Assessing the Impact of Condition-Based Maintenance as a Function of the Variation in Prognostics Performance Levels

by

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Preface

Before you lies the result of my Master Thesis research which I started in July 2019. It has been a journey with several bumps on the road, but thanks to the support from friends and family, this journey has ultimately been a well worth one. Especially thankful am I for my daily supervisors Floris and Wim. Their kind support and excellent guidance really enabled me to conduct this analysis. Furthermore, I would also like to thank KLM for allowing me to perform this research using their data and equipment. Their expertise was of great importance in achieving tangible results.

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Introduction

With the increasing availability of sensor data measuring aircraft health, it is expected that aircraft maintenance strategies will evolve into strategies more focused on the condition of components, known as condition-based maintenance. Current research is ongoing in how this information about the current and predicted future state of aircraft health can be translated into prognostics, the prediction of the time of failure. However, as with the adoption with any new technological development in the aviation industry, a requirement is that it is cost effective. Hence before investing in new developments a proper cost benefit analysis (CBA) should be done. This research attempts to provide new insights in performing cost benefit analyses considering various prognostics and health management (PHM) parameters. Furthermore a CBA model is developed and validated using real world data. The main research that is set out to be solved is as follows:

> What is the impact of a condition-based maintenance strategy applied to preventive and unscheduled maintenance on aircraft availability and total costs as a function of different PHM performance levels?

This thesis is structured as follows: in chapter 1 a scientific paper is provided, in which a distilled version of the literature study, methodology, results, and conclusion can be found. To provide more context to the reader, appendices are added that elaborate further on these subjects. Appendices A and B describes both a literature review, and project plan that preceded this research. Then in Appendix C the component failure distributions used are validated using MRO data. After that, in Appendix D the policy and planning algorithm used for the unscheduled maintenance module is described in more detail. And finally in Appendix E an overview of the unscheduled maintenance model input parameters is provided.

Chapter 1

Paper

Assessing the Impact of Condition-Based Maintenance as a Function of the Variation in Prognostics Performance Levels

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***Abstract*—As the profit margins of the airline industry are relatively low, it is of utmost importance to keep costs low in order for airlines to stay competitive. An important cost factor is maintenance costs, as it can take up around 10-20 % of the total direct operational costs. Currently, much development is taking place in developing condition-based maintenance (CBM) strategies. These strategies on the one hand leverage remaining useful life (RUL) predictions of components to enable better planning and lower repair costs while on the other hand less preventive maintenance tasks are required due to the increase of useful sensor data available. This paper develops insights in the potential benefits that CBM can have as a function of different prognostic performance levels. This is done by developing cost-benefit models which accept a wide range of parameters being able to simulate prognostic effectiveness on different aircraft fleets. Results are obtained by using real MRO and operator input data. The results show that CBM can be beneficial, given that the model has a sufficient specificity and the component supply chain scales accordingly.**

I. Introduction

As the profit margins of the airline industry are relatively low, it is of utmost importance to keep costs low in order for airlines to stay competitive. When looking at the direct operational costs, factors that play the biggest role are fuel costs, crew costs, maintenance costs, and depreciation costs [17]. Of these cost types, maintenance costs take up around 10 - 20 % of the total direct operational costs [24][9][22]. Aside from costs, aircraft availability is impacted as well by airline maintenance. Of all the total delays in 2011, Eurocontrol assessed that 12.7 % was due to technical and aircraft equipment problems, which was the highest non-reactionary delay category [8].

As aircraft became more and more complex, both the complexity of the maintenance operations and maintenance costs increased. As a result, maintenance strategies evolved in order to maintain aircraft reliability. A first attempt in maintaining and improving the reliability was the establishment of time limitations of components. This is still known as hard-time. However it was found that this relatively simple strategy was only limited effective for most components, at a relatively high cost [29]. As a result, the Maintenance Steering Group (MSG) was formed with the goal of improving maintenance effectiveness. Through several iterations, the focus was gradually shifted from hard-time to on-condition maintenance, during which reliability was ensured by inspecting, servicing, testing and calibrating the components [26]. This was deemed very successful as maintenance costs decreased, while reliability increased [33]. On-condition maintenance strategies increased in popularity and soon enough the MSG-2 program was released, with the addition of a strategy called condition monitoring [29]. This strategy included non-safety critical components, and looked specifically at exceedances of certain predefined threshold values of operational characteristics. Since then iterations have been performed, arriving at the current aircraft maintenance methodology document in use: MSG-3. In 2018 this document was updated to include the current trends in aircraft maintenance strategy: aircraft health monitoring [36].

Aircraft health monitoring is a more advanced strategy in measuring the condition of the aircraft. While in the MSG-2 documents a condition monitoring strategy was implemented, this was not considered preventive maintenance, as failure was allowed to occur. It was mostly used as category for components which neither had a hard time limit nor on-condition maintenance, and was meant for components which failure modes would not have an adverse effect on safety [14].

Aircraft health monitoring is possible due to the numerous amount of sensors that can be found in the more recently developed aircraft. For example the Airbus A350 boasts over 6000 sensors, that in total daily generate 300 GB of data [25]. Together with the development of new data technologies and a substantial increase in computational power, analysing this data has become a possibility. Being able to analyze data rapidly and thoroughly, the focus has been shifted towards prognostics: the act of estimating the remaining useful life (RUL) of a component, based on the current condition and trends in sensor data [31]. When applying prognostics to allow for an overall assessment of reliability with the purpose of reducing maintenance costs and maximize availability, the strategy is called prognostics and health management (PHM) [37] for aircraft systems and Structural Health Monitoring (SHM) for aircraft structures. By continually monitoring and analysing data using modern data analytical methods, faults can be detected earlier on, and the degradation trend of the component can be assessed leading to a prediction of the RUL. This estimation of RUL enables condition-based maintenance (CBM), resulting in potentially better planned maintenance, a reduction in unneeded inspections and increase in aircraft availability [4]. Another maintenance aspect for which a CBM approach can be beneficial is the currently done preventive maintenance checks. Airbus estimates that around 90 % of the current preventive maintenance tasks do not alter the aircraft condition [36]. By applying a CBM strategy, this percentage could be significantly decreased, as health measuring sensors would be able to substitute some maintenance checks tasks and therefore less ground time is required.

Currently, lots of research is conducted in interpreting sensor data and modeling RUL predictions [18] [27] [35]. Furthermore applications are already being developed. For instance Skywise, a product developed by Airbus, attempts to provide insights in the vast amount of data from data sources such as on-board sensor data, work orders, component data, and flight schedules [5]. Easyjet being one of the early adaptors of Skywise, found that the occurrence of delays due to technical errors has been decreased from 10 per 1000 flights, to just over three per 1000 flights [5]. KLM E&M developed a tool called Prognos that takes more of a bottom up approach. Instead of focusing on all data available, Prognos is built up component by component by looking at components that are critical according to KLM taking into account repair costs, and the delays and cancellations they cause [20].

However, still much is unknown in the potential value of CBM applications. Especially useful figures for carriers, are the decrease in maintenance costs and downtime resulting from these CBM improvements. A common challenge among the studies regarding the economic assessment of CBM is the availability of proper, usable data. This is because of various reasons, such as data complexity, and data availability due to sensitivity of this data. For this reason, only a handful studies use deterministic and historical maintenance data, and are able to provide estimates of CBM costs and benefits [10] [19] [16].

While research has been performed on what the effects of CBM can entail, a deeper analysis on the effect of PHM model performance, especially regarding false alarms, is needed. Furthermore the combination of a finely grained PHM modeling system integrated into a robust planning application for a fleet of aircraft has yet to be performed and may show emerging effects as maintenance opportunities are limited. Lastly, it is expected that CBM can have a big influence on the supply chain of components, yet it is unknown how the optimal supply chain conditions would change as CBM would be introduced. The goal of this research is therefore to holistically assess the CBM cost-benefits as a function of PHM performance levels, while taking into account the supply chain and limitation of maintenance opportunities, which can be helpful in establishing requirements for PHM models that in turn can determine the effectiveness of the CBM application. This is done for both preventive and unscheduled maintenance operations on fleet level using real carrier and MRO maintenance and component failure data.

The structure of this paper is as follows. In Section II a short review is presented of the recent literature involving cost-benefit analyses regarding CBM. In Section III the methodology is provided on how the cost-benefit assessment is modelled. This section also aims to present insights in the data and simulation techniques that were used. Then in Section IV, the findings of this assessment on several components for a fleet of aircraft are provided. In Section V the results are further described and consolidated. Finally conclusions and recommendations for further studies are presented in Section VI.

II. Literature review

Due to the upcoming availability of PHM systems, CBM is expected to be valuable regarding preventive as well as unscheduled maintenance. However many different approaches with respect to the assessment of value of CBM are taken. To provide structure in the myriad of methods found in literature, they are categorised in preventive and unscheduled maintenance. These methods are then reviewed and assessed in their corresponding subsection.

A. *Preventive maintenance*

Preventive maintenance mainly consists of maintenance tasks based on discrete events with a generally fixed interval. These are often based on flight hours (FH), calendar time, and/or flight cycles and categorised according to several groups as mentioned in the MSG-3 specifications [29].

Regarding preventive maintenance, CBM concepts have yet to gain ground. This however, is to be expected as the MSG-3 documents have not supported the use of PHM, or any other performance based indicators leading to CBM for a long time [1]. However recently adaptions to the MSG-3 methodology have been proposed allowing health monitoring systems as an alternative to classic preventive maintenance tasks [36].

Recently there have been some case studies and maintenance scheduling modelling approaches assessing the economic value it could bring. For instance similar case studies done by Dong, T. Haftka, and H. Kim [6] and Pattabhiraman et al. [23] focused on the impact of condition-based maintenance in structural aircraft maintenance. It was investigated whether structural health monitoring (SHM) techniques were able to reduce costs by skipping certain preventive maintenance actions. Pattabhiraman et al. [23] found that especially during the first four to eight C-checks of an aircraft, much costs could be saved, since inspections were not necessary yet. Three different approaches incorporating SHM were presented, all showing significant improvement in total costs over conventional preventive maintenance. However cost data used were averages in literature, and the cost modeling technique contained various assumptions, such as a 20% to 100% increase of costs when maintenance is unscheduled, and downtime costs were not taken into account. It should be noted however that extra costs due to the weight of sensors, were taken into account. These were considered quite substantial over a lifetime of an aircraft. Still it was found that CBM would lead to lifecycle cost savings ranging between 12.8 and 17.9 M$ per aircraft.

Dong, T. Haftka, and H. Kim [6] delved a bit deeper into the costs increase and savings associated with CBM. They also included costs increase due to the necessity of replacing the SHM systems during the lifetime of an aircraft. The big cost savings found in this study related to the reduction in time required for a C check. It was found that 12 days of C check could be saved, as the time of actual inspection was assumed to be much lower and surrounding structures were not needed to be removed in order to facilitate inspection. Another cost saving aspect came from the idea that SHM techniques enabled more regular crack size inspections during A checks, instead of C checks, and therefore a higher crack size threshold was allowed. The effect on scheduling repair actions according to these different inspection parameters is unfortunately left out as it might trigger unscheduled maintenance events, resulting in higher costs. Still the eventual cost savings were found to be in the same order as Pattabhiraman et al. [23].

Aside from these case studies, other studies took a more global approach in estimating the effects of CBM on preventive maintenance. An interesting approach was done by Hölzel, Schilling, and Gollnick [16] in which maintenance tasks and predicted unscheduled failure events were combined in task packages depending on the RUL or maintenance intervals. This task packaging might be especially beneficial in that due to prognostic information, interval of tasks can be escalated and some tasks can even be omitted. This is done by grouping tasks based on their task codes in task code groups (TCGs). Depending on the TCG, a task is either eliminated, the interval is escalated, or nothing changes. The limitation of this study is that only 2 global parameters, namely interval escalation and task substitution influence this impact, and hence no detail analysis of tasks is done. Though given the great number of tasks, this might be considered a reasonable assumption.

Taking only into account preventive maintenance, and assuming the most optimistic scenario, i.e. parameters of task redundancy being 1 and interval escalation being 100 %, a potential lifecycle maintenance costs saving of around 3 M€ per aircraft. This is relatively low considering the total maintenance cost modeled over a life cycle was estimated to be 76 M€, and the great number of maintenance tasks affected by these parameters. Comparing this number to the potential savings in previously shown studies regarding crack formation, show the complexity of analysing cost savings due to CBM. For instance, the time that is freed up due to task elimination and escalation, might be used to schedule extra flights. While Dong, T. Haftka, and H. Kim [6] assumed a reduction of loss of revenue depending on the days of maintenance saved, Hölzel, Schilling, and Gollnick [16] did not clearly explain what was done with the extra time gained. Applying the maintenance scheduling approach of Hölzel, Schilling, and Gollnick on a fleet of aircraft might reveal patterns in extra time available. These patterns can then be used to adapt the flight schedule, which in result can give a better estimation of the decrease in opportunity costs.

B. Unscheduled maintenance

Another aspect in which prognostics can provide benefits is the prevention of unscheduled maintenance. Unscheduled maintenance is the result of failure of components during flight or unexpected findings during regular maintenance. In these cases of unexpected failure two modes of action are available depending on the urgency: the repair can be postponed in which the term deferred defect (DD) is used, or the repair needs to take place before the aircraft is airworthy again. This mostly depends on redundancy and whether components are safety critical. Operators make use of a so called minimum equipment list (MEL) to determine this urgency. This MEL contains the airworthiness requirements of different components and specifies the maximum term of deferment. If it is not possible to defer the defect, hence the fault has to be repaired before the next takeoff while the aircraft is scheduled to fly, the term Aircaft on Ground (AOG) is used. These situations can get very costly as often flights are canceled and in case that the spare parts are not readily available, expedited shipping is required. Knowing when components are going to fail is therefore especially useful in these cases. It should be noted that carriers currently have specific buffer slots available, such that in the case of an AOG or an upcoming AOG situation, the aircraft can be maintained while another spare aircraft can continue operating. This of course comes with a high opportunity cost as it is generally deemed that the spare aircraft only operates when another aircraft is being maintained. CBM might be able to decrease these buffers required, and therefore decrease opportunity costs.

In order to quantify the cost-benefits related to condition-based maintenance with the use of a model, it is important to understand the parameters associated with PHM systems and their effects on CBM. A big factor in prognostics is uncertainty as it plays a big role in estimating the RUL. CBM can improve system performance, however uncertainty regarding prognostics needs to be mitigated and false alarms minimised before monitoring techniques can be implemented and made use of [34].

Saxena et al. [28] also had a look at uncertainty in prognostics and reviewed metrics used to assess algorithms, with the goal of providing an overview of the different metrics used in literature and suggesting new metrics that specifically cater to PHM requirements. Two of the metrics that play an important role were False Positives (FP) and False Negatives (FN). The missed alarms can be seen as a false negative: the algorithm did not anticipate the failure, while false positives indicate failure while there is none. A better way to formulate this with the change of predicted RUL as a function of time in mind, is by assessing FPs and FNs based on an acceptability range as function of time before anticipated failure.

Aside from existing metrics, the authors proposed several other new metrics for prognostics. One of them is the prognostic horizon. The definition of this is defined as ”the difference between the current time and end of life using data up to the current time index, provided the prediction meets desired specifications”. This metric has gained in popularity as it has been researched in [27] [10] [12] [15] [19]. At first it would be expected that as the prognostic distance is increased, the performance of the model would be increased as well. However, according to literature there is an optimal prognostic distance related to these components. Fritzsche and Lasch [13] showed why this is the case, and mentioned the decrease in forecast quality, increase in prognostics cost and increase in wrong delivered spare parts associated with a longer prognostic distance as crucial causes.

Already in 2002 a cost-benefit analysis was done regarding mostly prevention of unscheduled maintenance regarding engines of fighter aircraft [3]. The paper highlights both the prognostic and diagnostic benefits that PHM can have on unscheduled maintenance, such as reducing the Mean Time to Diagnose (MTTD). Feldman, Jazouli, and Sandborn [10] proved that not only PHM can improve inspections, but prognostic models can also be a valuable tool with respect to inventory management and that it can increase the operational availability of an aircraft. Kählert, Giljohann, and Klingauf [19] used empirical maintenance data in modelling the replacement of Line Replaceable Units (LRUs) while taking account stochastic parameters such as accuracy and prediction horizon.

Also based on deterministic data was the approach of Nicchiotti and Rüegg [21]. In this paper a data-driven approach was taken in predicting failure events. A combination of Central Management System data and logs of maintenance activities from a fleet of aircraft was used. Machine learning techniques used this data in predicting at least two flights ahead whether a component would fail. Results were that the precision was relatively high, hence false positives were low. Also considering the low recall rate, this method would prove to be beneficial only as an additional tool in helping decisions, and not yet as a standalone product.

With respect to the air conditioning system, Sun, Wang, and Ning [32] proposed a model that takes into account multiple sensor signals generating a single health index. Using this health index as input for a Bayesian failure prognostic method yielded satisfactory results in predicting the time of entering the degradation warning stage. In this case the relative prediction errors were below 8 %. An interesting conclusion from this study was that as closer the component was to its end of life (EOL), the predicted failure time is closer to the actual failure time, and hence the uncertainty is less. The key question what follows from this is then how this balance between an earlier more uncertain prediction of failure and a late but more certain prediction time influences the optimization of scheduling of maintenance tasks.

Feldman, Jazouli, and Sandborn [10] did a case study taking into account these uncertainties in predicting the precursor of failure of a multi-functional display. As part of the PHM cost benefit analysis, the optimal prognostic distance (PD) was determined. This prognostic distance is defined as the time horizon before actual failure, the prognostics system is able to indicate failure [27]. Unique in this study is that this precursor expected time to failure (TTF) is a distribution based on a sample of the distribution of the actual time to failure and prognostic distance. When a sample TTF is taken from the distribution of the precursor expected TTF, and this TTF is higher than the actual TTF of the instance it is assumed that unscheduled maintenance is required leading to higher costs. This paper also provides a cost-benefit analysis by comparing life-cycle and CBM investment costs of the CBM scenario to a baseline scenario. It was shown that the CBM scenario could either decrease costs by 19-81%, or increase costs by 2-7% compared to fixed interval replacements depending on the TTF distribution used. However it should be noted that false alarms were not taken into account.

There have been many papers looking into different approaches of modeling prognostics and predicting the RUL. However not a great amount of research has been done in how these approaches can be integrated into a planning model that can prevent unscheduled maintenance leading to potential cost savings. Vianna and Yoneyama [35] however combines the modeling of prognostics as well as modeling the effects on planning. This is done by focusing on the identification of degradation considering a multiple wear profile scenario and integrating this with a line maintenance planning model. This model was based on a combinatorial search algorithm.

The algorithm loops over all turnaround times within the planning horizon and finds the repair and service schedule that minimizes the operational costs. In doing this, constraints on resources and the corresponding MEL category are taken into account as well. Limitations are that only line maintenance is considered in this study. The study also claims parallelisation is allowed to perform the repair and servicing of different components, however dependencies between these activities such as available manpower and time is not considered. When considering a fleet of aircraft, this might prove to be especially difficult using a combinatorial search algorithm, and other simulation approaches such as an heuristic game approach [11], or a discrete event approach [19] might be beneficial. It might be interesting to see the results of a complete maintenance scheduling approach as done by Hölzel, Schilling, and Gollnick [16], while taking into account the methodology used in this paper.

Hölzel, Schilling, and Gollnick [16] took a more global approach and focused on the planning aspect of CBM by using a MILP model. Regarding prognostics, one global parameter was used to indicate the accuracy of the PHM application, and this accuracy was assumed to hold for all 12 subsystems for which a PHM application was considered possible. The effects of this reduction in unscheduled maintenance was found to be a relative low 1.5 % maintenance cost savings, mostly attributed to a decrease in delay costs. Once again false alarms were not defined.

With respect to DES, Kählert, Giljohann, and Klingauf [19] used this simulation technique in assessing the cost-benefits of a CBM approach by developing a cost-benefit analysis method suitable for LRU replacements. Using deterministic MRO component failure and maintenance data, failure events were simulated according to historic data, and based on prognostic horizon and PHM accuracy, the CBM effectiveness was assessed. The advantage of the DES approach here, is that it allowed to analyze the interdependencies between events, and cause and effects could be established. It was expected that a realistic PHM solution would be able to save approximately 20 % annual maintenance costs for the entire fleet. Yet it should be noted that investment costs and false alarms were not taken into account.

From this literature review it can be established that even though research has been performed on what the effects of CBM can entail, a deeper analysis is required in order for operators and MROs to start investing in CBM opportunities. An important factor here is PHM model performance. While accuracy has been reviewed in several papers, still much is unknown about the effects of false alarms, therefore it is deemed an important factor in this research. Furthermore the combination of a finely grained PHM modeling system integrated into a robust planning application for a fleet of aircraft has yet to be performed and may show emerging effects as maintenance opportunities are limited. Lastly, from literature it was seen that the supply chain effects play a major role on the effectiveness of CBM [10], therefore it might be of interest to assess how CBM affects the supply chain, and whether variation in supply chain parameters might enhance the effects of CBM. Considering these remarks, the goal of this research is therefore to holistically assess the CBM cost-benefits as a function of PHM performance levels which can be helpful in establishing requirements for PHM models that in turn can determine the effectiveness of the CBM application.

III. Methodology

A. *Research Design*

This paper attempts to estimate the potential CBM value by providing holistic models regarding preventive and unscheduled maintenance. These models are adaptive to various fleet sizes with aircraft containing various components, each having their own prognostic performance in terms of PH, false positive ratio and false negative ratio. Planning algorithms are then used to estimate how effective these prognostic performance levels are and what they mean in terms of costs and required aircraft ground time. It should be noted that these models are executed independently, hence a limitation is that the preventive maintenance scheduling results do not affect the maintenance opportunities used in the unscheduled maintenance module and vice versa. A global overview of the complete cost-benefit assessment model can be seen in Fig. 1.

The preventive maintenance model reviews the numerous regularly executed maintenance tasks of an airline described in the Approved Maintenance Programme (AMP). By using a simulation model, both downtime and various costs such as labour and opportunity costs can be compared in order to assess the potential benefits of the application of CBM. Besides this preventive maintenance module, an unscheduled maintenance module is developed as well. This module focuses on the various costs and downtime associated to swapping replaceable parts as described in the aircraft MEL list. Once again a simulation model is used, however this time with the goal of simulating component failures and responses of the prognostic systems, depending on its performance. The model accepts numerous input parameters which enable the assessment of CBM impact in various scenarios, such as scenarios with differences in the number of available maintenance opportunities, fleet sizes, and component spare availability.

B. *Preventive Maintenance Module*

As the application of prognostics to the AMP of most airlines is currently non-existent, scenarios with respect to task execution are created that take into account assumptions of potential future usages of prognostic systems. In these scenarios, the full AMP task list is assessed, and depending on their task group as defined in the MSG-3 specifications, either the interval between tasks is escalated, or the task is substituted with a prognostic system, meaning that it is no longer deemed necessary to be executed manually. Limitations of this approach are that both the interval escalation and task substitution parameters are heavily based on assumptions, although domain expert opinion, and are applied globally per task group, meaning that individual task control is not possible. The reason for this global application of prognostic parameters is that the task list used in this research consists of around 250 different tasks, and given the time limitation of this study, finely grained prognostic parameter input on task level was deemed out of scope.

The data used for this module is the AMP task list of a modern wide body aircraft and historic task data of a European carrier for their fleet. This task list provides all AMP tasks with their corresponding interval in terms of

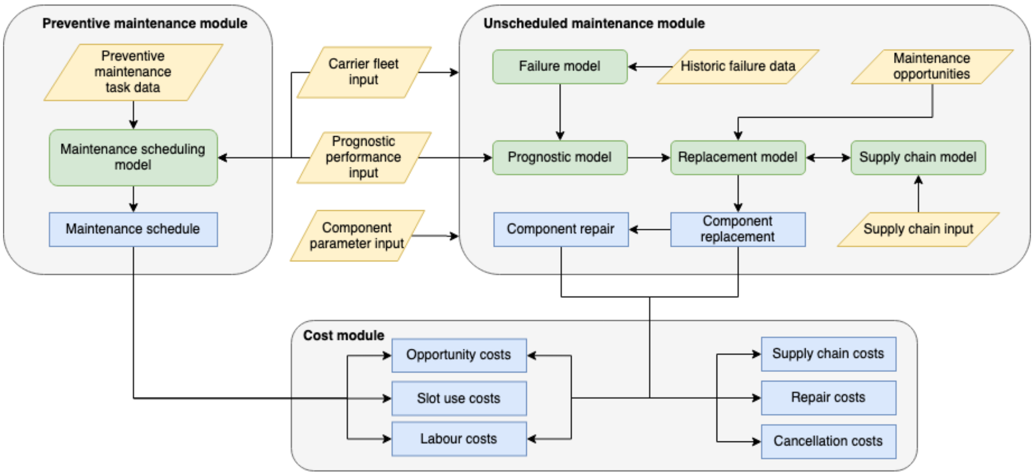


Fig. 1. Global overview of the cost-benefit assessment model

calendar time, flight hours or cycles. Then with the historic maintenance information available, costs per task in terms of labour cost, and maintenance time can be retrieved. Together with opportunity cost data from the carrier it is possible to estimate the potential benefits that CBM can bring.

To be able to properly assess task escalation and task substitution in terms of downtime and opportunity costs, it is essential that tasks are grouped in certain blocks, as it is currently done now. In here lies a classic optimization problem for MROs, as grouping multiple tasks means less trips to the hangar. However by grouping many tasks together, not all tasks are immediately due, as tasks are executed that are due in between the current and next maintenance check. This means that as the number of maintenance checks decrease, the average wasted interval time per task increases and thus the efficiency decreases. Where both wasted interval time and efficiency per task are defined with the following equations.

$$t_w = (t_{i-1} + v) - t_i \tag{1}$$

$$\eta = \frac{(t_w + v)}{v} \tag{2}$$

With t_w being the wasted interval time, t_{i-1} the time when the task was previously executed, t_i the next execution time, v the interval, and η the efficiency. As the task is executed, the next task occurrence is defined based on the last execution date, and not on the last due date, meaning that during the lifetime of an aircraft inefficiencies accumulate, leading to tasks needed to be executed more often. It is expected that when intervals are escalated due to prognostics, the overall efficiency increases as the efficiency loss per task occurrence decreases due to the increased interval. Still it is necessary to find an optimum in the creation of blocks so that the model approaches reality. For this reason a Mixed Integer Linear Programming (MILP) model is created that minimizes overall task and opportunity costs.

This model uses historic task data such as task duration, maximum time interval between task occurrences, labour hours required and task group information to form maintenance blocks containing task occurrences, while taking into account the limitation in number and labour hours available of maintenance opportunities such that all required preventive maintenance tasks are executed. The initial condition is the in-service date of the first aircraft. By varying task interval escalation and task substitution parameters for each task group, different optimal results in terms of task occurrence assignments and resulting costs are obtained. The first step is considering the baseline scenario (e.g. no interval escalation and task substitution), such that the model can be validated by comparing it to the airline's historic task data. After this, multiple scenarios with different prognostic parameters can be run to estimate the potential CBM benefits. The objective function of the MILP model is displayed in Eq. 3 and takes into account the wasted life costs, task labour costs, opportunity costs, and slot use costs. The model is performed for a fixed time, t_{end}, and supports a fleet of aircraft and different tasks per aircraft hence different aircraft types can be mixed.

$$obj: min \sum_{a\in A}\sum_{i\in I}\sum_{j\in J}[\frac{c_i}{v_i}\cdot n_{a,i,j} + c_i \cdot x^k_{a,i,j}] + \sum_{a\in A}\sum_{k\in K}[c^{opp\_fixed}_{a,k}\cdot w^k_a + \frac{c^{opp\_var}_{a,k}}{m_k}\cdot \sum_{i\in I(a)}\sum_{j\in J(i)} d_i \cdot x^k_{a,i,j}] \tag{3}$$

The model uses the following parameters:

Decision variables:

$x^k_{a,i,j}$	1 if occurrence j of task i of aircraft a is executed at opportunity k, else 0
$n^k_{a,i,j}$	Task execution waste time of occurrence j of task i of aircraft a
w^k_a	1 if aircraft a uses opportunity k, else 0
$m^{used}_{a,k}$	labour hours used by aircraft a at opportunity k

Coefficients:

v_i	maximum interval between occurrences of task i
t_k	time of opportunity k
d_i	labour hours required for task i
m_k	labour hours available at opportunity k
$c_{a,k}^{opp\_fixed}$	fixed costs of use of opportunity k by aircraft a
$c_{a,k}^{opp\_var}$	variable cost per labour hour of use of opportunity k by aircraft a
c_i	labour and material cost of execution of task i
b_a	start of service time of aircraft a
t_{end}	simulation end time

Sets:

A	set of all aircraft
$I(a)$	set of all tasks of aircraft a
$J(i)$	set of all occurrences of task i
K	set of all opportunities

The model is then constrained using the following 11 constraints. Eqs. 4 to 7 constrain the first occurrence of each task. Eq. 4 ensures that all first occurrences are executed. Eq. 5 enables each aircraft to have a different starting time of operation, and ensures that the first task occurrence is later than this date. Then in Eq. 6 it is ensured that the first task is executed no later than the maximum interval after the start of operation of the aircraft. Lastly, to obtain the first wasted life, Eq. 7 equates this to the remaining interval.

$$\sum_{k \in K} x_{a,i,1}^k = 1 \quad \forall i \in I(a), \forall a \in A \tag{4}$$

$$\sum_{k \in K} t_k \cdot x_{a,i,1}^k \geq b_a \quad \forall i \in I(a), \forall a \in A \tag{5}$$

$$\sum_{k \in K} t_k \cdot x_{a,i,1}^k \leq b_a + v_i \quad \forall i \in I(a), \forall a \in A \tag{6}$$

$$\sum_{k \in K} t_k \cdot x_{a,i,1}^k + n_{a,i,1} = (b_a + v_i) \quad \forall i \in I(a), \forall a \in A \tag{7}$$

Continuity is ensured with the following similar equations. Eq. 8 limits each occurrence to be executed at a maximum of one time, then Eq. 9-11 define which opportunities are available for this task occurrence depending on the previous occurrence. Finally similar to the first occurrence, the wasted life is obtained by Eq. 12.

$$\sum_{k \in K} x_{a,i,j}^k \leq 1 \quad \forall j \geq 2, \forall i \in I(a), \forall a \in A \tag{8}$$

$$\sum_{k \in K} [t_k - M] \cdot x_{a,i,j}^k - \sum_{k \in K} t_k \cdot x_{a,i,(j-1)}^k \geq 1 - M \\ \forall j \geq 2, \forall i \in I(a), \forall a \in A \tag{9}$$

$$\sum_{k \in K} t_k \cdot x_{a,i,j}^k - \sum_{k \in K} t_k \cdot x_{a,i,(j-1)}^k \leq v_i \\ \forall j \geq 2, \forall i \in I(a), \forall a \in A \tag{10}$$

$$\sum_{k \in K} [t_k - M] \cdot x_{a,i,j}^k - \sum_{k \in K} t_k \cdot x_{a,i,(j-1)}^k + n_{a,i,j} \geq v_i - M \\ \forall j \geq 2, \forall i \in I(a), \forall a \in A \tag{11}$$

$$\sum_{k \in K} M \cdot x_{a,i,j}^k + \sum_{k \in K} t_k \cdot x_{a,i,(j-1)}^k \geq t_{end} - v_i \\ \forall j \geq 2, \forall i \in I(a), \forall a \in A \tag{12}$$

Regarding opportunity usage, Eq. 13 helps in establishing whether an aircraft uses a maintenance opportunity leading to slot use costs. Eq. 14 then limits the labour executed at each maintenance opportunity depending on the labour availability.

$$\sum_{i \in I(a)} \sum_{j \in J(i)} d_i \cdot x_{a,i,j}^k - M \cdot w_a^k \leq 0 \quad \forall k \in K, \forall a \in A \tag{13}$$

$$\sum_{a \in A} \sum_{i \in I(a)} \sum_{j \in J(i)} d_i \cdot x_{a,i,j}^k \leq m_k \quad \forall k \in K \tag{14}$$

Since the model simulation time increases significantly for each additional maintenance opportunity or aircraft, the simulation complexity of the model is limited, as the simulation time would get too large. For this reason it is chosen to separate A-check and C-check tasks into different simulations, as runs containing multiple C checks, which have intervals of 2-3 years, would require a very long simulation time. Furthermore, the savings in wasted life costs for C-check tasks on task level are not expected to be accurate, as these tasks generally must be grouped together given that they are especially dependent on the completion of one another. This results in wasted life cost savings only to be beneficial when the entire C-check is moved, and this is generally not possible in the simulation, as not all intervals of the C-check tasks will be changed. Therefore the slot use costs will not be considered for C-check tasks.

C. Unscheduled Maintenance Module

The other module in this research is attributed to unscheduled maintenance. Similar to the preventive maintenance module, a simulation is used to estimate the effects of CBM. In this module however, the lifecycle of several components in a fleet of aircraft is simulated. The goal of this simulation is to obtain accurate and complete cost results of the different maintenance aspects of these components. To do this, the simulation model consists of several submodules that each take into account these different aspects.

The first aspect that is key in the maintenance operations is the simulation of failure. In literature, often an exponential distribution is used in estimating the time to failure (TTF) of components [10]. However in this case a vast database of historic failure data of components in a pool shared between carriers is available. Therefore, a parametric survival model is constructed for which the parameters of the underlying distribution are found by fitting this distribution using the historic data available. The Weibull distribution has been chosen as underlying distribution as it is capable of modelling a range of different failure patterns from infant-mortality, constant failure (exponential distribution) to wear-out. To obtain the Weibull parameters for this, a Maximum Likelihood Estimation (MLE) is done in the form of Eq. 15 [2]

$$L = \prod_{i=1}^{n} f(x_i|\theta_1, \theta_2, ..., \theta_k) \prod_{j=1}^{m} [1 - F(x_i|\theta_1, \theta_2, ..., \theta_k)] \quad (15)$$

In this equation, the first product group returns the likelihood of a given distribution parameter by multiplying the probability density function for each historic failure event i in all failure events n. Since newer aircraft are considered, many components being investigated have not yet failed. Therefore it is important to take this right-censored data into account as well, otherwise the distribution would be heavily biased towards early failure. This is done with the second product in the equation, for which the likelihood is determined by looking at the survival function for each component j in collection m that has not yet failed. For a 2-parameter Weibull distribution, the MLE equation is given by Eq. 16

$$L(\eta, \beta) = \prod_{i=1}^{n} \left[\frac{\beta}{\eta} \left(\frac{t_i}{\eta} \right)^{\beta - 1} \exp\left(- \left(\frac{t_i}{\eta} \right)^{\beta} \right) \right] \prod_{j=1}^{m} \left[\exp\left(- \left(\frac{t_i}{\eta} \right)^{\beta} \right) \right] \quad (16)$$

Here, η represents the scale parameter and β represents the shape parameter. The validation of the Weibull distribution found using this Maximum Likelihood Estimation is found in Appendix C.

The essence of the PHM approach of this module is contained in the prognostics module. The goal of this module is to estimate a remaining useful life (RUL) throughout the entire component lifecycle when it is installed in an aircraft. The accuracy of this RUL prediction varies depending on the accuracy of the model, prognostic horizon (PH) and actual RUL. Since the goal of this research is to find potential CBM benefits based on different prognostic performances, a model is developed that simulates RUL predictions as a function of prognostic performance levels, PH, and actual RUL.

It is assumed that during a flight the PHM system monitors various sensor data and uses statistical binary classification models to assess whether a component is about to fail or not. The binary classification model is used as this is one of the methods that is currently employed in practice. To provide a means of estimating the RUL, first a model is constructed that simulates such a binary classification model based on the prognostic performance parameters. This model is then inferred after each flight. Taking into account the model results of the last couple of flights, a expected RUL can be estimated.

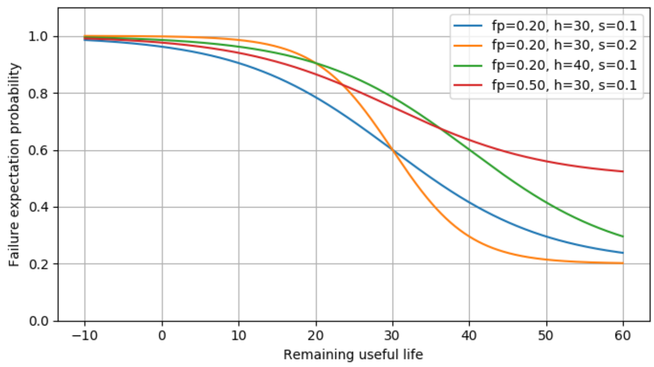


Fig. 2. Failure expectation probability for various parameter values

The binary classification model simulation is done by using a Bernoulli distribution with the probability parameter being a sigmoid function, as described in Eq. 17, which takes into account the actual RUL, and several prognostic parameters with fp being the false positive rate, h the PH, s a parameter indicating the steepness of the slope, and t the actual RUL. Fig. 2 gives an indication of how the failure expectation probability changes as different parameters are varied. The steepness parameter s is used to simulate different kind of failure modes with a very steep function being a unpredictable failure mode, while a gradual functions indicates the models ability to identify deterioration.

$$p(t) = \frac{1 - fp}{1 + e^{s \cdot (t - h)}} + fp \quad (17)$$

These classification outputs are then collected from the moment of installation of the component until failure, indicated by the example classification output points in Fig. 3. Then with sufficient points available, the failure expectation rate is obtained by acquiring the moving average on this detection output as indicated by the moving average points in Fig. 3. Given that the prognostic algorithm is of sufficient accuracy, it is expected that a trend is seen with the failure expectation rate approaching 1 as the component approaches the end of its actual RUL.

Aside from the false positive rate that takes into account false alarms, the false negative rate is also included as adjustable parameter in the PHM system. In this model it

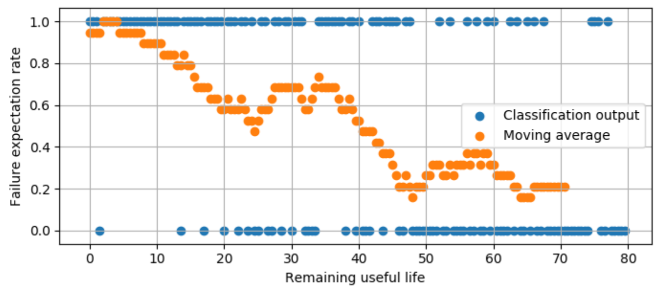


Fig. 3. Classification output and failure expectation rate as function of remaining RUL

is assumed that in the case of a false negative, a missed alarm event occurred, hence the prognostic system was either not able to estimate the RUL, or overestimated the RUL, such that this estimated RUL never reached the threshold triggering a maintenance action. The false negative rate is once again modeled using a Bernoulli distribution, with the probability being the false negative rate. Using this distribution it is decided whether PHM monitoring is enabled for this component. If not, the estimation of the RUL does not happen and the component is run until failure.

With the model being able to generate a failure expectation rate curve for each individual component, the last remaining step is translating this rate to an estimated RUL. This is done by acquiring the maximum likely RUL from the detection probability function given the moving averaged failure expectation rate. It should be noted that the number of points used for the moving average plays a big role in estimating the RUL and requires optimising. E.g. a small number decreases the resolution and result in an erratic RUL function with only a small estimated RUL values possible. More points contribute to an increased resolution, but introduce lag into the system, meaning that components might be only replaced after major damage has been done. The RUL estimation of the failure detection rate portrayed in Fig. 3 is displayed in Fig. 4.

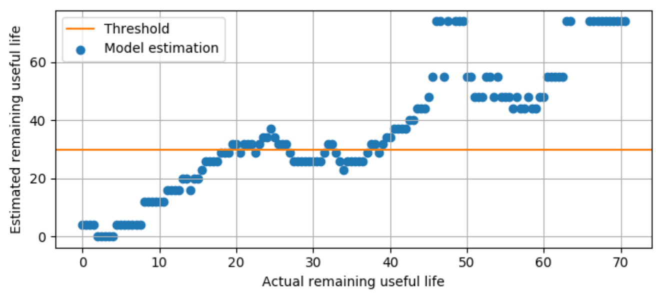


Fig. 4. Estimated RUL and actual RUL as a function of remaining RUL

As can be seen from this figure, the estimated RUL tends to follow the actual RUL curve. As with any CBM application, there should be a moment during which the estimated RUL meets desired specifications and action is taken by planning a maintenance event to swap the component. Since the goal of the prognostic model is to estimate the RUL accurately at the PH, the threshold value is chosen to be the PH as indicated by the orange line in Fig. 4. It should be noted that with different prognostic parameters, wavering around this threshold can occur. This can be addressed by taking action only after a minimum number of estimated RULs exceeds the threshold.

The next submodule, the maintenance planning submodule, is vital in the application of this prognostics module to multiple subsystems for a fleet of aircraft, as it considers the state of all components that require to be swapped. Once a component has failed, or a failure is expected, triggered by the PHM system, the resulting MEL condition is estimated. Depending on the number of failed and/or non-operating components for a given subsystem, a repair is required within a certain number of calendar days. These so-called MEL categories, ranging from AOG, e.g. the aircraft is deemed not airworthy, to the MEL D category, indicating 120 days. Obviously it is of great importance for the carrier to have the component swapped with a operational one, such that a costly AOG situation does not occur.

Once again a MILP model is used to plan these swaps for aircraft requiring component replacements, given the maintenance opportunities available. The model uses a priority system by looking at the MEL conditions, replacement component ordering costs, and opportunity costs. It is also able to reprioritise maintenance swaps by moving around the planned replacement to a different opportunity. This is for example preferred in the case with upcoming opportunities occupied, while an unexpected crucial failure occurs, resulting in a short MEL. In Appendix D this MILP model is further elaborated in detail.

The last submodule is the repair submodule. Here it is expected that due to the PHM systems, components are removed before failure and major repair costs are avoided. This is modeled by assuming two possible repairs; major and minor repairs with their corresponding costs and repair times. It is assumed that as the components reach the end of their useful life, the chance of major repair increases. Therefore the RUL range is discretised in a small number of RUL ranges, each having a different probability parameter for the Bernoulli distribution estimating whether a major or minor repair action is necessary.

Before a component is replaced, the new replacing component is requested from the pool. Depending on the time until AOG, a component is ordered or AOG ordered (expedited shipped), resulting in different order costs and shipping times. Once the component is available, it is replaced, and the removed component is sent to the pool, which in their turn send it to the shop for repair. In the shop it is determined whether major or minor repair is required, and therefore their corresponding cost and repair duration. After the repair, the component is sent back to the pool, where it can be ordered for the next aircraft. Other costs that are taken into account are the holding costs of the component pool as the storage of components and overhead require additional costs. In the case that many failures happen at the same time and there are no replacement component in the pool available, a lease action is initiated that come with a corresponding lease cost. An overview of this supply chain model used in this repair submodule can be seen in Fig. 5.

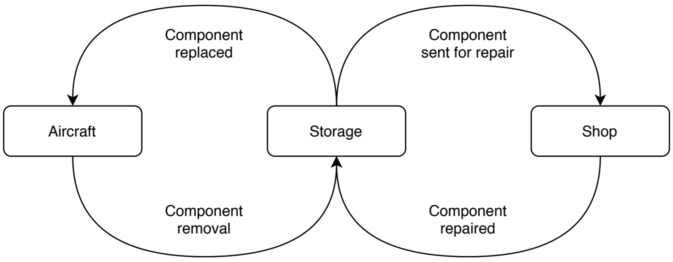


Fig. 5. Schematic overview of the location and actions being performed on components during replacement and repair.

The simulation technique used for this unscheduled maintenance model is a discrete-event simulation (DES). This is advantageous as in contrast to continuous simulation, no change in system state occurs in-between events, enabling a relative computing time-efficient method of simulation. Furthermore it is able to model the impact of the result of one event on the input of another event. This way causes and effects of specific events can be evaluated and assessed regarding their impact on costs and benefits [30]. A necessity in the execution of this simulation is to take into account the numerous probability distributions that model the inherent uncertainty of failure events and the PHM systems of this model. The simulation can not be executed in one go, as each run will present a different outcome due to the probabilistic nature of the stochastic data. A Monte Carlo simulation approach is used to provide an answer to this, by sampling a different random value from the probabilistic distributions for each run. After a large number of runs, the results are aggregated resulting in an expected result in terms of costs and downtime for the various input parameters.

IV. Results

With the separation of the maintenance operation in scheduled and unscheduled maintenance modules, results are obtained for each module.

A. *Preventive Maintenance Module*

The data used as input for this model is all A-check task data originating from the MRO. This allows the validation of the baseline model, i.e. the model without interval escalation and task substitution. In total, 244 different A-check tasks are considered, each having a specific maximum interval, and estimated labour hours required to finish it. The number of maintenance opportunities was chosen as such to ensure that all A-check tasks occurrences were able to be executed without additional waste. For this reason, 13 A-check opportunities were chosen for which their execution dates match the dates in the validation data. As can be seen in Fig. 6, the model was able to assign all tasks, however less task occurrences were needed as they were planned more towards the previous occurrence's due date. This resulted in an overall less equalised planning, however 23% less labour hours were required. It should be noted that dependencies between tasks were not considered. More on this can be read in Section V.

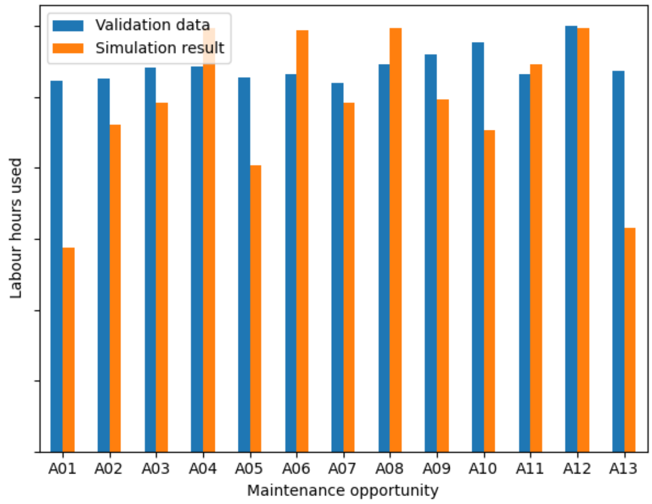


Fig. 6. Comparison of block task assignment model output to validation data

With a validated model available, the effects of CBM can be established by comparing various CBM scenarios with the baseline scenario. These scenarios correspond to a moderately optimistic scenario, scenario 1, and a more optimal scenario, scenario 2. The interval escalation and task substitution rates per task group are based on expert opinion of the MRO which data was used in this model, and can be seen in Table I. For the tasks groups that are heavily inspection based, task substitution was chosen as CBM action. This corresponds to future CBM systems being able to substitute these tasks with inspection using sensor data. Especially Functional Check (FNC) and Operational Check (CHK) tasks are heavily based on the acquisition of quantitative data. For this reason, a higher action rate is considered. For the tasks groups that are more action oriented, the CBM application here would be interval escalation. The idea here is that by PHM monitoring components on which these actions are performed, a better action due date can be established, leading to longer, more optimal intervals compared to the current conservative intervals used.

The length of this simulation has been chosen to be 1095 days such that 13 A-check opportunities per aircraft fit considering each extra aircraft's start of operation date is 60 days later than the previous one. First the CBM simulations are run for one aircraft. This is done once using the baseline input parameters, after which it is run for a total of 50 rounds per scenario for the two CBM scenarios, to take into account the stochastic effects of the task substitution parameter. The results in terms of costs can be seen in Fig. 7, while the changes in labour required per A-check is displayed in Fig. 8.

TABLE I
TASK INPUT PARAMETERS FOR REALISTIC AND OPTIMISTIC CBM SCENARIO

Task group	Number of tasks	CBM Action	Baseline [%]	Scenario 1 [%]	Scenario 2 [%]
General Visual Inspection (GVI)	54	Task substitution	0	25	50
Functional Check (FNC)	26	Task substitution	0	50	100
Detailed Inspection (DET)	32	Task substitution	0	25	50
Servicing (SVC)	8	Interval escalation	0	25	50
Lubrication (LUB)	22	Interval escalation	0	25	50
Restoration (RST)	17	Interval escalation	0	25	50
Discard (DIS)	26	Interval escalation	0	25	50
Operational Check (OPC)	54	Task substitution	0	50	100
Special Detailed Inspection (SDI)	5	Task substitution	0	25	50

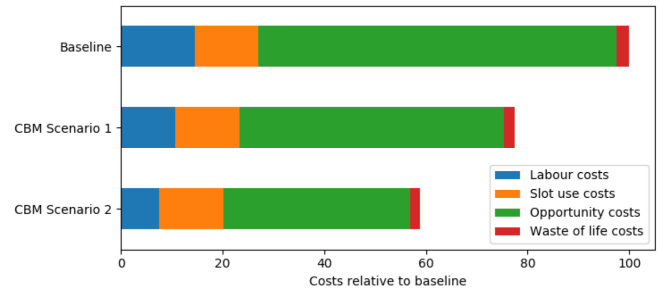


Fig. 7. Cost savings distribution of applying CBM

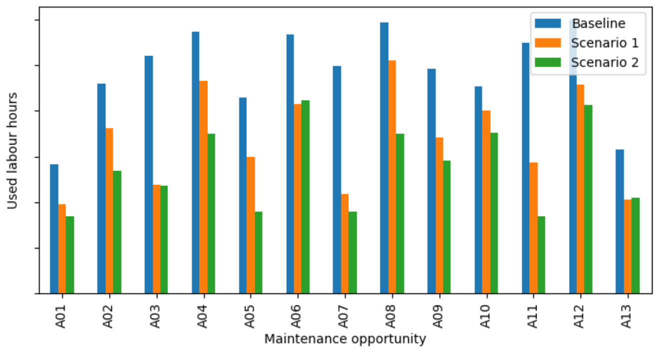


Fig. 8. Labour hours used per A-check for one aircraft.

It can be seen that the overall costs are decreased by 21 % for scenario 1, and 41 % for scenario 2. This is mainly due to the decrease in labour and opportunity costs, which each decreased by 24 % and 48 % for scenario 1 and 2 respectively. These decrease in opportunity costs correspond with the extra flight time available as less tasks are required to be executed. Considering the fixed initialisation and finalisation times required for an A-check, and the general duration of 24 hours for an A-check, results show that between 5 and 11 hours of A-check maintenance can be saved leading to an extra flight being possible depending on the destination. This justifies the opportunity costs as indeed planning an extra flight would be a possibility. Furthermore it can be seen that the same number of A-check opportunities are used, as the fixed slot costs remaining constant, and the waste of life costs are decreased by 13 % and 23 % for scenario 1 and 2 respectively. These results show that the decrease of costs somewhat linearly scale with the CBM application factor, mainly because the slot use costs remain constant as all 13 opportunities are used in all scenarios. As can be seen in Fig. 8, there is however more room available per maintenance slot, and considering multiple aircraft might expose additional benefits.

In Fig. 9 and Fig. 10 the cost reduction results of the preventive maintenance model are displayed for multiple aircraft considering CBM scenarios 1 and 2. In order to make the Monte Carlo simulation possible with respect to time constraints and take into account the limitation in computational power, for both the 2 aircraft and 3 aircraft cases, the maximum simulation run time was set to two hours.

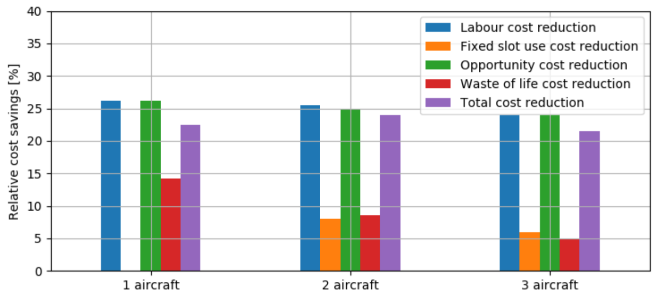


Fig. 9. Relative CBM cost savings in scenario 1 for a fleet containing 1, 2, or 3 aircraft.

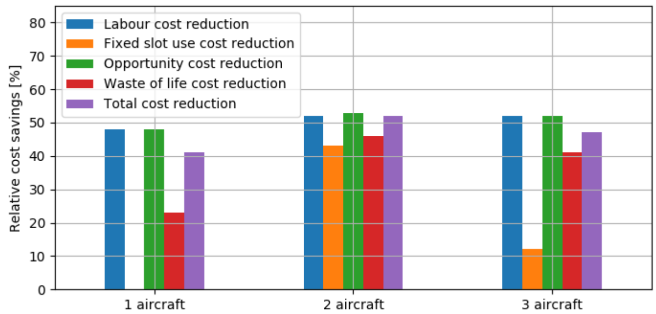


Fig. 10. Relative CBM cost savings in scenario 2 for a fleet containing 1, 2, or 3 aircraft.

Similar to the A-check results, it was found that with a CBM approach, labour and opportunity costs were decreased by 25% and 50% for the C-check tasks, corresponding to the results of both scenarios in the case where A-checks where considered.

B. *Unscheduled Maintenance*

For the unscheduled maintenance module, two subsystems are considered: an electrical generator (EG), and a cooling unit (CU). The EG might especially benefit from prognostics, given that already in the case of 1 out of the 4 generators not operating, a MEL B condition is triggered, indicating a replacement deadline of 3 days. For the simulation, the fleet including their start of operation days is mirrored to the fleet of the carrier whose component failure data is used. First the components are simulated individually. It is assumed that there is one maintenance opportunity available during which an aircraft can have its components replaced per week. The scenario parameters used can be found in Appendix E. To account for the stochastic nature of the simulation, each simulation is ran for a total of 100 rounds. The results for a variation in false positive and false negative rates considering three different subsystem configurations can be seen in Fig. 11-13.

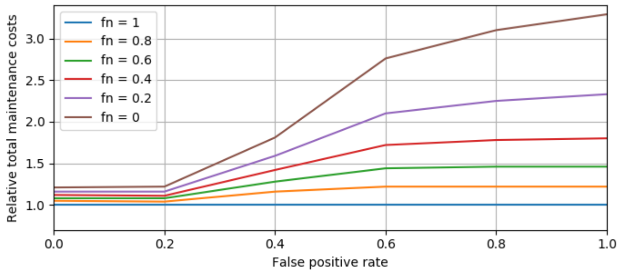


Fig. 11. Total cost changes considering the CU subsystem as a function of variations in false positive and false negative rates

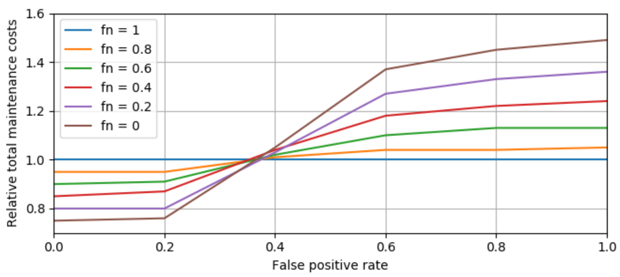


Fig. 12. Total cost changes considering the EG subsystem as a function of variations in false positive and false negative rates

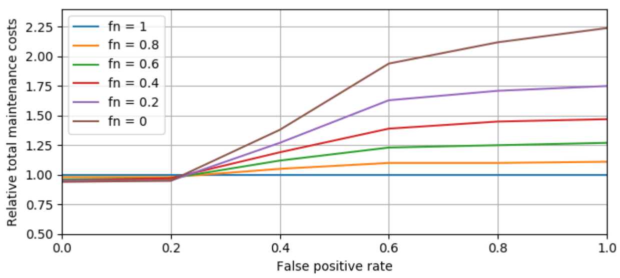
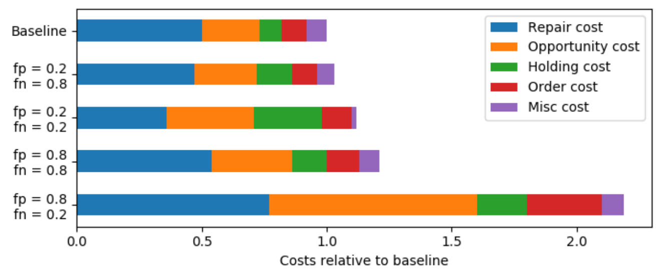


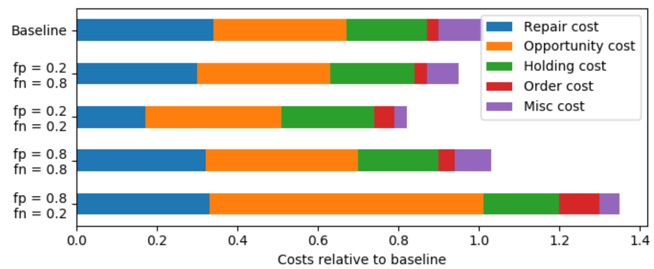
Fig. 13. Total cost changes considering the CU and EG subsystem as a function of variations in false positive and false negative rates

It can be seen that when only the CU subsystem was considered, no cost reduction was achieved regardless of the prognostic model performance. This is due to the model preferring minor repair cost over major repair cost and hence more replacements are executed. This especially impacts the CBM performance on the CU subsystem as in the baseline scenario replacements are only executed when required by a MEL deadline. This clearly shows the limitations of the replacement scheduling model. These limitations are further discussed in Section V.

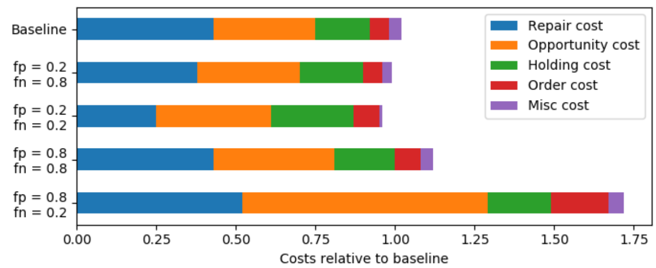
To assess how the total cost changes are achieved, 5 scenarios are considered for which the cost distributions are displayed. These scenarios represent the baseline, e.g. no prognostics applied, and combinations of relatively low and high false positive and false negative rates. This way the effects of false positive and false negative rates can be established while also the effects of a properly and a poorly performing model can be compared. Rates of 0.8 and 0.2 are used for respectively poor and favourable performance. These performance scenarios are then applied for the 3 cases mentioned before, e.g. considering the CU, EG, and the combination of the two. A breakdown of the relative change in costs of all these cases is shown in Fig. 14.



(a) Aircraft containing only the CU subsystem



(b) Aircraft containing only the EG subsystem



(c) Aircraft containing both the CU and EG subsystems

Fig. 14. Relative maintenance cost breakdown for different configurations

The major differences in opportunity costs and repair costs stem from the change in both the proportion of major and minor repairs and total number of repairs. Fig. 15 shows how for each scenario the total number of repairs varies, as well as the consistency of major and minor repairs. It shows clearly how the combination of a high false positive ratio with a low false negative ratio can contribute to such a high cost increase as seen in Fig. 14, even though the majority of these repairs are minor repairs.

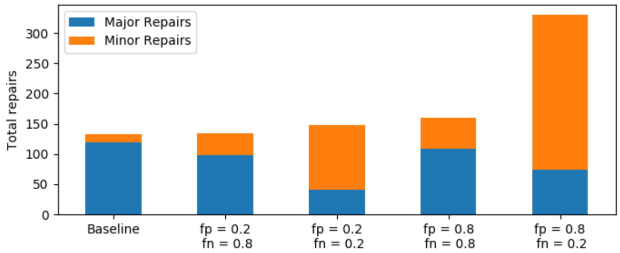
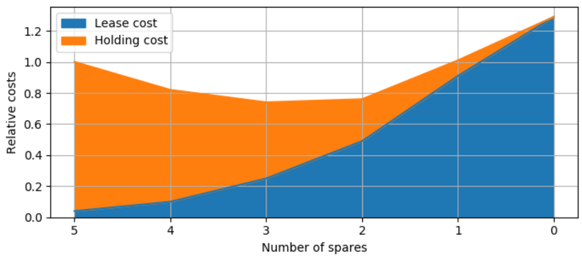
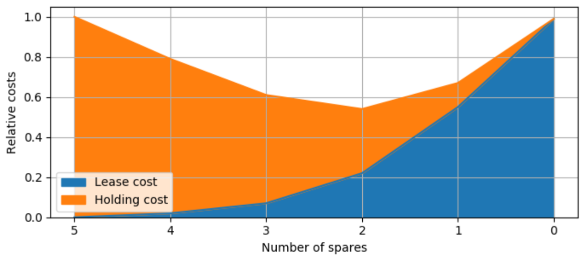


Fig. 15. Number of major and minor repairs for 5 scenarios

Lastly, the effects on the supply chain are investigated. This is done by comparing the baseline case to a case with a properly functional prognostics system, e.g. the case for which both the false positive and false negative ratios a value of 0.2 was used. Then for both components the starting stock of spare components is varied, and the lease and holding costs are obtained. Only these costs are considered, since the other costs remained constant. The result of this assessment can be seen in Fig. 16. It shows that the optimal number of spare parts change as the effectiveness in prognostics is varied.



(a) Baseline scenario without CBM



(b) CBM scenario with false positive and false negative ratios of 0.2

Fig. 16. Stacked costs as the number of spare components is varied.

V. Discussion

Looking at the cost savings results of CBM applied to preventive maintenance, it can be seen that in the most optimal CBM scenario for one aircraft, a cost reduction of 40% is achieved. When taking into account multiple aircraft, this would increase to a total cost reduction in the range of 46% to 52%, mostly due to slot use cost reductions which were not seen in scenarios considering only one aircraft. This is because the intervals between maintenance slots are simply too large and moving tasks from one opportunity to another opportunity earlier or later is not possible due to maximum interval constraints or cost effectiveness constraints.

However in the case that multiple aircraft are considered, more opportunities are available, and the average time between opportunities available is less. With the added benefit of aircraft in general requiring less maintenance opportunities due to CBM, as can be seen from Fig. 8, moving tasks between blocks and sharing maintenance opportunities between aircraft is possible and hence fewer maintenance slots are used. This leads to lower fixed slot use costs, and as seen by comparing Fig. 9 and 10, the effect is more pronounced as CBM is more effective. This is to be expected as more time is available per maintenance opportunity. When three aircraft are considered, this cost reduction decreases as both more optimal opportunities become occupied, and sharing opportunities among more than 2 aircraft might result in the fixed slot use cost outweighing the benefits of using a maintenance slot where only a fraction of the tasks can be executed. Another note here is the limitation in computational time that lead to the restriction in simulation run time. Given that the model simulating a fleet of 3 aircraft is more complex, it is expected that the difference between the optimal result and the result obtained in this simulation would be greater for a fleet of 3 aircraft compared to a fleet of 2 aircraft. Other algorithms need to be explored to acquire a more accurate estimation what the effects of CBM would be on a larger fleets.

As mentioned before, the main limitation is that the interval escalation and task substitution estimates are rather crude, as they are expert opinion assumed numbers, based on only the task group. Further research might be able to have a more detailed look into these tasks, such that these parameters can be obtained on task level resulting in a more accurate result. While doing so, also dependencies between tasks and improved efficiencies can be identified as tasks can be grouped together as required. Currently, dependencies between tasks are not considered, and this might result in the estimation of significantly lower waste costs as tasks need to be executed more often due to other tasks even though they are not due yet as seen in the validation data.

When looking at the effectiveness of the CBM model on unscheduled maintenance in Fig. 11-13, it can be seen that the effectiveness of the prognostic system is heavily dependent on the false positive rate, while the false negative rate acts as a multiplier. This is also visible in Fig. 15, which shows that with an increase of false positives more replacements and therefore repairs are needed. It should be noted that even with a very well performing prognostic system, the number of total repairs would increase, albeit the percentage of major repairs would decrease. For this reason, the opportunity cost in this model will not decrease.

This highlights the main limitation of this CBM model on unscheduled maintenance. Opportunity costs are defined as loss of revenue due to not operating the aircraft. However given that with a CBM approach, a failure is predicted ahead of time, a decrease in opportunity costs would also include cost savings by being able to choose more optimal component replacement opportunities. E.g. opportunities already assigned to the aircraft for other reasons, such that replacement of a component can be combined or scheduled at times where the aircraft is not required to be operational. However, due to the complexity of the total maintenance schedule of an aircraft and added complexity to the required planning algorithm, it was chosen to have a constant opportunity costs for each maintenance hour. This also affects the effectiveness of changing the PH in this simulation model, as with an increase in PH it would be expected that the planning efficiency increases as an upcoming failure is known earlier. Now the only effect of increasing the PH, is the additional time to schedule the replacement.

An interesting result is that the application of CBM would not always lead to cost reductions in this model. Comparing the most optimal CBM scenario (e.g. false positive and false negative rates of 0.2) between the three scenarios in Fig. 14, reveals that even though repair cost decrease, in some cases other costs such as opportunity and holding costs increase, resulting in an overall cost increase. The increase in opportunity costs can be attributed to the maintenance planning algorithm. In the case of prognostics not applied, it is assumed that components are only replaced when a MEL deadline is in place, e.g. two or more failures for the CU subsystem and one or more failures for the EG subsystem. However in the case of prognostics applied to the component, the component will be replaced regardless of the MEL status given that there is a higher probability of the component requiring a minor repair versus a major repair when replaced due to a prognostic alert. This highlights the importance of modeling the opportunity costs correctly.

The other cost type that increased for the CU subsystem is the holding cost. It is expected that when the percentage of minor repairs increase due to CBM, the average repair time decreases, and therefore the components spend less time in the repair shop and more time as spare stock. For this reason it is likely that a lower number of required spare stock is needed, however with this number being too low, an increase in lease costs is expected. To see how the optimum would shift as CBM is applied, the two scenarios are compared in Fig. 16. It is indeed seen that there are less spares required, as the optimum is shifted from 3 spares available to 2 spares available. Also the total cost reduction is increased, as in the baseline scenario this would be 22 %, versus the 45% in the CBM scenario.

Other limitations of this model are that the scheduling of replacements is based on the availability of a certain number of maintenance hours on a certain number of days per week. Cancellations are then modelled when the MEL deadline due to a component failure is before the next available opportunity. In reality however, maintenance is often mixed with other required tasks, therefore it is hard to assess how much actual maintenance time is available per component, and how quick this time is available after it is established that a component requires replacement. Delay costs are modeled as extra costs during troubleshooting of a failure before removal, as this is often the case that delays occur during troubleshooting. Yet this is of course a highly stochastic process, as different failure modes may occur and the troubleshooting time can significantly vary. Therefore a constant hourly delay factor is used based on hourly delay cost found in literature [7].

VI. Conclusion & Recommendations

It can be concluded that CBM can be beneficial for both the operator and MRO, as it would lead to overall lower maintenance costs and opportunity costs resulting from ground time. It was found that in the most optimistic scenarios a cost reduction of 46% to 52% was found regarding preventive maintenance, mostly based on a reduction of downtime and labour costs, while for the unscheduled maintenance a cost reduction of 20 % was found for the EG subsystem. Looking at preventive maintenance however, it shows that the extra benefits especially pay off in the most optimal scenario as in that case extra time would be available for an additional long-haul flight. Also, this scenario enables additional scheduling benefits considering the reduction in maintenance slots required. Still it should be noted that many assumptions were taken as tasks were considered by task group instead of individually, therefore more research is needed that goes more into detail regarding preventive maintenance tasks. This way more knowledge can be gained about how (potential new) sensors and prognostic algorithms can alter these tasks in terms of interval escalation or substitution, which on their turn affect the benefits in terms of a decrease in downtime and reduction in costs. Another aspect is the limitation of computational time. As the simulation time was already limited for fleets of aircraft, other optimisation algorithms should be explored that are able to provide accurate results without requiring early stopping.

When looking at unscheduled maintenance, it can be concluded that the false positive rate is the main factor in the effectiveness of prognostics. Given the investment costs required for developing and maintaining these models, a minimum precision, recall, and prognostic horizon can be formulated such that the investment is beneficial. However this improvement is mainly based on the reduction in repair costs and optimisation of the supply chain, as the optimal number of spare components varies as prognostic systems improve. Still much is unknown about the benefits that CBM can have considering a more optimal planning of component replacement is possible, as the failure of a component is known ahead of time. While it is expected that due to the preference of minor repairs over major repairs the number of replacements increases as the prognostic performance increases, it is not expected that the opportunity costs will increase accordingly, as the CBM approach enables smarter scheduling given a high enough prognostic horizon. As shown in the results, the opportunity costs are a significant part of the total costs, hence there might be more potential in reducing these costs and especially downtime, as the prognostic horizon is increased. More research is required to find out what this potential improvement would entail.

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Appendices

Appendix A

Research Methodologies

A.1 Executive Summary

With the increasing availability of sensor data measuring aircraft health, it is expected that maintenance strategies will change into strategies more focused on the condition of components, known as condition-based maintenance. Current research is ongoing in how this information about the state of aircraft health can be translated into prognostics, the prediction of the time of failure. This project proposal however focuses on the required performance levels of prognostic models for condition-based maintenance to be beneficial. A model is created that is able to simulate maintenance costs, delay and cancellation costs, loss of revenue costs and ground time as a function of prognostic model performance for certain components. Prognostic performance is assessed by the impact of false positives (false alarms) and false negatives (missed alarms), and is modeled over different prognostics horizons. Aside from the focus on components, another model will focus on the adaption of current preventive maintenance tasks, as it is expected that tasks can be substituted by prognostic models, or intervals can be extended due to the increase in information about system health. Taking into account the limitation of maintenance opportunities for a fleet of aircraft, a MILP model will optimize execution of these tasks and provides an estimate of the beneficiality of condition-based maintenance applied to preventive maintenance tasks. It is expected that the combination of both models will contribute to academia and industry as it further clarifies how prognostic performance impacts the quantified effects of a holistic approach to condition-based maintenance.

A.2 Introduction

The airline industry is growing in size and in order for airlines to stay competitive, cost savings are of great importance. When looking at the direct operational costs, according to [27], the factors that play the biggest role are fuel costs, crew costs, maintenance costs, and depreciation costs. Of these cost types, maintenance costs take up around 10 - 20 % of the total direct operational costs according to [47], [15], and [44]. Aside from costs, aircraft availability is impacted as well by airline maintenance. Of all the total delays in 2011, [14] assessed that 12.7 % was due to technical and aircraft equipment problems, which was the highest non-reactionary delay category. Delays and cancellations not only cause inconvenience for passengers, but lead to extra costs. [15] indicates that the delay costs can vary from € 53 per minute for short delays to € 249 per minute for longer delays depending on flight phase, location, and type of aircraft. A cancellation that is not announced timely can lead to costs of around €15,000 for a narrowbody aircraft and €78,000 for a long haul flight. It is therefore only logical that operators such as KLM and maintenance & repair organizations (MROs) such as KLM E&M, are looking for possibilities to minimise maintenance costs.

A current topic of research that might be able to deliver promising results with respect to this, is the execution of maintenance tasks based on the current and predicted future condition of aircraft components. This is also known as condition-based maintenance (CBM), and is a result of the increasingly available sensors of the newest generation of aircraft that are able to assesses the health of the aircraft. Two important aspects of CBM are diagnostics and prognostics. Diagnostics is important when the fault is taking place or has occurred already, and is according to [46], the act of knowing when a problem is taking place, and identifying and isolating the fault. Since the upcoming availability of sensor data, diagnosis of faults have been vastly improved as sensor data makes it easier to pinpoint the failure and potentially identify the failure mode. Recently the focus has been shifting more towards prognostics. According to the dictionary, prognostics is defined as ”something that foretells”. [24] however provides a better definition with regard to maintenance: ”Estimation of the Remaining Useful Life of a component”. The difference here with respect to diagnosis, is that prognostic is anticipating rather than reactive, as during the lifetime of a component or system, sensor data is used to predict the Remaining Useful Life (RUL). This is done by assessing how the actual operational profile deviates from the nominal one. The systems approach that takes into account prognostic data is called Prognostics and Health Management (PHM) and according to [61] can help in avoiding maintenance cost and improve system safety and mission availability.

There are several ways on how CBM can be integrated into current maintenance operations. With respect to scheduled preventive maintenance tasks, [25] looked at the possibilities of escalating intervals between tasks and even eliminating inspection tasks as it was suggested that sensor data could replace these tasks or provide a better estimation of the required interval. Aside from preventive maintenance tasks adaption, CBM can also reduce the occurrence and impact of unscheduled maintenance events. These benefits flow from the ability of PHM systems to predict the RUL of a component and allows components to be replaced based on their condition and not on a set time [66]. With the advantage of being able to monitor degradation it is expected that unscheduled maintenance will occur less as the component can be replaced before failure. Furthermore the availability of more accurate diagnostic information allows for a reduction in unscheduled maintenance time and can potentially turn the unscheduled task into a scheduled maintenance task.

Previous studies have mainly focused on the development of prognostic models, and potential benefits expressed in results of case studies for failure of single components. Yet the potential total benefits in terms of various key performance indicators (KPIs) for an aircraft fleet taking into account the limitation of maintenance opportunities and uncertainties in prognostics is rather unknown. The objective of this project is therefore to develop an assessment model that is able to capture the impact of PHM and CBM on the maintenance performance for a fleet of aircraft, taking into account the uncertainty of PHM systems. In section A.3 the state-of-the-art regarding assessment models of CBM and PHM is described, during which the gaps in literature are identified. Then in section A.4 the research questions, aim, objectives and sub goals are defined that follow from these gaps. In section A.5 the research methodology is described after which in section A.6 the experimental set-up is laid out. Then the expected results and outcome is discussed in section A.7. In section A.8 the project planning is discussed and finally section A.9 concludes this project plan.

A.3 State-of-the-art/Literature Review

In order to critically analyze the current value assessments available in literature, several different aspects of these models are evaluated. First it is important to assess how value is expressed and what KPIs are deemed important. Aside from this a major aspect is completeness of the assessment, both in terms of the types of maintenance taken into account, as well as the level of detail, and hence gives an idea about the value of the research done. Another major aspect is the modeling of prognostics, as it is expected that uncertainty can heavily influence the impact of CBM, and therefore accurate modeling of these uncertainties is of key importance for a proper value assessment.

With respect to unscheduled maintenance, there have been many papers looking into different approaches of modeling prognostics and predicting the RUL of components, so that replacement and repair of these components can be scheduled in advance. [67] do this by focusing on the identification of degradation considering a multiple wear profile scenario and integrating this with a line maintenance planning model. This model was based on a combinatorial search algorithm. The algorithm loops over all turnaround times within the planning horizon and finds the repair and service schedule that minimizes the operational costs. In doing this, constraints on resources and the corresponding MEL category are taken into account as well. Limitations are that only line maintenance is considered in this study. It might be interesting to see the results of a complete maintenance scheduling approach as done by [25], while taking into account constraints posed in this paper. The study claims parallelisation is allowed to perform the repair and servicing of different components, however dependencies between these activities such as available manpower and time is not considered. When considering a fleet of aircraft, this might prove to be especially difficult using a combinatorial search algorithm, and other simulation approaches such as an heuristic game approach used by [18], or a discrete event approach as presented by [30] might be beneficial.

According to [57], the advantage of a discrete event approach (DES) is that it allows to analyze the interdependencies between events, and hence cause and effect can be established. DES is also a method to discover unexpected bottlenecks, under- or over-utilization of resources, or failure to meet specified requirements. In contrast to continuous simulation, no change in system state occurs in between events, enabling a relative computing time-efficient method of simulation, enabling the simulation over long periods of time. [30] used this simulation technique and came up with a framework in assessing benefits with respect to unscheduled maintenance of PHM at Line Replaceable Unit (LRU) level. By simulating all relevant maintenance processes and dependencies using deterministic empirical data such as operation, line and component maintenance, troubleshooting, planning and logistics data, a good overview of benefits as result of PHM metrics was established. [54] researched uncertainty in prognostics and reviewed such metrics used to assess algorithms, with the goal of providing an overview of the different metrics used in literature and suggesting new metrics that specifically cater to PHM requirements. Two of the metrics that play an important role were False Positives (FP) and False Negatives (FN). The missed alarms can be seen as a false negative: the algorithm did not anticipate the failure, while false positives indicate failure while there is none. Aside from existing metrics, the authors proposed several other new metrics for prognostics. One of them is the prognostic horizon. The definition of this is defined as ”the difference between the current time and end of life using data up to the current time index, provided the prediction meets desired specifications”. [30] not only looked at the prognostic horizon, but also the impact of accuracy on the eventual cost savings regarding prevention of unscheduled maintenance. Yet in their analysis these parameters are assumed independent in contrast to the previously mentioned studies. Furthermore the impact of false positives, such as false alarms leading to No Fault Found (NFF) events, and false negatives, in case the failure is not detected on time, on the cost reduction is not very clear. Having a better analysis with respect to this might bring valuable conclusions in the desired sensitivity and therefore requirements of the PHM systems.

At first it would be expected that the higher the prognostic distance the better, yet it can be seen that there is an optimal prognostic distance related to these components. [21] showed why this is the case, and mentioned the decrease in forecast quality, increase in prognostics cost and increase in wrong delivered spare parts associated with a longer prognostic distance as crucial causes. [17] performed a case study taking into account these uncertainties in predicting the precursor of failure of a multi-functional display. As part of cost benefit analysis comparing unscheduled maintenance with a PHM approach, the optimal prognostic horizon was determined. Unique in this study is that this precursor expected time to failure (TTF) is a distribution based on a sample of the distribution of the actual time to failure and prognostic distance. When a sample TTF is taken from the distribution of the precursor expected TTF, and this TTF is higher than the actual TTF of the instance it is assumed that unscheduled maintenance is required leading to higher costs.

In terms of preventive maintenance tasks, [11] and [45] focused on the impact of condition-based maintenance in structural aircraft maintenance. It was investigated whether structural health monitoring (SHM) techniques were able to reduce costs by skipping certain scheduled maintenance actions. [45] found that especially during the first few maintenance stops, much costs could be saved since inspections were not necessary yet. Three different approaches incorporating SHM were presented, all showing significant improvement in total costs over conventional scheduled maintenance. However cost data used were averages in literature, and the cost modeling technique contained various assumptions, such as a 20% to 100% increase of costs when maintenance is unscheduled, and loss of revenue costs were not taken into account.

Aside from these case studies [25] took a more global approach in estimating the effects of CBM on preventive maintenance during which scheduled maintenance tasks and preventive tasks due to predicted failure of components are scheduled for a lifecycle of an aircraft. Using a Mixed Integer Linear Programming (MILP) model, maintenance costs and wasted life costs were minimized by grouping tasks together depending on predicted failure date or due date of preventive task. Wasted life costs being costs due to removal of components before their actual end of life and preventive maintenance tasks being executed before their maximum interval. This task packaging might be especially beneficial in that due to prognostic information, interval of tasks can be escalated and some tasks can even be omitted. This is done by grouping tasks based on their task codes in task code groups (TCGs). Depending on the TCG, a task is either eliminated, the interval is escalated, or nothing changes. The limitation of this study is that only 2 global parameters influence this impact, and hence no detailed analysis of tasks is done. Though given the great number of tasks, this might be considered a reasonable assumption. It should be noted that the tasks involved are either short to medium interval tasks. Tasks with an interval of more than 5 years and tasks belonging to D checks are still assumed to be block checks and planned separately.

Taking only into account scheduled maintenance, and assuming the most optimistic scenario, i.e. parameters of task redundancy being 1 and interval escalation being 100 %, a potential maintenance costs saving of around 3 million EUR was found. This is relatively low considering the total maintenance cost modeled over a life cycle was 76 million EUR, and the great number of maintenance tasks affected by these parameters. Comparing this number to the potential savings in previously shown studies regarding crack formation, show the complexity of analysing cost savings due to CBM. For instance, the ground time that is freed up due to task elimination and escalation, might be used to schedule extra flights. While [11] assumed a reduction of loss of revenue depending on the days of maintenance saved, [25] did not clearly explain what was done with the extra time gained. Using the maintenance scheduling approach of [25], applied on a fleet of aircraft might reveal patterns in extra time available. These patterns can then be used to adapt the flight schedule, which in result can give a better estimation of the decrease in opportunity costs.

The holistic approach of [25] encompassing both deterministic scheduled maintenance and unscheduled data is an eyeopener in assessing the potential value of CBM. However a deep analysis of prognostic parameters is lacking as component RUL is assumed to be deterministic in the scheduling of maintenance and sensitivity and precision of the PHM systems are not taken into account. Furthermore as the paper suggested, the effects on a fleet of aircraft have yet to be researched.

Gaps identified in this literature review are therefore the assessment of CBM on a bigger scope, taking into account its effect on both preventive maintenance and unscheduled maintenance for a fleet of aircraft. Especially interesting in this case are the emergent effects on aircraft availability and total maintenance costs as as a function of varying PHM performance levels.

A.4 Research Question, Aim/Objectives and Sub-goals

Having performed a literature study, gaps in literature were found. In this section research questions and objectives are presented that aim in answering these gaps.

A.4.1 Research Question(s)

The main research question that is set out to be solved is as follows:

> What is the impact of condition-based maintenance on aircraft fleet availability and total costs due to scheduled and unscheduled maintenance as a function of different PHM performance levels?

In order to be able to answer these question, the following sub-questions were defined:

- What is the effect on availability and costs when the planning of PHM based preventive maintenance tasks is modeled on fleet level for different fleet sizes?
  - Which tasks can be affected by PHM systems?
  - How does the execution of these tasks differ using a CBM strategy?
  - What scheduling model is suitable for taking into account this difference in execution of these tasks?
  - To what extent is the model able to simulate current preventive maintenance operations?
  - Which types of costs are affected by the use of a CBM strategy on preventive maintenance?
  - How does the ground time required change as a result of the adoption of a CBM strategy?
- What is the effect on availability and costs when unscheduled maintenance is affected by PHM models?
  - What are the extra maintenance costs of an unscheduled maintenance event?
  - Which components are suitable for adoption of a CBM approach?
  - What are the penalties in terms of availability and downtime costs due to unexpected failure of these components?
  - How can the actual remaining use of life for these components be determined?
  - How can the expected remaining use of life for these components be determined?
- What is the required PHM performance for CBM to be beneficial?
  - What is the minimum required prognostic horizon?
  - How do the false positives and false negatives rates influence each other?
  - What is the acceptable false positive rate?
  - What is the acceptable false negative rate?
  - How does the models accuracy vary as the prognostic horizon varies?

A.4.2 Research Objective

With these research questions in mind, the objective of this research can be established. The main research objective of this thesis is to understand the financial and operational benefits that condition-based maintenance can have by developing a model that is able to simulate maintenance actions over a fleet of aircraft taking into account various performance levels of prognostics and health management systems. In order to achieve this goal, several sub goals are defined. Firstly a scheduled maintenance model should be constructed that is able to simulate current preventive maintenance actions, and preventive maintenance task actions according to prognostic data. Only then a proper comparison can be made. Meanwhile another sub goal is the development of an unscheduled maintenance model that is able to output costs and availability as a function of PHM performance predicting the failure of components. With these models available, a sub goal is then to setup a case study by selecting preventive maintenance tasks and components of interest. With data from KLM available, a sub goal is then defined to validate the model. Having a valid model, the last sub goal is then to assess the prognostic benefits by constructing different performance level scenarios used as input for the model.

A.5 Theoretical Content/Methodology

The objective of this research is focused on the total impact of condition-based maintenance. However as the approach in modeling preventive maintenance tasks compared to component failure differs, the work can be split up in these two different parts having distinct methodologies.

With respect to preventive maintenance, the focus is on adaption of scheduled maintenance tasks. These originate from the maintenance planning document (MPD) formed by the aircraft manufacturer in which scheduled maintenance tasks are concretely outlined together with their intervals. Operators then use the MPD as source in order to generate their own maintenance program called the Aircraft Maintenance Program (AMP). It is expected that with the use of prognostic data, for certain tasks the interval can be extended, task duration can be limited, or the task is not required anymore as a sensor can replace its function. A framework to assess this has been setup by [25], looking at the different task categories and varying task escalation and elimination levels. A MILP model will be used to optimize planning according to these adapted task intervals, taking into account the limitation of maintenance opportunities, cost of performing maintenance tasks too early, and benefits of grouping tasks.

On the other hand unscheduled maintenance requires a different approach. Here the focus is on replacing failing components on time, so that the aircraft is not unexpectedly grounded and replacing components can be anticipated for. The methodology as described by [17] is of especial interest, as it shows how the estimated RUL of components can be estimated as a function of the prognostic horizon. Using this method, while also taking into account the trade off between false positive rate and false negative rate as a function of aggressiveness, for different time horizons an estimation can be made of the RUL. Then together with dependencies on other components and availability of a replacing component, the value of the PHM system can be estimated.

A.6 Experimental Set-up

A computer simulation will be the experimental method of choice for this research. A simulation will be run for a considerable part of the lifetime of a fleet of Boeing 787 aircraft in such a way that all preventive maintenance tasks and selected components have an impact as would be expected from the historic data available. Due to the broadness of assessing the total impact of condition-based maintenance and the complexity of interactions with respect to planning between preventive maintenance and unscheduled maintenance, it was decided to model these independently as separate modules in the simulation.

The preventive maintenance module contains a MILP model taking into account AMP tasks. Depending on the level of interval escalation, task elimination and change in task duration, for a certain fleet size and number of maintenance opportunities benefits in terms of maintenance costs and ground time can be assessed. By using real task data, ground time data and cost data from KLM, the model can be validated, and a baseline can be constructed.

The unscheduled maintenance module will be taking into account the top 15 components selected on failure occurances, current failure impact and prognostic applicability. Using a discrete event simulation (DES) framework, the states of these components can be tracked. As a function of various input parameters indicating the performance of the model, a prediction is made when the component is expected to fail. Taking into account these expected failures and dependencies between components and deferral of maintenance actions as listed in the MEL rules and according to policy, replacements are scheduled. Depending on the actual time before failure, costs and ground time are estimated. Using the models that KLM is already using in predicting failure of certain components, the model can be validated.

The simulation will be created in Python 3.7, and for the preventive maintenance module a MILP model using the software package CPLEX will be used. For the unscheduled maintenance module, the DES framework SimPy will be used, enabling the modeling of dependencies between events and keeping track of the various states the objects are in.

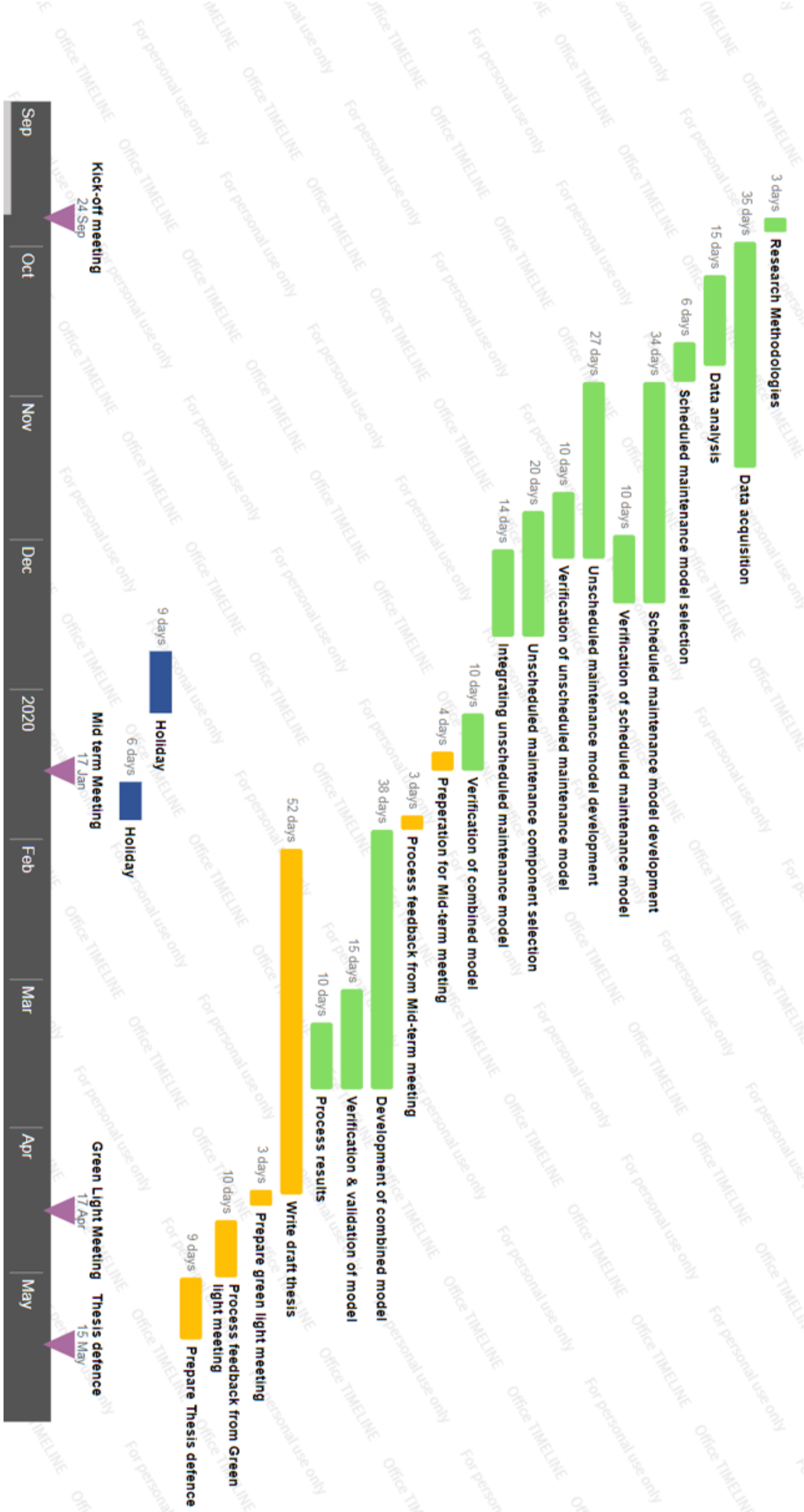
A.7 Results, Outcome and Relevance

The simulation will use data made available by KLM. For the preventive maintenance scheduling, task data containing the required interval, task duration, and material and labour costs are considered. Depending on the prognostic parameters such as interval escalation, task elimination, and task duration adaption, different schedules will be made, resulting in a different effect of wasted life, maintenance and labour costs, and ground time required, and hence a difference in cost of loss of revenue. As the simulation is setup to be general, different parameters that can be varied are the aircraft in fleet and occurrence of maintenance opportunities. Validation is done by comparing the model outcome to the current practice of preventive maintenance operations. By using dummy tasks of which boundary conditions are known, the MILP model can be verified. Ultimately it is expected that the decrease in costs and availability compared to the prognostic parameters will provide insight in the beneficiality of CBM.

Looking at unscheduled maintenance, data considered is the effects of unscheduled maintenance in terms of cost and ground time for different components. Using historic time to failure (TTF) data, a distribution can be established that can be used as input. Together with the replacement policies and historic data with respect to repair costs, direct maintenance costs, and delay and cancellation costs, the prognostic model can be evaluated. This model will be having several input parameters such as aggressiveness indicating tolerances towards false positives or false negatives, and the prognostic horizon. The expected outcome is an indication of potential cost savings in terms of the various cost categories for different prognostic performance levels. With this information available, minimum performance levels for PHM systems and a first order maximum cost estimation for PHM systems can be established. To assure the model's validity, performance of the current KLM prognostic model is used as input, after which the model's output in terms of costs and ground time is compared with the data available from KLM.

A.8 Project Planning and Gantt Chart

With the previously set up objectives, taking into account logistics, task dependencies and estimates of the time required for tasks, a project planning was created. This planning is illustrated in the form of a Gantt chart that can be found in Appendix A. It shows how the problem is split into two separate models each requiring verification. Once verified, the models are combined and validated using KLM data. Meetings with the supervisor will happen biweekly, however due to the unfortunate event of the supervisor leaving for Australia, meetings will occur in the form of video calls.



A.9 Conclusions

As the amount of sensor data available is only increasing with newer generations of aircraft, not making use of this in the maintenance process would be a potentially missed chance in lowering maintenance costs and increasing fleet availability. Much research has been conducted in the development of various theoretical models in predicting maintenance needs, however studies investigating the benefits as a function of prognostic performance levels are scarce. Especially unknown is the effect on fleet level considering prognostic uncertainties in terms of false alarms and missed alarms for different prognostic horizons.

This proposed research aims to provide insight of the complex effects that different prognostic performance levels have by quantifying the benefits of a CBM approach. By simulating both unscheduled maintenance and preventive maintenance operations for a fleet of aircraft, with the use of a discrete event simulation model and a MILP preventive maintenance planning model, different cost and availability factors can be assessed. With this approximation of benefits as a function of different prognostic parameter performance levels, requirements on PHM systems can be posed with a greater accuracy. This benefits both academia and the industry as it can provide more knowledge about the required performances of PHM models, possibly leading to further research into methods being able to achieve these performances.

Appendix B

Literature Study

B.1 Introduction

The airline industry is growing in size and in order for airlines to stay competitive, cost savings are of great importance. When looking at the direct operational costs, the factors that play the biggest role are fuel costs, crew costs, maintenance costs, and depreciation costs[27]. Of these cost types, maintenance costs take up around 10 - 20 % of the total direct operational costs[47][15][44]. Aside from costs, aircraft availability is impacted as well by airline maintenance. Of all the total delays in 2011, Eurocontrol assessed that 12.7 % was due to technical and aircraft equipment problems[14], which was the highest non-reactionary delay category. Delays and cancellations not only cause inconvenience for passengers, but lead to extra costs. Eurocontrol indicates that the delay costs can vary from € 53 per minute for short delays to € 249 per minute for longer delays depending on flight phase, location, and type of aircraft [15]. A cancellation that is not announced timely can lead to costs of around €15,000 for a narrowbody aircraft and €78,000 for a long haul flight[15]. It is therefore only logical that operators such as KLM and maintenance & repair organizations (MROs) such as KLM E&M, are looking for possibilities to minimise maintenance costs.

Being able to predict when failure is bound to occur by assessing how the actual operational profile deviates from the nominal one is called prognostics. The systems approach that takes into account prognostic data is called Prognostics and Health Management (PHM) and can help in avoiding maintenance cost and improve system safety and mission availability[61]. Using PHM, MROs and operators can conceptualize maintenance strategies that leverage the knowledge about the actual condition and prognostics of specific components. These strategies therefore enable maintenance being done based on the condition of systems and components and is therefore called condition-based maintenance (CBM). CBM will have an impact on how scheduled maintenance will be done, as inspection tasks might not be required anymore or the interval between tasks can be escalated [25]. CBM also allows components to be replaced on condition and not on a set time.[66] Furthermore, it is expected that PHM can reduce the occurrence and impact of unscheduled maintenance events. A prediction in the remaining useful life (RUL) of a component and more accurate diagnostic information allows for a reduction in unscheduled maintenance time and can potentially turn the task into a scheduled maintenance task [37].

Mostly due to the myriad of different aspects CBM can have an effect on, it is currently difficult to assess the potential value that CBM can bring to the airline industry. Therefore this literature study is carried out to find more about what this potential value entails. In section B.2 an overview is given on different maintenance strategies and the state of the art of CBM is treated. Then in section B.3 better insight is gained on the economic aspect of CBM, by looking at how CBM can bring value, and how this is evaluated in literature. The gaps in literature and research questions that follow from these gaps identified are then concluded in in section B.4.

B.2 Airline maintenance

Aircraft maintenance is an important aspect for the operator. On the one hand, it is bound by airworthiness requirements set by the authorities, while on the other hand it is an activity that when done optimally can strengthen the competitiveness of the airline. As such, there has been much development and aircraft maintenance has come a long way. This chapter is split up in two parts. First, in section B.2.1 an overview is provided of the different maintenance strategies. Then in section B.2.2 CBM is further explored, and state-of-the-art applications are discussed.

B.2.1 Maintenance strategies

This section aims to provide an overview of the different maintenance strategies used. In figure B.1, this overview is shown hierarchically. Of these strategies shown, corrective maintenance is treated first, after which the preventive and condition-based maintenance are treated.

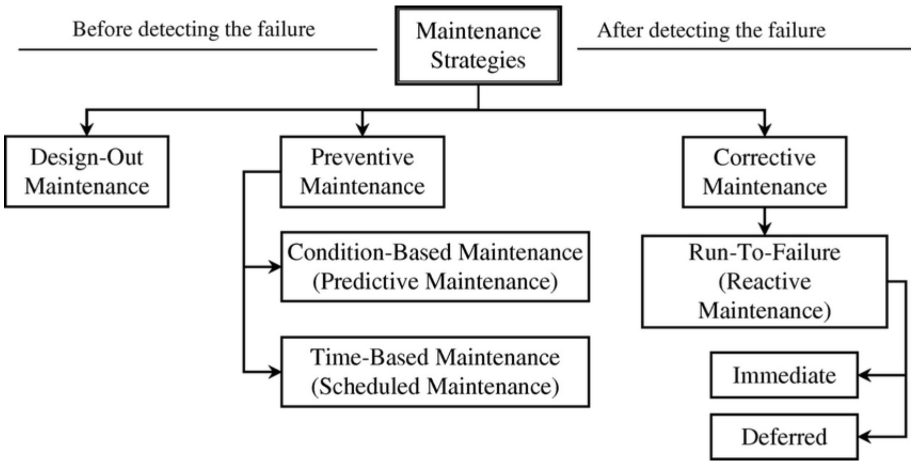


Figure B.1: An overview of different maintenance strategies [40]

Corrective maintenance
The first aircraft maintenance strategies presented themselves around 1950 and were based on the fact that components were relatively simple, therefore wear was the common mode of failure[1]. This resulted in the most commonly used strategy being Corrective Maintenance (CM), meaning that maintenance followed from failure. Maintenance, in this case, entails diagnosis of the problem, disassembly, replacement, repair, and/or assembly [34]. Since this maintenance occurs due to failure and therefore is not planned, it is considered unscheduled maintenance. Unscheduled maintenance is considered non-desirable for the following reasons [63]:

- Since the maintenance is unscheduled and availability is of high priority to the operator, costs regarding manpower and item availability are relatively high as the failure needs to be dealt with straight away.
- The downtime that follows from the aircraft being unavailable, brings extra costs to the operator.

- Secondary damages occur due to not detecting faults earlier on. This might cause extra unnecessary costs.

However, in various cases CM is still applied. For example, for some components which failure do not endanger safety-critical systems, a corrective maintenance strategy is used. The decision on this stems from failure analyses done in accordance with the MSG-3 methodology, which is further outlined in the next section.

Preventive maintenance
Rapid development in the aviation industry resulted in aircraft becoming more complex and an increase in competitiveness between operators. Larger jet aircraft such as the B707 and DC-8 were introduced, and a more reliable maintenance strategy was needed. The first attempt in improving the reliability was the establishment of time limitations of components. This is still known has hard-time, and is mostly defined by the manufacturer. Hard-time is expressed in flight hours (FH), calendar time, and/or flight cycles. However it was found that this relatively simple strategy was overall not very effective unless the component failure mode was dominant [56], furthermore for many items it was found that there is no effective application for a scheduled hard-time.

For this reason, a process-oriented approach was needed to structure preventive maintenance (PM) programs, hence the Maintenance Steering Group (MSG) was created. This group developed the MSG-1 program when the first wide-body aircraft such as the Boeing 747 was launched. In this program aside from hard-time, on-condition maintenance was also considered for components or systems that have detectable wear-out periods [49]. This on-condition maintenance meant that tasks were created to ensure reliability by inspection, servicing, testing and calibrating of components.

This program was very successful as it ensured higher reliability and safety for lower costs [63]. In the 70s the group released the MSG-2 program containing various improvements on MSG-1 and made this available for the newer aircraft launched at that time. One improvement was the development of an extra maintenance strategy called condition monitoring. For components that were not safety critical and did not have a hard-life or on-condition maintenance, replacement would occur when certain operational characteristics crossed predefined threshold values [56]. The distinction here is that the component is allowed to run to failure and thresholds are established to prevent future failure and secondary damage. An overview of the MSG-1 and MSG-2 decision logics can be seen in figure B.2.

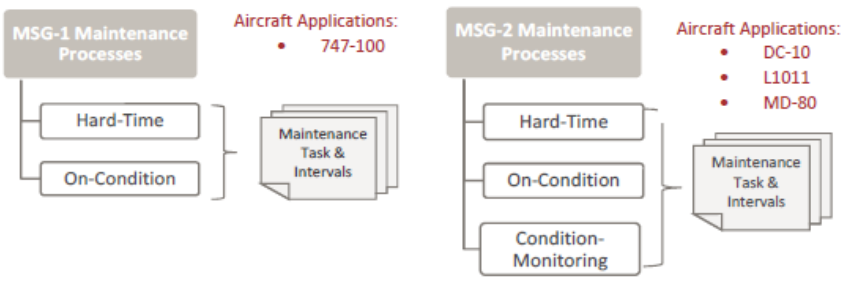


Figure B.2: MSG-1 and MSG-2 process decision logic [56]

In 1980 MSG-3 was released which improved upon a number of shortcomings of MSG-2. For instance, MSG-2 did not differentiate between maintenance done for economic or safety reasons. Furthermore, the bottom-up approach of MSG-2 in combination with the increasing complexity of aircraft led to the individual tracking of many different components. To account for this and to account for the ability to track hidden failure modes, the focus of MSG-3 was system level and a top-down approach [56]. Hence the consequences of failures and effect on aircraft operations became the main point of focus [49].

By looking at the effect of failure, a task or combination of tasks are created based on their difficulty and costs. Tasks are categorized in the following groups:

1. Lubrication/Servicing
2. Operational / Visual check
3. Functional check / inspection
4. Restoration
5. Discard

The result of the MSG-3 analysis, among other requirements, is then used in the process of generating a maintenance planning document (MPD) by the aircraft manufacturer in which scheduled maintenance tasks are concretely outlined together with their intervals. Operators then use the MPD as source in order to generate their own maintenance program called the Aircraft Maintenance Program (AMP).

It is common practice that the tasks with similar intervals are grouped in blocks. Eventually, these task blocks are executed during one letter checks that are alphabetically distinguished based on the intensity and interval of the tasks. In the airline industry the following checks are most commonly used:

- **A-Check**: This check occurs roughly every eight to ten weeks and generally contains lighter tasks such as general inspection, servicing of oil and replacement of filters [56].
- **C-Check**: A major check that happens about every two years. The structure of the aircraft is inspected [22] and a more detailed inspection of functional and operational systems is done [56]. Often these checks take about 1-2 weeks to finish.
- **D-Check**: This is the most rigorous check and occurs every 6 - 12 years [56]. During this check the paint is removed to inspect the structural elements of the aircraft thoroughly. Furthermore, the aircraft is mostly disassembled to be able to inspect all structural elements properly. This check takes about a month to complete [22].

With respect to task planning during these checks, KLM groups the smaller tasks based on their interval in 25 different A blocks. The A01 block then contains tasks with the lowest interval, which are required to perform every check, while tasks grouped in blocks with a higher number are performed with a greater interval. Every A-check these blocks are planned together with other tasks, sometimes arising from Service Bulletins (SBs) and Airworthiness Directives (ADs). SBs are bulletins from the Original Equipment Manufacturer (OEM) that contain possible modifications that operators can adopt for their aircraft. Often these changes enhance the aircraft and are worthwhile to execute, yet they are not mandatory [60]. Corrective actions that are mandatory are called ADs and generally flow from the regulatory aviation authority. The aircraft is deemed not airworthy until these ADs have been applied [58]. A SB can sometimes become a Mandatory SB, then a corresponding AD will be released by the regulatory aviation authority.

Another task planning approach more favourable by short-haul and/or low-cost carriers is the equalised system, where checks are shorter and work packages are more similar in size. This smaller size in work packages enable the work to be carried out overnight, improving on aircraft availability [59].

Still PM proved not to be ideal as these frequencies are based on Mean Time Between Failures (MTBF), which can vary greatly between components of the same type [64]. Depending on the type of component and variability in exposure, the acceleration of ageing differs and might result in an early failure causing a potential costly unscheduled maintenance action. More often however, since maintenance frequencies are taken rather conservative, components are replaced while they still have a good amount of service life remaining [13].

Various studies have since been presented in optimising this problem. The IEEE/PES Taskforce looked into various maintenance strategies and found that a fixed interval maintenance approach is the most frequently used. Still it was found that approaches that used mathematical models employing component deterioration and condition data, could maximize reliability while minimizing costs [5]. Such models and corresponding sensors could also help in decreasing the amount of scheduled maintenance inspection tasks required. This is especially beneficial as Airbus found that 90 % of the aircraft ground time for scheduled maintenance does not change the condition of the aircraft [69]. Approaches like this are generally considered condition-based maintenance.

Condition-based maintenance
Condition-based maintenance is typically categorized under PM as shown in figure B.1, since the objective is to prevent failure before it will occur. However due to the vastly different approach on the scheduling of maintenance, it can be considered a category on his own. Already in the 1950s to 1970s the US army started outlaying the foundations of condition-based maintenance strategies. By now this has become a topic of much interest not only for the US army, but also for other large corporations in the aerospace, automotive, military and manufacturing industries[48]. This is the case because CBM gives insight in remaining useful life (RUL), performance of a system, and therefore can prevent mission critical failures. Especially since the recent development in data technologies, more and more possibilities have opened up in gathering knowledge and using this knowledge to perform maintenance in an improved way, ensuring a higher availability while reducing costs.

Two aspects that enable CBM are diagnostics and prognostics. Diagnostics is important when the fault is taking place or has occurred already. It can therefore be seen as reactive[48]. It is the act of knowing when a problem is taking place, and identifying and isolating the fault [46]. Since the upcoming availability of sensor data, diagnosis of faults have been vastly improved as sensor data makes it easier to pinpoint the failure and potentially identify the failure mode. Diagnostics regarding this sensor data mainly boils down to pattern recognition[28]. This means that during failure, it can be seen that for certain parameters, sensor data show unexpected trends. Manual pattern recognition is costly and requires highly skilled professionals, therefore it is desirable that diagnostics is done by automatic systems. This is especially the case considering the hefty amount of sensors and daily data acquired on modern aircraft. An Airbus A350 for example, has 50,000 sensors generating 2.5 Tb data daily [3]. Fortunately, the recent developments in information technology enable analyzing this data in an automatic manner, and when considering the benefits that better diagnostics can bring, it is no wonder much development is taking place in this area.

Recently the focus has been shifting more towards prognostics. According to the dictionary, prognostics is simply defined as ”something that foretells”. NASA however provides a better definition with regard to maintenance: ”Estimation of the Remaining Useful Life of a component” [24]. The difference here with respect to diagnosis, is that prognostic is anticipating rather than reactive, as during the lifetime of a component or system, sensor data is used to predict the RUL. The advantage here being that it can be anticipated when failure is bound to happen. Hence replacing the component can be scheduled before actual failure, preventing possible high unavailability and maintenance costs.

Diagnostics and prognostics are often difficult to distinguish from each other. Faruk Eker et al. [16] defined two phases of prognostics as can be seen in figure B.3. The first phase can also be considered diagnostics as it assesses the current health conditions in terms of severity and degradation. Phase 2 is when predictions on degradation is done and the RUL is estimated. These are clear differences with diagnostics, as the focus with diagnostics is on failure mode and location detection and fault isolation.
A visualisation of prognostics can be seen in figure B.4. Here a damage assessment model estimates the damage growth, based on previously acquired data points. With the failure threshold in mind, a probability density function (PDF) of the RUL is estimated. Uncertainty plays a big role in estimating

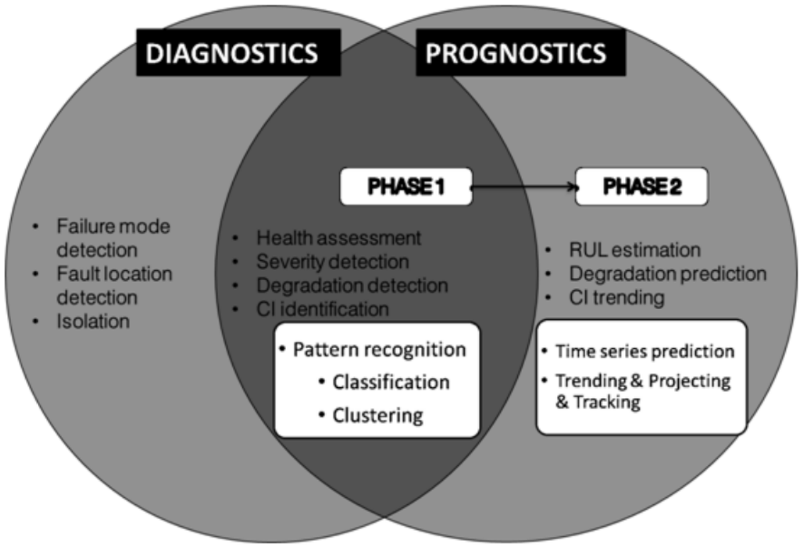


Figure B.3: An overview of similarities and differences between diagnostics and prognostics [16]

the RUL, this is also concluded by Vandawaker, Jacques, and Freels [66] as they found that CBM can improve system performance, however uncertainty regarding prognostics needs to be mitigated and false alarms minimized before monitoring techniques can be implemented and made use of.

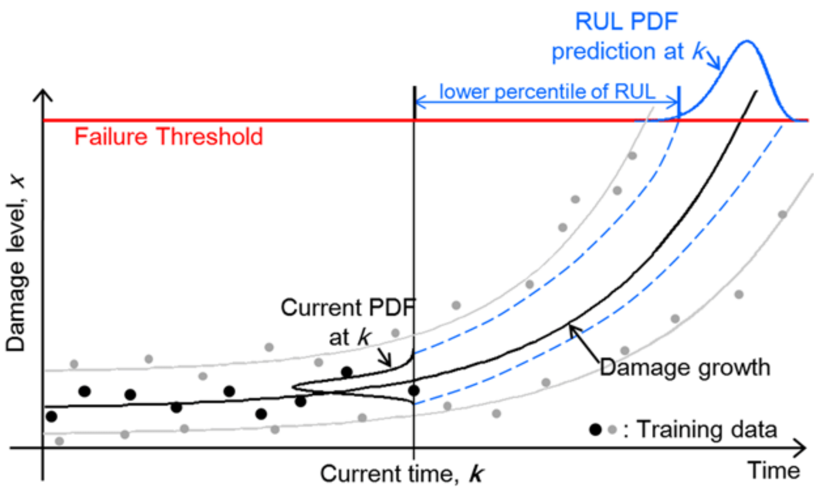


*Figure B.4: Prediction of RUL on trend data using different models [**an**]*

Saxena et al. [54] also had a look at uncertainty in prognostics and reviewed metrics used to assess algorithms, with the goal of providing an overview of the different metrics used in literature and suggesting new metrics that specifically cater to PHM requirements. Two of the metrics that play an important role were False Positives (FP) and False Negatives (FN). The missed alarms can be seen as a false negative: the algorithm did not anticipate the failure, while false positives indicate failure while there is none. A better way to formulate this with the change of predicted RUL as a function of time in mind, is by assessing FPs and FNs based on an acceptability range as function of time. This can be seen in figure B.5.

Aside from existing metrics, the authors proposed several other new metrics for prognostics. One of them is the prognostic horizon. The definition of this is defined as ”the difference between the current time and end of life using data up to the current time index, provided the prediction meets desired specifications”.

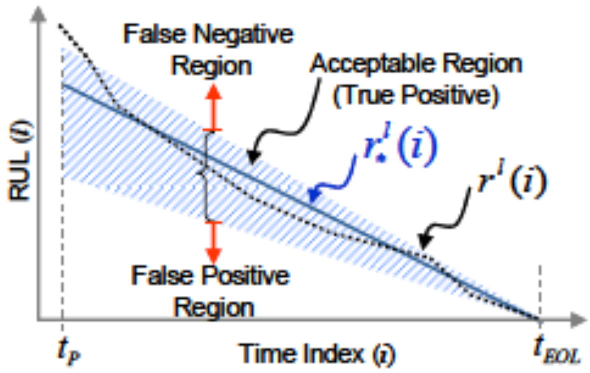


Figure B.5: Definition of FPs and FNs based on time to failure [54]

The prognostic horizon of two different algorithms can be seen in figure B.6. This metric has gained in popularity as it has been researched in [52] [17] [20] [31] [30]. The impact of this and other metrics with respect to potential cost savings according to literature is treated in section B.3.3.

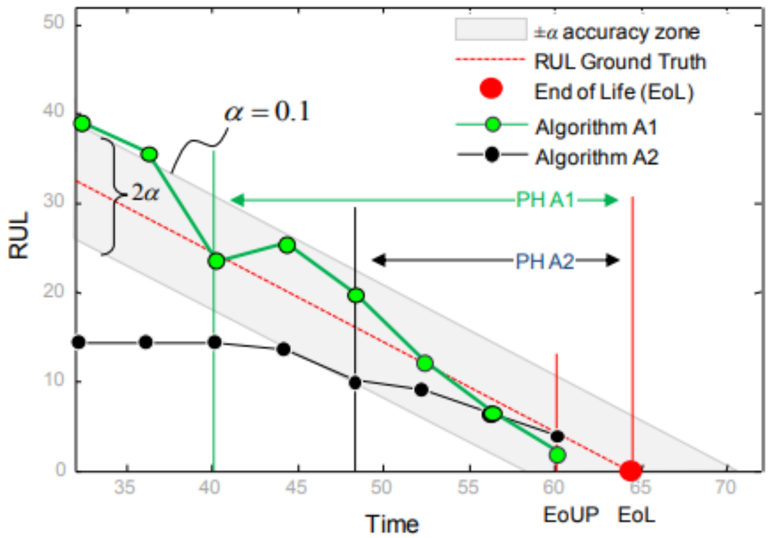


Figure B.6: Prognostic horizon of two algorithms [31]

Returning to the application of prognostic models at CBM level, the gist of CBM therefore is that, as the name suggests, maintenance is done based on the condition of components. There are various applications associated with this concept that can be found in literature. The next section attempts to highlight these.

B.2.2 State-of-the-art in condition-based maintenance

The concept of CBM can be translated into a myriad of different applications. To provide structure, these applications have been grouped into scheduled and unscheduled maintenance.

Scheduled maintenance

Regarding scheduled maintenance, CBM concepts have yet to gain ground. This however is to be expected as the MSG-3 documents have not supported the use of PHM, or any other performance based indicators leading to CBM for a long time[2]. However recently adaptions to the MSG-3 methodology have been proposed allowing health monitoring systems as an alternative to classic scheduled maintenance tasks[69]. Furthermore studies have shown how CBM can be beneficial regarding scheduled maintenance. This section will provide an overview of what aspects of scheduled maintenance might be affected regarding the literature available.

With regard to the structural airframe aspect of scheduled maintenance, Fitzwater et al. [19] looked at the development of cracks at a specific critical location on the F-15 fighter. These cracks would normally be found during manual Nondestructive Inspection (NDI) tasks, however this study looked into the possibilities of automating these tasks with the use of a piezo-electric sensor system. In this case the conclusion was drawn that a systems approach regarding structural issues might be more advantageous, as it was found unlikely that aircraft availability increased with one-off conditional solutions. This systems approach is what Pattabhiraman et al. [45] looked into a bit more. They also observed the formation of cracks, but then on all panels on an Airbus A320. With information acquired from on-board sensors and actuators, Structural Health Monitoring (SHM) techniques can assess the state of panels. With this information, two maintenance philosophies were developed to skip unnecessary inspection tasks such as Nondestructive Inspection (NDI) and Detailed Visual Inspection (DVI) tasks. The unique aspect of this is that the two maintenance philosophies can be considered hybrids between scheduled maintenance and pure CBM. It was found that both the hybrid philosophies as well as pure CBM can lead to substantial savings.

From these studies, it is shown that using prognostic information certain inspection tasks can be skipped. Looking also at scheduled maintenance tasks, Hölzel, Schilling, and Gollnick [25] enlarged the scope by looking at all tasks contained in the MPD of an Airbus A320. The categorization of tasks by task code in the MPD, enabled making assumptions on what impact PHM could have. Once again one aspect of the impact was task elimination. However, for other task types such as servicing and discarding, another aspect was found to be escalating the interval between these tasks.

Maintenance scheduling models

In literature several papers have looked at different modeling approaches with respect to optimizing the entire maintenance schedule according to prognostic data. For instance Li, Guo, and Zhou [38] looked at how prognostic data can influence the planning of scheduled maintenance tasks for an air force fleet of fighter aircraft. A mixed integer linear programming (MILP) model is used to optimize this fleet maintenance schedule with constraints on maintenance costs, remaining flying hours depending on prognostics and sortie requirements. Still this paper is highly theoretical as tasks are generic and therefore have random maintenance durations.

Hölzel, Schilling, and Gollnick [25] also used a MILP model to optimize the maintenance schedule, but used more deterministic data by taking the MPD into account. In this case the amount of task elimination and interval escalation was regulated to find the impact on costs and availability.

Another approach for fighter jet fleet CBM scheduling has been done by Feng et al. [18]. In this model, game theory is used to optimise the strategy of determining whether aircraft are bound for maintenance or not. Using a RUL distribution for components, and heuristic rules over various rounds, total maintenance costs are decreased while mission revenue is increased. Benefits of this approach is that hybrid game algorithm scales relatively good with respect to problem size, while still being able to find a global optimum relatively quickly.

Another approach is the use of a simple genetic algorithm (GA) in scheduling maintenance. This is done by Saranga [53]. The decision tree on what model should be used depends on the current time and state of the item investigated is shown in figure B.7.
As can be seen from the figure, GA is used when the end of life of the component is before the next scheduled maintenance time. This end of life can be based on set hard or soft time, or a prediction of mean residual life. GA is then used to determine whether to replace the component now or ground the aircraft as soon as the condition of the item is deteriorated beyond critical conditions. The algorithm

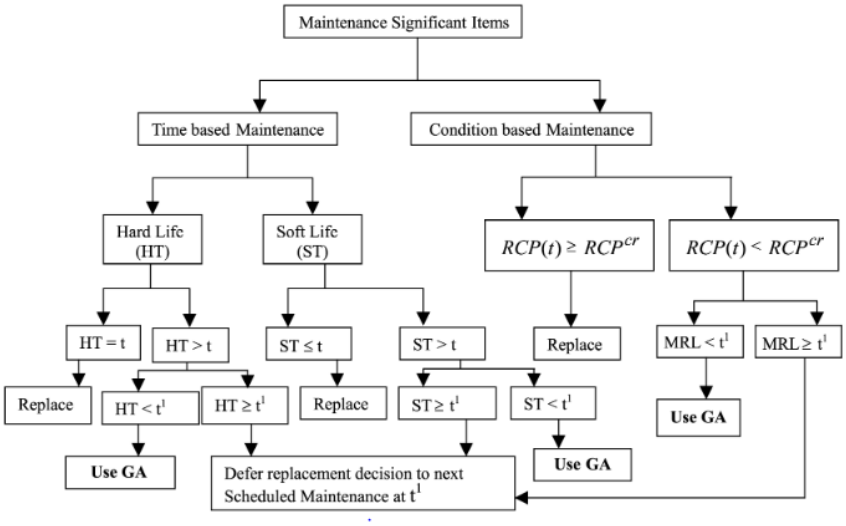


Figure B.7: Decision tree model on the various maintenance options [53]

works by assessing a fitness score, in this case a combination of various costs such as remaining life, risk and down time costs. The GA optimisation process works by forming a new population based on the survived options of the previous attempt. Here the fittest options are chosen and during crossover and mutation, a new population is formed which are once again assessed for fitness. This cycle continues until a stop condition is reached. Unfortunately Saranga [53] does not provide a detailed description how crossover and mutation is modeled.

The use of genetic algorithms in optimising maintenance has also been studied by Marseguerra and Zio [39]. In this study, the GA is coupled with MC simulations, to take into account stochastic variables such as failure rates and imperfect repairs. The advantage of GA as concluded by this study that it helps in guiding MC simulations with problems containing lots of different parameters. MC simulations based purely on these parameters might be too computationally intensive, a GA algorithm helps by evaluating the fitness of results and selecting and breeding on the best results. This eliminates the need of doing MC simulations on all possible values, enabling a faster convergence to an optimum.

Unscheduled maintenance

Another aspect in which prognostics can provide benefits is the prevention of unscheduled maintenance. Unscheduled maintenance is the result of failure of components during flight or unexpected findings during regular maintenance. In these cases of unexpected failure two modes of action are available depending on the urgency: the repair can be postponed in which the term deferred defect (DD) is used, or the repair needs to take place before the aircraft is airworthy again. This mostly depends on redundancy and whether components are safety critical. Operators make use of a so called minimum equipment list (MEL) to find out about this urgency. This MEL contains the airworthiness requirements of different components and specifies the maximum term of deferment. If it is not possible to defer the defect, hence the fault has to be repaired before the next takeoff while the aircraft is scheduled to fly, the term Aircaft on Ground (AOG) is used. These situations can get very costly as often flights are canceled and spare parts which are not available need expedited shipping. Knowing when components are going to fail is therefore especially useful in these cases hence research on the impact of prognostics models on prevention of unscheduled maintenance is plenty.

Already in 2002 a cost benefit analysis was done regarding mostly prevention of unscheduled maintenance regarding engines of fighter aircraft [6]. The paper highlights both the prognostic and diagnostic benefits that PHM can have on unscheduled maintenance, such as reducing the Mean Time to Diagnose (MTTD). Feldman et al. [17] proved that not only PHM can improve inspections, but prognostic models can also be a valuable tool with respect to inventory management and that it can increase the operational availability of an aircraft. Kählert, Giljohann, and Klingauf [30] used empirical maintenance data in modelling the replacement of Line Replaceable Units (LRUs) while taking account stochastic parameters such as accuracy and prediction horizon.

Also based on deterministic data was the approach of Nicchiotti and Rüegg [42]. In this paper a data-driven approach was taken in predicting failure events. A combination of Central Management System data and logs of maintenance activities from a fleet of aircraft was used. Machine learning techniques used this data in predicting at least two flights ahead whether a component would fail. Results were that the precision was relatively high, hence false positives were low. Also considering the low recall rate, this method would prove to be beneficial only as an additional tool in helping decisions, and not yet as a standalone product.

Currently there are already products on the market that can help in preventing unscheduled maintenance. For instance Skywise, a product developed by Airbus, attempts to provide insights in the vast amount of data from data sources such as onboard sensor data, work orders, component data, and flight schedules [8]. Easyjet being one of the early adaptors of Skywise, found that the occurrence of delays due to technical errors has been decreased from 10 per 1000 flights, to just over three per 1000 flights [8]. KLM E&M developed a tool called Prognos that takes more of a bottom up approach. Instead of focusing on all data available, Prognos is built up component by component by looking at components that are critical according to KLM taking into account delays and cancellations they cause [41].

Line maintenance planning models

Often unscheduled maintenance is carried out alongside routine pre-flight inspections in between two consecutive flight legs. These activities are known as line maintenance, and are usually performed at the platform when the aircraft is in operational condition. Especially in these conditions it is vital that unexpected events can be predicted and troubleshooting time is limited. Therefore the usage of prognostics might prove to be very beneficial. Vianna and Yoneyama [67] showed that different wear profiles could be identified using a multiple model (MM) approach. Consequently degradation was modeled and a RUL was estimated that was used as input for line maintenance scheduling algorithm. Benefits were found in a decrease in maintenance costs as well as an increase in availability.

Papakostas et al. [44] proposes a multi-criteria model that helps in obtaining an optimal line maintenance schedule. The four criteria that are being used are cost, operational risk, flight delay, and RUL. PHM enables the estimation of this RUL in terms of probability of failure. In figure B.8, two probability of failure graphs distributions are shown, while 7 different maintenance opportunities are considered. In this case the threshold for maximum probability of failure is set at 75 %, this cuts out alternatives 4 to 7. In accordance with the other criteria, the best alternative is then selected.

Olivares et al. [43] also presents a line maintenance planning model but uses a large neighbourhood search (LNS) algorithm. This works by first finding a feasible solution, then in the neighbourhood of this solution, attempts are made in finding a better solution. By swapping and shifting tasks, while taking into account the probability of failure, the total expected costs of repair is optimized. Probability of failure data is modeled after PHM data, and for the costs, delay and AOG costs are assumed. The method is considered quick, but as a result has a high probability of being stuck in a local minima.

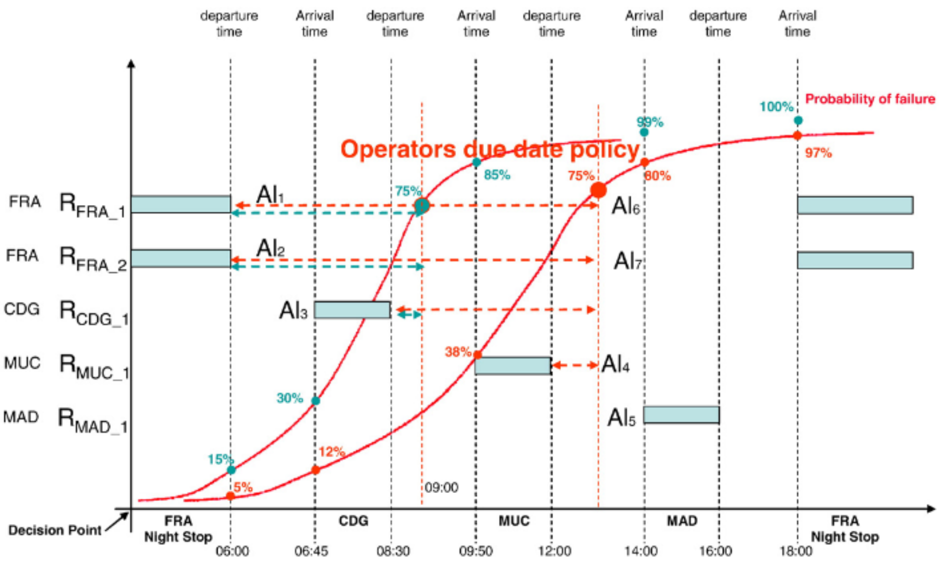


Figure B.8: Prediction of RUL on trend data using different models [44]

B.3 Economic assessment of condition-based maintenance

CBM due to the availability of PHM systems is expected to be valuable regarding scheduled as well as unscheduled maintenance. However many different approaches with respect to the assessment of value of CBM are taken. The purpose of this chapter is threefold, first an overview of the cost factors is given in section B.3.1. With these cost factors in mind, section B.3.2 provides an overview of literature describing different cost-benefit methodologies, and the key performance indicators (KPIs) they suggest. Lastly in section B.3.3 a critical analysis on literature is provided that attempts to evaluate different aspects on the quality of economic assessment that is done.

B.3.1 Cost factors

The main value that CBM can bring is the increase of operational efficiencies leading to a reduction in downtime and a reduction of maintenance costs [48]. First an overview of the classification of maintenance costs is given. Then the relationship between costs and availability is portrayed.

Maintenance costs

Maintenance costs can be split into direct maintenance costs (DMC) and indirect maintenance costs (IMC) [68]. An overview of these costs is given in figure B.9.

DMC consist mainly of labour costs and material costs and therefore generally scale with the amount of maintenance that is performed. Within DMC, costs can be separated further in both on-aircraft maintenance and off-aircraft maintenance costs [29]. On-aircraft maintenance is the maintenance that typically happens at the hangar or platform, including inspection, troubleshooting, and component replacement. Once a component is deemed defect it is sent to the shop for repair, hence the category shop-maintenance costs. Although these costs seem external and hardly influenceable, the No Fault Found (NFF) rate is a factor that PHM systems can influence [30]. This is the rate of when a component is removed following a complaint or fault, while during a check no anomaly is found.

IMC are however less concretely related to maintenance actions. These costs are mostly overhead costs and include aspects such as planning, administration, ground equipment, and inventory costs. These costs

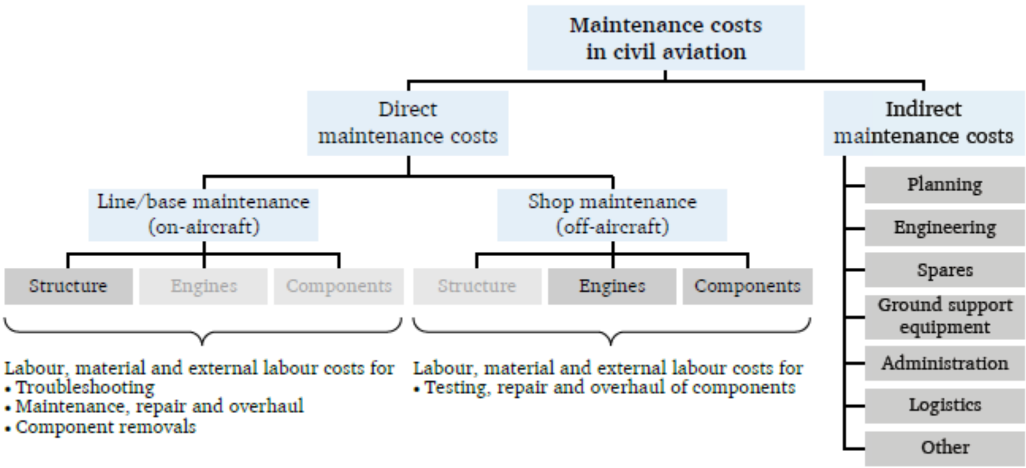


Figure B.9: Overview of how maintenance costs are classified [29]

are generally shaped by the size of aircraft maintenance operations, but can not be directly attributed to certain tasks. Measuring the influence of CBM might therefore pose difficulties. Still an indirect maintenance cost factor that received much interest regarding PHM is the domain of supply chain of spare parts. This is because PHM increases the predictability of components failing and therefore inventory management can be planned more optimally leading to less spare parts, and hence lower holding costs [21].

Cost of remaining life

Another aspect that is becoming more measurable with the onset of prognostics, is the cost of remaining life. These costs relate to how much time or cycles a component is replaced before the end of its remaining life. This remaining life can be expressed in different ways depending on the component [53]:

- Hard life: When this age of the component has been reached, it has to be replaced
- Soft life: Only when modules containing the component is recovered, the component is replaced when its soft life is reached.
- Degradation: There is no set age in cycles or time, only when a critical level has been measured using PHM systems the component is replaced.

Unavailability costs

Aside from the maintenance cost, Dupuy, Wesely, and Jenkins [12] stated that costs related to unavailability, are also vital in assessing the total costs related to maintenance. In literature this type of cost is sometimes regarded as indirect maintenance costs, but since the impact of condition-based maintenance might provide concrete benefit to these costs, unavailability costs are considered a separate category.

Unavailability costs can consists of a myriad of different costs having a different origin, such as passenger compensation costs related to unscheduled maintenance or loss of revenue due to scheduled maintenance. Looking at the literature there are different ways in how to provide more structure with respect to these costs. Kumar et al. [36] argue that downtime costs are only to be taken into account when the aircraft is expected to be in operation. However in these cases an optimisation of scheduled maintenance planning is not taken into account. Saranga [53] however stated that there will always be a loss of revenue associated due to both scheduled and unscheduled maintenance. These costs could also be defined as opportunity costs [51], and play an important role when considering prognostics in scheduled maintenance, as the escalation of task intervals or omitting of certain scheduled maintenance tasks might be beneficial with respect to availability.

Looking at unscheduled maintenance costs, a thorough review of delay costs has been done by Cook and Tanner [10]. Costs were essentially split up into strategic costs and tactical costs. The strategic costs are costs occurred during the planning stage before the day of operation of the flight. These include margins in the turn around time, and can also be considered opportunity costs as defined before. Tactical costs are all costs accumulated at the day of operation and consist of passenger, fuel, maintenance, fleet and crew costs. An overview of passenger delay costs depending on delay time can be seen in figure B.10.

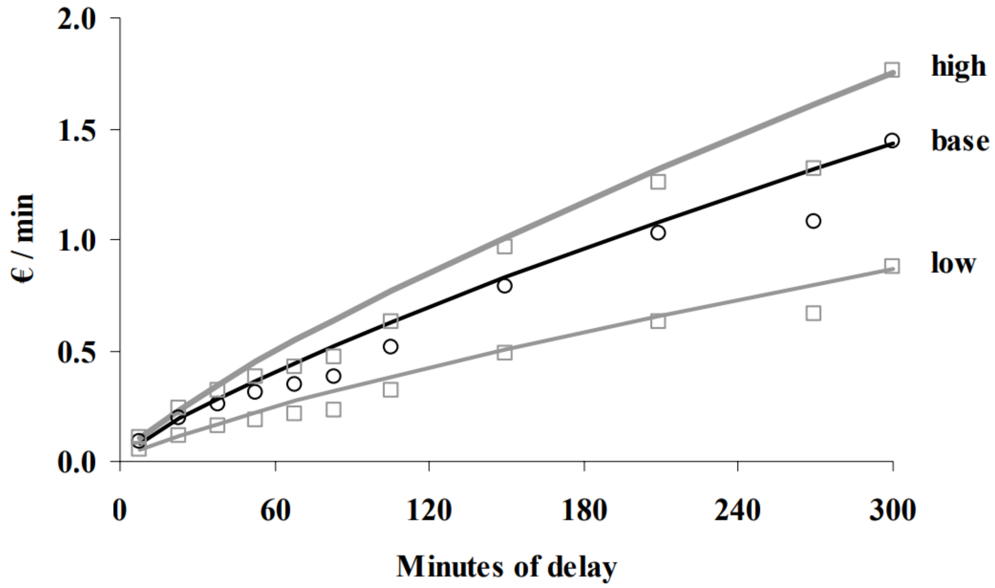


Figure B.10: Passenger costs as a function of delay time [10]

From this figure it can be seen that the per minute cost of delay increases as the delay takes longer. This is because passenger compensations such as vouchers and hotel accommodation is more pronounced as the delay time increases. When considering an airline at fleet level, a longer delay is also prone to cause reactionary effects, also known as 'knock-on' effects. When these happen earlier in the day, connecting flights and the subsequent flight on the same aircraft are especially affected giving rise to substantial costs [9].

This shows the importance of PHM systems in diagnosing the problem on time. For example Dupuy, Wesely, and Jenkins [12] showed that when maintenance information is already transferred while in flight, the CBM approach can have more value. A case study on the air conditioning system of the Airbus A340 [22] showed that CBM is able to prevent 20 to 80 % of the unscheduled maintenance operations depending on the availability of sensors. Some significant delays of more than 170 minutes could be prevented, leading to a substantial cost reduction.

B.3.2 Conducting a cost-benefit analysis

Already in 2002, Ashby and Byer [6] developed a cost-benefit methodology on aircraft engines using a bottom-up approach. In order to assess reliability mostly Failure Modes & Effects Criticality Analsysis (FMECA) source information is used. Together with data from historic line maintenance activities and part pricing information a cost-benefit analysis can be constructed. An engine is modeled as a collection of Line Replaceable Units (LRUs) and the basic engine, these determine whether engine parts can be swapped in a relative short amount of time or whether the engine has to be sent to the shop for repair. By using the FMECA data, failure modes that could be prevented with the use of PHM prognostics were assigned a 'prognostic potential', being a percentage of costs, sortie losses, mission aborts and inflight shutdowns that could be prevented. With these numbers, scheduled and unscheduled maintenance costs are calculated based on the calculation of the Mean Time to Diagnose (MTTD) of these components. An overview of the structure of this CBA methodology can be seen in figure B.11.

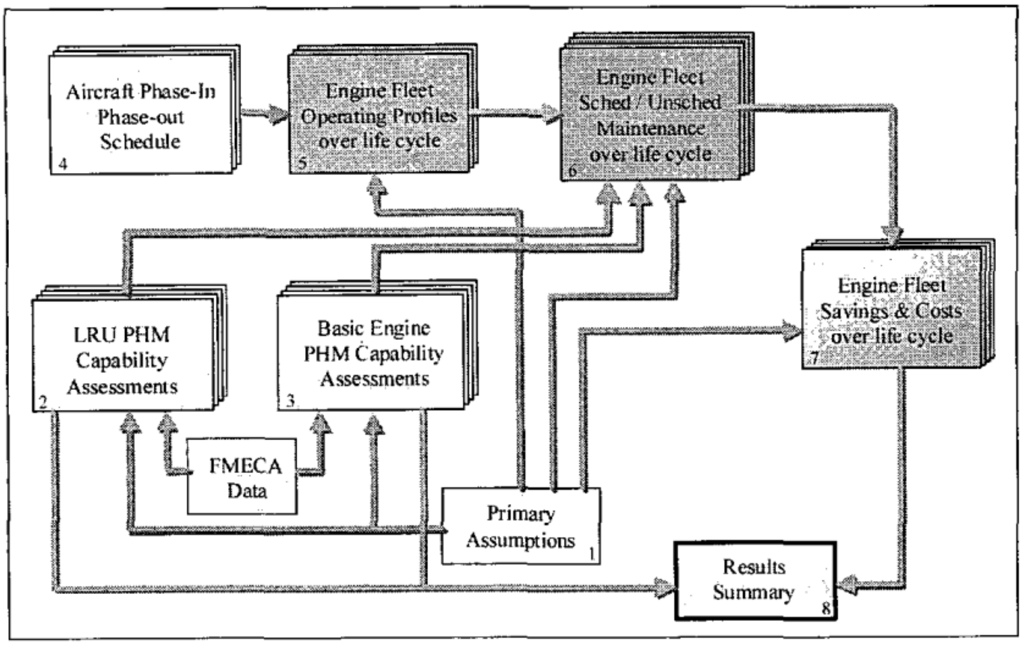


Figure B.11: An overview of the structure of the CBA methodology proposed by [6]

Using spreadsheets and data in terms of costs, manpower required, maintenance time required and maintenance and inspection frequencies, an overall cost benefit is established. Using a discount factor, the CBA can then be assessed over multiple years. The methodology can be seen as very preliminary, since PHM impact is mostly based on assumptions using a FMECA analysis and no simulations of PHM effects take place that are able to show emerging effects not taken into account by looking at individual components. This use of series of spreadsheets however do allow near zero computational times and sensitivity can therefore be very easily assessed.

Leao et al. [37] focuses on the application of PHM on legacy aircraft. The paper gives a very clear overview on benefits and costs that should be taken into account. Furthermore metrics are provided that express the result of the CBA. Benefits taken into account are the following in different steps depending on the implementation level.

1. **Benefits of monitoring and advanced diagnostics**
    - **Reduction of NFF rates.** Expressed in costs of NFF removal per component
    - **Improved aircraft dispatch reliability.** Expressed in delay and cancellation costs based on improved diagnostics.
    - **Reduction of scheduled maintenance tasks costs.** Expressed on task level by estimating cost of the automated task that replaces the manual task.
    - **Improvements on engineering developments.** Expressed rather subjectively on cost reduction of solving aircraft design issued faster due to PHM data.
2. **Benefits of Prognostics and CBM**
    - **Reduction on the number of interruptions.** Expressed in delay and cancellation costs based on replacing components before failure at event level.
    - **Reduction of scheduled maintenance tasks cost.** Expressed in maintenance tasks costs that can be eliminated.

- **Reduction of secondary damages.** Expressed in costs of other components damaged due to failure of one component.
- **Reduction of maintenance induced failures.** Expressed in costs of accidentally damaged components during maintenance tasks that could be avoided due to PHM.

3. **Benefits of a Complete Health Management Solution**

   - **Reduction in insurance costs.** Expressed in a discount on top of the annual insurance costs.
   - **Greater aircraft residual value.** Expressed in a discount on top of the annual reduction of aircraft residual value.

While most benefits are rather concrete in value and are therefore more straightforward to acquire, costs can be more subjective in their estimation. Leao et al. divided these costs in four categories:

1. **Development Costs.** Non recurring costs including research & development, design/management, validation & verification, certification, and IT infrastructure costs.
2. **Aircraft Costs.** These costs are based on the number of components that will be modified to be able to be monitored. Costs included are acquisition costs of sensors and other costs regarding installation and storage and processing of data directly related to the sensor.
3. **Operation/Maintenance Expenses.** Recurring costs based on the use of PHM systems. Expressed in maintenance costs of sensors and IT infrastructure, transmission costs, and extra fuel costs as a result of an increase in aircraft weight.
4. **PHM Side-Effects.** This is the cost of remaining life as described in section 3.1.1; useful remaining life is wasted due the removal of components before failure.

Having looked at the benefits and costs, financial metrics are provided that can translate the output of the CBA in clear terms for different stakeholders.

It was deemed that PHM development teams especially benefit from a cost-benefit analysis per subsystem or LRU. For example attributing costs and benefits to certain LRUs or subsystems might be an implantation technique that enables a better overview of which aspects benefit most from CBM. For operators Leao et al. mentions that especially direct and indirect maintenance costs might be of interest. Aside from this, there are other financial metrics recommended for aircraft OEM management. Yet these might be of importance as well for operators in deciding whether CBM has potential to add value. Two of these metrics are return on investment (ROI) and net present value (NPV).

Return on Investment

Return on investment (ROI) is defined as the difference between return and investment divided by the investment as defined in the central ratio in equation B.1. Feldman, Jazouli, and Sandborn [17] provided a methodology in determining the ROI in PHM applications, and for this used the right ratio in the equation.

$$ROI = \frac{Return - Investment}{Investment} = \frac{Avoided\ Costs}{Investment} - 1 \tag{B.1}$$

Feldman, Jazouli, and Sandborn focus purely on unscheduled maintenance by considering two scenarios: the regular unscheduled maintenance scenario during which the component is replaced at failure, and the PHM scenario using a precursor to failure. For both these cases investment costs and lifecycle costs are considered. The investment costs for the unscheduled maintenance scenario is defined as 0, since no investment is required. This leads to equation B.2, with C_{us} and C_{PHM} being the lifcycle costs for the unscheduled maintenance and PHM scenario, and I_{PHM} the investment costs for the latter one.

$$ROI = \frac{C_{us} - (C_{PHM} - I_{PHM})}{I_{PHM}} - 1 \tag{B.2}$$

The investment costs considered are associated with the realization of the PHM system, and contain costs such as development, training, testing, and documentation costs. But also recurring costs such as installation, assembly, and support costs as in data management and IT infrastructure costs are considered investment costs. Lifecycle costs in this methodology result from the use of the aircraft and therefore consist of the repair and replace costs of LRUs. The difference between the PHM scenario and unscheduled maintenance scenario is then the extra costs of downtime depending on when the failure takes place.

The advantage of this metric, is that it allows to describe the value of PHM in one number, making it easy to compare it to other investment opportunities. However in the case where the investment costs are largely unknown and therefore are based on a great number of assumptions, the ROI can vary greatly, resulting in a less meaningful metric.

Net Present Value
In most cases lifecycle costs are considered, hence costs over a long period of time are taken into account. To be able to capture the time value of money, the net present value (NPV) is used. As described in Hölzel, Schilling, and Gollnick [25], equation B.3 is used where C_0 is the initial investment, C_i is the cash flow in the i-th period, and r is the discount factor that represents the rate of return that could be achieved in other comparable investment opportunities.

$$NPV = -C_0 + \sum_i \frac{C_i}{(1+r)^i} \tag{B.3}$$

Using the NPV it can be immediately clear whether the case is worth investing. If the NPV is positive, the project is worth considering as the net value gained is more than would possibly be gained by other opportunities [47]. The NPV together with ROI, and other cost factors such as the earlier mentioned DMC and IMC, enable different stakeholders to each have a perspective on the value of CBM. It is therefore important of taking these different metrics into account when conducting a cost-benefit analysis.

B.3.3 Analysis of economic assessment in literature

This section attempts to provide a critical analysis of the literature regarding the value that CBM can have. Studies are evaluated on certain aspects that can be found in the subsequent sections. First a critical assessment is done on the data used in the various studies. Then more information is provided in how these studies use prognostics, and what value it has regarding CBM. After this, a critical assessment is made on how studies evaluate the effect of CBM on respectfully scheduled and unscheduled maintenance. Then CBA methods are assessed, after which it is analysed how these studies evaluate costs. Finally the assumptions and limitations of current CBA assessments found in previous sections are highlighted.

Data used
A common challenge among the studies regarding the economic assessment of CBM is the availability of proper, usable data. This is because of various reasons such as the complexity of the data and the availability due to sensitivity of the MROs and operators. For this reason only a handful studies use deterministic and historical maintenance data. It is therefore important to have a critical look on the data used and the assumptions that were made.

Dupuy, Wesely, and Jenkins [12] for example used a Weibull distribution to model part failure depending on the type of component. The assumption was that an aircraft consisted of components of three types: high infant mortality, constant failure, and aging effect failure patterns. These distributions were based on data retrieved from the FAA's Service Difficulty Reporting Site and analysis of failure patterns. Although the study provided an answer to the usefulness of CBM regarding the number of part replacement as function of different types of components, concrete value of CBM was hard to assess. Feldman, Jazouli, and Sandborn [17] used Weibull distributions as well in determining the time to failure. However due to a better simulation techniques, a clear definition of value in terms of ROI, and a deep assessment on prognostic parameters such as prognostic distance, a better assessment was made.

Due to the complexity of the impact of PHM and the various different kinds of data required to make an assessment of the total value of CBM, often case studies are presented that make use of more concrete data. For instance, Hongsheng et al. [26] focused on the air conditioning system, using reliability data from literature. PHM parameters were assumed to be an input to enable a sensitivity analysis. Unfortunately due to the many different parameters and great possibility in variation, e.g. PHM coverage ranging from 10% to 100%, it is hard to pinpoint the actual value that CBM can bring in this study, as the results were very spread out. This can also be observed in the study done by Gerdes, Scholz, and Galar [22], as they concluded that 20 % to 80 % of the maintenance actions of air conditioning systems that cause delay can be prevented depending on the availability of sensors. Data used in this study was however much more concrete, as it was in-service data from Airbus linking exact cause of failure to the amount of delay. Still a more profound evaluation could have been done by taking into account the prognostic assessment of these failures.

When looking at studies that use concrete data, two specific studies stand out, both using data from Lufthansa Technik AG. Kählert, Giljohann, and Klingauf [30] specifically looked at the prevention of unscheduled maintenance. An overview of data used and interaction between the different data structures can be seen in figure B.12.

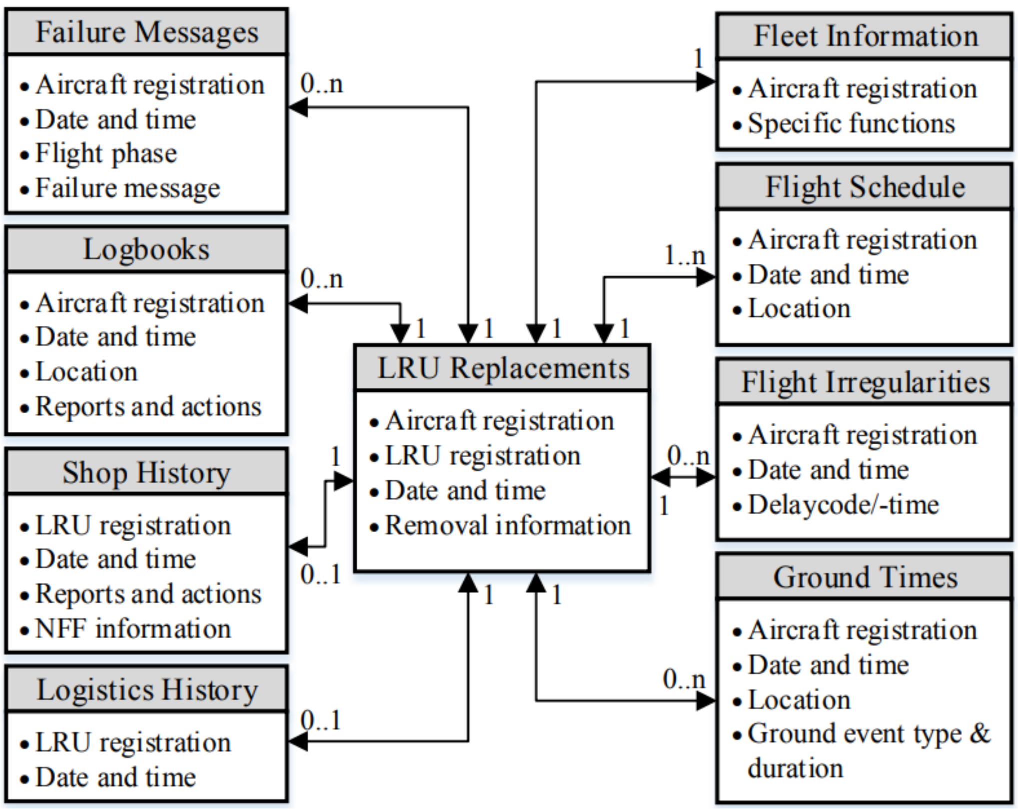


Figure B.12: Data and its dependencies used for event modeling [30]

This wealth of information, even though the authors note the incompleteness and sometimes lack of data quality, provided a more robust ground and holistic approach on assessing the value of CBM on avoidable unscheduled maintenance events.

Hölzel, Schilling, and Gollnick [25] however enlarged the scope, also taking into account scheduled maintenance. For example the availability of data regarding distribution of man-hours of maintenance tasks and maintenance duration, enables the formulation of a proper maintenance planning model.

In conclusion, the availability of data plays a substantial role in assessing the value that CBM can bring. However extensive data is often at least partially confidential, hence in many studies various assumptions are made when looking at a greater scope. Often case studies use more deterministic data resulting in tangible results, but extrapolating these benefits to the bigger picture is often impossible due to the many different aspects PHM influences. Hence in order to do a complete assessment of the value of CBM it is necessary to make proper, justifiable assumptions given the incompleteness of data, myriad of aspects PHM can potentially influence, and restriction of time.

Prognostic assessment

An important influence on the value that CBM can bring is PHM, as these systems help enabling CBM. In literature, various different assessments on the effect of value that prognostics offer have been done. This section aims to provide a critical overview of these assessments.

The kind of assessment done heavily depends on the data available. For example Gerdes, Scholz, and Galar [22] used historic failure data related to air conditioning systems. The paper further looked at current availability of sensors, and potential additional sensors that could prevent these failures. It was concluded that with the current sensors 20% of the failures could be prevented while assuming availability of additional sensors, 80 % of failures could be prevented. Unfortunately a deeper look on how these sensors could prevent failures with respect to prognostic information was not done, as it was assumed that there was a reliable conditioning monitoring system being able to prevent all failures given the availability of sensors. This of course is a big assumption, since for example missed detections, false positives, and prognostic horizon are not taken into account.

With respect to the air conditioning system, another study [62] proposed a model that takes into account multiple sensor signals generating a single health index. Using this health index as input for a Bayesian failure prognostic method yielded satisfactory results in predicting the time of entering the degradation warning stage. In this case the relative prediction errors were below 8 %. An interesting conclusion from this study was that as closer the component was to its end of life (EOL), the predicted failure time is closer to the actual failure time, and hence the uncertainty is less. The key question what follows from this is then how this balance between an earlier more uncertain prediction of failure and a late but more certain prediction time influences the optimization of scheduling of maintenance tasks.

Feldman, Jazouli, and Sandborn [17] did a case study taking into account these uncertainties in predicting the precursor of failure of a multi-functional display. As part of cost benefit analysis comparing unscheduled maintenance with a PHM approach, the optimal prognostic distance (PD) was determined. This prognostic distance is defined as the time horizon before actual failure, the prognostics system is able to indicate failure Sandborn and Wilkinson [52]. Unique in this study is that this precursor expected time to failure (TTF) is a distribution based on a sample of the distribution of the actual time to failure and prognostic distance. When a sample TTF is taken from the distribution of the precursor expected TTF, and this TTF is higher than the actual TTF of the instance it is assumed that unscheduled maintenance is required leading to higher costs. The results of simulations taking into account distributions based on electronic component reliability data from literature, implementation costs and operational profile can be seen in figure B.13.

At first it would be expected that the higher the prognostic distance the better, yet it can be seen that there is an optimal prognostic distance related to these components. Fritzsche and Lasch [21] showed why this is the case, and mentioned the decrease in forecast quality, increase in prognostics cost and increase in wrong delivered spare parts associated with a longer prognostic distance as crucial causes. A qualitative

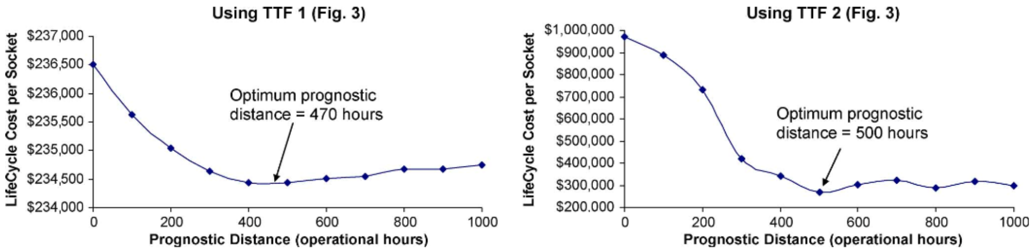


Figure B.13: Impact of prognostic distance on lifecycle costs of LRU socket [17]

overview agreeing with the result from Gerdes, Scholz, and Galar [22] can be seen in figure B.14.

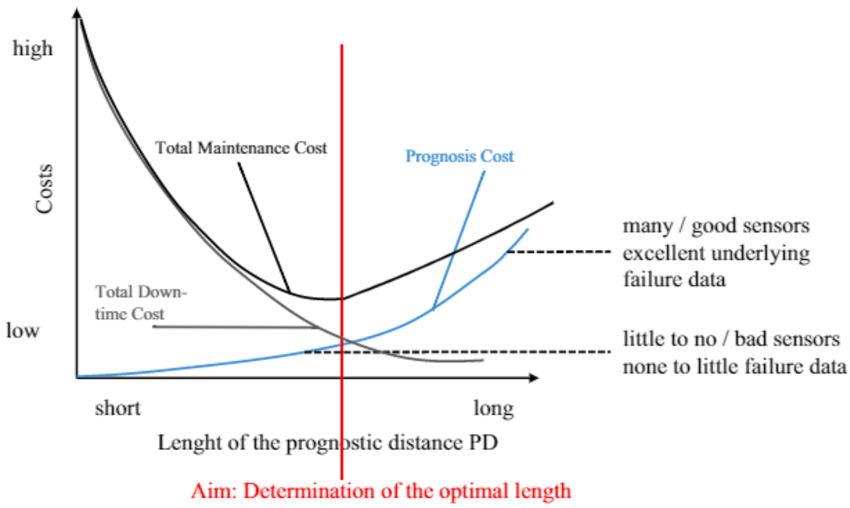


Figure B.14: Effect of prognostic distance on maintenance costs [21]

Kählert, Giljohann, and Klingauf [30] not only looked at the prognostic horizon, but also the impact of accuracy on the eventual cost savings regarding prevention of unscheduled maintenance. Yet in their analysis these parameters are assumed independent in contrast to the previously mentioned studies. Furthermore the impact of false positives, such as false alarms leading to NFF events, and false negatives, in case the failure is not detected on time, on the cost reduction is not very clear. Having a better analysis with respect to this might bring valuable conclusions in the desired sensitivity of the PHM algorithm.

As mentioned before, the holistic approach of Hölzel, Schilling, and Gollnick [25] encompassing both deterministic scheduled maintenance and unscheduled data is an eyeopener in assessing the potential value of CBM. However a deep analysis of prognostic parameters is lacking as component RUL is assumed to be deterministic in the scheduling of maintenance. Furthermore false positives and false negatives are not taken into account with respect to unscheduled maintenance, and might actually be of interest regarding the requirements of PHM systems and corresponding sensors.

Effect on scheduled maintenance

Scheduled maintenance has mostly be the domain of preventive maintenance, and current legislation makes it difficult in proving the benefits of CBM. Therefore in literature there has not been a lot of focus on the impact of CBM on scheduled maintenance. Still there have been some case studies and maintenance scheduling modelling approaches assessing the economic value it could bring.

For instance similar case studies done by Dong, T. Haftka, and H. Kim [11] and Pattabhiraman et al.

[45] focused on the impact of condition-based maintenance in structural aircraft maintenance. It was investigated whether structural health monitoring (SHM) techniques were able to reduce costs by skipping certain scheduled maintenance actions. Pattabhiraman et al. [45] found that especially during the first few maintenance stops, much costs could be saved since inspections were not necessary yet. Three different approaches incorporating SHM were presented, all showing significant improvement in total costs over conventional scheduled maintenance. However cost data used were averages in literature, and the cost modeling technique contained various assumptions, such as a 20% to 100% increase of costs when maintenance is unscheduled, and downtime costs were not taken into account. It should be noted however that extra costs due to the weight of sensors, were taken into account. These were over a lifetime of an aircraft quite substantial, but still it was found that CBM would lead to savings of at least 12 M$ per aircraft.

Dong, T. Haftka, and H. Kim [11] delve a bit deeper into the costs increase and savings associated with CBM. They also included costs increase due to the necessity of replacing the SHM systems during the lifetime of an aircraft. The big cost savings found in this study relate to the reduction in time required for a C check. It was found that 12 days of C check could be saved, as the time of actual inspection was assumed to be much lower and surrounding structures were not needed to be removed in order to facilitate inspection. Another cost saving aspect came from the idea that SHM techniques enabled more regular crack size inspections during A checks, instead of C checks, and therefore a higher crack size threshold was allowed. The effect on scheduling repair actions according to these different inspection parameters is unfortunately left out as it might trigger unscheduled maintenance events, resulting in higher costs. Still the eventual cost savings were found to be in the same order as Pattabhiraman et al. [45].

Aside from these case studies, Hongsheng et al. [26] and Hölzel, Schilling, and Gollnick [25] took a more global approach in estimating the effects of CBM on scheduled maintenance. In interesting approach was done by Hölzel, Schilling, and Gollnick [25] in which maintenance tasks and predicted unscheduled failure events were combined in task packages depending on the RUL or maintenance intervals as can be seen in figure B.15.

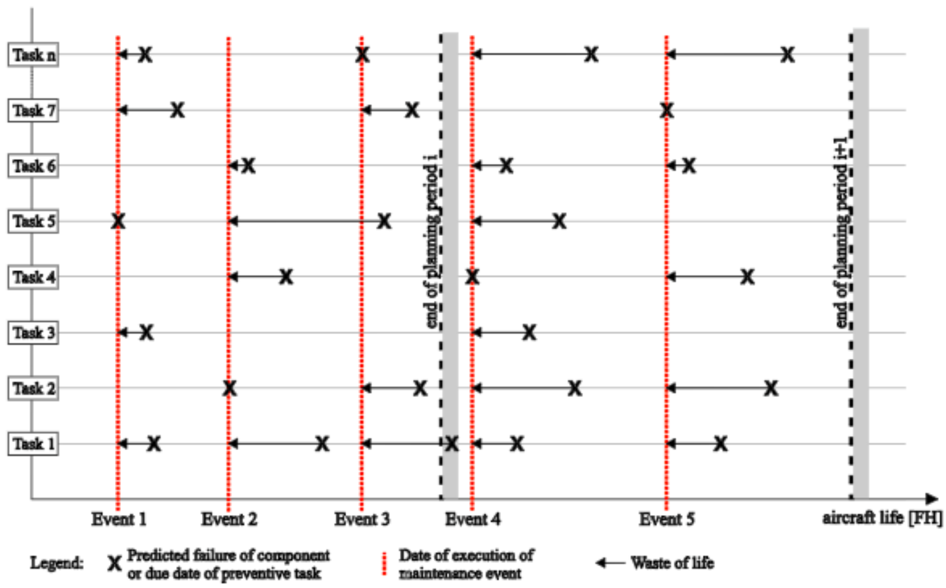


Figure B.15: Maintenance scheduling and task packaging [25]

This task packaging might be especially beneficial in that due to prognostic information, interval of tasks can be escalated and some tasks can even be omitted. This is done by grouping tasks based on their task codes in task code groups (TCGs). Depending on the TCG, a task is either eliminated, the interval is escalated, or nothing changes. The limitation of this study is that only 2 global parameters influence this impact, and hence no detail analysis of tasks is done. Though given the great number of tasks, this might be considered a reasonable assumption. It should be noted that the tasks involved are either short to medium interval tasks. D checks are still assumed to be block checks and planned separately.

Taking only into account scheduled maintenance, and assuming the most optimistic scenario, i.e. parameters of task redundancy being 1 and interval escalation being 100 %, a potential maintenance costs saving of around 3 million EUR was found. This is relatively low considering the total maintenance cost modeled over a life cycle was 76 million EUR, and the great number of maintenance tasks affected by these parameters. Comparing this number to the potential savings in previously shown studies regarding crack formation, show the complexity of analysing cost savings due to CBM. For instance, the time that is freed up due to task elimination and escalation, might be used to schedule extra flights. While Dong, T. Haftka, and H. Kim [11] assumed a reduction of loss of revenue depending on the days of maintenance saved, Hölzel, Schilling, and Gollnick [25] did not clearly explain what was done with the extra time gained. Using the maintenance scheduling approach of Hölzel, Schilling, and Gollnick [25], applied on a fleet of aircraft might reveal patterns in extra time available. These patterns can then be used to adapt the flight schedule, which in result can give a better estimation of the decrease in opportunity costs.

Effect on unscheduled maintenance

There have been many papers looking into different approaches of modeling prognostics and predicting the RUL. However not a great amount of research has been done in how these approaches can be integrated into prevention of unscheduled maintenance and what the potential cost savings are.

Vianna and Yoneyama [67] however combines the modeling of prognostics as well as modeling the effects on planning. This is done by focusing on the identification of degradation considering a multiple wear profile scenario and integrating this with a line maintenance planning model. This model was based on a combinatorial search algorithm, represented in figure B.16.

Algorithm 1: Planning Search Algorithm.

output: plan

$cost \leftarrow \infty$;

forall $\left[t^i_{\text{repair}}; t^i_{\text{serv}}\right]^n_{i=1}$ in TAT$(1 : t_{hor})$ **do**

  if $[t^i_{\text{repair}}]^n_{i=1} \in H_r$ **and** $[t^i_{\text{serv}}]^n_{i=1} \in H_s$ **and** $[t^i_{\text{repair}} - t^i_{\text{event}}]^n_{i=1} < \text{Lim}_{\text{MEL}}$ **then**

    if $C(\left[t^i_{\text{repair}}; t^i_{\text{serv}}\right]^n_{i=1}) < \text{cost}$ **then**

      $\text{cost} \leftarrow C(\left[t^i_{\text{repair}}; t^i_{\text{serv}}\right]^n_{i=1})$;

      $\text{plan} \leftarrow \left[t^i_{\text{repair}}; t^i_{\text{serv}}\right]^n_{i=1}$;

    end

  end

end

Figure B.16: Combinatorial search algorithm planning repair and servicing activities [67]

The algorithm loops over all turnaround times within the planning horizon and finds the repair and service schedule that minimizes the operational costs. In doing this, constraints on resources and the corresponding MEL category are taken into account as well. Limitations are that only line maintenance is considered in this study. It might be interesting to see the results of a complete maintenance scheduling approach as done in [25], while taking into account constraints posed in this paper. The study claims parallelisation is allowed to perform the repair and servicing of different components, however dependencies between these activities such as available manpower and time is not considered. When considering a fleet of aircraft, this might prove to be especially difficult using a combinatorial search algorithm, and other simulation approaches such as an heuristic game approach [18], or a discrete event approach [30] might be beneficial.

The advantage of a discrete event approach, is that it allows to analyze the interdependencies between events, and hence cause and effect can be established. [30] used this simulation technique and came up with a framework in assessing benefits with respect to unscheduled maintenance of PHM at LRU level. Unfortunately however, due to intellectual property reasons, the actual simulation model is not disclosed. Integrating this approach at LRU level and combining it with the holistic scheduled maintenance approach of Hölzel, Schilling, and Gollnick [25], might prove to give a better overview of CBM value. Especially considering that the prevention of unscheduled maintenance events by Hölzel, Schilling, and Gollnick [25] is mostly based on one PHM coverage parameter, while not considering prognostic parameters as done by Kählert et al.

Evaluation of methods
As mentioned in the previous section, simulation techniques have a big influence on how the cost-benefit analysis is performed. Depending on e.g. the complexity of the system involved and data available, different methods are chosen. An attempt was made to categorize the methods found in literature, an overview of different methods with corresponding sources can be found in table B.1. Four different methods are identified: scenario analysis, Monte Carlo simulation (MCS), discrete event simulation (DES), and a combination of the latter two.

Scenario Analysis
The scenario analysis (SA) is a method during which several scenarios are evaluated based on different input data. The kind of SA done by the sources presented in table B.1, generally makes use of a set of deterministic equations, as simulation is not used in these cases. The advantage of this method is that it is less computational heavy, Ashby and Byer [6] and Banks et al. [7] for example use spreadsheets that evaluate the cost-benefit of PHM systems. Since no simulations are taking place, the outcome is known within seconds making it a very suitable method to perform sensitivity analyses. The disadvantage here is that when considering systems containing multiple events, often a discrete set of equations can not accurately describe the complexity and the interactions within this system as SA works best for single events [57]. Many stochastic elements play a role for which assumptions must be made. This is also clear from Gerdes, Scholz, and Galar [22], as the event investigated was the reduction of unscheduled maintenance events due to failures in the air conditioning system. This was done by looking at historic failure data and setting up two scenarios: faults potentially prevented with data from sensors currently available, and faults that could potentially be prevented regardless of the current availability of a sensor. It was assumed that when a failure was preventable it was prevented and unavailability costs were decreased. This shows that although this method might provide a reasonable first impression of the order of costs and benefits, it is less suitable for a detailed analysis as stochastic elements (e.g. FPs and FNs) and effects between events can not be modeled well using SA.

Monte Carlo simulation
Often stochastic data is used to model uncertainty. In these cases the model can not be readily solved in one go, as each run will present a different outcome due to the probabilistic nature of the stochastic data. the Monte Carlo simulation (MCS) model provides an answer to this, by sampling a different random value from the probabilistic distributions for each run. After a large number of runs, the results are aggregated, and useful information is gained on how uncertainty influences the model. MCS are most useful when time does not play a role, as it is mostly used in assessing risk[32]. When a system with multiple events affecting each other is considered, DES or a combination of DES and MCS is often used.

For both Dong, T. Haftka, and H. Kim [11] and Pattabhiraman et al. [45] cracks on a great number of panels on a fleet of aircraft are simulated. The initial crack size and damage growth is sampled during each run. Once certain threshold values are crossed the aircraft is deemed ready for maintenance. Over

Table B.1: Different CBA methods used in literature

Method	Source
Scenario analysis	Leao et al. [37] Gerdes, Scholz, and Galar [22] Ashby and Byer [6] Banks et al. [7]
Monte Carlo simulation	Dong, T. Haftka, and H. Kim [11] Gilabert et al. [23] Pattabhiraman et al. [45]
Discrete event simulation	Vandawaker, Jacques, and Freels [66] Rodrigues and Yoneyama [50] Fritzsche and Lasch [21]
Discrete event simulation & Monte Carlo simulation	Vandawaker et al. [65] Feldman, Jazouli, and Sandborn [17] Hölzel, Schilling, and Gollnick [25] Kählert, Giljohann, and Klingauf [30]

the aircraft lifecycle the number of maintenance trips can then be determined taking into account the uncertainty of cracks being formed.

Discrete event simulation
As mentioned previously, DES is especially useful as time is of importance and complex systems are involved as it is able to model the impact of the result of one event on the input of another event. This way causes and effects of specific events can be evaluated and assessed regarding their impact on costs and benefits. DES is also a method to discover unexpected bottlenecks, under- or over-utilization of resources, or failure to meet specified requirements [57]. In contrast to continuous simulation, no change in system state occurs in between events, enabling a relative computing time-efficient method of simulation [30]. DES can be especially useful in simulating lifecycle costs of an aircraft, as the aircraft's health can be described as a state, while maintenance activities can be modeled as discrete events. Since a lifecycle of an aircraft will contain a great number of maintenance activities, DES enables the simulation to be done in a relative time-efficient manner.

Discrete-event simulation & Monte Carlo simulation
Often probabilistic elements are part of the CBA of CBM. To account for these while still taking the lifecycle of an aircraft into account, DES and MCS are combined. Kählert, Giljohann, and Klingauf [30] for example uses MCS to account for the stochastic input data, being distributions of empirical data such as the processing time of LRU replacements. Hölzel, Schilling, and Gollnick [25] also used the combination of DES and MCS, for which the MCS is used to analyze the probabilistic behaviour of component failure. Feldman, Jazouli, and Sandborn [17] uses a stochastic DES method, of which the stochastic elements being the MCS on the performance of PHM and various costs involved in the calculation.

Evaluation of costs
Various different approaches in assessing costs of CBM have been taken in literature. Various studies present methodologies to assess this value [37] [7] [6] [51]. Recently more and more studies have come available that use deterministic data resulting in more concrete results. Most of these are case studies zooming in at a certain element such as a LRU, while studies taking a global approach are much rarer, but might provide more merit as a decision support for the industry. An overview of assessed papers with respect to costs can be found in table B.2

A first observation from this overview is that cost assessment in literature mostly focuses on unscheduled maintenance, revealing the possible gap that enables a more complete picture of value CBM can offer. Although Hongsheng et al. [26] and Hölzel, Schilling, and Gollnick [25] provide similar models

Table B.2: Overview of cost assessment in literature

Paper	Domain	Maintenance costs	Downtime costs	Loss of revenue	Use of assumptions	Remarks
Vianna et al.[67]	Unscheduled Maintenance	+/-	+/-	+/-	Provides model and case study with assumed data	Takes into account additional operational costs due to MEL and degradation costs.
Gerdes et al.[22]	Unscheduled Maintenance	-	+	-	Deterministic delay data with delay cost data from literature	Only looks at preventable costs regarding delays
Pattabhiraman et al.[45]	Airframe Maintenance	+/-	-	-	Empirical expressions, unscheduled cost assumed	Takes into account extra fuel costs due to weight of sensors
Dong et al.[11]	Airframe Maintenance	+/-	-	+/-	Heavy use of assumptions	Takes into account cost of replacing SHM equipment
Feldman et al.[17]	Unscheduled Maintenance	+	+	+	Generalized from literature	Calculates ROI by comparing life cycle costs of LRU sockets
Fritzsche et al.[21]	Unscheduled Maintenance	+	+	+	Provides model and case study with assumed data	Also includes costs of supply chain and holding inventory
Saranga et al.[53]	Unscheduled Maintenance	-	+	+	Provides model and case study with assumed data	Also includes risk and secondary damage costs
Kählert et al.[30]	Unscheduled Maintenance	+	+	+	Mostly deterministic data	Also includes NFF and diagnostics costs, but not wasted life
Hongsheng et al.[26]	Aircraft level	+/-	-	-	Generalized from literature, heavy use of assumptions	
Hölzel et al.[25]	Aircraft to System level	+	+/-	+/-	Mostly deterministic data	Ouputs several KPIs such as NPV and ROI

in which PHM impact on scheduled maintenance is assessed, Hongsheng takes a case study approach, while Hölzel proposes a maintenance planning simulation approach. This enables a better estimation of the avoided costs with regard to interval escalation and omitting of maintenance tasks. Despite the ability of the model to conduct the maintenance planning optimisation on fleet level, this is not done since other modules did not support this. Scalability of the cost value assessment results from aircraft to network level can however be of much interest to operators.

While the main objective of some of these papers is to conduct a proper cost benefit analysis, other papers use a less detailed cost model in order to validate their model [67] [21] [53] [45] [11].

Vianna and Yoneyama [67] for example use mostly assumed values for costs in their case study. Still the paper comes up with unique costs aspects rarely seen in other papers, such as additional operational costs due to MEL conditions and degradation of components.

Fritzsche and Lasch [21] focuses on determining the optimal prognostic horizon and uses a relatively simple cost model, using mostly rounded assumed cost data. Although not accurate, inventory and ordering costs are taken into account as well. It should furthermore be noted that assumptions made in this study can be justified, since the objective is not to accurately predict potential cost savings, but assess the relative cost savings between different prognostic distances.

A similar approach is taken by Saranga [53] as the cost data here is purely hypothetical in order to validate their novel opportunistic maintenance model. Since the costs of the actual maintenance operation is considered similar, these are not taken into account. To account for the difference in scheduled and unscheduled downtime, costs of compensation, good will and logistic delay are taken into account. The cost for good will however are very difficult to estimate [9], and therefore it is questionable how these have been determined, even considering the hypothetical nature of the data. A main driver for the genetic algorithm used is the balance between probability of a component failing during its lifetime and the cost of replacing it before the actual end of life. This is nicely incorporated with the use of costs of risk and cost of remaining life. Once again costs of risks might be difficult to assess due to the unknown distribution of the hazard function, yet when properly assessed might provide a good first order impression of opportunistic maintenance.

Both Pattabhiraman et al. [45] and Dong, T. Haftka, and H. Kim [11] focus on the application of CBM to prevent unnecessary structural airframe maintenance due to fatigue cracks. Interestingly both papers end up with a similar total lifecycle reduction of around 12 million USD, while having a vastly different cost assessment. Pattabhiraman et al. [45] uses maintenance costs data from empirical sources such as Kumar [35]. However in assessing the extra costs due to unscheduled maintenance and cost reduction of the actual maintenance tasks, parameters are assumed that simply scale costs. Furthermore loss in revenue due to change in availability is also not taken into account. What brings most value to the calculated costs, is the modeled reduction in required maintenance trips.

Dong, T. Haftka, and H. Kim [11] approaches the problem in the same way regarding the split into modeling the required maintenance trips, and using this number to assess the total potential cost savings. The difference here is that more different costs are taken into account in a more detailed way, such as inspection costs, cost of removing/installing structures, costs of replacing SHM equipment, and most importantly according to the paper, net revenue saved. The downside is that cost values here are heavily based on various assumptions, making it difficult to validate total found cost savings.

The scope of Kählert et al. and their wealth of deterministic data enables an accurate modeling of costs. This modeling is event based, meaning that every event is associated with a cost, and the total costs is the accumulation of all event costs. These event costs are on their part an accumulation of process costs and operational irregularity expenses. Looking at the assumptions, a fixed delay costs per minute is assumed. Cook - University of Westminster [9] however showed that the delay costs might significantly increase per minute as the delay progresses. Also effects such as cancellations or AOG are included in this number. A modeling approach with more detail to these costs might for example bring benefits to assess how different prognostic parameters influence different kinds of costs.

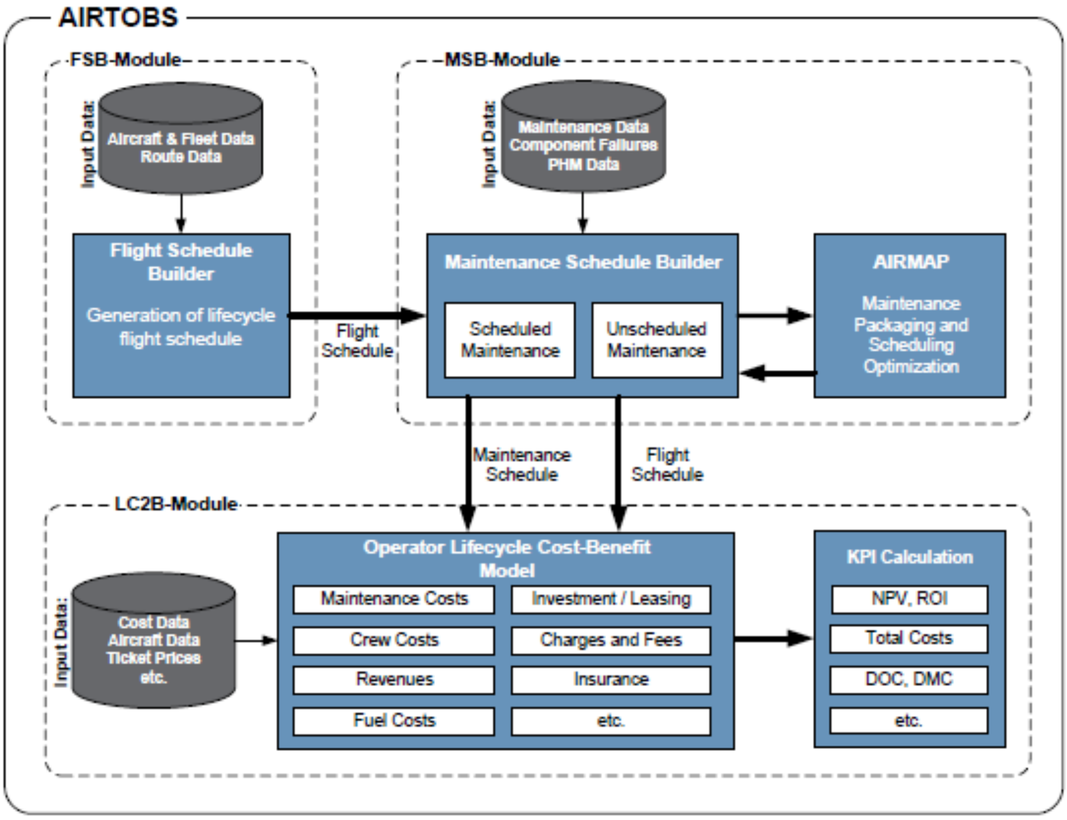


Figure B.17: Lifecycle cost-benefit model of Hölzel, Schilling, and Gollnick [25]

Hölzel, Schilling, and Gollnick [25] developed a Lifecycle Cost-Benefit Model (LC2B) module taking into account all maintenance aspects during the lifecycle of an aircraft and outputs various KPIs. An overview of this can be seen in B.17. Unfortunately the level of detail with regard to cost modeling is not presented and unfortunately delay and cancellation costs are calculated once again according to values from literature. An advantage however of the scope set by Hölzel et al. is the possibility to investigate extra opportunities in generating revenue by scheduling more flights depending on the performance of PHM.

Evaluation of assumptions & limitations

As mentioned in previous sections, various assumptions and limitations on the CBAs conducted in literature have been identified. This sections aims to provide an overview of these, by categorizing them and elaborating more on their effects.

Data used

According to a great number of papers [30] [20] [25] [26], this is the main barrier in providing a CBA with concrete results. Therefore often a sensitivity analysis is performed for which the variable is the percentage of systems PHM can be used for [25] [26], while other times generic failure distributions are taken from literature [17]. Feldman, Jazouli, and Sandborn [17] for example examined both a Weibull distribution and Exponential distribution of time to failure of a multi-functional display. For this reason a range of possible cost savings due to PHM equipment can be calculated, while with historic data available, this cost savings can be predicted more accurately. For example Gilabert et al. [23] calculates the Weibull distribution parameters based on historic data, providing a better estimate for failure.

Fritzsche, Gupta, and Lasch [20] especially outlines this problem with respect to finding the optimal prognostic distance. It was found that this parameter was heavily influenced by the data used, and only when good quality data is available this parameter can be sufficiently evaluated.

Especially when considering a CBA on aircraft or fleet level, these limitations of data are important. On this level, mostly sensitivity analyses take place that vary PHM coverage rates [25] [26]. This might give an indication of possible benefits, however using historic and deterministic data for validation as done by Kählert, Giljohann, and Klingauf [30] provides a much more accurate estimation of benefits. Using previous failure data, a much better estimation is performed on whether PHM can be effective and what the requirements of PHM applications should be. The limitation of Kählert, Giljohann, and Klingauf [30] is that the focus is only on unscheduled maintenance related to one component. The gap in literature here is that a CBA of both scheduled and unscheduled maintenance on aircraft or fleet level with deterministic data has not been performed yet. Taking into account the top contenders with respect to effect on costs and unavailability, a model can be constructed that can be validated by the prognostics data offered by KLM's PHM unscheduled maintenance prognosis tool called Prognos.

Prognostic parameters

Assumptions often done with respect to PHM is that diagnosis of the failure is perfect [11] [22] [25], a prognostic horizon (PH) is not taken into account [25] [22] [26], or false positives (false alarms) [17] [11] [22] [25], false negatives (missed alarms) [17] [22] [25] are not considered. Kählert, Giljohann, and Klingauf [30] show how this can impact the final results, as it was concluded that a PH was a very important measure on the effect of PHM. While both FP and FN were taken into account, their effects where combined in an accuracy parameter. Still both FP and FN have different effects, as the effect of a FP might result in a potential costly NFF, while a FN might result in extra unscheduled maintenance potentially giving rise to an increase in unavailability costs. How these each influence the results of a CBA, might bring value in determining FP & FN requirements for PHM systems. The same is true for the PH, and as Fritzsche, Gupta, and Lasch [20] concluded these requirements are a must to know, as they heavily impact the costs of PHM systems.

B.4 Conclusion

Having assessed the literature regarding condition-based maintenance and the economic assessment of this, gaps are identified that can be filled with new research.

When looking at the scope of economic assessment done, a gap identified is that a model that takes into account the effect of PHM on both unscheduled and scheduled maintenance on fleet level has not been developed yet. The effect on unscheduled maintenance is considered the prevention of non-routine maintenance events occurring because of unforeseen failures, while the effect on scheduled maintenance is largely contributed to the elimination of inspection tasks or escalation of task intervals.

Hölzel, Schilling, and Gollnick [25] come close in presenting a scheduling model that can be used for a fleet of same aircraft types, however prevention of unscheduled maintenance can only be modeled on aircraft level. Especially for an operator not outsourcing MRO activities such as KLM, the emergent effects on availability and costs can be very valuable. For instance availability has different effects on fleet level, i.e. planning of extra flights might be possible, while actual maintenance costs savings are expected to decrease because of the limit of aircraft that can be maintained simultaneously.

Having a good indication of what costs could be potentially saved with CBM is one thing, on the other hand it is important to assess whether it is actually beneficial in that investment costs do not outweigh the benefits. It is therefore important that prognostic parameters, highlighted in other studies such as prognostic horizon, false positives and false negatives are adequately taken into account. These determine sensor or system requirements and for this reason have a big influence on investment costs. Kählert, Giljohann, and Klingauf [30] took these parameters properly into account, however the scope was limited to unscheduled maintenance. Expanding the scope in order to have a better idea of the total potential cost savings depending on these parameters can be of great interest to an operator.

Taking these gaps into account, the following main research question is formulated:

What impact can condition-based maintenance have on fleet availability and maintenance costs?

To answer this question, the following subquestions are defined:

1. What is state-of-the-art in condition-based maintenance?
2. What metrics can be used to assess PHM performance?
3. How can scheduled and unscheduled maintenance tasks be affected by PHM?
4. How can availability be assessed in terms of cost?
5. What maintenance costs are taken into account?
6. What is the effect on availability and cost when the planning of PHM based scheduled maintenance tasks is modeled on fleet level for different fleet sizes?
7. What is the effect on fleet availability and costs when unscheduled maintenance is affected by PHM algorithms?
8. What metrics of PHM models are important and what level of performance is required in order for condition-based maintenance to be beneficial?

Appendix C

Component failure data validation

A condition for having proper prognostic model output data is that the input data should be as accurate to reality as possible. For this reason it is important that the failure modeling of components in the unscheduled maintenance module, is as accurate as possible. To ensure validity, it is therefore chosen to fit a failure distribution to the historic removal data. Then this distribution can be used to simulate component removals for a fleet of aircraft similar to the carrier of which the data is used. Comparing the outcome of this simulation to reality, the modeling error can be obtained and thus the model can be validated. This process is laid out in several sections of this chapter. First in section C.1 all data used will be discussed in detail, and the cleaning actions required will be treated. Then in section C.2 the right-censoring obstacle of this data will be treated. When the data is ready for fitting, in section C.3 the failure distribution function will be chosen, and the methodology of obtaining the best fitting parameters will be treated. With a distribution available the model validation methodology and results are treated in section C.4.

C.1 Removal data

The removal data used is a database with over 35.000 records of component removals across 25 carriers worldwide. An indication of the data structure with sample data can be found in Table C.1.

Table C.1: Sample component removal data

ID	Code	Reason	Cost	DUR	TYP	Last AC	OPR	New date	Install date	Removal date
2628	123456	Repair	20,000	25	789	AB-CDE	DD	2017-04-10	2017-04-10	2019-07-08
5708	789123	Modify	35,000	35	789	FG-HIJ	MM	2015-02-20	2017-02-11	2018-07-18

As can be seen in this table, a good selection of usable data is available. The ID represents the unique id for every component. The the Code field is the unique code for each component type. For example, there are several variations of the CU for each aircraft type. Each type has a different code, used in this database. Then the Just and Reason fields indicate whether the removal of the component was justified and what the reason for removal was. Cost and DUR indicate repair costs and duration. Information about the previous installed aircraft is provided with the TYP, Last AC, and OPR columns indicating the aircraft type, registration code and operator IATA code. Then the new, install, and removal dates indicate when the component went in operation for the first time, when the component was installed on the previous aircraft and when it was removed again.

Once this data was obtained it was of importance to filter it as only for specific components data was required. To do this, the data was filtered using the Code column on the codes for the component being investigated. A verification was done on the TYP column, to ensure only component from aircraft of the correct type were considered. The next step was filtering the data once more, as the prognostic algorithm used would only be evaluated on component failures, hence only removals due to component repair are considered. This is done by filtering the Reason column on Repair.

Once the data was properly filtered, it was time to clean it. First the data was analysed and validated. Simple validation tasks were done such as ensuring the removal date is later than the install date, and that the install date is the same or later date than the new date. Also a histogram of repair cost and repair duration was made. As expected a slight correlation was found between repair duration and repair cost. However, it was found that still quite some data points seemed to contain invalid data, such as costs defined as 0 (taking into account warranty), invalid dates or missing repair durations. Since cost data was originated from a different source, the data points with invalid cost data were not deemed unusable, however some data points were deemed unusable due to date issues, as they had removal dates which were the same. At first it was thought that these data points would indicate rogue units, e.g. units that simply were not repaired or failed straight away during the install. These data point however, turned out to be erroneous data introduced most likely by human input error. Therefore these data points were removed and the data points containing plausible values remained.

C.2 Censored data points

A next point of concern is the incompleteness of data. Since only data was available of removals, lots of healthy components were not taken into account yet, as they were never removed. So in the case a distribution was fit on the historic removal data, it was expected that when using this distribution in the simulation, too much removals would occur compared to reality. As can be read in the validation section C.4, this was indeed the case. Aside from this data being not available, the data also does not consider replacements as it is obviously still healthy. This means that the data is right-censored. The two challenges therefore are the estimation and generation of this missing data, and taking into account censoring as the maximum likely distribution parameters are obtained.

Luckily, the TTF data comes with metadata indicating the last aircraft components were removed from. With the public availability of start of service dates of aircraft, and the number of components per aircraft known, a timeline using the available data can be constructed. A schematic indication of such timeline can be seen in Fig. C.1.

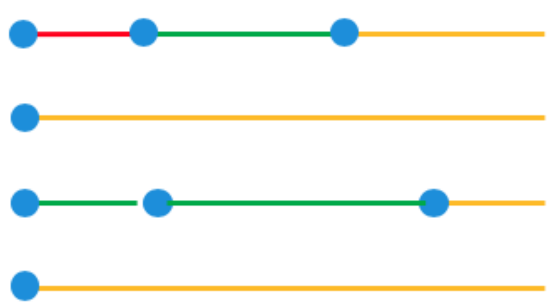


Figure C.1: Timeline of component replacements on 4 component slots on one aircraft

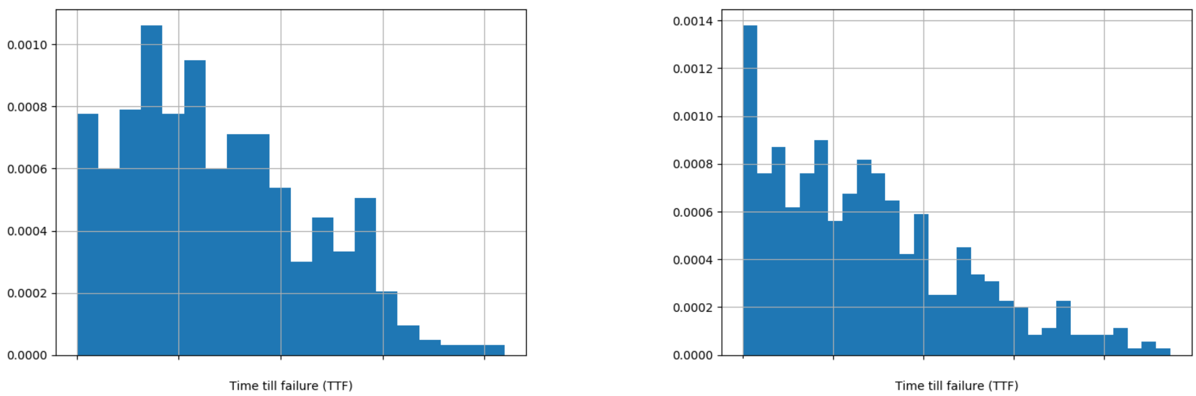
The blue dots represent the points during which a component at a certain socket is replaced. The green lines indicate the data that is available. The orange lines indicate right-censored data while the red line indicates non-censored unknown data. It is important to note that together with the start of service date of the aircraft, only the start and end points of the green data is available. Furthermore from the data available it is unknown which component replacement corresponds to which component slot on the aircraft. Therefore various assumptions and estimations are made in order to acquire these timelines.

Since for each replacement, a time of install and a time of removal is known, in many cases component removals can be attributed to the same component slot as one removal date corresponds with the other install date. Furthermore in various occasions the install date corresponds with the aircraft in-service date, making it easy to complete the timeline for this component slot. Often data is missing as components have install dates later than the in-service date of the aircraft and no component replacements can be places before this installation. Such an occasion is indicated with the red line in Fig. C.1. In the case that the install date is much later than the in-service date of the aircraft, an extra data point is generated to take into account this extra replacement. Once this is done for all missing non-censored data, the unknown data left is the right-censored data.

Generally, two kinds of right-censored data can be observed. First there are component slots for which no data is available, and it assumed that the component was installed at the in-service date of the aircraft, and the component is still operating. In the other cases, which happen for all remaining slots, it was deemed that at the time that the data was gathered, the component installed last, was still operating. So for all these components, right-censored data points were generated with the end time being the moment the data was obtained, and a parameter indicating that the data is right-censored.

C.3 Failure distribution function

With the data taking censoring into account, it was time to select a failure distribution function that was able to accurately model the data. From literature it was found that for a long time mainly exponential distributions were used to model time to failure (TTF) distributions [33]. However, with the recent increase in component complexity the Weibull distribution may prove to be more representative as a TTF distribution function [55]. Having the data available, a visual inspection was done on the non-censored TTF data. The histograms of the EG and CU TTF data are displayed in Figure C.2.



(a) CU subsystem *(b) EG subsystem*

Figure C.2: Histogram of historic TTF data for the EG and CU subsystem

Looking at the figures, it can be seen that an exponential distribution would seem to be a good fit, especially for the EG considering the high number of failures near the start. For the CU subsystem a

Weibull function seem to be a better fit considering the peak after the start. Since it is possible to reduce the Weibull distribution to an exponential distribution by adjusting the shape parameter to 1, a two-parameter Weibull distribution was used for modeling this data.

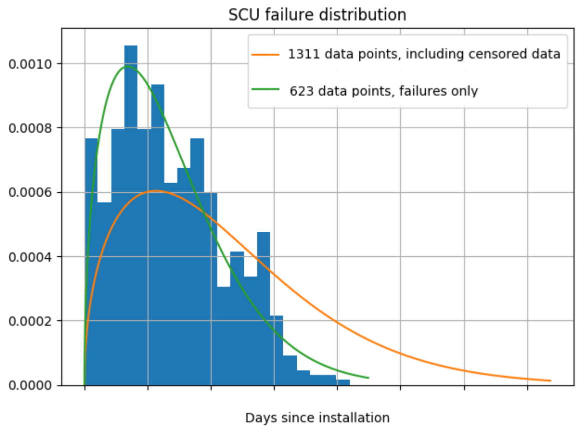
Using the maximum likelihood estimation (MLE) method, the shape and scale parameters were obtained for which the distribution fits the historic TTF best. Eq. C.1 shows the general equation that is used for the MLE taking into account non-censored and right-censored data points [4].

$$L = \prod_{i=1}^{n} f(t_i|\theta_1, \theta_2, ..., \theta_k) \quad \prod_{j=1}^{m}[1 - F(t_j|\theta_1, \theta_2, ..., \theta_k)] \tag{C.1}$$

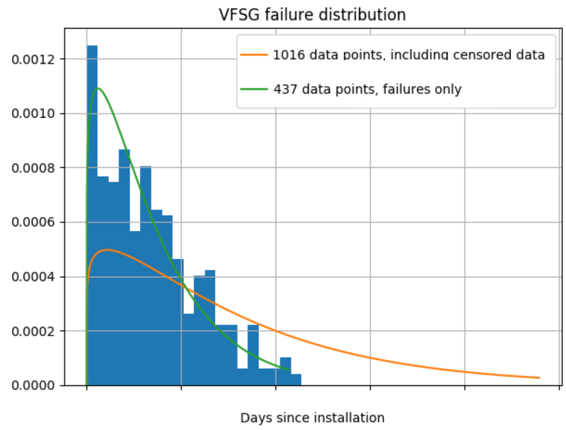
The first set of products take into account the non-censored data points, with f being the probability density function (pdf), t_i each replacement time data in all replacements n and θ_1,θ_2,...,θ_k being the parameters to be estimated. Then, the next set of products take into account the right-censored data by using the survival function. This function outputs the probability that the a component with time t_j has not been replaced yet, given the distribution parameters θ_1,θ_2,...,θ_k. In this case, these parameters would be the shape and scale parameters of the Weibull distribution. For a Weibull distribution this equation takes the form as seen in Eq. C.2.

$$L(\eta, \beta) = \prod_{i=1}^{n}\left[\frac{\beta}{\eta}\left(\frac{t_i}{\eta}\right)^{\beta-1} \exp\left(-\left(\frac{t_i}{\eta}\right)^{\beta}\right)\right] \quad \prod_{j=1}^{m}\left[\exp\left(-\left(\frac{t_i}{\eta}\right)^{\beta}\right)\right] \tag{C.2}$$

With η being the scale parameter, β the shape parameter, and t_i the time to failure for each ttf failure point i of all data points n. To enable easier manipulation of this function, first the logarithmic is taken of the function to obtain the log-likelihood function. To obtain the parameters for which the maximum likelihood is obtained, the partial derivative is then taken for both the shape and scale parameter and equated to 0. To reduce overhead in programming this from scratch, the Python package Lifelines was used. This package uses the adapted maximum likelihood estimation function as described in Eq. C.2 to generate the Weibull parameters given the censored and uncensored data. A comparison of the generated distribution functions with the historic data can be seen in Fig. C.3.



(a) CU subsystem



(b) EG subsystem

Figure C.3: Weibull distributions and a histogram of historic TTF data for the EG and CU subsystem

C.4 Model validation

In order to validate this model, a simulation was run considering the same boundary conditions as the historic TTF data. This means that the start of simulation would correspond to the first in-service date of the operator investigated, and the simulation end time being the moment at which the TTF data was gathered. Then the simulation model would simulate the operators fleet by considering the different in-service dates for its aircraft. At the in-service date of each aircraft or new component installation, the distribution was sampled for a TTF value. After this time, the component was replaced. Once the simulation ended, a comparison was made to the number of replacements that actually happened in this time frame. This way the model accuracy could be assessed and the model could be validated. To account for the stochastic nature of this data, this simulation is run for 1000 rounds, after which the number of failures are averaged. The results are displayed in Table C.2

Table C.2: Normalised replacement validation results of distributions for the CU and the EG subsystems

	CU replacements	EG replacements
Historic data	1.00	1.00
Simulation with only uncensored data	1.61	2.56
Simulation taking into account right-censoring	0.90	1.06

It can be indeed seen that accounting for the right-censored data is highly necessary as the number of replacements for both components not considering right-censored data is far from close to the validation data. The algorithm used in creating this right-censored data seem to be effective given the reduction in error to about 6% to 10%. Especially considering the low total number of components replaced in this time frame, and therefore low absolute error in number of components replaced, these distributions can be considered validated, and usable for the CBM model.

Appendix D

Unscheduled maintenance policy and planning algorithm

After either a component failure has occurred, or the prognostic system has forecasted a future failure, a decision should be made if and when this component will be replaced. Due to the consideration of a fleet of aircraft possibly simulating various subsystems containing different MEL thresholds, this is not necessarily a straightforward decision to be made. Furthermore, operators often have different policy regarding replacing components. While some operators would attempt to replace a failed component as soon as possible, other operators would rather replace components near the end of the MEL deadline in order to potentially reduce costs. In section D.1 the maintenance policy for the unscheduled maintenance model is defined, while in section D.2 this policy is encapsulated in a mathematical model that is used in the simulation.

D.1 Policy algorithm

The policy used in the simulation is mainly based on keeping repair costs low and avoiding cancellations as much as possible. In reality however, the policy often also considers combining the replacement action with other due maintenance in order to reduce downtime and as a result also reduce opportunity costs. When prognostics is available it is expected that this effect can even be enlarged, as component replacement decisions can be made much earlier. It should be noted however, that with earlier removals generally more replacements are required in an aircraft's lifecycle. With the availability of an aircraft's full maintenance schedule and accurate data on reductions in opportunity costs and downtime as a result of combining maintenance, an optimisation algorithm could be developed that strives for lowest total maintenance and opportunity costs. However due to either the data not available and complex nature of this data, together with the time limitations of this study, it was chosen not to do this. Still this might prove to be an interesting subject for further research, given reasonably accurate data.

The first priority of the algorithm used in this model is to prevent an AOG situation leading to unscheduled maintenance. An AOG situation is modeled as a situation for which either no maintenance opportunity is available before the expiry of the current MEL condition or for which the MEL is expired or simply too much components have failed leading to an immediate AOG situation. The next priority is then to plan a maintenance opportunity for components as soon as optimally possible depending on their MEL deadline. However in the case of a failed component without MEL deadline, a nonconsequential failure, it would not be useful to replace this component as it is not required, and replacing the component only causes downtime and cost. This is of course with the assumption that a non-operating component would not negatively impact the operations, which can often be not the case. In the case of prognostics this changes, as the benefit of replacing the failing component early might reduce the repair costs as it is more likely that only a minor repair is required. Still, in the case of nonconsequential failures it is decided that these components will be replaced together with the next occurring replacement resulting from another consequential failure. This way no extra opportunity is required and the opportunity costs can be limited. A overview of the actions for different situations are displayed in Table D.1, while an overview of the events taking place is portrayed in Fig. D.1.

Table D.1: Replacement policy for different component situations

(Expected) Situation	Actual Failure	Expected Failure
AOG	Unscheduled Maintenance	Schedule opportunity
MEL deadline	Schedule opportunity	Schedule opportunity
Nonconsequential failure	Defer and schedule together once another higher priority replacement is required	Schedule opportunity

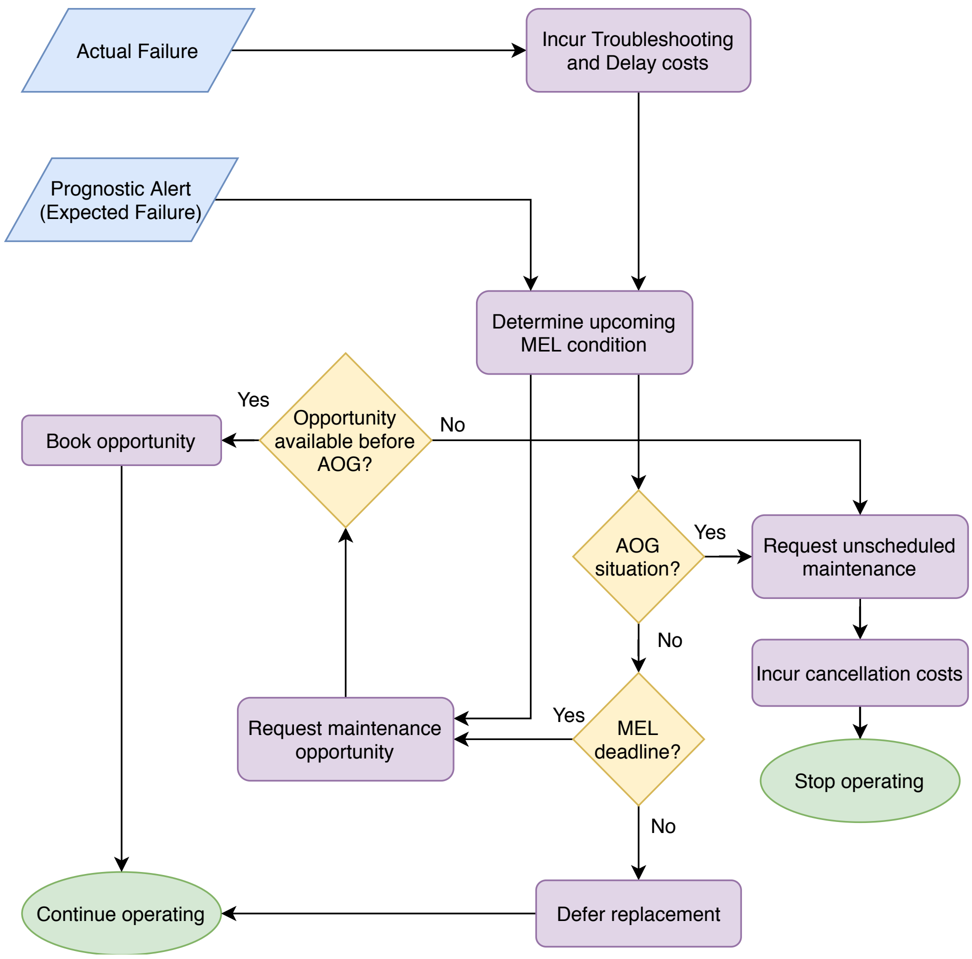


Figure D.1: Flowchart of actions taken after component failure or prognostic alert

D.2 Planning model

With this model in mind, a mixed integer linear programming (MILP) planning model was established that optimises maintenance slot allocations since multiple components coming from various aircraft are considered. The model takes into account the following aspects:

- **(Expected) MEL expiry date**: it is important to replace a component before MEL expiry as a resulting AOG situation corresponds with high cancellation and opportunity costs. In case of a prognostic alert, this would be the MEL deadline added to the estimated failure date, e.g. estimated RUL.
- **Capacity**: Each maintenance opportunity has a limit in hours available. Depending on the component, a certain number of hours are required for every replacement.
- **Concurrency**: It is expected that when multiple components are replaced simultaneously less overall time is needed. Therefore a fixed number of hours per aircraft is added for every maintenance occurrence the aircraft requires.
- **Priority**: Using the priority, an extra incentive can be placed in either replacing a component earlier or later than other components. It can also be used to prevent the aircraft from choosing a maintenance opportunity during which only a nonconsequentially failed component is replaced.
- **Ordering costs**: In order to swap the component, a working replacing component is needed which should be ordered from the component pool. Different options in shipping times with corresponding ordering costs exists. A specific AOG order option is available such that the component often arrive within 24-48 hours. In order to keep these costs low, it is likely that opportunities are selected for which the components can be ordered regularly.
- **Reassignment**: Despite not being an explicit aspect of the MILP model, it should still be noted that the overall planning model is able to reassign aircraft utilising specific maintenance slots as new failures emerge. E.g. in the case of a sudden failure resulting in the aircraft requiring maintenance within 10 days, the aircraft can utilise any upcoming maintenance slots given that the currently scheduled maintenance is not of a higher priority. A new opportunity is found for the currently scheduled maintenance, and this cascades until all maintenance actions are assigned an opportunity.

The MILP model used is represented by the following equations, starting with the objective equation D.1. The constraints are displayed in Eq. D.2 - D.6

$$
\begin{aligned}
min \sum_{a\in A}\sum_{s\in S(a)}\sum_{c\in C(s)}\sum_{k\in K}\left(c_a^{opp}\cdot d_s + p_{a,s,c}\cdot(t_k - t_{now})\right)x_{a,s,c}^k + \sum_{a\in A}\sum_{k\in K}\left(c_a^{opp}\cdot d_a^{fixed}\right)y_a^k + \\
\sum_{a\in A}\sum_{s\in S(a)}\sum_{c\in C(s)}\left[\left(c_a^{opp}\cdot(d_s + d_a^{fixed}) + c_a^{cncl}\right)x_{a,s,c}^{unsch} + \left(c_a^{opp}\cdot d_s + t_{max}\right)\cdot x_{a,s,c}^{defer} + c_s^{aog}\cdot z_{a,s,c}^{aog}\right]
\end{aligned}
\tag{D.1}
$$

$$
\sum_{k\in K} r_{a,s,c}^k \cdot x_{a,s,c}^k + s_{a,s,c}\cdot x_{a,s,c}^{unsch} + (1 - s_{a,s,c})x_{a,s,c}^{defer} = 1 \quad a\in A, s\in S(a), c\in C(s) \tag{D.2}
$$

$$
\sum_{k\in K} t^k \cdot x_{a,s,c}^k + M\cdot x_{a,s,c}^{defer} + M\cdot z_{a,s,c}^{aog} \geq t_{now} + t_{lead}^{a,s,c} \quad a\in A, s\in S(a), c\in C(s) \tag{D.3}
$$

$$
\sum_{s\in S(a)}\sum_{c\in C(s)} x_{a,s,c}^k - M\cdot y_{a,k} \leq 0 \quad a\in A, k\in K \tag{D.4}
$$

$$
\sum_{s\in S(a)}\sum_{c\in C(s)} p_{a,s,c}\cdot x_{a,s,c}^k - M\cdot y_{a,k} \geq 1 - M \quad a\in A, k\in K \tag{D.5}
$$

$$
\sum_{a\in A}\sum_{s\in S(a)}\sum_{c\in C(s)} d_s\cdot x_{a,s,c}^k + \sum_{a\in A} d_a^{fixed}\cdot y_{a,k} \leq a_k \quad k\in K \tag{D.6}
$$

Decision variables:

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

Coefficients:

$p_{a,s,c}$	priority of replacing component **c** of subsystem **s** of aircraft **a**
t_k	time of opportunity k
t_{now}	time when the model is run
t_{max}	Difference between time of latest opportunity and current time
d_s	hours required for replacement of component of subsystem **s**
d^{fixed}_a	additional fixed hours required for using a maintenance opportunity by aircraft **a**
a_k	hours available at opportunity **k**
c^{opp}_a	hourly opportunity costs of aircraft **a**
c^{cncl}_a	fixed cancellation costs of aircraft **a**
c^{aog}_s	Additional costs for AOG ordering a component of subsystem **s**
$r^k_{a,s,c}$	1 when opportunity k is available for replacement of component **c** of subsystem **s** of aircraft **a** considering MEL expiry due to (expected) failure of this component, else 0
$s_{a,s,c}$	1 when component **c** of subsystem **s** of aircraft **a** can not be deferred else 0

Sets:

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

The optimisation function attempts to minimise costs by assigning the aircraft to a fixed opportunity k for which components can be replaced. In case the (expected) failure is unconsequential, hence there is no MEL deadline, the coefficient $s^k_{a,s,c}$ is set to 0, otherwise it is 1. This coefficient leads to a switching effect in constraint D.2, and decides when in case there is no assignment to a fixed opportunity $x^k_{a,s,c}$, whether the replacement has to occur unscheduled ($x^{unsch}_{a,s,c}$) or can be deferred ($x^{defer}_{a,s,c}$). This constraint also takes into account the MEL expiry with the $r^k_{a,s,c}$ coefficient such that no opportunity can be selected after MEL expiry. Then in constraint D.3 for every replacement it is defined whether an AOG order is required. Constraint D.4 then helps in defining whether an aircraft makes use of an opportunity. This is then used in determining the fixed opportunity costs. As described in the policy, nonconsequentially failing components should only be replaced together with another replacement with a higher priority. Constraint D.5 ensures this is the case, as nonconsequential failures have priority 0, while other failures have higher priorities depending on how short the MEL deadline is. Finally, constraint D.6 ensurs that the capacity of each opportunity is not exceeded.

Appendix E

Unscheduled maintenance model parameters

For the unscheduled maintenance model, several input parameters were used. Mostly they were modeled after the MRO and operator data that was used in this research. Due to intellectual property reasons, absolute cost values are not displayed. Where possible relative values are used. Table E.1 displays global model parameters and replacement schedule modeling values that were used in all scenarios

Table E.1: Global replacement scheduling parameters

Total simulation run time	2555 days
Runs	100
Fixed additional maintenance hours	2 hours
Opportunities per week	1 per component
Hours per opportunity	8 hours

In table E.2 the unscheduled maintenance input values for both the CU and EG subsystem are displayed.

Table E.2: Unscheduled maintenance model parameter per subsystem

Parameter	**EG**	**CU**
Components installed per aircraft	4 components	4 components
MEL deadline 1 failure	3 days	-
MEL deadline 2 failures	AOG	10 days
MEL deadline 3 failures	AOG	AOG
MEL deadline 4 failures	AOG	AOG
Supply chain lead time	4 days	4 days
Supply chain lead time AOG order	1 day	1 day
Minor repair cost	26.6% of major costs	33.3% of major costs
Replacement duration	6 hours	2 hours
Repair time major repair	40 days	30 days
Repair time minor repair	14 days	14 days
Prognostic Horizon	20 days	30 days
Slope parameter s	0.25	0.1

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