A Prescriptive Maintenance Aligned Production Planning and Control Reference Process

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Research Paper

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Abstract

Digital innovations can improve various business processes, such as production planning and control (PPC). In the last years, prescriptive maintenance (PxM) emerged as a strategy to increase overall production performance, but an alignment of the PPC process with PxM has not been examined yet. To tackle this problem, a PxM-aligned PPC process is designed and evaluated in this study using a reference model development methodology, including a narrative literature review, a multivocal literature review, and eight expert interviews. The reference model shows where process elements benefit from PxM alignment, how alignment can be achieved from a process and output, data, function, and organization view, and where fits and gaps between theory and practice are.

Keywords: Prescriptive Maintenance, Production Planning and Control, Reference Model, Prognostics and Health Management

1 Introduction

A production planning and control (PPC) process is the heart of every manufacturing company and entails tasks such as resource planning, sequencing, or capacity control (Schmidt and Schäfers, 2017) to respond to customer requirements (Jacobs et al., 2011). PPC relies on an efficient production schedule and high availability of machines to meet customer demands. However, sudden machine failures and unplanned breakdowns jeopardize on-time deliveries and cause increased costs (Sillivant, 2015). While increasing production complexity makes it challenging to determine the best production plan, in the digital age, the advances in Prognostics and Health Management (PHM) and the emergence of Predictive Maintenance offer new opportunities to optimize PPC (Kuhnle et al., 2019). Different decisions, such as continuing the production, shutting down a machine, or reducing workload, can be improved by a remaining useful life (RUL) estimation (Chebel-Morello et al., 2017; Herr et al., 2014). Ultimately, this leads to a Prescriptive Maintenance (PxM) strategy that does not only predict failures but elevates PPC decisions (Ansari et al., 2019), e.g., by maintenance-friendly capacity building, parts procurement, or load rebalancing, which increase production efficiency and performance. While there is much disjunct research on PxM and PPC, little has been done to combine both disciplines (Ansari et al., 2019). Also, while condition monitoring and prognostics are widely represented in literature, it is essential to prescriptively apply the obtained knowledge in production and maintenance operations (Zhai et al., 2019), which only four percent of companies do (Institute of Technology Management, 2016; Nemeth et al., 2018).

As PPC is a process system, process models can reveal innovation potentials and help to increase flexibility and efficiency (Becker et al., 2012), whereas reference processes constitute generic templates of these models that can be instantiated in different contexts using different views (Rosemann and van der Aalst, 2007). For instance, there are reference models such as the Aachen PPC model (Schuh and Gierth, 2006), the Hanoverian supply chain model (Schmidt and Schäfers, 2017), and more (Hansmann, 2006;

Zelewski et al., 2008) that give universal recommendations on how to plan and control production. While these works specify requirements to conduct PPC, no work examines where production performance can be elevated by integrating PxM in the PPC process (Ansari et al., 2019). Additionally, while manufacturers have implemented predictive maintenance for some time (Zhai et al., 2020), it has not been researched how prescriptive measures have been derived from condition monitoring, diagnostics, or prognostics in practice, even though practitioners stress the potential of improving production processes through digitized maintenance (Roda et al., 2018). Therefore, this paper aims to design a PxM-enabled PPC reference process based on theoretical and practical insights to tackle the following research question:

How should companies adopt PxM in their production planning and control process?

As a scientific contribution, it should be highlighted which process elements benefit from PxM alignment, how alignment can be achieved, and where fits and gaps between theory and practice are. The developed model should also advance PHM and operations management research by showing how PxM can be applied to PPC. Practically, the reference process model should serve as a guideline to conduct PxM-aligned PPC and instantiate process models.

The following section presents related work and three theories central to this work: PPC, PxM, and reference process modeling. Subsequently, section three introduces the reference process modeling methodology and subordinate methods used for this research. The penultimate section introduces a PxM-aligned PPC reference model, including multiple views. Lastly, the work is concluded in section five.

2 Theoretical Foundations and Related Work

PPC is defined as the process of determining the production plan that satisfies the sales plan while meeting time, monetary, and qualitative goals. Production control also allows synchronizing resources and customizing products in real-time (Arnold et al., 2008; Moeuf et al., 2018; Usuga Cadavid et al., 2020). Pinedo (2012) focuses on core steps, such as master scheduling, material requirements and capacity planning, scheduling, dispatching, and shop floor management. While Oluyisola et al. (2020) agree on these steps, they also see sales and operations planning and purchasing as steps of PPC. All in all, there is no consensus on the PPC process, but there is agreement that a continuous flawless operation is essential for manufacturers, which is enabled through maintenance (Guillén et al., 2016).

In the past, ‘traditional’ maintenance strategies were either reactive or scheduled (Guillén et al., 2016). The former strategy refers to letting a machine break down before it gets restored. Such a breakdown is always unplanned and disrupts a production plan set up beforehand. In contrast, scheduled maintenance means maintaining resources in regular intervals (Selcuk, 2017). Here, a wrong choice of intervals necessitates too early maintenance (waste of RUL) or reactive maintenance.

One promising strategy that has emerged to tackle all these issues is condition-based maintenance (CBM) which supports PPC goals (Hadidi et al., 2012). CBM strategies can be generally distinguished into descriptive, diagnostic, predictive, and prescriptive maintenance (Ansari et al., 2020). Descriptive maintenance is looking at "What happened?" and tries to detect faults. Diagnostic maintenance is concerned with "Why did it happen?" and failure diagnostics. Predictive maintenance is enabled by predicting a machine's future through prognostics and answering the question "What will happen?". Lastly, prescriptive maintenance (PxM) transforms the previous insights into actionable results by answering the question "What should be done?" (Maguire et al., 2017).

The differences between the four types can be visualized when looking at the PHM process (Figure 1). Here, PHM is not a maintenance strategy but a collection of techniques that provide input for the four CBM types (Guillén et al., 2016). Figure 1 shows that decision-making enables PxM where an appropriate PPC configuration is chosen based on results (e.g., detected components, diagnosed faults, or predicted RUL) from the previous PHM steps (Skima et al., 2019). While the three prior strategies make only maintenance decisions (i.e., when, what, or how to maintain), PxM is defined as condition-based decision-making that includes maintenance and operations (e.g., production or logistics decisions). It is

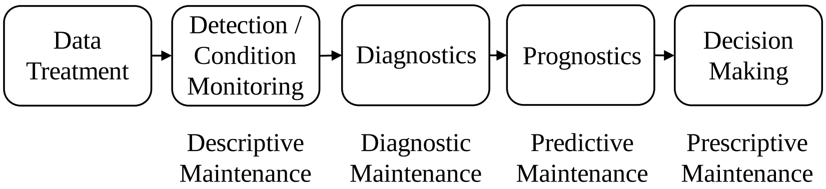

Figure 1. PHM process (adapted from Guillén et al., 2016)

based on PHM information (e.g., condition monitoring, diagnostics, and prognostics) and uses decision models (Bougacha et al., 2018; Wesendrup and Hellingrath, 2020), e.g., optimization, operations research methods (Bousdekis et al., 2018).

While PPC can highly benefit from PHM decision-making and PxM (Chebel-Morello et al., 2017), production and maintenance decisions are often optimized separately in the current literature (Ansari et al., 2019; Broek et al., 2020). Moreover, there is no guidance on how the benefits of PxM can be achieved by integrating PHM decision-making into different steps of the PPC process, such as capacity planning, scheduling, or shop floor management. Here, process models can help to indicate improvement potentials (Becker et al., 2012), especially as it was demonstrated that both disciplines already have their own disjunct processes. Process models typically comprise multiple views, such as the five views “process”, “output”, “data”, “function”, and “organization” of the architecture of integrated information systems (ARIS) proposed by Scheer (1999a). Views are pivotal to capturing the many facets of business processes, structuring, and streamlining them (Scheer, 1999a).

While process models are always specific to companies, reference processes can be further used as abstract models and templates to instantiate process models in various practical contexts (Scheer, 1999b). Reference models are not established for joint PPC and PxM (or any other CBM type). Still, there are some related reference process models for either PPC or CBM (a non-exhaustive list can be found in Table 1). For instance, Voisin et al. (2010) developed a prognosis process for maintenance decision-making. While they present steps to conduct prognostics from a processing and data view, they do not include any PPC function. The model of Bousdekis and Mentzas (2019) also lacks specific PPC functions, but acknowledges that maintenance actions must be synchronized with production, logistics, and quality management. The model by Ansari et al. (2019) and Glawar et al. (2019) goes a step further and pinpoints connections to the PPC steps production planning, control, cost modeling, and spare parts management. However, it is foremost a model for PxM with connections to PPC (and not a PPC reference model) and does not enable instantiating PPC process models.

On the other hand, Schuh and Gierth (2006) developed a comprehensive reference model of PPC extended by Schmidt and Schäfers (2017). It encompasses strategic, tactical, and operational PPC steps from master production scheduling to production control but does not integrate maintenance. In contrast, the standard IEC 62264 (International Electrotechnical Commission, 2016) specifies a data and process view of PPC and maintenance management, but it does not cover any CBM strategy. Therefore, a reference process model for PxM-aligned PPC is developed in this study to fill this gap.

References	**PPC**	**CBM**	**Reference Process**
(Voisin et al., 2010)	○	●	●
(Bousdekis and Mentzas, 2019)	○	●	◑
(Ansari et al., 2019; Glawar et al., 2019)	◑	●	◑
(Schmidt and Schäfers, 2017; Schuh and Gierth, 2006)	●	○	●
(International Electrotechnical Commission, 2016)	●	○	●

Characteristic ○ = not met / ◑ = partially met / ● = met

Table 1. Related works

3 Research Design and Methods

The method by Matook and Indulska (2009) was chosen to develop the reference process (Figure 2), which has been synthesized from many renowned works of reference modeling, encompasses seven phases and is, therefore, one of the more detailed methodologies (cf. Fettke, 2014). These seven phases of *problem definition*, *requirement analysis*, *information gathering*, *setting conventions and rules*, *documentation*, *construction and design*, and *evaluation* were concretized for this study as follows.

Problem definition. The model's scope, purpose, and audience are defined in this phase (Matook and Indulska, 2009; Rosemann and van der Aalst, 2007). The *scope* should encompass the functional areas of PPC and (condition-based) maintenance. Further, the *purpose* is to indicate how to plan and control production using PxM. Lastly, the model’s *audience* includes practitioners with a production or maintenance background who want to implement a PxM-aligned PPC process. Besides scientific knowledge, the model should also include practical evidence of PPC and PxM alignment to represent the practitioner perspective adequately and foster adoption.

Requirement analysis. Here, existing reference models that fulfill the problem definition have been searched. A narrative literature review of articles on Google Scholar with synonyms belonging to the keyword groups *"production planning and control"*, *"prescriptive maintenance"*, and *"reference process"* was carried out based on Paré et al. (2015). Ultimately, eleven PPC reference processes (no PPC reference process including any type of CBM was found) could be identified from which further model requirements were derived following Rosemann and van der Aalst (2007). First, because most models used a two-level structure (*granularity*), it was also adopted for the to-be-developed model. Lastly, the *views* process and output (subsection 4.1), data (4.2), function (4.3), and organization (4.4) are chosen and linked (4.5) based on Scheer (1999a).

Information gathering. Because the eleven PPC models found in the previous phase did not regard PxM, information was gathered to examine how PxM can be integrated. Thus, five semi-structured expert interviews (Table 2) were held using the methodology by Myers and Newman (2007). Here, experts were searched on the professional networking sites Xing and LinkedIn using the search terms *"production"* and *"predictive maintenance"*. The experts were interviewed in person or digitally and recorded for around 45 minutes to identify the potentials of PxM. The meetings always followed a four-step

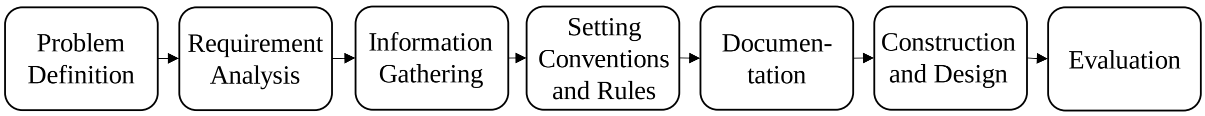

Figure 2. Research Design (Matook and Indulska, 2009)

ID	Firm Archetype	Size (employees)	Role
A	Analytics provider**	Micro (1-20)	Data Scientist
B	Consulting*	Fortune 500	Consultant
C	Manufacturer**	Fortune 500	Production Manager
D	Manufacturer *	Large (1001-5000)	Data Scientist
E	Manufacturer *	Large (1001-5000)	Head of Maintenance
F	Manufacturer *	Large (1001-5000)	Industry 4.0 Engineer
G	Manufacturer *	Large (1001-5000)	Maintenance Planner
H	Platform provider**	Fortune 500	Solution Architect

*Semi-structured (construction and design) **Process mapping (evaluation)

Table 2. Interviewed experts

structure (cf. Myers and Newman, 2007): a) the interview was opened, and researcher and interviewee introduced themselves, b) the purpose of the interview was explained, c) open questions about processual, technological, and organizational potentials, changes, and barriers of aligning PxM with PPC were asked, answered, and discussed, d) the meeting was closed. After the last interviews, no new concepts emerged, and no experts were contacted for further information gathering. The following sections indicate information gained from experts with a superscripted expert ID (from Table 2).

Parallel to the interviews, a multivocal literature review based on the methodology of Garousi et al. (2019) was used to identify opportunities of alignment between PxM and PPC. Beyond scientific sources, the review allows to include grey literature (e.g., company reports) to capture applications of PxM in practice and reveal research and practice gaps that explain a low adoption of prescriptive maintenance. For the scientific sources, the titles, abstracts, and keywords of the databases Scopus and Web of Science were queried with *("prescriptive maintenance" OR "predictive maintenance" OR prognostic* OR "condition based maintenance" OR "remaining useful life") AND "production planning"*. Further, the Google search engine was queried with (*"predictive maintenance" OR "prescriptive maintenance") AND "production" filetype:pdf* for grey literature. As the Google search retrieved almost 150,000 results, the search was stopped after theoretical saturation was reached (cf. Garousi et al., 2019). The queries returned an initial pool of 69 scientific and 154 grey sources. Afterward, two reviewers predefined the exclusion criteria 'no access', 'no production context', 'no relation to PxM', and 'no relation to process' and applied them within a title, abstract, and full-text review, which reduced the initial pool to a final pool of 52 publications (24 scientific, 28 grey).

Setting conventions and rules. Before analyzing the gathered information, rules must be set up to document, construct and design the reference process. First, a glossary based on previously identified terms was created. For instance, different authors used the term Predictive Maintenance, CBM, PxM, and PHM interchangeably, which was delineated in the glossary. Further, the event-driven process chain notation proposed by Scheer et al. (2005) was used to model the final reference process because it is relatively simple to understand and supports multiple views. Moreover, it can be easily extended and used for reference modeling (Rosemann and van der Aalst, 2007; Thomas and Scheer, 2006).

Documentation. In this phase, all information has been documented to guarantee consistency and transparency of the later model. According to Webster and Watson (2002), a concept matrix was set up for the eleven models of the narrative review. The reference processes were analyzed and decomposed into process elements, each equating to a concept. For instance, the model by Pinedo (2012) included the concepts master scheduling, material requirements and capacity planning, scheduling, dispatching, and shop floor management. Moreover, the interviews were all transcribed in their original language (German). Next, a data extraction form was documented to map the results from the interviews following Myers and Newman (2007) and the final pool of the review following Garousi et al. (2019).

Construction and design. First, a ‘basic’ PPC reference process (without PxM) was synthesized and aggregated from the concept matrix defined in the last phase. The process was the basis to investigate how the different steps can be aligned with PxM using mapped interview and review data. Therefore, the data extraction form introduced in the previous phase was used to categorize statements from the interviews and review into the views process and output, data, function, and organization. Statements that discuss PxM-related changes related to the process view were assigned to the process categories and elements from the ‘basic’ reference process. The processual changes through PxM were then combined with the ‘basic’ PPC process into one PxM-aligned PPC process. Statements that targeted the other views were inductively assigned whenever a new concept emerged from the material.

Evaluation. Lastly, the PxM-aligned process was evaluated with three further expert interviews (Table 2) using a process mapping methodology (Jacka and Keller, 2009). Here, broad expertise was deemed necessary, and thus, experts from firms that are knowledgeable of the alignment of PxM in different PPC contexts were chosen, including an analytics provider, a platform provider, and a world market-leading manufacturer. Here, the different models were presented during the interviews, and the experts were asked to adjust the reference process and give further insights into the different areas of the model. Finally, the research design led to a multi-view PxM-aligned PPC reference process model.

4 Prescriptive Maintenance Aligned Production Planning and Control Reference Process

4.1 Process and Output View

On a control level, the PPC process comprises eight process categories (first level, further written in bold letters) and 17 process elements (second level, further written in italic letters) shown in Figure 3. Figure 3 also highlights process elements that can be aligned with PxM, which is explicated next. The numbers after each process category show the share of white (denoted w), grey literature (g), and experts (e) addressing each process category.

For **master production scheduling** and **demand management** no improvements through PxM are reported due to the long planning horizon of *master production scheduling* and the relatively shorter impact of PxM. The master production schedule also integrates inputs from *customer-specific capacity planning* during demand management.

PxM is moderately promising for **requirements planning.** Here, *net requirements* are *calculated*, and *tactical capacity planning* can benefit from PxM through synchronizing maintenance interventions to minimize costs by allocating production requirements so that multiple machines reach their end of life simultaneously (Zhai and Reinhart, 2018). Additionally, emerging production-free windows can be planned on a mid-term time horizon (Ansari et al., 2019; Busse et al., 2018; Henke et al., 2019; Schuh et al., 2020), which is beneficial for machines with turnover intervals of two to twelve weeks[C, E].

PxM is highly promising for **source planning** and is mainly addressed in grey literature. Here, requirements are forwarded, and raw *materials* and *spare parts planning* is performed for which prognostics-based just-in-time spare parts delivery is an immense potential of PxM[A, B, E, F, G] (Busse et al., 2018; Microsoft, 2015). Further enabled by data-driven diagnostics, advanced PxM systems also determine spare part requirements autonomously (Henke et al., 2019; Leonard, 2020). There exist even solutions that provide the correct spare parts instantly via additive manufacturing (Schuh et al., 2020; Trebing + Himstedt, 2017); however, no research on this was identified. In contrast, when spare parts are not available before a breakdown, products that exert lower stress on assets can be produced to decelerate wear until the part is available (Zhai and Reinhart, 2018). Further, suppliers can diagnose faulty spare parts beforehand and, through PxM, deploy consignment stocks for their customers[B] or configure packages, comprising spare parts, lubricants, and tools matching to the faults[E].

PxM is also highly relevant for **production planning** to make maintenance suggestions days to hours before a machine is shut down[C]. For instance, in-house requirements are used to *calculate lot sizes*, but instead of calculating fixed economic lot sizes, dynamic production quantities that factor in the RUL can be prescribed (Li et al., 2020; Wang et al., 2019) to synchronize maintenance interventions and changeovers (Denkena et al., 2012) and reduce overall cost.

PxM-enabled *lead time scheduling* also generates production plans with economical maintenance windows by incorporating the RUL (Grimstad, 2019), especially for bottleneck machines (Paprocka et al., 2020). In the case of identical parallel machines, resources with increased costs (power, time) due to wear should be prioritized lower when scheduling operations (Morariu et al., 2020). Lastly, critical machines (e.g., high load, low RUL) are condition-monitored and flexibly rebalanced during *operational capacity planning*[E] (Henke et al., 2019; Paprocka et al., 2020). Here, a permanently available production can be envisioned through decisions based on a machine‘s RUL[B]. While some promising approaches exist, the experts also stressed that PxM-enabled production planning is still mainly done manually.

Production control was highly prevalent in all sources, and PxM has arguably the most potential here. After production is initiated, PxM can lead to better production control. PxM-enabled *sequencing*, which was mainly discussed in scientific literature, allows maximizing the total useful life of a machine (Rahmati et al., 2017, 2018; Zheng et al., 2013), and even the stress of different operations can be regarded (Ladj et al., 2016; Zhai et al., 2019) so that maintenance interventions can be combined (Denkena et al., 2012; Zhai and Reinhart, 2018). *Capacity control*, mainly discussed by grey literature and experts, also

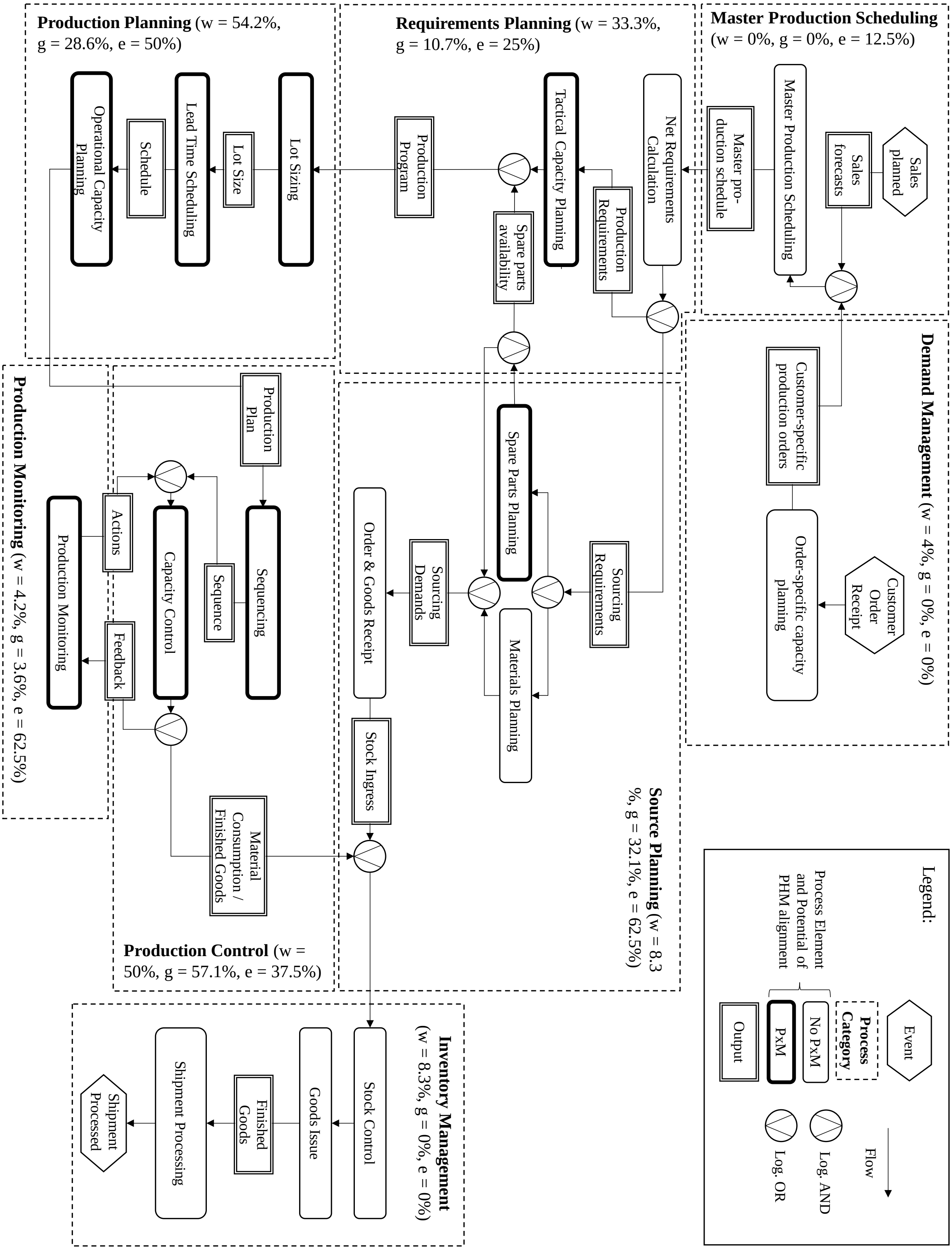

Figure 3. Process and output view

allows tuning the production rate to increase or inhibit the wear of the machine (Broek et al., 2020; Fritz and Brandner, 2019; Li et al., 2020; Messer, 2018; Müller, 2018; Njike et al., 2012; OSIsoft, 2020; Siemens, 2019; SitScape, 2018) and in this regard, slowing down machines to "make it" over the weekend or until the next economic maintenance point has considerable potential[C]. Further, production control activities can be delegated to autonomous cyber-physical production systems that can flush filters (Mulders and Haarman, 2017), relubricate (Schaeffler Technologies, 2019), or comprise a condition-based failsafe mechanism[E]. Moreover, PxM-enabled assets should include a control architecture that can switch between maximum capacity and maximum cost-saving depending on the RUL[A, C]. Unfortunately, the experts stress that most potentials of PxM-enabled production control are not realized yet.

PxM-aligned **production monitoring** can support a production flow by continuously measuring relevant KPIs such as costs or lead times (AspenTech, 2019; Glawar et al., 2019) and prescribing actions. *Production monitoring* can also be used to identify leaks through machine condition data[C]. Lastly, a potential of PxM-enabled production monitoring is the generation of information valuable for subsequent production stages by relating condition data and machine parameters to a product[F]. Vice versa, measuring product quality can also leverage PxM (Ansari et al., 2019) as PHM can be complemented by non-sensory quality information and product reject rates[A, D]. While current research focuses on analyzing sensor values to predict failure times, it could also predict product quality. Vice versa, product quality data or production parameters could also complement a machine's condition data to improve the RUL prediction. Further, it delivers valuable input for the prognostics algorithm, as different products are produced within different operating modes and reflected in the sensor data[E]. Interestingly, PxM for *production monitoring* was almost not prevalent in literature but highlighted by most experts[A, C, D, E, F].

Lastly, no applications of PxM for **inventory management** were reported. Here, the *stocks* of spare parts, finished and sourced products are *controlled*, and sales *goods* are *issued* before *processing* the *shipment* to the customer.

4.2 Data View

A PxM-aligned PPC process is typically enabled via data (*italic* letters) gained from multiple sources, as shown in Figure 4. For PxM and PPC, Ansari et al. (2019) and Do et al. (2006) distinguish between *material*, *machine*, and *process* data types that comprise many different data. Further, *process* data can also be distinguished into *maintenance*, *production*, *logistics*, and *sales*. Surprisingly, the latter two were not addressed by grey literature at all.

Machine data comprises historical failure events (Qi and Tao, 2018), often supplemented failure modes (Ansari et al., 2019). More sophisticated PxM solutions also use natural language processing to gain insights from fault-related text or audio[H] (Glawar et al., 2019). Additionally, images and video can be processed to aid in locating and repairing the fault (OMRON, 2020), but this has not been discussed in white literature. Further, condition data was mentioned by almost all sources, either from sensors[C, G] (Rødseth et al., 2017; Standardization Council Industrie 4.0, 2018) or experience[G] (Do et al., 2006). Mulders and Haarman (2017) also argue that mature prescriptions use data from similar machines (i.e., fleet data). Further, environmental data (e.g., ambient temperature) can improve PxM (Schuh et al., 2020). All condition data are then used to calculate PHM data, such as the degradation or RUL (Broek

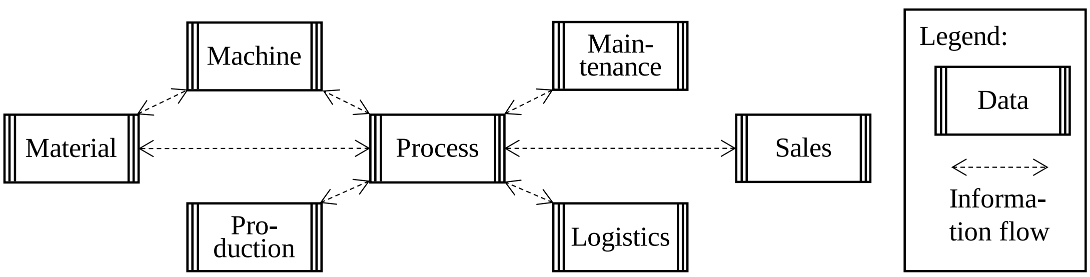

Figure 4. Data view

et al., 2020) which is then used to plan downtimes (Birtel, 2017). *Machine* property and master data can then be used to reschedule production[D] (Zarte et al., 2017).

Next, *material* data includes product quality data that can be "exploited to predict machine problems" (Do et al., 2006, p. 41). Either direct measurements exceeding tolerances (Ansari et al., 2019), scrap rates[E, F] (Schuh et al., 2020), or even images[D] can be used to pinpoint asset defects. Further, product properties (Do et al., 2006) or designs (Qi and Tao, 2018) can be used to estimate the wear and improve PPC prescriptions (e.g., producing less straining products on machines with high degradation).

The third type, *process* data, comprises data generated in the primary and support processes of the value chain. For PxM and PPC, four process data subtypes are relevant (cf. Figure 4). First, *production* data comprises information about the planning and control of manufacturing, such as the production program, which must respect planned downtimes, breaks, weekends, holidays, personnel, and spare parts resources (Denkena et al., 2012). Next, lot sizes (Li et al., 2020) and production schedules (Glawar et al., 2019) are critical data that need to be aligned with PHM data. Concrete production orders are derived from schedules (Qi and Tao, 2018), which comprise job and operation data (Paprocka et al., 2020). PxM approaches can then prescribe optimal production sequences based on production and setup times (Wang and Lu, 2016) and energy data (Maguire et al., 2017). Lastly, production parameter data[B,E], such as the production rate (Broek et al., 2020), is crucial for PxM. Lastly, cost data can be considered for PxM-enabled optimization of production decisions, such as setup or downtime costs (Wang et al., 2019).

Secondly, *maintenance process* data can include historical maintenance interventions[C], which provide insights for future service plans (Birtel, 2017). In agreement with the production plan and PHM data, suitable times and actions are determined (Zheng et al., 2013) considering maintenance cost data, such as failure, maintenance (Wang et al., 2019), parts, and (external) personnel cost (Rødseth et al., 2017).

Thirdly, *logistics* data must be considered when aligning PxM and PPC. Here, production orders and maintenance interventions can only be rescheduled when sufficient raw material inventory is available (Wang and Lu, 2016), and spare part orders, inventory, and demand data are aligned (Birtel, 2017), respecting lead times (Njike et al., 2012).

Lastly, *sales* data is relevant, so PxM decisions do not minimize maintenance costs and neglect customers. Demand, backorders, and delivery dates (Wang and Lu, 2016) are crucial data that must be respected in the PPC process to decrease lost sales costs and penalties (Wang et al., 2020) and increase revenue (Li et al., 2020).

4.3 Function View

Of course, the data above are typically stored in application systems that incorporate "processing rules of a function" (Scheer, 1999b, p. 36). A functional application system landscape of the PxM-aligned PPC process is shown in Figure 5.

The heart of PxM-aligned PPC is the *cyber-physical production system*. These are equipped with sensor technology (Balogh et al., 2018; Do et al., 2006; Rødseth et al., 2017; Schuh et al., 2020), can autonomously control the production and send preprocessed sensor data to a PxM system (Busse et al., 2018). Pressure, temperature, and vibration sensors are common, and wireless connectivity is crucial for a plant-wide connection[C].

PHM systems run the steps of the PHM process (Figure 1) data treatment, condition monitoring, detection, diagnostics, and prognostics using data-driven techniques (statistical or machine learning) to generate *PHM information* (e.g., alerts, fault modes and effects, RUL predictions). This information is forwarded to *computerized maintenance management* or *manufacturing execution systems* where PHM-based decisions are made. *PHM systems* can be equipped with dashboards for less mature CBM strategies (e.g., diagnostic, predictive); however, for PxM, dashboards are replaced by (semi-)autonomous decision-making functions[B]. Here, the results of the PHM algorithms must be interpretable, i.e., by using explainable artificial intelligence (Jalali et al., 2020). Further, due to their novelty, systems are often proprietary, non-standardized, and use heterogeneous technology stacks[B, D] (AspenTech, 2019; Balogh et al., 2018; Busse et al., 2018; Morariu et al., 2020; Siemens, 2019). PHM systems can be integrated

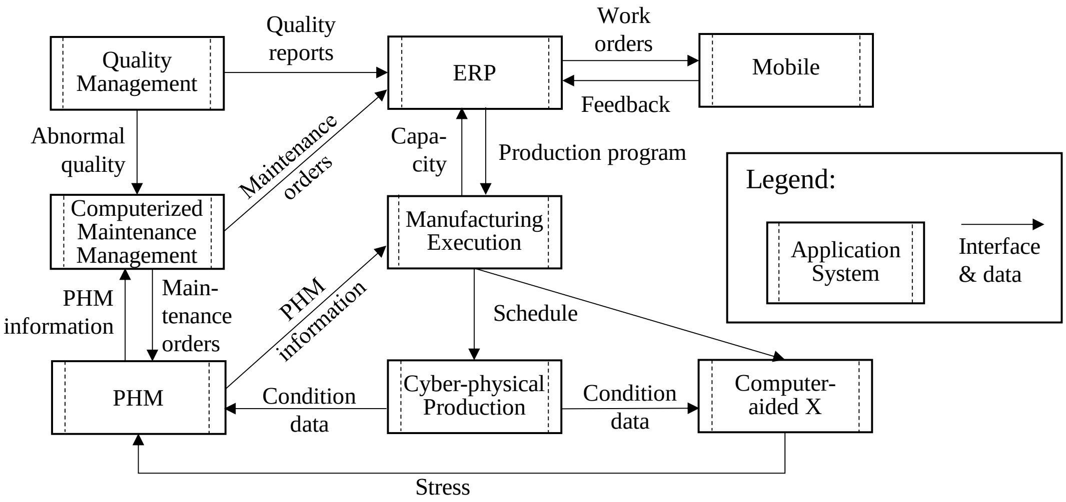

Figure 5. Function view

into *manufacturing execution*, *ERP* (*enterprise resource planning*), or *computerized maintenance management systems*.

General asset management is done via *computerized maintenance management systems* as soon as the RUL of a system necessitates a future action (Rødseth et al., 2017). Here, breakdowns are documented[B], and the maintenance schedule can be accessed[E]. The outputs are maintenance work orders that are automatically generated in coordination with the production plan[B].

Work orders are typically transmitted from *computerized maintenance management systems* to the *ERP* system. *ERP* systems represent the highest layer of technology and encompass many business functions (Do et al., 2006; Zarte et al., 2017), such as spare parts management (Ansari et al., 2019). Here information about customers, suppliers, sales, and material data can be combined in the joint maintenance and production planning (Zarte et al., 2017).

Work orders from *ERP* can also be relayed to *mobile application systems* (Scheffels, 2018). Mobile devices are used as peripherals of the service technician to upload reports, pictures, and access machine manuals[A, C, E] or manage work orders or spare parts, e.g., by using solutions with direct interfaces to ERP systems[C, E]. Mobile systems can be supported by more mature technologies that emerge in the plant, such as augmented reality[H]. While these systems are discussed mainly by experts, they are neglected in scientific works, e.g., due to a different focus on autonomous PxM-enabled PPC approaches in the literature. Still, the human is essential and can even leverage PxM by complementing diagnostics and prognostics algorithms through experience.

Quality management systems are used as supporting systems. They can be a new information source for *computerized maintenance management systems*, as abnormal product quality can indicate progressive wear (Do et al., 2006). Here, a connection to *PHM systems* has not been reported, but quality reports are forwarded to *ERP* (Ansari et al., 2019).

Penultimately, *manufacturing execution systems* link production planning with control (Glawar et al., 2019). Thus, they have a connection function[C] between ERP and shop floor systems and are central to PPC[B.] They enable autonomous PPC decisions, which are unfortunately often idealized and not feasible in practice and can only be tackled with plausibility analyses considering maintenance (Glawar et al., 2021), e.g., by optimization, simulation (Gutschi et al., 2019), or digital twins (Melesse et al., 2021). Using PxM, the systems could receive and transform production plans into machine allocations and schedules based on RUL (Ladj et al., 2016; Morariu et al., 2020). Further, manufacturing execution systems drive production monitoring as they relate production parameters to products[E].

Lastly, *computer-aided systems* (e.g., computer-aided design) have another supporting role (Qi and Tao, 2018). They can receive sensor data and production schedules to simulate stresses and wear of assets (McBeath, 2020) that improve the forecasts of PHM systems.

All in all, the function view is aligned when looking at theory and practice. Some mismatches concern the white literature, which focuses on standardized architectures for *PHM systems* that have not yet been put into practice. This becomes noticeable, as many non-standardized, proprietary systems are presented in grey literature, while experts further criticize this widespread use of 'homegrown' solutions. Nevertheless, the experts also say that interfaces between application systems are standardized, with protocols such as OPC UA already heavily in use in practice.

4.4 Organization View

Lastly, an organizational perspective is crucial for successful PxM and dictates how well it can ultimately be embedded into a manufacturer's process. Figure 6 demonstrates how a generic PxM-aligned PPC organization is structured. In the following, the different organizational units (*italic* letters) and their interactions are described.

Within PxM, *production* closely cooperates with maintenance planners (Microsoft, 2015) and aligns the production plan with prognosticated capacities. As machine operators are highly familiar with the peculiarities of their assets[B], they can also complement the maintenance crew by providing immeasurable knowledge, which increases flexibility (Do et al., 2006). Also, the first hypotheses of machine breakdowns come from them, which are then matched with the condition data by specialized employees[C]. Further, machine personnel should carry out minor interventions according to Kaizen or the 5S methodology[E, G], supported by Prescriptive Maintenance assistance tools (Henke et al., 2019).

More complex interventions are done by *maintenance*[E, G]. For instance, these can include relubrication, oil, oil filter, belt, or bearing exchanges[E]. Based on diagnostics, the complexity can be identified, and PxM can be used to schedule interventions, adjust available capacities based on the RUL (Rødseth et al., 2017), and combine maintenance interventions opportunistically (Ansari et al., 2019). Through PxM, a capable field technician is automatically assigned when maintenance demand is forecasted; the technician maintains the system using smartwatches, tablets (Scheffels, 2018), augmented reality (McBeath, 2020), or remote assistance solutions (McBeath, 2020; Microsoft, 2017). Thus, "blue-collar" workers become increasingly "white-collar", as the accompanying tools require interpreting big data[B]. This could be achieved via digital upskilling and explainable artificial intelligence, supporting PxM (Jalali et al., 2020). Further, spare parts and tools are ordered and bundled by *maintenance* to be easily retrieved[E] or are 3D printed (Schuh et al., 2020).

For spare parts, companies need to cooperate with *external providers* (i.e., suppliers or maintenance service providers) to identify whether parts or services can be supplied on time[E], or if production plans must be adjusted or machines slowed down to decrease stress and postpone their demands (Broek et al., 2020). Also, maintenance sometimes needs to be outsourced to third-party providers or the original equipment manufacturer[B], which is more costly[C], especially in the case of false positive predictions[B].

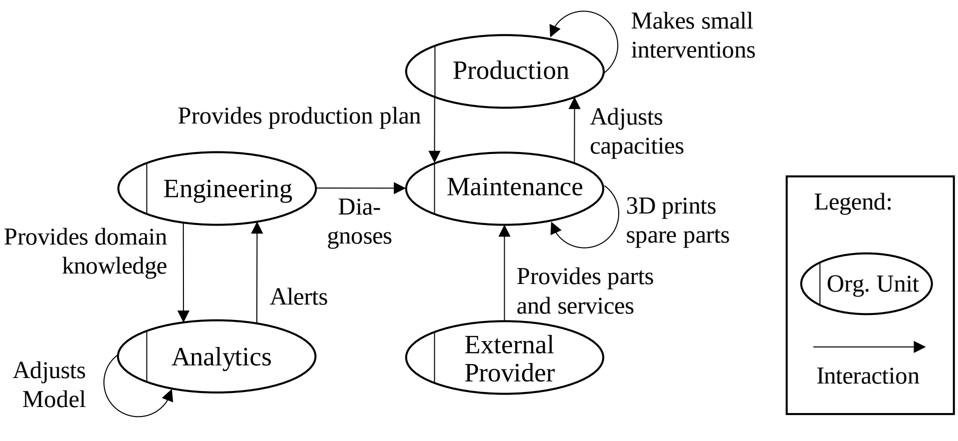

Figure 6. The organization view

Thus, many companies still require *engineering* units because there is no automatic, data-driven way to diagnose faults with zero uncertainty[B]. For instance, a centralized organization of experts can provide prognostics and diagnostics services to multiple plants[C]. Should a machine behave abnormal, the engineers analyze the RUL forecasts and failure behavior, aid decision-making, and give new insights to the PHM models. Here, experiential data from past logs can be retrieved via AI-enhanced approaches and integrated into decision models (Usuga-Cadavid et al., 2021).

The *analytics* unit continuously adapts the data-driven PHM model (e.g., diagnostics or prognostics) whenever insights require a change (Glawar et al., 2019). Moreover, the *analytics* units either perform data-driven diagnostics and prognostics as standalone organizations[C] or are integrated into other departments[B]. In the case of external analytics providers, model adaptions, problems, or new sensors to be added should at least be discussed regularly[A].

Lastly, PxM is a management topic and lighthouse project of many companies and is generally seen as value-adding[E]. However, managerial use case owners always decide whether an implementation is economical[B]. Either way, management support is crucial in implementing PxM for PPC.

All in all, organizational literature on PxM-enabled PPC is lackluster, as roles beyond *production*, *maintenance,* and *analytics* were only discussed by the experts who gave much more input on how the PPC activities of different organizational units are changed through PxM. The experts also highlight poor knowledge sharing due to data security concerns and protectionism.

4.5 Linked View

Lastly, the presented views can be linked according to the architecture of integrated information systems (Scheer, 1999a), as exemplified for the process element *sequencing* shown in Figure 7.

Input for *sequencing* is the *production plan* with *production data* such as orders, jobs, and operations. Then, machines capable of producing the ordered products are selected based on *machine data*. Depending on the properties of the products (*material data*) and the different stress levels their production causes, the jobs, and products can be sequenced on the different machines to control their end of life, e.g., synchronize it, or postpone it to the end of a shift or to a time point when spare parts are available. The whole *sequencing* process element is controlled via a *manufacturing execution system,* and the *production department* is responsible for supporting it. In the end, an optimized production *sequence* is forwarded.

5 Conclusion, Limitations, and Future Work

In this work, the potentials of PxM-aligned PPC were identified. For that, a PxM-aligned PPC reference process model was designed following the seven-phase method of Matook and Indulska (2009). First, existing PPC reference process models were collected and merged into a ‘basic’ PPC model. Through expert interviews and a multivocal literature review, potentials of alignment between PPC and PxM were identified, and the ‘basic’ model was complemented. In an evaluation phase, the final model was

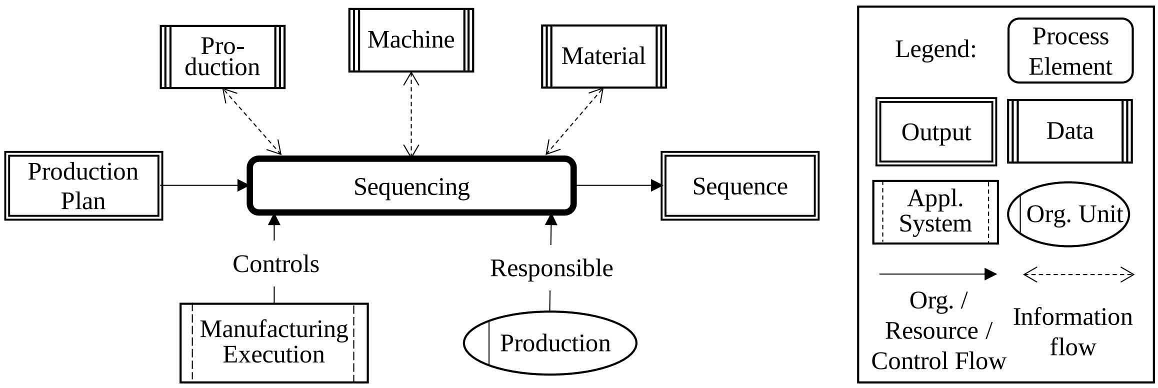

Figure 7. The linked view

assessed and adapted via process mapping with further experts. In the end, a four-view reference process model with eight process categories and 17 process elements was constructed. It could be shown that PxM has a high potential for 8 of the 17 process elements. As a scientific contribution, it was highlighted which process elements benefit from PxM alignment, how alignment can be achieved, what research gaps exist, and where practical adoption lags. The developed model also advances PHM and operations management research by showing how PxM can be applied to PPC. Practically, the theoretical reference process model can serve as a guideline to conduct PxM-aligned PPC and can be used to instantiate specific process models.

The conducted study has some limitations. First, the multivocal literature review was not exhaustive and could be extended using other databases or keywords. Additionally, the Google search was stopped as soon as theoretical saturation was reached, but whether or not relevant results can be found later depends on the Google page rank algorithm, which could also be biased (Langville and Meyer, 2012). Further, only German experts and no machine manufacturer were interviewed, which hinders a more objective overview of the practical application of PxM-aligned PPC. Moreover, the experts have a background in many different industries and company sizes, and it was not examined how far the results are generalizable. Therefore, the presented results can only be used for further research and practice to a limited extent. Still, we think that the model is still valuable to identify promising business cases of PxM for PPC for different companies.

Additionally, three expert interviews are not enough to thoroughly validate the model. For instance, Matook and Indulska (2009) propose a complex quality function-based evaluation approach evaluating five characteristics. While the three characteristics, generality, completeness, and understandability, have been validated to a certain extent, many authors suggest practical tests (e.g., Ahlemann and Gastl, 2007) to further test the two other characteristics, flexibility and usability.

Thus, a more robust evaluation and instantiation of the reference process model in case studies should be performed for future research. Also, extended literature reviews, expert studies, or surveys could further complement and validate the designed reference model. The model could also be used as a basis to concretize reference models specialized to different industries or company sizes. Additionally, the results led to multiple gaps that should be analyzed. First, it should be investigated how the practical adoption of PxM-enabled production planning, control, and monitoring can be fostered. Research should answer why production planning is still very manual in practice, why production control focuses on sequencing and not capacity control, and how production monitoring can be improved by linking sensor data, quality data, and production parameters. Further, especially source planning is disregarded by literature but rated as relevant by practitioners and should be incorporated in future research. Lastly, the processual changes introduced can lead to more resilient and sustainable production systems, and the actual effects should be demonstrated in future research. From a data view, it should be examined why logistics and sales data are not regarded in practice. In contrast, more research on supporting PxM and PPC with image, video, and text data should be done, which was seen as a considerable potential in practice. Further, almost no sources discussed the role of experiential data in PxM-enabled PPC. Functionally, the practical adoption of standardized PHM applications should be fostered. Moreover, it should be analyzed how explainable AI, e.g., on mobile or PHM systems, can increase transparency, and it should be examined how simulations or digital twins can increase the plausibility of PxM-enabled PPC prescriptions. Additionally, organizational changes through PxM should be addressed in research, e.g., by investigating the potential of digital upskilling the human-in-the-loop. Lastly, current practical challenges regarding successful cross-boundary knowledge sharing (e.g., protectionism) for PxM should be investigated.

While these open questions could lead to further insights, all in all, the PxM-aligned PPC reference process developed in this work shows how companies can align PxM with their production planning and control process.

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