Assessing the impact of condition-based maintenance on airline maintenance operations

MSc Thesis

Simon Daenens

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TU Delft

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This master thesis concludes my journey at Delft University of Technology. It has been 5 years of hard work and a lot of fun.

Simon Daenens
Delft, July 2021

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List of Abbreviations

AMP	Aircraft Maintenance Program
AOG	Aircraft On Ground
AUC	Area Under Curve
CBM	Condition-based Maintenance
DES	Discrete Event Simulation
FH	Flight Hour
FN	False Negative
FP	False Positive
FPR	False Positive Rate
IE	Interval Escalation
KPI	Key Performance Indicator
LCC	Lifecycle Cost
LRU	Line Replaceable Unit
MCS	Monte Carlo Simulation
MEL	Minimum Equipment List
MILP	Mixed Integer Linear Programming
PH	Prognostic Horizon
PHM	Prognostics & Health Management
ROC	Receiver Operating Characteristic
ROI	Return On Investment
RUL	Remaining Useful Life
SHM	Structural Health Monitoring
TN	True Negative
TP	True Positive
TPR	True Positive Rate
TS	Task Substitution
TTF	Time To Failure

Introduction

With an increase in sensor technology in newer generations of aircraft, the constant collection of sensor information allows to monitor the health of structural elements and systems, facilitating the prognostics and diagnostics of potential failures. This enables condition-based maintenance, a maintenance strategy aiming to maintain systems and structures right before failure. The implementation of this strategy requires a significant initial investment and therefore, the resulting benefits should be quantified in advance.

The objective of this research is to investigate the potential benefits of condition-based maintenance (CBM), and more specifically, the use of Prognostic & Health Management (PHM) systems operating with dynamic failure thresholds. The results of this research should give an indication of the feasibility of condition-based maintenance, as well as the prognostic performance levels required to yield an increase in earning potential for the airlines under investigation. The main motivation for this project is to demonstrate the true value of condition-based maintenance and to kick-start a global adoption of this promising strategy, by developing a flexible and holistic simulation tool.

This thesis report is organized as follows : In Part I, the scientific paper is presented. Part II contains the relevant Literature Study that supports the research. In part III, the project plan and research methodologies are presented. Finally, in Part IV, some additional material is presented.

I

Scientific Paper

Assessing the impact of condition-based maintenance on airline maintenance operations

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Abstract

Condition-based maintenance is an emerging maintenance strategy for aircraft, leveraging the constant collection of sensor information to facilitate diagnostics and prognostics of potential failures. The implementation of this strategy requires a significant initial investment and therefore, the resulting benefits should be quantified in advance. The objective of this research is to investigate the potential benefits of condition-based maintenance (CBM), and more specifically, the use of Prognostic & Health Management (PHM) systems operating with dynamic failure thresholds, with a focus on the required performance levels of the PHM systems. In this paper, a scheduling framework has been developed to schedule preventive maintenance tasks under application of prognostics, using a rolling-horizon scheduling approach to allocate tasks to appropriate maintenance blocks. The resulting maintenance schedule of a fleet of aircraft is subsequently used for the simulation of subsystem failures and the application of prognostics in order to anticipate them. Finally, the possibility of reducing maintenance cost, increasing fleet availability and improving operational reliability is investigated through a cost-benefit analysis. Results show significant improvements in terms of fleet availability and operational reliability, and minor reductions of maintenance cost. Moreover, the achieved benefits are shown to be in relation to the prognostic performance levels, and the scale to which condition-based maintenance is applied.

1 Introduction

Aircraft Maintenance, Repair and Overhaul (MRO) expenditures were estimated at $69 Billion in 2018, representing around 9% of airlines operational costs and are expected to reach $103 Billion in 2028 [IATA, 2019]. Therefore, the efficiency and quality of the maintenance process is of paramount importance for an airline operator. Currently, the standard maintenance strategy combines preventive and reactive maintenance. Preventive maintenance is often carried out at fixed time intervals, having the advantage of a fixed maintenance schedule and high reliability due to conservative time intervals, but at the inevitable cost of wasting part of the useful life. Reactive maintenance on the other hand is performed when a part is damaged, exploiting the entire useful life, but resulting in unexpected downtime and generally higher maintenance costs.

A new and promising solution to improve efficiency is condition-based maintenance (CBM). Condition-based maintenance is a maintenance strategy aiming to maintain systems right before failure using information about the actual condition of the systems, in order to keep reliability high and operating costs low [Walter and Flapper, 2017]. The constant collection of sensor information allows to monitor the health of structural elements and systems, facilitating the prognostics and diagnostics of potential failures and to schedule maintenance before the failure happens. A trade-off has to be made between the risk of failure during operation (leading to costly downtime) and the cost of premature maintenance (wasting remaining useful life of the system or component) [Walter and Flapper, 2017]. Condition-based maintenance has two main components: prognostics and health management (PHM), focused on remaining useful life (RUL) estimation; and post-prognostics decision-making, which relies on the prognostics output (RUL) for decision-support [Wesendrup and Hellingrath, 2020]. Effective prognostics & health management can change unscheduled maintenance to scheduled maintenance by planning a scheduled maintenance event before the estimated end-of-life [Fei et al., 2020], but also allows to skip unnecessary scheduled maintenance if no safety-threatening condition is observed [Wang et al., 2017].

Even though the technology is catching up, there is still a lot to accomplish in order to see CBM as the industry standard. First of all, in order to further stimulate developments of practical applications of CBM, it should be associated to an increase in earning potential through a proper cost-benefit analysis. Furthermore, certification requirements should be in place. Progress is being made in this area: MSG-3 methodology has been updated to allow aircraft health monitoring as an alternative to the classic scheduled maintenance task [Weiss, 2018]. Finally, a large part of the challenge is to apply CBM technology to different structures and systems and to adapt the maintenance processes and decision-making philosophy accordingly [Hirschmann, 2020].

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This paper proposes a model, capable of holistically assessing the economic impact of CBM on fleet level, where both the effects on scheduled and unscheduled maintenance are considered. This model should be usable to different airlines, characterized by different network types, aircraft types, fleet types, business models and maintenance policies. The structure of this research paper is as follows. In Section 2, the most relevant literature about the subject is pooled. Then, Section 3 elaborates on the proposed methodology concerning the modelling of the cost-benefit assessment tool. Section 4 illustrates the case studies presented in this paper. Thereafter, in Section 5, the results obtained for the case studies are described and discussed. Finally, conclusions are presented in Section 6.

2 Literature Review

Existing literature on condition-based maintenance for aircraft is extensive and covers various aspects necessary for an eventual implementation in practice. A large part of the literature focuses on the development of Prognostics and Health Management (PHM) frameworks, providing accurate and early RUL estimations for different systems and structures [Altay et al., 2014, Che et al., 2019, Sun et al., 2020, Verhagen and De Boer, 2018]. A common finding from the literature about this topic is that often, knowledge of the underlying physics can drastically improve model performance compared to a solely data-driven algorithm. Also, operational and environmental factors are shown to play an important role in system failure behavior, and including these in the model has a positive effect on the model's accuracy [Verhagen and De Boer, 2018].

Secondly, several researchers have developed maintenance scheduling approaches considering prognostics information. This covers applications in many fields, including line maintenance planning [Vianna and Yoneyama, 2018, Papakostas et al., 2010], reduction of unscheduled and scheduled maintenance activities [Hölzel and Gollnick, 2015], maintenance planning for a fleet of aircraft [Feng et al., 2017, Yang et al., 2018, Li et al., 2016], and the development of entire decision-making support systems for aircraft condition-based maintenance[Lin et al., 2017, Lin et al., 2018].

The third stream of literature analyzes the impact of prognostics and condition-based maintenance through cost-benefit analysis [Gerdes et al., 2016, Koops, 2018, Kählert et al., 2016, Feldman et al., 2009, Dong et al., 2020, Hongsheng et al., 2017, Hölzel and Gollnick, 2015, Vlamings, 2020], which is the main subject of this literature review.

A major challenge in the implementation of condition-based maintenance is the necessity of an up-front investment without direct benefits. The possible cost savings are difficult to quantify and hence a suitable cost-benefit analysis is needed to justify implementation of a condition monitoring system. A condition monitoring system will need to perform adequately, as the true benefit of condition monitoring lies in how early impending failures are detected and how accurately and precisely the time until failure is predicted [Busse et al., 2019].

Already in 2008, Leao et al. [Leao et al., 2008] presented a methodology for cost-benefit analysis on the application of PHM for legacy commercial aircraft. The methodology takes into account the lack of provisions for PHM systems on legacy aircraft, but also the availability of operation/maintenance data and experience. Although no cost-benefit analysis tool was developed, the authors gave valuable insights in all costs, benefits, risks, financial metrics and tools that should be considered or implemented in a cost-benefit analysis framework.

The cost-benefit models found in literature use different methods to evaluate the costs and benefits associated with PHM. Three main types of evaluation techniques were identified: scenario analysis, Monte Carlo simulation (MCS) and discrete event simulation (DES). Next to the variety in assessment methods, the scope of analysis varies from paper to paper, ranging from a simple maintenance event-based cost reduction calculation to a (nearly)-complete holistic multi-system economic assessment. Furthermore, some authors evaluate the effect of CBM on scheduled maintenance, while others look into the consequences for unscheduled maintenance. Considering both types of maintenance is of course also possible, and for a proper holistic assessment, necessary.

Gerdes et al. [Gerdes et al., 2016] have proposed a relatively simple approach to investigate the effect of unscheduled maintenance delays. The authors looked into historic delay and failure data related to delays caused by the air conditioning system, as indicated in the database of the Airbus A340-600 in-service report. Delays that could be prevented or reduced with the help of CBM were identified and it was shown that 80 percent of the maintenance actions causing departure delays can be prevented, should new sensors be introduced such that all fault causing systems can be monitored reliably. With the already existing sensors, it would be possible to avoid about 20% of delays causing maintenance actions. The results of this study, while promising, should be dealt with cautiously and critically. Only costs that are preventable due to reduction of delays are examined and no attention is given to the impact of possible errors associated with condition monitoring, e.g., false positives or false negatives, or performance metrics such as the prognostic horizon [Gerdes et al., 2016]. Another approach analyzing various scenarios with their associated cost is found in Koops [Koops, 2018]. Koops conducted a cost-benefit analysis to find the optimal operating point on the ROC curve, i.e., the optimal decision threshold for failure indication, and to analyze the net benefit of predictive maintenance compared to an approach without failure prediction (i.e., unscheduled maintenance). Kählert et al. [Kählert et al., 2016] computed the annual cost savings of PHM-based maintenance compared to unscheduled maintenance for on-condition maintained Line Replaceable Units (LRU), using discrete event simulation. Failure data is deterministic but input data for costs and process time is stochastic, therefore, Monte Carlo Simulation is used to represent the uncertain parameters. The aim of the study is to evaluate the financial potential of a component-specific PHM system and to specify component-based PHM parameters (Prognostic Horizon (PH) and accuracy). Feldman et al. [Feldman et al., 2009] calculated the Return On Investment (ROI) of a PHM system relative to unscheduled maintenance with a stochastic discrete event simulation, complemented with Monte Carlo Simulation to account for uncertainties in the inputs for the discrete-event simulation (i.e., the performance of the PHM system and the costs involved in the calculation). Furthermore, they looked into the effect of a PHM system on spare parts inventory management. With realistically assumed cost values, a positive ROI was demonstrated while accounting for both uncertainties in PHM performance and costs involved. However, more attention should be given to the impact of PHM at system level, as well as the inclusion of variability in the operational profile, false/missed alarm and random failure rates, time needed for maintenance, and system complexity [Feldman et al., 2009].

Dong et al. [Dong et al., 2020] have investigated the effect of Structural Health Monitoring (SHM) on the safety and lifetime cost of an airplane fuselage compared to scheduled, preventive maintenance. A lifecycle cost (LCC) analysis was conducted for both scheduled and condition-based maintenance. Monte Carlo Simulation was used to simulate uncertainties in the number of maintenance trips and the number of cracks repaired. In Hongsheng et al. [Hongsheng et al., 2017], three separate cost models are established: optimization of scheduled maintenance, optimization of unscheduled maintenance and error impact analysis. With the help of PHM, some of the scheduled maintenance tasks can be replaced by PHM monitoring, whereas for some tasks, the interval can be extended. Benefits for unscheduled maintenance include the possibility to reduce unscheduled maintenance events caused by failure of critical components with the help of prediction technology. Finally, the effects of prognostic errors in the PHM system such as false alarms and missed alarms on maintenance costs are evaluated. False alarms only result in additional checks and troubleshooting, while missed alarm events trigger unscheduled replacement or repair. Due to the lack of practical operating data, the authors opted to use Monte Carlo Simulation to evaluate working hours and cost of PHM-based maintenance [Hongsheng et al., 2017].

Hölzel and Gollnick [Hölzel and Gollnick, 2015] provide a holistic lifecycle cost-benefit analysis of a PHM system in future or present commercial aircraft. In the proposed approach, multiple subsystems are considered, and failure behavior is modelled individually for each subsystem. The methodology is based on discrete-event simulation for aircraft operation and maintenance, and scheduling of CBM tasks is done using an optimization algorithm. Both the effect on scheduled and unscheduled maintenance is analyzed. The assessment approach presented by Hölzel and Gollnick is generic and hence adaptable to different kinds of aircraft. Extension of this model to a fleet-level, where maintenance tasks can be scheduled for a fleet of different aircraft types on a network would allow for an even more realistic assessment of PHM [Hölzel and Gollnick, 2015]. Also, the inclusion of structural health monitoring in this model would be beneficial for its usability in practice.

Vlamings [Vlamings, 2020] made an effort to address the limitations in existing literature, especially those regarding the effects of false alarms as well as the effects of CBM on the supply chain, through the combination of a finely grained PHM framework integrated into a robust planning application for a fleet of aircraft. In his research, holistic models, adaptive to various fleet sizes with aircraft containing different components, to assess the effects on scheduled and unscheduled maintenance were developed and executed independently [Vlamings, 2020]. In his simulation model, the scheduled and unscheduled maintenance actions are disconnected. While this can give an indication of the benefits on each category, this assumption is not realistic, as these maintenance actions are coupled in real life. Furthermore, the number of systems considered in the unscheduled module is rather small compared to the overall number of systems in an aircraft and is thus not suited to give a representative indication of all the benefits resulting from CBM. Finally, all costs and benefits are expressed in a monetary value and the simulation model heavily relies on an accurate cost model, which is often confidential and difficult to obtain.

Having reviewed the extensive stream of literature about condition-based maintenance, the lack of a model suitable to deal with the complexity and variety of commercial aviation becomes apparent. As a logical next step in research, this paper aims to holistically assess the economic and operational impact of condition-based maintenance on fleet and network level, where both the effects on scheduled and unscheduled maintenance are considered. This model should be usable to different airlines, characterized by different network types, aircraft types, fleet types, business models and maintenance policies. This paper is innovative because it explores a novel condition-based maintenance strategy using dynamic failure thresholds, accounting for the age-dependent failure probability of components. Moreover, this paper dives deeper into the impact of varying prognostics performance levels on the possible benefits of condition-based maintenance. An attempt will be made to identify requirements for PHM performance levels for CBM to be beneficial and to find a good balance between false alerts and undetected faults from an economic point of view.

3 Methodology

In this paper, a simulation framework was developed to asses the benefits associated to condition-based maintenance. The simulation model developed in this paper includes two modules that can be executed independently or together. The model's building blocks are graphically depicted in Figure 1. The first module (M.1) simulates the effect of condition-based maintenance on scheduled maintenance. The second module (M.2) then simulates unscheduled maintenance through component failures and the use of prognostics to prevent these. In practice, these two types of strategies are used concurrently and their corresponding tasks cannot be planned independently. Therefore, when assessing the possible benefits of condition-based maintenance, the effect on scheduled and unscheduled maintenance should be considered in tandem.

For scheduled tasks described in the Aircraft Maintenance Program (AMP), the effect of prognostics translates into either task substitution (TS) or interval escalation (IE), depending on the task group: inspection-related tasks can be expected to be replaced (partly) by a PHM system, while the interval of service-related tasks could possibly be extended by more accurate knowledge about the failure behaviour of a component or structure. The rate at which task substitution or interval escalation could be realised, however, is rather uncertain and different for each task group. Therefore, assumptions have been made based on literature and on expert opinion in order to model this.

For unscheduled or corrective maintenance, prognostics aims to estimate the time of failure of components. This can trigger a preventive removal of a component at a more convenient time and at lower maintenance costs, expected to result in higher operational reliability and availability, while simultaneously saving on maintenance cost.

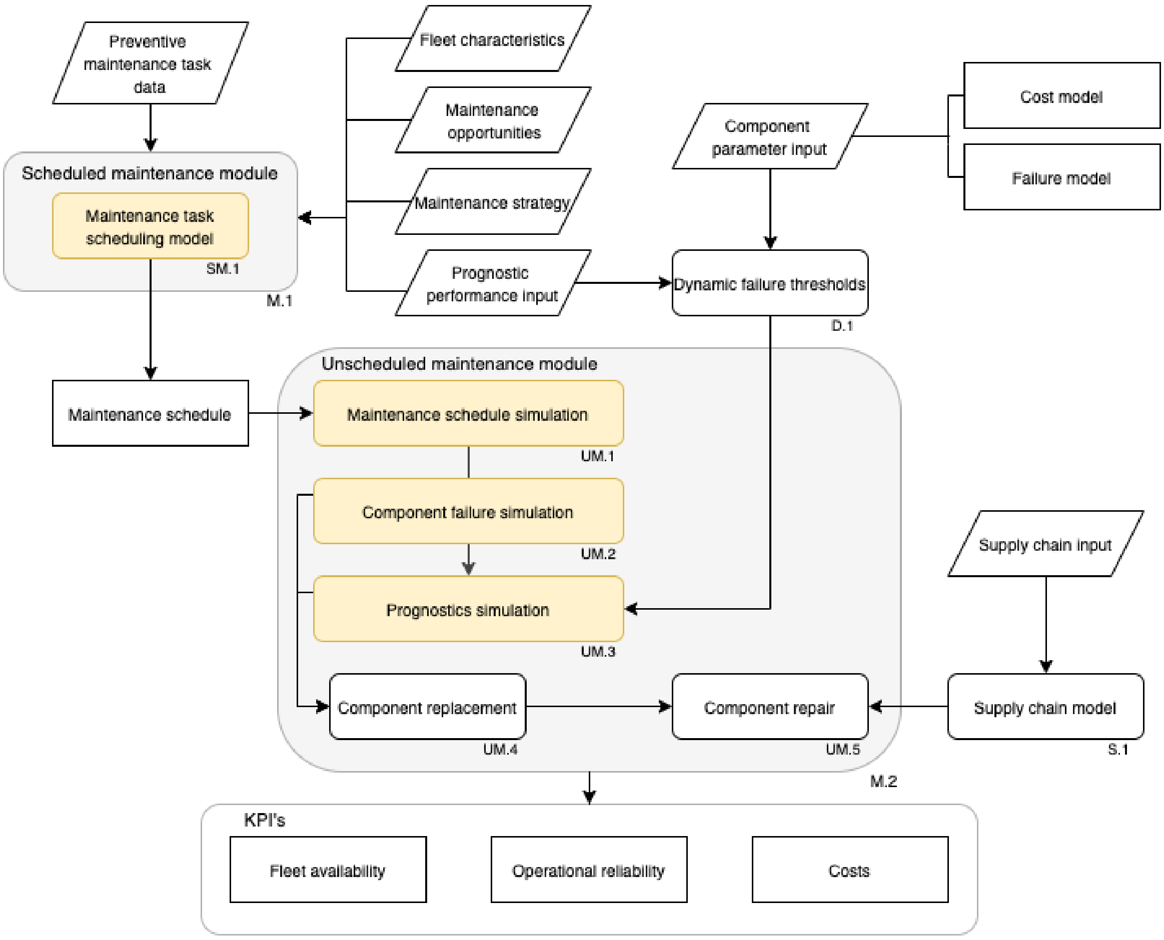

Figure 1: CBM simulation model

The two main modules of the simulator are depicted by blocks M.1 and M.2. These represent the model for scheduled and unscheduled maintenance, respectively. The scheduled maintenance module contains the maintenance task scheduling model (SM.1) and constructs the maintenance schedule for a fleet of aircraft, after which it evaluates the benefits of prognostics applied to scheduled maintenance tasks. This module is further explained in Section 3.1. The unscheduled maintenance module is built from different submodules and takes the maintenance schedule of the fleet as input. The three main simulation layers UM.1, UM.2 and UM.3 concern the simulation of the maintenance schedule (UM.1), component failures (UM.2) and prognostics (UM.3). In the event of failure of a component, the block UM.4 deals with the replacement of that component, after which the repair is simulated in block UM.5. The supply chain model (S.1) facilitates the repairs of components, and it simulates the inventory of spare parts as well as the ordering processes for replacements. The dynamic failure thresholds module, depicted by block D.1, concerns the optimisation of the failure thresholds to be used in the prognostics simulation. Finally, at the end of the simulation, relevant Key Performance Indicators (KPI's) are extracted.

3.1 Scheduled Maintenance Module

The scheduled maintenance module constructs the maintenance schedule for a chosen aircraft fleet and simulation horizon based on the tasks listed in the Aircraft Maintenance Program (AMP). The input data for this module contains historic task data and the AMP of a chosen aircraft. From this data, useful information such as task interval, duration and type can be extracted.

Maintenance opportunities are assumed to have limited capacity and the number of maintenance opportunities available per time unit can be chosen by the airline. Tasks are assigned a maintenance opportunity, taking into account their maintenance interval. The grouping of tasks in blocks results in a more efficient use of maintenance opportunities (less trips to the hangar), but leads to a waste of life. This waste of life is inevitable, but is easily compensated by the reduction in maintenance visits achieved by proper task packaging.

The scheduled maintenance module (M.1) concerns the packaging and scheduling of tasks to the available maintenance opportunities. Existing models available in the literature on this topic, and more specifically the scheduling model developed by [Vlamings, 2020], performs well for a limited fleet size and simulation horizon, but due to its long computation time, is not suited for large fleet sizes and long simulation horizons. Therefore, in this study, a new scheduling algorithm has been developed to be able to simulate larger aircraft fleets on longer time horizons. This algorithm schedules the tasks in a rolling horizon approach, performing a series of Mixed Integer Linear Programming (MILP) optimisations. The rolling horizon approach employed by the algorithm aims to divide the problem into smaller subproblems that are faster to solve, by carefully selecting which tasks to schedule in each optimisation period. For example, if task 1 has an interval of 100 FH and task 2 has an interval of 450 FH, it is of no use to schedule task 2 together with the first instance of task 1, as task 1 must be scheduled at least four times before the first instance of task 2 is due. The functioning of the algorithm is visualised in Figure 2.

The first step in the scheduling algorithm is to construct the set of all tasks for each aircraft (SA.1) and the set of maintenance opportunities (SA.2). These are constructed in advance, before the rolling horizon scheme. The set of tasks contains all the tasks from the AMP, and the set of maintenance opportunities is the set of all possible opportunities a maintenance block can be assigned to.

Prognostics is simulated based on values for task substitution (TS) and interval escalation (IE) based on the task group. Each task belongs to a certain task group, for which either task substitution or interval escalation is applicable. Then, based on the probability of task substitution, each task from the TS category is evaluated and either added to the task set or eliminated from the task set due to substitution by prognostics. For tasks in the IE category, the interval is extended with the predetermined factor for interval escalation. The updated task requirements (i.e., extended intervals or substituted tasks) are considered in constructing the set of tasks, which takes place in block SA.1 in Figure 2. The task groups and their corresponding task substitution probability or interval escalation rate are tabulated in Table 1 in Section 4.

Then, the rolling horizon scheme starts and the algorithm proceeds to find the task that will be due first after all tasks are scheduled once (SA.4). All tasks with a deadline before this value are selected (SA.5), and all maintenance opportunities before the latest deadline are considered (SA.6). This also marks the end of the current horizon. The selected tasks are scheduled in the current optimisation period (SA.7). After these tasks have been scheduled, based on the outcome of the optimisation and the allocation of tasks, the updated task deadlines can be determined and the earliest deadline is identified (SA.8). Finally, for all tasks scheduled before the earliest new deadline, the allocation is finalised and the deadline is updated (SA.9). The other tasks, those scheduled after the earliest new deadline, are reconsidered in the next optimisation period. The reasoning behind this is that when tasks are scheduled before their deadline, the next deadline of that task is moved earlier in time compared to the initial estimate. Consequently, tasks that are due after this new deadline and might have been scheduled sub-optimally, can be rescheduled together with the next instance of the task with the earliest new deadline in order to maximise their interval. This happens in case the optimisation allocates those tasks to an opportunity that is before their deadline but together with other tasks, because the advantages of grouping tasks in a single maintenance slots outweigh the possibility of maximising an individual task's interval.

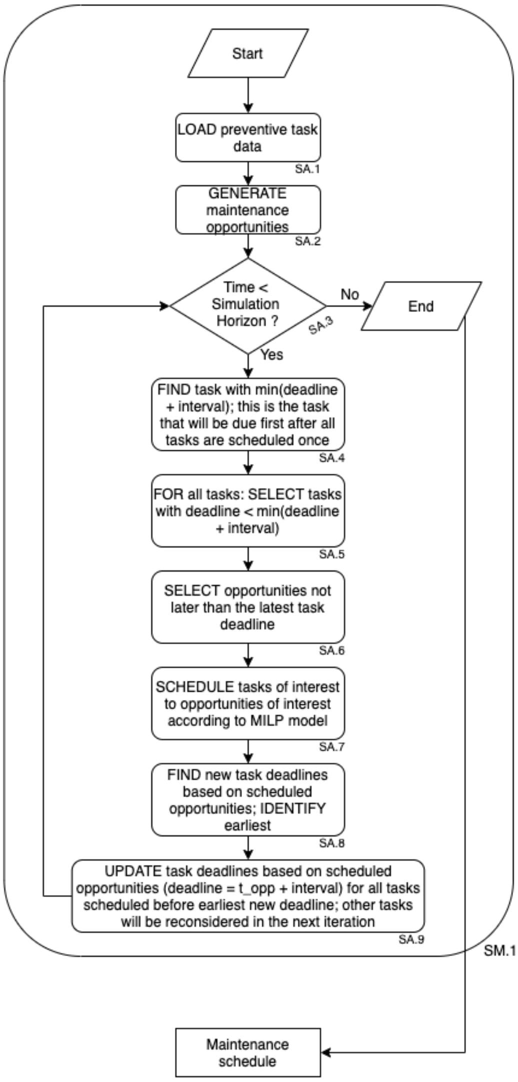

Figure 2: Scheduling algorithm flowchart (SM.1 in Figure 1)

Task packaging and scheduling is done using a Mixed Integer Linear Programming (MILP) model (SA.7, in Figure 2). Its objective function is displayed in Equation 1 and the model is constrained using Equations (2) to (8)

$$\min \sum_{a \in A} \sum_{i \in I} \left[\frac{t_{deadline} - t_k}{t_{interval}} \cdot t_{duration} \cdot x_{a,i}^k \right] + \sum_{a \in A} \sum_{k \in K} \left[c_{a,k}^{opp\_fixed} \cdot w_a^k \right] \tag{1}$$

$$\sum_{k \in K} x_{a,i}^k = 1 \quad \forall i \in I(a), \forall a \in A \tag{2}$$

$$\sum_{k \in K} t_k \cdot x_{a,i}^k \leq t_{deadline} \quad \forall i \in I(a), \forall a \in A \tag{3}$$

$$\sum_{k \in K} t_k \cdot x_{a,i}^k > max(t_{birth}, t_{prev\_opp}) \quad \forall i \in I(a), \forall a \in A \tag{4}$$

$$\sum_{a \in A} w_a^k \leq k_{capacity} \quad \forall k \in K \tag{5}$$

$$\sum_{a \in A} \sum_{i \in I(a)} t_{duration} \cdot x_{a,i}^k \leq k_{manhours} \quad \forall k \in K \tag{6}$$

$$\sum_{i \in I(a)} t_{duration} \cdot x_{a,i}^k - M \cdot w_a^k \leq 0 \quad \forall k \in K, \forall a \in A \tag{7}$$

$$\sum_{\substack{k \in K \\ \text{if } t_{prevblock} < k \leq t_{nextblock}}} w_a^k = 1 \quad \forall a \in A \tag{8}$$

Decision variables:

$x_{a,i}^{k}$	1 if task i of aircraft a is executed at opportunity k, else 0
w_{a}^{k}	1 if aircraft a uses opportunity k, else 0
m_{a}^{k}	labour hours used by aircraft a at opportunity k

Coefficients:

$t_{deadline}$	deadline of task i
$t_{interval}$	interval of task i
t_{k}	time of opportunity k
$t_{duration}$	duration of task i in man-hours
$c_{a,k}^{opp\_fixed}$	fixed penalty of using opportunity k by aircraft a
t_{birth}	start time of operation of aircraft a
t_{prev_opp}	time of the previous occurrence of task i of aircraft a
$k_{capacity}$	capacity of opportunity k
$k_{manhours}$	man-hours available at opportunity k
M	Big M
$t_{prevblock}$	time of previous block check
$t_{nextblock}$	$t_{prevblock}$ + block interval

Sets:

A	set of all aircraft
I(a)	set of all tasks of aircraft a
K	set of all opportunities

The objective function of the maintenance task packaging problem is depicted in Equation 1 and aims to balance interval maximisation and task grouping by simultaneously minimising the wasted life of tasks and the number of maintenance opportunities used by an aircraft. The first term concerns the minimisation of wasted life, and takes into account the duration of tasks as well as their interval to ensure that wasted life is minimised relative to a task's interval and duration. The second term minimises the number of maintenance opportunities used by an aircraft by penalising each opportunity that is used. Equation 2 ensures that each task is executed once in each horizon. Equation 3 states that each task must be executed before its deadline. Equation 4 describes that each task must be scheduled after execution of its previous instance, or when this task has not been done before, after the starting date of operation of aircraft *a*. Then, Equation 5 limits the capacity of a maintenance opportunity, i.e., the number of aircraft assigned to a maintenance opportunity cannot exceed the number of available slots. Equation 6 expresses that the total man-hours that can be assigned to a maintenance opportunity cannot exceed the man-hours available. Equation 7 helps to establish whether an aircraft uses a maintenance opportunity. Finally, Equation 8 is an optional constraint that is activated when the desired interval between periodic checks is given as an input to the model. This could be helpful especially when simulating smaller block check intervals (e.g., 750 FH instead of 1500 FH). This constraint takes all opportunities within a chosen interval (e.g., 1500 FH) and ensures that exactly one maintenance opportunity is used within this interval.

3.2 Unscheduled Maintenance Module

The scheduled maintenance module (M.1) was used to construct the maintenance schedule for the entire operating period of the aircraft, taking into account prognostics and its ability to substitute or extend the interval of certain tasks. However, not all systems are maintained regularly and failures can still occur, after which a corrective maintenance action is required. The unscheduled maintenance module (M.2) estimates the effect of condition-based maintenance on those subsystems that are normally maintained under a corrective maintenance policy by means of a lifecycle simulation of several subsystems in a fleet of aircraft. In contrast to the scheduled maintenance module where the effect of prognostics is applied globally, by task substitution probabilities and interval escalation rates based on task group, this module simulates the effect of prognostics on component level, where prognostics is applied to each specific component and failures can occur for individual components.

The scope of this module consists of three things: the simulation of preventive maintenance tasks as defined in the Aircraft Maintenance Program, the simulation of component failures (and their corresponding replacement actions), and finally, the preventive replacement of components triggered by prognostics. Additionally, the logistics and repair of components is dealt with in a separate logistics module. The simulation method of choice is a discrete-event simulation (DES), where all maintenance events are simulated and with the advantage that no change in state occurs in between events, enabling a computation time-efficient simulation method.

The simulation model is constructed with three different layers. The first layer (UM.1) simulates the block checks as constructed in the scheduled maintenance module. These block checks are simulated as events during the aircraft lifecycle at times dictated by the maintenance schedule.

The second layer (UM.2) concerns the simulation of failure of components, and their subsequent replacement. When a component is installed in an aircraft, its time of failure is randomly drawn from its failure distribution function. When the simulation reaches this time of failure, the component is assumed to fail. This triggers a maintenance request and the component is scheduled for maintenance.

The scheduling decisions that are made after component failure are shown in Figure 3, part of UM.2 in Figure 1. Based on the upcoming MEL condition, the replacement of a failed component can be either scheduled to an available opportunity, deferred, or when an Aircraft on Ground (AOG) situation is imminent, requested to be performed immediately. In the last case, the aircraft is grounded before the MEL deadline expires to replace the failed component and restore the airworthiness of the aircraft. This type of maintenance action is unfavourable for an airline, as it often results in disruptions to the flight schedule or AOG situations.

Deferral of a component replacement can occur only if no MEL deadline results from failure of that component. In this case, the component in question will be replaced at the next maintenance opportunity used by the aircraft. This is highly desirable, because the replacement can take place together with other maintenance tasks and thus requires no separate maintenance slot.

When a failure of a component activates a MEL deadline, this component should be replaced before that deadline expires. Ideally, this is done at an available maintenance opportunity, as otherwise, an AOG situation can occur. In the simulation model developed for this research, these opportunities can be either periodic checks as planned in the preventive maintenance module, or flexible maintenance slots, which are maintenance slots the airline keeps open to account for these events and can be booked by any aircraft in the fleet when necessary.

The scheduling of these maintenance requests is optimised using a Mixed Integer Linear Programming (MILP) model, described in Appendix A.

When the time of maintenance is known, a spare component can be ordered and the failed component can be replaced and sent to the component pool to be repaired.

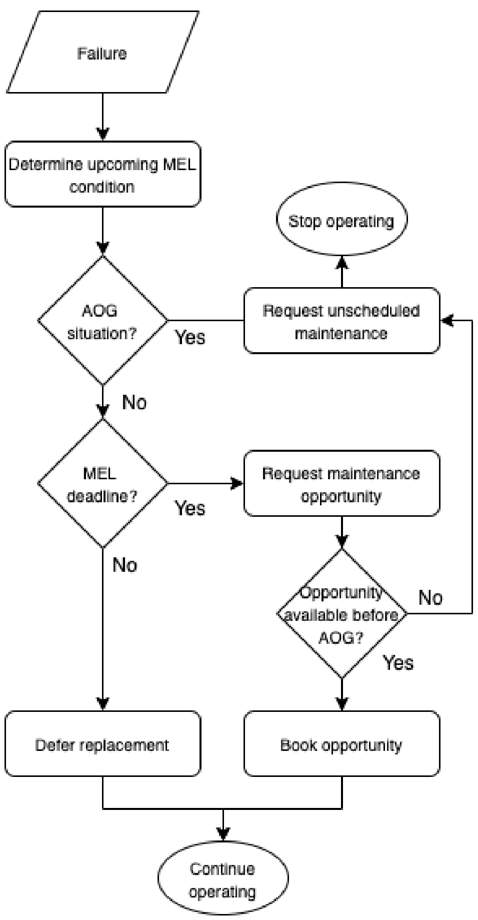

Figure 3: Failure of a component (UM.2, in Figure 1)

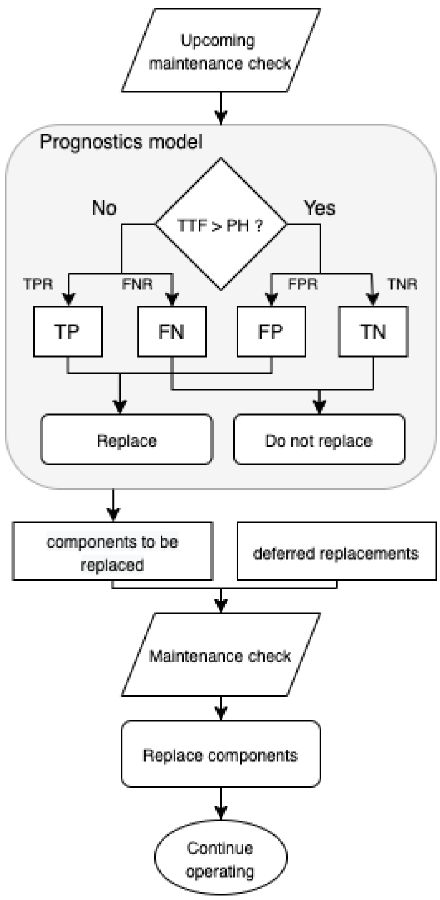

Figure 4: Simulation of prognostics (UM.3, in Figure 1)

Finally, the third layer (UM.3) introduces prognostics to the model. The strategy is based on [Freeman et al., 2021] and relies on prognostics to determine for each maintenance opportunity which components to replace preventively, based on the False Positive Rate (FPR) and True Positive Rate (TPR) associated to a chosen threshold.

The CBM approach proposed in this paper is based on [Freeman et al., 2021]. The authors of [Freeman et al., 2021] use prognostics at periodic checks only, however, they recognise that the possibility to anticipate upcoming failures between checks is left unused. Therefore, this study proposes a CBM approach where this limitation is addressed. Instead of only running prognostics at periodic checks, prognostics is run each time the aircraft is scheduled to undergo maintenance. This is expected to increase the rate at which upcoming failures can be detected and subsequently decrease the number of operational disruptions.

The proposed CBM approach can be simulated with either a fixed failure threshold, constant over a component's life, or dynamic failure thresholds. With fixed failure thresholds, the PHM system does not use component age as a prognostic parameter and a component is predicted to fail when a certain, fixed threshold is exceeded. This paper presents a novel CBM approach that uses dynamic failure thresholds, where the threshold is varied during the life of a component to account for age-dependent reliability of components. These dynamic thresholds are determined in advance for each subsystem and depend on the subsystem's failure behaviour, the cost of a preventive and a corrective maintenance action, and the age of the component. For more information about how these thresholds are obtained, the reader is referred to [Freeman et al., 2021].

The PHM system can operate at different combinations of FPR and TPR, as given by its Receiver Operating Characteristics (ROC) curve (Figure 5). Each point on this curve represents a combination of FPR and TPR, associated to a certain failure threshold. Therefore, determination of the cost-optimal failure threshold is equivalent to determining the optimal operating point on the ROC curve. The optimal operating point for each maintenance check is determined in advance for PHM systems with different performance levels, using the method developed by [Freeman et al., 2021]. The FPR and TPR associated to this operating point are then used in the classification of failure prediction outcomes to simulate prognostics, as indicated in Figure 4.

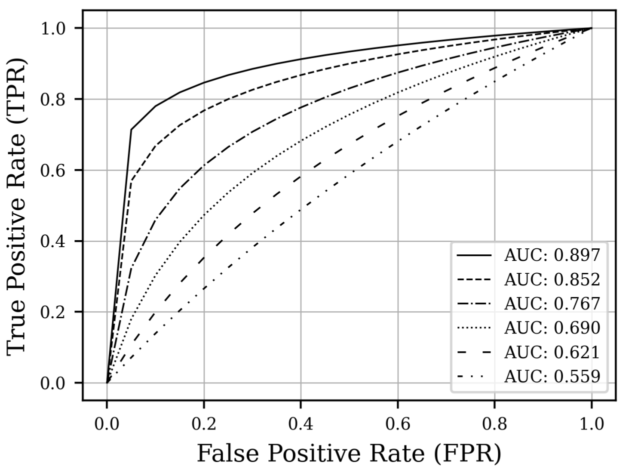

Figure 5: The ROC curves corresponding to the PHM systems used for simulation

Due to the unknown prognostic performance for the majority of existing PHM systems, this study will assess the benefits of CBM for varying prognostic performance levels. The variation in prognostic performance is modeled by different ROC curves, each with a different Area Under Curve (AUC). Minimal AUC (i.e., AUC = 0.5) corresponds to random classification, maximal AUC (i.e., AUC = 1) represents a PHM system with perfect information about a component's condition (i.e., TPR = 1, FPR = 0) [Metz, 1978]. The ROC curves with their corresponding AUC used for this study are shown in Figure 5.

The prognostics module is run right before each maintenance check to determine which components to replace (together with the tasks already assigned to the check) and works as shown in Figure 4. The time of failure sampled at initialisation of each component is evaluated to determine whether failure is imminent within the prognostic horizon. Then, based on the FPR or TPR, the event is classified as one of the four possible prediction outcomes:

- True Positive (TP): failure within prognostic horizon, detected by the PHM system
- False Positive (FP): no failure within prognostic horizon, but indicated as failure by the PHM system
- True Negative (TN): no failure within prognostic horizon, PHM system indicates no failure

- False Negative (FN): failure within prognostic horizon, not detected by the PHM system

In case of an FP or TP event, the component is replaced at the upcoming maintenance check. Note that the FPR and TPR can be assumed to be fixed (constant during the component's life) or dynamic (changing with increasing age of component). Both options are compared in Section 5. In case of a False Negative event, an upcoming failure within the prognostic horizon is simply not detected and the component fails at the pre-sampled time of failure.

To account for the stochastic nature in the determination of the time of failure and the prognostic classification of failures, Monte Carlo simulation is used to obtain reliable results.

4 Description of the Case Studies

In this paper, four case studies are presented. Case study 1 deals with scheduled maintenance, the other three cover unscheduled maintenance. Each case study aims to investigate a different area where the effect of condition-based maintenance can be evaluated. The case studies are explained in the following sections.

4.1 Case study 1: scheduled maintenance

In this case study, the effect of prognostics on scheduled maintenance tasks is investigated. For this purpose, the scheduled maintenance module is run independently. The aircraft for which the maintenance schedule is simulated is a modern wide-body aircraft, for which the Aircraft Maintenance Program (AMP) was obtained from a European airline. In total, 390 tasks are considered, corresponding to the tasks as listed in the Aircraft Maintenance Program (AMP). These tasks are categorized according to type, and for each category the task substitution or the interval escalation rate can be set according to the performance of the PHM system. In terms of PHM performance, two options were considered: a realistic scenario and an optimistic scenario, with task substitution and interval escalation rates given in Table 1. The percentages for these scenarios are as found in [Vlamings, 2020] and based on expert opinion of the MRO of which the data was used. Both of these CBM scenarios are compared to the baseline scenario, corresponding to preventive maintenance. Analysis was done for periodic check intervals of 1500 FH and 750 FH.

Table 1: Scheduled tasks

Task group	Number of tasks	CBM action	Baseline [%]	Scenario 1 [%]	Scenario 2 [%]
General Visual Inspection	139	Task substitution	0	25	50
Functional Check	28	Task substitution	0	50	100
Detailed Inspection	64	Task substitution	0	25	50
Servicing	9	Interval escalation	0	25	50
Lubrication	18	Interval escalation	0	25	50
Restoration	16	Interval escalation	0	25	50
Discard	30	Interval escalation	0	25	50
Operational Check	64	Task substitution	0	50	100
Special Detailed Inspection	6	Task substitution	0	25	50
Visual Check	16	Task substitution	0	0	0

Simulating larger fleets can be especially interesting in the unscheduled maintenance module or to investigate the scheduling of maintenance tasks to a fleet of aircraft with limited maintenance resources. However, this becomes more of a scheduling problem than a cost-benefit analysis of CBM on scheduled maintenance, as the task list is the same for each aircraft and a very similar number of labour hours will be required by each aircraft in the fleet.

Therefore, it is deemed more interesting to simulate larger fleets of aircraft in the unscheduled maintenance model, as unscheduled tasks are more variable and larger differences are expected on fleet level compared to single aircraft level due to competition for maintenance opportunities at variable times. When the preventive module is used as part of the unscheduled maintenance simulator, where a lifecycle simulation is conducted for a fleet of aircraft, the maintenance schedule is constructed for the entire fleet to take into account during the simulation. This case study concerns the changes in labour hours required for the scheduled maintenance tasks of a single aircraft.

4.2 Case study 2: unscheduled maintenance - prognostic performance

This case study aims to answer the the following research question: what are the required PHM performance levels to justify condition-based maintenance as an alternative to corrective maintenance?

In this study, all simulations are done on a synthetic fleet of 20 aircraft. This number was chosen to be able to properly simulate competition among aircraft in the fleet for flexible maintenance opportunities. While airlines usually have larger fleets, simulating larger airlines again shifted the focus of the study more towards the scheduling of tasks to limited maintenance opportunities with limited resources, without adding value to the cost-benefit analysis itself. For each aircraft, three subsystems are considered for analysis: an electrical generator (EG), a cooling unit (CU), and a compressor (COMP), with characteristics as shown in Table 2. Due to confidentiality reasons, absolute cost values cannot be shared and are therefore expressed as relative values. The simulation of unscheduled maintenance events covers a simulation period of 4224 days.

Table 2: Input parameters for the unscheduled maintenance module for the compressor (COMP), cooling unit (CU) and the electrical generator (EG)

Parameter	**COMP**	**CU**	**EG**
Number of components per aircraft	4	4	4
MEL deadline 1 failure	10 days	None	4 days
MEL deadline 2 failures	AOG	10 days	AOG
MEL deadline 3 failures	AOG	AOG	AOG
MEL deadline 4 failures	AOG	AOG	AOG
Supply chain lead time	4 days	4 days	4 days
Supply chain lead time (AOG)	1 day	1 day	1 day
Preventive cost (C_p)	0.4 C_c	0.325 C_c	0.3 C_c
Corrective cost (C_c)	C_c	C_c	C_c
Weibull [scale, shape]	[15000, 2]	[18684, 1.4]	[25580, 1.116]

In this study, different prognostic performance levels are simulated in order to determine the required prognostic performance levels per subsystem. The combinations of CBM strategy and PHM performance are set out in Table 3.

Table 3: PHM performance scenarios

Scenario	CBM strategy	ROC - AUC	Subsystems
1	Fixed failure threshold	0.897	EG
2	Dynamic failure threshold	0.897	EG
3	Fixed failure threshold	0.852 (baseline)	COMP, EG, CU
4	Dynamic failure threshold	0.852 (baseline)	COMP, EG, CU
5	Fixed failure threshold	0.767	COMP, EG, CU
6	Dynamic failure threshold	0.767	COMP, EG, CU
7	Fixed failure threshold	0.690	COMP, EG, CU
8	Dynamic failure threshold	0.690	COMP, EG, CU
9	Fixed failure threshold	0.621	COMP, EG, CU
10	Dynamic failure threshold	0.621	COMP, EG, CU
11	Fixed failure threshold	0.559	COMP
12	Dynamic failure threshold	0.559	COMP

The variation in prognostic performance is expressed by different ROC curves, where the difference in prognostic performance comes from the Area Under Curve (AUC); a larger AUC corresponds to better performance [Metz, 1978]. The baseline scenario is set at AUC = 0.852, and the AUC gradually decreases in steps of 10 %. For the EG, an ROC curve with AUC = 0.897 (baseline + 5 %) is included for analysis, as the outcome of the dynamic thresholds module for this subsystem with a PHM performance corresponding to the baseline scenario was not sufficiently favourable.

4.3 Case study 3: unscheduled maintenance - number of systems

Case study 3 investigates how the effectiveness of CBM evolves with an increasing number of systems subject to CBM. This is done by simulating an aircraft with a gradually increasing number of systems and comparing the results for condition-based maintenance with simulation results obtained for a corrective maintenance strategy.

The lack of subsystem data on a large scale resulted in a considerably important assumption to be made: when investigating the effect of CBM on an increased number of subsystems, all subsystems are assumed to be of the same type, with the same maintenance costs and similar failure behaviour. In reality, no two subsystems are exactly the same in terms of repair costs or failure behaviour, however, this could give an indication on how the benefits of CBM scale up with the number of systems to which CBM is applied.

4.4 Case study 4: unscheduled maintenance - effect of periodic check interval

This case study aims to investigate the effectiveness of CBM when the periodic check interval is decreased, resulting in more frequent hangar visits. This is expected to have a positive effect on the effectiveness of CBM, as more opportunities become available to detect upcoming failures. Furthermore, especially for a PHM system with a relatively low prognostic horizon, a lower check interval could positively influence the effectiveness of a CBM approach due to better capabilities to detect impending failures in between periodic checks.

For this case study, the aircraft is assumed to have three subsystems for which prognostics is available: a compressor, a cooling unit and an electrical generator. It should be pointed out that for a check interval of 750 FH, the prognostic horizon of the PHM system is assumed to be 500 FH, while the prognostic horizon in case of a check interval of 1500 FH is set at 1000 FH. This stems from the assumption that the check interval must be larger than the prognostic horizon of the PHM system made by [Freeman et al., 2021] in determining the dynamic failure thresholds. A second analysis then compares a PHM system with a prognostic horizon of 1000 FH to one with a prognostic horizon of 500 FH, with a periodic check interval of 1500 FH.

5 Results & Discussion

The following results are obtained from analysis of the case studies described in Section 4.

5.1 Case study 1

The preventive maintenance schedule was determined for an aircraft in order to assess the effectiveness of condition-based maintenance (CBM) in different scenarios. In Figures 6 and 7 the labour hours per maintenance check are shown for a check interval of 1500 FH. Purely preventive maintenance is compared to condition-based maintenance scenario 1 (Figure 6) and scenario 2 (Figure 7). The vertical bars represent the labour hours for each individual check, the horizontal lines indicate the average labour hours per check type, both for the CBM scenario and preventive maintenance as depicted in the legend. These plots graphically show the benefits of CBM in terms of labour hours required per check and the averages per check type are tabulated in Table 4. Here, the average labour hours per A- and C-check are indicated. Both the total labour hours as well as the labour hours for the specific task categories based on the nature of the CBM action (task substitution (TS) or interval escalation (IE)) are shown.

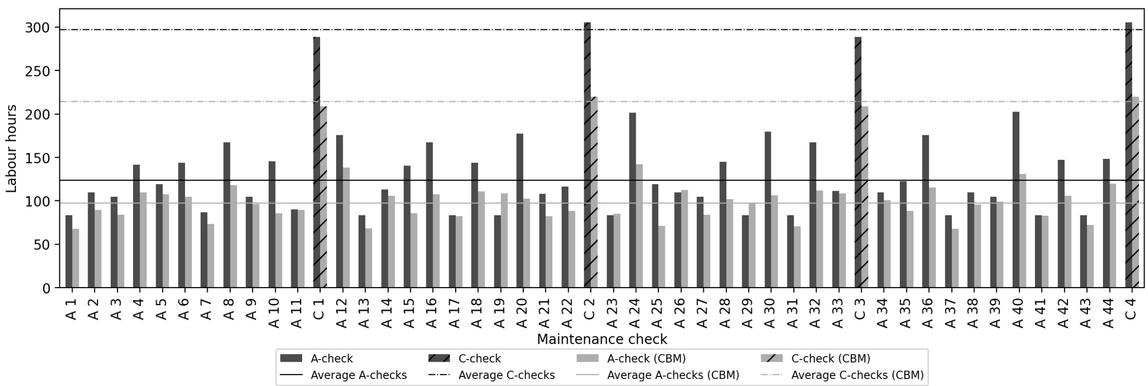

Figure 6: Results for one aircraft (scenario 1, check interval of 1500 FH)

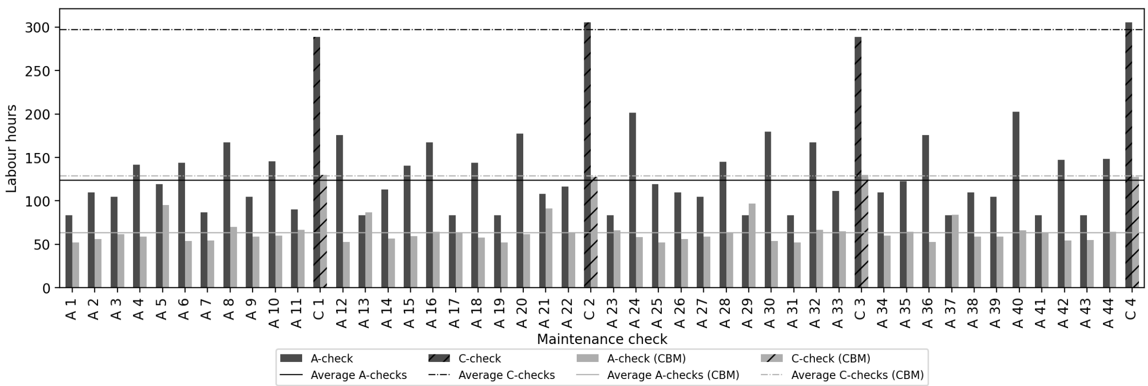

Figure 7: Results for one aircraft (scenario 2, check interval of 1500 FH)

Table 4: Average labour hours per check, check interval of 1500 FH

	Baseline	**CBM 1**	**CBM 2**
A-check			
Total (TS/IE)	124 (71/53)	97 (48/49)	63 (25/38)
C-check			
Total (TS/IE)	297 (279/18)	214 (196/18)	129 (114/15)

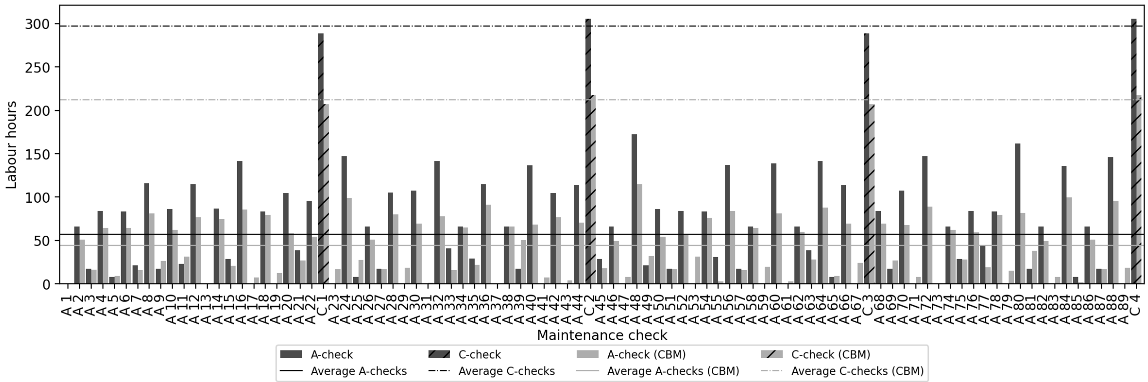

Figure 8: Results for one aircraft (scenario 1, check interval of 750 FH)

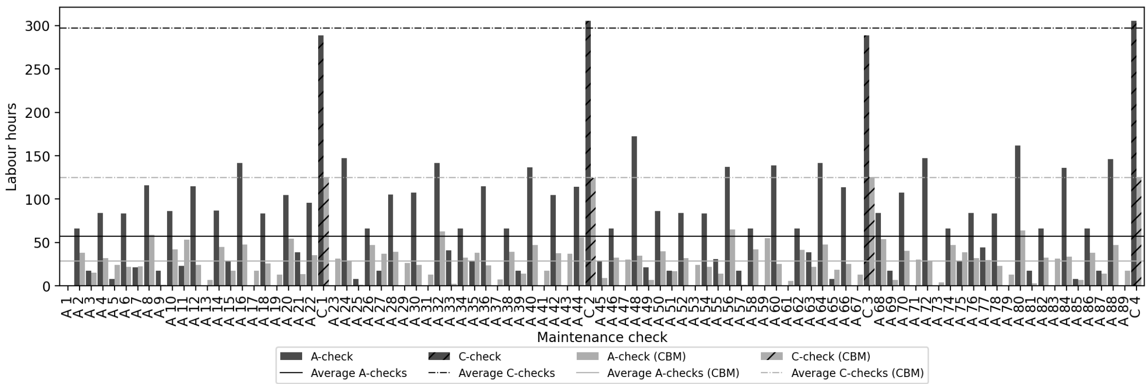

Figure 9: Results for one aircraft (scenario 2, check interval of 750 FH)

The same analysis was done for a check interval of 750 FH, for which the results are presented in Figures 8 and 9. CBM scenario 1 is compared to preventive maintenance in Figure 8, scenario 2 in Figure 9. The average results are then tabulated in Table 5.

Table 5: Average labour hours per check, check interval of 750 FH

	Baseline	**CBM 1**	**CBM 2**
A-check			
Total (TS/IE)	57 (34/23)	44 (23/21)	29 (13/16)
C-check			
Total (TS/IE)	297 (279/18)	212 (194/18)	125 (110/15)

In terms of scheduled maintenance, condition-based maintenance comes with considerable benefits, especially for those tasks that are inspection-related. Due to this inspection-related nature, a properly functioning PHM system could replace tasks of this type, at least partially, resulting in a decrease in the number of tasks, and thus labour hours still required at the actual block checks. The rate at which these tasks can be replaced largely depends on the performance and reliability of the PHM system, but the reduction in labour hours for tasks of this category is apparent in each scenario.

For the other type of tasks, those for which CBM enables interval escalation, the simulation results show that in order to benefit from CBM, better prognostics performance levels are required. The benefits for a realistic CBM scenario (scenario 1), are relatively limited, with a reduction in labour hours of only 7.5 % compared to a 32 % for the TS category. Only in a more optimistic CBM scenario, the effect of interval escalation becomes significant, with a reduction in average labour hours for an A-check of around 28 %.

With an interval of 750 FH between periodic checks, the reductions in labour hours per maintenance check due to interval escalation become slightly more pronounced. In a realistic CBM scenario, a reduction of almost 9 % can be reached on average, whereas for an optimistic scenario this can reach up to 30.5 %. This slight increase is expected, as with lower check intervals it is easier to actually extend the interval of a certain task due to an increased number of maintenance slots available.

Additionally, for C-check tasks of this type, very little benefit can be achieved, and only with relatively good prognostic performance. This can be explained by the fact that in this model, it is assumed that these tasks can only be executed at C-checks together with other C-check tasks. With the interval between consecutive C-checks being so large, for a single task to be deferred to the next C-check, its interval should be escalated by a substantial factor.

5.2 Case study 2

In this study, benefits are evaluated in three different areas: operational reliability, fleet availability and maintenance cost. Operational reliability is measured as the number of Aircraft on Ground (AOG) situations per aircraft per year; fleet availability correlates with the number of maintenance slots used per aircraft per year; and maintenance cost is expressed as the combination of repair, replacement and troubleshooting cost.

Figure 10 compares the changes in operational reliability, fleet availability and maintenance cost for the compressor for PHM systems with different performance levels. Similar plots are constructed for the cooling unit (Figure 11) and the electrical generator (Figure 12).

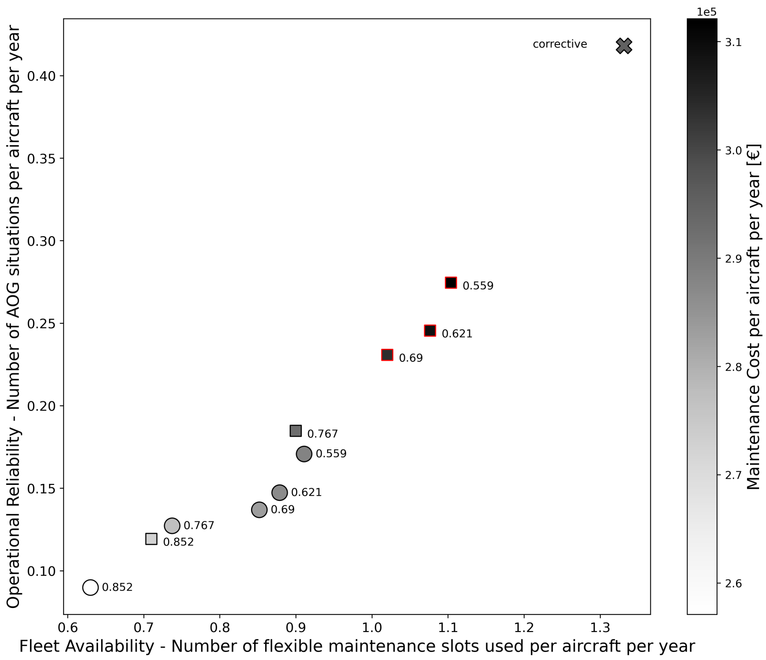

Figure 10: Comparison of different PHM performance levels for maintenance strategies using fixed failure thresholds and dynamic failure thresholds for the compressor. The squares correspond to fixed failure thresholds, the circles to dynamic failure thresholds. The red borders indicate that the CBM strategy is less cost effective than corrective maintenance.

For all three subsystems, the use of prognostics brings better operational reliability (less AOG situations) and better fleet availability (less maintenance slots required) no matter the prognostic performance. This is in line with what is expected, as the use of prognostics reduces the number of failed components and thus the amount of maintenance that needs to be scheduled without notice.

For the compressor, the number of AOG situations can be reduced up to 79 %, and the use of maintenance slots can be decreased by 53 %, with a cost reduction of 11.7 %. With the same prognostic performance, but for the electrical generator, AOG situations can be reduced by 48 % and the use of maintenance slots by 37 % at a cost reduction of 0.7 %; for the cooling unit, reductions of 71 % and 52 % can be achieved in AOG situations and number of maintenance slots, respectively, together with a 6.1 % decrease in maintenance cost. Note that for the electrical generator and the cooling unit, the benefits in availability and operational reliability are achieved by a fixed failure threshold, and for the compressor maximum benefit comes from the use of dynamic failure thresholds. Furthermore, it is clear from Figure 10 that with the same prognostic performance, the maintenance strategy using dynamic failure thresholds outperforms the one using fixed thresholds in all three

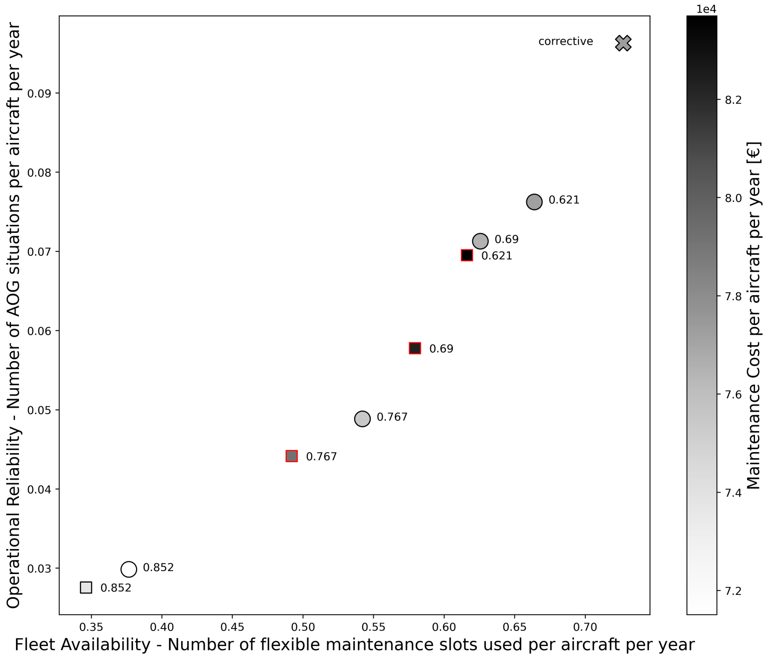

Figure 11: Comparison of different PHM performance levels for maintenance strategies using fixed failure thresholds and dynamic failure thresholds for the cooling unit. The squares correspond to fixed failure thresholds, the circles to dynamic failure thresholds.The red borders indicate that the CBM strategy is less cost effective than corrective maintenance.

areas of improvement (availability, operational reliability and maintenance cost).

Using the dynamic thresholds strategy, the use of prognostics is deemed beneficial for all performance levels investigated in this study, resulting in lower maintenance cost, better availability and more reliable operation. On the other hand, the fixed failure thresholds approach succeeds in improving availability and operational reliability, however, reducing the prognostic performance to AUC = 0.69 or lower increases the associated maintenance cost beyond what is achieved with corrective maintenance.

For the cooling unit (CU) and the electrical generator (EG), a remarkable difference is observed compared to the compressor. While the use of dynamic thresholds still reduces maintenance cost compared to a fixed thresholds strategy with the same prognostic performance, it is inferior in terms of availability and operational reliability. For the cooling unit, the use of PHM with dynamic thresholds is beneficial for all performance levels; with a fixed failure threshold, a cost reduction is only possible with a prognostic performance corresponding to an AUC of 0.852.

The electrical generator, which was initially expected to be less suited for condition-based maintenance, showed so in the results. Due to the dynamic thresholds determined beforehand for the baseline performance (AUC = 0.852) not suggesting the use of PHM for a large part of its useful life, a better performing PHM system (AUC = 0.897) was included for analysis. This turned out to be the only performance level that for both fixed and dynamic failure thresholds resulted in benefits in all three areas of improvement. A PHM system with AUC = 0.852 only achieved a cost reduction in combination with dynamic failure thresholds. All other performance levels did not achieve cost reductions and are thus not beneficial.

Based on the outcome of this first case study, the most conservative prognostic performance levels were determined. The chosen PHM system should be able to bring improvements in all three categories (i.e., availability, reliability and cost) and CBM strategies using fixed and dynamic failure thresholds. This yielded the following AUC characteristics for the ROC curves:

- COMP: AUC = 0.767
- CU: AUC = 0.852
- EG: AUC = 0.897

Figures 10 to 12 already show evidence of significant benefits associated with condition-based maintenance. Especially for the compressor, large benefits can be obtained in all three areas of investigation (operational reliability, fleet availability and maintenance cost). Operational reliability and fleet availability are improved regardless of prognostic performance. This can be explained by the fact that when prognostic information is available, component failures can be anticipated and faulty components can be replaced at convenient times.

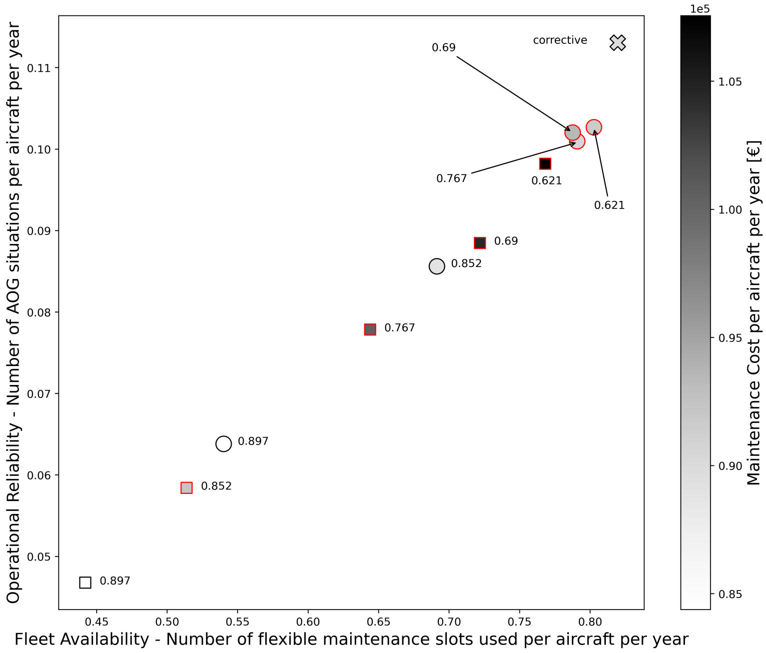

Figure 12: Comparison of different PHM performance levels for maintenance strategies using fixed failure thresholds and dynamic failure thresholds for the electrical generator. The squares correspond to fixed failure thresholds, the circles to dynamic failure thresholds.The red borders indicate that the CBM strategy is less cost effective than corrective maintenance.

In terms of maintenance cost, condition-based maintenance does not always have a positive impact. The use of PHM in combination with the dynamic thresholds strategy results in cost savings for all performance levels considered in this study. However, a fixed failure threshold is not always beneficial in terms of maintenance cost: a PHM system with an ROC curve with an AUC lower than 0.69 comes with higher maintenance cost than can be obtained with corrective maintenance. A possible explanation for this result is the higher rate of False Positives (FP's) resulting from a less accurate failure prediction.

With the results for the compressor in mind, the findings for the CU and the EG are somewhat counter-intuitive. Here, a fixed failure threshold is superior to dynamic thresholds in terms of availability and operational reliability. A possible explanation for this can be found in the failure behaviour, characterised by a Weibull distribution with a shape parameter closer to one, meaning a higher risk of early life failures and often less suited for preventive maintenance [Jiang and Murthy, 2011][Kay, 1976]. In addition to this, with the dynamic thresholds approach, it was determined not to use prognostics in the earliest periodic checks, therefore not detecting a more significant part of failed components. On the other hand, this is not so unexpected as the dynamic thresholds module optimises maintenance cost without considering operational reliability or availability. This is in line with the results, as the dynamic thresholds strategy outperforms the one with fixed thresholds in terms of cost and can therefore often be identified as the strategy of choice for many airlines.

It is clear that the benefits of prognostics are more pronounced in the compressor and the cooling unit. For these systems, aircraft availability, maintenance cost and operational reliability experience more significant improvements compared to the electrical generator. The shape factor of the Weibull failure distribution is expected to be the main cause. Where the electrical generator has a shape parameter of 1.116, wear-out failure behaviour is less pronounced and failure is more randomised, and the risk of early-life failures is higher [Jiang and Murthy, 2011]. A more specific investigation on the effect of the shape parameter could provide conclusive proof for this phenomenon.

5.3 Case study 3

Now that acceptable prognostic performance levels have been established, benefits associated to the scalability of CBM can be assessed. This is done by gradually increasing the number of systems under consideration. Simulations were done only for a PHM system with an associated ROC where AUC = 0.767 for the compressor, AUC = 0.852 for the cooling unit, and AUC = 0.897 for the electrical generator, as these were found to be the most conservative PHM performance still beneficial in terms of operational reliability, availability and maintenance cost. For this purpose, simulations are done on a single aircraft and per subsystem type.

Figure 13 presents the relative net benefit of two CBM strategies compared to purely corrective maintenance

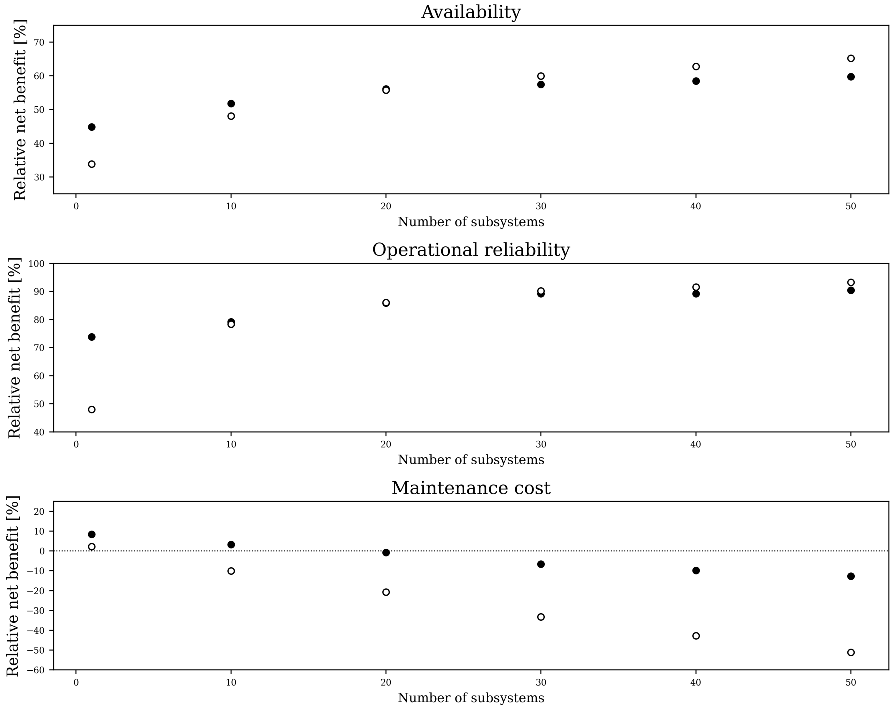

Figure 13: The relative net benefit of condition-based maintenance w.r.t. corrective maintenance for a varying number of subsystems of the same type as the compressor (COMP). The white dots on the plot correspond to fixed failure thresholds, the black dots to dynamic failure thresholds.

for an increasing number of subsystems of the same type as the compressor.

For the compressor, increasing the number of subsystems led to better availability and operational reliability compared to corrective maintenance, as can be seen in Figure 13. This observation is not surprising, as a high number of subsystems under corrective maintenance requires a large amount of maintenance actions within short notice. The effect of using prognostics to detect impending failures and replace components at more convenient times is therefore amplified, resulting in a larger difference in AOG situations and required maintenance slots between corrective and condition-based maintenance. On the other hand, the relative net benefit concerning maintenance cost that is achieved by condition-based maintenance is decreasing with increasing number of subsystems, and even drops below zero, indicating no benefit compared to corrective maintenance. In terms of cost, the maintenance strategy using dynamic failure thresholds performs significantly better than the one using fixed failure thresholds, with a loss of 12 % compared to 51 % achieved with a fixed threshold in the most extreme scenario with 50 subsystems.

This decline in cost-effectiveness of CBM for a larger number of subsystems comes from a substantial increase of the number of component replacements. In an aircraft with a larger number of components, more failures occur and therefore more maintenance events are required. Subsequently, because there are more maintenance events, prognostics is applied more often and preventive replacement of components takes place more frequently. This phenomenon has two consequences that could explain the growing disadvantages concerning maintenance cost. Firstly, with a higher number of preventive replacements comes a higher number of false positive replacements. This unnecessarily causes higher maintenance costs and this effect is increasing together with the number of components present in an aircraft. Secondly, the failure thresholds are optimised for a certain check interval. Due to more frequent maintenance visits for aircraft comprising multiple subsystems, this check interval decreases drastically, affecting the optimality of the predetermined failure thresholds and causing more preventive replacements than originally accounted for.

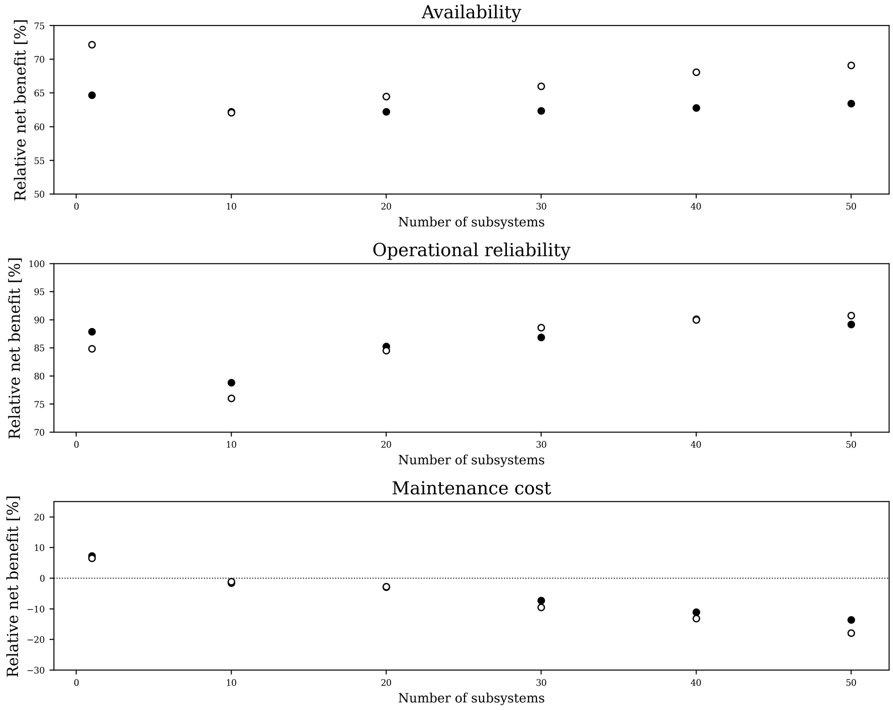

Figure 14: The relative net benefit of condition-based maintenance w.r.t. corrective maintenance for a varying number of subsystems of the same type as the cooling unit (CU). The white dots on the plot correspond to fixed failure thresholds, the black dots to dynamic failure thresholds.

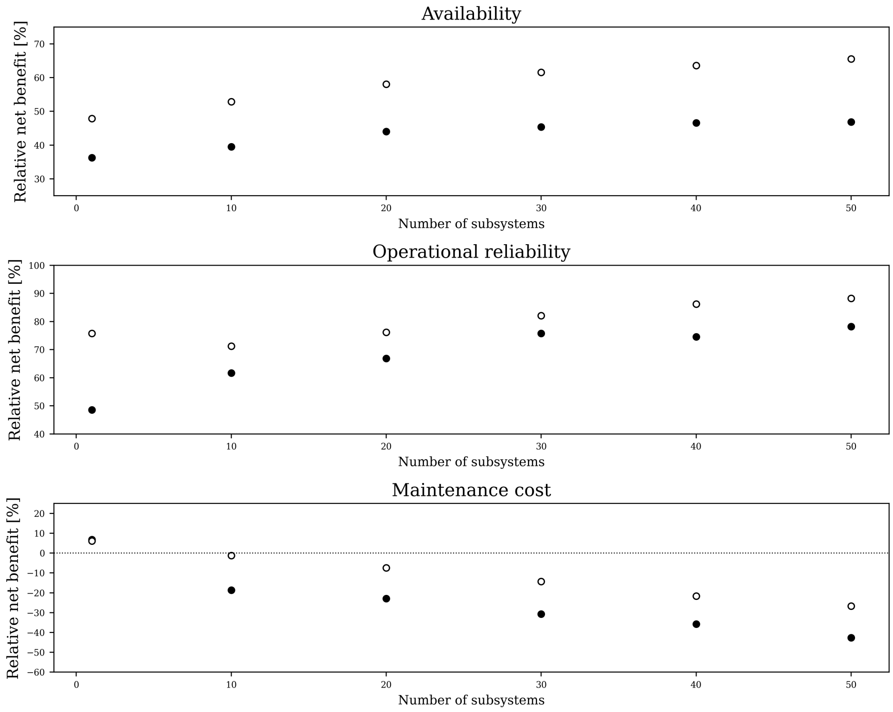

Figure 15: The relative net benefit of condition-based maintenance w.r.t. corrective maintenance for a varying number of subsystems of the same type as the electrical generator (EG). The white dots on the plot correspond to fixed failure thresholds, the black dots to dynamic failure thresholds.

For the cooling unit (Figure 14), an upwards trend can be observed again in terms of availability and operational reliability. However, the strategy using dynamic failure thresholds has a more constant performance regarding availability compared to fixed thresholds approach. For the electrical generator (Figure 15), the general trend is again upwards in terms of availability and operational reliability, and decreasing in terms of maintenance cost.

For the cooling unit and the electrical generator, similar trends as for the compressor can be observed in Figures 14 and 15. The results for the cooling unit show less differences in terms of maintenance cost between a maintenance strategy using fixed failure thresholds and one using dynamic thresholds, which is the expected result considering the results in Figure 11, where the performance of the two strategies for a PHM system operating with an ROC curve with AUC = 0.852 was shown to be comparable. For the electrical generator, when increasing the number of subsystems, the fixed failure thresholds strategy is more beneficial. This is partly explained by the fact that the dynamic thresholds are not optimised for the frequency of maintenance checks arising from the increased number of subsystems, therefore favouring the fixed thresholds strategy operating at a low TPR and FPR combination. Additionally, this is in line with Figure 12, where a fixed failure threshold achieved better fleet availability and operational reliability at a similar maintenance cost.

5.4 Case study 4

In this final case study, an analysis was performed to investigate the effectiveness of prognostics with a block check interval of 750 FH. In Figure 16, the relative net benefit of CBM compared to corrective maintenance is shown for periodic check intervals of 1500 and 750 FH.

Significant benefits for operational reliability and availability can be observed for both check intervals, with improvements of the operational reliability ranging from 55-66 % and a 36-50 % increase in availability. In terms of maintenance cost, with a maintenance approach using dynamic failure thresholds, cost savings of 5.2 % can be reached in case of a check interval of 750 FH, compared to a cost reduction of 6.9 % with a check interval of 1500 FH. Benefits associated with fixed failure thresholds are minor, with only a 0.8 % cost reduction for a check interval of 1500 FH and a 13 % increase in cost with an interval of 750 FH.

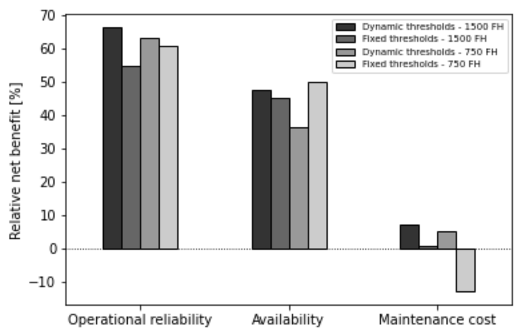

Figure 16: The relative net benefit of condition-based maintenance w.r.t. corrective maintenance for a periodic check interval of 1500 FH compared with an interval of 750 FH.

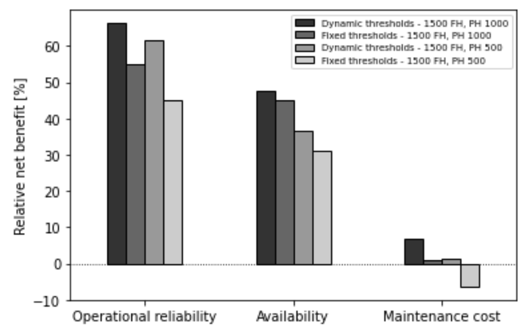

Figure 17: The relative net benefit of condition-based maintenance w.r.t. corrective maintenance for a periodic check interval of 1500 FH with a PHM system with prognostic horizon of 1000 FH compared to a prognostic horizon of 500 FH.

Finally, Figure 17 shows the difference in effectiveness of a PHM system with a prognostic horizon of 1000 FH compared to one with a prognostic horizon of 500 FH, with a periodic check interval of 1500 FH. A decline in effectiveness can be observed when the prognostic horizon is decreased.

With a decreased check interval, condition-based maintenance could still be an attractive alternative to corrective maintenance, especially considering the use of dynamic failure thresholds. Moreover, a PHM system with a smaller prognostic horizon could particularly benefit from a lower check interval.

6 Conclusion & Recommendations

The results presented in this paper suggest wide-ranging benefits for condition-based maintenance as an alternative to the combination of preventive and corrective maintenance. A first benefit is found in the reduction of maintenance time, with a positive effect on the availability of an aircraft. The duration of periodic checks can be reduced by 22-49 % for an A-check and 28-57 % for a C-check, depending on the efficacy of the PHM system. This is mainly realised by substituting tasks by a PHM system, but with sufficient performance of the PHM system, could also stem from interval escalation of several types of tasks. This could allow for more flight time per aircraft, aside from the scheduling benefits it can bring. A shorter maintenance block can be easier to fit in an aircraft's flight schedule and thus increase availability even further. Nonetheless, the results should be interpreted carefully and the assumptions that were made should not be neglected.

In the simulation of scheduled maintenance, prognostics is not modeled on task level and tasks are scheduled according to their deadline without considering task dependencies and which tasks should be executed together.

This has a notable effect on the composition of maintenance blocks, especially for a maintenance strategy with more frequent block checks. Where maintenance blocks in practice have an almost equal number of man-hours to be filled, in this simulation model maintenance blocks are less equalised.

Besides the reduction of periodic check durations, aircraft availability was shown to be improved by the lower number of maintenance slots required for unscheduled maintenance, by detecting faults in advance and replacing faulty components preventively. Similarly, a reduction in unscheduled maintenance actions causing AOG situations was observed, showing the potential of condition-based maintenance to improve the operational reliability of aircraft. Even at relatively low performance levels of the PHM system, the use of prognostics could realise enhanced availability and operational reliability.

Moreover, benefits in terms of maintenance cost can be achieved, given adequate performance levels of the PHM system. This benefit diminishes when the number of subsystems increases, and even becomes loss-making. The extent to which cost reductions are possible is heavily dependent on subsystem characteristics (i.e., failure behaviour and cost of preventive and corrective maintenance) and prognostics performance.

Due to a lack of subsystem data on a large scale, only three subsystems were considered for analysis. However, the obtained results can be generalised to other subsystems that have similar failure behaviour and a similar ratio of the cost of a preventive replacement and a corrective replacement. During this research, better results were observed for systems with a higher Weibull shape parameter, however, it could be interesting to investigate the effect of the Weibull shape and scale parameters on the effectiveness of prognostics to provide more conclusive proof regarding this observation. Also, in this study, only systems with similar ratios of preventive/corrective cost were considered, while in practice these ratios are more dissimilar among subsystem types. More research is necessary to conclusively determine the relation between the effectiveness of prognostics and these ratios.

Furthermore, in future research, the effects on availability and operational reliability could be modeled in more detail. In this study, the exact conflicts with an aircraft's flight schedule due to a maintenance opportunity are not specified. A maintenance action can conflict with the flight schedule, or it can be executed during non-commercial time. Therefore, in order to estimate benefits on operational reliability, this study assumes an AOG situation to take place whenever a maintenance slot is necessary outside the predefined flexible maintenance slots. It is important to note that the duration of AOG situations is not estimated in the simulation. The duration of an AOG situation influences the impact on operational reliability, so, while the absolute number of AOG situations can serve as an estimate for the impact on operational reliability, more specific results could be obtained when the duration of such event is taken into consideration as well.

Finally, the availability of flexible maintenance slots could be considered in the determination of the dynamic failure thresholds and the supply chain could be taken into account for the decision to replace a component preventively. For example, when there is a spare component available for a certain subsystem for which the failure threshold has not been exceeded, it might be interesting cost-wise to replace that component anyway to minimise holding costs, knowing that the component approaches its end of life. Similarly, the lead time to order a component can be considered: when a component is expected to fail, but the lead time to order a replacement is high, it could be more advantageous to wait until failure before scheduling the replacement.

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Appendices

A Appendix 1: MILP formulation unscheduled maintenance

Objective function:

$$\begin{gathered}\min \sum_{a\in A}\sum_{s\in S(a)}\sum_{c\in C(s)}\sum_{k\in K}\left(d_s + p_{a,s,c}\cdot\left(t_{deadline}-t_k\right)\right)x^k_{a,s,c} + \sum_{a\in A}\sum_{k\in K} w_{fixed}\cdot y^k_a + \\ \sum_{a\in A}\sum_{s\in S(a)}\sum_{c\in C(s)}\left[\left(w_{fixed}+w_{unsch}\right)\cdot x^{unsch}_{a,s,c} + \left(d_s + w_{fixed} + p_{a,s,c}\cdot\left(t_{deadline}-t_k\right)\right)\cdot x^{defer}_{a,s,c} + w_{aog}\cdot z^{aog}_{a,s,c}\right]\end{gathered} \tag{9}$$

s.t.

$$\sum_{k\in K} r^k_{a,s,c}\cdot x^k_{a,s,c} + s_{a,s,c}\cdot x^{unsch}_{a,s,c} + \left(1-s_{a,s,c}\right)x^{\text{defer}}_{a,s,c} = 1 \quad \forall a\in A, \forall s\in S(a), \forall c\in C(s) \tag{10}$$

$$\sum_{k\in K} t_k\cdot x^k_{a,s,c} + M\cdot x^{\text{defer}}_{a,s,c} + M\cdot z^{aog}_{a,s,c} \geq t_{\text{now}} + t^{a,s,c}_{\text{lead}} \quad \forall a\in A, \forall s\in S(a), \forall c\in C(s) \tag{11}$$

$$\sum_{s\in S(a)}\sum_{c\in C(s)} x^k_{a,s,c} - M\cdot y_{a,k} \leq k_{tasks} \quad \forall a\in A, \forall k\in K \tag{12}$$

$$\sum_{s\in S(a)}\sum_{c\in C(s)} p_{a,s,c}\cdot x^k_{a,s,c} - M\cdot y_{a,k} \geq 1 - M - k_{tasks} \quad \forall a\in A, \forall k\in K \tag{13}$$

$$\sum_{a\in A}\sum_{s\in S(a)}\sum_{c\in C(s)} d_s\cdot x^k_{a,s,c} \leq a_k \quad \forall k\in K \tag{14}$$

Decision variables:

$x^k_{a,s,c}$	1 if component c of subsystem s of aircraft a is replaced at opportunity k, else 0
y^k_a	1 if aircraft a uses opportunity k, else 0
$x^{unsch}_{a,s,c}$	1 if component c of subsystem s of aircraft a is replaced unscheduled, else 0
$x^{defer}_{a,s,c}$	1 if replacement of component c of subsystem s of aircraft a is deferred, else 0
$z^{aog}_{a,s,c}$	1 if replacement of component c of subsystem s of aircraft a requires an AOG order, else 0

Coefficients:

w_{aog}	$(d_{fixed} + w_{unsch})$
w_{unsch}	penalty for requiring an unscheduled maintenance opportunity (=10000)
w_{fixed}	penalty for requiring an extra maintenance opportunity (=100)
d_s	swap duration
$p_{a,s,c}$	priority of replacing component c of subsystem s of aircraft a
$t_{deadline}$	MEL deadline
t_k	time of opportunity k
a_k	time available at opportunity k

Sets:

A	set of all aircraft
S(a)	set of all subsystems of aircraft a
C(s)	set of all components of subsystem s
K	set of all maintenance opportunities

II

Literature Study
previously graded under AE4020

1
Introduction

Aircraft Maintenance, Repair and Overhaul (MRO) expenditures were estimated at $69 Billion in 2018, representing around 9% of airlines operational costs and are expected to reach $103 Billion in 2028 [25]. Therefore, the efficiency and quality of the maintenance process is of paramount importance for an airline operator. Currently, the standard maintenance strategy combines preventive and reactive maintenance. Preventive maintenance is often carried out at fixed time intervals, having the advantage of a fixed maintenance schedule and high reliability due to conservative time intervals, but at the inevitable cost of wasting part of the useful life. Reactive maintenance on the other hand is performed when a part is damaged, exploiting the entire useful life, but resulting in unexpected downtime and generally higher maintenance costs.

A new trend and promising solution to improve efficiency is condition-based maintenance (CBM). Condition-based maintenance is a maintenance strategy aiming to maintain systems right before failure using information about the actual condition of the systems, in order to keep reliability high and operating costs low [46]. The constant collection of sensor information allows to monitor the health of structural elements and systems, facilitating the prognostics and diagnostics of potential failures and to schedule maintenance before the failure happens. A trade-off has to be made between the risk of failure during operation (leading to costly downtime) and the cost of premature maintenance (wasting remaining useful life of the system or component) [46]. An extension of condition-based maintenance is predictive maintenance, where prognosis is employed to predict the future health and estimate the remaining useful life (RUL) of a system or a structural component [41]. Condition-based maintenance has two main components: prognostics and health management (PHM), focused on RUL estimation; and post-prognostics decision-making, which relies on the prognostics output (RUL) for decision-support [50]. Effective prognostics & health management can change unscheduled maintenance to scheduled maintenance by planning a scheduled maintenance event before the estimated end-of-life [11], but also allows to skip unnecessary scheduled maintenance if no safety-threatening condition is observed [47].

Even though the technology is catching up, there is still a lot to accomplish in order to see CBM as the industry standard. First of all, in order to further stimulate developments of practical applications of CBM, it should be associated to an increase in earning potential through a proper cost-benefit analysis, and more importantly, it should be investigated to which components CBM would be beneficial and to what extent CBM can be implemented. Furthermore, certification requirements should be in place. Progress is being made in this area: MSG-3 methodology has been updated to allow aircraft health monitoring as an alternative to the classic scheduled maintenance task [48]. Finally, a large part of the challenge is to apply CBM technology to different structures and systems and to adapt the maintenance processes and decision-making philosophy accordingly [22].

This literature review provides an overview of the current state-of-art in condition-based maintenance and focuses on the impact CBM can have on aircraft maintenance. An attempt is made to pool relevant literature in order to investigate the potential value of CBM. The structure of this literature review is as follows. In chapter 2, the state-of-the art in Prognostics and Health Management (PHM) is explored and different performance metrics are outlined. Maintenance scheduling models using prognostic information are then discussed in chapter 3. Next, chapter 4 introduces various cost-benefit analysis models and finally, in chapter 5, conclusions are drawn and the research objective is formulated.

2

Prognostics and Health Management for predictive maintenance

One of the major building blocks of a good condition-based maintenance (CBM) framework is the Prognostics and Health Management (PHM) system. This includes fault detection, diagnostics, prognostics and health management. Whereas diagnostics concerns identifying and quantifying damage that has already transpired, prognostics goes on e step further and tries to predict damage that is yet to occur. In condition-based maintenance, prognostics usually concerns the process of Remaining Useful Life (RUL) estimation of systems or components [41]. There exists research that uses RUL in a deterministic form [37][28], but the majority of research is based on stochastic RUL estimation, where the remaining life is given as a distributed random variable [12][10][24][7][44][15].

Generally, prognostics can be classified into three different approaches [41]:

- Statistics-based
- Data-driven
- Physics-based

All of these approaches have their advantages and disadvantages, as pointed out in Figure 2.1.

Approach	Advantages	Disadvantages
Statistics-based	Simple and easily applicable to other components	Not accurate and difficult to apply to new components
Data-driven	Quick implementation, low cost, and useful even if degradation is unknown	Large amounts of (useful) data necessary and thus difficult to apply to new components
Physics-based	Very accurate and specific	Applicability, time consuming and expensive

Figure 2.1: Different prognostics approaches and their main advantages and disadvantages [41]

Other than these three approaches, hybrid methods also exist. For example, Koops [26] has developed a hybrid data-driven/physics-based approach and showed its superiority compared to a conventional physics-based approach for aircraft unexpected engine removals [26].

2.1. Performance metrics

Various metrics exist to evaluate the performance of a prognostic algorithm. Uncertainties and prognostic performance levels can be considered by assessing the probabilities of false prognoses (false positives) and missed failures (false negatives). A false positive (FP) is when the prognostic system detects an impending failure early or when no failure is impending. A false negative (FN) on the other hand represents a missed failure: the prognostic system fails to detect an impending failure or detects it late [24]. True Positives (TP) and True Negatives (TN) then complete the four potential outcomes.

Going one step further, the True Positive Rate (TPR) and the False Positive Rate (FPR) can be defined as $TPR = TP/P$ and $FPR = FP/N$, where P and N denote the actual positives and negatives. True Negative Rate (TNR) and False Negative Rate (FNR) are given by $TNR = 1 - FPR$ and $FNR = 1 - TPR$. All rates can thus be expressed in terms of FPR and TPR, allowing for construction of the so-called Receiver Operating Characteristics (ROC) curve. The ROC curve captures all possible combinations of correct and incorrect predictions and can be directly related to cost-benefit analysis as can be seen in Figure 2.2 [26].

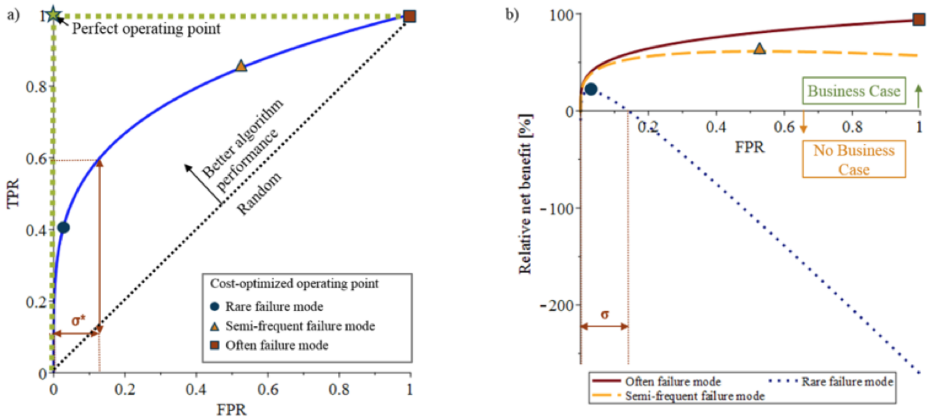


Figure 2.2: The ROC curve (a) and its relation to cost-benefit analysis (b) allowing for algorithm performance evaluation and optimization and finally, for identification of business cases with net relative benefit [26]

In Koops [26],the ROC curve was used to identify optimal prognostics performance levels in terms of false positive rate. For different failure modes, the optimal operating point on the ROC curve was identified from an economic point of view and associated to its relative net benefit. These points are indicated in Figure 2.2 for a rare, semi-frequent and often failure mode.

Each point on the ROC curve coincides with a different decision threshold above which the prediction is rated as positive (i.e. failure), illustrated in Figure 2.3 [26].

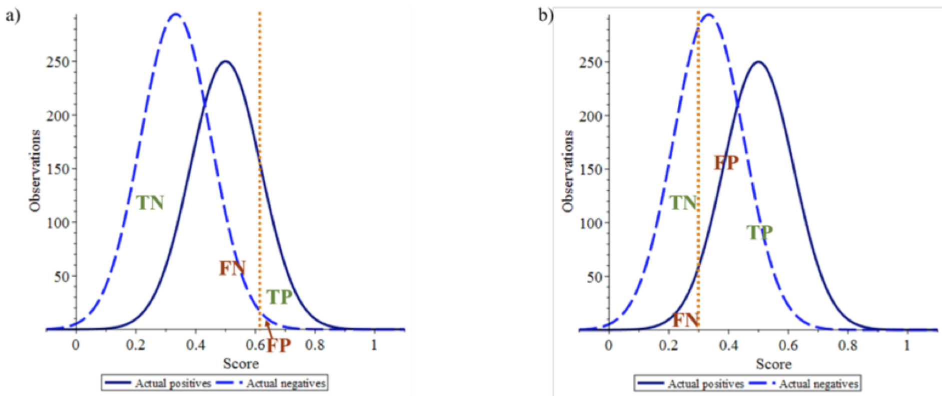


Figure 2.3: Distributions of actual positives (solid) and negatives (dashed) as a function of score, with (a) a rather strict decision threshold leading to fairly low FPR and TPR and (b) a rather lax decision threshold leading to fairly large FPR and TPR [26]

The ROC curve is also used by Nicchiotti and Ruëgg [36], who evaluate the performance of their prognostics algorithm using Precision and Recall metrics, defined as [36]:

$$P = TP/(TP + FP) \tag{2.1}$$

$$R = TP/(TP + FN) \tag{2.2}$$

Note that Recall corresponds to the True Positive Rate (TPR) and Precision is the percentage of correct prognostic alerts. The performance of the method is also evaluated by looking at the Area Under Curve (AUC) of the ROC curve, measuring the algorithm's discriminability between positive and negative instances. A large AUC is desired, as this allows for an operating point on the ROC curve where TPR is close to one and FPR close to zero [36].

Numerous researches also study the Prognostic Horizon (PH) or Prognostic Distance (PD) as a performance metric for prognostic algorithms [28][17][12]. The prognostic Horizon is the difference between the current time and the time when the prediction has crossed the failure threshold, utilizing data up to the current time and provided the prediction meets desired specifications; i.e. how long before system failure the prognostic algorithm can indicate failure with sufficient accuracy [39]. Fritzsche et al. [17] study the impact of Prognostic Distance on maintenance cost and propose a model to determine the optimal prognostic distance to minimize the total maintenance cost [17].

2.2. PHM frameworks

One of the main research topics in CBM is the development of a PHM framework for degradation modelling and RUL prediction. In the last decade, this has been researched by many different authors, resulting in numerous prognostics models for various aircraft systems and structures and using different types of data and algorithms.

An increase in availability of operational data and processing power led to the current popularity of data-driven prognostics approaches. Data-driven models rely on machine learning techniques to construct predictive models from operational and maintenance data [36]. According to Wen et al. [49], two of the most popular types of data-driven models are general path models and stochastic process models. The former is based on the idea of using parametric regression to capture the temporal evolution of the degradation signal. This type of model is relatively simple, and theories are well-established, but the degradation path is deterministic and therefore is not capable of capturing the temporal uncertainties inherent in the degradation process. This unexplained randomness is where stochastic process models come through. Examples of stochastic process models are the Gamma process, the inverse Gaussian process and Wiener process [49].

Altay et al. [3] developed a data-driven model, aiming to predict aircraft failure times taking into account aircraft type and age, using two methods using an artificial neural network (ANN) algorithm: backpropagation (BP) and genetic algorithms (GA). An advantage to this approach with ANN is that no assumptions are required, and historical data can easily be transformed into future estimates. The main drawback to this study is that the authors look at predicting general failure of the aircraft itself and not specifically at failures on component level, resulting in maintenance times but without an indication of where the fault takes place. This of course limits the usability of the model, especially in commercial aviation as it is imperative to know the location of any fault and not just whether a failure will occur or not [3].

A paper by Che et al. [8] presents a PHM model combining multiple deep learning algorithms for condition assessment, fault classification, sensor prediction and remaining useful life (RUL) estimation of aircraft systems. The broad scope of what this PHM model can achieve using multiple deep learning algorithms allows for accurate health management, which is important especially with the increasing complexity of aircraft. The model is tested on a dataset simulated with aircraft engine sensors, which consists of multiple multivariate time series and simulates fault modes including High Pressure Compressor (HPC) degradation and fan degradation. It is shown that the model has more accurate prediction and diagnosis results than traditional time series prediction models in dealing with multivariate time series of aircraft data [8].

Not all aircraft systems can be characterized by the same degradation behavior, therefore, different models for each system using different assumptions can account for these dissimilarities. Sun et al. [42] have developed a Bayesian failure prognostics approach for predictive maintenance of the aircraft Air Conditioning system (ACS). This method has been verified and shown to produce satisfactory prognostic output, where all the ACS failure precursors are identified and the relative errors for failure time prediction made are less than 8%, enabling proactive planning of future maintenance [42]. A method designed in Muller et al. [34] predicts failures in Boeing 747-8 hydraulic pump systems, having severe financial consequences should they be replaced in a context of unscheduled maintenance. This was done by means of a data processing approach based on Spatial-Temporal Density-Based Spatial Clustering of Applications with Noise (ST-DBSCAN), capable of detecting subtle changes in the hydraulic pump system of the Boeing 747-8. Notably, the authors show the importance of expertise in the involved physics for the preparation of the data [34].

This leads to the question whether incorporating the underlying physics into a data-driven prediction model could be beneficial. Indeed, Haider [20] showed that a hybrid physics-based / data-driven model can improve accuracy in a PHM system for the landing gear shock absorber, positively influencing maintainability safety, logistics, lifecycle costs, reliability and functionality. Especially if high accuracy is a critical factor, a physics-based approach proves to be advantageous [20]. It is also demonstrated by Koops [26] that a hybrid physics-based / data-driven approach obtains superior prediction performance compared to a pure physics-of-failure-based approach for aircraft engines, particularly for events caused by High Pressure Turbine (HPT) blade failures [26].

Another research topic that is gaining attention lately is the Proportional Hazard Model, which due to their ability to incorporate both event and condition monitoring data are considered popular survival analysis models [4]. Azar and Naderkhani [4] propose a time-dependent Proportional Hazard Model augmented with a semi-supervised machine learning approach for optimizing CBM decisions. Verhagen and De Boer [43] investigate the role of operational factors in the probability of occurrence of a maintenance event. The authors identified operational factors affecting component reliability and subsequently use statistical models incorporating these operational factors as covariates (the time-dependent and time-independent Proportional Hazard Model) to generate reliability estimates, aiming to reduce the number of unscheduled maintenance events. This technique is made possible partly by the increased storage and availability of sensor data to characterize operational conditions during flight. According to the authors, the proposed method is applicable to any component for which failure times, censored event and operational data is available. Moreover, it was found that in general, either of the proposed models (time-independent and time-dependent PHM models) do outperform time-based models. While the concept and results of this research are promising, follow-on research could enhance the validity of this method. Especially, validation should be done using a separate set of maintenance event data to show its applicability to real-life decision-making [43].

Operational factors leading to unit-to-unit heterogeneity, as well as time-varying dynamics or random effects of imperfect repair can also be modeled in stochastic degradation processes such as the Wiener process [27]. For instance, Wen et al. [49] propose a multiple change-point Wiener process as a degradation model for RUL prediction, utilizing a Bayesian approach to account for between-unit heterogeneity. This model is especially useful in degradation processes showing two or more distinct phases in the degradation path. Examples of these processes include automotive lead-acid batteries first degrading slowly and then evolving rapidly after the system has degraded to a certain level, or the vibrational signal in bearings, where two distinct phases can be easily observed. The proposed model was applied to a case study of rotational bearings, where it was demonstrated that the prognostic framework can effectively improve the RUL prediction accuracy [49].

In contrast to CBM-based maintenance models that assume known failure distributions (i.e. estimated from historical observations or expert's knowledge) that remain fixed during the maintenance decision process, several studies use Bayesian updating methods to update posterior distributions of unknown failure parameters. Shi et al. [40] investigate the use of prognostic information in maintenance decisions for complex multi-component system. Using a rolling-horizon approach, a condition-based maintenance decision-framework is developed, leveraging multi-source dynamic information, e.g. online deterioration data and environmental conditions, to update unknown degradation parameters using a Bayesian approach. The predictive system reliability is computed and triggers preventive maintenance when it is below the requirement. Furthermore, a dynamic-priority-based heuristic algorithm seeks the optimal maintenance grouping using a rolling-horizon approach, such that maintenance decisions are repeatedly optimized whenever new information becomes available [40].

Another prognostics approach for multi-component systems is described by Walter and Flapper [46]. Here, the authors obtain a predictive distribution for the system survival time, based on which of the system's components currently function or not, and the age of the functioning components. In contrast to conventional CBM policies based on a continuous degradation signal e.g. amount of vibration of rotating equipment, this method uses the status of the system's components (working/not working) and the reliability block diagram to calculate the residual life distribution (RLD). An advantage of this approach is that the authors include the ageing of components and possible failures in the determination of the cost-optimal moment for replacement by modelling the time to failure of components by a Weibull

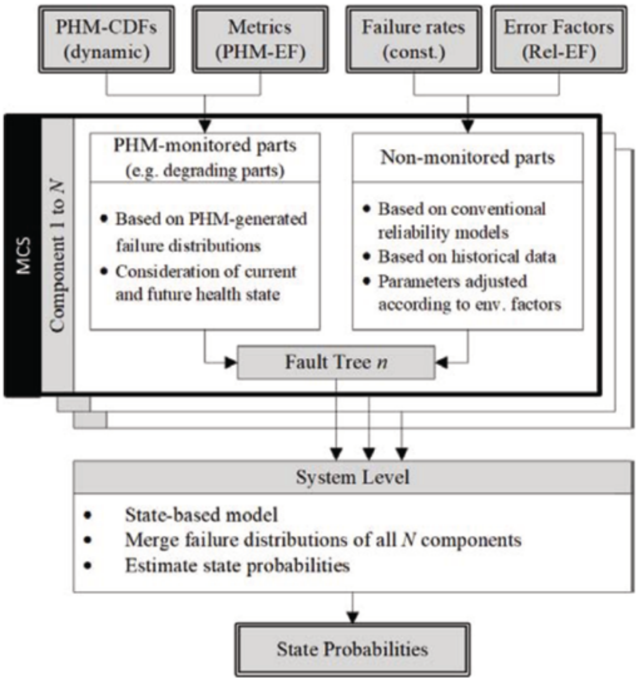


Figure 2.4: The extended dynamic hybrid reliability model (DHRM) uses Monte Carlo Simulation (MCS) to propagate uncertainties through each component's Fault Tree [21]

distribution with fixed shape parameter in combination with Bayesian updating to update the scale parameter for the component lifetimes. Besides, this approach could make CBM possible for more systems, for which a continuous degradation signal is lacking. Limitations to this study include the assumption that component failure times are observed precisely; uncertainties in failure detection should be accounted for by including a probabilistic observation model assigning probabilities to false positives and false negatives. Additionally, the authors disregard the possibility of common cause failures, i.e., simultaneous failures with a common root cause, drastically reducing the system reliability [46].

Continuing the integration of PHM solutions into multi-component systems, Heier [21] presented a framework which can be used to assess the propagation of algorithm-specific uncertainties in a multi-component system, aggregating multiple RUL estimations up to system level. In the proposed method, multiple algorithms, each with an individual performance, are used in a collaborative fashion to predict the reliability of a system containing multiple PHM-monitored components. Monte Carlo Simulation (MCS) was used to propagate the related uncertainties. The building blocks of the resulting dynamic hybrid reliability model (DHRM) are illustrated in Figure 2.4.

Importantly, considerable simplifications were made in this research, as artificially generated data was used in the case study for an exemplary cooling fan. Nevertheless, the author succeeded to show how uncertainties of the different algorithms propagate through a multi-component system model. He also highlighted the importance of uncertainty propagation in a field where multiple PHM algorithms work together towards a multi-component system prognosis [21].

2.3. SHM frameworks

Already in 2000, Boller [6] described the possible the integration of Structural Health Monitoring (SHM) into the aircraft design process, with the objective of sensors and non-destructive testing (NDT) becoming an integral part of aircraft structures. Different monitoring methods are considered, i.e. loads monitoring and damage monitoring. As the name suggests, loads monitoring is based on operational loads and uses either conventional strain gauges or flight parameters. Damage monitoring is a technique allowing to directly monitor the damage itself, using sensors integrated in a structure. The author has identified various principles and sensors, see Figure 2.5, based on the type of material and the damage parameter to be monitored, sensor signal processing is discussed, and aspects to consider for optimizing

Maerial	Damage	Parameter	Mon. Technique	Damage detection	Rel. cost	Benefit
Metal	Crack	Length	Visual	Observation and length measurement		
		Stress/strain	Strain gauge	Change in allowabel strain		
			Load sequence	Fatigue life evaluation		
		Flight param.	Load sequence	Fatigue life evaluation		
		Sound	Acoustic emission	Burst		
			Ultrasonics	Change in refelected signal		
		Vibration	Modal analysis	Change in FFT-spectrum		
				Change in mode shape (curvature)		
			Lamb waves	Change in transmitted waves		
		El. resistance	Crack gauge	Change in resistance		
			Eddy current	Change in resistance		
	Wear	Thickness	Visual	Observation and thickness measurement		
		Sound	Acoustic emission	Burst		
			Ultrasonics	Change in reflected signal		
	Corrosion	Thickness	Visual	Observation of corrosive product		
		Sound	Acoustic emission	Special friction events		
			Ultrasonics	Change in reflected signal		
		Vibration	Modal analysis	Change in FFT-spectrum		
				Change in mode shape (curvature)		
			Lamb waves	Change in transmitted waves		
		El. resistance	Eddy current	Change in resistance		
		Chem. reaction	Chem. sensing	Occurance of chem. reaction		

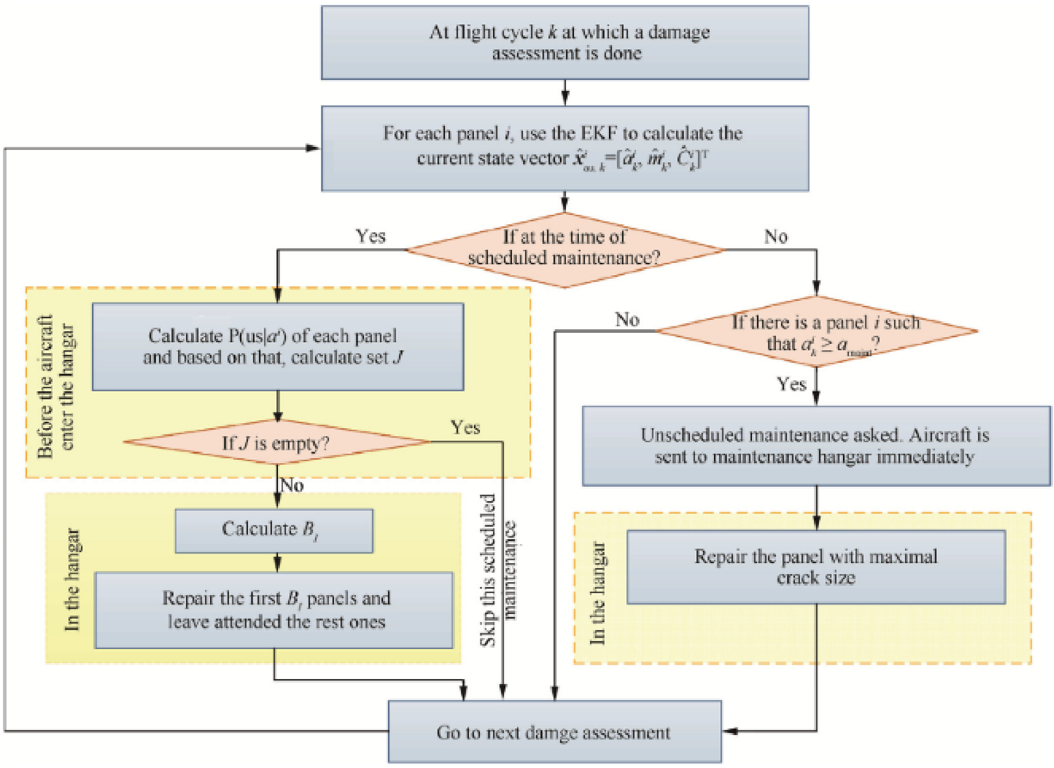
Figure 2.5: Structural Health Monitoring principles - summary [6]

structural health monitoring strategies are outlined. All this opens up possibilities regarding reduced inspection cost, better confidence in advanced materials and more lightweight design [6].

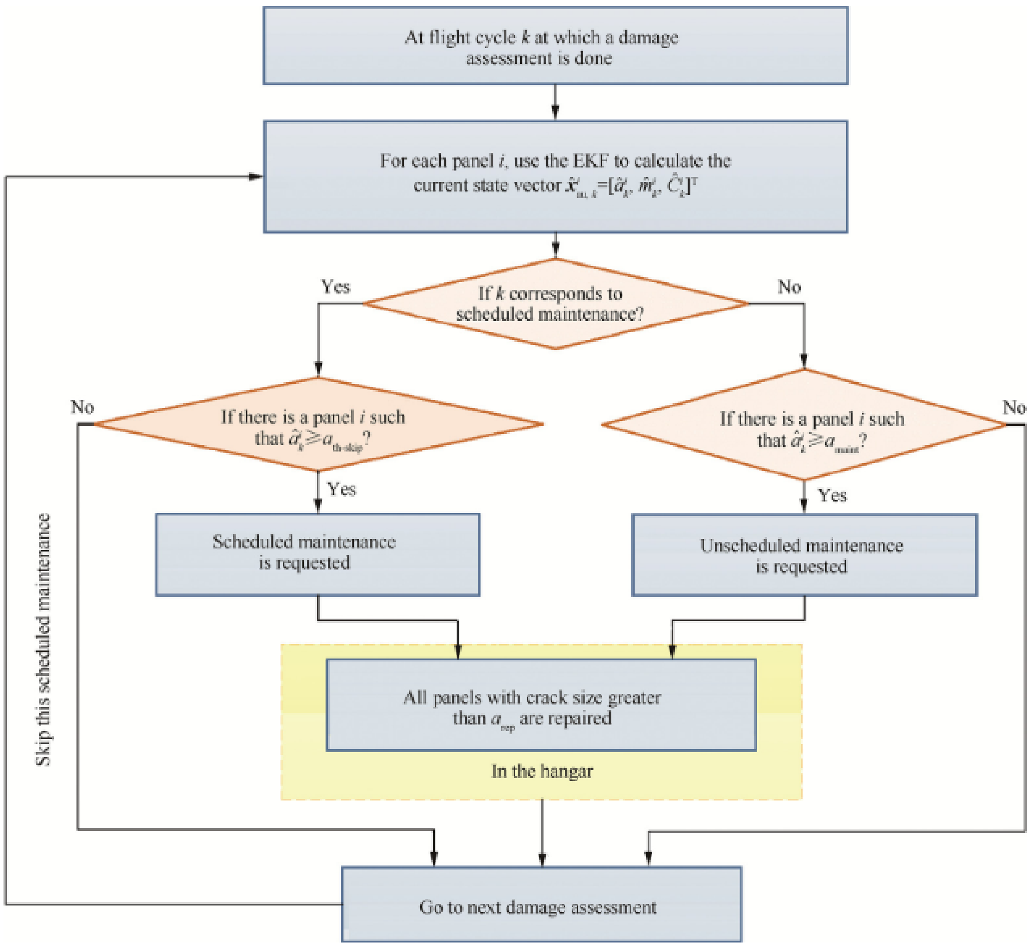
The increasing use of composite materials in aircraft structures gives rise to an increasing interest in SHM for composite structures. Boller et al. [5] described the state-of-the-art of non-destructive testing (NDT) techniques for composite materials, the main ones being visual inspection, optical methods, eddy-current, ultrasonic inspection, laser ultrasonics, acoustic emission, vibration analysis, radiography, thermography and Lamb waves. Diamanti and Soutis [9] describe these methods, with an emphasis on advantages and disadvantages as well as their applicability for damage detection in composites. Lamb waves are deemed an attractive technique for non-destructive inspection of structures and are shown to be able to successfully monitor damage evolution in composite laminated structures. Both Diamanti and Soutis [9] and a more recent review by Güemes et al. [19] refer the reader to Boller et al. [5] for the state-of the art in SHM.

The airplane fuselage is a frequently studied structure to be considered for SHM. Dong et al. [10] use piezoelectric wafer active sensors (PWAS) as structural health monitoring system in order to model fatigue crack growth in the airplane fuselage skin. The condition-based maintenance process then tracks this growth continuously and requests maintenance when safety is compromised. The value of the proposed method was assessed by means of a lifecycle cost analysis. Wang et Al. [47] propose a cost driven predictive maintenance (CDPM) policy, incorporating the "future system reliability", i.e. the probability that a component operates normally until the next maintenance interval, as a prognostics index and compare this policy to two other maintenance policies: scheduled maintenance and threshold-based SHM maintenance. This is realized by incorporating the information regarding predicted damage size distribution (described with the Paris-Erdogan model) and the cost ratio between scheduled/unscheduled maintenance into an optimal panel repair policy. Uncertainty sources are accounted for by a state-space mode using the Extended Kalman filter (EKF) to incorporate noisy measurements into the degradation model. The damage distribution is then quantified analytically utilizing a first-order perturbation method [47].

With their CDPM policy, the authors propose to have traditional scheduled maintenance in tandem with unscheduled maintenance. At each scheduled maintenance stop, the cost-optimal policy decides to either skip or trigger the current stop; removing scheduled maintenance or adding unscheduled work. In between two scheduled maintenance stops, unscheduled maintenance could also be triggered when a crack exceeding a safety threshold is detected. The flowchart of the proposed CDPM policy is shown in Figure 2.6a and can be compared to that of threshold-based maintenance in Figure 2.6b. Comparison results of the simulation of a fleet of aircraft with the three different maintenance policies indicate that adopting the proposed CDPM methodology can result in a lower number of maintenance stops and repaired panels as well as a decreased structural maintenance cost per aircraft [47].



(a) CDPM



(b) Threshold-based maintenance

Figure 2.6: Flowchart of CDPM and threshold-based maintenance [47]

Nascimento and Viana [35] proposed a prognosis model to predict fatigue crack length for large fleets of aircraft where operational factors such as duty cycle variation, harsh environments, inadequate maintenance and problems with mass production are taken into account. These factors obviously would lead to large discrepancies between designed and observed useful lives. For this purpose, a physics-informed neural network was developed, merging physics-informed and data-driven layers in a new recurrent neural network. Parts that are well understood can hence be modeled using physics-informed layers, while parts that are poorly characterized are modeled using data-driven layers. The model was tested by predicting fatigue crack length for a fleet of 300 airplanes subject to different mission mixes, and was proven to be able to model fatigue crack growth in a successful way [35].

2.4. Overview

In this chapter, different prognostics models have been discussed and it reflects the wide variety that exists among these models as well as the differences in model choice for different systems. A common finding from these articles is that often, knowledge of the underlying physics can drastically improve model performance compared to a solely data-driven algorithm. Also, operational and environmental factors play an important role in system failure behavior and including these in the model has a positive effect on the model's accuracy. Finally, the amount of research on condition-based maintenance for safety-critical systems, such as aircraft structures, is growing, and with the appropriate change in regulations could prove to be a game-changer in the aircraft maintenance industry. Together with a good condition-based maintenance strategy, these prognostics models show promising capabilities towards an evolution in aircraft maintenance.

3
Integrated Prognostics and Maintenance Scheduling Models

Whereas the previous chapter focused on prognostics, this chapter deals with post-prognostics decision-making and reviews the existing literature on integrated prognostics and maintenance scheduling models.

Several papers have developed different modeling approaches with respect to maintenance scheduling considering prognostics information. Research has been done in many directions; including line maintenance optimization, reduction of unscheduled and scheduled maintenance activities, maintenance planning for a single aircraft or for an entire fleet, and the development of entire decision-making support systems for aircraft condition-based maintenance.

3.1. Line maintenance

Line maintenance can be defined as unscheduled maintenance resulting from unplanned events and scheduled maintenance checks where servicing and/or inspections do not require specialized facilities, training or equipment [44]. An example of a study on the optimization of line maintenance with the use of CBM was found in Papakostas et al. [37], proposing an approach to support decisions to be made at line maintenance during turn-around-time (TAT), referring to tasks that have to be executed at either the current or successive airports. It selects the sequence of tasks with the best utility to be performed at the current airport. The decision for the allocation of the other tasks is deferred to the next decision point, if allowed by the RUL of the affected components. In contrast to the traditional reactive process, focused on resolving unscheduled maintenance activities (troubleshooting), this approach aims to reduce unscheduled maintenance events and their inevitable consequences. A drawback in this study is that uncertainty in RUL prediction is not accounted for and maintenance decisions are made based on a deterministic RUL estimation. Uncertainty inherent to RUL prediction increases the risk of unscheduled costs and delays and should thus be incorporated in the maintenance planning model [37].

Vianna and Yoneyama [44] propose a methodology for predictive line maintenance optimization of redundant aeronautical systems subjected to multiple wear conditions. The optimization algorithm searches for the planned date to repair and service all redundant components within a planning horizon, i.e. four days from now, with the objective to minimize costs while complying with all operational constraints and to satisfy all dispatch requirements. The prognostic method used to obtain the RUL distribution in this paper can be classified as a model-based approach and is based on a nonlinear version of the Kalman filter (EKF) and integrated with a multiple model technique in order to identify the most suitable wear profile and RUL distribution. Uncertainties in the RUL distribution are then incorporated in the planning model by means of Monte Carlo Simulation [44].

3.2. Aircraft fleet scheduling

Another topic that is frequently researched in existing literature is maintenance scheduling for a fleet of aircraft based on prognostics information. For instance, Feng et al. [13] introduced a multi-agent model for CBM of an aircraft fleet based on heuristic rules, which can react to dynamic events and is able to generate maintenance schedules, in order to design a fleet maintenance Decision Support System (DSS). This method was verified using a simulation of a fleet consisting of 10 aircraft on a 3-wave continuous mission, with two maintenance teams available. The results indicated an improvement in fleet availability while meeting mission demands, rationalizing the utilization of resources and providing support for online maintenance decision making. While this approach could indeed be an improvement for decision-making in a CBM framework, the authors assumed that the RUL estimation is accurate, and the maintenance strategies are therefore based on accurate RULs. However, in reality, uncertainties are intrinsic to prognostics and should thus be incorporated in the model [13].

A couple years later, Feng et al. [14] came up with an optimization method for CBM of an aircraft fleet taking into account prognostics uncertainty based on an improved genetic algorithm (GA). Uncertainty was accounted for by considering the RUL distribution of all Line Replaceable Modules and to transform this into the failure probability of the aircraft. The optimization problem was to find a fleet CBM strategy with acceptable risk and lowest cost. The authors have verified this method with a case study of a fleet of 10 aircraft but important aspects that have been simplified were the cost and consequences of risk as well as the effect of random failures [14].

Feng et al. [15] modelled the fleet CBM problem as a two-stage dynamic decision-making problem, formulated as an integer programming problem with binary variables, and solved using a heuristic hybrid game (HHG) approach consisting of a competition game and a cooperative game. The RUL distribution of all Line Replaceable Modules (LRM) served as input to the model. Uncertainties in the RUL were taken into account by adopting random distributions for the RUL, which differ for different LRMs due to their different usages. A case study regarding a fleet of 20 aircraft was conducted in order to verify the proposed method, showing that the hybrid game algorithm yields the optimal solution quickly and that the computation complexity increases slowly with increasing problem scale. This new solution method has a higher efficiency and can obtain a solution with higher quality than the method based on an improved genetic algorithm (GA), as proposed earlier in Feng et al. [14], to solve the same CBM fleet problem. However, the simplifications in the aircraft and fleet reliability model, for instance due to the consideration of each LRM as a key component, could be addressed in future work [15].

In a paper by Li et al. [31] a condition-based maintenance scheduling method incorporating stochastic inputs such as maintenance duration, remaining flying hours and number of incoming airplanes was developed for a fleet of fighter aircraft. The optimization problem was formulated with a MIP model and solved by the commercial solver CPLEX. The remaining flying hours of each aircraft are inputs based on the prognostic process with uncertainties quantified using probability distributions. In this model, this is done rather simplistically by assuming a uniform distribution, U(0,200) for the initial remaining flying hours. An improvement would be to have a more realistic RUL distribution estimate as an input to the scheduling model. A numerical example considering a fleet of 20 fighter aircraft helped to show that this method can lead to higher aircraft availability and lower unscheduled maintenance cost, as well as more predictable and efficient scheduling capacity [31].

The fleet maintenance problem was already solved in Feng et al. [15] using a parallel game approach, but due to different constraints and objectives, the aforementioned approach was not deemed suitable for a similar problem presented in Yang et al. [51]. Therefore, Yang et al. [51] developed a heuristic sequential game approach to tackle the problem of fleet-level selective maintenance, considering phased-mission with short breaks and condition-based maintenance (CBM) with the objective to reduce the repair frequency and cost. In this method, the RUL for all subsystems was assumed to be normally distributed, accounting for uncertainties associated with prognostics. The capacity of this approach was verified by use of a case study of a fleet consisting of 12 aircraft, showing a reduction in maintenance frequency and costs [51].

3.3. Decision-making support

Finally, there have been some papers focusing on an entire maintenance decision-making support system, covering all aspects from data acquisition to maintenance decision-making. Lin et al. [32] established a maintenance decision-making support system (MDMSS), integrating the process of data acquisition (real-time status monitoring of aircraft), data processing (reliability assessment of aircraft structures) and maintenance decision-making. The last was done with a multi-objective decision-making model based on CBM (MODM-CBM) aiming to reduce the maintenance cost and to maximize the fleet avail-

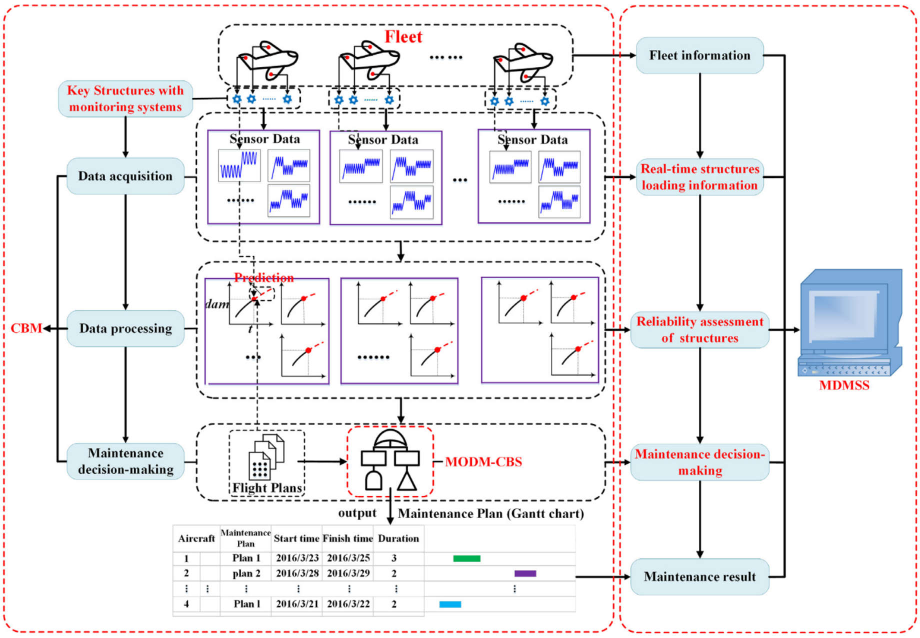


Figure 3.1: The process of maintenance decision-making for an aircraft fleet [32]

ability. A structural reliability evaluation method based on the real-time load information was proposed for processing the data. It combines the linear cumulative damage model of the stress-life method and the crack propagation life model of the probability-damage-tolerance (PDT) for maximum practicality and the ability of handling high reliability problems while taking stochastic factors into consideration. The process of maintenance decision-making with MDMSS for an aircraft fleet is outlined in Figure 3.1.

The proposed decision-making model is validated with a case study on a fleet of 10 aircraft consisting of three repairable structures with predictable RULs obtained by the proposed reliability model. This model can serve as a good basis for decision-making support based on CBM, however, the scope should be enlarged and for example, non-structural reliability should be integrated in the model [32].

Zooming in on the multi-objective decision-making model (MODM-CBM), Lin et al. [33] dived deeper into the MODM-CBM framework established in Lin et al. [32]. In this paper, a multi-objective decision-making model, based on CBM (MODM-CBM), is discussed from the perspective of a fleet of aircraft to achieve high performance with minimum cost and maximum availability. A two-models-fusion framework, integrating the probability-damage-tolerance (PDT) and the model-based particle filter (PF), is proposed for reliability prediction of aircraft structures subjected to fatigue loads. Note that this is a different reliability prediction model compared to the previous article. The framework of MODM-CBM is illustrated in Figure 3.2 [33].

Koops [27] identified Prescriptive Maintenance as an emerging maintenance practice. It is a maintenance practice in which outcome-focused recommendations, based on knowledge about when and why failures are likely to occur are produced. In this paper, a decision-support tool based on a probabilistic framework for determining best-action solutions within prescriptive maintenance was developed on the example of repair/replacement decision support. A maintenance scenario in which either preventive or corrective maintenance can take place is investigated, however, the author also suggests a degradation model based on the Wiener process, capable of modelling the temporal evolution of a degradation process and random effects of imperfect repair, to be embedded into a predictive/prescriptive maintenance scenario, allowing for continuous update of the RUL and more optimal maintenance planning and cost. Key metrics for evaluating business value and risk are identified and based upon these, the best action is prescribed in a probabilistic framework. These metrics include the mean cost difference between alternatives, risk of taking the wrong decision, expected opportunity loss and expected value of information [27].

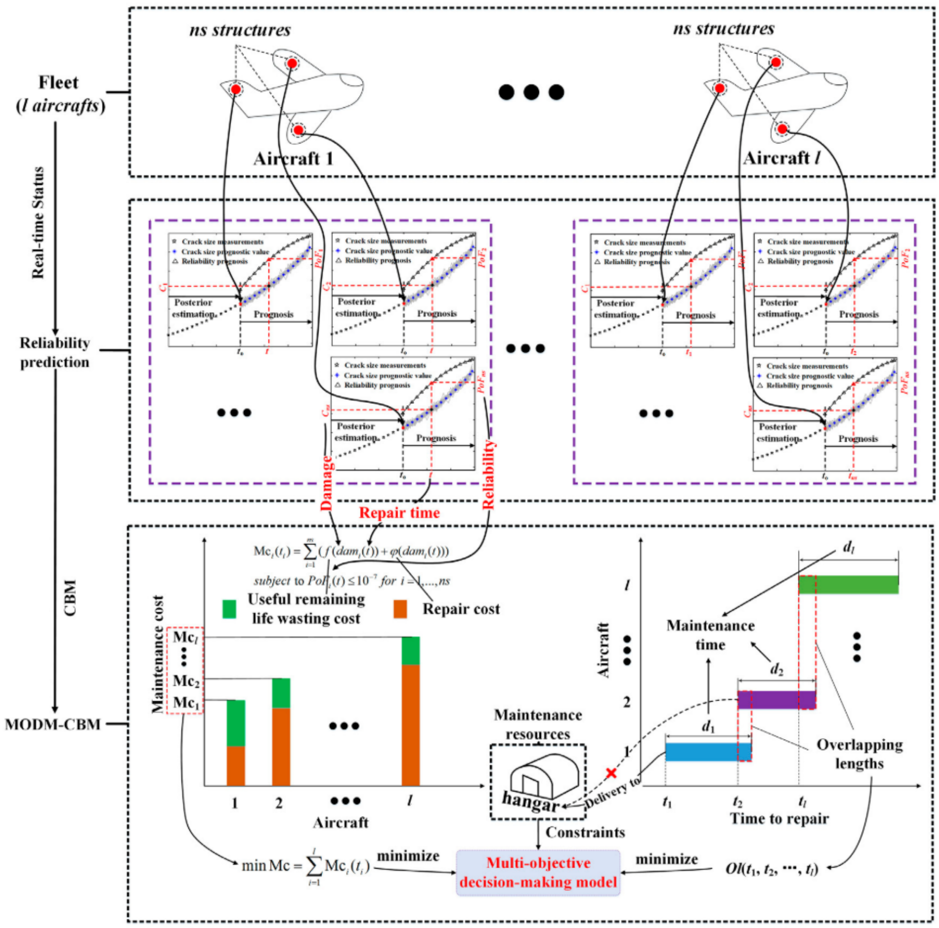


Figure 3.2: The modelling framework for MODM-CBM [33]

3.4. Logistics and spare parts management

According to Leao et al. [30], another area where condition-based maintenance can improve the aircraft maintenance process is in logistics and stock optimization for spare parts. Pogačnik et al. [38] used historic data of maintenance services and aircraft parameters to develop a fault forecasting model that can be used to give early information on requested spare parts, enabling more cost-efficient spare parts logistics. This was shown to have a positive impact on both maintenance service time and costs of spare parts. By incorporating the lean methodology into the maintenance process, the authors have succeeded to reduce the maintenance time for a typical seven-day C-check by 14%. Earlier orders of materials as a consequence of better fault forecasting also lead to reduced costs of the project [38].

Fritzsche and Lasch [16] present an integrated logistics model of spare parts maintenance planning, with the objective to guarantee a high supply of spare parts and an optimal interaction of various network levels. A prognostics-based preventive maintenance strategy is used to predict failure times of components, transfer unscheduled maintenance into scheduled maintenance, and balance spare parts inventory and transportation cost.

A three-level model is proposed with the idea of splitting the planning process into three simpler sub-areas and aiming to optimize the logistics network for a given flight plan and location network. The first level, airport/turnaround, is responsible for the movement of the aircraft according to the flight schedule and the life time of its components. Once a component is bound to run out of RUL, the optimal exchange point and location is calculated. A message is forwarded to the logistics network (level 3) and the aircraft is transferred to the repair facility (level 2) at the calculated destination. Validation of the model showed that the proposed three-level model for maintenance planning can achieve significant cost savings and improved inventory management, given that an excellent prognosis is available [16].

3.5. Overview

In this chapter, various aspects in which CBM can improve aircraft maintenance have been explored. For instance, short-term line maintenance planning models with the application of CBM have been developed. Another stream of literature considered more high-level aircraft fleet condition-based maintenance planning, albeit in a simplified setting compared to commercial aviation with the main limitations of a small fleet operating from a single base, and the monitoring of the failure behavior of the aircraft but not of its systems individually. Furthermore, entire decision-making support systems for condition-based maintenance have been developed, considering all phases from data acquisition to maintenance decision-making. Finally, the effects of CBM on the logistics supply chain have been explored, with the main idea to use fault forecasting to predict required spare parts in advance.

4

Cost-benefit Analysis of condition-based maintenance

Research about PHM frameworks aims to minimize uncertainty in RUL prediction and prognostic information. Nevertheless, this uncertainty cannot be eliminated and thus required performance levels for a PHM framework should be established. This can be realized by conducting a cost-benefit analysis (CBA), where the impact of a prognostics framework on the airline's costs and benefits is quantified and analyzed.

A major challenge in the implementation of predictive maintenance is the necessity of an up-front investment without direct benefits. The possible cost savings are difficult to quantify and hence a suitable cost-benefit analysis is needed to justify implementation of a condition monitoring system. That condition monitoring system will need to perform adequately, as the true benefit of condition monitoring lies in how early impending failures are detected, correctly diagnosed and how accurately and precisely the time until failure is predicted [7].

4.1. Evaluation of costs

Already in 2008, Leao et al. [30] presented a methodology for cost-benefit analysis on the application of PHM for legacy commercial aircraft. The methodology takes into account the lack of provisions for PHM systems on legacy aircraft, but also the availability of operation/maintenance data and experience. Although no cost-benefit analysis tool was developed, the authors gave valuable insights in all costs, benefits, risks, financial metrics and tools that should be considered or implemented in a cost-benefit analysis framework.

Leao et al. [30] suggest to divide the benefits of PHM into four categories: (1) benefits of monitoring and advanced diagnostics, (2) benefits of prognostics and condition-based maintenance, (3) benefits of complete health management and (4) intangible benefits. The first three categories are classified according to increasing complexity, from relatively simple developments (1) to a complete PHM solution (3). Therefore, each of the first three categories includes the benefits and costs of the previous ones. All benefits are outlined below, but for a more elaborate discussion and quantification, the reader is referred to [30].

1. Benefits of Monitoring an Advanced Diagnostics
    - Reduction of no fault found rates (NFF)
    - Improved aircraft dispatch reliability
    - Reduction of scheduled maintenance task costs
    - Improvements on engineering developments
2. Benefits of Prognostics and CBM
    - Reduction of the number of interruptions

- Further reduction of scheduled maintenance tasks cost
- Reduction of secondary damages
- Reduction of maintenance induced failures

3. Benefits of a Complete Health Management Solution
   - Benefits of PHM for logistics
   - Reduction of insurance costs
   - Greater aircraft residual value
4. Intangible Benefits Intangible benefits include competitive benefits due to enhanced aircraft reliability and safety. Also, the database resulting from the collection of aircraft condition monitoring data could be useful for training or R&D purposes.

The aforementioned benefits do not come for free and therefore, Leao et al. [30] have listed the costs to be considered in order to realize these benefits. They are categorized these into four categories: (1) development costs, (2) aircraft costs, (3) operation/maintenance expenses and (4) PHM side effects.

1. Development Costs
   - Research & Development
   - Design/Management
   - Development tests/validation & verification
   - Certification
   - IT infrastructure
2. Aircraft Costs
   - Costs associated to the acquisition and installment of the PHM equipment including the on-board data storage/transmission system and the additional sensing technology, for each modified component.
3. Operation/maintenance expenses
   - Recurring expenses associated to the operation and maintenance of the PHM system
4. PHM side-effects
   - The cost of wasted remaining useful life of the components

Again, for a more detailed explanation and quantification of these cost aspects, the reader is referred to [30].

Furthermore, the authors have identified the most important risk factors to be taken into account in the development process of a PHM framework. These concern the technology maturity, the agreements with suppliers and the certification of the modifications to the aircraft and the maintenance plan.

A cost-benefit analysis can be useful to different types of stakeholders. Leao et al. [30] have defined three main clients to which CBA might be useful and they have pointed out appropriate financial metrics for each of them. The PHM development team might benefit most from knowing the cost/benefit per system, making it easier to define where (not) to apply PHM. For aircraft operators, it might be more useful to express the cost-benefit results in terms of percentage of Direct/Indirect Maintenance Costs (DMC/IMC), or Direct/Indirect Operating Costs (DOC/IOC). Finally, the aircraft OEM Management will commonly require a business plan for the implementation of PHM technologies, supplemented with metrics such as return on investment (ROI), internal rate of return (IRR), net present value (NPV), economic value added (EVA), payback time or cashflow.

Lastly, Leao et al. [30] presented some tools in order to provide better insight in the CBA results: Sensitivity Analysis, to indicate where to invest in order to obtain the greatest benefits; Monte Carlo Simulation, to account for uncertainty in CBA; and Optimization, to obtain the most cost-effective choice.

By examining the existing literature on cost-benefit analysis of PHM systems, it becomes clear that the list of cost and benefit factors presented by Leao et al. is rather extensive. Although some researchers have identified additional cost factors, (e.g. MEL tasks required to be performed when the aircraft operates under degrading conditions, such as flying only below a certain altitude or with the APU turned on; or degradation costs caused by a component operating under degrading condition, for instance engines consuming more fuel due to lower efficiencies [44]) most of the cost factors found in literature are considered.

Vianna et al [44] have also identified quite some cost factors, but they only focused on operational costs. In this work, the following costs were considered. The residual cost due to preventive removal, the previously mentioned costs resulting from MEL tasks and operation under degrading condition, cancellation and delay cost, and finally, repair and servicing cost [44]. The cost of repair or a maintenance activity in general is the cost factor most frequently seen in literature. Vianna et al. [44] include in this cost factor all necessary operational support expenses to perform the repair of the aircraft, but some authors choose to divide this into smaller blocks.

For instance, Kählert et al. [28] divide this into labor, material and overhead expenses, including troubleshooting, planning, (sub)system maintenance and logistics. On the other hand, they recognize cost factors such as operational irregularity charges, which include delay and cancellation costs (AOG). The avoidable costs that are identified by Kahlert et al. [28] are delay costs, costs of NFF events, logistics costs of NFF events and costs of the diagnosis process.

Another possibility to look at maintenance activity cost is found in Hongsheng et al. [23], where a formula is defined for scheduled and unscheduled maintenance separately and including maintenance activity cost factors such as maintenance man-hours, fixed costs of a scheduled/unscheduled maintenance activity and material costs, but also including ground time conversion costs, associated with opportunity loss and assumed fixed for scheduled maintenance and depending on ground time in case of an unscheduled event [23].

Finally, maintenance activity cost can be classified according to when the maintenance activity takes place. Feldman et al. [12] make a distinction between an event during preparation phase, during the flight mission and during downtime, where it is evident that a maintenance event during the mission is the most expensive and a maintenance event during downtime the least. Feldman et al. [12] also divide the cost-contributing activities in implementation costs and cost avoidance. The former embodies the cost of enabling RUL determination for the system and comprises recurring (base cost of an LRU and additional cost for PHM), non-recurring (PHM engineering cost) and infrastructural costs (annual infrastructure). Cost avoidance is defined as the value of changes to availability, reliability, maintainability and failure avoidance [12].

Dong et al. [10] conduct a lifecycle cost (LCC) analysis of an airplane for both scheduled and condition-based maintenance applied to an aircraft's fuselage equipped with a SHM system. They also consider implementation costs and avoided costs and base their analysis on cost factors that increase/decrease due to adopting a CBM approach. Increasing cost factors included in the calculation are manufacturing cost, SHM equipment replacement cost, and additional fuel cost due to the extra weight of SHM equipment. Costs that decrease due to CBM include net revenue saved due to shortened downtime, inspection cost, crack repair cost and cost for removing/installing surrounding structures. The main factor leading to cost savings was found to be the reduced net revenue lost due to shortened downtime. Although diverse cost factors are discussed, their quantification is heavily based on assumptions, which makes the results difficult to validate [10].

Another approach with respect to consideration of cost factors is presented by Koops [26]. Koops focusses on costs associated with engine maintenance, and specifically on costs resulting from different failure prediction scenarios (false/true positive/negative) compared to the reference scenario where reactive maintenance is performed in the event of engine failure. The costs considered in this study are shop visit costs (including repair or replacement costs), contingency damage costs, logistics costs, contribution loss due to unexpected AOG situations and false alarm costs. For all cost factors, a distinction has been made for whether a failure takes place in-flight or on-ground [26].

Lastly, Hölzel and Gollnick [24] conduct a lifecycle cost-benefit analysis, but do not provide cost estimates for the development and implementation of PHM systems. Instead, they derive maximum acceptable investment costs for PHM systems based on the analysis results. Cost-contributing factors that are taken into account in the simulation are maintenance cost, crew cost, revenue, fuel cost, investment cost, charges and fees, insurance, etc. Input data related to cost are ticket price revenue, aircraft investment cost, labor rate, fuel price, delay cost, inflation and discount rate [24].

4.2. Evaluation of methods

The cost-benefit models found in literature use different methods to evaluate the costs and benefits associated with PHM. Three main types of evaluation techniques were identified: scenario analysis, Monte Carlo simulation (MCS) and discrete event simulation (DES). Next to the variety in assessment methods, the scope of analysis varies from paper to paper, ranging from a simple maintenance event-based cost reduction calculation to a (nearly)-complete holistic multi-system economic assessment. Furthermore, some authors evaluate the effect of CBM on scheduled maintenance, while others look into the consequences for unscheduled maintenance. Considering both types of maintenance is of course also possible, and for a proper holistic assessment, necessary.

4.2.1. Effect on unscheduled maintenance

Gerdes et al. [18] have proposed a relatively simple approach to investigate the effect of unscheduled maintenance delays. The authors looked into historic delay and failure data related to delays caused by the air conditioning system, as indicated in the database of the Airbus A340-600 in-service report (ISR). Delays that could be prevented or reduced with the help of CBM were identified and it was shown that 80 percent of the maintenance actions causing departure delays can be prevented, should new sensors be introduced such that all fault causing systems can be monitored reliably. More realistically, with the already existing sensors, it would be possible to avoid about 20% of delays causing maintenance actions.

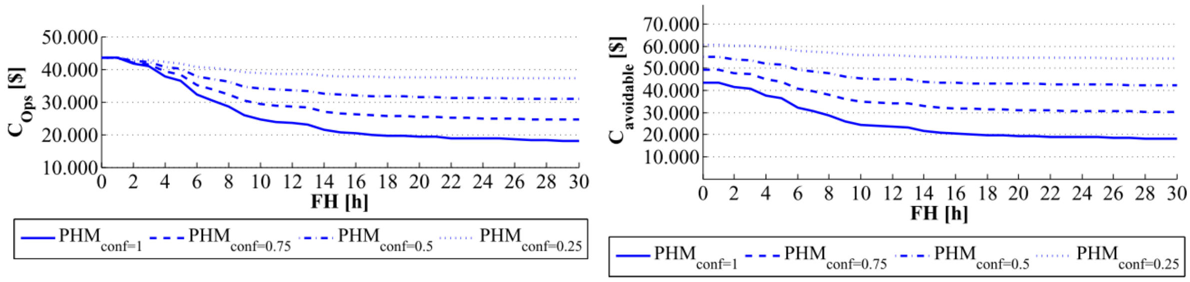
The results of this study, while promising, should be dealt with cautiously and critically. Only costs that are preventable due to reduction of delays are examined and no attention is given to the impact of possible errors associated with condition monitoring, e.g. false positives or false negatives, or performance metrics such as the prognostic horizon [18]. The performance of the PHM system has a significant impact on the benefits that can be realized by condition-based maintenance [26][28][24].

Another approach analyzing various scenarios with their associated cost is found in Koops [26]. Koops conducted a cost-benefit analysis to find the optimal operating point on the ROC curve, i.e. the optimal decision threshold for failure indication, and to analyze the net benefit of predictive maintenance compared to an approach without failure prediction (i.e. unscheduled maintenance). This was done by analyzing maintenance event rates and failure probabilities for various cost scenarios. A drawback is that the author neglects the fact that a false positive results in more frequent maintenance actions and that she does not consider the cost-benefit on a lifecycle basis, but instead looks only at the cost reduction potential for an individual maintenance action.

Kählert [28] computed the annual cost savings of PHM-based maintenance compared to unscheduled maintenance for on-condition maintained LRUs, using discrete event simulation. Failure data is deterministic but input data for costs and process time is stochastic, therefore, Monte Carlo Simulation is used to represent the uncertain parameters. The aim of this study is to evaluate the financial potential of a component-specific PHM system and to specify component-based PHM parameters (PH and accuracy). A test case was conducted on LRU-specific data for the Air Data Inertial Reference Unit (ADIRU) using the Lufthansa Airbus A320 fleet. Analysis showed that for instance, if an ideally working PHM system with a PH of 4 FC or 9 FH is used, 60% of the delays could have been avoided completely. Furthermore, sensitivity analysis showed that an effective cost reduction requires a reliable prognosis (high confidence) as well as a sufficient PH (high number of FH). The reductions for realistic PHM systems (confidence < 1, short PH) appear to be low. If the parameters of an exemplary PHM system are set a confidence equal to 0.5 and a PH of 2 FH, the potential savings reach \$987 per year only. If in this case investment costs of PHM systems are considered, the cost-benefit might turn out negative in the end [28].

Kahlert et al. [28] evaluate the impact of PHM systems on the costs of operational irregularities (delay costs) and on all avoidable costs (delay costs, costs of NFF events, logistics costs of NFF events and costs of diagnosis processes). Figure 4.1 show the savings potential of different PHM systems with varying accuracy and PH. Figure 4.1a shows the impact on delay costs, Figure 4.1b shows the impact on the total avoidable MRO costs. Whereas the accuracy reduces costs in both categories, operational and MRO costs, a longer PH primarily allows to prevent more delays [28].

Whereas Kählert et al. [28] took a deterministic approach towards incorporating failure data in a dis-



(a) Impact on delay costs

(b) Impact on total avoidable MRO costs

Figure 4.1: Savings potential of different PHM systems with varying accuracy and PH [28]

crete event simulation, Feldman et al. [12] calculated the ROI of a PHM system relative to unscheduled maintenance with a stochastic discrete event simulation, complemented with Monte Carlo Simulation to account for uncertainties in the inputs for the discrete-event simulation (e.g. the performance of the PHM system and the costs involved in the calculation). Furthermore, they looked into the effect of a PHM system on spare parts inventory management. The case study presented in this paper focused on a precursor to failure PHM approach for an avionics LRU in a commercial aircraft (multifunction display in a Boeing 737-300). The precursor to failure methodology is used to forecast a unique time to failure (TTF) distribution for each instance of an LRU. Then, based on this TTF distribution, either a scheduled maintenance activity or an unscheduled maintenance activity is performed, and relevant costs are accumulated. The general process flow of the methodology for analyzing the ROI is illustrated in Figure 4.2.

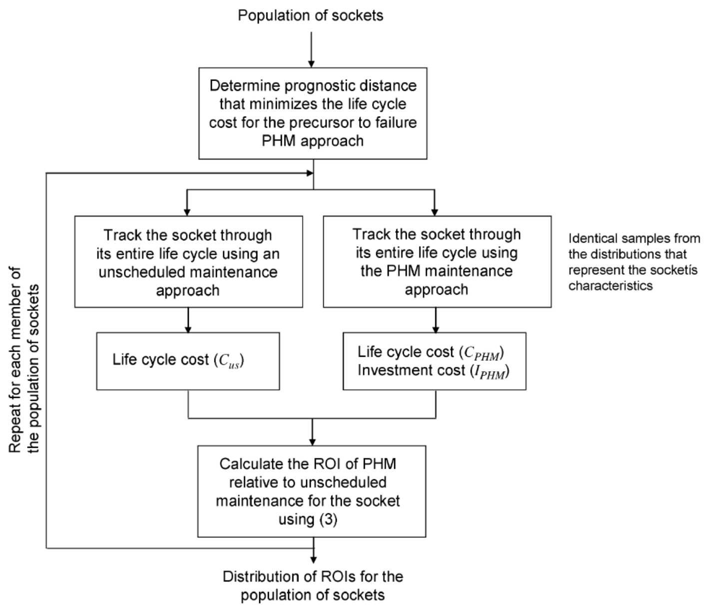


Figure 4.2: Process flow chart of the methodology to calculate the ROI of a precursor to failure PHM approach relative to unscheduled maintenance [12]

With realistically assumed cost values, based on credible sources and provided with a thorough reflection, a positive ROI was demonstrated while accounting for both uncertainties in PHM performance and costs involved. However, more attention should be given to the impact of PHM at system level, as well as the inclusion of variability in the operational profile, false/missed alarm and random failure rates, time needed for maintenance, and system complexity [12].

4.2.2. Effect on scheduled maintenance

Dong et al. [10] have investigated the effect of Structural Health Monitoring (SHM) on the safety and lifetime cost of an airplane fuselage compared to scheduled, preventive maintenance. A lifecycle cost (LCC) analysis was conducted for both scheduled and condition-based maintenance. Monte Carlo Simulation was used to simulate uncertainties in the number of maintenance trips and the number of cracks repaired. Results showed that about 10% of the lifecycle costs can be saved by adopting a CBM approach. It was found that condition-based maintenance based on SHM can add value not only in terms of predictability, number of maintenance trips and the number of cracks repaired. Also inspection time for heavy maintenance checks can be reduced, due to efficient health monitoring and less time spent and damage done on the removal/installation of surrounding structures [10].

In Hongsheng et al. [23], three separate cost models are established: optimization of scheduled maintenance, optimization of unscheduled maintenance and error impact analysis. With the help of PHM, some of the scheduled maintenance tasks can be replaced by PHM monitoring, whereas for some tasks, the interval can be extended. Benefits for unscheduled maintenance include the possibility to reduce unscheduled maintenance events caused by failure of critical components with the help of prediction technology. Finally, the effects of prognostic errors in the PHM system such as false alarms and missed alarms on maintenance costs are evaluated. False alarms only result in additional checks and troubleshooting, while missed alarm events trigger unscheduled replacement or repair.

The simulation model can evaluate maintenance man-hours, costs and unscheduled maintenance events before and after PHM implementation. Due to the lack of practical operating data, the authors opted to use Monte Carlo Simulation to evaluate working hours and cost of PHM-based maintenance. A case study was performed for the air conditioning system of a short-distance transport aircraft, showing that the total man-hours, costs and number of unscheduled maintenance events of PHM-based maintenance are significantly lower than for traditional preventive maintenance and in the ideal state, where system coverage and fault detection rate are assumed 100%, it can reduce 56% of maintenance man-hours, save 60% maintenance cost, and avoid 88% of unscheduled maintenance events [23]. A valuable feature in this paper is the fact that the authors considered the effect of various performance parameters of the PHM system on the cost estimation. Effects from PHM system coverage, fault detection rate, false/missed alarm rate, task redundancy rate and interval extension parameter are taken into account and shown to be significant, but often neglected in literature.

Hölzel and Gollnick [24] provide a holistic lifecycle cost-benefit analysis of a PHM system in future or present commercial aircraft. In the proposed approach, multiple subsystems are considered, and failure behavior is modelled individually for each subsystem. The methodology is based on discrete-event simulation for aircraft operation and maintenance, and scheduling of CBM tasks is done using an optimization algorithm. Both the effect on scheduled and unscheduled maintenance is analyzed.

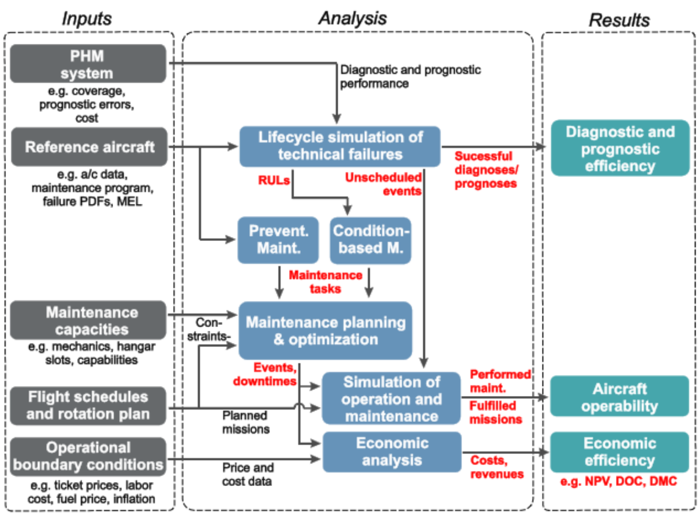


Figure 4.3: Assessment approach in Hölzel and Gollnick [24]

The economic analysis in this paper follows the assessment approach as outlined in Figure 4.3, which is based on the lifecycle cost-benefit model AIRTOBS (Aircraft Technology and Operations Benchmark

System), see Figure 4.4. AIRTOBS models all relevant economic parameters along the aircraft lifecycle and consists of three main modules. The Flight Schedule Builder (FSB) generates a flight schedule for the entire lifecycle based on airline route data and assumes full aircraft availability. Then, the Maintenance Schedule Builder (MSB) executes a discrete-event simulation of the flight operation and maintenance events. Finally, the Lifecycle Cost-Benefit (LC2B) module conducts a cost-benefit analysis based on the simulation results [24].

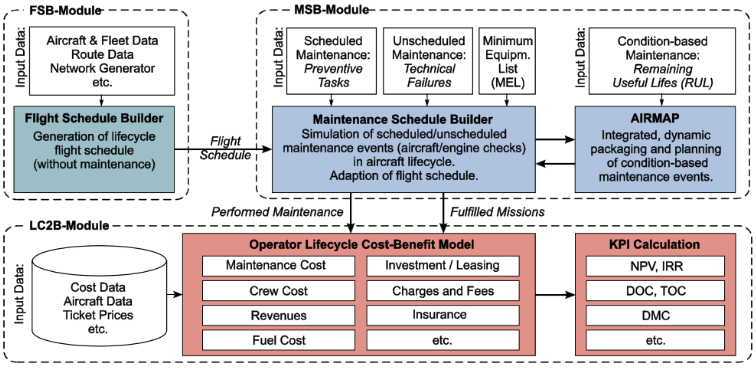


Figure 4.4: AIRTOBS architecture [24]

The scope of this analysis approach is rather large, covering the simulation of the flight and maintenance schedule, the dynamic task packaging and planning of condition-based maintenance events, considering uncertainties in component failure behavior and prognostic errors (false positives/negatives, NFFs), and evaluating the simulation results in a lifecycle cost-benefit analysis. The economic analysis requires a large amount of input data, giving an indication of the depth of the analysis:

- PHM system: specification of the covered failure modes of subsystems, prognostic performance levels and costs
- Reference aircraft: aircraft data, scheduled maintenance program, MEL, subsystem failure behavior, etc.
- Maintenance capacities at considered airports: number of mechanics, slots, capabilities, etc.
- Operational and boundary conditions: ticket prices, labor cost, inflation, etc.

At the core of this study lies condition-based maintenance planning, i.e. the allocation of maintenance tasks based on RULs determined by a PHM system. In the proposed approach, each ground time of an aircraft is seen as a maintenance opportunity, to which an appropriate maintenance task package can be assigned. By dynamically grouping the maintenance tasks, the number of maintenance events can be reduced, and efficient use can be made of each maintenance opportunity [24].

A case study is conducted, with a focus on the investigation of the operational and economic impact of prognostic errors and the statistical variance of the results due to the probabilistic modeling in the aircraft lifecycle simulation. An aircraft similar to an Airbus A320 with an operating lifecycle of 25 years, operated by a full-service network carrier on a short-range rotation with a daily utilization of 8.75 FH is used in this study. 15 of the 25 subsystems considered are potential candidates for PHM implementation. For this reference aircraft, a simplified task-based maintenance program is compared to a condition-based maintenance approach. The impact of PHM is assessed by varying performance parameters of the PHM system (unscheduled event prevention, false alarms, missed failure rate, task redundancy and interval escalation) and examining the resulting unscheduled maintenance events, technical delays, aircraft utilization, maintenance man-hours, costs (direct maintenance costs per flight hour), etc. [24]

The assessment approach presented by Hölzel and Gollnick [24] is generic and hence adaptable to different kinds of aircraft. Extension of this model to a fleet-level, where maintenance tasks can be scheduled for a fleet of different aircraft types on a network would allow for an even more realistic assessment of PHM [24]. Also, the inclusion of structural health monitoring in this model would be beneficial for its usability in practice.

Vlamings [45] made an effort to address the limitations in existing literature, especially those regarding the effects of false alarms as well as the effects of CBM on the supply chain, through the combination of a finely grained PHM framework integrated into a robust planning application for a fleet of aircraft. In his research, holistic models, adaptive to various fleet sizes with aircraft containing different components, to assess the effects on scheduled and unscheduled maintenance were developed and executed independently. This is of course not representative in practice, where scheduled and unscheduled maintenance are performed in tandem.

The unscheduled maintenance module employs a discrete-event simulation (DES) technique, with the advantage that no change in state occurs in between events, enabling a computing time-efficient simulation method. This technique is used in combination with Monte Carlo Simulation to account for uncertainty of failure events. The proposed model simulates predicted failures for the components under investigation and plans maintenance actions accordingly using a Mixed Integer Linear Programming (MILP) formulation with the objective to minimize costs. Then, it compares the cost savings enabled by CBM for different prognostics performance levels and investigates the effects on the supply chain. In the performed case study regarding unscheduled maintenance, an electrical generator and a cooling unit are considered, and results show that the effectiveness of the prognostic system heavily depends on the false positive rate. Furthermore, the importance of accurately modeling the opportunity costs, for which data is often difficult to obtain, was highlighted.

The scheduled maintenance module approach in this paper considers around 250 different tasks, for which either task substitution or interval escalation can be enabled by CBM. Task grouping to maintenance opportunities is performed by a MILP model that minimizes task and opportunity cost. In order to limit simulation time, A-, and C-check tasks are simulated separately. Results show significant cost savings, but should be dealt with cautiously and critically, as estimates for interval escalation and task substitution are assumed based on expert opinion [45].

Despite the good quality of the research done by Vlamings [45], factors such as limited time resulted in considerable limitations. In the simulation model, the preventive and reactive maintenance actions are disconnected. While this can give an indication of the benefits on each category, this assumption is not realistic, as these maintenance actions are coupled in real life. Furthermore, the number of systems considered in the reactive module is rather small compared to the overall number of systems in an aircraft and is thus not suited to give a representative indication of all the benefits resulting from CBM. Finally, all costs and benefits are expressed in a monetary value and the simulation model heavily relies on an accurate cost model, which is often confidential and difficult to obtain.

Finally, in a paper by Busse et al. [7], another holistic approach for cost-benefit analysis is proposed. While not aircraft-specific, the authors propose a well-explained framework for cost-benefit analysis of prognostic systems, where especially the RUL prediction modelling in terms of accuracy and precision, and the two proposed maintenance strategies could be integrated in a more airline-specific model considering the appropriate costs and benefits. The purpose of the presented approach is to investigate which potential cost-savings PM might generate as a function of its maturity and specific performance metrics. The building blocks of the proposed CBA method are shown in Figure 4.5.

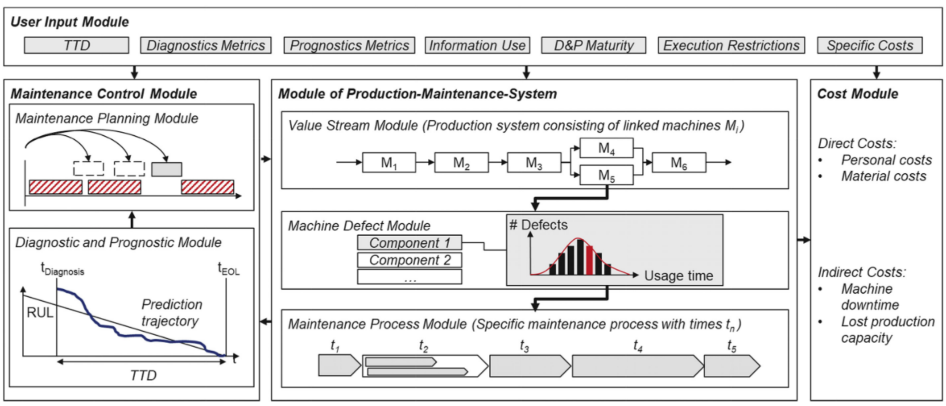


Figure 4.5: Building blocks of the CBA method in Busse et al. [7]

Busse et al. [7] mainly focus on two fields: the modelling of diagnostics and prognostics (D&P)

information and the modelling of different integration options for the condition monitoring system (CMS) into the production system, both part of the Maintenance Control Module.

The temporal performance of the RUL prediction is modelled with a stochastic process, from the perspective of both availability and its trajectory. The former indicates when the first prognosis is available, the latter is an indication of how the quality of the prediction develops over time. In the proposed model, the prognostic trajectory is modeled using Brownian Motion with drift ad transferred to the RUL diagram, see Figure 4.6, and therefore can be defined exclusively with the metrics of accuracy and precision; the average distance between the predicted RUL and the real RUL, and the spread of the predicted RULs, respectively.

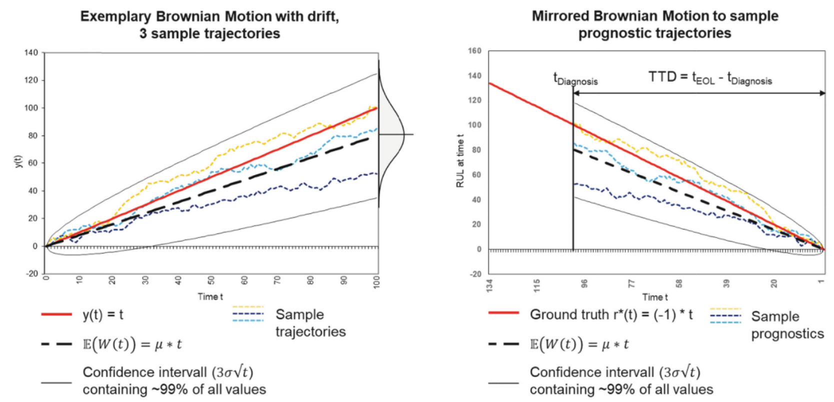
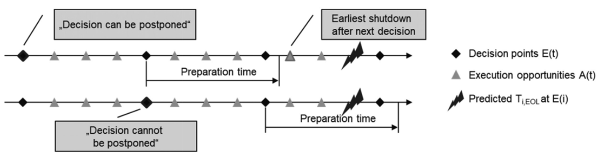
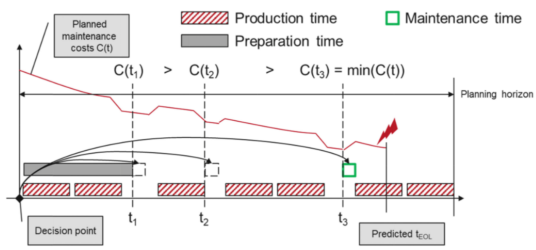


Figure 4.6: Brownian Motion with drift and transfer into RUL space [7]

The D&P information is then integrated using two prediction-based control strategies, see Figure 4.7. Trigger strategies (Figure 4.7a) consider a limit value, typically the predicted RUL, in order to initiate a maintenance activity immediately. Planning strategies(Figure 4.7b) on the other hand, use predictions to plan future maintenance activities while minimizing the associated cost. While the aforementioned planning strategies could offer a higher cost reduction potential compared to trigger strategies, they might require more complex maintenance management systems. Different maturity levels of CMS are reflected through these differences in strategies.



(a) Trigger strategy



(b) Planning strategy

Figure 4.7: Exemplary logic of the trigger and planning strategies [7]

Lastly, the authors conduct a case study where a single machine is modelled with one component being monitored and show the potential for substantial cost reductions. Even though this gives an indication of the validity of the proposed approach, the costs and benefits identified by the authors are not specific to the airline industry, hence the case study will not be discussed in this literature review.

4.3. Overview

Whereas the previous chapters focused on how aircraft maintenance can be improved by means of CBM, in this chapter, literature was pooled on the cost-benefit analysis of CBM applications. This stream of literature focused on identifying if and where the application of CBM could be beneficial, which is the main focus of this literature review. First of all, different cost factors were identified, followed by a discussion on how cost factors were considered in literature. Then, the different evaluation methods used in literature were outlined and the effects on scheduled and unscheduled maintenance were summarized. While many papers investigated the effects on either scheduled or unscheduled maintenance, some authors addressed both strategies and performed a more holistic cost-benefit analysis. The key papers discussed in this chapter, together with the previously identified benefits to condition-based maintenance are summarized in Table 4.1 by means of a compliance matrix. In this compliance matrix, the research domain (scheduled/unscheduled maintenance) and the investigated benefits are visualized, giving a clear overview of the limitations in terms of the impact of CBM considered in each paper. Most papers show promising results in terms of benefits of condition-based maintenance, but the question remains to what extent and for which systems condition-based maintenance is actually beneficial, in a scenario where realistic airlines are considered.

Table 4.1: Condition-based maintenance benefits compliance matrix

	Preventive Maintenance	Corrective Maintenance	Reduction of No-fault-found (NFF) rates	Improved aircraft dispatch reliability	Reduction of scheduled maintenance task costs	Reduction of number of interruptions (increased availability)	Benefits for logistics	Reduction in wasted life
Kahlert et al. [28]		X	X	X		X	X	
Hongsheng et al. [23]	X	X	X	X	X	X		X
Feldman et al. [12]		X		X			X	
Dong et al. [10]	X				X	X		
Koops [26]		X	X	X			X	
Hölzel and Gollnick [24]	X	X	X	X	X	X		X
Vlamings [45]	X	X	X	X	X	X	X	X
Gerdes et al. [18]		X		X		X		

5

Conclusion

Existing literature on condition-based maintenance for aircraft is extensive and covers various aspects necessary for an eventual implementation in practice. A lot of research focuses on the development of PHM frameworks, providing accurate and early RUL estimations for different systems and structures. Other papers focus on dynamic maintenance scheduling based on these RUL estimates and analyzing the impact of prognostics on costs and benefits. A large stream of literature considers a single aircraft, and in most cases even a single subsystem where prognostics is applied. There are papers dealing with fleet condition-based maintenance scheduling, but mostly in a simple setting where all aircraft operate from the same base and limited to a relatively small number of aircraft (mostly for military purposes). Finally, research has been done regarding cost-benefit analysis of condition-based maintenance. Models found in existing literature usually are based on heavy assumptions regarding costs, as this data is often confidential, inaccurate, or even non-existent. Cost factors such as maintenance or opportunity costs are difficult to quantify and are different for each airline, and therefore, expressing all benefits of CBM in a monetary value is not an optimal approach. Furthermore, most existing models zoom in on a specific aspect that benefits from CBM, such as the effect on unscheduled maintenance [18][26][28][12], the effect on scheduled maintenance [10] or they attempt to combine these [23][24], either for a single subsystem or for an aircraft comprising multiple systems.

A logical next step in research would be the **development of a model, capable of holistically assessing the economic and operational impact of CBM on fleet and network level, where both the effects on scheduled and unscheduled maintenance are considered and planned in tandem. This model should be flexible and usable to different airlines, characterized by different network types, aircraft types, fleet sizes and compositions, and maintenance policies (i.e. block maintenance or equalized maintenance)**

This research will dive deeper into the impact of varying prognostics performance levels, such as the influence of the prognostic horizon or the effects of false positives/negatives and their differences on the consequences for safety-critical and non-safety-critical tasks. An attempt will be made to identify requirements for PHM performance levels for CBM to be beneficial and to find a good balance between false alerts and undetected faults from an economic point of view.

In contrast to the approach as in Holzel and Gollnick [24], focusing on 25 systems with a non-parametric failure distribution; and the approach in Vlamings [45], where only 2 systems are subjected to CBM, but failure behavior is modeled with a parametric distribution validated with historical data, this research will improve this aspect in two ways. Firstly, the quantity of systems where CBM is enabled will be increased by developing an index based on a number of characteristics to determine to which extent tasks or systems can benefit of CBM. Then, the second aim is to model the failure behavior of these systems accurately by clustering all systems based on their failure behavior and estimating remaining useful life for each system individually, based on a parametric estimation determined for each cluster.

Most research concerning cost-benefit analysis of CBM considers metrics such as return on investment or lifecycle costs, expressing all benefits in a monetary value. However, cost models differ for each airline and a maintenance organization has no direct influence on this cost structure and thus on an airline's profitability. What maintenance organizations are able to do is to perform maintenance while maximizing the airline's earning potential, that is, the plannable availability, operational reliability, and cost. Therefore, the proposed model will enable the airline to maximize the earning potential by maximizing plannable availability, while complying with operational reliability requirements, in contrast to existing cost-benefit analysis tools expressing everything in a monetary value and minimizing cost.

This research will attempt to close the gaps in existing literature with the following research question in mind:

"What is the impact of CBM on aircraft maintenance for different types of airlines, characterized by different network types, aircraft types, fleet sizes and compositions, and maintenance policies, and can it be associated to an increase in earning potential for the airline?"

This work will build upon a simulation model developed by B. Vlamings [45] and expand its scope in order to answer the following subquestions:

- How can prognostic performance be modelled?
  - How can the actual remaining useful life of selected components and structures be determined?
  - How can the expected remaining useful life of selected components and structures be modeled?
  - What metrics can be used to assess prognostic performance?
  - What is the impact of false positives / false negatives?
  - How does the decision threshold for failure indication influence the false positive / false negative rate?
  - Is there an optimal decision threshold for failure indication? Can this failure threshold be dynamically assigned and if so, on what factors does this threshold depend?
- What are the effects of CBM on scheduled and unscheduled maintenance, and how can this be modeled?
  - Which scheduled tasks can be replaced by or subjected to CBM and to what extent?
  - For which structures or systems can PHM/SHM reduce the amount of unscheduled maintenance?
  - How can the effect on scheduled and unscheduled maintenance be modeled in sync?
  - How are maintenance opportunities defined in the simulation?
  - How can task packaging be done efficiently and how are unscheduled tasks added to scheduled work packages?
- How can the impact of CBM be quantified and how can the cost-benefit analysis be tailored to specific airline needs?
  - Which cost factors should be considered and how can they be quantified?
  - Which benefits result from adopting a CBM approach and how can they be quantified?
  - How can the effect of CBM be modeled on fleet level?
  - How can the model be extended to support different fleet configurations (type, size, aircraft types) and how does this affect the impact of CBM?
  - How can different maintenance strategies be incorporated in the model?
  - How can different network types and their corresponding maintenance opportunities be modelled?
- What PHM performance levels are required for CBM to be beneficial?
  - What is the required prognostic horizon?
  - What is an acceptable false positive / false negative rate?

III

Research Methodologies
previously graded under AE4010

1

Research Methodologies

Executive Summary

With an increase in sensor technology in newer generations of aircraft, a promising maintenance strategy, known as condition-based maintenance is emerging. The constant collection of sensor information allows to monitor the health of structural elements and systems, facilitating the prognostics and diagnostics of potential failures. The objective of the proposed research is to investigate the potential benefits of condition-based maintenance for different types of airlines, with a focus on the required performance levels of the prognostic algorithms. The condition-based maintenance strategy will be simulated for a fleet of aircraft and aircraft fleet availability will be compared to the current practice in maintenance operations. The simulation method of choice is a discrete-event simulation model, combined with a Mixed-Integer Linear Programming (MILP) planning model to optimally schedule maintenance events. Requirements on performance levels of the prognostic algorithms will be determined by assessment of the prognostic horizon and the impact of false and missed alarms. The results of this research should give an indication of the feasibility of condition-based maintenance, as well as the prognostic performance levels required to yield an increase in earning potential for the airlines under investigation. The main motivation for this project is to demonstrate the true value of condition-based maintenance and to kick-start a global adoption of this promising strategy, by developing a flexible and holistic simulation tool.

1.1. Introduction

Aircraft Maintenance, Repair and Overhaul (MRO) expenditures were estimated at $69 Billion in 2018, representing around 9% of airlines operational costs and are expected to reach $103 Billion in 2028 [25]. Therefore, the efficiency and quality of the maintenance process is of paramount importance for an airline operator. Currently, the standard maintenance strategy combines preventive and reactive maintenance. Preventive maintenance is often carried out at fixed time intervals, having the advantage of a fixed maintenance schedule and high reliability due to conservative time intervals, but at the inevitable cost of wasting part of the useful life. Reactive maintenance on the other hand is performed when a part is damaged, exploiting the entire useful life, but resulting in unexpected downtime and generally higher maintenance costs.

A new trend and promising solution to improve efficiency is condition-based maintenance (CBM). Condition-based maintenance is a maintenance strategy aiming to maintain systems right before failure using information about the actual condition of the systems, in order to keep reliability high and operating costs low [46]. The constant collection of sensor information allows to monitor the health of structural elements and systems, facilitating the prognostics and diagnostics of potential failures and to schedule maintenance before the failure happens. A trade-off has to be made between the risk of failure during operation (leading to costly downtime) and the cost of premature maintenance (wasting remaining useful life of the system or component) [46]. An extension of condition-based maintenance is predictive maintenance, where prognosis is employed to predict the future health and estimate the remaining useful life (RUL) of a system or a structural component [41]. Condition-based maintenance has two main components: prognostics and health management (PHM), focused on RUL estimation;

and post-prognostics decision-making, which relies on the prognostics output (RUL) for decision-support [50]. Effective prognostics & health management can change unscheduled maintenance to scheduled maintenance by planning a scheduled maintenance event before the estimated end-of-life [11], but also allows to skip unnecessary scheduled maintenance if no safety-threatening condition is observed [47].

Even though the technology is catching up, there is still a lot to accomplish in order to see CBM as the industry standard. First of all, in order to further stimulate developments of practical applications of CBM, it should be associated to an increase in earning potential through a proper cost-benefit analysis, and more importantly, it should be investigated to which components CBM would be beneficial and to what extent CBM can be implemented. Furthermore, certification requirements should be in place. Progress is being made in this area: MSG-3 methodology has been updated to allow aircraft health monitoring as an alternative to the classic scheduled maintenance task [48]. Finally, a large part of the challenge is to apply CBM technology to different structures and systems and to adapt the maintenance processes and decision-making philosophy accordingly [22].

The goal of this project is to develop a model, capable of holistically assessing the economic impact of CBM on fleet and network level, where both the effects on scheduled and unscheduled maintenance are considered. This model should be usable to different airlines, characterized by different network types, aircraft types, fleet types, business models and maintenance policies. The structure of this project plan is as follows. In section 1.2, a literature review is carried out in an attempt to pool the relevant literature and the current state-of-the-art. Then, in section 1.3, the research questions and objectives are formulated. In section 1.4, the methodology and theoretical concepts are presented, followed by the experimental set-up, which is outlined in section 1.5. The expected outcome of the proposed research project is briefly discussed in section 1.6. Then, in section 1.7, the planning of the project is presented and finally, section 1.8 covers the main conclusions and takeaways from this project plan.

1.2. State-of-the-art/Literature Review

Existing literature on condition-based maintenance for aircraft is extensive and covers various aspects necessary for an eventual implementation in practice. A large part of the literature focuses on the development of Prognostics and Health Management (PHM) frameworks, providing accurate and early RUL estimations for different systems and structures. Other papers focus on dynamic maintenance scheduling based on these RUL estimates and lastly, the third stream of literature analyzes the impact of prognostics and condition-based maintenance through cost-benefit analysis, which is the main subject of this literature review.

In the last decade, numerous researchers have contributed to the literature on PHM frameworks for various aircraft systems and structures, using different types of data and algorithms. A common finding from the literature about this topic is that often, knowledge of the underlying physics can drastically improve model performance compared to a solely data-driven algorithm. Also, operational and environmental factors are shown to play an important role in system failure behavior, and including these in the model has a positive effect on the model's accuracy [43].

Secondly, several researchers have developed different modeling approaches with respect to maintenance scheduling considering prognostics information. This covers applications in many fields, including line maintenance optimization [44] [37], reduction of unscheduled and scheduled maintenance activities [24], maintenance planning for a fleet of aircraft [15] [51] [31], and the development of entire decision-making support systems for aircraft condition-based maintenance[32] [33].

Still, a major challenge in the implementation of predictive maintenance is the necessity of an upfront investment without direct benefits. The possible cost savings are difficult to quantify and hence a suitable cost-benefit analysis is needed to justify implementation of a condition monitoring system. A condition monitoring system will need to perform adequately, as the true benefit of condition monitoring lies in how early impending failures are detected and how accurately and precisely the time until failure is predicted [7].

Already in 2008, Leao et al. [30] presented a methodology for cost-benefit analysis on the application of PHM for legacy commercial aircraft. The methodology takes into account the lack of provisions for PHM systems on legacy aircraft, but also the availability of operation/maintenance data and experience. Although no cost-benefit analysis tool was developed, the authors gave valuable insights in all costs, benefits, risks, financial metrics and tools that should be considered or implemented in a cost-benefit analysis framework. By examining the existing literature on cost-benefit analysis of PHM systems, it becomes clear that the list of cost and benefit factors presented by Leao et al. [30] is rather extensive. Although some researchers have identified additional cost factors, (e.g. MEL tasks required to be performed when the aircraft operates under degrading conditions, such as flying only below a certain altitude or with the APU turned on; or degradation costs caused by a component operating under degrading condition, for instance engines consuming more fuel due to lower efficiencies [44]) most of the cost factors found in literature are considered.

The cost-benefit models found in literature use different methods to evaluate the costs and benefits associated with PHM. Three main types of evaluation techniques were identified: scenario analysis, Monte Carlo simulation (MCS) and discrete event simulation (DES). Next to the variety in assessment methods, the scope of analysis varies from paper to paper, ranging from a simple maintenance event-based cost reduction calculation to a (nearly)-complete holistic multi-system economic assessment. Furthermore, some authors evaluate the effect of CBM on scheduled maintenance, while others look into the consequences for unscheduled maintenance. Considering both types of maintenance is of course also possible, and for a proper holistic assessment, necessary.

Gerdes et al. [18] have proposed a relatively simple approach to investigate the effect of unscheduled maintenance delays. The authors looked into historic delay and failure data related to delays caused by the air conditioning system, as indicated in the database of the Airbus A340-600 in-service report (ISR). Delays that could be prevented or reduced with the help of CBM were identified and it was shown that 80 percent of the maintenance actions causing departure delays can be prevented, should new sensors be introduced such that all fault causing systems can be monitored reliably. More realistically, with the already existing sensors, it would be possible to avoid about 20% of delays causing maintenance actions. The results of this study, while promising, should be dealt with cautiously and critically. Only costs that are preventable due to reduction of delays are examined and no attention is given to the impact of possible errors associated with condition monitoring, e.g. false positives or false negatives, or performance metrics such as the prognostic horizon [18]. The performance of the PHM system has a significant impact on the benefits that can be realized by condition-based maintenance [26][28][24]. Another approach analyzing various scenarios with their associated cost is found in Koops [26]. Koops conducted a cost-benefit analysis to find the optimal operating point on the ROC curve, i.e. the optimal decision threshold for failure indication, and to analyze the net benefit of predictive maintenance compared to an approach without failure prediction (i.e. unscheduled maintenance). Kahlert [28] computed the annual cost savings of PHM-based maintenance compared to unscheduled maintenance for on-condition maintained LRUs, using discrete event simulation. Failure data is deterministic but input data for costs and process time is stochastic, therefore, Monte Carlo Simulation is used to represent the uncertain parameters. The aim of this study is to evaluate the financial potential of a component-specific PHM system and to specify component-based PHM parameters (Prognostic Horizon (PH) and accuracy). Whereas Kahlert et al. [28] took a deterministic approach towards incorporating failure data in a discrete event simulation, Feldman et al. [12] calculated the Return On Investment (ROI) of a PHM system relative to unscheduled maintenance with a stochastic discrete event simulation, complemented with Monte Carlo Simulation to account for uncertainties in the inputs for the discrete-event simulation (e.g. the performance of the PHM system and the costs involved in the calculation). Furthermore, they looked into the effect of a PHM system on spare parts inventory management. The case study presented in this paper focused on a precursor to failure PHM approach for an avionics LRU in a commercial aircraft (multifunction display in a Boeing 737-300). The precursor to failure methodology is used to forecast a unique time to failure (TTF) distribution for each LRU. Then, based on this TTF distribution, either a scheduled maintenance activity or an unscheduled maintenance activity is performed, and relevant costs are accumulated. With realistically assumed cost values, based on credible sources and provided with a thorough reflection, a positive ROI was demonstrated while accounting for both uncertainties in PHM performance and costs involved. However, more attention should be given to the impact of PHM at system level, as well as the inclusion of variability in the operational profile, false/missed alarm and random failure rates, time needed for maintenance, and system complexity [12].

Dong et al. [10] have investigated the effect of Structural Health Monitoring (SHM) on the safety and lifetime cost of an airplane fuselage compared to scheduled, preventive maintenance. A lifecycle cost (LCC) analysis was conducted for both scheduled and condition-based maintenance. Monte Carlo Simulation was used to simulate uncertainties in the number of maintenance trips and the number of cracks repaired. In Hongsheng et al. [23], three separate cost models are established: optimization of scheduled maintenance, optimization of unscheduled maintenance and error impact analysis. With the help of PHM, some of the scheduled maintenance tasks can be replaced by PHM monitoring, whereas for some tasks, the interval can be extended. Benefits for unscheduled maintenance include the possibility to reduce unscheduled maintenance events caused by failure of critical components with the help of prediction technology. Finally, the effects of prognostic errors in the PHM system such as false alarms and missed alarms on maintenance costs are evaluated. False alarms only result in additional checks and troubleshooting, while missed alarm events trigger unscheduled replacement or repair. The simulation model can evaluate maintenance man-hours, costs and unscheduled maintenance events before and after PHM implementation. Due to the lack of practical operating data, the authors opted to use Monte Carlo Simulation to evaluate working hours and cost of PHM-based maintenance [23].

Hölzel and Gollnick [24] provide a holistic lifecycle cost-benefit analysis of a PHM system in future or present commercial aircraft. In the proposed approach, multiple subsystems are considered, and failure behavior is modelled individually for each subsystem. The methodology is based on discrete-event simulation for aircraft operation and maintenance, and scheduling of CBM tasks is done using an optimization algorithm. Both the effect on scheduled and unscheduled maintenance is analyzed. The economic analysis in this paper follows an assessment approach based on the lifecycle cost-benefit model AIRTOBS (Aircraft Technology and Operations Benchmark System). AIRTOBS models all relevant economic parameters along the aircraft lifecycle and consists of three main modules. The Flight Schedule Builder (FSB) generates a flight schedule for the entire lifecycle based on airline route data and assumes full aircraft availability. Then, the Maintenance Schedule Builder (MSB) executes a discrete-event simulation of the flight operation and maintenance events. Finally, the Lifecycle Cost-Benefit (LC2B) module conducts a cost-benefit analysis based on the simulation results [24]. The assessment approach presented by Hölzel and Gollnick [24] is generic and hence adaptable to different kinds of aircraft. Extension of this model to a fleet-level, where maintenance tasks can be scheduled for a fleet of different aircraft types on a network would allow for an even more realistic assessment of PHM [24]. Also, the inclusion of structural health monitoring in this model would be beneficial for its usability in practice. Finally, in a paper by Busse et al. [7], another holistic approach for cost-benefit analysis is proposed. While not aircraft-specific, the authors propose a well-explained framework for cost-benefit analysis of prognostic systems, where especially the RUL prediction modelling in terms of accuracy and precision, and the two proposed maintenance strategies could be integrated in a more airline-specific model considering the appropriate costs and benefits. The purpose of the presented approach is to investigate which potential cost-savings PM might generate as a function of its maturity and specific performance metrics. Busse et al. [7] mainly focus on two fields: the modelling of diagnostics and prognostics (D&P) information and the modelling of different integration options for the condition monitoring system (CMS) into the production system. The temporal performance of the RUL prediction is modelled with a stochastic process, from the perspective of both availability and its trajectory. The former indicates when the first prognosis is available, the latter is an indication of how the quality of the prediction develops over time. In the proposed model, the prognostic trajectory is modeled using Brownian Motion with drift and transferred to the RUL diagram. The D&P information is then integrated using two prediction-based control strategies. Trigger strategies consider a limit value, typically the predicted RUL, in order to initiate a maintenance activity immediately. Planning strategies on the other hand, use predictions to plan future maintenance activities while minimizing the associated cost [7].

Vlamings [45] made an effort to address the limitations in existing literature, especially those regarding the effects of false alarms as well as the effects of CBM on the supply chain, through the combination of a finely grained PHM framework integrated into a robust planning application for a fleet of aircraft. In his research, holistic models, adaptive to various fleet sizes with aircraft containing different components, to assess the effects on scheduled and unscheduled maintenance were developed and executed independently [45].

Despite the good quality of the research done by Vlamings [45], factors such as limited time resulted in considerable limitations. In the simulation model, the preventive and reactive maintenance actions are disconnected. While this can give an indication of the benefits on each category, this assumption is not realistic, as these maintenance actions are coupled in real life. Furthermore, the number of systems considered in the reactive module is rather small compared to the overall number of systems in an aircraft and is thus not suited to give a representative indication of all the benefits resulting from CBM. Finally, all costs and benefits are expressed in a monetary value and the simulation model heavily relies on an accurate cost model, which is often confidential and difficult to obtain.

Having reviewed the extensive stream of literature about condition-based maintenance, the lack of a model suitable to deal with the complexity and variety of commercial aviation becomes apparent. A large stream of literature considers a single aircraft, and in most cases even a single subsystem where prognostics is applied. There are papers dealing with fleet condition-based maintenance scheduling, but mostly in a simple setting where all aircraft operate from the same base and limited to a relatively small number of aircraft (mostly for military purposes). Finally, research has been done regarding cost-benefit analysis of condition-based maintenance. Mainly, existing models zoom in on a specific aspect that benefits from CBM, such as the effect on unscheduled maintenance [18][26][28][12], the effect on scheduled maintenance [10] or they attempt to combine these [23][24], either for a single subsystem or for an aircraft comprising multiple systems. A logical next step in research would be the development of a model, capable of holistically assessing the economic impact of CBM on fleet and network level, where both the effects on scheduled and unscheduled maintenance are considered. This model should be usable to different airlines, characterized by different network types, aircraft types, fleet types, business models and maintenance policies.

This research will dive deeper into the impact of varying prognostics performance levels, such as the influence of the prognostic horizon or the effects of false positives/negatives and their differences on the consequences for safety-critical and non-safety-critical tasks. An attempt will be made to identify requirements for PHM performance levels for CBM to be beneficial and to find a good balance between false alerts and undetected faults from an economic point of view.

1.3. Research Question, Aim/Objectives and Sub-goals

This research will attempt to fill the gaps as identified in the literature review with the following research questions and objective in mind:

1.3.1. Research Question(s)

The research question is formulated as follows:

"What is the impact of CBM on aircraft maintenance for different types of airlines, characterized by different network types, aircraft types, fleet types, business models and maintenance policies, and can it be associated to an increase in earning potential for the airline?"

The following subquestions will serve as guidelines throughout the project in order to answer the main research question:

- How can prognostic performance be modelled?
  - How can the actual remaining useful life of selected components and structures be determined?
  - How can the expected remaining useful life of selected components and structures be modeled?
  - What metrics can be used to assess prognostic performance?
  - What is the impact of false positives / false negatives?
  - How does the decision threshold for failure indication influence the false positive / false negative rate?
  - Is there an optimal decision threshold for failure indication? Can this failure threshold be dynamically assigned and if so, on what factors does this threshold depend?
- What are the effects of CBM on scheduled and unscheduled maintenance, and how can this be modeled?
  - Which scheduled tasks can be replaced by or subjected to CBM?
  - For which structures or systems can PHM/SHM reduce the amount of unscheduled maintenance?
  - How can the reduction in unscheduled maintenance be translated to scheduled maintenance?
  - How can the effect on scheduled and unscheduled maintenance be modeled in sync?

  - How are maintenance opportunities defined in the simulation?
  - How can task packaging be done efficiently and how are unscheduled tasks added to scheduled work packages?

- How can the impact of CBM be quantified and how can the cost-benefit analysis be tailored to specific airline needs?
  - Which cost factors should be considered and how can they be quantified?
  - Which benefits result from adopting a CBM approach and how can they be quantified?
  - How can the effect of CBM be modeled on fleet level?
  - How can a tail assignment module be implemented in order to schedule multiple maintenance opportunity scenarios?
  - How can the model be extended to support different fleet configurations (type, size, aircraft types) and how does this affect the impact of CBM?
  - How can different maintenance strategies be incorporated in the model?
  - How can different network types and their corresponding maintenance opportunities be modelled?

- What PHM performance levels are required for CBM to be beneficial?
  - What is the required prognostic horizon?
  - What is an acceptable false positive / false negative rate?

1.3.2. Research Objective

The main research objective of this thesis is:

> "To investigate the potential benefits of condition-based maintenance by developing a simulation model, capable of holistically assessing the economic and operational impact of CBM on fleet and network level. In this model, both the effects on scheduled and unscheduled maintenance should be considered and planned in tandem. The model should be flexible and usable to different airlines, characterized by different network types, aircraft types, fleet types, business models and maintenance policies.".

In order to reach this goal and to make the project more tangible, several sub-goals have been defined. First of all, the data will need to be processed and the models for scheduled and unscheduled maintenance should be adapted to the renewed objectives. Then, both models should be combined in order to reflect a realistic maintenance scenario. Another sub-goal of this project is to tune the model to specific airline needs, by including aspects such as a flexible maintenance scheduling module with tail assignment possibilities. Furthermore, the model should be validated with real data provided by KLM. Having a validated model, meaningful case studies should be set up to reflect the different maintenance strategies in different types of airlines, and finally, the data obtained from these case studies should be carefully analysed and discussed in order to formulate valuable recommendations about the potential benefits of condition-based maintenance.

1.4. Theoretical Content/Methodology

This work will build upon a simulation model developed by B. Vlamings [45] with theoretical concepts established by Holzel and Gollnick [24] and Feldman et al. [12]. Where Vlamings opted to separate the simulation of scheduled tasks and unscheduled repairs, this research will attempt to couple these different types of maintenance actions.

The scheduled tasks are given in the Aircraft Maintenance Program (AMP), in which all tasks are outlined together with their interval. The effect of condition-based maintenance on these tasks will be modeled using a framework developed by Holzel and Gollnick [24]. In this framework, tasks are categorized and based on these categories, tasks can be subjected to varying levels of interval escalation or task substitution. Interval escalation is assumed to be a consequence of prognostics where the interval of certain tasks can be extended as a consequence of more accurately predicting the failure behavior of components. Task substitution on the other hand can be applied to tasks that can be replaced by sensors, such as inspection. A Mixed-Integer Linear Programming (MILP) model will be used to schedule these tasks with their adapted intervals, taking into account the limitation of maintenance opportunities and with the objective of maximising aircraft availability.

The outcome of the scheduled maintenance planning module will then be fed into a discrete-event simulation framework to simulate unexpected failure of components, which are maintained according to a reactive maintenance strategy. Here, prognostics is applied to estimate the remaining useful life of the components under consideration, in order to schedule these for maintenance right before expected failure. An important factor here is to deal with imperfections in these algorithms, characterized by False Positives and False Negatives (false and missed alarms, respectively). Feldman et al. [12] have described a methodology of interest, where the remaining useful life is estimated as a function of prognostic horizon. These estimations will subsequently be incorporated in a MILP planning model to assign repair actions to maintenance slots. A discrete-event simulation will then be carried out to simulate the effects of condition-based maintenance over the entire life of the aircraft and different scenarios will be simulated corresponding to different types of airlines.

1.5. Experimental Set-up

The experimental set-up for this research consists of a computer simulation model developed in Python 3.7. Additionally, the SimPy package will be used for the discrete-event simulation of unscheduled repairs, and the CPLEX software will be used for optimisation of mathematical model concerning maintenance scheduling. As the problem size is expected to be rather large, the efficiency of the code will be important in determining the runtime of the simulation model.

The models regarding scheduled and unscheduled maintenance will run independently and in series. Both models will be constructed and validated using data from KLM. The model regarding scheduled maintenance will comprise a MILP model, solved using CPLEX, to schedule the AMP tasks, as provided by KLM. The unscheduled maintenance model will be able to simulate the failure behavior of different subsystems. A discrete-event simulation will be set up in SimPy to track the states of each component, and maintenance actions will be scheduled according to maintenance policy, using a MILP model solved by CPLEX. The computer model will be able to simulate failure and prognostics, and will be validated using failure data from KLM.

1.6. Results, Outcome and Relevance

The data to be used in this project will be made available by KLM. For the simulation of scheduled maintenance tasks, the Aircraft Maintenance Program (AMP) will be used together with historical task data of all tasks performed on a fleet of Boeing 787 aircraft. The data from the AMP contains all tasks required to be performed, together with their interval and scheduled hours. The historical task data contains information on all tasks ever performed on the aircraft fleet. This data is thus not limited to preventive tasks, but maintenance activities such as repairs are also included in this list.

The simulation model for unscheduled maintenance tasks will use failure data provided by KLM, based on historic time to failure data. This data will be used to simulate the maintenance impact of prognostics on the availability and operational reliability of a fleet of aircraft. Therefore, the expected outcome constitutes the changes in ground time due to maintenance of a condition-based maintenance strategy, compared to a strategy using a combination of scheduled and unscheduled maintenance.

The purpose of this data is not only to aid in developing parts of the model, but also to verify and validate the model. The vast amount of historical data allows to test and verify the program for different scenarios, as well as to validate the results with the current maintenance practice. The simulation will be run for different scenarios corresponding to different airline types with different maintenance strategies. Therefore, this project will aim to show the benefits of condition-based maintenance on a larger scope as opposed to any previous work.

1.7. Project Planning and Gantt Chart

In order to ensure an efficient progress of this research project, a proper planning should be in place. A Gantt Chart will aid in keeping track of all activities and milestones to be achieved, and is presented in **??**. The project will consist of two main phases: before the midterm review, the model will be developed and a proof-of-concept will be established; after the midterm review, the model will be fine-tuned and results will be analysed.

1.8. Conclusions

With an increase in sensor technology in newer generations of aircraft, a promising maintenance strategy, known as condition-based maintenance is emerging. The constant collection of sensor information allows to monitor the health of structural elements and systems, facilitating the prognostics and diagnostics of potential failures.

It goes without saying that such radical changes require a large up-front investment, a shift in maintenance regulations and adapted maintenance policies. This research will contribute to the adoption of condition-based maintenance, by investigating its possible benefits for different types of airlines. The benefits will be expressed in terms of changes in fleet availability and operational reliability. A model will be developed as a tool to simulate and quantify the changes resulting from a condition-based maintenance strategy compared to the current practice in aircraft maintenance. Results from this research should give airlines an indication if condition-based maintenance could yield an increase in profits and efficiency, but also for which systems and to what extent the possible benefits would outweigh the investment costs. Finally, requirements on performance levels for the prognostic algorithms will be investigated and special attention will be given to the impact of false and missed alarms.

IV

Supporting work

1

Appendix 1: An overview of airline maintenance strategies

Prior to World War II, maintenance was rarely based on scientific theories and the common strategy was corrective maintenance, with the purpose to restore the functionality of failed items. This approach to maintenance is classified as a reactive approach [2].

As a consequence of increasingly complex items in aircraft by the late 1950s, aircraft maintenance required more downtime and resources, resulting in higher costs and decreasing availability. This forced the industry to shift from corrective maintenance towards preventive maintenance, with time-based maintenance being the norm. Traditional time-based maintenance policies were soon found to be ineffective, and a task force was formed by the FAA to investigate these traditional time-based policies, leading to the first formal "FAA - Airlines Reliability Program" [2].

In 1968, by the time the Boeing-747 was launched, the first structured maintenance program procedure was being published, titled "Boeing-747 Maintenance Steering Group (MSG) Handbook: Maintenance Evaluation and Program Development (MSG-1)". With MSG-1, besides the already known process of Hard Time (HT), other processes were introduced to classify the scheduled maintenance requirements, i.e. On-Condition (OC) and Condition Monitoring (CM) [2].

The systematic MSG-1 methodology was considered to justify a generic solution and resulted in the publication of a second document to develop the maintenance programs for newer aircraft, MSG-2. The shared objective of the two MSG methodologies was the development of scheduled maintenance programs, assuring safety and reliability, while minimizing the associated cost. Both documents followed the same process, but MSG-2 was non-aircraft type-related [2].

As the fuel price increased throughout the years, pressure to decrease maintenance costs was rising in order to keep total operating cost tolerable. Additionally, new regulations, new damage tolerance rules for structures and the advancement of new-generation aircraft gave rise to an improved maintenance planning document, MSG-3. For the major differences and improvements between MSG-3 and previous versions, see Figure 1.1. MSG-3 integrated principles of Reliability-Centered Maintenance (RCM), a methodology focused on effectively managing the risk of function losses through effective maintenance policies, i.e. Preventive Maintenance, Predictive Maintenance, or Redesign. It comprises a top-down, system-level and consequence-driven approach [2].

Method-ology	Characteristics
MSG-1 **(1968)**	• Bottom-up approach • Component level • Maintenance process oriented • Aircraft type-related (Boeing-747) • Using On-Condition and Condition-Based Maintenance
MSG-2 **(1970)**	• Same as MSG-1 • Generic document, non-aircraft typerelated
MSG-3 **(1980)**	• Generic document • Top-down approach • System level • Maintenance task oriented • Emphasis on structural inspection programs • More rigorous decision logic diagram • Distinction between safety and economy • Hidden functional failure treatment

Figure 1.1: Overview of the main conceptual differences and improvements between MSG-3 and previous versions of the methodology [2]

Since its original publication, MSG-3 has been revised several times and it remains the industry standard. The MSG-3 guidelines provide task-oriented logic to determine suitable scheduled maintenance tasks. These tasks will eventually be allocated into scheduled work packages or letter checks, characterized by an alphabetic designation. The three most commonly used letter checks in the airline industry are the A-Check, C-Check and D-Check, all having different tasks and time intervals [1]:

- A-Check: Typically consists of a general inspection of the interior/exterior of the aircraft and is performed biweekly to monthly. Examples of A-check tasks include checking and servicing oil, lubrication, filter replacement, operational checks, and inspections.
- C-Check: Generally scheduled every 12-20 months depending on the operator, aircraft type and utilization. Examples of C-check tasks are functional and operational systems checks, cleaning, servicing, minor structural inspections and Service Bulletin requirements.
- D-Check: Occurs every 6-12 years depending on aircraft type and utilization and generally takes several weeks to complete. During this check, most structurally significant items are inspected and many of the aircraft's internal components are functionally checked, repaired/overhauled, or exchanged.

Other than these "letter checks", MSG-3 allows maintenance tasks to be grouped into packages in a more efficient way. A distinction can be made between block check packaging and phased check (or equalized/segmented check) packaging.

In the block check packaging method, tasks are grouped under a letter check (i.e. A, C & D-Checks). This method is characterized by a small number of relatively large work packages, resulting in a relatively long maintenance ground time. Each letter check incorporates the work covered by preceding checks, plus the tasks specific to that letter check, resulting in an increasing amount of man-power, technical skills and specialized equipment. Advantages of this method include simplified planning & scheduling of work packages, more efficient sequencing of long jobs as well as the accomplishment of modifications and the rectification of non-routines [1].

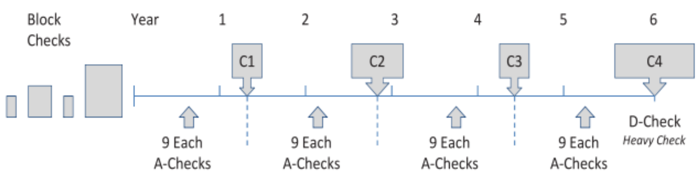


Figure 1.2: Block maintenance program example [1]

The phased check divides tasks into smaller packages that may be accomplished more frequently than the packages in a block check, in order to even out the maintenance workload over time and to shorten each period of down-time. Segments of heavy maintenance tasks can for example be divided equally over an appropriate number of C-checks. This method can result in reduced ground time and thus increased aircraft availability and has the potential to reduce sporadic need for manpower, as well as the advantage of flexibility for task grouping. On the other hand, production planning & scheduling complexity is increased and time for accomplishment of major modifications and to identify & rectify non-routine maintenance is limited [1].

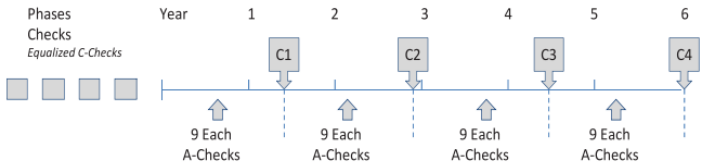


Figure 1.3: Phased maintenance program example [1]

The minimum scheduled maintenance requirements to be used in the development of an approved continuous airworthiness maintenance program are outlined in the Maintenance Planning Document (MPD). This document provides maintenance planning information necessary for operators to develop a customized maintenance program. The scheduled maintenance tasks as provided by the MPD should not be considered as all-inclusive, as each individual airline has final responsibility to decide what to do and when to do it, except for the maintenance requirements under the category "Airworthiness Limitations" (AL) or "Certification Maintenance Requirements" (CMR) [1].

Two possible options for an operator's maintenance program are a generic maintenance program and a customized maintenance program. The former reflects all applicable scheduled maintenance tasks for a particular fleet of the operator, based upon the latest revision of the MPD. It provides operators a ready-to-use maintenance program and schedule where tasks are clustered into dedicated checks. This type of maintenance program is often not in line with an airline's operation and thus not cost-effective. A customized maintenance program on the other hand takes into account the actual aircraft usage and aims to achieve maximum utilization of task intervals. This approach is more cost-effective if managed properly, reduces ground time, makes better use of man-power and task scheduling is optimized [1].

Other than the scheduled maintenance activities required by the MPD, unscheduled maintenance events can be triggered by the unexpected failure of a component or system. Although the aircraft may continue to fly safely due to its built-in redundancy, the equipment generally needs to be fixed before the next take off. If the functional state cannot be restored during turnaround time, the flight will be delayed until the fault is eliminated [18]. The Minimum Equipment List (MEL) defines if the aircraft needs to stay grounded (aircraft on ground, AOG) and specifies the rectification interval of a component or its function. Different MEL categories correspond to different times for fault rectification and serve as an indication for a failure's priority and operational risk [28].

2

Appendix 2: Model verification and validation

With a simulation model as a tool for the cost-benefit analysis of an application such as condition-based maintenance, a major concern is the model's correctness and its ability to represent reality as closely as necessary. This is addressed through verification and validation. According to [29], verification aims to determine whether a computer program performs as intended, i.e., debugging the program. Validation is then concerned with establishing whether a simulation model is an accurate representation of the system under study [29].

In this study, verification of the model was a continuous process, where each new addition to the model was immediately verified. Scheduling models, for scheduled and unscheduled maintenance, were verified with a smaller subproblem for which the optimal solution was known. Comparing the solution of the simulation model to the algebraically obtained solution showed that the scheduling model was implemented correctly. Then, in order to facilitate the verification of the discrete-event simulation model, each event was logged and the logfile containing these events was saved after each simulation run. Whenever an error was raised, the logfile could be inspected to trace back the error to its cause. Additionally, this logfile was used as an extra verification tool for the scheduling model for unscheduled maintenance tasks, and each new addition to the simulation model.

Validation of the scheduling model for preventive maintenance tasks was done by comparing the model output with real-world data obtained from an airline. A simulation was run for the same time period airline data was available, and the number and duration of maintenance checks was determined. As can be seen in Figure 2.2, both the number of maintenance checks as well as their duration were different for the simulation model and the validation data. For the time period covered in the simulation, the simulation model schedules 16 A-checks, while the validation data shows 18 A-checks in the same time period. This is due to a different interval between block checks chosen for the simulation model and does not necessarily mean that the model is invalid. When the simulation model is run with a different check interval, the maintenance opportunities as in the validation data can be easily replicated with the same number of maintenance checks. Important to add here is the assumption that the number of flight hours per day is constant over the entire operating period of the aircraft, resulting in relatively constant maintenance intervals. In real life however, the number of flight hours per aircraft per day is not necessarily constant, and hence the task intervals in days can differ. So, while a maintenance check interval of 1500 FH in the simulation always translates to the same number of days, in real life this is not the case, and the check interval expressed in days between maintenance checks is not constant over the aircraft's life.

In both cases, with an interval of 1500 FH (Figure 2.2), and with an adapted interval to replicate the validation data (Figure 2.1), the composition of maintenance blocks in the simulation model is dissimilar to the validation data. In the validation data, maintenance blocks are more equalised, while in the simulation output, tasks are planned with the objective of maximum interval utilisation, resulting in a non-equalised maintenance schedule. Moreover, the output of the simulation model requires 2 % less total labour hours over the entire simulation period compared to the validation data; with the adapted interval, a 3.9 % increase in total labour hours is observed.

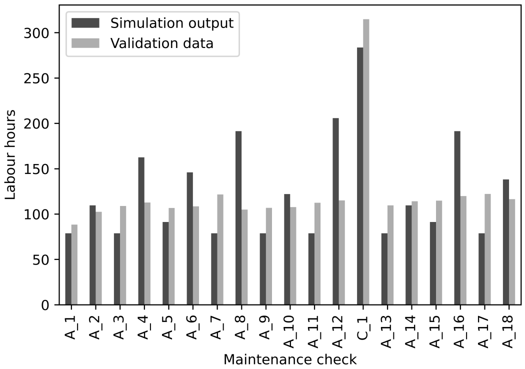


Figure 2.1: Labour hours per maintenance check for the validation data and the simulation output with an adapted interval to replicate the validation data

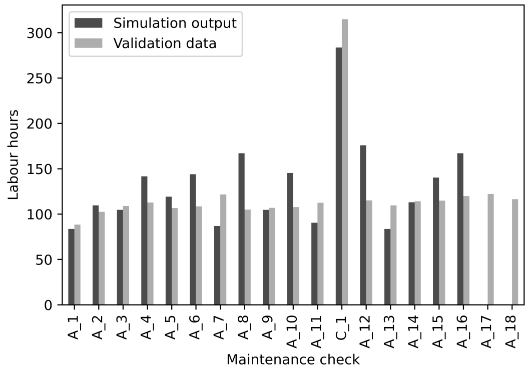


Figure 2.2: Labour hours per maintenance check for the validation data and the simulation output with an interval of 1500 FH between periodic maintenance checks

While these discrepancies can be observed between the simulation output and the validation data, this is not regarded as invalid for the purpose of the simulation. Factors such as packaging of tasks into realistic work packages, taking into account dependencies between tasks are omitted from the simulation, possibly resulting in a different maintenance schedule. However, all tasks are correctly scheduled considering their individual interval, as verified earlier and therefore, the effect of prognostics on these tasks can be investigated and quantified.

Concerning the validation of the unscheduled maintenance module, no airline data was available regarding the operational lifecycle of an aircraft equipped with the subsystems under consideration. However, previous models using the same failure modelling approach have been concerned with the validation of the failure modelling approach and the failure distribution functions used in this research [45]. Therefore, this data is considered to be valid to represent the failure behaviour for the subsystems and therefore the simulation of component failures and their corrective maintenance actions.

Additionally, in order for the simulation of condition based maintenance and the use of prognostics to be validated, it should be checked whether the FPR/TPR combinations as seen in the output of the simulation correspond to those known to be achievable by the PHM system, described by its ROC curve. For each maintenance check, a cost-optimal operating point on the ROC curve is chosen, yielding a failure threshold corresponding to a certain TPR and FPR. The number of true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN) for each check in the simulation is recorded and should be according to the FPR/TPR corresponding to the chosen operating point on the ROC curve. This was validated by keeping track of all events and their types, i.e. TP, FP, TN, FN and checking if their probability of occurrence corresponds to the chosen operating point for each maintenance check.

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