Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen

doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P3259-cd

A prescriptive maintenance policy for degrading units in a civil aircraft context

Nicola Esposito

Université d'Angers, France. E-mail: nicola.esposito@univ-angers.fr
(currently at Scuola Superiore Meridionale, Italy)

Laurent Saintis

Université d'Angers, France. E-mail:laurent.saintis @univ-angers.fr

Bruno Castanier

Université d'Angers, France. E-mail:Bruno.castanier @univ-angers.fr

Sylvain Verron

Université d'Angers, France. E-mail:sylvain.verron @univ-angers.fr

Massimiliano Giorgio

Università di Napoli Federico II, Italy. E-mail:massimiliano.giorgio@unina.it

The goal of this paper is to propose a maintenance policy for a deteriorating system which integrates concepts of modern prescriptive maintenance. In particular, the policy focuses on systems where inspections cannot be performed at all times and repairs/replacements incur high costs. This is the case, for example, of some aviation applications where inspections can be performed when the aircraft is grounded, and interventions such as repairs or replacements may necessitate specialized equipment or incur significant delays.
In this paper, we propose a maintenance policy where it is assumed that the system under study must work, with prespecified performances, for a fixed time horizon, at the end of which it is systematically replaced, regardless of its state, for a cheap/negligible price. Within this time horizon, inspections are regularly planned which return the true degradation level of the unit. If a failure is detected at an inspection time, corrective replacements can be carried out immediately, albeit incurring a much higher cost than the preplanned replacement at the end of the mission. Another possible action that the policy can take is to derate the system. This action entails voluntarily reducing the performances of the system (thereby incurring a cost) with the aim of decelerating its degradation process and mitigating the risk of failure. The optimal maintenance policy is defined by optimizing an economic performance criterion. The lifetime of the unit is defined by using a failure threshold model.

Keywords: gamma process, prescriptive maintenance, derating.

1. Introduction

Today, aircraft operational performance (reliability, availability, maintenance costs, etc.) is a key factor in flight punctuality and airline profitability, synonymous with profits and customer satisfaction (Manikar et al. 2022). Airlines monitor the performances of their aircraft very carefully, as it strongly reflects the quality of their internal operational organization (operations, maintenance, engineering) and therefore their profitability (Saintis et al. 2006). This performance is symbolized by operational reliability, which encompasses the frequency of technical failures and associated necessary maintenance tasks that lead to an interruption in operations, defined as a delay of over 15 minutes at take-off, a flight cancellation, or a diversion. For airlines, these unscheduled service interruptions generate not only direct costs in the form of increased fuel consumption, crew accommodation/duty time, passenger accommodation, and financial compensation, but also indirect costs in the form of image loss and impact on customer loyalty, among others (Saintis et al. 2009).

A typical mission for a short-haul aircraft can be composed, for example, of ten round trips from the main base to an external base. After the last landing, the aircraft is scheduled to recover overnight at the main base, in preparation for the next mission (which may differ from the first). During this recovery period, time-intensive maintenance actions can be performed, clearing the aircraft of possible critical failures (Hugues et al. 2004).

On the other hand, during the mission, the possibility of performing maintenance actions is limited. However, when the aircraft is on the ground (during a stopover between two flights), it is regularly inspected, and the degradation level of some subsystems can be measured. If these inspections reveal some highly degraded or failed state, then emergency maintenance operations can be planned. By definition, maintenance performed on the aircraft during the mission is on-line maintenance, which incurs a high cost. Conversely, at the end of the mission, preplanned maintenance actions can be performed with a negligible effect on the mission.

In this context, we aim to conceive a maintenance policy which integrates elements from modern prescriptive maintenance, a new framework that is gaining increased attention from the maintenance literature (see Meissner et al. 2021, Pinciroli et al. 2023, and Giacotto et al. 2025).

In a prescriptive maintenance context, decisions are taken by optimizing a performance measure that accounts for all functionalities of a system (Longhitano et al. 2021). In practice, this is often implemented (Esposito et al. 2022, Esposito et al. 2023) by assuming that, among the possible maintenance actions, the policy can adjust some operating parameters which voluntarily reduce the performances of the system, incurring a cost, but at the same time mitigating the probability of adverse events.

In this paper, we propose a prescriptive maintenance policy that can be applied, for example, to a non-critical subsystem of an aircraft, such as an electrical power converter supplying passenger cabin equipment. The driving idea is that, within the context of the rigid schedule of the aircraft's mission, adjusting some operational parameter (such as the output power of the power converter), may offer an additional degree of freedom which may provide an overall more convenient tradeoff.

The rest of the paper is organized as follows. Section 2 describes in detail the proposed policy. Section 3 illustrates the adopted degradation model. Section 4 describes the formulation of the cost function. Section 5 presents the results of an applicative example, while Section 6 closes the paper.

2. Policy description

The unit is assumed to operate under an aeronautics-like exploitation cycle. This cycle (hereinafter referred to as "mission") is composed of a predetermined number n of "active" periods (APs) (encompassing taxiing, flight, and in general all activities from departure gate to arrival gate) during which the unit experiences substantial operational stresses and degradation. The mission also includes "inactive" periods (corresponding to time intervals where the aircraft is grounded) during which maintenance interventions can be carried out. We assume that during these latter periods the unit does not degrade.

The failure of the unit occurs when its degradation level passes for the first time a predetermined threshold, say w_M. We assume that failure is not self-announcing, meaning that it can be detected only through an inspection. The mission is deemed successfully complete if the unit remains operational at the end of the n-th AP. The endpoints of the APs (i.e., the epoch at which the period ends) are denoted by $\tau_1, \tau_2, \dots, \tau_n$, where $0 < \tau_1 < \tau_2 < \cdots < \tau_n$.

We suppose that at the end of each AP an inspection is carried out which reveals the exact degradation level of the unit. A failed unit remain inoperative until the end of the mission. This scenario incurs a penalty cost that is proportional to the portion of the mission where the unit has been inoperative.

Conversely, an unfailed unit continues to operate until the end of the next AP.

The policy is developed by assuming that at the inspection time (i.e., at the end of each AP), it is possible to derate the unit. This action reduces operational stress and slows down degradation (and thus reduces the failure risk), though incurring a cost linked to the performance loss. The decision about derating or not a unit is made by using a condition-based rule.

The derating factor (i.e., the amount of derating) is determined adaptively based on the measured degradation level and on the current age of the unit. Table 1 summarizes the condition-based rule which informs decision-making at the i-th inspection time τ_i. In Table 1, w_i is the measured degradation level at τ_i, u_{i+1} denotes the value of the derating factor in the $(i+1)$-th AP (i.e., between τ_i and τ_{i+1}), and $g(w_i, \tau_i; \boldsymbol{\xi})$ is a function which adaptively determines the derating factor accounting for the current degradation measurement w_i and the age of the unit τ_i (and is indexed by the parameters vector $\boldsymbol{\xi}$.

Table 1. Condition-based rule which informs decision-making at the inspection time.

Degradation at τ_i	Decision
$w_i > w_M$	Unit is inoperative until the end of the mission
$w_i \leq w_M$	Continue operation in the next AP, set derating factor for the next AP to $u_{i+1} = g(w_i, \tau_i; \boldsymbol{\xi})$

At the end of the n-th AP the mission is terminated and the unit is replaced regardless of its state.

This action restores the unit to an "as good as new" state and, consequently, the time elapsing between two successive replacements defines the cycle of a renewal process.

The components of the vector $\boldsymbol{\xi}$ are the design parameters vector of the policy, whose optimal value $\boldsymbol{\xi}^*$ should be determined by minimizing a selected cost function, which accounts for costs linked to the performance loss incurred by potential derating.

3. Degradation modeling

The gamma process (Van Noortwijk 2009) $\{Y(t); t \geq 0\}$ is a monotonic increasing Markovian stochastic process characterized by gamma-distributed independent increments. Hence, it is fully defined by an initial condition (here $Y(0) = 0$) and the probability density function (pdf) of its generic increment $\Delta Y(t_1, t_2) = Y(t_2) - Y(t_1)$:

$$f_{\Delta Y(t_1,t_2)}(\delta) = \frac{\delta^{\Delta\eta(t_1,t_2)-1}}{\theta^{\Delta\eta(t_1,t_2)} \cdot \Gamma\big(\Delta\eta(t_1,t_2)\big)} \cdot e^{-\frac{\delta}{\theta}}, \quad \delta > 0 \quad (2)$$

where $t_2 > t_1$, θ $(\theta > 0)$ is the scale parameter, $\Gamma(\cdot)$ is the complete gamma function, $\Delta\eta(t_1, t_2) = \eta(t_2) - \eta(t_1)$ is the shape parameter, and $\eta(t)$ is a non-negative monotonic increasing function referred to as the age function. The functional form $\eta(t) = a \cdot t$ is a very common choice in the literature.

Following Tseng et al. (2009) and Esposito et al. (2023), modifying the derating factor is supposed to only impact the age function of the gamma process, while the scale parameter remains constant. Based on this, on the fact that the derating factor can only be changed at the inspection times (i.e., it stays constant in between inspections), and knowing that the gamma process has independent increments, the degradation process is fully specified. In fact, denoting by $\{W(t); t \geq 0\}$ the degradation process of the unit, the probability density distribution (pdf) of the degradation increment between two inspections $\Delta W_i = W(\tau_i) - W(\tau_{i-1})$ can be expressed as:

$$f_{\Delta W_i}(\delta) = \frac{\delta^{\Delta\eta_i(\tau_{i-1},\tau_i)-1} \cdot e^{-\frac{\delta}{\theta}}}{\theta^{\Delta\eta_i(\tau_{i-1},\tau_i)} \cdot \Gamma\big(\Delta\eta_i(\tau_{i-1},\tau_i)\big)}, \quad \delta > 0 \quad (3)$$

where $\Delta\eta_i(\tau_{i-1}, \tau_i) = \eta_i(\tau_i) - \eta_i(\tau_{i-1})$ and $\eta_i(t) = a \cdot u_i \cdot t$. The expression of η_i, where u_i is the derating factor assigned by the policy at τ_{i-1}, gives explicit evidence of how the derating affects degradation.

Then, to obtain $W(\tau_i)$, (i.e., the degradation level at the i −th inspection), it suffices to compute:

$$W(\tau_i) = \sum_{j=1}^{i} \Delta W_j.$$

Computing $W(\tau_i)$, consequently, necessitates knowing the sequence of derating factors assigned by the policy $\{u_k, 1 \leq k \leq i\}$, which themselves depend on the sequence of observed degradation measurements $\{w_{k-1}, 1 \leq k \leq i\}$. This interdependence introduces mathematical complexity which prevents us from formulating a simple expression for the distribution of $W(\tau_i)$. For this reason we resorted, in this paper, to Monte Carlo simulation.

We assume that the failure of the unit is defined by the first (and only) passage time of its degradation process to a predefined threshold, denoted by w_M. Consequently, the lifetime X of the unit is defined as:

$$X = \inf\{x: W(x) > w_M\}.$$

Given that the derating factor of the unit can (potentially) change multiple times over the course of its lifetime, it is not possible to express the cumulative distribution function (cdf) of X with a simple formulation. However, we can express the complementary conditional cdf of X given the value of the degradation measurement $W(\tau_i) = w_i$ at time τ_i, under the assumption that $w_i < w_M$ and that the derating factor is fixed to 1 as:

$$\begin{aligned}\bar{F}^+_{X|W(\tau_i)}(x|w_i) &= P(X > x|W(\tau_i) = w_i) \\ &= P(W(x) \le w_M|W(\tau_i) = w_i) = \\ &= \begin{cases} 1, & x \le \tau_i \\ F^+_{\Delta W(\tau_i,x)|W(\tau_i)}(w_M - w_i|w_i) & x > \tau_i \end{cases}\end{aligned} \quad (4)$$

Where the "+" at the superscript in $\bar{F}^+_{X|W(\tau_i)}(\cdot\,|\,\cdot)$ and $F^+_{W(x)|W(\tau_i)}(\cdot\,|\,\cdot)$ indicates that the cdf is formulated under the assumption of derating factor fixed to 1. The cdf $F^+_{\Delta W(\tau_i,x)|W(\tau_i)}(w_M - w_i|w_i)$ is formulated as:

$$F^+_{\Delta W(\tau_i,x)|W(\tau_i)}(w_M - w_i|w_i) = \frac{\gamma\left(a\cdot(x-\tau_i), \frac{(w_M - w_i)}{\theta}\right)}{\Gamma\left(a\cdot(x-\tau_i)\right)} \quad (5)$$

where $\gamma(\cdot\,|\,\cdot)$ is the lower incomplete gamma function.

The probability in Eq. (4) can be intended as the conditional probability that a unit which is not failed at time τ_i survives until time x, given the degradation measurement $W(\tau_i) = w_i$ at τ_i, under the assumption that the derating factor does not change from its maximum value 1.

Therefore, at any inspection time τ_i, given the measured degradation level $W(\tau_i) = w_i$, we can evaluate the probability of surviving the rest of the mission, with derating factor set to 1 as:

$$F^+_{\Delta W(\tau_i,\tau_n)|W(\tau_i)}(w_M - w_i|w_i) = \frac{\gamma\left(a\cdot(\tau_n-\tau_i), \frac{(w_M - w_i)}{\theta}\right)}{\Gamma\left(a\cdot(\tau_n-\tau_i)\right)} \quad (6)$$

4. Formulation of the cost function

The cost model is formulated considering a failure penalty cost rate c_{pen} and costs related to the derating.

Specifically, the penalty cost is computed as the product of c_{pen} and the duration for which the unit remains inoperative during the mission. Since failure is not self-announcing, this duration should rigorously include also the time the unit spends in a failed state before the failure is detected. For simplicity, in this paper, we assume that this time is equal (i.e., can be approximated) as half of the AP where the failure occurs. So, for example, if a unit fails within the i-th AP (and therefore failure is detected at time τ_i) then the penalty cost will be equal to:

$$c_{pen}\cdot\left(\tau_n - \tau_i + \frac{\tau_i - \tau_{i-1}}{2}\right)$$

On the other hand, the cost of operating the unit with derating factor u_i in the ith AP (i.e., between τ_{i-1} and τ_i) is computed as the product of a cost rate $c_u(u_i)$ (which depends on the specific derating factor assigned) and the length of the AP $\tau_i - \tau_{i-1}$. The adopted cost function is the long-run average maintenance cost rate, formulated as (see Ross 1983):

$$CM(\boldsymbol{\xi}) = \frac{E\{C(\boldsymbol{\xi})\}}{\tau_n} \quad (7)$$

where $C(\boldsymbol{\xi})$ is the maintenance cost over the course of the whole mission, which can be computed as:

$$C(\boldsymbol{\xi}) = \sum_{i=1}^{l}\Delta C_i + c_{pen}\cdot(\tau_n - \tau_l)$$

where ΔC_i is the cost increase in the ith AP, whose value depends on the measured degradation level at τ_i and is reported in Table 2, and l is the number of APs in which the unit has been in operation. If the mission is successfully completed $l = n$, otherwise $l = \min_l(W(\tau_l) > w_M)$.

Table 2. Possible scenarios at each inspection time and corresponding maintenance costs and cycle length increments.

Degradation at τ_i	ΔC_i
$w_i > w_M$	$0.5\cdot\left(c_{pen} + c_u(u_i)\right)\cdot(\tau_i - \tau_{i-1})$
$w_i \le w_M$	$c_u(u_i)\cdot(\tau_i - \tau_{i-1})$

4.1. *Description of the simulator*

Due to the mathematical complexity arising from the interdependence between the derating and the degradation process, we resort to Monte Carlo simulation to evaluate the expression of the cost function in Eq. (7). The expectation is computed as: $E\{C(\boldsymbol{\xi})\} = \sum_{j=1}^{K} C[j]\,/K$ where K is the number of simulated runs and $C[j]$ is the maintenance cost in the j-th simulated run. The pseudocode implemented to compute $C[j]$ is detailed in Table 3.

Table 3. Pseudocode used to compute $CM\{\boldsymbol{\xi}\}$

	SIMULATOR
1	**For** $j = 1$ **to** K
2	$w_0 \leftarrow 0,\ \tau_0 \leftarrow 0,\ u_1 \leftarrow 1,\ C[j] \leftarrow 0,$
3	**For** $i = 1$ **to** n
4	$\Delta w \leftarrow$ *sample from* ΔW_i
5	$w_i \leftarrow w_{i-1} + \Delta w$
6	**If** $w_i > w_M$ **then**
7	$C[j] \leftarrow C[j] + 0.5 \cdot \left(c_{pen} + c_u(u_i)\right) \cdot (\tau_i - \tau_{i-1})$
8	**Go to** line 13
9	**Else**
10	$C[j] \leftarrow C[j] + c_u(u_i) \cdot (\tau_i - \tau_{i-1})$
11	$u_{i+1} \leftarrow g(w_i, \tau_i; \boldsymbol{\lambda})$
12	$i \leftarrow i + 1$
13	$C[j] \leftarrow C[j] + c_{pen} \cdot (\tau_n - \tau_i)$
14	$j \leftarrow j + 1$
15	$CM(\boldsymbol{\xi}) \leftarrow sum(C)/(K \cdot \tau_n)$

The number of simulated runs K should be determined by balancing numerical accuracy and computational complexity, which both increase with K. Once a sufficiently high value of K is adopted, the optimal cost CM^* and the corresponding optimal set of design parameters $\boldsymbol{\xi}^*$ can then be determined by numerically optimizing (over the design parameter space) $CM(\boldsymbol{\xi})$. In this paper, the simulation algorithm illustrated in Table 3 has been implemented in Matlab® and the optimization is conducted via a genetic algorithm.

5. Numerical example

In this section, we present the results of an example of application of the proposed policy, along with an exploratory sensitivity analysis.

To fully specify the policy, it is necessary to select a functional form for $g(\cdot)$. In this paper, for simplicity, we chose a step function where only three values of the derating factor are considered:

$$g(w_i, \tau_i; \boldsymbol{\lambda}) = g(w_i, \tau_i; \xi_1, \xi_2) = \begin{cases} u_{min} & \bar{F}^+_{X|W(\tau_i)}(\tau_n|w_i) \leq \xi_1 \\ u_{med} & \xi_1 < \bar{F}^+_{X|W(\tau_i)}(\tau_n|w_i) \leq \xi_2 \\ 1 & \bar{F}^+_{X|W(\tau_i)}(\tau_n|w_i) > \xi_2 \end{cases} \quad (8)$$

where ξ_1 and ξ_2 are design parameters of the policy, u_{min} is the minimum allowable value of the derating factor, u_{med} is an intermediate level ($u_{min} < u_{med} < 1$), and $\bar{F}^+_{X|W(\tau_i)}(\tau_n|w_i)$ is the cdf in Eq. (4). As explained in the previous Section, Eq. (4) represents the conditional probability, given the latest degradation measurement $W(\tau_i) = w_i$, of surviving the rest of the mission, under the assumption that the derating factor is fixed to 1. Consequently, adopting the function $g(\cdot)$ as in Eq. (8), essentially, leads the policy to always set the derating factor to 1, unless the probability of surviving the rest of the mission (under the assumption that the derating factor is fixed to 1) is lower than a certain threshold ξ_2. In this latter case, the derating factor will be adjusted either to an intermediate level u_{med} or to the minimum level u_{min}, depending on whether the probability of surviving the rest of the mission is greater than another threshold ξ_1.

The choice of the functional form in Eq. (8) allows us to determine the derating factor by taking a holistic view of the system. In fact, $g(w_i, \tau_i; \xi_1, \xi_2)$ simultaneously accounts for the current state of the system, its age, and the length of the remaining part of the mission.

From Eq. (8) it is possible to derive, at any inspection time τ_i ($i = 1, \dots, n$) the values α_i^1 and α_i^2 that correspond, respectively, to $\bar{F}^+_{X|W(\tau_i)}(\tau_n|\alpha_1(i)) = \xi_1$ and $\bar{F}^+_{X|W(\tau_i)}(\tau_n|\alpha_2(i)) = \xi_2$.

The values $\alpha_1(i)$ and $\alpha_2(i)$ can be envisaged as two age-dependent degradation thresholds. Consequently, the derating factor adjustment can also be summarized as follows:

$$u_{i+1} = \begin{cases} u_{min} & w_i > \alpha_1(i) \\ u_{med} & \alpha_2(i) < w_i \leq \alpha_1(i) \\ 1 & w_i \leq \alpha_2(i) \end{cases}$$

Table 4 reports the values of the parameters of the degradation model and of the cost model used in the example. The inspection times are $\tau_i = i, \forall i = 1, \dots, n$ and $n = 10$. Simulations are conducted with $K = 10^6$.

Table 4. Values of the parameters of the cost model and of the degradation process.

c_{pen}	w_M	a	θ	u_{min}	u_{med}
4	10	2	0.5	0.75	0.9

Given that only three values of the derating factor are considered, also the function $c_u(u)$ will take only three values:

$$c_u(u) = \begin{cases} 0.3 & u = u_{min} \\ 0.1 & u = u_{med} \\ 0 & u = 1 \end{cases} \quad (9)$$

Table 5 reports the value of the optimal cost CM^*, along with the corresponding optimal values of the design parameters ξ_1^* and ξ_2^*.

Table 5. Optimal value of the long-run average maintenance cost rate and corresponding values of the design parameters.

CM^*	ξ_1^*	ξ_2^*
0.237	0.351	0.523

Figure 1 shows the behavior of the cost function $CM(\boldsymbol{\xi})$ in the proximity of the optimum. The values of CM displayed in each panel of this figure have been obtained by letting one design parameter vary (i.e., ξ_1 for the first panel and ξ_2 for the second) in the proximity of the optimum while the other is set to its optimum value (see Table 5). Figure 1 confirms that the set of values $\boldsymbol{\xi}^* = \{\xi_1^*, \xi_2^*\}$ reported in Table 5 is a minimum for $CM(\boldsymbol{\xi})$.

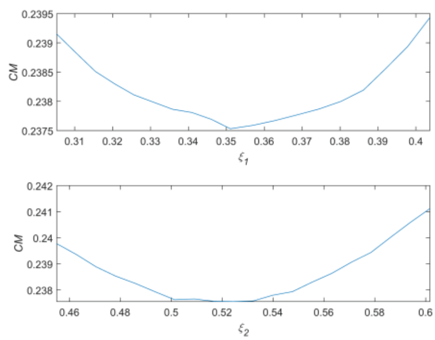

Fig. 1. Behavior of the cost function $CM(\boldsymbol{\xi})$ in the proximity of the optimum.

Figure 2 gives a visual representation of the policy. In this figure, the thin solid lines depict the degradation paths of 30 simulated runs under the optimal policy. The red and green dashed horizontal lines represent (from top to bottom, respectively) the corrective and preventive thresholds, while the two dotted blue curves report the values of α_1 and α_2.

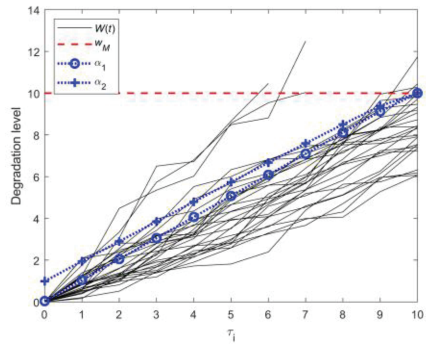

Fig. 2. Degradation evolution of 30 simulated runs under the optimal policy.

To highlight the utility of adopting the prescriptive action, we compared the performances of the proposed policy (hereinafter denoted as P_A) against those of a special case of P_A, denoted as P_B, where the derating is not available and $u_i = 1$, $\forall i = 1, \ldots, l$. Rigorously, P_B can be obtained from P_A by setting $\xi_1 = \xi_2 = 0$.

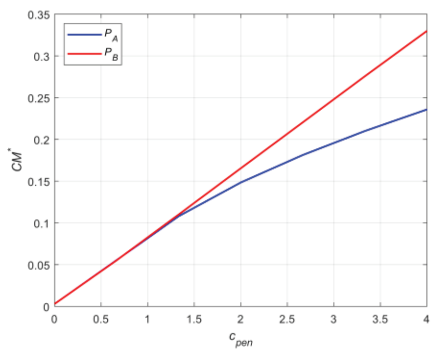

Fig. 3. Optimal values of CM^* obtained under P_A and P_B as a function of the failure penalty cost c_{pen}.

Figure 3 depicts the optimal cost CM^* obtained under both P_A and P_B, as a function of the failure penalty cost c_{pen}.
Figure 3 shows that the difference between the optimal cost yielded under both P_A and P_B increases as c_{pen} increases, implying that P_A outperforms P_B progressively more and more.
Figure 3 reflects the fact that, as already mentioned, the rationale behind the adoption of the prescriptive action is to use the derating to manage the probability of surviving the mission. As the failure penalty cost increases, it becomes more and more important to manage this probability.

Figure 4 further corroborates this explanation. It reports the optimal values of ξ_1 and ξ_2 obtained under P_A as a function of c_{pen}. The figure gives evidence of how, as the failure penalty cost increases, the probability that the derating factor will be adjusted from 1 to u_{med} or u_{min} increases.

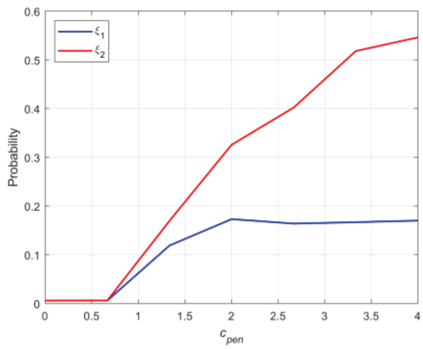

Fig. 4. Optimal values of ξ_1 and ξ_2 obtained under P_A as a function of c_{pen}.

Some more insights into how the policy P_A achieves the cost saving with respect to P_B can be obtained by analyzing how the optimal cost CM^* splits into the contributions of failure penalty- and derating factor-related costs, denoted as CM_{pen} and CM_u, respectively (of course it is $CM_{pen} + CM_u = CM^*$). Figure 5 reports these contributions under P_A (in blue) and P_B (in red), in the case $c_{pen} = 4$.

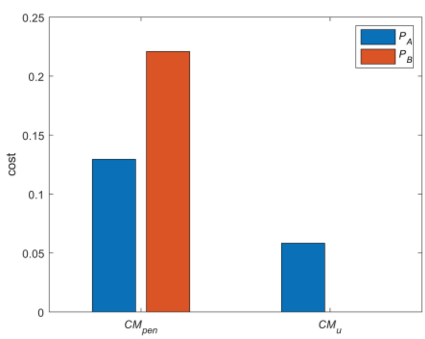

Fig. 5. Optimal value CM^* under P_A (in blue) and P_B (in red) split into its contributions CM_{pen} and CM_u when $c_{pen} = 4$.

Obviously, the contribution CM_u obtained under P_B is null. From Figure 5 we can observe that the contribution of CM_{pen} is significantly lower under P_A then under P_B, meaning that the policy P_A can minimize (compared to P_B) the probability of failure and therefore increase the probability that the mission will be completed successfully. Of course, CM_u will compensate a part of these savings but, in the considered setup, when $c_{pen} = 4$, adopting P_A over P_B will generate savings of 39.9%.

6. Conclusions

In this paper, we proposed a prescriptive maintenance policy for a degrading unit which undergoes an aeronautics-inspired exploitation cycle. The policy is developed assuming that the unit must complete a prespecified mission and that, within this mission, inspections can be performed which return the exact degradation level of the unit. This information can then be used, to decide whether to derate the unit or not. Derating has the effect of reducing the performances of the unit, therefore decelerating the degradation process of the unit and reducing the risk of failure. However, it incurs a cost linked to the performance loss.
The driving idea of the policy is to investigate if and how, when the maintenance intervention epochs are constrained, for example by the aircraft mission, the derating can offer an additional degree of freedom and provide a better overall tradeoff. Obtained results show that, in the adopted setup, the proposed prescriptive policy can provide noticeable savings with respect to a similar policy where the derating action is not available.

References

Manikar S. S., J. Jézégou, P. de Saqui-Sannes, P. Asseman, and E. Benard (2022). A hybrid approach of machine learning and expert knowledge for projection of aircraft operability. *Iop Conference Series: Materials Science and Engineering 1226(1),* 012046.

Saintis, L., Hugues, E., Bes, C., & Mongeau, M. (2006). Methods to asses the operational reliability of an aircraft system : Problem of dependency between component states. *15th Lambda-Mu Fiabilité Maintenabilité Conference*. 15th Lambda-Mu

Saintis L., Hugues, E., Bes, C., & Mongeau, M. (2009). Computing In-service aircraft reliability. *International Journal of Reliability, Quality and Safety Engineering*, *16*(02), 91.

Longhitano, D., K. Tidriri, C. Bérenguer, and B. Echard (2021). Proposition of a generic decision framework for prescriptive maintenance. In *World congress on engineering asset management*, pp. 263-273. Springer International Publishing.

Meissner R., A. Rahn, and K. Wicke (2021). Developing prescriptive maintenance strategies in the aviation industry based on a discrete-event simulation framework for post-prognostics decision making. *Reliability Engineering & System Safety 214*, 107812.

Pinciroli L., P. Baraldi, M. Compare, and E. Zio (2023). Optimal operation and maintenance of energy storage in grid-connected microgrids by deep reinforcement learning. *Applied Energy 352*, 121947.

Giacotto A., H.C. Marques, and A. Martinetti (2025). Prescriptive maintenance: a comprehensive review of current research and future directions. *Journal of Quality in Maintenance Engineering.* Doi: 10.1108/JQME-07-2023-0064.

Esposito N., B. Castanier, and M. Giorgio (2022). Prescriptive block replacement policy for production degrading systems. *IFAC-PapersOnLine 55(10)*, 1974-1979.

Esposito N., B. Castanier, and M. Giorgio (2023). An adaptive prescriptive maintenance policy for a gamma deteriorating unit. In *Proceedings of the 33rd European Safety and Reliability Conference (ESREL2023)*, pp. 960-967. Research Publishing, Singapore.

Van Noortwijk J. M. (2009). A survey of the application of gamma process in maintenance. *Reliability Engineering & System Safety, 94(1)*, 2-21.

Tseng, S. T., N. Balakrishnan, and C. C. Tsai (2009). Optimal step-stress accelerated degradation test plan for gamma degradation processes. *IEEE Transactions on Reliability 58(4)*, 611-618.

Ross, S. (1983). *Introduction to Stochastic processes.* Academic press, New York.