An Operational Availability Optimisation Model Based on the Integration of Predictive and Scheduled Maintenance

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ABSTRACT

Health monitoring technologies are increasingly widespread in the aviation industry. Following that, several model-based and data-driven prognostics methods for remaining useful life estimation have flourished in the pursuit of improving predictive maintenance for different types of components. Recent papers showcased the significant challenges to achieve forecast accuracy posed by the inherent uncertainty involved in the functional dynamics of complex systems. Nevertheless, the ability to pinpoint times to failure by itself is not enough to yield better maintainability given that scattered standalone interventions may increase total downtime. This study depicts the problem and proposes a solution consisting of an innovative model that optimizes operational availability through the dynamic allocation of flight-hours to aircraft in a fleet based on the integration of predictive and scheduled maintenance, while accounting for prognostics uncertainty. An illustrative case study involving multiple components of a small aircraft fleet was used to test the method and produced results that demonstrate the model's validity and effectiveness. The main contributions of the study are twofold. It adds on the theoretical complexity by tackling systems of systems instead of the predominant single component approach, and it provides a model with an optimising objective function to improve maintenance planning in real-life.

1. INTRODUCTION

In the aviation industry, there is an ongoing change in maintenance strategy towards more proactive, precise, and effective approaches to planning that are known as Integrated Vehicle Health Monitoring (IVHM) and Prognostics and Health Management (PHM) (Fritzsche, Gupta and Lasch, 2014). While IVHM refers to "an integrated vehicle level system deployed on a fleet of platforms" and may not include prognostics, "PHM is used where this predictive element exists" (Society of Automotive Engineers [SAE International] aerospace recommended practice, 2019). This process has been fuelled by the evolution and spread of condition monitoring technologies enabling continuous health assessment of more and more components (de Jonge & Scarf, 2020). Additionally, thanks to advances in data processing and communication within data buses, and the transmission to ground stations, it is now possible for support teams to have abundant, precise, and organised health status data in almost real time.

Prognostics tries to anticipate future needs building upon diagnostics information to estimate the prognostics distance or Remaining Useful Life (RUL) (Fritzsche et al., 2014). It projects the expected evolution from the current health status throughout a set of planned operations according to a physical model or extrapolating from a data-based trend. This process is immersed in uncertainty and tackling it is paramount (Vandawaker, Jacques and Freels, 2015), hence prediction methods are gaining a lot of attention and many studies have reported progress in the refinement of prognostics algorithms to provide more accurate predictions as to when failures are expected to occur.

Ideally, maintenance should be endowed with timeliness and efficiency. Timeliness in the sense of intervening only when necessary, preferably right on the verge of a failure occurrence. Efficiency meaning that it should be effective in attaining recovery within the least possible time to return the equipment to operation, and at minimum cost.

In reality though, either due to regulatory restrictions or to the inexistence of mature condition monitoring technology for some systems, aircraft safety still relies and will continue to be heavily dependent on periodical checks. These inspections are mostly designed during the aircraft development phase.

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On this stage, the various hard-time preventive maintenance tasks are grouped to be performed in batches accommodating, and invariably shortening, the different mandatory maximum intervals to avoid hazardous or catastrophic consequences.

It is known that risk avoidance feeds on the lack of information, thus traditional preventive maintenance intervals, defined mainly before the system's entry-into-service, can be excessively conservative. Hence, it becomes clear how the modern condition monitoring and prognostics technologies come to maintenance's aid in the quest for its goals. On one hand, it allows for a maximization of equipment usage by estimating and continuously updating its RUL as the operation progresses. This prediction also helps to prevent further damage that could arise from dependant failures triggered by the unwanted event, although it is necessary to acknowledge and remark that a residual risk of failing before the expected time remains. On the other hand, with long enough anticipation notice of impending failures, maintenance can prepare and pre-allocate the necessary resources to perform the intervention faster.

In this interim, it is important to emphasize the stochastic nature of predictions. The RUL is obviously not a deterministic value. Therefore, it should always be accompanied by its confidence interval. The adequate level of confidence will vary on a case-by-case basis, but some degree of confidence is always required for the estimate to make sense. It should also be noticed that, since a 100% confidence interval is statistically impracticable, failures will keep happening, and corrective maintenance will still be a reality despite of the advances in condition monitoring technologies.

It results that corrective, preventive and predictive maintenance are likely to continue coexisting in the foreseeable future. With effect, Wilmering and Ramesh (2005) establish that prognostics is only "part of an effective integrated Health Management solution" and that it is key to an efficient methodology to find a balance between diagnostic, prognostic and schedule maintenance approaches.

Considering the situation above, the problem that follows is that the continuous migration of previous preventive tasks and of those which would be otherwise failures into Condition-Based Maintenance (CBM) tasks do not translate directly into better supportability. As a matter of fact, the ability to pinpoint when failures might take place by itself may conversely increase the overall downtime along the lifecycle. That is because the sparse distribution in time of planned watertight interventions derived from accurate predictions is inefficient for it requires repetitive setup times and does not benefit from the synergy of the batched preventive checks.

It turns out that the full realisation of the potential benefits offered by IVHM requires yet the compatibilization between predictive and preventive (time-based) maintenance tasks as defended by Shi, Zhu, Xiang, and Feng (2020) and Ahmadi, Fransson, Crona, Klein, and Söderholm (2009), without disregarding the potentially unescapable need for corrective interventions.

A gap in this research area was identified and therefore, to the extent of our knowledge, this article is amongst the first in the aviation field to propose an integrated solution addressing both technical and decision-making sides of incorporating prognostics into the broad scope of dynamic operational and maintenance planning for multiple non-identical components and multiple aircraft.

In this sense, this study proposes a novel approach synthesized in a theoretical model that launches the basis for further developments in terms of its future expansion, validation, and implementation. The solution developed passes through integrating preventive and CBM interventions of various components on a single timeline for each aircraft, and from that it optimally distributes a designated number of flight-hours among the fleet members seeking to maximize the alignment of tasks, i.e., make them coincide in time, within a pre-defined range, as much as possible. It might require to sacrifice acting exactly on the imminence of a predicted failure, but this is in line with one of the research avenues recommended by the extensive literature review on maintenance optimization carried out in the work by de Jonge and Scarf (2020), where it is stated that "the concept of unpunctual maintenance that has been studied in time-based maintenance settings could be extended to condition-based maintenance settings". The problem modelling demonstrated the solution requires heuristic methods to find the sought-after alignment, which indeed generates the expected reduction in total downtime along the period under analysis.

In terms of the maintenance information flow, this study is concentrated on the Prognostic Assessment (PA) and Advisory Guidance (AG) levels or functional blocks considering the Open System Architecture for Condition-Based Maintenance (OSA-CBM) standard as a reference and the interpretation promoted by Li, Verhagen and Curran (2020). Discussing specific prediction models is out of the scope, but the one proposed here deals with the uncertainty in the forecasts which are inputs fed into the model and represent a critical aspect permeating the prognostics science.

Consequently, the uniqueness of this study resides in two main points. First, its breadth of scope for it encompasses both the technical side of component prognostics and the management side affecting an entire fleet maintenance programming. That notwithstanding, the second differential to note is that, while most studies focus on individual items or systems, the model hereby proposed embraces multiple components of multiple aircraft in a single framework. In particular, the mechanism for overlapping predictive and preventive tasks to reduce overall downtime is a pioneer method in this area.

The article is organised as follows. Section 1 presents the context, motivates the need, states the problem, and outlines the solution proposed. Section 2 presents a cohesive literature review highlighting the theoretical foundations underlining the theoretical framework construction. Section 3 describes the modelling approach followed by the author to assure scientific coherence and soundness in the process and explains the model's limitations and its mathematical formulation. Section 4 demonstrates an application of the model using a fictitious scenario and discusses the results based on a comparison against a baseline. At the end, Section 5 concludes with the final considerations emphasizing the strengths and fragilities found in the model during its verification process and recommends routes to further expand it and deepen research on the subject.

2. Literature Review

This study drew its basis from a focused literature review on the subjects related to IVHM integration with traditional scheduled maintenance planning. In this sense, the work conducted by Bousdekis, Magoutas, Apostolou and Mentzas (2015) was especially welcome for its comprehensive review of the state-of-the-art publications about proactive maintenance.

Initially, it is necessary to register that the research done indicated that the majority of references found in the area are concerned with technical and specific models that seek to process the different signals provided by electronic sensors of many different components in order to extract useful and reliable information to support diagnostics and prognostics conclusions (Baek, 2007; Eliaz & Latanision, 2007; Lv, Zhang, and Jiayang, 2015; and Sudolsky, 2007). The issues involved in raw data processing are not considered in this text since the model hereby proposed operates in a higher level and considers the condition-based forecasts as inputs to P-F curves.

These curves are a central concept in the condition monitoring and failure prognostics theory, reason why it is the point from which the modelling process takes off in the next section. They are used for estimating the Remaining Useful Life (RUL) of an equipment, or Prognostics Horizon as named by Julka, Thirunavukkarasu, Lendermann, Gan, Schirrmann, Fromm and Wong (2011), because they define a trend line from the current condition or a point where a failure process begins (the potential failure point "P") to the estimated/projected point when a failure is expected to take place ("F") (Bousdekis et al., 2015). It is worth clarifying that although many authors are keen on the definition of "P", nowadays there are intricate model-based projection algorithms that are used to predict failure irrespective of detecting the start of a failure process base on health data analysis (Petrillo, Picariello, Santini, Scarciello and Sperlí, 2020).

Nevertheless, it must be acknowledged that the indication that a failure process is in progress may come up at different stages and the RUL or prognostics distance (PD) may vary from minutes to several hours. It depends on the degradation pattern which can be anything from a smooth descent to a sharp decline (Jennions, 2013). If the failure process is too fast or if its detection can only occur when PD is already too short, the advantage provided by the prognostics anticipation might have only an immediate operational repercussion (Dibsdale, 2013). For maintenance planning though, only prognostics distances greater than the flight duration are worth considering since it cares about the implications of forecasts for the support team on the ground.

On that basis and according to Peppard (2010), predictive maintenance is only possible if the degradation pattern displayed in the P-F curve is reasonably consistent, i.e., it roughly follows a certain gradient profile for a given part type in every cycle of its operational life. In addition, not only the decay speed and profile have to be consistent, but it is also important that the curves are sufficiently well-behaved to present a reasonably low dispersion in terms of the uncertainty range around the failure expected time.

Nevertheless, prognostics are in their essence based on stochastic models and therefore will always bear a certain degree or margin of error embedded in the forecast (Ferreiro, Arnaiz, Sierra and Irigoien, 2012; Singh, Singh and Srivastava, 2016). Using the definition given by Grenyer, Dinmohammadi, Erkoyiuncu, Zhao and Roy (2020), the knowledge provided by condition monitoring data can help mitigating epistemic uncertainty, but the aleatory component of uncertainty "represents statistical variables that constantly fluctuate and therefore cannot be reduced". Consequently, any technique or solution approach to problems involving this feature should be able to deal with probability and uncertainty.

Unfortunately, a considerable portion of the approaches to predictive tasks programming found on the literature focus solely on average values, disregarding the inherent risks to estimates and the importance of establishing reasonable confidence levels. However, since this is an intrinsic part of the problem, the authors believe that the uncertainty ranges around RUL estimates shall be reflected in the model otherwise risking to compromise its validation, as defended by Ferreiro et al. (2012), Singh et al. (2016), Grenyer et al. (2020) and Adhikari and Buderath (2016).

A recent publication by Shi et al. (2020) scoured the literature and identified that most studies on CBM and prognostics are restricted to single items. Their review showed a general "lack of CBM models for multi-component systems", in special those capable of leveraging the use of "multi-source dynamic information for effective inspection and maintenance planning". Targeting this gap, they developed a method to minimize maintenance cost for a multi-component system composed by k-out-of-n subsystems serially connected based on the use of dynamic information discretely updated upon periodical inspections. It is considered that the gap was partially filled since the study was restricted to cost optimization and the evaluation of one single platform, while in many cases complex systems are managed in fleets and downtime may also result in intangible costs (loss of future revenue, cost of opportunity etc).

In addition, the references surveyed often cited the need to translate IVHM capabilities into actual benefits by means of implementing changes to present courses of action, both in maintenance and operations decision-making processes, to justify the investment and open way for further IVHM progress (Esperon-Miguez, John and Jennions, 2013; Li et al., 2020). In fact, this is a key aspect of the whole IVHM concept, but it has been facing hitches in becoming integrated to the maintenance plan because of regulatory restrictions and lack of an objective framework to conciliate the different needs and possibilities offered by all the data being generated, processed, and transmitted with precision and in real time (Hölzel, Schröder, Schilling and Gollnick, 2012).

Furthermore, it has been noticed a general concern about the cost effectiveness of maintenance acting surgically on the imminence of each monitored component loss of function. Whereas it improves the exploitation of useful life to its maximum, the dispersion of standalone condition-based interventions could severally jeopardize operation by increasing total downtime as the proportion of predictive maintenance tasks increases. In this sense, the awareness brought by the health monitoring and prognosis equipment and algorithms is a double-edged sword. Based on that, it was understood that a model intending to make feasible the integration of predictive tasks in a maintenance strategy should address this issue and try to combine the occurrences in a way that cause them to coincide in time as much as possible.

Thereby, in view of all the references consulted, it is clear the need for cost-effectively integrating predictive maintenance into a fleet preventive maintenance plan, and that means to conciliate estimated values of RUL, along with their inherent uncertainty, with hard time interventions. Also, it was verified that the technological means to support that are already in place and the precision levels of diagnostics, fault isolation and prognostics are rapidly improving. Nevertheless, a gap has been identified due to the absence in the literature of a solution designed to address this challenge, and it is with the aim of filling this gap that this study follows on to the next section

3. Model Development

The scientific approach employed to ensure a sound problem formulation and development of a viable solution algorithm started by identifying and selecting the parameters pointed in the literature as the most relevant and influent to maintenance planning. Following that, the parameters were integrated in a dynamic framework structured on the logical rules governing the relationships between those parameters and restricted by the assumptions adopted to limit its scope. After that, the modelling process is wrapped-up with a verification test using fictional data to demonstrate its coherence and consistency, thus attaining the objective posed in this article.

The problem is stated as the inefficiency in yielding benefits from the use of IVHM technologies and prognostics algorithms caused by the increasing migration of time-based tasks to sparsely distributed and isolated condition-based tasks, which may increase the total downtime of an air fleet. It results that the full realisation of the potential advantages offered by IVHM and PHM requires yet the compatibilization between predictive and preventive (time-based) maintenance tasks in an integrated planning framework.

For the integration of these two maintenance approaches, it is important to state that the current modelling process established time-based maintenance checks as fixed deadlines, while predictive times to failure are taken as dynamic thresholds allowed to move as the operation progresses and the estimates are updated.

In terms of scheduled maintenance, there are basically two possible categories into which a fleet might fall depending on its intensity of use. That is because time-based tasks like those resulting from an MSG-3 analysis are usually constrained both in calendrical time and by operational times or cycles. Therefore, if the operation falls into the low utilization category, then the aircraft maintenance packaging will be designed according to calendrical deadlines, otherwise it will be programmed based on the operational aging. On this paper, the former category is adopted due to the authors' experience showing this to be the most common case for military aircraft, in special fighter jets during peace times.

At this point, it is important to highlight that the scope of this analysis is tightly defined because the adopted assumptions and simplifications are essential to understand the problem at hand, and this is considered an initial approach since nothing similar was found in the literature.

The low utilization premise notwithstanding, the model proposed should not be considered unable to handle the high intensity category, which can be contemplated via elementary changes in the formulation.

On with the model development, the framework construction departs from aircraft data provided in standard P-F curves as explained in the previous chapter. As shown below by Fig. 1, it is interesting to notice that in a complex system such as an aircraft there might be many (hundreds, if not thousands) different P-F curves relative to each sensor enabled component in the platform. Not only that, another sensitive aspect that must be regarded when dealing with prognostics data is the uncertainty inherent to any forecast, which means that the expected failure point estimate is not of much help on its own but should be regarded in conjunction with its variation boundaries for a certain confidence level defined in accordance with the user's risk tolerance.

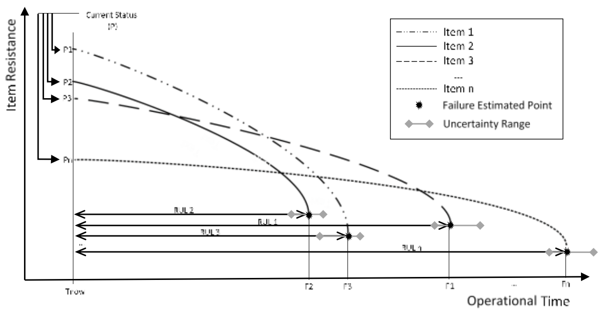

Fig. 1- Aircraft Components' P-F Curves Representation.

One issue that stands out is that different items may follow distinct aging units like calendar time, flight cycles, flight hours, number of shots among many others. The solution to that is to perform a migration from the operational parameter axis (power-up hours, flight hours, flight cycles etc.) to a calendrical or continuous time axis, which can be done by applying a utilization factor according to each component's life counter. For simplicity, this utilization factor was considered to represent an even distribution of a certain number of operational hours (OPH) over the time before the next scheduled intervention. In this case, it is also important to notice that this factor must not overcome the low utilization threshold for obvious reasons. It is valid to note that assuming uniform distribution of OPH is not a limitation of the model given that any other transfer function representing the operational profile, if known, may be applied to the conversion.

In result, the estimated RUL, originally in operational hours or whatever other parameters, is converted into a new value RULC, now expressed in continuous time as displayed in Fig. 2. In this graph the scheduled maintenance time is fixed, but the items RULC can be flexed by changing the aging speed through the utilization factor.

For simplicity, the conversion was initially modelled following a linear function, but other types of relationship could be applied within the model with no harm to the method or its results as explained before. Many other factors can be considered such as the application factor, relative to the proportion of actual utilization of an item per flight hour, or the degree to which an item is demanded and therefore aged according to the mission profile to be performed.

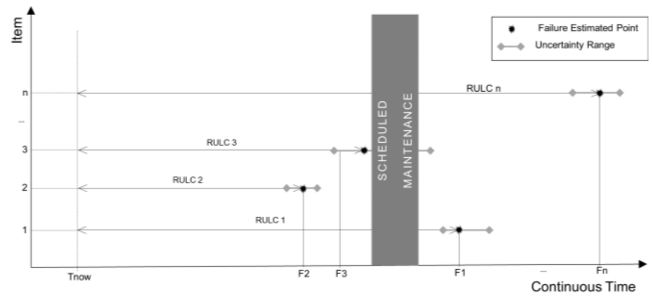

Fig. 2 - Remaining Useful Life in Continuous Time Domain (RULC).

Still on the same illustration, it is possible to verify that the prognostics information can lead to the scattering of efforts over isolated standalone tasks, each requiring a complete cycle of setup and demobilization, rendering the direct application of condition-based optimal intervention time ineffective both in terms of availability and cost.

The solution to this issue hereby proposed is to adjust operational hours distribution with a view to maximize the overlap of expected failure times and respective confidence intervals (henceforward called "moving platforms") amongst various items, and most importantly with the scheduled maintenance check. The latter is considered a higher priority target in the model. This is because a moving platform once merged onto a preventive maintenance stop usually becomes diluted in the overall effort and its downtime can be completely absorbed within it. Another advantage is that usually for those checks a considerable amount of resources are made available, and therefore are hard to move for they represent significant costs to the ownership and are planned considering long-term lifecycle implications (Deng, Santos and Curran, 2020).

With this purpose in mind and considering that each aircraft pertaining to a fleet will have its own distinctive set of P-F curves, the flight-hours to be distributed and performed by each equipment before its programmed inspection are established as the decision variables of the model. The OPH are then used to calculate the utilization factors, thus being the sole responsible for changes in the RULC values.

A fundamental constraint that helps the model to converge is related to the fact that a fleet is usually subject to a maximum number of flight-hours that can be performed over a specified period due to business or budgetary guidance. In other words, the sum of each aircraft OPH must not exceed the total value assigned to the fleet but ideally should be as close to the limit as possible. The OPH appointed to each plane will be spread over its respective Time to Scheduled Maintenance (TSM) as can be seen in Fig. 3.

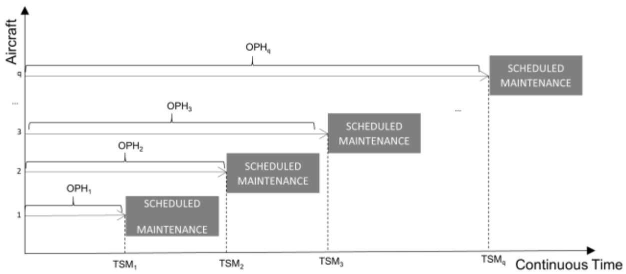

Fig. 3 – Fleet Scheduled Maintenance Standard Diagonal Distribution.

Before proceeding to the formal statement of the problem and considering that models are simplified representations of reality, it is imperative to delimitate the context envisaged in the model creation. The scenario consists of a fighter jet fleet that operates from a single base with the aircraft returning to it after each mission. It means that the problem is restricted to optimising operations by aligning the expected time when maintenance events may happen without particular concern regarding the location where the necessary resources must be in place. Considering a network of operational bases is one of the possible future extensions to this inaugural version of the model.

In addition, the scope of analysis must be delimited by establishing the assumptions adopted and the limitations imposed:

- For each aircraft, the model is restricted to the next scheduled maintenance stop (henceforth also referred to as inspection or check). It does not affect the model whether the next inspections of different aircraft are of the same category (e.g., checks A or C) or not, but the key point here is that it does not see future programmed interventions beyond that. This is in line with the recommendation by Fritzsche et al. (2014) that the planning horizon when using prognostics “should be long enough to take appropriate actions and short enough so that forecasts of future failures are reliable”. Indeed, the longer the projection, the higher the uncertainty levels and the lower the planning’s reliability.

- The component’s location is not considered for the purpose of maximizing the moving platforms overlapping. Time coincidental tasks involving items closely located, for instance on the same bay in the aircraft, may offer higher advantage since it could reduce downtime, but it was considered neglectable at this initial phase of the model.

- There is no health deterioration outside operational time. RUL is not diminished during idle periods, including maintenance stops.

- The exchange of components between aircraft aiming to improve results is not allowed.

- The optimisation considers predictive maintenance tasks packaging for each aircraft in separate.

- Possible differences in duration between maintenance tasks were considered irrelevant, thus this parameter was not implemented in the framework under development. Depending on the case, it is possible to further improve the model by loading a priority factor onto longer tasks.

In face of all considerations and analysis above presented, it is postulated that the best possible result for combining predictive tasks and scheduled checks is achieved by maximizing the level of overlapping between RULC estimated ranges and inspection periods in the time continuous domain.

Moreover, let us consider the following parameters to formulate the problem:

- q = total number of aircraft.
- n = number of items monitored.
- AE = total fleet flight-hours assigned.
- uk = utilization factor
- LUL = maximum rate of use to remain in the Low Utilization class.
- RULC = estimated remaining useful life in continuous time.
- $RULC^{max}$ = RULC upper limit for a given confidence level.
- $RULC^{min}$ = RULC lower limit for a given confidence level.
- TSM_k = time until scheduled intervention for aircraft k.
- PR = priority factor assigned by the user to ascertain the level of priority given in the model to overlapping with the scheduled check over the alignment between individual predictive tasks.

With that, arranging the parameters according to their specific roles and bearing in mind the aim of maximizing overlapping, it results the statement of Eq. (1) as the objective function:

$$\max F_{(OPH_k)} = \sum_{k=1}^{q}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\left(RULC_{i,k}^{max} - RULC_{j,k}^{min}\right)}{\left(RULC_{j,k}^{max} - RULC_{i,k}^{min}\right)} + PR * \sum_{k=1}^{q}\sum_{i=1}^{n}\frac{RULC_{i,k}^{max} - TSM_k}{RULC_{i,k}^{max} - RULC_{i,k}^{min}}\ , \forall i \neq j \qquad (1)$$

Where:

$$RULC_{i,k} = \frac{RUL_{i,k}}{u_k} = \frac{RUL_{i,k}}{OPH_k / (TSM_k)} \quad (2)$$

Subject to the following constraints:

i. $RULC_{j,k}^{min} \leq RULC_{i,k}^{max} \leq RULC_{j,k}^{max}, \forall i \neq j;$

ii. $RULC_{i,k}^{min} \leq TSM_k \leq RULC_{i,k}^{max};$

iii. $\sum_{k=1}^{q} OPH_k = AE;$

iv. $OPH_k \mid u_k \leq LUL, \forall k = 1, \dots q.$

N.B.: constraint "i" refers only to the first half of the objective function, and constraint "ii" just to the second term.

It is necessary to point out that the first summation in the equation is more sensitive in cases where degradation rates change in different ways for different items with the variation of use intensity.

With regards to the second factor, one could make the case that the higher the parcel of the moving platform left before the inspection, the higher the risk that a failure might occur and demand for a reactive maintenance, which would mean a higher cost and have a negative impact over the aircraft availability. The equation already seeks to avoid it, but it is recognized that a third factor could be inserted in the formulation to represent the cost of this risk, thus reinforcing its aversion power, especially for items to which failure comes with secondary undesirable effects.

Another factor that could be added to the equation is the possibility of advancing predictive actions for those items eventually falling a little after the inspection. This would require a delimitation over how much of an item's life could be abbreviated to the advantage of the combination aimed by the model. In this case, the formula would confer a prize to any anticipation possible for the benefit obtained in terms of economy and opportunity but would also penalize proportionally the loss of a fraction of expected useful life.

4. RESULTS AND DISCUSSION

With the intention of verifying the coherence and consistency of the framework built over the previous chapter, a set of fictitious data was assembled to represent a possible scenario for the model application.

The proposed case study consists of a fleet comprised by three aircraft each containing five monitored components for which there is IVHM data available as revealed by Table 1.

Table 1 - Current RUL per component and aircraft.

	Component current RUL (Operational Hours)				
Aircraft	1	2	3	4	5
1	200	205	194	202	215
2	120	132	125	143	156
3	230	246	223	225	248

In addition to that, the uncertainty range for a confidence level of 90% is also known and can be verified in Table 2.

Table 2 - RUL uncertainty limits for a 90% confidence level.

	RUL Estimates 90% Confidence Level Bounds				
Limit	1	2	3	4	5
Upper	1.08	1.10	1.12	1.05	1.15
Lower	0.90	0.85	0.90	0.95	0.90

Completing the input data required by the problem formulation, the aircraft scheduled maintenance interventions are staggered monthly in a diagonal resulting on the times to inspections from current date represented in Table 3.

Table 3 - Time Before Maintenance per aircraft.

Aircraft	Time Before Inspection (Months)	Time Before Inspection (Hours)
1	2	1440
2	3	2160
3	4	2880

Lastly, it was considered that the total number of flight-hours assigned to the fleet in analysis amounts to 500 flight-hours. With that, two baseline scenarios were created against which the optimised solution will be compared. The baseline cases reflect the two most common distribution rules used in practice as per the authors experience.

The baseline scenario 1 applies the same utilization factor to all members of the fleet as represented by Fig. 4, Fig. 5 and Fig. 6.

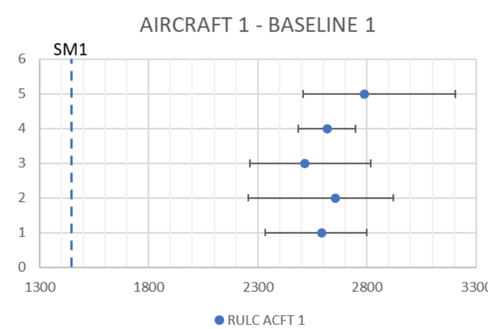

Fig. 4 – Aircraft 1 on Baseline Scenario 1.

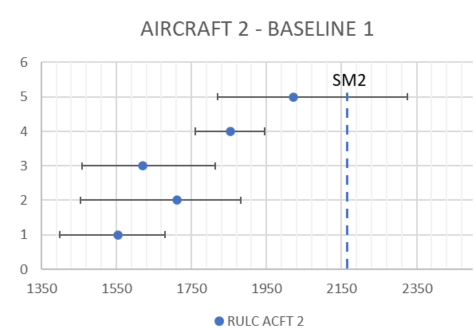

Fig. 5 – Aircraft 2 on Baseline Scenario 1.

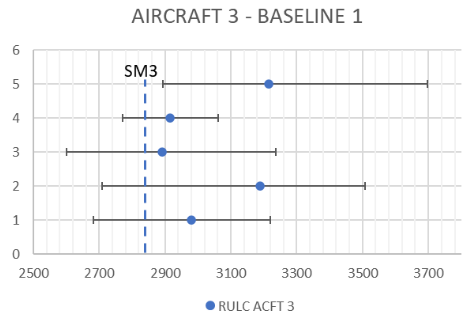

Fig. 6 – Aircraft 3 on Baseline Scenario 1.

The baseline scenario 2 splits the available flight-hours evenly among the fleet members resulting in the situation represented by Fig. 7, Fig. 8 and Fig. 9.

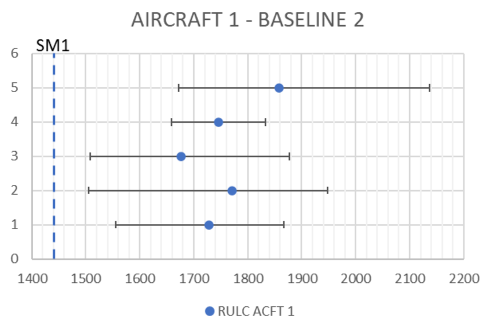

Fig. 7 – Aircraft 1 on Baseline Scenario 2.

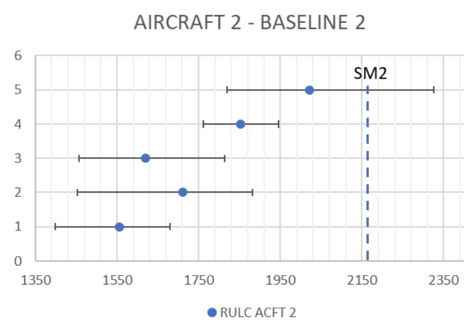

Fig. 8 – Aircraft 2 on Baseline Scenario 2.

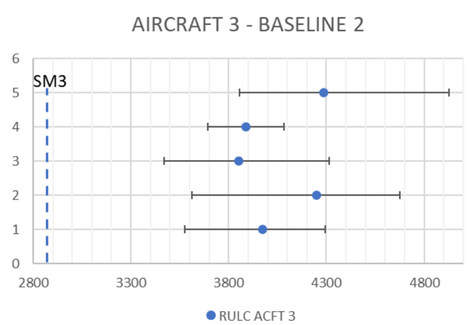

Fig. 9 – Aircraft 3 on Baseline Scenario 2.

With a view to find the best possible division of these operational hours between the three aircraft, the input data and the equations that form the model were inserted and built on a Microsoft Excel © spreadsheet. The optimisation was carried on with the help of an Excel add-in called Solver ©, which is a program able to optimise a given objective function subject to a set of constraints using three different methods to find the correspondent values of the decision variables.

For the case under analysis, the Simplex Linear Programming method could not find a solution since the problem behaviour does not follow a linearity rule. From the other two possibilities, the best result was obtained by the non-exact Evolutionary method, which is based on a genetic algorithm, followed closely by the non-exact GRG Nonlinear method. The results can be compared on Table 4.

Table 4 - Solver optimisation methods results comparison.

Method	$F_{(OP)}^{max}$	OPH1	OPH2	OPH3	AE
Simplex LP	N/A	N/A	N/A	N/A	N/A
Evolutionary	7.3842	177.1	112.5	210.0	499.7
GRG Nonlinear	7.3479	176.0	112.5	211.5	500.0

The results analysis and discussion can also benefit from a graphical illustration of how the different RULC are allocated in time based on the utilization rates resultant from the flight-hours assigned to each aircraft. The graphs plotted on Fig. 10, Fig. 11 and Fig. 12 represent the panorama ensued by the best solution found.

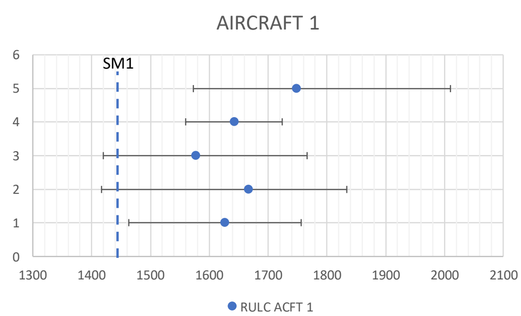

Fig. 10 – Aircraft 1 resulting panorama.

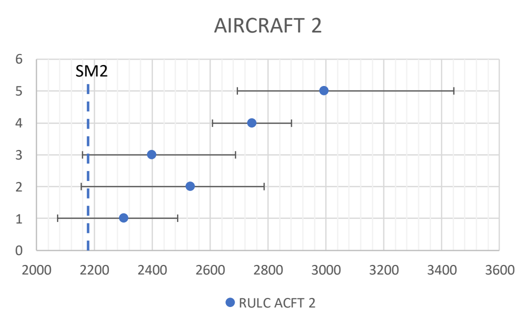

Fig. 11 – Aircraft 2 resulting panorama.

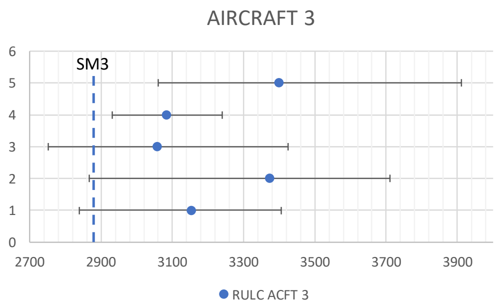

Fig. 12 – Aircraft 3 resulting panorama.

The charts testify the results robustness by showing compliance and coherence with the objective pursued. In fact, the pictures corroborate that the framework was able to adjust the AE distribution in a way to maximize the number of overlaps among the moving platforms and between these and the periodical checks for each aircraft while reducing the risk of failure occurrence before the intervention.

Table 5 summarizes the results presenting the number of operational hours distributed to each aircraft on all scenarios analysed and an example of resulting downtime due to predictive maintenance tasks was calculated for comparison purpose. For this matter, it was considered that each task takes 8 hours to be performed and that the task will be absorbed within the scheduled inspection duration in case its moving platform overlays with the check before the respective item's RUL estimate, therefore offering less risk of running into failure. Although the overlaying between moving platforms was also improved, the potential benefit was not included in the final calculations because that would require further discussion about the impact residual risks could offer to the possible reductions in downtime. This discussion demands a refinement in the model, which is recommended further down this paper.

Table 5 – Optimisation results vs baseline scenarios.

Scenario	Aircraft (OPH)			Downtime (Hours)
	1	2	3	
Baseline 1	111.1	166.7	222.2	88
Baseline 2	166.7	166.7	166.7	120
Optimal	177.2	112.6	210.1	56

From the data presented above it results that the solution offered by the model yields a reduction in total downtime of 36.4% against the strategy used in baseline 1 and of 53.3% when compared to that deployed on the baseline scenario 2.

The experience with the software employed was positive. Despite the heavy limitations imposed, the results provided were impressively good in terms of the economies of scale achieved.

Another positive aspect worth emphasizing is the flexibility and adaptability of the model to deal with scenario changes, making it ideal to highly dynamic situations such that of the IVHM and PHM data, which is constantly updated by new rounds of information arriving from the operations. This fast adjustment to changes provoked by new information was yielded by the intrinsic features built-in the framework, particularly its mathematical foundation and the ability to work with the uncertainty inherent to failure time forecasts. Flexible maintenance planning is indeed a required feature to improve "asset utilization and to reduce downtimes (maintenance opportunity times)" according to Ferreiro et al. (2012). Besides that, the model demonstrated to be adjustable to each user's priorities by means of allowing the free attribution of weights and the use of levels of confidence compatible with their risk tolerance.

Finally, the successful model verification cleared the path for its future expansion through the addition of parameters such as those identified in the mathematical formulation process and possibly the easing of limitations or riddance of some assumptions, which are going to disclose its full potential.

5. Conclusion

The research and modelling efforts were successful in attaining the pursued objective once they managed to identify and relate the key parameters necessary to account for in deciding the best way to combine predictive, scheduled and corrective maintenance tasks to form optimal maintenance strategies.

On top of that, by taking into account the utilization rate using the allocated flight-hours as decision variables, the model integrated the operational and maintenance systems in a single framework that support decision to improve strategies on both fields.

Moreover, the basic case study elaborated for the model verification confirmed the modelling process soundness in correctly framing the problem and showing the solution viability using operational research techniques. However, further research needs to be done to expand the problem's size and submit the model to simulation to validate its results.

The complexity of representing a real aircraft fleet imposes challenges to the mathematical solution and a computational challenge to simulation, but the proposed framework offers built-in features that facilitates its implementation being able to cope with dynamic scenarios like those involving IVHM data for a dynamic maintenance planning using a mix of maintenance strategies.

Another important remark is that the literature review exposed both a growing need for effective ways to yield benefit from IVHM technologies in maintenance and a staggering lack of objective and technical solutions to the problem. On this regard, this paper showed its relevance and novelty contributing to research in the area by adding on the theoretical complexity by tackling systems of systems instead of the predominant single component approach that has limited practical use, and it provides a model showing the value of using an optimising objective function to improve maintenance planning in real-life.

In other words, the main contribution provided by this study is a simple and expandable model that takes advantage of latest prognostics information developments and allows for better operational planning with less maintenance costs and downtime. With effect, from the case study, the theoretical model showed potential to cope with different levels of uncertainty from multiple components reducing total downtime when compared to the baseline scenario.

At the end, it is recommended for further studies the expansion and deepening of this seminal work by either eliminating a few of the adopted assumptions or incorporating in the formulation other factors such as location of the faulty part and time required to perform the task. Also, it is unlikely that a generalized version of the current model can be handled by standard software packages like the one used in this text, thus it is arguably going to require the development of a dedicated and specialized tool to disclose the model's full potential, what is also suggested to be targeted by future research efforts.

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BIOGRAPHIES

Danilo G. Figueiredo-Pinto was born in Brazil in 1983. In 2005 he obtained his BSc in Electronic Engineering from the Aeronautics Institute of Technology (ITA) in São José dos Campos - Brazil, where he is currently a DSc candidate. After graduation, he began his career in the Brazilian Air Force (BAF) as an officer at the São Paulo Aeronautical Depot (PAMA-SP). There, over six years, he worked in various roles ranging from maintenance and inspection team leader to logistics and contract manager responsible for providing support both organically and via contractors such as EMBRAER and LATAM to several programmes including the Brazilian presidential air fleet. After ranking first of his class on the Logistics Specialization Course at the Air Force Institute of Logistics (ILA) he was granted an international experience and in 2013 obtained his MSc in Defence Acquisition Management by Cranfield University at the Defence Academy of the United Kingdom, being awarded the Best International Student prize. On his return to Brazil, he became a logistic consultant and actively participated in different projects, especially helping in the development of the EMBRAER C-390 Millennium maintenance plan and leading the BAF Initial Provisioning List calculation team. He is also a senior lecturer at ILA and a content creator for many courses, including postgraduate, provided by the Institute. His research interests are in data analytics and machine learning areas applied to prognostics and health management of complex systems, particularly with regards to aviation predictive maintenance and the development of dynamic maintenance planning methods and models.

Fernando T. M. Abrahão was born in Brazil where he graduated as a military aviation pilot at the Brazilian Air Force Academy in 1988. After specializing in Logistics at the Brazilian Air Force Institute of Logistics (ILA) he obtained a MSc in Maintenance Management, Logistics Management and Acquisition Management from the Air Force Institute of Technology (AFIT) at Dayton, OH, United States of America in 1998. He also concluded his DSc in Transports Engineering in the University of São Paulo (USP) in 2005. During his fruitful career, among many other roles, he was responsible for the aviation systems acquisition and lifecycle management department at the Coordinating Committee of Combat Aircraft Programme (COPAC) and also a senior lecturer of the Logistics Specialisation course promoted by ILA. Currently he is the head coordinator of the Logistics Engineering Lab (AeroLogLab) at ITA, where he was also the Administration Pro-Rector between 2014 and 2015.

Ip-Shing Fan is currently on the Education and Scholarship pathway. He was born and studied in Hong Kong, graduated with First Class Honours in Industrial Engineering. He completed his graduate engineer training at Qualidux Industrial Co Ltd in Hong Kong. He was awarded the Commonwealth Scholarship and completed his PhD in Computer Integrated Manufacturing in Cranfield. After returning to Hong Kong, he worked as CADCAM Manager in Qualidux Industrial Co Ltd, responsible for the introduction of CAD, CAM, and CNC in plastic injection design and engineering. In 1990, Fan started to work in The CIM Institute, endowed by IBM in Cranfield, to carry out research, education, and consultancy in new applications of computers in manufacturing. He led many European and UK funded research programmes to create new tools and methods in knowledge-based engineering design, business performance, quality management, supply chain, and complexity science. He has a passion to understand the underlying reasons and develop better approaches to help organisations work more effectively. He looks at the world with a socio-technical lens to explore the complex interactions between people systems and technology systems. The knowledge span includes system engineering, business process analysis, quality and performance management system, organisation design and behaviour, technology induced change, human psychology and motivation. The application domains include aerospace, engineering, manufacturing, business services, IT, education, health, local government.