Annual Reviews in Control 53 (2022) 370–381

Contents lists available at ScienceDirect

Annual Reviews in Control

journal homepage: www.elsevier.com/locate/arcontrol

Full Length Article

Towards smart production planning and control; a conceptual framework linking planning environment characteristics with the need for smart production planning and control

Mina Rahmani [a,*], Anita Romsdal [a], Fabio Sgarbossa [a], Jan Ola Strandhagen [a], Mathias Holm [b]

[a] *Department of Mechanical and Industrial Engineering, NTNU, 7491 Trondheim, Norway*
[b] *Brynild AS, 1601 Fredrikstad, Norway*

ARTICLE INFO

Keywords:
Production planning and control
Smart technologies
Industry 4.0
Case study
Food

ABSTRACT

Rapid advances in Industry 4.0 have the potential to transform production planning and control (PPC) through the emerging concept of smart PPC. This paper provides a visionary perspective by addressing the gap in research on how the characteristics of a company's planning environment impact on the need for, and potential benefit of, smart PPC. The paper posits that the potential of smart PPC to improve PPC performance increases with the complexity of the planning environment. A set of propositions is developed for how 12 product, market, and process variables impact on the need for smart PPC. These are operationalized into a conceptual framework that can be used as a tool by practitioners and academics to assess a company's need for smart PPC. A case study from the food sector illustrates the applicability of the framework and describes three potential applications for how four elements of smart PPC (real-time data management, dynamic production planning and re-planning, autonomous production control, and continuous learning) can be used to address key PPC challenges and open new opportunities for improving PPC. Future research should strengthen the validity and applicability of the proposed framework through additional cases across industrial sectors and carry out case studies, surveys, and structural equation modeling to investigate the specific relationship between planning environment characteristics, smart technologies, and the elements of smart PPC.

1. Introduction

Smart manufacturing is a well-established concept. Through the use of emerging technologies, production systems are increasing their performance and simultaneously generating increasingly large volumes of data. The potential use of this data for production planning and control (PPC) and performance improvements has been widely promoted in industry and academia but with limited adoption (Chavez et al., 2017; Fatorachian & Kazemi, 2021; Kusiak, 2017; Nagy et al., 2018). Unprecedented opportunities are provided to not only support human decision-making but also automate planning and control tasks and make way for more integrated, dynamic, and real-time PPC. Many studies have investigated the application of Industry 4.0 for smart manufacturing (Mittal et al., 2018; Qi & Tao, 2018; Wang et al., 2021; Zheng et al., 2018), and there is a growing number of papers on how emerging technologies can be used for ***smart PPC*** (see Bueno et al., 2020 for an overview). However, few empirical case studies have been reported that specifically focus on the role of PPC in achieving smart manufacturing or how Industry 4.0 can be used to improve PPC (Moeuf et al., 2018; Oluyisola, 2021; Ren et al., 2015; Sun et al., 2019).

From a contingency perspective, before we start implementing new technologies for smart PPC, we need to understand in which situations such technologies have the largest potential to improve PPC performance. For this purpose, we adopt the definition of Oluyisola et al. (2020), where smart PPC is understood 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 data sources.

This paper provides a visionary perspective on the emerging concept of smart PPC by investigating the relationship between the planning environment characteristics of a company and the need for smart PPC. The ***purpose of the paper*** is to provide ***a structured tool*** that can guide academics and practitioners in ***evaluating the need for smart PPC***

* Corresponding author.
E-mail address: mina.rahmani@ntnu.no (M. Rahmani).

https://doi.org/10.1016/j.arcontrol.2022.03.008
Received 10 January 2022; Received in revised form 29 March 2022; Accepted 30 March 2022
Available online 14 April 2022

through an assessment of a company's planning environment characteristics.

Firstly, we use literature to identify the variables of a company's production planning environment with regards to product, market, and process characteristics. The resulting framework contributes to the literature on PPC through a structured way to describe a company's planning environment, with illustrations of how different variables complicate PPC. The paper's second contribution is towards the literature on smart PPC, where we develop a conceptual framework that links planning environment characteristics with the need for smart PPC. The framework was developed from a set of propositions on how each variable impacts on the need for smart PPC. Lastly, the paper contributes with empirical insights from a case study. The case illustrates how the proposed framework can be used in a company to identify the most challenging PPC aspects and assess the need for smart PPC, and outlines some potential applications of smart PPC.

The structure of the paper is as follows. Section 2 describes the theoretical background for the paper with regards to smart PPC and production planning environment characteristics. In section 3, the framework and propositions linking the production planning environment characteristics with the need for smart PPC are presented. The framework is subsequently used in the case study in section 4. Section 5 concludes the paper by outlining the main contributions and providing directions for future research.

2. Theoretical background

Industry 4.0 and the emergence of associated smart technologies are expected to have considerable impact on PPC. However, some recent studies indicate that many companies are facing challenges in their efforts towards adoption of smart technologies and realization of smart PPC (Bean & Davenport, 2019; Oluyisola, 2021). Many of these challenges are related to the characteristics of the planning environment (Oluyisola et al., 2020), and an understanding of these characteristics is therefore important in order to identify the needs and opportunities for smart PPC. Below, we first define and describe smart PPC and then present a framework for mapping the planning environment characteristics that constrain PPC.

2.1. Smart production planning and control

A company's PPC function is concerned with operating and coordinating the company's resources on a day-to-day basis. The purpose is to ensure the availability of materials and other variable resources needed to supply the goods and services which fulfill customers' demands (Bertrand et al., 1990; Slack et al., 2013). PPC encompasses decision-making processes and policies about planning (estimating, routing, scheduling, and resource loading) and control (dispatching, expediting, inspecting, evaluating, and taking corrective action) of production processes and resources (Slack et al., 2013).

A number of enterprise systems have emerged to support the PPC task, from material requirements planning (MRP) and manufacturing resource planning (MRPII) systems to the more advanced enterprise resource planning (ERP) systems. Later, manufacturing execution systems (MES) and advanced planning and scheduling (APS) systems have emerged to address some of the limitations of ERP systems. However, these also have their limitations, including being too simplistic and rigid, with limited ability to adjust schedules to real-time or near-real-time data, as well as being very expensive and requiring employees with specialized skills (Oluyisola, 2021). In addition, such systems are still based on periodic planning even though demand is continuous (Oluyisola, 2021).

The developments within Industry 4.0 now present new opportunities for creating a real-time connection between resources, services, and humans through smart technologies such as cyber-physical systems (CPS), the internet of things (IoT), big data analytics (BDA), and machine learning (ML) (Oluyisola et al., 2020; Stock et al., 2018). Building on the Industry 4.0 framework, smart PPC has emerged as a result of the integration of Industry 4.0 technologies and capabilities into PPC (Oluyisola et al., 2020).

Building on previous literature, smart PPC can be understood as consisting of four main elements; real-time data management (Saad et al., 2021), dynamic production planning and re-planning (Saad et al., 2021), autonomous production control (Saad et al., 2021), and continuous learning (Oluyisola et al., 2020).

Real-time data management: it consists of tracking, collecting, analyzing, and protecting data from internal and external sources to provide adaptive and responsive planning, scheduling, and execution (Saad et al., 2021). Real-time data acquisition technologies such as radio frequency identification (RFID) tags (Grunow & Piramuthu, 2013), real-time localization systems (RTLS) (Reuter et al., 2017; Saad et al., 2021), and sensors and actuators (Malek et al., 2017) provide access to real-time data based on the current situation and offer more and qualified data for PPC decision-makers to support and facilitate PPC (Strandhagen et al., 2011; Zheng et al., 2018). It should be noted that real-time data is not only about the accuracy of the data, it is also about getting the required information at the required time (Arica & Powell, 2014). Therefore, by applying real-time data management, PPC decision-makers and managers can recognize deficiencies and prevent potential errors and problematic issues on the shopfloor (Arica & Powell, 2014), allowing decision-makers to plan and re-plan dynamically.

Dynamic production planning and re-planning: smart PPC provides a company with the ability to respond quickly to changes or unplanned events in the production processes. Capabilities for dynamic scheduling and rescheduling are required to automatically deal with such disruptions – enabled by access to real-time data and participation of all main internal and external parties in the production planning (Saad et al., 2021). Dynamism here refers to the rate of change in elements of an organization's environment that are not directly within its control (Makkonen et al., 2014). Causes of such changes are events that can be categorized into two groups: resource-related and job-related (Ouelhadj & Petrovic, 2009). Examples of resource-related events include machine breakdown, operator sickness, unavailability or failures of tools, loading restrictions, delay in the arrival or shortage of materials, and defective material. Job-related events include rush jobs, job cancellations, due date changes, early or late arrival of jobs, job priority changes, and job processing time adjustments (Ouelhadj & Petrovic, 2009). Dynamic production planning and re-planning thus provide opportunities for a company to plan and re-plan efficiently, reduce labor costs, increase production speed and responsiveness, and improve product quality control (Li et al., 2006; Oluyisola et al., 2020).

Autonomous production control: autonomy can be understood as a system's ability to make decisions without external instructions and to perform activities without the need for external forces (Scholz-Reiter & Freitag, 2007). The task of production control is to ensure that schedules are executed with the consideration of potential disruptions (Grundstein et al., 2017). Autonomous production control seeks to enhance the performance of production systems by enabling an object, such as a resource, pallet, or order, to make decisions on its own without human involvement (Martins et al., 2018). Machine-to-machine (M2M) communication enables "smart devices" to communicate with each other independently and make joint decisions without direct human intervention (Verma et al., 2016). Self-optimizing production control is necessary in such systems to continually assess the current situation, and as a consequence, the job allocations to the machines can be adapted at any moment (Köchling et al., 2016). Application of advanced data processing, data analytics, data storage, and cloud technologies can be used to support control systems in solving real-time problems, thus achieving higher flexibility, robustness (Bendul & Blunck, 2019), and reliability (Bueno et al., 2020) and paving the way towards autonomous production control (Saad et al., 2021).

Continuous learning: many companies have made significant investments in technologies to automate production processes, while many PPC decisions are still made based on expert experience (Bresler et al., 2020). The production and PPC-related expertise, experience, and tacit knowledge of operators, planners, and managers should be captured and modeled so they can be used for PPC decision-making (Bresler et al., 2020). Continuous learning can further be integrated into PPC through the application of ML algorithms that run independently, without human intervention (Oluyisola et al., 2020). Continuous learning is currently not well addressed within PPC (Oluyisola et al., 2020), but as an element of smart PPC, it can enable the evolution of "digital thinking", which will bring improvements to make smarter, faster, and more accurate decisions (Thomas et al., 2018).

2.2. Production planning environment characteristics

The characteristics of a company's planning environment constrain the company's PPC decisions and policies and affect the efficacy of PPC (Hong et al., 2010; Jonsson & Mattsson, 2003; Romsdal, 2014). Thus, an analysis of these characteristics provides an understanding of the environment within which PPC is conducted and can assist in identifying the PPC contexts where smart PPC is most beneficial.

Following the approach of Jonsson and Mattsson (2003), for the purpose of this study, we describe planning environments in terms of their product, market, and process characteristics. Building on the framework of Romsdal (2014), we identified 12 variables that we expect to have the largest impact on the need for smart PPC. For our purposes, some variables from the Romsdal framework have been excluded or adjusted, while others have been added, depending on their expected impact on the need for smart PPC. The variables "demand uncertainty" and "supply uncertainty" are changed to "demand variability" and "supply variability" respectively because variability can be modeled and, in some ways, controlled thanks to the analysis of data collected from the market. Further, "product perishability" is instead expressed as the "ability to keep inventory" to include also other factors that impact this ability. The variable "stock-out rates in retail stores" is not included since it does not have a direct effect on PPC. "Make-to-order lead time" is changed to the more generic term "process lead time". The variable "plant, processes and technology" is replaced by the two variables "process flexibility" and "process complexity" since these better describe the planning environment.

The revised framework is presented in Table 1, where each variable is firstly defined, and then some non-exhaustive examples are provided to illustrate how each variable can impact PPC. The examples were logically derived in a discussion among the authors.

2.3. Research gap

Very few empirical case studies have been reported that specifically focus on the role of PPC in achieving smart manufacturing or on how Industry 4.0 can be used to improve PPC (Bueno et al., 2020; Moeuf et al., 2018; Oluyisola et al., 2022; Ren et al., 2015; Sun et al., 2019).

Bueno et al. (2020) conducted a systematic literature review investigating the relationship between PPC and Industry 4.0. They developed an analytical framework for how PPC in Industry 4.0 is affected by smart capabilities. A number of smart capabilities based on five Industry 4.0 technologies were identified, including real-time, autonomy, adaptability, and dynamic capabilities. Product, market, and production process factors that influence smart PPC capabilities were identified, but the study did not investigate *how* the different factors affect the performance of smart PPC. The authors concluded that more research is needed into the question of fit between Industry 4.0 technologies and their integration into PPC in different production environments.

Another recent study on smart PPC is Oluyisola et al. (2020), who propose an incremental, conceptual model of smart PPC. They described a path for how Industry 4.0 technologies can be used in the transition

Table 1
Production planning environment characteristics and their impact on production planning and control

Category	Variable	Definition	Examples of challenges for production planning and control
Product	Product complexity	Number of levels in the bill of material, number of items on each level (Jonsson & Mattsson, 2003), and interrelatedness of product components (Lamming et al., 2000)	A high number of components and interrelatedness between components increase PPC complexity. Any changes in the production of one component can affect the production of many end products – requiring replanning and resource-demanding monitoring and control, particularly in situations with shared capacity. High complexity increases the need for volume flexibility and often leads to smaller batch sizes in order to respond quickly to changes in demand.
	Product variety	Number of product variants (Jonsson & Mattsson, 2003)	High product variety means production volume is spread over many product variants. This complicates demand forecasting, materials planning, and PPC of raw materials, components, and finished products. A large number of variants increases the number of changeovers and limits the ability to exploit economies of scale through large batches.
	Product life cycle	Stage and length of a product's life cycle from launch to termination (Aitken et al., 2005; Christopher et al., 2009)	Short product life cycles and frequent product launches and terminations require high product mix and volume flexibility and lead to frequent changes to the product mix. Low demand predictability at launch and termination stages requires an ability to quickly adapt to changes in demand, favoring smaller batches which lead to more frequent changeovers.
	Product volume and variability	Volume related to market demand and variability of volume (Aitken et al., 2005)	Low volumes per variant often lead to small batch sizes and a high number of changeovers to satisfy demand. High volume variability requires high volume flexibility in order to deliver the required variants within the lead time. This typically limits the ability to exploit economies of scale through large batch sizes and can lead to high inventories and high risk of obsolescence.

(*continued on next page*)

Table 1 (*continued*)

Category	Variable	Definition	Examples of challenges for production planning and control
Market	Delivery lead time	The time window between the placement of customer order until its delivery to the customer (Milgate, 2001)	Short delivery lead time requirements require high mix and volume flexibility. This can be achieved through frequent changeovers or using finished goods inventory as buffers against demand and supply variability. Any disturbances such as machine breakdowns or lack of raw materials can require replanning and additional changeovers.
	Delivery lead time variability	Variability related to lead time predictability (Aitken et al., 2005)	High delivery lead time variability reduces forecast accuracy and the ability to use inventory to buffer against demand and supply variability. This typically leads to more frequent changeovers to meet customer demand within lead time requirements and can require frequent replanning.
	Demand variability	Predictability and stability of demand (Lee, 2002)	High demand variability complicates demand planning and reduces the accuracy of demand forecasting. Often large inventories are used to buffer against demand variability in order to be able to respond quickly to changes in demand – but this increases the risk of obsolescence and scrapping.
	Ability to keep inventory	Perishability of raw materials, intermediates, and finished goods inventories (Coelho & Laporte, 2014)	Limited ability to keep inventory, e.g., due to perishability or risk of obsolescence, limits the possibility to use inventory to buffer against demand and supply variability. This favors frequent production in smaller batches, increasing the number of setups and changeovers and limiting the ability to exploit economies of scale.
Process	Process lead time	The time between starting and terminating a process (Karmarkar, 1993)	Long process lead times lead to high levels of work-in-process (WIP) inventory and limit the ability to quickly adjust production volumes in response to changes in demand and supply. Long lead times increase the need for controlling queues and flows of products.
	Process flexibility	Ability to change product volume (Jordan & Graves, 1995) and produce different types of products (Hopp et al., 2010)	Low process flexibility complicates several PPC decisions, such as product assignment and capacity. Rigid processes with long setup times favor large batch sizes and infrequent changeovers, which again reduces volume and product mix flexibility and the ability to respond quickly to changes in demand or supply. Machine breakdowns and changes in production processes further complicate control.
	Process complexity	Number of processes (Jonsson & Mattsson, 2003) and interrelatedness of processes (Jacobs, 2013)	A high number of production processes complicate planning and control, particularly when processes are interrelated. Challenges include difficulties in establishing and controlling lead times, determining routings, monitoring backlogs, controlling queues and WIP, and coordinating flows of semi-finished items and components with the production of end products.
	Supply variability	Predictability and stability of supply (Lee, 2002)	High supply variability reduces the ability to quickly increase production volumes if inputs are not available. High inventory levels are therefore often used to buffer against low stability and predictability. Production should continuously monitor supply to foresee and manage shortages and attempt to manage variability through dynamic planning.

from connected to transparent, and finally intelligent and smart production systems. The study used a set of attributes to describe and compare the planning environments and Industry 4.0 initiatives in four empirical cases. However, the study did not investigate *how* the different variables impact on the degree of need for, or potential benefits of, Industry 4.0 for smart PPC.

Saad et al. (2021) proposed and tested a hierarchical requirements model for smart PPC, consisting of criteria, drivers, and technologies. The three main criteria in the model were real-time data management systems, dynamic production planning, and autonomous execution control. The authors used the smart small and medium sizes enterprises (SME) technology readiness assessment (SSTRA) methodology to measure SMEs' technology capability to implement Industry 4.0. However, this methodology did not consider any planning environment characteristics in the assessment of the requirements for smart PPC.

In the most recent study on smart PPC, Oluyisola et al. (2022) propose a 5-step methodology for designing and developing smart PPC. Here, the first step consists of determining the objectives and priorities for developing smart PPC with regards to the fit with planning environment variables. However, the authors do not identify or propose any frameworks or tools that can assist companies assess this fit, or the degree to which a company can benefit from smart PPC.

Although the literature on smart PPC is growing, there appears to still be a gap with regards to how one can assess a company's need for smart PPC and how this need is linked to the characteristics of the production planning environment.

3. A framework linking production planning environment characteristics with the need for smart production planning and control

Based on the research gap identified in section 2.3, the purpose of this paper is to provide a structured tool that can guide academics and practitioners in evaluating the need for smart PPC through an analysis of company planning environment characteristics.

For this purpose, we started with the variables from the framework in Table 1 because it provides a structured set of variables that have an impact on PPC. Since the literature on the relationship between planning environment characteristics and smart PPC is scarce, logical assumptions have been used to develop a set of propositions on how the variables impact the need for smart PPC. "Need" is here understood as the degree to which smart PPC is expected to be beneficial for PPC, i.e., improve PPC performance. A scale was assigned to each variable, where the variable at its most challenging setting is associated with a high need for PPC. The assumption is that a variable at its most challenging setting complicates PPC, thus increasing the expected benefit of applying elements of smart PPC to address the challenges.

The propositions are summarized in the framework in Table 2. For each variable, the degree of need for smart PPC is indicated by a scale of one, two, or three stars. One star (*) indicates that the variable is at its most favorable setting, i.e., a situation in which the characteristic does not significantly complicate PPC and smart PPC is therefore not expected to lead to considerable improvements in PPC performance. Two stars (**) indicate that the variable is at a medium setting, i.e., a situation where smart PPC is expected to provide some benefit. Three stars (***) indicate that the variable is at its least favorable or most challenging setting, where smart PPC is expected to provide considerable benefits for PPC. The righthand column provides non-exhaustive examples of how some parts of the four elements of smart PPC identified in section 2.1 can be beneficial in PPC, where **R** = real-time data management; **D** = dynamic production planning and re-planning; **A** = autonomous production control; and **C** = continuous learning. With the rapid development of smart technologies, the potential applications of

Table 2
Framework linking planning environment characteristics with the need for smart PPC

Category	Variable	Proposition	Need for smart PPC *	 **	 ***	Examples of how elements of smart PPC can be beneficial
Product	Product complexity	The higher the product complexity, the higher the need for smart PPC.	Low	Medium	High	Through smart PPC a company can more efficiently collect, store and update product data **(R)** and enable dynamic changes and replanning, with associated effects on capacity and material requirements **(D)**.
	Product variety	The higher the product variety, the higher the need for smart PPC.	Low	Medium	High	Smart PPC can simplify the management of a high number of product variants through a more proactive definition and analysis of product families, combining both objective (data-driven) and subjective (based on planners' experience) clustering **(R; C)**.
	Product life cycle	The shorter the product life cycle, the higher the need for smart PPC.	Long	Medium	Short	When the product mix changes frequently, access to more up-to-date product data is essential **(R)** so that PPC processes can be adapted **(D)** or can adapt themselves **(A)** quickly to a new product mix.
	Product volume and variability	The higher the volume variability, the higher the need for smart PPC.	Low	Medium	High	The higher the volume variability, the more essential is the ability to foresee product volume behavior over time. Forecasting accuracy relies on the availability of up-to-date demand data **(R)** and knowing how to exploit this data in PPC in a smart way **(C)**.
Market	Delivery lead time	The shorter the delivery lead time, the higher the need for smart PPC.	Long	Medium	Short	Short delivery lead time requires the use of up-to-date demand data for use in PPC decision-making **(R)**, enabling the production system to respond quicker to sudden changes in demand, such as customer rush orders **(D)**.
	Delivery lead time variability	The higher the delivery lead time variability, the higher the need for smart PPC.	Low	Medium	High	Data on lead time variability can be used by planners to better predict the behavior of the delivery system **(R; C)** and when needed, dynamically re-plan production or change inventory allocation **(D)**.
	Demand variability	The higher the demand variability, the higher the need for smart PPC.	Low	Medium	High	For producers, more up-to-date demand data is an essential input to PPC to foresee, manage and respond quickly to changes in demand **(R; D)**. AI tools can be used to automate some demand forecasting tasks **(A)**
	Ability to keep inventory	The lower the ability to keep inventory, the higher the need for smart PPC.	High	Medium	Low	Product perishability limits the producer's ability to use inventory as a buffer against demand variability. Thus, continuous insights into demand can be used to improve and support forecasting **(R; C)** and dynamically adjust lot sizes in e.g. processing or packing **(D)**.
Process	Process lead time	The longer the process lead time, the higher the need for smart PPC.	Short	Medium	Long	When process lead times are long, processing data can be used to have a continuously updated and accurate overview of the entire process and its potential variability **(R; C)**. This can be used to enable autonomous decision-making **(A)**, dynamic re-planning **(D)**, and support decision-making **(C)**.
	Process flexibility	The lower the process flexibility, the higher the need for smart PPC.	High	Medium	Low	When a process is inflexible and setup times are long, the process cannot easily be adapted to changes in the planning environment. Instead, accurate, detailed, and real-time process data can be used to assess system constraints and limitations **(R; C)** and further enable dynamic replanning through e.g. autonomous control **(D; A)**.
	Process complexity	The higher the process complexity, the higher the need for smart PPC.	Low	Medium	High	High process complexity means a process cannot be easily adapted to changes in the planning environment. Instead, accurate, detailed, and real-time process data **(R)** can be used for autonomous control **(A)** or be combined with tacit knowledge for use in PPC decision-making **(C)**.
	Supply variability	The higher the supply variability, the higher the need for smart PPC.	Low	Medium	High	Highly variable supply limits the producer's ability to adapt to changes in the planning environment. Instead, up-to-date internal data and information from suppliers **(R)** can be used to foresee and manage variability through dynamic re-planning **(D)** and enable autonomous planning and control of purchasing, inventory, and production **(A)**.

these for PPC purposes are almost endless. The examples provided in Table 2 are therefore meant as inspiration and illustration of how various elements of smart PPC can be operationalized to support a company in addressing the most challenging setting of each variable. The examples are generated based on the insights of the authors from previous research and case studies, combined with inspiration from existing literature on smart PPC, mainly Bueno et al., 2020, Moeuf et al., 2018, Oluyisola et al., 2021, and Oluyisola et al., 2022.

4. Case study; planning environment characteristics and potential applications of smart PPC in food production

In this section, we first provide a short introduction to food production and introduce the case company. We then present the case findings with regard to the company's planning environment characteristics and use the framework in Table 2 to identify the need for smart PPC. Based on this, we propose and describe three potential applications of smart PPC which can address the identified needs for smart PPC.

The case study was conducted as part of the research project DigiMat, using design science as the overall research strategy. In this approach, research is driven by practical problems, and specific solutions are developed, realized, and evaluated in close collaboration among company representatives and researchers (Van Aken & Romme, 2009). The researchers provide key competencies and development resources and act as drivers of the research and development activities. The company representatives contribute with their knowledge, experience, and insights to practical challenges in discussions, development work, and testing of new solutions. The research processes in the DigiMat project consist of four phases. In phase 1, the current situation is analyzed to identify problems, weaknesses, and improvement potential within specific topics. This forms the basis for phase 2, where conceptual solutions are developed based on a study of available techniques and solutions. In phase 3, specific solutions are developed in collaboration between researchers and practitioners. In phase 4, selected elements of the solutions from phase 3 are deployed and tested in the form of applications, demonstrators, and prototypes. The project activities on smart PPC in the company are currently in phase 3, where specific smart PPC applications are being developed, and a selection of these are described in section 4.3.

In addition to the researchers, company representatives from several functions were involved in data collection, mapping, analysis, and development of the conceptual solutions, including managers and employees in the supply chain, production planning, forecasting, shopfloor, sales and marketing, and IT. Data was collected using traditional case study techniques such as interviews, observations, site visits, and quantitative data from company information systems and supply chain partners. The data was analyzed using traditional qualitative and quantitative techniques and methods. The proposed smart PPC applications were developed in workshops and discussions among researchers and company representatives, building on previous and ongoing smart PPC initiatives in the company and using literature studies to augment the solution designs.

4.1. Introduction to food production

Food production, like other homogenous products such as chemicals, paint, and pharmaceuticals, is a process industry in which standardized products are manufactured in large amounts. Food products are often made in batches, where raw materials and intermediates are accumulated and processed together in lots. Typically, the stock of raw materials is not more than a few days due to the perishability of the raw materials (Romsdal, 2014). With each manufacturing stage, the number of product variants increases, as a small number of raw materials and other inputs are turned into a broad range of finished goods via a divergent product structure. The packaging process is crucial because it is often at this stage that the product becomes customer specific, e.g., sized, packaged, and labelled for a specific market or consumer (Romsdal, 2014).

There are several physical processes and stock points in the material flow of food production, including receiving of inputs (e.g., raw materials, ingredients and packing materials), processing, packing (which is often combined with cutting and labelling), and delivery. Typically, there are three stock points; raw materials before processing, unpacked bulk products between the processing and packing stage, and end products packed in consumer packaging. The production processes and stock positions are illustrated in Fig. 1.

Processing lead times in food production are typically much longer than customers' delivery lead time expectations. Producers therefore mostly use a make-to-stock strategy for production, and customer orders are filled from finished goods inventory. This strategy is complicated by the fact that finished goods can expire in inventory if demand is lower than the amounts produced. Conversely, if demand is higher than expected, producers commonly use overtime and other costly measures to avoid stock-outs and loss of customer goodwill.

Food producers operate within a supply chain consisting of many actors, including primary producers and suppliers of other production inputs (packaging material, ingredients, etc.), the industrial production unit, a wholesale or distribution unit, retailers, and consumers. A typical industrialized food supply chain is shown in Fig. 2.

Many countries have seen major structural changes in food supply chains over the past decades, with emergence of large brand owners and industrial processors on one hand, and consolidation of the wholesale and retail stages on the other. However, food supply chains still involve many actors, with limited cooperation, coordination and information sharing between supply chain stages. Thus, producers' information about end customer demand is distorted, making it difficult for producers to balance supply with demand.

4.2. Introduction to case company

Brynild AS is a medium-sized, family-owned food producer with approx. 230 employees and an annual revenue of EUR 90 mill. The company's Norwegian factory produces approx. 50 variants of sugar confectionery products, 50 chocolate variants, and 80 nut variants. The Norwegian market for confectionery and snacks products is dominated by large international actors and Brynild has a market share of approx. 14 %. Their main customers are the three Norwegian grocery wholesaler – retailer dyads that control 100 % of the retail market, with wholesalers typically requiring a 98 % service level and two to three days delivery lead time. Consumer demand for snacks and confectionery products is highly seasonal and affected by a high frequency of promotional activities and new product launches. Brynild's products have 5-24 months shelf life, and products that approach or pass their industry-standard sell-by date are either scrapped or sold at reduced prices through alternative sales channels.

Brynild currently has limited access to data from the downstream supply chain beyond orders from wholesalers, negotiations with retailers regarding timing and product variants for promotional activities and product launches, and the opportunity to buy aggregated sales data from a national grocery database. Due to buy-back agreements, Brynild carries a large portion of the risk associated with seasonal products, while having little or no insight into actual consumer demand or influence over inventory levels in retail stores. The customers' requirements for high service levels and short delivery lead times mean that orders must be met from inventories of finished goods. The limited access to demand information complicates demand planning and PPC and limits the company's ability to quickly respond to changes in demand, particularly related to campaigns and new product launches. The consequences include loss of revenues and customer goodwill in out-of-stock situations, scrapping of unsold products in several supply chain stages, and physical and administrative handling and destruction of unsold products.

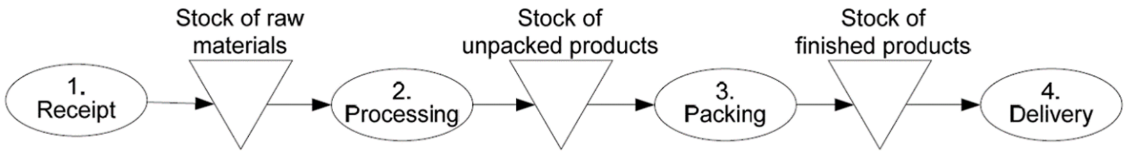

Fig. 1. Typical processes and stock points in food production (based on Méndez & Cerdá, 2002; van Dam et al., 1993)

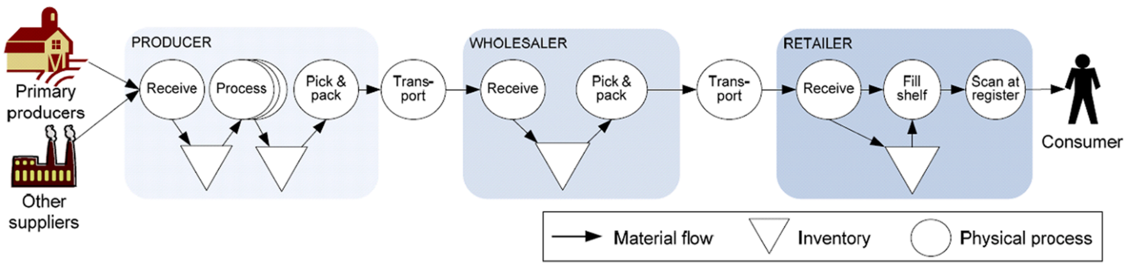

Fig. 2. Typical industrialized food supply chain (Romsdal, 2014)

Production is organized in two main steps: processing and packing. Both steps are carried out on large integrated and automated processing lines, and there is a large inventory of intermediates between processing and packing. There are considerable setup times. Most of the material flow before, after and between production lines is carried out manually, although some material handling is carried out by conventional robots and automated machinery, and more recently also collaborative robots (COBOTs) and automated guided vehicles (AGVs).

The company's production strategy is mainly make-to-stock for standard products, with build-up of inventory of seasonal and new products weeks and months in advance of customer orders. The two production steps are planned and controlled separately. Production plans are based on forecasts and inventory levels, with some make-to-order for campaign products where retailers share demand estimates 5-8 weeks before the campaign starts. A 52-week forecast is generated using traditional forecasting methods in the ERP system. The system adjusts the forecast with inventory levels to arrive at the weekly net requirement. The production planners then manually adjust this with information about confirmed orders, planned campaigns, new product launches, and the need for seasonal build-up of inventory to generate the weekly production plan. The ERP planning module does not have functionality to optimize safety stock levels, batch sizes or production sequence so this is also done manually by the planners. After a rough-cut capacity planning once a week, the planners perform the MRP calculations and manually plan volumes and timing of variants per production line per day to meet estimated demand. The daily plan is communicated to the shopfloor for sequencing, execution and control.

4.3. Case findings on planning environment characteristics and the need for smart PPC

An analysis of the current PPC processes in Brynild revealed some potentials for improvements. Firstly, the planners make a lot of repetitive decisions and spend a lot of time making the same decisions every time. Thus, there is unexploited potential to automate PPC. In addition, data used for PPC is imperfect, e.g., data captured from the internal production environment and received or bought from the supply chain is often both incomplete, delayed, or not detailed enough. Further, planning is periodic while demand is continuous, which means that PPC is not carried out in real-time based on updated information about new events. PPC is also performed with static parameters, for instance, batch sizes that are not adjusted to fit with changes in demand.

After the analysis of the PPC processes, the planning environment characteristics of the company were analyzed using the framework in Table 2. Table 3 summarizes the findings and identifies the corresponding need for smart PPC for each variable, indicated with bold in the table. The characteristics were identified based on interviews, site visits, document reviews, and workshops. The number of stars per variable was determined in a discussion between researchers and company representatives.

The joint assessment by the researchers and company representatives is that the need for smart PPC in the company is fairly high. Six of the variables are in the most challenging setting: one product variable (product variety), three market variables (delivery lead time requirements, demand variability, and ability to keep inventory), and one process variable (processing lead times). In addition, four variables are in a medium setting: three product variables (product complexity, product life cycles, and volume variability) and one process variable (process complexity). Only two variables are in the most favorable setting: one market variable (delivery lead time variability) and one process variable (supply variability).

With regards to the planning environment characteristics' consequences for PPC, the large demand variations, combined with the very limited ability to keep inventory, constrain the volumes that can be produced with the company's selected make-to-stock production strategy. Combined with the insights from the analysis of the PPC processes, there appears to be a potential to reduce dependence on forecasts and finished goods inventory to meet customer requirements for service level and delivery lead time, for instance, through more responsive and dynamic PPC and increased automation in material handling. There is also a potential to reduce manual decision-making, for instance, by increasing the degree of system support in PPC. Further, autonomous production control and event management could be enabled through the capture and use of more real-time data from production lines. One element in this is the potential to capture and model shopfloor operators' skills and tacit knowledge for integration into PPC systems. In sum, it was concluded that there appears to be a strong need and potential for smart PPC in the company.

4.4. Proposed applications of smart PPC

Based on the findings documented in section 4.3, three applications of smart PPC have been identified as promising. Below, the three proposed applications are described with regard to their industrial motivation, objectives, opportunities for smart PPC, and the expected results.

4.4.1. Use of point-of-sales (POS) data for new product launches

Industrial motivation: forecasting demand for new products is a

Table 3
Company planning environment characteristics and need for smart PPC

Category	Variable	Characteristic	Importance of smart PPC *	**	***
Product	Product complexity	Medium number of raw materials and intermediates, high number of finished products. Combination of divergent and convergent product structure.	Low	**Medium**	High
	Product variety	High and increasing variety in products and packaging sizes, particularly for promotions. Combination of fast and slow-moving items.	Low	Medium	**High**
	Product life cycle	Medium and decreasing life cycle, with frequent product introductions and high failure rates.	Long	**Medium**	Short
	Product volume and variability	High product volumes and medium volume variability.	Low	**Medium**	High
Market	Delivery lead time	Short time between order receipt and delivery (2-3 days).	Long	Medium	**Short**
	Delivery lead time variability	Low delivery lead time variability, with fixed days for order and delivery.	**Low**	Medium	High
	Demand variability	High and increasing variability caused by seasonality and high and increasing frequency of promotional activities. Strong presence of bullwhip effect.	Low	Medium	**High**
	Ability to keep inventory	Very limited ability to keep inventory due to medium (raw materials and finished products) to high (intermediates) perishability.	High	Medium	**Low**
Process	Process lead time	Product dependent, but generally long lead times (2-3 weeks).	Short	Medium	**Long**
	Process flexibility	Dedicated equipment, long setup times and two-step production process, resulting in low product type flexibility and high-volume flexibility in processing, and low product type and low volume flexibility in packing.	High	Medium	**Low**
	Process complexity	Mainly two steps; processing and packaging. High integration of processes within each step.	Low	**Medium**	High
	Supply variability	Some variability, mainly caused by seasonality, but generally high reliability.	**Low**	Medium	High

particularly challenging task since historical data is not available as an indicator of future demand (van Steenbergen & Mes, 2020). This significantly complicates production planning for new products since these need to be produced several weeks and months prior to launch to meet expected demand. Different types of new products will result in different demand profiles (Gelper et al., 2016; Surathkal et al., 2017), where the demand for a completely new product is likely to differ from that of an extension within an already existing brand, such as a new flavor or a new packaging size. Qualitative methods such as expert opinions and surveys are the most widespread techniques applied for demand estimation of new products as they do not require historical data (Kahn, 2002). Thus, demand and production planning for new products is a highly resource-demanding process, and failure to correctly estimate demand can lead to overproduction, where excess inventory is sold at reduced prices or scrapped, or not producing enough to satisfy demand, leading to out-of-stock situations, revenue loss, and dissatisfied customers and consumers. By continuously monitoring and analyzing POS data, food producers can get an early indication of the demand profile of a new product, identifying when and at what level the demand peaks and stabilizes. These insights can then be used to continuously adjust production plans.

Objective: to develop PPC processes and decision support tools to exploit POS data for continuous learning and dynamic PPC before, during, and after new product launches.

Opportunities for smart PPC: the use of POS data for PPC for product launches involves three elements of smart PPC. Firstly, a (near) *real-time data management* is required to store and analyze POS data from retail stores. The data should be as detailed and updated as possible to enable continuous analysis and tracking of consumer demand as a basis for PPC, rather than solely relying on demand estimates and historical order data from wholesalers. For the purposes of production planning, insights from the POS data analysis should be combined with internal data such as production plans, inventory levels, customer orders, and purchasing orders to determine a production plan for the coming period. In addition, a collaboration process should be established with customers (both wholesalers and retailers) for continuous information sharing and collaboration before and during the product launch period. Internally, the company should set up a cross-functional team to ensure close collaboration and information sharing between different functions, enabling the production system to quickly adjust production plans and schedules in response to any unexpected changes in demand. Rather than operating with static and fixed lot sizes in processing and production, during the launch period, production should aim for more *dynamic production planning and re-planning.* Production planners can, for instance, use dynamic lot sizes to quickly adjust production volumes to changes in demand. Also, the production of the new product could be planned more frequently to enable adjusting production volumes to insights into demand from the POS data analyses. Finally, the POS data could be used to support *continuous learning* among the sales and marketing staff, both associated with new products and also for other types of demand. Using BDA and ML on the historical POS data can identify effects on demand of various sales initiatives towards retail stores, such as the extra spacing in stores, locations and types of instore product displays, types of price displays, and joint exposure with other products. POS data can also be analyzed to identify how demand patterns of new product launches vary with product types, degree of newness, differences in demand between types and geographic locations of retail stores, etc. These insights can then be used in the planning of future product launches.

Expected results: several studies have found that when manufacturers get real-time access to POS data, the delay of the initial response to demand fluctuations such as product launches can be significantly reduced, increasing forecast accuracy and service levels, compared to a situation without access to POS data (see e.g., Mason-Jones & Towill, 1997; Småros, 2005). It has also been found that using real-time data for dynamic lot-sizing enables quicker response to changes in demand (Gu et al., 2017). Although this comes at the expense of higher setup costs, these must be weighed against potential revenue losses and costs of scrapping and lost customer goodwill resulting from failing to match supply with demand. In addition, POS data can provide better insights that can be used to improve the effectiveness of in-store sales initiatives for all types of demand, including campaigns and new, seasonal, and standard products.

4.4.2. Decision support for production planning and control

Industrial motivation: PPC is a complex and time-consuming task in many companies. Planners typically have a large number of options in planning, such as moving products between production lines or time periods, changing a production line's capacity, and changing the production mix. Because of the enormous amounts of data and the complicated relationships among data, and the dynamic nature of the decision-making environment, PPC systems often fail to provide solutions or visualizations that reflect the changing constraints and environment (Zhang, 1996). This lack of visualization capabilities means that planners often rely on their cognitive powers and experience to make PPC decisions rather than on formalized rules and complex data sets from internal and external sources. On the other hand, many planning tasks involve making repetitive decisions with the same outcomes, such as performing the same planning tasks on fixed days and using fixed parameters (e.g., batch sizes, fixed ABC product classifications, and fixed production sequences). Many of these decisions could be carried out by computer systems. In addition, shopfloor operators often use tacit knowledge, for instance, when determining if a disturbance in a production run requires immediate attention or if it can wait until the end of the run. 'Tacit knowledge' is an intrinsic understanding of how things work and enables humans to intuitively produce strategies and solutions when faced with a new situation (Reber, 1989). If these skills and tacit knowledge were captured and modeled, they could be used to support and automate PPC decision-making. Food production further typically uses the hierarchical approach to PPC, where material flow and capacity are coordinated across planning levels, using an aggregation logic in terms of time, material, location, and resources (Arica et al., 2013). As a result, the dynamics of decision-making on the shopfloor are neglected (Meyer et al., 2011), and the ability to react to events happening on the shopfloor, or to new information from the external environment is limited after plans and schedules have been frozen and initiated.

Objective: to improve the speed and quality of decision-making in planning and control.

Opportunities for smart PPC: existing and emerging technologies provide unprecedented opportunities for capturing data from production systems and supply chains. However, this data needs to be shared, stored, processed, combined, and analyzed for decision-making purposes to unlock the true value of the data for PPC. Some of the data are already automatically captured through sensors, cameras, and other technology. In addition, operators possess highly valuable tacit knowledge, which they use in decision-making. If this tacit knowledge could be captured, it could be stored, shared, analyzed, modeled, and combined with other types of data – and further utilized in the transfer of manual work to automated systems (Johnson et al., 2019). The captured tacit knowledge thus provides a basis for *continuous learning* and should inform the design of new and emerging technologies. In addition, it can replace human decision-makers, be used to redesign systems to augment/assist human operators in their manual decisions, and be used to optimize the introduction and implementation of new systems and processes (Johnson et al., 2019). A key element of dynamic PPC is the ability to understand, control and predict the outcomes of an event, such as accepting a new order, changing a batch size or production schedule, or changing inventory policy (*dynamic production planning and re-planning and autonomous production control*). *Real-time data management* is required to collect, analyze and visualize the different data, such as inventory, production, demand, etc., to support human decision-making. Further, AI and BDA can be used to identify patterns and alternatives with the most beneficial outcomes. This can be done by creating a digital twin or digital shadow of the system under evaluation – which in turn can be used to simulate the effects of alternative decisions on performance, such as costs, lead times, and inventory and service levels.

Expected results: use of data for decision support can enable faster and more accurate decision-making. The use of simulation and visualization further provides effective decision support tools for human planners. Many PPC decisions currently made by humans could be carried out more efficiently and with a higher degree of precision by computer systems. Automation of PPC reduces the risk of human errors, reduces the time spent on PPC, and frees up time for humans to focus on more complex and value-adding tasks. In addition, formalizing and modeling tacit knowledge of experience-based rules of thumb used in planning and shopfloor control into computer systems safeguards this type of knowledge and reduces the risks associated with absenteeism and turnover of key planning resources. Increased automation of data capture and the establishment of a real-time data management system make adequate data for PPC available to all relevant functions and reduce the need for manual information sharing and coordination. Further, more dynamic and real-time based PPC decision-making will enable higher responsiveness in the production system to changes in both the internal and external environment. And finally, simulation allows a fast, risk-free, and cost-effective way of evaluating alternative options before implementation.

4.4.3. Autonomous control of material flow and handling equipment

Industrial motivation: material handling is essential to guarantee the flexibility of production systems in food producers such as Brynild. There is a general trend in the sector to move away from the traditional solution with highly integrated production lines which span the whole production process from the input of raw materials through processing and packing, where conveyors are used to connect and move products between machines and production steps (Fragapane et al., 2020; Sgarbossa et al., 2020; Sgarbossa et al., 2021). Such solutions are typically very efficient and productive but have limited flexibility due to long changeover times and fixed layout. In a smart PPC scenario, each production step can be performed in separate machines – where material handling is flexible and can transport products between different production stages. This enables higher flexibility in production plans, as well as autonomous control of material flow.

Objective: to increase flexibility in food production through autonomous control of material flow and handling equipment.

Opportunities for smart PPC: cloud technologies represent a recent advancement in production systems. So-called cloud manufacturing affects PPC through the possibility of sharing real-time information about the status of products and all resources, equipment, and machines involved in the production systems (*real-time data management)*. The availability of Industry 4.0 technologies, such as indoor positioning technologies (IPT) as part of IoT, motion tracking and control, and cloud computing is making material handling systems one of the most feasible solutions for increasing the flexibility of production systems, guaranteeing flexible production plans through their autonomous control. The concept of cloud material handling system (CMHS, see e.g., Sgarbossa et al., 2021), has been introduced and developed by the authors in the Logistics 4.0 Laboratory at NTNU. Here, the solutions provided by transportation service providers and platforms, such as Uber, are brought into production environments. In the CMHS, the "customers" are the products (in unit loads) which autonomously request transport from one point to another. Forklifts and other material handling equipment are the "cars" that can be used to transport products in the system. The transport requests made by the products are dynamically assigned to the most suitable equipment by an intelligent control system based on advanced dynamic rules (*autonomous production control*). The functioning of the CMHS is similar to a MES. The main difference is the real-time localization of the products and material handling equipment due to the IPT implementation and the sharing of their attributes/functions along with positions, which enable autonomous scheduling and control of all the components in the system. However, while with MES operators need to confirm every change in the status of the product (e.g., when the product is moved from one point to another), using CMHS the status of the product is automatically updated, allowing autonomous control of the system. Moreover, the tracking and control of each material handling equipment allows data collection about their performance and so enables autonomous adjustment of the assignment policies to the most suitable equipment available. Assignment policies can evolve from basic heuristic rules such as longest waiting time (LWT) and shortest travel distance (STD) to more advanced rules based on ML/AI algorithms, such as deep reinforcement learning (DRL).

Expected results: preliminary studies have demonstrated through simulation models that CMHS performs better than traditional material handling system where job allocation is static and predetermined or where MES is implemented. CHMS improves the utilization of forklift and other material handling equipment, assisting the operators in selecting the most appropriate mission and how to perform it. It allows the reduction of idle time and execution since handling activities are optimized. The application of ML/AI algorithms for dispatching leads to higher potential throughput and improves the agility of the system, assisting the prepositioning of forklifts.

4.5. Insights from case study

The case study used the framework for smart PPC to identify the degree to which the company can expect to benefit from smart PPC by identifying the project, market, and process variables which complicate PPC the most. Next, the three proposed applications illustrated how different elements of smart PPC can be used to both solve some of the challenges in the company's current PPC and exploit some of the opportunities of emerging smart technologies. Table 4 provides an overview of the proposed applications, indicating the elements of smart PPC addressed in each.

The purpose of the applications was not to address all four elements in each nor to provide an exhaustive list of potential smart PPC applications. Rather, the applications are meant as illustrations of how some elements of smart PPC can be used to solve specific challenges and open new opportunities for improving PPC performance. This can support companies in improving their PPC and assist in strategic decision-making about the further development of PPC and investments in smart technologies.

The proposed applications illustrate how technologies can enable the use of new types of data from a company's operators, operations, and

Table 4
Proposed applications and link to elements of smart PPC

Smart PPC element / Smart PPC application	Real-time data management	Dynamic production planning and re-planning	Autonomous production control	Continuous learning
Use of POS data for product launches	X	X		X
Decision support for PPC	X	X	X	X
Autonomous control of material flow and handling equipment	X		X	

supply chain. This data could be combined with existing data for use in PPC, thus providing more complete and real-time data sets. Further, data can be used in new ways in PPC, e.g., by digitizing tacit planning knowledge and using AI, BDA, and visualization to support, improve and automate PPC decision-making. Additionally, data can enable dynamic production planning where real-time information about events can be used to re-plan or dynamically change parameters such as batch size and production sequences.

5. Conclusions and directions for future research

There are great expectations both in industry and academia around the potential of Industry 4.0 to transform and improve operations. A plethora of technologies are emerging, and many companies are struggling to decide the technologies in which to invest. The purpose of this paper was, therefore, to provide a structured tool that can guide academics and practitioners in evaluating the need for smart PPC, thus addressing the gap in research with regards to how the characteristics of a company's planning environment impact on the need for smart PPC.

The paper has three main contributions. Firstly, it demonstrates a structured way to describe a company's planning environment with regards to product, market, and process characteristics and illustrates how different characteristics complicate PPC. The insights from such a mapping of planning environment characteristics can be useful also for other purposes, e.g., in supply chain design decisions (Sun& Cooper, 1998), for identifying production planning and control methods (Jonsson & Mattsson, 2003), and for identifying the need for efficiency vs. responsiveness (Romsdal, 2014).

Secondly, the propositions in Table 2 provide insights into how different planning environment characteristics impact on the need for smart PPC. The underlying assumption is that the potential of smart PPC to improve PPC performance increases with the complexity of the planning environment. The most challenging setting of each variable represents key challenges for PPC in general – and thus increases the potential benefits of utilizing Industry 4.0 technologies for smart PPC. The proposed framework can be used by companies both to identify the most challenging aspects of their planning environments, prioritize the areas where smart PPC has the highest potential to improve PPC performance and select the elements and smart technologies that can enable the required level of PPC "smartness".

Thirdly, the case study illustrates how the framework in Table 2 can be used to analyze a company's planning environment characteristics and assess the need for smart PPC. Although the case company operates in the food sector, companies in other sectors can find inspiration from the ideas described in the proposed applications.

Some important insights on the applicability of the proposed framework and directions for further research emerged through the case study. The assessment of each variable was based on subjective qualitative judgments in the project team. Although there was little or no disagreement in the group in the assessment, quantifying the variables and defining thresholds for the scales and assignment of stars would have made the framework more objective and eased its application. Further, some variables were more important than others in determining the need for smart PPC, thus the framework could be expanded with the possibility to assign weights to each variable. The case also showed that variables can exert pressures for smart PPC in opposite directions. However, we expect that using smart PPC to address the variables that complicate PPC the most will not have a negative impact on the variables that are in a more favorable setting.

Future research on smart PPC should strengthen the validity and applicability of the proposed framework through additional cases across industrial sectors. In addition, a broader survey and structural equation modeling should be carried out to identify specific relationships between planning environment characteristics and the need for smart PPC. Given that there is a close link between a company's production planning environment and its selected customer order decoupling point

(CODP) (also called market interaction strategy or order fulfillment strategy), it would also be interesting to investigate if there are certain smart technologies that are more suited to support PPC in companies applying an engineer-to-order strategy compared to companies that follow a make-to-order, assemble-to-order, or make-to-stock strategy. Future research should also investigate the relationship between the variables of the production planning environment, the elements of smart PPC, and the existing and emerging smart technologies, for instance, through case studies and surveys.

From a practitioner's perspective, a number of challenges remain to be solved for companies in the transition towards smart PPC, including:

- *Value of data;* data and digitalization are essential parts of smart PPC, but the quantitative value of sharing and using data for PPC is still not fully known. Thus, it is difficult for supply chain actors to agree on the distribution of costs and risks associated with capturing, storing, processing, and sharing data.
- *Which data to use and share;* we still do not know exactly which data is useful for PPC. Challenges remain related to issues such as capturing too much data, not enough data, not the right data, and incompatible data formats.
- *Cost of technology;* companies may be reluctant to invest in smart technologies for PPC due to both the upfront investment and the hidden costs of technology associated with the need for maintenance, upgrades, higher-skilled employees, etc. They may also find it difficult to choose and prioritize between technologies.
- *Infrastructure;* realizing the potential benefits of smart PPC requires investments in infrastructure, e.g., for data capture in processing lines and automation of physical processes. In addition, there are challenges associated with integrating and implementing the different technologies.
- *Resistance to moving from conventional enterprise systems*: organizations may have invested significantly in conventional information systems, such as ERP and MES. The benefits achievable from adopting and integrating further digital technologies need to be investigated and demonstrated.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The work was carried out as part of the innovation research project "DigiMat; smart, transparent and sustainable food supply chains", with financial support from the Research Council of Norway (project no. 226686), NTNU, and the participating industrial partners.

References

Aitken, J., Childerhouse, P., Christopher, M., & Towill, D. (2005). Designing and managing multiple pipelines. *Journal of business logistics, 26*(2), 73–96.
Arica, E., & Powell, D. J. (2014). A framework for ICT-enabled real-time production planning and control. *Advances in Manufacturing, 2*(2), 158–164.
Arica, E., Strandhagen, J. O., & Hvolby, H.-H. (2013). Handling Unexpected Events in Production Activity Control Systems. In C. Emmanouilidis, M. Taisch, & D. Kiritsis (Eds.), *Advances in Production Management Systems. Competitive Manufacturing for Innovative Products and Services Berlin, Heidelberg*. Springer.
Bean, R., & Davenport, T. H. (2019). Companies are failing in their efforts to become data-driven. *Harvard business review*, 5–8.
Bendul, J. C., & Blunck, H. (2019). The design space of production planning and control for industry 4.0. *Computers in Industry, 105*, 260–272.
Bertrand, J. W. M., Wortmann, J. C., & Wijngaard, J. (1990). *Production control: a structural and design oriented approach*. Elsevier.
Bresler, M., Romsdal, A., Strandhagen, J. O., & Oluyisola, O. E. (2020). Principles and Research Agenda for Sustainable, Data-Driven Food Production Planning and Control. In *IFIP International Conference on Advances in Production Management Systems*.
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*, Article 106774.
Chavez, R., Yu, W., Jacobs, M. A., & Feng, M. (2017). Data-driven supply chains, manufacturing capability and customer satisfaction. *Production Planning & Control, 28*(11-12), 906–918.
Christopher, M., Towill, D. R., Aitken, J., & Childerhouse, P. (2009). Value stream classification. *Journal of Manufacturing Technology Management*.
Coelho, L. C., & Laporte, G. (2014). Optimal joint replenishment, delivery and inventory management policies for perishable products. *Computers & Operations Research, 47*, 42–52.
Fatorachian, H., & Kazemi, H. (2021). Impact of Industry 4.0 on supply chain performance. *Production Planning & Control, 32*(1), 63–81.
Fragapane, G., Ivanov, D., Peron, M., Sgarbossa, F., & Strandhagen, J. O. (2020). Increasing flexibility and productivity in Industry 4.0 production networks with autonomous mobile robots and smart intralogistics. *Annals of operations research*, 1–19.
Gelper, S., Wilms, I., & Croux, C. (2016). Identifying demand effects in a large network of product categories. *Journal of Retailing, 92*(1), 25–39.
Grundstein, S., Freitag, M., & Scholz-Reiter, B. (2017). A new method for autonomous control of complex job shops–Integrating order release, sequencing and capacity control to meet due dates. *Journal of manufacturing systems, 42*, 11–28.
Grunow, M., & Piramuthu, S. (2013). RFID in highly perishable food supply chains–Remaining shelf life to supplant expiry date? *International Journal of Production Economics, 146*(2), 717–727.
Gu, Q., Visich, J. K., Li, K., & Wang, Z. (2017). Exploiting timely demand information in determining production lot-sizing: an exploratory study. *International Journal of Production Research, 55*(16), 4531–4543.
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: An International Journal*.
Hopp, W. J., Iravani, S. M., & Xu, W. L. (2010). Vertical flexibility in supply chains. *Management science, 56*(3), 495–502.
Jacobs, M. A. (2013). Complexity: Toward an empirical measure. *Technovation, 33*(4-5), 111–118.
Johnson, T. L., Fletcher, S. R., Baker, W., & Charles, R. (2019). How and why we need to capture tacit knowledge in manufacturing: Case studies of visual inspection. *Applied ergonomics, 74*, 1–9.
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*(8), 872–900.
Jordan, W. C., & Graves, S. C. (1995). Principles on the benefits of manufacturing process flexibility. *Management science, 41*(4), 577–594.
Kahn, K. B. (2002). An exploratory investigation of new product forecasting practices. *Journal of Product Innovation Management: An international publication of the product development & management association, 19*(2), 133–143.
Karmarkar, U. S. (1993). Manufacturing lead times, order release and capacity loading. *Handbooks in operations research and management science, 4*, 287–329.
Kusiak, A. (2017). Smart manufacturing must embrace big data. *Nature, 544*(7648), 23–25.
Köchling, D., Gausemeier, J., Joppen, R., & Mittag, T. (2016). Design of a self-optimising production control system. In *DS 84: Proceedings of the DESIGN 2016 14th International Design Conference*.
Lamming, R., Johnsen, T., Zheng, J., & Harland, C. (2000). An initial classification of supply networks. *International Journal of Operations & Production Management*.
Lee, H. L. (2002). Aligning supply chain strategies with product uncertainties. *California management review, 44*(3), 105–119.
Li, D., Kehoe, D., & Drake, P. (2006). Dynamic planning with a wireless product identification technology in food supply chains. *The International Journal of Advanced Manufacturing Technology, 30*(9-10), 938–944.
Makkonen, H., Pohjola, M., Olkkonen, R., & Koponen, A. (2014). Dynamic capabilities and firm performance in a financial crisis. *Journal of business research, 67*(1), 2707–2719.
Malek, Y. N., Kharbouch, A., El Khoukhi, H., Bakhouya, M., De Florio, V., El Ouadghiri, D., Latré, S., & Blondia, C. (2017). On the use of IoT and big data technologies for real-time monitoring and data processing. *Procedia Computer Science, 113*, 429–434.
Martins, L., Fernandes, N. O., & Varela, M. (2018). Autonomous production control: a literature review. *International Conference on Innovation, Engineering and Entrepreneurship*.
Mason-Jones, R., & Towill, D. R. (1997). Information enrichment: designing the supply chain for competitive advantage. *Supply Chain Management: An International Journal*.
Méndez, C. A., & Cerdá, J. (2002). An MILP-based approach to the short-term scheduling of make-and-pack continuous production plants. *Or Spectrum, 24*(4), 403–429.
Meyer, G. G., Wortmann, J., & Szirbik, N. B. (2011). Production monitoring and control with intelligent products. *International Journal of Production Research, 49*(5), 1303–1317.
Milgate, M. (2001). Supply chain complexity and delivery performance: an international exploratory study. *Supply Chain Management: An International Journal*.
Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). *Journal of manufacturing systems, 49*, 194–214.
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*(3), 1118–1136.

Nagy, G., Illés, B., & Bányai, Á. (2018). Impact of Industry 4.0 on production logistics. In *IOP Conference Series: Materials Science and Engineering*.

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

Oluyisola, O. E. (2021). *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.* Trondheim: Norwegian University of Science and Technology.

Oluyisola, O. E., Bhalla, S., Sgarbossa, F., & Strandhagen, J. O. (2022). Designing and developing smart production planning and control systems in the industry 4.0 era: a methodology and case study. *Journal of Intelligent Manufacturing, 33*(1), 311–332.

Ouelhadj, D., & Petrovic, S. (2009). A survey of dynamic scheduling in manufacturing systems. *Journal of scheduling, 12*(4), 417–431.

Pagh, J. D., & Cooper, M. C. (1998). Supply chain postponement and speculation strategies: how to choose the right strategy. *Journal of business logistics, 19*(2), 13.

Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access, 6*, 3585–3593.

Reber, A. S. (1989). Implicit learning and tacit knowledge. *Journal of experimental psychology: General, 118*(3), 219.

Ren, L., Zhang, L., Tao, F., Zhao, C., Chai, X., & Zhao, X. (2015). Cloud manufacturing: from concept to practice. *Enterprise Information Systems, 9*(2), 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.

Romsdal, A. (2014). *Differentiated production planning and control in food supply chains*. Trondheim: Norwegian University of Science and Technology.

Scholz-Reiter, B., & Freitag, M. (2007). Autonomous processes in assembly systems. *CIRP annals, 56*(2), 712–729.

Sgarbossa, F., Peron, M., & Fragapane, G. (2020). Cloud material handling systems: Conceptual model and cloud-based scheduling of handling activities. *Scheduling in Industry 4.0 and Cloud Manufacturing* (pp. 87–101). Springer.

Sgarbossa, F., Peron, M., Fragapane, G., Mikkelsen, A. V., & Dahl, A. H. D. (2021, 15 June). Cloud material handling systems: concept development and preliminary performance analysis. *BVL international scientific symposium on logistics, Digital event*.

Slack, N., Brandon-Jones, A., & Johnston, R. (2013). *Operations Management*. Pearsons Education.

Småros, J. (2005). *Information sharing and collaborative forecasting in retail supply chains*. Helsinki: Aalto University.

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.

Strandhagen, J., Dreyer, H. C., & Romsdal, A. (2011). Control model for intelligent and demand-driven supply chains. *Managing Global Supply Chain Relationships: Operations, Strategies and Practices* (pp. 49–70). IGI Global.

Sun, D., Huang, R., Chen, Y., Wang, Y., Zeng, J., Yuan, M., & Qu, H. (2019). PlanningVis: A visual analytics approach to production planning in smart factories. *IEEE transactions on visualization and computer graphics, 26*(1), 579–589.

Surathkal, P., Dey, M. M., Engle, C. R., Chidmi, B., & Singh, K. (2017). Consumer demand for frozen seafood product categories in the United States. *Aquaculture Economics & Management, 21*(1), 9–24.

Saad, S. M., Bahadori, R., Jafarnejad, H., & Putra, M. F. (2021). Smart Production Planning and Control: Technology Readiness Assessment. *Procedia Computer Science, 180*, 618–627.

Thomas, A., Haven-Tang, C., Barton, R., Mason-Jones, R., Francis, M., & Byard, P. (2018). Smart systems implementation in UK food manufacturing companies: a sustainability perspective. *Sustainability, 10*(12), 4693.

Van Aken, J. E., & Romme, G. (2009). Reinventing the future: adding design science to the repertoire of organization and management studies. *Organization Management Journal, 6*(1), 5–12.

van Dam, P., Gaalman, G., & Sierksma, G. (1993). Scheduling of packaging lines in the process industry: An empirical investigation. *International Journal of Production Economics, 30-31*(0), 579–589. https://doi.org/10.1016/0925-5273(93)90123-3

van Steenbergen, R., & Mes, M. R. (2020). Forecasting demand profiles of new products. *Decision support systems, 139*, Article 113401.

Verma, P. K., Verma, R., Prakash, A., Agrawal, A., Naik, K., Tripathi, R., Alsabaan, M., Khalifa, T., Abdelkader, T., & Abogharaf, A. (2016). Machine-to-Machine (M2M) communications: A survey. *Journal of Network and Computer Applications, 66*, 83–105.

Wang, B., Tao, F., Fang, X., Liu, C., Liu, Y., & Freiheit, T. (2021). Smart manufacturing and intelligent manufacturing: A comparative review. *Engineering, 7*(6), 738–757.

Zhang, P. (1996). Visualizing production planning data. *IEEE Computer Graphics and Applications, 16*(5), 7–10.

Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., Yu, S., & Xu, X. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering, 13*(2), 137–150.