Maintenance scheduling optimization based on prognostics and limited spare parts

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by

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This thesis is confidential and cannot be made public until July 22, 2030.

Preface

This report represents my graduation research for the master Aerospace Engineering in Air Traffic and Operations at Delft University of Technology. I have had the opportunity to carry out this project at KLM Engineering & Maintenance. This experience would not have been possible without the help of my supervisor S. Stokkers and the whole Predictive Maintenance team. Thank you for being so welcoming from the very beginning and for continuously challenge me to improve my research. I really enjoyed working with you and I learned a lot of valuable things for my future career.

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This thesis is also the final milestone of these two years in the Netherlands. Thank you to my mum for giving me this opportunity and to the rest of my family and my friends for the support. I had a wonderful time and I am very proud of the result.

M. Carrillo Galera
Delft, July 2020

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Nomenclature

List of Abbreviations

ACARS	Aircraft Communication Addressing and Reporting System
AFI	Air France Industries
AHM	Airplane Health Management
ALNS	Adaptive Large Neighborhood Search
AOG	Aircraft On Ground
APU	Auxiliary Power Unit
ATA	Air Transport Association
ATS	Air Traffic Services
CAA	Civil Aviation Authority
CBM	Condition-Based Maintenance
CDF	Cumulative Density Function
CU	Cooling Unit
CWLU	Crew Wireless LAN Unit
DMC	Direct Maintenance Costs
E&M	Engineering and Maintenance
EASA	European Aviation Safety Agency
FAA	Federal Aviation Administration
FDE	Flight Deck Effect
FMS	Flight Management System
GA	Genetic Algorithm
HPP	Homogeneous Poisson Process
HUMS	Health and Usage Monitoring System
IMC	Indirect Maintenance Costs
KLM	Royal Dutch Airlines
KPI	Key Performance Indicator
KS	Kolmogorov-Smirnov
LNS	Large Neighborhood Search
LRM	Line Replaceable Module
MCC	Maintenance Control Centre
MDP	Markov Decision Process
MEL	Minimum Equipment List

MLE Maximum Likelihood Estimation

MMEL Master Minimum Equipment List

MPD Maintenance Planning Document

MRB Maintenance Review Board

MRO Maintenance, Repair and Overhaul

MSG-3 Maintenance Steering Group Part 3

MSG Maintenance Steering Group

MTTR Mean Time To Repair

NFF Not Fault Found

NPV Negative Predictive Value

OAM Original Aircraft Manufacturer

OLS Ordinary Least-Squares

PDF Probability Density Function

PdM Predictive Maintenance

PHM Prognostics and Health Management

PH Prognostic Horizon

PPV Positive Predictive Value

QAR Quick Access Recorder

RUL Remaining Useful Life

SLA Service Level Agreement

TAT Turn-Around Time

TO Technish Onderhoud

TTF Time To Failure

TTR Time To Repair

TWLU Terminal Wireless LAN Unit

List of Symbols

Γ^a Degradation indicator alert threshold

Γ^f Degradation indicator failure threshold

$\Gamma_{c_{i,n}}(t)$ Degradation indicator at time t of component $c_{i,n}$

C^d Flight schedule disruption cost due to aircraft failure

C^M Cost of major component repair

C^m Cost of component repair

C^m Cost of minor component repair

C^g Cost of using a generic slot

C^{Ld} Leasing daily cost per component

C^{Lf} Leasing fixed cost per component

C^{MEL} Cost of MEL violation per aircraft per day

C^{nc}	Non-critical failure cost factor
$C^{slot}(t^u_{i,j})$	Cost of using slot $t^u_{i,j}$
$c_{i,n}$	Component n of aircraft i
$D_{t^u_{i,j}}$	Duration of slot $t^u_{i,j}$ (hours)
$F_{RUL}(t - t^a_{c_{i,n}})$	CDF of the RUL of component $c_{i,n}$ after a predictive alert has been triggered
$H(c_{i,n}, t)$	Health state of component $c_{i,n}$ a time t
I	Number of aircraft in the fleet
k	Minimum number of operable components for aircraft dispatch
$M(t^u_{i,j})$	Maximum capacity of slot $t^u_{i,j}$
N	Number of components per aircraft
$N_{spares}(t)$	Number of available spare parts at time t
$P^f_i(t)$	Failure probability of aircraft i at time t
$P^f_{c_{i,n}}(t)$	Probability that component $c_{i,n}$ has failed at time t
PH	Prognostic Horizon (days)
R	Required time to perform a component replacement (hours)
RI^{MEL}	MEL Replacement Interval
s	Prognostic sensitivity
$t^a_{c_{i,n}}$	Time at which a predictive alert is triggered in component $c_{i,n}$
$t^u_{i,j}$	Starting time of slot j of aircraft i of type u
t^{st}	Stock-out time
t_0	Current time
$t^{f,n}_i$	Time of n-th component failure in aircraft i
t^{MEL}_i	MEL deadline of aircraft i
TAT	Turn-Around Time (days)
TAT_a	Turn-Around Time when the component is in alerted state (days)
TAT_f	Turn-Around Time when the component is in failed state (days)

1 Introduction

1.1. Motivation

The competition in the airline industry has tremendously increased throughout the last decades. According to the IATA Vision 2050 Report [5], over 1300 airlines were created in the past 40 years, mainly due to the more extensive liberalization of market access. Most of these new entrants were low-cost carriers, which has intensified even more the aim of airlines to find ways to stay competitive. Efforts have mainly focused on ticket pricing, network optimization, and new financial practices, such as aircraft leasing. Besides, the latest aircraft models are using more efficient engines and materials to reduce fuel consumption. However, these practices are predicted to result only in small enhancements in cost reduction [37].

According to the IATA 2016 Maintenance Cost Report [21], the Maintenance, Repair, and Overhaul (MRO) worldwide costs in 2016 were 67.6B$, representing around 9.5% of airlines' operating costs. Moreover, new generations of aircraft are increasingly being equipped with sensors that provide data about the components' health state. The high costs incurred in MRO activities and the development of techniques for data processing and health monitoring are generating a great interest in the development of maintenance schedules that incorporate component diagnosis and prognostics information. In this way, the traditional corrective and preventive maintenance policies are being replaced by the novel predictive maintenance (PdM).

PdM is enabled by prognostics. As a whole, the aim of prognostics is to predict the components' failure times. Therefore, it can enable a more effective maintenance planning by reducing unscheduled maintenance events. In addition, it can also allow to predict and effectively distribute the demand for spare parts, and to reduce the repair costs due to lower component degradation levels.

Maintenance scheduling with prognostics inputs has been already addressed in multiple studies. However, the majority of them fail to properly describe the component degradation behavior due to the lack of actual aircraft sensor data in their models. Besides, the great majority of existing literature takes assumptions that hugely differ from a real airline operation, such as infinite maintenance capacity, or infinite availability of spare parts.

1.2. Research Scope

This research proposes a framework to optimize maintenance schedules of a fleet of aircraft based on prognostic information. The considered prognostics are the predictions of the PdM tool developed by the Predictive Maintenance team in KLM Engineering & Maintenance (E&M), *Prognos*. It is therefore out of the scope of this research to develop a prognostic model for aircraft components.

The considered component and aircraft is the Cooling Unit (CU) of the Boeing 787. Each aircraft is equipped with 4 CUs. The CU was selected for the case study as the predictive algorithms integrated into *Prognos* have proven to be successful in predicting failures with promising accuracy and precision values. Indeed, the B-787 aircraft is the first 'more electric aircraft' from Boeing, which makes it a perfect candidate to perform prognostics due to the huge quantity of sensor data collected during flights. Moreover, this aircraft model is of great interest from a cost savings perspective as it is operated in long haul routes with high demand, meaning that a decrease in technical delays can be very significant.

This research deals with repairable components. Repair by replacement is the only policy considered in this study, meaning that the faulty components are replaced with available spare parts and the faulty components are sent to the repair shop to be fixed. The joint MRO service Air France Industries (AFI) and KLM E&M has multiple warehouses and repair shops distributed all over the world, providing spare parts for over 200 airlines. However, for the sake of simplicity, it is considered that there is a unique logistic warehouse and repair shop located in Amsterdam-Schiphol.

Finally, maintenance actions can be only performed in a set of opportunities given by the maintenance slots. Historic aircraft maintenance slots data are considered as an input for the maintenance optimization model, meaning that it is out of the scope to optimize the maintenance opportunities themselves.

1.3. Research Objective and Questions

The objective of this research is to generate optimal maintenance schedules that take into account prognostics about the condition of aircraft components as well as the availability of slots and spare parts by developing a maintenance scheduling optimization model for aircraft components. It is also crucial to assure that the developed algorithm is operational for KLM E&M.

It is necessary to achieve some sub-goals to reach the main research objective:

- Determine how to incorporate component prognostics as an input in the maintenance scheduling model.
- Translate aircraft maintenance slots into maintenance opportunities that can be used as input for the scheduling model.
- Definition of available spare parts and translation into a scheduling input.
- Development of an optimization model for maintenance scheduling.
- Perform a case study in KLM E&M to validate and verify the optimization model as well as to assure it is operational.

Based on the research goal, the main research question can be formulated as follows:

How to optimize maintenance schedules of a fleet of single-aircraft type integrating component prognostics and the availability of maintenance slots and spare parts, in order to reduce the airline operating costs?

The main research question can be split into sub-questions composed as follows:

1. How to model the prognostics information about aircraft components?
2. What kind of uncertainties do the prognostics have?
3. How can prognostics be modeled as input for maintenance scheduling?
4. How can resources availability be incorporated in maintenance scheduling?
   (a) How can maintenance slots availability be modeled?
   (b) How can spare parts availability be modeled?
5. How can the optimization model be generated?
   (a) How to define the objective function such that the operating costs are minimized (costs of repair, cost of stock-out, cost of MEL violation, cost of flight schedule disruption, etc.)?
   (b) How to solve the optimization problem?
6. How can the optimization model be verified and validated by a case study in KLM E&M?
7. What conclusions, such as potential advantages and influencing factors, can be drawn from the model output?

1.4. Report Structure

The structure of this report is as follows. Part I presents the scientific paper, in which the research questions presented above are answered. Part II elaborates in the literature study carried out in preparation for the research. Chapter 2 briefly elaborates on the evolution of maintenance in the airline industry to understand how this study fits on it. Chapter 3 presents an introduction to prognostics together with a review of its main algorithms and potential benefits. Chapter 4 elaborates on the existing literature in maintenance scheduling from a modeling perspective. It includes how prognostics and availability of resources have been modeled, component criticality issues that should be considered, the objective functions used, and the main solution approaches. Chapter 5 presents the current practices in KLM E&M in terms of what kind of prognostics are currently available and how they are used in maintenance scheduling. Chapter 6 summarizes the research gaps that were previously identified and presents the novelty and relevance of this study from both an academic perspective, and from

KLM E&M perspective. Finally, Part III further elaborates in the thesis work. Appendix A presents the Validation and Verification. Appendix B provides an extension of the sensitivity analysis introduced at II. Appendix C provides some guidelines on how the proposed model should be implemented in KLM E&M and it proposes additional suggestions for improvement of the current practices within the company. Finally, Appendix D elaborates on the benefits of incorporating prognostics in maintenance scheduling from the perspective of different departments within KLM E&M and it provides some suggestions for future work.

I

Master of Science Thesis Paper

Multi-component aircraft maintenance scheduling with component Remaining-Useful-Life prognostics and limited spares

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Abstract

This paper proposes a model for maintenance scheduling of a fleet of aircraft based on component Remaining-Useful-Life prognostics and a limited stock of available spares. A discrete-time, rolling horizon approach is proposed, resulting in a sequence of scheduling time windows. For each time window, the goal is to find an optimal maintenance schedule, while taking into account component prognostics and available spares. Moreover, the scheduling model considers three stages in decreasing order of maintenance priority, from critical aircraft leading to grounded condition, to predictive alerts, to non-critical failures. An Adaptive Large Neighborhood Search algorithm is used to solve this aircraft maintenance problem. The framework is illustrated in a case study regarding the Cooling Unit (CU) in a fleet of aircraft. The results show that a cost-efficient maintenance schedule for a large fleet of aircraft is generated with an outstanding computational performance. Moreover, we show that in the long-run the aircraft operating costs are significantly reduced, even when considering limited spares.

Keywords: aircraft maintenance scheduling, prognostics, adaptive large neighborhood search, spare parts

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1. Introduction

The competition in the airline industry has rapidly increased during the last decades, especially with the entrance in the market of low-cost carriers. The high costs incurred in Maintenance, Repair and Overhaul (MRO) activities are generating a great interest in the improvement of maintenance operations as a way to stay competitive in the market.

In recent years, the new generations of aircraft are increasingly being equipped with sensors that monitor the component's health condition. At the same time, new techniques for data storage and processing are being developed to effectively analyze and make use of this data. This stimulates the shift towards data-driven, predictive aircraft maintenance.

Data-driven, predictive aircraft maintenance is enabled by prognostics. Prognostics aims to predict the components' failure time. Therefore, prognostics can enhance maintenance planning by reducing unexpected failures, as well as enable a more effective use of spare components [1, 2, 3]. It can also reduce the component repair costs due to lower degradation levels [4]. However, there is a lack of knowledge of how to incorporate a prognostic model based on aircraft sensor data in the creation of maintenance schedules, considering also the availability of the required resources to perform maintenance.

This study address this research gap by providing a novel approach to generate optimal maintenance schedules for aircraft components that takes into account prognostic information and the availability of repairable spare parts and maintenance slots. Maintenance scheduling problems of such multi-component systems are known to be NP-complete, especially those considering operation limitations, such as spare parts availability [5, 6]. We propose a discrete-time, rolling horizon approach, resulting in a sequence of multiple time windows. For each time window, we define a maintenance scheduling model divided into three stages in decreasing order of maintenance priority. An exact solution method for this problem should consider all possible combinations of assignments of aircraft to slots and component replacements, which would take too much computational time. Thus, we propose a heuristic solution approach named as Adaptive Large Neighborhood Search, meaning that an optimal solution is not guaranteed. The framework is illustrated in a case study regarding the Cooling Unit (CU) in a fleet comprising 13 wide-body aircraft.

The remainder of the paper is structured as follows. A brief literature review is given in the next section. Section 3 elucidates the maintenance scheduling problem. Section 4 provides the mathematical formulation of the optimization model. Section 5 elaborates on the solution methodology. We illustrate our maintenance scheduling model for a fleet of $I = 13$ aircraft in Section 6. Section 7 presents a long-run model performance analysis using Monte Carlo simulation. Finally, section 8 provides the conclusions and recommendations for future work.

2. Literature review

Over the past years, several studies that consider prognostics in maintenance planning optimization have been published. *Prognostics* has been modeled in different ways. State transition probability prognostics defines the probability of transition from "healthy" to "degraded" or "failed" state based on the estimated component degradation [7, 8]. Classification or binary prognostics evaluates whether a component is going to fail in the upcoming days with a given sensitivity and precision [9]. Remaining Useful Life (RUL) prognostics estimates the expected failure time of the components. The RUL prediction uncertainty has been included in the optimization framework with three different approaches. The first one is to include the risk of failure in the objective function [10, 8]. The second one is to optimize the maintenance decision under an acceptable risk by restricting the maximum system failure probability [11, 12, 13]. The third method is to build a safety interval around the RUL estimation. In [14], the RUL is diminished by a safety factor to account for the time needed to trigger maintenance and for the prognostic uncertainties. In [15], the 95% Confidence Interval of the RUL prediction is used to define the maintenance execution window for each component.

However, the great majority of the studies dealing with prognostics in maintenance optimization lack a deep operational context by assuming immediate repairs or infinite inventory stock. The number of studies dealing with *repairable components* is even more scarce. In [16], a framework to optimize the maintenance times of repairable components with RUL prognostics is proposed. First, an initial schedule with the predicted RUL is built. Next, a second optimization is performed to prevent the stock-out of spares by avoiding that the overlaps in the expected repair times exceed the stock level.

Regarding the *objective functions*, most of the literature has focused on reducing operational costs [17, 18, 7, 10, 7, 14, 9, 19, 20], maximizing revenue [4], and maximizing aircraft availability [16]. A few studies have also adopted a two-fold objective, such as minimum cost and maximum availability [12, 11, 21].

In terms of *solution approaches*, the main trend is to use meta-heuristic algorithms to solve multi-aircraft maintenance optimization problems. A Genetic Algorithm (GA) is proposed in [22] to optimize the maintenance schedules of the key Line Replaceable Module (LRM) based on the RUL distribution. The authors in [12] also use GA to optimize the maintenance times of aircraft structures based on real-time crack growth data. In recent years, Large Neighborhood Search (LNS) has become a popular method for solving scheduling problems [23]. In [16], a LNS algorithm is proposed with a neighborhood definition through *swapping* the execution times of two different maintenance tasks or *shifting* all maintenance tasks to every available maintenance time. The authors in [24] introduced an improved LNS algorithm named as Adaptive Large Neighborhood Search (ALNS) for the pickup and delivery problem. Differently to traditional LNS which defines a unique sub-heuristic, ALNS is composed of several competing sub-heuristics that are used with a frequency based on their historic performance. Consequently, ALNS has improved robustness as it can adapt to different solution characteristics.

3. Problem description

Taking into account Remaining-Useful-Life prognostics of aircraft components, information about slots available to perform maintenance and limited spares, we are interested in finding an optimal assignment of aircraft to maintenance slots, and in particular, which components of these aircraft should be replaced in these slots (see Figure 1).

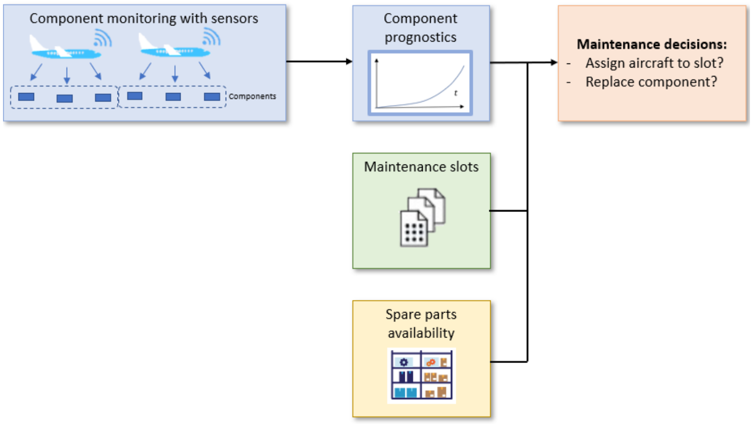


Figure 1: Maintenance of repairable components with RUL prognostics and spares - Problem description.

3.1. Multi-component aircraft system description

We consider a homogeneous fleet of I aircraft. Each aircraft has N identical, repairable components. Each component is assumed to fail independently of the other components. Upon failure, a component is replaced with a brand-new one, while the failed component is sent for repair. The Minimum Equipment List (MEL) [25] requires that at least k components out of N, $k \leq N$, are functional so that the aircraft can be operated. As soon as $(N-k+1)$ components fail, the aircraft can no longer be operated. Following MEL, a replacement interval, RI^{MEL} is specified, i.e., as soon as $(N-k)$ component failures occur, the aircraft can still be dispatched for a maximum of RI^{MEL} time interval. If none of the $(N-k)$ components are repaired within this RI^{MEL} period, then the aircraft is considered inoperable.

Let $t_i^{f,n}$ denote the time when the n^{th} component failure occurs in aircraft i, $i \leq I$, $n \leq N$. Then, the MEL deadline of aircraft i is defined as:

$$t_i^{MEL} = \min(t_i^{f,(N-k)} + RI^{MEL}, t_i^{f,(N-k+1)}) \tag{1}$$

If no maintenance action is taken before the MEL deadline, the aircraft is assumed to be in Aircraft-On-Ground (AOG) condition. The cost of MEL violation per day per aircraft is denoted as C^{MEL}.

3.2. Component's Remaining-Useful-Life (RUL) prognostics

Let $c_{i,n}$ denote the nth component of aircraft $i \leq I$, $n \leq N$. We assume that each component $c_{i,n}$ is equipped with sensors that measure the component's degradation level. Let $\Gamma_{c_{i,n}}(t)$ denote the degradation level at time t of component $c_{i,n}$. Based on the degradation level, a component is said to be: i) healthy, ii) alerted (when an alert has been triggered, notifying that a failure is expected in the near future), or iii) failed. Formally, we define the health state of component $c_{i,n}$ at time t, denoted by $H(c_{i,n}, t)$, as:

$$H(c_{i,n}, t) = \begin{cases} 0, \text{if the condition of component } c_{i,n} \text{ is healthy at time t,} \\ 1, \text{if the condition of component } c_{i,n} \text{ is alerted at time t,} \\ 2, \text{if the condition of component } c_{i,n} \text{ is failed at time t.} \end{cases} \tag{2}$$

Initially, the component is in a healthy state $H(c_{i,n}, t) = 0$ for $t = 0$. The component remains healthy until an alert is triggered, i.e., $H(c_{i,n}, t) = 0$ for $0 < t < t^a_{c_{i,n}}$, where

$$t^a_{c_{i,n}} = \inf\{t : \Gamma_{c_{i,n}}(t) \geq \Gamma^a\}, \tag{3}$$

with Γ^a an alert threshold. As soon as Γ^a is exceeded, an alert it triggered to notify that a failure is most likely to occur within a prognostic horizon of PH days.

Given that an alert is triggered, $H(c_{i,n}, t) = 1$ for $t \geq t^a_{c_{i,n}}$. Also, as soon as the alert is triggered, we assume that the evolution of the degradation of component $c_{i,n}$ at time $t > t^a_{c_{i,n}}$ follows:

$$\Gamma_{c_{i,n}}(t) = \theta e^{\lambda t}, \ \ \lambda, \theta > 0. \tag{4}$$

We assume that the component fails at some random time due to the fact that it reaches a degradation level Γ^f. Formally,

$$\Gamma_{c_{i,n}}(t) = \begin{cases} 0, & \text{if } H(c_{i,n}, t) = 0, \\ \Gamma^f, & \text{if } H(c_{i,n}, t) = 2, \\ \theta \exp \lambda t, & \text{if } H(c_{i,n}, t) = 1, \end{cases} \tag{5}$$

where Γ^f denotes the maximum degradation level for failure. A component is assumed to fail when its degradation indicator reaches Γ^f, but it can also fail before that time.

Then the cdf of RUL for component $c_{i,n}$, given that a predictive alert has been triggered for a prognostic horizon of PH days, is:

$$F_{RUL}(t - t^a_{c_{i,n}}) = P(RUL \leq (t - t^a_{c_{i,n}})), t > t^a_{c_{i,n}}. \tag{6}$$

Figure 2 shows an example of the cdf of the RUL after a predictive alert has been triggered for $PH =$ [redacted] days.

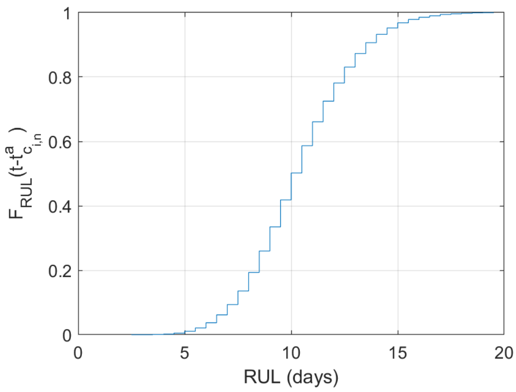


Figure 2: Example of a cdf for RUL, given an alert has been triggered, PH = [redacted] days.

From eq. (2) and (6), the probability that a component $c_{i,n}$ has already failed by time t is defined as:

$$P^f_{c_{i,n}}(t) = \begin{cases} 0, & \forall\, t \text{ such that } H(c_{i,n}, t) = 0, \\ F_{RUL}(t - t^a_{c_{i,n}}), & \forall\, t \text{ such that } H(c_{i,n}, t) = 1, \\ 1, & \forall\, t \text{ such that } H(c_{i,n}, t) = 2. \end{cases} \tag{7}$$

Since there are N components per aircraft and at least k need to be operational for dispatch, let $P^f_i(t)$ denote the failure probability of aircraft i by time t, i.e., the probability that at least $(N-k+1)$ components of aircraft i have failed at time t. For example, for $N = 4$ and $k = 2$, $P^f_i(t)$ is defined as:

$$P^f_i(t) = \sum_{m=1}^{4} (1 - P^f_{c_{i,m}}(t)) \cdot \prod_{\substack{n = 1 \\ n \neq m}}^{4} P^f_{c_{i,n}}(t) + \prod_{n=1}^{4} P^f_{c_{i,n}}(t) \tag{8}$$

Let C^d denote the cost of a sudden aircraft failure which leads to a flight schedule disruption.

Degradation-related repair costs

The component repair costs are assumed to be linearly proportional to the degradation level $\Gamma_{c_{i,n}}(t)$. Defining $C^M > 0$ as the cost of a major component repair and $C^m > 0$ as the cost of a minor repair, the cost of repairing component $c_{i,n}$ at time t is defined as:

$$C^r(\Gamma_{c_{i,n}}(t)) = \frac{C^M - C^m}{\Gamma^f} \Gamma_{c_{i,n}}(t) + C^m. \tag{9}$$

For a fully degraded component, $\Gamma_{c_{i,n}}(t) = \Gamma^f$, the repair cost is equal to the cost of major repair.

3.3. Maintenance slots

A maintenance slot is considered to be a time interval during which maintenance can be performed. We consider two types of slots: aircraft-specific slots, and generic maintenance slots. Aircraft-specific slots are slots that are assigned exclusively to a specific aircraft, whereas a generic slot can be assigned to any aircraft.

Maintenance slots are defined by their starting time. Let $t^u_{i,j}$ denote the starting time of slot j of type u for aircraft i, where $u \in \{s, g\}$. Here, $u = s$ denotes a specific slot, while $u = g$ denotes a generic slot. Let $D_{t^u_{i,j}}$ denote the duration of slot $t^u_{i,j}$. Let R denote the required time to perform a component replacement. We assume that the maintenance is performed in series, one aircraft after another. Then, the maximum capacity of slot $t^u_{i,j}$ is defined as:

$$M(t^u_{i,j}) = \begin{cases} 1, & \text{if } u = s \\ \lfloor \frac{D_{t^u_{i,j}}}{R} \rfloor, & \text{if } u = g. \end{cases} \tag{10}$$

In aircraft-specific slots, only one aircraft can be scheduled for maintenance at a time, and only the aircraft to which the slot has been assigned to. Also, we assume that when several components of the same aircraft are scheduled for replacement, the replacements are grouped and performed in parallel. In this way, the aircraft is assigned a single maintenance slot.

Finally, it is also assumed that generic slots have a higher usage price compared to specific slots. The cost of using slot $t^u_{i,j}$ is defined as:

$$C^{slot}(t^u_{i,j}) = \begin{cases} 0, & \text{if } u = s, \\ C^g, & \text{if } u = g, \end{cases} \tag{11}$$

where C^g denotes the cost of using a generic slot.

3.4. Limited spares for repairable components

We consider repairable aircraft components. A repairable is defined as a component that, after removal, undergoes a repair process such that it can be used again, instead of being discarded [26, 27]. Figure 3 illustrates our limited spares for repairable components model. When a component fails, it is removed from the aircraft while a spare, as-good-as-new component, from the warehouse is installed instead. We consider a limited amount of spare components. If no spare component is available in the warehouse to be installed, then a component is leased from an external supplier. The faulty component is sent for repair to a repair shop. Once repaired, the component is sent back to the warehouse, its state is as good-as-new, and it remains available for re-use.

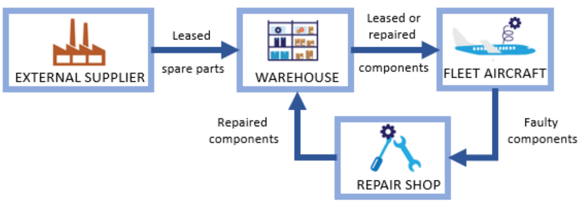


Figure 3: Illustration of the limited spare components model for a fleet of aircraft.

Let TAT denote the time it takes for a faulty component to be removed from the aircraft, repaired to an as-good-as-new state, and be sent to the warehouse. Let $N_{spares}(t)$ denote the number of available spare components at the warehouse at time t.

If the demand for replacements exceeds the number of available spares, then we say that there are component stock-outs. A stock-out occurs when a component is replaced at time t, while there are no spare components in the warehouse at time t, i.e. $N_{spares}(t) = 0$. Equivalently, this occurs when the number of overlapping TATs exceeds the initial number of available spares in the warehouse.

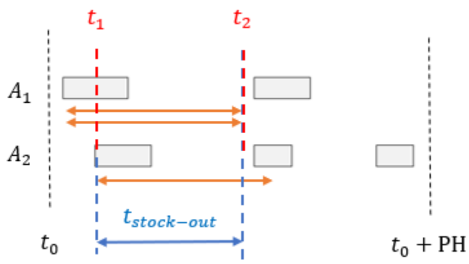


Figure 4: Stock-out illustration, having an initial stock of 2 spares. As components replacements are executed, the stock of available spares changes over time.

Figure 4 illustrates the concept of stock-out. The orange arrows show the TAT of the replaced components in the maintenance slots (grey boxes). Here, we assume that the initial stock of available spares is 2, i.e., $N_{spares}(t) = 2$, $t \in [t_0, t_0 + PH]$. Given that two components are replaced for aircraft 1, the warehouse becomes empty, $N_{spares}(t) = 0$, $t \in [t_1, t_2]$. Thus, the component of aircraft 2 is in stock-out. The time of stock-out (blue arrow) is defined as the time interval when the number of overlapping TATs exceeds the initial number of available spares.

When a stock-out occurs, we assume that an additional component is immediately leased at a fixed cost C^{Lf} plus a daily cost C^{Ld} per day of lease. Any component that becomes available at the warehouse can be used to terminate a leasing, i.e., we do not keep track of the specific components that are leased.

4. Rolling-horizon maintenance scheduling - model formulation

We propose a discrete-time, rolling horizon approach where a sequence of time windows with a duration of PH days is considered. For every time window, we consider as input the set of maintenance slots available, the RUL prognostic for each component at the beginning of the time window, and the availability of spares. We are interested in optimizing the assignment of aircraft to maintenance slots as well as determining which components should be replaced in these slots. Figure 5 shows an example of a sequence of two time windows with $PH=$ [redacted] days, t_0 the starting time of the time window, and $t_0 + PH$ the end time.

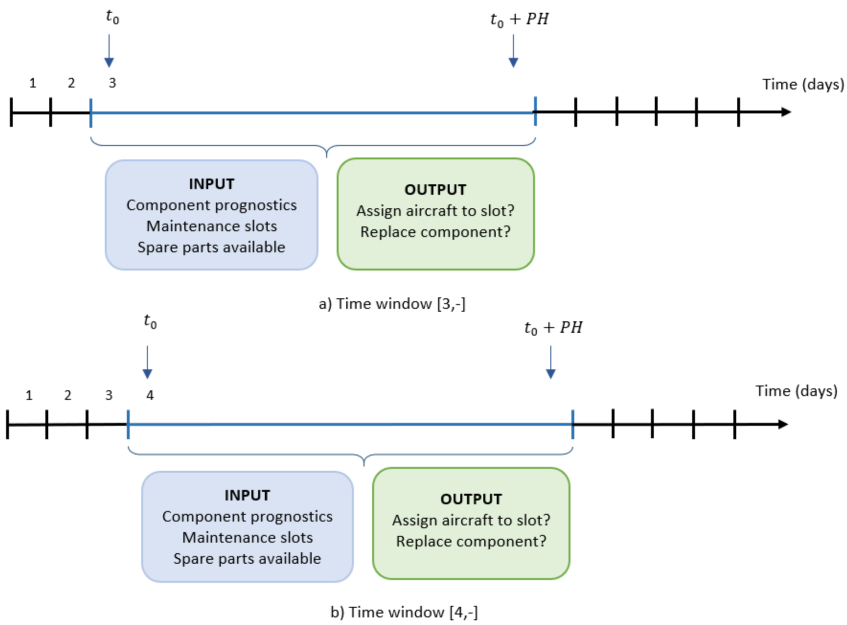


Figure 5: Illustration of the rolling horizon approach, $PH =$ [redacted] days.

We first introduce the following notation.

Let $A = \{i,\ \ i \in \{1, 2, \dots, I\}\}$ denote the set of aircraft with available maintenance slots in the time window $[t_0, t_0 + PH]$. Let $t_i = \{t^u_{i,j},\ j \in \{1, 2, \dots, J_i\},\ u \in \{s, g\}, i \in A\}$ denote the set of starting times of the maintenance slots in the time window $[t_0, t_0 + PH]$, $i \in A$, with J_i the last slot index of aircraft i within the time window. Let $c_i = \{c_{i,n},\ n \in \{1, 2, \dots, N\}, i \in A\}$ denote the set of components of aircraft i.

Decision Variables

We consider the following decision variables:

$$Y_{i,j} = \begin{cases} 1, & \text{if aircraft } i \text{ is scheduled for maintenance at slot } t^u_{i,j} \\ 0, & \text{otherwise.} \end{cases}$$

$$X_{i,j,n} = \begin{cases} 1, & \text{if component } n \text{ of aircraft i is scheduled for replacement at slot } t^u_{i,j} \\ 0, & \text{otherwise.} \end{cases}$$

Auxiliary Variables

We define the following auxiliary variables.

First,

$$Z_{\substack{i,n,t^u_{i,j}+\alpha \\ \alpha=\{0,1,\dots,TAT\}}} = \begin{cases} 1, & \text{if } X_{i,j,n} = 1 \\ 0, & \text{otherwise,} \end{cases}$$

which represent the time period when the component is under repair, from the moment the component is removed from the aircraft until the end of the TAT, i.e., during $[t^u_{i,j}, t^u_{i,j} + TAT]$.

Second,

$$s(t) = \begin{cases} \sum_{i \in A} \sum_{c_{i,n} \in c_i} Z_{i,n,t} - N_{spares}(t), & \text{if } \sum_{i \in A} \sum_{c_{i,n} \in c_i} Z_{i,n,t} > N_{spares}(t) \\ 0, & \text{otherwise,} \end{cases}$$

which represents the amount of components in stock-out at time t. Since a component is leased when there is a stock-out, $s(t)$ also represents the number of leased components at time t.

Third,

$$new^{st}(t) = \begin{cases} s(t) - s(t-1), & \text{if } s(t) > s(t-1) \\ 0, & \text{otherwise,} \end{cases}$$

which represents the number of newly leased components at time t.

Maintenance priority-driven scheduling stages

For each time window, we consider 3 scheduling stages, in the following decreasing order of the maintenance priority. First, we consider critical aircraft for maintenance scheduling. Then, we consider non-critical aircraft that have alerted components. Lastly, we consider non-critical aircraft that have failed components.

Definition 1. *We say that an aircraft $i \in A$ is critical at time t_0 if it has more than $(N-k)$ either failed or alerted components, or it has $(N-k)$ failed components. Formally, an aircraft i is said to be critical if:*

$$\left(\sum_{c_{i,n} \in c_i} 1_{H(c_{i,n}, t_0) > 0} \geq (N - k + 1) \right) \vee \left(\sum_{c_{i,n} \in c_i} 1_{H(c_{i,n}, t_0) = 2} = (N - k) \right) \tag{12}$$

Let C denote the set of aircraft that meet the aircraft criticality condition (12)*, $C \subset A$, as follow: $C = \left\{ i, i \in A \;\middle|\; \left(\sum_{c_{i,n} \in c_i} 1_{H(c_{i,n}, t_0) > 0} \geq (N - k + 1) \right) \vee \left(\sum_{c_{i,n} \in c_i} 1_{H(c_{i,n}, t_0) = 2} = (N - k) \right) \right\}$*

i) 1st stage: Scheduling critical aircraft for maintenance

The first stage aims to schedule critical aircraft for maintenance.

Objective function

We consider the following objective function for the first stage.

minimum cost per aircraft:

$$\begin{aligned} min \sum_{i \in A} \sum_{t^u_{i,j} \in t_i} & \left[Y_{i,j} \cdot C^d \cdot P^f_i(t^u_{i,j}) \right] + \left[Y_{i,j} \cdot C^{MEL} \cdot (t^u_{i,j} - t^{MEL}_i)^+ \right] + \left[Y_{i,j} \cdot C^{slot}(t^u_{i,j}) \right] \\ & - \left[\sum_{c_{i,n} \in c_i} X_{i,j,n} \cdot \left[C^M - \left[\frac{C^M - C^m}{\Gamma^f} \Gamma_{c_{i,n}}(t^u_{i,j}) + C^m \right] \right] \cdot (1 - P^f_{c_{i,n}}(t^u_{i,j})) \right] \end{aligned} \tag{13}$$

minimum cost of fleet:

$$min \sum_{t \in [t_0, t_0 + PH + TAT]} \left[s(t) \cdot C^{Ld} \right] + \left[new^{st}(t) \cdot C^{Lf} \right] \tag{14}$$

The first objective in (13) aims to minimize the costs of individual aircraft. The first term represents the costs related to flight schedule disruption due to aircraft failure. The second term represents the cost of a MEL violation if an aircraft is scheduled in a maintenance slot after its MEL deadline. The third term is the cost of using a maintenance slot. Finally, the last term is the repair cost savings (see negative sign) obtained by using prognostics. The repair cost savings are defined as the difference between a major repair cost and a component repair costs ($C^M - C^r$), where C^r is given by (9). The repair cost savings are applicable if and only if the component is not failed by $t^u_{i,j}$, with a probability of $(1 - P^f_{c_{i,n}}(t^u_{i,j}))$. This means that the later an alerted component is replaced, the closer the repair cost will be to the cost of a major repair due to a higher degradation indicator. In this case, the saved costs will be lower. Besides, the probability that the component has not failed decreases for later replacement times.

The second objective in (14) aims to use available spare components such that the total number of leased components is minimized. The first term represents the leasing costs per day. By summing $s(t)$ over the time interval $t \in [t_0, t_0 + PH + TAT]$, we obtain the total leasing time. The second term represents the initial fixed costs when spare components are newly leased. Summing $new^{st}(t)$ over the time interval $t \in [t_0, t_0 + PH + TAT]$, we obtain the total number of leased spare components.

Before we discuss the constraints, we introduce the auxiliary parameter b_{i,n,t_0} to specify when a component $c_{i,n}$ is considered for replacement at the time window $[t_0, t_0 + PH]$ as follows:

$$b_{i,n,t_0} = \begin{cases} 1: & \text{if } H(c_{i,n}, t_0) > 0 \\ 0: & \text{if } H(c_{i,n}, t_0) = 0. \end{cases} \tag{15}$$

Constraints

$$X_{i,j,n} \leq b_{i,n,t_0} \qquad \forall \quad c_{i,n} \in c_i, \quad t^u_{i,j} \in t_i, \quad i \in A \tag{16}$$

$$M \cdot Y_{i,j} - \sum_{c_{i,n} \in c_i} X_{i,j,n} \geq 0 \qquad \forall \quad t^u_{i,j} \in t_i, \quad i \in A \tag{17}$$

$$\sum_{t^u_{i,j} \in t_i} Y_{i,j} = 1 \qquad \forall \quad i \in C \tag{18}$$

$$\sum_{t^u_{i,j} \in t_i} Y_{i,j} = 0 \qquad \forall \quad i \notin C \tag{19}$$

$$\sum_{c_{i,n} \in c_i} X_{i,j,n} \geq Y_{i,j} \cdot \left(\sum_{c_{i,n} \in c_i} b_{i,n,t_0} - (N - k) \right) \qquad \forall \quad t^u_{i,j} \in t_i, \quad i \in C \tag{20}$$

$$\sum_{c_{i,n} \in c_i} X_{i,j,n} \geq Y_{i,j} \cdot \left(\sum_{c_{i,n} \in c_i} 1_{H(c_{i,n}, t_0) = 2} - (N - k - 1) \right) \qquad \forall \quad t^u_{i,j} \in t_i, \quad i \in C \tag{21}$$

Constraint (16) ensures that healthy components are not scheduled for replacement. Constraint (17) ensures that if at least one component is scheduled for replacement in a slot, then the aircraft is scheduled for maintenance in that slot. Here, M is a large, positive constant. Constraint (18) ensures that critical aircraft are always scheduled in a maintenance slot. Constraint (19) ensures that non-critical aircraft are not scheduled for maintenance within stage 1. Constraints (20) and (21) schedule for replacement at least the minimum number of components to solve aircraft criticality. When a component is replaced, it is assumed that its health state becomes healthy. Constraints (20) and (21) intend to solve the first and second terms of Definition 1, respectively.

i) Second Stage: Scheduling alerted components for non-critical aircraft

Once the critical aircraft have been scheduled for maintenance in stage 1, the second stage aims to schedule as many components with predictive alerts as possible for non-critical aircraft. In this way, it is expected that some repair costs are saved due to the lower component degradation levels. In this stage, there is a unique objective function with some differences relative to the first objective function of the first stage (13). In this stage, leasing components for non-critical aircraft is not allowed.

Objective function

$$max \sum_{i \in A} \sum_{t^u_{i,j} \in t_i} \left[\sum_{c_{i,n} \in c_i} X_{i,j,n} \cdot \left[C^M - \left[\frac{C^M - C^m}{\Gamma^f} \Gamma_{c_{i,n}}(t^u_{i,j}) + C^m \right] \right] \cdot (1 - P^f_{c_{i,n}}(t^u_{i,j})) \right] - \left[Y_{i,j} \cdot C^{slot}(t^u_{i,j}) \right] \tag{22}$$

The objective function in (22) aims to maximize the operational cost savings of individual aircraft. The two terms have been explained in the first optimization stage, (13) . The first term of (22) is the repair cost savings due to prognostics, while the second term is the cost of using a maintenance slot. The missing two terms compared to objective function (13) are left out since the aircraft failure probability is negligible and since there are no MEL violations in non-critical aircraft.

Constraints

In addition to constraints (16) and (17), we consider the following three constraints.

$$\sum_{t^u_{i,j} \in t_i} Y_{i,j} \leq 1 \qquad \forall \quad i \in A \tag{23}$$

$$\sum_{t \in [t_0, t_0 + PH + TAT]} new^{st}(t) = 0 \tag{24}$$

$$\sum_{i \in A} Y_{i,j} \leq M(t^u_{i,j}) \qquad \forall \quad t^u_{i,j} \in t_i, \quad i \in A \tag{25}$$

Constraint (23) ensures that an aircraft is scheduled for maintenance at most once in a time window. Constraint (24) ensures that no spare components are leased. Constraint (25) ensures that the number of aircraft scheduled in a slot is less than the maximum slot capacity. This constraint is not included in the first stage since infinite capacity is assumed for all critical aircraft.

iii) Third Stage: Scheduling failed components for non-critical aircraft

The third stage aims to schedule aircraft with less than $(N-k)$ failures as long as there are enough spare components. Scheduling failed components of non-critical aircraft may lead to high repair costs as well as repair shop overload. On the other hand, this stage aims for a high aircraft availability.

Objective function

$$max \sum_{i \in A} \sum_{t^u_{i,j} \in t_i} \left[\sum_{c_{i,n} \in c_i} C^{nc} \cdot X_{i,j,n} \right] - \left[Y_{i,j} \cdot C^{slot}(t^u_{i,j}) \right] \tag{26}$$

The objective function in (26) aims to maximize the number of replaced failed components. Here, C^{nc} denotes a non-critical failure cost with $C^{nc} > C^g$, such that aircraft can be scheduled in both generic and aircraft-specific slots.

Constraints

We consider constraints (16), (17), (23), (24), and (25) as in the case of the 2nd stage scheduling.

5. Maintenance scheduling approach: Adaptive Large Neighborhood Search

Considering the complexity of our problem, we suggest a heuristic solution approach. We propose an Adaptive Large Neighborhood Search (ALNS) algorithm to solve the maintenance scheduling problem with prognostics and the availability of spare components. We solve each of the three maintenance scheduling stages (see Section 4) using an ALNS algorithm (see Figure 6). We first provide a generic description of the ALNS algorithm. Next, the heuristics of each of the three scheduling stages are explained.

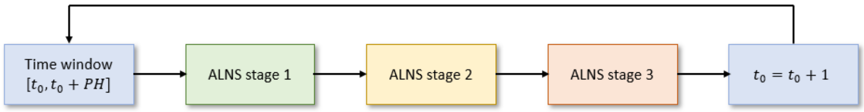


Figure 6: A rolling-horizon maintenance scheduling approach.

5.1. ALNS - generic description

The ALNS algorithm has two phases: 1) a constructive heuristic, which provides an initial feasible solution, and 2) an improvement heuristic, which iteratively improves this initial solution by means of an adaptive *destroy and repair* approach.

```
1  Function ALNS: (s ∈ S)
2    s_best = min(f(s))
3    Tabu list = S
4    while stop-criterion is not met:
5        for each s ∈ S:
6            S′ = Neighborhood (s)
7            if S′ is found:
8                for each s′ ∈ S′:
9                    if f(s′) < f(s_best):
10                       s_best = s′
11                   if accept (s′):
12                       S  ←  s′
13                       Tabu list  ←  s′
14               end
15           remove current s from S
16       end
17   end
18 return s_best and f(s_best)
```

Figure 7: ALNS pseudo-code.

Figure 7 shows the pseudo-code of the proposed ALNS algorithm. First, an initial set of feasible solutions S is assumed. We consider a solution to be a set of assignments of aircraft to maintenance slots and components to be replaced in these slots. Next, the global optimum s_{best} is initialized in line 2 by evaluating all initial feasible solutions $s \in S$ by the objective function $f(\cdot)$. A Tabu list is initialized in line 3 with S, i.e., the solution space to be explored. In lines 5-6, for each current solution s, a neighborhood search function selects a sub-heuristic depending on the state of s with the aim to obtain a set of neighbor solutions S'. This Neighborhood search function is different for each of the three stages. This is further explained in Section 5.1. If S' is found, then each neighbor solution $s' \in S'$ is evaluated. In lines 9-10, if s' is better than s_{best}, then s_{best} is updated. Also, if an acceptance criterion is met (line 11), s' is stored in S such that this solution is further explored in a future iteration. Besides, s' is stored in the Tabu list (line 13). Finally, the current solution, s, is deleted from S so that it is not explored in future iterations (line 15).

Acceptance criterion

We consider the following acceptance criterion: all solutions which are not in the Tabu List (non-evaluated solutions) are accepted.

Stopping criterion

We stop the search when: i) the solution space to be explored, S, is empty as no new solutions are found, or ii) when a limit of maximum 100 iterations is reached.

Neighborhood search function (see line 6 of the ALNS pseudo-code in Figure 7)

In contrast to [24] where the focus is on the historical performance of the *destroy and repair* methods, in this paper, a sub-heuristic is selected according to the current solution state to find a set of neighbor solutions. Three solution states are considered: i) solutions with aircraft with MEL violations (in stage 1), ii) solutions with component stock-outs (in stage 1), and iii) solutions with the possibility to improve the repair cost savings (in stages 1 and 2) or to maximize the number of replacements (in stage 3). These sub-heuristics are explained in Sections 5.2, 5.3, and 5.4, respectively.

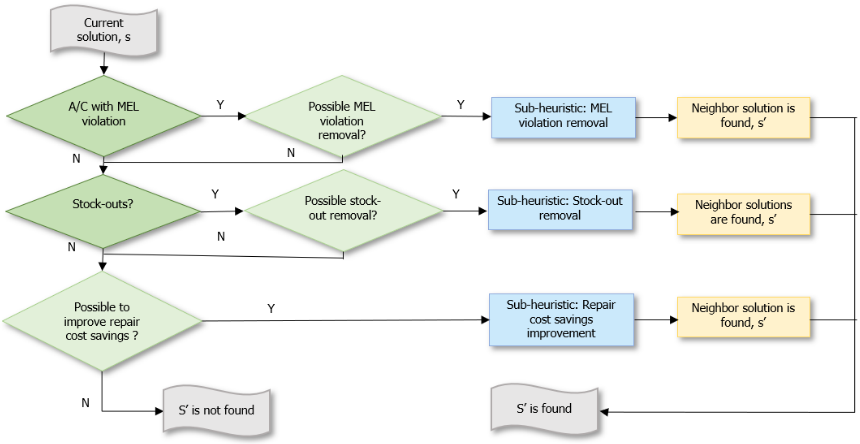


Figure 8: Neighborhood search function - stage 1 (see line 6 of ALNS pseudo-code, Figure 7)

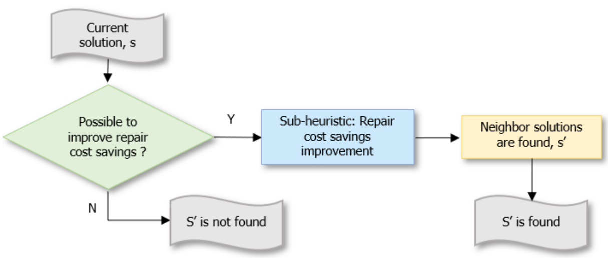


Figure 9: Neighborhood search function - stage 2 (see line 6 of ALNS pseudo-code, Figure 7)

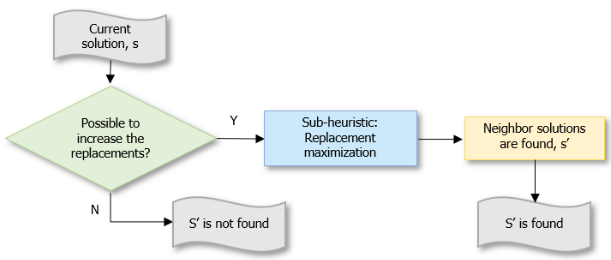


Figure 10: Neighborhood search function - stage 3 (see line 6 of ALNS pseudo-code, Figure 7)

Figure 8 shows the neighborhood search function of the 1st stage. This function first checks if there are aircraft with MEL violations in the current solution s and whether these can be removed. If this is the case, a sub-heuristic "MEL violation removal" is applied to search for a neighbor solution, s'. If there are no MEL violations, or they cannot be removed, then the function checks whether there are stock-outs in the current solution s and if any can be removed. If yes, a sub-heuristic "Stock-out removal" is used to find neighbor solutions s'. If no stock-outs are found, or they cannot be removed, then it is checked whether the repair cost savings can be improved in the current solution. If that is the case, then a sub-heuristic "Repair cost savings improvement" is applied to find the neighbor solution. If not, then the algorithm could not find any neighbor solution.

Figure 9 shows the neighborhood search function for the 2nd stage. It is checked whether the repair costs savings can be improved in the current solution. If that is the case, a sub-heuristic ”Repair cost savings improvement” is applied to find the neighbor solutions. If not, then the algorithm could not find any neighbor solution.

Lastly, Figure 10 shows the neighborhood search function in the 3rd stage. It is checked whether the number of component replacements can be increased in the current solution. If that is the case, a sub-heuristic ”Replacement maximization” is applied to find the neighbor solutions. If not, then the algorithm could not find any neighbor solution.

5.2. ALNS for the 1st scheduling stage: critical aircraft

1st stage scheduling - Constructive heuristic

The constructive heuristic finds an initial feasible solution as follows: each critical aircraft is scheduled for maintenance in the earliest available slot. Once this slot is identified, it schedules for replacement a number of components given by the lower bound in constraints (20) and (21).

The design of this heuristic is motivated by the fact that it is expected that the earlier an aircraft is scheduled, the lower the chance of aircraft failure and the higher the repair cost savings per component (see first and fourth terms in (13)) are. Also, from (20) and (21), a minimum amount of components needs to be scheduled for replacement to solve aircraft criticality.

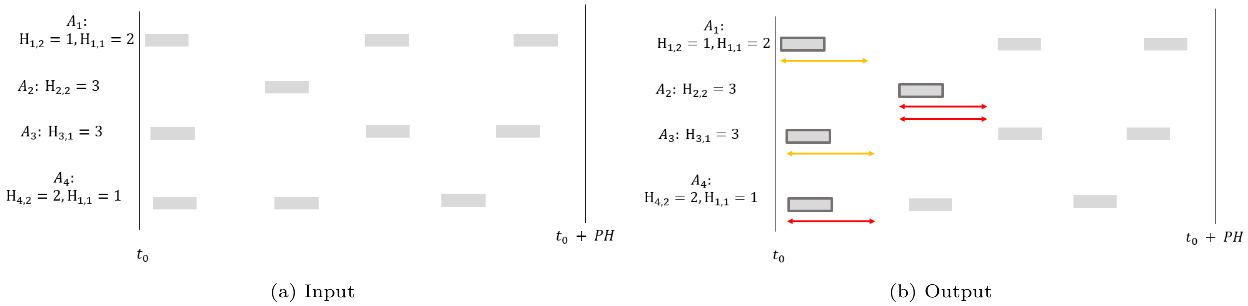


Figure 11: Example of constructive heuristic (1st stage), where $H_{i,x} = \sum_{c_{i,n} \in c_i} 1_{H(c_{i,n},t_0)=x}$.

Figures 11a and 11b show an example of the constructive heuristic, with $N = 4$, $k = 2$. The grey boxes represent the available maintenance slots of 4 aircraft in a time window $[t_0, t_0 + PH]$. The orange and red arrows represent the TAT of the scheduled alerted and failed components, respectively. Here, aircraft A_1 has 2 alerted components and 1 failure, meaning that A_1 is critical (see (12)). Also, only one component needs to be replaced to solve aircraft criticality (see constraint (20)). Since alerted components have lower repair costs compared to failed components, an alerted component is scheduled for A_1. Similarly, aircraft A_2 has 3 failed components, i.e. A_2 is critical (see (12)). Here, two failed components need to be replaced to solve aircraft criticality (see constraint (21)). Finally, A_3 has 3 alerted components, while A_4 has 2 failures and 1 alert. Thus, one alert and one failure are scheduled for A_3 and A_4, respectively. Again, all aircraft are scheduled at their first available slot.

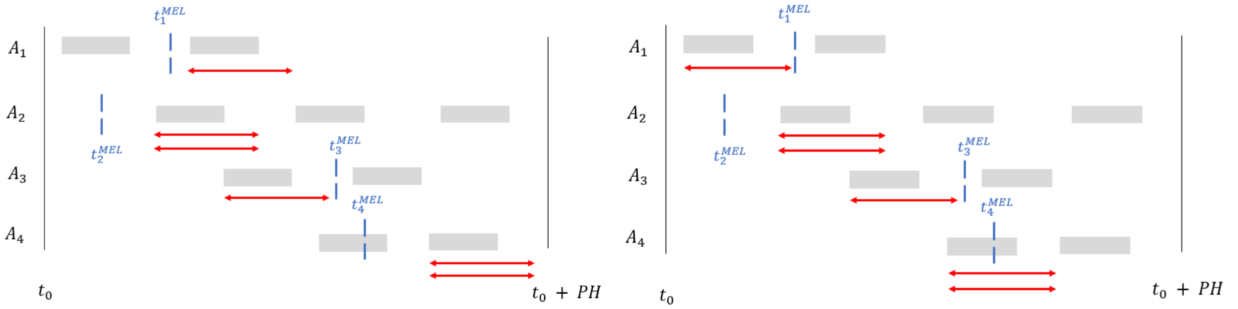
1st stage scheduling - Improvement heuristic

The output of the constructive heuristic is the input of the improvement heuristic. The improvement heuristic tries to iteratively improve the current solution through a Neighborhood search function (see line 6, Figure 7), which selects a sub-heuristic based on the current solution state. Three sub-heuristics are proposed: MEL violation removal, stock-out removal, and repair cost savings improvement.

a) MEL violation removal sub-heuristic

This sub-heuristic aims to remove MEL violations. Here, an aircraft has a MEL violation if it is scheduled for maintenance in slots after a MEL deadline, i.e., $t^u_{i,j} > t^{MEL}_i$. Thus, all aircraft that have a MEL violation are removed from the current maintenance slot and are scheduled in an earlier slot, if possible.

As an example, in Figure 12a, the blue dotted lines represent the MEL deadlines of 4 aircraft. Except for A_3, all aircraft are scheduled after their MEL deadline. A_1 and A_4 have an available earlier slot than the one at which they are scheduled, while A_2 does not have any earlier slots. Thus, only A_1 and A_4 are removed from their current slot and re-scheduled in an earlier slot.

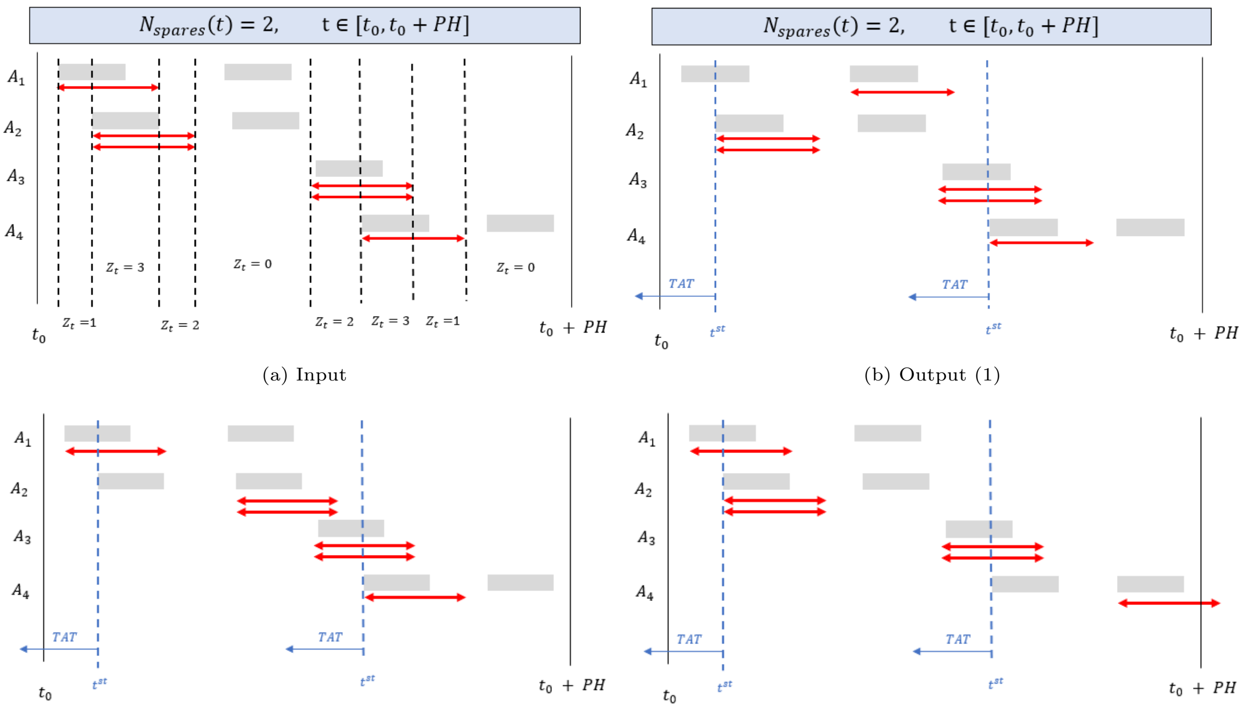


(a) Input (b) Output

Figure 12: Example of MEL violation removal sub-heuristic (1st stage)

b) Stock-out removal sub-heuristic

This sub-heuristic aims to reduce the number of leased/stock-out spare components. Let the stock-out times t^{st} be defined as: $t^{st} = \min\{t : \sum_{i \in A} \sum_{c_{i,n} \in c_i} Z_{i,n,t} > N_{spares}(t)\}$. All aircraft which are scheduled in slot $t^u_{i,j}$ and meet the condition $t^{st} - TAT < t^u_{i,j} \leq t^{st}$ are removed from the current slot and re-scheduled in the next available slot.



(a) Input (b) Output (1)

(c) Output (2) (d) Output (3)

Figure 13: Example of stock-out removal sub-heuristic (1st stage), where $Z_t = \sum_{i \in A} \sum_{c_{i,n} \in c_i} Z_{i,n,t}$

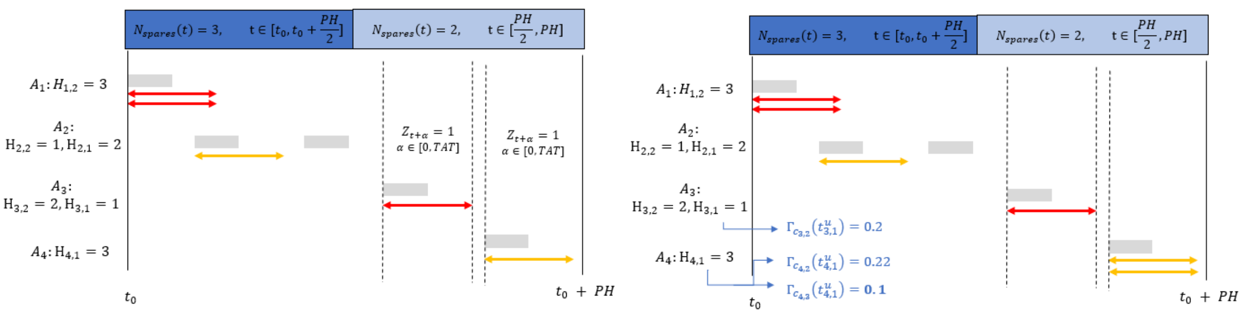
In Figure 13a, we assume that the initial stock of available spares is 2, i.e., $N_{spares}(t) = 2$, $t \in [t_0, t_0{+}PH]$. There are two stock-out times at the beginning of the slots where A_2 and A_4 are scheduled for maintenance. For the first stock-out time, A_1 and A_2 are scheduled in slots meeting the condition $t^{st} - TAT < t^u_{i,j} \leq t^{st}$.

Thus, A_1 and A_2 are scheduled to their next slots (Figures 13b and 13c, respectively). For the second stock-out time, A_3 and A_4 are scheduled in slots meeting the condition $t^{st} - TAT < t^u_{i,j} \leq t^{st}$. However, A_3 does not have a later available slot. Thus, only A_4 is scheduled at its next slot (Figure 13d).

c) Repair cost savings improvement sub-heuristic

This sub-heuristic aims to improve the current solution by scheduling the alerted component with the highest repair cost savings such that no stock-out is generated. First, the slots where scheduling one more component does not lead to stock-out, are identified; i.e. $t^u_{i,j}$ such that $\sum_{i\in A}\sum_{c_{i,n}\in c_i} Z_{i,n,t^u_{i,j}+\alpha} < N_{spares}(t^u_{i,j}+\alpha)\forall\alpha \in [0,1,..,TAT]$. Next, the component degradation indicator at these slots is evaluated for the alerted components which are not already scheduled. Finally, the component with the lowest degradation indicator is scheduled for replacement.

Figure 14a shows an example where the number of spare components decreases from 3 to 2 in the considered time window. The slots at which A_3 and A_4 are scheduled would not lead to stock-out if an additional component is scheduled, since $\sum_{i\in A}\sum_{c_{i,n}\in c_i} Z_{i,t^u_{i,j}+\alpha} = 1$ and $N_{spares}(t^u_{i,j}+\alpha) = 2$, $\alpha \in [0,1,...TAT]$. A_3 has one alerted component that has not been scheduled, while A_4 has two. The degradation indicator of these components at the considered slots is evaluated in Figure 14b. Since component $c_{4,3}$ has the lowest degradation indicator, this component is scheduled for replacement.



(a) Input (b) Output

Figure 14: Example of repair cost savings improvement sub-heuristic (1st stage), where $H_{i,x} = \sum_{c_{i,n}\in c_i} 1_{H(c_{i,n},t_0)=x}$ and $Z_t = \sum_{i\in A}\sum_{c_{i,n}\in c_i} Z_{i,n,t}$

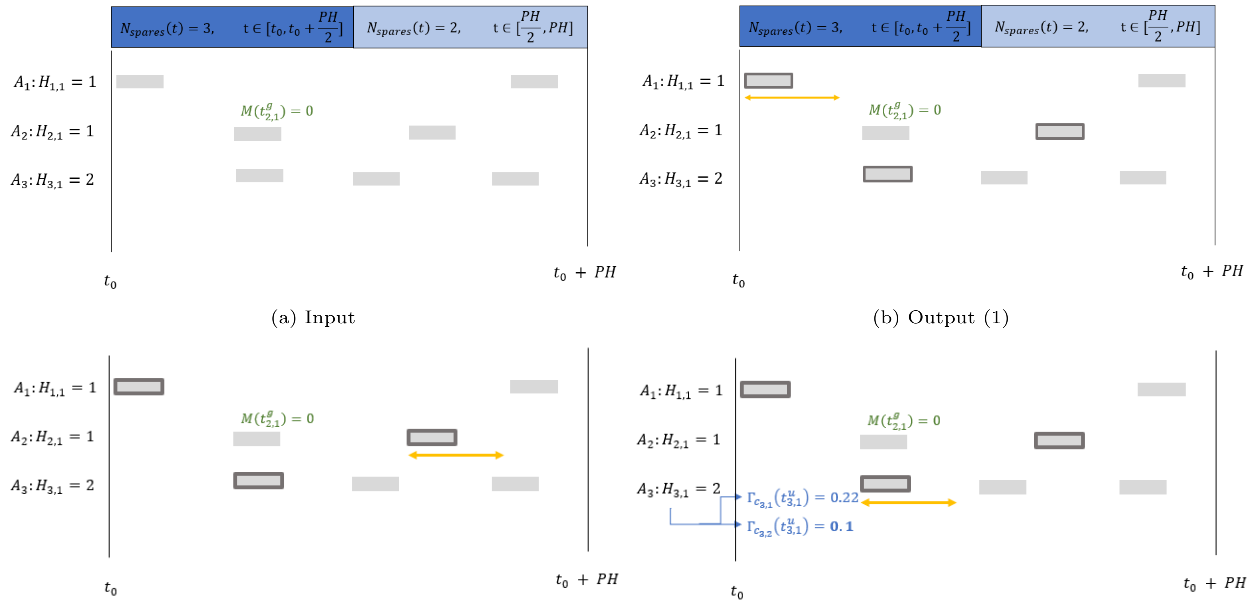
Updating step

Once a solution for the 1st stage is obtained, the number of available spare components is updated, the slot capacity is decremented for every new aircraft scheduled for maintenance, and the health state of the components is updated.

5.3. ALNS for the 2nd scheduling stage: non-critical aircraft, scheduling alerted components

2nd stage scheduling - Constructive heuristics

Similarly to the 1st stage, the constructive heuristic in the 2nd stage aims to generate an initial feasible solution. First, the slots that have available spare components for at least $t = TAT$ days are identified, i.e., $N_{spares}(t^u_{i,j}+\alpha)_{\alpha\in[0,1,...,TAT]} \geq 1$; and that have capacity to schedule at least another aircraft, i.e., $M(t^u_{i,j}) \geq 1$. Then non-critical aircraft with alerted components are scheduled, one by one, in the earliest available slot meeting the previous conditions. Only one component per aircraft is scheduled. If an aircraft has more alerted components, then the component with the lowest degradation indicator (and highest repair cost savings) is scheduled.



(a) Input

(b) Output (1)

(c) Output (2)

(d) Output (3)

Figure 15: Example constructive heuristic (2nd stage), where $H_{i,x} = \sum_{c_{i,n} \in c_i} 1_{H(c_{i,n},t_0)=x}$

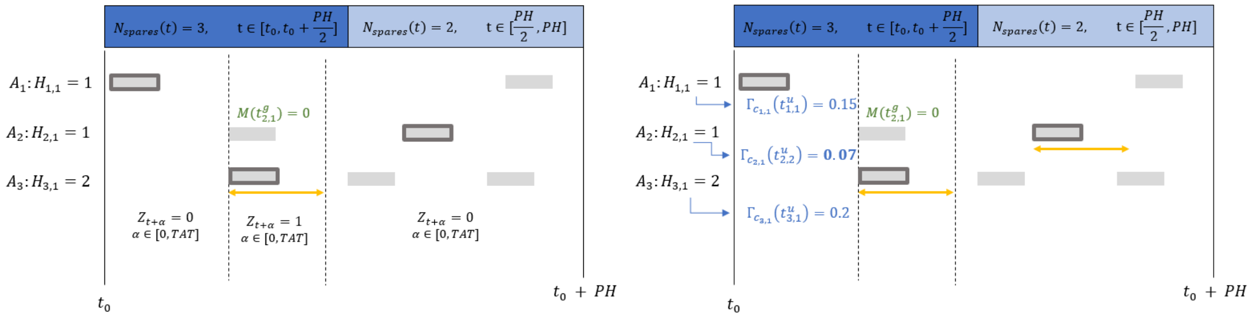
Figure 15a shows an example where the number of available spare components decreases from 3 to 2. Thus, all slots have an available spare component for at least $t = TAT$ days. Also, all slots have the capacity to schedule another aircraft, except for the first slot of aircraft A_2. Figure 15b highlights with a darker border the earliest slots meeting the previous two conditions. Since A_1 and A_2 have only 1 alerted component, then two initial feasible solutions are generated by scheduling each of them (see Figures 15b and 15c). A_3 has two alerted components, but component $c_{3,2}$ is scheduled as it has the lowest degradation indicator (see Figure 15d).

2nd stage scheduling - Improvement heuristics

Here we consider a Repair cost savings improvement -stage 2 sub-heuristic, which is slightly different from the sub-heuristic in stage 1. In the 2nd stage, there are no MEL violations or component stock-outs since we now consider non-critical aircraft only.

a) Repair cost savings improvement sub-heuristic - stage 2

This sub-heuristic schedules the component with the lowest degradation indicator (or highest repair cost savings), provided that no stock-outs are generated and that there is enough slot capacity. First, the aircraft with any unscheduled alerted components are identified. Then, i) the aircraft has been already scheduled for maintenance or ii) it has not been scheduled yet. For the first case, the degradation indicator needs to be evaluated in the already scheduled slot provided that the no stock-out condition is met. For the second case, the degradation indicator needs to be evaluated in the earliest available slot that fulfills the no stock-out and slot capacity conditions. From both cases, the component with the lowest degradation indicator is scheduled.



(a) Input (b) Output

Figure 16: Example of repair cost savings improvement sub-heuristic (2nd stage), where $H_{i,x} = \sum_{c_{i,n} \in c_i} 1_{H(c_{i,n},t_0)=x}$ and $Z_t = \sum_{i \in A} \sum_{c_{i,n} \in c_i} Z_{i,n,t}$

Figure 16a shows an example where all slots fulfill the no stock-outs and available capacity conditions, except for the first slot of A_2. The earliest slots meeting these conditions are highlighted. A_1 and A_2 have one alerted component, while A_3 has 2, but one has been already scheduled. The degradation indicator of these alerted components is evaluated at the highlighted slots (see Figure 16b). Component $c_{2,1}$ is scheduled for replacement since it has the lowest degradation indicator. Thus, aircraft A_2 is scheduled in slot $t^u_{2,2}$.

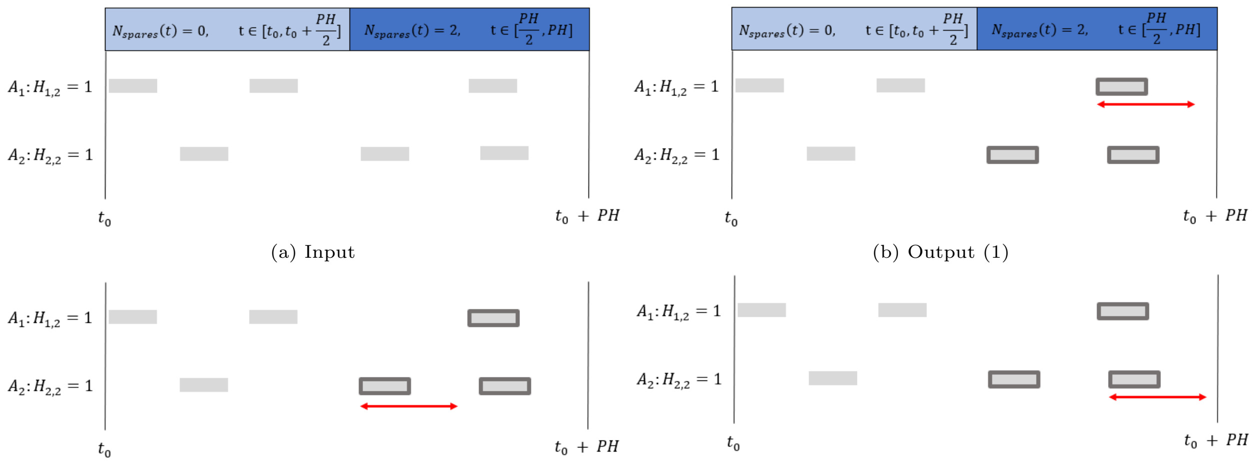
Update step

Once a solution for the 2nd stage is found, the number of available spare parts, the slot capacity, and the component health state are updated.

5.4. ALNS for the third optimization stage: non-critical aircraft, scheduling failed components

3rd stage scheduling - Constructive heuristics

The algorithm to find the initial feasible solution is quite similar to the one designed in the second optimization stage. First, it is necessary to identify slots meeting the availability of spare parts condition, i.e., $N_{spares}(t^u_{i,j} + \alpha)_{\alpha \in [0,1,\ldots,TAT]} \geq 1$, and slot capacity condition, i.e., $M(t^u_{i,j}) \geq 1$. Once these slots are found, the next step is to schedule one by one non-critical aircraft with failed components in all slots meeting the previously stated conditions. Only one component per aircraft is scheduled for replacement.



(a) Input (b) Output (1)

(c) Output (2) (d) Output (3)

Figure 17: Example constructive heuristic (3rd stage), where $H_{i,x} = \sum_{c_{i,n} \in c_i} 1_{H(c_{i,n},t_0)=x}$

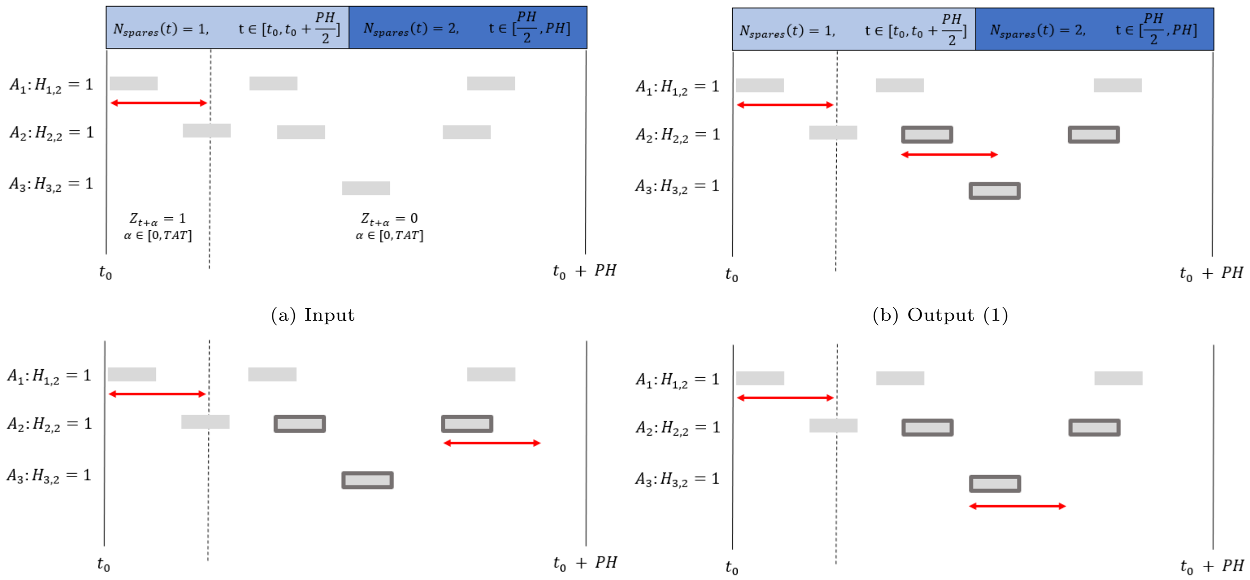
In Figure 17a, $N_{spares}(t)$ changes from 0 to 2 in the considered time window. Hence, only the slots located in the area where $N_{spares}(t) = 2$ meet the availability of spare parts condition (see highlighted slots in Figure 17b). Aircraft A_1 is scheduled in the first initial feasible solution in Figure 17b. The second and the third initial feasible solutions are shown in Figures 17c and 17d by scheduling A_2 at each of its two highlighted slots.

3rd stage scheduling - Improvement heuristics

We consider the following sub-heuristic for the 3rd stage scheduling.

a) Replacement maximization sub-heuristic

This sub-heuristic schedules the maximum amount of components provided no stock-outs are generated. First, the slots where scheduling another component would not lead to stock-out, i.e., $\sum_{i\in A}\sum_{c_{i,n}\in c_i} Z_{i,n,t^u_{i,j}+\alpha} < N_{spares}(t^u_{i,j}+\alpha)\ \forall\ \alpha \in [0,1,..,TAT]$, and that have capacity for at least one more aircraft, i.e., $M(t^u_{i,j}) \geq 1$, are identified. Then, each non-critical aircraft with failed components is scheduled in every identified slot.



(a) Input (b) Output (1)

(c) Output (2) (d) Output (3)

Figure 18: Example of replacement maximization sub-heuristic (3rd stage), where $H_{i,x} = \sum_{c_{i,n}\in c_i} 1_{H(c_{i,n},t_0)=x}$ and $Z_t = \sum_{i\in A}\sum_{c_{i,n}\in c_i} Z_{i,n,t}$

Figure 18a shows an example where all slots meet the no stock-out and available capacity conditions, except for the first slot of A_2 which does not meet the no stock-out condition. The slots meeting these conditions are highlighted. Here, A_2 is scheduled at its first and second highlighted slots (see Figures 18b and 18c) and A_3 at its only available slot (Figure 18d).

Update step

Once a solution is found, the number of available spare parts, the slot capacity, and the component health state are updated.

6. Maintenance scheduling - numerical results

We illustrated our maintenance scheduling model for a fleet of $I = 13$ wide-body aircraft. Each of the aircraft is equipped with $N = 4$ identical cooling units. The failure of $k = 2$ or more CUs in an aircraft leads to the aircraft being inoperable, i.e, Aircraft-on-Ground (AOG), which, in turn, leads to delays and costs. We also assume $N_{spares} = 3$. We consider a prediction horizon of $PH = -$ days, i.e., we evaluate the probability of CU failure for the next [redacted] days. Also, the MEL replacement interval is assumed to be $RI^{MEL} = -$ days, and the $TAT = -$ days. Finally, we assume the following costs: $C^{MEL} = -, C^d = -, C^M = -, C^m = -, C^g = -, C^{Lf} = -, C^{Ld} = -, C^{nc} = -$.

We illustrate the maintenance schedule model in Section 4 by considering a period of 61 days (see Figure 19). Here, aircraft $1, 2, \ldots, 13$ has $2, 1, 1, \ldots, 5$ specific slots available, respectively. There are 10 generic slots (G).

For the component RUL prognostics model, we consider the following parameters. For all $13 \cdot 4$ components, we initialize the health index at some time t^{init} as follows. First, we consider that each component $c_{i,n}$ is installed as brand new at some time in the past $t^{init} - \Delta_{i,n}, \Delta_{i,n} >> 61$. Next, we sample a random time to failure (TTF), $TTF_{c_{i,n}} \sim Weibull(a, b)$. Thus, the random failure time of component $c_{i,n}$

is $t^{init} - \Delta_{i,n} + TTFc_{i,n}$. In our numerical example, we assume $TTFc_{i,n} \sim Weibull$ [redacted], following an analysis of historical CU failures. Here, [redacted] is the scale parameter and [redacted] is the shape parameter of the Weibull distribution. We next generate an alert for component $c_{i,n}$ PH days before its random failure time $t^{init} - \Delta_{i,n} + TTFc_{i,n}$ with probability $s =$ [redacted], where s is the probability that a component failure is highlighted in advance by means of an alert, i.e., s is seen as the prognostic sensitivity. Finally, given a predictive alert is generated for component $c_{i,n}$, a RUL prognostic is determined in the form of RUL CDF based on historical data.

Figure 19 shows the maintenance scheduling results, taking into account the maintenance slots, spares, and component RUL prognostics. For simplicity, here $t^{init} = 1$. Aircraft $i = 4$ is scheduled at a generic slot to replace component 1 and at a specific slot for component 3. Aircraft $i = 5$ uses a generic slot for component 2, while aircraft $i = 7, 9, 12$ use a specific slot each for components $3, 1, 2$, respectively. Aircraft $1, 2, 3, 6, 8, 10, 11, 13$ are not scheduled for maintenance. These results are obtained in 13sec using an Intel Core i7 8-th Gen of 3.5 GHz computer processor.

[redacted]

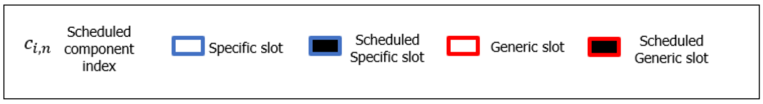


Figure 19: Multi-component maintenance schedules for a fleet of 13 aircraft and a period of 61 days.

Tables 1 shows the details regarding the aircraft scheduled for maintenance: aircraft $i \in \{4, 5, 7, 9, 12\}$ are scheduled for maintenance at slots beginning at times $27, 37, 54, 48, 3, 52$, respectively. Aircraft $i = 9$ has component $c_{9,1}$ scheduled for replacement, for which an alert was triggered already. Aircraft $i = 4$ has components $c_{4,3}$ and $c_{4,1}$ scheduled for replacement, which are also in an alerted state. Finally, aircraft $i = 7, i = 5$ and $i = 12$ have components $c_{7,3}$, $c_{5,2}$ and, $c_{12,2}$, respectively, scheduled for replacement and their state is failed.

t_0	i	$t_{i,j}^{u\,*}$	u	$H(c_{i,1}, t_0)$	$X_{i,j,1}$	$H(c_{i,2}, t_0)$	$X_{i,j,2}$	$H(c_{i,3}, t_0)$	$X_{i,j,3}$	$H(c_{i,4}, t_0)$	$X_{i,j,4}$
2	9	3	s	1	1	0	0	0	0	0	0
24	4	27	g	0	0	0	0	1	1	0	0
35	4	37	s	1	1	0	0	0	0	0	0
40	7	48	s	0	0	0	0	2	1	2	0
44	5	54	g	0	0	2	1	0	0	2	0
48	12	52	s	0	0	2	1	0	0	2	0

Table 1: Multi-component maintenance schedule - detailed results.

Table 2 shows the costs related to the aircraft that have been scheduled for maintenance at each time window. In the time window $[2, 12]$, an alerted component is replaced in aircraft $i = 9$, resulting in repair cost savings of [redacted]. In time windows $[24, 34]$ and $[35, 45]$ two alerted components of aircraft $i = 4$ are replaced, resulting in repair cost savings of [redacted], and [redacted], respectively. In the time window $[40, 50]$, aircraft $i = 7$ is scheduled, but it does not have any cost savings since the replaced component is in failed state. In time windows $[44, 54]$ and $[48, 58]$ aircraft $i = 5$ and $i = 12$ are scheduled with a leasing and MEL costs of [redacted] and [redacted], and [redacted] and [redacted], respectively. In addition, there are no flight schedule disruption costs (1st term of eq. (13)) in all time windows considered.

$[t_0, t_0 + PH]$	MEL costs 2nd term eq. (13)	Slot usage costs 3rd term eq. (13)	Repair cost savings 4th term eq. (13)	Leasing costs 2nd & 1st term eq. (14)
$[2, 12]$	0	0	[redacted]	0
$[24, 34]$	0	[redacted]	[redacted]	0
$[35, 45]$	0	0	[redacted]	0
$[40, 50]$	0	0	0	0
$[44, 54]$	[redacted]	[redacted]	0	[redacted]
$[48, 58]$	0	0	0	[redacted]

Table 2: Costs per time window $[t_0, t_0 + PH]$, with $C^{Lf} = -$ the fixed costs to lease a component.

7. Long-run analysis of maintenance scheduling strategies using Monte Carlo simulation

We now consider a period of $\Delta = 365$ days for a fleet of $I = 13$ aircraft. We analyze three different strategies for maintenance: S1) only critical aircraft are scheduled for maintenance (stage 1, Section 4), S2) critical aircraft are scheduled and alerted components in non-critical aircraft are considered for scheduling (stages 1-2, Section 4), and S3) critical aircraft scheduled, and alerted and failed components in non-critical aircraft are considered for scheduling (stages 1-2-3, Section 4). We are interested in which strategy performs best in the long-run.

We conduct a Monte Carlo simulation to evaluated the expected performance associated with the three scheduling strategies. For each simulation run, we initialize the TTF of each component as discussed in Section 6. We consider the following performance indicators:

a) Total expected costs due to MEL violations (MEL costs) for 365 days (see 2nd term of eq. (13)).

b) Total expected costs due to component leasing (Leasing costs) for 365 days (see 3rd and 4th terms of eq. (14)).

c) Total expected repair cost savings for 365 days (see 4th term of eq. (13)).

d) Total expected component repair costs (Repair costs) for 365 days, defined as:

$$\sum_{t \in [0,365]} \sum_{i \in A} \sum_{c_{i,n} \in c_i} X_{i,j,n} \cdot C^M - RS,$$

where RS is the total expected repair cost savings for a period of 365 days, as defined in c).

e) Total expected number of component replacements, defined as:

$$\sum_{t \in [0,365]} \sum_{i \in A} \sum_{c_{i,n} \in c_i} X_{i,j,n}.$$

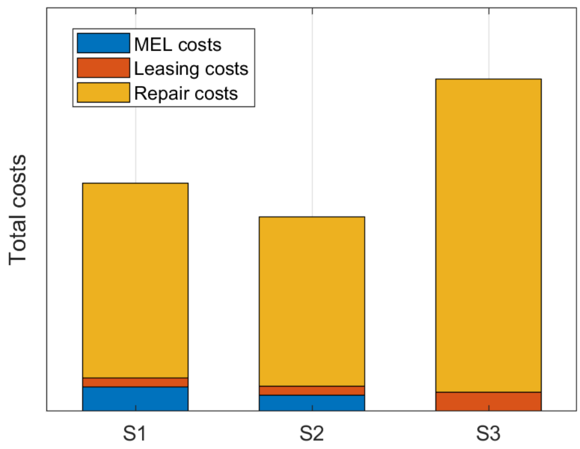


Figure 20: Total expected costs in a period of 365 days

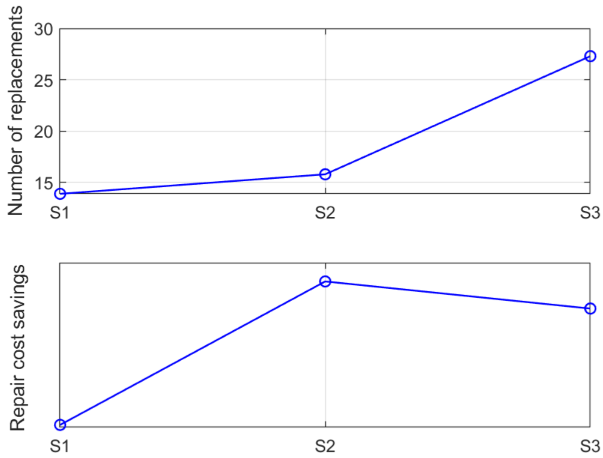


Figure 21: Expected performance in a period of 365 days

The results show that S2 is the best performing strategy, i.e., to use only the 1st and 2nd optimization stages. Comparing S2 to S1, even though the number of replacements is higher in S2, the repair costs are lower. This is because in S2, the components with predictive alerts are scheduled before the aircraft becomes critical. Thus, the repair cost savings are higher. Also, the MEL costs are reduced in S2 by preventing unexpected failures of some components that would lead to MEL violations.

S3 has the worst performance in terms of costs. Compared to S2, the number of replacements is considerably higher, which leads to an increase in leasing costs. The repair cost savings are lower because some components without repair cost savings are replaced, using spare parts that cannot be used anymore in more profitable replacements. Thus, the repair costs are considerably higher. However, S3 has the lowest of MEL violation costs since all the unexpected component failures leading to a MEL violation are prevented.

The results are obtained in a computational time of 42sec for S1, 60sec for S2 and 78sec for S3, using an Intel Core i7 8-th Gen of 3.5GHz.

7.1. Sensitivity Analysis - Maintenance of critical aircraft and alerted components (S2)

In the previous section, it is shown that S2 is the best performing maintenance strategy. In this section, we further analyze the impact of available spare parts, the size of the scheduling time window PH, and the size of the fleet on the S2 strategy.

The impact of spare parts

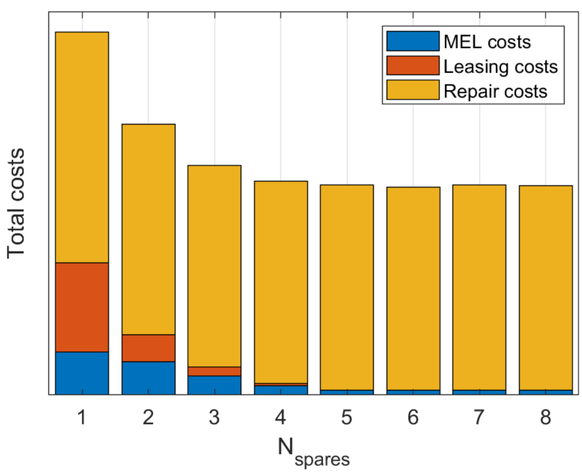


Figure 22: Impact of the number of spare components on the costs associated with S2, analyzing a period of 365 days.

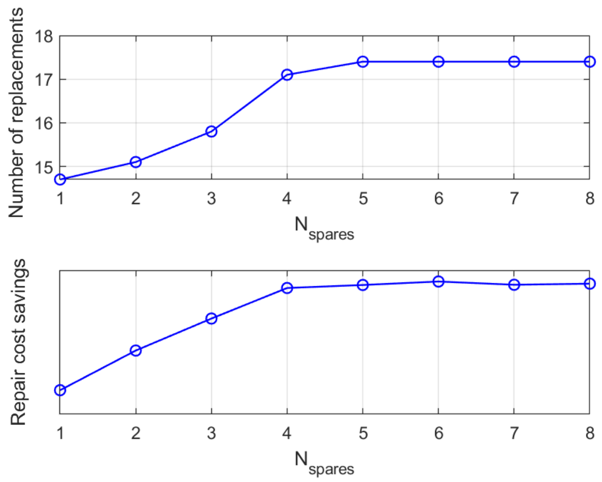


Figure 23: Impact of the number of spare components on the performance of S2, analyzing a period of 365 days.

Figures 22 and 23 show that the number of replacements increases as the number of spare components increases. As more resources become available, the number of possible component replacements increases. However, 5 spares is a switching point, i.e., no additional replacements occur even though when the number of spare parts increases beyond 5. The repair cost savings and the total costs follow a similar behavior as the number of replacements, relative to an increasing number of spares.

Another impact of having a larger number of spare parts is that the leasing costs decrease. Furthermore, some failures leading to MEL violations are avoided by performing more replacements, which results in lower MEL costs.

The impact of PH

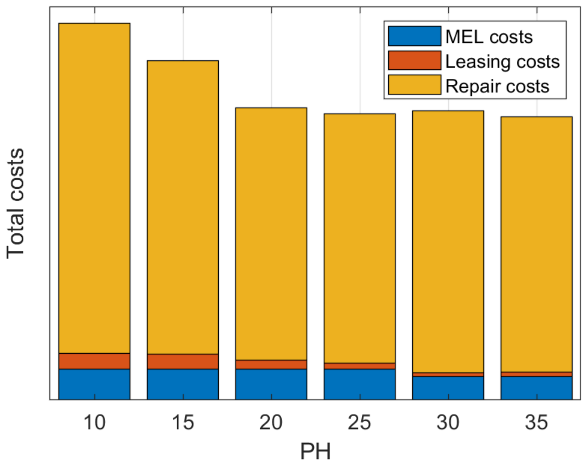


Figure 24: Impact of PH on the costs associated with S2, analyzing a period of 365 days.

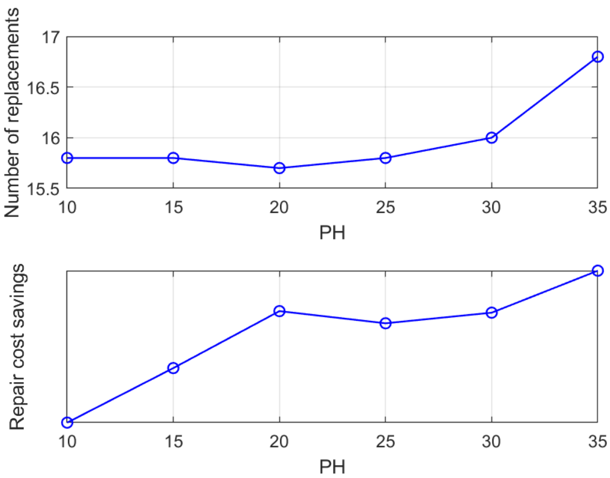


Figure 25: Impact of PH on the performance of S2, analyzing a period of 365 days.

Figures 24 and 25 show that higher prognostic horizons generate greater repair cost savings. The repair costs are assumed to be a linear function of the component degradation level. Moreover, the degradation level is an exponential function of time, meaning that replacing the components at slightly earlier times can have a substantial effect on the repair cost savings. Besides, the probability that the components have not already failed at the replacement time is higher at earlier times, improving also the repair cost savings.

Higher prognostic horizons provide an enhanced inventory planning flexibility in two aspects. First, the spare components leasing costs are reduced (see Figure 24). Second, the number of replacements can be slightly increased. This occurs at prognostic horizons greater than 30 days (see Figure 25). This is because the size of the time window is greater than TAT. Thus, the same component can for example be used at a replacement occurring at the beginning and at the end of the considered time window. In addition, a slightly higher number of replacements can avoid a few failures leading to MEL violations. Thus, the MEL costs have a small step change at a prognostic horizon $PH = 30$ days.

The impact of the fleet size

We now consider the impact of a large aircraft fleet size on the costs and performance of the S2 maintenance strategy. Specifically, we consider a fleet size of 10, 20, 30, 40 and 50 aircraft and a proportionally adjusted number of spare components of 2, 4, 6, 7 and 8, respectively.

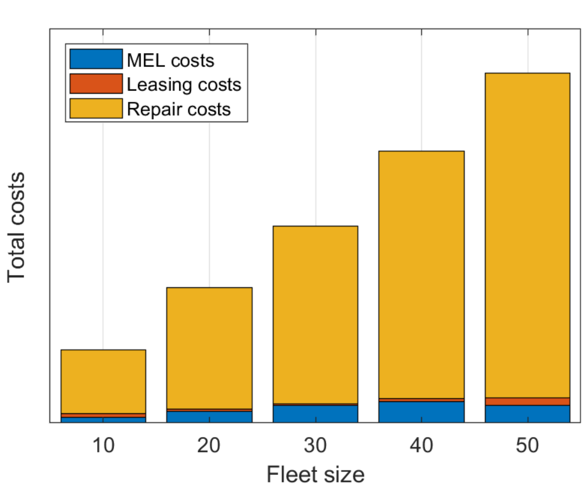


Figure 26: Impact of the fleet size on the costs associated with S2, analyzing a period of 365 days.

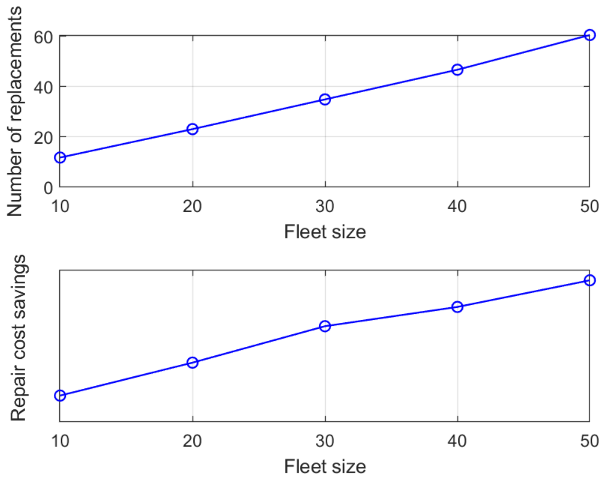


Figure 27: Impact of the fleet size on the performance of S2, analyzing a period of 365 days.

Fleet size	10	20	30	40	50
Algorithm running time (min)	0.7	1.3	3.6	4.6	6.2

Table 3: Algorithm running times for different fleet sizes (min)

Figure 27 shows that the number of replacements and the repair cost savings are an increasing linear function of the fleet size. The repair costs also increase with the fleet size (see Figure 26), even though the repair cost savings are higher, due to a greater amount of component replacements. The MEL violation and the spare part leasing costs seem to remain stable for all fleet size values.

The maintenance scheduling algorithm running times are given in Table 3. The results show that our proposed approach requires a very low computational time, being able to schedule for maintenance a fleet of 50 aircraft for a period of 365 days in 6.2 min.

8. Conclusion

A model to optimize the maintenance schedules of a fleet of single-type aircraft based on component prognostics and the availability of spare parts and maintenance slots has been proposed. First, a discrete-time, rolling horizon approach has been defined, where a sequence of time windows of duration PH is considered. For every time window, the prognostics for each component, the availability of spare parts, and the set of maintenance slots available are considered as input. Then, a discrete-time scheduling optimization model has been proposed to find the optimal assignment of aircraft to maintenance slots as well as determining which components should be replaced in these slots. For each time window, three optimization stages are considered in the following decreasing order of maintenance priority: critical aircraft, non-critical aircraft with predictive alerts, and non-critical aircraft with failures. An ALNS algorithm has been proposed to solve each of the three stages. As an illustration, we have considered the CU component of a fleet of 13 aircraft. The results in a period of 61 days show that the methodology can find the optimal assignment of aircraft to slots as well as which components are replaced in these slots in only 13 seconds.

Next, we have considered a period of 365 days to analyze the long-run model performance. Three different strategies have been defined: S1) schedule only critical aircraft (1st stage), S2) schedule critical aircraft and consider non-critical aircraft with predictive alerts (1-2 stages), and S3) schedule critical aircraft and consider non-critical aircraft with predictive alerts and failed components (1-2-3 stages). The results show that S2 has the greatest performance in terms of cost reduction. Particularly, S2 is able to substantially lessen the repair costs compared to S1 and S3.

Finally, we have conducted a sensitivity analysis to analyze the impact of the number of spare parts, PH, and the fleet size. The results show that a higher number of spare parts can increase the number of component replacements and decrease the total costs, but there is a switching point after which no additional improvements are achieved. Also, greater prognostic horizons can rise the repair cost savings, while providing an improved inventory planning flexibility by reducing the spare part leasing costs and slightly increasing the component replacements. However, long prognostic horizons can lead to the waste of some component useful life, so a trade-off should be considered. Finally, we have considered a larger fleet size and we have shown that the proposed algorithm is able to successfully solve the maintenance scheduling problem of a fleet of 50 aircraft in 365 days in only 6.2 minutes.

As future work, the model could be extended to consider multiple components, instead of a single component type. The same procedure should be followed for other k-out-of-N components to analyze what is the most optimal strategy to follow within S1, S2 and S3. For example, a high k would result in more frequent critical aircraft, so maybe S1 would be the best strategy.

Moreover, we suggest considering additional cost factors, such as labor cost, or wasted component useful life costs. Considering labor costs can lead to grouping more component replacements in a single maintenance slot, also using spare parts that could be used in a more profitable replacement. The cost of wasted useful life would reduce the benefit of using a high PH to reduce the repair cost savings.

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II

Literature Study (previously graded under AE4020)

2

Airline Maintenance Scheduling

The integration of component prognostics in airline maintenance operations is part of the ongoing development of a new maintenance strategy in the airspace industry. To comprehend how this project fits in this process, it is essential to briefly review the evolution and the current practices of maintenance scheduling in the airline industry. This chapter presents a brief overview of the evolution of scheduling in airline maintenance in section 2.1, the current practices and maintenance types in 2.2, and it ends with the classification of aircraft components in section 2.3.

2.1. Evolution of Airline Maintenance Scheduling

Aircraft maintenance has tremendously evolved since the first stages of aviation. In the early era of aircraft, maintenance was only carried out when it was needed, meaning that no action was taken until a failure had occurred. This strategy is called corrective maintenance. Although airplanes were rather simple by this time, this practice became more expensive with the increasing complexity of aircraft that emerged in the upcoming years. Therefore, a more advanced approach for maintenance was needed.

The introduction of the Boeing 747 in 1968 supposed the start of the first generation of jumbo jets in addition to the start of a novel method to address maintenance programs. The Boeing Company together with the Federal Aviation Administration (FAA) introduced the so-called Maintenance Steering Group (MSG) concept [35]. This approach was so successful in the B747 that it was generalized for other types of aircraft by the Air Transport Association (ATA). The MSG process evolved along time to the current MSG-3 Revision 2, which was firstly introduced in 1980 with the MSG-3 process. MSG-3 is said to be a top-down and task-oriented approach. By top-down, it is meant that the consequences of failure and how it affects the system operation are analyzed, whereas task-oriented means that the MSG-3 logic allows to select appropriate tasks to prevent system failure and maintain its reliability.

The result of the MSG-3 logic leads to an initial maintenance schedule to be used by the operator. It is published in a document called Maintenance Review Board (MRB) created by the Original Aircraft Manufacturer (OAM), which is addressed as the Maintenance Planning Document (MPD) by Boeing and Airbus [56]. The MPD contains the maintenance tasks and intervals that must be performed in the aircraft in addition to some additional tasks suggested by the OAM.

2.2. Airline Maintenance types

Based on the MPD, each operator has the responsibility to develop its maintenance program that contains a summary of all maintenance tasks and their due dates. The maintenance activities contained in the maintenance program are known as *Scheduled Maintenance*. Nevertheless, it exists the possibility that unforeseen events requiring maintenance actions occur, which is known as *Unscheduled Maintenance*.

Scheduled maintenance

Scheduled maintenance can be further divided into Line Maintenance and Base Maintenance. Line maintenance is performed on the tarmac (at or near gate/terminal) on in-service aircraft. The performed tasks correspond to the lightest maintenance: transit checks and daily checks. Base maintenance is carried out in a hangar in an out-of-service aircraft and it includes any major aircraft modification or heavy maintenance. As the aircraft needs to be released from service, base maintenance is ideally uniquely carried out routinely at predefined intervals according to the airline maintenance program. Aircraft maintenance intervals are fixed due to strict regulations and rigorous safety standards. These hangar checks are usually named as letter checks: A-, B-, or C-checks, ordered from the lightest and more frequent to the heaviest and less frequent maintenance.

Letter checks intervals for the Boeing 787-9 in KLM E&M are shown in Table 2.1.

Interval Specification	A-Check	B-Check	C-Check
Flight Hours	[redacted]	-	[redacted]
Flight Cycles	[redacted]	-	[redacted]
Calendar Time	[redacted]	[redacted]	[redacted]
Number of Blocks	[redacted]	[redacted]	[redacted]

Table 2.1: Letter checks intervals for Boeing 787-9 defined by KLM E&M. Based in [18].

To ease planning, operators usually cluster maintenance tasks in blocks, which can be then assigned to letter checks. It should be noted that not every maintenance task has the same frequency. As it can be seen in Table 2.1, A-checks in B787-9 are composed of [redacted], meaning that maintenance tasks will not be the same in every block. [redacted]
Furthermore, maintenance tasks that are less time extensive compared to the letter checks are performed in line maintenance instead.

The grouping and assignment of maintenance tasks are carried out by the airline planning and scheduling department. Based on the flight schedules and the interval times defined by the maintenance program, this department schedules all maintenance checks such that all maintenance tasks are performed at the right time and the schedule does not exceed available resources and hangar capacity. In addition, it should be noted that maintenance scheduling is a highly dynamic process and the resulting maintenance schedule is constantly subject to changes.

Unscheduled Maintenance

Unscheduled maintenance raises from unusual or unforeseen conditions that are not related to the normal aircraft operation. A wide range of situations can occur during flight, such as bird strikes, hard landing, lightning strikes, turbulent air, etc. Depending on the component criticality, failure may produce a grounded aircraft until the fault is corrected. Some aircraft components are allowed to fail due to their redundancy as long as the crew is aware of the malfunction and a serviceability check is performed. However, the maintenance action can be deferred at most to the end of the interval specified in the Minimum Equipment List (MEL). This will be explained more into detailed in section 4.3.

2.3. Aircraft components

When a component receives maintenance, it is normally replaced by a spare part and the faulty component is either discarded or fixed. Aircraft components can be divided into three categories [6]:

- Rotables: these components can be tracked by a serial number that is assigned either by the airline or the OAM. Financially, they are the most expensive components and they are treated as assets by the airline. According to the life-cycle characteristics, rotables are considered to be infinitely repairable. This means that they will be included in the airline inventory until fleet retirement. Examples of rotables: aircraft engines, airspeed indicator, Flight Management System (FMS), etc.

- Repairables: they are untraceable as they do not have a serial number. Financially, they are also treated as assets by the airline, but their purchase price is less compared to rotables. From a life-cycle perspective, they can be reconditioned for a limited amount of times over a period which is lower than the fleet life. Examples of repairables: structural panels, Auxiliary Power Unit (APU) starter, fire detector, etc.

- Expendables: these components are untraceable too. From a financial perspective, they are normally considered as assets until they are installed in the aircraft. Their purchase cost is lower than repairables. These items are subject to only one use as the repair cost is usually higher than the cost of acquiring a new component. Examples of expendables: lamps, filters, fasteners, seals, etc.

3
Prognostics

Before reviewing the literature in maintenance scheduling with prognostics, it is important to have some insight into prognostics and its potential uses. This chapter elaborates on the definition of prognostics and its main algorithms and it concludes with a summary of the main benefits that prognostics can have for the airline industry.

3.1. Prognostics and Health Management (PHM)

Prognostics and Health Management (PHM) is a new engineering approach for systems health assessment. It is based on real-time operational information and the prediction of the system's future state based on sensor data [34]. It is generating high interest in maintenance scheduling and planning research due to its promising potential to replace traditional maintenance strategies, like corrective and preventive maintenance, with more advanced maintenance strategies, such as Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM).

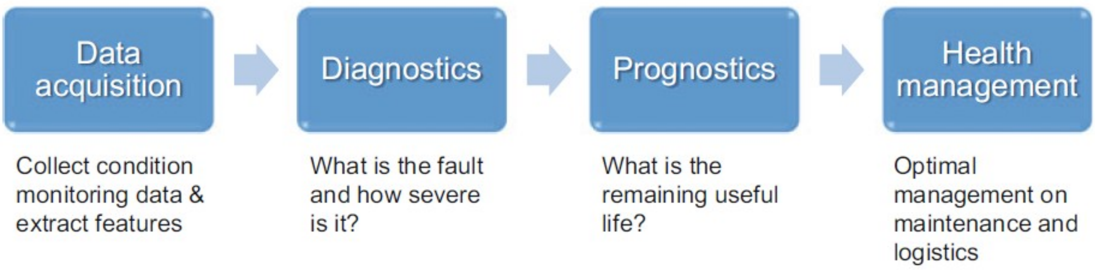

Figure 3.1: Main steps of PHM. Adopted from [34]

Figure 3.1 shows the main steps in PHM. The first step is data acquisition. It consists of collecting and processing sensor data to detect patterns and features. The next step is diagnosis, in which the fault for any anomaly is found and it is identified how severe it is compared to a failure threshold. The third step is prognostics, in which time to failure predictions are estimated. The last step is health management and it intends to optimize maintenance based on diagnosis and prognostics information.

3.2. Prognostic algorithms

Prognostics algorithms can be categorized as experience-based, data-driven and physics-based.

Experience-based prognostics

Experience-based prognostics is not usually considered in the existing literature. However, some publications [23, 65] include it as another category.

Experience-based prognostics makes use of experience feedback data collected during a substantial time (such as failures times, repair times, etc.) to tune the parameters of an assumed reliability model (like exponential, Poisson, Weibull, etc.) [65]. The most widely used model is the Weibull distribution as it can successfully represent several phases of the component's life [57].

This approach is easy and cheap to implement. However, experience-based methods are not suitable if there is not a significant amount of feedback data (like in new systems). Also, the resulting prognostics information is less accurate than the results obtained by physics-based and data-driven methods [65]. Therefore, this approach is not recommendable for systems were prognostics information is crucial.

Physics-based prognostics

This approach assumes that a physical model that describes the system's degradation is available. Then, the model is combined with sensor data to estimate the physical model parameters. Due to noise data and uncertainty in the operating conditions, most of the algorithms tune the model parameters using probability distributions [34]. The obtained model can be then used to make predictions about the component's behavior.

The main advantage of physics-based algorithms is that their results are usually intuitive as they are based on physical phenomena, which makes it easier for verification and validation. Besides, the model can also be easily adapted for small changes in the system. Nevertheless, this approach requires a high understanding of the system since the model needs to capture its physical behavior. If any major phenomenon is forgotten or misunderstood, it can fail to make accurate failure predictions.

Data-driven prognostics

It consists of estimating the future trend of the component degradation based on past and currently collected data. Consequently, data-driven approaches require extensive data collection to account for all possible modes of failure as a function of the current state.

This method does not require any physical knowledge; therefore, its results do not need to be compliant with any physical behavior. However, this also has risks as it involves accepting a result that may not be intuitive due to the ignorance of the physics behind the problem. According to literature, [4, 8, 34, 73] data-driven algorithms can be classified into two groups: machine learning approaches and statistical approaches.

Machine learning approaches make use of a training dataset for the learning process and a test dataset for model verification. In literature [4, 8, 73], the most used Machine learning algorithms are Artificial Neural Networks, Support Vector Machine, Bayesian methods, and Markov models.

Statistical approaches estimate the degradation and the Remaining Useful Life (RUL) of a component using monitoring data and a probabilistic model. The data is firstly fitted into the model and then, the tuned model can be utilized to determine the future degradation trend.

Prognostics Algorithm	Advantages	Disadvantages
Experience-based	· Easy and cheap implementation	· A large amount of data is needed, not suitable for new systems · Less accurate than physics-based and data-driven approaches
Physics-based	· Intuitive output · Easy adaptation to system small changes	· Requires high understanding of the system · Inaccurate predictions if any major phenomenon is forgotten or misunderstood
Data-driven	· Accurate · Does not require physical system understanding	· A large amount of data is needed, not suitable for new systems.

Table 3.1: Summary of advantages and disadvantages in prognostics algorithms.

Hybrid prognostics

It also exits the possibility that different prognostics algorithms can be combined at the same time. These are called hybrid prognostics and they aim to include the advantages of the different prognostics approaches while minimizing their limitations. All the different combination possibilities that can be found in the literature are summarized in Figure 3.2.

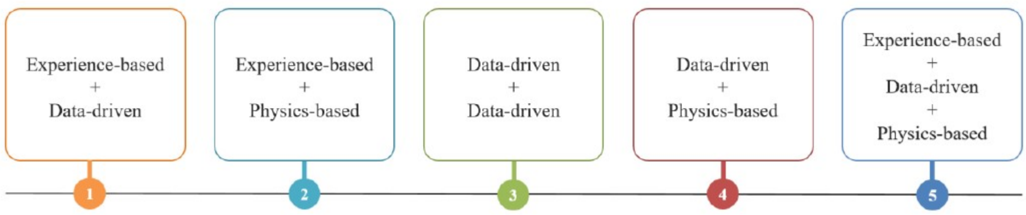

Figure 3.2: Hybrid approaches possibilities. Adopted from [8]

3.3. Prognostics benefits from a Predictive Maintenance perspective

As it was mentioned in the first section, PHM is gathering great interest in maintenance operations research due to its promising potential to replace traditional maintenance strategies (like corrective and preventive maintenance) with more advanced maintenance strategies, such as CBM and PdM. PdM is a strategy that forms part of CBM, and it aims to predict failures before their occurrence, meaning that prognostics is indeed the key input for PdM. When comparing PdM with corrective and preventive maintenance, the advantage of PdM lies in the more extended use of the component useful life while avoiding unexpected failures and their related downtime costs [34]. In this way, PdM can combine the advantages of corrective and preventive maintenance while minimizing costs, as observed in Figure 3.3.

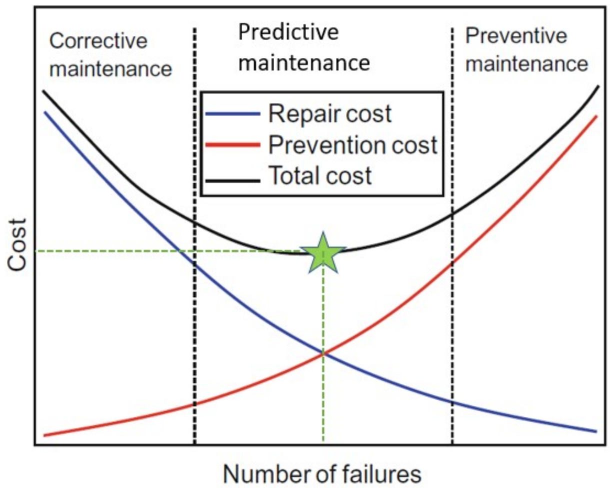

Figure 3.3: Maintenance strategies versus cost. Based on [34]

PHM solutions have already been implemented in several industrial fields giving optimistic results. In the United Kingdom, the Civil Aviation Authority (CAA) developed a Health and Usage Monitoring System (HUMS) that measured the health and performance of helicopters [41]. As a result, the helicopters' accident rates were reduced by more than one half. To illustrate the economic impact of PHM, another study sponsored by the National Science Foundation was carried out in five companies where a PHM solution had been implemented in their products. Total savings of around 855M $ [38] were reported due to failure avoidance and productivity and efficiency enhancement, among others.

In the airline industry, new aircraft generations are increasingly being equipped with sensors to monitor the health state of their systems and components. Moreover, these new generations (such as the B787, A350, and Embraer E2) are being "e-enabled" by incorporating systems that allow the automatic communication with ground-based stations of operators and Air Traffic Service (ATS) providers. Examples of these systems include the Aircraft Communication Addressing and Reporting System (ACARS), Broadband Satelite Communications, Terminal Wireless Local Area Network Unit (TWLU), Crew Wireless Local Area Network Units (CWLU), etc. [50]. The combination of these two factors offers the possibility of accessing to an enormous amount of valuable data, which is indeed the main enabler of the current state and future development of predictive maintenance in the airline industry.

The potential benefits of the use of prognostics in the airline industry have been already studied. Overall, it can be said that prognostics can improve airline operating costs [1], more specifically it reduces maintenance and irregular operations costs.

Firstly, prognostics allows for a more effective component maintenance planning by reducing the number of unscheduled events and their related costs [28, 37, 48]. In Europe, 5.8% of the flights are delayed due to technical issues and consequential delays in subsequent flights [29], which is commonly named as the "snowball effect". The associated yearly costs are estimated to be as much as 2.8B € in the European airline industry. Reducing the percentage of technical induced disruptions can save costs up to 334M € per year while reducing the delays from 2 to 4 minutes would represent a yearly cost reduction of up to 396M € [29].

Besides, prognostics enables to decrease the costs of repair activities by replacing components at a lower degradation level and avoiding major repairs [22, 67]. Diagnosis and prognosis also allow for easier fault troubleshooting [28, 36], which together with less major maintenance activities, can reduce maintenance times [48]. Consequently, aircraft availability is increased, which could even lead to more extensive aircraft utilization. According to the Clean Sky 2 Technical Program [29], the benefit of prognostics in aircraft utilization would produce a profit increase of up to 200M € per year in European carriers.

[1] According to IATA [7], an airline operating costs include Planning, Crew, Maintenance, Airport Services, and Irregular Operations costs

Lastly, applying prognostics in MRO activities also yields economic benefits. Prognostics in supply chains enables the prediction of spare parts demands which helps to avoid stock-out costs [25, 32]. L. Li et al. [39] and N. H. Kim et al. [34] found that supply chains with prognostic information were more efficient in planning as they could react more proactively considering demand forecasts provided by prognostics. Similarly, E. Topan et al. [66] found out that the use of imperfect advance demand information in inventory supply decisions could yield substantial savings. Also, J.P. Sprong [64], carried out a single-component case study in KLM E&M and estimated that supply chain costs could be reduced by 20% with a proactive supply chain that made use of prognostics. Furthermore, G. Nicchiotti et al. [48] and J.P. Sprong [64] found out that it was easier for supply chain departments to reach the desired service level due to the reduction of repair times with the use of prognostics. According to Little's Law [44], a reduction in repair times could also imply a reduction in the inventory levels. This can be explained as follows; the necessary inventory to fulfill the demand of spare parts can be estimated with Little's Law [44].

$$L = \lambda \cdot W \tag{3.1}$$

Where L is the necessary inventory, λ is the component removal rate and W is the average Turn-Around Time (TAT) or time to repair. Based on this expression, it can be deduced that provided the component removal rate is not increased as much as the decrease in TAT, a reduction in repair times (or TAT times) also implies a reduction in the inventory levels.

However, it should be noted that the potential benefits that the use of prognostics can have are dependent on a great variety of factors. According to M. Roemer et al. [55], prognostics accuracy, or degree of closeness to the true remaining useful life value, is the most important factor in determining the benefits of prognostics. N. Hözel et al. [27] identified additional elements affecting the potential benefits, such as operational constraints and the influence of a component in the system's reliability and safety. For this reason, the advantages of the implementation of prognostics are not the same for all systems; they are subject to the system itself and its operational constraints and specifications.

4

Maintenance Scheduling Modeling

This chapter elaborates in the state-of-the-art of academic research in the field of component maintenance scheduling with prognostics and resources availability. It includes how prognostics and availability of resources were modeled, component criticality issues that were considered, and the objective functions and main solution approaches for optimization.

4.1. Prognostics

Prognostics has been already addressed in academic research about maintenance operations. However, as the integration of sensors in components for health monitoring is an expensive technique and access to data has strict barriers, some studies propose degradation models that do not make use of sensor data. In these studies, maintenance is triggered when the degradation level reaches a given predefined threshold. The most common degradation models are Wiener [12, 22, 46] and Gamma process [60]. Moreover, other studies utilize historical failures to find the best fit of a predefined reliability model that describes the failure probability at different times. The most common reliability model is the Weibull distribution [9, 16, 54] as it can be used for all phases of the component's life [57]. Also, W. Wang [70] assumed a Homogeneous Poisson Process (HPP) to model the failure probabilities of components as it was proven that when the number of identical components was large, the failure times were approximately exponential, and they could be therefore described with an HPP.

The problem that arises when sensor data is not used is that the prognostics may fail to describe the component's actual behavior in its operating conditions. Consequently, these models would not be suitable to be used in a real industrial application.

Focusing on the modeling of prognostics in literature, three different possibilities can be found: RUL prognostics, component state transition probability, and classification prognostics.

4.1.1. RUL prognostics

In most of the studies that make use of prognostics in maintenance scheduling, the used prognostics is the component's RUL given as a probability distribution. In these models, the expected value of the RUL is used as the main input for the scheduling task. Nevertheless, there are three main trends to take prognostics inaccuracies into account.

The first one is to include a constraint in the model that restricts the maximum allowable risk of system failure [20, 40, 42, 43, 74]. More specifically, Q. Feng et al. [20] considered a fleet of 10 aircraft containing each 4 Line Replaceable Module (LRM) components. For each component in every aircraft, there was information about its health status in the form of component failure probabilities. The aircraft was considered to fail when any of the LRM failed, and it was decided that the failure probability should not be more than 10^{-8}.

$$P_i = 1 - \prod_{j=1}^{4} [1 - p_{ij}] < 10^{-8} \quad \forall \quad i \in I \tag{4.1}$$

The second one is to include the risk of failure in the objective function [13, 54, 68]. L. Ramos Rodrigues et al. [54] developed a maintenance scheduling model for aircraft bleed air systems that included the probability of aircraft failure times the costs that aircraft unavailability would imply, named as cost of aircraft on ground. It is worth mentioning that the used PHM algorithm to find the failure probability distribution was based on the study carried out by Gomes et al. [24]. It consisted of finding the least square regression of the component's degradation indexes 30 days before failure. Then, failure times were Monte Carlo simulated (assuming that the time of failure is when the degradation index was equal to 100%) and fitted into a Weibull distribution to find the failure probability distribution.

The last possibility to account for prognostics inaccuracies was presented by J.I. Aizpurua et al. [3]. In their study, the deterministic RUL estimation was diminished with a safety factor to account for the time needed to trigger maintenance and for prognostics uncertainties. It was determined that a conservative value was desired to avoid component failure. Therefore, the worst-case scenario was assumed by estimating the safety factor as the sum of the confidence interval and the maximum time to trigger maintenance. A comparable approach was followed by Y. Wang et al. [71]. They used the mean (μ) and the standard deviation (σ) of the component's RUL prediction to find the maintenance execution window for each component. The interval was chosen to be the 95% Confidence Interval, $[\mu - 2\sigma, \mu + 2\sigma]$.

4.1.2. State transition probability

Other studies do not have an estimation of the RUL but use as prognostics input the transition probabilities from a "healthy" or "degraded" state to a "failed" state according to the component current degradation level [9, 47, 68]. In this literature, a Markov Decision Process (MDP) is used to find the optimum action at each state. As the transition probabilities are dependent on time and the previously chosen actions, MDP is a dynamic optimization technique that uses a rolling horizon to find the optimal actions for each state. M. Baars [9] and K. Verbert et al. [68], considered as available actions either "To maintain" or "Not maintain" a component, while K. Nguyen et al. [47] and X. Yao et al. [75] included two more actions; "Order spares" or "Not order". MDP will be explained more into detail in Section 4.5.

4.1.3. Classification prognostics

Finally, there is also the possibility that prognostics have a classification (or binary) format. A. Engelke [19] developed a Monte Carlo Tree Search optimization model that used as input whether a component would fail in 10 days. Prognostics uncertainties were considered by using the Negative Predictive Value (NPV) and the Positive Predictive Value (PPV) of the prognostics tool as punishments factors in the Monte-Carlo Tree Search. In this way, component schedules that had a low PPV (lower than 50%) and a high NPV (higher than 50%) were punished. The confusion matrix and the definitions of NPV and PPV are as follows:

	Prediction outcome	
True outcome	**Positive** (Fault)	**Negative** (No fault)
Positive (Fault)	True positive (TP)	False negative (FN)
Negative (No fault)	False positive (FP)	True negative (TN)

Figure 4.1: Confusion matrix for binary classification prognostics. Adopted from [36]

$$NPV = \frac{TN}{TN + FN} \qquad PPV = \frac{TP}{TP + FP} \tag{4.2}$$

I. Van den Hof [67] and J. Sprong [64] carried out academic studies in KLM E&M with an alike prognostic input to the one considered by A. Engelke [19]. The prognostics used were predictive maintenance alerts in aircraft components. When a component was alerted it meant that the component would fail in a predefined Prognostic Horizon (PH) with a given probability equal to the prognostic tool accuracy. The PH is defined as the time from the failure prediction until the time of expected failure (see Figure 4.2). The prognostic tool also had a given sensitivity and precision. Sensitivity is defined as the percentage of total failures that the prognostic tool can successfully detect, meaning that the rest of the failures will occur without previous detection. Precision is the probability that a predictive alert truly results in a fault found event (true positive). The expressions for accuracy, sensitivity, and precision are presented in Table 4.1

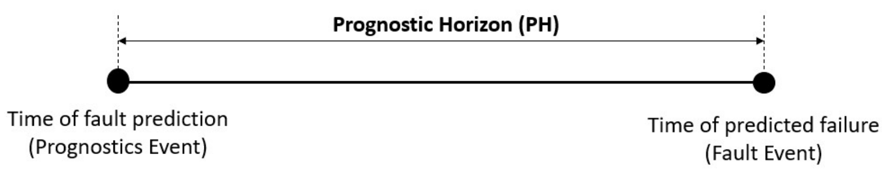

Figure 4.2: Prognostics Horizon definition. Based on [31]

Metric	Accuracy	Description
Accuracy	$Acc. = \frac{TP+TN}{TP+TN+FP+FN}$	Correct predictions to all predictions
Sensitivity or recall	$Sens. = \frac{TP}{TP+FN}$	Correct hits to real positive cases
Precision	$Prec. = \frac{TP}{TP+FP}$	Correct hits to positive predictions

Table 4.1: Prognostics Metrics in [67] and [64]. Based on [36]

The prognostics metrics are a function of the PH. K. Verbert et al. [68] and A. Kählert [36] already stated that the prognostics accuracy increases for lower PH, or what it is the same, for closer times to failure. If early replacements are performed, the risk of Not Fault Found (NFF) events increases (due to lower precision) as the degradation level cannot be properly confirmed [36]. However, late predictions also lead to a high risk of unscheduled failure, therefore a trade-off between prognostics accuracy and timeliness must be made [68].

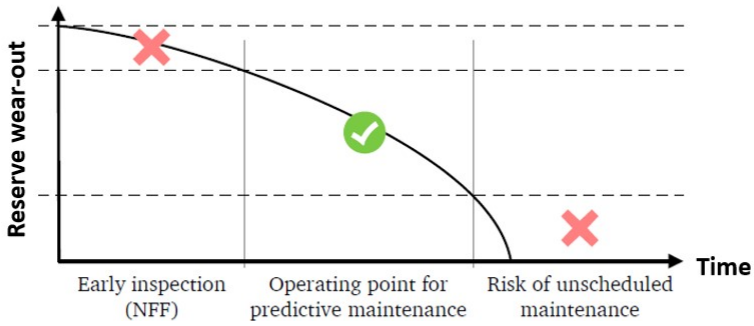

Figure 4.3: Optimum operating point for Predictive Maintenance as a function of PH. Adopted from [36]

I. Van den Hof [67] defined 4 different maintenance scheduling policies for k-out-of-N components (e.g. replacement when there is one damaged component, repair when at least 2 out of 4 components are damaged, etc.) and analyzed the effect of various PHs and prognostics sensitivities in the policies' output with discrete simulation techniques. However, the study did not develop an optimization model for components maintenance scheduling but instead defined 4 different policies to explore the potential benefits of using prognostics in maintenance scheduling.

4.2. Resources availability in maintenance scheduling

This section presents the existing research in maintenance scheduling that considers spare parts and maintenance slots availability.

4.2.1. Spare parts availability

Infinite availability of spare parts is a usual assumption in most of the studies dealing with maintenance scheduling, even though it is an essential factor to be considered in airline maintenance planning. W. Olivares et al. [69] modeled expendables spare parts availability as a cost factor in the objective function. When no spare parts were available for replacement, the next flight would be canceled, so cancellation costs were added to the objective function. C. A. Irawan et al. [30] also considered expendable spare parts availability in different time slots through a binary variable (1: if spare parts were available, 0: otherwise). Only time slots with available spare parts were considered as a feasible solution for the optimization problem. Furthermore, J. Cai et al. [12], W. Wang et al. [70], and Q. Liu et al. [45] solved the spare parts availability problem by coupling the optimization of maintenance intervals and spare parts inventory.

However, none of these studies considered repairable spare parts. In this case, components which are removed from the aircraft are transported to a repair shop where they are fixed. A new component is placed in the aircraft provided there are available spare parts in the warehouse or logistics pool. Otherwise, the replacement will not be performed until a component is fixed in the repair shop, or until it is purchased or leased from an external contractor.

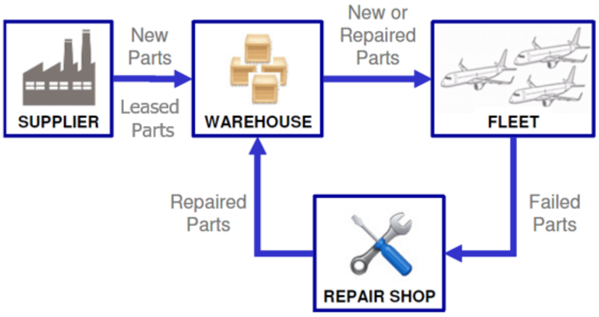

Figure 4.4: Supply chain of repairable components. Based on [53]

L. Ramos Rodrigues et al. [53] considered repairable spare parts in a maintenance scheduling model with prognostics input. An initial maintenance schedule was obtained according to the predicted RUL and a second optimization was performed to avoid stockout of spares. The overlaps in the expected repair times (or expected amount of components in the repair shop) were counted, and it was assured that this number never exceeded the spare part level by shifting maintenance actions to earlier times. Note that the time from component removal, until it comes back to the available inventory, should account for removal, shipping, and repair times. However, L. Ramos Rodrigues [53] and I. Van den Hof [67] considered that the time off-wing was only given by the repair TAT, which is usually contracted through a Service Level Agreement (SLA).

4.2.2. Maintenance slots availability

The great majority of studies aiming to optimize maintenance scheduling with prognostics assume that maintenance capacity is unlimited and that replacements can be therefore performed at any time. Only a few works of literature consider maintenance slot availability as input. Slots have been included in two different ways in literature: as hangar available slots [19, 22], or as maintenance opportunities between missions [15, 74].

In the maintenance scheduling process of a real airline, considering only hangar available slots is not enough; aircraft-specific maintenance opportunities need to be considered as well. The operating schedule of an aircraft provides the times when the aircraft will be on the ground and, therefore when maintenance can be scheduled. The problem is that tail numbers are assigned to a schedule only a few days before the operation, consequently it is almost impossible to determine the exactly available maintenance opportunities beforehand. Most airlines have different rotation schemes where aircraft are planned. They operate with this expected operating schedule and use the rotation scheme as a baseline to reassign tail numbers if an unexpected event occurs. To deal with this problem, M. Baars [9] used all the different rotation schemes as input to find a heuristic solution for the problem. Another approach would be to find the general maintenance schedule that accounts for all possible operating schedules in the rotation scheme. Nevertheless, this approach was too complex and it was left out of the scope of the project.

4.3. Component Criticality

Critical components are usually redundant in aircraft so that a single component failure does not result in a nonoperational aircraft. They are usually labeled as k-out-of-N components, which means that the aircraft is operational if from the N total number of components, at least k have not failed. When the number of failures is equal to $(N-k)$, the system may be still be operated during a time interval defined by the Minimum Equipment List (MEL). This document is created by the operator based on the Master Minimum Equipment List (MMEL) approved by the CAA (European Aviation Safety Agency (EASA) in Europe), by considering the operator's particular aircraft equipment and operational conditions [1]. The MMEL distinguishes four different component categories according to their rectification intervals.

Category	Rectification Interval
A	Instant
B	Within 3 calendar days, excluding the day of discovery
C	Within 10 calendar days, excluding the day of discovery
D	Within 120 calendar days, excluding the day of discovery

Table 4.2: EASA MMEL rectification intervals. Adopted from [1]

In literature, there is some research about the maintenance optimization of k-out-of-N systems that consider repairable spare parts [61–63]. A single system is considered in all of them, meaning that fleet-level optimization is not part of the scope, which is not the case for this study. Besides, prognostics is not considered either. Nevertheless, there are three main aspects which are very relevant for this research.

The first one is when to initiate maintenance. The system is still operational when $N-k$ failures have occurred. Nonetheless, it is also possible to initiate maintenance when $m \leq N-k$ components have failed to prevent system downtime if one additional failure occurs. K. Smidt-Destombes et al. [61], proposed a model that initiated maintenance when $m=N-k$ components had failed due to the high maintenance set-up costs. However, A. van Harten et al. [62] and M. van der Heijden et al. [63] stated that the minimum number of failures to initiate maintenance also depends on the time needed to trigger maintenance. If this time was equal to 0, then maintenance was triggered when the system was inoperable, $m=N-k+1$. However, when the time to trigger maintenance was greater than 0, it was compared to the expected time of system failure to decide on the right failure level to initiate maintenance, $m<N-k+1$.

The second relevant aspect that is worth mentioning is how many components should be replaced in a maintenance slot. At the time of maintenance, all failed components could be replaced, just the right amount to recover the system operation, or an amount in between these two values. K. Smidt-Destombes et al. [61] and M. van der Heijden et al. [63] considered that all failures should be replaced at the time of maintenance. If the number of spares was not enough, then maintenance had to be delayed until enough spares were available. Nevertheless, A. van Harten et al. [62] estimated that only the right amount of failures to recover system operation had to be repaired.

The last relevant factor is the priority replacement rules for degraded and failed components. K. Smidt-Destombes et al. [61] and M. van der Heijden et al. [63] considered only failed and healthy components, but A. van Harten et al. [62] also included components in a degraded state. In maintenance slots when both degraded and failed components could be found, priority was given to degraded components rather than already failed components as the required repair times were smaller. Moreover, when the number of degraded components was not sufficient to recover the system's operation, some failed components were repaired as well.

4.4. Objective functions for maintenance scheduling

Regarding single-component or multi-component scheduling, some studies have only focused on finding the optimal replacement intervals of single components with prognostics information [9, 12, 45, 54, 60, 70]. Nevertheless, to develop a reliable maintenance schedule, it is necessary to optimize maintenance from a fleet-level that incorporates all other aircraft and components in the fleet. In this way, it is ensured that resources stock-outs are avoided.

In existing literature, the most common objective is to find the optimum maintenance time [9, 19, 46, 60, 69, 74], time and action [54, 68], or even time and spare part orders [12, 45, 70, 75], that reduces maintenance costs (e.g. [3, 9, 13, 19, 31, 36, 46, 47, 49, 54, 60, 69], etc.) or maximizes the revenue [22]. It is also possible that instead of minimum costs or maximum revenue, the objective function is to maximize aircraft availability [53], minimize the unused maintenance capacity [40] or even a twofold objective, such as minimum cost and maximum availability [42, 43, 45], or minimum cost and repair frequency [74].

Focusing on the maintenance costs factors, two categories can be defined: indirect and direct maintenance costs [33]. Direct Maintenance Costs (DMC) are related to the costs of labor and material which are expended in the component replacement. Indirect Maintenance Costs (IMC) refer to all other costs that cannot be assigned to a maintenance activity, such as facilities, tools, administration, the keeping of records, etc. As this research focuses on comparing the costs of component maintenance in different maintenance slots, IDM will not be further discussed.

In existing literature with a minimum cost or maximum revenue objective function, the most common DMC factors can be divided into six different categories.

The first one is the life-average costs [19, 68, 71], also called preventive removal costs by W. Vianna et al. [69], or utilization costs by M. Baars [9]. This category refers to the costs related to the unused RUL of the component. Therefore, maintenance repairs that are close in time will have a higher life-average cost (see Figure 4.5). This cost factor also helps to reduce the repair frequency, which can also have a detrimental effect on the repair shop labor workload. K. Verbert et al. [68] defined it as:

$$C_{av.life}(t) = \frac{C_m}{t - t_{mnt}}$$

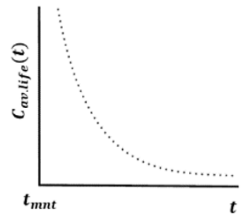

Figure 4.5: Average-life costs. Adopted from [68]

Where C_m is the total cost of performing maintenance and t_{mnt} is the time when the previous maintenance action was carried out.

The second one is the repair costs. They represent the actual costs to bring a component to a reliable and safe condition. In this research, perfect repairs are considered, meaning that component condition after the repair is “as-good-as-new”. In some studies, it is considered that the repair costs per replacement are fixed [20, 53]; however, some others assume that the repair costs are a function of the component degradation level [22, 42, 67, 69]. In this way, longer maintenance intervals have higher repair costs as the component damage level is greater. I. van den Hof [67], defined major and minor repair costs depending on which moment after the Prognostics Event (predictive alert) the component replacement was carried out.

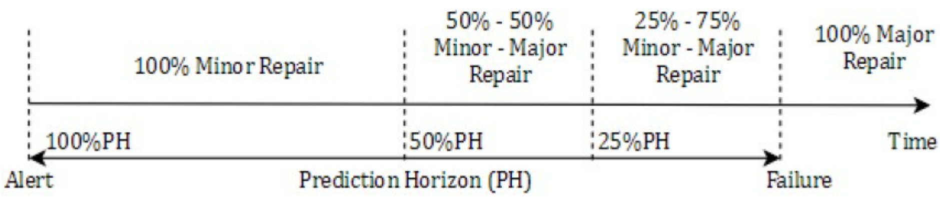

Figure 4.6: Repair costs as a function of PH. Adopted from [67]

H. Ghamlouc et al. [22], accounted for the increase in repair costs for higher degradation levels by considering two scenarios: component failure occurring after the considered maintenance time, and the component failure happening before maintenance. The expected maintenance repair cost was estimated by adding the expected costs of both scenarios times their probabilities.

$$\mathbb{E}[C_{repair}(t_k)] = P(T_{fail} > t_k) \cdot C_{preventive}(t_k) + P(T_{fail} \leq t_k) \cdot C_{corrective}(t_k) \tag{4.3}$$

Where t_k is the time of the considered maintenance slot, $C_{preventive}(t_k)$ is the expected preventive repair cost at maintenance slot t_k, and $C_{corrective}(t_k)$ is the expected repair cost at maintenance slot t_k due to early failure.

The third type of DMC is costs related to risk [9, 22, 68]. They refer to the increase of the component failure probability for later maintenance times. It is generally defined as the probability that the component failure occurs before the considered maintenance slot multiplied by the additional costs related to the component failure.

$$\mathbb{E}[C_{risk}] = P\big(T_{fail} < t\big) \cdot C_{failure}$$

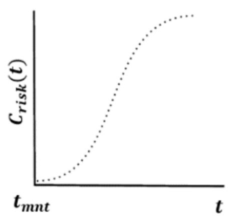

Figure 4.7: Risks costs. Adapted from [68]

The fourth category is the stock-out costs, which are defined as the costs incurred due to lack of resources available, such as spare parts or maintenance technicians [15, 53]. They are generally modeled as stock-out costs per unit time multiplied by the expected time until the resources are available again.

$$\mathbb{E}[C_{stockout}] = C_{stockout} \cdot \mathbb{E}[t_{stockout}] \tag{4.4}$$

The fifth type is the failure costs [9], which represent the costs derived from the operation under failure conditions. Some non-safety critical components do not cause an AOG event when a failure occurs provided they are replaced within the interval specified in the MEL. In the time interval ranging from the component failure to the end of the MEL interval, the aircraft can be still operated, but at higher operation costs. These costs can comprise a wide range of sources, such as extra fuel costs, or costs due to additional degradation in other dependent components. W. Olivares et al. [69] estimated the additional operational costs within the MEL interval as follows:

$$C_{MEL} = C_{op} \cdot (t_{repair} - t_{event}). \tag{4.5}$$

Where C_{op} is the additional operational cost per time, t_{repair} is the time of repair and t_{event} is the time of MEL interval start.

The last cost category is the spare parts leasing costs. Spare parts insourcing is normally a rare technique due to its high costs however, it is an option that should be considered in a maintenance scheduling model with spare parts availability input. I. van den Hof [67], allowed only spare parts leasing when there were no spare parts available and the MEL deadline was violated. The leasing costs were estimated to be 10% of the component purchase price.

4.5. Solution Approaches

Different approaches have been followed to solve aircraft maintenance optimization problems with component diagnosis and prognostics inputs. A summary of the most used frameworks that can be found in this section.

4.5.1. Markov Decision Process (MDP)

The first main solution approach is the Markov Decision Process (MDP). MDP is a powerful tool for solving sequential optimization problems in multiple random decision epochs [14]. This algorithm is very quick and elegant if the process can be properly described by a set of well-defined states. Under each state, there is a set of different actions that can be chosen, and the decision influences the transition probability from one state to another. For higher complexity processes with difficult state definition, this approach becomes inefficient. For this reason, the found studies that utilize MDP are applied at a single component-level optimization [9, 68, 75] with reduced and well-defined state and action spaces.

M. Baars [9] defined the state space only as three possible component conditions: nominal operation, anomaly detected or failed component. Nevertheless, K. Verbert et al. [68] also included information regarding the cost associated with the maintenance strategies and whether previous maintenance had been planned. The possible actions in both studies were either ”To Repair” or ”Not Repair” a component. X. Yao et al. [75] combined the optimization of inventory stock and maintenance schedules. Therefore, the state space also included information about the inventory level and the number of periods for which a component had been in the same state. In this case, the possible actions were either ”To Repair” or ”Not Repair” a component and either ”To order” or ”Not order” a spare part.

In terms of solution methods, X. Yao et al. [75] and M. Baars [9] used the value iteration algorithm to solve the MDP. This approach is efficient for problems with a finite number of states and actions per state as it can easily converge to the optimal solution. However, dynamic optimization or reinforced learning methods are more suitable for problems with a higher complexity. K. Verbert et al. [68], used dynamic optimization as the reward and the state transition functions were known. However, it was suggested that if the reward function or the transition probabilities were unknown, reinforcement learning was desired to cope with the uncertainty.

4.5.2. Large Neighborhood Search (LNS)

The second solution framework that will be analyzed is Large Neighborhood Search (LNS). LNS is a meta-heuristic algorithm that was firstly introduced in the context of Vehicle Routing [59], but in recent years it has become a popular method for solving transportation and scheduling problems [52]. The general idea behind LNS is to build an initial feasible solution and then gradually improve it by ”destroying” and ”repairing” different parts of the current solution. The set of the found solutions is named as the neighborhood of the current incumbent solution. Therefore, the LNS algorithm can be divided in two stages: the initial solution stage, and the improvement solution stage.

In the first stage, an initial feasible solution is found. This solution needs to fulfill all the constraints, but it does not need to be particularly good regarding the objective function value. The improvement stage is defined by three steps. The first one is the destruct process, in which a part of the incumbent solution is fixed while the rest is released. The second step is the repairing process, in which the new values for the variables that were released in the previous step are found. The last step is the acceptance rule, in which it is determined if the found neighborhood solution is accepted or rejected. To avoid getting trapped in local optimal, some authors recommend to avoid accepting only improving solutions. For example, [51, 52] accepted all improving solutions and used a simulated annealing approach to define the probability that a worse solution was accepted.

The three steps in the improvement solution stage are repeated until the stopping criteria is met. It can be defined in multiple ways, such that a maximum number of iterations [51] or time [11], or maximum number of iterations without solution improvement [17].

A critical step in LNS is the neighborhood definition. The larger the neighborhood is, the longer it takes to find the local optimum in each iteration, but the greater the quality of the local solutions and the accuracy of the final optimal solution are [2]. For this reason, in combinatorial problems with a high number of different possibilities, the neighborhood is usually delimited. More specifically, L. Ramos Rodrigues et al. [54] proposed a neighborhood definition by means of one of the following functions: *swapping* the maintenance execution times of two different tasks, or *shifting* all possible maintenance tasks to every available maintenance time.

Traditional LNS usually defines a unique ”destroy” and ”repair” strategy to be used in all the iterations. However, this approach may lack robustness as it may not be able to adapt to different solution characteristics. For example, some ”destroy and repair” methods can have a good performance in the first iterations of the search, while they can have a very poor one at later iterations. For this reason, S. Ropke et al. [51] proposed a heuristic named as Adaptive Large Neighborhood Search (ALNS) for the pick up and delivery problem with time windows. This heuristic is composed of a number of competing sub-heuristics (”destroy and repair” methods) which were used with a frequency based on their historic performance. In this way, ALNS has certain intelligence as the best performing sub-heuristics are selected more often. After each iteration, the ”destroy and repair” methods were given a score depending on the quality of the found solution. For example, different scores were granted to new best global, non-improving but non-visited, or already visited solutions. In order to select the ”destroy and repair” method, S. Ropke et al. [51] and A. Hottenrott [26] proposed a roulette-wheel selection principle.

4.5.3. Genetic Algorithm (GA)

The third and last solution approach that will be analyzed is the Genetic Algorithm (GA). It is another optimization strategy that has also been widely used to solve complex non-linear and NP-complete combinatorial problems, resulting in acceptable solutions [58]. GA is a meta-heuristic algorithm based on Darwin's evolution theory. It starts with an initial population of solutions and each member is evaluated by means of an objective function. In each iteration, a random population is selected with a bias on the best solutions and genetic operations (crossover and mutation) are applied. The stopping rule in GA can be set as a maximum number of iterations without cost improvement, maximum computation time or maximum iteration number.

Do et al. [15], optimized maintenance grouping of tasks with repairman availability input using a GA. The initial tentative planning was generated by optimizing component-level maintenance. Then, the first population of solutions was created by generating random groups of maintenance activities. For each solution that violated the repairmen's capacity constraint, the solution was adjusted to recover feasibility by either shifting maintenance activities or hiring more repairmen. This research also proposed a ”linear ranking selection” algorithm, based on J. Baker [10], to select pairs of parent solutions for the Crossover phase such that fitter solutions had a higher chance to be chosen as a parent.

It should be noted the Crossover operation differs for every problem, but the most usual are the single-point crossover and two-point crossover [15, 20, 72]. Also, Mutation operation is usually added to GA to prevent the algorithm to fall into a local extreme. Nevertheless, the mutation probability is normally set to a very low value such that the GA does not convert into a random search.

4.6. Summary of the most important literature

An overview of the existing literature in maintenance scheduling with prognostics that can be used as a starting point in this research is summarized in the next table.

Ref.	Year	Prognostics	Prognostics uncertainty	Spare parts	Maint. Slots	Obj. function	Solution method	Field of study
[22]	2019	Assumes a Wiener-based stochastic process to simulate degradation (from 0 to 1). RUL estimation is the expectation of the empirical distribution of the first hitting time (degradation = 0.65) calculated with Monte Carlo simulations.	Includes a probability of failure before and after maintenance in the obj. function.	No	Hangar maintenance slots equally separated in time.	Maximum revenue	Monte Carlo simulation	Wind turbines
[54]	2015	Obtains a degradation function by least-squares, then uses Monte Carlo simulations to generate times to failure (degradation=100%) and assumes Weibull distribution. RULs computed by inserting time in CDF.	Includes the probability of system failure in the obj. function.	No	No	Min total expected cost of repair	LNS. Initial solution according to the ”efficiency of the trouble-shooting task”. Swap two tasks and shift one task neighborhood delimitation.	Line maintenance
[42]	2017	Uses an Artificial Neural Network and a crack growth model (data-drive and physical) to estimate the failure probability.	A constraint in the maximum allowable failure probability. It must be less than 10e-7.	No	No	Min cost (repair and remaining useful life waste) and max availability (minimize the number of times repairs overlap).	Non-dominated sorting GA.	Aircraft structures
[20]	2014	The prognostics input is RUL for each component given as a probability density function.	Two constraints in the maximum allowable risk: mission risk (any aircraft fails) and security risk (individual aircraft fails)	No	No	Minimum cost	Improved GA.	Commercial Airline
[68]	2017	The degradation process model is constructed by mixing all possible fault degradation models. Failure occurs when degradation reaches a threshold. The failure time can be estimated as a probability density function.	Considered in component-level optimization by including the probability of failure before maintenance in the obj. function.	No	No	Two-stage optimization: -Component-level: delay or repair decision based on min. cost (direct, indirect and risk costs). -System-level: maintenance time for min. system downtime.	-Component-level: MDP -System-level: Not stated but suggests that pattern search heuristics or evolutionary algorithms could be used.	Railway network

Table 4.3: Summary of most important literature (part 1)

Ref.	Year	Prognostics	Prognostics uncertainty	Spare parts	Maint. slots	Obj. function	Solution method	Field of study
[19]	2019	Classification prognostics input. {1: predicted failure in 10 days, 0:no predicted failure in 10 days}.	Negative predictive value (NPV) and positive predictive value (PPV) are considered as punishment factors in the obj. function.	No	Hangar maintenance slots. Two categories defined: Tail-specific and General slot.	Min cost (life-average and hangar slot use costs).	Monte-Carlo Tree search.	Commercial airline
[67]	2019	The prognostic tool triggers predictive alerts X days before predictive failure. X= Prognostic Horizon (PH). For different PH, the tool has different sensitivity values.	Considers the sensitivity of prognostics. Prognostics precision is ignored: no Not Fault Found (NFF) events.	Repairable components. Assumes that the time from removal until arrival at the inventory pool is only given by the TAT. TATs are fixed within contracts.	No	Min cost(component procurement, repair, leasing, and replacement costs).	Dynamic discrete event simulation. It proposes different maintenance policies and checks the costs of each policy.	Commercial airline (KLM E&M)
[53]	2013	The prognostic input is the RUL given as a normal distribution, but it only considers the expected RUL in the optimization.	Not stated	Repairable components. The spare parts inventory level is assumed from literature. Fixed TAT.	No	Max a/c availability by reducing the probability that multiple similar components are simultaneously in the repair shop.	Not stated, but it seems to be LNS. Neighborhood delimitation by shifting maintenance to later times.	Commercial airline
[71]	2019	The prognostics input is RUL for each component given as a probability distribution.	Uses a 95% Confidence Interval to determine the maintenance execution window	No	No	Min total workload by grouping maintenance, min number of unexpected failures and min wasted useful life.	Multi-objective Evolutionary Algorithm	Car fleet maintenance
[43]	2018	Uses Bayesian Inference and a crack growth model (data-drive and physical) to estimate the failure probability.	A constraint in the maximum allowable component failure probability.	No	No	Min cost (repair and wasted useful life) and max availability (minimize the aircraft repairs overlaps).	Multi-objective particle swarm optimization.	Aircraft structures
[69]	2018	Uses a Kalman filter to find the component degradation trend. Maintenance is triggered when a threshold is reached.	Not stated	Yes, but expendables. The lack of spare parts leads to flight cancellation costs	No	Min operational costs: preventive removal, flight cancellation, operation under degraded condition, flight delay, degradation, repair, and servicing costs.	Not stated. but suggests heuristics such as LNS or GA	Line maintenance

Table 4.4: Summary of most important literature (part 2)

5

Current state-of-the-art in KLM E&M

After reviewing the existing search from an academic perspective, this section focuses on the current state of prognostics and its use in maintenance scheduling in KLM E&M.

The Predictive Maintenance team of KLM E&M aims to develop tools that allow to benefit from the opportunities that Big-Data offers. One of its main projects is the development of a predictive maintenance tool called *Prognos*. The objective of *Prognos* is to predict upcoming failures before Flight Deck Effects (FDE) or in-service failures. Note that a FDE is a trigger from the aircraft health monitoring systems (Airplane Health Management (AHM) for Boeing aircraft and Airman for Airbus) upon malfunction detection. The development of predictive algorithms is based on Machine Learning and Deep Learning techniques that use data from historical AHM messages and component removals combined with the information provided by sensors installed in the aircraft components. Sensor data can be transmitted during flight through ACARS, or after each flight through wifi Gatelink. After each flight, the Predictive Maintenance team receives the Quick Access Recorder (QAR) file, which contains a large number of aircraft flight parameters recorded several times a second. During flight, *Snapshots* of sensor data are sent, but the Predictive Maintenance team has started to move to continuous data. The data from both sources is then decoded and analyzed to be used to improve the predictive models.

Figure 5.1: Sensor data flow in Prognos of data transmitted after flight. Adopted from [67].

For each monitored flight, the relative time compared to the whole flight length that different component operating parameters (like average temperature, RPM, etc.) are above a given value is recorded. Then, a degradation indicator is computed by averaging this quantity over several past flights. If for a given flight this degradation indicator exceeds a defined threshold, then a predictive alert is created.

The threshold value is defined and optimized per component by the Predictive Maintenance team and other stakeholders so that the predictive alert is triggered [redacted] days before the predicted failure time with a 100% precision (No NFF events). When a predictive alert is triggered, it is sent to the Maintenance Control Centre (MCC), which is composed of experts responsible for planning short-term maintenance. Upon alert reception, the MCC experts value the degradation indicator trend of the alerted component, and if they agree that the component is showing an abnormal behavior leading to failure, then the component is decided to be scheduled for replacement. The next step is to verify that the 4Ms[1] are available (material, method, machine, and men). If that is the case, then a spare part will be ordered, and the component will be scheduled for maintenance in an available slot. Otherwise, the component will fail after some time and corrective maintenance policy will be applied.

Prognostic tools must have a high confidence level in terms of precision to be accepted by maintainers [48]. The [redacted] PH was desired by MCC to add flexibility in short-term planning, but a higher PH may also provide an acceptable level of precision while allowing for reduced repair costs and increased flexibility in spare part planning.

[1] Term used in KLM E&M and other carriers to define the necessary conditions to perform a maintenance activity. It stands for Material, Method, Machine, and Men

6

Research Gap & Research Relevance

This chapter elaborates on the novelty and relevance of this research from an academic perspective and for KLM E&M. To do so, the research gaps that were defined in the previous chapters are clearly identified. The next step is to state and explain the main contribution that this study offers to fill these gaps.

6.1. Academic Perspective

Maintenance scheduling with prognostics has been widely studied, especially within the aviation industry (e.g. [19, 20, 40, 42, 47, 53, 54, 67], etc.). However, some studies included prognostics that were derived from a presumed or simulated degradation or reliability model [9, 12, 16, 22, 46, 54, 60, 70]. The lack of sensor data in prognostics is not reliable as the actual component degradation may not be properly captured and therefore, it would not be suitable for a real industrial application. Furthermore, there is little insight into how to include prognostics uncertainties in the form of sensitivity, accuracy, and precision in a maintenance optimization model. I. van de Hof [67], studies with a simulation the effect of different PHs and prognostic sensitivities in the output of four different maintenance policies. However, the research did not develop an optimization model that considers prognostics uncertainties in the scheduling task.

Regarding resources availability, there is a clear research gap, as it can be observed in Table 4.3 and Table 4.4. A common assumption is infinite maintenance capacity or infinite availability of spare parts [13, 20, 40, 42, 43, 54, 60, 68]. However, commercial airlines' inventories are usually scarce due to the high spare parts purchase and holding costs. In addition, aircraft maintenance can only be performed in specific slots which are determined based on the aircraft operating schedule and available hangars. For this reason, studies that do not consider the availability of resources fail to reflect an actual airline operation. Therefore, their models are not suitable to be implemented in the industry due to the risk of resource stock-outs and AOG events. Moreover, this research deals with repairable spare parts. There is a limited amount of studies that consider repairable spare parts availability together with prognostics in maintenance scheduling optimization [53, 67]. On top of that, none of them also considered the availability of maintenance slots as an input.

Component redundancy is also part of this research. As it was previously stated, redundant components are usually labeled as k-out-of-N components, which means that the aircraft is operational provided at least k out of the N components have not failed. Existing literature that also considers repairable spare parts [61–63] provides relevant insights in deciding the minimum amount of failures to initiate maintenance, the number of components to be replaced in a maintenance slot, and the priority replacement rules for degraded and failed components in k-out-of-N systems. Nonetheless, these studies do not include prognostics and fleet-level optimization.

To sum up, there is not a research in literature that develops a model for maintenance scheduling optimization for k-out-of-N systems that includes prognostics and the availability of maintenance slots and spare parts that could be implemented in a commercial airline. From this perspective, the main contributions of this study are:

- Developing an optimization model for maintenance scheduling of k-out-of-N systems that takes as input prognostics from aircraft components, repairable spare parts stock level, and maintenance slots. Validation and verification with a case study in a commercial airline will be carried out to assure that the model is suitable to be used in real operations.
- By considering prognostics uncertainties, this study provides valuable insights into how to incorporate prognostics uncertainties in maintenance scheduling optimization models.
- Providing additional knowledge in the potential benefits and drawbacks that the use of prognostics can have for a commercial airline.

6.2. KLM E&M Perspective

KLM E&M is carrying out a lot of investigation in predictive maintenance applications that allow for more efficient maintenance. With the *Prognos* application developed by the Predictive Maintenance team of KLM E&M, some unscheduled maintenance events and related technical delays are already being avoided, but there is little insight in the whole range of capabilities that *Prognos* may have in maintenance scheduling. For example, using *Prognos* in maintenance scheduling optimization can allow a more efficient inventory planning if the demand for spare parts is properly distributed. Furthermore, there is a lack of knowledge of how prognostics uncertainties should be taken into account in developing maintenance schedules.

In this framework, this research intends to:

- Provide a tool for optimum aircraft maintenance scheduling that takes into account *Prognos*' predictions and resources availability information (spare parts and maintenance slots).
- Provide insights into how *Prognos* inaccuracies should be taken into account in the optimization model.
- Explore the potential benefits for KLM E&M that a more extensive use of *Prognos* can have in maintenance planning.
- Provide an additional feature that could be implemented in *Prognos*, so that KLM and other potential future customers can enjoy these additional benefits.

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III

Further elaboration on thesis work

A

Verification and Validation

The verification and validation process is needed to check the correctness of the developed model. The verification intends to check that the model is an accurate representation of the designed conceptual model. The validation determines whether the model appropriately represents reality.

A.1. Verification

The verification of the developed model has two parts. The first one is a step-by-step testing and debugging process while the second is a whole model test.

In the step-by-step process, the model was tested with a reduced fleet number and an increased frequency of component failures. Whenever the output did not match the expected outcome of the designed model, the implemented code was carefully reviewed and debugged. Furthermore, the model was checked by a data-scientist specialized in Python, which is the programming language used.

In the whole model test, the model output was analyzed to study its consistency. For that purpose, two tests were performed and a hypothesis was tested in each of them. The model was considered to be verified if both hypotheses were proven to be true. The first test was to decrease the prognostic sensitivity. A lower number of component failures are previously detected by the prognostic tool for lower sensitivity values. Therefore, the expected outcome was that the model schedules less alerted components, leading to a reduction in repair cost savings. The second test was to decrease the available number of spare parts. As fewer spares are available, the expected model outcome was to have a reduced number of component replacements.

A.2. Validation

Even though *Prognos*' alerts are already being used in KLM for maintenance scheduling, this practice only relies on experts' opinions. There is not a tool that optimizes component maintenance schedules that considers *Prognos*' predictions and availability of spare parts and maintenance slots information. Therefore, this makes the developed model very difficult to validate. However, if the model is slightly adjusted, it can simulate the prior situation at KLM before the beginning of the use of *Prognos*. In this way, there are two Key Performance Indicators (KPI) that can be successfully validated: the number of replacements and the number of spare parts leasings in a year.

Before *Prognos* was used, KLM had a corrective maintenance strategy. In k-out-of-N components, no maintenance action was carried out until the aircraft had at least [redacted] failed components. Once the aircraft was scheduled in a maintenance slot, then x components could be replaced, ranging from [redacted]. This number depended in the amount of available spare parts at the maintenance slot time, meaning that as many components as possible would be replaced if there were enough spares:

[redacted]

To simulate this corrective maintenance strategy, the model is adapted as follows. The prognostic sensitivity is set to 0 and only the first stage of the optimization model (S1) is used. Besides, the first objective function is changed such that more components are replaced if there are enough available spare parts.

The first objective function of the first optimization stage is modified for validation purposes as follows:

$$min \sum_{i \in I} \sum_{t^u_{i,j} \in t_i} - \left[Y_{i,j} \cdot \sum_{c_{i,n} \in c_i} X_{i,j,n} \cdot C^{val} \right] + \left[Y_{i,j} \cdot C^{MEL} \cdot (t^u_{i,j} - t^{MEL_i})^+ \right] + \left[Y_{i,j} \cdot C^{slot}(t^u_{i,j}) \right] \tag{A.1}$$

A new cost factor C^{val} is added, being $C^{g} < C^{val} < C^{MEL}, C^{Lf}$. In this way, more components are scheduled for replacement in critical aircraft if spare part leasing is not required.

To validate the number of leasings KPI, the spare level before the use of *Prognos* is used as input.

As $N_{spares_{val}}$ needs to be an integer, a Monte Carlo simulation is performed with the rounded upper and lower values. The following validation results are obtained in a period of 365 days.

$N_{spares_{val}}$	**Number of component replacements KLM**	**Number of component replacements output**	**Number of spare part leasing KLM**	**Number of spare part leasing output**
$\lfloor N_{spares_{val}} \rfloor$	-	-3.636%	0	1.1
$\lceil N_{spares_{val}} \rceil$	-	-7.727 %	0	0.1

Table A.1: Validation results

Table A.1 shows that the number of replacements in a year differs by 3.6% and 7.7% for a spare level of $\lfloor N_{spares_{val}} \rfloor$ and $\lceil N_{spares_{val}} \rceil$, respectively. Regarding the number of leasings, a spare level of $\lceil N_{spares_{val}} \rceil$ gives an outcome that is closer to reality. However, it should be noticed that in a real operation KLM has a spare aircraft that can be used to cover the flight schedule when there is any disruption, such as a stock-out event. This would explain why this KPI model outcome is slightly higher compared to the real value. Overall, the results are quite close to reality, so it can be said that the model is successfully validated.

B

Sensitivity Analysis (additional work)

This section continues to elaborate on the sensitivity analysis introduced in Part I. Here, we study the impact in the long-run performance of the prognostic sensitivity, the TAT, and the TAT as a function of the component health state.

B.1. Impact of prognostic sensitivity

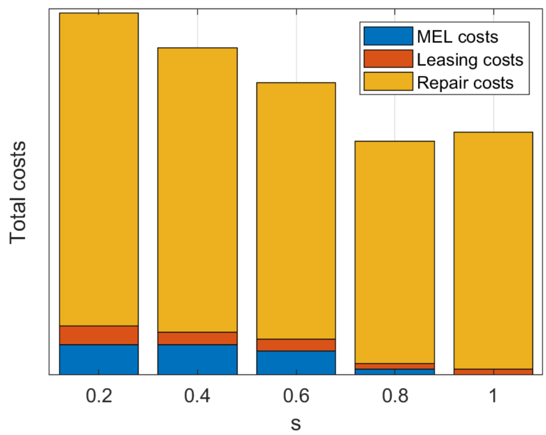

Figure B.1: Impact of s on the costs associated with S2, analyzing a period of 365 days.

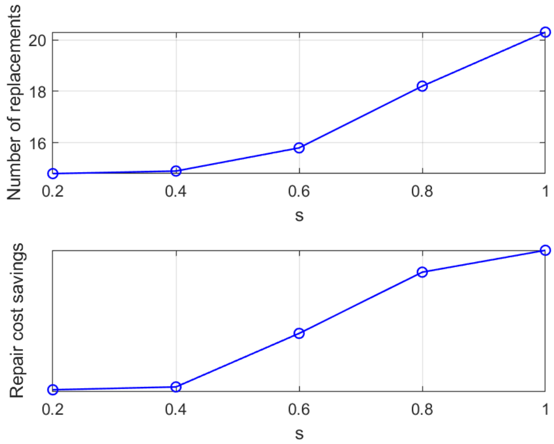

Figure B.2: Impact of s on the performance of S2, analyzing a period of 365 days.

As the prognostic sensitivity increases, more component failures are previously highlighted with predictive alerts. Therefore, the number of component replacements increases with sensitivity (see Figure B.2). Also, because more alerted components are replaced, the repair cost savings are greater for higher sensitivity values. There is a point at which the improvement in repair cost savings does not compensate for the increase in repair costs due to more replacements. This occurs at a sensitivity value of 0,8 (see Figure B.1).

Finally, an enhanced failure prediction due to higher prognostic sensitivity has a favorable effect on the MEL costs by avoiding some unexpected component failures leading to MEL violations, reaching even a value of 0 costs when $s = 1$.

B.2. Impact of TAT

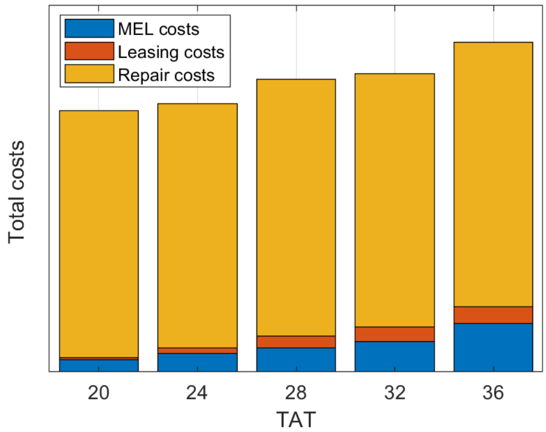

Figure B.3: Impact of TAT on the costs associated with S2, analyzing a period of 365 days.

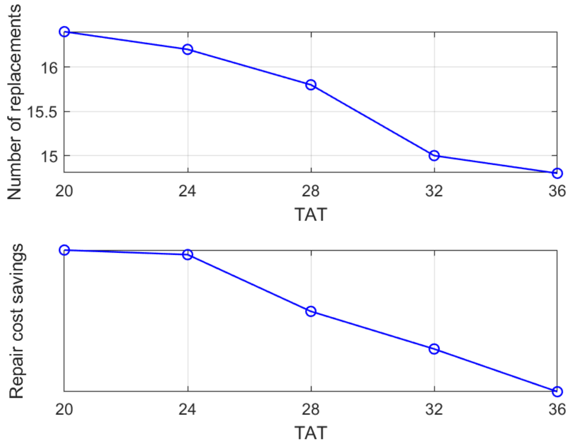

Figure B.4: Impact of TAT on the performance of S2, analyzing a period of 365 days.

The results show that the effect of TAT is very similar to the number of spare parts, but they are opposite. Reducing the TAT is comparable to increasing the number of spare parts. Therefore, the impact of lower TATs is the increase in the number of replacements, and consequently, the repair cost savings.

The MEL costs are improved for lower TATs because by increasing the number of replacements, some component failures leading to MEL violations are avoided.

As a last remark, lower TATs also reduce the spare part leasing costs.

The fact that the impact of lower TATs is similar to an increase in spare levels can be considered as a major benefit. It would avoid multiple component purchases, which sometimes are not even possible due to the scarcity issues of some aircraft components.

B.3. Impact of TAT as a function of the component health state

One of the benefits of using prognostics is that the TATs can be reduced. Lower degradation levels require shorter repair times [48]. Besides, diagnosis and prognosis also allow for easier fault troubleshooting [28, 36]. In this section, we assume that the TAT is a deterministic value that depends on the component health state.

$$TAT = \begin{cases} TAT_f, & \text{if } H(c_{i,n}, t_0) = 2 \\ TAT_a, & \text{if } H(c_{i,n}, t_0) = 1 \end{cases} \tag{B.1}$$

The value of TAT_f remains the same as TAT in the previous sections.

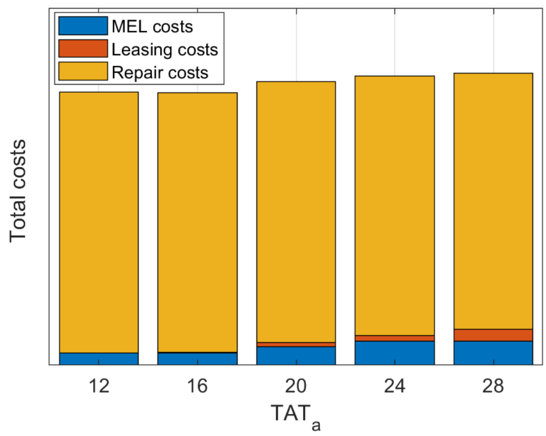

Figure B.5: Impact of TAT_a on the costs associated with S2, analyzing a period of 365 days.

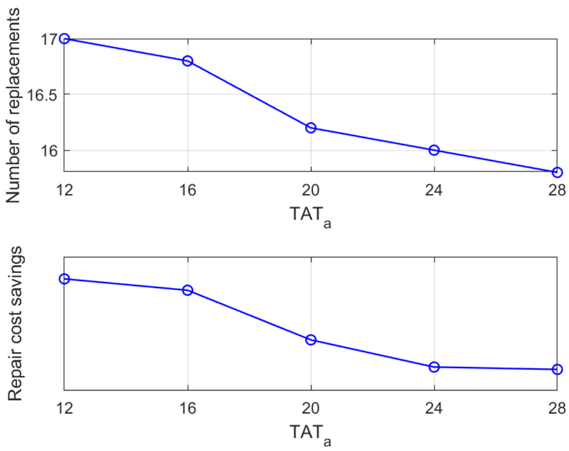

Figure B.6: Impact of TAT_a on the performance of S2, analyzing a period of 365 days.

The results are quite similar to the previous section. They show that the number of replacements slightly increases for lower TAT_a. Due to the increment in replacements, the repair cost savings raise as well.

There is also a reduction in the MEL violation costs and leasing costs for lower values of TAT_a.

C

Operational implementation

This chapter provides some guidelines on how the proposed model should be implemented in KLM E&M and it proposes additional suggestions for improvement of the current and future practices within the company.

C.1. Model implementation for the CU component

Based on the long-run model results, the best strategy to follow to minimize the MEL violation, spare part leasing, and repair costs seems to be Strategy 2 (S2). This policy includes the first and second optimization stages: critical aircraft and non-critical aircraft with predictive alerts. Critical aircraft in the CU component include aircraft with 3 or more either failed or alerted components, and aircraft with 2 failed components. The group of non-critical aircraft with predictive alerts are defined by aircraft with 1 or 2 alerted components.

In terms of spare parts and maintenance slots, an actual estimation of the inventory stock level from Component Services could be included in the model to accurately estimate the number of available spare parts at every time. In addition, updated information on the available maintenance slots from MCC could be included as an input too.

In this way, a new feature could be implemented in *Prognos* by including the proposed model and the previously indicated inputs. The new functionality would be able to make recommendations to MCC and other user customers regarding the most optimal maintenance schedule based on component prognostics, the current inventory levels, and the available maintenance slots.

C.2. Recommendations for current practices

Based on the sensitivity analysis results, some recommendations for the improvement of the current practices can be made. However, these suggestions are subject to the veracity of the taken assumptions.

C.2.1. Spare parts stock

In terms of spare parts stock, the current scenario seems to be quite close to the optimal. KLM provides MRO services to other airlines, meaning that the spare parts are not only going to be used by KLM, but also by the rest of the customer airlines. For this reason, N_{spares} was estimated using the proportion of the number of components ready to be installed in the warehouse at which the supply chain is aiming, times the ratio of 787s from KLM and from the rest of airline customers in the pool. Therefore, to increase N_{spares} by 1, the supply chain department should aim to have [redacted] additional spare parts ready to be installed in the warehouse, which could be achieved by either purchasing them or increasing the repair rate. The total costs would be reduced by 6.78% per year, which would not compensate for the high cost of either purchasing [redacted] components or increasing the man-hours to raise the repair rate. In addition, the B787 components have scarcity issues, so purchasing so many components might not be feasible either. Moreover, it should be noted that the estimation of N_{spares} is an assumption and the complexity of the supply chain system is higher than the one assumed for this research. Multiple inventory locations, component shipping times, demand from other airlines, and stochasticity of repair times should be included in the model for a more accurate conclusion.

C.2.2. Prognostic Horizon

In terms of the prognostic horizon, a PH higher helps to enhance the inventory planning flexibility, particularly if $\frac{PH}{TAT} \gtrsim 1$. This flexibility is shown by slightly increasing the number of replacements and reducing the spare part leasing costs. Moreover, the greatest benefit appears to be the increase the repair cost savings due to lower component degradation levels. For example, a PH of 35 days would increase the repair cost savings by

97.89%. However, such a high PH value would also increase the wasted component useful life. Therefore, a PH of [redacted] days seems to be the best option. However, this claim is subject to the veracity of the assumption about the linear relation between the component repair costs and the degradation level. The current available historical data is not enough to build a reliable function between the repair costs and the degradation level. Therefore, this assumption should be reviewed in the future when more failure cases data becomes available.

C.2.3. Prognostic sensitivity

Focusing on the prognostic sensitivity, higher sensitivity values increase the number of replacements as well as the repair cost savings. However, there is a point at which the improvement in the repair cost savings does not compensate for the increase in repair costs due to the additional replacements. Therefore, the optimum value in terms of minimum total costs seems to be around $s = 0.8$. However, it should be noted that a sensitivity of $s = 1$ would also eliminate the MEL costs. A solution to benefit from both aspects could be to set a threshold in the minimum repair cost savings to perform a component replacement. Fewer component replacements would be performed with $s = 1$, decreasing in this way the repair costs, while the MEL costs would remain the same.

C.2.4. Turn-Around Time

Finally, a reduction in the TAT can have the same effect as higher inventory stocks. The effect of the TATs belonging to replacements initiated by predictive alerts (Section B.3) has of course a lower impact compared to the effect of changing all the TATs (Section B.2). Nevertheless, it is more feasible from an operational perspective that the TAT of replacements initiated by predictive alerts can be reduced due to less troubleshooting times. If TAT_a is reduced to [redacted] days ([redacted] reduction compared to TAT_f), the effect seems to be quite similar to increasing N_{spares} by 1. This increased planning flexibility can be considered as a major benefit due to the previously mentioned scarcity issues of the B787 components. In addition, this would allow to reduce the serviceable stock level or maybe even borrow some of it to third party airlines for additional income.

As a last remark, it should be noted that these optimal parameters are found by changing a single parameter and assuming that the rest of them remain unchanged. This can be not true for some cases, such that the prognostic horizon and the prognostic sensitivity, which may be dependent on each other.

D
Conclusions and future work

This last chapter elaborates on the benefits of predictive maintenance that could be observed in this research and potential additional advantages from different perspectives within KLM. Finally, it provides some suggestions for further research.

D.1. Benefits of PdM

A comparison with the traditional corrective maintenance policy was not carried out as it was overlapping with previously carried researches within the company. However, the potential benefits of PdM could be already observed. The relevance of incorporating and extending the developed model within KLM can be analyzed from the perspective of the warehouse, the repair shop, and airframe operations departments.

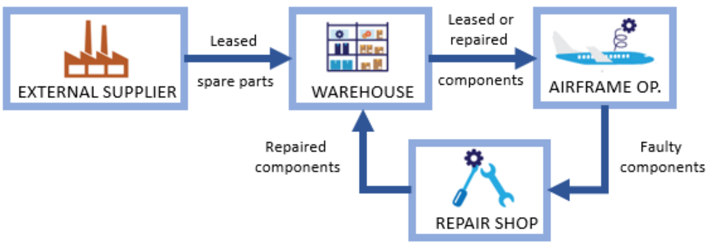

Figure D.1: Relation (simplified) between repair shop, warehouse, and airframe operations departments.

D.1.1. Relevance from the warehouse perspective

In this research, it has been proved that from a warehouse perspective, integrating *Prognos* inputs in maintenance decision making helps to enhance the inventory planning flexibility by decreasing the component stock-out events.

The use of prognostics can allow a reduction in the TAT due to lower repair and troubleshooting times. This was not included in the scope of this research, however, it has been proved that lower TAT have a similar impact as having a greater inventory stock. This can be considered as a major benefit, especially for those components with scarcity issues, such as those for the B787. In addition, this would allow to reduce the serviceable stock-levels or maybe even borrow them to third party airlines for additional income.

Moreover, it may be also beneficial to include *Prognos* predictive alerts to the warehouse department such that it becomes more "proactive". A shift from a "reactive" to a "proactive" warehouse could suppose a more efficient use of the serviceable stock levels. Reducing the number of unscheduled component removals allows to schedule the component deliveries to avoid peak removals. In this way, the on-hand serviceable stock could be sent to other airline customers which would also help to reach the desired service levels. Similarly, KLM E&M could also borrow some of the serviceable stock to third party airlines for additional income.

Besides, a more "proactive" warehouse could gain time flexibility in two different aspects. The first one is that components could be shipped from another location if there are no spares available at the scheduled time of replacement. This would increase the number of component replacements and help to further reduce the stock-out events. The second aspect is related to the agreed shipping times for unscheduled and scheduled removals. For some operators, KLM E&M has [redacted] to deliver a MEL C component, whereas it has [redacted] for a scheduled request. If the number of unscheduled removals is converted into scheduled using *Prognos*, KLM would be buying itself more time to deliver the components on time, thereby increasing its service level and customer satisfaction. At the same time, the number of urgent shipments would be reduced, also leading to a delivery cost reduction.

D.1.2. Relevance from the repair shop perspective

It has been proved that integrating *Prognos* alerts in maintenance scheduling improves the component repair cost savings. Particularly, avoiding compressor failure in the CU component dramatically reduces the repair costs.

Moreover, lower degradation levels can also reduce the component repair times. The troubleshooting times may be improved too as more context and specific information would be available, i.e., the predictive alert would be triggered in a specific component, thereby reducing the time needed for diagnosis. A reduction in the repair and troubleshooting times would enable a decrease in the TAT, which has major benefits from a supply chain perspective as it was previously mentioned in the former subsection.

Furthermore, it would be beneficial that *Prognos* alerts are incorporated in the repair shop together with an indication of the work scope of the component. This would allow a better resources and workload planning.

An additional potential advantage from the repair shop perspective is to use *Prognos* alerts for OEMs warranty claims. OEMs will not accept warranty claims for premature removals, but in the future, *Prognos* may be used as an additional proof of component degradation. However, this requires that *Prognos* models are validated with OEMs.

D.1.3. Relevance from airframe operations perspective

It has been proved that integrating *Prognos* inputs in maintenance decision making helps to lessen the MEL violation costs, which would turn into a reduction of hard costs, i.e. costs due to flight cancellations and delays, as well as into an increase in the aircraft availability.

Apart from the hard costs, soft costs would be also reduced. Avoiding flight cancellations and delays enhances customer satisfaction, which also helps to increase the chances that these customers choose the same airline in the future.

D.2. Suggestions for further research

In terms of the proposed model, it is suggested as future work that the model is extended to consider multiple components, instead of a single component type. The same procedure should be followed for other k-out-of-N components to analyze what is the most optimal strategy to follow within S1, S2, and S3.

Additional cost factors could be also considered, such as ”not fault found” (NFF), ”labor cost”, or ”wasted component useful life” costs. NFF events can lead to less efficient maintenance planning as some healthy components would be replaced, using a spare part that could be used for another more profitable replacement. Considering labor costs can lead to group more component replacements in a single maintenance slot. The cost of wasted useful life would reduce the benefit of using a high PH to reduce the repair cost savings.

Furthermore, multiple warehouse and repair shop locations as well as the demand from other airlines should be further researched by including a more complex inventory system. As a last suggestion, the model should include in the future real-time RUL and TAT estimations. However, that technology is not available yet.

In terms of the future scope of *Prognos*, it is recommended that KLM adopts a predictive maintenance policy for as many components as possible, especially those having high repair cost savings potential and leading to frequent MEL disruptions. It should be also assured that the ratio $PH/MTTF$ is small such that the impact in the wasted component useful life is not very significant. Furthermore, it should be guaranteed that the developed prognostic models are as accurate as possible. The only way to successfully push towards a change into predictive maintenance is by building a reliable tool with a low number of NFF events.

D.3. Final remarks

After carrying out this research, the final conclusion is that traditional corrective and preventive maintenance policies should be replaced by predictive maintenance as long as safety is not compromised. New generations of aircraft are being equipped with sensors that monitor the components’ health state. This, together with the development of data science, is allowing the change from a ”reactive” to a more ”proactive” aircraft maintenance. KLM should keep on pushing towards this change by investing in more advanced aircraft monitoring systems and developing predictive models for more components. The Covid-19 situation has hugely affected the airline industry in every aspect, which may affect the funding related to predictive maintenance. However, this situation should be regarded as an opportunity to think about new prognostic models and ideas to implement. Predictive maintenance is expected to have a major impact on the future of aircraft maintenance and KLM should enable its development to keep its competitive advantage in the airline market when the situation comes back to normality.