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RESEARCH PAPER

A framework for conceptualizing integrated prescriptive maintenance and production planning and control models

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ABSTRACT

Goal: This study aims to support researchers and managers in conceptualising new integrated prescriptive maintenance (PxM) and production planning and control (PPC) models.

Design / Methodology / Approach: We perform a systematic literature review based on Thomé et al. (2016) and analyse literary findings using qualitative content analysis and quantitative correlation analyses.

Results: This work identifies 94 integrated PxM and PPC planning models and 47 outcomes, 16 decision variables and 34 environment entities. Based on the quantitative analyses of these components, we derive a normative framework to guide researchers and practitioners in conceptualising integrated models.

Limitations of the investigation: The study is limited to only one scientific database. Additionally, the quantitative analyses might be sensitive due to a low sample size for some components, and we only measure the linear dependency between two components. Lastly, we do not address solution algorithms.

Practical implications: The framework constitutes a tool for managers to construct integrated models tailored to their specific planning problems, fostering alignment between production and maintenance departments, plans and controls.

Originality / Value: We provide a descriptive overview and normative guidance in the selection of components that can or should be used for future PxM-aligned PPC planning studies, pinpointing possible research gaps.

Keywords: Prescriptive maintenance; Production planning and control; Condition-based maintenance; Modelling; Review.

1 INTRODUCTION

Production planning and control (PPC) is the backbone of any manufacturer. It determines the production plan that satisfies customer demands while meeting monetary, time, or performance objectives (Cadavid et al., 2020). PPC comprises stages such as lot sizing, scheduling, and capacity control (Schmidt and Schäfers, 2017). These, however, are jeopardised by sudden breakdowns, which disrupt set-up plans (Zarte et al., 2017). Hence, continuous flawless production is crucial to be competitive, which can be achieved with appropriate maintenance planning (Mostafa et al., 2015). However, maintenance and production departments make different planning decisions under conflicting objectives (Varnier and Zerhouni, 2012) despite a significant interdependency between maintenance and production plans (Dehghan et al., 2023).

To support these issues, novel technologies push manufacturing toward a new industrial revolution (Frazzon et al., 2019). As a result of this, through Industry 4.0, condition-based maintenance emerged (Cordeiro et al., 2019), ultimately leading to prescriptive maintenance (PxM). PxM facilitates self-configuring maintenance and production planning and control and contributes to moving closer to zero defect manufacturing (Psarommatis et al., 2021) and a maintenance-free

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factory (Glawar et al., 2022).

While 'traditional' maintenance strategies are reactive or static, the paradigm of condition-based maintenance and its most mature form, PxM, enables predicting failures and prescribing optimal actions based on sensor data analyses. Instead of only predicting maintenance actions (i.e., predictive maintenance), PxM offers ways to jointly optimise PPC and maintenance planning (Wesendrup and Hellingrath, 2022). For instance, it enables opportunistic maintenance by synchronising machine usage so that maintenance activities can be grouped (Koochaki et al., 2012). However, this requires close collaboration between production and maintenance planners, but research shows that these departments still make isolated, suboptimal and conflicting plans even though maintenance plans need to incorporate production constraints and vice versa (Varnier and Zerhouni, 2012). Consequently, only a few manufacturers have adopted PxM for their PPC decision-making (Mulders and Haarman, 2018).

Planning and control decisions are typically made via optimisation or simulation models (Goby et al., 2023) that are grouped under the collective term 'planning model' (Stadtler and Kilger, 2015). Research addressed the need of integrated planning models (Budai et al., 2008) by developing many joint PxM and PPC planning models (Bousdekis et al., 2019). However, these models are highly specific to the use case, and it is unclear how decision-makers can construct adequate planning models for their own, novel production contexts. First, there is no general overview showing what objectives exist, which decisions could be relevant, or where the boundaries of planning models should lie. Second, there is no guidance on which of these components should be considered (together) and how they can be systematically selected in order to derive an effective planning model. Therefore, this research should answer the following research questions (RQ1 and RQ2):

RQ1: *What components do integrated PxM and PPC models comprise?*

RQ2: *How can key components be systematically chosen to construct specific integrated PxM and PPC models?*

To address the first research question, the literature is examined to identify components of integrated PPC and PxM planning models. For the second question, the interrelations of the identified components are analysed, and a guiding framework for selecting relevant components is developed. Theoretical contributions include providing a descriptive overview and normative guidance in the selection of planning-relevant components that can or should be used for future PxM-aligned PPC planning models, pinpointing possible research gaps. This may assist scholars in identifying components that could be: a) outcomes representing and quantifying the intended goal of their planning problem, b) PPC and maintenance decisions benefiting from PxM, and c) determining the appropriate level of specificity and abstraction of the planning environment. As a practical contribution, a collection of diverse 'building blocks' of planning models is offered. Managers can use this collection, guided by a normative tool, to construct integrated models tailored to their specific planning problems, fostering alignment between production and maintenance departments, plans, and controls.

The following section introduces the theoretical foundations of PPC, PxM, and planning models, as well as related works at the intersection of these areas. Section 3 describes the methodology of our literature review. Section 4 presents the literature review that highlights the components regarded in PxM and PPC planning models and answers RQ1. To answer RQ2, Section 5 analyses the interrelations of these components and proposes a framework that guides researchers and practitioners in conceptualising planning models. In the final section, the findings are discussed, further research ideas are presented, and the work is concluded.

2 FUNDAMENTALS

As this work investigates the intersection of PxM, PPC and planning models, it is pivotal to understand the theoretical fundamentals of these sovereign research streams and the state of research.

Production Planning & Control and Prescriptive Maintenance

Production planning and control (PPC) is the 'nervous system' (Kiran, 2019, p. 1) of every manufacturing company, and its goal is to generate a plan allowing to continuously manufacture products in the correct quantity and quality at the right time and with minimum costs (Oluyisola et al., 2020). Planning horizons are typically long-term, strategic, mid-term, tactical, and short-term, operational (Stadtler and Kilger, 2015). Long-term plans are typically made for years to weeks, medium-term plans for weeks to days, and short-term plans and controls are made daily or even in real-time (Bonissone and Iyer, 2007). Over these horizons, PPC comprises the steps program-, requirements-, source-, and production planning, production control, monitoring, inventory and order management, and dispatching. However, breakdowns jeopardise plans made over different planning horizons, which can be tackled by a good maintenance strategy (Broek et al., 2020).

Traditional maintenance strategies are either reactive or preventive (Wagner and Hellingrath, 2021). The former causes unplanned disruptions, long downtimes, and losses in production capacity; the latter is often overly strict and causes unnecessary maintenance or, in the worst case, maintains too late (Liu et al., 2023). Condition-based maintenance tackles all these issues by maintaining machines based on their condition through acquiring and analysing sensor data (Broek et al., 2021). Condition-based maintenance is supported by prognostics and health management, a process comprising fault detection, diagnostics, prognostics and decision-making (Guillén et al., 2016). Each step builds upon its predecessor and enables different maturity levels of condition-based maintenance strategies (Ansari et al., 2019). PxM is the most mature level of condition-based maintenance, turning knowledge into value through decision-making (Skima et al., 2019). It answers the question of 'How should something happen?' by providing actionable recommendations. Optimally, these condition-based recommendations are not limited to maintenance decisions but also address PPC, leading to condition-based production (Broek et al., 2021).

Maintenance and production planning, however, are often performed separately, even though they are highly interdependent (Dehghan et al., 2023). Here, PxM provides an opportunity to align both with integrated PPC and PxM planning models.

2.1 Planning Models

While the domains of PPC and PxM are broad and span many functions of a manufacturing company, not every detail can be regarded in planning. Therefore, one must use simplified abstractions of real planning problems, so-called planning models. Planning models are either optimisation or simulation models, and they prepare decisions by recognising and analysing decision problems, forecasting future developments, identifying and evaluating possible solutions and selecting good ones (Stadtler and Kilger, 2015). In order to construct planning models, it is helpful to identify components of established PxM and PPC models, which is the goal of this work. Here, Starr (1966) defines three basic dimensions of building blocks: *outcomes*, *decision variables* and *environment.*

Table 1 - Related works

References	*PPC*	*PxM*	*Outcomes*	*Decision variables*	*Environment*
(Regal and Pereira, 2018)	◑	●	○	○	●
(Ansari et al., 2019; Cho et al., 2020; May, G. et al., 2022)	●	●	○	○	◑
(May, M. C. et al., 2022)	●	◑	○	○	●
(Bousdekis et al., 2018)	◑	●	◑	●	○
(Psarommatis et al., 2021)	◑	●	●	●	○
(Gutschi et al., 2019)	○	●	●	◑	◑

●= fully, ◑ = partially, ○ = not addressed

Source: The authors themselves.

The dimension *outcomes* represents a manufacturer's aims. *Outcomes* can be used as objectives which are always maximised (e.g., a component of this dimension could be throughput), minimised (e.g., cost), or used as a constraint (e.g., service level). Further *outcomes* quantify whether objectives have been achieved or enable the analyses of why the objectives have been missed. For instance, if the primary *outcome* is to increase the throughput, machine availability could be an intermediary *outcome* to identify reasons for failure. *Decision variables* are the decisions that can be changed to achieve the *outcomes* (e.g., number of maintenance staff, production plans). In contrast, the *environment* comprises entities that are considered fixed, such as products, production lines or human resources (of course, depending on the planning problem, these can theoretically be *decision variables*).

2.2 Related Works

This work reviews PPC and PxM planning models to identify their *outcomes*, *decision variables*, and *environment*. To highlight the research gap and to build on existing literature, related works have been identified using a narrative literature review methodology (Paré et al., 2015). Hereby, we focussed on 'holistic' works, such as reviews, standards, reference models, ontologies, or frameworks, by querying *Google Scholar* with keywords related to PxM, PPC and planning models. REFERENCES

presents these works and how well they address the four planning model dimensions.

Regal and Pereira (2018) developed a comprehensive ontology for condition-based maintenance systems focusing only on spare parts sourcing. Vice versa, some works cover all steps of the PPC process (cf. Section 2.1) but include a limited *environment* (Ansari et al., 2019; Cho et al., 2020; May, G. et al., 2022). In contrast, May, M. C. et al. (2022) propose a generic simulation ontology for production encompassing a detailed *environment* and addressing the whole PPC process.

In contrast to these ontologies, Bousdekis et al. (2018) review condition-based decision-making methods. Therefore, they only address the *decision variables* and *outcomes* of these approaches. Further, Psarommatis et al. (2021) investigate PxM for quality-related PPC to achieve zero defect manufacturing, albeit they only address control *decision variables* and some key performance indicators as *outcomes*. Lastly, the work from Gutschi et al. (2019) proposes a framework for simulation-based evaluation of maintenance strategies. Due to the limited environment, only a handful of examples of the different components of planning models are analysed, and PPC decisions are not addressed.

In conclusion, no existing work covers all planning model dimensions, highlighting the outlined research gap. Still, these works are a valuable basis for our research.

3 METHODOLOGY

A systematic literature review has been conducted using the eight-step methodology by Thomé et al. (2016) to fill the outlined research gap.

Step 1: Planning and formulating the problem. / As explained in the last section, the existing body of literature has been checked by querying major journals and scientific databases, and the identified research gap should be illuminated by addressing the abovementioned research question.

Step 2: Searching the literature / Step 2 comprises another, subordinate seven-step approach to search for literature. First, Scopus, the most extensive scientific database, has been selected as the database (i) and queried with the following keywords (ii) returning 521 hits:

TITLE-ABS-KEY("production" AND ("predictive maintenance" OR "prescriptive maintenance" OR prognost OR "condition-based maintenance") AND (optimisation OR planning) AND (scheduling OR requirements OR "production planning" OR "production control" OR sourc* OR monitor* OR inventory))*

Additionally, Web of Science and IEEE Xplore databases have been queried with the same keywords to check whether a theoretical saturation has been reached. Multiple relevant publications were sampled and analysed for each database, but no novel components emerged. Thus, it was deemed that Scopus was sufficient for a representative review. Next, all abstracts were reviewed by two reviewers (iii), and the following inclusion criteria were applied (iv):

- Primary subject should be production.
- Primary subject should be condition-based maintenance.
- Publication should contain a planning model (e.g., optimisation, simulation).
- Complete English text should be accessible.

Following these criteria separately, both reviewers had an inter-rater agreement of 91.04% and a Cohen's κ of 70.63%, which implies substantial agreement (Rafieyan, 2016). 94 relevant publications remained, which were used for further analysis (v).

The entire process of the literature identification is summarised in Figure 1 in the commonly used PRISMA notation.

Step 3: Data gathering & Step 4: Quality evaluation / The remaining 94 publications were then scanned for planning-relevant components being the manifestation of the dimensions as presented in Section 2.2. The dimensions are based on the building blocks of Starr (Starr, 1966) and comprise *outcomes*, *decision variables* and *environment*.

Step 5: Data analysis and synthesis & Step 6: Interpretation / 47 *outcomes*, 16 *decision variables* and 34 entities comprising the *environment* were identified. All components from these three dimensions were statistically analysed to reveal which components to address when considering other components using phi correlation. The correlation is measured between two components and can lie between +1, which signifies perfect correlation, and -1, which signifies perfect anti-correlation (Akoglu, 2018).

Step 7: Presenting the results & Step 8: Updating the review / To check whether the general methodology is apt, an intermediate result of the review that focuses on quality control as a small subset of PPC has been peer-reviewed and presented [ANONYMIZED_FOR_REVIEW].

3.1 Components of PxM and PPC Planning Models

The following section presents the literature review findings classified by the three dimensions and answers the first research question.

3.2 Outcomes

Outcomes comprise the primary goals that should be achieved using a planning model, as well as further intermediary measures that quantify whether the goals have been met. All in all, 47 outcomes could be identified and classified into a time, money, and performance hierarchy as shown in Figure 2.

Money / Monetary outcomes are most addressed. Here, *profit* is the central measure of economic performance and is calculated by revenue plus cost. *Revenue* can also be exclusively considered, e.g., when trying to maximise production regardless of cost. For instance, Broek et al. (2020) state that the revenue is proportional to the production rate of a system, which depends on its deterioration. A unique form of *revenue* is the *asset value* that depends on the maintained machine state (Rasay et al., 2022).

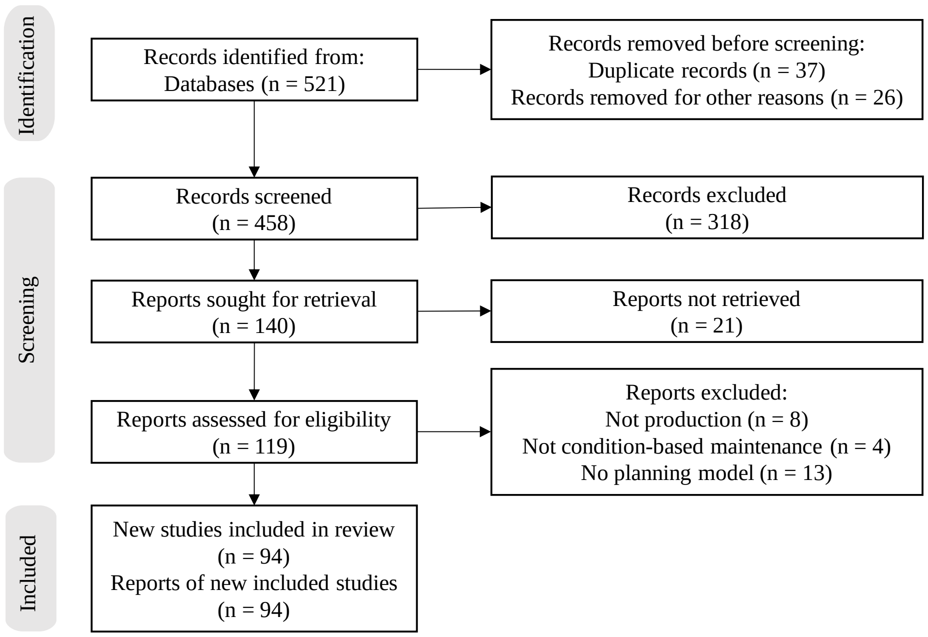

Figure 1 - PRISMA flowchart of literature search
Source: The authors themselves.

The pendant to *revenue* is *cost*. When decomposing *cost*, *maintenance cost* is a primary factor. As a budgetary constraint, it can prevent over-maintenance (Ong et al., 2021). PxM can also reduce *production costs* by timely maintenance of resources that would otherwise increase operating costs. Further, *set-up cost* is a factor of *production cost*. Here, models try to find a good balance between small lot sizes so that the risk of an intermediate breakdown is low and big lot sizes to reduce the number of costly set-ups (Tasias, 2022). Another important outcome is *quality cost*, which comprises *product quality cost* caused by scrap or rectifications and often occurs in degraded machines (Salmasnia et al., 2020).

Time / *Tardiness* is the delay or lateness in completing a production order and an indicator of *shortage* or *late costs* (Bougacha et al., 2019). Generally, PxM leads to fewer breakdowns, better schedule adherence and better due date estimates (Bougacha et al., 2018). Further, *lead time* is vital for efficient spare parts sourcing, and *travel time* can be used if maintenance teams travel far between the assets to be maintained (Xia et al., 2021). The estimation of *mean time between failure* and *remaining useful life* is essential for condition-based maintenance (Bouzidi-Hassini et al., 2015). How well production and maintenance synergise is characterised by *availability*, the ratio of *uptime* to the sum of *down-* and *uptime* (Yang et al., 2022). *Downtime* typically includes *set-up*, *maintenance* and, if only performable on stopped machines, *inspection times*. *Maintenance times* depend on the competence level of a technician, and might increase with machine degradation or be constant (Liu et al., 2023). *Uptime* comprises *idle* and *processing times*. The *processing time* depends on the degradation level and can be increased by decelerating the production speed to extend the remaining useful life (Esposito et al., 2022). Lastly, the most common time outcome is the *makespan*, which includes all *down-* and *uptime* components.

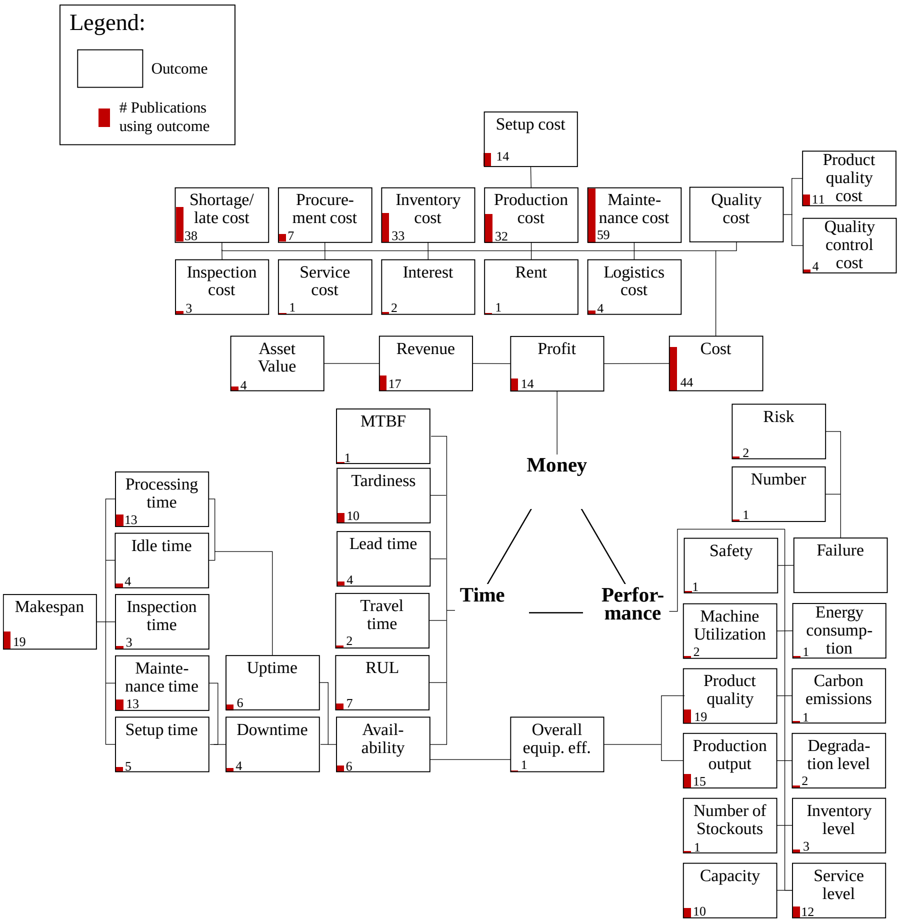

Figure 2 - Outcomes
Source: The authors themselves.

Performance / The last outcome type includes *production output* and *quality*. While a higher production rate leads to higher output, it also leads to higher degradation and lesser quality products (Tsao et al., 2020), which requires good balancing. Both outcomes are typically used with the time metric *availability*, which is called the *overall equipment effectiveness* and allows for balancing all three outcomes. Another prevalent outcome is *capacity*, which signifies the share of available inventory, maintenance, or production resources (van Rooij and Scarf, 2020). Additionally, *machine utilisation* is another measure of an asset's efficiency.

Further, outcomes include risk-related measures, such as the *degradation level*, the *number* and *risk of failures*, and *safety*. Lastly, there exist two environmental outcomes, *carbon emissions* and *energy consumption*, that can be reduced through PxM (Mi et al., 2020).

3.3 Decision Variables

Decision variables represent the decisions that can be made within PxM and PPC. All identified decision variables are either maintenance- or production-related; however, all reviewed works integrate at least one decision from each type. Figure 3 shows the identified decision variables and how often they have been addressed in the literature.

Maintenance-related / The decision of *when to maintain* is most prevalent as PxM enables much more exact remaining useful life predictions. Typically, decisions about whether to maintain are made at each planning period (Rasay et al., 2022), or time points are implicitly defined by setting condition thresholds after which machines are automatically maintained (Wang et al., 2020). While the decision on maintenance times can be made in isolation, through PxM, it is also possible to change production plans and controls to create opportunistic maintenance windows in which multiple machines can be maintained at once (Si et al., 2019).

Next, decisions on *how to maintain* define whether machines or components can be maintained (e.g., lubricated), repaired, or fully replaced (Mi et al., 2020). Depending on their extent, these different maintenance levels restore the machine to different states (Ghaleb et al., 2020).

The decision variable on *what to maintain* is relevant for machines with multiple critical systems or components and limited maintenance resources (Xia et al., 2021). Similar to maintenance interventions, some models also plan *inspections* where the machine condition is checked.

PPC-related / Regarding PPC, most works optimise the *sequence* by integrating condition information, e.g. using operation-specific stress indicators (Zhai et al., 2019). By respecting the deterioration operations cause, optimal production sequences allow for postponing increased failure risks to periods with less demand (van Rooij and Scarf, 2020). *Lot sizes* can also be dynamically calculated according to the degradation level to minimise the risk of breakdowns (Darendeliler et al., 2020).

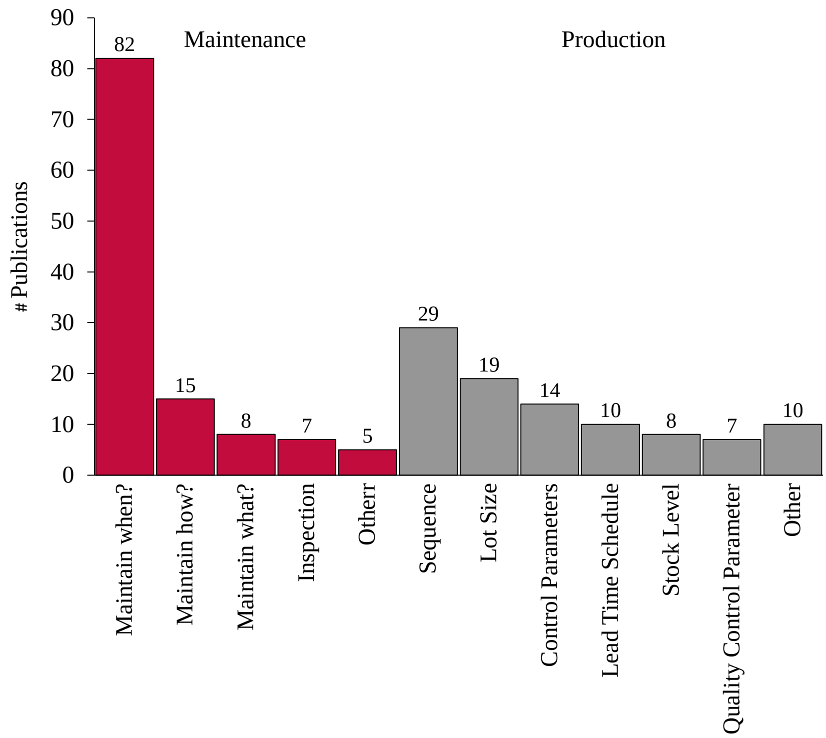

Figure 3 - Decision variables
Source: The authors themselves.

On a shorter time horizon, *machine control parameters* allow real-time production control based on the machine's condition. Here, different machine components can be controlled, so their remaining useful life is synchronised, and all can be maintained opportunistically (Björsell and Dadash, 2021). Typically, this is achieved by controlling production speed, rate, or throughput, which also de- or accelerates degradation proportionally (Esposito et al., 2022). Next, *lead time schedules* are decision variables on a tactical level that define the quantities and due dates of production orders (Bougacha et al., 2019).

Further, the hedging of *stock levels* can be dynamised so that spare parts or finished goods buffers are built up depending on machine degradation (Hellingrath and Cordes, 2014). Condition data can also reveal product quality issues from degraded machines and vice versa, and PxM can help to set appropriate *quality control parameters* (Ma and Lv, 2019).

3.4 Environment

Figure 4 depicts an entity-relationship model of the environment, which comprises all planning-relevant entities that are 'not under the decision-maker's control' (Starr, 1966, p. 117) and can be classified as production- (solid frame), machine- (dotted), and maintenance-related (dashed). Additionally, we highlight the number of publications addressing each entity using red bars.

Production-related / Planning models start with a *demand* that must be fulfilled, which is planned through *forecasts* or *orders* already issued by *customers*. While *forecasts* try to match the customers' actual orders, the production period is flexible. Instead, *customer orders* typically have a due date that must be adhered (Xanthopoulos et al., 2017). From the demand, a *master production schedule* is derived that comprises *finished products* and their quantities. In a PxM context, a pivotal property of products is their quality, which decreases and leads to non-conforming items the more a machine deteriorates (Ma and Lv, 2019).

Concrete *production orders* can be generated based on the *master production schedule*.

Production orders produce a specific *product* (Bougacha et al., 2020) and are based on *customer orders* (make-to-order) or *forecasts* (make-to-stock).

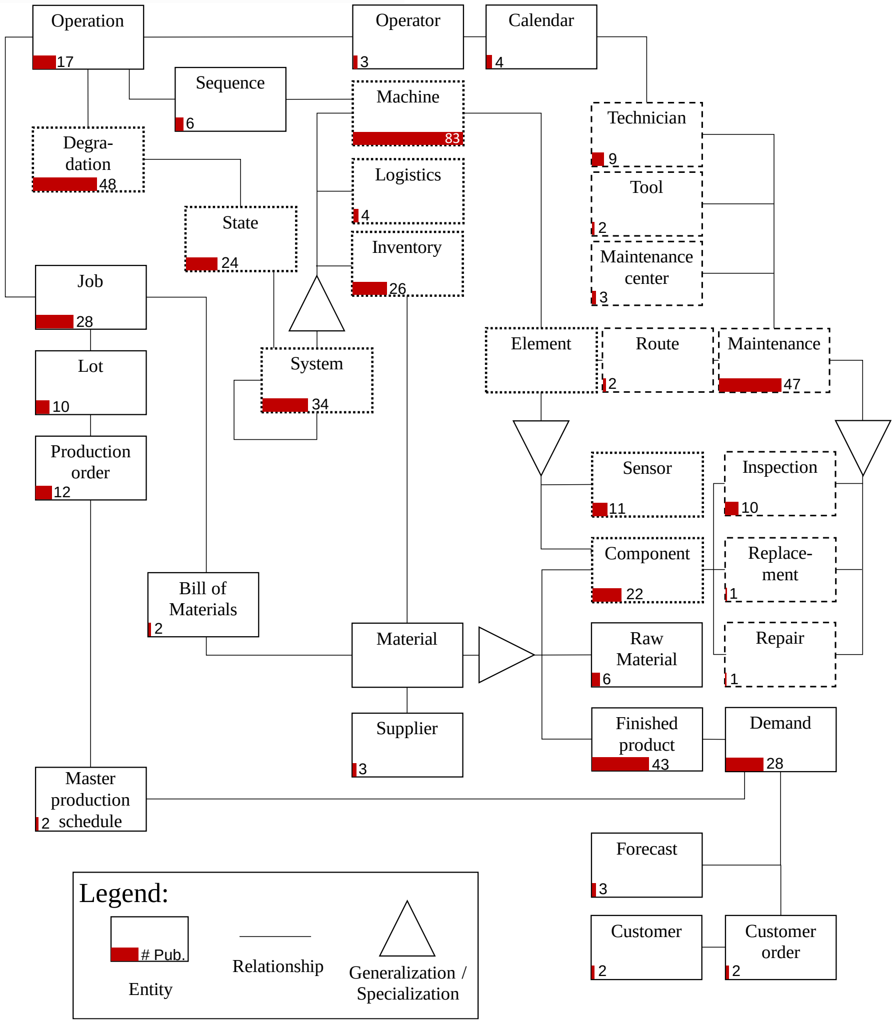

Figure 4 - Environment
Source: The authors themselves.

Production orders result in one or multiple *lots* of a specific size (Zheng et al., 2021) converted into specific *jobs*. *Jobs* define the different *operations* that need to be performed and depend on the *bill of materials*, which provides the *raw materials* that are sourced from *suppliers* (Tsao et al., 2020) and are required to produce the end *product* (Morariu et al., 2020). Depending on the manufacturing process, jobs can be non-preemptive, i.e., they cannot be resumed after a breakdown and cause scrap (Kung and Liao, 2022), highlighting the importance of PxM to prevent breakdowns during production. Further, a *job's* energy consumption can increase due to machine *degradation* (Ghaleb et al., 2020).

Operations of a *job* are supported by machine *operators* that load, monitor and unload *machines* (Negri et al., 2021) and work based on shift *calendars* (Padovano et al., 2021). Outside of these shifts, production cannot be started and optimally, PxM postpones maintenance interventions or breakdowns to the next working period (Elbasheer et al., 2022). *Operations* are typically ordered on *machines* within a *sequence* (Bencheikh et al., 2018). An *operation* is the most granular planning entity of PPC and causes *degradation*.

Machine-related | Machines as the mainstay of PxM and PPC can produce one or various (semi-)finished *products* (Bougacha et al., 2019). Manufacturing these *products* degrades the *machine* and often reduces its production rate (Leo and Engell, 2022), which can also be lowered manually to decelerate *degradation* (Broek et al., 2021). For instance, CNC *machines* can work with different cutting speeds, feed rates, and various tools (Bougacha et al., 2020).

Machines can be structured within a hierarchy of *systems*. For instance, a *machine* can be part of a production line (Negri et al., 2022), which can be part of a plant (Schreiber et al., 2019). Any production *system* can be in a specific *state* based on its *degradation* (Rasay et al., 2022). In PPC and PxM planning, at least three states are distinguished: operational, failure, and under maintenance (Ruiz Rodríguez et al., 2022).

Besides production *machines*, *logistics*, for instance, conveyor belts, forklifts (Negri et al., 2021) and *inventory systems*, for instance, buffers (Padovano et al., 2021), can be part of the manufacturing ecosystem. At the other end of granularity, *machines* comprise *elements* that are either *sensors* (Bouzidi-Hassini et al., 2015) or functional *components* (Ruiz Rodríguez et al., 2022). Both have different costs (Bougacha et al., 2020) and need different times for *repairs* or *replacements* (Ruiz Rodríguez et al., 2022).

Maintenance-related / In case *machines* are scattered across multiple plants, maintenance *routes* must be defined that comprise different *maintenance* interventions (Xia et al., 2021). *Maintenance* interventions require specific processing times, which may depend on the *machine's degradation state* (Ghaleb et al., 2020). Moreover, *maintenance* can be of different quality, which ranges from not improving the system to restoring it to an as-good-as-new state (Zheng et al., 2021). Time and quality depend on the *tools* used (Liu et al., 2023), the skill level of the *technician* (Ruiz Rodríguez et al., 2022) and the performed type of intervention. While most *technicians* work on the premises of the production facility, some enterprises have separate maintenance centres (Bencheikh et al., 2018), which is essential for PxM planning.

In conclusion, the presented components show the different facets that can be considered for PPC and PxM planning, which is an excellent first step. However, 'the art of model building' (Stadtler and Kilger, 2015, p. 72) is choosing the right detail level and what to include and exclude.

3.5 Guiding the Development of Planning Models

Various outcomes, decision variables and the environment of PPC and PxM can be regarded within planning models. While the framework shows all possible components, not all can be included. For that, 'classical' operations research literature suggests identifying the principal elements (i.e., relevant components from each of the three dimensions) of a decision problem (Taha, 2017).

Here, *outcomes* (i.e. the main objective) are the typical starting point (even though, technically, any dimension could be used) from which further components can be identified using a phi correlation analysis (cf. Section 3). In the following, we present how further planning model components can be derived from a chosen *outcome* using this correlation analysis.

3.6 Deriving Planning Model Components

To choose an appropriate outcome, a manufacturer should first think about where they underperform compared to industry benchmarks or whether specific outcomes are pivotal to them (e.g., a premium product manufacturer prioritises product quality over everything). As our review includes 47 different outcomes, we will limit the following discussion to the five most prevalent ones, which provide a good mixture of money, time, and cost outcomes. For the others, the full cross-correlation between all reviewed components of all dimensions is accessible at [ANONYMIZED_FOR_REVIEW]. We showcase how further model components can be derived from these outcomes using the correlation coefficients (shown in parentheses).

Cost / Cost is the most common outcome and is closely intertwined with the outcomes *maintenance* (.58), *stockout* (.53) and *inventory cost* (.32). Correspondingly, its main decision variables are decisions on *lot sizes* (.40), *how to maintain* (.32) and *stock levels* (.30), which have a direct effect on the outcome.

Makespan / In contrast, the second-most addressed outcome, *makespan*, represents another extreme, inversely correlated to *cost* (-0.38). A reduction of this outcome can be mainly achieved by adjusting the *sequence* (.65). Accordingly, *jobs* (.56) and *operations* (.73) must be considered when employing PxM to minimise the *makespan*. Whether the outcome is attained can be further analysed by observing *idle times* (.25) or the *tardiness* (.24) of the production.

Profit / On the one hand, reducing *cost* might lead to slow production processes, while on the other, achieving a minimal *makespan* might be a considerable investment. Hence, *profit* can be a good outcome that balances the two extremes. In contrast to cost, profit is extended by *revenue* as a pivotal outcome (.72). Here, either real-time *machine control parameters* (.27) or tactical *lead time schedules* (.26) are relevant decision variables to increase *profit*. For instance, increasing a machine's production rate increases production revenues as more orders can be fulfilled. However, it negatively influences costs, as higher rates lead to more breakdowns and vice versa (Broek et al., 2020).

Service level / While *cost*, *makespan*, and *profit* are predominant PxM and PPC outcomes, they are only indirectly customer-related. Instead, the *service level* represents an outcome of customer-focused manufacturers (e.g. premium producers). Interestingly, *components* (.38) and *maintenance centres* (.31) are pivotal in the environment of planning models. Here, the degradation and timely sourcing of components is crucial to avoid prolonged production outages (Lukitosari et al., 2019), and at best, it is entirely outsourced to dedicated maintenance centres (Bencheikh et al., 2018). As a fallback, companies can also sustain the service level by adjusting their *stock level* (.36). Service levels are seldom maximised or minimised but instead used as constraining factors, while other outcomes, such as *machine utilisation* (.28), are targeted (Schreiber et al., 2019).

Production output / Lastly, maximising production output is a well-regarded performance outcome. It is often jointly analysed as part of *overall equipment effectiveness* (.40), which, besides output, regards *quality* and *availability* (Antao et al., 2018). Analogically, the outcome *uptime* (.38), part of availability, is strongly, and the *failure risk* (.26) is moderately correlated. *Personnel* (.40) is deemed the most relevant outcome to achieve a high production output, and models should plan the number of employed operators and maintenance technicians well.

3.7 Framework

Based on these relational analyses, Figure 5 shows a normative guiding framework for developing integrated PPC and PxM planning models. It highlights the different dimensions, namely *outcomes, decision variables and environment* of planning models described in the previous sections and offers guidance on how to devise PxM-aligned PPC planning models by following three steps.

The first step (1) includes *choosing an outcome* and deriving first-level correlated components, as explained in the previous two subsections. These lay the foundation for additional relevant components. In the next step (Step 2), a planner must *iteratively derive further components* from the identified first-level components. To facilitate that, we have performed an extensive phi correlation analysis between all components available at [ANONYMIZED_FOR_REVIEW].

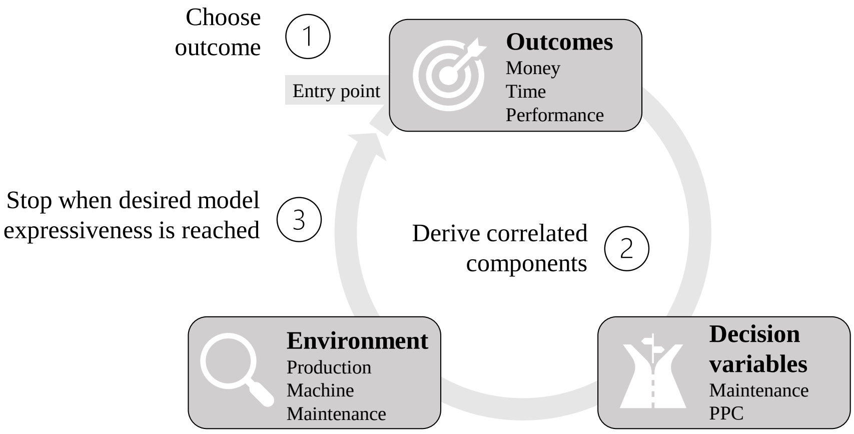

Figure 5 - Guiding framework
Source: The authors themselves.

For demonstration, principal components (i.e. components addressed in 16 or more models and positive correlations of 0.1) and their interconnections are visualised in a correlation network (Figure 6). Here, the node size represents the number of papers addressing the components, while the edge (size) represents the correlation and interdependency of two connected components. The figure exemplifies which components a planner should include in planning models if they regard another component. Lastly (Step 3), the planner should *stop when an adequate model expressiveness has been reached*, e.g., by consulting an expert or when the correlation of chosen components drops below a certain threshold (e.g., < 0.2). By performing the proposed steps, relevant components of PxM and PPC models can be derived, and planning models can be systematically adapted to a specific planning context.

4 CONCLUSION

To conclude, this research answers the question of how integrated PPC and PxM planning models can be conceptualised. To address the first research question, the literature was examined to identify components of integrated PPC and PxM planning models. Hereby, a structured literature review has been used to obtain almost 100 individual planning models and identify components from the dimensions of *outcomes, decision variables,* and *environment*. For the second question, the interrelations of the identified components were analysed, and a normative guiding framework has been developed and tested, highlighting how key components can be systematically chosen for a specific planning model.

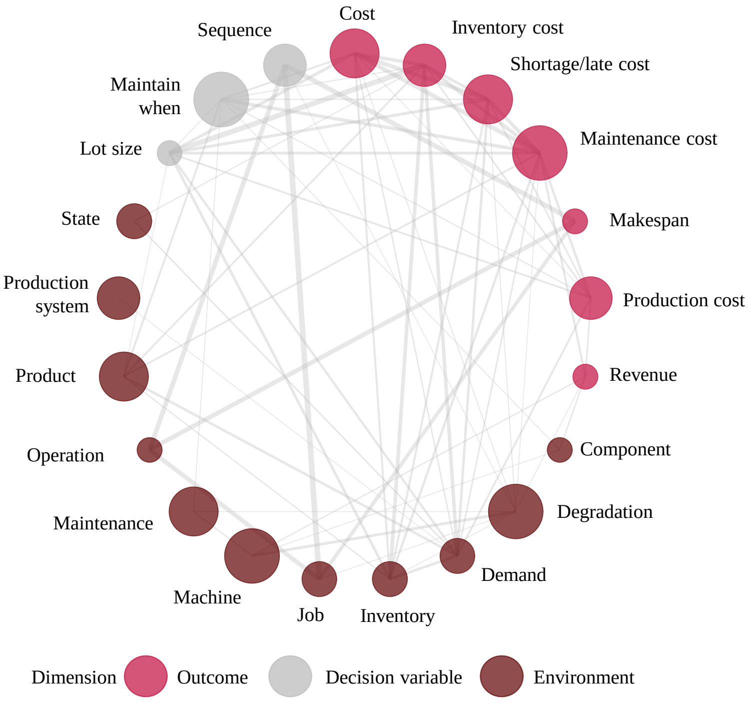

Figure 6 - Correlation network
Source: The authors themselves.

Nevertheless, this research comes with some limitations. First, only literature from one scientific database, *Scopus*, was selected, and no additional sources were identified in forward and backward searches. Samples from the databases *Web of Science* and *IEEE Xplore* did not lead to new components or insights and were thus not included. While an excellent theoretical saturation could be reached with almost 100 relevant hits on Scopus, new components may emerge when obtaining even more literature. Furthermore, the review is only based on scientific works, and practice-oriented materials are not used. Hence, using multiple scientific databases (e.g., *Web of Science*) or including practical grey literature, expert interviews, or surveys could reveal more key components or change the outcomes of the performed analyses.

Additionally, the limited sample size leaves some components not well-addressed. Therefore, the statistical analyses might not be robust for rarely used components. This can lead to unreliable recommendations on what to consider. However, it is also not imperative that strongly correlated components must be regarded or that a consideration of weakly correlated ones is never warranted. Instead, it is recommended that the framework is always consulted with field experts (e.g., production and maintenance managers) and that the correlation scores are only used as an initial recommendation. Moreover, as a review, our work only shows what has been used (in the past) and not what should be used (in the future).

Further, a correlation only measures the linear dependency of two variables. However, reality is not two-dimensional, and complex interdependencies between combinations of various variables exist. Additionally, the solution methods used (e.g., linear programming and genetic algorithms) have not been discussed, as the optimal choice is not influenced by the domain characteristics of the planning problem but by the specific planning instance (Branke et al., 2016). Here, the reader is referred to hyper-heuristics that automatically configure to the specific problem instance (e.g., Pessoa et al., 2020). Additionally, multi-criteria decision-making could be used in future works, especially for models with multiple objectives. Here, Chakraborty (2023) and Jamwal et al. (2021) present overviews of multi-criteria decision-making methods in manufacturing contexts. Furthermore, the usefulness of multi-criteria decision-making has been demonstrated for condition-based maintenance applications (Gedikli and Cayir Ervural, 2020).

While it was shown how our framework guides modellers, our underlying review also reveals potential for future research. First, current research mainly focuses on core manufacturing operations, but only a few publications include sourcing-related decision variables. Moreover, while PxM planning often anticipates failures, its potential to identify and control product quality deviations can be further investigated. Thirdly, almost half of all planning models tried to minimise costs, but the ability of PxM to improve business performance and productivity is highly underrepresented. Next, PxM is a maintenance strategy that enables sustainable or net-zero manufacturing, but current literature focuses almost solely on its economic impacts. Further, it was shown that PxM enables autonomous, flexible machine controls, which can only be attained by decentralised planning. While many of the reviewed works demonstrated how to perform decentralised PxM for single decision variables, the interaction between different de- and centralised planning models was never demonstrated. Lastly, PxM planning models for PPC rarely address the human-in-the-loop. Thus, we propose that future research on PxM and PPC planning models should address a) sourcing decisions, b) the effects of quality, c) maintenance not only as a cost-driver, d) sustainability, e) decentralised planning and f) the human-in-the-loop.

To conclude, our work makes valuable contributions to theory and practice. As a theoretical contribution, it provides a descriptive overview and normative guidance in the selection of components that can or should be used for future PxM-aligned PPC planning studies, pinpointing possible research gaps. As a practical contribution, the framework constitutes a tool for managers to construct integrated models tailored to their specific planning problems, thus, integrating PxM and PPC, fostering alignment between production and maintenance departments, plans and controls..

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