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Criticality-based predictive maintenance scheduling for aircraft components with a limited stock of spare components

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We propose a criticality-based scheduling model for aircraft component replacements. We schedule maintenance for a fleet of aircraft, each equipped with a multi-component system. The maintenance schedule takes into account a limited stock of spare components and the Remaining-Useful-Life prognostics for the components. We propose a component replacement scheduling model with three stages of maintenance criticality: i) critical aircraft that are not airworthy due to a lack of sufficient operational components, ii) predictive alerts for expected component failures, and iii) non-critical aircraft with some failed components. An Adaptive Large Neighborhood Search (ALNS) algorithm is developed to solve this criticality-based aircraft maintenance planning problem. The framework is illustrated for a fleet of aircraft, each equipped with a k-out-of-N system of components. A predictive maintenance planning is obtained within an outstanding computational time (less than 6 seconds for a fleet of 50 aircraft). Moreover, it is shown that the proposed planning with 3-levels of criticality ensures aircraft airworthiness while making cost-efficient use of maintenance slots.

Keywords: Predictive Aircraft Maintenance, Spare Components Management, Maintenance criticality

1. Introduction

Airlines spend approximately 3.14 million dollar on maintenance per aircraft per year (IATA (2019)). Striving for costs savings, aircraft maintenance is shifting to predictive maintenance where failures of components are anticipated and maintenance is performed accordingly. Here, onbard sensors are used to monitor the health condition of aircraft components.

One of the key enablers for predictive aircraft maintenance are the Remaining-Useful-Life (RUL) prognostics, which guide the maintenance planners on when to perform maintenance, and which maintenance tasks to perform. These predictive maintenance tasks are usually planned using threshold-based policies, i.e., as soon as the degradation of a component exceeds a threshold, a maintenance action is planned. These thresholds are determined based on using Monte Carlo simulation (Lee and Mitici (2020); Nguyen et al. (2014)), semi-regenerative processes (Huynh et al. (2018)), Bayesian networks (Nielsen and Sørensen (2018)) or heuristics (Wang et al. (2009)). Other predictive maintenance planning methods studies employ (Partially Observable) Markov Decision Processes (Papakonstantinou and Shinozuka (2014); Andriotis and Papakonstantinou (2019)).

For aircraft maintenance, maintenance tasks are planned during periods of time when the aircraft is on the ground at a location suitable for maintenance (maintenance slots), and when there are sufficient resources to carry out the tasks. Fixed maintenance slots for predictive aircraft maintenance planning are considered in Yiwei et al. (2017) for the cracks in an aircraft, in Nguyen and Medjaher (2019) for turbofan engines, in Vianna and Yoneyama (2017) for an aircraft hydraulic system, for aircraft bleed systems in Vianna et al. (2015), for aircraft cooling units in de Pater and Mitici (2021) and for aircraft brakes in Lee and Mitici (2020).

At the same time, one of the crucial resources to carry out the planned maintenance is the availability of spare components during these maintenance slots. A lack of spare components may lead to additional delays, an increase of aircraft unavailability and additional maintenance costs due to component leasing (Nguyen and Medjaher (2019)). The management of spare parts for predictive aircraft maintenance has been discussed in Nguyen and Medjaher (2019); Vianna et al. (2015). In Nguyen and Medjaher (2019), a Long

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Short-Term Memory Neural Network is applied to obtain RUL prognostics of turbofan engines. These RUL prognostics are then used to plan maintenance for one turbofan engine and to determine the optimal moments to order a new spare. In Vianna et al. (2015), a Large Neighbourhood Search algorithm is applied to plan maintenance for an aircraft in the time between flights, based on the condition of the aircraft components. In these studies, however, the maintenance of only a single aircraft is considered, taking into account RUL prognostics and and a limited stock of spare components.Moreover, the components considered in these studies are non-repairables. Complementary to these papers, we consider the maintenance planning of a fleet of aircraft equipped with repairable components, where RUL prognostics and a shared stock of spare components are considered.

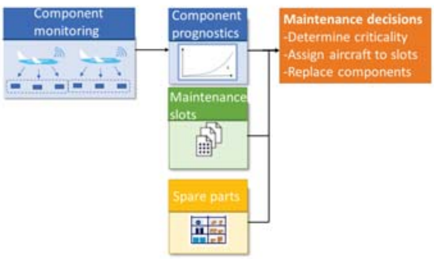


Fig. 1.: Overview - predictive maintenance planning with maintenance slots, RUL prognostics and a stock of repairable spare components.

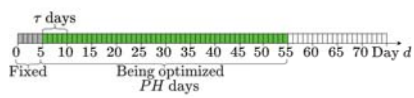
In this paper, we propose a predictive aircraft maintenance planning heuristic for a fleet of aircraft. Each aircraft is equipped with a system of multiple, identical components that are repairables, i.e., upon failure, a component is replaced with a spare component, and the failed component is sent to a repair shop to be repaired. Once repaired, the components are returned to service. The degradation level of each component is monitored and RUL prognostics are generated. Based on these RUL prognostics, three levels of aircraft/component criticality are defined. These criticality levels are used to plan component replacements with an Adaptive Large Neighbourhood Search (ALNS) heuristic. Moreover, this predictive maintenance planning is constraint by the availability of maintenance slots, and by the availability of spare components, shared between the aircraft in the fleet (see Figure 1). We show that our approach leads to a cost-efficient use of the maintenance slots.

2. Problem description

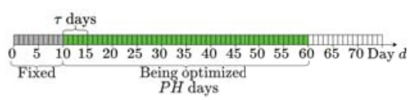
We consider a fleet of aircraft, each equipped with a system of N identical, repairable components. The aim is to schedule maintenance for the aircraft, i.e., to assign aircraft to maintenance slots, and subsequently decide which component(s) to replace in these slots. We propose a discrete-time, rolling horizon approach where a sequence of time-windows with a duration of PH days is considered. For each time window, we consider as input the set of maintenance slots available, the updated RUL prognostics for each component at the beginning of the time-window, the component and aircraft criticality level, and the availability of spare components. We are interested in minimizing the total cost of assigning aircraft (and specific components) to maintenance slots.

2.1. *Rolling horizon approach*

We consider a sequence of time-windows $[d_0, d_0+PH)$ from day d_0 to day $d_0 + PH$. At the beginning of each time-window, at day d_0, the component prognostics and criticality levels for each component and for each aircraft are updated. Then, a maintenance planning for this time-window is generated, i.e., aircraft are assigned to maintenance slots available in this time-window. We shift to the next time-window as follows. We first fix the planning of the first $\tau \leq PH$ days, in the time-window $[d_0, d_0 + \tau)$, and then go to the next iteration. In this next iteration, the RUL prognostics and criticality levels are updated, and a maintenance planning for new time-window $[d_0 + \tau, d_0 + \tau + PH)$ is generated. This is repeated for several time-windows de Pater and Mitici (2021).



(a) $d_0 = 5$



(b) $d_0 = 10$

Fig. 2.: Illustration - rolling horizon approach for three iterations with $PH = 50$ days, $\tau = 5$ days.

Figure 2 shows our rolling horizon approach for $\tau = 5$ and $PH = 50$. In Figure 2a, the maintenance planning is created for the planning time-window $[5, 55)$. All maintenance decisions before day $d_0 = 5$ are fixed. Then, we fix the first five days of the maintenance planning made at day $d_0 = 5$ as well, i.e., we fix all maintenance decisions during days $[5, 10)$. In the next iteration, at day $d_0 = 10$, we update the prognostics and maintenance is scheduled for the planning time-window $[10, 60)$ (see Figure 2b). Again, the maintenance decisions of the first five days, $[10, 15)$, are fixed.

2.2. *Multi-component aircraft system*

Let A denote a fleet of aircraft, each equipped with a multi-component system with N identical, *repairable* components. Let C_a denote the set of components in this multi-component system of aircraft $a \in A$. We assume that each component fails independently of the other components in the system.

We consider maintenance planning for a k-out-of-N system, i.e., according to the Minimum Equipment List (MEL) at least k out of N components need to be operational for an aircraft to be permitted to fly (EASA (2018)). Thus, an aircraft is permitted to fly if at least $k+1$ or more components are operational. However, if exactly k components are operational, then the aircraft is still allowed to fly for a maximum of V days (EASA (2018)). Once more than k components fail, or k components are failed for more than V days, an aircraft in in an *Aircraft-On-Ground* (AOG) condition and can thus no longer fly. Many aircraft systems are k-out-of-N systems, for example gear landing brakes (Lee and Mitici (2020)), hydraulic pump systems (Vianna et al. (2015)), and cooling systems (de Pater and Mitici (2021)).

When a decision is made to replace a component, this component is replaced with an *as-good-as-new* spare component. At the same time, the replaced component is sent to a repair shop, restored to an *as-good-as-new* condition and subsequently added to the stock of available spare components. We assume that a repair takes Δ days.

A component can be failed at the moment of replacement, or it can be replaced in anticipation of a near-future failure. When a non-failed component is replaced, it is relatively inexpensive to repair the component, since the damage to the component is not significant. In contrast, when a failed component is replaced, the damage is large and it is thus more expensive to repair this component. If a component is failed at the time of replacement, an extra costs c^{ex} is thus incurred to repair the component.

Let N^{sp} denote the number of initially available spare components. We say that a *stock-out* occurs if a replacement of a component is planned, but no spare component is available. When a stock-out occurs, an additional component is leased. The lease is terminated as soon as at least one component has been repaired.

2.3. *Components' degradation and RUL prognostics*

Let $c \in C_a$ denote a component of the multi-component system C_a of an aircraft $a \in A$. Let $X_d^{a,c}$ denote the degradation level of component c at the beginning of day d. We model the degradation of the components using a stationary Gamma process with independent increments, similar to Huynh et al. (2018): the degradation increment between day d and day $d+1$ (i.e., $X_{d+1}^{a,c} - X_d^{a,c}$), follows a gamma distribution with shape parameter α and scale parameter β. Moreover, we assume that the degradation of an "as-good-as-new" component is $X_0^{a,c} = 0$. A Gamma process is often used in literature to model the degradation of components, such as haul truck motors (Wang et al. (2009)), aircraft landing gear brakes (Lee and Mitici (2020)) and LEDs (Ling et al. (2014)).

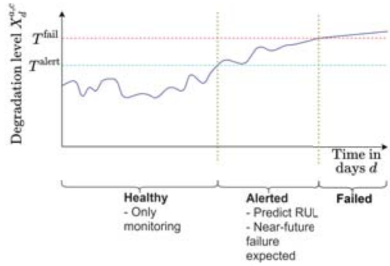


Fig. 3.: Degradation level of a component $c \in C_a$ of aircraft $a \in A$ over time, from healthy to alerted to failed.

Based on the level of degradation, a component is said to be: i) Healthy, when the degradation level $X_d^{a,c}$ is below an alert threshold T^{alert}.

ii) Alerted, as soon as the degradation level $X_d^{a,c}$ exceeds an alert threshold T^{alert}. Here, the component is expected to fail in the near future;

iii) Failed, when the degradation level $X_d^{a,c}$ exceeds a failure threshold T^{fail}.

These 3 states of the component are shown in Figure 3.

As soon as a component is alerted, RUL prognostics are generated and updated every new planning time-window starting at day d_0. Using these RUL prognostics, we determine P_{acd}^{fail}, the probability that component $c \in C_a$ of aircraft $a \in A$ fails by the beginning of day $d > d_0$, as follows (Huynh et al. (2018)):

$$\begin{aligned} P_{ac(d_0+\delta)}^{\text{fail}} &= P(RUL \le \delta | X_{d_0}^{a,c} = x) \\ &= 1 - P(X_{d_0+\delta}^{a,c} < T^{\text{fail}} | X_{d_0}^{a,c} = x) \\ &= 1 - P(X_{d_0+\delta}^{a,c} - X_{d_0}^{a,c} < T^{\text{fail}} - x | X_{d_0}^{a,c} = x) \\ &= 1 - F_{\delta\alpha,\beta}(T^{\text{fail}} - x), \end{aligned} \tag{1}$$

where $F_{\delta\alpha,\beta}$ is the CDF of a Gamma distribution with shape parameter $\delta\alpha$ and scale parameter β.

Using $P_{acd}^{\text{fail}}, \forall c \in C_a, a \in A$, we determine the probability that the aircraft system of N components fails at the beginning of a future day $d > d_0$, denoted by P^{AOG}_{ad}. Equivalently, this is the probability that the aircraft equipped with this multi-component system is in an AOG-condition at the beginning of a future day $d > d_0$. This probability can be calculated for a k-out-of-N system as follows:

$$P^{\text{AOG}}_{ad} = P\big(i \in \{(N-k)+1, \dots, N\} \text{ components fail before the beginning of day } d \text{, or exactly } (N-k) \text{components fail before the beginning of day } d-V\big).$$

2.4. *Aircraft criticality levels*

Based on P^{fail}_{acd} and P^{AOG}_{ad}, we define the following three stages of criticality for an aircraft and its components, in decreasing order of priority.

Criticality level 1: If the probability that an aircraft $a \in A$ is in an AOG-condition at the end of the planning time-window exceeds a reliability threshold $0 < r \leq 1$ (i.e., if $P^{\text{AOG}}_{a(d_0+PH)} \geq r$), then we say that the aircraft is *critical*.

Criticality level 2: If a component $c \in C_a$ in a non-critical aircraft $a \in A$ is alerted at day d_0, it is desirable to plan a replacement for this component as soon as possible (to prevent the cost c^{ex} of replacing an already failed component).

Criticality level 3: If a component $c \in C_a$ in a *non-critical* aircraft $a \in A$ is already failed at day d_0, replacing this failed component can still be beneficial to avoid that aircraft a becomes critical in the future.

2.5. *Maintenance slots*

A maintenance slot is a time interval during which maintenance can be performed on an aircraft. We consider 2 types of maintenance slots: aircraft-specific slots, and generic slots. Aircraft-specific maintenance slots are slots to which only a specific aircraft can be assigned. A generic maintenance slot is a slot to which any aircraft can be assigned. During a generic slot, at most m aircraft can be maintained at the same time.

2.6. *Maintenance costs*

We assume the following maintenance costs:

i) The costs of assigning aircraft to maintenance slots. An assignment of an aircraft to an aircraft-specific slot incurs a cost c^{spec}. An assignment of an aircraft to a generic slot incurs a cost c^{gen}. We assume that $c^{\text{spec}} < c^{\text{gen}}$.

ii) The cost of leasing spare components, which consists of a fixed costs of leasing a spare component, c^{Lf}, and an additional cost for each day the spare component is leased, c^{Ld}.

iii) The costs *savings* due to replacing an alerted component in anticipation of its failure (criticality level 2). Because a component replacement requires the assignment of an aircraft to a maintenance slot, which costs c^{spec} or c^{gen}, the maintenance planning heuristic would tend to postpone replacements until the aircraft is critical (several failed components). However, replacing failed components is expensive (c^{ex}). We therefore strive to replace components in anticipation of their failure by introducing costs savings to the total cost of the maintenance planning. If at current day d_0 we plan to perform a component replacement at day $d \in [d_0, d_0 + PH)$, then the saved repair cost we subtract from the total cost is $c^{\text{ex}} \cdot (1 - P^{\text{fail}}_{acd})$.

iv) The cost savings due to replacing a failed component to avoid future critical aircraft (criticality level 3). Because a component replacement requires the assignment of an aircraft to a maintenance slot, which costs c^{spec} or c^{gen}, the maintenance planning heuristic would tend not replace failed components in a non-critical aircraft (few failed components). Accumulating failed components, however, increases the change of having a critical aircraft in the future. We therefore introduce a cost saving of c^{rep} when replacing a failed component of a non-critical aircraft, which we subtract from the total costs.

v) The cost of having an aircraft in an AOG-condition. Let c^{AOG} denote the cost of an aircraft being in an AOG-condition for 1 day. The cost of aircraft $a \in A$ being in an AOG-condition at day $d \in [d_0, d_0+PH)$ is $c^{\text{AOG}} \cdot P^{\text{AOG}}_{ad}$. In general, c^{AOG} is very high relative to other maintenance costs.

3. Adaptive Large Neighbour Search for predictive aircraft maintenance

We propose an Adaptive Large Neighbourhood Search (ALNS) heuristic (Pisinger and Ropke (2010)) for the predictive maintenance planning problem, based on the criticality of the aircraft and components. In ALNS, an existing solution is improved with an improvement heuristic, that consists of a destroy heuristic, that first destroys the current solution, i.e., it makes the solution infeasible, and subsequently a repair heuristic, that repairs the solution again, i.e., it makes the solution feasible. In ALNS, there are several destroys and repair heuristics considered. At the beginning of each iteration, one of the destroy and one of the repair heuristics are randomly selected.

An overview of the ALNS heuristic is given in Algorithm 1. Let s denote a feasible maintenance planning for the time period $[d_0, d_0 + PH)$ with costs $c(s)$. As input, we use an initial feasible maintenance planning s^{in}, created with a simple constructive heuristic. The current solution s^{cur} and the best solution s^{best} are initialized with this initial solution s^{in} (line 2 in Algorithm 1).

We also consider a set DH with all destroy heuristics, and a set RH with all repair heuristics. In line 2, we initialize the weights w^{dh} for all destroy heuristics $dh \in DH$ and the weights w^{rh} for all repair heuristics $rh \in RH$ with one. Following initialization, we aim to improve the current solution (line 3-15 in Algorithm 1). First, a destroy heuristic $dh \in DH$ and a repair heuristic $rh \in RH$ are selected using the roulette wheel principle with the weights of the heuristics (lines 4-5 in Algorithm 1, Ropke and Pisinger (2006)).

Next, we compute a new temporary solution s^{temp} by first applying the destroy, and subsequently the repair heuristic to the current solution s^{cur} (line 6 in Algorithm 1). This temporary solution can be accepted or discarded. If we accept the temporary solution (line 7-9), then the current solution s^{cur} is updated. We accept a solution using simulated annealing, as suggested by Pisinger and Ropke (2010). Here, we initialize the temperature Φ with the initial temperature Φ^{in} in line 2, and update the temperature each iteration with the decrease factor γ, $0 < \gamma < 1$ (line 10). Next, we update the best solution (line 11-13) and the weights w^{dh} of the destroy heuristic dh selected in line 4 and w^{rh} of the repair heuristic rh selected in line 5 as follows (line 15):

$$\begin{aligned} w^{dh} &\leftarrow \lambda * w^{dh} + (1-\lambda)\omega \\ w^{rh} &\leftarrow \lambda * w^{rh} + (1-\lambda)\omega, \end{aligned} \tag{2}$$

where

$$\omega = \begin{cases} \omega_1 & \text{if the new solution is the global best} \\ \omega_2 & \text{if the new solution is better} \\ & \text{than the current solution} \\ \omega_3 & \text{if the new solution is accepted} \\ \omega_4 & \text{if the new solution is rejected,} \end{cases} \tag{3}$$

with $\omega_1 \geq \omega_2 \geq \omega_3 \geq \omega_4 \geq 0$. As stopping criterion (line 15), we use a maximum number of iterations I.

Bellow we introduce the constructive heuristic, the destroy heuristics in DH and the repair heuristics in RH.

3.1. *Constructive heuristic*

The constructive heuristic finds an initial feasible solution with low costs based on the *criticality* of the aircraft. First, maintenance is scheduled for each *critical* aircraft (criticality level one, see Section 2.4) in the earliest available aircraft-specific slot. If there is no such aircraft-specific slot available within the planning window, then maintenance is scheduled in the earliest available generic slot instead. In this slot, first the alerted component(s) of the aircraft are replaced, and then sufficiently many failed components such that $P^{\text{AOG}}_{d_0+PH} < r$.

Next, the maintenance for all remaining, *non-critical aircraft with one or more alerted components* is scheduled one by one (criticality level 2). Here, each aircraft is assigned to the earliest available aircraft-specific slot and all alerted components are replaced. If there is no such aircraft-specific slot available within the planning window, then the aircraft is not assigned to any slot. The replacement of the failed components in non-critical aircraft (criticality level 3) is not scheduled yet.

Algorithm 1 Adaptive Large Neighbourhood Search (Pisinger and Ropke (2010)).

1: **input:** A feasible solution s^{in}
2: $s^{\text{cur}} = s^{\text{in}}$; $s^{\text{best}} = s^{\text{in}}$; $w^{dh} = 1 \quad \forall dh \in DH$; $w^{rh} = 1 \quad \forall rh \in RH$; $\Phi = \Phi^{\text{in}}$
3: **repeat**
4:    Select a destroy method $dh \in D$
5:    Select a repair method $rh \in R$
6:    Compute $s^{\text{temp}} = rh(dh(s^{\text{cur}}))$
7:    **if** accept(s^{temp}, s^{cur}, Φ) **then**
8:       $s^{\text{cur}} \leftarrow s^{\text{temp}}$
9:    **end if**
10:    $\Phi \leftarrow \gamma \cdot \Phi$
11:    **if** $c(s^{\text{cur}}) \leq c(s^{\text{best}})$ **then**
12:       $s^{\text{best}} \leftarrow s^{\text{cur}}$
13:    **end if**
14:    update w^{dh} and w^{rh}
15: **until** Number of iterations $\geq I$
16: **return** s^{best}

3.2. *Destroy heuristics*

We consider the following 6 destroy heuristics. Note that these heuristics do not lead to an infeasible solution, as is usually the case for general ALNS (Ropke and Pisinger (2006)). Instead, the aim of the destroy heuristics is to either improve the solution directly, or to allow a repair heuristic to improve the solution.

i) **Remove a stock-out** This destroy heuristics aims to directly improve the solution by preventing that a component is leased. Specifically, let day $d' \in [d_0, d_0 + PH)$ be the first day in the planning time window during which a new component is leased. This heuristic randomly selects a scheduled replacement during a day $d < d'$, and it randomly selects a scheduled replacement during a day $d \geq d'$. Both these scheduled replacements are removed.

ii) **Remove an assignment of an aircraft to a generic slot** This destroy heuristic aims to directly improve the solution by removing one randomly selected assignment of an aircraft to a generic slot.

iii) **Remove all scheduled replacements for a critical aircraft** This destroy heuristic removes all scheduled replacements for one randomly selected critical aircraft.

iv) **Randomly remove one scheduled replacement** This sub-heuristic randomly removes one scheduled replacement of a component in an aircraft.

v) **Randomly remove two scheduled replacements** This sub-heuristic randomly removes two scheduled replacements of two different components, in two different aircraft.

vi) **No removal** This sub-heuristic does not remove any scheduled replacements.

3.3. *Repair heuristics*

Usually, in ALNS a repair heuristic *repairs* the solution after the destroy phase, i.e., ensures that the solution is feasible again. Since we do not have an infeasible solution after the destroy phase, we instead focus solely on improving the solution. The repair heuristics that we consider are based on the *criticality* of the aircraft and components.

i) **Greedy scheduling of maintenance for one critical aircraft (criticality level 1)** We randomly select an aircraft $a \in A$ that is still critical, even with the scheduled replacements in the current solution. For this aircraft, we identify and schedule replacement(s) in a greedy way such that the cost decreases as much as possible (or increase as little as possible), while the solution remains feasible. Furthermore, to avoid AOG-events, we require that at least enough component replacements are planned such that $P^{\text{AOG}}_{a,d_0+PH} < r$, i.e., such that the aircraft is not critical anymore in the solution.

ii) **Greedy scheduling of the replacements of one or two alerted components (criticality level 2)** We greedily schedule the replacements of 2 randomly selected, alerted components. If there are less than 2 alerted components, we schedule the replacement of one alerted and one failed component, or of 2 failed components instead. The replacements for the 2 components are scheduled in a greedy way, i.e., such that the cost decreases as much as possible, while the solution remains feasible. If the costs increase when the replacements of the 2 randomly selected components are scheduled, the replacement of only one of the 2 components is scheduled in a greedy way instead.

iii) **Greedy scheduling of the replacements of one or two components** We greedily schedule the replacements of two randomly selected, alerted or failed components (criticality level 2 and 3). The replacements for the 2 components are scheduled in a greedy way, i.e., such that the cost decrease as much as possible, while the solution remains feasible. If the costs increase when the replacements of the 2 randomly selected components are scheduled, the replacement of one component is scheduled in a greedy way instead.

iv) **No extra replacement scheduled** In this heuristic, no extra replacements are scheduled.

Table 1.: Parameter values for the maintenance planning model

Cost parameters		
c^{Lf}	$4 \cdot 10^4$	Fixed leasing cost
c^{Ld}	10^3	Daily leasing costs
c^{gen}	10^4	Cost of a generic slot
c^{spec}	1	Cost of an aircraft-specific slot
c^{ex}	$5 \cdot 10^3$	Cost savings per replaced non-failed component
c^{rep}	2	Cost savings per replaced component
c^{AOG}	$2 \cdot 10^5$	Daily cost of an AOG-event
Rolling horizon parameters		
PH	50 days	Optimisation time-window
τ	5 days	Size of the sliding step
Component-related parameters		
N	4	Number of components per system
k	2	Number of components required to be operational
Δ	28 days	Repair time for a component
V	10 days	Maximum number of days an aircraft can fly with k functional components
N^{sp}	10	Initial stock of spare components
Degradation parameters		
α, β	0.1	Shape and scale parameter of the Gamma distribution, respectively
T^{fail}	1000	Failure threshold
T^{alert}	950	Alert threshold
ALNS algorithm parameters		
ω_1=4, ω_3=2		Weight-updates (see eq. (3))
ω_1=4, ω_3=2		
λ	0.9	Factor to retain weight (see eq. (2))
I	500	Maximum number of iterations
Other parameters		
m	2	Capacity of a generic slot
r	0.01	Reliability threshold

4. Case study

In this section, we consider the maintenance planning for a fleet of 50 aircraft and an initial shared stock of $N^{\text{spares}} = 10$ components. Each aircraft is equipped with a k-out-of-N system, with $k = 2$, $N = 4$ and $V = 10$. The other parameters are given in Table 1.

4.1. *Maintenance planning for one time window with 3 levels of criticality*

We illustrate the maintenance planning model for one time window of days $[845, 895)$. Figure 4 shows the maintenance planning created at day 845. These results for a fleet of 50 aircraft are obtained in 5.03 seconds on a computer with an Intel Core i7 processor at 2.11 GHz and 8Gb RAM. At day 845, there is one aircraft with one failed

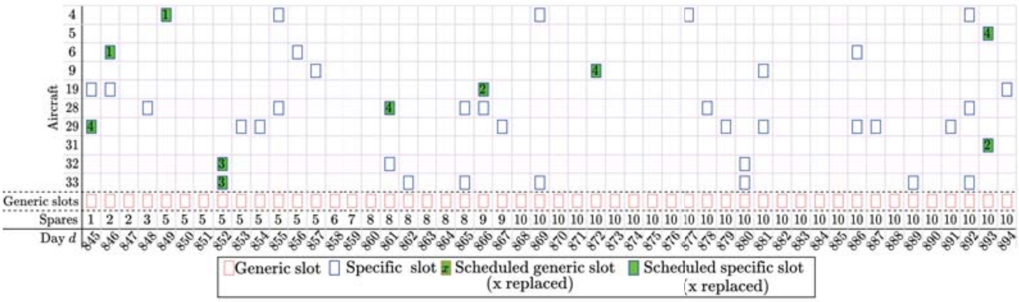


Fig. 4.: Maintenance planning created at day 845. “Spares” is the number of spare components initially available at the beginning of each day.

component (aircraft 19) where component two is failed, and 9 aircraft with one alerted component.

Figure 4 shows the maintenance planning created at day 845. Here, we only show the aircraft with a failed or alerted component. At the beginning of the planning time-window, there are only a few spare components available. These are used to replace the alerted components of aircraft 4, 6, 29, 32 and 33. For aircraft 9 and 28, there are aircraft-specific slots available at the beginning of the planning time-window as well. However, to avoid leasing a spare component, the replacement of the two alerted components for these aircraft are postponed to later aircraft-specific slots at time 872 and 861, respectively. The probability of failure for these two alerted components is relatively low compared to the other alerted components, for which maintenance is scheduled earlier. When new spare components become available, they are used to replace the failed component in aircraft 19, and the alerted components in aircraft 28, 9, 5 and 31. No generic slots are used in this solution, and no components are leased.

4.2. *Aircraft maintenance with 3-levels of criticality vs. 2-levels of criticality: Long-term performance*

In this section, we evaluate the long-term performance of our maintenance planning approach for a fleet of 50 aircraft and a total period of 5 years using Monte Carlo simulation.

We consider two different maintenance strategies for the long-term evaluation, First, we consider the case where aircraft maintenance is performed using all *3-levels of criticality*, as considered in Section 2.6 and 4.1. We compare this strategy with the strategy where maintenance is only scheduled for the first *2-levels of criticality*: i) alerted and failed components in critical aircraft, and ii) alerted components in non-critical aircraft.

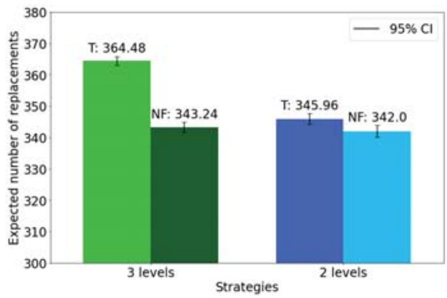
Figure 5 shows the number of replacements, and the number of aircraft assignments to generic maintenance slots. In both cases, no AOG-events occur, since components are replaced before an AOG-event occurs, due to the large cost associated with an AOG-event. As expected, the total number of replacements is lower when performing maintenance with two levels of criticality than with three levels of criticality. On the other hand, Figure 5b shows that when performing maintenance with 2-levels of criticality, aircraft are more often assigned to an expensive, generic maintenance slot than when performing maintenance with a 3-levels of criticality.

The results show that performing maintenance with 2-levels of criticality is slightly more beneficial in terms of the total number of replacements, while performing maintenance with 3-levels of criticality leads to significantly less assignments to expensive, generic maintenance slots.

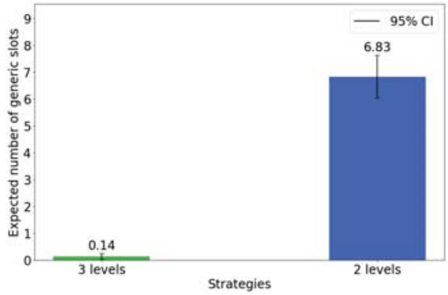
5. Conclusions

We have proposed a rolling-horizon predictive aircraft maintenance planning approach for a fleet of aircraft, taking into account component RUL prognostics, a limited stock of spare components and fixed maintenance slots. Based on these RUL prognostics, three levels of aircraft/component criticality are defined: i) critical aircraft for which the airworthiness is threatened due to (upcoming) component failures, ii) alerted components in non-critical aircraft with a predicted near-future failure and iii) failed components in non-critical aircraft. These criticality levels are used to plan maintenance tasks with an Adaptive Large Neighbourhood Search heuristic.

We show that our approach is successful in planning maintenance for a large fleet of aircraft, while guaranteeing aircraft airworthiness. Moreover, we show that performing maintenance using a three levels of maintenance criticality requires significantly less expensive, generic maintenance slots than when performing maintenance using a 2 levels of maintenance criticality.



(a) Expected total number of replacements (T), and the expected number of components that were not failed at the moment of replacement (NF).



(b) Expected number of assignments of an aircraft to a generic maintenance slot.

Fig. 5.: Long-term maintenance performance for a period of 5 years, while scheduling maintenance for 3 and for 2 levels of criticality.

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