Approaches of Production Planning and Control under Industry 4.0: A Literature Review

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Abstract:

Purpose: Industry 4.0 technologies significantly impact how production is planned, scheduled, and controlled. Literature provides different classifications of the tasks and functions of production planning and control (PPC) like the German Aachen PPC model. This research aims to identify and classify current Industry 4.0 approaches for planning and controlling production processes and to reveal researched and unexplored areas of the model. It extends a reduced version that has been published previously in Procedia Computer Science (Herrmann, Tackenberg, Padoano & Gamber, 2021) by presenting and discussing its results in more detail.

Design/methodology/approach: In an exploratory literature review, we review and classify 48 publications on a full-text basis with the Aachen PPC model's tasks and functions. Two cluster analyses reveal researched and unexplored tasks and functions of the Aachen PPC model.

Findings: We propose a cyber-physical PPC architecture, which incorporates current Industry 4.0 technologies, current optimization methods, optimization objectives, and disturbances relevant for realizing a PPC system in a smart factory. Current approaches mainly focus on production control using real-time information from the shop floor, part of in-house PPC. We discuss the different layers of the cyber-physical PPC architecture and propose future research directions for the unexplored tasks and functions of the Aachen PPC model.

Research limitations/implications: Limitations are the strong dependence of results on search terms used and the subjective eligibility assessment and assignment of publications to the Aachen PPC model. The selection of search terms and the texts' interpretation is based on an individual's assessment. The revelation of unexplored tasks and functions of the Aachen PPC model might have a different outcome if the search term combination is parameterized differently.

Originality/value: Using the Aachen PPC model, which holistically models PPC, the findings give comprehensive insights into the current advances of tools, methods, and challenges relevant to planning and controlling production processes under Industry 4.0.

Keywords: production planning and control, Industry 4.0, industrial internet of things, exploratory literature review

To cite this article:

1. Introduction

Production planning and control (PPC) involves planning and scheduling the production and realizing the initial plan by tackling disturbances that occur during its execution (Eversheim & Wiendahl, 2000). High schedule reliability, short lead times, high capacity utilization, and low inventory level are the objectives of a PPC concept (Wiendahl, 1996). These objectives maintain their validity also in the context of Industry 4.0 (Kuprat, Mayer & Nyhuis, 2015). Therefore, the management may adopt different strategies like centralization, standardization, integration, and decentralization (Schuh, 2007). The cyber-physical production system (CPPS) summarizes the technological progress in computer science, information and communication technologies, and manufacturing automation (Monostori, 2014) and influences the interaction between PPC functions and the resources needed for production. Literature labels this technological change as Industry 4.0 and Industrial Internet of Things (Jeschke, Brecher, Meisen, Özdemir & Eschert, 2017; BITKOM, VDMA & ZVEI, 2015). According to its first mention at a fair in Hannover, Germany, the term Industry 4.0 refers to a new industrial revolution driven by the Internet of Things consisting of interconnected cyber-physical systems (CPS) (Kagermann, Lukas & Wahlster, 2011). Arguing that stakeholders, representation, and geographical focus comprise the only criteria which allow discriminating between the terms Industrial Internet of Things and Industry 4.0 (Bledowski, 2015), this paper follows Jeschke et al. (2017) and uses both terms as synonyms.

Meudt, Wonnemann and Metternich (2017) categorized existing PPC concepts in the German literature and found a diverse terminology and classification of PPC's steps and processes. The present literature review is based on the Aachen PPC model published in Schuh and Stich (2012) because it is a widespread concept in German-speaking countries (Meudt et al., 2017). The Aachen PPC model describes PPC regarding its tasks, processes, process architecture, and functions. The task view specifies the tasks of PPC in a universal and hierarchical abstraction. The process view provides a temporal and logical order, that is, a process for these tasks resulting in a procedure for order fulfillment. The process architecture view connects tasks with these processes and relates them to enterprise or network-level. The function view describes the requirements of an IT system that supports PPC. Each function belongs to one of the tasks (Schuh & Stich 2012). For reviewing recent approaches that solve the Aachen PPC model's tasks, the task and function view are used to classify and structure the findings in this paper.

This paper extends a reduced version of this literature review investigating current advances in PPC in Industry 4.0 published previously in Procedia Computer Science (Herrmann et al., 2021) and pursues the three sub-goals in an extended form:

1. To identify current Industry 4.0 approaches for planning and controlling production processes,
2. To classify novel approaches according to the functions of the Aachen PPC model,
3. To reveal researched and unexplored tasks and functions of the Aachen PPC model of Industry 4.0.

The scope is limited to PPC of products and services in the manufacturing industry and neglects approaches considering primarily environmental aspects and sustainability. This paper serves as a comprehensive introduction to the field of PPC under Industry 4.0 to researchers and gives orientation to practitioners who want to exploit Industry 4.0 solutions in their production.

Chapter 2 gives an overview of the related work and existing literature reviews discussing outlooks on future research and development challenges of PPC in the context of Industry 4.0. Chapter 3 describes the methodology and results of the exploratory literature review. Additionally, we present a multi-layer cyber-physical PPC architecture and the results from two distinct cluster analyses based on a developed classification scheme. Chapter 4 explores the different layers of the cyber-physical PPC architecture in the light of the publications reviewed and points out research gaps in current literature. Chapter 5 discusses researched and unexplored fields and future research perspectives for PPC in Industry 4.0 concerning the related work of chapter 2 and the Aachen PPC model. Chapter 6 closes the paper with its implications, limitations, and future outlook.

2. Related Work

Several literature reviews exist which study the impacts of Industry 4.0 and reveal future research perspectives. Awan, Sroufe and Shahbaz (2021) analyze the interests and expectations of stakeholders regarding IoT, its impact on circular economy management and present different tools and best practices for addressing upcoming challenges. Ivanov, Dolgui and Sokolov (2019) study the impact of Industry 4.0 on supply chain management and control of the ripple effect. Other authors review literature about the potential impacts of big data analytics and its current trends on areas like supply chain management or inventory management (Kache & Seuring, 2017; Maheshwari, Gautam & Jaggi, 2021).

A technology-oriented view of development in PPC in the context of Industry 4.0 gives Monostori (2014). The author describes the expectations, as well as directions for research and development for CPPSs. Robustness, self-X technologies, real-time control, autonomy, and transparency, to name a few, are outlined as the main expectations. These developments are based on artificial intelligence, biological inspiration, reconfigurability, digitalization, and the manufacturing system as a set of autonomous, cooperating holons. Monostori (2014) identifies the realization of autonomous and cooperative production systems that adapt to the context in which they operate as primary research and development challenges for CPPSs. Other research directions are the predictability and robustness of dynamic systems and the fusion of virtual systems with real systems and humans. Operating in a smart factory significantly influences the organization of the sequential and timely order of operations and the assignment of resources.

Scheduling has been studied by several literature reviews. Zhang, Ding, Zou, Qin and Fu (2019) review recent research on the job shop problem under Industry 4.0. They classify the approaches into five categories: primary type, multi-machine type, multi-resource type, multi-plant type, and smart factory type. The authors also refer to the last category as the Smart Factory Flexible Job Shop Problem (SFFJSP). They conclude that current research focuses on the first two categories of the job shop problem, although they do not reflect the complexity of reality. Furthermore, Zhang et al. (2019) point out the limitations and research challenges of existing approaches to solve the SFFJSP. Thereby, they will focus on smart decentralized scheduling utilizing the smart agent and Industry 4.0 technologies like barcodes, radio frequency identification (RFID) technology, and sensors to reduce the computational workload required to solve the complex, dynamic and flexible job shop problems. Furthermore, they point out the limitations and research challenges of existing approaches to solve the SFFJSP. Existing scheduling techniques for the semiconductor industry's complex job shop scheduling problem from an Industry 4.0 perspective are reviewed in Waschneck, Altenmüller, Bauernhansl and Kyek (2016). The authors provide an overview of dispatching heuristics, hyper-heuristics and machine learning, mathematical programming, and other approaches such as the shifting bottleneck heuristic, genetic algorithms, and intelligent multi-agent systems (MAS). They remark the need for decentralization and autonomous decision-making. Flexibility and adaptability project into areas such as rescheduling, process qualification management, lot-sizing, product portfolios, and robustness. The authors expect IT systems' vertical and horizontal integration to emerge and integrate the supply chain, material handling systems, cluster tools, and statistical process control. They close with machine learning and MASs as promising approaches to address the different research areas and recommend combining the existing approaches for practice. Parente, Figueira, Amorim and Marques (2020) conduct a literature review to analyze opportunities and challenges in major areas of Industry 4.0, namely, CPSs, the internet of things and services, horizontal and vertical integration, and adaptive manufacturing. They present scheduling areas critical for future research and discuss which steps recent literature has already covered. According to their review, autonomous and decentralized decision-making, optimization trade-offs considering new interactions, self-scheduling, and machine proactiveness are areas for future research. Jiang, Yuan, Ma and Wang (2021) summarize and analyze production scheduling literature in the context of centralized and decentralized, distributed, and cloud manufacturing scheduling. They review current production scheduling approaches like heuristic and meta heuristic algorithms, simulation methods, and artificial intelligence methods. Sustainability or mass customization represent new challenges in scheduling research, and Industry 4.0 technologies lead to new scheduling modes. They identify self-organization, collaboration, big data, and the digital twin as current development trends.

In distributed control architectures like MAS or holonic production systems, the control behavior may become myopic. Bendul and Blunck (2019) propose a framework for PPC and Industry 4.0, establishing three categories serving as a design space for production systems that implement a distributed control architecture. Each of the categories of design, scheduling, and control provides dimensions for designing the production. The authors argue that decentralization helps to reduce the complexity of a production system. However, at a certain degree of decentralization, the emergent behavior of the system becomes myopic. Myopic means the inability of a production system's entities to anticipate the system and future consequences of their decisions. The proposed framework supports the classification of novel approaches for distributed production control.

Kuprat et al. (2015) examine the Aachen PPC model's tasks, particularly the planning aspect in the context of Industry 4.0. The production requirements planning and in-house production planning will benefit from frequent delay-free data exchange between the planning and cyber-physical systems. That results in high quality and actuality of production data and avoids possible disturbances. The high flexibility of resources caused by Industry 4.0 will facilitate the matching of capacity offer and demand. Production requirements planning will be able to react in real-time to disturbances (machine breakdowns, capacity absence) and check and adapt master and planning data frequently. The in-house production planning system can plan lot-sizes, makespan, and work-in-progress dynamically. Thereby, cross-company tasks and long-term planning tasks are still executed by centralized planning systems.

To distinguish our research from existing studies related to reviewing PPC under Industry 4.0, the related work was assessed for the degree it discusses four defined aspects given in Table 1. Merely Kuprat et al. (2015) discuss changes implied through Industry 4.0 considering a holistic PPC model. Other authors provide more details about the Industry 4.0 technologies used to realize the reviewed approaches. All authors discuss Industry 4.0 characteristics and how they affect PPC at least to some degree. Concrete algorithms used to solve complex PPC tasks under Industry 4.0, mainly scheduling tasks, are given in four articles. None of the authors investigate current Industry 4.0 approaches for planning and controlling production processes considering all four aspects. Table 2 gives details about the existing literature reviews described above (it shows only those studies of the related work which represent an actual systematic literature review). As can be observed, the reviews narrowly focus on scheduling literature which is often concerned with specific problems like the job shop problem or flexible flow shop problem. The Aachen PPC model describes PPC in a more holistic fashion, where scheduling merely represents a small part.

Author(s)	Holistic PPC Model	Industry 4.0 Technologies	Industry 4.0 Characteristics	Algorithms
Monostori (2014)	-	◖ (Mostly)	◗ (Partially)	-
Zhang et al. (2019)	-	◖ (Mostly)	◣ (Briefly)	● (Fully)
Waschneck et al. (2016)	-	-	◖ (Mostly)	◖ (Mostly)
Parente et al. (2020)	-	◣ (Briefly)	◖ (Mostly)	◖ (Mostly)
Jiang et al. (2021)	-	◣ (Briefly)	◖ (Mostly)	● (Fully)
Kuprat et al. (2015)	● (Fully)	-	◗ (Partially)	-
Bendul and Blunck (2019)	-	◣ (Briefly)	● (Fully)	-

● Fully discussed   ◖ Mostly discussed   ◗ Partially discussed   ◣ Briefly discussed   - Not discussed

Table 1. The degree to which four aspects of PPC under Industry 4.0 are discussed in the related work

Author(s)	Database	Search Strategy	Time Period	No. of Papers	Scope
Zhang et al. (2019)	Google Scholar	"Job shop scheduling"	1986-2016	122	Job shop problem under Industry 4.0

Parente et al. (2020)	Elsevier Scopus, Science Direct, Springerlink Journals, IEEE Xplore, Google Scholar	First-level:
		  Keyword 1
		  • Industr* AND 4.0,
		  • Fourth industrial revolution,
		  • Technology-related (e. g. "Cyber-physical", "internet of things",
		  Keyword 2
		  Sched*
		Second-level:
		  Keywords
		  Critical scheduling areas identified in the first-level review
			First-level: 2010-2019 Second-level: 2001-2019	97	Production scheduling

Jiang et al. (2021)	Ei Compendex	Keyword 1:
		  • Scheduling OR production scheduling
		  • Resource scheduling OR task scheduling OR task decomposition OR service composition optimisation OR service optimal selection OR task-service matching
		Keyword 2:
		  • Single machine OR parallel machine OR flow shop OR job shop OR manufacturing system OR Multifactory OR multiplant OR distributed OR multi-agent system OR agent-based system OR Cloud manufacturing
			2000-2019	808	Production scheduling

Table 2. Scope of related Literature Reviews

3. Exploratory Literature Review
3.1. Methodology

The literature review was conducted in German and English from November 23rd until December 28th. Conference papers and journal articles in the publication status accepted or higher published from 2014 to 2019 were included. This period was chosen since Google Trends indicates that the search popularity of "Industry 4.0" and "Industrial Internet of Things" began to rise significantly in 2014 (Google Trends, 2020a,b). The literature review was performed in an exploratory fashion. A first search iteration with a limited number of publications from only two databases serves to pilot and optimize the search term combination and content to be stored from each publication. Based on these improvements, the second search iteration is conducted with the remaining databases. Figure 1 illustrates the paper selection process of the two search iterations and the corresponding databases used.

The databases IEEE Xplore Digital Library (IEEE), ISI Web of Knowledge (WoK), and Google Scholar (GoSc) were used to search for international publications. To find publications from German researchers and institutions, the databases Bielefeld Academic Search Engine (BASE), GoSc, and WISO were employed. In all databases, search results were filtered by the period determined above and sorted by relevance. In GoSc, the limit "Only German search results" was not applied. To mitigate geographical bias, both "Industry 4.0" and "Industrial Internet of Things" were included as search terms since their respective focus lies on the German-speaking region and globally (Bledowski, 2015). Therefore, both terms act as synonyms in the present literature review. Publications that have a manufacturing context automatically appear by adding the search term PPC. Accordingly, including the terms "Internet of Things" suffices, and it is not necessary to explicitly include the term "industrial" in the literature

search. However, since corresponding IT systems greatly influence the quality of PPC, it is advisable to include the term "Manufacturing execution system" (Schuh, 2007).
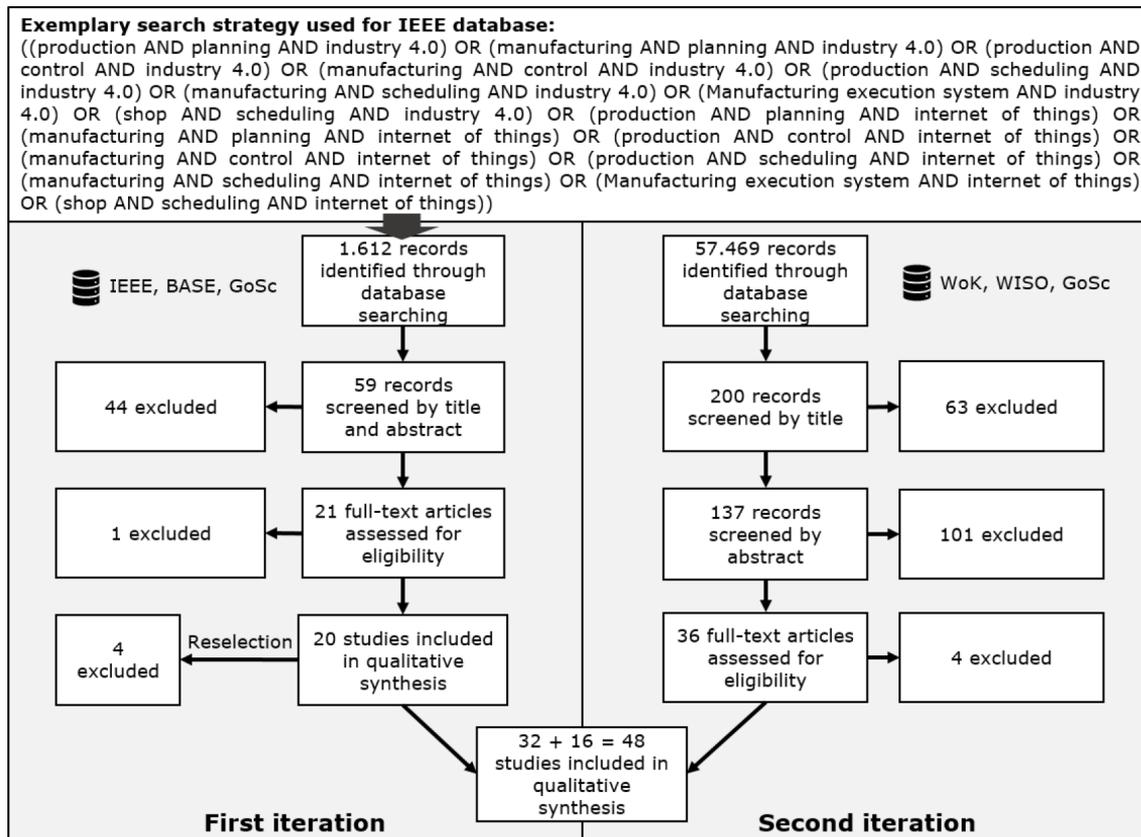

Exemplary search strategy used for IEEE database:
((production AND planning AND industry 4.0) OR (manufacturing AND planning AND industry 4.0) OR (production AND control AND industry 4.0) OR (manufacturing AND control AND industry 4.0) OR (production AND scheduling AND industry 4.0) OR (manufacturing AND scheduling AND industry 4.0) OR (Manufacturing execution system AND industry 4.0) OR (shop AND scheduling AND industry 4.0) OR (production AND planning AND internet of things) OR (manufacturing AND planning AND internet of things) OR (production AND control AND internet of things) OR (manufacturing AND control AND internet of things) OR (production AND scheduling AND internet of things) OR (manufacturing AND scheduling AND internet of things) OR (Manufacturing execution system AND internet of things) OR (shop AND scheduling AND internet of things))

Figure 1. Exemplary search term combination and paper selection process

The search term combination used in IEEE consists of "production"/"manufacturing"/"shop", "planning"/"control"/"scheduling" and "Industry 4.0"/ "Internet of Things", as well as "Manufacturing execution system" and "Industry 4.0"/"Internet of Things". An example of the IEEE search term combination incorporates Figure 1. The combination of the German terms for BASE consisted of "Produktion"/"Fertigung" and "Planung" and "Industrie 4.0" or "Produktion"/"Fertigung" and "Steuerung" and "Industrie 4.0" as well as "Manufacturing Execution System" and "Industrie 4.0".

In IEEE and BASE, the first search iteration retrieved 1.516 (IEEE) and 96 (BASE) publications. Next, the title and abstract of each publication were screened. A publication had to be assignable to the considered tasks and functions from the Aachen PPC model shown in Figure 2 and to contribute to at least one of the three sub-goals stated in chapter 1. Schuh (2007) as well as Schuh and Stich (2012) give a comprehensive portrayal of the tasks and their corresponding functions. Hence, the following criteria lead to the exclusion of a publication:

- The publication does not discuss its results in the context of Industry 4.0,
- The publication does not focus on planning and controlling production processes,
- The publication focuses on tasks and functions of the Aachen PPC model that are out of scope (e. g. network tasks).

Retrieved publications of each database were screened iteratively until ten publications were selected. In the next step, the selected publications were assessed for eligibility based on their full text. The initial search term combination was extended because the BASE literature search retrieved less than ten publications. The term "Industrie 4.0" was replaced with "cyber-physisch" due to the close relationship between both terms (Sucky,

Gampl, Ruh, Stelzer & Weidinger, 2015). However, the modified search term combination leads only to one further publication, so that the remaining five publications were collected from GoSc.

Figure 2. Considered tasks (bold font) and functions (thin font, below)
of the Aachen PPC model (Schuh & Stich, 2012, modified)

Applying the same inclusion and exclusion criteria as in the title and abstract screening, full-text analysis was performed. Further publications were analyzed if a publication was excluded from the study due to its content in this stage. This process was executed iteratively until ten publications per database were selected. Since the English search term combination provided many results, the term "cyber-physical" was not incorporated.

The full-text review of 20 publications obtained in the first search iteration gave confidence in the validity of the search term combinations. Therefore, in the second search iteration, the same search term combinations were used. However, the content be stored from each publication has been adapted. The content of each publication was documented using the following categories:

- Aims and objectives (e. g. maximization of productivity in a flow shop),
- Resources within a production environment (machines and equipment, orders and jobs, human operators, materials, finished and unfinished products),
- Type of approach concerning PPC (e. g. rule-based algorithm, data-driven),
- Characteristics of the approach presented (e. g. decentralized, real-time, robust),
- Types of disturbances considered,
- Relevant previous works of the publication at hand,
- Applied Industry 4.0 technologies.

In the second search iteration, it was searched in the remaining databases with the same limits applied as in the first iteration. The other databases' analyses resulted in 737, 1.697, and 53.423 publications for WoK, WISO, and GoSc, respectively. The first 200 publications per database were sorted by relevance, their title and abstract were screened, and publications were selected. After the full-text screening, four publications were sorted out, lacking a connection to Industry 4.0, PPC, or addressing a task of the Aachen PPC model that is not considered in this publication. After the second search iteration was carried out, the publications from the first search iteration were reselected to assure that the individual selecting publications in both iterations applied the same strategy. Finally, 48 publications were selected for the qualitative synthesis, and one individual conducted the full-text literature review.

A classification scheme was developed to evaluate each reviewed publication's coherence with the functions of the Aachen PPC model, which are aligned to the five tasks considered (see Figure 2). Oriented at Schuh and Stich

(2012), these functions were broken down into three components that, if possible, were mutually exclusive. A component represents a low-level activity or a set of actions that contribute to a function's execution. For each publication, it was checked how many components of each function the approach presented fulfills. To fulfill means that the considered publication implements the respective component or contributes to implementing that component if used in the same PPC system. Figure 3 shows how an exemplary publication fulfills three components of the function Production order monitoring, part of in-house PPC.

Figure 3. Example of the methodology of the classification scheme for one exemplary function

The example publication fulfills two components of Production order monitoring. Since it was only possible to break down each function into three components at most, a subjective assignment of a publication to a function was included as another measure of coherence to achieve an ordinal scale of five levels. The scale is also shown in Figure 3. Including the subjective assignment, a coherence score of three is computed in the example, that is, strong coherence of the exemplary publication with Production order monitoring.

3.2. Results

Figure 4 plots the number of reviewed publications per publication year from 2014 to 2019. Figure 5 lists the conferences and journals from which the publications were retrieved. A list of the papers selected for the literature review provides Appendix A.

The publications examined on a full-text basis mainly address the task of in-house PPC. Figure 6 lists the characteristics of the approaches reviewed and the corresponding authors. 15 of 48 publications outlined a particular scheduling problem of which seven are flexible or hybrid (e. g. Wang, Zhong, Dai and Huang, 2016), five are a job shop scheduling problem (e. g. Wang, Jiang and Lu, 2018), and ten a flow shop scheduling problem (e. g. Fu, Ding, Wang and Wang, 2018).
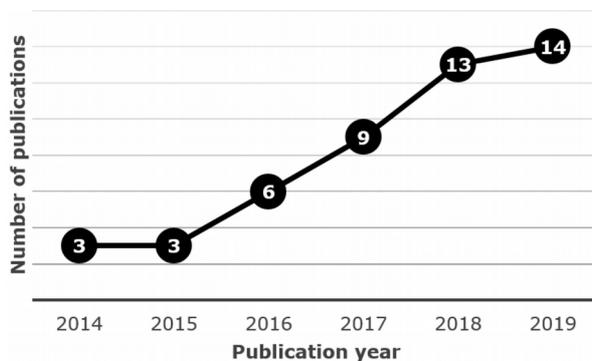

Figure 4. Number of Publications per Year from 2014-2019

Conference/Journal	No.
IEEE Access	5
ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb	5
Computers & Industrial Engineering	2
International Journal of Production Research	2
Journal of manufacturing systems	2
Applied Soft Computing	2
International Conference on Enterprise Systems	1
International Conference on Automation Science and Engineering (CASE)	1
Internet of Things Journal	1
International Conference on Emerging Technologies and Factory Automation (ETFA)	1
IET Collaborative Intelligent Manufacturing	1
Journal of Industrial Information Integration	1
International Conference on Future IoT Technologies (Future IoT)	1
International Journal of Computer Integrated Manufacturing Technologies	1
Journal of cleaner production	1
The International Journal of Advanced Manufacturing Technology	1
Journal of Mechanical Engineering Science	1
IEEE Conference on Systems, Process and Control (ICSPC)	1
International Journal of Intelligent Systems	1
Sustainability	1
International Journal on Interactive Design and Manufacturing (IJIDeM)	1
Advanced Engineering Informatics	1
Computer Networks	1
IEEE Transactions on Automation Science and Engineering	1
IEEE Transactions on Industrial Informatics	1
International Conference on Control, Decision and Information Technologies (CoDIT)	1
Winter Simulation Conference (WSC)	1
Transactions on Industrial Informatics	1
IEEE International Conference on Mechatronics and Automation	1
International Conference on Engineering, Technology and Innovation (ICE/ITMC)	1
Workshop on Metrology for Industry 4.0 and IoT (MetroInd4. 0&IoT)	1
BHM Berg-und Hüttenmännische Monatshefte	1
Simulation in Production and Logistics	1
Werkstatttechnik Online	1
e & i Elektrotechnik und Informationstechnik	1

Figure 5. Conferences and Journals of the reviewed Publications

The reviewed approaches apply numerous Industry 4.0 technologies. These technologies and how they contribute to a CPPS or smart factory describe Monostori (2014) and Chen, Wan, Shu, Li, Mukherjee and Yin (2017). Chen et al. (2017) present a hierarchical architecture for a smart factory composed of a terminal layer, cloud application layer, network layer, and physical resource layer. They assign representative Industry 4.0 technologies to each layer. These comprise e. g. RFID technology, wireless sensor networks, cloud computing, or smart devices for human-computer interaction.
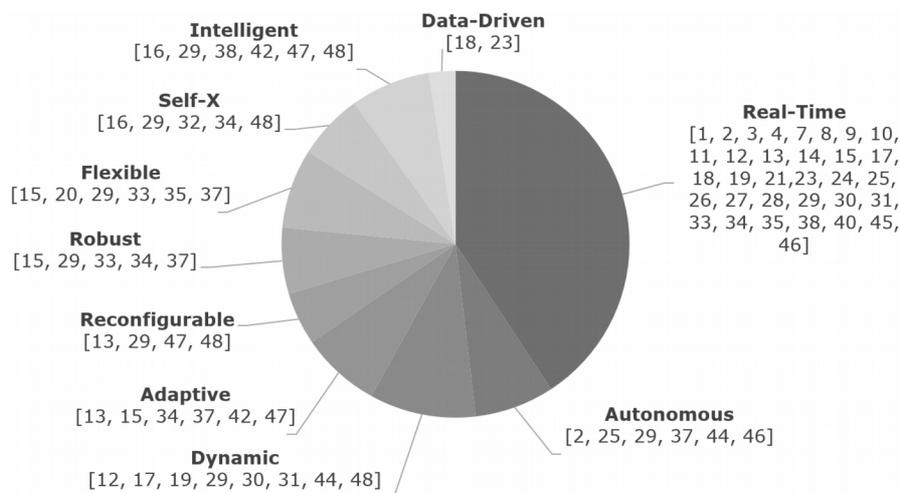

Figure 6. Characteristics of the Approaches reviewed (assigned publication numbers below each characteristic given in Appendix A)

Pinedo (2012) presents a reference architecture for a scheduling system. It consists of three modules for database management, schedule generation, and a user interface as well as a shop floor data collection system. Figure 8 combines the two architectures described above into a single architecture for cyber-physical PPC. It shows current Industry 4.0 technologies used for realizing a PPC system in a smart factory. A layer of the smart factory architecture (Chen et al., 2017) is assigned to each module of the scheduling system architecture (Pinedo, 2012). Each layer shows the Industry 4.0 technologies currently used for scheduling systems and how they interconnect. RFID tags and readers, sensors, smart sensors, and wireless sensor networks constitute the most popular Industry 4.0 technologies employed. A significant part of the publications addressed some type of scheduling problem. Hence, the reviewed approaches are classified according to the classification scheme for scheduling problems found in Zhang et al. (2019), extended by the classes policy, instruction systems, MAS, and simulation for the remaining approaches.

The identified publications focus on the control of production. In particular, the reviewed approaches tackle different disturbances occurring during production. The different disturbance types considered in the selected publications were classified using the scheme of Matson and McFarlane (1998). Figure 7 presents the distribution of the disturbance occurrences over the different disturbance categories considered in the papers reviewed. 66% of disturbances belong to the class of internal disturbances, 30% to downstream disturbances, and 3% to upstream disturbances. Seventy disturbance types are considered in total. Figure 8 incorporates the various disturbances below the classification of approaches. An objective function expresses the objectives of each approach reviewed. A classification of all objective functions is also shown in Figure 8. However, since the authors defined these classes, they are not necessarily mutually exclusive. The most popular approaches, disturbances, and objectives in the architecture are highlighted in bold.
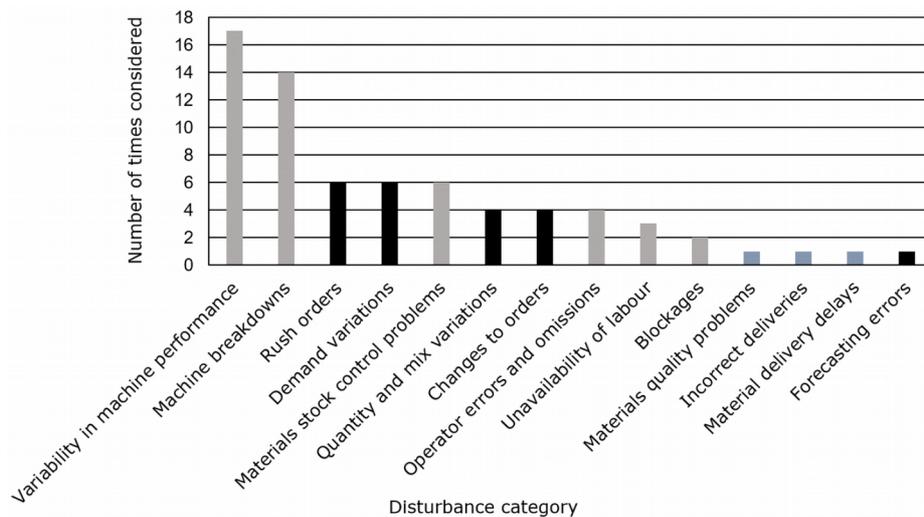
Figure 7. Distribution of the disturbance occurrences considered (Internal disturbances: grey, Downstream disturbances: black, Upstream disturbances: blue)

Using the classification scheme for measuring the coherence of a publication with a component, Rank order clustering was carried out. The subjective assignment is excluded in the cluster analysis. The resulting clusters consist of publications that fulfill a specific set of components. Because in the full-text examination, one publication turned out to be a previous work of another, the former is left out in the two cluster analyses. Out of 72 components, 40 are not fulfilled by any of the reviewed publications, or they represent the subjective assignment. Thus, 32 components remain for Rank order clustering. Figure 9 and Figure 10 show the results of Rank order clustering and the classification scheme, which has been reduced to 32 components. Three clusters can be observed. In the following, the green cluster is labeled cluster A, the orange one cluster B, and the blue one cluster C. Cluster B is a subset of the components of cluster A.
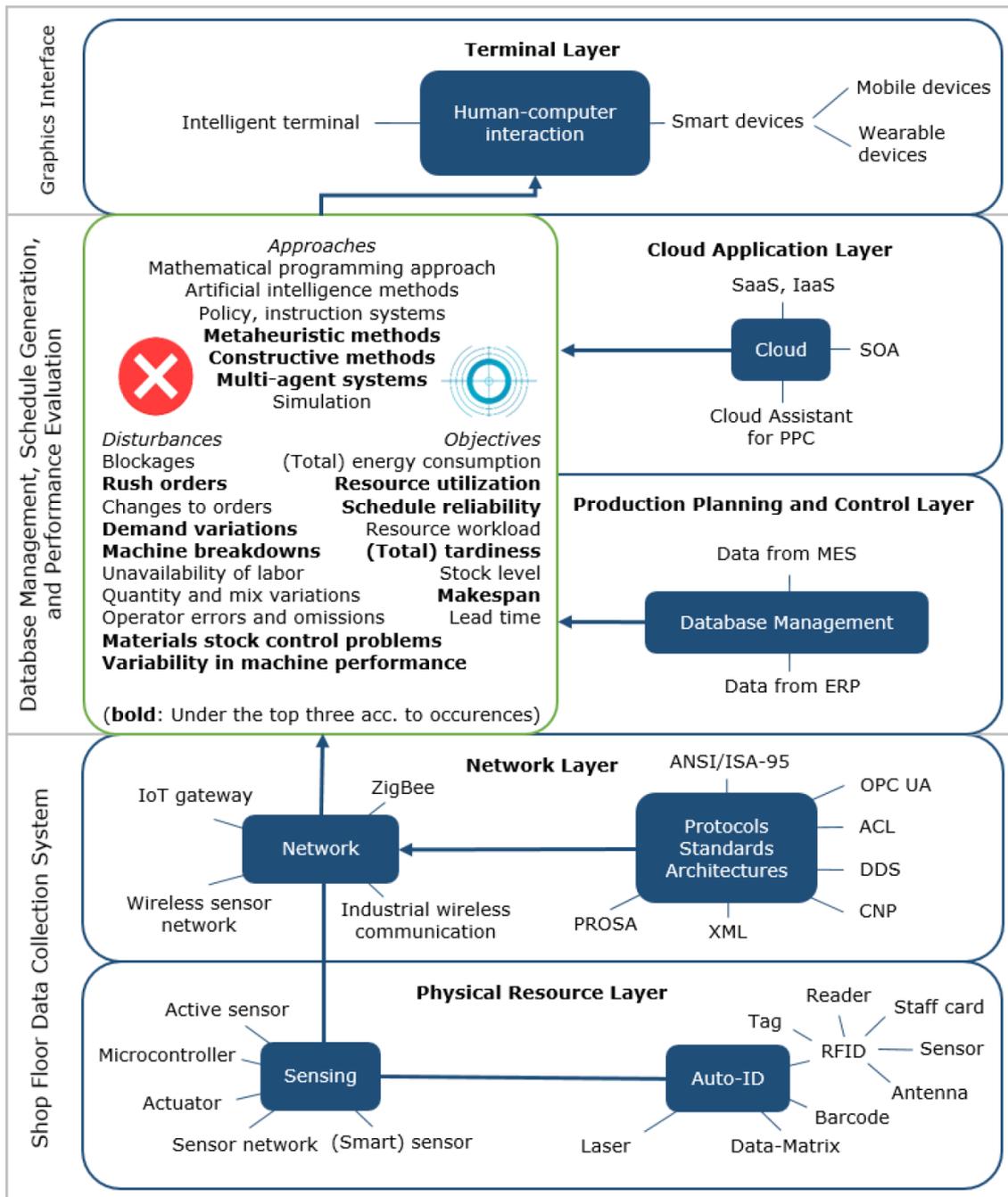
Figure 8. Cyber-physical PPC architecture. Reprinted from Herrmann et al. (2021) with permission from Elsevier

Three components belong to the function of job shop planning and two to the function of resource monitoring within cluster A. Within cluster B, three components belong to the function of job shop planning and one to the function of resource monitoring, implying a high similarity between the two clusters. Two components within cluster C belong to the function of production order monitoring and one to the function of resource monitoring. With twelve publications belonging to cluster A, 15 to cluster B, and 18 to cluster C, cluster C is the largest. However, cluster C has the smallest number of attributes as the cluster sizes get smaller, with an increasing number of attributes (components). Four or more publications still fulfill some components that are not included in any cluster. Most of these components belong to the functions of production requirements planning, namely, process planning, production order scheduling, lot-sizing, and capacity planning. The components of the functions within the tasks order management, controlling, and data management are hardly addressed by the reviewed publications, that is, by less than four publications.

	Components																															
Publ.	17	10	32	1	29	5	25	24	8	7	16	9	20	3	28	4	26	6	15	23	19	18	30	2	31	11	27	21	12	13	14	22
[12]	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0
[20]	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
[19]	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	1	1	0	0	1	0	0	0	0
[18]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0
[2]	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0
[31]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0
[21]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	1	0
[36]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	1	0
[46]	1	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	1	0	1	1	1	0	0	0	0	0	0	1	0	1	0
[22]	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	1	0	0	0	1	1	0	1	0
[26]	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
[44]	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	1	0
[6]	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1	0
[4]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0	1	1	1	0
[41]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	1	1	0
[47]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	1	1	0
[24]	0	0	0	0	0	0	0	0	1	1	1	0	0	1	0	1	0	1	0	1	0	0	0	1	0	0	0	0	1	1	1	0
[8]	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	1	0	0	1	1	1	0
[45]	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	1	1	1	0
[37]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1	1	0	0	0	1	0	0	1	1	1	0
[10]	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	0	0	1	1	1	0
[5]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1	1	0
[34]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	1	1	1	0
[29]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	1	1	1	0
[32]	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	1	0	1	0	0	0	0	0	1	1	1	1	0
[14]	0	0	0	0	0	0	1	1	0	1	1	0	1	0	0	1	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0
[48]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1
[30]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	1	0	0	0	1
[40]	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	1
[15]	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	0	1
[42]	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	1	0	1	1
[33]	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	1
[9]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	1	1
[27]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	1	1	1
[38]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	0	0	0	0	0	0	0	1	1	1
[39]	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	1	1
[11]	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	1	1	1
[13]	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	1	0	0	0	0	0	1	0	1	1	1
[16]	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
[35]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	1	1
[23]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	1	1
[1]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	1	1	1	1
[7]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	1	1	1	1
[28]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	0	0	0	0	0	1	1	1	1	1
[3]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0	0	1	0	0	1	1	1	1	1
[25]	0	1	0	0	0	1	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0	1	0	1	1	1	1	1
[17]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1

Figure 9. Rank order clustering matrix of 47 publications (Green: cluster A; orange: cluster B; blue: cluster C). Reprinted from Herrmann et al. (2021) with permission from Elsevier

Spectral clustering gives three clusters with the scores (coherences) that every publication has for the functions of the Aachen PPC model. Figure 11 shows the average coherence of each publication with the functions within a

cluster that are non-zero. Cluster F represents the largest research stream focusing narrowly on job shop planning and, to a small extent, process planning, production order monitoring, and resource monitoring. The latter two functions are rather present in cluster D combined with less coherence with job shop planning. Three members in cluster E indicate a sparsely populated but narrowly focused research stream that focuses on process planning.

Production requirements planning		No.
Process planning	Issuing of process plans (manufacturing process plans, assembly process plans, line checking plans, …)	1
	Administration of alternative process plans/operation plans (e. g. due to the change of the lot-size, material, capacity utilization, …)	2
	Resource assignment to the process plans (Maschines, means/tools for line checking, personnel, …)	3
Production order scheduling	Monitoring of production order status	4
	Determination of the different operation times (setup time, processing time, transport times, …)	5
	Backward/forward scheduling	6
Lot-sizing	Quantity bundeling of similar operations	7
	Merging or splitting of production order quantities or operations	8
Capacity planning	Capacity requirements planning on the basis of the production order schedules	9
	Capacity supply planning based on shift plans, day plans, week plans, etc.	10
	Matching of capacity requirements and capacity supply	11
In-house PPC		
Job shop planning	Resource utilization planning (e. g. machine utilization planning, personnel utilization planning)	12
	Sequence planning	13
	Rule-/Knowledge-based job shop planning or simultaneous planning of resources with optimization algorithms	14
Production order release	Availability check of resources at release date/time	15
	Production order release and the release sequence according to different criteria	16
	Provision of the required resources	17
Production order monitoring	Data processing and overview of target status and actual status of work in progress, quantities and schedule	18
	Derivation of measures for the optimization of the production execution	19
	Tracing of the production order origin and initiator (e. g. customer)	20
Resource monitoring	Overview of target status and actual status of orders on specific resources, WIP, as well as related maintenance and customer orders	21
	Data processing and overview of machine parameters, breakdowns, condition, …	22
	Overview of queued orders	23
Order management		
Customer order management	Release of customer orders with all data relevant for the execution in the different departments	24
	Monitoring of customer orders (order status, target and actual progress) and invoicing	25
Project management (Controlling)		
Project control	Reporting of planned and actual schedule (Gantt-charts, critical path method)	26
Project controlling	Reporting and detailed tracking of project cost and changes over time	27
Product data management (Data management)		
Master data management	Implementation of additional information to master data sets	28
BOM-management	Management and selection of alternative BOMs according to selection criteria	29
Classification	Support for the traceability and reusability of material data through classification systems	30
Drawing management	Material master data administration and exchange via ERP-/PPS-, CAD- and EDM-/PDM-Systems	31
	Provision of drawing management functionalities, like drawing attachment to data sets in ERP- or PPS-systems	32

Figure 10. Rank order clustering of 47 publications (Green: cluster A; orange: cluster B; blue: cluster C). Reprinted from Herrmann et al. (2021) with permission from Elsevier
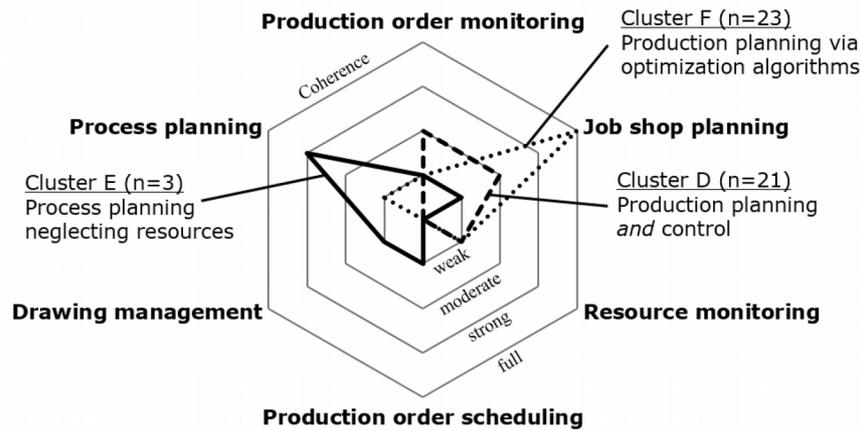
Figure 11. Spectral clustering: Average coherence of the different
clusters with the functions (Herrmann et al., 2021, modified)

4. Exploring the Cyber-physical PPC Architecture

Several publications reviewed employ Auto-ID technology and RFID technologies illustrated in Figure 8. Enabling tracking and tracing of lots and batches, reducing cycle time, or ensuring timely preventative maintenance are a few of several benefits of Auto-ID technology (Chappell, Ginsburg, Schmidt, Smith & Tobolski, 2003). Mainly, machines, workers, materials, and products are equipped with RFID technology to enable production data collection and real-time perception of the shop floors' state (e.g. Wu, Li & Sun, 2019; Wang, Jiang & Lu, 2016).

While Auto-ID and RFID technology focus on identifying objects and are present in many of the publications reviewed, sensors provide a way for collecting data of the manufacturing process itself. Active sensors require a physical stimulus like electric current to work, e.g., a sensor for color identification which needs to illuminate the area to be analyzed. Passive sensors operate using the physical stimulus of the signal to be perceived like an infrared sensor (Kalsoom, Ramzan, Ahmed & Ur-Rehman, 2020). Passive sensors were used in several publications (see e. g. Wang, Zhang, Liu and Wu, 2018 or Legarretaetxebarria, Quartulli, Olaizola and Serrano, 2017), but active sensors were used in one publication (Wu, Li & Sun, 2019). Whereas the use of these sensors is rather traditional, smart sensors provide abilities for analyzing collected data on their own using embedded algorithms and interfaces for communication (Kalsoom et al., 2020). Five publications state the use of smart sensors for shop floor data collection; however, merely one of the publications provided details about which capabilities these sensors implemented (see e.g. Wang, Jiang et al. 2018; Zhang, Wang, Wu & Qian, 2015). Other authors state the use of wireless sensor networks (e.g. Mourtzis & Vlachou, 2018; Zhang, Liu, Liu, Yang Li, Huisingh et al. 2018) or, in one case, using a Raspberry Pi (Leusin, Frazzon, Maldonado, Kück & Freitag, 2018). Thus, some benefits of smart sensors like wireless communication, being physically small, or data pre-processing capability (Kalsoom et al., 2020) seemed to be exploited by the approaches reviewed, however, not particularly prominent.

Together Auto-ID and sensing technologies help to build the smart object (Zhang et al., 2015), in particular, Siafara, Kholerdi, Bratukhin, Taherinejad and Jantsch (2018) present an architecture of an autonomous cooperating object that integrates many functions in different modules to build up an entity that can perform a variety of tasks. Next to the communication with other entities, it takes sensor and actuator data as an input to react to anomalies, faults, and errors in the production and either reacts with automatic compensations or by informing a human operator.

Protocols, standards, and architectures were employed for enabling communication and integration of developed approaches. ANSI/ISA-95, a standard for enterprise-control system integration, was used by authors to present their methods in the context of horizontal and vertical integration into the enterprise (Rossit, Tohmé & Frutos, 2019a). Open Platform Communications Unified Architecture (OPC UA), Extensible Markup Language (XML), Data Distribution Service (DDS), and the ZigBee protocol (assigned to networking, because of existing ZigBee-devices) act as enablers for shop floor communication between CPSs and in MAS (e.g. Mourtzis and Vlachou, 2018 or Wang, Jiang et al., 2016). The Agent Communication Language (ACL) and the Contract Net

Protocol (CNP) were used particularly dedicated to MAS (Wang, Zhang et al., 2018; Wang, Wan, Zhang, Li & Zhang, 2016). Finally, a holonic control architecture (HCA), namely, the product-resource-order-staff-architecture (PROSA), is used to model, implement, and control the work environment in a Java Agent Development Environment (Sadik, Taramov & Urban, 2017).

An overview of the publications dealing with a specific PPC problem-solving approach gives Figure 12. Many of the publications reviewed dealt with explicitly or implicitly stated multi-objective optimization problems involving a high number of decision variables, constraints, and the requirement to be solved in real-time (e.g. Rahman, Sarker & Essam, 2015). Therefore, constructive methods like bottleneck-based heuristics or priority dispatch rules were the most popular methods used to solve the PPC problems. In the case of metaheuristics, genetic algorithms, particle swarm optimization, chemical reaction-based optimization, fireworks algorithms, simulated annealing, ant colony algorithms, or tabu search were employed. Additionally, simulation helped e.g. to analyze decisions by simulating future scenarios of production (e.g. Schuh, Reuter, Hauptvogel & Brambring, 2014). Other authors use petri nets for assistance in problem-solving, e. g. Wang, Jiang et al. (2016) use petri nets to model resource constraints triggered by shop floor events to solve an ant colony optimization problem. However, these methods mainly enable to plan and control the production or a sub-set of the production from a centralized perspective. The MASs consisted of agents assigned to different production entities that are able to self-organize their actions by communication and mostly by some negotiation mechanism (e.g. Wang, Zhang et al.; 2018; Dombrowski & Dix, 2017).
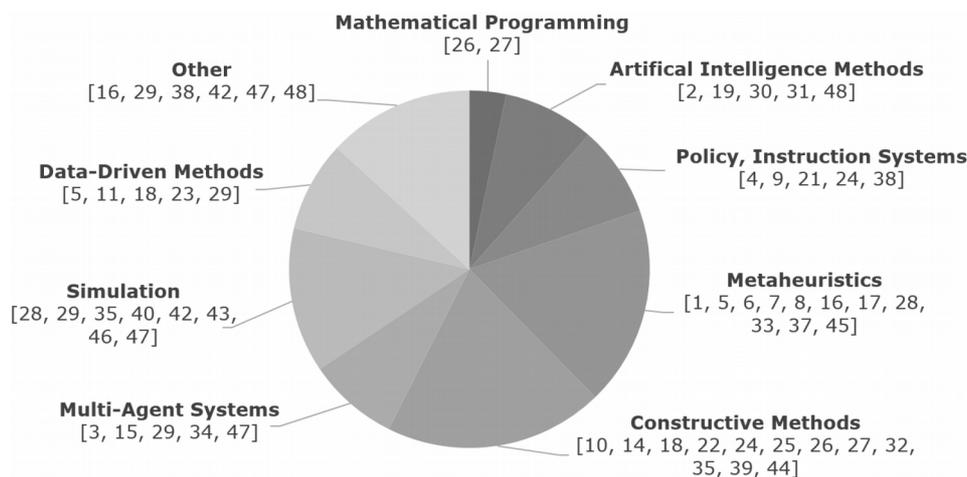

Figure 12. Approaches for PPC problem-solving (assigned publication numbers below each approach given in Appendix A)

Throughout the reviewed publications, artificial intelligence and data-driven methods appeared with a moderate frequency. To name a few, Wang, Sun, Zhang, Thomas, Duan and Shi (2016) present an interesting approach using online multitask reinforcement learning and decision-making to coordinate custom manufacturing tasks in a flexible manufacturing system among cooperative machines. Zhang et al. (2015) construct a decision tree that classifies exception events of the production using Algorithm C4.5 and historical data. An exception cause diagnosis and determination is carried out by fuzzy methods, namely, the Fuzzy Interactive-Dichotomizer3 algorithm and a fuzzy matching method. Bruno and Antonelli (2018) use a classification tree to assign tasks in a human-robot collaborative assembly work cell. Subramaniyan, Skoogh, Salomonsson, Bangalore and Bokrantz (2018) predict future bottleneck machines with an auto-regressive integrated moving average model based on a sliding window of past real-time manufacturing execution system (MES) data. Other authors also present approaches based on data analytics; however, these rather seem to be data-driven without employing classical techniques from the field of big data analytics (Rossit et al., 2019a). Again, other authors state the use of intelligent analytics of production data but do not provide details about concrete techniques used (Shen, David, De Pessemier, Martens & Joseph, 2019).

The scarce appearance of salient data-driven and artificial intelligence methods for PPC in our literature review suggests that several uses cases can be drawn from the Aachen PPC model to develop innovative contributions

using these approaches. Our findings fit with Cadavid, Lamouri, Grabot, Pellerin and Fortin (2020) of smart planning and scheduling being the most explored area of artificial intelligence in PPC, which resembles the in-house PPC task of the Aachen PPC model.

Few authors provided details for the cloud layer and PPC layer of the architecture depicted in Figure 8. In the architecture, the implementations of the methods, techniques, and approaches are assumed to be part of these layers. Yang and Takakuwa (2017) propose to integrate their presented methods into ERP and MES environments. Other authors merely mention the use of ERP and MES data or the interaction with these systems (Subramaniyan et al., 2018). Details about ERP and MES systems were generally very scarce in the literature reviewed.

For the cloud layer, some more information could be retrieved. Mourtzis and Vlachou (2018) present a real-time and adaptive shop floor scheduling and control approach realized as a software-as-a-service (SaaS) in a cloud environment, including infrastructure-as-a-service (IaaS). Lin, Li, Kong, Chen, Huang and Wang (2018) implement their methods in an advanced planning and scheduling shell (RAPShell) (Zhong, Pang, Pan, Qu & Huang, 2012), offering SaaS in a service-oriented architecture. RAPShell supports and receives decisions from human production schedulers. An interesting approach represent MASs supported by a cloud assistant. Wang, Wan et al. (2016) use a coordinator within a cloud layer designed for big data analytics that coordinates the agents. It aims to balance their loads and to increase efficiency and performance through assisting in global optimization. Similarly, Tang, Li, Wang and Dong (2017) propose a real-time dynamic scheduling method based on a cloud-assisted self-organized architecture, where agents self-organize production execution. Cloud assistance of distributed and autonomous control systems like MAS may represent a promising approach to overcome the risk of myopic behavior, as described by Bendul and Blunck (2019).

The human-computer interaction assigned to the graphics interface layer is enabled through intelligent terminals and smart devices. Authors mention an industrial personal computer (Wang, Zhang et al., 2018), an intelligent terminal (Zhang et al., 2018), or a supervisory control terminal (Wang, Wan et al., 2016), but do not provide more details about their use. Mostly workers are equipped with smart devices, which they refer to as mobile or wearable devices. These devices comprise smartphones and tablets to enable communication between a human operator and the software system (Schuh et al., 2014). Other authors even used wearable devices for shop floor state perception, e.g., to allow inertial sensing of the human operator's movements (Fera, Greco, Caterino, Gerbino & Caputo, 2019). Although few publications reported smart, mobile, or wearable devices, Khakurel, Melkas and Porras (2018) provide many categories and benefits of wearable devices in the work environment. The use of wearable devices for shop floor state perception in connection to PPC and its method represents a promising area of future research.

5. Discussion and Future Research

The reviewed publications focus on the detailed PPC, that is, the in-house PPC. Merely four publications are assigned to the functions of the task production requirements planning. Searching for current literature specifically about the functions process and capacity planning suggests a high availability of Industry 4.0 approaches in these areas (e.g. Trstenjaka & Cosic, 2017; Chien, Dou & Fu, 2018; Huka, Grenzfurtner, Zauner & Gronalt, 2021). In contrast, lot-sizing and production order scheduling have not been related to Industry 4.0 approaches in the current literature. A reason could be that traditional approaches remain more useful in these areas than current Industry 4.0 approaches since they do not require sophisticated approaches like machine learning or optimization methods. We note that we reviewed several scheduling studies related to production order scheduling, but in the context of the Aachen PPC model, this function is defined as production order monitoring and rough backward and forward scheduling. Therefore, scheduling literature does not apply for this function but rather for functions of in-house PPC.

It is proposed to investigate further how the opportunities and technologies of Industry 4.0 are deployed in production requirements planning. Research should be conducted in studying the automated issuing of process plans or the dynamic administration of alternative process plans. Smart objects may be able to autonomously generate a robust process plan based on the current shop floor state perceived through communication with

other entities. As already investigated in Ruppert and Abonyi (2018), methodologies for estimating and determining variable processing times should be extended to different areas. In particular, research can be devoted to predicting the times and resources needed to manufacture a specific product through intelligent algorithms and historical data. Further research should be carried out on how dynamic lot-sizing and quantity bundling can be realized through real-time data and benefit the economic efficiency of production. Here data-driven lot-sizing based on past inventory cost and order cost may apply. Based on real-time data availability, it is worth investigating how to improve capacity requirements planning to match capacity demand and supply in a dynamic Industry 4.0 environment. Also, the positive and negative impacts of reconfigurable production lines on capacity planning represent a potential area of research.

Kuprat et al. (2015) point out that Industry 4.0 will cause improvements for the planning aspect of PPC; however, that does not fit with the findings of this literature review. In contrast, the reviewed approaches concentrate on production control. Although many publications are classified into job shop planning, it should be noted that many of the approaches within do not exclusively limit their scope to the activities that are carried out before the production order release. This is underlined by many approaches utilizing real-time shop floor data, as stated in chapter 3.2, and also with regards to how in-house PPC is described in the Aachen PPC model. The improvement of production control through higher data availability and quality is a match between the authors' outlook and the findings of this publication. The approaches reviewed stand out in high exploitation of the increased data availability and quality gained through Industry 4.0 technologies (see chapter 3.2). Further research activities should be carried out in improving the production order release, e. g. through developing intelligent or data-driven release criteria and dynamic provision of resources at release time.

Zhang et al. (2019) question if recent research focuses enough on the use of new technologies to solve the job shop problem. As stated in chapter 3.2, a significant part of the reviewed papers presents a particular scheduling problem using Industry 4.0 technologies shown in Figure 8. Parente et al. (2020) and Jiang et al. (2021) present a large body of research and new paradigms concerning scheduling under Industry 4.0. We see scheduling as an area of ongoing research with promising developments towards exploiting Industry 4.0 technology and its capabilities. Our literature review supports this expectation. However, PPC and scheduling deal with many uncertainties occurring during production control provided in the present literature review. Future research might consider upstream disturbances like material quality problems and property variations or supplier production problems resulting in spontaneous unavailability of materials, as several works already consider most of the remaining disturbances. Besides, based on our review, cloud manufacturing possibilities in the context of in-house PPC and scheduling problems should be leveraged in future studies since they received little attention in the papers reviewed. As stated in chapter 4, distributed control architectures may benefit from a cloud assistant, which drives the possibly myopic decisions of autonomous production units towards the global optimum.

The findings of this literature review support the outlooks for adaptive and flexible approaches of PPC under Industry 4.0 in Waschneck et al. (2016) and autonomous, cooperative, intelligent, or robust production systems in Monostori (2014). A variety of approaches applying metaheuristics, MAS, as well as policy and instruction systems, to name a few, was reviewed. Data-driven planning, scheduling, and control of production should be further researched, and methods from artificial intelligence should be exploited. Cadavid et al. (2020) present several use cases that are very similar to the considered functions of the Aachen PPC model (ordered from most to least occurrences in the literature according to their review):

- Smart planning and scheduling,
- Time estimation,
- Process control and monitoring,
- Inventory and distribution control,
- Smart design of processes.

Chapter 4 already mentions the use of wearable devices for shop floor state perception. Based on Khakurel et al. (2018), we propose using more than smartphones and tablets as smart devices. Smartwatches can contribute to motion and position tracking of workers or assist in communication. Sensing technologies like heart rate monitors, electromyography, or emotion measurement can help consider human factors in scheduling problems. Additionally, eyewear like augmented reality glasses can support tracking, communication, and decision-support to the human operator. In this regard, we also propose to develop new solutions for supporting the decision-making of human operators in production as a future research direction.

In the present literature review, the supporting tasks of the Aachen PPC model, order management, controlling, and data management, received little to no attention. Again, searching for current literature specifically about their functions suggests different availabilities of Industry 4.0 approaches in these areas. Recent studies outline the requirement of horizontal and vertical customer integration (e. g. Hozdić, 2015), but very few studies could be found explicitly investigating algorithms and technologies that could be useful in this area. Current approaches for PPC may lack horizontal and vertical integration. It is proposed to investigate how to involve the customer in the planning, releasing, and monitoring real-time manufacturing systems. The task controlling (strongly related to project management in the Aachen PPC model) also received little attention in current literature. Studies exist that investigate current trends of Industry 4.0 and project management related to manufacturing (López-Robles, Otegi-Olaso, Cobo, Bertolin-Furstenau, Kremer-Sott, López-Robles et al. 2020), but they do not reflect the administration, planning, control, and controlling aspects of project management in detail. However, the availability of real-time data and the possibility of including cost-related objective functions in scheduling systems suggests a high applicability of Industry 4.0 approaches in this area. Real-time information could support a detailed cost tracking that helps report cost and changes of cost over time and perform more detailed budgeting. Studies about data management related to several Industry 4.0 approaches like scheduling, machine learning, or big data analytics exist (Raptis, Passarella & Conti, 2019). However, in the Aachen PPC, data management's functions like bill of materials (BOM)-management or drawing management model focus on more traditional activities that do not require sophisticated technological solutions and algorithms. Dynamic and intelligent data storage, alternative BOMs, a digital twin's influence on drawing management, and how it connects to the PPC represent future research topics. We propose to use Figure 13 as a reference for generating new research ideas. By selecting a cell with a low number, the row and column can be concatenated to form a new idea, e.g. "intelligent drawing management".

	Process planning	Production order scheduling	Lot-sizing	Capacity planning	Job shop planning	Production order release	Production order monitoring	Resource monitoring	Customer offer management	Customer order management	Project administration	Project planning	Project control	Project controlling	Master data management	BOM-management	Classification	Drawing management
Real-time	8	17	4	6	30	12	28	27	0	3	0	0	6	2	2	1	1	5
Autonomous	2	2	1	1	6	4	5	5	0	0	0	0	0	0	1	0	0	1
Dynamic	4	2	0	1	4	3	7	7	0	0	0	0	0	2	0	1	1	3
Adaptive	0	1	1	0	6	3	6	5	0	0	0	1	0	0	0	0	0	0
Reconfigurable	1	1	0	0	3	2	4	3	0	0	0	0	0	0	0	0	0	0
Robust	2	0	1	0	5	2	5	5	0	0	0	0	0	0	0	0	0	0
Flexible	2	0	1	1	5	2	5	5	0	0	0	0	0	1	0	0	0	0
Self-X	2	2	0	0	4	2	4	5	0	0	0	0	0	0	0	0	0	0
Intelligent	1	2	0	0	5	2	5	5	0	0	0	1	0	0	0	0	0	0
Data-driven	0	0	0	0	2	2	1	2	0	0	0	0	0	0	0	0	0	0

Figure 13. Industry 4.0 characteristic and Aachen PPC model function matrix

Based on the reviewed approaches outlining a specific understanding of each Industry 4.0 characteristic (see Figure 6), we formulated definitions for each characteristic in Table 3. Providing current solution techniques,

objectives, possible uncertainties (disturbances), architectures, and technologies, our cyber-physical PPC architecture may assist in conceptualizing new research ideas in more detail. However, we are aware that not all rows and columns may produce a well-articulated research idea as e.g. "reconfigurable master data management" may not be a meaningful area for future research. Finally, as is observable in Figure 4, research in the area of PPC under Industry 4.0 gained attention over the past years, and a rising trend can be projected for the future.

Industry 4.0 Characteristic	Definition
Real-time	A system's ability to respond to an event within a defined time period.
Autonomous	A system's ability to execute high-level tasks without detailed programming and to perform decision-making without human control.
Dynamic	A system whose state varies over time.
Adaptive	A system's ability to maintain a specific functionality while changing its internal structure to environmental changes.
Reconfigurable	A modular system's ability to rapidly change between predefined internal structures to respond to changing requirements.
Robust	A system whose performance is relatively insensitive to the potential realizations of the parameters and conditions under which it operates.
Flexible	A system's ability to respond to changing conditions and requirements by providing a large variety of functionalities.
Self-X	A system's ability to self-configure ("plug-and-play"), self-diagnose its current state, or self-optimize without human intervention.
Intelligent	A system's ability to improve its functionality and adaptability to changing environments through perceiving its environment and learning from errors and deviations.
Data-Driven	A system which controls its activities based on continuous analysis of collected raw data.

Table 3. Industry 4.0 characteristic definitions

6. Conclusions

6.1. Implications

Since 2014, the term Industry 4.0 gained popularity in research and thus influenced the development of concepts for PPC. Recent studies envision a CPPS that can handle high complexity and perform autonomous and intelligent decision-making based on the shop floor's real-time data. The presented exploratory literature review identifies 48 relevant papers from different conferences and journals based on the findings of two search iterations. These papers are reviewed and classified concerning the Aachen PPC model. Rank order clustering and spectral clustering are carried out to reveal the functions of the Aachen PPC model. As shown in chapter 2, several literature reviews focus on scheduling. Our reviewed literature resembles this trend. Scheduling emerges as a major area of research that contributes to in-house PPC and the cluster analyses show high research activity in that area. Production requirements planning, cross-sectional tasks, and data management received little to no attention in current PPC literature. Researchers can build upon these literature gaps.

The identified functions form the basis for an architecture of cyber-physical PPC, showing Industry 4.0 technologies, current optimization methods, optimization objectives, and the management of disturbances. Each layer of the cyber-physical PPC architecture was explored in light of the literature reviewed. The results are discussed in comparison with the research directions described in previous studies and literature reviews. Unexplored tasks and functions of the Aachen PPC model are identified, and future research directions are proposed. An Industry 4.0 characteristic and Aachen PPC model function matrix can help to generate new research ideas for PPC under Industry 4.0.

The present study adds to the previous publication (Herrmann et al., 2021) by analyzing and discussing the reviewed literature in more detail. It extends the related work considered and distinguishes itself more clearly from existing studies.

6.2. Limitations

The focus on scheduling literature could be caused by including the search term "scheduling" in the search strategy of our literature review. We observed a strong dependence of results on the search terms used, and the search terms are defined broadly. Thus, literature about specific tasks and functions of the Aachen PPC model like data management, process planning, or project controlling could not have been retrieved from the databases in the first place. Therefore, the cluster analyses may be biased by the search terms chosen, and unexplored areas of the Aachen PPC model could have been found to be well researched if the right literature had been retrieved. Additionally, during title, abstract, and full-text eligibility assessment of publications, scheduling problems were more easily assignable to the functions of the Aachen PPC model than other approaches reviewed. This could be another cause for the focus on scheduling literature also in the present study.

The present contribution is based on a comprehensive classification scheme. The authors summarized each function of the Aachen PPC model into four components. This process was subjective and different authors might summarize the functions into different components. Also, some components might summarize a greater part of a function than other components. We question if the coherence score explained in Figure 3 can be expressed as a Likert scale upon which the cluster analyses can be applied. In this regard, the assignment of each publication to the components was a subjective process. Another subjective process was the literature selection and full-text analysis of each article because one author conducted these steps. Including more individuals in the selection and detailed review process could have lead to a more objective eligibility assessment and information retrieval from each publication. The subjective eligibility assessment and assignment of publications to the Aachen PPC model are part of the main limitations of this review.

Choosing a model different from the Aachen PPC model could have slightly changed the present study's findings. Despite different terminologies, from the overview in Meudt et al. (2017), we conclude that existing PPC concepts are similar enough for our purpose. The search terms of this literature review do not depend on the PPC concept used. Thus, the literature retrieved would have been similar to another PPC concept; however, the cluster analyses would change due to the different terminologies.

6.3. Future Outlook

For future research, we propose not only focusing on the scheduling aspect of PPC but also considering other areas included in the Aachen PPC model. Additionally, literature about the unexplored tasks and functions of the Aachen PPC model should be reviewed to reveal if the scarce research identified in these areas in the present study holds.

Declaration of Conflicting Interests

Funding

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Appendix A. Papers included in the Literature Review

Publ. No.	Date	Author(s)
1	2018	Nahhas, Lang, Bosse & Turowski
2	2019	Kast, Albrecht, Feiten & Zhang
3	2018	Wang, Zhang et al.
4	2019	Framinan, Fernandez-Viagas & Perez-Gonzalez
5	2019	Shen et al.
6	2019	Fu., Zhou, Guo & Qi
7	2019	Wu., Li et al.
8	2019	Rahman, Janardhanan & Nielsen
9	2019b	Rossit, Tohmé, & Frutos
10	2019	Saif, Guan, Wang, He, Yue & Mirza
11	2019a	Rossit, Tohmé & Frutos
12	2018	Ruppert & Abonyi
13	2018	Mourtzis & Vlachou
14	2018	Lin et al.
15	2018	Leusin et al.
16	2018	Fu et al.
17	2018	Zhang et al.
18	2018	Subramaniyan et al.
19	2018	Bruno & Antonelli
20	2018	Chien et al.
21	2018	Wang, Jiang et al.
22	2017	Sadik et al.
23	2017	Zhang, Wang, Liu & Qian
24	2017	Shim, Park & Choi
25	2017	Grundstein, Freitag & Scholz-Reiter
26	2016	Hsu & Yang
27	2017	Legarretaetxebarria et al.
28	2016	Wang, Zhong et al.
29	2016	Wang, Wan et al.
30	2015	Zhang et al.
31	2016	Wang, Sun, Zhang., Thomas, Duan & Shi
32	2014	Engelhardt, Weidner & Reinhart
33	2019	Brik, Bettayeb, Sahnoun & Louis

Publ. No.	Date	Author(s)
34	2018	Tang et al.
35	2017	Yang & Takakuwa
36	2019	Kourtis, Kavakli & Sakellariou
37	2019	Wu, Tian & Zhang
38	2016	Wang, Jiang et al.
39	2017	Sousa, Varela, Alves & Machado
40	2019	Fera et al.
41	2016	Wolfsgruber & Lichtenegger
42	2014	Schuh et al.
43	2015	Reuter, Brambring & Müller
44	2015	Grundstein, Schuhkraft, Freitag, & Scholz-Reiter
45	2014	Vernim, Hees, Teschemacher, Wagner & Reinhart
46	2015	Aurich, Kasakow & Menck
47	2017	Dombrowski & Dix
48	2018	Siafara et al.