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Developing prescriptive maintenance strategies in the aviation industry based on a discrete-event simulation framework for post-prognostics decision making

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ABSTRACT

The aviation industry is facing an ever-increasing competition to lower its operating cost. Simultaneously, new factors, such as sustainability and customer experience, become more important to differentiate from competitors. As aircraft maintenance contributes about 20% to the overall cost of airline operations and can significantly influence other objectives of an airline as well, maintenance providers are required to constantly lower their cost share and contribute to a more reliable and sustainable aircraft operation. Subsequently, new condition-monitoring technologies have emerged that are expected to improve maintenance operations by reducing cost and increasing the aircraft's availability. As many of these technologies are still in their technological infancy, it is necessary to determine the expected benefit for the airline operations with the given technological maturity and to develop suitable maintenance strategies that incorporate the newly gained insights. With this paper, a discrete-event simulation framework is developed that uses established parameters to describe a condition-monitoring technology's performance and subsequently develops a suitable prescriptive maintenance strategy. Therefore, it enables the adjustment of the optimization goal for the developed strategy to incorporate performance features beyond the frequently used financial indicators. The developed capabilities will be demonstrated for the tire pressure measurement task of an Airbus A320.

1. Introduction

The aviation industry is facing an ever-increasing competition for lower operating costs in order to gain competitive advantages and, subsequently, market shares [1]. With the liberalization of the aviation market and the emergence of low cost carriers, traditional airlines faced the challenge to lower their operating costs in order to remain competitive [2,3]. Additionally, factors influencing the passenger experience, such as flight delays and cancellations, have become an increasingly critical indicator of the carrier's quality as passengers expect an affordable service that operates reliably on time [4]. As a result, air transport operators seek to minimize their cost while achieving high standards of safety and service, i.e. improving their operability [5]. As aircraft maintenance contributes between 7% and 17% to an airline's Direct Operating Cost (DOC) [6–8] and can additionally cause significant operational irregularities [9,10], Maintenance, Repair, and Overhaul (MRO) providers are increasingly required to reduce their respective DOC share.

Additionally, the ecological impact of aviation is continuously gaining in importance due to the increasing environmental awareness of customers, society, and politics [11]. In 2016, the aviation sector was accountable for about 3.6% of the total anthropogenic Greenhouse Gas (GHG) emissions. This share, however, is expected to increase due to the projected steady growth of air traffic [12]. Consequently, higher sustainability requirements for all involved aviation stakeholders, including MRO providers, can be expected. Although the true environmental impact of maintenance has not been exhaustively examined in previous studies yet, Airbus, in conjunction with the European Commission, indicates its contribution's significance [13].

Subsequently, aircraft operators and MRO providers have started to employ new, emerging digital technologies to detect faults at an early stage and project upcoming failures before they occur. Thus, these approaches are expected to have a significant positive impact on the overall maintenance operations and sustainability. Groenenboom [14] estimates the worldwide savings potential by employing digitalization technologies to improve maintenance operations and adjacent logistics processes to be about \$3 bn. per year. Driven by this potential, multiple efforts in research and industry have been undertaken to develop a

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Acronyms

CBM	Condition Based Maintenance
CND	Cannot Duplicate
DES	Discrete-Event Simulation
DMC	Direct Maintenance Cost
DOC	Direct Operating Cost
EOL	End of Life
GHG	Greenhouse Gas
LCBA	Lifecycle Cost-Benefit Analysis
LRU	Line Replaceable Unit
MLG	Main Landing Gear
MPD	Maintenance Planning Document
MRO	Maintenance, Repair, and Overhaul
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
NFF	No Failure Found
NLG	Nose Landing Gear
PAX	Passenger
PH	Prognostic Horizon
PHM	Prognostics and Health Management
RCM	Reliability Centered Maintenance
ROI	Return on Investment
RUL	Remaining Useful Lifetime
TAT	Turnaround Time
TPIS	Tire Pressure Indication System
UTC	Universal Time Coordinated

variety of PHM technologies for the early fault detection and the projection of the fault progression.

Feldman et al. [15] proposed a maintenance decision making approach in order to determine the expected Return on Investment (ROI) for different maturity levels of PHM technologies on the example of a multi-functional display for Boeing's 737. A similar approach was chosen by Hölzel et al. [16]. They considered different PHM maturity levels for their discrete-event Lifecycle Cost-Benefit Analysis (LCBA) in order to calculate the expected financial implications with the introduction of such technologies. Kählert et al. [7] also used a discrete-event logic to calculate the avoidable cost resulting from unscheduled maintenance events on a single component level for different levels of PHM technological maturity. Leao et al. [17] presented in their work a theoretical concept to conduct a cost–benefit analysis for the implementation of PHM technologies on legacy aircraft analytically through a set of maintenance related cost equations. Thus, they can attribute the implications to a limited number of involved stakeholder.

The analysis of different maintenance strategies towards their expected implications for multiple stakeholders has been sparse in research. One of the few exemptions is the work by Godoy et al. [18] who developed an optimized preventive maintenance strategy under consideration of an in-house or subcontracted spare parts management. Their aim was to optimize the business performance along the supply chain, i.e. by maximizing the asset availability or minimizing the necessary spare part stock level.

All previously mentioned efforts provide valuable insights into the evaluation of cost or benefits for the application of PHM technologies. However, the majority of these PHM systems are still at lower levels of their technological maturity, as they mainly have been demonstrated under laboratory conditions. Therefore, it is necessary to incorporate different maturity parameters to reflect on differences in diagnostics and prognostics performance. The conducted literature research showed that there is hardly any work existing specifically examining the effects of different technological maturity levels of PHM systems. One of the existing works stems from Lee and Mitici [19], who developed an agent-based model that incorporates factors of aircraft operations and maintenance scheduling. They compared various maintenance strategies, i.e. Condition Based Maintenance (CBM), time-based maintenance and predictive maintenance, to evaluate their individual effects towards factors such as safety and maintenance efficiency. They also considered different technological maturities in terms of artificially added measurement errors. In a previous study [20], we also examined the effects of different technological maturity levels for an aircraft tire maintenance task. In particular, we examined occurring changes of the cost savings potential over the conventional maintenance approach through a variation of the underlying Prognostic Horizon (PH). However, both of these studies neglected the consideration of varying fleet utilization degrees of PHM systems.

In addition to the limited consideration of different technological maturity levels, existing studies almost exclusively focus solely on cost aspects and neglect other relevant objectives that can be affected. Particularly, adversarial environmental effects of specific maintenance decisions are usually neglected or estimated in an over-simplified approach as economic input–output analysis (ref. Chester and Horvath [21],Sohret et al. [22],Dallara et al. [23]). Albeit not being within the research area of aviation maintenance, Nakousi et al. [24] presented a maintenance scheduling approach that allows the simultaneous optimization of maintenance costs and GHG emissions for a mining truck fleet. They also considered aspects of the imperfectness of restorative maintenance actions in order to derive an optimized maintenance plan that minimizes the maintenance costs while maintaining or even increasing the individual truck's production rate. However, their paper also lacks the consideration of different stakeholders and varying PHM maturity levels.

Finally, the vast majority of existing methods possess an asset-centric view, i.e. they focus in their evaluation analyses on the asset, e.g. the aircraft, itself rather than incorporating adjacent processes within the involved stakeholders. Examples for this asset-centricity are from Aizpurua et al. [25] and Shi et al. [26], respectively. Aizpurua et al. [25] developed a dynamic maintenance scheduler that incorporates prognostics information for critical items and subsequently derives restorative actions. Shi et al. [26] described a similar framework that allows the grouping of preventive maintenance tasks for various systems based on their projected reliability and a given minimum reliability threshold. Both of them focused in their respective publications on the minimization of maintenance cost.

In summary, the following limitations exist in research that need to be addressed:

- Maintenance decision optimization is often done for either preventive maintenance or PHM technologies without consideration of varying technological maturity levels and fleet utilization degrees.
- Most existing work solely focuses on the asset itself and, therefore, allows only a limited consideration of multi-stakeholder scenarios and of the asset's behavior in its ecosystem.
- Studies strongly utilize monetary factors to measure their framework's performance with little to no consideration of non-monetary aspects, e.g. adversarial environmental impact.

Thus, the aim of this paper is to develop a prescriptive maintenance decision making algorithm that enables users to assess the economic and ecologic impacts for the key stakeholders *aircraft operator* and *line maintenance provider*. This decision making algorithm will be applied for different technological maturity levels of the underlying PHM technology and for varying utilization degrees within a given fleet. Subsequently, we want to allocate the expected impact to the respective stakeholder to identify potential improvements or drawbacks for their individual objectives. Based on our previous work [20], we will utilize the developed discrete-event simulation environment PreMaDe (Prescriptive Maintenance Developer) and extend its functionalities to allow the evaluation of the above mentioned scope. Within this paper, these effects shall be demonstrated with the help of a Tire Pressure Indication System (TPIS) for an Airbus A320. The corresponding pressure maintenance task suits the intended analysis since – for the conventional maintenance approach – it occurs frequently, due to its short time intervals, and possesses a comparably limited technological complexity to simulate degradation [20].

Summarizing, with the here presented work, we will extend the existing knowledge in the area of maintenance decision making in the aviation industry by:

- deriving and quantifying optimized maintenance decisions for different stakeholder perspectives with the introduction of PHM technologies.
- examining the effect of different technological maturity levels and utilization degrees within a fleet to derive minimum performance criteria for the developed condition monitoring technology.
- extending the scope of traditional maintenance decision making goals with their predominant orientation towards the maximization of monetary objectives by including non-monetary aspects, e.g. through the consideration of an adversarial environmental impact.

Having presented the scope of this paper, the remainder of this work is structured as follows: After a brief overview of the evolution of legacy aircraft maintenance strategies, we will discuss different proactive maintenance approaches, particularly prescriptive aircraft maintenance, with their individual key features and characteristics. Based on these insights, we will then present the concept and structure of the underlying decision making tool PreMaDe and, finally, estimate the expected implications of the developed prescriptive maintenance approach for the involved stakeholders.

2. Evolution of aircraft maintenance strategies

In order to identify the key features of new maintenance strategies resulting from a continuous condition monitoring, we need to examine the foundations of conventional aircraft maintenance and to define its main objectives and limitations. For the understanding of this section and the rest of this paper, it is necessary to define two fundamental distinctions of maintenance strategies that we use in the following sections. These are:

Corrective maintenance. This maintenance strategy includes all maintenance actions that are issued and completed **after** a failure occurrence, i.e. reacting on a system failure and rectifying it as a consequence of it.

Proactive maintenance. All forms of maintenance that include regular functionality checks to either identify upcoming faults or project failures **prior** to their occurrence are defined to be proactive.

2.1. Conventional aircraft maintenance

The basis for aircraft maintenance builds on the approach of Reliability Centered Maintenance (RCM), i.e. a generic decision process to identify preventive measures that are needed to manage and control failure modes which otherwise could result in functional failures [27]. The key assumption of the RCM approach is that the reliability of an item depends on its design and its condition at the time of manufacturing [5]. According to Nowlan and Heap [28], effective maintenance and inspection requirements can be derived for this approach based on the following procedure:

- Examination of key contributors leading to a functional failure,
- Consideration of the expected consequences from an occurring failure, and
- Determination of preventive measures and their consequences for safe and reliable operation.

These aspects will be thoroughly evaluated to determine a cost-effective preventive, i.e. scheduled, maintenance program that can ensure the operational safety [29]. However, it has to be noted that the main target of RCM is not to avoid failures per se, but to mitigate their consequences towards operational safety [30]. Hence, the RCM approach will concentrate on the preservation of a system's functionality rather than focusing on the correct mode of operation for all its hardware components [5].

Once the applicable maintenance tasks have been defined, the necessary intervals for task execution need to be determined. Historically, these intervals have been derived from statistics of past operations (e.g. through the Mean Time To Failure (MTTF)) or are based on engineering experience with comparable systems [31]. However, as Rausand [32] emphasizes, especially for new systems, there is often a lack of knowledge about the degradation behavior and failure mechanisms. Hence, in order to ensure a safe operation, applicable maintenance intervals will often be estimated conservatively, resulting in shorter maintenance intervals than actually necessary. Additionally, they will be closely monitored until sufficient information about the system degradation has been obtained, leading to an excess of (unnecessary) maintenance activities. [31,32]

Although the development of scheduled maintenance tasks has become increasingly sophisticated, a large portion of aircraft maintenance activities results from unscheduled maintenance. These are tasks that have not been accounted for in the regular planning procedure and are primarily issued due to detected system abnormalities. By definition, unscheduled maintenance is non-routine maintenance; thus, these terms are often used synonymously [33,34]. Although unscheduled maintenance is most often associated with a chosen corrective maintenance approach, there is also the possibility to have unscheduled maintenance as a consequence of previously conducted scheduled maintenance task, e.g. removing a failed component that has been identified through routine testing [27,34,35].

As Ackert [36] points out, the amount of non-routine maintenance tasks regularly exceeds the number of routine maintenance tasks for matured system conditions after the first heavy base maintenance event. Similar results have been stated by Kählert [8] and Heisey [33] in their work. While Kählert [8] determines that unscheduled maintenance accounts for 88% of an airline's Direct Maintenance Cost (DMC), Heisey [33] emphasizes that non-routine labor and material cost are the primary causes of increasing maintenance cost. Subsequently, operators and manufacturers strive to reduce non-routine maintenance because of its effect on schedule reliability and airplane downtime [33].

2.2. Condition-based aircraft maintenance

To overcome the limitations of the current scheduled maintenance approach, aircraft maintenance providers are shifting their focus from a time-based maintenance schedule towards a condition-based maintenance logic. As stated before, the main goal for RCM is to assure a system's functionality and not necessarily to provide a continuous insight into the system's state of degradation. This approach leads to unnecessary maintenance tasks and its elimination offers a significant savings potential for the maintenance task execution itself as well as for surrounding processes [17]. Subsequently, many condition-monitoring technologies have been developed over the course of the years, e.g. for hydraulic systems [37,38], aircraft engines [39–41], and airframe structures [42,43]. All these developed methods' key objective is to enable a constant insight into a system's state of degradation and, ultimately, project failure events before their occurrence. [44,45]

In addition to this, multiple strategies have been derived to allow an exploitation of the generated insights (ref. Fig. 1) [46]. In general, two main groups of proactive maintenance measures can be distinguished: *diagnostic* and *prognostic* maintenance. Diagnostic maintenance is characterized by its capability to detect and isolate upcoming faults

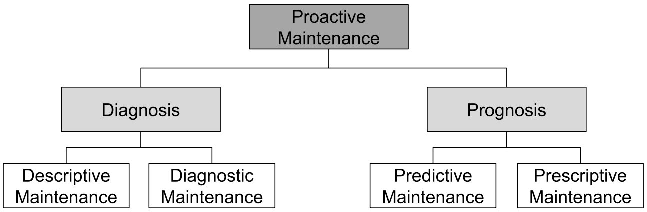


Fig. 1. Classification of proactive maintenance strategies (based on [44,48,51]).

within a system or component at an early stage due to abnormal sensor readings or system behavior [47]. Extending this insight into the current state of degradation by future utilization and projecting the degradation propagation until the point of failure will subsequently enable prognostic maintenance [47]. As of this paper, we will not discuss all different proactive maintenance strategies in detail, but briefly describe them and primarily focus on the most recent development of prescriptive maintenance strategies. For additional information, interested readers are kindly referred to Ansari et al. [48], Nemeth et al. [49], and Soltanpoor and Sellis [50].

The evolution of the individual strategies with their respective major objectives can be seen in Fig. 2. As the figure illustrates, the generated benefit has increased and is still expected to increase continuously with every extension of the maintenance strategy's scope. However, that benefit comes at the cost of a steadily increased level of complexity. In general, four major development steps can be identified (although some papers may argue that there are additional development steps, e.g. in [54]). These are:

- **Descriptive Maintenance**: The most fundamental form of proactive maintenance that is based on records of historical maintenance data and observed failure events to identify what observed equipment failure has resulted in which specific maintenance measure. [48,55]
- **Diagnostic Maintenance**: This approach additionally considers information about operating and system conditions to develop cause–effect-relationships and to allow the clear identification of root causes leading to the ultimate system failure. [48,49]
- **Predictive Maintenance**: As arguably the most discussed maintenance strategy in recent years, the focus here is on extending the knowledge about degradation mechanisms and extending the degradation propagation into the future to project system failures. Subsequently, this approach utilizes the knowledge discovery process and combines insights into the experienced degradation in the past with anticipated operating loads in the future in order to support a maintenance decision making process. [49,50,55]
- **Prescriptive Maintenance**: This approach will utilize the information about degradation projections and extend the scope of the maintenance decision making process beyond the asset itself, e.g. the aircraft. Thus, by consideration of the surrounding ecosystem, a prescriptive maintenance strategy will allow a holistic analysis and optimization of maintenance measures. [48]

Conventional – and even established proactive maintenance approaches – possess a strong asset-centricity, i.e. the knowledge about a system's Remaining Useful Lifetime (RUL) provides only an indication about their respective condition and does not consider any limitations in adjacent processes [56]. Thus, information about the system's degradation status does not necessarily guarantee the generation of any benefit for the involved stakeholders. Prescriptive maintenance strategies will, therefore, extend the scope of the maintenance decision making process to proactively schedule necessary maintenance related downtimes in order to avoid system failures while minimizing any adversarial effects on the involved stakeholders. Ultimately, this approach will utilize the knowledge about the projected equipment failure together with information such as

- necessary ground resources and their availability,
- needed spare parts and their required logistic lead times, and
- the minimum downtime for the maintenance task completion

to evaluate possible maintenance opportunities towards their expected implication on the involved stakeholder's objectives. Subsequently, this approach will select the maintenance opportunity for task execution that allows the optimization of the chosen target function, e.g. the minimization of the total maintenance related cost. [48,50,55,57]

3. Proactive maintenance approaches

A key aspect in the development of proactive maintenance approaches is the generation of a continuous insight into an asset's state of degradation through PHM technologies. As Vachtsevanos and Goebel [58] and Saxena et al. [59] recommend the definition of minimum performance criteria for the efficient development of PHM technologies, we will need to identify relevant indicators to describe these technological capabilities. These will serve as input factors for our simulation to parametrically describe the maturity level of the underlying condition-monitoring technology. Additionally, in order to enable a complete evaluation of the expected impact of such a technology for the involved stakeholders, we need to consider their respective objectives. The corresponding evaluation metrics will be addressed by the results of our simulation environment.

3.1. Evaluating the technological maturity of PHM systems

The definition of suitable performance measurement metrics for PHM systems has been the focal point for multiple work, e.g. in Leao et al. [17],Mikat [60],Saxena et al. [61], and Wheeler et al. [62]. Based on these approaches, we will introduce typical evaluation metrics and briefly describe their respective scope. In general, we need to distinguish between metrics for diagnostics and prognostics systems, respectively. On one side, diagnosis metrics focus solely on the monitoring system's capability to reliably detect upcoming faults in an early stage of their development. On the other side, prognosis metrics aim towards the evaluation of the timeliness and precision of the resulting failure projection.

For the field of *diagnostics performance* evaluation, one of the most comprehensive works is from Kurtoglu et al. [63]. They introduce the following distinction for the individual performance measurements:

- Detection metrics measure the monitoring system's ability to correctly indicate a malfunction, e.g. in terms of the fault detection rate or the false positive rate for detection.
- Isolation metrics focus on the correct determination of the fault mode and fault location, e.g. time to isolate or the isolation misclassification rate.
- Temporal metrics allow an indication of the timeliness of a diagnostics system to respond to an existing malfunction.
- Static metrics evaluate the overall correctness of the fault detection and isolation.

As these performance measurements are expressed in terms of probabilities, the corresponding diagnostics system will need to be subject to an extensive testing routine prior to its utilization. [63]

For the category of *prognostics metrics*, Saxena et al. [61] and Saxena and Roemer [64] provide a good overview of different existing approaches. They emphasize the distinction between *online* (also referred to as in-situ) and *offline* performance metrics. Offline performance metrics will compare the characteristics of the failure prediction with the system's true End of Life (EOL). Thus, these metrics require knowledge about the system's historical failure data and, therefore, only allow a retrospective analysis. These metrics will subsequently allow an evaluation of the prognostic quality, e.g. in terms of the timeliness of the projection or the false alarm rate of the forecast. In order to

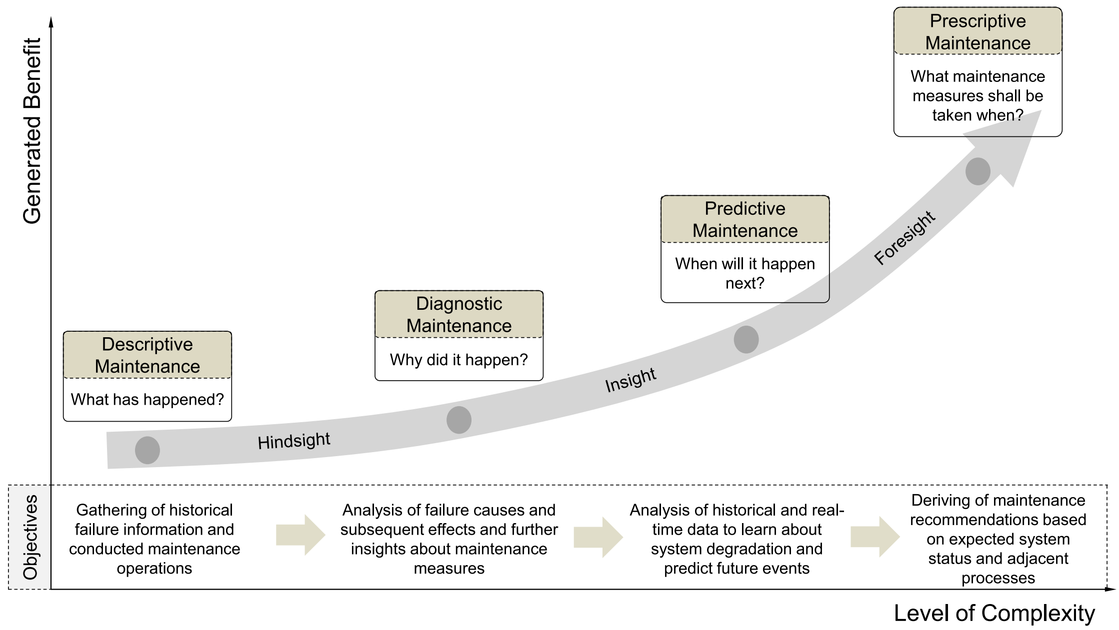


Fig. 2. Development of proactive maintenance strategies (based on [48,52,53]).

enable such an analysis and evaluation of the equipment's degradation projection throughout its whole lifetime, the underlying systems must have been subject to run-to-failure conditions. Although this category of metrics has been more thoroughly investigated, for many real-world applications this failure data does not exist due to practicality issues or safety concerns. As a result, online performance metrics have been developed. These measurements have the objective to evaluate the observed, true degradation with respect to the projected deterioration for each individual time instance. As a consequence, these metrics do not require any prior knowledge about the true EOL and can be applied throughout the whole process of degradation even before the occurrence of a failure. [64–67]

At this point we will not further discuss each existing metric, but focus on a few general observations with regard to the evaluation of a PHM system's technological maturity:

- For the support of the maintenance decision making process during live aircraft operation, online performance evaluation metrics for the current system status are predominantly important.
- In order to provide a comprehensive picture of such a technology's capability, it is not sufficient to focus on individual parameters for the description of the respective technology's performance. Thus, a thorough evaluation will require the provision of – at least a selection of – the above mentioned performance parameters.
- The economical and ecological evaluation, however, mainly relies on offline evaluation metrics, representing statistical averages for this type of diagnostics and prognostics technology.

3.2. Benefits of proactive maintenance approaches

The determination of possible improvements with the introduction of PHM technologies for various aspects of an airline's ecosystem has been subject of multiple research work already, e.g. in Kählert [8],Hölzel [9],Leao et al. [17],Lee and Mitici [19],Aizpurua et al. [25],Hess et al. [51],Ashby and Byer [68],Hess et al. [69],Rodrigues et al. [70],Sandborn and Wilkinson [71],Sprong et al. [72],Starr [73], and Wheeler et al. [62]. As a general observation, the identified improvements can be clustered into three different groups: *operator-related*, *MRO-related*, and *logistics-related* [62]. Although these clusters allow the general attribution of expected implications to an individual stakeholder, this association may not be exclusive, i.e. the expected benefit may be attributable to multiple involved stakeholders. For example, the reduction of technically-induced flight delays is primarily beneficial for the operator, but can also be an expression of the increased effectiveness of maintenance measures by the MRO provider. The individual objectives and corresponding metrics can vary for each stakeholder (as shown in Table 1) and can effectively lead to different prescriptive maintenance strategies, depending on the goal of the generated maintenance schedule.

For the *operator*, the overall objective is the assurance of a reliable aircraft operation to achieve a high asset availability for revenue generation [17,51,68,74]. According to Wheeler et al. [62], this objective can be subdivided into the following targets: minimization of necessary Turnaround Times (TATs), minimization or complete avoidance of flight delays or cancellations, and optimal exploitation of the aircraft systems' MTTF. Besides that, the U.S. Department of Defense [44] emphasizes the capability to perform and complete an assigned mission as a critical factor for aircraft operations. Although this has been stated primarily from a military perspective, this parameter can be translated as the number of unplanned, technically-induced diversions for civilian operations.

The primary objective for an *MRO provider* is the reduction of maintenance cost. In order to achieve this objective, the following targets can be derived [17,68,69,74]:

- avoidance of No Failure Found (NFF) or Cannot Duplicate (CND) events, i.e. events where a reported in-flight failure cannot be repeated on the ground in order to allow an isolation of the failure,
- reduction of shop visit cost, e.g. through a reduction of material scrap, and
- efficient utilization of available maintenance resources, e.g. through a reliable forecast of maintenance needs and avoidance of unscheduled tasks.

The reduction or complete avoidance of NFF events will not only improve the maintenance process itself as it reduces the occupational time for the necessary ground resources, but will also have implications on the logistics system as it reduces the amount of necessary spare parts inventory. Additionally, MRO providers thrive to reduce the average maintenance downtime for the aircraft by reducing the time needed

Table 1
Possible evaluation metrics for exemplary objectives of the respective stakeholder.

Stakeholder	Objective	Metric
Operator	Reduce number of flight delays	No. of flight delays
	Reduce number of flight cancellations	No. of flight cancellations
	Increase availability	Aircraft utilization, Avg. turnaround time
	Increase reliability	No. of diversions, MTTF
MRO provider	Reduce maintenance events	No. of maintenance events
	Avoid component removals	No. of component replacements
	Reduce time for troubleshooting	Avg. maintenance downtime
	Maintenance cost reduction	Avg. maintenance cost per aircraft
	Improved sustainability	Avg. maintenance related emissions per aircraft

for fault identification and isolation as well as the subsequent Mean Time To Repair (MTTR) [17,62,68,72,73]. As stated before, a reduction in maintenance downtimes will automatically improve the aircraft's availability which is a key target for the operator. Besides these targets for the line maintenance, MRO providers also aim for a reduction of the necessary shop maintenance cost following a Line Replaceable Unit (LRU) removal by avoiding unnecessary replacements or costly third party repairs [68,72,73]. Finally, the introduction of diagnostic and prognostic capabilities to allow an early fault detection, for limiting the subsequent damage propagation, will enable MRO organizations to reduce hard-time scheduled functionality check tasks while also predict and schedule necessary restoration measures in advance [17,62,68].

4. Prescriptive maintenance simulation framework

After we have discussed the theoretical foundations of aircraft maintenance strategy development and presented possibilities to evaluate proactive maintenance approaches, we focus in this section on the presentation of the underlying simulation concept for post-prognostics decision making. The prescriptive maintenance development and simulation framework PreMaDe of DLR's Institute of Maintenance, Repair and Overhaul is programmed with the logic of a Discrete-Event Simulation (DES). By changing the simulations variables only at times when an event occurs and storing all occurred changes in an object-specific event calendar, a DES is suitable to detect, flexibly adapt to, and analyze different behaviors of the underlying system [75,76]. PreMaDe is programmed in Python to benefit from its open source character and avoid limitations of commercially available products.

4.1. Theoretical foundations of the simulation tool

PreMaDe is based on the idea of the functional relationship stakeholder model shown in Fig. 3. Since a key aspect for prescriptive maintenance is its holistic approach with the inclusion of all key participants in the decision making process, we have defined the following stakeholder as entities in our simulation routine (in accordance with Wheeler et al. [62]):

- the *operator*, who is responsible to conduct flights while checking for curfew restrictions,
- the *maintenance provider*, subdivided into the divisions of line- and shop maintenance, who is responsible to comply with regulatory requirements for a continuing airworthiness and the restoration of the aircraft's condition, and
- the *logistics provider*, who ensures the timely supply of repair material and manages the necessary inventory of spare parts.

In order to base the derived maintenance decisions on the prediction of individual component failures, it is necessary to additionally include information about (anticipated) system degradations. Although not a stakeholder entity per se, the corresponding *system degradation module* will subsequently allow the calculation of each incremental health deterioration for every individual flight segment with the assumed ambient conditions. All the shown stakeholders are represented through a designated object entity within the simulation environment. PreMaDe is further intended to be built in a modular way and combines all these individual object entities through defined input–/output-interfaces to allow a certain flexibility for future developments.

To limit the scope of this paper, we solely focus on the interaction between the operator and line maintenance to describe their functional dependencies and demonstrate these in our use case scenario. An exemplary extract for this interaction in the specific simulation routine can be seen in Fig. 4. In accordance with the object-orientation, all related entities obtain preprocessed inputs for a faster simulation time. Additionally, the parameters are saved as attributes at the time of the object's initialization. The program will execute the shown routine from left to right and top to bottom with the following essential steps.

4.1.1. User specifications read-in

The various allowable settings (as presented in Section 5.1) will be read in together with necessary database inputs, e.g. the airport database with all information about an airport's timezone and curfew restrictions. These information will be stored within a designated object and serve as central reference point for key settings throughout the whole subsequent simulation run. It has to be noted that the underlying flight routes, used for the subsequent simulation run, will only contain flight and turnaround times. Thus, the simulation routine will create the corresponding flight schedule by itself (ref. Section 4.1.3).

4.1.2. Aircraft fleet and systems initialization

Aircraft and their respective components are the essential object entities that are iterated among the involved stakeholders within the simulation loop and whose attributes are changed to reflect a continuous degradation and aging. They feature individual event calendars to document all flight operations and maintenance tasks that have been conducted with or on the respective aircraft. They further have their individual clock times to track their progression in the simulation run and to identify interactions with the other involved stakeholder, e.g. the time of the execution of maintenance slots. To incorporate different time zones and ensure the correct comparison, all clock times are converted into the Universal Time Coordinated (UTC) format. All aircraft and related systems are assumed to be new at the time of their initialization, i.e. they have not experienced any degradation and their maintenance intervals are set to start with the simulation starting date.

4.1.3. Operator module initialization

The operator is responsible to ensure the correct assignment of flights segments to the individual aircraft within the fleet. In order to avoid violations of curfew restrictions, the flight operator object will be supplied with necessary information about non-operating hours within the underlying flight network. At the time of the operator's initialization, all aircraft will be supplied with an ideal, theoretical flight schedule, according to the user specifications for the intended flight routes. This schedule represents the maximum number of feasible flights for the given flight rotation and applicable curfew restrictions, without any downtimes for maintenance or possible operational irregularities.

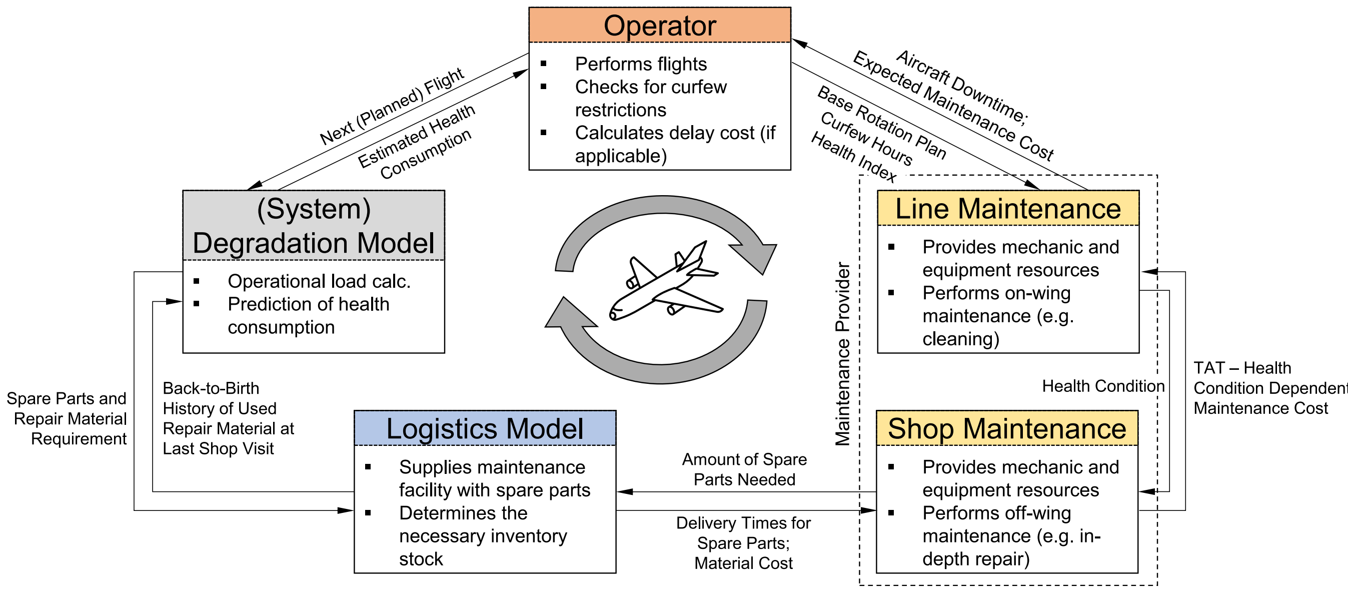


Fig. 3. Functional stakeholder model for aircraft maintenance.

4.1.4. Line maintenance provider initialization

An essential part of the line maintenance object is the creation of maintenance stations. These stations are equipped with a certain resource capacity for manual maintenance task execution that can be assigned to specific aircraft when available and needed. These stations also feature their individual event calendars and have their clock times. Additionally, the maintenance provider will ensure the continuing airworthiness for the fleet by monitoring the required functional check intervals, projecting restoration needs, and restoring system conditions.

4.1.5. Initialization of maintenance resources

For this study, we solely focus on necessary mechanics as the required maintenance resources and do not consider any additional ground support equipment. Although these maintenance resources are part of the line maintenance stations, they are created independently since they have individual characteristics (e.g. age, experience level, qualifications). These become particularly important when considering different kinds of maintenance tasks that require specific training or including aspects of imperfect maintenance. The created objects will possess a specific shift duration and are responsible for the execution of the maintenance task. Subsequently, they also feature individual event calendars to track their tasks.

4.1.6. Execution of simulation routine

After all entities have been initialized and necessary information has been assigned to the respective object, the simulation run will be started. The execution of the simulation routine features the following specific steps.

Selection of aircraft. With progression of the simulation, the individual timestamps of the involved object entities will advance differently depending on the duration of their previous event, e.g. a flight segment or a maintenance downtime. Thus, as a first step, the aircraft object with the least progression of its individual clock time will be selected for the next simulation iteration. If there are multiple aircraft with the same clock time they will be chosen according to their alphabetical order of their registration.

Execution of next flight segment. The selected aircraft will first perform the next flight according to its flight schedule. The respective flight segment with essential information such as the take-off, landing, and turnaround time will be stored as an event in the aircraft's event calendar. With the completion of the flight, the aircraft's degradation status will be adjusted according to the precalculated health consumption for this flight segment. Other essential aircraft parameters, such as its age, will be updated similarly. In case of an operational irregularity that has lead to the cancellation of the following flight segment, these attributes will not need to be updated. Thus, only the corresponding flight event will be marked as *cancellation* and stored in the event calendar for later analysis, e.g. the aircraft utilization. Finally, the individual clock time for the aircraft will be forwarded to the ending time of the respective flight event.

Checking for necessary maintenance and resource availability. After the aircraft's arrival and its experienced progression in system deterioration and age, it needs to be checked whether or not a maintenance task is due to be performed. A maintenance event can be issued by one or multiple of the following triggers:

- The time since the last completion of a scheduled functionality check exceeds the applicable time interval according to the aircraft's Maintenance Planning Document (MPD) (expressed in terms of flight cycles, flight hours, or calendar days).
- The degraded system condition after completion of the flight is outside of the acceptable limits defined by the manufacturer.
- Based on the predicted system condition and the expected implications on the involved stakeholders (ref. Section 4.2), the aircraft is scheduled to complete a restoration maintenance task.

In order to avoid the issuance of any of these triggers at an airport that is not part of the maintenance base network, all these criteria will also be projected to the next expected time of arrival at a designated line maintenance station. If any of these criteria apply, the respective maintenance provider entity will further check the availability of necessary mechanics. The earliest possible starting time for the maintenance task will be the aircraft's arrival time plus any applicable cool-down times for the respective system after landing. If an unoccupied resource is available, it will be assigned to execute the maintenance task on the aircraft. Otherwise, the aircraft object's timestamp will be forwarded until the necessary maintenance task can be completed. After completion of the task, the maintained system's condition will be restored to its equivalent new condition, neglecting any imperfectness of the maintenance. All the corresponding events, i.e. system cool-down time and maintenance task execution, will be stored in the event calendars of the aircraft and chosen mechanic, respectively. Additionally, any occurring waiting times for service will be stored in the aircraft's event calendar.

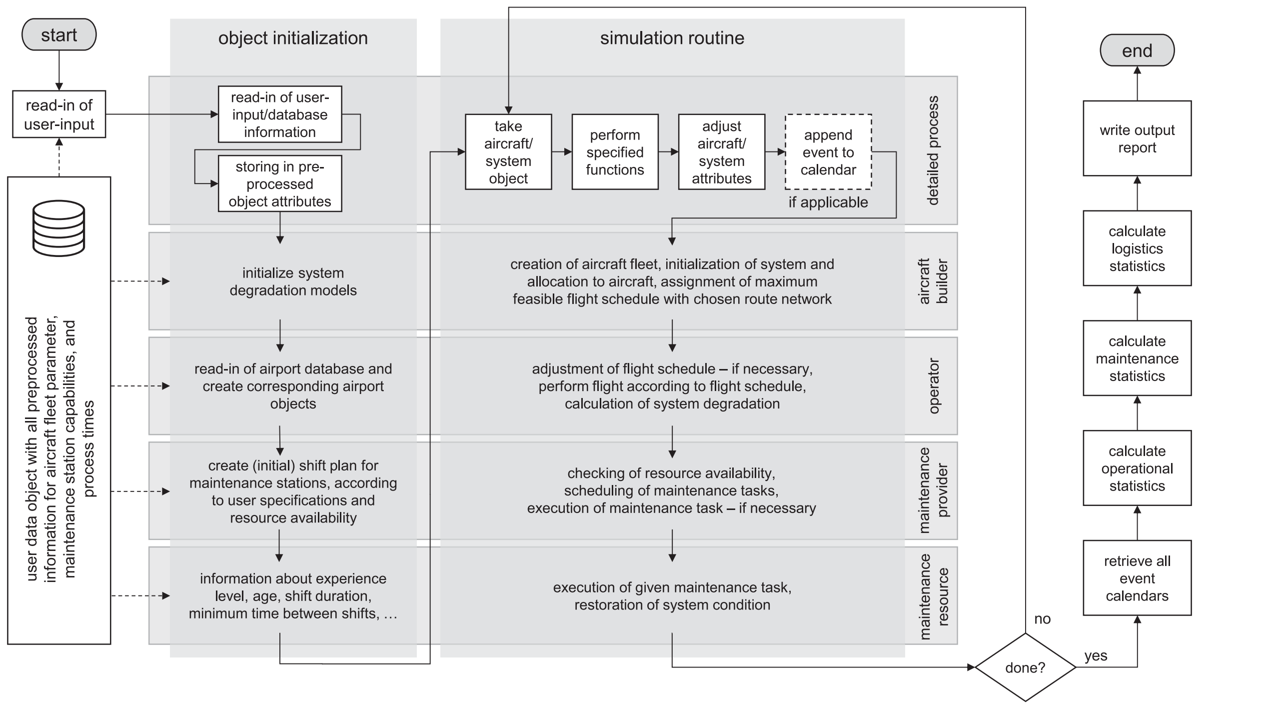


Fig. 4. Process simulation routine of the tool PreMaDe.

With the completion of the maintenance tasks, the initially created flight schedule will need to be adjusted accordingly. Thus, for all successive flight segments, the intended take-off and landing times will have to be adapted to incorporate the occurred maintenance downtime. As this downtime is required to retain the aircraft's airworthiness, these adjustments will not lead to any operational irregularity cost.

Scheduling of next maintenance downtime. This step only applies if the respective aircraft is capable to project upcoming failures and, therefore, allows the proactive scheduling of maintenance requirements. Given the individual system's prognostic horizon, it first needs to be checked whether or not any upcoming failures can already be reliably predicted. If so, the underlying prescriptive maintenance algorithm (ref. Section 4.2) will calculate the expected implications for the involved stakeholders. This calculation will be done for all successive maintenance opportunities until the time of failure in order to choose the maintenance base visit that optimizes the chosen objective, e.g. the minimization of the total cost or the maximization of the ground resource utilization.

Termination criterion for simulation. After completion of all necessary maintenance tasks and progression of the aircraft specific timestamp, the next aircraft will be selected and iterated accordingly. The simulation is completed once all aircraft timestamps have progressed by the required simulation time span.

4.1.7. Retrieval and analysis of event logs

After the simulation has been completed, the generated event calendars will be retrieved and analyzed. By varying the input parameter to reflect different maintenance approaches and various technological maturity levels, the expected benefits for the involved stakeholders can be calculated based on the entries in these event calendars.

4.2. Prescriptive maintenance planning

After the presentation of the theoretical design of the simulation framework, this section deals with the essential aspects of a prescriptive maintenance strategy.

The basic principle for the identification of maintenance downtimes that allow an optimization of the chosen objective function is depicted in Fig. 5. It consists of the analysis of individual maintenance opportunities, starting with the time of the earliest prediction until the ultimate system's failure occurrence. A maintenance opportunity is defined as an aircraft's layover at one of its designated maintenance bases. The execution of a maintenance task at one of these visits will lead to certain implications for every involved stakeholder, i.e. the operator, the line and shop maintenance provider, and the logistics supplier. Thus, for every opportunity, the implications for a chosen objective function will need to be calculated in order to subsequently select the layover that allows an optimization of this function.

Fig. 6 shows a comparison of different maintenance decision outcomes for various underlying strategies: corrective, diagnostic, predictive, and prescriptive maintenance (ref. Section 2). The corresponding time for maintenance task execution – as a result of each maintenance strategy – is indicated by a rectangle around the respective time instance t_x. It has to be noted that the underlying aircraft system, operational load, and subsequent degradation are assumed to be equal

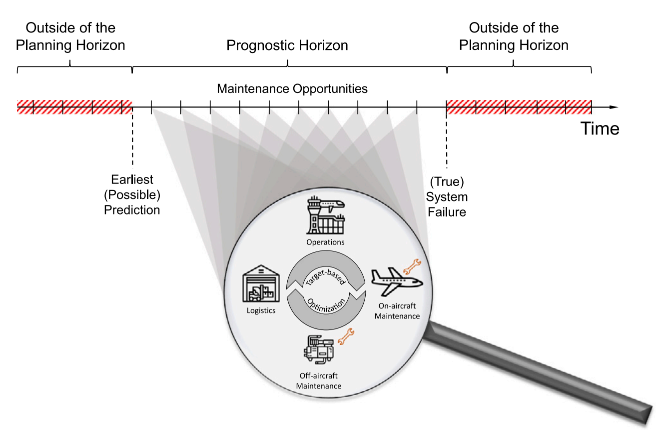
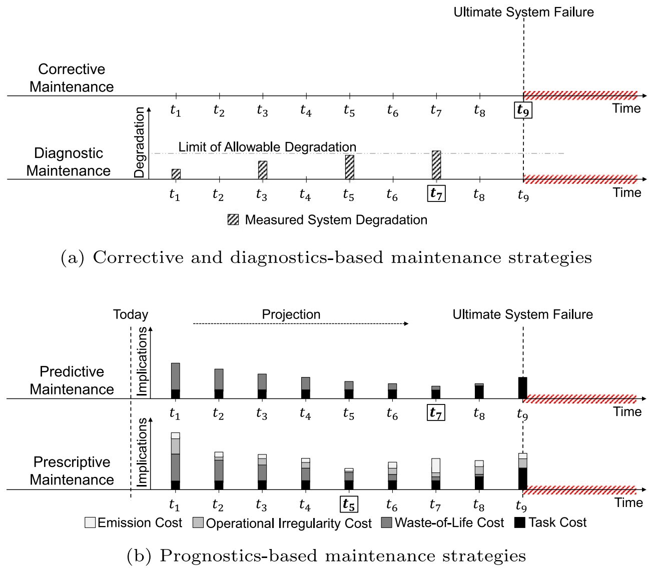


Fig. 5. Approach of deriving prescriptive maintenance decisions.



(a) Corrective and diagnostics-based maintenance strategies

(b) Prognostics-based maintenance strategies

Fig. 6. Comparison of maintenance decisions for different maintenance strategies.

for each of these depicted cases in Figs. 6(a) and 6(b). Each individual time step $t_1, \dots, t_9$ symbolizes a maintenance opportunity. We assume for the shown scenario that the system will ultimately fail and require a maintenance task at time instance t_9.

The first subplot (ref. Fig. 6(a)) shows the maintenance decision for a corrective and a diagnostic maintenance approach, respectively. Since a strictly corrective maintenance approach has no functionality checks prior to a failure occurrence, there is no information about any degradation progression available. Subsequently, the restorative maintenance task will be issued at time instance t_9 with the system's failure. In contrast, a diagnostic maintenance strategy will incorporate regular functionality checks – in this exemplary scenario at the time instances t_1, t_3, t_5, and t_7. Each measured condition will be either automatically or manually compared against a predefined degradation threshold, e.g. given by the manufacturer or regulatory authorities. In order to avoid system failures, this threshold is usually chosen more conservatively with some safety margin incorporated. Once the degradation has exceeded the allowable limit (ref. time instance t_7), a corresponding maintenance task will be issued.

By taking the capabilities of failure projections into account (as shown in Fig. 6(b)), we will not only be able to compare the current system degradation against a given threshold, but also forecast future degradation. This projection is indicated by the dashed line on the very left in Fig. 6(b); therefore, at the current time stamp, all maintenance opportunities are still in the future. Additionally, these prognostics-based maintenance approaches will extend the scope beyond the mere consideration of degradation progress by quantifying the expected (monetary) implications. As discussed in Section 2.2, predictive maintenance approaches are characterized by their asset-centricity; thus, the related cost elements can only include those that are directly linked to the system, i.e. task and waste-of-life cost. Subsequently, a predictive maintenance approach will try to balance the growing task costs due to an increased required work scope (close to a failure occurrence) with penalty cost for premature part replacements (which steadily decrease towards the system's failure). In the shown scenario, these cost aspects are minimal at time instance t_7. Ultimately, the prescriptive maintenance strategy will additionally consider aspects of adjacent processes and stakeholders, e.g. operational irregularity cost or penalty cost for any maintenance-related emission. In the shown scenario, this consideration leads to shift of the favorable maintenance downtime at time instance t_5. Albeit being more expensive from a mere asset-centric perspective, the superiority of other factors, e.g. the necessary resource availability or the compliance with higher environmental standards, will lead to a more holistic consideration in the maintenance decision making process.

In a previous study [20], we have developed a prescriptive maintenance strategy that focused exclusively on the reduction of waiting times for occupied ground resources. For this paper, we will extend this scope by including avoidable operational irregularity cost as well as adding adversarial environmental impacts into the decision making process. Thus, the overall objective for the developed prescriptive maintenance strategy is to minimize the total maintenance related cost. For a better understanding of its implementation, the underlying program routine for this paper is also presented in terms of a pseudocode example (ref. alg. 1). The corresponding function for each maintenance opportunity is defined as

$$\sum_{s \in S} c_s^{maint} + c_s^{waste} + c_k^{oi} \tag{1}$$

with maintenance tasks for all sub-systems s of the respective aircraft system S at aircraft k. According to Eq. (1), the expected total cost are composed of the following cost components:

Maintenance-related cost. This includes all costs that can directly be related to the execution of the respective maintenance tasks, e.g. cost for personnel, material cost, etc. Thus, they depend on the necessary work scope and can be calculated through the following equation:

$$c_s^{maint} = t_s^{dur} \cdot c_{labor} + c_s^{mat} + c_s^{emission} \cdot e_s^{task} \tag{2}$$

with t_s^{dur} as the duration for the task completion, c_{labor} as the labor cost for the involved mechanic, c_s^{mat} as the cost for the necessary repair material, e_s^{task} as the task-related environmental impact, and $c_s^{emission}$ as the corresponding penalty factor for emissions.

Cost of waste-of-life. These cost are the result of premature maintenance or replacement and the underutilization of the available system lifetime, as discussed by Hölzel [9] and Meissner et al. [20]. This underutilization factor is calculated as follows:

$$h_{remain} = \frac{(p_f^{proj} - p_{rest})}{(p_{new} - p_{rest})} \tag{3}$$

where p_f^{proj} represents the projected system condition after flight segment f, p_{rest} represents the restoration threshold for the simplest form of restorative maintenance, e.g. a tire pressure restoration, and p_{new} symbolizes the system's nominal new condition.

This underutilization factor will subsequently be used to calculate the waste-of-life cost.

$$c_s^{waste} = max\,(0,\, h_{remain} \cdot c_s^{maint}) \tag{4}$$

It has to be noted though that this value cannot be below zero.

Operational irregularity cost. These costs are the result of avoidable extended maintenance downtimes, e.g. through an insufficient availability of necessary mechanics. They strongly depend on the specific time of the day when the delay is occurring, the extent of the delay, and the subsequent flight schedule. In order to minimize their financial loss, airlines may decide to cancel flight segments completely, whenever the anticipated cost of an aircraft delay are higher than the cancellation of flight segments due to delay propagation effects, i.e. subsequent flight schedule changes due to inevitable curfew collisions. Thus, these operational irregularity cost are defined as

$$c_k^{oi} = \min\left(\sum_{f \in D} c_f^{delay}, \sum_{f \in C} c_f^{cancel}\right) \tag{5}$$

where c_f^{delay} represents the delay cost for an individual flight segment of all successive delayed flights D and c_f^{cancel} represents the alternative cancellation cost for the flight segment of all canceled flights C.

Algorithm 1 Algorithm to schedule prescriptive maintenance downtimes

```
Input: flightplan, PH_thr, stations_MRO, stations_operation
Output: scheduled maintenance event
procedure ScheduledMaintenanceEvent(flightplan)
    events ← list                                        ▷ Create empty list to append all maintenance opportunities
    for each flight ∈ flightplan do                      ▷ Iterate through all planned flights
        if RUL_flight ≤ PH_threshold then                ▷ Check if RUL after flight is within prognostic horizon
            if station_destination ∈ stations_MRO then   ▷ Check if flight destination is part of MRO network
                events.append(MaintenanceTask(t_land, station_destination))   ▷ Call external function (ref. alg. 2)
            end if
        end if
    end for each
    tmp_memory ← ∞                                       ▷ Create memory variable for minimization of maintenance cost
    for each opportunity ∈ events do                     ▷ Iterate through all maintenance opportunities
        h_remain ← (p_proj − p_rest)/(p_new − p_rest)    ▷ Calculate the remaining system condition (ref. Eq. (3))
        c_wol ← h_remain · c_expected                    ▷ Calculate the resulting, expected waste-of-life cost (ref. eq. (4))
        c_delay ← t_delay · n_Pax · l_Pax · c_Pax^delay  ▷ Calculate possible delay occurrence cost (ref. eq. (6))
        if station_destination ∈ stations_operation then ▷ Check if current flight destination is an operating hub
            c_cancel ← n_Pax · l_Pax · c_Pax^cancel      ▷ Calculate possible flight Cancellation cost (ref. eq. (7))
        else
            c_cancel ← ∞
        end if
        c_oi ← min(c_delay, c_cancel)                    ▷ Calculate the minimum operational irregularity cost (ref. eq. (5))
        c_total ← c_oi + c_wol + c_expected              ▷ Calculate the expected total maintenance-related cost (ref. eq. (1))
        if c_total < tmp_memory then
            maintEvent ← {FC, mechanic, station_destination, c_total}   ▷ Store relevant maintenance information
            tmp_memory ← c_total
        end if
    end for each
    return maintEvent                                    ▷ Return dictionary with information about scheduled maintenance event
end procedure
```

Algorithm 2 Function to obtain maintenance task information based on the availability of required staff

```
function MaintenanceTask(t_land, station_destination)
    t_start,theoretical ← t_land + t_cool                ▷ Account for necessary system cool down time
    for each mechanic ∈ station_destination do           ▷ Iterate through all available mechanics of the station
        if t_start,duty ≤ t_start,theoretical < t_end,duty then   ▷ Check if the respective mechanic is on duty
            t_wait ← max(0, t_start,theoretical − t_start,real)   ▷ Calculate the waiting times for service
            c_expected ← c_MH · t_dur + c_material + e_task · c_emission   ▷ Calculate the task execution cost (ref. eq. (2))
            dict_mechanics ← {mechanic, t_wait, t_dur, c_expected}   ▷ Store information for each mechanic in dictionary
        end if
    end for each
    memory_minCost ← ∞
    for each entry ∈ dict_mechanics do                   ▷ Iterate through all available mechanics
        if c_expected < memory_minCost then              ▷ Select the mechanic with the lowest task execution cost
            dict_mechanic,task ← entry                   ▷ Store entry for function output
            memory_minCost ← c_expected                  ▷ Store cost value in memory
        end if
    end for each
    return dict_mechanic,task                            ▷ Return dictionary with maintenance task information for chosen mechanic
end function
```

The individual delay cost can be calculated with the following equation:

$$c_f^{delay} = c_{pax}^{delay} \cdot n_{Pax} \cdot l_{Pax} \cdot t_{ops}^{delay} \tag{6}$$

with c_{pax}^{delay} as the average delay cost per passenger and minute, n_{Pax} as the maximum seating capacity of the aircraft, l_{Pax} as the passenger load factor for the respective delayed flight, and t_{ops}^{delay} as the operational delay time. As mentioned before, the occurring delay costs need to be accumulated for all delayed flights D until the delayed aircraft flight schedule caught up with the originally intended one. Similarly, the expected cancellation costs can be calculated through

$$c_f^{cancel} = c_{pax}^{cancel} \cdot n_{Pax} \cdot l_{Pax} \tag{7}$$

where c_{pax}^{cancel} represents the average cancellation compensation for each passenger. It has to be kept in mind that a flight cancellation may not be feasible at any given station, e.g. for remote destinations, as the aircraft may need to be repositioned then, adding additional cost. Additionally, although the individual delay and cancellation compensations may vary depending on the time of their occurrence throughout the day, we simplify the calculation by utilizing an average for these compensation cost.

With all these cost contributions calculated, we can now estimate the total expected cost for each maintenance opportunity and subsequently schedule the maintenance task at an opportunity with minimal resulting maintenance related cost. It has to be noted that the number of maintenance opportunities under consideration significantly depends on the prognostic horizon of the underlying failure projection and the distribution of available maintenance bases within the given flight network.

5. Use case scenario

With all the theoretical foundations set, we will demonstrate the working principle of PreMaDe with the help of a use case scenario. For this use case we have chosen the tire pressure measurement task of an Airbus A320, as it significantly contributes to the overall scheduled maintenance expenditures [20]. Albeit its comparably short maintenance task times for the execution of functional checks and pressure restoration tasks, the high frequency of required manual functionality checks results in a significant potential for maintenance related cost savings. As of this paper, we will examine different levels of technological maturity for the underlying tire pressure monitoring system and vary its utilization degree, i.e. the ratio of aircraft within the fleet that continuously monitor the tire pressure and are following the prescriptive maintenance approach.

5.1. Simulation input parameter

The first step for this simulation requires the definition of general characteristics for the underlying fleet (ref. Table 2). This includes the definition of the simulation time span, the aircraft type, the fleet size, and compensation payments in the event of an operational irregularity. For this paper, we ran the simulation for a time span of 30 calendar days and examined an exemplary fleet of five Airbus A320 with a seating capacity of 180 Passenger (PAX), operating on short- and medium-haul flights.[1] The passenger load factor has been chosen randomly within a range of 64% and 95% for the underlying flight network. As the necessary turnaround time between each flight can significantly vary, we randomly generated these TATs with a lower limit of 45 min and an upper limit of two hours. Each of the respective aircraft has its main operations hub at Munich airport (MUC). All manual maintenance work, e.g. manual functional checks and pressure restorations, can only be conducted at this airport which serves as the only maintenance base within the chosen flight network.

With these general parameters set, we need to define key maintenance parameters for the tire pressure management task. An overview of related inputs is provided in Table 3. For the system specific parameters, a distinction between the sub-systems Nose Landing Gear (NLG) and Main Landing Gear (MLG) is necessary. All tires are assumed to be manufactured by Goodyear which provides the required maintenance threshold and the lower acceptable pressure limit for the respective task [77]. For example, an NLG tire with a pressure read of 169 psi will require a detailed inspection for any damages together with a repressurization. In order to allow a certain flexibility for operators, Goodyear has incorporated a safety margin for allowable degradation between the tire's nominal new condition and a lower acceptable pressure limit. If a tire surpasses the maintenance threshold for a detailed inspection (161 psi or 154 psi, respectively), the tire will need to be replaced. As NLG and MLG tires vary in their dimensions, we assumed the associated cost to differ as well, in accordance with Lufthansa Technik [78]. Similarly to these cost assumptions, we have calculated various CO_2 emissions for the individual tasks (see lower part of Table 3). These estimates incorporate the following aspects:

- the average travel distance for the mechanic to get to the aircraft,
- the power consumption for the storage of necessary ground equipment and repair material, and
- the emissions resulting from the production of replacement tires.

To incorporate these CO_2 emissions into the cost calculation, we assume a necessary payment for every ton of emission, e.g. through a taxation as discussed in Osterkamp [79].

As of this paper, we will refrain from describing the conventional tire pressure management approach in more detail. Interested readers are kindly referred to Meissner et al. [80].

In order to determine the necessary downtime for the maintenance task execution, we have used the process time information shown in Table 4. As Goodyear [77] states, the correct measurement of the tire's pressure requires the completion of a cool-down time of 180 min after the last landing. This waiting time is necessary to avoid temperature induced pressure changes. It has to be noted that these cool-down times will not occupy any mechanic resource but only lead to an extended downtime for the aircraft. The subsequent maintenance task times have been retrieved based on information provided by Airbus [81]. Similarly to the maintenance task cost, we have distinguished the task times for the NLG and MLG tires, respectively.

Besides these parameter inputs, we have made the following assumptions for this simulation:

- A_1 Maintenance events, i.e. functional checks and restoration tasks, can occur any time throughout the day, but only at designated maintenance hubs.
- A_2 Traveling times for the mechanic at the maintenance base have been neglected.
- A_3 A mechanic can only serve one aircraft at a time and will only be responsible for the tire pressure restoration task; thus, the resource will be available when no tire maintenance task within the fleet is due.
- A_4 As sub-system, e.g. NLG and MLG, can degrade differently, the resulting maintenance tasks will be conducted on a sub-systems level.
- A_5 A restoration maintenance task will reset the component to a condition 'as good as new'.
- A_6 Ground support equipment, e.g. a trite jack, will always be available when needed and does not experience degradation; therefore, it does not need to be restored.

5.2. Simulation results

With these simulation inputs, we will now examine the implications on maintenance and operations for different maintenance strategies and technological maturity levels of the underlying condition monitoring technology. The conventional tire pressure maintenance approach will serve as our baseline scenario. Starting from there, we subsequently examine the following:

- First, we will analyze the effects for the operator and MRO provider with an automated tire pressure monitoring. Thus, the functional check interval will remain unchanged and only the manual tire pressure measurement will be suspended.
- Second, we will incorporate a prescriptive maintenance approach that is based on the correct and timely prediction of remaining useful lifetimes. In a previous study, we have identified a prognostic horizon of six flight cycles as the necessary lower performance threshold for such a failure projection [20]. Thus, we use this prognostic horizon as the time span for the underlying condition monitoring system and vary the utilization degree for a prescriptive maintenance approach within the fleet.

[1] The respective flight schedule is based on an excerpt for a Lufthansa A320 with the registration D-AIPA. The historical flight schedule has been retrieved from www.flightradar24.com.

Table 2
Operational parameter.

Description	Parameter	Value	Unit
Simulation begin	t_{start}	01/01/2020	–
Simulation time span	t_{sim}	30	days
Fleet size	n_{ac}	5	–
Aircraft type	AC_{type}	A320	–
Seating capacity	n_{pax}	180	Pax
Passenger load factor	l_{pax}	[64, 95]	%
Operations hub & maintenance station	AP_{hub}	MUC	–
Turnaround time	t_{tat}	[45, 120]	min
Delay cost per minute and passenger	c_{delay}	0.25	$
Cancellation cost per passenger	c_{cancel}	700	$

Table 3
System specific parameter.

Description	Parameter	Value (NLG)	Value (MLG)	Unit
New condition	p_{new}	187	180	psi
Conventional functional check interval	i_{conv}	3	3	days
Lower acceptable limit	p_{accept}	178	171	psi
Maintenance threshold restoration	p_{rest}	170	162	psi
Maintenance threshold inspection	p_{insp}	161	154	psi
Cost functional check	c_{func}	10	11	$
Cost restoration	c_{rest}	50	55	$
Cost inspection	c_{insp}	100	110	$
Cost replacement	c_{repl}	1000	1100	$
Emission functional check	e_{func}	0.061	0.067	$kg.CO_2$
Emission restoration	e_{rest}	0.31	0.34	$kg.CO_2$
Emission inspection	e_{insp}	1.23	1.35	$kg.CO_2$
Emission replacement	e_{repl}	3.68	4.04	$kg.CO_2$
Cost emission	c_{emis}	100	100	$\frac{\$}{Ton_{CO_2}}$

Table 4
Process times.

Description	Parameter	Value (NLG)	Value (MLG)	Unit
Cool-down time	t_{cool}	180	180	min
Time functional check	t_{func}	1	1	min
Time restoration	t_{rest}	10	12	min
Time inspection	t_{insp}	45	50	min
Time replacement	t_{repl}	90	105	min

As first parameter, we want to analyze how the total maintenance related cost change with an increasing utilization degree of an automated condition monitoring and failure projection with the fleet. The utilization degree is defined as ratio of proactively maintained aircraft and the total fleet size. Thus, a ratio of 50% represents an equal split within the fleet of aircraft maintained proactively through a continuous condition monitoring and aircraft that are maintained conventionally with hard-time, interval-based functional checks. The calculated total maintenance related cost include the maintenance task cost itself as well as any cost from resulting operational irregularities, i.e. flight delays or cancellations. The development of these cost is shown in Fig. 7. As can be seen from the graph, the total cost continuously decrease with an increasing technology utilization within the fleet. However, with at least 40% of aircraft within the fleet capable of projecting upcoming maintenance needs at least six flight cycles in advance, the total cost savings seem to hit a plateau with only minor improvements of further introduction of the prognostics technology.

This observation can be supported by considering the individual composition of these total cost for the different scenarios. Fig. 8 shows the absolute values for the maintenance task execution and the resulting operational irregularity cost, respectively. Evidently, by comparing the scales of these two shares, cost resulting from operational irregularities significantly outweigh the mere maintenance task cost. With an increased introduction of prescriptive maintenance approaches within the fleet, these delay and cancellation cost drop from $120,000 for the conventional approach with a manual tire pressure measurement to

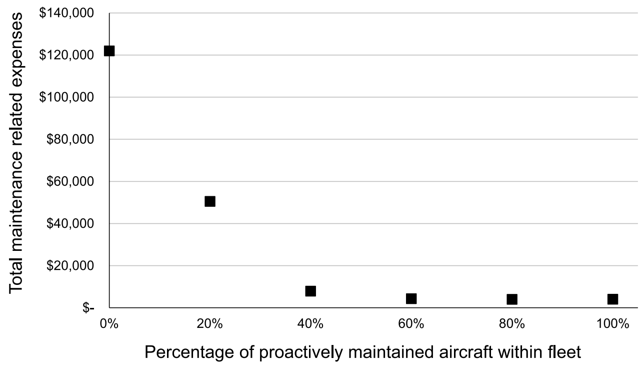


Fig. 7. Total maintenance related cost for different percentages of proactively monitored aircraft within the fleet.

about $7,000 for a utilization degree of at least 40% and, ultimately, to about $4,000 for a prescriptive maintenance approach of the whole fleet. While the operational irregularity cost eventually reach a plateau, the maintenance task cost can continuously be decreased through an increased introduction of prescriptive maintenance capabilities. This can mainly be attributed to the increasing avoidance of detailed manual inspection tasks due to the increasing continuous condition monitoring and prognosis (ref. Table 5).

With this decrease of total maintenance tasks in general, and detailed inspections in particular, there is an additional saving potential of CO_2 emissions. Fig. 9 shows this relative saving potential in terms of cost and emission in relation to the conventional maintenance approach. As can be seen, the mere automation of the functional check task will result in a cost reduction and an equal contribution towards the reduction of adversarial environmental impacts. Like the maintenance task cost, the CO_2 emissions also steadily decrease with an increasing utilization of a prescriptive maintenance strategy, reaching a maximum reduction of roughly 30% for the emission and 40% for the task cost, respectively. The spread in saving potential for high degrees of utilization is the result of different weightings for the individual maintenance tasks. Maintenance cost in our simulation are more sensitive towards tasks that are with their scope beyond a simple repressurization. Thus, the complete avoidance of these tasks will subsequently yield a higher proportion of additional saving percentage, compared to the environmental impact.

The examination of individual maintenance tasks with their associated task times is shown in Fig. 10. It shows the distribution of the individual maintenance task times, i.e. system cool-down times, waiting times for occupied resources, and task execution times. All shown values are normalized by the total downtimes for an average aircraft maintained in accordance with the conventional approach.

Table 5
Avg. number of maintenance tasks per aircraft for different maintenance approaches and degrees of utilization.

Maintenance approach		Restorations	Detailed inspections
Conv.	0%	57.2	2.0
Proactive	20%	56.8	1.6
	40%	56.0	1.2
	60%	54.4	0.8
	80%	53.6	0.4
	100%	53.2	0.0

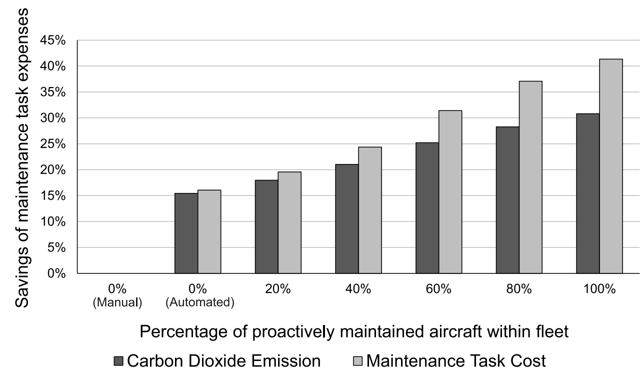


Fig. 9. Saving potential of maintenance task cost and carbon dioxide emission.

As we can see, the total downtime decreases continuously up to a prescriptive maintenance fleet utilization of about 40%. Additionally, the plot shows a continuous reduction of waiting times for the necessary ground resources up to a utilization degree of about 80% while the actual task execution times virtually remain unchanged, regardless of the maintenance approach. However, the necessary cool-down times change significantly, not only in their share of the individual bar but also in relation to the benchmark scenario. The reason for this is our chosen prescriptive maintenance approach with the underlying minimization objective. As described in the assumptions (ref. Section 5.1), the individual sub-systems can degrade differently and, therefore, will be maintained independently from one another for the proactive maintenance scenario. Subsequently, the algorithm will allocate each sub-system maintenance task to its preferred maintenance slot in order to avoid unnecessary delays. As the system cool-down time is deemed essential by the manufacturer, its occurrence does not classify as unnecessary. While the conventional maintenance approach has the same functional check interval for both sub-systems, leading to a combined restoration task for all sub-systems, the prescriptive approach will frequently have the sub-systems served individually at different maintenance opportunities. Therefore, the share of cool-down

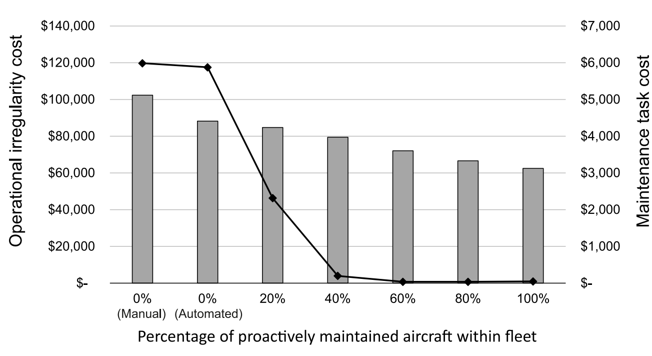


Fig. 8. Cost composition of maintenance related cost.

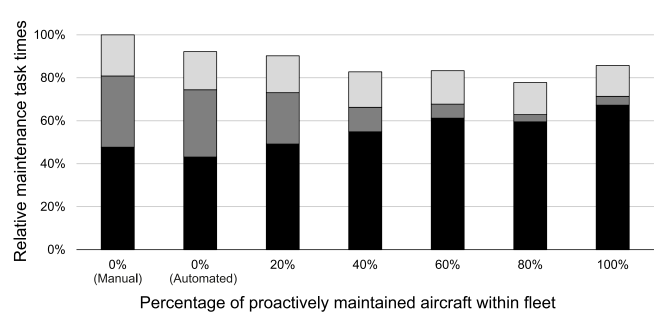


Fig. 10. Distribution of maintenance related servicing times.

Table 6
Summary of the resulting performance metrics for the involved stakeholders for different maintenance strategies and degrees of utilization.

Strategy	MRO provider				Operator			
	CO_2 emission (in kg.)	Maintenance cost	Detailed inspections	restorations	Number delays	Delay (in hrs.)	Delay cost	Avg. asset utilization
Conv. manual	25.03 -%	$5,347.60 -%	2.0 -%	57.2 -%	10.6 -%	20:00 -%	$119,729.25 -%	91.3% - PP
Conv. auto.	21.17 −15.4%	$4,488.50 −16.1%	2.0 0.0%	57.2 0.0%	10.6 0.0%	20:00 0.0%	$117,506.61 −1.9%	91.4% +0.1 PP
Pres. 40%	19.77 −21.0%	$4,044.50 −24.4%	1.2 −40.0%	56.0 −2.1%	1.4 −86.8%	02:44 −86.4%	$3,914.28 −96.7%	90.4% −1.0 PP
Pres. 100%	17.32 −30.8%	$3,136.50 −41.3%	0.0 −100%	53.2 −7.0%	1.0 −90.6%	02:06 −89.5%	$900.54 −99.2%	87.4% −4.6 PP

times increases with an increased utilization of the proposed prescriptive maintenance approach. Subsequently, reducing the necessary cool-down time before the maintenance task execution will lead to significant savings for the related maintenance downtime.

5.3. Conclusion of this study

In this section we will provide a concluding overview of the presented use case results and briefly discuss limitations of the chosen approach. All the relevant findings for the different maintenance approaches (conventional vs. prescriptive) and utilization degrees are summarized in Table 6 and compared to the conventional maintenance approach which serves as our benchmark. The shown parameters are assigned to the stakeholders MRO provider and operator and should reflect their individual objectives as presented in Table 1. We have selected only two representative utilization degrees to limit the complexity of the table. Thus, we have chosen a utilization degree of 40% and 100%, respectively. As can be seen there, almost all related objectives will continuously improve with an introduction of the proposed prescriptive maintenance approach. The only exception here is the average asset utilization parameter, expressed as the ratio of the maximum number of feasible flights with the given flight schedule and the actual number of completed flights after maintenance execution. This utilization strongly depends on the number of maintenance downtimes and their individual duration. As we have discussed in the previous section, our prescriptive maintenance strategy schedules maintenance tasks on a sub-system level, depending on the sub-system's respective state of degradation. Thus, although the number of average maintenance tasks per aircraft decreases and the average task execution time remains virtually unchanged, the increase of necessary cool-down times reduces the availability of the respective aircraft. Consequently, as a next step in the improvement of the underlying prescriptive maintenance algorithm, the opportunity cost as the result of a lower aircraft utilization will need to be included in the optimization routine as well.

Based on this study, we can identify the following central findings:

- F_1 The mere automation of functional check tasks will only yield slight improvements over the conventional maintenance approach. This is mainly caused by the missing projection of upcoming maintenance needs to effectively avoid operational delays due to the unavailability of necessary ground resources.
- F_2 A prescriptive maintenance approach that is applied on only a fraction of the total fleet can already contribute significant cost savings by relaxing emerging competition for the limited ground resources.
- F_3 A prescriptive maintenance utilization degree of at least 40% of all aircraft within the fleet will reduce the operational irregularities almost completely. However, any further introduction of the underlying condition monitoring technology into the fleet will only result in slight additional operational improvements.
- F_4 Reducing or completely avoiding necessary times for the system to cool down before executing the maintenance task will help to significantly reduce the resulting maintenance downtimes. Subsequently, this reduction can help to improve the asset utilization.

Additionally, this study has the following limitations that need to be addressed in future work:

- L_1 In order to derive holistically optimized maintenance schedules, it is necessary to include all essential stakeholders of the airline ecosystem. These include, beyond the operator and line maintenance provider that have been covered here, the logistics provider and shop maintenance facilities.
- L_2 The maturity of the underlying PHM technology is currently only evaluated through the parameter of the prognostic horizon. As has been discussed in Section 3.1, a variety of applicable performance parameters exist that can be used to describe a diagnostics and prognostics system capability.

6. Summary and outlook

In this paper, we have presented an approach to develop and evaluate prescriptive maintenance strategies based on the technological maturity of an underlying PHM system.

After reviewing conventional aircraft maintenance approaches, we have shown the development of multiple existing proactive maintenance approaches and have discussed their key features. We further have defined prescriptive aircraft maintenance and the necessary aspects that need to be considered in order to derive these holistically optimized maintenance schedules.

As the focus of this study was the support of post-prognostics maintenance decisions and, therefore, strongly relies on the quality and timeliness of failure projections, we have further examined existing approaches to evaluate a PHM technology's performance to serve as parameter input for our simulation. Additionally, in order to allow a holistic consideration of all involved stakeholders, we have discussed central objectives for the example of aircraft operators and MRO provider. The corresponding evaluation metrics to these objectives serve as performance indicators to determine the resulting quality of the developed maintenance approach within our use case scenario. The relevant stakeholders have been introduced through a stakeholder model that simultaneously builds the foundation of our used discrete-event simulation framework PreMaDe.

The working principle of the developed prescriptive maintenance algorithm has been demonstrated for the example of a tire pressure measurement task, as this frequently occurring scheduled maintenance task has significant implications for the current, legacy maintenance operations. With a varying ratio of proactively and conventionally maintained aircraft within a fleet, we could analyze the subsequent effects on the different objectives and performances metrics. We demonstrated for a condition monitoring system with a prognostic horizon of six flight cycles that the total cost savings seem to reach a plateau with only minor expected improvements beyond a minimum utilization degree of 40%. We further analyzed the effects on other key metrics for the considered stakeholders in order to provide an exhaustive evaluation of the developed maintenance strategy for different levels of technological maturities. These showed a possible reduction of maintenance task cost by up to 41.3%, a reduction of CO_2 emissions by up to 30.8%, and a reduction of avoidable delay minutes up to 89.5%. The corresponding delay cost through a proactive maintenance scheduling approach could be reduced by as much as 99.2%. However, due to the condition-based maintenance approach on a sub-system level, the average aircraft utilization has decreased by up to 4.6 percentage points as the total amount of necessary system cool-down times before maintenance execution is increasing.

We concluded our study by presenting the limitations of the current simulation setup which will need to be addressed in future work. As we have focused in this paper solely on the interaction of aircraft operations and line maintenance, the next development steps will have to include additional stakeholders for the maintenance decision making process. Additionally, an extension of the involved stakeholders will require an adapted prescriptive maintenance algorithm. In order to allow a holistic optimization, this algorithm needs to be able to incorporate (a set of) each stakeholders objectives to derive subsequent maintenance decisions.

CRediT authorship contribution statement

Robert Meissner: Conceptualization, Methodology, Software, Validation, Data curation, Writing - original draft, Visualization. **Antonia Rahn:** Conceptualization, Data curation, Writing - original draft, Reviewing and editing. **Kai Wicke:** Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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