Aligning the Production Planning and Control Process with Prognostics and Health Management

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Abstract

Production planning and control (PPC) is the heart of any manufacturing company and entails tasks such as resource planning, sequencing, or capacity control. While an increasing complexity within production makes it difficult to determine the best production plan, the advances in PHM and the emergence of predictive maintenance also offer new opportunities to optimize PPC. While there is much research on PHM and PPC, little has been done to align both disciplines. Through post-prognostics decision-making, different PPC decisions, such as continuing the production, shutting down a machine, or reducing its workload, can be elevated by a remaining useful life (RUL) estimation. However, it is unclear how exactly this prognostics information can be exploited and how processes, organization, and technology must be aligned to attain a more efficient and flexible production. Further, PHM has long been implemented beyond research, but it is unknown whether and how practitioners intertwine it with their PPC. This work aims to analyze how processual, organizational, and technological changes through PHM can lead to advanced PPC. This goal is attained by means of a multivocal literature review (MLR) in which scientific PPC and PHM literature and standards are analyzed, and an aligned PPC process proposed. The findings are juxtaposed with grey literature, revealing fits and gaps between research and practice, and a research agenda is presented.

1. Introduction

Prognostics and health management (PHM) enables improved maintenance decisions and ultimately reduces costs, and increases a machine's reliability and availability (Ladj et al., 2017). However, PHM can also improve production planning and control (PPC) by incorporating information, such as the remaining useful life (RUL), in post-prognostics decision-making (Kuhnle et al., 2019; Wesendrup & Hellingrath, 2020).

For instance, Scheffels presents a case study where the production output of Porsche Macan bodies could be increased from 18 to 21 pieces per hour by implementing PHM (2018). Beyond improving the maintenance process by introducing smart-assistance systems, the production process could also be improved by adjusting welding parameters through PHM insights (Scheffels, 2018). All in all, this could be achieved without new machines but by improving PPC through PHM alignment. As the next step, Porsche envisions a self-optimizing production based on PHM (Scheffels, 2018). While this case demonstrated one example, it is unclear how prognostics information can be exploited in general and how processes, organization, and technology must be aligned to attain a more efficient and flexible PPC (Ansari et al., 2019).

Jacobs et al. define the task of PPC as "to manage efficiently the flow of material, to manage the utilization of people and equipment, and to respond to customer requirements by utilizing the capacity of our suppliers, that of our internal facilities, and (in some cases) that of our customers to meet customer demand" (2011, p. 2). In this regard, process models and standards exist (e.g., Jacobs et al., 2011; Kistner & Steven, 2001; Schmidt & Schäfers, 2017; Schuh, 2006), typically comprising steps from master production scheduling to planning, controlling, and monitoring the production. While PPC strives to maximize efficiency, breakdowns can lead to costly disruptions of the production flow. Here PHM can provide crucial information to adjust the production plan and avoid all consequences of a breakdown (Chebel-Morello et al., 2017). To implement PHM, ISO-13374 entails a process for condition monitoring, and ISO-13381 for prognostics, which can be condensed to a complete PHM process as Guillén et al. (2016) presented (cf. Figure 1).

However, while previous works specify processual, technological, and organizational requirements to conduct PPC or PHM, no work combines both areas to examine where and how the PPC process can be elevated by aligning it with PHM. The state-of-the-art comprises single solutions for specific PPC problems, such as production scheduling (e.g., Zhai et al., 2019) or lot-sizing (e.g., Cheng et al., 2017). Seldomly,

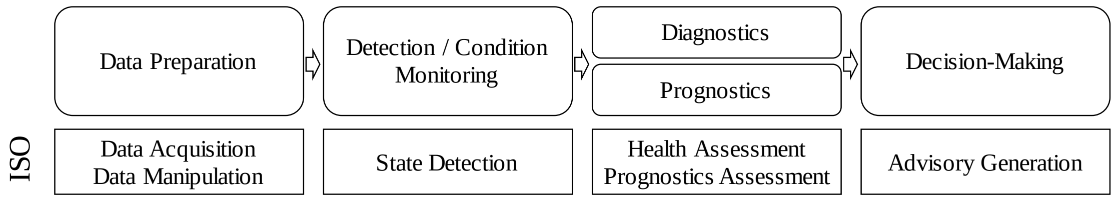

Figure 1. PHM process (based on Guillén et al., 2016).

it is examined how well these translate to practice, and empirical evidence shows that most companies still use simple algorithms to manage their production (Seitz et al., 2018). Further, only a few related works tried to summarize where the PPC process can benefit from PHM beyond specialized applications, shown in Table 1. For example, Voisin et al. propose a generic process for prognosis, showing which actors, steps, and data are included (2010). While the process is very detailed, it mainly focuses on PHM elements and does not show how these can be intertwined with PPC. Further, Bousdekis et al. present a unified architecture for proactive maintenance, comprising PHM process elements such as prognostics and decision-making, user roles, and sensor and database integration (2019). While they connect their architecture to production planning, they do not specify how exactly an integration is accomplished. Finally, Ansari et al. propose a prescriptive maintenance model for production systems and describe different roles (e.g., maintenance manager, knowledge engineer), data and information systems (IS), and dependencies between strategic, tactical, and operational PHM and PPC processes (2019). However, they do not link their work to detailed PPC process elements or the state of practice.

In contrast, this work aims to analyze how PHM can be aligned with PPC on a processual, technological and organizational level while incorporating a practitioner's perspective through a multivocal literature review (MLR). This is achieved by answering the following research questions: 1) "Which PPC processes can benefit from PHM, and what information systems and organizational units are involved?", 2) "How must the PPC process be aligned to achieve the benefits?" and 3) "How is it currently done in practice, and what is the disparity to research?".

Table 1. Related works

Reference	Scientific Method	Process	PPC Focus	Practice
(Voisin, Levrat, Cocheteux, & Iung, 2010)	Business process modeling	X		
(Bousdekis et al., 2019)	Conceptual modeling and case studies	X		X
(Ansari et al., 2019)	Literature review and case study	X	(X)	
This work	Multivocal Literature Review	X	X	X

The remainder of this paper is structured as follows: The following section introduces the methodology of this work, a multivocal literature review, and presents the analyzed literature. In section three, the main contribution of this work, a PHM-aligned PPC process, is demonstrated. Section four juxtaposes findings from research and practice and identifies gaps. The last section concludes the paper and establishes a research agenda.

2. Multivocal Literature Review

An MLR based on Garousi et al. was used to attain the aim of this study (2019). Beyond scientific literature, an MLR also includes grey literature (e.g., company reports) that gives more insights into the state of practice. For this paper, academic literature is assumed to represent a theoretical and grey literature a practical perspective.

For the scientific literature, the titles, abstracts, and keywords from the databases Scopus, Web of Science, and IEEE Xplore have been queried with the following string:

("predictive maintenance" OR prognostic OR "condition-based maintenance" OR "remaining useful life") AND "production planning"*

On the other hand, the Google search engine has been queried with two strings to retrieve grey literature.

a) *"predictive maintenance" "production" filetype:pdf*

b) *"prescriptive maintenance" "production" filetype:pdf*

While these led to many results, Garousi et al. propose a theoretical saturation threshold after which "no new concepts emerge" (2019) which confines the search.

After the initial pool has been collected, the titles and full texts of the scientific and grey literature were examined by two reviewers. Papers that were not relevant (e.g., no PPC or PHM relation) were excluded from the search. In the end, 52 publications (25 scientific and 27 grey papers) were identified as appropriate.

As a next step, Garousi et al. determine that a concept map must be defined, after which the literature is analyzed (2019).

Fitting to the research goal, the perspectives process, organization, and IS are chosen. From the found concepts, an adapted PPC process is modeled in the event-driven process chain notation (cf. Scheer et al., 2005). Through this model, it becomes clear how a PPC process must be aligned to exploit PHM.

2.1. PPC Process Categories Addressed in PHM Literature

Based on the models from Jacobs et al. (2011), Kistner and Steven (2001), Schmidt and Schäfers (2017), Schuh (2006), and the IEC 62264 standard (International Electrotechnical Commission, 2016), a basic PPC process with eight process categories is synthesized and depicted in Figure 2.

The PPC process typically starts with *master production scheduling* which transforms the sales plan into an aggregate plan for producing products that regards customer orders and order promises from *demand management* (Jacobs et al., 2011). From the master production schedule, sourcing and production requirements can be derived within *requirements planning*. Here, net requirements are determined for which a make-or-buy decision is made (Schmidt & Schäfers, 2017). External requirements are forwarded to *source planning*, where they are procured; for internal requirements, a tactical production program is set up and sent to *production planning* (Kistner & Steven, 2001). Here, the initial plan is coordinated with available resources (material, machines, personnel), and a schedule is created (International Electrotechnical Commission, 2016). Subsequently, *production control* defines concrete sequences, dispatches the production, and controls capacities (International Electrotechnical Commission, 2016; Schmidt & Schäfers, 2017). Adherence to predefined business objectives (e.g., efficiency) is continually checked through *production monitoring* (Schmidt & Schäfers, 2017). Lastly, finished and sourced products are forwarded to *inventory management*, where they are collected and dispatched to satisfy customer demand (Kistner & Steven, 2001).

From this process, it was examined how many publications addressed the different process categories. Table 2 shows the

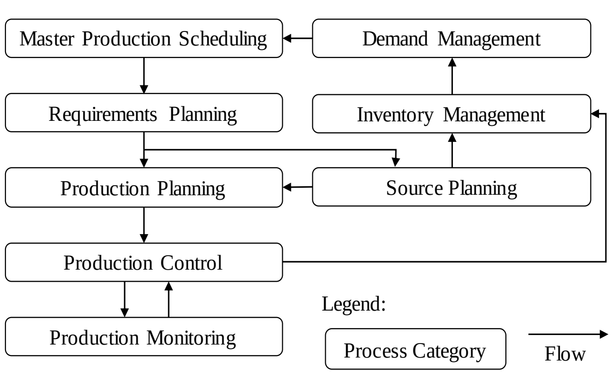

Figure 2. Process categories of PPC

Table 2. Literary prevalence of PPC process categories

Process Category	Papers	%
Demand Management	1	2%
Master Production Scheduling	0	0%
Requirements Planning	11	21%
Source Planning	11	21%
Production Planning	20	38%
Production Control	29	56%
Production Monitoring	3	6%
Inventory Management	3	6%

number of papers that discussed one of the eight process categories and their share of all 52 publications; the total percentage can add up to more than 100% whenever works demonstrated the integration of PHM for more than one category. It can be seen that the shorter the planning horizon of the PPC process category, the more it is aligned with PHM, which makes sense because a short-term RUL estimation is most reliable. Thus, *demand management* and *master production scheduling* receive almost no attention. On the other hand, the mid-term planning categories *requirements* and *source planning* have medium prevalence in the literature. The most recognition is given to *production planning* and *production control*, highlighting the short-term nature of PHM. Lastly, p*roduction monitoring* and *inventory management* receive low attention. A reason could be the more supportive role in the PPC process. While the reviewed papers were only allocated to the different process categories in this section, a deeper analysis of how PHM affects the PPC process can be found in section four. However, before this analysis can be made, it must be examined how IS and organizational roles are changed by aligning PPC with PHM.

2.2. The Role of Information Systems

IS are crucial to control the performance of business processes (O'Brien, 2003). They are sociotechnical systems that "collect, process, store, and distribute information" (Piccoli & Pigni, 2016, p. 56). Through the alignment with PHM, existing IS must be adapted or newly integrated into the PPC process. This section demonstrates which IS are relevant for a PHM and PPC and how an alignment is achieved.

Cyber-physical production systems (CPPS) are characterized by autonomy, connectedness, and responsiveness (Monostori et al., 2016). In this work, they comprise production assets, including sensors, controllers, actuators, or interfaces. They can enable the transformation to a heterarchical production through PHM by capturing relevant condition data over sensors (Balogh et al., 2018; Do et al., 2006; Rødseth et al., 2017; Schuh et al., 2020), cleaning and preprocessing them over onboard programmable logic controllers (Busse et al., 2018), and autonomously tuning the production schedule based on prognostics information (Glawar et al., 2019). While *CPPS* can be independent, they are leveraged when connected to other information systems.

In this work, *PHM systems* are IS that fulfill the functionalities of ISO-13374 and ISO-13381 and transform sensor values from CPPS into prognostics and health information. However, there is no clear definition in the literature, and further terms, such as "prognosis system" (Ladj et al., 2016, p. 2084) or "predictive maintenance analysis system" (Zarte et al., 2017, p. 3377) are used. For instance, Morariu et al. developed a system based on Apache, with map-reduce algorithms running on Spark to compress sensor data, which are then sent to Kafka. Here clustering, classification, and a long short-term memory neural network are used to calculate an RUL forecast (2020). While further works used an Apache infrastructure (Balogh et al., 2018), many other variations exist, such as PHM systems based on Matlab (Busse et al., 2018) or commercial solutions (AspenTech, 2019; Siemens, 2019). Furthermore, PHM systems can be standalone IS, or they can be embedded into manufacturing execution systems building a close link between PHM and PPC (Standardization Council Industrie 4.0, 2018).

The role of *manufacturing execution systems (MES)* is established. MES operate at the "interface between heterarchical autonomous production control and hierarchical production planning" (Glawar et al., 2019, p. 485). They contain valuable information such as machine downtimes and performances, historical and planned production programs (Ansari et al., 2019; Zarte et al., 2017) and are an adequate interface between PPC and PHM. An MES is a tool to establish a maintenance-oriented production (Zhai & Reinhart, 2018). This can be done by mixed product and operation scheduling, which intelligently stresses the different CPPS to perform opportunistic maintenance (Ladj et al., 2016; Morariu et al., 2020).

Overall asset management can be realized in *computerized maintenance management systems (CMMS)*. A CMMS contains maintenance data and is used for administering maintenance interventions. Typically, a PHM system sends a notification to the CMMS whenever the RUL of a machine is shorter than the maintenance planning horizon (Rødseth et al., 2017). In this case, the CMMS balances the maintenance costs with the risk of failure (Glawar et al., 2019). When maintenance must be done, a CMMS manages human resources to notify the nearest capable maintenance worker (SitScape, 2018). In addition, the intervention can be supported with a mobile app in which the worker can look at historic maintenance interventions and best practices that can be evaluated and complemented (Scheffels, 2018).

In parallel, *quality management systems (QMS)* can support PHM systems by monitoring the production process. They contain quality data and regular measurements of products (Ansari et al., 2019). If these are abnormal, they indicate machine problems (Do et al., 2006) which might not be seen in the sensor data.

Enterprise resource planning (ERP) systems support functions beyond manufacturing operations. After interventions have been scheduled, ERP systems update the production plan and regard the reduced capacity (Do et al., 2006). They also contain information about customers, suppliers, article prices, lead times, bill of materials, work plans (Zarte et al., 2017), and demand which can be exploited to optimize PHM and PPC (Wang et al., 2020). Beyond more tactical planning of maintenance, ERP systems also store information about spare parts (e.g., stock, cost), and through PHM, they are enabled to order spare parts just-in-time (Ansari et al., 2019).

Of course, all of the presented IS are not operating as information silos but are connected via interfaces enabled by *standards and protocols*, as shown in Figure 3. Sometimes IS are also offered as integrated solutions, e.g., the CMMS SAP 'Plant Maintenance' module of the SAP ERP solution. Typically, sensor values are transported over internet of things gateways or event hubs (Microsoft, 2017; Schuh et al., 2020). As the controllers of the CPPS have limited storage capacities, these values can be preprocessed (Do et al., 2006) before they are sent to the PHM system. The messages follow a standard protocol such as OPC-UA and can be sent in real-time, e.g., with two hertz (Busse et al., 2018). Further, the RUL is calculated and communicated with the MES (Glawar et al., 2019) or CMMS (Rødseth et al., 2017). From the CMMS, maintenance work orders are forwarded to the ERP system (Do et al., 2006). These work orders should also be returned to the PHM system as feedback. The work order input of the ERP necessitates a change of the production plan that must be relayed to the MES for hierarchical production planning. Alternatively, the PHM system can forward the RUL directly to the MES, which can decentrally adjust the production rate or schedule of the CPPS (Glawar et al., 2019). Lastly, QMS can support PHM by reporting abnormal product quality to the CMMS.

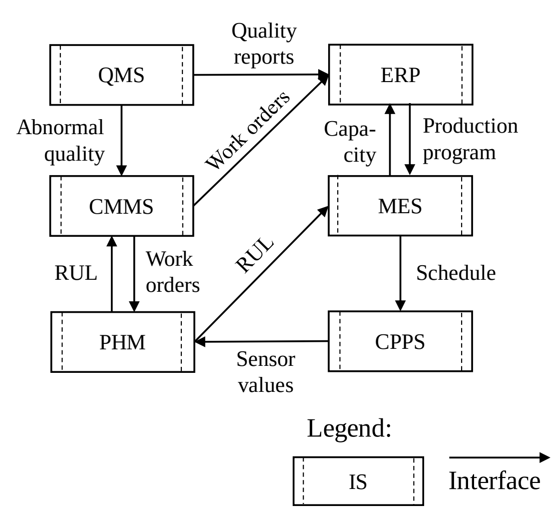

Figure 3. PHM PPC information systems landscape

2.3. Organizational Alignment

Additionally, it is essential to look at organizational contexts to analyze how PPC can be better aligned with PHM. Unfortunately, only a few reviewed works focus on this aspect to analyze the change of roles that work at the interface of PHM, production, and maintenance.

Even though automation generally increases when integrating PHM, the *maintenance* personnel is still in the loop. When the RUL drops below a certain threshold, a capable field technician is automatically assigned to maintenance interventions, e.g., via smartwatch or tablet (Scheffels, 2018). Here, automatically detecting the fault via diagnostics is crucial to assign the maintenance employee with the right skillset. In addition, technicians use data-driven remote monitoring and diagnostics tools (Microsoft, 2017) to verify problems; here, experience from the technician that cannot be measured can complement the RUL forecast (Do et al., 2006), so it can be better interpreted. Finally, after a problem has been confirmed, the technician can maintain the machine supported by virtual walkthroughs or remote assistance (Microsoft, 2017). Of course, this is always done in coordination with a maintenance planner who receives information about the urgency of different actions (Ansari et al., 2019). The urgency is defined within a maintenance schedule that balances time-based preventive maintenance and condition-based predictive maintenance actions and simulates different scenarios. Based on the RUL estimation, the planner can schedule future tasks, adjust the available capacities (Rødseth et al., 2017), or bundle opportunistic maintenance interventions (Ansari et al., 2019). Here, the maintenance planner typically uses a recommender dashboard (Glawar et al., 2019), supported by post-prognostics decision-making which is shared with the production planner (Rødseth et al., 2017).

Of course, *production* planners must always closely cooperate with maintenance planners (Microsoft, 2017) and work with the adjusted production capacities. On an operational level, machine operators may add flexibility to the PHM systems because they can also provide knowledge that cannot be measured by sensors (Do et al., 2006). Thus, they can interpret RUL forecasts by factoring in the stress that currently manufactured products or the future production schedule exert on the machine. Further, production personnel can also be empowered through PHM and autonomous production. For example, minor maintenance interventions can be distributed to factory workers supported by intelligent support systems (Henke et al., 2019). These systems include knowledge gained from PHM (e.g., fault isolation, diagnostics), which substitutes the expertise from trained maintenance personnel.

Lastly, *information technology* personnel should still support the day-to-day business in the plant. For instance, a knowledge engineer updates the RUL forecasting algorithm whenever new insights necessitate that PHM models must be adapted (Glawar et al., 2019).

3. A PHM-ALIGNED PPC PROCESS

Considering the processual, technological, and organizational changes introduced, an aligned PPC process is proposed in Figure 4. Here, the process categories depicted in Figure 2 and Table 2 are picked up again and split into multiple process elements. In the following, the former is written in bold, the latter in italic letters. Additionally, process elements where PHM alignment is possible are marked with a bold frame in Figure 4.

Demand management. The process starts with *customer order receipts*, which are then considered in *order-specific capacity planning*. Denkena et al. propose an event-driven simulation that adjusts planned make-to-stock production volumes based on stock, customer orders, and RUL. Here, different quantities are tested to calculate all possible variants that do not cause a delivery interruption (2012). Besides sales forecasts, incoming orders are also used for *master production scheduling*.

Master production scheduling. Because *master production scheduling* has a long-term planning horizon, no improvements can be made with PHM.

Requirements planning (general). In contrast, machine breakdowns can be regarded in the mid-term production planning (Glawar et al., 2019). Here, the maintenance threshold and production quantity are jointly determined to satisfy the demand (Wang et al., 2020). From the incoming master production schedule, a secondary and *net requirements calculation* is done, and it is defined whether the production requirements should be produced in-house or sourced externally.

Source planning. In the latter case, *source planning* is conducted. Besides raw *materials planning*, *spare parts planning* must also be done (Ansari et al., 2019; Maguire et al., 2017). Through PHM, spare parts can be ordered just in time (Busse et al., 2018; Microsoft, 2015). Here, the RUL and information from ERP (e.g., costs, lead times) are balanced and jointly optimized to minimize the total cost (Ansari et al., 2019; Oracle, 2019; Standardization Council Industrie 4.0, 2018). This step is often done as decision support where suitable spare parts are suggested (Vilsbeck, 2020). Advanced solutions go even further and automatically trigger maintenance orders or spare parts procurement, e.g., via additive manufacturing (Schuh et al., 2020; Trebing + Himstedt, 2017). Here, the CPPS go beyond simple sensor reading and determine their demands autonomously (Henke et al., 2019; Leonard, 2020). After the parts are ordered and received, they are forwarded to *inventory management*, where proper spare parts management guarantees delay-free maintenance interventions (Ansari et al., 2019; Busse et al., 2018). Spare parts availability also plays an ongoing role in in-house requirements planning.

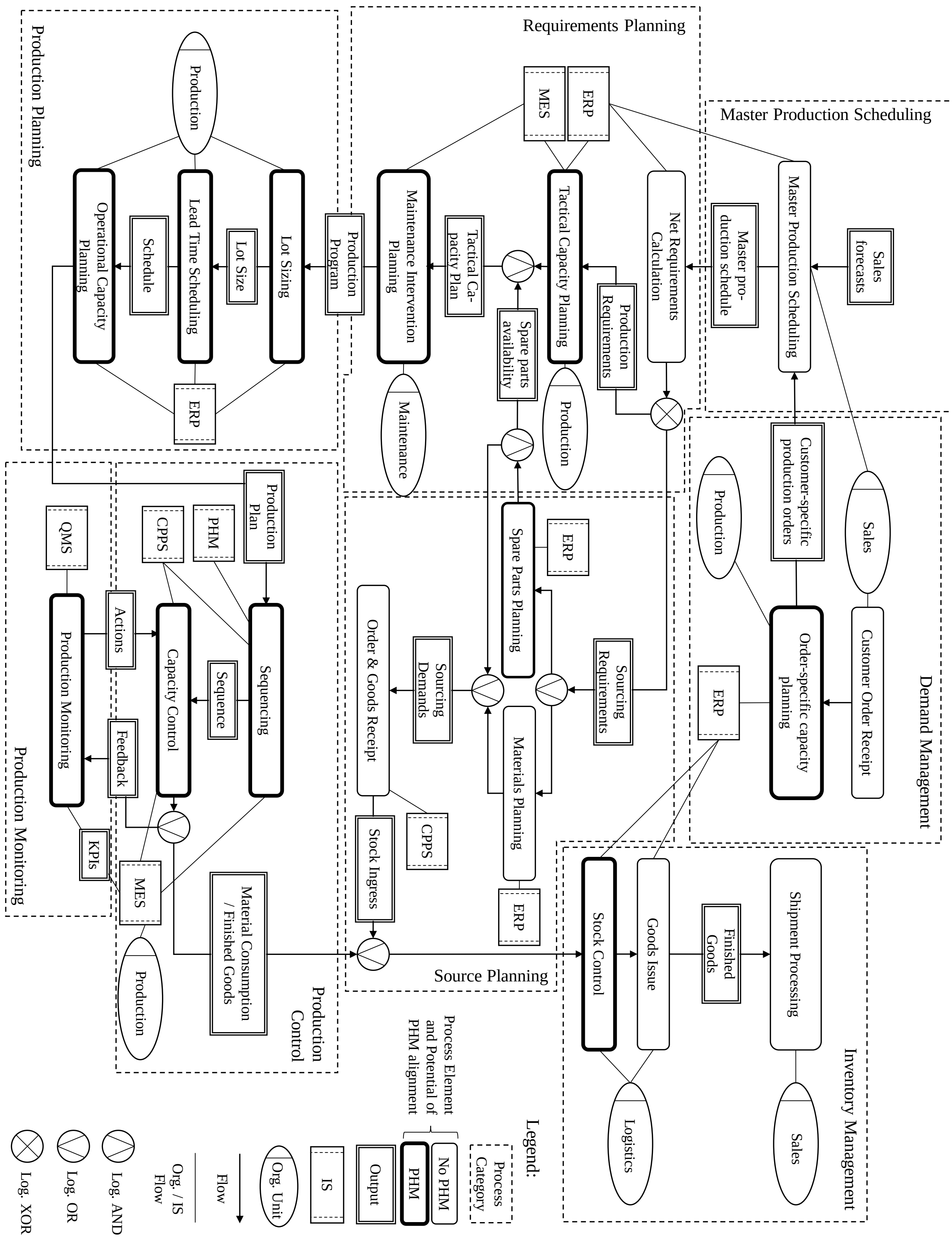

Figure 4. PHM-aligned PPC process

Requirements planning (in-house production). In the case of in-house production, the resulting production requirements are input to *tactical capacity planning*. For instance, the best action can be determined jointly with the production requirements in a mid-term time horizon (AspenTech, 2019). In this step, production requirements from the MES or ERP system are matched with available capacities (Glawar et al., 2019). Then, based on optimization criteria, the production planner can control the capacity of resources via a dashboard in the MES (Rødseth et al., 2017). Furthermore, an advanced PPC process synchronizes the time of failure by selectively controlling the production so that several machines can be serviced simultaneously (Zhai & Reinhart, 2018). On the other hand, the tactical capacity plan can also be set up by isolated production and maintenance planning (Denkena et al., 2012). Either way, the resulting program is used, together with the availability of the spare parts, for *maintenance intervention planning* by searching gaps and idle times in the production and scheduling maintenance (Ansari et al., 2019; Busse et al., 2018; Henke et al., 2019; Schuh et al., 2020).

Production planning. Afterward, the tactical production program is forwarded to operational *production planning*, typically done in ERP by the production department (Do et al., 2006). 'Traditional' production planning is hierarchical and tries to achieve cost-optimal production plans. Through an alignment with PHM, the process is made more flexible. First, the production program coming from *requirements planning* is the input of *lot sizing*, which can enormously benefit from PHM (Glawar et al., 2019; Morariu et al., 2020; Shamsaei & van Vyve, 2017). As the deterioration rate depends on the manufactured products and their lot size, economic production quantity calculations must also factor in the RUL (Li et al., 2020). For instance, Wang et al. developed a heuristic integrating PHM to calculate the lot size that minimizes the total cost while satisfying demand. Here, production times, failure risk, capacities, setup costs, and many more variables were regarded (2019). As breakdowns are exceptionally costly during a lot, advanced solutions try to tune the lot size so that the machine can be maintained during changeovers (Denkena et al., 2012).

Similar to *lot sizing*, *lead time scheduling* can also be a means to generate production-free periods that can be exploited for maintenance (Denkena et al., 2012) and can heavily benefit from PHM (Grimstad, 2019). Here, concrete starting and endpoints of production orders and predictive maintenance interventions are determined (Zarte et al., 2017). The dependency between different production orders and maintenance actions can be structured in a network plan to optimize maintenance costs (Glawar et al., 2019) and production output (Li et al., 2020). In most cases, the lead time schedule is drafted with unlimited capacities and then forwarded to *operational capacity planning* (Schmidt & Schäfers, 2017).

During *operational capacity planning*, unavailable machines are now respected in the production plan. While the unavailability was typically updated based on the planned maintenance interventions (Do et al., 2006), now, with PHM, machine allocations are flexibly and continuously optimized regarding their RUL (Henke et al., 2019). Further, critical machines are also identified by low RUL and high future scheduled load so that production can be rebalanced optimally (Paprocka et al., 2020). More sophisticated solutions even include spare parts procurement in their capacity plan. For instance, the capacity of a machine can be reduced, and only lots that stress the machine components less are planned for it whenever a spare part is not available. On the other hand, capacity can also be increased when an earlier repair is desired (Zhai & Reinhart, 2018).

Production Control. After a final production plan is devised, production control is the next process category. It is typically done in an MES and starts with *sequencing*, where, based on the lead time schedule and the determined dates, the concrete production sequences are defined. PHM can lead to better sequencing quality (Denkena et al., 2020), load balancing, and optimization of production control (Bonfietti, 2018). This is made possible by maintenance-oriented *sequencing*, which ultimately increases machine availability (Zhai & Reinhart, 2018). For instance, many reviewed publications draw on the vast body of production scheduling theory and develop flexible methods to tackle the dynamicity of the non-deterministic time of maintenance (Rahmati et al., 2017, 2018; Zheng et al., 2013). Rahmati et al. develop a CBM-based algorithm where different jobs must be scheduled on multiple degrading machines. They implement condition monitoring to observe the reliability of the systems and implement four metaheuristics to optimize the *sequencing* (2018). Further, Zhai et al. introduce stress equivalents that indicate the level of degradation that each job incurs on a machine (2019) to facilitate an even better *production control*. While the used methods are computationally expensive, it could be possible to deploy them to autonomous CPPS in the future (Glawar et al., 2019), which receive a job-specific RUL forecast from the PHM system (Ladj et al., 2016). Ultimately, *sequencing* can be used to control the time of required maintenance actions, which leads to more flexible and efficient production, e.g., by merging maintenance interventions or postponing them to production-free periods (Denkena et al., 2012; Zhai & Reinhart, 2018).

After the production sequence is defined, *capacity control* ensures optimal production. A promising potential of PHM is the adjustment of machine parameters based on generated prognostics information to reduce wear and tear (Schuh et al., 2020). Most publications discuss sophisticated CPPS that can autonomously adapt their production rate to slow down the degradation of a machine (Broek et al., 2020; Fritz & Brandner, 2019; Li et al., 2020; Messer, 2018; Müller, 2018; Njike et al., 2012; OSIsoft, 2020; Siemens, 2019; SitScape, 2018). Messer describes an example where slowing down equipment by 15% delays a failure by 72 hours (2018). This extended window could be used to maintain the machine at an economic point in time. Broek et al. developed the only reviewed scientific model that can adjust production rates based on PHM. Instead of planning the machine's whole operation ahead (e.g., as seen for sequencing), they only schedule the following maintenance action using a Markov decision process formulation (2020). This can, for instance, be solved through PHM-enabled reinforcement learning, which is "scalable" and "adapts to changing conditions" (Device Insight & Sentian, 2020, p. 19). Besides production rates, other instances can intelligently relubricate themselves (Schaeffler Technologies, 2019) or clean contaminated heat exchanger filters by pumping more volume (Mulders & Haarman, 2017). Finally, if a breakdown is inevitable, the CPPS must automatically shut down based on condition monitoring information to prevent costly damages or product rejects (Busse et al., 2018). The shutdown can be supported by "pre-maintenance load shedding" (Maguire et al., 2017, p. 8), mitigating sudden stoppages.

Capacity control can only work with proper *production monitoring*. Here, the adjustments made are continuously monitored and checked against a cost model (Ansari et al., 2019). In the end, it is not primary to lengthen the RUL of a system at any price but to minimize the total costs and maximize productivity. For instance, Aspen Mtell offers agents that monitor assets scores in real-time (AspenTech, 2019). Typically, monitoring is done in the MES via KPIs (e.g., lead time, efficiency) predetermined by the production planner (Glawar et al., 2019). The MES can also be supported by a QMS that monitors product quality information (Ansari et al., 2019), leading to new knowledge for PHM beyond sensory details. In return, *production monitoring* derives the proper actions from the monitored information and returns them to *production control*.

Inventory management. After production is completed, material consumption and manufactured goods are forwarded to *inventory management*. Finally, they can be issued and shipped to the customer, which concludes the PPC process.

4. RESEARCH-PRACTICE GAPS

All in all, it could be shown that aligning PPC with PHM holds much potential to improve performance because production can be made more flexible and efficient. However, a gap between what is researched and applied in practice was identified throughout the literature review. Consequently, academic and grey literature is juxtaposed to analyze whether scientific potentials are realized in practice and what implications the practical findings have for researchers.

Figure 5 shows the practical and theoretical congruence of aligned PPC and PHM. It is assumed that the theoretical prevalence π_t of PHM for one of the eight PPC process categories can be measured by the share of scientific papers which address this category (shown on the x-axis). It can be calculated

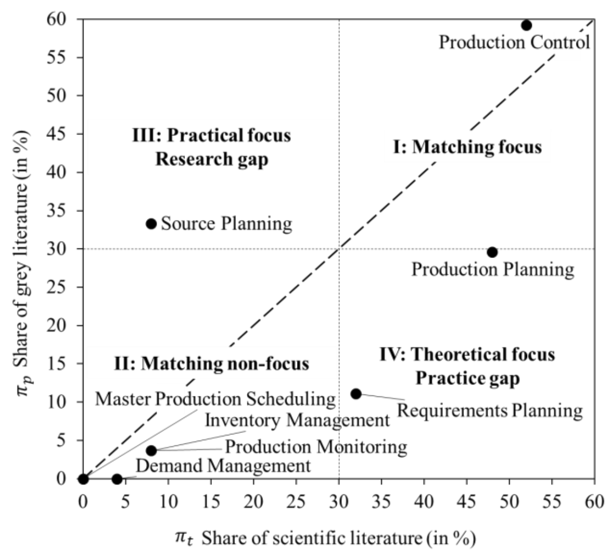

Figure 5. Share of scientific (x-axis) vs. grey literature (y-axis) addressing different process categories

by Equation (1), where $\#P_t(c_i)$ is the number of scientific papers that discuss category c_i.

$$\pi_t = \frac{\#P_t(c_i)}{\#P_t} \qquad \forall i \in [1,8] \tag{1}$$

Vice versa, the practical prevalence π_p is represented by the share of grey literature and shown on the y-axis. For calculation, Equation (1) can be used by replacing $\#P_t$ by $\#P_p$ (p stands for practice). The figure can be separated into four quadrants where four different levels of congruence between theory and practice can be derived. The top-right quadrant (I) denotes high prevalence and congruence and the bottom-left low prevalence and high congruence (II). The top-left (III) and bottom-right (IV) quadrants depict categories with low alignment. Quadrant III includes PPC categories that are highly prevalent in practice but proportionally less discussed in the literature (vice versa for quadrant IV). Generally, the closer points are to the dashed diagonal through the origin ($x = y$), the higher their theory-practice alignment.

Production control is the only category in quadrant I and a central focus of research and practice ($\pi_t = 52\%, \pi_p = 59\%$). Here, PHM seems to deliver the most promising results by enabling a more flexible and autonomous production. While there appears to be congruency at first glance, there are some significant deviations between process elements. While scientific literature focuses on sequencing, practice is more focused on real-time capacity control. Most papers discussing machine profile and parameter adjustments come from grey literature, only one from scientific sources. On the other hand, many scientific works deal with computing optimal production sequences. The drawback of most of these approaches is that they are static or computationally expensive. Ladj et al. developed a fast genetic algorithm, but it requires complete knowledge about job-specific degradation and must be restarted whenever an unexpected change in the production occurs (2016); something that might be impractical in reality.

In quadrant II we can see process categories whose overall prevalence is low. For these categories, an alignment of PPC and PHM is presumably not promising. As a strategic category, *master production scheduling* ($\pi_t = 0\%, \pi_p = 0\%$) has a too long planning horizon for prognostics information to be helpful. Further, planning is typically done on an aggregated level and not per machine. *Demand* ($\pi_t = 4\%, \pi_p = 0\%$) and *inventory management* ($\pi_t = 8\%, \pi_p = 4\%$) are at the beginning, respectively, end of the PPC process. While they are crucial process categories, an alignment with PHM happens at other levels of the PPC process. Lastly, *production monitoring* is barely discussed in the literature ($\pi_t = 8\%, \pi_p = 4\%$), and the focus is more on deriving direct, actionable decisions for other categories.

In quadrant III, it can be seen that *source planning* is predominantly featured in the grey literature ($\pi_t = 8\%, \pi_p = 33\%$), indicating a possible research gap. From a practical perspective, efficient condition-based spare parts procurement is a lucrative and straightforward initial business case for employing PHM. In contrast, only a few scientific papers discussed this category. While spare parts procurement is researched standalone or in other domains (e.g., Espíndola et al., 2012), there is a definitive lack of aligned PPC, PHM, and source planning.

Lastly, quadrant IV includes process categories that are underrepresented in practice. Moderately many academic papers discuss r*equirements planning* ($\pi_t = 32\%, \pi_p = 11\%$). There exist many examples of using gaps in the production plan for maintenance interventions in grey (e.g., Schuh et al., 2020) and scientific literature (e.g., Busse et al., 2018). Additionally, the latter also discusses sophisticated solutions that economically merge the maintenance of multiple machines by controlling the planned load (Zhai & Reinhart, 2018); however, this trend has not made the transition to practice yet.

Lastly, *production planning* is almost as highly represented as *production control* in scientific literature, but the prevalence in grey literature is moderate ($\pi_t = 48\%, \pi_p = 30\%$). The deviation can be explained by the process element *lot sizing*, which received considerable attention in research, but none in practice. In the former, PHM was used to dynamically adjust the lot size to optimize machine breakdowns and minimize costs (Wang & Lu, 2016). In practice, it seems that more 'traditional' methods are used, and PHM is not regarded.

5. CONCLUSION

A PHM-aligned PPC process was introduced in this work by conducting a multivocal literature review and demonstrating how PPC benefits from PHM. To summarize, the research questions raised at the beginning can be answered as follows.

1) "Which PPC processes can benefit from PHM, and what information systems and organizational units are involved?"

Seven of the eight presented PPC process categories can benefit from PHM to different extents. However, the benefits can only be attained by integrating different information systems (e.g., CPPS, PHM, ERP systems) and collaborating between production, maintenance, and information technology departments.

2) "How must the PPC process be aligned to achieve the benefits?"

The analysis showed that PHM is beneficial for short-term production planning and production control, moderately prevalent in requirements and source planning, and applicable to production monitoring and inventory management. A PPC process with 18 process elements was developed, which shows how benefits can be achieved through the alignment of PHM.

3) "How is it currently done in practice, and what is the disparity to research?"

A research-practice comparison revealed that PHM for production control is highly relevant. Further, production and requirements planning are underrepresented in practice, while a research gap exists for source planning. The remaining process categories are less frequently discussed in scientific and grey literature.

While good insights could be generated, this work also comes with limitations. First, the literature review is not exhaustive, though the number of retrieved results might still be significant enough to deliver some interesting takeaways. Further, the algorithm of the Google search for grey literature could be biased towards the researcher. While two researchers reviewed the grey literature, it was only retrieved by one. Moreover, grey literature offers only a confined practical perspective. Because most authors were companies selling PHM-related software or services, they tend to publish success stories and things that 'sell well'. Additionally, the review only shows how PHM is currently intertwined in literature and not everything possible. Furthermore, the prevalence of literature does not say anything about the usefulness and impact of integrating PHM for specific PPC elements. There is no single best way to align PPC and PHM. Its success can depend on many things, such as the maturity of PHM, PPC process, organization, or the firm's technological and data quality. An empirical analysis could shine a light on these aspects. Especially organizational factors should be much more researched, as only a few papers addressed them. Lastly, it was also demonstrated that real-time production and capacity control adds much flexibility to PPC. In the future, more focus should be on heterarchical, autonomous production control. Optimization, used in many papers, might not be the best way to approach this, as it is too static, hierarchical, and requires knowledge that might not be available a priori.

Moreover, the analysis of research practice gaps reveals some opportunities for future research. First, less focus on sequencing and more on capacity control (e.g., automatic machine parameter adjustment) would better match the practical prevalence. It could also be explored why post-prognostics sequencing is not adopted in practice. Additionally, researchers should include source planning in their works, as this is crucial for practical applicability. Lastly, the practice gap for requirements planning and lot sizing should be examined further.

To conclude, this work shows where PPC can benefit from an alignment with PHM and how this can be achieved on a processual, technological and organizational level.

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