Multi-objective Analysis of Condition-based Aircraft Maintenance Strategies using Discrete Event Simulation

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Multi-objective analysis of condition-based aircraft maintenance strategies using discrete event simulation

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Key Words: aircraft maintenance, condition-based maintenance, discrete event simulation, multi-objective analysis

SUMMARY & CONCLUSION

As aircraft maintenance is transitioning towards data-driven condition-based maintenance (CBM), its cost and performance objectives need to be re-evaluated: how are these objectives related under various CBM strategies?; which objectives are conflicting?; what are the trade-offs between the conflicting objectives?; what is the impact of this transition on aircraft maintenance? We propose a methodology based on discrete-event simulation to analyze CBM of aircraft from the perspective of multiple objectives. The simulation considers an aircraft operations model, systems of multiple, redundant aircraft components, stochastic degradation models for components, and specific CBM strategies. In particular, we analyze two CBM strategies for component replacement, which are based on sensor monitoring and remaining-useful-life prognostics. As objectives for these strategies, we consider the minimization of the number of component replacements, the number of unscheduled replacements, the number of degradation incidents, the delay caused by maintenance, and the mean number of flight cycles to replacements (MCTR). We identify the main conflicting objectives and generate Pareto fronts. We show non-trivial trade-offs between the performance-oriented objectives (the number of degradation incidents and the delay due to maintenance) and cost-oriented objectives (MCTR). In fact, the CBM strategy based on remaining-useful-life prognostics dominates the other strategies in the *knee* region of the Pareto fronts. This implies that the transition towards data-driven CBM strategies can reduce the cost while maintaining the performance. Moreover, the proposed methodology is readily applicable to analyze general aircraft systems and other maintenance strategies.

1 INTRODUCTION

With the increasing use of condition monitoring systems, the maintenance of aircraft is undergoing a paradigm shift where data analysis is central [1, 2]. Traditionally, aircraft maintenance tasks are executed at fixed time intervals. These strategies are referred to as time-based maintenance (TBM) [3]. Nowadays, TBM is gradually replaced by condition-based maintenance (CBM), where sensor data are used to specify when and which maintenance tasks to execute. An example of CBM is the case when a maintenance task is executed as soon as sensor data indicate degradations above accepted levels [4]. Advanced CBM analyzes sensor data to estimate the remaining-useful-life (RUL) of components [4]. This estimated RUL is further used to schedule maintenance tasks, in anticipation of failures.

Transitioning from TBM to CBM requires the consideration of multiple objectives. One main objective of CBM for aircraft is the reduction of maintenance costs [5, 6]. Additionally, aircraft maintenance aims to comply with aircraft operational regulations [3, 7], to limit the need for unscheduled maintenance tasks [8], to reduce aircraft delays due to maintenance [9], and to utilize the aircraft as much as possible [10]. Given these multiple objectives, it is of interest to understand how they are impacted by maintenance strategies, how they are related to each other, and what are the trade-offs between them.

In this paper, a methodology based on discrete-event simulation is proposed to analyze the relation between multiple objectives of aircraft maintenance, and to identify the trade-offs between them. Specifically, a general aircraft maintenance model is proposed for which a discrete-event simulation is conducted. The aircraft maintenance model considers the operation of the aircraft, systems of multiple, redundant aircraft components, and a stochastic degradation model for aircraft components. With this framework, multiple objectives are analyzed for a sensor-based CBM, a RUL-based CBM, and, for comparison reasons, a traditional TBM strategy. Then, conflicting objectives are identified and Pareto fronts are obtained. The resulting Pareto fronts show that the CBM strategies are located in the attractive Pareto *knee* region where conflicting objectives are balanced.

2 METHODOLOGY

Multiple objectives of the maintenance of multi-component aircraft systems are analyzed by means of a discrete event simulation. Below we introduce the aircraft maintenance model that is being simulated. This aircraft maintenance model is based on our study in [4].

2.1 *Multi-Component Aircraft Maintenance Model*

We model the maintenance of multi-component aircraft systems considering the following events: aircraft operation (aircraft arrival and departure), degradation of components, maintenance tasks (component replacement, component inspection, and sensor monitoring), and degradation incidents when the components reach such a high level of degradation that the system becomes inoperable.

The aircraft is operated based on a sequence of flight cycles, each cycle i being defined by a departure and an arrival time (see Figure 1). The aircraft departs from the airport at time τ_i^{dep} and arrives at the arrival airport after a flight-time $\Delta\tau_{i,}$, where $\Delta\tau_i \sim \mathcal{N}(\overline{\Delta\tau}_i, \sigma_i^2)$. If an arrival time is $\tau_i^{\text{arr}} = \tau_i^{\text{dep}} + \Delta\tau_i$, then the time interval between this arrival and the successive departure is referred to as ground-time. Maintenance tasks are performed during ground-time. If a task is not completed until the next departure time τ_{i+1}^{arr}, the departure is delayed (see Figure 1).

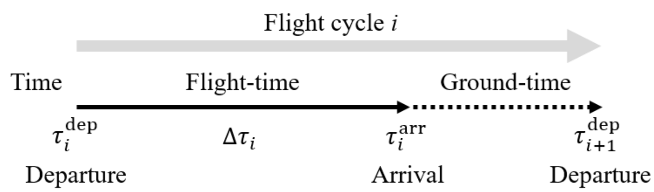

Figure 1. Flight cycle, where maintenance tasks can be executed during ground-time.

The aircraft consists of components that degrade during flight-time. Let the degradation level of a component at time t be $Z(t)$. A new component without degradation has $Z(t) = 0$. We say that the component is *inoperable*, considering a safety margin of degradation, if

$$Z(t) \geq 1. \qquad (1)$$

We consider components that degrade monotonically and gradually over time, as is the case of bearings that wear out over time or brake pads that erode over time. For such components, a Gamma process is shown to model well the degradation [11]. Similarly, we assume that the degradation increment resulting from flight cycle-i follows a Gamma distribution [11]:

$$Z(\tau_i^{\text{arr}}) - Z(\tau_i^{\text{dep}}) \sim \text{Gamma}(\alpha, \beta) \qquad (2)$$

where, α is the shape parameter, and β is the scale parameter of the Gamma process. It is assumed that the degradation is negligible during ground-time, i.e.,

$$Z(\tau_i^{\text{dep}}) - Z(\tau_i^{\text{arr}}) = 0. \qquad (3)$$

Following equations (2) and (3), $Z(t)$ becomes a piecewise Gamma process.

Over time, the components undergo maintenance. As for the maintenance tasks, we consider component replacement, component inspection, and sensor monitoring.

Component replacement: When a component is replaced with a new one at time t, the degradation process is reset to be $Z(t) = 0$. The time Δt_{Rep} spent for the replacement of this component is modeled as an exponential time, i.e., $\Delta t_{\text{Rep}} \sim \text{Exp}(\bar{\delta}_{\text{Rep}})$.

Component inspection: When a component is inspected, the degradation level is known with an error. Let $\hat{Z}(t)$ be the degradation level obtained following an inspection. Then,

$$\hat{Z}(t) = Z(t) + \epsilon_{\text{Ins}},$$

where $\epsilon_{\text{Ins}} \sim \text{N}(0, \sigma_{\text{Ins}}^2)$. The inspection time Δt_{Ins} is assumed to follow an exponential distribution, i.e., $\Delta t_{\text{Ins}} \sim \text{Exp}(\bar{\delta}_{\text{Ins}})$.

Sensor monitoring: For modern aircraft equipped with condition-monitoring systems, sensors are used to automatically monitor the degradation level of the component. Let $\tilde{Z}(t)$ be the degradation level of the component obtained from sensor monitoring. Then

$$\tilde{Z}(t) = Z(t) + \epsilon_{\text{Sen}},$$

where $\epsilon_{\text{Sen}} \sim \mathcal{N}(0, \sigma_{\text{Sen}}^2)$. We assume that the sensor error is larger than the inspection error, i.e., $\sigma_{\text{Ins}}^2 \leq \sigma_{\text{Sen}}^2$. Compared to other tasks that require an execution time, we assume that sensor monitoring is instantaneous, i.e., $\Delta t_{\text{Sen}} = 0$.

Figure 2 shows an example of the degradation of a component following equations (2) and (3). The gray regions represent flight-times, while the hatched regions represent ground-times. $Z(t)$ jumps after each flight-time following equation (2). During the 5th ground time, the component is replaced, and after time $\Delta t_{\text{Rep}} = 2.5$, the degradation level of this component is reset to zero. In this example, this component is replaced before its degradation level exceeds a level of inoperability $\eta = 1$.

For redundancy, an aircraft system often consists of multiple components. Here, we say that a multi-component system has redundancy ${}_n\text{C}_m$ if the system consists of n components and needs to have at least m operable components, $(0 < m \leq n)$. As soon as more than $(n - m)$ components become inoperable in a system with redundancy ${}_n\text{C}_m$, we say that a *degradation incident* occurs. The main objective of aircraft maintenance is to avoid degradation incidents, and to keep the aircraft systems operable.

We consider two aircraft systems, each of which consists of 4 components with redundancy ${}_4\text{C}_3$, i.e., a total of 8 components. We assume that the components follow the same Gamma process with parameters α and β as in equation (2), and that the degradation of one component is independent of the degradation of the other components.

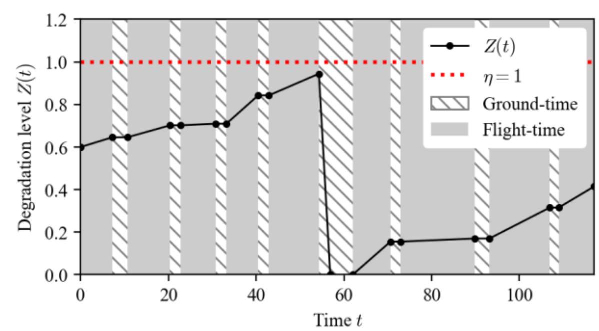

Figure 2. Example of component degradation over time.

2.2 *Aircraft Maintenance Strategies and Parameters*

Maintenance strategies determine the execution of maintenance tasks, i.e., which types of tasks should be executed, and when should these tasks be executed. In this study, we consider a TBM strategy named fixed-interval inspection (FII) [12], and two CBM strategies, named sensor-based replacement (SBR), and RUL-based replacement (RBR). These strategies are discussed in detail in [4].

1) The fixed-interval inspection (FII) strategy is a TBM

strategy that schedules component replacements based on periodic inspections performed by mechanics, without sensor monitoring [12]. Under the FII strategy, all components are inspected every d_{Ins} flight cycles. If upon inspection it is observed that the degradation of a component exceeds a threshold ($\hat{Z}(t) \geq \eta_{\text{Rep}}$), then the replacement of this component is scheduled within d_{Rep} flight cycles. The FII strategy has been widely implemented in traditional aircraft maintenance [4, 12].

2) The Sensor-based replacement (SBR) strategy is a CBM strategy that utilizes sensor monitoring, instead of inspections performed by mechanics [4]. Under the SBR strategy, sensors measure the degradation level $\tilde{Z}(t)$ of components and report this after each flight-time. If $\tilde{Z}(t) \geq \eta_{\text{Rep}}$, where η_{Rep} is a degradation threshold, then the component is replaced within d_{Rep} flight cycles. Unlike the component inspections in the FII strategy, sensor monitoring does not cause any delays.
3) The RUL-based replacement (RBR) strategy is a CBM strategy which uses the sensor data indicating the level of degradation to estimate the remaining-useful-life of the component, RUL[4]. Here, RUL is estimated based on the last sensor monitoring data $\{\tilde{Z}(t') \text{ for } 0 < t' \leq T\}$, where T is the current time. We consider the following linear model to estimate the degradation level of a component at time $T + t$:
$$\tilde{Z}(T + t) = c_0 + c_1 t.$$
The coefficients c_0 and c_1 are estimated after every flight cycle based on the most recent sensor data using the ordinary least square method. Then, after each flight cycle we predict RUL as follows [4]:
$$RUL = \min\{t \mid c_0 + c_1 t \geq 1\} \tag{4}$$
Lastly, if RUL is below a threshold $RUL_{\min}$, a component replacement is scheduled within d_{Rep} flight cycles.

Each of the three maintenance strategies has its own parameters. For instance, the FII strategy has the parameters d_{Ins}, and η_{Rep}; the SBR strategy has the parameter η_{Rep}; and the RBR strategy has the parameter $RUL_{\min}$. In this paper, we consider the parameter values given in Table 1. Each parameter has its range, and its value is selected from evenly distributed l-levels following full factorial design (FFD) [13]. For example, for the values of $RUL_{\min}$, we consider the range $20 \leq RUL_{\min} \leq 60$ with steps of 1, which leads to a 41-level FFD.

Table 1 – Maintenance strategies and their parameters

Strategy	Parameter	Range	Step	Level
FII	d_{Ins}	[20, 80]	10	7
	η_{Rep}	[0.95, 1.00]	0.002	26
SBR	η_{Rep}	[0.95, 1.00]	0.001	51
RBR	$RUL_{\min}$	[20, 60]	1	41

2.3 *Multiple Objectives of Aircraft Maintenance*

In general, aircraft maintenance has multiple objectives, i.e., keeping the aircraft systems operational while minimizing maintenance costs and maximizing the quality of service. We introduce the following objectives [4, 5, 8, 9].

- N_{Inc} – The number of *degradation incidents*. This directly represents the performance of a maintenance strategy from the perspective of keeping the aircraft systems operable [4]. A low N_{Inc} implies that it is less likely to have inoperable systems considering ${}_n\mathrm{C}_m$ redundancy.
- N_{Rep} – The number of component replacements. Since maintenance tasks require new components, manpower, and other resources, the number of component replacements gives a direct indication of the maintenance cost [5]. A small N_{Rep} is preferred as long as the aircraft systems are kept operational.
- N_{Unsch} – The number of unscheduled component replacements. Component replacements are scheduled in advance (before d_{Rep} flight cycles) in order to have time to prepare the necessary resources. When a component replacement is necessary but there is not enough preparation time because the failure was unexpected, we call this an *unscheduled* component replacement. Because unscheduled replacements involve higher costs and delays [8], it is desired to minimize N_{Unsch}.
- T_{D} – Aircraft delay caused by maintenance tasks. Among many causes of aircraft delay, maintenance is the second most likely cause of delays longer than one hour [9]. Thus, it is of interest to complete the maintenance tasks before a next departure time τ_{i+1}^{dep}. This is achieved by scheduling maintenance tasks only when enough ground-time is available.
- *MCTR* – The mean number of flight cycles to component replacement. This measures the exploitation time of the components. A high *MCTR* implies that the maintenance strategy utilizes the component efficiently and does not waste the useful life of the component [4]. Thus, it is desired that *MCTR* is maximized.

The goal is to minimize (or maximize) all these objectives by selecting a maintenance strategy with proper parameter values. However, some objectives may conflict with others. Therefore, their relation and trade-offs are analyzed next.

2.4 *Discrete Event Simulation of Aircraft Maintenance*

Based on the aircraft maintenance model in Section 2.1, we conduct a discrete event simulation of 10 years of aircraft operations, to estimate the objective values of different maintenance strategies and parameters. A maintenance strategy and specific parameter values are referred to as a case. Specifically, a case is defined as a tuple of (*strategy*, *parameter*), e.g., (the RBR strategy, $RUL_{\min} = 30$). Considering the ranges and levels of the parameters in Table 1, we simulate 7×26 cases for the FII strategy, 51 cases for the SBR strategy, and 41 cases for the RBR strategy, which results in a total of 274 cases. For each case, we run the discrete event simulation 10^4 times and estimate the objectives using Monte Carlo methods.

3 *SIMULATION RESULTS: MULTI-OBJECTIVE ANALYSIS*

Using simulation, the objective values of the 274 cases are obtained. Again, each case corresponds to a maintenance strategy and its specific parameter values. Below we present the results obtained.

3.1 *Relation Between Multiple Objectives*

Figure 3 shows $\binom{5}{2}$ pairs of objective. Circle, triangle, and square markers denote the objective values of cases with the FII, SBR, and RBR strategies, respectively. Except for $MCTR$, all objectives are considered for minimization.

Each plot in Figure 3 shows the relation of a pair of objectives, where some pairs of objectives are conflicting (plots (2) – (7)), while other pairs of objectives are improved together (plot (1), plots (8)-(10)). Some relations (whether conflicting or not) can be expected before simulations. For example, it is expected that as $MCTR$ increases, N_{Rep} decreases (see plot (1)). However, since their trend and trade-off are not trivial, the simulation results can be analyzed further to obtain an in-depth understanding of the characteristics of these objectives and the maintenance strategies considered. For example, in plot (1), the relation between $MCTR$ and N_{Rep} is neither linear nor inversely proportional. Rather, when $N_{\text{Rep}} = 2.4$, $MCTR$ suddenly drops from 1200 to 1250. This is because $MCTR$ can be significantly different depending on the moment when components are replaced, even if the same number of component replacements are performed.

More interesting relations between conflicting objectives are shown in Figure 3, plots (2) – (7). For example, in plot (6) it is shown that fewer degradation incidents occur (low N_{Inc}) when components are replaced often (high N_{Rep}), i.e., there is a trade-off between N_{Inc} and N_{Rep}. However, the trade-off is unclear under the SBR strategy where there are nearly zero degradation incidents but different numbers of replacements. This shows that in some cases of the SBR strategy, the components are replaced unnecessarily often. A similar trade-off is shown between N_{Unsch} and N_{Rep} in plot (5). The similarity between plots (5) and (6) is because N_{Inc} and N_{Unsch} are positively correlated, as shown in plot (8).

Table 2 – The Pearson correlation coefficient of objectives for 274 cases of maintenance strategies and parameters.

	Group-1		Group-2		
	$MCTR$	N_{Rep}	N_{Unsch}	N_{Inc}	T_{D}
$MCTR$	–	0.69	-0.77	-0.76	-0.80
N_{Rep}	0.69	–	-0.40	-0.47	-0.50
N_{Unsch}	-0.77	-0.40	–	0.90	0.73
N_{Inc}	-0.76	-0.47	0.90	–	0.70
T_{D}	-0.80	-0.50	0.73	0.70	–

The analysis based on Figure 3 is reinforced by the analysis of the correlation between the considered objectives using the Pearson correlation coefficient (see Table 2). The Pearson correlation coefficient quantifies the linear correlation between two objectives. A positive coefficient between two objectives implies that they are likely to be improved together, while a negative coefficient implies that they conflict with each other. For example, the Pearson coefficient between T_{D} and $MCTR$ is -0.80, which represents the trade-off shown in plot (4) of Figure 3.

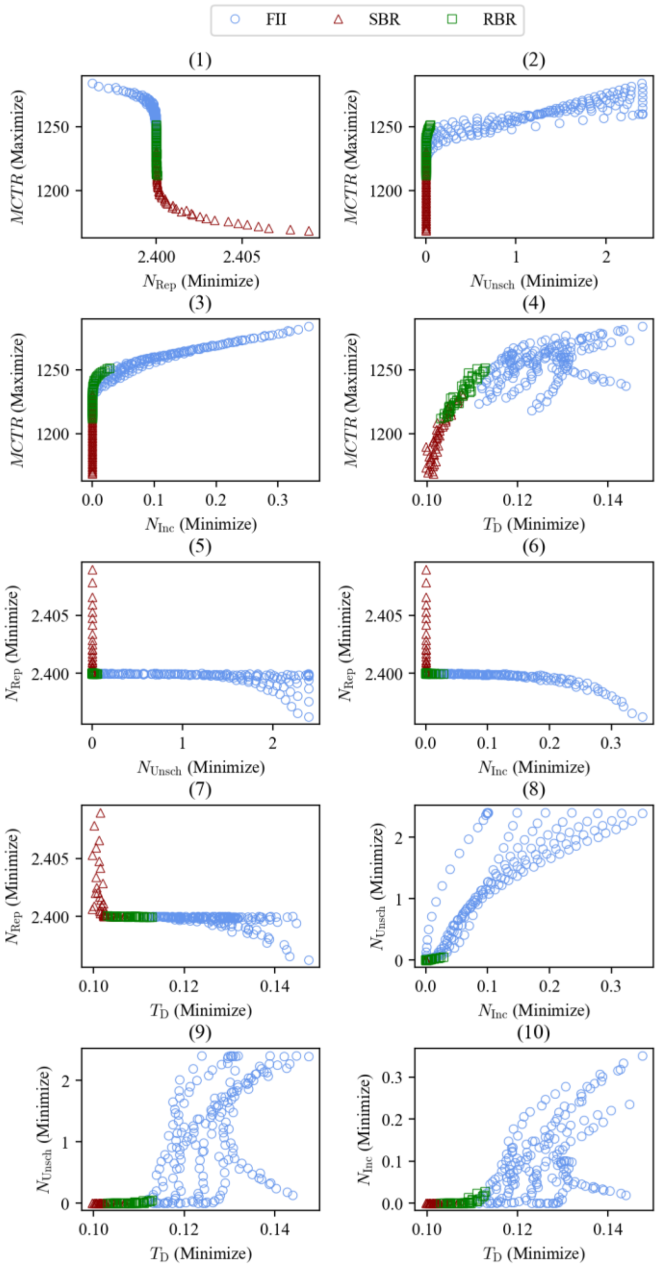

Figure 3. Pairwise objectives of the aircraft maintenance for the FII, SBR and RBR strategies.

Based on the Pearson correlation coefficient values, we categorize the objectives into two groups such that the objective pairs within the same group have positive coefficients (see Table 2). Group-1 is {$MCTR$, N_{Rep}}, and Group-2 is {N_{Unsch}, N_{Inc}, T_{D}}.

$MCTR$ and N_{Rep} in Group-1 are positively correlated as both of them measure the exploitation time of a component. Since the exploitation of components is directly related to the cost of maintenance, these objectives imply an economic benefit of the maintenance. On the other hand, N_{Unsch}, N_{Inc}, and T_{D} in Group-2 measure the number of undesired events, i.e., unscheduled maintenance, degradation incidents, and aircraft delay due to maintenance. In other words, these objectives represent the performance of the maintenance. The conflict between Group-1 (Cost) and Group-2 (Performance) shows the general trade-off between the performance and the cost of aircraft maintenance.

Although aircraft maintenance has various objectives, it is useful to analyze the maintenance strategies based on a small number of representative objectives [14]. To consider both performance and economic aspects, we analyze the aircraft maintenance based on two objectives, one chosen from Group-1 and one from Group-2. In particular, we chose $MCTR$ from Group 1 since it better represents the economic value because the variance of N_{Rep} is very small compared to that of $MCTR$ (see the scales of N_{Rep} and $MCTR$ in plot (1) of Figure 3). For the objective representing performance (Group 2), N_{Inc} or T_D are chosen. N_{Unsch} is not chosen because it is strongly correlated with $MCTR$ (coefficient 0.9 in Table 2), and therefore N_{Unsch} is improved together with $MCTR$.

3.2 *Trade-off bettween Aircraft Maintenance Objectives*

Following the analysis in Section 3.1, in this subsection we analyze the trade-offs between Group 1 objective $MCTR$ and Group 2 objectives N_{Inc} and T_D. Pareto fronts are generated for $\{MCTR, N_{\mathrm{Inc}}\}$ and $\{MCTR, T_D\}$ by collecting non-dominated cases from the total 274 cases (the FII, SBR, or RBR strategy with their parameter values, see Table 1).

Figure 4 shows the Pareto front for the objectives $MCTR$ and N_{Inc}. Since these two objectives are conflicting, no single solution achieves a maximum $MCTR$ and a minimum N_{Inc} simultaneously. Rather, we should trade-off $MCTR$ for N_{Inc}. For instance, the number of degradation incidents can be minimized ($N_{\mathrm{Inc}} \leq 10^{-4}$) if we accept a small $MCTR \leq 1235$. Or, if we want to extend $MCTR \geq 1250$, then N_{Inc} is increased to 0.02.

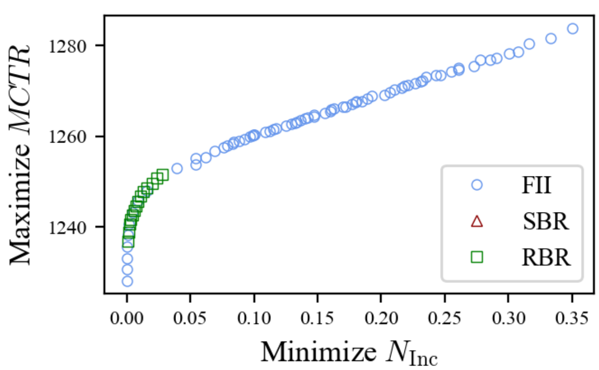

Figure 4. Pareto front considering MCTR and N_{Inc}.

The Pareto front in Figure 4 also provides insight into the maintenance strategies considered. In all cases, the SBR strategy is dominated by the FII or RBR strategies, thus not shown in the Pareto front in Figure 4. This means that the RBR or FII strategies are preferred when considering $MCTR$ and N_{Inc}. More interestingly, the cases considering the RBR strategy are located in the middle, or in the extruded region of the Pareto front, which is called the *knee region* [15]. The non-dominated solutions in the knee region are generally preferred because they provide a balanced solution, i.e., both objectives are moderately optimized. Outside of the knee region, an objective is significantly deteriorated to achieve a slight improvement in the other objective, which is less preferred for aircraft maintenance [15, 16]. By comparing plot (3) of Figure 3 and Figure 4, it can be seen that the FII strategy cases in this knee region are dominated by the RBR strategy cases. In Figure 4, the non-dominated FII strategy cases cause either a large number of degradation incidents $N_{\mathrm{Inc}} \geq 0.04$ or a low $MCTR \leq 1240$, but the non-dominated RBR strategy cases achieve a small $N_{\mathrm{Inc}} \leq 0.04$ and a moderate $MCTR \geq 1240$. This indicates that CBM using RUL prognostics (the RBRstrategy) is beneficial when we aim to improve both $MCTR$ and N_{Inc}.

Figure 5 shows the Pareto front between $MCTR$ and the delay T_{D}. Unlike the Pareto front in Figure 4, the SBR strategy is visible in the lower-left corner of the Pareto front in Figure 5. These non-dominated SBR strategy cases have a low delay ($T_{\mathrm{D}} \leq 0.1$) but they are not cost-effective ($MCTR \leq 1230$). The RBR strategy, on the other hand, is located in the middle of the Pareto front, where $0.105 \leq T_{\mathrm{D}} \leq 0.115$ and $1230 \leq MCTR \leq 1250$. In this region, many FII strategy cases are dominated by the RBR strategy cases (compare plot (4) of Figure 3 and Figure 6). Thus, when both objectives are considered with similar importance (knee region), the introduction of the RBR strategy improves both objectives.

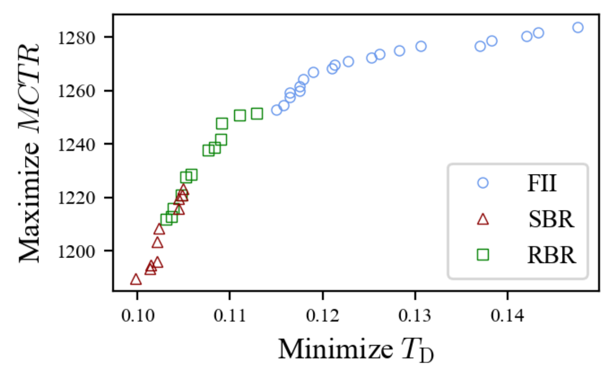

Figure 5. Pareto front considering MCTR and T_D.

Overall, these results show that CBM using RUL prognostics (the RBR strategy) has a benefit in improving both the performance (N_{Inc}, T_{D}) and cost ($MCTR$) of aircraft maintenance.

4 CONCLUSION

We have conducted a multi-objective analysis of aircraft condition-based maintenance strategies, using discrete event simulation. Our aircraft maintenance model covers the general features of the maintenance of multi-component aircraft systems, such as aircraft operations, stochastic degradation of aircraft components, redundancy of aircraft systems, and maintenance strategies.

We have considered as objectives the minimization of the mean number of flight cycles to component replacement

($MCTR$), the number of replacements (N_{Rep}), the number of degradation incidents (N_{Inc}), the number of unscheduled replacements (N_{Unsch}), and the delay due to maintenance (T_{D}). Based on their correlation and trade-off, we chose two pairs of conflicting objectives to represent the performance and cost of aircraft maintenance. We constructed Pareto fronts between these conflicting objectives under condition-based maintenance strategies (the SBR and RBR strategies), and a traditional time-based maintenance strategy (the FII strategy). The results show that the advanced CBM strategy (the RBR strategy) dominates the other strategies in the knee region of the Pareto fronts. This suggests that the introduction of CBM in aircraft maintenance achieves a balance between the performance and the cost of maintenance.

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