Production Planning and Control in Industry 4.0: Overview on Challenges of Data-Driven PPC Systems

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Abstract: The integration of Industry 4.0 technologies offers significant potential to transform production planning and control (PPC) systems, but organizations face various challenges in adopting data-driven solutions. This paper examines 51 review articles published between 2019 and February 2025 and identifies 30 different challenges categorized into entry barriers, data-related issues, complexity of PPC tasks, and operational constraints. Overcoming these challenges will require not only technical solutions, but also holistic approaches, including interdisciplinary research. Future work should involve practitioners to evaluate the relevance of these challenges, as their importance has not been assessed from an industry perspective.

Keywords: Production Planning and Control, Industry 4.0, Artificial Intelligence

1. INTRODUCTION

In today's competitive manufacturing landscape, companies face increasing pressure to enhance production efficiency, flexibility, and responsiveness. Data-driven production planning and control (PPC) systems offer immense potential to transform manufacturing processes and help organizations navigate these challenges. PPC is the process of organizing, coordinating, and managing manufacturing processes. It involves planning the production schedule, allocating resources, managing inventory, and monitoring progress (Büttner et al. (2022)). However, despite the benefits that data-driven PPC provides, the successful implementation and maintenance of these systems are often hindered by various barriers and obstacles.

While much of the existing literature focuses on the advances in technologies and trends within Industry 4.0, only a limited number of studies explicitly address challenges. Many papers mention challenges in passing, but they do not provide a holistic overview. As a result, there is a clear gap in the literature regarding a comprehensive understanding of the diverse challenges organizations encounter when adopting data-driven PPC approaches. This paper aims to fill this gap by systematically collecting and analyzing the challenges identified in the literature on data-driven PPC. We will identify challenges related to data-driven PCC, describing them and their interdependencies, and clustering them into categories that include entry barriers, constraints, data-related challenges, and complexities arising from PPC tasks and their integration.

To accomplish this, we conduct a systematic review of recent literature published within the last five years, identifying barriers reported in three different databases. Our work contributes to the existing body of knowledge by providing a comprehensive overview of the challenges related to data-driven PPC systems. By categorizing these challenges, we aim to facilitate problem-solution fits, highlighting the various expert disciplines that may need to be involved in developing effective solutions. This structured framework will serve as a valuable reference for both researchers and practitioners, guiding future efforts to address the complexities of implementing and maintaining data-driven PPC systems.

2. THEORETICAL BACKGROUND

The Aachen PPC model, which incorporates these technologies, represents a forward-thinking approach to PPC in the context of Industry 4.0. It leverages real-time data and machine learning algorithms to optimize core functions such as production scheduling, demand forecasting, and inventory management (Büttner et al. (2022)). This shift toward data-driven PPC systems marks a significant milestone in the evolution of production management, offering the potential for more adaptive, efficient, and responsive manufacturing systems.

In the era of Industry 4.0, the core functions of PPC— demand forecasting, production scheduling, inventory management, and capacity planning—are being fundamentally transformed by the integration of advanced technologies such as IoT, machine learning, and real-time analytics. These functions, which were traditionally managed using static models and manual interventions, are now becoming more dynamic, data-driven, and responsive to real-time production conditions.

For example, demand forecasting has evolved from relying on historical sales data to incorporating real-time data from connected devices, enabling manufacturers to make more accurate predictions and respond more quickly to changes in market demand (El Jaouhari et al. (2022)).

Similarly, production scheduling is becoming more flexible, with machine learning algorithms optimizing schedules based on real-time data, minimizing downtime, and improving resource utilization (Herrmann et al. (2022)). This shift toward adaptive scheduling systems not only improves operational efficiency but also enhances the overall flexibility of production systems.

Inventory management is another area significantly impacted by Industry 4.0 technologies. IoT-enabled tracking systems provide real-time visibility into stock levels, allowing for more efficient resource allocation and reducing waste (Büttner et al. (2022)). These systems help optimize inventory levels by providing up-to-date information on stock movements, thereby reducing overstocking and stockouts.

Capacity planning has also benefited from advancements in AI and machine learning. By analyzing real-time production data, these technologies can predict fluctuations in demand and production conditions, enabling manufacturers to optimize production capacity in a more agile and responsive manner (Arinez et al. (2020)). This allows for better alignment of production resources with actual demand, improving overall efficiency and reducing production bottlenecks.

The use of data-driven solutions is gaining momentum in the industry to address increasingly complex PPC tasks while maintaining an efficient PPC system. The challenges that arise are described in the literature, but there is no work that systematically presents existing challenges. Most of the relevant literature focuses on trends and technologies in the realm of Industry 4.0. However, only a limited number specifically tackle the associated challenges. Jewapatarakul and Ueasangkomsate (2022) discusses digital transformation in manufacturing and service sectors. However, this work does not have a clear focus on PPC.

In contrast, Manta-Costa et al. (2024) describes trends and challenges associated with using machine learning in manufacturing. However, the authors focus solely on papers related to predictive maintenance, quality control, and personal manufacturing. Shang et al. (2023), Ghanbarifard et al. (2023), and Waubert de Puiseau et al. (2022) discuss promising technologies such as graph knowledge, digital twins, and reinforcement learning that can enhance production planning and control. However, their emphasis is primarily on the technologies themselves and the challenges associated with their implementation, with little focus on PPC. Huang et al. (2023) and Agrawal et al. (2023) describe challenges related to specific industry sectors. Furthermore, Roshid et al. (2024) focuses on challenges related to logistics.

To integrate these fragmented perspectives and insights, we will collect and analyze the stated challenges within the literature, as described in the following sections.

3. METHODOLOGY

This study conducted a systematic review of the literature to identify challenges in data-driven production planning and control (PPC) systems within the context of Industry 4.0. A search was performed in the Scopus, Web of Science, and IEEE Xplore databases, focusing on peer-reviewed review articles published within the past five years (2020 to 2025). The search query combined key terms related to challenges, data-driven methods, and core PPC functions (see Figure 1).

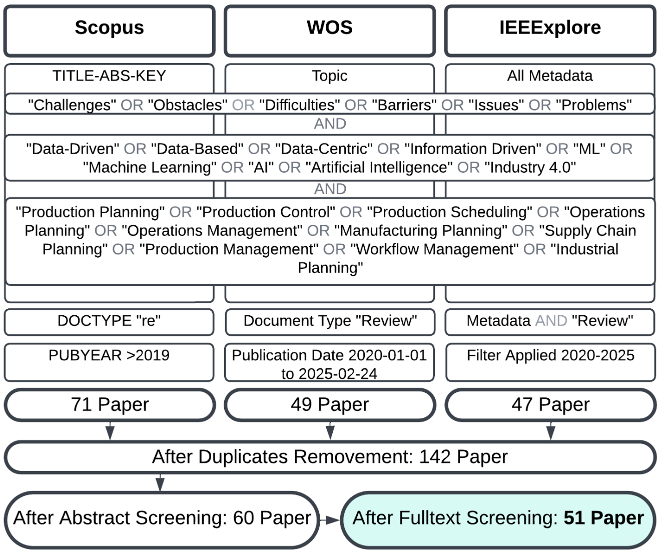

Fig. 1. Database collection conducted on February 25, 2025, across the three databases, with duplicate removal and abstract and full-text screening, resulting in 51 papers included in the analysis of challenges.

The retrieved review articles were cleaned for duplicates, reducing the data set to 142 papers. These papers were then screened in a two-stage review process: first, an abstract screening to ensure relevance to PPC in manufacturing and its challenges within the Industry 4.0 context, followed by a full-text screening. This process identified 51 relevant review papers (see Figure 1).

The final selection of articles was then analyzed in detail. We extracted and categorized the challenges discussed in these papers, identifying recurring themes and issues related to data-driven PPC systems. Recurring challenges were grouped into third-level categories. To refine this categorization, we systematically compared challenges to identify similarities and merged closely related topics into second-level categories. Finally, these second-level categories were further analyzed for overarching similarities, leading to the formation of first-level categories representing the main challenges. The results of this categorization process are presented in the following section.

4. RESULTS

The 51 articles varied in their scope and focus regarding PPC under Industry 4.0. While some had a holistic view on PPC (Prashar et al. (2022)), others focused on specific tasks such as scheduling (Manuel Parente and Marques (2020)). Additionally, the articles differed in their technological emphasis, ranging from a general focus on AI (Rakholia et al. (2024)) to specific AI methods like reinforcement learning (Panzer and Bender (2022)) and other Industry 4.0 technologies like IIoT (Mantravadi et al. (2020)).

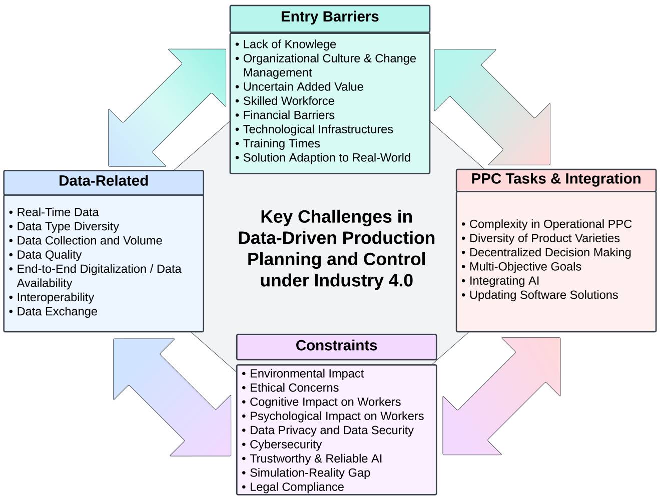

Fig. 2. Overview of key challenges of data-driven PPC clustered into four interconnected challenge categories.

In addition, some reviews focused on specific industries such as additive manufacturing (Inayathullah and Buddala (2025)). A detailed overview of the reviewed articles can be found in our github repository with supplemntary material to the study (Götte and Mäule (2025)).

Extracting the challenges regarding data-driven PPC mentioned in these papers (third-level challenges) revealed recurring themes, regardless of the varying scopes of the articles. Overall, there was significant diversity in the stated challenges, with none of the papers covering all aspects. The categorisation process of the identified third-level challenges across the 51 articles resulted in 30 second-level challenge categories, which we could further group into four main first-level categories:

- Challenges identified as entry barriers to implementing data-driven solutions for PPC systems.
- Challenges related to required data.
- Challenges arising from the characteristics of the PPC tasks and their operational integration.
- Challenges stemming from constraints while using modern data-driven solutions for PPC systems.

Figure 2 provides an overview of the categorization. Following this, the challenges grouped by the main categories are presented in detail. For better readability, referenced sources will only be cited exemplarily. The complete mapping, including the corresponding article sources for each category, can be found in the supplementary github repository (Götte and Mäule (2025)).

These categories are not isolated, but are highly interdependent, as highlighted in the graphical abstract (see Figure 2). For example, as the demands for PPC tasks and their integration increase, so do the entry barriers due to the need for additional resources. Furthermore, the data-related challenges serve as conditions that create both entry barriers and constraints that make a data-driven PPC solution viable.

Moreover, the challenges themselves do not always fit neatly into to a single category. For example, the challenge of data privacy and data security represents a constraint but it is also data-related. Therefore, we emphasize that these categories are not exhaustive and are intended to provide a broader perspective.

4.1 Entry Barriers

To implement data-driven PPC, companies must overcome several barriers and challenges. First, Moreira et al. (2024) state that there is a *lack of knowledge* about technologies and automation, and Agrawal et al. (2023) mention an unawareness of Industry 4.0 technologies. Furthermore, technology is advancing rapidly, making it difficult to keep up with the pace of change (Degu Workneh and Gmira (2022)). In combination with the *uncertain added value* of implementing these new technologies (Dieste et al. (2022)), the initial motivation to implement data-driven PPC may be lacking.

When motivated, there remains the challenge of *adapting solutions to real-world* scenarios that effectively address the specific use cases within the organization. Esteso et al. (2023) state that selecting the best solution approach is difficult. A gap between research and reality is also mentioned. For example, the modeled use cases often prove to be under-complex with respect to real-world applications (Degu Workneh and Gmira (2022)). The applicability of existing solutions also depends on the acceptance (Rakholia et al. (2024)) and integration (Moreira et al. (2024)) within the organization. *Organizational culture and change management* are necessary to implement data-driven solutions. In addition to internal collaboration and the willingness of employees to adopt data-driven decision making, a digital strategy is required (Dieste et al. (2022)). Xu et al. (2021) states that organizational readiness for data-driven solutions is essential.

Furthermore, the implementation of data-driven PPC imposes different resource demands for companies. On the one hand, it is necessary to build up an appropriate *technological infrastructure* (Culot et al. (2024)), ranging from basic needs such as an adequate internet connection for communication and data transfer processes, which may be lacking in rural areas (Abdulghani and Winkler (2023)), to extensive computing capacities for machine learning processes (Fatima and Rahimi (2024)).

It also requires resources to keep *training times* within acceptable limits (Zhang et al. (2024)). The acquisition of such infrastructure is further accompanied by *financial barriers* ranging from high initial investment costs (Rakholia et al. (2024)) to the cost of operating, for example through cloud computing services (Mathieu et al. (2024)). Finally, implementing the solutions places high demands on *skilled workforce*, amidst a general shortage of skilled personnel (Moreira et al. (2024)) and the need to adapt the existing workforce to work with AI (Virmani and Ravindra Salve (2023)).

4.2 Data-Related

To implement data-driven solutions, data is essential. This data must first be collected through *end-to-end digitization* and must secondly be *available* (Culot et al. (2024)). *Data collection* represents an initial challenge (Usuga Cadavid et al. (2020)). At the time of collection, it is not always clear which data will be valuable, so the *data volume* must be managed, which is particularly challenging for small and medium-sized enterprises (SMEs) (Mathieu et al. (2024)). A significant amount of data in production involves *real-time data*, which imposes extra requirements on data processing capabilities. Real-time data is generated irregularly, but it is essential for making timely decisions (Tang et al. (2024)).

Data utilization is further complicated by the existence of *data type diversity*. Data type diversity can be attributed to the significant volumes of data generated in the age of data, as well as the complexity and heterogeneity of data Dieste et al. (2022). Additionally, *data quality* must be ensured. This is compromised by misspellings, punctuation errors, incomplete data, and other input inaccuracies (Mathieu et al. (2024)). Despite the technical perspective of data quality, the base population for the data plays a critical role. If the data reflects a past reality that should not be replicated, i.e., if there is a historical bias in the data, an AI trained on this biased data may lead to an inaccurate solution (Esteso et al. (2023)).

One challenge that is often mentioned is inadequate *interoperability*. The standardization of data structures and content is essential to enable seamless communication between different systems. This issue relates to interactions within manufacturing, where various software systems need to work together (Friesen et al. (2022)). It also concerns the need for *data exchange* across companies. This is complicated by the lack of standards, security requirements, and ultimately by the need for trust among supply chain partners (Mantravadi et al. (2020), Agrawal et al. (2023)).

4.3 PPC Tasks and Integration

Today's PPC operations are becoming increasingly complex due to a number of factors. PPC faces increasingly complex requirements as the growing *diversity of product varieties* leads to variations in materials, dimensions, and geometry, which complicate and challenge production processes. Furthermore, PPC systems become more complicated due to *decentralized decision-making*. Shifting towards this approach in scheduling poses coordination difficulties and affects global optimization among different agents (Manuel Parente and Marques (2020)). As the number of participants rises and not all information can be shared with everyone, this challenge becomes more significant (Halty et al. (2020)). Other reasons for the *complexity in operational PPC* may include the need to integrate manufacturing and logistics across entire supply chains (Luo et al. (2023)), multi-machine scheduling (Manuel Parente and Marques (2020)), and a fundamentally high level of interdependency among processes (Frazzon et al. (2020)).

The complexity of PPC leads to greater difficulties in integrating new data-driven solutions. *Integrating AI* systems with existing equipment can lead to technical complexity and compatibility issues, requiring careful planning to minimize disruption and downtime (Elahi et al. (2023)). Additionally, these systems must be kept up to date by *updating solutions*. As new scenarios arise, these models must be retrained (Vivas et al. (2024)). This challenge also includes hardware considerations (Dieste et al. (2022)).

Finally, one aspect that complicates PPC is the need to achieve *multi-objective goals*. In addition to traditional objectives such as utilization and production time, goals such as due date compliance and low-maintenance efforts must now be integrated into PPC systems. These objectives may conflict with each other and require trade-offs. This is primarily a challenge of an economic, ecological, and social nature rather than a technological one (Vivas et al. (2024)).

4.4 Constraints

When applying data-driven PPC, several constraints need to be considered. First, the solutions must meet *legal requirements*, e.g. regarding the safety of human-robot collaboration (Yin and Li (2023)) or the use of AI (Rakholia et al. (2024)). Furthermore, the security of these systems needs to be ensured. For example, threats related to *cybersecurity* need to be managed (Patalas-Maliszewska et al. (2024)) to ensure that the systems are not interrupted from outside. Mantravadi et al. (2020) mentioned that there is also a lack of standards in this area. Additionally, *data privacy* (Moreira et al. (2024)), security (Culot et al. (2024)), and confidentiality (Mantravadi et al. (2020)) play a crucial role in enabling safe data-driven PPC.

Despite these safety aspects, the solutions need to be trustworthy and reliable in their functionality. Especially for AI solutions based on extracting knowledge through machine learning from databases, the reliability of the results is a critical issue. Everything can work perfectly from a technical perspective, but the result can still be wrong. For instance, a trained AI model may make decisions about a new product for which there is no existing production data (Rahmani et al. (2022)).

Furthermore, imbalanced data can lead to inaccurate outcomes, as short-term data sets may insufficiently capture seasonal patterns (Ahamed et al. (2024)). In general, AI solutions may lack generalizability, especially in uncertain situations (Degu Workneh and Gmira (2022)) and may destabilize critical tasks (Vivas et al. (2024)). In order to evaluate the models' trustworthiness during their application, interpretability (Fatima and Rahimi (2024)) and explainability (Shang et al. (2023)) of the AI models' results are crucial. Lack of transparency may even hinder their adoption (Rakholia et al. (2024)).

Additionally, the generalizability of models trained on simulations, like most reinforcement learning approaches applied to scheduling, can sometimes be compromised due to a *simulation-reality gap* (Vivas et al. (2024)), which may result from unconsidered parameters in the simulations (Panzer and Bender (2022)). The generalizability of models from research is further complicated by a gap between research and reality. Esteso et al. (2023) found in their review that only 9% of the analyzed papers were based on real-world applications.

The data-driven PPC solutions could also have an impact on humans, which needs to be considered appropriately. The implementation of these solutions might affect workers' roles (Abdulghani and Winkler (2023)) and might result in unwanted *psychological impacts* such as anxiety (Patalas-Maliszewska et al. (2024)). Furthermore, *ethical* *concerns* and issues may arise with the integration of data-driven PPC itself (Moreira et al. (2024)), for example through potential job displacement (Abdulghani and Winkler (2023)) or specific solutions like AI models themselves if they show biases (Abdulghani and Winkler (2023)).

Finally, while integrating and running data-driven PPC, its *environmental impact* must be considered (Zhang et al. (2024)). Wang et al. (2021) state that integrating intelligent and green manufacturing is a current issue to be solved. Especially the potentially high energy consumption of the technologies (Dieste et al. (2022)) plays a crucial role in managing the environmental impact.

5. CONCLUSION

This work presented a comprehensive overview of existing challenges for data-driven PPC systems stated in research reviews. Data-driven solutions hold enormous potential to help address the many challenges of increasingly complex manufacturing. While implementing data-driven solutions presents new challenges, we encourage their adoption. In general, we see widespread adoption of AI-driven solutions to address the increasing complexity of PPC.

For some of the identified challenges, solutions already exist from both industry and academia. However, technology-solution fits can help to determine what challenges a technology or methodology can address and what challenges remain unaddressed. This work lays the groundwork for these types of technology -solution fits.

We see three main limitations. First, the foundation of this work is based on academic papers, which only partially reflect the real problems faced by companies. Second, the findings are qualitative in nature. While some challenges may exist, they may not have a significant impact. In contrast, challenges such as the need for a technological infrastructure are critical for the successful implementation of data-driven solutions. Third, the challenges vary by region and industry. It would also be useful to distinguish between product-driven and process-driven manufacturers. Future works should evaluate the results through surveys conducted within the industry, differentiating between various industry sectors. We also encourage performing technology-solution fits that address these challenges and the publication of the results. Finally, we want to encourage researchers to find solutions to the presented challenges.

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