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A MILITARY AIRCRAFT FLEET SUPPORT MANAGEMENT MODEL BASED ON THE OPTIMAL INTEGRATION OF PREDICTIVE AND SCHEDULED MAINTENANCE

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In loving memory of my grandfather João Batista de Figueiredo

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"It is by logic that we prove, but by intuition that we discover. To know how to criticize is good, to know how to create is better".

Henri Poincare

Resumo

Os avanços em tecnologias de sensoriamento, a expansão das técnicas de análise de dados e o aprimoramento dos algoritmos de aprendizagem de máquina permitiram o surgimento de novas estratégias de manutenção na aviação, com potencial para melhorar a disponibilidade das frotas concomitantemente a maiores reduções de custos. O problema que se impõe diante dessas novas abordagens é que a migração direta de tarefas preventivas programadas, previamente empacotadas em inspeções periódicas, para tarefas baseadas em predição pode resultar em um aumento do índice de indisponibilidade da frota. A integração otimizada da manutenção preditiva dentro do plano de manutenção geral cumpre papel fundamental neste cenário. As intervenções baseadas em predição buscam explorar ao máximo a vida útil dos equipamentos e, ao mesmo tempo, evitar riscos aumentados de incorrer em eventos de falha. Apesar dos avanços nas capacidades diagnósticas, a incerteza inerente a prognósticos representa um desafio substancial, que deve estar refletido em qualquer esforço de modelagem desse tipo de problema, especialmente quando as projeções se estendem por horizontes de tempo mais longos visando a permitir maior antecipação ao planejamento e preparação da operação e da manutenção. Uma grande parte dos estudos na área focam apenas no aumento da precisão das predições para um único componente. Outra parte significativa da literatura trabalha com monitoramento de condição para múltiplos componentes, mas restritos a um único vetor ou plataforma. Outros estudos se restringem a usar estimativas de vida útil remanescente, sem considerar os níveis de confiança associados aos resultados apresentados. Esta tese propõe um modelo inovador, que integra dinamicamente as tarefas de manutenção preditiva e programada em uma estrutura única, com o objetivo de otimizar a disponibilidade da frota. O conceito inicial foi verificado e demonstrado por meio de exemplos exploratórios, que posteriormente foram expandidos para lidar com maior quantidade de aeronaves e componentes sujeito a menor número de premissas, com isso provendo maior robustez à validade da solução. O modelo resultante foi testado e validado por meio da implementação de um modelo de simulação híbrido, baseado em agentes e eventos discretos, criado com o software Anylogic©. Os resultados obtidos demonstraram o valor da contribuição deste estudo e confirmaram o potencial esperado para ganhos de disponibilidade, tendo apresentado uma redução estatisticamente consistente do tempo de indisponibilidade para os cenários analisados, centrados em um frota militar operando a partir de uma única base. A análise dos resultados também evidenciou as vantagens oferecidas pela integração da manutenção preditiva ao plano de manutenção tradicional. Ao final, as limitações do estudo foram reconhecidas e explicitadas à medida que as conclusões foram apresentadas.

Abstract

Advances in sensor technologies, the expansion of data analytics techniques and the improvement of machine learning algorithms have enabled new aviation maintenance strategies with potential to further improve fleet availability while also reducing costs. The problem facing these new approaches is that the direct migration of scheduled tasks previously packed in periodic checks to prediction-based ones can result in increased total downtime for the fleet. The optimised integration of predictive maintenance with the overall maintenance plan plays a key role in this scenario. The forecast-based interventions seek the maximum exploitation of equipment's useful life whereas avoiding incremented risks of running into failure. In spite of those enhanced diagnosis capabilities, the uncertainty inherent to predictions of future health states remains a substantial challenge that needs to be reflected in any modelling process, especially when projected over long enough horizons as to allow for better operations and maintenance planning and preparation. A significant number of studies in the field focus solely on increasing forecast accuracy for a single component. Another large portion of the literature deals with multi-components condition monitoring problems restricted to a single platform. Other studies consider only remaining useful life estimates without accounting for the levels of confidence associated with the results provided. This thesis proposes an innovative model that seamlessly integrates predictive and scheduled maintenance tasks in a single operational framework with the objective of optimizing overall fleet availability. The initial concept was demonstrated and verified by the means of exploratory examples, and then expanded to address larger numbers of aircraft and components with fewer assumptions granting more robustness to the solution. The ensuing model was tested, verified and validated with the implementation of a mixed agent-based and discrete-event simulation model created with Anylogic©. The results demonstrated this study's contribution value and confirmed the expected potential to generate gains in availability, having displayed a statistically consistent reduction in total downtime for the case under analysis, which consists of a military fleet of fighter jets operating from a single base. Subsequentially, the results analysis clarified the advantages provided by the integration of predictive maintenance into traditional scheduled maintenance plans. At the end, the limitations of this study were acknowledged and highlighted as conclusions were drawn. The final comments point to potential further developments offered by his approach which led to recommendations for future studies.

Figures

Tables

Acronyms

ABS	Agent-Based Simulation
AMMS	Aircraft Maintenance Management System
CBM	Condition-Based Maintenance
CBM+	Condition-Based Maintenance with prognostics
CV	Coefficient of Variation
DES	Discrete-Event Simulation
DMC	Direct Maintenance Cost
DT	Downtime
ECM	Engine Condition Monitoring
FH	Flight-Hour
IPS	Integrated Product Support
IVHM	Integrated Vehicle Health Management
LCC	Life Cycle Cost
LORA	Level of Repair Analysis
MEL	Minimum Equipment List
METRIC	Multi-Echelon Technique for Recoverable Item Control
MGSS	Maintenance Ground Support System
MMEL	Master Minimum Equipment List
MSG-3	Maintenance Steering Group 3
MTA	Maintenance Task Analysis
MTBF	Mean Time Between Failures
MTBM	Mean Time Between Maintenance
OEM	Original Equipment Manufacturer

OPH	Operational Hour
PBL	Performance Based Logistics
PD	Prognostics Distance
PLR	Performance Life Remaining
PH	Prognostics Horizon
PHM	Prognostics & Health Management
RAMS	Reliability, Availability, Maintainability and Safety.
RCM	Reliability Centered Maintenance
RUL	Remaining Useful Life
RULC	Remaining Useful Life in Continuous time
SDS	System Dynamics Simulation
TPM	Technical Performance Measurement
TSM	Time to Scheduled Maintenance (Check)
TTCL	Time to Check – Lower Bound
TTCU	Time to Check – Upper Bound
TTF	Time to Fail

Symbols

AE	total assigned fleet flight-hours
A_o	Operational Availability
$APPX_{ik}$	average component application factor considering the mix of flight types performed by each aircraft
$\mathbf{L}_{ij}$	matrix indicating whether a pair of components are on the same access area or not with cell values proportional to the efficiency gain provided by each pair
LUL	maximum rate of use to remain in the low utilization operational category.
n	number of items monitored
q	total number of aircraft
RULC	estimated remaining useful life in continuous time.
$RULC_{max}$	RULC upper bound for a given confidence level.
$RULC_{min}$	RULC lower bound for a given confidence level.
$s_{i,j}$	supply availability (Boolean variable, 1 = yes, 0 = no).
SCLEN	scenario length in calendar time.
TSM_k	time until scheduled intervention for aircraft k.
T	total number of flight or mission types
u_k	utilization factor.
UTILFC	utilization factor in flight cycles per calendar hour.
UTILFH	utilization factor in flight hours per calendar hour.
$\mathbf{V}_{tk}$	decision matrix with the number of flights type t assigned to aircraft k

Summary

1 Introduction

A core aspect shared by recent technologies emerging in aviation is their ability to sense the surrounding environment, acquire the data to assess their functioning performance, and then generate, process and communicate the resulting information. Besides, ambient conditions, temperature, pressure, vibration readings, load, angle of deflection, flow rate, humidity, change rate of moving parts, like valves and actuators, are all examples of parameters that are now possible to be constantly monitored with a wide range of sampling rates due to digitalisation of aircraft operations and support (SCOTT; VERHAGEN; BIEBER; MARZOCCA, 2022).

It comes with no surprise that those technologies mean higher production costs and result in more components embedded in the aircraft, which enhances the number of possible failures in the system as a whole. Therefore, in order to provide a return on this investment and make it profitable, it is necessary to exploit the opportunity it presents for streamlining maintenance by eliminating unnecessary tasks and removals while making the most of each monitored component's useful life without running into failure and risking further damage and costs.

In the literature, these technologies have been encapsulated under the terms IVHM (Integrated Vehicle Health Monitoring), or the more specific term for aviation AHM (Aircraft Health Monitoring), and PHM (Prognostics and Health Management) which together encompass the change in aviation maintenance strategy towards more proactive, precise, and effective approaches to planning (FRITZSCHE; GUPTA; 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" (SAE INTERNATIONAL, 2019a). In other words, the diagnostics capabilities provided by IVHM resulted in a new engineering approach called PHM that not only "enables real-time health assessment of system under its actual operating conditions" but also predicts "its future state based on up-to-date information" (KIM; AN; CHOI, 201 7, p.1).

The value added by the embedded IVHM technologies are bifold. On one hand there is a reliability and safety enhancement brought by onboard precise and timely diagnostics (IMRBPB, 2018), and the provision of enhanced guidance to the crew as to how to respond to an impeding or materialized failure event. The anticipation of a situation and/or the correct identification and prescription of how to deal with it are precious aids in critical scenarios. On the other hand, when there is the possibility of establishing a prognostics and the prediction timeframe is more elongated, there are implications to the support system which can be directly translated into higher availability and less costs. Reasonably, IVHM have been regarded in the market as one of the few technologies that contributes to "reducing both maintenance and operational costs, while improving overall safety" (DIVAKARAN; SUBRAHMANYA; RAVIKUMAR, 2018).

Inherent levels of uncertainty in the forecasts represent the greatest obstacle to the reliance on prognostics due to feared impact on the latter. This is a challenge that needs to be undertaken and overcome as a condition to make predictive maintenance a reality in aviation. This aspect is of key importance meaning that uncertainty must be measured and be present as a fundamental parameter in any model dealing with PHM.

As a matter of fact, this issue is so widely present that most studies focused on solutions for long-term maintenance planning report severe difficulties in handling the onerous accumulated effect of uncertainty in reliability parameters and operational profiles projected over the planning horizon, thus limiting it. With effect, even most recent studies such as the one conducted by Hu, Miao, Zhang, Liu and Pan (2021) recommend strategies balancing short and long-term maintenance performance targets.

In synthesis, the defence of a business case for justifying the investment in IVHM technologies, and hence PHM, depends on it being able to effect a positive impact on at least one of the RAMS (Reliability, Availability, Maintainability & Safety) factors, as defended by Pomfret, Jennions and Dibsdale (2011) and concurred by Sandborn (2013). The potential for worldwide cost savings is significant and is estimated to be "about $3 bn. per year", which is coherent with the potential savings of EUR 700 million per year in the European aviation industry alone claimed by ReMAP (2022), when considering improved "maintenance operations and adjacent logistics processes" (GROENENBOOM, 2019 *apud* MEISSNER; RAHN; WICKE, 2021, p. 1), but it depends on how those technologies are exploited as explained next.

The analysis of this new scenario where the aircraft counts with widespread smart components, and the investigation of how the current maintenance planning can accommodate and benefit from the new diagnostics and prognostics capabilities, showed that the direct application of predictive maintenance may not bring about the expected improvements, but actually increase downtime and jeopardize the overall maintenance planning of a fleet.

In order to understand why the direct application of prediction-based tasks is a problem and its severity, it is first necessary to consider the dynamics of aviation maintenance. In an ideal world, maintenance would only take place when and if necessary. The perfect moment to act would be on the imminence of a failure event, or before the failure process start to jeopardize the overall equipment's health, in such a way as to maximise the use of a component's useful life without running into failure (LEE; DE PATER; BOEKWEIT; MITICI, 2022).

This level of timeliness, meaning the precision on timing the intervention on the verge of its failure, depends on the continuous monitoring of indicative parameters, which historically has been very restricted, though successfully proven, to engine trend monitoring (or Engine Condition Monitoring – ECM) and a few other components that presented observable signs of wear such as oil dripping rate, or the thickness of brake disks as in the research done by Lee et al. (2022).

Unfortunately though, a relatively large portion of aircraft parts have relied on periodical scheduled maintenance checks either based on calendar time or operational hours, and this current practice is pointed out by Divakaran et al. (2018) as a driver responsible for increasing maintenance costs steeply. Those events frequently include hard time preventive replacement tasks requiring the removal of a faultless working components from the aircraft, sometimes unnecessarily sacrificing relevant remaining portions of useful life.

It is also important to remark that for a long time there was still another difficulty in keeping track of the operational performance of aeronautical items, which was the manual recording of occurrences and paper-based inspection reports. The low quality of data has been historically noted and criticized in the literature as pointed out by Dibsdale (2020). In this sense, IVHM technologies represent a new era for maintainability and reliability analysis improvement (DIBSDALE, 2020). On this thought, it is important to remark that the use of IVHM-based tasks has faced considerable resistance in the field of aviation maintenance due to its disruptive features and the change of culture it represents (RAJAMANI, 2020).

Throughout the last decade, many scientific works have been carried out and published demonstrating the potential to reduce costs and improve safety offered by IVHM/AHM. This process has yielded credibility to this new approach, which then earned traction as an improvement embraced by defence forces and air companies worldwide and increasingly accredited by aviation authorities and also the MSG-3 board (SAE INTERNATIONAL (2022), IMRBPB (2018a)).

In fact, it is expected that predictive maintenance will be incorporated as certified for maintenance credit, meaning "to gain approval for a Health Management application that adds to, replaces, or intervenes in previously accepted maintenance credits" (SAE, 2018, p.3), in the next edition of the ATA MSG-3 following the current one released in 2018, which is an amendment already advised by EASA IP 180 (IMRBPB, 2018).

The initial adoption of predictive maintenance yielding maintenance credits should be restricted to functional failures falling within failure effect categories 6, 7 and 9 (AIRLINES FOR AMERICA, 2015), those with non-safety consequences (MOUBRAY, 1999). Once the implementation is tested on the field, and in case the expected safety levels preservation or enhancement is confirmed, the use of IVHM/AHM and prognostics-based maintenance tasks can be extended to more critical failures with safety implications, namely those with failure effect categories 5 or 8.

With regards to the effectiveness, a maintenance task will only be effective if the failure rate function, that is the conditional probability of failure, follows an age reliability pattern whose curve increases at some point in time, especially when there is a clear moment after which the failure rate picks up in pronounced "wear-out behaviour" as posed by Nowlan and Heap (1978, p.46). This effectiveness criterium was an important finding and was essential to the development, scaled operations and commercial success of the platforms such as the Boeing 747-100.

With effect, modern large carriers were benefited from a shift off the overhaul paradigm with the advent of the Maintenance Steering Group (MSG) in 1968, but it was only in 1978, with the development of the MSG-3 maintenance planning methodology, that unnecessary tasks were really eliminated and maintenance got leaner (O'CONNOR; KLEYNER, 2012).

The MSG-3 approach (AIRLINES FOR AMERICA, 2015), also known as Reliability Centred Maintenance (RCM), has since become a worldwide standard in maintenance plan development. In its framework, it considers effectiveness as a requirement for a maintenance task creation, hence providing "a strong and well tested analytical logic which helps eliminate and minimize emotion from the decision making process of determining if a maintenance task is needed or not" (NAKATA, 2016). Nakata (2016) claims that conversion to MSG-3 can yield a reduction of up to 30% reduction in scheduled maintenance costs for an air carrier.

In fact, one of the key aspects of this methodology is that a maintenance task should only be created if it is both applicable and effective. On top of that, unnecessary maintenance may as well increase failure rates since the intervention can induce failures as stated by Tan and Raghavan (2007) and corroborated by the example mentioned by Eliaz and Latanision (2007) who pointed out that maintenance was responsible for 16% of the failures presented by equipment in the Israel Air Force.

However, due to a series of difficulties such as data immaturity or high uncertainty levels leading to excessive risk avoidance measures, ineffective maintenance tasks with premature replacements continue to be carried on by aircraft operators all over the world as noted by Dibsdale (2020). At this point, it is important to emphasize that the maintenance planning document is first created during the aircraft development, when little operational data is available and the system failure patterns are fundamentally only partially known.

The maintenance plan should therefore keep evolving with the fleet operation. In the past, the collection and analysis of statistically relevant failure data used to depend on each operator's fleet size and on the availability of resources to conduct the process. This represented a strong limiting factor to the identification of opportunities for adjustment, and the ensuing proposal and approval of changes that could lead to updating the plan in compliance with the OEM and aviation authorities.

Nowadays, this operational data-driven evolution has become easier once data collection is improved and many modern systems connect back to their OEM sending operational data automatically, which helps the manufacturers to get to know better their products behaviour on the field, thus improving their recommendations and thresholds based on actual reliability information.

In face of all the facts presented so far, this work identified that the migration of tasks previously carried on within the scope of a periodical check to scattered prognostics-based moments results in increments to the overall fleet downtime due to the loss of the synergy generated by the traditional periodical maintenance tasks packaging.

This problem of losing synergy and increasing downtime means that IVHM-based technologies might actually compromise some key logistics indicators, including operational availability, despite the potential advances and benefits that can be promoted by the abundance of accurate and timely data.

Moreover, it is relevant to add that some corrective actions previously executed in response to failures of non-monitored items, those with constant failure rates and exponentially distributed time between failures, called "condition monitoring" items in the old MSG terminology, are also expected to migrate to prognostics-based ones. In this case it is understood that there is no loss to the support level of service, but instead an enhancement in safety and a reduction of costs and downtime motivated by the change.

The hypothesis raised in this thesis is that a method for integrating predictive and preventive maintenance in a single dynamic and adaptative framework that optimally distributes flights or flight-hours amongst the fleet members minimizing total downtime is a solution capable of tackling the impact caused by the migration of scheduled tasks to condition-based tasks on the fleet availability. In other words, the hypothesis is that if a method optimally assigns flights or flight-hours to fleet members in a way as to increase the overlay rate between maintenance tasks, allowing them to be conducted simultaneously, than it will lead to downtime minimization.

The rationale behind the proposed solution is to find the perfect trade-off balance between the following concurrent objectives:

- Maximize the use of a condition monitored component's useful life without increasing the risk of a condition monitored running into failure (condition and prognostics-based maintenance acting on the lower bound of the RUL confidence interval);
- Maximize the overlay between predictive tasks and periodical checks (opportunistic maintenance planning).
- Minimize the disruption effects caused by random time-dependent events such as non-monitored items failures.
- Test the solution's robustness against scenario variability within reasonable range.

It is valid to remark that the three first objectives together are equivalent to, or can be expressed as minimizing the total maintenance downtime without increasing the risk of a condition monitored item running into failure.

In order to test the posed hypothesis the optimization problem was modelled, mathematically formulated and then tested against varying conditions to verify its effectiveness and generalisation potential, and finally it was executed in parallel with a simulation model to check its robustness against time dependent circumstances. The simulation model was developed in order to validate the optimisation model, which carries the solution proposed and represents the core of this study, besides investigating how long the solution is expected to withhold when subjected to random failure events that may bring disruption to its planning.

It is important to highlight that the literature review conducted by the author showed that this research targets a problem unexplored by related works and the novel method developed is an original contribution to knowledge, consisting in the first published work proposing to reduce downtime by dynamically allocating flight hours with a view to maximizing the overlaying of predictive and preventive maintenance tasks.

In order to guarantee that the novelty of this study has been preserved until its publishing date, the Scopus data base was used to monitor correlated publications with alerts triggered whenever a new article came out matching the keywords related to this study.

The main original contribution arising from this study is providing a framework where predictive maintenance can be optimally accommodated within a scheduled maintenance plan with limited impact on the failure risk index thus generating the benefit of maximizing the use of components useful life while also minimizing the fleet's total downtime.

Furthermore, considering that the framework also allows for better planning of resources required for the maintenance interventions, and also for managing the risks of running into failure, another major contribution is the reduction in Direct Maintenance Costs (DMC) by making use of prognostics data.

The originality of both contributions has been confirmed by the presentation of a seminal work that initiated this thesis and was presented at the European Prognostics and Health Management Conference in 2021 (Figueiredo-Pinto et al., 2021). In that opportunity, the work was presented and discussed with the academic community in the field, and the claims regarding its novelty were not disputed by any of the participants.

The following chapters will delve into the depths of each concept, method, process and claim so far introduced. The thesis document as a whole has been arranged in a logical and fluid way forming a structure that reflects the creative process as well as abiding by the scientific method's rigours:

- Introduction: provides context and motivation to the study. States the problem, the hypothesis and the objectives set out by the author. Justifies the relevance and novelty of the research project. Lists the main contributions arising from the work conducted.
- Literature Review: scours the publications on the topic. Explain the core concepts and discuss the state-of-the-art of science in the field. Provides support to the claims of novelty and originality of the contributions offered by this thesis.
- Methodology: delineates the optimisation algorithm developing process, which comprises the kernel of this study. Explains the verification and validation processes, establishing the roles for the analytical and simulation models. Substantiates the results by guaranteeing the scientific method has been respected.
- Results and Analysis: presents the results obtained and discusses their implications in terms of testing the hypothesis, and the extent to which the

research objectives have been met. Provides in-depth discussion of the model's strengths and limitations.

- Conclusion: consists in the recollection and interpretation of the main findings and achievements contrasted with the research objectives thus communicating the balance in support of the thesis conclusion. It wraps up the conducted work with the results obtained, states the contributions provided by this research and acknowledges the work's limitations as well as indicates trails for future developments.

2 Literature Review

2.1 Review Strategy

The subject targeted by this research is trending upwards in recent years considering the annual numbers of publications. The revision of related works showed this increase in interest by researchers worldwide and some measures were taken to avoid falling behind with all new developments in this rapidly evolving topic. The Elsevier SCOPUS© database was used as the main tool to scan the most recent publications falling within the following very strict set of keywords:

- IVHM or “Integrated Vehicle Health Management”;
- PHM or “Prognostics and Health Management”;
- Aviation or Aircraft or Aerospace or Aeronautic*;
- Predictive Maintenance or “Condition-Based Maintenance”;

As a consequence, the author has been able to cope with all the latest relevant publications written in English related to the research while it was being conducted thus guaranteeing up-to-date literature coverage. That is to say that the author is confident in stating that the novelty of the study has been preserved since the gap identified in the literature has not been filled other than by the papers emerging from this thesis.

The survey returned 364 documents as summarized in Figure 1 which shows the evolution of research related to IVHM and PHM in aviation maintenance over the last 25 years with the first mention to prognostics and health management going back to Smith, Schroeder, Navarro and Haldeman (1997) who studied this capability for the Joint Strike Fighter (Lockheed Martin F-35 Lightning II).

This way, it consists in a relatively new knowledge domain and there is clearly an upward trend established after 2015 reaching its peak in production in 2021, only rivalled by a spike in 2012. With reason, the review conducted by Scott et al. (2022) noted an increase in the number in publications of both original and review papers reflecting the growing attention from the aviation community towards this topic. The authors mention a recent “surfeit of review papers as well as original research papers studying the various aspects of detection, diagnostics, prognostics and decision support” (SCOTT et al., 2022, p.2) and dedicated their efforts to conducting the first predictive maintenance review paper focused on military applications within the defence context.

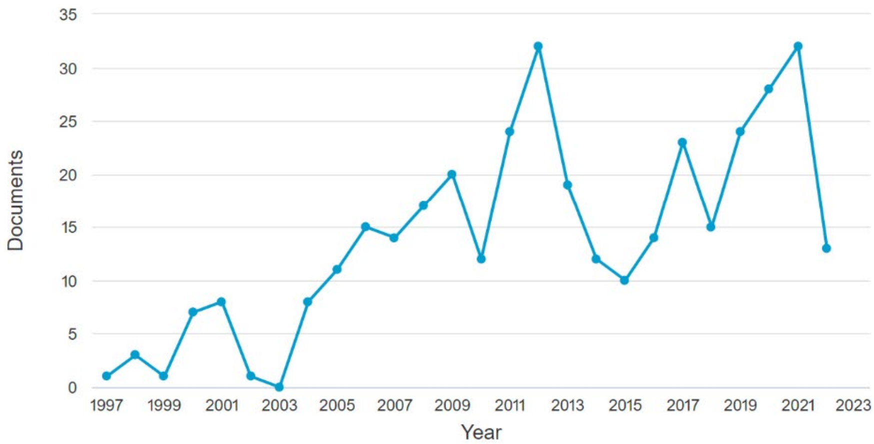

Figure 1 – Literature research results (SCOPUS, 2022).

Following that, the filter was narrowed down to the most recent works and a manual selection based on the abstracts was carried out picking those more relevant and, in particular, those better correlated to the IVHM/PHM 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, and also the review by Scott et al. (2022) for the same reason however more for its particular focus on support and operations of fixed-wing defence aircraft.

The next sections introduce important concepts that are found in the literature and used in this study. Once some of them may have different connotations, it is necessary to explicitly state the meaning adopted by the author considering the context in which they are deployed in the development of the model that represents the core of this thesis.

2.2 Integrated Product Support

The essence of any logistics support system lies in its integrative nature with crossfading intersections between its elements. It is formed by an amalgam of different support aspects that must be balanced and work in coordination to make it efficient and effective in delivering continuity to operations at an affordable cost. This is known in the literature as Integrated Product Support (IPS), formerly also called Integrated Logistics Support (ILS). This framework is composed by 12 elements, the IPS elements, a theory extensively discussed in the international specification by ASD/AIA (2021) and Blanchard (2014).

The doughnut chart portrayed in Figure 2 is an adaptation of the illustrations by the aforementioned works created with the aim of illustrating that design influence is at the core of this structure, being the central element from which supportability irradiates, and that data, or logistics information in the terminology by Blanchard (2014), and also encompasses technical publications in this case, permeates and connects all other elements. The inner elements are those attached to resource investments subject to scarcity and the outer ones are dynamic elements that exert supportability power by making use of resources and data in the management, control and improvement of logistics operations such as maintenance, PHSTT (Packaging, Handling, Storage, Transportation and Testing) and training.

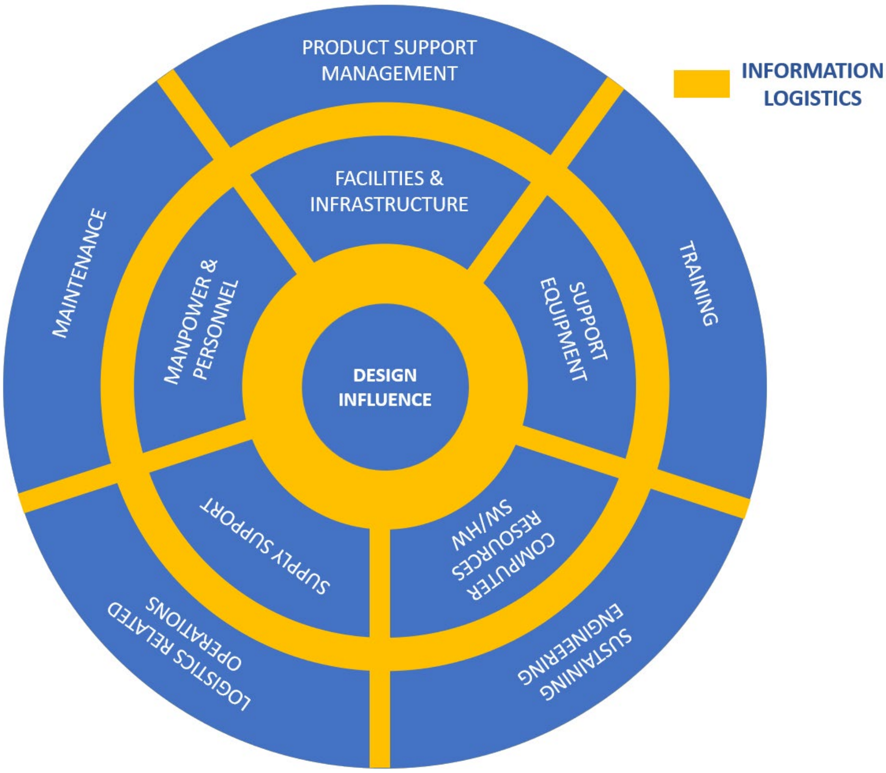

Figure 2 – The IPS elements.

It is interesting to note that materiel, money and data are the flowing entities in this framework. However, while money and materiel are consequences of decisions taken, data is the raw material required for good decision making. In this sense, data is the binding element of this structure connecting the other elements and enabling improvement.

The importance of data is stamped in the vision and objectives of the IPS Specifications (ASD; AIA, 2021) where it declares the aim to improve data quality and enable secure data sharing and exchange through the life of products and services.

As mentioned before in this thesis, historically, the low quality of data collected from operations has been considered an issue hampering potential improvements that could result from a better understanding of the system's performance in service (BLANCHARD, 2014). However, the advent of IVHM has made available high quality in abundance, with an accurate and timely flow that enables creating a health profile updated in real time (SAE

INTERNATIONAL, 2019b). With that, the IPS elements can indeed work fully integrated in a dynamic fashion evolving with and learning from operations.

Considering that IVHM depends on sensing technologies installed onboard, this capability is completely aligned with the long sought objective of having de facto design for supportability by integrating support considerations into equipment design. Although it is possible to enable legacy platforms with condition monitoring system through retrofit for targeting specific issues, the vast majority of new aviation projects already have IVHM requirements included in their scope since the design phase as depicted by Figure 3.

This embedment of IVHM functionalities within the DNA of a project is necessary because IVHM is not restricted to a self-contained subsystem monitoring the performance of others or a "federated, compartmentalized, isolated system that performs one main function" in the words by SAE (2021, p.6). It is rather a system of systems which resides within subsystems throughout the whole aircraft system with requirements unfolding all over the support network. SAE (2021, p.6) concurs affirming that IVHM is "often distributed across aircraft on-board, fleet, on-ground and up-to enterprise level, such that IVHM requirements can be found throughout all aircraft systems (and ground support systems)".

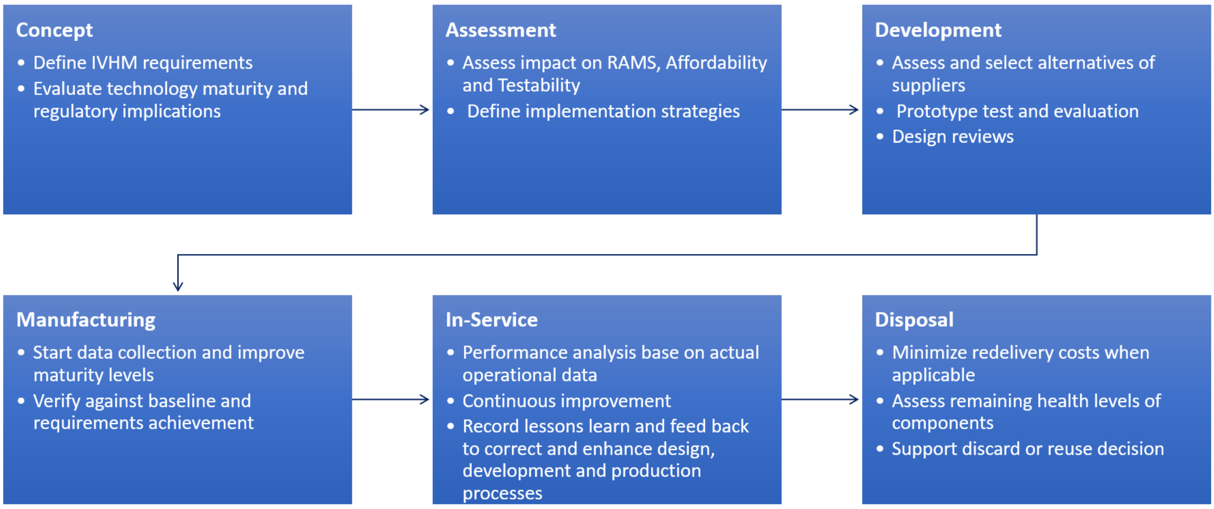

Figure 3 – IVHM requirements in the product lifecycle.

2.3 Performance Metrics

The establishment of metrics for evaluating the IPS performance is important to enable control of the extent to which the quantitative and measurable supportability requirements are being met and to check the achievement of design goals (BLANCHARD, 2014). As the adage goes, it is only possible to manage something if you can measure it. Still according to Blanchard (2014), this approach is known as Performance Based Logistics (PBL) and has been intensively applied in the defence sector for contracting out logistics support. The key aspect to be understood is that although different metrics can be related distinct logistics elements, the performance requirements must be set and met for the system as a whole. It is in the right composition of the many Technical Performance Measures (TPM) that lies the guarantee of an effective support.

This thesis is concerned with improving the overall level of service delivered by the support system and operations management to a fleet. In order to do that, it makes use of metrics to assess whether the proposed solution is able to achieve the intended gains or not.

These metrics generally have their roots in parameters within the famous RAMS (Reliability, Availability, Maintainability and Safety) factors which characterise the system (GALAR and KUMAR, 2016). Safety is preponderant in aviation and depends mostly on reliability and maintainability metrics.

As a matter of fact, the reliability levels of aeronautical components have to meet minimum system requirements demanded by regulatory authorities which are initially checked in laboratory tests. Maintainability metrics gauge the level to which it is possible to cost-effectively maintain the system abiding to those requirements throughout its lifetime (REGATTIERI; GIAZZI; GAMBERI; GAMBERINI, 2015).

The in-service performance may differ from the expected and in case it falls below target there must be an action. This action may consist in the creation of a maintenance task, if applicable and effective, or require system reengineering to improve robustness sometimes ending up even with the replacement of the problematic item by an alternate better performing one. This is all part of the asset management whose ultimate goal is continuous improvement of system performance as defended by Galar and Kumar (2016).

Availability is a high level systemic metric calculated as a function of Reliability and Maintainability, therefore availability is a dependent variable emerging from reliability and maintainability parameters.

Using the terminology promoted by Blanchard et al. (1995), reliability deals with the uptime characteristics with parameters like:

- MTBF (Mean Time Between Failures): only takes into account stops caused by failure events;

- MTBUR (Mean Time Between Unscheduled Removals): a more embracing metric that accounts for all unscheduled component removals regardless to the motivation;

- MTBUMA (Mean Time Between Unscheduled Maintenance Actions): similar to the previous, but considers all unscheduled maintenance interventions besides those involving removals;

- MTBM (Mean Time Between Maintenance): an omnibus term that also includes preventive driven maintenance stops.

Maintainability for its turn is “an inherent characteristic of system or product design” and refers to the achievable degree of ease, accuracy, safety and economy in the execution of maintenance actions propitiated by the design (BLANCHARD; VERMA; PETERSON, 1995). Maintainability is concerned with metrics of downtime, that is when the equipment is not operational, such as:

- Maintenance Downtime (MDT): the total time the system spends in non-operational status motivated by maintenance related causes. It encapsulates:

    - Mean Corrective Maintenance Time (Mct) or Mean Time to Repair (MTTR): expected value of the probability distribution governing the time dedicated to troubleshooting and clearing an equipment’s failure;

    - Mean Preventive Maintenance Time (Mpt): expected value of the probability distribution related to the time spent on preventive actions. It is divided into:

        - Mean Predictive Maintenance Time (Mpdt): portion of Mpt due to condition-based and predictive maintenance;

        - Mean Scheduled Maintenance Time (Msdt): part of Mpt associated with periodic inspections, checks and overhauls.

- Maintenance Labour Hours/System Operating Hour (MLH/OPH): rate between the number of maintenance manhours spent per system’s operating hour. This is a good indicator of the effort required to keep the system working;

- Turnaround Time (TAT): in aviation it can refer to the time necessary to recommit a landed aircraft back to take off for another flight. It may as well describe the time a repairable item spends in the maintenance pipeline, that is the time spent by an item in the circuit from when it is removed from the operational platform passing through the maintenance shop until it is made available back at the spares inventory shelves (BLANCHARD et al., 1995).

Maintenance costs are also part of maintainability’s scope since the supportability of a system is significantly dependent on its affordability. On this matter it is imperative to remark that although in general terms the downtime metrics above are directly proportional to costs (REGATTIERI et al., 2015), i.e. the more manhours spent and the longer a system stays inoperative due to maintenance, the more expensive it becomes, the conversion depends on various scenario-specific factors such as the support arrangement and wages policy, which will implicate transport, storage and inventory costs that can only be evaluated on a case-by-case analysis.

In fact, this is a reflex of the integrated nature of support. In reason of that, any intended solution meant to reduce maintenance costs will require a bespoke treatment, not necessarily liable to generalisation. In here, it is worth disclaiming that this issue is the reason why the solution developed in this thesis does not make the leap to cost. It is a straightforward conversion, but it could only go as far as a case study, which is not meant at this time when the intention is to create a generalist application.

Both concepts of reliability and maintainability are stochastic, with reliability focused on increasing the probability of an item staying operational for longer periods, while maintainability analysis seeks to reduce the expected time demanded to turnaround the asset and give it back to the operational line.

2.4 Maintenance

Maintenance is defined as conserving or restoring an equipment's ability to perform its intended functions (BLANCHARD et al., 1995, KINNINSON (2004)). When the action is proactive and takes place before a failure takes place, the action is considered preventive maintenance and is associated to terms like overhaul, restore, inspection and rectification.

When the action is reactive and takes place after failure event, it is called corrective maintenance and associated to terms such as repair, recovery and rectify (note that this is a more generic term used for both cases). Based on those definitions, condition-based and predictive maintenance interventions are considered subclasses of the preventive maintenance type.

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, due to regulatory restrictions or the inexistence of mature condition monitoring technology for some types of systems, aircraft safety still relies and will continue to be heavily dependent on periodical checks mostly designed during the aircraft development, where hard-time preventive maintenance tasks are grouped to be executed in batches.

There is evidence in the literature pointing out that this gathering or packing of tasks is currently loosely performed to accommodate the different mandatory requirements within the aircraft maintenance schedule thus invariably shortening the intervals to avoid hazardous or catastrophic consequences. In this sense, IVHM/AHM, as an end-to-end application, offers the possibility of not only better adjusting those intervals, but in some cases it can even support the replacement of a periodical scheduled task requirement (IMRBPB, 2018).

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 rather conservative and are expected to go through an optimisation process as operations progress according to Gonçalves and Trabasso (2018).

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 (TAN; RAGHAVAN, 2007).

Complex systems demand through life support, making maintenance a significant cost in the asset's lifecycle. In result, supportability requirements have been developed and are increasingly being incorporated into system's design. The arise of IVHM technologies is a clear evidence of this issue's relevance since it is concerned with improving support by continuously monitoring components (DIVAKARAN et al., 2018), thus allowing for better understanding of system's actual operational behaviour, resulting in more accurate reliability analysis and higher maintainability due to anticipated triggering of maintenance, supply and operations workflows.

It supervenes to remark at this point that a central attribute of this research consists in studying maintenance as an integrated collection of corrective, scheduled, condition-based and prediction-based interventions seeking to keep or restore the designed functions of a system. This is in line with the recommendation by the Society of Automotive Engineers (SAE INTERNATIONAL, 2018b, p. 7) which suggests that an effective fleetwide health management solution depends on the implementation of an efficient methodology "with the right mix of diagnostic, prognostic and scheduled maintenance approaches".

In agreement with this view, Wilmering and Ramesh (2005, p.1) establish that prognostics is only "part of an effective integrated Health Management solution". In addition to those, the first type of maintenance that ever existed, the reactive or corrective actions mostly called repairs, must not be forgotten given that it continues to be demanded since it stems directly from the inherent randomness of the physical world, sometimes rendering scheduled or periodical tasks ineffective. On the other hand, it must be perceived that it also arises from the quintessential element to any forecast, namely uncertainty, hence remaining able to surprise even the most advanced monitoring and prognostics systems.

It is necessary to register that the scanning of literature indicated that the majority of references on the correlated subjects are concerned with technical and very specific models seeking to process the different signals provided by electronic sensors of various different components in order to extract useful and reliable information to support diagnostics and prognostics conclusions (BAEK, 2007; ELIAZ; LATANISION, 2007; LV; ZHANG; JIAYANG, 2015; SUDOLSKY, 2007) or creating methods to improve prediction accuracy as in the work by Yang, Wang, Cai and Li (2023). The issues involved in raw data processing are not considered in this thesis since the model hereby proposed operates in a higher level and considers the condition-based forecasts as inputs to P-F curves.

At this point, in order to set expectations accordingly, it is important to position this research in terms of its level of application in the maintenance information flow. Taking as a reference the standard specification called Open System Architecture for Condition-Based Maintenance (OSA-CBM), largely adopted in the industry and especially promoted through the design principles of the international standard number 13374 (ISO, 2003) and as a functional model by the Society of Automotive Engineers (SAE INTERNATIONAL, 2018b), this study is concentrated on the so called Advisory Generation (AG) and Prognostics Assessment (PA) functional blocks or levels.

Before moving on, it is also important to highlight that some authors in the literature such as the North American Department of Defense (DoD, 2020) make a distinction between the terms CBM (Condition-Based Maintenance) and predictive maintenance or CBM+ (CBM with prognostics) whereas another part of the references, for instance Tan and Raghavan (2007), associates CBM with prediction based actions.

On this text, CBM refers both to current health assessment or diagnostics, and also to prognostics, or future health states, hence being interchangeable with CBM+.

Considering the description provided by Figure 4, it becomes apparent that the present study expands the deployment of processed high level information provided by CBM systems onto the operations and maintenance management, closing the gap pointed by Li, Verhagen and Curran (2020, p.3) who stated that OSA-CBM architecture “lacks connection with the higher-level methodology and framework” and also “lacks to provide detailed application case of integrating aviation health management systems into supporting infrastructure for aircraft maintenance”.

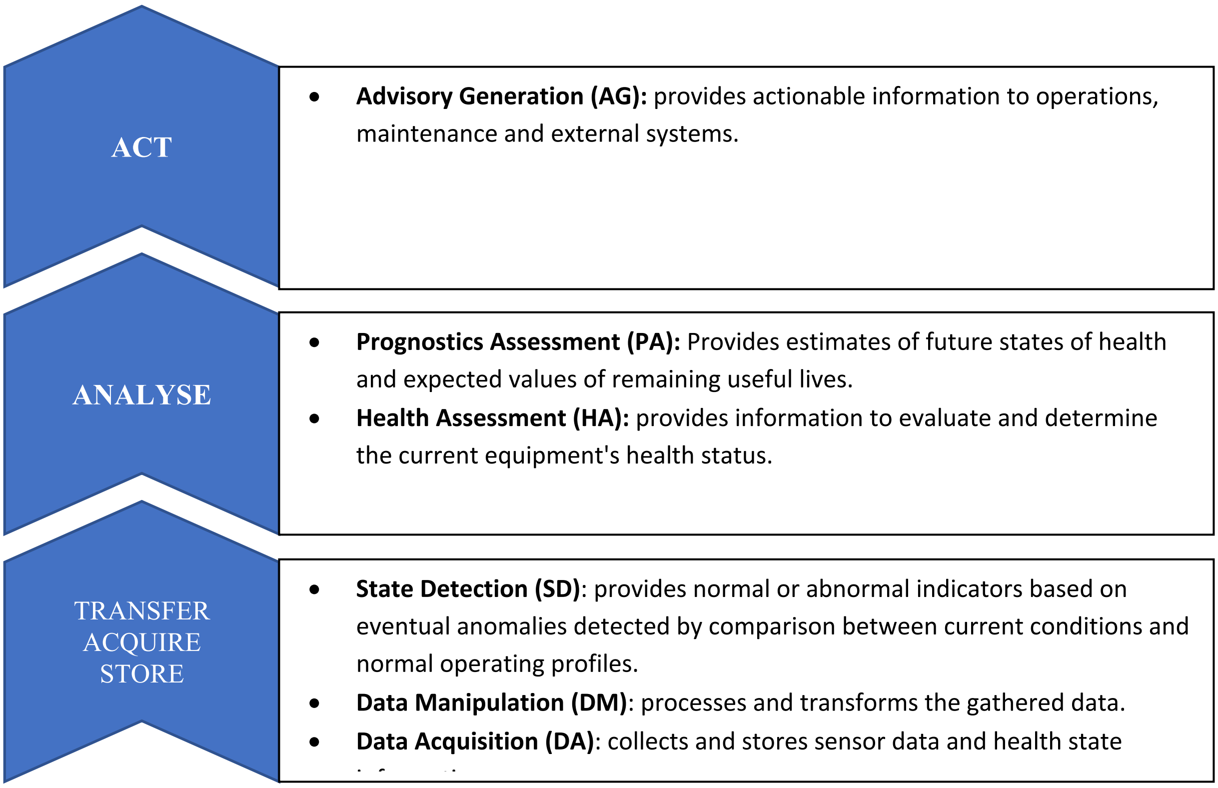

Figure 4 – OSA-CBM/IVHM functional blocks (adapted from SAE International (2018b)).

In light of the above, this study acknowledges the value and complexity of all processes involving health data collection, treatment and analysis which take place at the predecessor functional blocks and will use their product as an input to the proposed model. The quality and accuracy of each one of the diagnostics and prediction methods will be reflected in the confidence levels embodied by this methodology as explained in the next chapter.

The objective herewith is to investigate possibilities to enhance decision making related to assigning flight-hours or missions to fleet members in the best possible way as to minimize total downtime. In other words, the approach adopted by this endeavour consists in analysing prognostics data and suggesting optimal lines of actions for the fleet manager based on that.

It is interesting to notice that despite the reiterated use of the acronym IVHM due to its prominence in the literature, being the original concept created by the north American National Space Agency (NASA), this thesis actually expands the concept to an aviation scenario where the term Integrated Fleet Health Management (IFHM) would more appropriate as it was also defended by Dibsdale (2020) for these cases. Some authors, for instance Feather, Goebel, and Daigle (2010) use yet a third acronym, namely Integrated Systems Health Management (ISHM).

2.5 The Failure Mechanism

In this text the terms failure and functional failure are used interchangeably always referring to the loss of a system's function, that is when a piece of equipment ceases to deliver an expected function judging by predefined or standard operational requirements. Complex systems perform multiple functions simultaneously, so that it follows failures may affect partially or totally a system's capacity to operate depending on its design properties and the type and number of failure modes, i.e. events causing functional failures, occurred (MOUBRAY (1999), DIBSDALE (2020). In this sense, for the sake of this study whenever the term failure is mentioned it refers to the state of inoperability that characterises a faulty item, or equally the total loss of function.

The P-F curves, which were already present in the work by Moubray (1999) and continue to get traction, 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 chapter. They are used for estimating the Remaining Useful Life (RUL) of an equipment, or Prognostics Horizon (PH) as named by Julka, Thirunavukkarasu, Lendermann, Gan, Schirrmann, Fromm and Wong (2011). RUL is defined by Si, Wang, Hu and Zhou (2011, p.1) as a random variable representing "the useful life left on an asset at a particular time of operation".

It may also be referred to in the literature as Time to Fail Assessment (TTF) or Performance Life Remaining (PLR) and its precision relies on "understanding the component age, usage conditions, identification of the incipient failure and its severity, rate of degradation, and predicted usage" (SAE INTERNATIONAL, 2018b).

It is valid to note that the same publication classified it as "probably the highest value element of a predictive health management program" and also "the most difficult to achieve", what is also supported by the review of RUL estimating models by Si et. al. (2011), where it is noted that RUL estimation impacts on operational performance and costs. This is a central concept which is largely exploited in this thesis because it is critically important to several IPS elements such as maintenance and spare parts provision (supply support) and also fundamental to prognostics and health management.

The P-F curve and RUL concepts are intimately related because while the former defines a trend curve from the current condition, or a point where a failure process begins or becomes detectable (the potential failure point "P"), to the estimated/projected point when a failure is expected to take place (the functional failure point "F") (BOUSDEKIS *et al*. (2015); MOUBRAY (1999)), the latter is the expected value of the delta in time between "P" and "F".

It should be noted that both points are dynamic and are expected to move as time passes and the operation progresses.

The basic health degradation behaviour that results in a RUL estimate and the associated levels of uncertainty, which are directly proportional to the forecast degree of anticipation as pointed out by Lee et al. (2022), is illustrated in Figure 5. In other words, the further in time the failure prediction point is estimated, the lower is the precision of the forecast, therefore the larger is the confidence interval. This shows how dynamic the situation is given that even the confidence intervals change as the operation develops, which requires constant adjustment to planning.

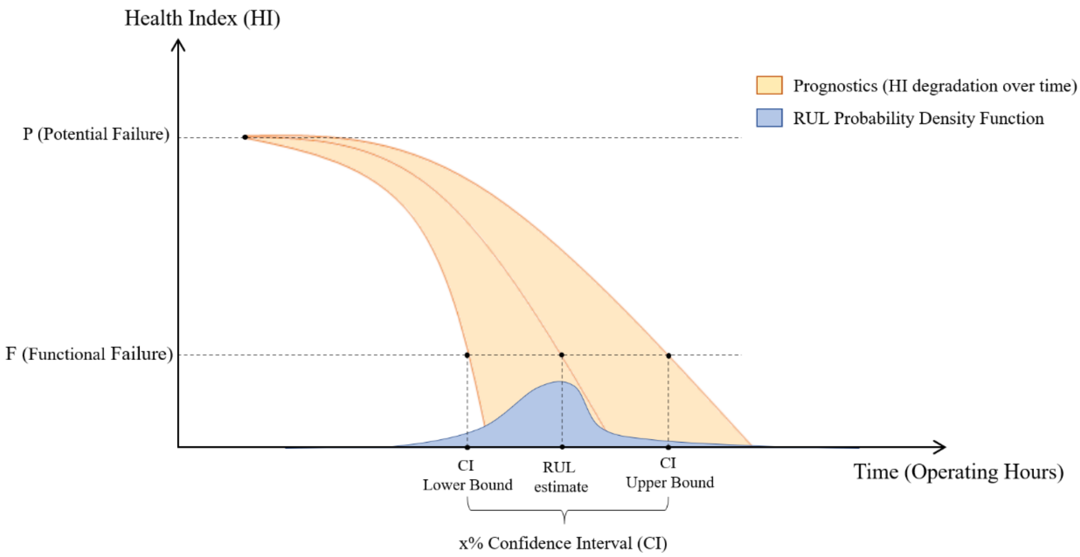

Figure 5 – Remaining Useful Life (RUL) estimation.

It is worth clarifying that although many authors are keen on the definition of the potential failure point “P”, which marks the first noticeable signs that a failure process is in course, nowadays there are intricate model-based projection algorithms that are used to predict failure irrespective of detecting the start of a failure process based on health data analysis (PETRILLO; PICARIELLO; SANTINI; SCARCIELLO; SPERLÍ, 2020).

At this stage, it is valid to point out that P-F curves are dynamic and their forecasts change ongoing with the operation. They depend on the correct functioning of the sensors enabling smart components in modern aircraft. This holds true regardless to the method issuing the prognostics being model-based or data-driven. Even though the former “relies on stochastically modelling the system degradation evolution” as explained by Nguyen and Medjaher (2019, p. 251), the periodic check of the actual health state on which the system finds itself as indicated by the sensors is key to adjust the theoretical prediction otherwise risking wrong maintenance decisions.

Following that, notwithstanding the fact that the increasing number of sensor offers an opportunity for streamlining maintenance by eliminating unnecessary tasks and removals, it must be cautioned that this lean maintenance may not be fully achieved yet due to the variability of approaches adopted. With effect, many items require reiterated inspections to adjust forecasts, meaning several maintenance interventions, while others can only predict a failure very close to its occurrence limiting the benefits provided by the prognostics with respect to proactively anticipating maintenance actions or avoiding the failure occurrence.

If the condition-monitored equipment demands periodical inspections for performing prediction adjustments, then the more sensor-enabled items, the more interventions there will be. The frequency of intervention per se is not a problem if those interventions can be grouped into packages, practice known as opportunistic maintenance according to Lee et al. (2022). In this case a single stop would update several estimations and also serve to opportunistically perform neighbouring predicted or scheduled tasks.

Nevertheless, it must be recognised that the initial indication that a failure process is in progress may come up at different stages of the component's lifecycle with the initial RUL expected value, or PH, or even prognostics distance (PD), varying 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 is limited to an immediate operational repercussion (DIBSDALE, 2013), or, at most, it may give maintenance a head start to pre-allocate resources for the repair/replacement on the destiny where the aircraft will land when datalink services such as ACARS (Aircraft Communications, Addressing and Reporting System) are available. For the purpose of the maintenance planning methodology proposed on this thesis though, only prognostics distances greater than the flight duration are worth considering since it requires enough time flexibility for adjusting the flights or flight-hours assignment in a way as to cause the RUL forecasts to move and overlay with other tasks. In other words, if the failure process is shorter than the flight duration it will not have an implication for the method herein developed.

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.

This smooth behaviour is not guaranteed though, given that components are subject to multiple dependent competing failure processes which can result not only from internal degradation, but also from random shocks or sharp load variations as examined by Wu, Wei, Zhang and Bai (2023).

With a view to clarifying the ways in which failures are treated in this thesis, a definition of the failure mechanism is in due order. In reliability analysis (MOUBRAY (1999); DIBSDALE (2020)), the general failure process is well explained. It is important to understand that from design, the engineering of any component admits the possibility of failure. It is realistic to affirm that production or manufacturing processes are not perfect, indeed inherent reliability does not reach a hundred percent, and bear some variability which Kinninson (2004) impute to entropy.

It means that the items composing every approved production batch present resistance, strength, or level of perfection as called by Kinninson (2004), varying within a predefined tolerable range which can be directly traced to health indexes. The outgoing tests performed by quality control usually submit the product to stress with the aim of identifying and rejecting items that fail to meet the minimum standards.

Allied to the stochasticity driven by quality of manufacturing processes, the load to which each product will be subjected also varies according to environmental and operational changes. The curves on Figure 6, adapted from the work by O'Connor and Kleyner (2012) exemplify an initial situation where the weakest of serial products still presents enough strength, or resistance to withstand even the upper side of the load curve.

The orange curve represents the probability density function of the instantaneous stress load random variable to which a component is subjected. Nowlan and Heap (1978) exemplify this with the variation in atmospheric turbulence exerting different load levels on the aircraft structure. On the other hand, the blue curve demonstrates the probability density function of the level of resistance to failure offered by the component. The variability occurs because the production process of manufactured items involves tolerance limits within which range the product is accepted, as also posed by Nowlan and Heap (1978). With time and operation, the accumulated action of environmental factors and the stress load to which the item has been subjected throughout its life, this resistance to failure declines and wears out to a point in which eventually it is not sufficient to withstand the load and the functional failure occurs.

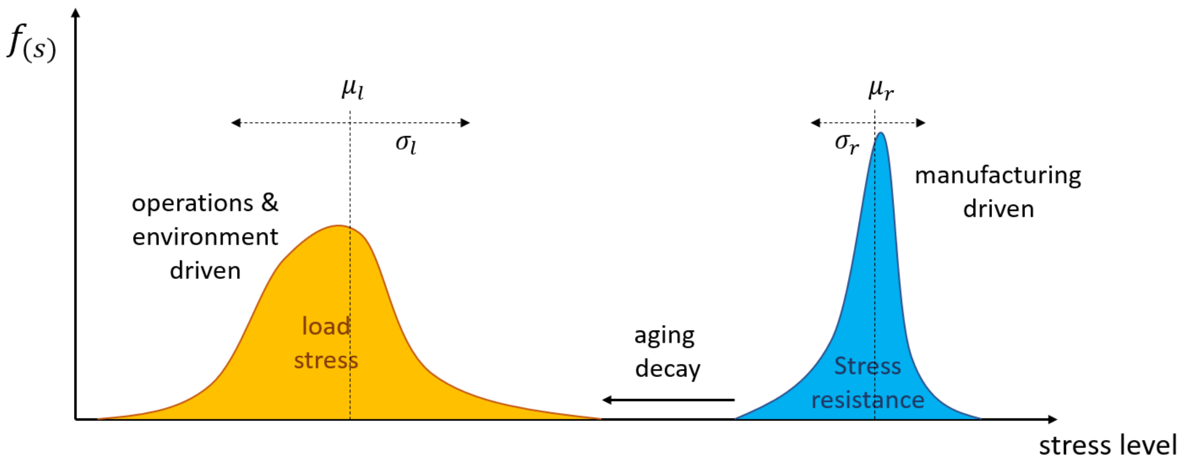

Figure 6 – The mechanism of failure – resistance (or strength versus load variation).

In other words, as the items age or wear out with time and operations, resistance tends to decay giving in to entropy (KINNINSON, 2004) and at some point the curves start to overlay, increasing the failure rate. This process can so also be subject to non-linear behaviour due to load shocks (WU et al., 2023) which is expected to be captured by anomaly detection algorithms. In this case there might be intermittent symptoms which make diagnosis significantly harder.

In this interim, it is also important to notice that in aviation there are several layers, or echelons of maintenance planning according to the respective level of intervention they refer to. There are simple tasks which happen on a daily basis and do not demand complex procedures, therefore they can be planned and rapidly processed on the ramp or after the aircraft finish their flight schedule.

There are other checks which demand several weeks planning due to the complexity of the tasks and the need of special manpower, equipment and spare parts. In this sense, predictive maintenance can help on this quest, but its potential may be significantly reduced if the uncertainty involved prevents it from being used for long-term planning.

2.6 The Role of Uncertainty

Notwithstanding the improvements in the precision of forecasts, prognostics are in their essence predicated on stochastic models and therefore will always bear a certain degree or margin of error embedded in the forecast (FERREIRO; ARNAIZ; SIERRA; IRIGOIEN, 2012; SINGH; SINGH; SRIVASTAVA, 2016).

Corroborating this idea, Zaitseva, Levashenko and Rabcan (2023, p.1) establish that any mathematical model, as an approximation of system behaviour, embeds uncertainty. The authors separate uncertainty into two categories: aleatory uncertainty – caused by the random nature of the studied phenomena, and epistemic uncertainty – caused by incomplete, ambiguous, vague or incorrect information about the phenomena and overall “lack of knowledge about the system behaviour”.

Following this definition, Grenyer, Dinmohammadi, Erkoyiuncu, Zhao and Roy (2020) defend that the knowledge provided by condition monitoring data, enhancing the representational capacity of the model, can help mitigating epistemic uncertainty, but the aleatory component of uncertainty “represents statistical variables that constantly fluctuate and therefore cannot be reduced”. Arguably, this reduction is actually possible with the advent of new equipment endowed with more precise measuring capability which aims exactly at reducing aleatory uncertainty. In that sense, it would be better stated that aleatory uncertainty can be reduced, but it cannot be eliminated. With reason, Zaitseva et al. (2023) and Yang et al. (2023) both concentrated their efforts in targeting sources of epistemic uncertainty.

The aleatory component of uncertainty will remain present, unless the event is consummated, but rather than being ignored it must be assessed and reflected on every analysis in order to give the decision maker better situational awareness. Consequently, any technique or solution approach to problems involving this feature should be able to deal with probability and uncertainty.

Kefalas, Stein, Baratchi, Apostolidis and Back (2022) corroborate this statement, while also pointing out that most studies unfortunately focus on point estimates in spite of considering confidence intervals, and explain that while epistemic uncertainty configures a reducible part of the total uncertainty in a modelling process, there will always be a portion of the aleatory parcel of uncertainty that is not liable to elimination.

Unfortunately, a considerable portion of the approaches to predictive tasks programming found on the related studies 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 author believes 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).

Likewise, it must be added that not only RUL is a random variable, but also the many reliability and maintainability metrics, as well as the high level system metrics such as availability and even supply metrics such as number of backorders and items in the pipeline are all random variables.

In the extensive theory long consolidated by the various works dedicated to steady-state scenarios, mean values are applied throughout the models and the deterministic results obtained are automatically regarded as valid and taken for their face value. This is the case, for instance, of the Multi-Echelon Technique for Recoverable Item Control (METRIC) propagated by Sherbrooke (2004) in his seminal work.

With effect, when a phenomenon meets all the requirements of a Poisson process, like the independency between events, over a long time the mean values are likely to hold and be verified recurrently in a way that the method turns out to be completely sensible and adequate to support decisions focused on the long term.

Nevertheless, that is not to say the stochasticity is irrelevant or has been overcome. In fact, if the asset operations are not evenly distributed for example, the solution tend to lose effectiveness. That is because the mean values of variables on their own are not able to represent stochastic behaviour of their respective distributions, much less so for larger degrees of variance.

Besides, when tactical decisions with shorter horizons are at hand, just knowing the expected number of failures over a predefined period is not sufficient given that the timing when the event happens is of key importance.

This should be kept in mind and indeed be of academic concern because this is already a market demand and is reflected by the industry in the area, with software companies such as the Swedish Systecon AB, focused on providing decision support tools to logistics managers, commercializing a suite of three software to attend the customers' needs. In their case, one program runs over a static deterministic model which considers only mean values as input, while the second is a simulation software where the initial solution is submitted to the scenario variability incorporated in the operations profile. The last software component is dedicated to costs and takes into account outputs from both the previous instances, therefore also bearing stochasticity.

2.7 The Research Gap

A recent publication by Shi Zu, Shiang and Feng (2020) scoured the literature and identified that most studies on CBM and prognostics are restricted to single items, trend which continues to hold true as shown by correlated studies such as the one performed by Lee et al. (2022) whose application focused solely on landing gear brake disks.

Nonetheless, it is well known in logistics that only systemic optimization can deliver true value to the operator. 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.

That notwithstanding the gap identified in that study remains uncovered since the proposed solution 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 (loss of brand value or credibility, customer satisfaction) and indirect costs (loss of future revenue, cost of opportunity etc).

Even more recently, the work by Chen, Shi, Lu, Zhu and Jiang (2022, p. 79) stated that existing works in the literature fail to integrate the RUL prediction and maintenance decision-making sides of a system's PHM, but rather perform these "two tasks separately and hierarchically".

Reinforcing this argument, Lee et al. (2022) also noted that rare are the studies managing to integrate "prognostics into actual maintenance planning frameworks to prescribe RUL-driven maintenance tasks". In this interim, it is fair to mention that Nguyen and Medjaher (2019, p. 251) had already tried to fill this gap by presenting a "dynamic predictive maintenance framework based on sensor measurements".

Further on, the Chen *et al.* (2022) also pointed out that the uncertainty inherent to forecasts "has not aroused wide concern and this may reduce the credibility of point prediction". Those assertions are important to be made because they corroborate the claim that this thesis comprehensiveness is differentiated and novel. In fact, although the study by Chen *et al.* (2022) does tackle both sides of PHM and took uncertainty onboard, which is already an advance compared to most of the literature, it did not contemplate multi-component or multi-platform systems as proposed herein.

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; 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; GOLLNICK, 2012).

Furthermore, it has been noticed a general concern about the cost effectiveness of making use of forecasts and letting maintenance act surgically on the imminence of each monitored component loss of function. On one hand, when the failure process import value loss or greater recovery costs, the benefits of postponing the maintenance action must be balanced against those extra costs. On the other hand, the benefit of maximum exploitation of useful life must also be weighed against the dispersion of standalone condition-based interventions which could severely 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 offers advantages and new possibilities, but it also may render disadvantages and increase downtime. 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.

In face of that, and with a view to positioning this research amongst its pairs in the literature, a comparative analysis was drawn on Table 1 where it can be verified the uniqueness and originality of the present effort. The table comprises only those studies directly comparable for using either or both RUL estimates algorithms and maintenance decision-making techniques.

Table 1 – State-of-the-art summary

	Aspects covered in the study							
Study	I	II	III	IV	V	VI	VII	VIII
Rodrigues (2018)			X	X		X		
Nguyen and Medjaher (2019)	X	X	X	X	X			
Deng *et al.* (2020)		X			X		X	
De Pater and Mitici (2021)	X	X	X	X	X		X	
Shi et al. (*2021*)	X	X	X	X		X		X
Chen *et al.* (*2022*)	X	X	X	X	X			X
Figueiredo-Pinto (2022)	X	X	X	X	X	X	X	X

I. Corrective maintenance included in the model
II. Scheduled maintenance included in the model
III. Predictive Maintenance included in the model
IV. Forecast algorithms contemplated
V. Operations and maintenance optimisation – maintenance decision making
VI. Multicomponent model
VII. Multiplatform model

VIII. Uncertainty included in the model

In special, it should be noted that the two main characteristics that differentiate this work from its closest pairs in the literature are represented by aspects VI and VII on the table above. The ability of the models hereby developed to tackle scenarios with multiple platforms, meaning more than one aircraft in our specific case, and multiple components within those platforms is unparalleled in the literature so far as this review is concerned.

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 time-based interventions. Also, it was verified that the technological means to support this approach 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 where the methodology deployed is unravelled in detail.

3 Methodology

This research methodology follows an inductive approach where the initial analytical optimisation model is deployed on a basic case and tested under a set of constraints and conditions, which are then gradually eliminated and subjected to varying conditions thus expanding the model and allowing the solution to be generalised. In other words, the methodology departs from a specific scenario and evolves in the direction of generalising the solution using more complex scenarios and incorporating statistical variability thus demonstrating whether its effectiveness holds true in face of different conditions and parameters.

In a nutshell, the methodology is comprised by a dyad with the main part consisting of an analytical model which was initially verified and published, which was later improved and expanded, followed by a second part entailing a simulation model that runs in parallel with the optimisation algorithm in order to incorporate stochasticity and time dependencies with the aim of checking the validity and robustness of the primary results against a dynamic setting with statistically varying conditions.

The flowchart portrayed in Figure 7 represents the modelling architecture on which the research procedures execution was based.

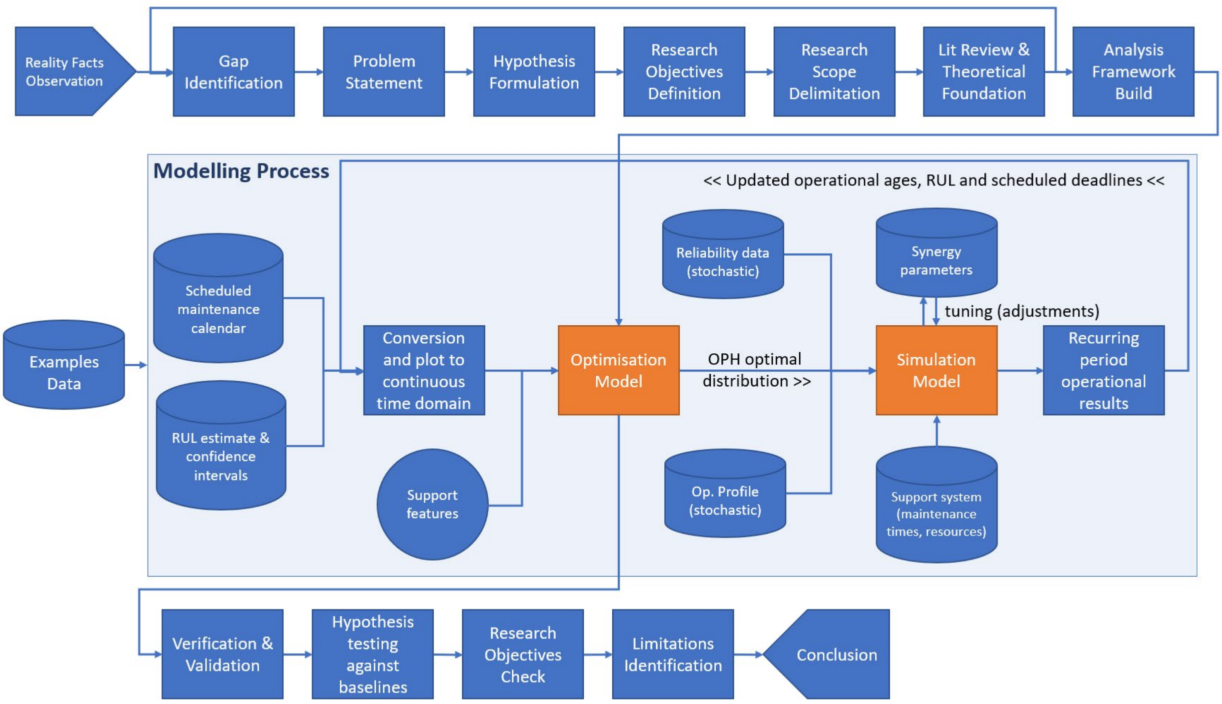

Figure 7 – Methodology design flowchart.

As it can be seen on the upper thread of blocks, the methodology starts with the observation of reality in search of a phenomenon that is worth studying in depth and is liable to improvement. In doing so, the change in maintenance strategy towards the use of sensing data to increase timeliness, assertiveness and cost-effectiveness emerged as the theme.

The investigation, as demonstrated in the previous chapter, raised questions regarding the possible loss of synergy caused by the substitution of scheduled periodical tasks for condition and prognostics-based ones and also identified a gap in the literature consisting of the missing link between data analytics and prognostics algorithms with the operations and maintenance management. Those questions led to the problem formulation where it is found that the missing link is essential to bring IVHM to fruition, otherwise risking its potential for value creation.

Once the problem has been explicitly stated, the methodology raises an hypothesis with a potential solution to tackle the problem. In synthesis, the hypothesis raised by the study is that the operational hours distributed amongst the fleet members can be used as decision variables in an optimisation model seeking to minimize downtime, thus also increasing operational availability.

With that in mind, the research objectives are then explicitly listed aligned with the scope delimitation. Naturally, the integrated support system of large-scale complex equipment has a myriad of parameters with intricated implications and ramifications so that it is only reasonable to set clear boundaries limiting the analysis to make the problem treatment feasible.

Next, the research methodology deepens the literature review, which in reality had started even before the process beginning. In truth, it is obvious that the motivation driving the research proposal has its roots in two inseparable reality factors, namely the author’s working experience and the previous publications the author’s read as part of his job and professional education. At this point, there is a loop on the flowchart meaning that eventual findings in the literature have to be fed back to the departing point of the research process updating the assumptions and the overall background affecting the problem state and the following steps.

Building upon all the information gathered, the research methodology proceeds to the creation of an adaptative and dynamic framework which was structured to integrate all relevant parameters in an arrangement sustained by the rules dictating their links and relationships translated by a mathematical expression as explained on the following section.

The crucial question here resides in devising how the different maintenance parameters interact, for example, how the different RUL estimates and scheduled maintenance deadlines can be disposed in a single formulation in the form of an objective function in order to create an optimisation model that maximises the crossover between them?

At first, together with a series of input data such as RUL estimates, respective confidence intervals, maintenance times, components commonality of location within the aircraft and support features such as inventory levels, the framework is populated and inserted into a static optimisation model which then uses a non-exact method, which is necessary given the complexity of the problem, to try and maximize the overlay of maintenance tasks.

In other words, this initial approach formulates the problem as an equation which calculates the total intersection between predictive and periodic checks for all components on each aircraft across the fleet. That is called a multi-component, multi-platform approach. Maximizing this function also translates as minimizing total downtime and may help to reduce maintenance costs given that tasks performed simultaneously save setup and active maintenance time and resources. This is the most creative part of the methodology and where the main contribution of this study resides.

In order to verify and guarantee the originality and reasonability of this proposal, the basic model has been published (FIGUEIREDO-PINTO et al., 2021) and presented to the PHM Society in Europe and at the IVHM Technical Review at Cranfield University in the United Kingdom. It has therefore been published and the results have not been challenged nor have the novelty and originality claims been disputed.

This feedback supported the continuation of the project with the expansion of the model formulation, especially incorporating corrective maintenance aspects for mitigating the failure risk index, and the creation of a hybrid simulation model where time-dependent parameters of the problem could be captured and their aspects and effects analysed against the indicative results obtained with basis on a steady state setting.

It is important to notice that, at this stage, the research methodology expands significantly the solution's robustness by eliminating some assumptions, thus widening the scope and incorporating time-dependent characteristics hence adding the stochasticity involved in the scenario onto the solution. This step is indeed accomplished by an enhanced problem formulation and the use of a connected simulation model running with basis on the optimal solution provided by the analytical model. On this matter, it is important to clarify that both models, analytical and simulation, are inseparable parts of the methodology developed in this study.

With that, it can be stated that the proposed solution is able to provide coverage to all types of maintenance intervention (predictive, scheduled and corrective), and is also tested against time-dependent aspects and nuances using simulation, unveiling aspects that could not be captured by the analytical model on which the optimisation is based.

The expanded formulation of the problem together with the integration between the analytical and simulation models provide a robust method for verifying and statistically validating the claimed gains delivered by the solution developed in terms of downtime reduction and also fleet maintenance management calibration of decision parameters such as the level of confidence required and the anticipation or delay allowed for each type intervention.

Although both parts are tightly connected and mutually dependent, each model has its own very specific objectives. Whereas the optimisation model is responsible for providing the best possible distribution of operational hours to the fleet members, the simulation model is the only one capable of dealing with those aspects dependent on the moment when the events take place, in special the failure events.

In this particular, it is important to remind that the occurrence of failures is a possibility both for non-monitored items, such as those with exponentially distributed reliability, and for IVHM-enabled items due to the remainder parts of the RUL probability density functions not covered by the confidence intervals.

As a result, despite the proactive maintenance attempts to avoid them, failure events can still occur and hit the system at any moment. In face of that fact, and bearing in mind a downtime reduction solution based on the maximum coincidence of maintenance activities in time, the precise moment when a failure happens does matter once its impact on maintenance planning changes depending on the concurrent status of surrounding circumstances.

Indeed, this is not just a matter of estimating the quantity of events during a predefined period, which is very useful for estimating stock levels as implemented in the OPUS10 © software by the Swedish company Systecon ©, but also of evaluating the various consequences of unexpected interruptions on each different situation (or iteration in the case of simulation results). The exact status of other variables when the fault happens makes a significant difference to decisions regarding possible synergies. Given the impossibility of pinpoint those occasions, the replication analysis provided by simulation becomes necessary.

In more detail, it is also important to understand that the envisaged dyad mechanism that fulfils this methodology is based on the exchange of information between both parts as depicted in Figure 8. As explained before, the optimisation model is the core intelligence combining the relevant and applicable maintenance parameters signalled by the literature in a single formulation that allows for the statement of the problem as an operational research objective function that works as a proxy for fleet total downtime minimization.

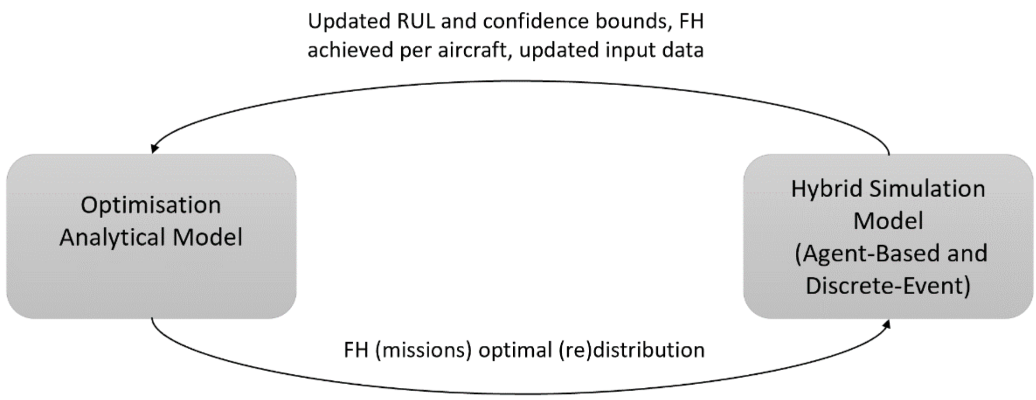

Figure 8 – Integrated Solution Dyad Mechanism.

After implementing, testing and adjusting the core mechanism, the methodology moves on to the verification and statistical validation processes. The verification consists of testing to demonstrate and certify that the requirements set out in the modelling process have been correctly implemented in the solution. This is carried out by testing the models and checking if they are producing coherent results in such a way as to answer the question: have we built the models right? (SAE INTERNATIONAL, 2021).

The validation on its turn entails the analysis to determine whether the requirements for a product, in our case the integrated solution, are correct and complete. This step in reality is only possible with real data, which could not be made available for this research at this point where the new Brazilian Air Force fleets are still very incipient in their operational lives. However, with the use of Monte Carlo simulation, i.e. reiterate generation of random numbers within a reasonably wide range, it is possible to vary extensively the input data creating significantly different random scenarios in order to perform a test of robustness which is a statistical indicative of validation success, thus answering the question: are we building the right models? (SAE INTERNATIONAL, 2021).

Approaching the end of the process, the methodology conducts a hypothesis testing to verify whether the results both from the analytical and simulation models support the conclusion that employing the developed solution can effectively reduce downtime given a certain significance level or not. This is a fundamental step before proceeding any claim can be truly posed.

In any case, that is confirming or denying the hypothesis, the next step is to check out the extent to which the research objectives were met considering that those are the study's true *raison d'etre*. This analysis leads then to the final discussions regarding the impact and findings of the study establishing the advances, original contributions and acknowledging the limitations stemming both from the scope delimitation and also from what the results themselves could not substantiate.

With a view to enlighten the modelling process conducted in the backbone of this methodology, the following sections are dedicated to explaining the development of each model on a step-by-step basis. This way, the author understands that the modelling process itself is an original contribution and form part of the methodology, what leaves the next chapter fully focused on the presentation and discussion of results.

3.1 Initial Optimisation 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 identified in the literature as the most relevant and influent to maintenance planning. Subsequently, the parameters were integrated in a dynamic framework structured on the logical rules governing the relationships among those parameters respecting some limitations and the assumptions adopted to limit the scope. After that, the modelling process is wrapped-up with a verification test using fictional data with an aim to prove its coherence and consistency, thus attaining the objective posed in this article.

The problem is stated as the inefficiency in the use of the beneficial IVHM technologies and prognostics algorithms caused by the increasing migration of packaged time-based and repair tasks to sparsely distributed and isolated condition-based tasks, which may increase the total downtime of an air fleet. In face of that, it turns out 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. Moreover, this compatibilization should also ideally account for corrective maintenance interventions.

In order to integrate those maintenance approaches, it is important to establish that time-based maintenance checks are considered fixed deadlines in the model, 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 in which a fleet might fall in depending on its intensity of use. That is because the time-based tasks like those resulting from an MSG-3 analysis are usually constrained both in calendrical time and by operational parameters such as operating times, flight hours or cycles.

Therefore, if the operation falls into the low utilization category, that means the aircraft maintenance packaging is 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 is quite a common case for military aircraft, in special fighter jets during peace times. It is worth mentioning that this is the case for many projects within the Brazilian Air Force.

At this point, it is important to highlight that the scope of this analysis was tightly defined because the assumptions and simplifications adopted throughout the methodology are essential to help understand the modelling of the problem at hand, and this is an initial approach gradually expanded.

The low utilisation premise notwithstanding, the model proposed should not be considered unable to handle the higher utilisation categories, which can be contemplated via elementary changes in the formulation. In synthesis, the time domain can be converted to any other unit given that all life parameters are transferred from its original aging tally to the same basis where comparison can be drawn. It is conceded that the effectiveness achieved by the model in terms of downtime reduction may vary depending on the governing parameter and the dynamics of age related parameters, but the method remains applicable to all cases.

On with the model development, the framework construction departs from data provided in standard P-F curves as explained in the previous chapter. As shown by Figure 9, 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.

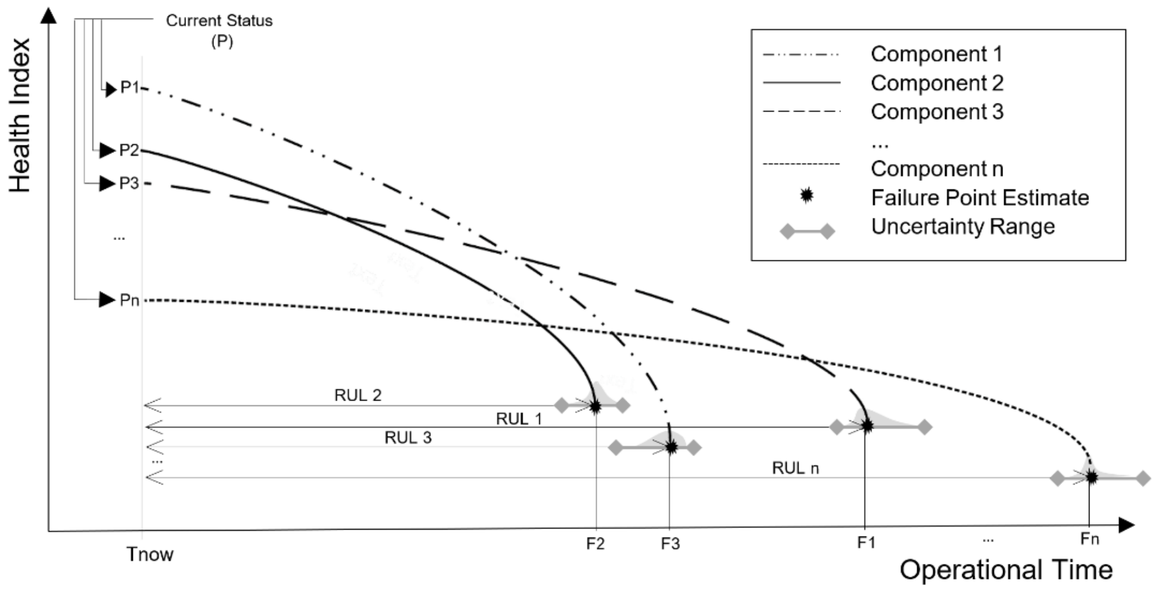

Figure 9 – Aircraft Components' P-F Curves Representation.

A sensitive aspect also represented in the figure above and that must be regarded when dealing with prognostics data is the uncertainty inherent to any forecast, which means that the expected failure point in time on its own is not of much worth, but should be regarded in conjunction with its variation boundaries for a certain confidence level defined in accordance with the user's risk tolerance.

The use of unilateral intervals, i.e. considering only the lower bound and leaving open the other end of the interval, is arguably more appropriate given that the risk of running into failure only exists before the confidence interval once the lower bound is set as the stop point. However, for the sake of calculating overlays between intervals, the bilateral option is adopted for measuring intersection between open-ended intervals would not be possible in some situations. Bearing that in mind, the level of confidence should be adjusted accordingly, e.g. a 90% bilateral confidence interval represents in practice a 95% unilateral confidence interval and vice-versa.

One issue standing out and already highlighted is that different items may follow different aging units like calendar time, flight cycles, flight hours, number of shots, power-up time etc. The solution to that is to perform a migration from the operational parameter axis (power-up hours, flight hours, flight cycles, mission specific fractional time, etc.) to a calendrical or continuous time axis, which can be done by using 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 quantity of operating parameter units over the scenario length. In this case, it is also important to notice that this factor for the platform as a whole, i.e. the aircraft, must not overcome the low utilization threshold for obvious reasons. It is valid to note that assuming uniform distribution for the ageing parameter does not represent a limitation in the model since 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 parameter RULC now expressed in continuous time as displayed in Figure 10. In this graph the scheduled maintenance time is fixed, but the items RULC can be moved by changing the aging intensity via the aircraft utilization factor.

The conversion was modelled following a linear function, but other types of relationship could be applied within the model with no harm to the method or to its results. In reality, many other factors can be taken into account such as the application factor, relative to the proportion of actual utilization of an item per flight hour on each type of flight, or the degree to which an item is demanded and therefore aged according to the mission profile to be performed. The application factor is used in the example used to test the expanded version of the model further down this text.

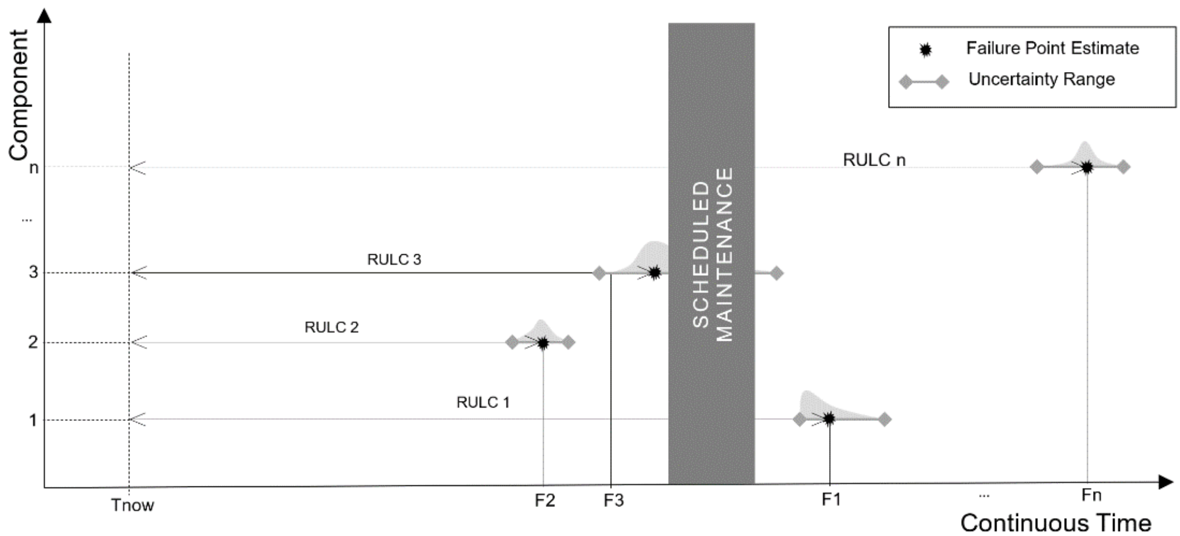

Figure 10 – RUL in Continuous Time Domain (RULC).

Still on the same illustration, it is possible to verify that the prognostics information can lead to the scattering of efforts over isolated singular tasks each requiring a 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 as hereby proposed is to maximize the alignment, crossover or coincidence of expected failure times accompanied of their respective confidence intervals (henceforth called “moving intervals” in the model) amongst various items, and most importantly with the scheduled maintenance check. The latter is considered a better target in the model because a moving interval once merged onto the scheduled 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 *et al.*, 2020).

With this purpose in mind and considering that each aircraft pertaining to a fleet will have its own distinct set of P-F curves, the numbers of flight-hours, or operational hours (OPH) to be distributed and performed by each equipment over the scenario length 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 operational effort in a specified period due to business and budgetary guidance. In other words, the sum of each aircraft executed OPH must not exceed the fleet assigned top effort, except for some acceptable pre-established margin, but should be as close to the limit as possible. Initially, the OPH appointed to each plane will be spread over its respective Time to Scheduled Maintenance (TSM) as can be seen in Figure 11.

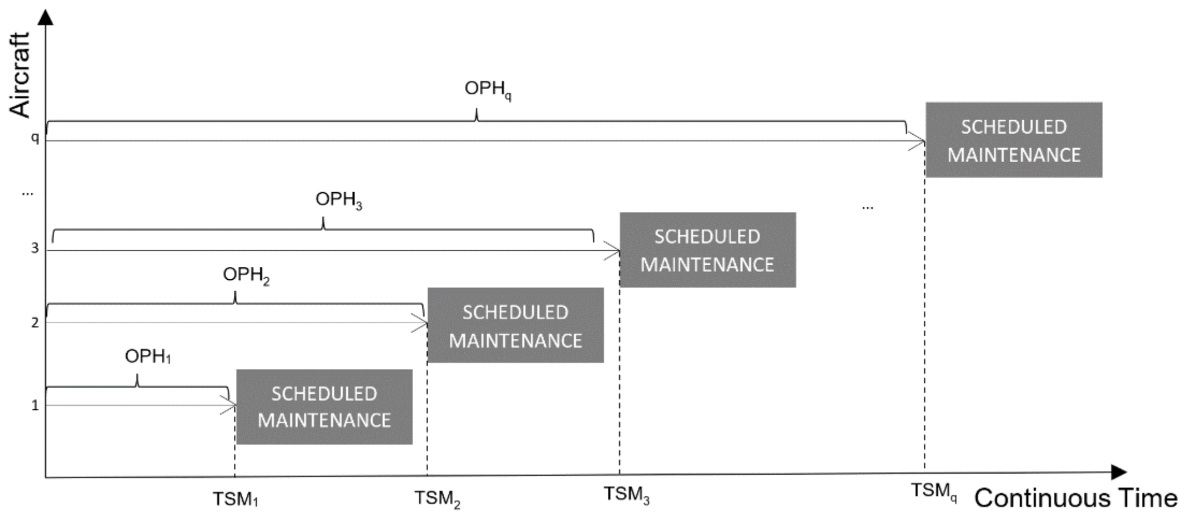

Figure 11 – Fleet Scheduled Maintenance Standard Diagonal Distribution..

Before proceeding to the problem formal statement 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 the same base and returns 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 elating the assumptions adopted and the scope delimitations imposed for the initial modelling effort:

- For each aircraft, the model is restricted to the next scheduled maintenance stop (henceforth also referred to as inspection). It does not affect the model whether the next inspections of different aircraft are the 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 Fritzsche *et al.* (2014, p. 78) who recommends 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 and the lower the planning’s reliability.

- The component’s location is not particularly considered for the purpose of optimizing the moving intervals overlay. However, time coincidental tasks involving items closely located in the same access area, for instance on the same bay in the aircraft, may offer higher advantage since it could reduce downtime, and to represent that and stimulate the model to favour this cases a matrix was inserted in the formulation.

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

- The exchange of components between aircraft aiming to improve results, practice known in the industry as “robbing” or “cannibalization”, is not allowed.

- The optimisation considers predictive maintenance tasks packaging for each aircraft in separate. The alignment of tasks on different aircraft does not contribute to downtime reduction. On the contrary, due to resource constraints, the staggering of tasks on different aircraft is considered of more interest and effectiveness towards that goal. The overlaying tactics of the proposed solution can be reversed for that matter, but this is out of scope in the present research.

- Possible differences in duration between maintenance tasks were considered irrelevant, all tasks therefore take the same time to be executed. This parameter was not implemented in the initial framework although it will be implemented, tested and discussed on the expanded model. 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 and scheduled maintenance packages is achieved by maximizing the level of superposition or overlaying in the time continuous domain of moving intervals (forecasts with their confidence range) between components and with the periodic inspection.

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

- q = total number of aircraft.
- n = number of items monitored.
- AE = total flight-hours assigned to the fleet.
- u_k = utilization factor, restricted to LUL.
- $\mathbf{L}_{ij}$ = co-location matrix indicating whether components are on the same access area, the cells values are proportional to the efficiency gain provided by performing the pair of tasks together.
- $s_{i,j}$ = supply availability (Boolean variable, 1 = yes, 0 = no).
- LUL = maximum rate of use to remain in the Low Utilization class.
- OPH_k = operational hours assigned to aircraft ‘k’ (decision variable);
- RULC = remaining useful life estimated value 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 given by the modeller to coincidences with the scheduled maintenance over amongst items RULC;

With that, arranging the parameters according to their specific roles and bearing in mind the aim of maximizing overlay, it results in the statement of Equation 1 as the objective function to be optimized:

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

For:

$k = 1{:}\,q$

$i, j = 1{:}\,n$

Where:

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

Subject to the following constraints:

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

ii. $OPH_k \mid u_k \leq LUL, \forall k = 1, \ldots q;$

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

With regards to the second factor which focus on the overlay between predictive tasks and periodic checks, one could make the case that the higher the fraction of the moving interval (the confidence range regarding a RUL expected value) 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 circumvent it, but it was identified that a third negative factor could be created representing a penalty function related to the aforementioned risk to reinforce aversion, especially for items to which failure comes with secondary undesirable effects. This third term is included in the expanded model and is discussed in more detail on the next section. Apart from this case, on all other types of overlay, the stop point when a maintenance intervention should be performed covering all intersecting tasks must be the lower bound of the most imminent demand regardless if the crossover is between predictive tasks or involve scheduled checks as illustrated in Figure 12.

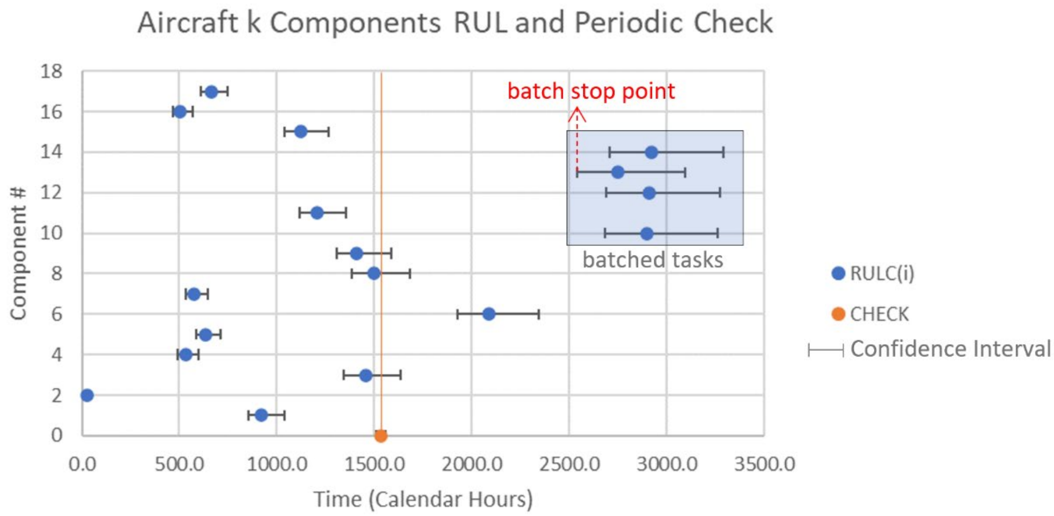

Figure 12 – Batched tasks stop point.

Another aspect that was found desirable to include in the solution 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 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. Once the level of anticipation is defined, the implementation in the formula is straightforward just by adding this fraction to the second term both in the AND function and on the difference between TSM_k and $RULC_{i,k}^{max}$ on the numerator. This is considered an add-on which involves subjective aspects for a decision regarding the anticipation level chosen, which is tested in the simulation model.

3.2 Expanded Model Development

The objective function in the previous section calculates a proxy value that refers to the degree of intersection between different maintenance tasks. However, in order to make the formula results more palpable and also focus on the final target, a function was added programmatically to convert that value to the actual resulting downtime.

With that, for every overlay where tasks are stacked to be performed simultaneously at the same stop, regardless of how many, the model considers the total time for that intervention as being the duration of the longest task in the batch, or the check duration if the overlay involves a periodical inspection. This is a reasonable argument considering the assumptions where resources are not considered a bottleneck and that tasks are independently carried on. With that, tasks can be performed in parallel without interfering negatively with each other. Where there is resource scarcity, tasks may have to be queued in which case simulation will be made necessary for the analysis.

It is valid to point out that the stop point continues to be the lower confidence bound of the most imminent grouped task with a view to minimize the failure risk, although it may anticipate a little the stop time of some overlaying components. Considering that the confidence interval tends to shrink as the failure moment approaches and the forecast becomes more accurate, this possible loss of remaining useful life for some stacked tasks is considered neglectable.

In result, the target becomes indeed minimizing total downtime, composed by the sum of all stops, instead of the maximization of the quantity representing the degree of overlay as we had before. The objective function thus reads:

$$minF_{(v_{t,k})} = \sum_{k=1}^{q}(SDT_k + PDT_k) + \sum_{k=1}^{q}\sum_{i=1}^{n} FRI_{i,k} \qquad (3)$$

Subject to:

i. $V_t^{min} \leq \sum_{k=i}^{q} v_{t,k} \leq V_t^{max}, \forall t = 1, \ldots T, v_{t,k} \in \mathbb{N};$

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

iii. $u_k = \frac{1}{SL} * \sum_{t=1}^{T} (v_{t,k} * FDur_t), \forall k = 1, \dots q.$

Where:

- q = total number of aircraft.
- n = number of items monitored.
- u_k = utilization factor for aircraft "k" calculated by the ratio of resulting operating hours from the assigned flights by the scenario length, restricted to LUL.
- $FDur_t$ = flight duration in hours of flight type "t';
- $v_{t,k}$ = number of flights type "t" assigned to aircraft "k";
- V_t^{min} = minimum number of flights type t that must be performed by the fleet;
- V_t^{max} = maximum number of flights type t allowed to be performed by the fleet;
- SDT_k = scheduled maintenance downtime for aircraft "k" related to periodical checks within the scenario length;
- SL = scenario length in calendar hours;
- PDT_k = predictive maintenance downtime for aircraft "k" considering overlays;
- $FRI_{i,k}$ = failure risk index for component "i" in aircraft "k", calculated for all components whose predictive task overlays with a scheduled check and has a segment of its confidence interval left before the check start time. This term is given by the expression :
    - $FRI_{i,k} = (\int_{RULCL_{i,k}}^{TTCL_k} pdf_{i,k}(t)dt) * CMDur_i, \forall k = 1, \dots q, \forall i = 1, \dots n$

      Where:

        - $pdf_{i,k}(t)$ = RULC probability density function for component "i" in aircraft "k" in calendar hours;
        - $RULCL_{i,k}$ = time marking the lower bound of RULC confidence interval for component "i" in aircraft "k" in calendar hours;
        - $TTCL_k$ = time marking the start time of the periodic check for aircraft "k" in calendar hours;
        - $CMDur_i$ = corrective task duration for component "i";

As it can be seen above, the decision variables in the expanded model are the number of flights of each type assigned to each aircraft member of the fleet as opposed to the OPH as in the initial model. This new layer adds the capacity to represent different utilisation profiles considering the aging parameters followed by different components and also according to environmental conditions. For instance, longer flights will degrade less the cycle-based components compared to shorter flight.

Another example is the use of application factor ($APPX_{i,k}$). This is a necessary parameter to represent cases of partial or severe use. For instance, depending on the mission to be performed some flights might require the use of night vision auxiliary equipment or a Synthetic Aperture Radar, while others don't. The wear severity can also change depending on the flight performed, for instance propeller blades are expected to age faster when the aircraft operates on unpaved runways as opposed to tarmac. With that, this new layer acts as a step before converting all aging parameters to the time continuous domain and empowers the solution once it adds versatility and complexity to the model hence increasing the number of possible combinations to decide on. With that, the RULC calculation in the expanded model is given by Equation 4.

$$RULC_{i,k} = {RUL_{i,k}}\big/{u_{k*}APPX_{i,k}} \qquad (4)$$

Where:

- $RUL_{i,k}$ = remaining useful life estimated value for component "i" in aircraft "k";
- $RULC_{i,k}$ = RUL in continuous time for component "i" in aircraft "k";
- $APPX_{i,k}$ = application factor of component "i" in aircraft "k" calculated as an average application factor over the mix of flight type quantities assigned to "k".

The SDT is calculated multiplying the number of checks each aircraft has scheduled for the period covered by the scenario length by their correspondent durations. It is important to notice that this parcel is not optimisable in the model, but it is resultant from a fixed input from the overall maintenance diagonal schedule followed by the fleet.

For its turn, PDT is calculated following a routine implemented according to the pseudocode bellow.

```
/* import input data such as scenario length, number of aircraft, number of components,
tasks and check durations, time to check for each aircraft, components RUL, number of
flights required per type etc */
      read input_data_file;
/* defines the decision matrix with aircraft in columns and flight types in rows
```

```
    V = matrix[T,q]
/* calculates the resulting number of flight cycles (FC) and flight hours (FH) per
aircraft and respective utilization factors*/
    for k=0, k<q, k++
        for t=0, t<T, t++
            FC[k]=FC[k]+V[t,k]
            FH[k]=FH[k]+V[t,k]*FDur[t]
        UTILFH[k]= FC[k]/SCLEN;
        UTILFC[k]= FH[k]/SCLEN;
/* calculates RULC and respective lower and upper bounds for each component on each
aircraft also taking into account the average application factor APPX of each
component per aircraft according to the mix of flight types assigned */
    for k=0, k<q, k++
        for i=0,i<n,i++
            if OPH[i]==FH
                RULC[i,k]=RUL[i,k]/UTILFH[k]*APPX[i,k]
                RULCU[i,k]=RULU[i,k]/UTILFH[k]*APPX[i,k]
                RULCL[i,k]=RULL[i,k]/UTILFH[k]*APPX[i,k]
            else
                RULC[i,k]=RUL[i,k]/UTILFC[k]*APPX[i,k]
                RULCU[i,k]=RULU[i,k]/UTILFC[k]*APPX[i,k]
                RULCL[i,k]=RULL[i,k]/UTILFC[k]*APPX[i,k]
*/ check if a component’s moving interval (RULCL-RULCU) overlays with the aircraft
periodic check following the function in the basic model, if positive the predictive
task downtime is absorbed within the check. Also, if there is a portion of the moving
interval before the check start, calculate the failure risk associated */
    for k=0, k<q, k++
        for i=0, i<n, i++
        if overlay(Check(k),RULCInt(i,k))==True
            downtime[i,k]=0;
            if RULCL[i,k]<TTCL(k) */ given that there is an overlay, if the
moving interval lower bound is smaller than the check start time, then the risk index
must be calculated */
            pdf[i,k] = //expression for the probability density function i,k
```

```
                FRI[i,k] = Integrate(pdf[i,k],RULCL[i,k],TTCL[k])*CMDur[i]
        else
                downtime(k,i)=dt(k,i);
*/next the overlay between components is verified and calculated as in the previous model*/
    for k=0,k<q,k++
        for i=0,i<n,i++
            for j=i+1,j<n,j++
                if overlay(RULCInt[k,i],RULCInt[k,j])==True
            aggregate i,j in tuple; */group the components in a tuple to calculate the resulting downtime in the end*/
*/calculate the resulting PDT
                        for k=0,k<q,k++
                        for i=0,i<n,i++
                            if (i is in a tuple?)
                                if overlay(tuple,Check(k)==True) */if there is any component in the group overlaying with a check, the tasks in the tuple are absorbed within the check duration*/
                                    DT(tuple)=0;
                                else if (TDur(i)==Large(Tuple)) */on the contrary, the tuple duration is the duration of the component task with the longest duration*/
                                    PDT=PDT+DT(i)
                        else DT(i)=0;
        else */in case the component is isolated, its downtime is added to total PDT*/
            PDT=PDT+DT(i)
```

The basic idea builds on the initial model and includes the expected downtime due to expected corrective interventions, that is:

i - overlaying predictive tasks are performed simultaneously and take as long as the longest task in the group;

ii - predictive tasks overlaying with the check are absorbed within the duration of the check;

iii - due to the previous condition, any predictive task overlaying with scheduled check that has a segment of its confidence interval before the check start time implies a risk of failure proportional to the portion this segment represents of its total failure probability as exemplified in Figure 13. This quantity, which represents the probability part of risk, is then multiplied by the corrective maintenance task duration, which is normally longer than a preventive task for it requires more steps to be concluded thus representing the impact side of risk. Summing up all cases like that result in the number of expected failures arising from the assumed risk. In this interim, it is important to remark that failures falling outside confidence intervals and those alien to any preventive effort are not optimizable in the model, although they affect the simulation results and so their impact can be evaluated by the integrated method.

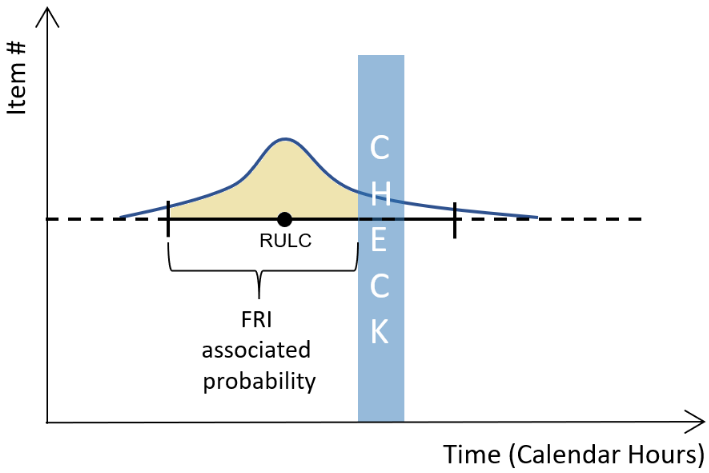

Figure 13 – Failure Risk Index (FRI) illustration.

In result, the model seeks to minimize the failure risk index associated with these cases where the task is delayed to be incorporated by the check and part of the moving interval is ran over. This way, the expanded model is able to minimize overall downtime handling predictive, scheduled and corrective maintenance altogether as shown by the results in the next chapter.

Also, in order to compare the results from utilizing the proxy objective function (overlay maximization) and the downtime minimization one, the initial model was augmented accordingly resulting in the formulation shown by Equation 5.

$$\max F_{(v_{t,k})} = \mathrm{PdOverlay}_{(i,j,k)} + \mathrm{pr1} * \mathrm{ChOverlay}_{(i,check,k)} - \mathrm{pr2} * \mathrm{FRI}_{(i,check,k)} \;, \forall i \neq j \qquad (5)$$

Where:

$$PdOverlay_{*i,j,k)} = \sum_{k=1}^{q}\sum_{i=1}^{n}\sum_{j=1}^{n}((RULC_{j,k}^{min} \leq RULC_{i,k}^{max}) \cap (RULC_{i,k}^{max} \leq RULC_{j,k}^{max})) * \frac{(RULC_{i,k}^{max} - RULC_{j,k}^{min})}{(RULC_{j,k}^{max} - RULC_{i,k}^{min})} * \; (1 + L_{ij})(s_i * s_j)(TDur_i + TDur_j)$$

$$ChOverlay_{(i,check,k)} = \sum_{k=1}^{q}\sum_{i=1}^{n}\left((RULC_{i,k}^{min} \leq TSM_k) \cap (TSM_k \leq RULC_{i,k}^{max})\right) * \frac{RULC_{i,k}^{max} - TSM_k}{RULC_{i,k}^{max} - RULC_{i,k}^{min}} * s_i * TDur_i$$

$$FRI_{(i,check,k)} = \sum_{k=1}^{q}\sum_{i=1}^{n}\left((RULC_{i,k}^{min} \leq TTCL_k) \cap (TTCL_k \leq RULC_{i,k}^{max})\right) * \frac{TTCL_k - RULC_{i,k}^{min}}{RULC_{i,k}^{max} - RULC_{i,k}^{min}}$$

As it can be seen above, the model now includes a third term aimed at reducing the risk of incurring into failures due to the postponement of tasks involved in overlays with periodical checks, as explained before. The terms highlighted in red refer to an attempt to enable the model to prioritize the overlay of tasks with longer duration for that can yield larger reductions in downtime. Considering that this addition to the formulation increased the algorithm processing time significantly, the cost-effectiveness of this enhancement will be assessed within the tests reported on the next chapter.

3.3 Simulation Model Development

Following the development and verification of the optimisation model as described in the previous section, a multi-method simulation model was developed using a software called Anylogic©. This resource was deployed as a mean to validate the proposed solution through the use of replication analysis. It should be noted that coupled with the correspondent hypothesis testing, this is a reasonable validation method when there is no real data available or accessible given that the process relies on the variability between each instance of simulation.

Additionally, as explained before, the simulation environment offers the possibility of building scenarios with a much better representation of reality and its nuances, what can't be translated into a static mathematical model.

According to Borschev and Grigoryev (2021), analytical models are adequate when the number of parameters is manageable, the system behaviour is linear and there are clear dependencies between the agents and variables.

However, when there are too many parameters, non-linear influences, time and causal dependencies and counter-intuitive behaviour, then only simulation modelling can provide a reasonable method to test and validate the solution. The latter represents better the case at hand particularly because of time and causal dependencies which can also motivate emerging behaviours which might not be modelled at first, but result from the underlying designed rules of interaction between the agents.

For instance, the advent of a failure may result in jeopardy to planning and flight-hours being carried over to the next optimisation period, or it can happen in a favourable moment when adjoining tasks may be opportunistically performed at the same time and end up resulting in less downtime. In other words, depending on the moment when the event is triggered, the outcome changes. This is not possible to implement in a static model.

The simulation model developed falls onto the hybrid or multi-method category because it makes use of two different types of simulation namely Discrete Event Simulation (DES) and Agent-Based Simulation (ABS). A third type of simulation category available in the software is System Dynamics Simulation (SDS), but it was not used within the model at this stage. This integration of methods increase the possibilities and flexibility for developing the model and also enhances the solution's uniqueness.

3.3.1 Agent-Based Simulation

The ABS approach is the adequate type of simulation when it is necessary to focus and programme the internal dynamics of an agent. Therefore it was used to represent the model agents' behaviours and the possible states they can assume as the scenario evolves.

The model built counts with many different agents such as the maintenance centre, push-back tractors, the aircraft and auxiliary agents responsible for integrating the ABS and the DES parts of the simulation. The aircraft though is the central piece and the one with the most complex internal dynamics as described below.

Each aircraft for example can assume seven different internal states as shown by Figure 14 and transitions between them according to predefined rules, which are presented further down this section. In addition, each aircraft carries within itself a set of parameters and variables that serves for interactions, condition monitoring and for statistical purposes as can be verified in Figure 15.

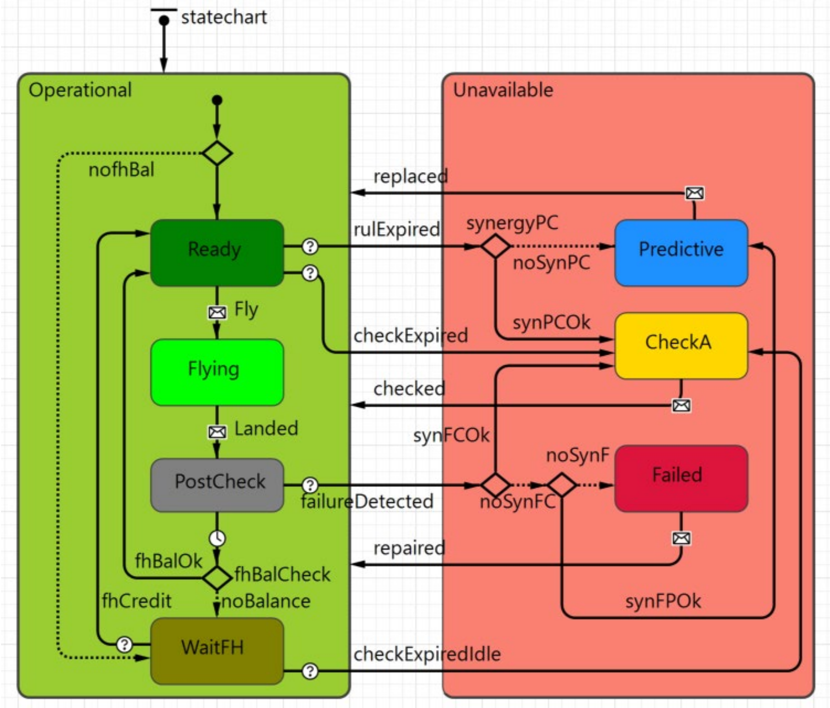

Figure 14 – Aircraft agent internal behaviour and states (Anylogic©).

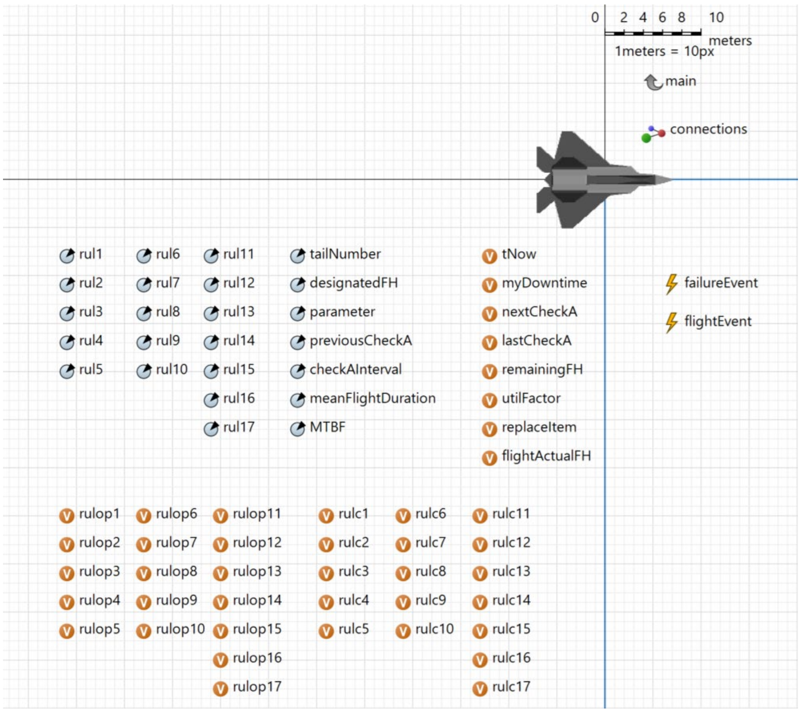

Figure 15 – Aircraft agent parameters, variables and events (Anylogic ©).

The seven internal states that an aircraft can assume as depicted in Figure 14 are divided into two main umbrella categories: Operational and Unavailable. When there is no maintenance due to be carried out in an aircraft, the platform is considered Operational. Within this category, the aircraft can be on the ground, dispatchable, but waiting to depart according to the flight schedule. This state is called “Ready” in the model.

Besides that, once it is called upon the schedule, the plane can also be in-flight, actively operating, state called “Flight” in the model.

After each flight the aircraft passes through a post-flight check (“PostCheck” state) that verifies possible failure occurrences resulting from the flight and whether it needs repair or not. On this state, it also computes and updates all operational tallies in order to verify if there is any impeding preventive intervention that requires the aircraft to be sent to the maintenance centre. In case the answer is negative to all possible maintenance demands, the aircraft returns to the flight line.

Although it moves back straight to the hot bay, the aircraft can still assume two different states at this point. Because of that, the model also verifies whether the aircraft remaining flight-hours, considering the balance against the missions and flight-hours assigned to that specific tail number, is sufficient to fly another mission.

If positive, the airplane then moves back to the “Ready” state. Otherwise it enters a state called “Wait FH” where it stays awaiting for the next round of optimisation run and a new set of operational hours, or it might inherit the surplus of non-performed flight-hours initially designated to other aircraft that suffered some kind of hinderance, such as a failure event, that prevented it from accomplishing its quote.

On the other side, there are three possible primary causes for the equipment unavailability, each one represented by a different internal state within the “Unavailable” composite state.

The prognostics system may have indicated an impeding failure based on a single or multiple components’ RUL forecast. In this case, the aircraft requires that component to be replaced, so its internal state transition to “Predictive” and a task is due to be performed by the maintenance centre technicians.

At this point the model makes use of an auxiliary agent named “Maintenance Request” that is sent, along with the tail number requesting the service as a parameter, to the discrete-event part of the simulation, hosted in the “Main” agent, specifically to the predictive maintenance circuit that is presented further ahead. Once the maintenance work is successfully completed the aircraft is made available and re-enters the Operational state.

Another possible cause is the proximity of the periodic check expiration date. In this situation the aircraft also needs to be brought into the maintenance centre and undergo the full package of scheduled tasks which is usually a longer stop compared to standalone out-of-phase interventions. In this case, the active internal state changes to “CheckA”.

The auxiliary agent “Maintenance Request” is again demanded, but this time it enters the check circuit in the discrete-event part of the simulation model. After the check, the aircraft goes back to the flight line for it has recovered its operational condition. The balance of assigned flight-hours is also performed on this return.

The third cause is the differential brought by simulation to the integrated solution, that is the occurrence of a failure event. This event can arise or be originated from a condition-monitored item whose failure happened outside the adopted confidence interval, that is, before its lower bound. Clearly, it is impossible to guarantee prevention to all conceivable failure modes given that a 100% confidence is obviously economical and operationally unrealistic.

Another possibility is that the failure stroke one of the non-monitored components. These failures usually follow a constant failure rate function, and the time between the events follows an exponential distribution as pointed out by Blanchard (2014), Elsayed (2012), O’Connor and Kleiner (2012) and Moubray (1999). In this case where periodical checks are not effective and condition-based is not possible, failures are unavoidable, therefore it is an expected situation and must be modelled in order to improve reality adherence.

Irrespective of components having effective preventive tasks or not, reminiscent failures can still happen. Since all reliability data is attached to operation parameters such as flight cycles, flight-hours and power cycles, in the simulation a failure can only happen during the active operation, i.e. when the equipment is in the “Flying” state.

Whenever a failure event is triggered during the flight, according to the failure rates programmed, the aircraft assumes the internal state “Failed” what causes it to be sent to the repair cycle via the use again of the Maintenance Request auxiliary agent.

At this point, it should be noted that the same auxiliary agent is deployed on all maintenance circuits and that is because it has a variable which can assume any type of intervention and based on that deliver the equipment to the right circuit.

Moreover, it is important to observe that the primary causes of unavailability may affect the airplane in isolation or combined. Any combination is possible and must be reflected in the model. In fact the number of actual combinations is what the analytical model seeks to increase. The implementation of those combinations was done with the insertion of branches, or decision points (represented by the diamond shapes in Figure 14), where potential synergies are verified and, if possible, more than one type of maintenance task is then performed in parallel, improving efficiency and saving time.

As a result of this dynamics in the implementation, a random failure event may cause either a disruption, in which case the accomplishment of the operational hours distribution commanded by the optimisation algorithm might be endangered, or it could instead signify an opportunity to bring forward other impeding maintenance demands, in which case the failure impact can be neutralized and absorbed within the same downtime.

The level of anticipation allowed is set by a group of parameters which can be adjusted and are further discussed in the simulation results section.

As it can be seen, the internal dynamics of the agent is governed by the transition rules. Because of that, the different types of transitions used in the model are explained in the next subsections, although it should be remarked that there are other possibilities available, which haven't been employed.

At this point, it is worth mentioning that the Anylogic© software is based on the Java© programming language and it allows the user to implement tailored codes within properties for all actions, functions and algorithms intended for every block, state and transition.

Another advantage provided by the open and flexible structure employed by the software is that it allows the creation of libraries to integrate the simulation model with external programmes and codes written in other programming language such as Python©, which for instance is better to tackle data analytics problems.

3.3.1.1 Transitions triggered by messages

These transitions depend on the arrival of a message to become active and transfer the agent between states. The messages can be of different types, even agents can be regarded as messages, and the transition can be fired unconditionally, depend on the evaluation of specific values or expressions, or even consist in a particular type of string message. The transitions "Fly", "Landed", "Repaired", "Checked" and "Replaced" are all examples of this type of transition. A example of message-triggered transition is displayed in Figure 16.

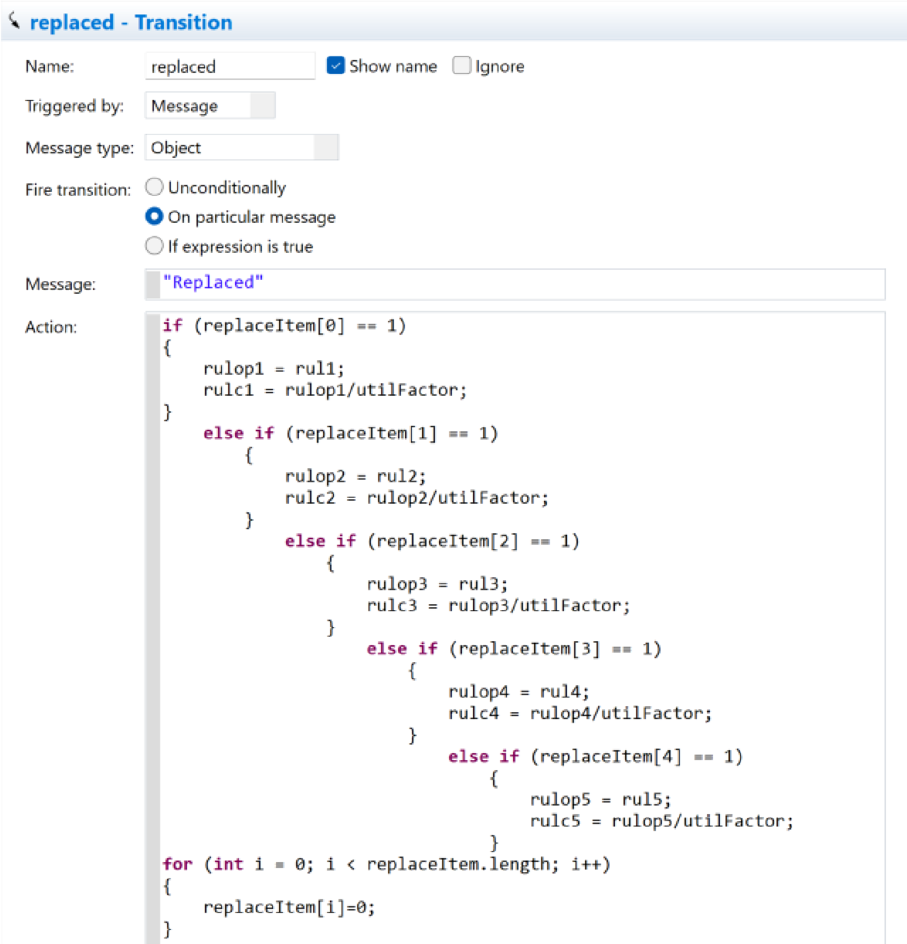

Figure 16 – Message-triggered transition "replaced" (Anylogic©).

3.3.1.2 Transitions triggered by condition

These are transitions that constantly monitor a certain condition waiting for it to be met by the simulation experiment. Once the condition becomes true, the transition is fired. The "rulExpired", "checkExpired", "failureDetected", "fhCredit" and "checkExpireIdle" are examples of this type of transition. They also count with an action box where commands can be implemented as displayed by the example in Figure 17.

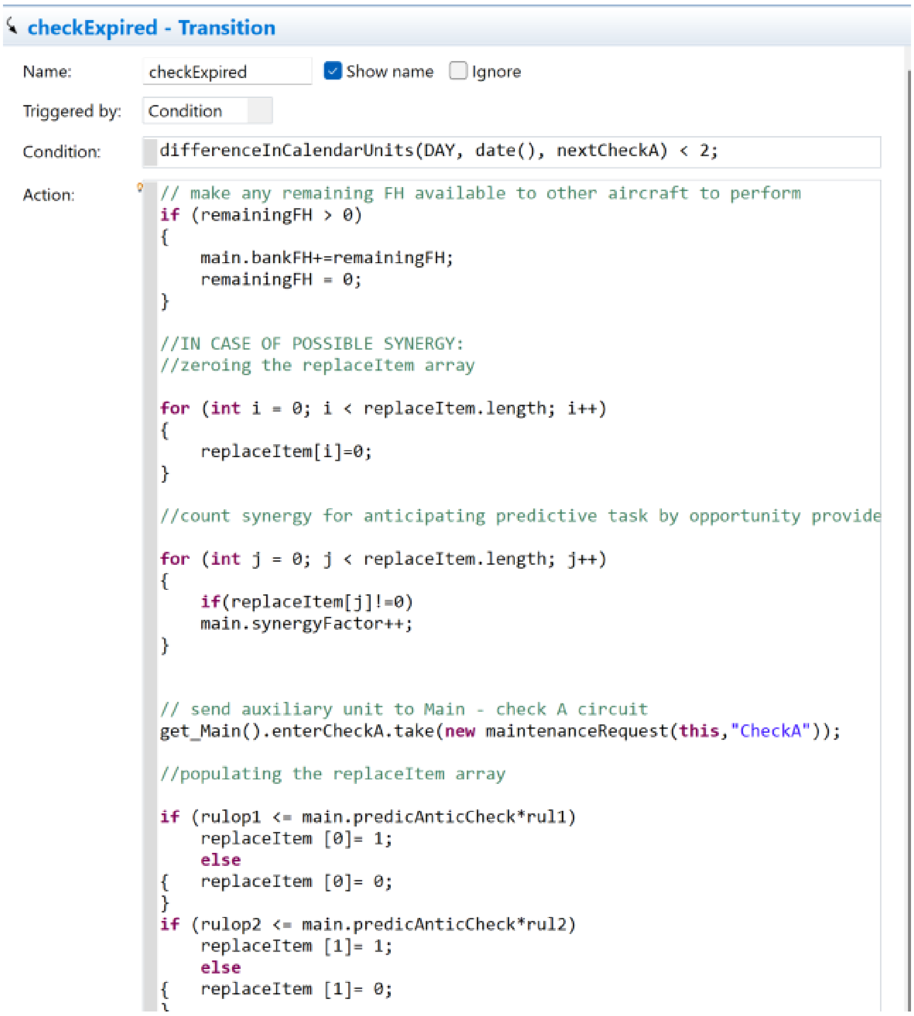

Figure 17 – Condition-triggered transition “checkExpired” (Anylogic©).

3.3.1.3 Transitions triggered by timeout

These are time-dependent transitions that are fired when the countdown is finished. These timers can have deterministic values or draw from a predefined distribution as showed in Figure 18 with the example of the “postCheckOK” transition.

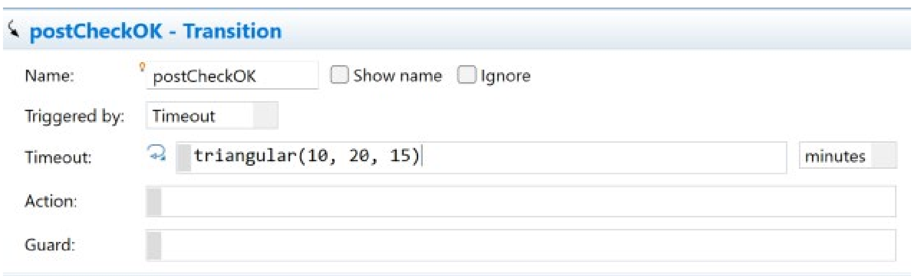

Figure 18 – Timeout transition “postCheckOK” (Anylogic©).

3.3.1.4 Transitions from branches

These are a special type of condition-based transitions that come out of a branch, or decision node. Each branch has a default transition that is followed in case all other exits are false. The “noSynPC”, “noSynF” and “noBalance” are examples of default transitions, and “synFOk”, “synPCOk” and “synFCOk” are examples of conditional transitions coming out of decision nodes as illustrated in Figure 19.

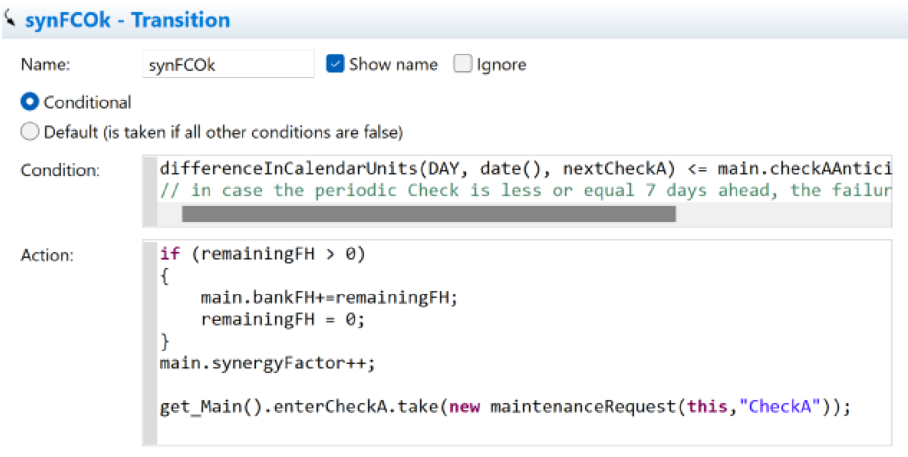

Figure 19 – Conditional transition out of a branch “synFCOk” (Anylogic©).

3.3.2 Discrete-Event Simulation

The flight and maintenance routines, for their turn, are better represented using DES because this type of simulation facilitates the sequencing of phases and their respective processes. In this case the time only passes during events’ durations, and it remains frozen outside of it, avoiding transmission of spurious variable values and the unwanted concurrence of tasks.

This type of simulation is widely used in the logistics field because it is specially adequate for representing sequence of activities as it is the most common frame on which fits the base scenario for maintenance and support processes.

3.3.2.1 Flight DES circuit

The flight circuit can be observed in Figure 20. This implementation allows for a detailed representation of the flight process including the aircraft push-back, storage, taxi, the pre and post flight checks, and the flight route.

The available aircraft are allocated on the flight line in bays. From there, when the flight schedule triggers the flight event, they are taken to the pre-flight check bay where the dispatchability is assessed. If the aircraft is considered good to go, then the transition out of its active internal state is fired and the agent performs the flight.

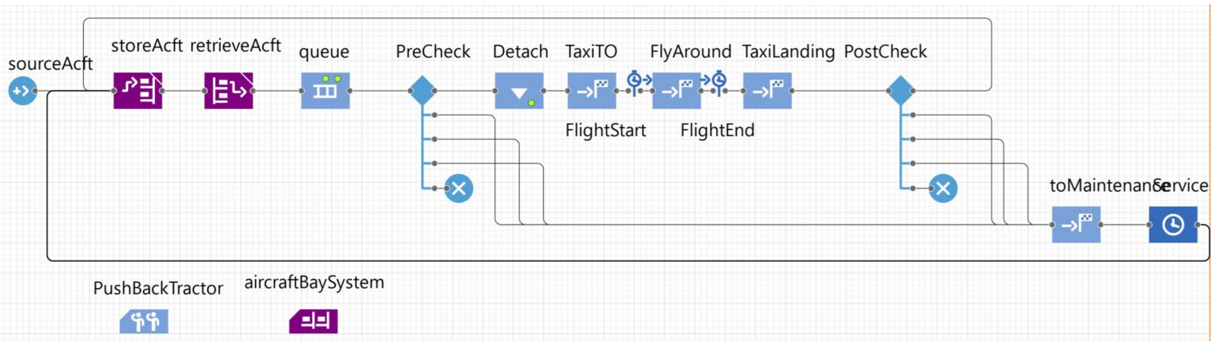

Figure 20 – Flight routine implemented using DES (Anylogic©).

The flight duration can be deterministic and pre-defined, or be stochastically determined by an expression, by the speed and flight path, or even by the route when it travels between airfields. The flight time distributions and the resulting durations drawn by the simulation will affect the ratio between operations parameters such as flight hours and flight cycles. As a consequence, items may age in marginally different ways than expected, what causes the moving intervals dynamics to change and also affect the no longer optimal flight hours distribution.

3.3.2.2 Corrective maintenance DES circuit

This part of the DES simulation is dedicated to perform corrective maintenance tasks in response to failure events triggered internally to the aircraft during their operation. It takes longer the preventive maintenance interventions for it requires the step of troubleshooting, i.e. investigating to understand what is motivating the functional loss and what needs to be done, which can bear a significant degree of complexity as explained by Tan and Raghavan (2007).

The process entails the removal of the faulty item followed by a supply availability check. At this point there is an interface with another large field for exploration in this kind of problem, which is the inventory management. The item being removed can be a repairable part or a discardable unit, and each category has a different type of treatment.

The inventory levels calculation is out of scope within this research and is considered as an input in the model. This simplification only means a boundary to the scope with no negative or debilitating implication to the solution proposed. With effect, the only relevant information regarding the inventory is whether the spare part is available or not for immediate replacement of the failed item.

The implication can be translated in terms of delay time. If there is no stock available, the aircraft will remain on the ground waiting for the part to arrive. Once verified the replacement is available, the aircraft can be subjected to the repair task. At this point it may have to wait in a queue because the resources necessary for the task are scarce and could be seized by other aircraft. Otherwise the aircraft will undergo maintenance immediately and can be returned to the flight line within the timeframe of the active corrective action duration as can be seen in Figure 21.

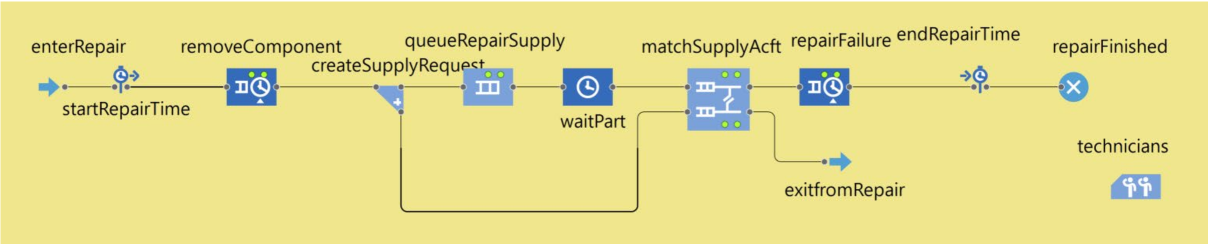

Figure 21 – Corrective maintenance circuit (Anylogic©).

At the end of this process the downtime is incremented with the spent by the aircraft to overcome it. In case there is any synergic task performed together, the respective parameter are updated as well.

3.3.2.3 Scheduled maintenance DES circuit

This fraction of the DES model can be multifaceted since the model can handle the entire maintenance plan with the various types of checks such as Check A, Check C, Check D and others. Each one of those types of checks has a particular duration, scope and periodicity. For simplicity, only the type Check A was implemented. Nevertheless, it is valid to clarify that it is completely possible to execute the addition of other inspection types, but it is a sophistication that would not improve the contribution sought by this study.

The scheduled intervention also requires a kit of materiel to be accomplished and the availability of this is verified pretty much in the same way as implemented for the repair circuit. The main difference here is in the availability parameter that is predominantly set to attend the necessity given that here the maintenance can be planned ahead and the maintenance centre can be prepared in arrears. The circuit is the one shown by Figure 22.

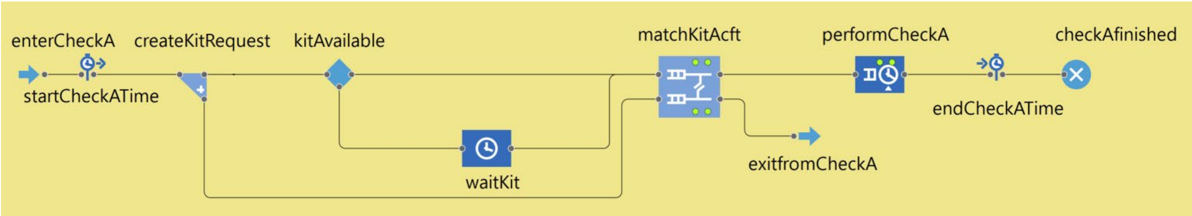

Figure 22 – Scheduled maintenance circuit (Anylogic©).

At the end of the inspection process the overall fleet downtime is incremented with the time spent by the aircraft on it and the variable that counts the time until the next check is reset. In case there is any synergic task performed together, the respective parameter are updated as well.

3.3.2.4 Predictive maintenance circuit

This circuit is used when the agent detects that one or more of its components is depleting its Remaining Useful Life, that is, that it prognostics horizon is approaching the lower level boundary of the RUL confidence interval.

The process have approximately the same stages as the repair, with the exception that it does not require lengthy troubleshooting as it might be case with a fault investigation. The circuit is represented in Figure 23.

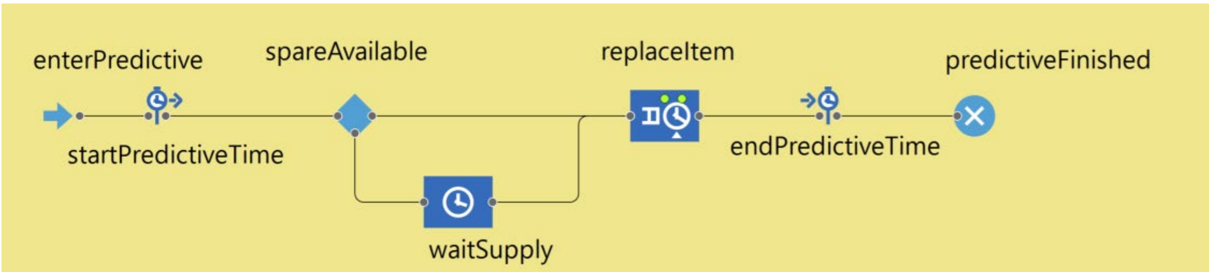

Figure 23 – Predictive maintenance circuit (Anylogic©).

At the end of the replacement process the total fleet downtime is incremented by the amount of time spent by the aircraft on its phases and the remaining useful life of the replaced components is calculated again. In case there is any synergic task performed together, the respective parameter are updated as well.

3.3.3 System Dynamics Simulation

The SDS is ideal for monitoring holistic parameters of the system modelled which have a continuous rate of change such as each aircraft's time to inspection, but it was unnecessary for the simulation model used in this thesis.

The software used offers seamless integration between the three types of simulation presented above, but that also represents a challenge for the creativity process since there are many possible modelling approaches to represent the targeted system.

On the other hand, the process of conceiving the simulation model also helps in understanding the real system since any relevant aspect of reality neglected or misinterpreted will most likely become apparent as an error or inconsistency during the simulation experiment.

For instance, the point within the moving platform when the aircraft must be stopped has to be explicitly defined in the simulation whereas it wasn't necessary for the analytical model calculations, although it had already been decided as the most imminent lower bound for safety and risk mitigation purpose. The interval at which the optimisation algorithm needs to be run recurrently, in order to compensate for unscheduled events without compromising the capacity planning at the maintenance facility, is not clear at the beginning, but the simulation provides a strong support for the analysis and the discussion will be present in the thesis.

A third aspect with limited possibilities to reproduce in a static model and worth emphasizing is the dynamic behaviour of the moving intervals which tends to shrink as the operation progresses and each component gets closer to its failure point estimate (FEATHER et al., 2010). In the simulation model, the changes in forecast accuracy can be modelled with more freedom following any distribution desired, whereas in the analytical model this behaviour was emulated by the use of percentages.

Finally, the simulation also permits executing sensitivity analysis to identify the drivers behind the performance metrics, automatic parameter variation and multiple runs for statistical analysis.

4 Results and Analysis

4.1 Basic Analytical Model Results

With the intention of verifying the coherence and consistency of the framework built as explained over the previous chapter, a set of fictitious data was assembled to represent a possible scenario for the model application. It should be noted that this initial model was built with the intention of serving as a proof of concept with a size chosen to enable a detailed explanation of the method. Following this, and given that the initial results give enough support to pursue this path, the expanded model subjects the method to a larger more complex setting.

The case study proposed consists of a fleet composed by three aircraft each containing five monitored components for which there is IVHM data available as revealed by Table 2.

Table 2 – Current RUL expected value 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 3.

Table 3 – 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

The co-location matrix $\mathbf{L}_{ij}$ for this example is portrayed on Table 4. This symmetric matrix tells the model whether two components are located in the same access area or inspection zone. The model assimilates the potential synergy offered by this architectural characteristic and prioritises their overlay over those that require different setups and different access procedures like the opening of panels, or doors, and the disassemble of parts to clear the way for accessing the faulty component. The cell values are proportional to the gain provided by each pair in terms of downtime reduction. That is, when the tasks involved have long preparation and access times, the cell value for that pair should be higher.

Table 4 – Components' Co-Location Matrix

	Components' Co-Location Matrix				
ITEM	1	2	3	4	5
1		0	1	0	0
2	0		0	0	0
3	1	0		1	0
4	0	0	1		0
5	0	0	0	0	

Moreover, for this example, the supply parameters were all set to 1 in order to signal the stock availability of every component. This is a necessary assumption at this stage of the model development. With effect, the inventory levels are very dynamic variables and their changes cannot be captured or accommodated in a static mathematical model. At least this is valid for the case under analysis because the planning horizon is set until the next periodic inspection for each aircraft, i.e. a time span of months.

The supply parameters are useful when the optimisation algorithm can be run on a frequent basis thus adapting to the changes in the scenario evaluated. This is going to be approached in more detail and discussed in the simulation model.

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 5.

Table 5 – Time Before Scheduled Maintenance (TSM) per aircraft.

Aircraft	TSM (Months)	TSM (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, and this target should not fall below 495 flight-hours or surpass a limit of 505 flight-hours, i.e. a 1% margin. With that, two baseline scenarios were created against which the optimised solution will next be compared. The baseline cases reflect the two most common distribution rules used in practice as per the authors experience.

The results discussion can also benefit from a graphical illustration of how the different RULC are allocated in time from the utilization rates resultant of the flight-hours assigned to each aircraft. The baseline scenario 1 applies the same utilization factor to all members of the fleet as represented by Figure 24, Figure 25 and Figure 26.

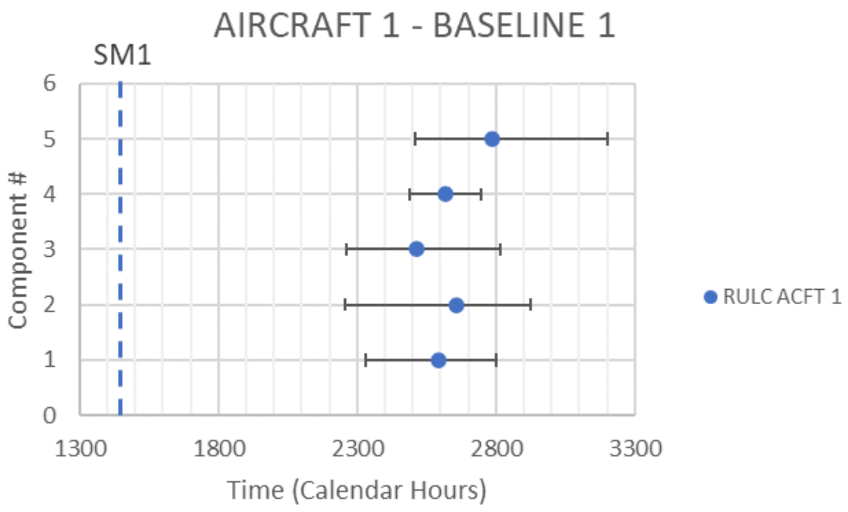

Figure 24 – Aircraft 1 on Baseline Scenario 1.

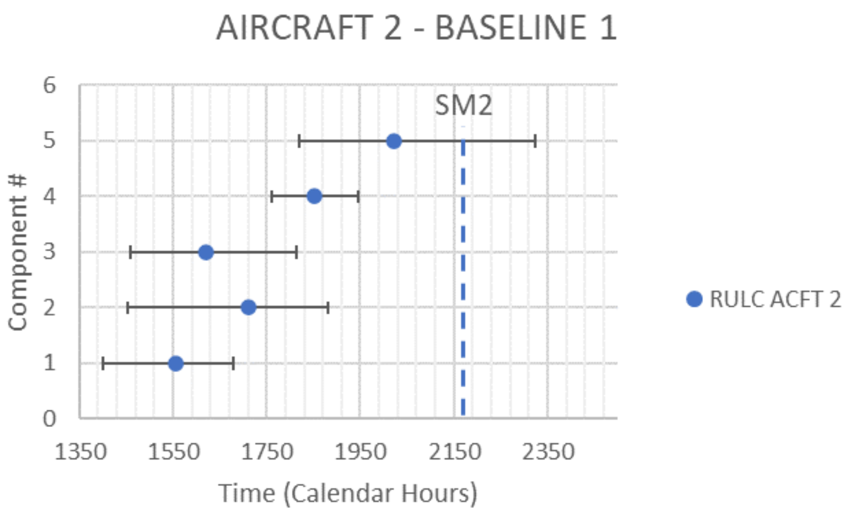

Figure 25 – Aircraft 2 on Baseline Scenario 1.

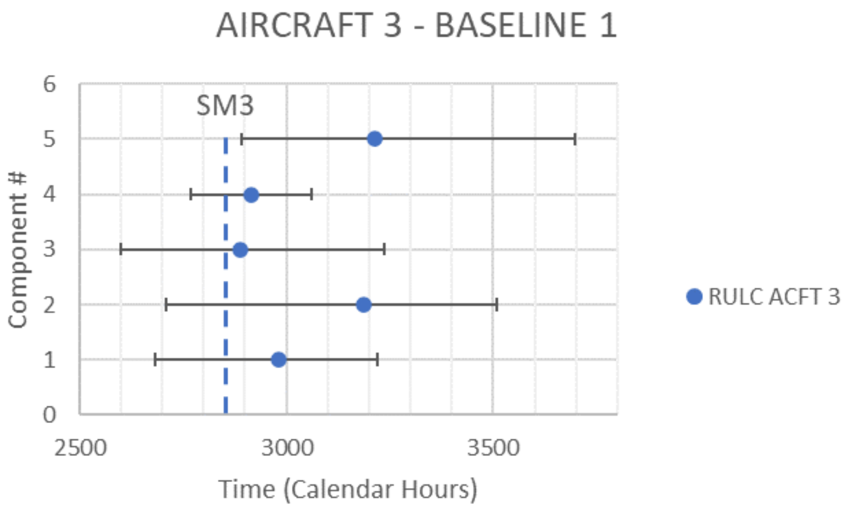

Figure 26 – Aircraft 3 on Baseline Scenario 1.

The baseline scenario 2 splits the available flight-hours evenly among the fleet members resulting in the situation represented by Figure 27, Figure 28 and Figure 29.

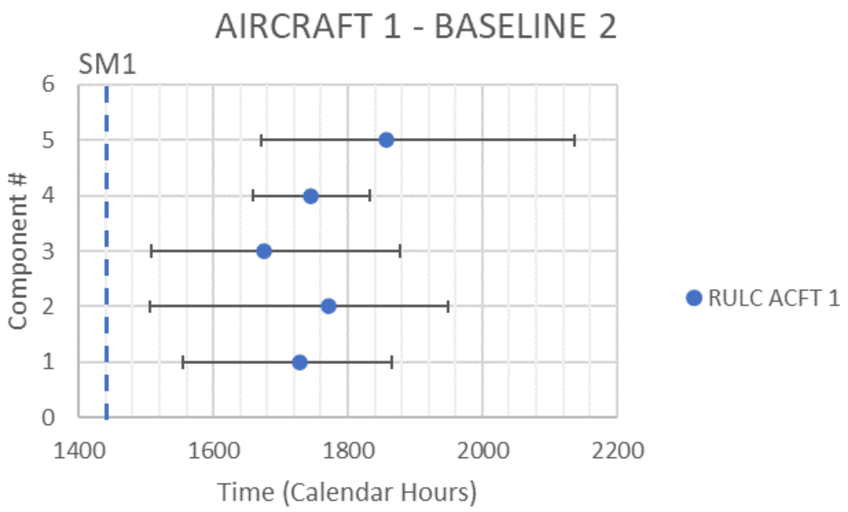

Figure 27 – Aircraft 1 on Baseline Scenario 2.

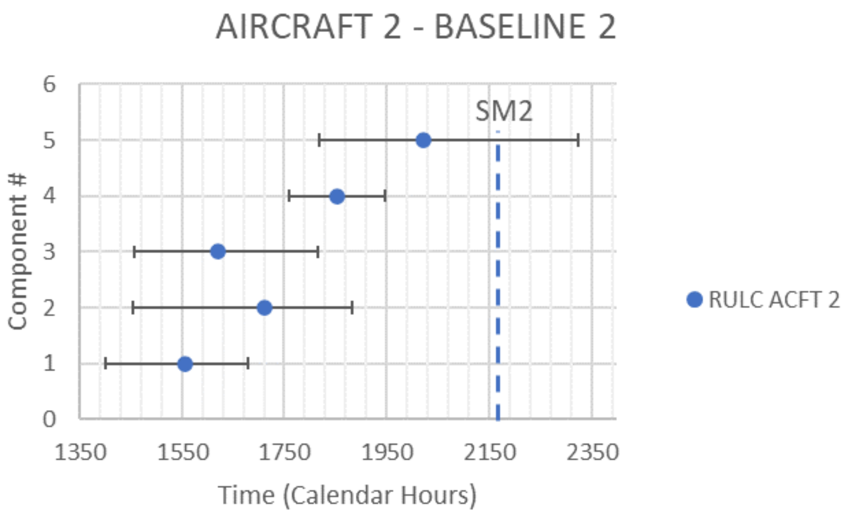

Figure 28 – Aircraft 2 on Baseline Scenario 2.

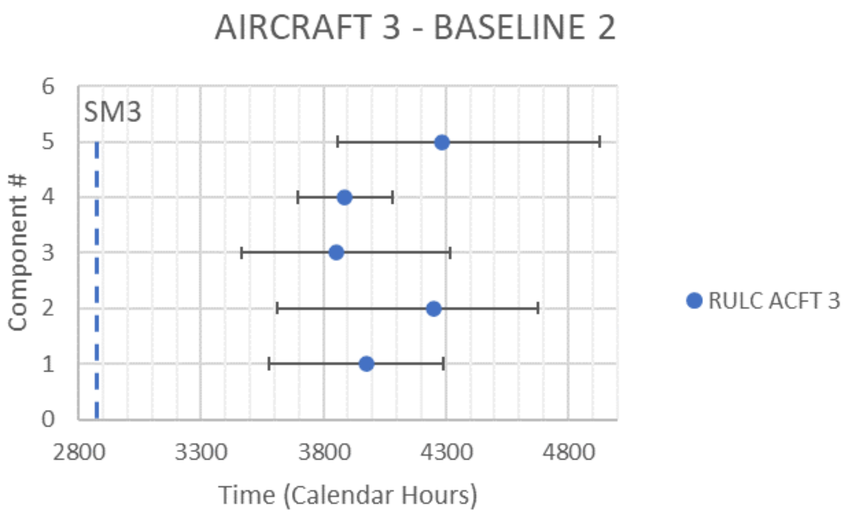

Figure 29 – Aircraft 3 on Baseline Scenario 2.

With a view to find the best possible division of these operational hours between the fleet members, 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 the Excel add-in called Solver ©, which is a program able to optimise a given objective function subject to a set of constraints offering up to three different methods to find the correspondent values of the decision variables.

For the case under analysis, obviously the Simplex Linear Programming method could not be considered since the problem behaviour does not follow a linearity rule. From the remaining 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 6.

Table 6 – Solver optimization methods results comparison.

Method	$F_{(OP)}^{MAX}$	OPH_1	OPH2	OPH3	AE
Evolutionary	7.3842	177.12	112.55	210.01	499.7
GRG Nonlinear	7.3479	176.01	112.50	211.49	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 Figure 30, Figure 31 and Figure 32 represent the panorama ensued by the best solution found.

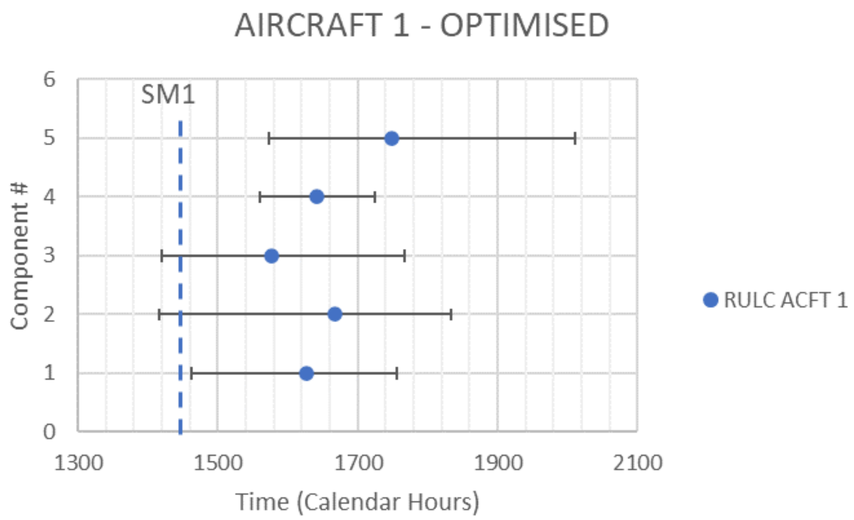

Figure 30 – Aircraft 1 resulting panorama.

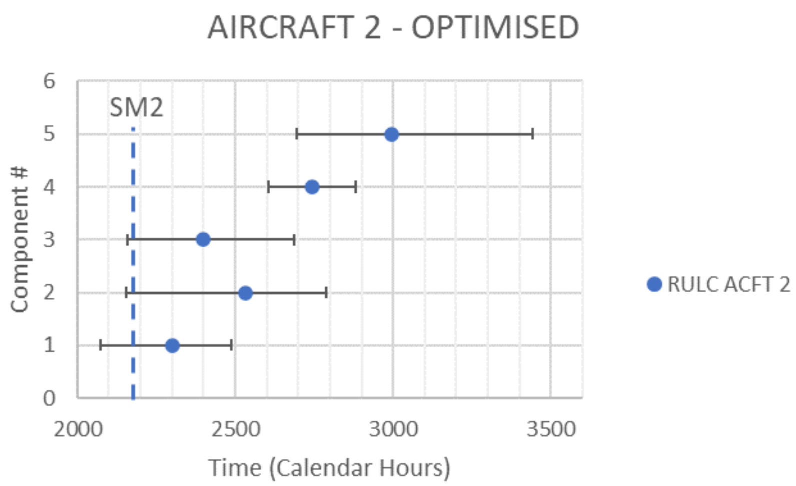

Figure 31 – Aircraft 2 resulting panorama.

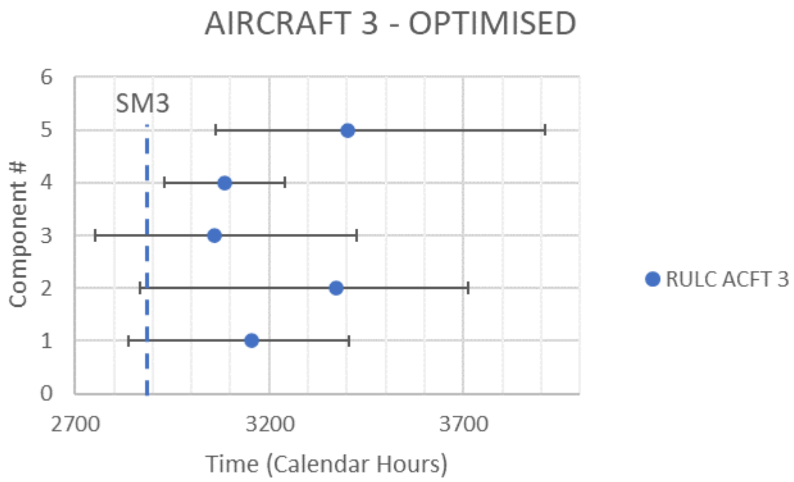

Figure 32 – Aircraft 3 resulting panorama.

The charts testify the numeric results and show 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 overlaps extension amongst the moving intervals and between these and the periodical checks for each aircraft while reducing the risk of failure occurrence before the intervention.

In order to clarify what the results mean in terms of downtime reduction, Table 7 summarizes them 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 approximately 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 intervals was also improved, the benefit in terms of downtime reduction was not substantial and require further discussion. This aspect showed that a refinement in the model is due, which is accomplished further down this thesis with the expanded model. Basically the possibility of increasing the overlay between moving intervals generating downtime reduction is very limited when all components follow the same transfer function converting their RUL to the common time domain, thus the main contributions so far could be observed in the integration of predicted task with scheduled checks. Nevertheless, the transfer functions can differ significantly when items follow different operating parameters, have different application factors depending on the type of flight, or are exposed to different degrees of load severity, nuances that are included in the expanded model enhancing the possibilities of obtaining gains from increased predictive tasks overlay rate.

Table 7 – Optimisation results vs baseline scenarios

	Aircraft (OPH)			Downtime (Hours)
Scenario	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. Despite the limitations imposed on this basic example, the results provided were impressively good in terms of the economies achieved. Within the strategy and methodology laid down for this research, this initial test served as a proof of concept and a test indicative of its potential. With effect it has been published and presented to the scientific community in several occasions as during the Prognostics and Health Monitoring Society Conference in 2021. The work in Figueiredo-Pinto et al. (2021) has attracted a lot of attention and there was no dispute against the novelty and originality claims, nor to the method deployed or the model formulation.

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 and the reassurance received from academia cleared the path for its expansion through the addition of parameters such as those identified in the mathematical formulation process, the easing of limitations or even the riddance of some assumptions, thus disclosing its full potential.

In order to enhance the solution's robustness and promote the model's generalisation following our inductive method, a Monte Carlo simulation was conducted using Microsoft Excel ©. Keeping the same case settings in terms of fleet size and number of components, the RUL values were set to roam stochastically following an uniform distribution between 5 operational hours (set as the minimum necessary to produce any logistic impact) and 200 operational hours (maximum reasonable forecast horizon). A total of 100 different scenarios were created, each one with a specific set of initial random data. The total downtime resulting from the application of Baseline 1 and Baseline 2 rules of flight-hours distribution was calculated per scenario instance. Following that, the optimisation algorithm was run for the individual case sets and the resulting downtime was recorded.

In this interim, it is important to highlight that the objective function depicted by Equation 1 works as a proxy in such a way that maximizing that expression leads to minimize total downtime.

In order to translate the proxy result into downtime, an overlay-downtime conversion matrix as the one illustrated below in Table 8 was created for each aircraft. These matrixes count the number of overlays between tasks and inspections, and calculate the impact in downtime reduction based on the rule below.

The rule applied for this example, which may be adjusted according to each scenario without significant implications, is that overlayed predictive tasks take the same amount of time as a single one would, for they all have the same duration and can be performed in parallel. When the overlay happens between a predictive task and the inspection, then that task is absorbed within the check duration.

Table 8 – Overlay-downtime conversion matrix example

Overlay Matrix Aircraft x						
Item	Check	1	2	3	4	
1	0					
2	0	1				
3	0	1	1			
4	0	0	0	0		
5	1	0	0	0	0	Downtime
Total	1	2	0	0	0	40

The objective is to verify to what extent the gains projected by the case study presented before will uphold in face of different scenarios and varying conditions. With that, instead of comparing single outputs from baseline and optimised solutions, the comparison is now drawn between the downtime probability distributions with a view to test whether the expected downtime value using the optimisation mode is indeed significantly different (and better) from the ones presented by the baseline scenarios or not.

The results from the Monte Carlo Simulation are summarized in the Table 9 and the graphical views of the distributions are displayed in Figure 33, Figure 34 and Figure 35.

Table 9 – Downtime mean and variance per scenario

Total Downtime	Baseline 1	Baseline 2	Optimised
Mean	159.6	150.1	101.7
Variance	273.1	343.2	379.3
Standard Deviation	16.5	18.5	19.5

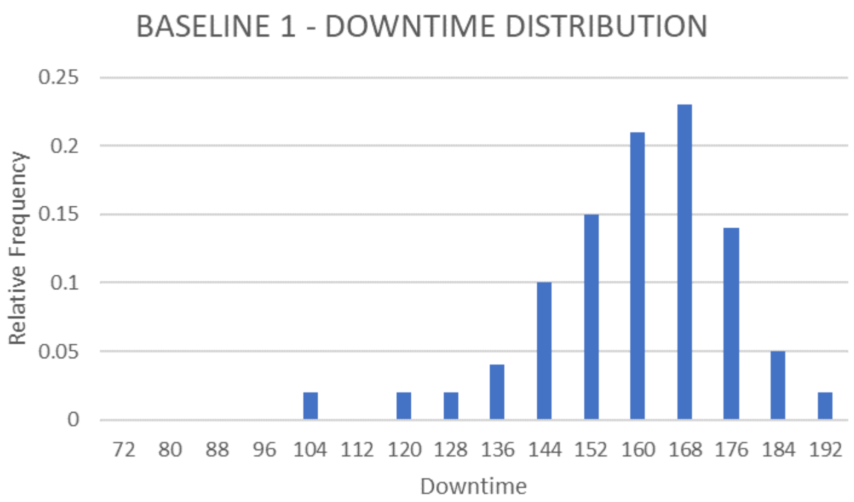

Figure 33 - Baseline 1 scenario downtime distribution

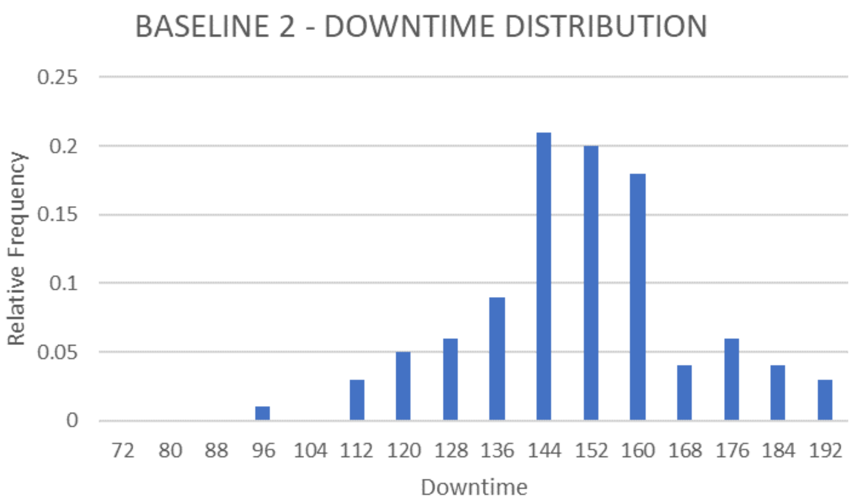

Figure 34 – Baseline 2 scenario downtime distribution

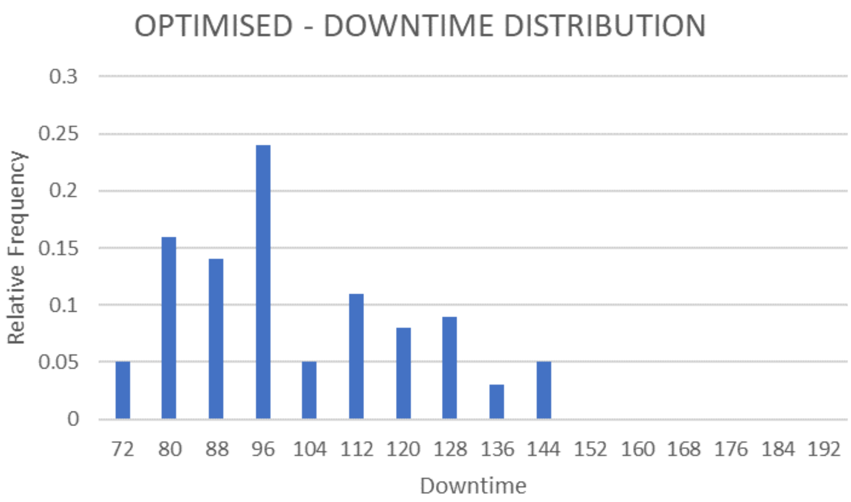

Figure 35 – Optimised scenario downtime distribution

Using the data provided above and considering that both mean and variance are unknown for any of the scenarios analysed, a hypothesis test was performed to determine if it is possible to affirm that the downtime is indeed reduced with a 5% significance level.

Since it is not possible at first to infer whether the variances of the distributions can be considered the same, a F-test for variances was conducted and the results are presented on Table 10 and Table 11.

Table 10 – F-Test for baseline 1 and optimised scenarios variances

	Baseline 1	Optimised
Mean	159.6	101.68
Variance	275.8787879	383.0884848
Observations	100	100
Df	99	99
F	0.720143776	
P(F<=f) one-tail	0.052022977	
F Critical one-tail	0.717328593	

Table 11 – F-Test for baseline 2 and optimised scenarios variances

	Baseline 2	Optimised
Mean	150.08	101.68
Variance	346.660202	383.0884848
Observations	100	100
Df	99	99
F	0.904908959	
P(F<=f) one-tail	0.310037564	
F Critical one-tail	0.717328593	

Based on the p-values (~ 0.052 for B1 vs Optimised, and ~ 0.310 for B2 vs. Optimised) presented above, both of them larger than the established significance level of 0.05, we cannot deny that the distributions have equal variances. Therefore, in order to check if it is safe to conclude that the expected value of total downtime is relevantly lower in the optimised scenario, and since we don't know the real distribution followed by the variables, a homoscedastic t-test was performed and the results are displayed on Table 12 and Table 13 below.

Table 12 – Homoscedastic t-Test for baseline 1 and optimised scenarios' means

Homoscedastic t-Test B1 vs OD	Baseline 1	Optimised
Mean	159.6	101.68
Variance	275.8787879	383.0884848
Observations	100	100
Pooled Variance	329.4836364	
Hypothesized Mean Difference	0	
Df	198	
t Stat	22.56298892	
P(T<=t) one-tail	6.2299E-57	
t Critical one-tail	1.652585784	
P(T<=t) two-tail	1.24598E-56	
t Critical two-tail	1.972017478	

Table 13 – Homoscedastic t-Test for baseline 2 and optimised scenarios' means

Homoscedastic t-Test B2 vs OD	Baseline 2	Optimised
Mean	150.08	101.68
Variance	346.660202	383.0884848
Observations	100	100
Pooled Variance	364.8743434	
Hypothesized Mean Difference	0	
Df	198	
t Stat	17.916728	
P(T<=t) one-tail	1.32604E-43	
t Critical one-tail	1.652585784	
P(T<=t) two-tail	2.65208E-43	
t Critical two-tail	1.972017478	

Based on the analysis of the tests' outputs, it is now possible to state that the optimisation method promotes a reduction in the fleet total downtime given that the t-Tests demonstrated that the mean value of the downtime distribution for the optimised scenario is lower than the mean values of the other two scenarios with 5% significance level. With effect, the p-value is so low that the significance level could be improved and safely brought to the 1% level, and the conclusion would remain the same.

The results corroborate the initial expectations and helped to increase the solution's strength. The significant gains primarily pointed out by the initial approach held true when submitted to the Monte Carlo simulation, what prompts to the conclusion that the claims of downtime reductions promoted by the analytical model may be generalised. One interesting point to note is that there was not a higher overlay between items with synergy recorded in the co-location matrix. This indicates that the marginal gains obtained in performing two specific tasks are not enough to drive the model towards it.

A key aspect to be observed is that the downtime reduction converged to an average of 34.2% (36,3% and 32,2% against baselines 1 and 2 respectively) on the simulation, which shows the importance of testing several scenarios. The initial data used to test the model was particularly not suited to baseline 2, therefore it created the wrong impression that this strategy was worse. As a matter of fact, the optimised solution delivers roughly the same gains compared to both baselines, reason why it was deemed unnecessary to perform tests against both references in the expanded model, but rather only baseline 2 was used for its stronger results in the simulation.

On the other hand, it is important to take into consideration the fact that extraneous failure events, meaning those not related to the risk index in the model, might have a negative impact on planning, causing disruption and affecting the downtime reduction propelled by the analytical model. Since the optimisation model is static and considers a steady state scenario, the investigation about the failure effects on planning require a dynamic model that is capable to handle time dependencies.

In fact, apart from the corrective maintenance events already contemplated in the expanded model, overall system failures could be embedded in the analytical model assuming constant failure (exponential reliability), which is a standard assumption in the aviation industry and many tools such as Systecon OPUS 10© applies it. However, the event timing can't be defined and just the number of failures uniformly distributed will not suffice to allow for conclusions with respect to the potential disruptive role of failure and its ensued corrective maintenance actions.

4.2 Expanded Analytical Model Results

As explained in the previous chapter, the expanded model deals with more parameters and counts with less assumption. With that, in order to properly test this enhanced version, a more challenging scenario, which also offers more possibilities for improvement, was created with 7 aircraft each one composed by 17 different components with QPA (Quantity Per Aircraft) equal to 1.

Besides that, instead of distributing flight hours, the model now assigns quantities of flight types to be performed by each aircraft over an entire scenario horizon, instead of just up to the next periodical check. The global scenario input data is displayed on Table 14.

Table 14 – Expanded model global input data

Parameter	Value
Scenario length (calendar hours)	2.160
Check duration (calendar hours)	48
Assigned fleet flight-hours (AE)	1.200 (+/-2%)
Assigned flights type 1 (FT1) – 1FH/FC	400 (+/-2%)
Assigned flights type 2 (FT2) – 2FH/FC	200 (+/-2%)
Assigned flights type 3 (FT3) – 4FH/FC	100 (+/-2%)
RUL Confidence Level (CL)	0.9
Maximum usage rate (LUL)	0.137
Priority factor 1 (PR1)	1.5
Priority factor 2 (PR2)	3.0
Corrective maintenance duration (calendar hours)	12

It is worth mentioning that the maximum usage rate showed on the table, or the limit to stay in the low utilisation category, is equivalent to 1.200 flight hours per aircraft per calendar year or 13.7% of the total elapsed time.

It also should be reminded that the priority factors are flexible parameters that can be adjusted according to the scenario/user. The values for this case were defined with basis on tests that pointed better results with PR1 equal to 1.5, weighing 50% more the overlay with the periodical check as opposed to between predictive tasks, and PR2 at 3.0, thus boldly influencing the model to reduce the failure risk. It is key to understand that these values are flexible and intended to allow the user to balance the terms in the equation according to their interest and what makes more sense to their planning. It is also important to remember that these values are only used by the overlay maximisation objective function, and not by the downtime minimization one.

The corrective action duration is the same for all components and it is set to take longer than the prediction-based ones in order to reflect the extra time spent on setting up the resources and on troubleshooting when compared to a planned or expected event that allowed for anticipation.

The input data pertaining to the aircraft is exposed on Table 15.

Table 15 – Aircraft input data

	Aircraft						
Parameter	1	2	3	4	5	6	7
TTCL (Cal Hours)	168	504	840	1176	1512	1848	2184
TTCU (Cal Hours)	216	552	888	1224	1560	1896	2232

The TTCL and TTCU parameters delimit the periods when the periodical checks are executed. It should be noticed that they are staggered in such a way as to allow each aircraft to be attended at a time, which is standard in aviation when the agenda allows. During these periods the aircraft is grounded and no component or aircraft aging is computed in the model.

One important aspect that demands clarification is the fact that aircraft number 7 inspection falls shortly after the scenario length. This is not a problem and will happen every time the next inspection for a given aircraft is outside the scenario length. The next inspection is a necessary input to the model and needs to be accounted for in the current distribution because it might overlay with moving intervals within the scenario length causing an impact on the current period of evaluation.

In reality, the expanded model can handle longer time spans, even when it embraces more than one periodical check per aircraft. In this case, another overlay summation, and the correspondent downtime calculations, must be added in the formulation for each scheduled intervention. It does not affect the model functioning and, with effect, the distribution of hours is restricted to the scenario length, so the assigned flights can only happen within this period according to each calculated utilization rate in any case.

Next, the input data related to the components is presented in Table 16.

Table 16 – Components input data

			Application Factor				
Component	Qty/Acft (QPA)	Operational Parameter	FT1	FT2	FT3	Task Duration (TDur)	Stock Level (s)
1	1	FH	100%	100%	100%	4	1
2	1	FH	100%	100%	100%	4	3
3	1	FH	100%	100%	100%	4	5
4	1	FH	100%	100%	100%	6	2

Component	Qty/Acft (QPA)	Operational Parameter	Application Factor FT1	FT2	FT3	Task Duration (TDur)	Stock Level (s)
5	1	FH	100%	100%	100%	4	3
6	1	FH	25%	50%	100%	4	4
7	1	FH	100%	100%	100%	6	2
8	1	FH	100%	100%	100%	8	1
9	1	FH	100%	100%	100%	8	1
10	1	FH	50%	50%	50%	8	1
11	1	FC	100%	100%	100%	4	3
12	1	FC	100%	100%	100%	8	2
13	1	FC	100%	100%	100%	6	2
14	1	FH	100%	0%	0%	4	2
15	1	FH	100%	100%	100%	6	3
16	1	FH	100%	100%	100%	6	2
17	1	FH	100%	100%	100%	6	1

The table above displays the aging parameter driving the components wear and the application factor for each component per flight type. For example, it can be seen that component 14 is not engaged on flight types 2 and 3, but it operates full time when the aircraft housing it performs flight type 1. It also informs how long it takes to perform a predictive task for each component.

Another information available is the inventory level. For the analytical model, it suffices to state that they are all larger than zero, thus all items are included in the calculation. With effect, the absence of stock leads the analytical model to eliminate the item from the analysis, given that it is not worth arranging its predictive task if it cannot be successfully executed, which would be pointless at this point in the analysis. The same data is used in the simulation model where those levels change as the operation progresses.

The co-location matrix considered indicates commonality of access between components 1 and 2, 3 and 4, 6 and 7, and between 10 and 12.

Finally, the model requires a list with the components' RUL and respective confidence intervals. The expected RUL values are randomly generated between 5 and 150 FH or FC as illustrated by Table 17, which is meant to be both realistic in terms of future projections and also providing a wide enough variation to test the model.

Table 17 – Example of RUL values

	Aircraft						
Component	1	2	3	4	5	6	7
1	72	26	85	74	64	92	110
2	25	103	33	75	2	79	30
3	14	55	82	48	101	115	73
4	56	57	96	84	37	79	56
5	113	63	86	37	44	106	107
6	107	73	26	46	78	81	21
7	103	73	38	82	40	112	41
8	8	81	41	20	104	101	41
9	106	54	61	57	98	33	86
10	76	62	42	33	99	104	68
11	31	61	96	109	38	84	106
12	72	41	15	69	90	98	102
13	36	75	33	102	85	99	81
14	109	73	28	37	47	10	115
15	43	34	41	27	78	98	25
16	33	110	119	44	35	24	75
17	41	20	88	39	46	105	11

The confidence intervals were set to represent a coefficient of variation of 6.7%, meaning the rate between the standard deviation and the mean value in probability density function (i.e. $CV = {}^{\sigma}/_{\mu}$). Considering a gaussian distribution, the 90% confidence interval spreads approximately 3σ around the mean value, i.e. a length of around 20% of the mean value. This reference represents a good representation of reality given that the closer is the RUL value, the more precise the forecast becomes, and narrower the confidence intervals, which is a behaviour well emulated by the use of percentages.

Firstly the model in Equation 5 was put to test, namely the one focused on maximizing the overlay rate, both without and with the task duration terms (TDur), and the results are summarized on Table 18 with the distributions behind the downtime average values depicted on Figure 34 and Figure 35. It should be noted that all results following on this section are based on 100 iterations with randomly generated RUL values. The detailed results for each iteration can be found on Appendix A.

Table 18 – Expanded model results using Max Overlay objective function

	Without TDur			With TDur		
Results	Overlay	DT	FRI	Overlay	DT	FRI
Mean	75.31	650.02	1.80	783.95	648.64	1.55
Variance	86.05	468.43	1.26	8438.83	391.99	0.85
Std Dev	9.28	21.64	1.12	91.86	19.80	0.92

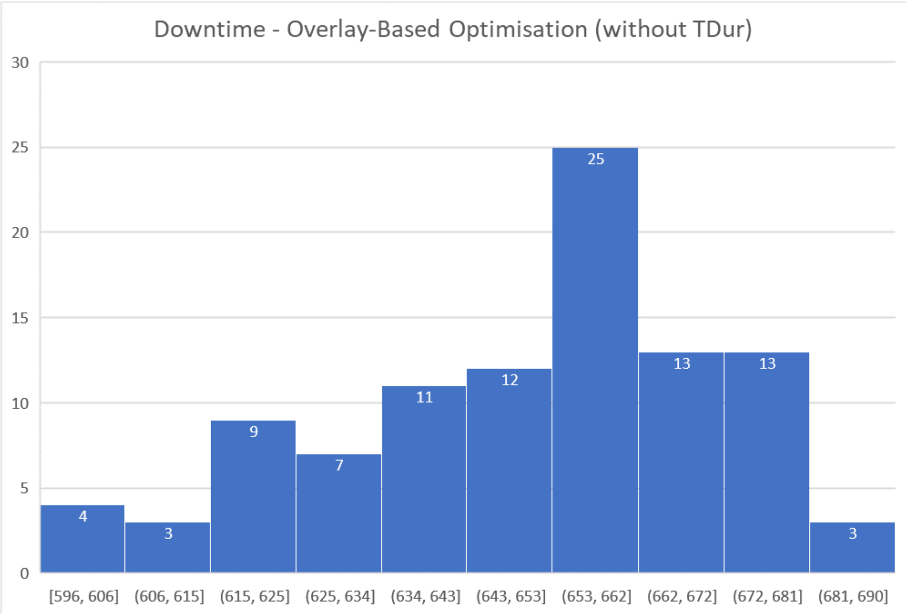

Figure 36 – Downtime distribution using overlay-based optimisation without TDur

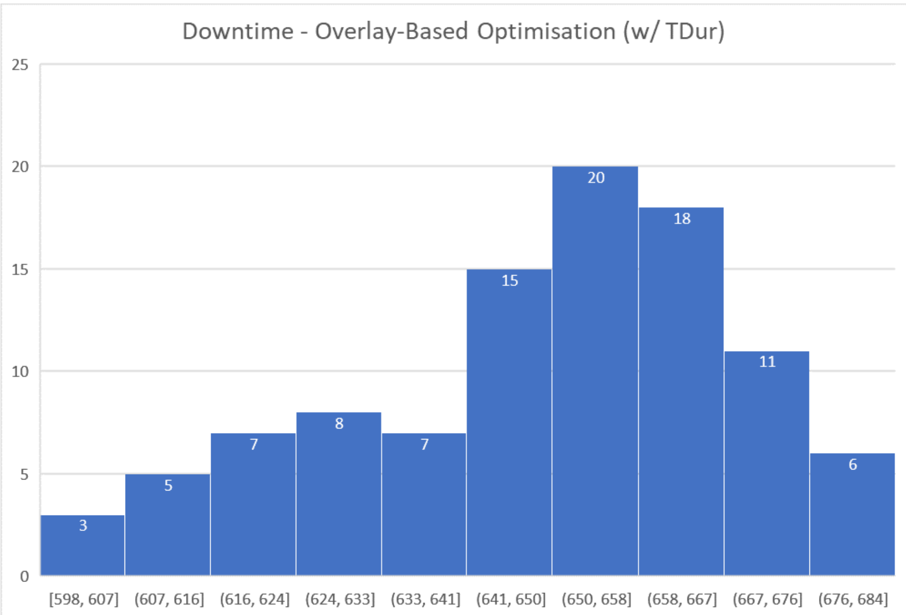

Figure 37 – Downtime distribution using overlay-based optimisation with TDur

Then the downtime minimization model was deployed on the same basis and the results are exposed on Table 19 and Figure 36. As expected, the downtime results for this function do not change significantly since the formulation was not affected by the changes involving TDur, therefore the 200 tests were consolidated on the graph presented by Figure 36. The results for the model with TDur were included in the table to provide a proper reference to compare the overlay rate results obtained from its equivalent in the maximum overlay equation.

Table 19 - Expanded model results using Min Downtime objective function

	Without TDur			With TDur		
Results	Overlay	DT	FRI	Overlay	DT	FRI
Mean	62.89	612.74	0.54	698.97	615.26	0.75
Variance	78.04	418.45	0.14	9635.66	378.88	0.27
Std Dev	8.83	20.46	0.37	98.16	19.46	0.52

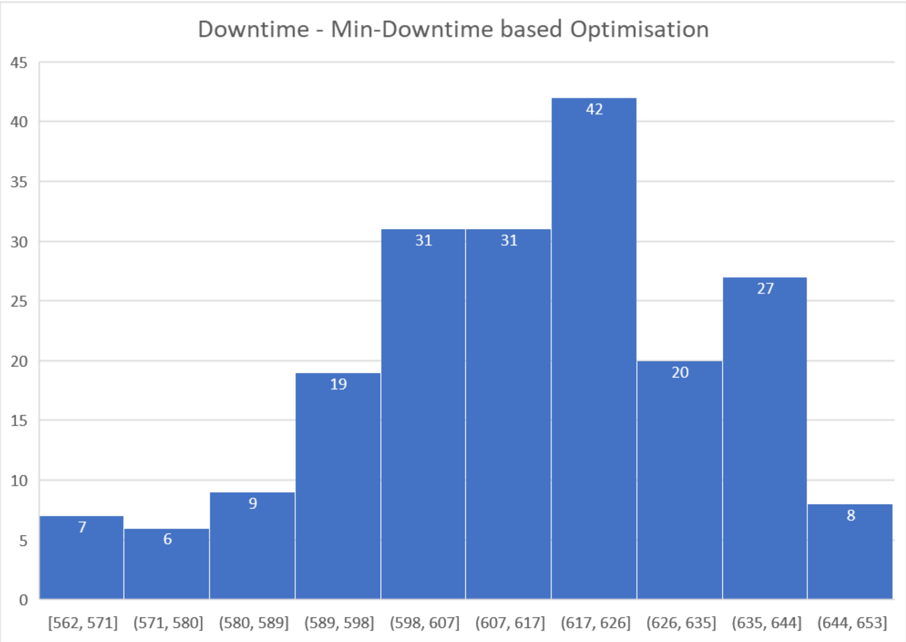

Figure 38 – Downtime distribution using downtime-based optimisation

The baseline scenario results considering an even distribution of flights of each type amongst the fleet members can be seen on Table 20 and are also represented on Figure 37. In this case, the results for downtime and FRI are obviously rigorously the same.

Table 20 – Baseline for comparison with expanded model results

	Baseline without TDur			Baseline with TDur		
Results	Overlay	DT	FRI	Overlay	DT	FRI
Mean	55.91	672.12	3.14	632.18	672.12	3.14

	Baseline without TDur			Baseline with TDur		
Results	Overlay	DT	FRI	Overlay	DT	FRI
Variance	57.32	619.35	1.81	6099.59	619.35	1.81
Std Dev	7.57	24.89	1.36	78.10	24.89	1.35

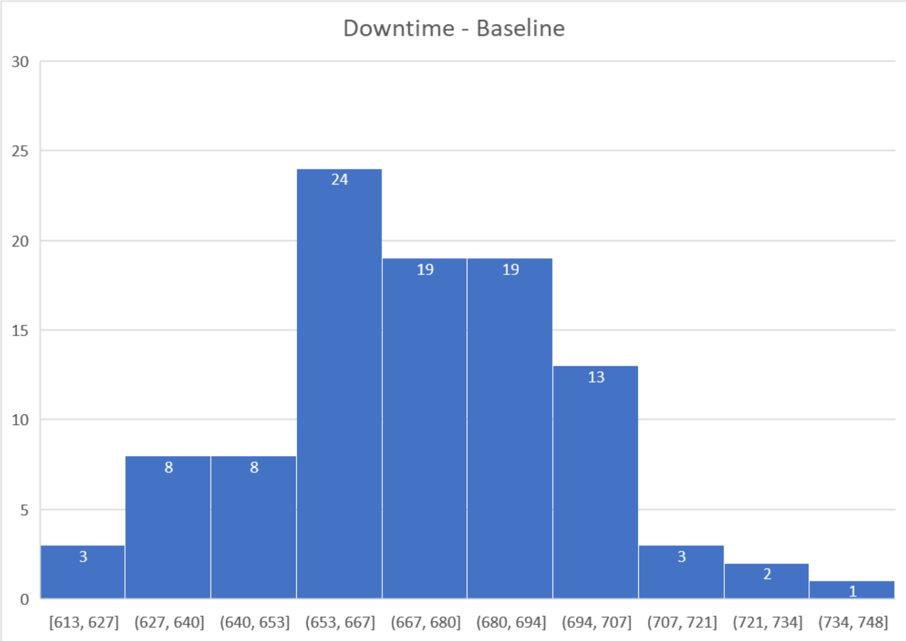

Figure 39 – Downtime distribution using baseline strategy

The optimal results were again obtained using the Evolutionary optimization method. The processing time averaged less than a minute to reach a solution without TDur and roughly 2 minutes when taking the task durations into consideration. In this interim, it is worth mentioning that the results obtained through this non-exact method are not necessarily the global optimum or the best solution. Therefore, the downtime results presented arguably may still be improved with the use of more powerful heuristics.

The average gains obtained are presented on Table 21 and the discussion follows afterwards.

Table 21 – Expanded model results summary against baseline

	Objective Function		
Results against baseline	Max Overlay w/ TDur	Max Overlay w/out TDur	Min Downtime
Overlay	+24.01%	+34.70%	+10.56%
Downtime	-3.49%	-3.34%	-8.46%
Downtime (checks discounted)	-6.99%	-6.67%	-16.92%
FRI	-50.81%	-43.11%	-76.15%

The results above lead to the conclusion that the maximization of overlaying rates between moving intervals and periodical checks does induce downtime reduction and vice-versa. In fact, as it can be verified on Appendix A, out of 100 iterations focused on minimizing downtime, 89 resulted in higher overlay rates, while 97% of the iterations focused on maximizing overlays resulted in downtime reduction.

However, it has to be pointed out that the maximizing overlay function achieved lesser results when compared to the formulation where the minimization of downtime is directly targeted. The explanation is that insisting on increasing the overlay extension may sometimes lead to inefficiency given that the smallest crossing between moving intervals and checks is already enough to join tasks, feature better captured by the downtime minimization model. As a consequence, the downtime focused model was able to deliver a reduction 2.42 times greater than that generated by the overlaying maximization one.

It should be clarified that although the models consider the total downtime in the formulation, including the portion relative to the time spent on the ground due to periodical checks, a fair evaluation of the model performance should discount these fixed values once they cannot be reduced or supressed. These lean values are presented in the row called "Downtime (checks discounted)" and are the final results taken into consideration for the analysis.

Another important result brought by Table 21 is the reduction in the failure rate index effected by the models. The reductions on both formulations are substantial, but again the focus on downtime yielded better performance. Considering the disruptive impact caused by failures, it is also an important and welcome improvement that the model is able to deliver and confirms the intention of integrating seamlessly predictive, scheduled and corrective maintenance interventions.

With regards to the use of TDUR or not in the formulation, the results do show a little improvement from a 6.67% downtime reduction without TDur to 6.99% using the task duration related terms in the equation.

Considering the variability in the results, at this point it is no possible to conclude that using this term provides better results as a rule. Bearing in mind yet the increase in processing time, which was almost doubled, it apparently is not worth including this term in the formulation. However, it is conceded that this term may bring more significant gains in cases where the difference in duration between the tasks is more prominent. Therefore, it is concluded that this term should be kept in the model, especially when processing capacity is not a bottleneck.

Moreover, it is important to highlight that in comparison with the results obtained in the basic model testing, the enhanced solution offered more modest results although still very relevant. This performance accommodation was expected and is due to the elimination of assumptions, the addition of the failure risk index, and in face of a significantly more complex scenario with added constraints on the decision variables, which passed from float values to integers representing the number of flights assigned to each aircraft.

Nevertheless, it was possible to identify that the more nuanced and varied the components behaviour in terms of how they age and how they are deployed, the higher the potential for the model to achieve better downtime reductions, especially those related to the overlaying between predictive tasks, compared to the reference strategy. Differences in aging parameters (e.g. operating hours, operating cycles, flying hours, thermodynamic cycles, calendar time, power-up cycles etc), application factors (e.g. mission systems only engaged in specific situations or flight phases) and also in wear severity due to environmental conditions are all contributing factors increasing the number of alternative solutions therefore enhancing the possibilities for model to deliver better results. As a consequence, it is plausible to presume that the enhanced model might benefit from scenarios with more components given that the same assumptions, constraints and formulation are conserved.

In order to check if the results hold up statistically, and in the same as it has been done for the basic model, a hypothesis testing battery is performed next considering the maximum overlay with TDur and the downtime minimization objective functions. As before, first the variances are compared in order to check if they can be considered equivalent. The outcomes for the variance analysis of the baseline against the overlay maximization and downtime minimization are respectively displayed on Table 22 and Table 23.

Table 22 - F-Test for Max Overlay and Baseline downtime distribution variances

F-Test OL-BL	Max Overlay	Baseline
Mean	648.64128	672.12452
Variance	391.9919849	619.3478535
Observations	100	100
df	99	99
F	0.632910864	
P(F<=f) one-tail	0.011905368	
F Critical one-tail	0.717328593	

Table 23 - F-Test for Min Downtime and Baseline downtime distribution variances

F-Test DT-BL	Min DT	Baseline
Mean	615.2593	672.12452
Variance	378.8839702	619.3478535
Observations	100	100
df	99	99
F	0.611746643	
P(F<=f) one-tail	0.00761996	
F Critical one-tail	0.717328593	

On both cases, the results indicate the existence of enough evidence in the data to believe that the variables distributions variances are different. Following that, and acknowledging that the real distribution followed by the downtime variables is unknown, heteroscedastic t-tests were performed to compare the mean values and the results are displayed on Table 24 and Table 25.

Table 24 – Heteroscedastic t-Test for Max Overlay and Baseline downtime distribution means

t-Test: Two-Sample Assuming Unequal Variances	Max OL	Baseline
Mean	648.64128	672.12452
Variance	391.9919849	619.3478535
Observations	100	100
Hypothesized Mean Difference	0	
df	188	
t Stat	-7.384302154	
P(T<=t) one-tail	2.41548E-12	
t Critical one-tail	1.652999113	
P(T<=t) two-tail	4.83097E-12	
t Critical two-tail	1.972662692	

Table 25 - Heteroscedastic t-Test for Min DT and Baseline downtime distribution means

t-Test: Two-Sample Assuming Unequal Variances	Min DT	Baseline
Mean	615.2593	672.12452
Variance	378.8839702	619.3478535
Observations	100	100
Hypothesized Mean Difference	0	
df	187	
t Stat	-17.99828059	

t-Test: Two-Sample Assuming Unequal Variances	Min DT	Baseline
P(T<=t) one-tail	5.58213E-43	
t Critical one-tail	1.653042889	
P(T<=t) two-tail	1.11643E-42	
t Critical two-tail	1.972731033	

Analysing the tests' output and considering the infinitesimal low p-value on both cases it is possible to comfortably conclude that there is enough evidence sustaining the hypothesis that the mean values of the distributions are indeed different. More precisely, the tests showed that in both cases the expected downtime values are smaller than the average downtime provided by the baseline strategy.

This result confirms the initial hypothesis set out on this research once the method developed for integrating predictive and preventive maintenance, and also minimizing the risk for corrective interventions, which consisted in a mathematical dynamic and adaptative model that optimally distributes flight-hours amongst the fleet members, is able to minimize total downtime, therefore being a valid solution capable of tackling the impact caused by the migration of scheduled tasks to condition-based ones both on availability and cost. Indeed the cost reduction results from the synergy created by the solution and is a direct implication of reducing downtime and the need for resources associated with it.

In face of the previously analysis and discussion, it can be ascertain that the model development allowed for many tests which gradually led to improving the formulation culminating in the downtime reduction represented by Equation 3 which is faster to run, more flexible, counts with less assumptions and reached better results in terms of downtime reduction. The deployment of this model in real scenarios such as the Gripen NG and KC-390 Millennium of the Brazilian Air Force with tens of aircraft and health monitored components will require higher data processing power to enable it to be run in a sensible time and allow for timely decision making. Notwithstanding the amount of data and operations to process, the implementation can be leaner and more sophisticated with the use of proper programming language such as Python©, which offers many data analysis libraries, and also investigating alternative heuristics which may be able to converge faster and effectively find a good enough solution.

4.3 Simulation Model Results

Initially it is important to register that the process of building the simulation model proved to be a good catalyst for keen reality observation contributing to enhance the knowledge about the real system targeted and also improving the awareness of subtle aspects which could be otherwise unintentionally neglected.

The aspects herein identified are emphasised throughout the text and will be a central part of the discussion that follows after the presentation of the results. That notwithstanding, it is interesting to mention that the simulation results are also key to support the generalisation and better understanding of the solution's applicability.

The input data to the model is imported from a Microsoft Excel© spreadsheet, which is connected to the model as a database. The input table with randomly generated data is available in the Appendix B – Simulation Input Data. It is important to remark that the data on the table is only the initial data from where the simulation departs.

After that, as the fleet ages, all the model's parameters vary and the remaining useful life estimates are updated or replaced according to what happens in the simulation instances, they can even be reset after a predictive intervention or a failure. The same is valid for the last check date and the aircraft age.

In order to extract immediate dynamic value and understand better the results from the simulation, besides being able to record and export output data and watch their behaviour during the experiment, meaning live feedback, a control panel was developed showing the actual outcomes from each iteration such as downtime, the portion to which each type of maintenance accounts for, the quantity of synergic integrations of tasks performed (the so-called opportunistic maintenance planning successes) the actual distribution of each downtime parcel, the availability behaviour (or any other measure of effectiveness, or service level chosen), the actual aircraft MTBF and the adjustment parameters.

All of this can be seen in Figure 38. On top of that, it is also worth to remind that the simulation counts yet with a bulit-in programmable console that records specifics events which the modeller might be interested in either for debugging or for detailed statistical analysis purposes.

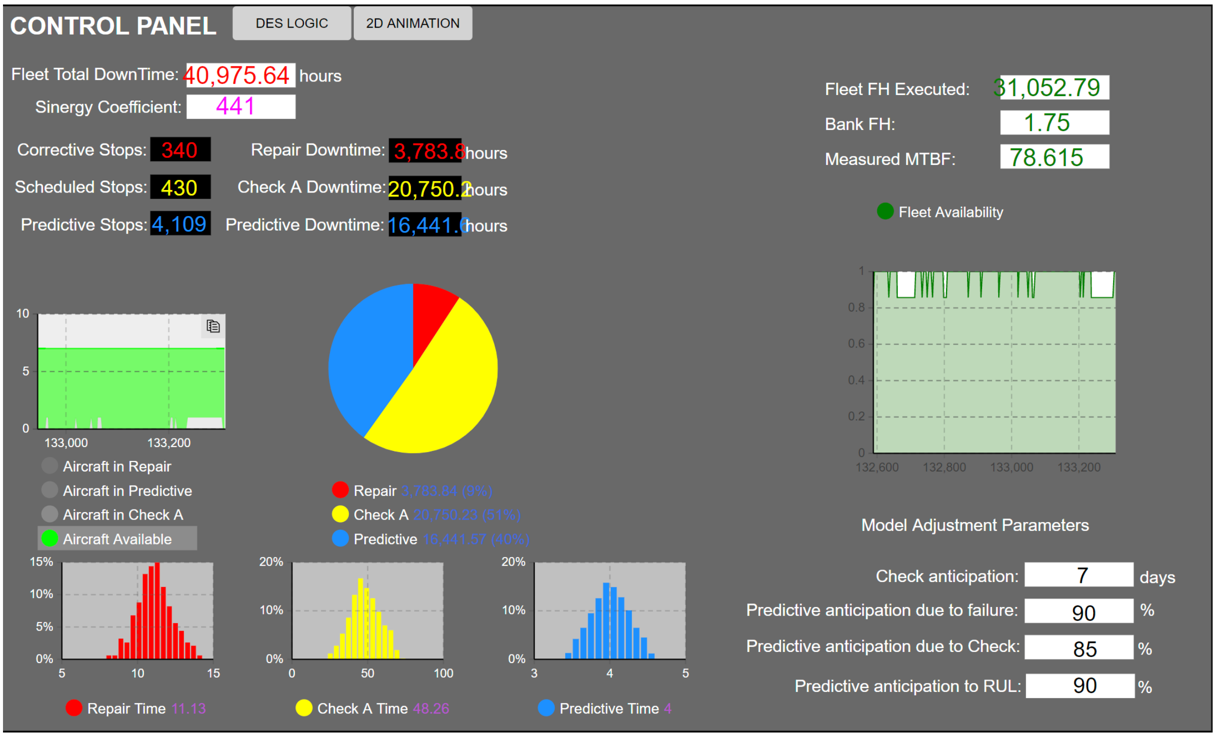

Figure 40 – Simulation control panel.

On the control panel it is possible to verify that the simulation model records the accumulated downtime across all members of the fleet, which is the target variable that the solution seeks to minimize. It also indicates the causes driving downtime by showing in relative and absolute values the contributions by each type of maintenance task to the total moored hours. Along with that, it also shows the resulting distribution of the random variables representing each maintenance type duration.

On the top-right part of the panel the accumulated hours flown by the fleet can be checked. This data indicates the percentage of requested flight time that was actually performed and it can be used to calculate the maintenance hours per operational hour ratio, which is one of the main supportability metrics in aviation.

The instantaneous amount accumulated in the flight-hours bank balance also can be monitored and its behaviour can shed light on the disruption level caused by logistics delays or by failure events that could not be avoided. The more hours accumulated, the higher the disruption level.

The system availability is also displayed within the panel and recorded for post simulation analysis. As mentioned before, this is a dependent variable which is a function of both reliability and maintainability parameters. Since the optimisation model is concerned with reducing downtime, the effect on availability is only partial, but given that this is the most well-knowns systemic measure of effectiveness, it is also important to monitor.

Finally, the panel also accounts for the adjustment parameters. These are constants which can be calibrated in order to increase or decrease the maintenance thresholds flexibility thus affecting opportunism behaviour of the system. More specifically, they tell the model how much it can bring forward a scheduled check or an impending prognostics-based task, that is before the lower bound of the confidence interval is reached, considering that the aircraft was grounded for any other given reason.

In face of that, the dyad solution tests were initiated by inputting the distribution promoted by the conventional method. This cases consist in the baseline against which the optimal distribution is compared in order to reach a conclusion whether the expected gains calculated by the analytical algorithm holds in face of the added complexity brought by the simulation model.

The baseline scenario (BL) splits the available flights/flight-hours equally between the fleet members in what is the most straightforward line of management. The optimal distribution (OD) for its turn is the direct application of the values output by the analytical model.

For each strategy, a total of 100 replications was performed according to the input list below and the co-location matrix represented on Table 26 resulting in the comparative downtime histograms depicted in the following figures.

- Scenario length: 3 months.
- RUL confidence level: 90%
- q = 7 aircraft.
- n = 17 items monitored.
- AE = 1200FH to performed within the scenario length divided in 3 flight types.
- s_i = supply level.
- LUL = 1.752FH/year or 20% maximum rate of use.
- Check A interval = 90 days.
- Check A duration = 48 hours.
- Predictive task average duration: 8 hours.
- Corrective task average duration: 12 hours.

Table 26 – Co-location matrix for components in the simulation case

	Components' Co-Location Matrix in Simulation																
Item	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1																	
2	1																
3	0	0															
4	0	0	1														
5	0	0	0	0													
6	0	0	0	0	0												
7	0	0	0	0	0	1											
8	0	0	0	0	0	0	0										

	Components' Co-Location Matrix in Simulation																
Item	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
9	0	0	0	0	0	0	0	0									
10	0	0	0	0	0	0	0	0	0								
11	0	0	0	0	0	0	0	0	0	0							
12	0	0	0	0	0	0	0	0	0	1	0						
13	0	0	0	0	0	0	0	0	0	0	0	0					
14	0	0	0	0	0	0	0	0	0	0	0	0	0				
15	0	0	0	0	0	0	0	0	0	0	0	0	0	1			
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Based on that, the resulting distributions of operational hours and flights recommended by each strategy, baseline and minimum downtime optimal, are shown on Table 27 and Table 28 respectively.

Table 27 – Operations distribution (baseline)

Missions		Aircraft							Total
Flight type	FH/Cycle	1	2	3	4	5	6	7	
1	1	57	57	57	57	57	57	58	400
2	2	28	28	28	29	29	29	29	200
3	4	14	14	14	14	14	15	15	100
FC		99	99	99	100	100	101	102	
FH		169	169	169	171	171	175	176	

Table 28 – Operations distribution (minDT optimal)

Missions		Aircraft							Total
Flight type	FH/Cycle	1	2	3	4	5	6	7	
1	1	95	22	58	46	42	69	68	400
2	2	12	15	62	5	42	37	27	200
3	4	2	23	30	2	18	14	11	100
FC		109	60	150	53	102	120	106	
FH		127	144	302	64	198	199	166	

The expected resulting downtime, overlay and FRI for both approaches are displayed on Table 29.

Table 29 – Downtime, overlay and risk expected results (Analytical Model)

Strategy	Baseline	Optimal minDT
Overlay	694.67	724.98
Downtime	689.97	610.41
FRI	3.15	0.22

Using those operational distributions as input, the simulation model was executed 50 times for each strategy resulting in the graphs shown by Figure 41 and Figure 42.

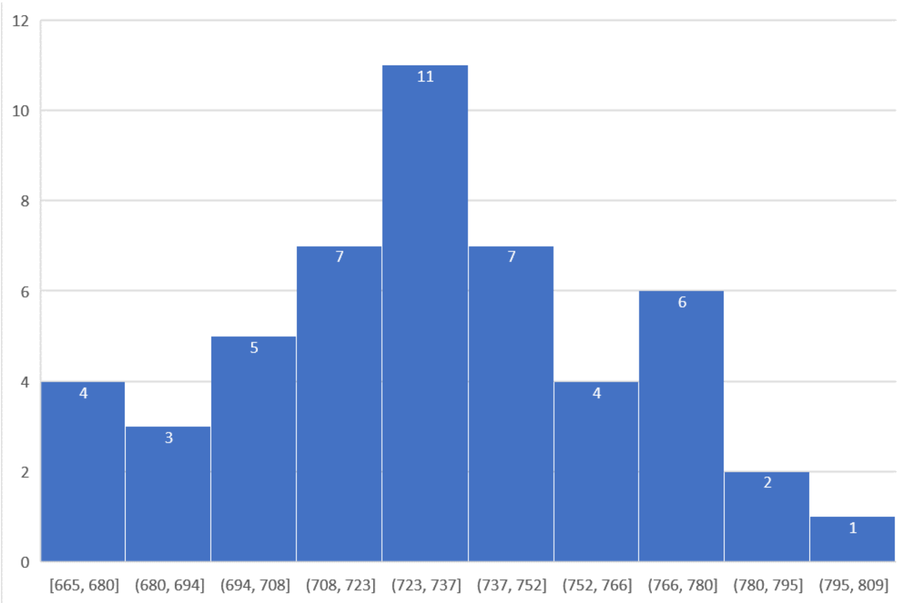

Figure 41 – Baseline downtime replication results histogram.

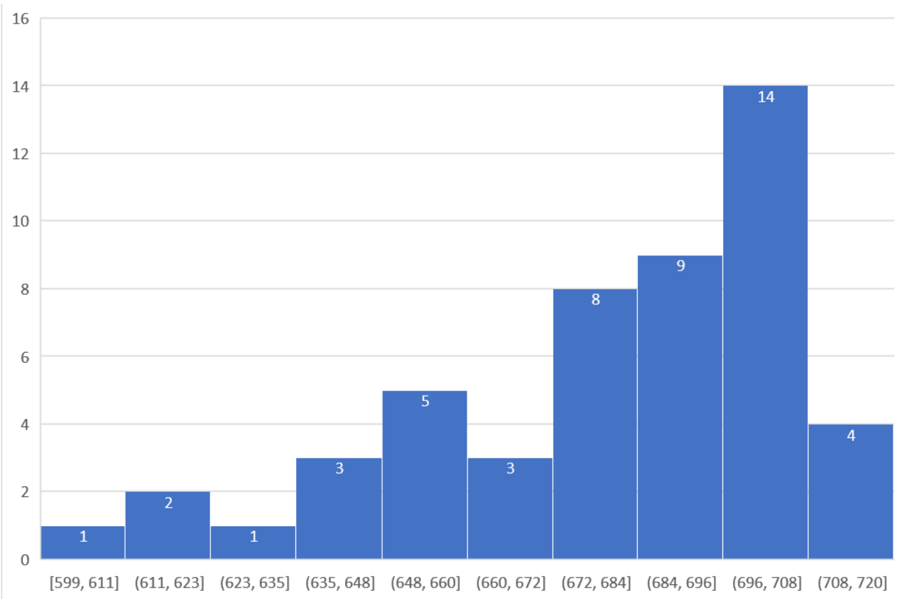

Figure 42 – Optimal downtime replication results histogram.

As it can be observed on the figures above, for the baseline test the downtime values ranged from 665 to 809 calendar hours with and average of 729.99 calendar hours spent on the ground by the fleet members undergoing maintenance.

The scenario using the optimal distribution on its turn varied from approximately 599 to 720 calendar hours with an average value of 679.81 calendar hours spent on the ground by the fleet members undergoing maintenance. This result is on average around 6.9% better than baseline.

In terms of the downtime per executed flight time ratio, the two scenarios managed to achieve more than 98% of the designated hours and the results are as follows:

- Baseline: 0.612 calendar hours of downtime per flight hour;
- Optimised Distribution: 0.567 calendar hours of downtime per flight hour.

Using the raw data output recorded from the simulation model above and considering that both the population's mean and variance true values are unknown for any of the scenarios analysed, a hypothesis test was performed to determine if it is possible to affirm that the downtime is indeed reduced with a 5% significance level.

Since it is not possible at first to infer whether the variances of the distributions can be considered the same, F-tests for variances were conducted pairwise and the results are presented on Table 30.

Table 30 – F-Test for B and OD simulation results variances

	Baseline	Optimised
Mean	729.9868	679.8126
Variance	1022.021214	808.1560156
Observations	50	50
df	49	49
F	1.264633554	
P(F<=f) one-tail	0.207071191	
F Critical one-tail	1.607289463	

Based on the p-value above (p-value~=0.207), considerably higher than the required significance level of 0.05, it is possible to conclude with basis on the data analysed that there is not enough evidence to deny that the distributions of downtime variables for baseline and optimisation strategies do have equal variances.

Therefore, in the same way as it has been done before in this text for the analytical results, in order to test the hypothesis and check what is safe to conclude regarding the expected value of total downtime using the optimised operational hours distribution compared to the baseline results, and since we don’t know the real distribution followed by the variables, a homoscedastic test was performed for comparison and the results are displayed on Table 31.

Table 31 – Heteroscedastic t-Test for B and OD simulation output downtime mean values

Heteroscedastic t-Test B vs OD	Baseline	Optimised
Mean	729.9868	679.8126
Variance	1022.021214	808.1560156
Observations	50	50
Hypothesized Mean Difference	915.0886148	
df	0	
t Stat	98	
P(T<=t) one-tail	8.293137861	
t Critical one-tail	2.99273E-13	
P(T<=t) two-tail	1.660551217	
t Critical two-tail	5.98546E-13	

The t-test confirmed that the mean values representative of each scenario’s downtime distribution are significantly different. The p-value for the one-tailed comparison is extremely low, and more importantly also considerably lower than the significance level adopted.

Those results evidently support the argument that the optimisation algorithm is indeed capable of reducing downtime and consequently supporting the fleet demand at a lower maintenance cost.

An important aspect to observe is the disrupting role played by failure events and their deleterious effects to planning entailing that the analytical model calculated optimal flight distribution cannot hold for too long as the effects brought about by the faults to the accomplished number of flight-hours and the anticipation of tasks for synergy reasons amount. With effect, on both cases the simulated downtime was higher than the expected value from the analytical model calculation, especially when considered that during the simulation period the check on aircraft number 7 was not performed. Moreover, while the analytical model over all the random iterations calculated an expected downtime reduction around 11.5% (or 22.4% disregarding the checks downtime), in the simulation model it could only reach 6,8% (or 11.3% disregarding the checks downtime).

One possible reason worth investigating is that the optimised scenario is meant to be dynamic and evolve with the operation whereas the baseline policy is static. With that in mind, the simulation was set to stop every fortnight and call the analytical model to re-optimise and update the distribution according to what has happened up to that moment. This link is expected to reduce the effects of failure disruptions on the overall maintenance planning.

Once more, the results are based on 50 replications considering the same input data as before, this time only for the optimised scenario given that it would be pointless to stop for the baseline once the approach doesn't change. The results are portrayed on the distribution in Figure 43.

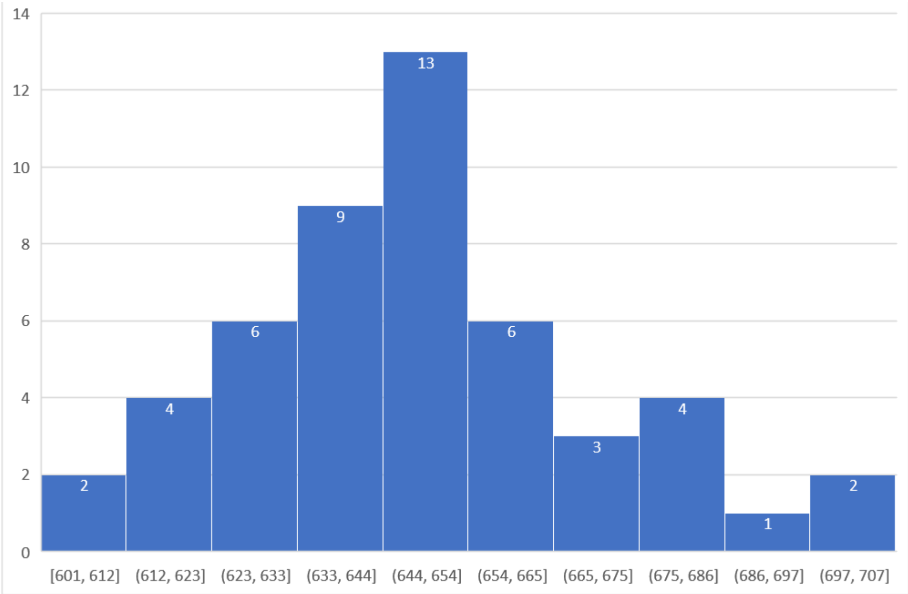

Figure 43 – Simulation downtime with link to analytical model for updating distribution

In the same line as done before, the statistical analysis comparing the downtime distribution with recurrent updates against the previous one is summarized on Table 32 and Table 33.

Table 32 – F-Test for single and recurrent optimised simulation results variances

	Single	Recurrent
Mean	679.8126	648.1244
Variance	808.1560156	508.5453149
Observations	50	50
df	49	49
F	1.589152415	
P(F<=f) one-tail	0.054151714	
F Critical one-tail	1.607289463	

Table 33 – Homoscedastic t-Test for single and recurrent simulation output mean values

Homoscedastic t-Test B vs OD	Baseline	Optimised
Mean	679.8126	648.1244
Variance	808.1560156	508.5453149
Observations	50	50
Hypothesized Mean Difference	658.3506652	
Df	0	
t Stat	98	

Homoscedastic t-Test B vs OD	Baseline	Optimised
P(T<=t) one-tail	6.17502806	
t Critical one-tail	7.51938E-09	
P(T<=t) two-tail	1.660551217	
t Critical two-tail	1.50388E-08	

The results confirm that there is indeed enough evidence to sustain the claim that the latest distribution presents a mean value lower than the previous one with 5% significance level.

Following the analysis supported by that, it can be seen that the mean value of the distribution presented in Figure 43 is 648.12 calendar hours, which represents an improvement in downtime reduction of 4.6% (or 8% disregarding the scheduled inspections downtime). Despite this improvement, compared to the expected savings projected by the analytical model it is still 6.2% (or 31.2% disregarding the scheduled inspections downtime) worse. Part of this difference is explained by the timing when failures occur.

On this, it is key to clarify that the range of downtime results observed so far in the simulation is mainly caused by the differences on the moments when random failures strike the fleet members. While on the bright side they can happen in convenient moments and coincide with preventive maintenance tasks, hence being completely diluted in the batch efforts or at most redounding in a minor hinderance. On the other side they may occur at moments when there is no neighbouring programmed or expected tasks that may be anticipated and joined with, therefore causing extra downtime time for its repair and also with the potential to cause further unavailability due to the disruption of the overall operational planning by misaligning the previously overlayed tasks.

Based on the results above discussed, it is possible to conclude that recurrently updating the operations distribution via periodical executions of the analytical model does yield the benefit of mitigating disruptions and external interferences that affect the model's efficiency.

In other words, the optimisation model needs to receive updated data from the operation, run again and feedback a new optimal flight-hours assignment on a certain frequency. The tests showed that the rerunning cycle length depends on a series of factors, the most important being the failure rate.

With that, and considering that the technology nowadays allows for instantaneous operational data gathering as flights occur, and near immediate database update on the ground stations, the cycle can be set according to the user convenience as long as it does not exceed the limit where the scenario has changed substantially enough to compromise the optimality of the operational hours distribution.

In practical terms the optimisation algorithm can be linked to this system and the solution can be constantly renewed. For the simulation purpose, the experiment was interrupted on a fortnightly basis and the optimisation algorithm repeatedly called and run, feeding back the updated distribution according to the remaining flight hours in the scenario.

Furthermore, the simulation showed that level of confidence defined in the analytical model and the level of anticipation allowed or tolerated have significant impact on the fleet downtime resulting from the experiment. Ceteris paribus, these parameters values can be adjusted and improved following an investigation of how the results change as the values vary.

The tests demonstrated a univocally and direct relationship between the level of tolerance and the resulting system effectiveness. In other words, the higher the margin represented by the anticipation factors, the higher the number of synergic events leading to downtime reduction. This behaviour is according to the reasonably expected once the more flexible the policy, the more room there is to create synergy.

The problem here is that excessive use of anticipation may lead in the medium or long term to the alignment of preventive checks resulting in maintenance hangar overload and therefore also causing availability reduction. This finding is considered a good start point for further research since the investigation requires the development of regulatory compliant and effective criteria to help indicating the optimal margin for each operation/scenario. This is out of scope of the present study, but it is worth to remark that this is an example of aspects only possible to identify when dealing with a dynamic model such as the simulation model developed herewith.

5 Conclusion

The results reached by this research endeavour confirmed the ability of the proposed method and solution to answer the objectives set out at the dawn of this work. It complied with the intended use of IVHM/AHM data to maximize the utilisation of a condition monitored component's useful life in lieu of acting prematurely, while dealing with the inherent uncertainty through the use of random variables expected values associated with their confidence intervals to minimize the risk of a condition monitored item running into failure, by timing the maintenance point of action at their lower bounds and with the use of the Failure Risk Index. Ultimately and most importantly, the research culminated in the development of a model that demonstrated the ability to optimally distribute flights or flight hours to effectively minimize a fleet downtime based on the augmentation of the overlay rate between predictive tasks and scheduled checks.

The research strategy was successful in so far as the literature review pointed out to the relevance and maturity of the theme, which had a clear gap in linking prognostics methods for predictive maintenance with operations and maintenance planning that is, ultimately, what creates value to asset stakeholders. That gap has been fulfilled by the proposed solution and derives from rigorously following the flowchart set out in the designed methodology, and the novelty and originality of the contribution has been preserved despite the various works being published concurrently with this thesis development.

The initial model, analytical in its essence, served as a proof of concept indicating the potential gains offered by the optimisation algorithm. The primary results were subjected to the scrutiny of the scientific community in several different opportunities and were validated by it. With effect, the novelty claim, the methodology and the algorithm construction have not been disputed, and the relevance of the subject matter is reflected in the substantial level of attention drawn by the publication in the 2021 European Conference of the PHM Society.

The main contribution offered by this thesis is synthesized in the expanded model formulation, represented by the objective function in Equation 3. It is an unprecedented method to dynamically coalesce maintenance events in time with the aim of minimizing downtime for a complex system fleet via the optimal distribution of flights or flight-hours based on the overlaying of predictive and scheduled maintenance while also minimizing the risk of incurring in failures associated with the monitored items.

The use of Monte Carlo simulation provided robustness to the solution allowing for a generalisation of results given that it becomes evident the claimed downtime reductions hold up statistically. Not only that, it also confirmed this research hypothesis that if the overlay rate between moving intervals and periodic checks is increased then the overall downtime is reduced. Likewise, it demonstrated that the model was strongly able to also minimize the failure risk index concurrently to the main objective.

The hybrid simulation model for its turn exposed the analytical model frailties as it takes into account the complexities of the flying system time dependencies which cannot be grasped in a static mathematical model. This implementation meant a great challenge to a formulation conceived in a steady-state paradigm, but it was essential to validate the model's adherence to reality and its applicability as a decision support tool for a fleet manager.

The simulation deployment also helped to better understand the implications of assumptions initially adopted to limit the scope and make the optimisation algorithm viable. In this sense, it proved to be a great research tool. One of the most critical representative of this improvement is the treatment and consequences of failure occurrences. These events are not ruled out either in the original model or in the simulation, but while in the analytical model they are represented by a risk index associated with the monitored components, in the simulation experiment it was possible to add random system failures and evaluate the consequences related to the moments when failures strike.

For instance, during the simulation experiments it was possible to understand that if a failure event happens in a point in time far away from any periodic or condition-based intervention, the isolated stop to tackle that individual fault might disrupt the flight schedule and compromise the achievement of the planned flight-hours for the period, causing components to age less than expected and misaligning the moving intervals. In doing so, it unveiled that the optimisation model implementation requires recurrent runs with input data updated according to what happened during operations in order to keep the effectiveness of the method.

Conversely, if the functional loss takes place at a more propitious moment when there is the possibility of coalescing other maintenance activities, then it might be used as an opportunity to synergically process differed tasks or perform neighbouring preventative tasks of impeding predicted failures or near expired scheduled tasks simultaneously.

As demonstrated, the effects related to time dependency can only be captured using simulation because it is not a matter of how many failures happen during a period, as it is usually considered in models focused in steady state scenarios, but when exactly it happens changes de results. The simulation therefore is recommended as a tool to enhance decision support to operations planning insofar as it helps to better understand the scenario, calibrate the anticipation factors according to the user's interests and also investigating time-dependent nuances, consequences and trade-offs.

In this line of thought, another contribution provided by this thesis was the analysis of how the adjustment of parameters driving the anticipation or delay thresholds can improve the overall results. This was an aspect enlightened by simulation which cannot be perceived, tested or enhanced otherwise.

Considering the innovative trait of this scientific work, it is reasonable to argue that it opened an unbeaten path for investigation and as such it is prone to enhancements, especially those where the use of machine learning and better heuristics are concerned with a view to improve the methods employed in the initial solution developed. In this sense, it is worth mentioning that the model could be expanded beyond the initial scope defined for this thesis. While the verification and validation processes intended at this stage would not benefit from incorporating support resources limitations and detailed maintenance tasks features as those contemplated by prescriptive maintenance, it must be noted that flexibility and adaptability are built-in characteristics of the model design resulting the its ability to be expanded and absorb further parameters for real life implementation. Indeed, some aspects such as inventory levels are already in the analytical model and can be further studied from this formulation.

That notwithstanding, the simulation model developed herewith also offers a sensible basis on which to build upon for future research where it can be expanded to incorporate support elements which were not contemplated within the scope of this thesis.

At this point, it is important to highlight that although the Anylogic© simulation software is impressively vast and flexible, it does require a significant amount of computational processing power which grows exponentially with the size and complexity of the model.

Therefore it is recommended that anyone willing to expand the current model to include further levels of detail should take into account whether the necessary infrastructure is in place to support the development. On the other hand, given the need for recurrent executions of the analytical model in a real deployment, it is important that the optimisation model is able to run in a lean, light and fast way. Thankfully for the implementation of the analytical model it is possible to resort to already existing powerful and lean programming languages such as Python© which have a myriad of data analytics libraries that can provide more efficient heuristics to reduce the need for processing power thus speeding up the processing time.

The possible developments envisaged by the author include mainly:

- The incorporation of rules to avoid stopping simultaneously more aircraft than the maintenance capacity is able to service prioritising with basis on the calculated gains promoted by tasks overlay on each aircraft member of the fleet. On the flipside, the concurrent stop of more than one aircraft might be desirable and create synergy by sharing deployed resources in the hangar. This is also a possible extension to the model, which could seek to overlay stops up to a maximum service capacity.

- The expansion to embrace commercial jets operations allowing aircraft to operate and be serviced in different locations. This would yield a substantial increase in complexity due to the many local capacity parameters that would have to be replicated on each base and all the flight schedule implications following delays due to failures and lack of required resources. No doubt this is a challenging expansion, but it would severely widen the current model's range of applications.
- The use of specific confidence levels to each component according to its criticality instead of a single confidence level to all items.

Reflecting upon the process and the results obtained it becomes clear that aviation maintenance is facing the beginning of a new era. The opportunities to streamline maintenance are significant, technology is in place, massive quantities of data are made available in both timely and accurate fashion, data analytics algorithms and applications are in frantic development, and regulators are anointing to the certification for maintenance credits and the incorporation of AHM/IVHM in the preventive maintenance planning methodology.

In summary, this research was able to raise an extensive panorama of this new setting and closed the gap found in the literature by proposing a method that successfully managed to extract actual value from the information produced by smart components.

The signs of positive payoffs are convincing, therefore deepening the approach developed is encouraged and is expected to bear fruits for real life implementation. With effect, the study results showed that for IVHM-enabled system platforms, with condition and prognostics-based maintenance interventions, the conventional way of performing flight assignment and/or the distribution of operational hours, represented by baseline scenarios, may render CBM+ items to actually increase downtime. On the contrary, the optimisation method developed can support better decision making and potentialize the use of information to distribute flights or flight-hours in a way as to reduce downtime thus increasing availability and reducing costs.

Extrapolating the current scenario onto the future, and considering the steady growth in the use of sensing technologies, health data processing and prognostics algorithms, there will be a point where the definition of a single maintenance plan to all aircraft of the same model will no longer make sense. In this likely situation, individual dynamic maintenance plans will be required and the optimisation model developed can help to minimize downtime impact offering a better way of packing tasks than what is currently adopted in Maintenance Review Board Documents (MRBD) as previously discussed in the text.

Finally, it is important to remark that for new and sophisticated platforms such as the Gripen NG and KC-390 Millennium there is an abundance of operational data automatically generated in approximate real-time. With this raw information constantly being fed into and housed by well-structured databases linked to dedicated analytics tools such as the MGSS (Maintenance Ground Support System) and the AMMS (Aircraft Maintenance Management System) that accompany the SAAB system, the input required by the optimisation solution is already available and the benefits can start to be reaped with the integration of the analytical model and those systems in a duplex communication channel thus providing support to decision makers both in the support and operational organisations.

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Appendix A – Expanded Model Results

TEST	Max Overlay w/ TDur			Max Overlay W/out TDur			Min DT			Baseline			
	OL	DT	FRI	OL	DT	FRI	OL	DT	FRI	OL w/ TDur	OL ~~TDur~~	DT	FRI
1	966.52	610.73	3.4	84	607.138	1.96	871.32	577.26	0.58	666.58	55.1	632.636	2.47
2	789.73	674.19	2.42	79.5	677.476	4.77	651.54	608.2	1.13	717.53	71.4	700.084	0.93
3	826.48	651.41	1.8	70.2	661.804	1.28	741.56	594.91	0.45	594.13	53.7	674.472	3.94
4	900.68	661.31	1.23	83.8	655.146	5.02	657.7	618.33	0.4	591.79	64.8	664.48	4.85
5	976.17	604.37	0.4	78.7	597.426	0.87	920.85	569.33	0.31	675.24	66	643.044	2.13
6	755.44	656.8	0.82	91.4	667.664	5.53	686.5	630.65	0.8	525.76	52.1	679.6	2
7	839.89	656.92	1.57	67.4	680.182	0.94	559.8	650.65	0.62	599.04	55.5	692.14	2.05
8	878.06	641.51	1.25	91.4	663.892	5.34	669.83	614.41	0.59	645.09	72	726.256	7.62
9	731.27	669.53	0.33	61	660.656	3.02	533.99	629.84	1.1	552.32	49.6	679.08	2.32
10	834.58	623.45	1.8	77.9	652.844	2.48	648.2	606.89	0.33	638.81	67.6	698.756	5.62
11	738.94	627.19	0.67	70.3	648.766	1.92	736.72	606.97	0.27	607.57	62.9	642	1.67
12	786.36	683.81	1.56	70.7	670.828	1.56	592.72	633.41	0.18	592.31	56.6	699.704	1.83
13	731.96	636.77	3.38	77.2	672.514	3.38	672.86	588.44	0.5	532.29	56.5	706.736	3.22
14	762.74	662.79	2.67	84	650.976	3.42	749.94	621.85	0.54	545.71	56.9	681.404	4.58
15	883.49	660.01	1.36	74	654.304	2.43	705.71	641.59	0.23	715.24	65	657.708	0.16
16	830.95	646.7	2.78	79.3	646.014	2.78	823.64	616.27	0.37	736.5	68	669.716	2.57
17	777.54	666.4	4.46	76.6	658.128	4.46	760.38	615.11	0.94	693.83	67.4	670.968	3.61
18	673.28	666.48	1.34	66.9	669.168	1.96	659.77	621.98	0.42	564.68	51.5	673.528	1.81
19	770.92	642.67	1.36	72.2	659.75	2.2	741.17	617.86	0.21	617.64	56.8	631.132	2.14
20	656.83	648.25	1.87	76.2	660.148	3.16	598.17	612.04	0.62	595.03	53.8	655.204	2.33
21	770.92	667.12	1.03	80.3	667.78	2.2	748.08	627.08	0.94	670.25	61	723.748	5.21
22	740.76	672.82	2.48	71.6	662.04	4.45	723.31	637.33	1.23	623.21	56.7	682.764	3.03
23	858.12	664.85	1.19	83.7	620.726	0.62	799.94	602.22	0.69	696.57	50.8	676.2	2.8
24	784.84	650.03	1.67	63.8	648.408	0.96	775.87	636.57	1.16	622.14	40.5	662.15	2.42
25	822.6	598.32	0.96	82.4	611.274	1.23	792.99	561.72	0.16	708.19	62.8	654.224	3.73
26	749.8	674.65	3.95	76.7	653.248	1.41	690.42	635.92	1.29	529.44	43.8	681.796	5.17
27	787.6	673.41	1.48	72.5	656.06	0.75	640.44	619.42	0.87	584.21	51	675.876	2.77
28	777.52	646.33	1.51	82.8	643.8	1.65	789.4	614.93	1.18	595.58	48.4	660.036	2.97
29	866.16	606.63	1.54	72.8	642.358	0.96	809.79	587.86	0.73	851.25	51.8	613.36	1.42
30	837.24	633.68	0.34	79.9	675.738	1.46	587.39	600.95	0.27	635.29	56.8	694.112	2.24
31	741.96	643.5	0.69	75.9	638.882	0.64	717.55	622	0.37	616.76	56.6	672.17	2.98
32	696.42	663.37	2.53	69.5	671.884	0.18	629.78	637.52	1.44	566.06	47.8	705.88	5.35
33	738.14	656.64	0.43	71.4	657.126	1.12	705.33	643.91	0.36	600.81	51.5	672.988	1.76
34	910.47	611.77	2.94	87.1	622.198	0.76	893.86	589.99	0.93	788.73	66.7	632.752	3.04
35	631.4	676.97	1.02	66.1	675.808	1.46	628.28	639.02	0.09	549.61	47.3	747.592	4.59
36	744.22	656.72	2.47	75	653.108	1.21	701.1	625.19	1.59	706.66	58.6	663.74	4.05
37	773.44	656.73	3.77	66.1	651.23	0.85	695.34	634.11	0.94	578.32	52.9	657.952	1.29
38	638.7	666.2	1.5	64.1	636.818	1.56	610.39	641.88	0.73	603.49	50.1	660.108	3.16
39	961.28	607.47	1.62	90.9	596.454	2.08	891.69	586.27	1.51	818.15	73.1	613.06	1.95
40	702.7	620.68	0.99	65.6	638.7	0.25	655.62	588.44	0.04	602.77	51.7	650.94	3.8
41	688.76	656.86	0.45	73.2	667.938	1.11	626.3	634.61	0.06	606.34	50	687.052	4.54
42	763.04	647.37	0.87	61.9	641.118	0.66	708.07	614.98	0.09	717.19	60.5	682.744	5.63
43	812.74	622.67	1.54	77.6	615.564	1.63	802.57	605.63	1.08	735.98	64.7	630.42	1.15
44	763.6	660.53	0.42	74.6	659.654	1.63	659.91	624.01	0.56	634.58	56.8	672.268	3.36
45	767.16	613.52	0.88	75.7	620.71	1.55	710.34	590.12	0.2	613.51	56.1	624.916	0.82
46	716.65	663.62	1.08	76	653.948	0.36	620.65	610.41	1.15	568.43	52.5	687.472	1.44
47	822.73	635.86	1.84	75.6	615.916	1.47	715.03	592.1	0.38	676.01	57.7	671.784	4.43
48	826.85	667.95	1.48	75.9	662.266	1.32	608.39	636.42	0.22	598.89	52.9	693.48	3.1
49	858.26	642.38	1.7	84.8	637.212	1.04	771.91	621.29	0.68	750.82	66.5	651.048	1.21
50	784.1	662.35	2.25	68.5	678.554	3.38	742.1	620.52	0.42	588.51	50.3	694.952	3.79
51	912	663.16	2.51	84.6	660.164	1.68	615.91	641.36	0.52	615.9	53.8	689.28	1.6
52	670.85	640.83	1	73.9	679.072	2.69	599.78	626.03	0.93	591.17	51.1	695.576	5.52
53	804.92	649.66	2.01	77.7	634.02	1.85	751.14	595.29	0.68	662.61	59.4	672.168	2.61
54	677.17	683.98	2.78	66.2	690.306	1.32	627.09	643.22	0.85	570.55	49.8	703.948	2.96
55	787.09	662.88	0.82	72.1	664.774	1.18	603.11	625.38	0.87	716.73	59	664.704	3.58
56	752.45	625.61	1.63	70.1	608.422	1.89	668.07	577.97	0.74	631.64	55.8	629.788	2.76
57	1113.45	621.89	1.47	100.8	630.458	1.71	1048.51	595.05	1.95	867.89	74.9	644.236	4.47
58	859.99	649.17	3.26	69.6	658.73	1.55	763.48	610.79	0.81	703.52	57.9	661	2.5
59	666.45	663.91	0.55	47.3	673.114	2.33	548.05	625.76	0.72	520.91	43.7	678.772	5.44
60	788.5	619.19	0.48	72.8	632.922	0.64	685.18	599.42	1.24	657.99	57.5	633.208	1.41
61	823.19	651.04	0.84	79.9	645.988	2.41	784.6	629.35	1.61	604.77	51.3	695.112	4.74
62	789.13	648.29	1.51	81.9	656.726	0.62	739.43	614.47	0.6	634.32	59.1	657.624	4.23
63	971.56	622.89	2.86	99.7	599.256	0.67	809.07	575.03	1.21	774.92	66.5	627.612	3.49
64	722.85	642.38	0.22	73.7	658.43	2.45	622.09	612.1	1.49	596.9	53.2	661.232	2.89
65	709.08	684.21	1.69	61.6	679.638	1.26	566.03	642.77	0.44	559.92	50.9	689.104	2.33

66	784.45	651.43	0.87	72.2	675.934	2.03	763.03	637.08	0.66	581.63	53.7	681.408	2.16
67	701.88	676.26	0.95	68.5	683.22	2.7	600.26	646.4	0.41	549.13	47	714.952	3.79
68	871.19	664	0	80.5	648.84	1	739.35	620.12	0.38	641.68	53.5	711.34	6.05
69	650.58	654.43	1.89	60.5	648.158	1.31	613.56	610.39	0.96	586.81	50.9	659.104	1.58
70	666.19	650.96	2.13	70.4	626.938	1.01	578.13	615.95	1.11	501.33	43.2	689.904	3.33
71	872.27	655.85	1.47	84	646.47	3.75	793.91	616.8	0.07	768.52	66.8	664.784	1.93
72	822.53	652.46	1.34	84.1	642.12	0.2	711.56	621.41	0.69	755.98	67.8	668.588	3.76
73	720.51	658.65	2.28	59.9	659.458	2.36	675.6	616.19	0.2	574.61	49.2	670.676	3.02
74	732.31	659.6	1.44	71.9	652.216	1.32	635.79	600.25	1.51	623.83	53.8	671.468	2.36
75	735.88	651.6	0.89	74.5	655.358	1.71	592.08	605.23	1.97	584.51	51.8	663.204	3.08
76	933.45	651.37	1.61	87.3	661.226	1.97	873.23	595.23	0.3	780.48	68.3	664.38	4.85
77	747.5	631.22	2.15	76.1	626.466	2.27	715.89	599.45	1.25	627.2	54.5	653.1	3.25
78	728.71	652.28	1.32	71.6	658.72	1.55	633.49	606.48	1.34	627.08	52.4	659.056	3.62
79	695.23	624.148	2.36	77.1	624.148	2.36	641.02	627.42	0.13	551.51	47.1	661.696	3.67
80	816.52	612.85	1.19	87.2	596.894	1.93	755.86	569.39	0.68	733.43	63.2	637.812	4.24
81	870.33	651.01	1.76	71.6	637.224	0.48	777.23	614.32	0.07	655.19	56.6	655.44	1.8
82	603.47	668.91	1.2	65.9	666.25	1.5	472.02	648.66	2.47	442.64	35.6	698.352	4.29
83	1023.14	632.66	2.84	105.6	633.826	3.32	972.02	596.61	0.06	754.45	65.8	695.884	5.18
84	740.27	623.53	0.7	81.8	633.224	1.23	665.16	606.54	0.79	632.79	54.9	642.592	2.09
85	676.44	667.37	0.87	62.8	678.708	1.36	644.95	638.03	0.19	561.57	47.6	693.72	1.65
86	779.46	661.37	0.31	73.2	662.082	1.49	689.55	636.65	0.25	636.14	58.2	687.54	2.55
87	646.92	654.12	1.68	65.51	651.422	0.69	626.64	620.56	0.98	560.88	46.4	683.144	2.88
88	871.05	642.07	0.19	79.6	665.684	0.53	766.55	624.62	0.24	647.62	55.5	711.024	3.98
89	744.72	643.11	0.84	71.5	624.556	1.72	637.81	613.22	1.41	617.04	55	662.928	2.31
90	800.99	632.2	0.94	71.7	643.182	1.59	766.92	620.87	0.45	611.8	55	656.68	2.1
91	922.3	631.1	2.69	90	628.464	0.78	828.52	590.72	2.32	678.98	63.4	663.976	2.77
92	771.13	668.33	0.22	72.9	672.796	1.92	637.27	642.85	1.19	586.06	51.3	690.616	4.32
93	613.49	684.26	1.32	63.4	685.87	1.1	567.18	635.06	0.47	530.09	47.2	696.872	1.94
94	795.78	644.53	1.72	73.5	640.1	0.75	743.21	613.26	0.3	646.06	57.2	680.704	3.58
95	708.34	630.19	3.54	70.4	623.786	2.57	586.46	598.54	1.16	593.06	48.6	677.724	4.98
96	660.87	658.19	0.76	68.8	666.01	1.85	536.8	618.66	1.54	526.39	46.1	669.464	3.28
97	839.48	635.87	0.54	82.4	663.796	2.57	685.26	601.66	0.34	563.96	49.2	693.068	4.36
98	818.9	640.16	0.94	91.2	624.568	1.91	758.87	616.5	0.97	711.47	67.3	651.044	2.88
99	756.56	669.48	2.36	68.1	670.548	2.46	674.13	622.81	1	575.27	55.5	687.888	3.51
100	773.17	637.18	0.66	68.8	660.478	0.41	671.67	605.6	0.52	644.72	56.3	662.724	1.73

Appendix B – Simulation Input Data

	tailNumber						
Input parameter	1	2	3	4	5	6	7
ageFH	453	558	247	398	475	455	224
TTCL	168	504	840	1176	1512	1848	2184
rul1	139	79	31	143	146	110	150
rul2	149	57	88	90	94	12	22
rul3	51	16	98	13	88	90	69
rul4	88	21	44	125	35	53	25
rul5	12	6	39	76	137	14	145
rul6	56	104	134	108	97	147	31
rul7	143	141	68	53	96	13	76
rul8	101	149	63	37	95	7	90
rul9	122	15	90	74	80	90	35
rul10	19	149	109	83	122	88	56
rul11	26	31	65	140	80	110	32
rul12	120	112	60	78	85	122	126
rul13	97	87	103	137	39	133	12
rul14	53	86	9	29	127	13	27
rul15	82	77	66	119	35	89	43
rul16	79	76	26	131	37	124	32
rul17	66	141	144	119	100	105	99
MTBF	73	73	73	73	73	73	73

FOLHA DE REGISTRO DO DOCUMENTO

1. CLASSIFICAÇÃO/TIPO	2. DATA	3. REGISTRO N°	4. N° DE PÁGINAS
TD	24 de janeiro de 2023	DCTA/ITA/DM-065/2022	125

5. TÍTULO E SUBTÍTULO:

A military aircraft fleet support management model based on the optimal integration of predictive and scheduled maintenance.

6. AUTOR(ES):

Danilo Garcia Figueiredo Pinto

7. INSTITUIÇÃO(ÕES)/ÓRGÃO(S) INTERNO(S)/DIVISÃO(ÕES):

Instituto Tecnológico de Aeronáutica – ITA

8. PALAVRAS-CHAVE SUGERIDAS PELO AUTOR:

PHM (Prognostics and Health Management); IVHM (Integrated Vehicle Health Management); Optimisation; Hybrid Simulation; Complex Systems Support; Aviation Maintenance; Predictive Maintenance; Maintenance Modelling; Military Aviation.

9.PALAVRAS-CHAVE RESULTANTES DE INDEXAÇÃO:

Logística (administração); Manutenção de aeronaves; Manutenção preditiva; Planejamento; Sistemas complexos; Consciência situacional; Aviação militar; Frotas aéreas; Pesquisa operacional.

10. APRESENTAÇÃO: **(X) Nacional ( ) Internacional**

ITA, São José dos Campos. Curso de Doutorado. Programa de Pós-Graduação em Ciências e Tecnologias Espaciais (PG/CTE). Área de Gestão Tecnológica. Orientador: Dr. Fernando Teixeira Mendes Abrahão. Defesa em 19/12/2022. Publicada em 2022.

11. RESUMO:

Advances in sensor technologies, the expansion of data analytics techniques and the improvement of machine learning algorithms have enabled new aviation maintenance strategies with potential to further improve fleet availability while also reducing costs. The problem facing these new approaches is that the direct migration of scheduled tasks previously packed in periodic checks to prediction-based ones can result in increased total downtime for the fleet. The optimised integration of predictive maintenance with the overall maintenance plan plays a key role in this scenario. The forecast-based interventions seek the maximum exploitation of equipment's useful life whereas avoiding incremented risks of running into failure. In spite of those enhanced diagnosis capabilities, the uncertainty inherent to predictions of future health states remains a substantial challenge that needs to be reflected in any modelling process, especially when projected over long enough horizons as to allow for better operations and maintenance planning and preparation. A significant number of studies in the field focus solely on increasing forecast accuracy for a single component. Another large portion of the literature deals with multi-components condition monitoring problems restricted to a single platform. Other studies consider only remaining useful life estimates without accounting for the levels of confidence associated with the results provided. This thesis proposes an innovative model that seamlessly integrates predictive and scheduled maintenance tasks in a single operational framework with the objective of optimizing overall fleet availability. The initial concept was demonstrated and verified by the means of exploratory examples, and then expanded to address larger numbers of aircraft and components with fewer assumptions granting more robustness to the solution. The ensuing model was tested, verified and validated with the implementation of a mixed agent-based and discrete-event simulation model created with Anylogic©. The results demonstrated this study's contribution value and confirmed the expected potential to generate gains in availability, having displayed a statistically consistent reduction in total downtime for the case under analysis, which consists of a military fleet of fighter jets operating from a single base. Subsequentially, the results analysis clarified the advantages provided by the integration of predictive maintenance into traditional scheduled maintenance plans. At the end, the limitations of this study were acknowledged and highlighted as conclusions were drawn. The final comments point to potential further developments offered by his approach which led to recommendations for future studies.

12. GRAU DE SIGILO:

(X) OSTENSIVO **( ) RESERVADO** **( ) SECRETO**