A Process-based Review of Post-Prognostics Decision-Making

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ABSTRACT

Condition-based maintenance (CBM) and prognostics and health management (PHM) are established paradigms that evidently offer a competitive advantage to a company. However, to make a business case, it must be examined where PHM and a remaining useful life (RUL) estimation can lead to substantial benefits. These benefits are strongly tied to the decision-making that succeeds prognostics. While the prognostics component of PHM is well examined, research on post-prognostics decision-making (PDM) is still in its infancy. It is generally assumed that PHM can lead to benefits for business processes beyond 'traditional' maintenance management. Unfortunately, there is no overview for which processes (such as production scheduling or route planning) PDM can be applicable and how exactly specific optimizations and their corresponding benefits can be achieved. This work provides a structured literature review on PDM and identifies studies that exploit the RUL prediction for optimizing business processes. The review synthesizes the following aspects within a PDM framework: a) which processes are improved through post-prognostics decision-making, b) what decisions must be made, and c) what novel benefits are achieved and which challenges arise. This review enables scholars to identify how current prognostics research can be extended to the decision stage of CBM and PHM and aids practitioners in pinpointing how operations can be optimized through PDM.

1. INTRODUCTION

Over the past decade, condition-based maintenance (CBM) and prognostics and health management (PHM) proved to increase the reliability, safety, maintainability, availability, supportability, and economic affordability of a system (Sun, Zeng, Kang, & Pecht, 2012). Through collecting and analyzing condition monitoring data, CBM facilitates improved decisions about maintenance interventions (Jardine, Lin, & Banjevic, 2006; Montgomery, Banjevic, & Jardine, 2012) and is thus a significant improvement of more traditional strategies, such as corrective or time-based maintenance. Prognostics and health management (PHM), a set of tools that enable CBM, help to estimate the remaining useful life (RUL) of a system through prognostics methods. Prognostics generally implies a reduction in overall costs (Elattar, Elminir, & Riad, 2016).

PHM approaches generally follow the process depicted in Figure 1 that is based on the standard ISO 13374 and was adapted by Guillén, Crespo, Macchi, and Gómez (2016). First, data is acquired and preprocessed. The continuous monitoring of condition data can be used to detect anomalies, which is, in turn, further evaluated by analyzing its cause through diagnostics (Katipamula & Brambley, 2005). Further, prognostics are used to split a system's health indicator into two (healthy and degraded) or more health stages and to predict the RUL (Lei et al., 2018). While an accurate RUL prediction is essential for PHM, the benefits are only attained in the post-prognostics decision step (Skima, Varnier, Dedu, Medjaher, & Bourgeois, 2019). Here the optimization of the maintenance strategy is essential to "convert health-related information to values" (Jia, Huang, Feng, Cai, & Lee, 2018), but objectives of adjacent business processes from production or supply chain management, must also be regarded (Bousdekis, Lepenioti, Apostolou, & Mentzas, 2019).

In contrast to prognostics, research on post-prognostics decision-making (PDM) is still in its infancy (Bousdekis, Magoutas, Apostolou, & Mentzas, 2018). Throughout the years, some decision-making methods that incorporate prognostics information were developed for electronic systems, aerospace, and wind energy (Skima et al., 2019). Unfortunately, these are isolated, specialized applications, and it is unknown which adjacent processes and operations must be generally considered. This, however, is imperative to leverage the benefits of PHM. More so, because some decisions that are made within business processes are structurally similar. For instance, the assignment of aircraft to missions, jobs to machines, or maintainers to routes is similar,

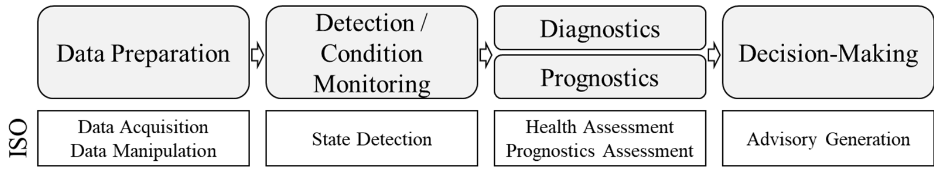

Figure 1. PHM process (based on Guillén, Crespo, Macchi, & Gómez, 2016).

and all of these processes are affected by a maintenance decision.

Bousdekis et al. conducted a review of PDM by examining the different combinations of prognostics and decision-making methods (2018). The review does not examine the underlying processes that are optimized but is method-focused. There also exist further reviews that either are not process-focused (Bousdekis et al., 2019), focus on the prognostics stage (Alaswad & Xiang, 2017), concentrate on non-prognostics maintenance (Almeida, Ferreira, & Cavalcante, 2015; Ding & Kamaruddin, 2015; Jonge & Scarf, 2019; Ruschel, Santos, & Loures, 2017; Sharma, Yadava, & Deshmukh, 2011; Vasili, Hong, & Ismail, 2011) or address only spare parts procurement (Horenbeek, Buré, Cattrysse, Pintelon, & Vansteenwegen, 2013). In contrast, this work provides a structured literature review on PDM by analyzing existing applications and characterizing the processes that can be optimized through PHM.

PDM applications generally follow a specific' post-prognostics decision-making' process that is depicted in Figure 2. First, a prognostics algorithm predicts the RUL of the system. The RUL, among other factors such as costs, is then incorporated in one or multiple objectives (e.g., minimization of cost, maximization of availability). These objectives can then be achieved by choosing the best decision out of a set of possible decisions, e.g., through means of optimization. The decision should optimize adjacent areas and business processes, while some challenges must be met.

In this literature review, processes, different representations of RUL, objectives, and decisions are examined. Because a review is limited to already published research, it should not serve as an exhaustive overview, but a guide on what tools of PDM are useful to consider for specific processes. Prognostics and decision-making algorithms are not considered as they are domain-agnostic, i.e., they do not depend on the to-be-optimized business process. The former depends on available expert knowledge, data, and requirements towards algorithm efficiency, which is a big research stream on its own (Atamuradov et al., 2017). The latter depends on the instantiation of the problem, which is the subject of current research on the so-called per-instance algorithm selection problem (Kerschke, Hoos, Neumann, & Trautmann, 2019). Because the review focuses on general applicability of PDM for process optimization without regarding specific instantiations, the algorithms are not discussed in-depth.

The organization of the paper follows the PDM process depicted in Figure 2: the literature review, including the processes, the handling of uncertainty in an RUL prediction, and the objectives of PDM are explained next (section 2). A typology of decisions, their relation to processes, and their co-occurrence are addressed in section 3. Challenges that emerge in PDM and benefits that can be leveraged are explained in section 4. The work concludes and presents a research agenda in section 5.

2. LITERATURE REVIEW

The literature review was conducted following Brocke et al. (2009) that encompasses six steps: definition of review scope, conceptualization of topic, literature search, analysis and synthesis and research agenda. For the literature search, titles, abstracts, and keywords of all indexed articles in the databases Scopus and Web of Science were gathered with the following query:

("predictive maintenance" OR prognostic* OR "condition-based maintenance") AND ("prognostic* based" OR "post prognostic*" OR "prognostic* informed") AND (decision OR optimization)

Articles were then evaluated by their title, abstract and full text and excluded if not relevant for the research. Articles were most often excluded because they did not encompass the decision-making phase of PHM (e.g., Qiao & Zhu, 2015). Other works were excluded because they discuss general frameworks and do not focus on specific applications (e.g. Iyer, Goebel, & Bonissone; Zhang, Cui, & Zhang,

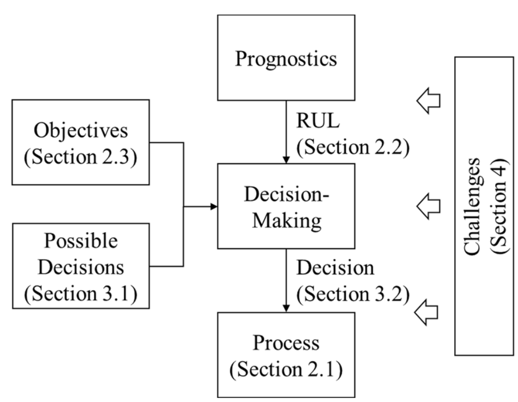

Figure 2. Post-Prognostics Decision-Making Process.

2013) or because they dealt with medical prognosis (Lin, Huang, Simon, & Liu, 2019). All in all, 21 relevant publications have been collected. While the review will be presented synoptically in the following, a detailed analysis can be found in Table 6 of the appendix.

2.1. Processes

The majority of the retrieved literature focuses on mathematical process optimization. This is in line with Skima et al. (2019) which observed that it is the case with most of the research works related to the decision stage of PHM. A full list of identified publications and their optimized processes can be found in Table 1.

The majority of works integrated prognostics results for production. Herr, Nicod, and Varnier optimized the production schedule of a platform of parallel machines performing independent and identical tasks (2014). The output of the machines had to satisfy a specific demand, while not all machines need to produce at all times, and their production profile could be adjusted. The goal was to extend the horizon in which the whole platform could meet the demand without maintenance, and to minimize maintenance costs by grouping systems to be repaired. The work has been extended and applied to a real example of a multi-stack fuel system (Chrétien, Herr, Nicod, & Varnier, 2015, 2016).

Haddad, Sandborn, and Pecht used a real-options approach to adjust the production speed and optimize the maintenance time of four turbines of a wind farm (2011a, 2011b). The optimization aims to maximize the profit based on current energy prices and RUL. With the same objective, Niknam, Kobza, and Hines focused on bearings of a wind turbine (Niknam et al., 2015). Beyond the current energy price, they also included the current wind speed in their optimization, which can be used to adjust the rotor speed and angle appropriately to maximize RUL.

Ladj, Varnier, Tayeb, and Zerhouni aim to minimize total maintenance costs by offering heuristic and exact solutions to schedule production jobs for a single multi-functional deteriorating system (2017). Their work offers novel research by a) incorporating the RUL as a random distribution and b) factoring in that different jobs exert different stresses on the machine that affect degradation. The work was extended to a flow shop scheduling problem with multiple machines, where the objective was to minimize the makespan (Ladj, Tayeb, Varnier, Dridi, & Selmane, 2017). Bougacha, Varnier, Zerhouni, and Hajri-Gabouj also focus on "traditional" production scheduling (2018). In addition to job-specific degradation and stochastic RUL, they consider different production profiles, that decrease the degradation rate, but also decelerate production speed.

Table 1. Processes optimized by post-prognostics decision-making.

Process	No. of works
Production	9
Route planning	4
Spare parts procurement	3
Maintenance management	3
Mission planning	1
Warranty management	1

Multiple publications used prognostics information for route planning. Skima et al. optimized the production route of a conveyor based on multiple micro-electro-mechanical systems (2019). Each system is equipped with PHM capabilities, and the route is optimized in real-time with Dijkstra's algorithm to minimize the traveled distance and maximize the overall RUL of the system. Many publications also focus on route optimization of maintainers. Terrissa, Meraghni, Bouzidi, and Zerhouni use the PHM08 challenge turbofan dataset (Saxena & Goebel, 2008) and a genetic algorithm to assign a set of maintainers to multiple degrading systems based on each respective geographical location (2016). Based on this algorithm, a route planning of multiple maintainers to maintain cell towers was further developed (Meraghni, Terrissa, Ayad, Zerhouni, & Varnier, 2018; Meraghni, Terrissa, Zerhouni, Varnier, & Ayad, 2016). The optimal routes are obtained by considering the locations of the assets, labor, and travel costs.

Furthermore, spare parts procurement is highly dependent on PDM because the RUL is vital for managing the tradeoff between maintenance and inventory policies (Horenbeek et al., 2013). Aghdam and Liao modeled a procurement process of wind turbine gearboxes as a Stackelberg game (2012). Here, two operators determine the time of maintenance and purchase while considering RUL, order, and maintenance costs in a competition. Aghdam and Liao discuss the same process in another work (2014). Another optimization was identified that traded off shortage vs. holding and corrective vs. preventive maintenance costs (Wang, Hu, Wang, Kong, & Zhang, 2015). Beyond the uncertainty of the RUL, Wang et al. also regarded the lead time as stochastic.

Evidently, prognostics information is also used to optimize maintenance management without regarding further processes. Bole, Goebel, and Vachtsevanos considered a system whose maintenance costs increased proportionally to its RUL and found an optimal maintenance policy through a Markov decision process and dynamic programming (2015). In two further publications, a level of repair analysis for the optimal maintenance action of an aircraft composite was presented (Thyagarajan & Gollnick, 2017, 2018). The considered actions were 'repair', 'replace' or 'discard'.

One work used RUL information for the mission planning of fighter aircraft (Li, Guo, & Zhou, 2016). Here, a semidiurnal flight and maintenance schedule was set up for one month to minimize maintenance costs subject to a specific sortie requirement.

Lastly, PDM was used for warranty management of PHM-capable systems (Ning, Sandborn, & Pecht, 2013). Based on the RUL prediction, the warrantor can choose an optimal warranty strategy that can either be a part-based, lifetime or customized extended warranty.

Now, to understand how exactly these processes can be improved by PDM, one must start at the very beginning of the PDM cycle (Figure 2), which is the RUL prediction that is returned by prognostics.

2.2. Remaining Useful Life and Uncertainty

The output of prognostics is the RUL estimation. For PDM, it is relevant to know how the uncertainty of the prediction is represented. A typical example of uncertainty in PDM is depicted in Figure 3. Through analyzing the condition monitoring (CM) history, the RUL is forecasted. Because several sources of uncertainty influence prognostics, the RUL is often represented stochastically, e.g., through a probability density function (PDF). The challenge is to not only find the optimal time to maintain but also optimize the processes presented in the last section, e.g., by determining the production schedule (e.g., Bougacha et al., 2018) or the perfect order time of spare parts (e.g., Wang et al., 2015). Thus, uncertainty plays a critical role that must be formalized within decision-making (Sankararaman, 2015). In the identified literature, uncertainty was considered in different ways (as seen in Table 2).

Multiple publications expressed the RUL by assuming that it originates from a specific distribution, such as Weibull (Aghdam & Liao, 2014), Gaussian (Wang et al., 2015), exponential (Bougacha et al., 2018; Skima et al., 2019) or uniform (Li et al., 2016). In the optimal case, uncertainty can be reduced if the decision-making determines future usage and, thus, the degradation of the system. For example,

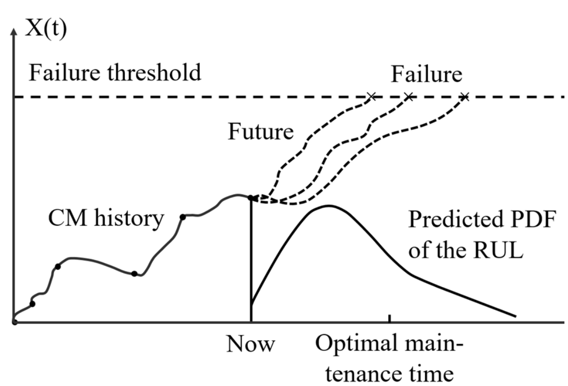

Figure 3. Uncertainty in PDM. Adapted from Wang et al. (2015).

Table 2. RUL representations.

Uncertainty representation	No. of works
Distribution	5
Deterministic	4
(Markov) transition probabilities	4
Fuzzy logic	1
Monte Carlo simulations	1
Point estimate (No uncertainty)	6

Herr et al. determine the subset of running systems and their running profiles and factor in how much degradation is caused per each time period (2014). Multiple authors used Markov decision processes that use probabilities to transit from one stage to another (Bole et al., 2015; Thyagarajan & Gollnick, 2017, 2018) or supposed transition probabilities outside of Markovian decision processes (Haddad et al., 2011a). Ladj, Tayeb et al. expressed the RUL as a fuzzy value (2017). Haddad et al. used Monte Carlo simulations (2011b) to incorporate uncertainty. Lastly, 6 of the 21 publications present the RUL as a simple point-estimate and do not consider uncertainty. On the one hand, prognostics methods, such as neural networks or support vector machines might only return deterministic point-estimates (Kan, Tan, & Mathew, 2015; Sikorska, Hodkiewicz, & Ma, 2011). On the other, an uncertainty representation might be omitted for simplicity reasons, as uncertainty increases the complexity manifold, and a solution might require a stochastic program.

Evidently, uncertainty is inherent to every PDM problem, and most of the reviewed works employ a way to represent it. Future works can make use of the abovementioned RUL representations. Nevertheless, whether and how to integrate uncertainty is an intricate question, and for a detailed discussion of uncertainty in prognostics, the reader is referred to Sankararaman (2015).

2.3. Objectives for Decision-Making

As the name suggests, post-prognostics decision-making relies on the prognostics output (RUL); however, it is only one of many factors. For instance, Herr et al. tolerate the breakdown of machines when overall maintenance costs can be minimized through grouping machines (2014). Even though the RUL predictions suggest to maintain the systems earlier, they are weighed off against savings through opportunistic maintenance.

For that, every decision-problem is subject to one or multiple objectives that comprise the RUL, among other aspects. The objective function must be matched with the goal of the to-be-optimized process. Aghdam and Liao try to minimize the overall procurement and maintenance cost, which is a function of the spare part order price, holding costs, and repair costs (2014). The latter is higher if maintenance happens after the RUL (reactive maintenance). Table 3 depicts the different objectives of PDM found in the literature and their constituent variables (besides RUL). The objective functions were categorized by the classification of Yan (2014). In the table, it can be seen that objectives are either related to cost minimization or value maximization (availability, overall equipment effectiveness (OEE), logistics).

The majority of works (15) tried to minimize costs. In the case of production, these could be costs associated with production losses or repair (Ladj, Varnier et al., 2017); for spare parts procurement, shortage, and holding costs were considered. Other approaches (5) tried to maximize availability by maximizing the useful life of a system (Skima et al., 2019). Two works considered the maximization of the OEE, by minimizing the makespan (Ladj, Tayeb et al., 2017) or the total transfer time (Skima et al., 2019). Here, the machines, jobs, and their respective properties (number, release dates, processing time) are considered essential to model the optimization. At last, one logistic objective, the minimization of the travel distance, was considered within two works. Meraghni et al. considered a route optimization for cell tower maintenance that incorporated the locations of the towers as well as maintenance personnel availability in the decision-making (2016). It is to note that three publications consider multiple objectives (Herr et al., 2014; Niknam et al., 2015; Skima et al., 2019), and thus, the sum of objectives in Table 3 is 24.

In conclusion, it can be seen that different objectives become relevant when we consider that a maintenance actions affects adjacent processes. When considering a maintenance decision in a vacuum, maintenance costs might be of primary concern, but when also acknowledging other business areas, objectives such as availability or overall equipment effectiveness must be given priority. Lastly, if the objectives of PDM are clear, PDM methods, such as optimization, can propose optimal decisions.

Table 3. Objectives of PDM.

Objective	Variables
Costs (15)	Bid price, holding costs, inspection costs, lateness or stockout penalty, material costs, order price, PHM costs, production costs, production loss, reactive and preventive maintenance costs, shortage costs, travel costs, transportation costs, wages and labor cost
Availability (5)	Capacity, demand, number of systems, working conditions
Overall Equipment Effectiveness (OEE) (2)	Degradation stress per job, maintenance duration, number of machines, production jobs, production time
Logistics (2)	Locations of systems, location of warehouses, personnel availability and subcontracting, transportation times

3. POST-PROGNOSTICS DECISIONS

Domain-specific knowledge about costs and processes is essential when making optimal decisions. Many processes, however, share some similarities in what decisions are made and what challenges arise that span over multiple different domains.

For example, route planning problems like the traveling salesman problem (TSP) can be expressed as scheduling problems, e.g., the job shop problem (JSP). For example, the TSP is a JSP with one job (salesman) and multiple machines (cities). Thus, some decisions are used within different processes (here: route planning and production). Nevertheless, the underlying decision problem is very alike, and many processes deal with the same challenges, such as uncertainty or real-time decision-making. While domain-specificity is relevant for decision-making, the underlying nature of the decision problem is equally essential when researching PDM.

3.1. Typology of Decisions

Bougacha et al. state that decisions are either maintenance-related, operational (production, automatic control, logistics), or a mix of both (2018). Skima et al. analyzed several applications and concluded that the three main decisions in PDM are maintenance optimization, control, and mission reconfiguration (2019). Cui also specified that maintenance decisions can be divided into decisions about when, where, and how to maintain (2008). Based on these works and the results of the literature review, the following typology of decisions is proposed.

Maintenance. The fundamental decision of which system is maintained (what?) at which time (when?) and what maintenance action (how?) is performed.

System (what?). Before maintaining, it is necessary to know which system or component must be maintained. Often the decision problems examine multiple assets. The decision-maker must then consider which system to maintain. Ladj, Tayeb et al. consider a permutation flow shop problem with multiple production machines with varying RUL values (2017). The PDM algorithm determines which machine needs maintenance, and the maintenance action is inserted between the production schedule.

Time (when?). In cases where the system is chosen, the choice of the maintenance time is often also a necessity. However, also in single-system cases, the maintenance time is crucial. The chosen maintenance time has a direct effect on dependent processes. For instance, the optimal maintenance time can determine the optimal order time for a required spare part (Aghdam & Liao, 2014).

Action (how?). Lastly, it must be determined how to maintain the system. Most works specify only one possible action, e.g., the system can only be replaced entirely (Wang et al., 2015). Some works optimize the choice from a set of actions, e.g., Thyagarajan and Gollnick optimize the decision on whether to repair, replace, or discard a component (2018).

Operational. Operational decisions go beyond maintenance decisions. Here, further operations are considered, such as scheduling and routing, automatic control, logistics, and service.

Scheduling and routing. In scheduling and routing, a fit between the scheduling of maintenance and other tasks, such as the production schedule, must be found. In other terms, all problems, representable as a TSP or JSP, fall under this type. Production scheduling, route planning, as well as mission planning, comprise scheduling and routing decisions. The first considers a production schedule (e.g., Bougacha et al., 2018), the second a sequence of destinations (e.g., Meraghni et al., 2016) and the latter an assortment of machines, such as aircraft, to missions (e.g., Li et al., 2016).

Automatic Control. Prognostics results can also be used for automatic system control. For instance, a pneumatic conveyor belt can be actuated to use only healthy valves (Skima et al., 2019), stress of fuel cells can be balanced between healthy and degraded cells by automatically controlling the energy output (Chrétien et al., 2015), and the rotor speed of a wind turbine can be automatically adjusted based on a prognostics model incorporating RUL and current wind speed (Niknam et al., 2015)

Logistics. When considering maintenance, logistic decisions must also be derived. These can include that spare parts are ordered to be available at the exact time of maintenance or that a maintenance crew is deployed just-in-time when the asset is at a remote location. Wang et al. proposed a spare part ordering method that finds the optimum between shortage and holding costs (2015). Meraghni et al. presented a route optimization for remote assets where the maintenance crew must arrive before failure (2018).

Service Adjustment. PDM can also be applied when adjusting the service offer of a company, such as warranty or full-service contracts based on RUL (Ning et al., 2013).

It must be noted that processes can comprise multiple decisions, and the main strength of PDM is to consider not only decisions about maintenance but also operational decisions conjointly. Vice versa, not all decisions must be regarded at once. Choosing the right set of decisions will facilitate good decision-making, but for that, the use of decisions within processes must be analyzed more extensively.

3.2. What Decisions to Consider for a Process

The majority of identified processes combine many decisions, but not all decisions are relevant for each process. To provide guidance on which decision(s) to consider for a business process, a relationship matrix was developed based on Ruschel et al. (2017). The matrix is depicted in Table 4 and can be calculated with Eq. (1).

$$\frac{\#(P(p_i) \cap P(d_j))}{\#P(p_i)} \qquad \begin{array}{l}\forall i \in [1, \dots, 6],\\ \forall j \in [1, \dots, 7]\end{array} \tag{1}$$

Here, the intersection of the number of publications P that address process p_i and the decision d_i is divided the number of publications that address p_i. Cells highlighted in bold correspond to a strong relation, italic letters represent median relationships, and non-highlighted rows have a weak or no relation. The strong and median relations are also plotted in Figure 4 and give insights about which decision should be regarded when trying to optimize a specific process. The numbers in the figure represent the number of works that address the particular process or decision. The sum of publications comprising individual decisions is greater than 21 because a process can consist of multiple decisions.

It is important to note that a decision-maker would typically consider multiple processes. By connecting processes to underlying decisions, a better understanding of how structurally similar decisions can help to improve different processes is facilitated. This can be seen by looking at which decisions are connected to different processes. It can be seen that route planning should consider the decision of what system to maintain at which time and that it can be represented as a scheduling and routing decision. On the other hand, the scheduling and routing decision cannot only be found there but also within production and mission planning processes. The analysis facilitates PDM by revealing relations between different processes that are not trivially evident. For example, ideas and advances in mission planning research could be generalized and adapted to production

Table 4. Relation matrix of processes and decisions.

	s	t	a	sr	au	l	se
pr	.22	*.67*	.22	*.67*	*.67*	.00	.00
rp	**.75**	**.75**	.00	**.75**	.25	*.50*	.00
sp	.00	**1.00**	.00	.00	.00	**1.00**	.00
mm	.00	.00	**1.00**	.00	*.33*	.00	.00
mp	**1.00**	**1.00**	.00	**1.00**	.00	.00	.00
wm	.00	.00	.00	.00	.00	.00	**1.00**

Legend: pr = production; rp = route planning; sp = spare parts procurement; mm = maintenance management; mp = mission planning; wm = warranty management; s = system; t = time; a = action; sr = scheduling and routing; au = automatic control; l = logistics; se = service

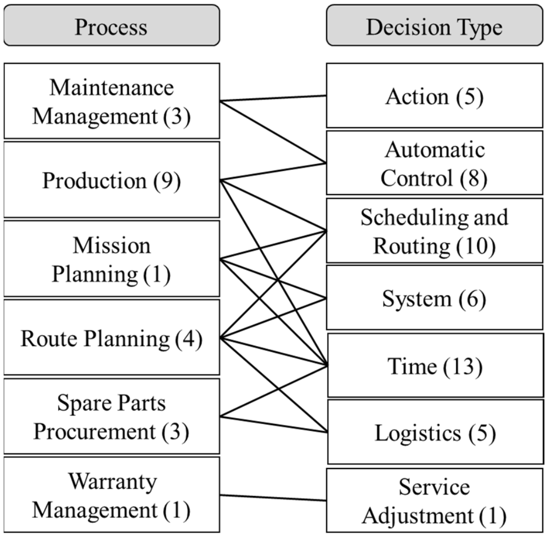

Figure 4. Relations between processes and decisions.

research as one underlying decision is alike.

Now that it is known which decisions might be regarded for which business process optimization, we can also analyze which decisions are often regarded in conjunction with others. For that, a co-occurrence matrix was developed following a similar principle as the first matrix. The calculation of a co-occurrence factor was calculated by Eq. (2).

$$\frac{\#(P(d_i) \cap P(d_j))}{\#P(d_i)} \quad \forall i,j \in [1,\ldots,7] \tag{2}$$

Here the cardinality of the intersection of publications that address two decisions d_i and d_j is divided by the number of publications that contain d_i. The factor is calculated for each combination of two decisions (and their reciprocals). The final co-occurrence matrix can be seen in Table 5. The co-occurrence ratios are highlighted analog to Table 4. Again, median and strong relations are plotted (Figure 5). Arrows are used to depict whether a decision strongly depends on another, e.g., if a maintenance action is considered, time and automatic control should also be considered. Bi-directional arrows indicate a bi-lateral dependence, e.g., if a system decision is made, a time decision should also be made and vice versa.

Table 5. Co-occurrence matrix of decisions.

	s	t	a	sr	au	l	se
s	-	**1.00**	.17	**.83**	.17	*.33*	.00
t	*.46*	-	.13	*.44*	.17	*.38*	.00
a	.20	*.40*	-	.07	.18	.00	.00
sr	*.50*	**.70**	.10	-	.20	.15	.00
au	.13	*.38*	.25	*.38*	-	.00	.00
l	*.40*	**1.00**	.00	*.40*	.00	-	.00
se	.00	.00	.00	.00	.00	.00	-

Legend: s = system; t = time; a = action; sr = scheduling and routing; au = automatic control; l = logistics; se = service

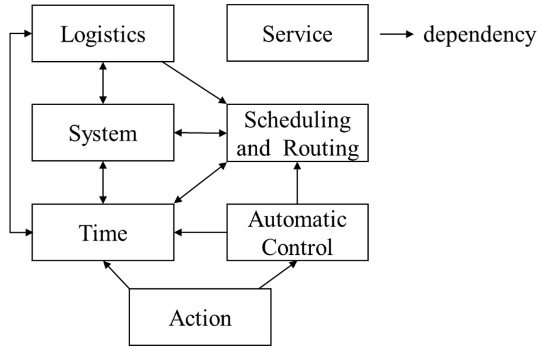

Figure 5. Co-occurene of decisions.

Figure 5 also shows a chronological and operational order between different decisions. It can be seen that logistics decisions, like the appropriate supply of spare parts (cf. Wang et al., 2015), heavily rely on the decision of what system to maintain at what time. Logistics decisions are often made jointly with scheduling and routing decisions that determine the point at which logistics requirements must be fulfilled, e.g., between production jobs (cf. Bougacha et al., 2018). Only after a schedule or route has been determined an automatic control action can be made to adjust a system during operation, e.g., actuating healthy systems (cf. Skima et al., 2019). While most publications focused on one or a few decisions, all should be acknowledged for post-prognostics.

4. CHALLENGES AND BENEFITS OF POST-PROGNOSTICS DECISION-MAKING

Decision-making based on prognostics results must be able to cope with a combination of challenges that do not occur in 'traditional' maintenance. When these challenges are addressed, however, they can leverage the benefits of prognostics.

Real-time nature of CBM. In the best case, condition data is collected in short intervals. On the one hand, this causes data volume challenges; on the other, an increased velocity must be handled. This is critical, as optimization algorithms can have a high computational complexity for larger problems (Herr et al., 2014), and new condition data might invalidate prior results. Especially for automatic control decisions, that are made in real-time, computationally efficient PDM algorithms must be found. Some successful publications were identified that capitalize on the real-time nature of prognostics. For instance, Skima et al. used incoming condition data to automatically control a pneumatic conveyor and maximize its useful life (2019).

Uncertainty. Uncertainty is a major risk in PDM, and its management an integral part of PHM (Niknam et al., 2015). As the future is unknown, uncertainty plays a significant role when forecasting the RUL (Sankararaman, 2015). In section 2.2, different solutions for managing uncertainty were presented. Uncertainties can have different causes, such as model uncertainty, training bias, or future usage uncertainty (Sun et al., 2012). At least the latter can be reduced, as fault growth is dependent on the future usage of the system (Bole et al., 2015), which is the outcome of PDM (e.g., a job schedule). If possible, this outcome should be returned to the prognostics algorithm in a feedback loop (Bougacha et al., 2018).

Closed-loop PDM. In theory, this feedback loop is challenging to employ, because knowledge about future usage is worthless when it is not known how much wear is exerted by it. The majority of works employed no feedback loop at all and only few presumed that job-specific degradation is known in advance (cf. section 2.2). Moreover, none of the works employed more complex prognostics methods such as neural networks or support vector machines that are proven to be very useful PHM tools (Lei et al., 2018). Due to their 'black-box' nature and weak 'explanation ability' (Kotsiantis, 2007), a feedback loop might be even harder to implement.

Generalizability. As mentioned earlier, some processes comprise inherently similar decision problems. For instance, the assignment of jobs to machines, maintainers to repair tasks or aircraft to sorties are alike. Nevertheless, research is often addressing specific problems and instantiations in isolation. Many scientific ideas and findings might be generalizable and transferable to other domains.

5. CONCLUSION AND RESEARCH AGENDA

In the conducted literature review, current applications of PDM have been examined, and a generic PDM process was synthesized. A final PDM framework that synthesizes the findings of the review can be seen in Figure 6. Through an in-depth analysis, processes that can be optimized through PDM were identified. It could be seen that the RUL as a result of prognostics comes in various forms that represent its inherent uncertainty. This uncertainty needs to be adequately addressed within the decision-making phase of PDM, along with different objectives that can consider costs, availability, OEE, and logistics. The typification of decisions revealed that seven distinct decisions exist and that the same decisions are used in different types of processes. Through analyzing relations and co-occurrences of processes and decisions, the modeling of PDM problems is facilitated by disclosing which decisions are predominantly used for which business processes. All in all, the real-time nature, potential to reduce uncertainty in a closed-loop, and its potential to be used in multiple domains are challenges that, when addressed, make PDM a great tool to reduce

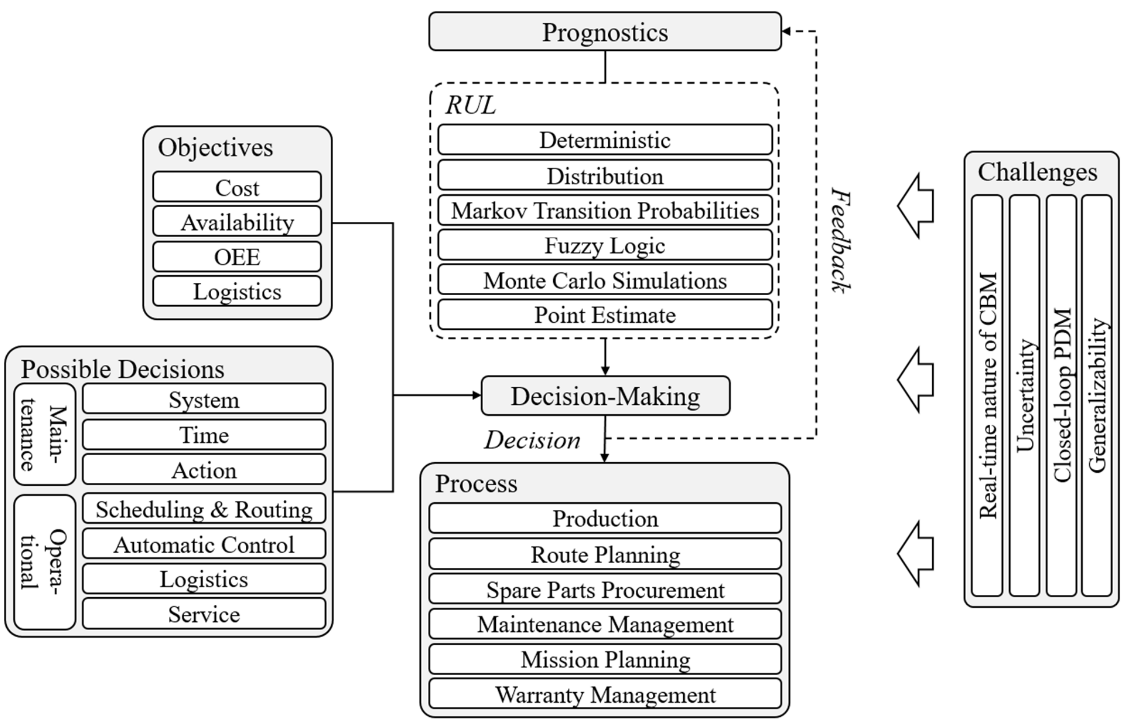

Figure 6. A Framework for Post-Prognostics Decision-Making

costs and improve performance.

Conclusively it is to note that this review is representative and by no means exhaustive. Especially the keywords "prognostic* based", "post prognostic*", and "prognostic* informed" restrict the reviewed works. Consequently, there might be, e.g., RUL representations that can be found in prognostics research that were not used in the reviewed works on PDM. Additionally, there might be connections between processes and decisions that were not revealed in the review because there was no literature on the subject or because existing publications were not included. It is therefore desirable to extend the scope of the review and test the framework further by applying it within a case study. Still, the review revealed significant findings, and almost every second queried paper was deemed relevant. The majority exploited prognostics information in a new and innovative way, which includes methods that are not only used to optimize the decision of what, when, and how to maintain, but also optimize related processes, such as production or spare parts procurement.

At last, the review also revealed research gaps that should be addressed in future research.

- The review focuses on currently applied process optimization. Further processes that can benefit from PDM must be identified, e.g., by looking at processes that make use of the identified characteristics (decisions, objectives).
- The review must be extended through more explorative research (e.g., expert interviews), and the findings be tested by applying the framework in case study research.
- Future research in PDM needs to address its real-time nature, uncertainty, establish closed-loop feedback between decision-making and prognostics, and should be generalizable.
- Job-specific degradation is often not known in advance, but the knowledge might be inherent in the prognostics algorithm. Together with the future usage plan returned by PDM, it must facilitate improved predictions through closed-loop feedback.
- There is a distinctive potential for generalization of scheduling and routing decisions. A general abstraction of the decision-problems to a scheduling problem (according to Conway, 1967) might facilitate future research that is valuable to multiple processes and domains.

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APPENDIX

Table 6. Publication-Concept Matrix

	Process						RUL						Objective				Decision						
Reference	pr	rp	sp	mm	mp	wm	dt	d	tr	f	mc	pt	c	av	oe	l	s	t	a	sr	au	l	se
Skima et al., 2019		x						x						x	x						x		
Bougacha et al., 2018	x							x					x					x		x			
Meraghni et al., 2018		x										x				x	x	x		x		x	
Thyagarajan & Gollnick, 2018				x					x				x						x				
Ladj, Tayeb et al., 2017	x									x					x		x	x	x	x			
Ladj, Varnier et al., 2017	x						x						x					x		x			
Thyagarajan & Gollnick, 2017				x					x				x						x				
Chrétien et al., 2016	x						x							x						x	x		
Li et al., 2016					x			x					x				x	x		x			
Meraghni et al., 2016		x										x				x	x	x		x		x	
Terrissa et al., 2016		x										x	x				x	x		x			
Bole et al., 2015				x					x				x						x		x		
Chrétien et al., 2015	x						x							x						x	x		
Niknam et al., 2015	x											x	x	x				x	x		x		
Wang et al., 2015			x					x					x					x				x	
Aghdam & Liao, 2014			x									x	x					x				x	
Herr et al., 2014	x						x						x	x						x	x		
Ning et al., 2013						x		x					x										x
Aghdam & Liao, 2012			x									x	x					x				x	
Haddad et al., 2011a	x								x				x				x	x			x		
Haddad et al., 2011b	x										x		x					x			x		

Legend: Process - pr = production; rp = route planning; sp = spare parts procurement; mm = maintenance management; mp = mission planning; wm = warranty management
RUL – dt = deterministic; d = distribution; tr = (Markov) transition probability; f = fuzzy number; mc = Monte Carlo simulation; pt = point estimate (no uncertainty)
Objective – c = costs; av = availability; oe = overall equipment effectiveness; l = logistics
Decision - s = system; t = time; a = action; sr = scheduling and routing; au = automatic control; l = logistics; se = service