the realities of their adoption and use have been much more challenging than anticipated. In this paper, we explore these challenges and present a conceptual model, a use-case matrix and a product–process framework for a smart production planning and control (smart PPC) system and illustrate the use of these artefacts through four case companies. The presented model adopts an incremental approach that companies with limited resources could employ in improving their PPC process in the context of industry 4.0 and sustainability. The results reveal that while make-to-order companies are more likely to derive greater benefits from a smart product strategy, make-to-stock companies are more likely to derive the most benefit from pursuing a smart process strategy, and consequently a smart PPC solution.

Keywords: production planning and control; smart manufacturing; internet of things; machine learning; industry 4.0; case study

1. Introduction

"Is pollution profitable?", asked Bragdon and Marlin [1] five decades ago as the sustainability question became a forefront topic for manufacturing managers and business management researchers. Ever since, it has become popular for companies to list sustainability goals as an integral part of their mission, even though, many fail to take tangible, significant steps to improve sustainability in operations—a practice called 'green-washing' [2]. However, since the turn of the twentieth century, there has been growing interest among managers and researchers in having sustainability as a source of competitive advantage while simultaneously addressing the growing market pressure from global consumers and supply chain (SC) partners [3,4]. This pressure, it is argued, has led towards the more holistic triple bottom-line performance measurement for manufacturing and supply chain operations management as well as the emergence of sustainable manufacturing paradigms such as the circular economy, lean and green operations, and eco-logistics [4]. In order to address this challenge, every element of manufacturing must be involved, most importantly, those elements tasked with managing all the others —that is, production planning control (PPC).

The goal of PPC is to produce what the market demands at the expected quality, volumes, time, at minimum costs, on an ongoing basis as well as to be able to adjust to disruptions to the system when necessary. The PPC system includes all the tools and processes that are required to work towards achieving that goal [5]. PPC is a critical function for manufacturing managers. One of the key elements in operations management research is the fit of the PPC system to the production system, as the level of fit often decides the efficiency, profitability and long-term viability of a production enterprise. However, in practice today, PPC managers must deal with several challenges such as changing regulatory policies, climate change and other global phenomena all of which appear to put the world in a state of near-perpetual turbulence. In order to deal with the increased complexity and new market demands, production managers continually attempt to improve product and process flexibility, thereby leading to increasing depth of bill-of-materials and greater variation in production routings [6]. This causes PPC to be more challenging and the consequence is that a significant proportion of production lead time is still wasted as queueing or waiting time [7].

Furthermore, recent developments in information and communications technology (ICT) paradigms—within the concept of industry 4.0—indicate the potential of transforming all stages in the lifecycle of products (from design, sourcing, manufacturing, to distribution, consumption, and recycling) by enabling real-time planning and control of the factory and supply chain operations and thereby minimizing waste [8–10]. While several conceptual studies on smart manufacturing have been published, mainly focusing on manufacturing systems configuration and features, very few empirical in-depth case studies have been reported in the literature that specifically focus on the management processes of such systems [11,12]. Additionally, only a few of these studies address the importance of production planning and control in achieving the vision of smart manufacturing [11,13,14]. We think that this is a missed opportunity, as the PPC process is analogous to a brain for the production system and is the most critical "smartness" element of a smart factory. Furthermore, addressing the subject from the perspective of PPC enables firms to gradually advance in a holistic manner towards smart and sustainable manufacturing.

Consequently, this study addresses how a 'smarter' or machine-intelligent PPC system (hereafter, smart PPC) can be achieved in practice, and the sustainability implications of such a system and its processes. Smart PPC combines emerging technologies and capabilities in the industry 4.0 framework with PPC processes in order to improve the performance of the production system through real-time, data-driven, and continuous learning from a more diverse range of data sources than usual. The following is a non-exhaustive list of possible goals for smart PPC: to use real-time demand and production system data, i.e., reduce uncertainty from forecasts; to be dynamic, thus updating frequently, and reactive to real-time data; to use an expanded set of factors and data including telemetry data; to be able to accurately predict short-term requirements and support increased flexibility; and to capture and use the experience of the operators in the production system. If these goals can be achieved, it will lead to more precise planning processes, a reduction or elimination of various sources of waste, and ultimately to a competitive advantage. Thus, this paper seeks to answer the following research questions (RQs):

RQ1: What are the elements of a smart PPC system?
RQ2: What are the constraints, enablers and use-cases of smart PPC in practice?
RQ3: What are the implications of smart PPC for sustainable manufacturing?

In order to answer these questions, we present a concept for such a smart PPC system, adopting an incremental approach. While we will attempt to illustrate a typical architecture of such a system, the software architecture details are not the focus of this paper. Rather, through RQ1, we address components—inputs, processes and outputs—of the system and assume the generic service-oriented architecture. This approach is the basis for many notable architectures for emerging industry 4.0 applications [15]. RQ2 is ever more pertinent now as the dust settles on the industry 4.0 wave and results about successes and failures in early implementations begin to trickle into the public domain. The latter is an important gap in this relatively young research field, as there is limited know-how of the strategic implementation of industry 4.0 [16,17]. Thus, this study lays the foundation for an approach towards industry 4.0 through smart PPC.

The remainder of the paper is structured as follows: we present the theoretical background to the conceptual model in Section 2. We describe the underlying framework guiding the concept development, together with the case selection, data collection and analysis processes in Section 3.

Thereafter, we present the developed framework and conceptual model in Section 4. We illustrate this model using the cases in Section 5. We follow this with a thematic discussion in Section 6. We then wrap-up with the conclusions, research limitations and future research topics in Section 7.

2. Theoretical Background

The literature is replete with studies investigating disparate elements of PPC and elements of industry 4.0. However, there is much insight to be gained from a holistic view of PPC and industry 4.0 for smart PPC to be realizable, and consequently, the vision of smart and sustainable manufacturing. Therefore, this section revisits the theory on hierarchical PPC systems, its processes and challenges and industry 4.0 as a foundation for smart PPC. The section concludes with a literature on constrains, enablers and an attempt to present a theory—the structural contingency theory—to explain the smart PPC concept and its application in the selected cases.

2.1. The PPC System and Processes

PPC is often described using hierarchical frameworks which presents the various elements of the PPC process at varying levels of detail and time horizon. This hierarchy supports the 'drilling down' approach that business managers seek when making decisions regarding their production systems. One notable PPC framework, created by Vollmann et al. [6], is the basis for most traditional planning systems in production today. The framework describes the strategic (long-term), tactical (medium-term) and operational (short-term) stages as the common levels of planning that exists within a typical enterprise resource planning (ERP) system regardless of the type of industry in question. While this framework has faced some criticism for not capturing the several feedback loops that are witnessed in real life production systems, it remains popular due to its comprehensiveness and its built-in optimization capabilities [18].

Nevertheless, several others PPC frameworks also exist, for example Bonney [19], which present a slightly different take on the PPC process and highlight the importance of feedback loops. Notably, these loops are more frequent and important in the tactical and operational stages of PPC. Moreover, regardless of whether the system in question is built on a hierarchical framework, PPC systems have become colossal, difficult to implement and maintain, and unwieldy to adapt to the needs of today's production environment [18]. Taking these loops into consideration, we adapt the three-domains framework into a holistic PPC framework, as depicted in Figure 1.

The strategic level adopts a long-term, aggregated view of manufacturing operations. The process begins with sales and operations planning (S&OP) which aims to balance overall demand with the available capacity. S&OP receives demand data (volumes per product family per planning period) and in some cases meta data (such as forecast uncertainty) as input from demand management (DM) and future available aggregate capacity as input from resource planning (RP). Thereafter, the aggregated plan generated at this level is disaggregated from the product family into individual products. Since the plan is aggregated and with a relatively larger time horizon than others, it is not often accurate. The relevant data for this stage typically includes demand forecast data which can be computed from historical demand data or estimated from experience by the sales and marketing team or a combination of the two [6]. The primary output is the master production scheduling (MPS), which encompasses the purchasing and production plans at an individual product level by time period, typically weeks. The output of this level is the input to the tactical level.

At the tactical level, the MPS records are combined with bill of materials data and inventory data in order to calculate the components' and parts' requirements, and make recommendations to release replenishment orders for materials, a process called materials requirements planning (MRP). Based on the production system's capabilities and lead times which dictates the capacity requirements planning (CRP) process, it is possible to release detailed material and capacity plans with shorter time horizon (typically weekly). These plans are revised frequently, and the output of this stage is production plans and replenishment orders for materials, which in turn is the input for the operational stage.

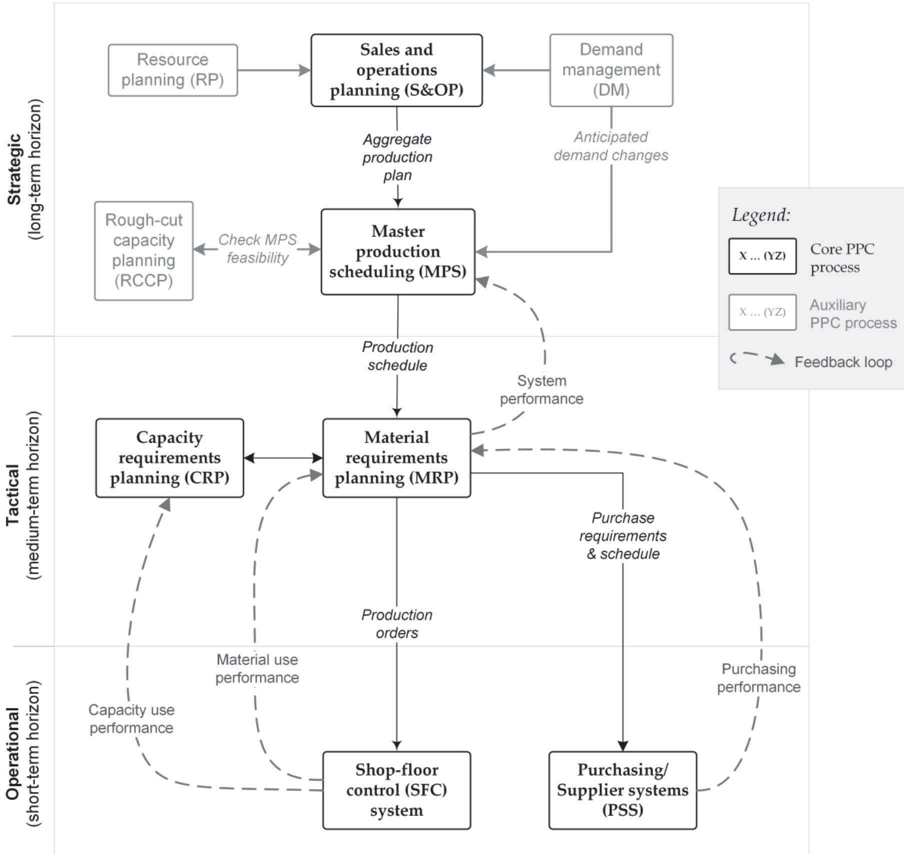


Figure 1. The production planning control (PPC) system levels and processes (adapted from [6,19,20]).

Finally, at the operational level, the concern is about how to execute the production order using the materials and capacity plans from the MRP and CRP. The processes entail day-by-day, shift-by-shift detailed scheduling, the coordination of the actual manufacturing processes (shop floor control, SFC), and the issuance of purchasing schedules to the purchasing function or supplier systems (PSS) for the supply of materials required to execute daily operations [6,19]. The documents at this level are purchase orders at the component level and work orders and job lists at work centres. This stage also involves the control, measurement, and evaluation of the performance of the production operations and suppliers.

2.2. PPC Challenges

One key limitation of PPC at the strategic level is that it implicitly assumes that the effect of extraneous factors such as weather or industrial policy changes, global economic downturns and other disruptions average out from year to year. This often leads to the use—by planners and operators—of excessive capacity, buffers and safety stock in the production system. Furthermore, since the data is aggregated, the quality often varies depending on how data-driven the company is. Challenges include quality of data in the long term (as the business environment continues to change), frequency of update, etc. In this case, having real-time data does not necessarily lead to any advantage provided the data is accurate. Perhaps more important is the span of the data, in which case "longer is better" in order to enable various simulation scenarios. Finally, managers of production systems often must make resource planning and flexibility related investment decisions based mainly on uncertain forecast data [6]. Therefore, the S&OP process must overcome variations in historical demand, uncertainties in demand forecasts, and unavailability of demand data. Similarly, the MPS process must deal with issues related to data integrity and completeness, estimation of product-level demand, inventory variability leading to difficulty in estimating available-to-promise, rescheduling frequency periodic scheduling while events alter production system, and a lack of feedback on the accuracy of resource planning.

At the tactical level, the challenges of traditional PPC include planning complexity due to data integrity concerns, product mix exacerbated by increasing product customization needs, estimation of production volumes, control principles that minimizes work-in-process inventory, etc. [6]. Thus, the MRP process must deal with issues regarding the updatedness of bill-of-materials with respect to (w.r.t.) components and levels; inventory data accuracy—what is produced and exact storage location; and lot-size determination and revision policy. The CRP process must handle the updatedness of process routes/charts and recipes; accuracy and integrity of production instructions; process variability; variability in resources capabilities and capacity; and continually monitor the size of buffers [20]. Production managers deal with all these challenges using levelling and lot-sizing techniques within the constraints of the planning solution that the company employs. They must also deal with the limitation that the production planning process is run periodically while the demand situation is continuously changing. They must also manage the contrast between the objectives of long-term planning versus short-term scheduling—that is, levelling versus the minimization of earliness and tardiness and nonexecution [21].

As shown earlier, at the operational (short-term) level, the status of the production system is changing in real-time and the agility and precision of the PPC system in adapting to the changing production environment is critical. However, the reality in most factories is that it is challenging to track and accurately predict work-in-process inventory and resource status, and the system is continuously being disrupted by rush-jobs and unplanned machine breakdowns or large changeover and set-up times [9,22]. Specifically, the PO process is challenged by the reliability of supplier quality and timeliness accuracy [23]. Furthermore, SFC processes and systems handle collection of operations data in real-time, job tracking on the shop-floor, resource performance tracking, and estimating and updating production schedule after rush jobs. Yet, a significant proportion of production lead time continues to be wasted in the form of queueing or waiting time [7]. Moreover, the manufacturing technologies are increasingly becoming sophisticated, and the SFC systems are required to handle a disparate set of data types and sources.

Overall, a few underlying challenges commonly affect the strategic, tactical and operational levels of the PPC system. Promotions and campaigns which are becoming commonplace can significantly disrupt supply chains. In addition, the quality and completeness (w.r.t. the span of breadth) of data and information used is a common challenge affecting resource efficiency and demand fulfilment [24]. These become even more important as systems become increasingly computerized and automated.

2.3. Towards Smart PPC in the Era of Industry 4.0

The temporal proximity or 'real-time' needs of PPC is a major uphill climb for conventional enterprise systems such as the ERP, manufacturing execution system (MES), or advanced planning and scheduling (APS) systems. Moreover, another critical limitation of these systems is that deviations are common between information in these enterprise systems and the reality on the shop floor and across the supply chain [25]. Furthermore, these enterprise systems are commonly configured to collect data from a narrow range of sources in the production system typically from production lines and perhaps warehouse inventories. However, in many production systems and value chains, several more factors influence performance. For example, in the food and beverages industry, the weather affects not only the production but also the distribution and consumption rates of numerous products. Being able to capture and use data from a broad range of sources presents an opportunity for better PPC performance in the current era. These limitations can be addressed by Industry 4.0.

Industry 4.0 envisages a state of manufacturing in which the product's end-to-end lifecycle stages are integrated, the manufacturing systems and internal functional units are networked (vertical integration), and the external value creation network is integrated (horizontal integration) [12,26,27]. This vision is enabled by the recent advances in technologies, including cyber-physical systems, internet of things (IoT), big data analytics (BDA), machine learning (ML), augmented reality, cloud and edge computing, and additive manufacturing [12,28]. Therefore, with all things connected, data generated from these integrated systems with the plant and across the value chain will enable real-time control (and, consequently, dynamic re-planning and rescheduling) of the factory and supply chain [8,9]. IoT, BDA and ML connected to and run via the cloud can address these temporal proximity needs of a smart and sustainable production value chain [29]. This specific collection of emerging technologies is at the cutting edge in the development of information systems (IS), having seen tremendous investments in research and development in the previous decade partially due to the significant reduction in the costs of computation power and data storage [29]. The cost reductions have been possible due to the reducing cost of hardware and the economies-of-scale achieved in cloud computing [17].

Furthermore, a key tenet of industry 4.0 is that manufacturing systems will be sentient and autonomous [29]. This will enable the development of real-time planning and control of the plant and supply chain operations thereby minimizing wastes in the system as every product will be produced as close as possible to when it is required by a customer [9]. In addition, the ability of BDA and ML tools and technologies to manage data with ordinarily challenging diversity (or variety) is an opportunity. Since computerization of the planning process is, by itself, not new, and enterprise systems and spreadsheet solutions have been used for decades, many production managers find it challenging to step into this new way of using data and ICT [30].

In addition, digital technologies have the potential to improve social and environmental sustainability when developed into organizational capabilities [16]. In a recent study, Dubey, et al. [31] found that BDA improves sustainability performance among Indian firms, consistent with previous studies. However, they also found that the primary driver for its adoption was its expected economic impact rather than any social or environmental benefit. This latter point further highlights previous findings which reveal how economics drives most transformational efforts including those publicized as sustainability programmes [2]. Meanwhile in another similar survey-based study in Brazil, Dalenogare, et al. [32] found that the maturity of certain digitalization technologies within the local context can lead to different expectations in their contributions to operational and sustainability performance. In their study, they found a strong positive correlation between the use of sensor technologies and the resulting big data with operational performance (agreeing with [31]) but failed to find a significant relationship between industry 4.0 and sustainability. They also found, contrary to popular belief, that not all technologies are expected to lead to operational performance improvements.

However, more recently, studies are beginning to indicate that numerous companies are struggling in their efforts to become more data-driven and attain smart operations [17]. The realities of the adoption and use of BDA, ML, cloud computing, and related smart technologies have been much more challenging than anticipated. From anecdotal evidence with industry partners, and as the extant literature shows, certain projects are likely to succeed while others are more likely to fail depending on the structure of the supply chain, the characteristics of the production system, and the products attributes. In other words, there is the question of contextual 'fit' with the planning environment factors in terms of whether a company that applies these technologies in manufacturing operations will succeed or fail [16,33]. Therefore, the selection and implementation of smart technologies towards a smart PPC system requires some consideration for the constraints of each technology and the characteristics of the production system.

2.4. Constraints, Enablers and the Structural Contingency Theory

From the above discussion, it is therefore evident that it is not sufficient for a manufacturing firm to select a technology and apply it and expect great results without due consideration for the intra- and inter-organizational factors that play a role in this regard [34]. Intraorganizational factors are those that define the working principles and the control of processes within an organization. Examples of such factors include the production process, products attributes, and human resource management systems. Interorganizational factors, such as the pressures from supply chain partners and the intensity of competition in an industry, can constrain or enable a company's adoption of industry 4.0 technologies for PPC to enable a better synchronization of planning efforts within the supply chain [35,36]. While these factors can be expected to play a role in the fit of industry 4.0 technologies with the production system, the extent and the nature of this influence is unknown.

In a related study focused on the extended enterprise view, Ngai, et al. [37] identified cultural issues, functionality requirements and legacy IT infrastructure, organizational and people-related challenges, technical support and training of relevant personnel as the critical success factors for successful ERP implementations [37]. Koh, et al. [38] extended these ideas and identified barriers, drivers, and critical success factors for enterprise-wide ERP (ERPII) implementation across supply chains. They observed that while vendors and suppliers tout real-time information, better decision-making power, and efficiencies in operations as the key drivers for ERPII implementation, users and customers are more concerned with how ERPII can provide new simpler and shorter ways for value creation, core competency integration, customer demand responsiveness, and improved product innovation or customization. They further identified barriers such as organizational inertia, resistance to change by employees, cost, gap between the theory and practice of the extended enterprise, disparate data standards and data inaccuracy as important factors. In addition, organizational structure and the learning culture have also been identified as critical factors [34].

More recently, de Sousa Jabbour, et al. [39] extended the concepts related to critical success factors into research on how industry 4.0 can enhance environmental sustainability in manufacturing. They selected 11 nontechnical factors including management leadership, strategic alignment, training and capacity building, empowerment to be innovative and discover new uses, national and regional differences, and organizational culture. However, the presence of other studies with conflicting results indicates that the influence of organization culture on the sustainability performance of firms implementing digitalization and industry 4.0 remains unclear [31]. Arguably, the influence of these internal and external factors varies based on the context that each production manager must consider when planning their manufacturing operations. Considering all these factors, the production enterprise is only likely to achieve the expected performance benefits of industry 4.0 if the technologies are configured and implemented in a manner that fits with the characteristics of its production system. Furthermore, certain industries (such as the engineering and equipment manufacturing industries) expect a long-term strategic benefit and are willing to pursue industry 4.0 regardless of possible challenges or implementation risks [33].

An appropriate foundational theory for addressing these kind of research problems is the structural contingency theory, which argues that organizational processes must align with the organization's environment [40]. As an example, Hicks, et al. [41] applied the structural contingency theory to explain the characterization of different engineer-to-order (ETO) archetypes in accordance with how ETO companies reorganize their internal and external supply chains to remain competitive in the face of changes in their production environments. Thus, it can be argued that the use of technologies in production systems ought to fit with the characteristics of the system. While sensor technologies have a wide application domain for example, in order to derive value from these sensors, several contextual factors must be considered. Often, what works in one industry will lead to poor results in another, like in the case of RFID application in the control of plastic pipes manufacturing [22,42]. Similarly, the structural contingency theory can also be used to explain for the influence of the supply chain and industry context [40,41].

3. Methodology

Following a description of the PPC system, its processes, and current challenges, and after developing a case for smart PPC and highlighting the constraints and enablers of such a system from the applicable industry 4.0 and PPC theory, we proceed to develop a conceptual model of smart PPC and case data to illustrate its use. Case research is fitting for research on subjects where there is a need to capture details and the nuances of complex phenomena like in the case of a PPC system being transformed by new advanced technologies [43]. Since one of the purpose of study is to identify and describe key/salient variables (i.e., constraints and enablers) and draw maps (or scope) of these variables for smart PPC, the research design will benefit from using a few, in-depth case studies with data collection by way of observations, interviews, historical reports and survey questionnaires [44].

3.1. Conceptual Model Development

After collating and analysing the problem with current PPC systems, and considering alternatives for improving their performance, we chose (among the alternatives) to investigate the potential of emerging industry 4.0 (I4.0) technologies. Due to our interests in resource-constrained manufacturers, we chose to build our concept on an incremental model which enables gradual advancements towards a desired state. We chose the model by Schuh et al. [34] which presents an incremental view of the stages of evolution towards the goal of an agile manufacturing company—that is, be able to respond accurately (using data rather than mostly managerial intuition), quickly (almost in real-time) and continuously (rather than at set, often long periodic intervals). They also highlighted how the model was developed from empirical data, with case studies, and the benefit for small and medium enterprises (SMEs) who have limited financial capacity and risk appetite towards seeming adventurous industry 4.0 projects. This previous point is particularly relevant because even though the reduction in computation costs is enabling digitalization and industry 4.0, small and medium-sized manufacturing companies which employ a large part of the global population are the ones that are more likely to be disrupted by the ongoing market transformation [12].

3.2. Data Collection and Analysis

The use of empirical data is important in this research area because the object of study is new and evolving [44]. Furthermore, there is great scientific and managerial benefit to document the actual experience of companies attempting to make advancements in the subject of this study. The cases selected for this study are members of a large industrial research network, and have made had a sizeable, publicized digitalization effort within the past three years. Two are semi-process manufacturing companies and the other two are discrete manufacturing companies. An overview of cases and interviewees is presented in Table 1. We began by analysing potential cases using available data from secondary sources and published reports about the case companies, their market situation, and each company's competitive environment. This was to ensure that each company to be included in the study met the requirements that they operated within a supply chain (SC) experiencing some changes due to digitalization and that they will be willing to participate in this study by sharing insights regarding their efforts as it relates to our research questions. From this pool, four companies were eventually selected.

An interview protocol was developed to highlight the data required to address our research questions and preliminarily administered in company A. The sections in the protocol followed the classification of PPC environment factors described in Jonsson and Mattsson [45]—namely, markets (covering the demand and supply factors), product attributes and process characteristics. This was then followed by a description of the PPC system, process, and challenges; finally, digitalization initiatives and sustainability considerations were then discussed. After the first interview, the protocol was updated to address the gaps in the framing of the research questions, thereby eliminating ambiguity and ensuring consistency at the point of subsequent interviews. The revised protocol (Appendix A) was then administered with respondents from company A and thereafter administered in the other case companies B, C and D. In order to reduce social desirability bias, we assured interviewees that the collected data will be anonymized if and when it is to be used in publications, similar to Wilhelm, et al. [46]. After collecting case data through interviews, we proceeded to transcribe the interview data while ensuring sufficient detail and structure for a thematic analysis and discussion [47].

Table 1. Overview of cases and interviews (real names of companies anonymized).

Case	Category Description	Total no. of Industry 4.0 (I4.0) Projects	No. of I4.0 Projects Affecting PPC	No. of Projects with SC Partners	Interviewee(s)	No. of Meetings
Company A	Confectionery products	>3	2	1	Production planners SC director	2 2
Company B	PVC pipes & drainage subsystems	>5	2	1	SC manager Technical projects engineer Innovation manager	1 2 1
Company C	Equipment for small & large ships	>3	1	-	Master planner	1
Company D	Agricultural & industrial balers	>3	1	1	Production manager Innovation manager	2 1

4. The Smart PPC Concept

This section presents the developed smart PPC concept and a description of its elements—that is, addressing RQ1. As companies digitalize their manufacturing operations in the move towards industry 4.0, they progress in stages. Schuh et al. [34] identified six progressive stages that an operation on the path towards smart manufacturing should follow. These are computerization, connectivity, visibility, transparency, predictive capacity, and adaptability. To simplify, in line with industrial practices, we reclassified the six stages into three—connected, transparent, and intelligent. These three stages, depicted in Figure 2, relate easily to the managers of production systems who seek better tools to improve their ability to respond quickly and accurately to changes in the business environment. A description of the theory behind each stage, the conceptual model and a table of potential use-cases for smart PPC is provided in the subsections below.

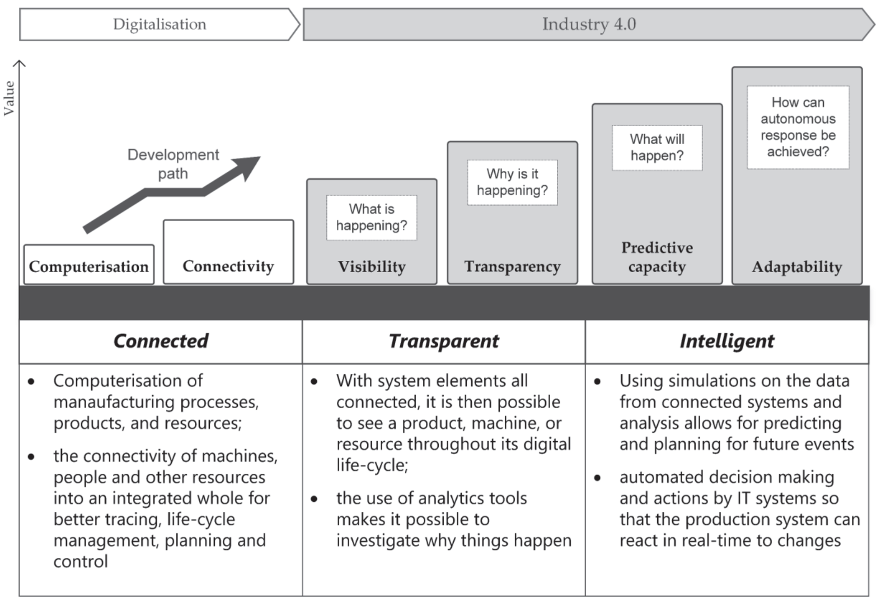


Figure 2. The path towards the development of smart production systems (adapted from Schuh et al. [34]).

4.1. Connected

The computerization of PPC processes is, by itself, not new. ERP systems and spreadsheets have been used for decades and almost every production system today is planned and controlled to a certain extent by either of these technologies. Moreover, the use of spreadsheets does not appear to be waning even with the advances in ERP systems and other planning solutions, probably due to the flexibility and ease of use that spreadsheet solutions afford most production planners [48,49]. In addition, production processes nowadays tend to have more electronic components and programable logic controllers (PLC), thereby enabling greater automation of production processes. Increasing computerization implies that all elements in a production system have a digital life and can therefore be connected to a digital industrial network in the smart factory.

On the contrary, connectivity is only just becoming widespread in this decade of digitalization and industry 4.0, as sensors and networking infrastructure gradually become ubiquitous and more affordable [29]. This sensing will be achieved using auto-identification and telemetry data collection sensor technologies such as radio frequency identification (RFID) technology, beacons and IoT devices [50]. Furthermore, since the move from the internet protocol version 4 (IPv4) to the new internet protocol version 6 (IPv6) standard, which can theoretically allow up to 3.4*10E38 internet addresses, it is now possible to connect things that hitherto would have been too complicated or expensive to connect to the internet [34,51]. Therefore, with the increasing ease of connecting 'things' to networks, everything can be connected, traced, tracked, measured, and improved and all the data generated by the action or movement of things can then be used to improve the design of systems, and the planning and management of operations. Consequently, tracking and tracing items of resources within a factory and in the supply chain becomes much easier [29].

IoT sensors can, through IoT edge devices, interact with the physical production system by sending location, status, and compute requests, and by receiving data and instructions from services hosted on cloud infrastructure. IoT Edge devices are more suited when there is a need for quick reaction (e.g., action to prevent a crane from collapsing if the sensor data already detects that this might happen, or action to prevent an automated tractor from colliding with an approaching operator) particularly when there is higher-than-acceptable device-to-cloud data transfer latency, and when bandwidth could be a challenge (e.g., on offshore platforms that use satellite internet connection and have several functions that demand the available bandwidth) [52].

Consequently, real-time planning and control of the production system and supply chain becomes possible. Examples abound particularly in the retail industry, which gained popularity in the past two decades due to the performance improvement achieved in inventory management and distribution logistics [53,54]. The same principles are now being applied in job shops, production lines and warehouses at equipment manufacturers [22,55]. Thus, computerization and connection enable smart PPC by enabling the determination of the precise location of products, routes travelled in the factory, status of machines and other resources, frequency of use, idle times and nonvalue-added time, etc., all of which is information that can then be processed with data analytics solutions in order to obtain insights into the state of the system, why the system is performing in a certain manner, and the performance of the PPC processes that are employed to manage that system.

4.2. Transparent

When 'things' are computerized and connected, it is possible to make a digital model of not only individual machines or factories but also components and final products moving through the production processes—that is, a digital shadow of the entire system and all its elements [34,56]. The digital shadow represents a digital state map of the production system and accepts data from the connected elements of that system to present it in a form that is typically visual, and which production managers and planners can use to simulate and plan future states and operations of the system. Meanwhile, a digital twin goes a step further and, in addition to accepting data, can send action instructions to the production system [57]. Thereafter, the data can be collected from within the factory or on a truck transporting raw materials or other critical components or from the sensor-enabled pallets at customer warehouses. It then becomes possible for a production planner to analyse the data in order to determine the sources and root-causes of logistical problems at the strategic, operational and tactical levels using dashboards with real-time KPIs collected from integrated enterprise and IoT systems [34,58].

Regardless of the type used, or even in cases where no digital shadow or twin is used but that KPI data specific to the production system are sent to a database for processing and analysis, there is a tendency for this data to be enormous and of high-dimensionality if they are collected from several IoT sensors in a typical production system. This situation presents both an opportunity and a challenge. First, the abundance and breadth of data enables higher precision of simulation models of production systems [58]. However, this also creates a case in which standard data processing technologies are not capable to derive insights from such (big) data. As such, new emerging technologies and methods for big data analytics such as MapReduce and Hadoop would be required to derive value from all the data being generated [14]. Moreover, even when the data processing challenge is overcome, there is also the causality problem which requires an understanding of the underlying engineering principles and business context to translate data correctly (e.g., translating sensor measure depth in a raw material silo into estimated volume of weight of materials in the silos) and to establish cause and effect relationships from the data that is generated by the system and the production and logistics KPIs of interest [34].

Hence, when used appropriately, BDA enables the transparency of process performance, critical materials, critical paths, supplier delivery performance, process material yield, and other factors that affect the behaviour and output of the system [9,31,36,58]. However, this smart PPC level still requires a production planner who is highly skilled in both production planning and BDA tools to actively examine the data, process and analyse it, and make decisions. With the increasing research on and wide application of ML and artificial intelligence (AI), there is potential for a machine-intelligent, self-optimizing PPC system which can handle all the relevant processes, process all the data, and interact with planners periodically, as determined by the production managers.

4.3. Intelligent

An intelligent system should be able to combine data from several sources about itself and its environment in order to learn and autonomously predict events which may influence its performance with regard to predetermined goals. In production, that implies being able to predict production delays, supplier delays, reduction in demand, etc. in order to avert a performance failure. Recent industrial interests in ML have led to significant advances which make these technologies and methods more feasible now for PPC than, say, a decade ago. Research into the use of AI approaches to planning and scheduling production systems have been going on since the 1980s, although those were in the form of expert systems and knowledge-based systems [59]. However, it is the interest of companies such as Google, Facebook and Amazon with vast compute and human resources that has extended the capabilities and possible use-cases of ML and also extended neural networks (a type of ML) to new depths (i.e., deep learning) with advanced techniques and applications.

There are three types of ML—supervised, unsupervised, and reinforcement learning—and all three types have been explored in PPC research, although limited empirical case studies have been reported. Supervised and unsupervised ML techniques have been applied in planning and control for predicting supply disruptions [60,61]. Reinforcement learning has been experimented upon for real-time scheduling [62]. Other noteworthy empirical studies of ML use in PPC have also been published. Using case studies, Garetti and Taisch [20] explored the use of artificial neural networks (ANN) for the selection of a production control strategy in the context of a valve manufacturer, and as a decision support system for plant parameter definition at the paint shop of a wagon manufacturer, thereby highlighting the pros and cons of each method and the implementation challenges. Except for a few cases such as these, most of the ANN research output at that time lacked real-life application [63].

Furthermore, these cases have been applied to static, one-off PPC problems, while research that examines the dynamic case of real-time learning PPC system was rare.

However, in the last decade, deep learning has received enormous attention from the software industry and has witnessed significant application in industries beyond manufacturing. Prior to that, several studies were published that investigated the use of ML methods in subsets of the PPC system. For example, Hruschka [64] used the marketing variables (current and one-month lagging advertising budget, as well as the retail price), along with an exogenous variable (average monthly temperature) to predict sales for an Austrian consumer brand. However, the author highlighted how computer processing power was a challenge due to the low learning speeds of ANN at that time.

In current production environments, an autonomous solution can be built using robotic process automation (RPA) with event-driven or scheduled applications and data pipelines for a connected system of applications. According to Wróblewska, et al. [65], RPA can facilitate an iterative upgrading of solution modules and therefore enables continuous learning. Thus, smart systems can be pre-programmed so that they not only run independently but also learn and improve without human intervention. Nevertheless, the case study in [65] (as with most cases in the RPA literature) was within financial services and document management. Despite the potential benefits, we find that there is currently little application in production management, and more so in PPC.

4.4. Conceptual Model and Matrix of Use-Cases for Smart PPC

The eventual conceptual model of such a smart PPC system is illustrated in Figure 3.

The smart PPC system incorporates the different levels of the PPC domains and intelligently manages all the key processes using data from diverse sources and allows human intervention. It should also provide a mechanism for continuous feedback from the production system to handle events that occur, in the same manner that a human-managed PPC system would work. Furthermore, when viewed in terms of PPC challenges, several use-cases can be identified (from the literature) for each of the three stages that leads to a smart-PPC system, as depicted in Table 2.

Table 2. A matrix of use-cases for an incremental adoption of smart PPC.

Challenges in PPC levels	***Connected Use-cases (with IoT—Internet of Things)***	***Transparent Use-cases (with BDA—Big Data Analysis)***	***Intelligent Use-cases (with ML—Machine Learning)***
Strategic			
Sales and operations planning (S&OP): *1. Variability in historical demand* *2. Uncertainty in forecast demand* *3. Unavailability in demand data* *4. Investment assessment for green and brown field resource capacity*	Real-time point-of-sale data Real-time goods-in-transit data	Demand summary Visibility in production resource performance patterns	Detect demand patterns Identify emerging customer groups Balance inventory and service levels
Master production scheduling (MPS): *1. Data integrity and completeness* *2. Estimation of product-level demand* *3. Inventory variability leading to difficulty in estimating available-to-promise* *4. Rescheduling frequency is periodic, while change events are continuous* *5. Feedback on accuracy of resource planning*	Identify material locations in real-time	Visibility of system performance for various product mix	Continuous lot-size optimization Multi-sourcing of data with error-detection mechanisms Multi-horizon scheduling and planning with KPIs
Tactical			
Materials requirements planning (MRP): *1. Data integrity* *2. Bill-of-materials updatedness w.r.t. components and levels* *3. Inventory data accuracy – what is produced and exact storage location* *4. Lot-size determination and revision*	Connected materials are easier to track and trace	Enables transparency into the consumption of materials	Continuous lot-size optimization Intelligent planning of inventory control policy
Capacity requirements planning (CRP): *1. Process routes/charts updatedness w.r.t. updates to processes and recipes* *2. Data accuracy and integrity* *3. Process variability* *4. Variability in the capabilities and capacity of resources*	Capturing the behaviour of production assets	Enables robust lifecycle assessment of assets and precise capacity planning	Predicts when capacity may fall below requirements to meet production plans

Table 2. *Cont.*

Challenges in PPC levels	*Connected Use-cases (with IoT—Internet of Things)*	*Transparent Use-cases (with BDA—Big Data Analysis)*	*Intelligent Use-cases (with ML—Machine Learning)*
Operational			
Purchasing function or supplier systems (PSS): *1. Reliability of supplier quality* *2. Supplier quantity and timeliness accuracy*	Traceability of supplied parts lifecycle	Visibility intro supplier performance	Real-time delivery estimation and stakeholder engagement
Shop floor control (SFC): *1. Collect operations data in real-time* *2. Job tracking on the shop-floor* *3. Resource performance tracking* *4. Estimating and updating production schedule after rush jobs*	Connected "things" – parts, finished goods, machines,	Visual control for jobs and resource performance tracking in real-time	Real-time resource allocation ML for production control

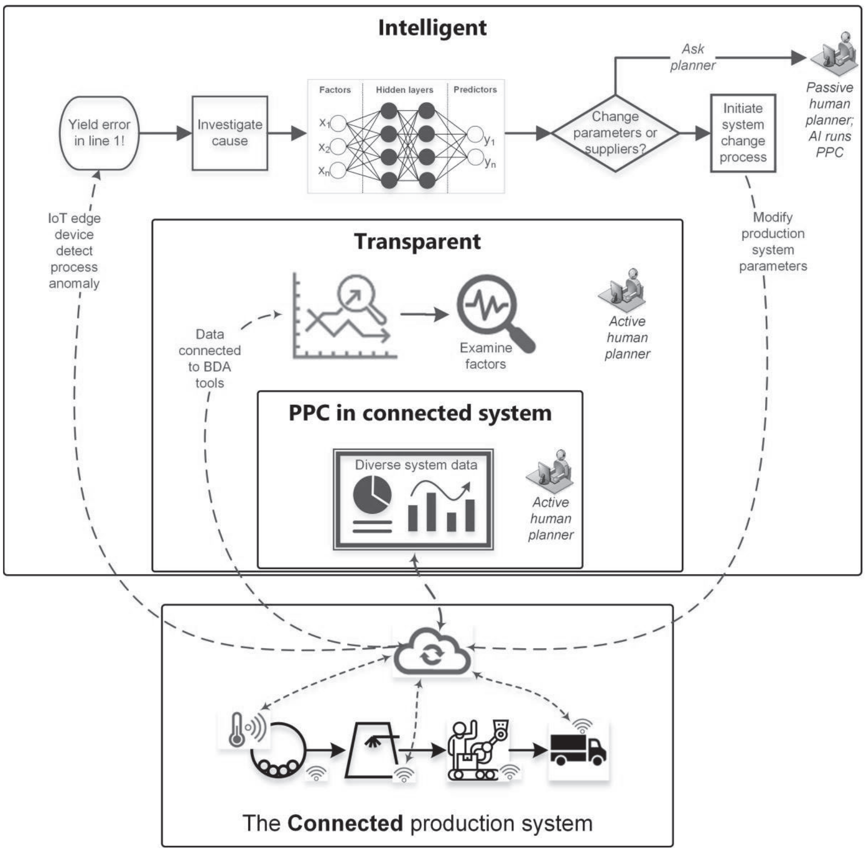


Figure 3. Conceptual model of smart PPC in a connected production system.

In general, smart PPC should perform better since it will be using a vast array of endogenous data from the production system and exogenous data from its environment. Moreover, for certain industries such as in process or semi-process production, there may be a greater opportunity to incorporate more data into the production planning and control processes.

5. Case Studies

In this section, we illustrate the theory with findings from case studies, by analysing current practices for PPC, digitalization and sustainability. For each case, we present a general overview and market factors, products, production process, PPC system and process, PPC challenges, digitalization initiatives and sustainability consideration in the current PPC processes at the case companies.

5.1. Company A: Confectionery Products

Market factors and general overview: Company A is a food company, manufacturing nuts, sweets (including pastilles) and chocolate from its single factory situated in Norway. In addition, the company also distributes fast-moving consumer goods for an international brand within Norway, leveraging its supply chain in the Norwegian market. The business encompasses all the value creation processes from product development, purchasing, logistics and production, to sales and marketing of mainly own brands. The company manages its product development, purchasing, production, supply chain logistics, sales and marketing along with its partners. Company A offers its products through the grocery industry, an industry valued at NOK 180 billion. In the business year 2018 and 2019, the company reported a turnover of NOK 750 million (USD 81 million). Many the sweets are impulsively purchased when customers are at the cashier stands in grocery stores. The level of competition is very high with economies-of-scale in product development being a key driver for market performance in the sweets market.

Products: Company A has a small R&D department which is tasked with developing and testing new products. After a new product is approved, the supplier inputs are certified for quality, as the food industry is highly regulated due to potential safety risks to the consuming public. Currently, Company A has both the British Retail Consortium and the Det Norske Veritas (DNV) for its processes and supply chain. The company manufactures products under seven brand names. Under the confectionery section, Company A produces 19 product families.

Production process: Company A's factory is divided into three sections, one each for confectionery, chocolate, and nuts-based products. Due to regulatory requirements regarding the transference of allergens, the movement of people and materials across sections is controlled. Most critically, nuts-based products cannot be transported to the other sections producing products which will not be marked for potential nut-allergens. The production technology strategy for the future is to use flexible manufacturing systems —that is, machines that can process several products.

PPC system and process: Company A has a production planner role, responsible for making the final production schedule and monitoring its execution. Production plans are generated within the enterprise resource planning system. Company A currently uses Excel templates with formulas based on estimates of the relationships between planning variables. The planning process is heavily influenced by the promotions in Xmas, Easter, and other periods that are dictated by Company A's partners' marketing teams. Furthermore, production input materials are delicate and must be kept at narrow environmental limits; set-up time in the production process is high and finished goods and work-in-progress (WIP) inventory is also high; packaging lines are semi-independent, and product intermediates need to be transported to another section within the factory for packaging. In addition, schedules for each week are made at the end of the previous week based on firmed customer orders and MPS values; and the factory has a combination of processes with varying throughputs and levels of automation.

PPC challenges: The consequences of these challenges are as follows: highly seasonal, impulsive demand; queues/waiting and poor asset utilization due to poor material flow; high WIP inventory due to the combination of processes with varying throughputs and levels of automation; resource constraints and capacity limitations due to the fixed flow manufacturing processes; large swings in resource requirements due to the current heuristics-based planning approach. Furthermore, the bottleneck process (drying) limits the ability to increase plant throughput in its current form; production lead time is high due to high lot size and high set-up times; finished goods inventory is typically large due to the large number of products (51 from the confectionery business alone); high demand variation from promos; and problematic scheduling due to the multiple routes and large number of input materials.

Current and planned digitalization initiatives contributing to smart PPC: Company A has implemented several automation projects in the past few years such as using robots in packaging and palletizing, using visual control and dashboards, etc. One such dashboard projects on the production lines provides direct access to data from the production line, thereby providing the planner real-time access into the status of the processes. The company is currently implementing a digital system which collects data from its production line and sends it to a data warehouse where BDA tools can be used to harness this data and generate meaningful insights. Despite these efforts, Company A struggles with its development of BDA and potential use of ML. While there may be several reasons for this, one of which is the complexity of the existing ERP system. The sheer cost of modifications and upgrades was highlighted as a major hinderance regarding the move to the use of smarter PPC through BI and big data analytics. However, new cloud solutions such as Microsoft Azure and Amazon Web Services offer a means to overcome such challenges.

Sustainability considerations in the PPC process: There are no explicit environmental sustainability considerations for the ongoing industry 4.0 initiatives. However, while the aims are purely economical, there is an implicit, unintended social benefit—that is, to improve the decision-support tools for operators, thereby reducing stress. There is also an environmental benefit through waste reduction in the production system.

5.2. Company B: Plastic Pipes and Custom Drainage Subsystems

General overview and market factors: Company B is a large producer of plastic pipe systems and is a member of one of Europe's leading conglomerates in the market for plastic pipes and associated parts. Company B's piping systems have been used in water, sewage, cable protection, electrical installations and gas. The company has factories in Norway, and trading operations in Sweden, Norway, Finland and the Baltic States; it is a market leader in the supply of plastic pipe systems in that region of Europe. A considerable share of the production is exported, particularly large dimensioned polyethylene (PE) pipes for which Company B has developed a strong global brand reputation. However, the competition is stiff, final customers are SMEs and are often price sensitive.

Products: Company B manufactures and markets a wide range of quality pipe systems, providing tailor-made solutions for municipal infrastructure as well as for the industrial and house-building sectors. In addition, PE pipes, polyvinylchloride (PVC) pipes, and plastic-protected cables are produced to stock in a wide range of colours. There is also a section for customized solutions, mainly drainage solutions such as manholes and curved pipes with precise angular dimensions.

Production process: The main products, PE and PVC pipes, are produced using injection moulding and blow forming. The PVC pipes are produced in several similar production lines, and the processes are fully automated from feeding the raw materials into the mixing chamber and then dosing this mix into the moulding lines. For a few of the production lines, particularly those producing the smaller units, the packaging at the end of the lines is fully automated. In the customized goods department, a substantial amount of manual work is involved with the operators cutting, milling, grinding and welding high-strength section of large PE pipes.

PPC system and process: There is no production planner title at Company B, but the function of production planning is jointly managed by the production manager and the supply chain manager. The sections in the factory have different control principles, with the PE, PVC, and plastic-protected cables mostly produced to inventory (except for cases where property developers or municipality projects place a large order). The company also produces customized drainage solutions such as manholes and curved pipes.

PPC challenges: The challenges associated with PPC at Company B centre around tracking and tracing materials and components in the factory, inaccurate inventory levels in the input materials' warehouses, and suboptimal material flow in certain sections of the factory. Purchasing is based on inventory levels in the ERP system. There is the issue of inventory levels of input components (e.g., pipe covers) not matching what is on the ERP system. This is due to outdated product data and BOM data on the ERP system; failure by operators to update the materials register when materials are consumed; and losses during the movement of products from the factory to other locations. It also happens that drawn-down pallets are occasionally returned to the warehouse after a batch is produced, and where it is still counted as a full pallet, since the measurement system counts pallets and not a measure of the contents. The pallet count is only reduced when a full pallet is emptied. The storage location of items can occasionally be haphazard since the factory has several storage facilities within the factory complex and operators occasionally forget to move pallets of consumables to the designated locations.

Current and planned digitalization initiatives contributing to smart PPC: Company B is involved in projects to improve material flow within the factory and the production efficiency of the operation. At the operational level, these include a pilot project investigating the use of autonomous guided vehicles (AGVs), and an investigation and pilot of ML for an autonomous error detection and classification in the PVC production lines. The company has also investigated the use of RFID for material control in the shop floor and warehouses. In addition, Company B is also involved in a collaboration project for a digital platform solution for the industry which will enable closer interaction with the final customers and create new product configuration discoveries.

Sustainability considerations in the PPC process: Company B maintains an environmental account and tracks its carbon footprint. From the planning perspective, the production department operates a small recycling station which grinds waste or defective products which can then be reused in manufacturing new products. However, the planning processes aims to have an inventory of potential demand due to the competitive nature of the market and thus keep a large inventory which is not lean in that sense, but one that the company deems necessary to compete in its market.

5.3. Company C: Equipment for Small and Large Ship Manufacturers

General overview and market factors: Company C is a global supplier of heavy-duty propulsion, positioning and manoeuvring systems to shipping yards and marine companies with a turnover of 1000 million NOK (130 million USD) in 2014 and a workforce of just over 500 employees. The company, which has a subsidiary in Germany, manufactures thrusters which are used in manoeuvring large maritime vessels and smaller boats. Company C designs and produces all its products in-house to customer specifications, taking full responsibility for the delivered system. Only a few components are outsourced from nearby, tightly integrated suppliers.

Products: Company C offers electric, hybrid and diesel drive systems and provides service and support for the entire lifetime of the supplied system. In general, product complexity is relatively high; demand varies highly and is relatively low in comparison with, for example, an automobile engine manufacturing plant. Product variety is also high and typically require considerable engineering time and competence, due to the degree of customization accepted from customers. In addition, products have a very deep and wide product structure vis-à-vis the bill of materials (BOM). The company also manufactures a few small standardized thrusters.

Production process: Raw materials are purchased using estimates from order backlog received from suppliers and kept in inventory. The purchased raw materials (e.g., sheet metal) are taken to the machining department based on the material estimates from the manufacturing BOM in line with the production orders released to the shop floor. The welding and final assembly for most customer orders are difficult to plan due to the significant variation in the throughput time. For the complete product from order confirmation to delivery, the throughput time can be a few weeks for smaller, more common systems and months for the more complex products.

PPC system and process: Products are made to order. Due to the variability in the welding and final assembly processes, production planning is typically focused on machine availability planning. Currently, production planning is performed using a combination of simple Microsoft Excel spreadsheets and the ERP system Infor M3 enterprise management system. Although equipped with an untested finite capacity option, Company C, like several other companies in this industry, does not use this functionality. The reason in this case was the lack of experience with the functionality and the concern of the production planners that the plans could be disrupted and thus, lead to unpredictable consequences if used; therefore, the company uses the default setting, which the planning team is more comfortable with. A key company objective is to maximize output while maintaining the current cost levels—that is, to maximize throughput without increasing overtime cost or additional cost due to subcontracting.

PPC challenges: Complex, highly customizable production leads to variations in the production planning, so much so that planning then relies on shift planning with large planning buffers. In addition, material planning is order-driven and not forecast based due to the high holding cost of components and materials. Demand exhibits large variability due to the increasing chaotic global economy which affects customers, thereby making forecasting problematic. The consequence of all these and the current PPC system is that orders are consistently late by up to four weeks, which is why the planners always use a three-week buffer in the production plans.

Current and planned digitalization initiatives contributing to smart PPC: There is the smart welding project which aim to use robots to improve the quality, speed and cost performance of the welding process. There is also a plan to develop a rough-cut-capacity planning MS Excel tool for the planners and the sales team to be able to quickly check available-to-promise (ATP) capacity before confirming a new customer order. Finally, there is a new plasma and water cutting machine with an integrated software for managing the production process and inventory of steel plates.

Sustainability considerations in the PPC process: The company has sustainability goes which include improving the sustainability rate, reducing energy consumption, designing products to minimize environmental impact and identifying environmental contribution to the value chain. However, these are not explicitly measured in relation to the performance of the PPC processes.

5.4. Company D: Agricultural and Industrial Balers

General overview and market factors: From its headquarters in Norway, Company D began operations in 1949, manufacturing small, detachable tools for its local farming community. With its increasing innovation capacity, the company produced the world's first chopping baler with a coupled forage harvester in 1986. Further innovations in product development followed with the production of the integrated baler machine in 1987, and the world's first compactor in 2002. It has been found that there is an increase of up to 20% in milk production when cows consume forage stored in the form of bales compared to those consuming forage stored in silos. The effect of this improvement in agricultural milk production has led to increasing demand for bale production machines—a form of combine harvesters. In addition, the ease of transportation of bales compared to forage stored in silos spurred the demand for these products, which also includes demand in other industries, such as in the industrial waste management industry. This new application area is gaining increasing attention due to the improved ease of transportation and handling after compacting refuse into bales wrapped in plastic foil.

Products: Company D manufactures several variants of its novel baling machines, which are broadly classified into three product families. The first product family is the oldest, and the second and third product families have been developed in response to market needs. The third family of products has a variant used in waste management industry for baling refuse waste into smaller volumes and has lately experienced increasing demand. This variant also has higher strength properties to meet the needs of non-agricultural industries.

Production process: The production facility is organized in a functional layout. There are several workstations within the various departments, beginning from cutting, welding, painting, drying, and final assembly before shipment to customer. There are 10 welding stations and 15 assembly stations. Some of the welding is automated after several years of research and development.

PPC system and process: Company D uses an MRP system—Visma Business—for tracking the purchase and consumption of materials from inventory, but not for production planning. Production planning is done using a customized MS Excel template with formulas and prebuilt functions. Production control is done using another customized solution which is integrated into the material database within the MRP system. The production planner, who is also the plant manager, leads the planning meeting once every week where the sales and technical team leads the evaluation of new orders, and available capacities to meet the new production plan.

PPC challenges: Due to the level of customization and the complexity of the products produced by Company D, several challenges are being faced in the PPC process. For example, there is a substantial variation in the reported task completion times and a significant amount of aggregation in planning process, using averages and large buffers. Furthermore, the working time that operators record each day differs from the actual working time since it often happens that progress is updated in batches and not in real-time. Moreover, the Excel template used for production planning only considers the availability of resources in terms of total aggregated man-hours regardless of skill, but the template does not consider the differences—for example, even though there are 80 available hours in the electrical department and 20 available hours in the hydraulics department, the total of 100 hours might be misleading if 50 percent of the operations required for the day in question is hydraulics. This is a major issue since some of the assembly operations require specialist technicians.

Current and planned digitalization initiatives contributing to smart PPC: Company D ventured into the development of precision farming solutions in 2014 and is increasing the digital capability of its products to improve product lifecycle. There are also lean efforts, like kit-based planning to improve the assembly operation. In addition, there is an ongoing research project to develop and test a decision support tool for selecting geography-oriented marketing and a method for sharing plans and forecasts in Company D's value chain using new ICT technologies.

Sustainability considerations in the PPC process: Sustainability is not an explicitly considered element in the PPC process, even though the company has sustainability goals which are top priority for management, and which guide the overall operation of the business.

6. Insights from the Literature and Case Studies

Following the case description and analysis, in this section, we reflect on our findings from the cases by analysing the cross-case observations in Section 6.1. Thereafter, we discuss these findings within the backdrop of the literature presented earlier. The discussion is structured according to the two remaining research questions (RQs). Having addressed RQ1 in Section 4, we address RQ2 in Section 6.2 by discussing how extant enterprise planning systems, company and industry attributes, and supply chain structure enable or inhibit smart PPC as seen from the cases studies. Thereafter, we discuss the sustainability implications of smart PPC (RQ3) and attempt an explanation for why the case data revealed little explicit influence of sustainability KPIs on current PPC processes in the observed cases. We conclude this section with a brief discussion of a few managerial implications of these findings (Section 6.3).

6.1. Cross-Case Summary

A comparison of the case companies is presented in Table 3 below. While there are commonalities among the case companies, such as the trend of using simpler planning tools like spreadsheets, a common theme was the lack of KPIs for sustainability in the PPC planning process. Moreover, PPC challenges were more materials-related for the (semi-) process, make-to-stock (MTS) companies A and B and more capacity-related for the make-to-order (MTO) companies C and D.

Table 3. Cross-case summary of planning environment attributes and industry 4.0 initiatives.

	Company A	**Company B**	**Company C**	**Company D**
Classification	Semiprocess; MTS[2]	Semiprocess; MTS	Discrete; MTO[2]	Discrete; MTO
Product and market	Supplies nuts, sweets, and chocolate products to few large retail chains	Supplies plastic pipes to contractors and wholesalers	Supplies propulsion systems to builders of ships and boats	Supplies large balers to final consumers
Supply chain structure	Customers (the wholesalers) current have more power in SC	Customers (the wholesalers) current have more power in SC	Dominant player in its SC; produces most components in-house	Small player in the lager agricultural equipment and systems industry
Planning tools	Microsoft (MS) Excel for capacity and enterprise resource planning (ERP) for materials planning and control	ERP for all planning and control	MS Excel (uses ERP system for inventory control)	MS Excel (uses ERP system for inventory control)
Key PPC challenges	Large variations in plans vs. output; poor visibility of operations	Material tracking; excessive inventory	Available-to-promise capacity difficult to estimate	MRP inefficiencies in final assembly; large CRP buffers
Connected initiatives[1]	Operator dashboard access to planner	Radio frequency identification (RFID) for the connected factory	-	Connected dashboard with the SFC systems; connected product sending data to cloud
Transparent initiatives[1]	New dashboard for planning and scheduling	Dashboard for production lines	RCCP[2] tool to support sales process	Upgrade of planning tool for resource specificity
Intelligent initiatives[1]	ML for higher planning precision	ML for quality control in lines	-	ML for processing product use data and predicting service needs
Sustainability consideration in PPC process	Not considered explicitly, except at the strategic level	Yes, as a measure of the quantity sent to recycling.	Not considered explicitly, except at the strategic level	Not considered explicitly, except at the strategic level

[1] *Smart planning initiatives* include both those that are recently deployed within the past three years or currently being developed or piloted. [2] MTS = Make-to-stock; MTO = Make-to-order; RCCP = rough cut capacity planning.

6.2. Constraints and Enablers in Transitioning towards Smart PPC

6.2.1. The Influence of Extant Enterprise and Data Systems Influence Smart PPC

In this paper, we examined PPC (a function that is ordinarily performed by ERP systems) and we presented a new system which uses existing tools and takes advantage of emerging smart technologies namely IoT, BDA and ML. Hence, this study could have also been carried out, perhaps, as an investigation of the extended capabilities of enterprise systems. Indeed, some authors consider ERP systems as the foundation for smart manufacturing operations [66] and we saw this same perspective in a few of the case companies.

Interestingly, these companies also appear to be averse to having their transition to smarter PPC tied to their ERP systems. For example, a manager at Company A complained about the company's need to upgrade to the latest version of the ERP system being used at the company. However, the same manager simultaneously raised concerns about the expensiveness of offers from IT vendors for the implementation of some of the upgrades that management desires to prepare the company for IoT, BDA and ML utilisation.

Furthermore, while the current ERP (and other enterprise) system(s) technology has led to better business processes and financial planning [30], its value as a complete production management solution remains limited in practice. One reason for this is the cost of the regular upgrades to latest versions with up-to-date functionalities. This is somewhat linked to the issue of customization and its implications for buggy integration with future upgrades and security updates of the core ERP system. The other reason is the complexity of most ERP installations which leads to numerous companies using their ERP systems for MPS and MPR but not for detailed day-to-day or shift-to-shift scheduling, a function now reserved for spreadsheets such as Microsoft Excel. Therefore, in order to have smarter production systems, managers investigating any or all the triad of smart PPC technologies go with the development of new cloud-based solutions which then connects to the ERP database through a data warehouse solution.

In addition, the form and quality of the data generated by extant enterprise systems are very important, and the ability to handle different formats can be a critical factor in determining success [24,36]. There are two types of data that production systems generate—stream and batch—and these data types require different types of processing in order to derive insights from them. While it would be expected that a company which has enhanced processes and updated, standardized enterprise solutions are more likely to have the foundation to advance faster into smart PPC, we could not find any evidence for that within the case companies. In fact, the company that was most keen on smart PPC was one which was using an older, nonagile ERP solution—that is, Company A.

However, both companies A and B had a significant amount of automation and process sensors which can easily be reconfigured and connected to the internet for a smart PPC solution. Using the stream data in the ERP and from the PLCs of the machines in the production line, Companies C and D instead pursued solutions that could enhance their capacity planning processes, which were their most critical PPC challenges (from their managements' perspective). In addition to extant data sources, Company A also sees potential in using exogenous data and historical data in improving the precision of its production planning process. However, the quality of historical data records which such a smart PPC system would need is in a form that cannot be used without arduous pre-processing. This data quality problem was more prevalent than anticipated and was also influential in determining the ease or difficulty of beginning or advancing towards smart PPC—consistent with Bean and Davenport [17].

6.2.2. The Influence of Planning Environment Variables

We also identified that process-based companies are more likely to benefit from (and therefore, should follow) a smart process strategy, with smart PPC as the driver. For MTO companies, we find that the path to smart control is towards smart products with simplified PPC processes that will continue to allow human control for the required process flexibility. In addition, previous studies have shown that certain industrial sectors such as steel, chemical and plastics and SMEs in general pursue industry 4.0 primarily for operational benefits, while large companies tend to seek long-term strategic benefits from industry 4.0 technologies [33]. As PPC processes contribute more towards operational performance, one would expect similar results. Furthermore, from the case studies, we see why this may be the case. Company C, which is the largest of all four case companies, is a global market leader in its industry and the industry has a high barrier of entry where each product is typically very expensive and highly customized and the products are critical components of the ships they are installed on. In addition to a few projects to automate certain production processes like welding—a very difficult task to automate for MTO production—Company C has focused mostly on innovative technologies that enhance the products by increasing their digital content and making them “connected”. The same holds true for Company D.

For Companies A and B, the products are standardized, have no digital element, are more difficult to digitize (even though pallets can be), and are more likely to be produced from raw materials which are chemically transformed in semi- or fully automated production lines. Therefore, the greater interest of Companies A and B in smart PPC is understandable because they are more inclined to pursue smart processes (and, consequently, smart PPC) rather than smart products, illustrated in Figure 4 below. This can be explained by the fact that these two environments have different kinds of PPC challenges and data generation processes. Process manufacturing tends to have more automated production lines that already generate data and little product complexity, which implies that process data is also consistent and repeatable, thereby enabling smart PPC. The same reason also enables more data granularity for analysis and in a format that is amenable to BDA and ML.

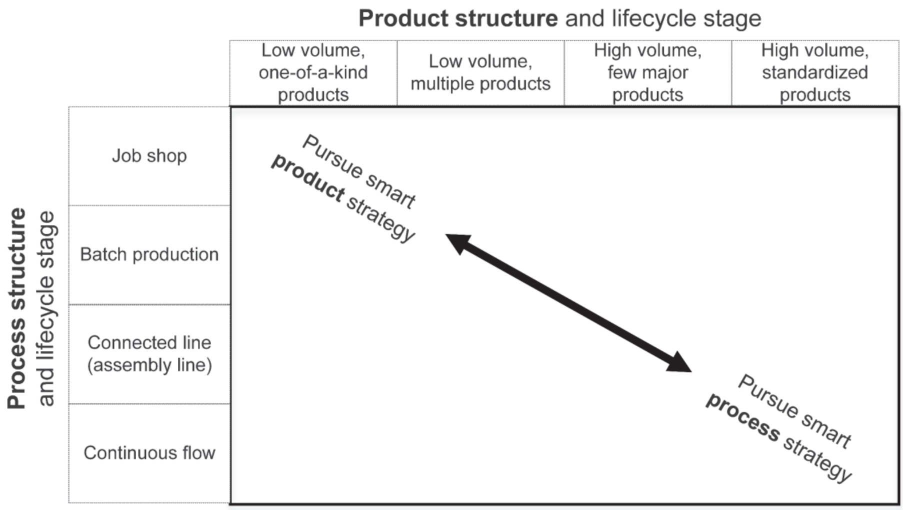


Figure 4. Product-process framework for smart PPC (Adapted from [67]).

In addition, process manufacturing, as seen in Companies A and B, is more amenable to exogeneous telemetry factors which can play a greater role in final production output, particularly when the production is not sufficiently isolated from its environment. Meanwhile, complex products producers with job shop layouts are more focused on balancing workloads and planning human operator requirements due to the high labour content. Furthermore, complex products manufacturers tend to have functional layouts and require much more manual or operator activity. This implies that complex products manufacturers are less likely to generate data in a consistent and repeatable format which, along with the high human content of the operation, makes it less amendable to process digitization.

Hence, MTO operations tend to benefit more from process simplification, improved coordination, and a smart product strategy rather than from a smart process strategy.

Finally, we found evidence to support the observation by Veile et al. [16] regarding the success/failure of industry 4.0 projects in terms of horizontal integration. For example, Company C—which is more powerful relative to other members of its supply chain—tended to dictate the pace of industry 4.0 related innovation within its supply chain. Moreover, the intensely competitive industries tend to have more innovations activities. In this case, we found that Company A, which has a relative small market share in a highly competitive food industry is more eager to pursue innovations that foster horizontal integration to the extent possible with its supply chain partners and has encouraged joint research projects with its major customers, which are mostly retail conglomerates.

6.3. Sustainability and Managerial Implications

Studies have shown (for example, in the automotive industry [33]) that anticipated operational and strategic gains are the primary drivers of industry 4.0 solutions, despite some of its core sustainability benefits. In this regard, our findings align with the results of previous studies as all the case companies in this study—except one (Company B)—had no any explicit sustainability measures or factors driving the PPC process, even though in all but one of the cases, planners were aware of the sustainability goals of their companies and their internal KPIs. The reasons for this are unclear, but it could be because of the following.

First, the level of societal consciousness regarding sustainability is rather high in Norway and it will be difficult to find a company which does not have "sustainability" somewhere in its mission, vision, or core value statements. Furthermore, all the companies in this study have had lean improvement programs at some point in the past decade and demonstrate all the visible elements of lean in their factories. Coupled with the high level of decision making permitted in Norwegian factories, it appears that the responsibility for sustainability has been given to operators on the shop floors in line with a bottoms-up approach. Although this has good benefits, it limits the true sustainability performance to only broad measures like carbon footprint, thereby missing the opportunity to have a truly robust sustainability strategy. Smart PPC will address this, for example, by explicitly enabling the integration of environmental and social KPIs with the financial. Smart PPC can enable sustainability KPIs to be included in the performance parameters of the system, thereby enabling these companies to actively and comprehensively act on their overarching sustainability goals. However, it will require new competences and training from operators and production planners and may also lead to stress and overextension, as observed by Birkel et al. [68].

Secondly, it has also been reported in the literature that managers will occasionally invest in a new fad (e.g., blockchain) or new technology (e.g., cloud computing, a critical enabler of data analytics and BI) due to the fear of missing out. A study of SMEs in Malaysia found that the likelihood that an SME adopts cloud computing increases when competitors are already using the same technology [69]. However, the key question is one regarding the fit of organizational structures, products and production processes, market and PPC processes, and how these issues can influence the use of any new technology in general and IoT, BDA and BI tools in smart PPC specifically. Ultimately, the greatest value is obtained when managers pursue the smart product or process direction that is fitting for their type of company.

In general, managers of companies producing complex, high variety low volume product are more likely to derive most value from pursuing a smart product strategy while those with standard, nonelectronic products in mass production environments are more likely to derive more value from a smart process strategy. In the latter case, a smart PPC solution has great potential and can drive an efficient, autonomous learning production system while tangibly addressing sustainability goals.

7. Conclusions

One important limitation of extant of research within industry 4.0, its technologies and their applicability, is the limited empirical content. In this paper, we attempted to bridge this gap by delving deep into the processes and operations of four case companies in four different types of industries and spanning both MTS and MTO production environments. In answering the need for a systematic, low-risk adoption of industry 4.0 and its technologies, this posed three guiding questions to guide out research for a solution, namely, to describe a smart PPC, the constraints and enablers of such a system and the sustainability implications for manufacturing. We proposed an incremental, conceptual model for development of the smart PPC system within manufacturing companies and exemplified this model with use-cases and the case studies.

7.1. Contributions to Theory

The theoretical contributions of this study to extant research are three-fold. First, the proposed conceptual model and matrix of use-cases can serve as a reference for production managers and other decision makers struggling in efforts to make their production systems more data-driven and intelligent. Moreover, while technologies such as data analytics and BI methods are not new in PPC research, the combination with IoT and the incremental implementation smart PPC approach reduces the risk and enables a natural maturation to smart manufacturing, both essential indicators for SMEs and companies with limited innovation R&D budgets.

Secondly, we found that industry 4.0 implementations should not only integrate adequately with an organization's existing processes and systems, but also with its planning environment. In other words, the planning environment variables—product, production process, and market (i.e., supply and demand processes)—should dictate how industry 4.0 is approached, and consequently, each firm's implementation of smart PPC. Furthermore, the intensity of competition in a firm's industry can influence its need for, and adoption of, smart PPC solution. Companies in highly competitive industries, which are not market leaders are more likely to join the smart 'bandwagon' and in doing so, fail to achieve the fit that is necessary for implementation success.

Third, we have argued that even though the industry currently has no explicit sustainability KPIs guiding the PPC processes, this can be ameliorated in a smart PPC system. This last point is double-edged. On the one hand, we can build environmental KPIs into a smart PPC solution to reduce waste and other deleterious effects of manufacturing operations, while on the other hand, a mature smart PPC solution might lead to a reduction in the need for human planners where one planner could end up comfortably handling an operation hitherto managed by several planners.

7.2. Limitations and Future Research

Considering how limited the sample size for this study is, no bold claims can be made regarding the generalizability of its findings. We have explored the questions of interest through four case companies all based in Norway, albeit with varied company sizes, reach, market positions, and industry structures. Therefore, the location of these companies (being based in Norway) could have influenced our findings as opposed to, say, being situated in Germany which has a much diverse and extensive industrial economy or even neighbouring Sweden which has a larger industrial base. Furthermore, we also expect that the intensity of promotion of smart operations will be greater in industries which are of national strategic importance such as the oil and gas servicing industries in Norway or the automotive manufacturing industry in Germany. Therefore, our findings may be skewed in the sense that it may not reflect the current level of activity on the topic at a national level, for example.

In addition, the technologies in question are evolving and we have studied these case companies only for a short period of time, while the future development paths of these technologies (and vision of industry 4.0) are unknown. Moreover, this study did not capture the effect of popular improvement concepts like lean as factors in our case studies, even though there may be an association with industry 4.0 [70]. This was not without consideration though, as we observed that all four companies had mature lean programmes—with signs of visual control, 5S, and Kanban clearly visible in their factories. Furthermore, this study focused primarily on the perspective of the company and not the supply chain, although the influence of both the supply chain and, to a lesser extent, industry structure was considered as planning environment factors throughout the study. While this choice was fitting for this study as it allows for a nuanced investigation of the subjects, a focus on the supply chain might also yield interesting insights. Nevertheless, since the aim of this study was to explore a relatively young research area, we deem that the research design is adequate for the stated objectives based on the guidelines in Eisenhardt [71].

Future research could extend this study using a large sample size survey to further rigorously test if and to what extent the insights from this study are generalizable. A follow-up large scale national or international survey can address the limitations highlighted above. For example, while this study indicated that process and semi-process MTS producers are likely to favour a smart process strategy as compared to complex products MTO producers, future studies could also investigate what other factors—in addition to extensive process automation and the low or non-existent digital component of products—influence this choice and how these factors can be addressed by the producers of complex products. From the organizational perspective, the skills and capabilities of production planners and systems developers will be a critical success factor for achieving smart PPC, and studies that investigate the required skill sets and how to institutionalize that knowledge will be valuable insights for industry. Finally, with regard to the implementation of the smart PPC system, longitudinal studies that evaluate actual performance improvements achievable in practice when using a fully developed smart PPC system could reveal how much of an effect a smart PPC system can have on improving operational performance and sustainable manufacturing in the factories of the future.

Author Contributions: Conceptualization, O.E.O., F.S. and J.O.S.; methodology, O.E.O.; validation, O.E.O., F.S. and J.O.S.; formal analysis, O.E.O.; investigation, O.E.O.; resources, J.O.S.; data curation, O.E.O.; writing—original draft preparation, O.E.O.; writing—review and editing, O.E.O. and F.S.; supervision, F.S. and J.O.S.; project administration, J.O.S.; funding acquisition, J.O.S. Please turn to the CRediT taxonomy for the term explanation. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by The Research Council of Norway, under the BIA project Manufacturing Network 4.0, number 247637.

Acknowledgments: The authors thank the companies in the completed Manufacturing Network 4.0 project and the ongoing DigiMat project for granting access to company employees for interviews, for factory visits, and for general insights about their respective industries. The authors also express gratitude to the anonymous reviewers for their recommendations and comments during the review process.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. —Interview Guide

1. About the PPC environment variables: demand and supply characteristics, product attributes, and production system:
    a. Describe the demand characteristics of your market
    b. Describe the supply characteristics of your market
    c. Describe your products' attributes in terms of
        i. Bill of materials levels
        ii. Level of digital/electronic functions;
        iii. Shelf-life;
        iv. Number of process routes (no. of production lines could be an indicator)
    d. Describe your production system in terms of
        i. layout;
        ii. level of automation;
        iii. level of product customization;
        iv. intensity of operator input
2. PPC process and system: process, inputs, outputs, technologies, key stakeholders, current challenges

a. Describe the planning process from beginning to the end, step-by-step.
b. Level of standardization:
    i. To what extent is the planning process standardized? What decisions is a planner allowed to use his discretion for?
c. Highlight the following for the planning process:
    i. Frequency of production planning meeting;
    ii. General planning accuracy and how much planning buffer is usual;
    iii. Planning horizon;
    iv. Detailed scheduling horizon;
    v. Frequency of rescheduling
d. PPC process data:
    i. Describe the input and output data for every step of the planning process;
    ii. What are the sources of these data and in what format is it?
    iii. Are these data used for improvement of the planning process?
e. Describe (if any) the technology used for each step of the process (Excel, paper, SAP modules, etc.)

3. History of use of data-driven decision-making:
    a. Data-driven methods in planning and controlling operations. This is with regards to not just having data from automated production lines, but do you use this data in planning and scheduling or is it used mostly for quality control?
    b. Does your company use any of the following:
        i. General business KPIs?
        ii. KPIs for PPC process performance?
        iii. Lean manufacturing elements: 5S, Visual control, SMED, Kanban, Heijunka, Just-in-time, etc.?
        iv. Data-intensive improvement methodologies such as statistical process control, six-sigma, etc.
4. Digitalization approach and initiatives in general
    a. Has your company completed any digitalization initiative/project in the last 3 years?
        i. If yes, how many?
        ii. Which technologies and which use-cases?
        iii. What was the expected business or operations outcome?
        iv. Which initiatives failed, and succeeded?
        v. What challenges did you face during the implementation and use?
    b. Is your company currently working on any digitalization initiative/project?
        i. If yes, how many?
        ii. Which technologies and which use-cases?
        iii. What was the expected business or operations outcome?
        iv. What challenges are you facing with the development, implementation and use?
    c. Is your company planning any future (within the next 1–3 years) digitalization initiative/project?
        i. If yes, how many?

ii. Which technologies and which use-cases?
iii. What is the expected business or operations outcome?

5. Smart PPC decision making initiatives and the supply chain
    a. In addition to the initiatives/projects mentioned above, are there any others that perhaps where smaller, but addressed or affected the PPC process directly or indirectly?
    b. Has the company considered any initiative because other partners in the SC are developing that?
    c. Or was is mandated by the SC partner(s)? If yes, rank this customer among several other customers?
6. What is your opinion on potential of smart technologies in improving the PPC process? (process, inputs, challenges eliminated)
    a. Which elements of your planning process and system can be enhanced using smart technologies?
    b. What do you think are possible limitations of having smart PPC?
7. How does this contribute to your sustainability goals?
    a. Do you have specific sustainability goals for the year? If yes, what are they?
    b. Do you currently have KPIs related to sustainability goals?
    c. How do the company's sustainability goals affect your PPC processes and activities?
    d. Do planners use sustainability parameters when driving the PPC process?

References

1. Bragdon, J.H.; Marlin, J. Is Pollution Profitable. *Risk Manag.* **1972**, *19*, 9–18.
2. Galpin, T.; Whitttington, J.L.; Bell, G. Is your sustainability strategy sustainable? Creating a culture of sustainability. *Corp. Gov.: Int. J. Bus. Soc.* **2015**, *15*, 1–17. [CrossRef]
3. Flint, D.J.; Golicic, S.L. Searching for competitive advantage through sustainability. *Int. J. Phys. Distrib. Logist. Manag.* **2009**, *39*, 841–860. [CrossRef]
4. Singhal, K. Sustainable Operations Management. *Ssrn Electron. J.* **2005**, *14*, 482–492. [CrossRef]
5. Wiendahl, H.-H.; Von Cieminski, G.; Wiendahl, H.-P. Stumbling blocks of PPC: Towards the holistic configuration of PPC systems. *Prod. Plan. Control.* **2005**, *16*, 634–651. [CrossRef]
6. Vollmann, T.E.; Berry, W.L.; Whybark, D.C.; Jacobs, F.R. *Manufacturing Planning and Control for Supply Chain Management*, 5th ed.; The Mcgraw-Hill/Irwin Series in Operations Decision Sciences; McGraw-Hill: New York, NY, USA, 2005.
7. Arnold, J.R.T.; Chapman, S.N.; Clive, L. *Introduction to Materials Management*, 7th ed.; Pearson Prentice Hall: Upper Saddle River, NJ, USA, 2012.
8. Ivanov, D.; Tsipoulanidis, A.; Schönberger, J. Digital Supply Chain, Smart Operations and Industry 4.0. In *Universitext*; Springer Science and Business Media LLC: Berlin, Germany, 2018; pp. 481–526.
9. Strandhagen, J.O.; Vallandingham, L.R.; Fragapane, G.; Strandhagen, J.W.; Stangeland, A.B.H.; Sharma, N. Logistics 4.0 and emerging sustainable business models. *Adv. Manuf.* **2017**, *5*, 359–369. [CrossRef]
10. Fatorachian, H.; Kazemi, H. Impact of Industry 4.0 on supply chain performance. *Prod. Plan. Control.* **2020**, 1–19. [CrossRef]
11. Moeuf, A.; Pellerin, R.; Lamouri, S.; Tamayo, S.; Barbaray, R. The industrial management of SMEs in the era of Industry 4.0. *Int. J. Prod. Res.* **2017**, *56*, 1118–1136. [CrossRef]
12. Machado, C.G.; Winroth, M.P.; Da Silva, E.H.D.R. Sustainable manufacturing in Industry 4.0: An emerging research agenda. *Int. J. Prod. Res.* **2019**, *58*, 1462–1484. [CrossRef]
13. Sun, D.; Huang, R.; Chen, Y.; Wang, Y.; Zeng, J.; Yuan, M.; Pong, T.-C.; Qu, H. PlanningVis: A Visual Analytics Approach to Production Planning in Smart Factories. *Ieee Trans. Vis. Comput. Graph.* **2019**, *26*, 1. [CrossRef]
14. Ren, L.; Zhang, L.; Tao, F.; Zhao, C.; Chai, X.; Zhao, X. Cloud manufacturing: From concept to practice. *Enterp. Inf. Syst.* **2013**, *9*, 186–209. [CrossRef]

15. Trunzer, E.; Calà, A.; Leitão, P.; Gepp, M.; Kinghorst, J.; Lüder, A.; Schauerte, H.; Reifferscheid, M.; Vogel-Heuser, B. System architectures for Industrie 4.0 applications. *Prod. Eng.* **2019**, *13*, 247–257. [CrossRef]
16. Veile, J.W.; Kiel, D.; Müller, J.M.; Voigt, K.-I. Lessons learned from Industry 4.0 implementation in the German manufacturing industry. *J. Manuf. Technol. Manag.* **2019**. [CrossRef]
17. Bean, R.; Davenport, T.H. "Companies Are Failing in Their Efforts to Become Data-Driven." Harvard Business Review. Available online: https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven (accessed on 29 December 2019).
18. Leitão, P. Agent-based distributed manufacturing control: A state-of-the-art survey. *Eng. Appl. Artif. Intell.* **2009**, *22*, 979–991. [CrossRef]
19. Bonney, M. Reflections on production planning and control (PPC). *Gestão Produção* **2000**, *7*, 181–207. [CrossRef]
20. Garetti, M.; Taisch, M. Neural networks in production planning and control. *Prod. Plan. Control.* **1999**, *10*, 324–339. [CrossRef]
21. Sánchez-Herrera, S.; Montoya-Torres, J.R.; Solano-Charris, E.L. Flow shop scheduling problem with position-dependent processing times. *Comput. Oper. Res.* **2019**, *111*, 325–345. [CrossRef]
22. Oluyisola, O.E.; Strandhagen, J.W.; Buer, S.-V. RFId technology in the manufacture of customized drainage and piping systems: A case study. *Ifac-Pap.* **2018**, *51*, 364–369. [CrossRef]
23. Oluyisola, O.E.; Salmi, T.E.; Strandhagen, J.O. Causes of Delivery-Time Variance in Maritime-Equipment Manufacturing Supply-Chains: An Empirical Study. In *Proceedings of the Nonlinear Model Predictive Control*; Springer Science and Business Media LLC: Berlin, Germany, 2018; pp. 415–421.
24. Gustavsson, M.; Wänström, C. Assessing information quality in manufacturing planning and control processes. *Int. J. Qual. Reliab. Manag.* **2009**, *26*, 325–340. [CrossRef]
25. Schuh, G.; Potente, T.; Hauptvogel, A. Methodology for the Evaluation of Forecast Reliability of Production Planning Systems. *Procedia Cirp* **2014**, *17*, 469–474. [CrossRef]
26. Stock, T.; Seliger, G. Opportunities of Sustainable Manufacturing in Industry 4.0. *Procedia Cirp* **2016**, *40*, 536–541. [CrossRef]
27. Stock, T.; Obenaus, M.; Kunz, S.; Kohl, H. Industry 4.0 as enabler for a sustainable development: A qualitative assessment of its ecological and social potential. *Process. Saf. Environ. Prot.* **2018**, *118*, 254–267. [CrossRef]
28. Hermann, M.; Pentek, T.; Otto, B. Design Principles for Industrie 4.0 Scenarios. In *Proceedings of the 2016 49th Hawaii International Conference on System Sciences (HICSS)*; Institute of Electrical and Electronics Engineers (IEEE): Piscataway, NJ, USA, 2016; pp. 3928–3937.
29. Iansiti, M.; Lakhani, K.R. Digital Ubiquity: How Connections, Sensors, and Data Are Revolutionizing Business. *Harv. Bus. Rev.* **2014**, *92*, 19.
30. Reynolds, G. *Information Technology for Managers*; Nelson Education: Toronto, ON, Canada, 2015.
31. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Papadopoulos, T.; Luo, Z.; Wamba, S.F.; Roubaud, D. Can big data and predictive analytics improve social and environmental sustainability? *Technol. Soc. Chang.* **2019**, *144*, 534–545. [CrossRef]
32. Dalenogare, L.S.; Benitez, G.; Ayala, N.F.; Frank, A.G. The expected contribution of Industry 4.0 technologies for industrial performance. *Int. J. Prod. Econ.* **2018**, *204*, 383–394. [CrossRef]
33. Müller, J.M.; Kiel, D.; Voigt, K.-I. What Drives the Implementation of Industry 4.0? The Role of Opportunities and Challenges in the Context of Sustainability. *Sustainability* **2018**, *10*, 247. [CrossRef]
34. Schuh, G.; Anderl, R.; Gausemeier, J.; ten Hompel, M.; Wahlster, W. *"Industrie 4.0 Maturity Index." Managing the Digital Transformation of Companies*; Herbert Utz Verlag: Munich, Germany, 2017.
35. Banker, R.D.; Bardhan, I.R.; Lin, H.C. Plant Information Systems, Manufacturing Capabilities, and Plant Performance. *Mis Q.* **2006**, *30*, 315. [CrossRef]
36. Wamba, S.F.; Akter, S.; Edwards, A.; Chopin, G.; Gnanzou, D. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *Int. J. Prod. Econ.* **2015**, *165*, 234–246. [CrossRef]
37. Ngai, E.W.; Law, C.; Wat, F. Examining the critical success factors in the adoption of enterprise resource planning. *Comput. Ind.* **2008**, *59*, 548–564. [CrossRef]
38. Koh, L.; Gunasekaran, A.; Goodman, T. Drivers, barriers and critical success factors for ERPII implementation in supply chains: A critical analysis. *J. Strat. Inf. Syst.* **2011**, *20*, 385–402. [CrossRef]
39. Jabbour, A.B.L.D.S.; Jabbour, C.J.C.; Foropon, C.; Filho, M.G. When titans meet – Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technol. Soc. Chang.* **2018**, *132*, 18–25. [CrossRef]

40. Sousa, R.; Voss, C.A.; Voss, C. Contingency research in operations management practices. *J. Oper. Manag.* **2008**, *26*, 697–713. [CrossRef]
41. Hicks, C.; McGovern, T.; Earl, C.F. A Typology of UK Engineer-to-Order Companies. *Int. J. Logist. Res. Appl.* **2001**, *4*, 43–56. [CrossRef]
42. Høyer, M.R.; Oluyisola, O.E.; Strandhagen, J.O.; Semini, M.G. Exploring the challenges with applying tracking and tracing technology in the dairy industry. *Ifac-Pap.* **2019**, *52*, 1727–1732. [CrossRef]
43. Meredith, J. Building operations management theory through case and field research. *J. Oper. Manag.* **1998**, *16*, 441–454. [CrossRef]
44. Handfield, R.B.; A Melnyk, S. The scientific theory-building process: A primer using the case of TQM. *J. Oper. Manag.* **1998**, *16*, 321–339. [CrossRef]
45. Jonsson, P.; Mattsson, S.-A. The implications of fit between planning environments and manufacturing planning and control methods. *Int. J. Oper. Prod. Manag.* **2003**, *23*, 872–900. [CrossRef]
46. Wilhelm, M.; Blome, C.; Wieck, E.; Xiao, C.Y. Implementing sustainability in multi-tier supply chains: Strategies and contingencies in managing sub-suppliers. *Int. J. Prod. Econ.* **2016**, *182*, 196–212. [CrossRef]
47. Yin, R.K. *Case Study Research: Design and Methods*, 4th ed.; Sage Publications: Thousand Oaks, CA, USA, 2009.
48. Klaus, H.; Rosemann, M.; Gable, G. What is ERP? *Inf. Syst. Front.* **2000**, *2*, 141–162. [CrossRef]
49. De Man, J.C.; Strandhagen, J.O. Spreadsheet Application still dominates Enterprise Resource Planning and Advanced Planning Systems. *Ifac-Pap.* **2018**, *51*, 1224–1229. [CrossRef]
50. Liao, Y.; Deschamps, F.; Loures, E.D.F.R.; Ramos, L.F.P. Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. *Int. J. Prod. Res.* **2017**, *8*, 1–21. [CrossRef]
51. Davies, J. *Understanding IPv6*, 3rd ed.; Microsoft Press: Seattle, WA, USA, 2012.
52. Chen, B.; Wan, J.; Celesti, A.; Li, D.; Abbas, H.; Zhang, Q. Edge Computing in Iot-Based Manufacturing. *IEEE Commun. Mag.* **2018**, *56*, 103–109. [CrossRef]
53. Kärkkäinen, M. Increasing efficiency in the supply chain for short shelf life goods using RFID tagging. *Int. J. Retail. Distrib. Manag.* **2003**, *31*, 529–536. [CrossRef]
54. Ustundag, A.; Tanyas, M. The Impacts of Rfid Technology on Supply Chain Costs. *Transp. Res. E Logist. Transp. Rev.* **2009**, *45*, 29–38. [CrossRef]
55. Huang, B.; Wang, W.; Ren, S.; Zhong, R.Y.; Jiang, J. A proactive task dispatching method based on future bottleneck prediction for the smart factory. *Int. J. Comput. Integr. Manuf.* **2019**, *32*, 278–293. [CrossRef]
56. Park, K.T.; Nam, Y.W.; Lee, H.S.; Im, S.J.; Noh, S.D.; Son, J.Y.; Kim, H. Design and implementation of a digital twin application for a connected micro smart factory. *Int. J. Comput. Integr. Manuf.* **2019**, *32*, 596–614. [CrossRef]
57. Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W. Digital Twin in manufacturing: A categorical literature review and classification. *Ifac-Pap.* **2018**, *51*, 1016–1022. [CrossRef]
58. Kuo, Y.-H.; Kusiak, A. From data to big data in production research: The past and future trends. *Int. J. Prod. Res.* **2018**, *57*, 4828–4853. [CrossRef]
59. Kusiak, A. Artificial Intelligence and Operations Research In Flexible Manufacturing Systems. *Infor: Inf. Syst. Oper. Res.* **1987**, *25*, 2–12. [CrossRef]
60. Brintrup, A.; Pak, J.; Ratiney, D.; Pearce, T.; Wichmann, P.; Woodall, P.; McFarlane, D. Supply chain data analytics for predicting supplier disruptions: A case study in complex asset manufacturing. *Int. J. Prod. Res.* **2019**, 1–12. [CrossRef]
61. Monostori, L.; Markus, A.; Van Brussel, H.; Westkämpfer, E. Machine Learning Approaches to Manufacturing. *Cirp Ann.* **1996**, *45*, 675–712. [CrossRef]
62. Shiue, Y.-R.; Lee, K.-C.; Su, C.-T. Real-time scheduling for a smart factory using a reinforcement learning approach. *Comput. Ind. Eng.* **2018**, *125*, 604–614. [CrossRef]
63. Corsten, H.; May', C. Artificial neural networks for supporting production planning and control. *Technovation* **1996**, *16*, 67–93. [CrossRef]
64. Hruschka, H. Determining market response functions by neural network modeling: A comparison to econometric techniques. *Eur. J. Oper. Res.* **1993**, *66*, 27–35. [CrossRef]
65. Wróblewska, A.; Stanisławek, T.; Prus-Zajączkowski, B.; Garncarek, Ł. Robotic Process Automation of Unstructured Data with Machine Learning. *Position Pap. 2018 Fed. Conf. Comput. Sci. Inf. Syst.* **2018**, *16*, 9–16. [CrossRef]

66. Haddara, M.; Elragal, A. The Readiness of ERP Systems for the Factory of the Future. *Procedia Comput. Sci.* **2015**, *64*, 721–728. [CrossRef]
67. Hayes, R.H.; Wheelwright, S.C. Link Manufacturing Process and Product Life Cycles. *Harv. Bus. Rev.* **1979**, *57*, 133–140.
68. Birkel, H.; Veile, J.W.; Müller, J.M.; Hartmann, E.; Voigt, K.-I. Development of a Risk Framework for Industry 4.0 in the Context of Sustainability for Established Manufacturers. *Sustain.* **2019**, *11*, 384. [CrossRef]
69. Hassan, H. Factors Influencing Cloud Computing Adoption in Small and Medium Enterprises. *J Inf. Commun. Technol.* **2020**, *16*, 21–41.
70. Buer, S.-V.; Strandhagen, J.O.; Chan, F.T. The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda. *Int. J. Prod. Res.* **2018**, *56*, 2924–2940. [CrossRef]
71. Eisenhardt, K.M. Building Theories from Case Study Research. *Acad. Manag. Rev.* **1989**, *14*, 532. [CrossRef]

Paper 5

Oluyisola, O. E., Bhalla, S., Sgarbossa, F., & Strandhagen, J. O. (2021). Designing and Developing Smart Production Planning and Control Systems in the Industry 4.0 Era: A Methodology and Case Study. under review at the *Journal of Intelligent Manufacturing*.

[This paper is awaiting publication and is therefore not attached]

ISBN 978-82-326-5860-2 (printed ver.)
ISBN 978-82-326-6785-7 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (online ver.)

NTNU

Norwegian University of
Science and Technology