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ABSTRACT

Maintaining high-complexity aircraft requires resilient and data-driven maintenance planning. This article presents the Efficient Task Allocation and Packing Problem Solver (ETTAPS), a novel framework that integrates predictive analytics and optimisation models to generate adaptive maintenance schedules. ETTAPS employs a trial-and-error approach to optimise maintenance intervals, leveraging a branch-and-cut solver combined with First-Fit Decreasing (FFD) task grouping to minimise costs and enhance aircraft availability. Additionally, a Random Forest model, retrained using a rolling 24-month data window, continuously refines predictions, leading to progressive cost reductions and improved system reliability over multiple maintenance cycles. Our results demonstrate that ETTAPS significantly reduces maintenance costs and increases aircraft availability by efficiently grouping tasks and incorporating real-world constraints, such as mechanic skill levels, task dependencies, and resource limitations. The framework addresses key gaps in MSG-3 and certification analysis, improving task scheduling efficiency and ensuring long-term operational resilience. Furthermore, ETTAPS lays the groundwork for integration with digital twins, real-time anomaly detection, and flight planning systems, supporting a more intelligent and proactive approach to aircraft maintenance.This research advances resilience and sustainable aviation maintenance planning by optimising costs, reducing downtime, and proactively adapting to operational demands. By aligning with Industry 4.0 and aviation sustainability goals for 2050, ETTAPS contributes to the next generation of intelligent maintenance systems.

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1.0 Introduction

The aviation industry has made significant strides recently and continues to work toward a sustainable future. In terms of product, the incorporation of industry 4.0 concepts, use of improved materials such as carbon fibre composites, titanium alloys, and 3D-printed structures, adoption of advanced propulsion systems such as more efficient turbofans and hybrid and electrical engines, along with advancements in aerodynamics that reduce drag and improve fuel efficiency, have led to the development of more efficient and sustainable aircraft designs [Song and Liu(37), Yusaf et al.(43)].

Challenges in Preventive Maintenance

The main problem dealt with in this work is that, in the initial steps of the life cycle, PM tends to be conservative due to the limitations faced by maintenance engineers. These limitations are mainly related to the lack of models and simulations specially developed for the development of dependability, applied to the design of aircraft since their conception. The consequences are consistent with what Russel(34) presents regarding the performance of aircraft fleets such as the MD F-4 Phantom 2, which were only operated in a mature manner, from the perspective of their supportability, almost at the end of their life cycle.

Limitations in Analytics and Tools

Other limitations are the lack of maturity in predictive and prescriptive analytics, and the absence of efficient tools to monitor changes and forecast dependability data (like reliability, availability, maintainability, cost, and safety) during the development and operating phases. This may result in inefficient maintenance plans, i.e., more costly than they could be, and lower than possible operational availability. This increases interest in dynamic maintenance programs, like described by Salonen and Gopalakrishnan(35).

Limitations in existing analytics and tools significantly hinder the development of optimal maintenance strategies. In particular, predictive and prescriptive analytics are not yet developed enough to accurately predict when parts will fail and suggest maintenance actions that are both cost-effective [e.g., Lei et al.(26); Goyal and Purohit(17)]. This immaturity often leads to inaccurate predictions, resulting in unnecessary maintenance or, conversely, unexpected failures and costly downtime, as illustrated by case studies in industries such as aviation and manufacturing.

Additionally, our current tools often lack the necessary features to monitor changes in crucial dependability data, such as real-time sensor data and degradation trends. This has been shown in studies that look at the flaws in condition-monitoring systems and Internet of Things (IoT) frameworks [e.g., Tsang et al.(39)]. This makes it challenging to dynamically adjust maintenance plans in response to changing operating conditions, leading to potentially suboptimal schedules and reduced operational availability.

Some new studies, like those using machine learning for maintenance [Li et al.(27); Wen et al.(41)] and digital twin technology for real-time simulation and monitoring [Tao et al.(38)], show promise for ways to get around these problems. However, further development and testing are necessary.

During our broad research of Maintenance Repair & Overhaul (MRO) tools, we found significant drawbacks when adding machine learning. AMOS uses external Machine Learning (ML) technologies with poor internal integration, creating data silos and reducing real-time adaptability. Traxx has powerful ML capabilities but is expensive and demanding with a sophisticated cloud implementation. For sophisticated applications, OASES has limited ML support, static maintenance planning, and scalability. ML use is difficult for smaller operators due to data quality and vendor lock-in, and TRAX may be expensive. OASES and others serve smaller operators without ML, exposing resilient maintenance planning scalability and adaptation issues. Up to this moment, an exploratory analysis identified no resilient maintenance plan employing these technologies.

Defining the Task Allocation and Packing Problem (TAPP)

To solve this problem, it is necessary to efficiently allocate tasks to maintenance packages (scheduled stoppages), and then schedule the tasks in each package to minimize the maintenance duration. We named this problem as *Task Allocation and Packing Problem (TAPP).*

Some recent studies investigated the issue of PM scheduling for a high-complexity mechanical device with different failure modes [Duan et al.[7]]. Another presented an optimization for a disassembly sequence planning approach applied to PM [Kheder et al.[25]]. Gonçalves et al.[16] discussed how to set up an initial maintenance program for unmanned aerial vehicles (UAVs) following the Maintenance Steering Group (MSG-3) approach. Gill and Szrama[14] presented a method for adopting and developing an effective aircraft maintenance program using proper tools for risk analysis, optimal interval assignments, and effective maintenance task selection.

Maintenance Planning in the Aeronautical Context

In the aeronautical context, two different processes are used in the initial maintenance requirements of an aircraft: type certification (TC) process for aircraft maintenance, and Maintenance Review Board (MRB) [FAA[11]]. Through the MRB process, manufacturers, regulatory authorities, vendors, operators, and industry together develop the initial scheduled maintenance and inspection requirements for new aircraft [Ahmadi et al.[1]].

Nevertheless, several crucial elements, including the expenses associated with implementing corrective measures based on the likelihood of item failures, the costs incurred from production disruptions, the benefits derived from the subsequent maintenance package, and the utilization of predictive analytics methodologies, are frequently overlooked. Thus, investigating the possibility of including issues related to costs and savings in the aircraft development stages is an important problem for researchers.

Emerging Technologies in Maintenance

Further, the introduction of state-of-the-art technologies has made it possible to move from maintenance planning based on experiences and assumptions to smart sensors, ML, and big data analytics support. These new technological possibilities enable predicting events that were previously difficult to predict [Salonen and Gopalakrishnan(35)].

Gunda et al.(18) used ML to identify and categorize records into common failure modes, which identified distinct variations in failure frequencies over time and across equipment types. These findings helped inform a number of ongoing activities focused on further, including equipment reliability simulation analyses, spare parts inventory management, and cost model estimates for operations and maintenance.

Cardoso and Ferreira(5) stated that it is extremely common in maintenance applications to start from data of different types and from various sources, which led them to treat data with predictive analytics tools in the analysis of maintenance data. One of the main objectives of the ML models used was to predict the probability of failure occurring within a certain time window.

Problem Definition

Airlines face increasing pressure to optimize aircraft maintenance planning to **reduce costs, minimize downtime, and enhance operational availability**. Traditional maintenance strategies often rely on static scheduling or reactive approaches, leading to inefficiencies in resource allocation and increased operational disruptions.

By leveraging **predictive analytics and optimization methods**, airlines can shift toward **data-driven maintenance planning** that dynamically adapts to evolving operational conditions. However, a key challenge lies in **efficiently integrating predictive insights into actionable maintenance schedules**, ensuring that maintenance **tasks are optimally grouped and resources are effectively utilized**.

This study seeks to address the question: *How can predictive analytics and optimization methods be combined to improve aircraft maintenance planning, ensuring cost-effectiveness and operational resilience while maintaining regulatory compliance?*

Proposed Solution for TAPP

To solve the TAPP, this paper proposes a data learning model, working in a closed-loop with an optimization model, to generate a resilient maintenance plan. The aim is to support the development of an initial maintenance plan assuring adequate maturity at entry to service, and proactively update it throughout their life-cycle.

Figure 1 presents a general idea of the proposed solution, which will be detailed in Section 3.

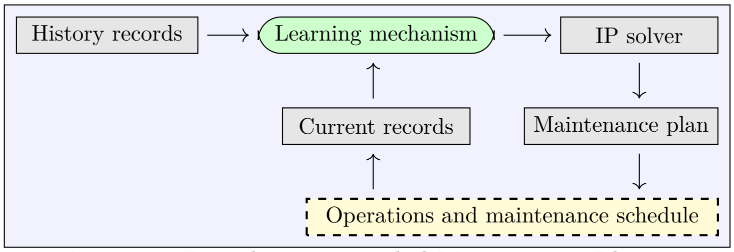

Figure 1: Data-learning-guided Maintenance Planner

Article organization

The remainder of this article is structured as follows: **Section 2** reviews relevant literature on aircraft maintenance planning and optimization. **Section 3** introduces the Efficient Task Allocation and Packing Problem Solver (ETTAPS) framework. **Section 4** details the methodology and modeling techniques. **Section 5** presents the results and discusses the findings. Finally, **Section 6** concludes the paper and suggests future research directions.

2.0 Literature Review

This section presents a review of the literature concerning the maintenance plan development, the maintenance data required, and discusses the use of predictive analytics to improve the efficiency of a new product's maintenance.

The study by Plastropoulos et al.[(32)] explores the transition to smart hangars, emphasizing the integration of Industry 4.0 technologies like AI, robotics, and digital twins to enhance maintenance efficiency and sustainability. These advancements align with the principles of predictive and prescriptive maintenance discussed in the literature, addressing challenges such as analytics maturity and legacy system integration. Proposed solutions, including human-machine collaboration and energy efficiency, complement strategies like dynamic maintenance programs and the Task Allocation and Packing Problem (TAPP). Together, these efforts highlight the potential of smart hangars to reduce downtime, optimize costs, and support aviation's sustainability goals by 2050.

2.1 Development of the aircraft maintenance requirements

This study focuses on the development of initial maintenance plans for transport-category aircraft complying with 14 CFR Part 25 and operating under 14 CFR Part 121 regulations. The manufacturer's Instructions for Continued Airworthiness (ICAs), required by the CFR 25.1529 and CFR 25.1729, typically form the basis of an approved air operator's maintenance plan.

For transport category aircraft, maintenance tasks and intervals are specified in either the Maintenance Task Board (MTB) or in the Maintenance Review Board (MRB) report, depending on the aircraft's capacity [FAA[(9)]].

Additional maintenance information required for developing the operator's maintenance plan is provided in the type certificate holder's Maintenance Planning Document (MPD) or relevant chapters of the maintenance manual.

For non-transport category aircraft, maintenance requirements can be developed in accordance with FAA Order 8110.54 or, alternatively, through the MRB/MTB process [FAA (10)].

The initial maintenance requirements for a new commercial aircraft are derived from the Type Certification (TC) and the MRB processes. Modifications to an aircraft's design, performance, or systems that are not covered by the original TC require a Supplemental Type Certificate (STC), as defined in 14 CFR Part 21. STCs introduce changes that can significantly impact continuing airworthiness.

The STC approval process, similar to the TC process, necessitates a thorough evaluation and may require revisions to the ICAs. This includes updates to the MSG-3 data and maintenance requirements, potentially leading to the creation of new maintenance tasks, revisions to existing tasks, or even the deletion of obsolete tasks.

2.2 Emerging technologies

Digital technology and the use of e-maintenance features permit real-time data analysis and the ability to monitor and predict the health of systems. This improves condition-based maintenance effectiveness and allows for the implementation of predictive and prescriptive maintenance strategies.

Proper maintenance strategies can ensure the cost-effective and safe use of high-complexity systems [Mlynarski et al. (29)]. In this sense, high-complexity systems need to perform planned PM to reduce the probability of sudden failures, restore functionalities, and extend their useful life as much as possible.

The aviation industry has made significant strides recently, not only in developing sustainable aircraft designs but also in enhancing operational efficiency through proactive maintenance strategies. In alignment with Industry 4.0 concepts, advancements in maintenance planning now integrate predictive analytics and optimization frameworks to reduce downtime and improve aircraft availability. These strategies complement improvements in aircraft design, such as the use of carbon fiber composites, titanium alloys, and 3D-printed structures, by ensuring that maintenance processes are as innovative and efficient as the aircraft themselves. Additionally, the adoption of advanced technologies like prognostic health monitoring and digital twins has enabled the aviation sector to anticipate and address maintenance needs, creating resilient and adaptive maintenance plans that align with sustainability and operational goals [Song and Liu (37), Yusaf et al. (43)].

Kabashkin (24) presents a study with a comprehensive framework for integrating digital twins into aircraft lifecycle management. The framework leverages IoT sensors, big data analytics, machine learning, 6G communication, and cloud computing to create a robust ecosystem. A key achievement is the integration of physics-based, data-driven, and hybrid models to enhance predictive maintenance and decision-making. However, limitations include challenges in real-time data integration, ensuring model accuracy, and data security concerns due to multi-stakeholder involvement.

Giacotto et al. (13) present a framework for prescriptive maintenance that deals with issues that come up in Industry 4.0 settings, such as combining different types of data sources and creating accurate models that can predict when equipment will break down or become less useful. The authors highlight the importance of considering maintenance actions based on predicted outcomes and costs, as well as the need for scalable frameworks. The study focuses on developing a holistic and scalable smart prescriptive optimisation framework that provides an optimal course of action and can be extended across industries and assets with different technological maturities. The results show that the framework works to make maintenance more efficient and effective. This impacts numerous industries and paves the way for proactive and effective maintenance practices in digitalisation and prescriptive analytics.

2.3 Maintenance plan development and data

In the aeronautical industry, the operators are required to have a continuing analysis and surveillance system to ensure the effectiveness of the maintenance and inspection program [FAA(8)]. This enforces that the optimal maintenance strategy for a component or a multi-component system can significantly influence, minimising costs and downtime [Rebaiaia and Ait-kadi(33)]. In the case of a new engineered system, data from an existing, similar system can be reasonably used [O'Connor and Kleyner(30)].

To check how reliable a system is at first, you can also use military or commercial standard guidelines, like MIL-HDBK-217F, NPRD (*Non-electronic Parts Reliability Data*), and FMD (*Failure Mode/Mechanism Distributions*). The concepts and guidelines for dependability testing throughout system development can be found in MIL-HDBK-189C.

[Usuga-Cadavid et al.(40)] stated that the dynamic nature of data during the development and operational phases presents both opportunities and challenges for maintenance planning. While data mining and ML tools can extract valuable insights from this evolving data to improve maintenance decisions, the complexity of these systems can hinder understanding and interpretation. Specifically, the interaction between human operators and the predictions generated by ML models can be difficult to grasp, potentially limiting the adoption and effectiveness of these tools.

2.4 Maintenance program evolution

We assume that the objective of maintenance program evolution is to keep the maintenance plan updated to maintain its effectiveness. In the operational phase, we establish a program to control in-service dependability. The program encompasses a collection of regulations and methodologies aimed at observing and assessing performance, as well as issuing notifications if any corrective measures are deemed necessary. Furthermore, it offers the necessary data to support the modification of the maintenance plan.

Although it can occur at any phase of the product's life cycle, the optimisation analysis is more effective if carried out as early as possible. According to Blanchard and Blyler(3), without a focus on the dependability aspects from the start of the system design, several logistical support problems are prone to occur, impacting the system performance and costs.

During the operational phase, a program for controlling in-service dependability is established, as required by CFR 14 Part 121.373.

The *Continuing Analysis and Surveillance System* program is a set of rules and methods for keeping an eye on and judging performance, as well as sending out alerts if any corrective actions are thought to be needed. Furthermore, it offers the necessary data to support the modification of the maintenance plan.

In addition to alterations derived from its continuing performance and effectiveness analysis, the maintenance plan may be modified in response to major repairs, *Airworthiness Directives*, or *Service Bulletins*.

Furthermore, after a certain period of operation, the *Type Certificate Holder* and operators can propose to the authorities a program to implement a complete evolution of the MRB report. The guidelines for running this evolution process are described in the *International MRB/MTB Process Standard*(21).

A framework for a resilient maintenance plan is expected to collect, analyse, and evaluate data using ML tools to proactively spot areas where the current maintenance strategy can be improved.

2.5 Maintenance optimization approaches

de Jonge and Scarf(23)'s review offers a comprehensive overview of maintenance optimization models, categorizing them by system characteristics and optimization criteria. The paper highlights the increasing importance of data-driven approaches and identifies key research gaps. While focusing primarily on theoretical models, it provides a valuable resource for researchers and practitioners, facilitating model selection and guiding future research in this dynamic field. The review's structured approach and insightful discussion of trends contribute significantly to the understanding of maintenance optimization.

2.6 Predictive Maintenance with Machine Learning

This subsection describes a system for predictive maintenance using ML. The system leverages historical data on maintenance and equipment failures to proactively plan future maintenance tasks.

Hu et al.(20)'s review provides a comprehensive overview of *Prognostics and Health Management (PHM)*, focusing on the interconnectedness of design, development, and decision-making. The paper covers data acquisition, feature extraction, prognostic model development, and decision strategies, highlighting the role of enabling technologies. While comprehensive, a deeper dive into the specific challenges of individual techniques could be beneficial. Overall, the review offers valuable insights for researchers and practitioners, providing a framework for understanding and implementing effective PHM systems.

As stated before, the work of Kabashkin(24) proposes a comprehensive digital twin framework for aircraft lifecycle management, using IoT, big data, machine learning, 6G, and cloud computing to enhance predictive maintenance via integrated models. Challenges include real-time data integration, model accuracy, and data security, which federated learning and blockchain aim to address, supporting predictive maintenance's digital transformation.

Cao et al.[4] propose a data fusion method for failure rate analysis and maintenance plan optimization for civil aircraft parts. The approach integrates data from multiple sources, including maintenance records, sensor data, and expert knowledge, to improve the accuracy of failure rate predictions. While the concept of data fusion is promising, the paper could benefit from more detailed explanations of the specific techniques used and a more thorough evaluation with real-world data. The focus on failure rate prediction, while important, leaves open the question of how these predictions are incorporated into a full maintenance optimization framework.

Key points of ML to predictive maintenance:

- The ML model continuously analyses maintenance records and predicts potential equipment degradation based on predefined thresholds.
- With dynamic maintenance plans, the model generates maintenance plans that adapt to changes in equipment performance, aiming to:
  - Ensure equipment is available for use when needed; and
  - Avoid unnecessary maintenance while preventing failures.

Data handling:

- In the early phases, use historical data from similar systems to generate initial maintenance plans.
- As actual data is collected, the model's accuracy improves, leading to more efficient maintenance plans.

Benefits of ML tools in predictive maintenance:

- Proactive maintenance helps prevent unexpected equipment failures.
- Optimized maintenance plans avoid unnecessary repairs.
- Equipment is more frequently available for use when needed.

Overall, this system uses machine learning to analyse historical and real-time data, enabling the creation of dynamic and data-driven maintenance plans that optimize both equipment performance and cost efficiency.

2.7 An aircraft fleet as a resilient system

The resilience of a high-complexity system can be understood as its ability to fulfil its mission through attributes that protect its functionalities and parts while also allowing for precision in information, situational awareness, and the ability to diagnose and recover from any one of these features.

It is necessary to contextualize the environment where aircraft fleet operate and the meaning of resilience for a more profound understanding of the objectives of this work. Every high-complexity aerospace system is a system that operates to meet service-level requirements (for the market, in the case of the private sector fleet, and for readiness, in the case of defence systems, [Goerger et al.[15]].

Figure 2 shows the behaviour of support performance for an aircraft fleet. It considers the entire life cycle from the conceptual phase through *Conception*, *Research & Development*, *Production*, *Operation & Support*, and *Disposal*.

From the beginning of the conceptual phase to the delivery of the first aircraft, there is an expected growth in service level and dependability requirements (*Curve 1*). A late entry of supportability requirements can lead to the case of *Curve 2*.

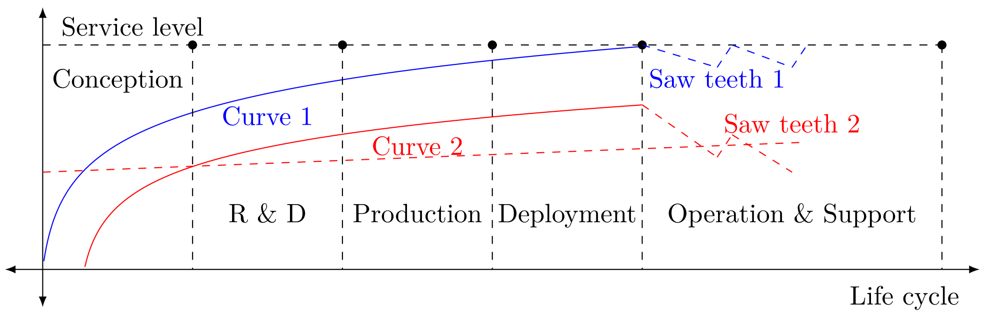

Figure 2: Observed support performance behaviour.

By observing what happens after the delivery of the first aircraft, the service levels may present degradation that, if not treated properly and in a timely manner, would imply benefit/cost degradation for the fleet. The performance demonstrated in *Saw teeth 1* considers system that automatically realigns and corrects the entire maintenance and support program to prevent such eventual degradation.

A system that adheres to *Curve 1* and its continuity throughout the operation and support phase (*Saw teeth 1*) represents a support system that learns and is resilient throughout the entire fleet life-cycle.

A system that behaves like *Curve 2* represents a support and maintenance system that took too long to be developed. It is expected to have a great delay in its maturity target (if it gets there). The performance of this product until its maintenance must therefore imply a series of wastes and extra costs (*Saw teeth 2*) that the present paper aims to avoid.

We hypothesize that, with the use of the framework proposed, we expect that the system will learn to improve the maintenance plan by intelligently exploring historical data acquired during product development and operation.

3.0 Description of proposed method

We consider a continuous optimization of maintenance planning by integrating predictive analytics (*Learning mechanism*) into the solution process to common issues the industry faces in developing the initial (*Conception* and *Development* phases of the life-cycle) maintenance program.

The certification and maintenance review board process tells the optimization module what tasks need to be done and how often they need to be done. It then uses the available maintenance data (history and current records) to figure out how to assign tasks to the predefined maintenance packages.

Our proposed integer programming (IP) solver looks at each grouping of tasks into maintenance packages based on how much they are expected to cost, whether they need to be fixed before or during the preventive task, and the money that will be lost or not gained when the system is down.

Among the maintenance tasks are the preparation tasks, which are maintenance actions that are performed before and after the main tasks (access openings, energy supply, compressed air supply, air conditioning, etc.). The proposed method also considers the economy generated by allocating common preparation tasks once, minimizing the repetition of these common tasks, which would represent extra resource consumption.

Field data from the operations and maintenance schedule is collected and monitored to be used to feed back into the resilient planner's database, enabling the continued learning process (the ML pipeline). Figure 1 presents a high-level schematic of the proposed task allocation procedure.

Predictive Maintenance for Aeronautical Engines with Machine Learning

We accomplished a case study that applies machine learning to aircraft engine sensor data to predict failures. Using historical maintenance logs and sensor readings, we trained models to identify failure patterns and optimize predictive maintenance.

Below is a description of the three common types of machine learning strategies employed.

- To predict a continuous value we used **Random-Forest Regression**: Time-to-Failure (TTF), for each cycle/engine, is the number cycles between that cycle and last cycle of the engine in the training data.
- To categorize data into one of two distinct cycle bands, we used **Binary Classification:** if the remaining cycles (TTF) is less than a specific number of cycles (e.g.. 30) then the engine will fail in this period. Otherwise the engine is fine.
- **Multi-class Classification** was used to categorize failure risk into predefined cycle bands (e.g., 0-15, 16-30, 30+ cycles before failure). These bands allow maintenance teams to prioritize inspections and schedule preventive maintenance before failure occurs.

The insights gained from this case study provide a foundation for applying predictive maintenance models to other aircraft components. Future research will explore integrating these models with the ETTAPS framework to optimise fleet-wide maintenance schedules.

4.0 Methodology and Modelling

The IP solver used in this work was the *Computer Infrastructure for Operations Research (CoIn-OR) Branch and Cut (CBC)* developed and maintained by Forrest et al.[12], as well as *Python 3*, with the following libraries: *NumPy* (Harris et al.[19]); *pandas* (McKinney et al.[28]); and *scikit-learn* (Pedregosa et al.[31]).

4.1 Maintenance Plan Development Process

Figure 3 presents the flow of information to generate the initial maintenance requirements and appropriately allocate them in the operator's maintenance plan.

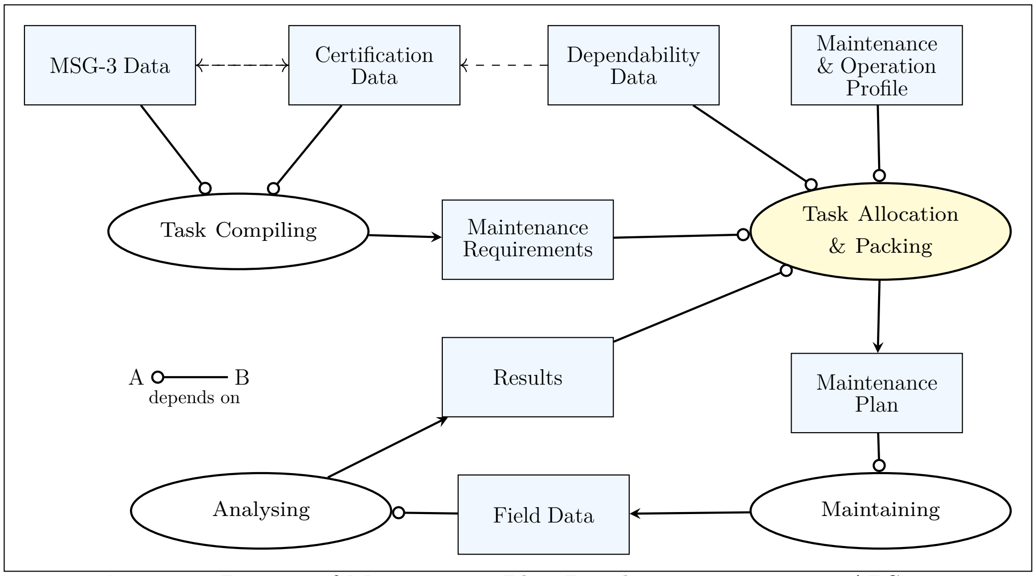

Figure 3: Process of Maintenance Plan Development using ETTAPS.

The *Object Process Methodology (OPM)* guided the design of Figure 3. OPM is a conceptual modeling language and methodology for capturing knowledge and designing systems, specified as *ISO/PAS 19450*. OPM was conceived and developed by Dori[(6)] and is chosen for its ability to concisely represent both the structural (objects) and behavioral (processes) aspects of this complex system.

MSG-3 Data, which gives maintenance guidelines from the *Maintenance Steering Group 3* process, is an object in the maintenance plan development process that stands for important information or physical things. Certification Data, encompassing data from aircraft type certification, including safety requirements; *Dependability Data*, representing *Reliability, Availability, Maintainability, and Safety (RAMS)* data; *Maintenance & Operation Profile*, detailing the operational context and maintenance history of the aircraft or fleet; *Maintenance Requirements*, specifying the necessary maintenance tasks and procedures; The Results section contains the outcomes from the *Analysing* process, such as predictive or prescriptive models.

Maintenance Plan, outlining the scheduled maintenance activities, task allocation, and resource allocation; and *Field Data*, which is collected during the execution of the maintenance activities.The representation of links between objects and processes takes the following form: There are solid arrows that show how objects are used or fed into processes. For example, the *MSG-3 Data* and *Certification Data* instrument is used for task compilation, dependability data, the maintenance and operation profile, maintenance requirements, and results.

The maintenance plan instruments are used for task allocation and packing. The field data instruments are used for analysis. Control links (dashed arrows) show how objects influence or constrain processes; for example, *Dependability Data* controls *Task Allocation & Packing*. Procedural links *A depends on B* indicate process dependencies; for example, *Analyzing* depends on *Field Data*.

Some important things to notice about the diagram are the feedback loop: field data informs analysis, and results inform task assignment and packing. This shows that maintenance planning is an iterative process. Multiple objects influence the central task allocation and packing process, which in turn produces the maintenance plan. The diagram emphasizes a data-driven approach, highlighting the importance of data from various sources (*MSG-3, Certification, Dependability, Field*). Finally, it illustrates a systematic process, moving from high-level guidelines to specific tasks and schedules.

4.2 Predicting Maintenance Needs with Machine Learning

This system uses historical data to predict future maintenance needs for equipment. Here's how it works:

- **Learning from the past:** We analyse past maintenance data using a technique called supervised learning. This helps us identify a mathematical relationship (the mapping function) between changes in various factors and future maintenance outcomes.
- **Identifying important factors:** Not all information in the data is equally important for predicting future needs. We carefully select the most relevant factors (features), such as maintenance date, labour hours, and material costs, to improve the accuracy of our predictions.
- **Choosing the best fit:** We use a specific technique called Random Forest regression to explore different types of relationships between the chosen features and the desired outcome. This helps us find the best mathematical formula (the mapping function) to represent that relationship.
- **Making predictions:** Once we have a reliable mapping function, we use it to predict future outcomes based on new maintenance data. This allows us to estimate various aspects like:
  - **Preventive maintenance needs:** When might equipment need routine maintenance to avoid failure?
  - **Failure rates and probabilities:** How likely is the equipment to fail in the future?
  - **Operational availability:** How much uptime can we expect from the equipment?
- **Feeding the results:** The predictions generated by the mapping function are provided to the IP solver. This solver uses these predictions to optimize future maintenance plans.

ETTAPS employs a two-stage approach. A *Random Forest* model (100 trees, max depth 10) predicts component failure probabilities, time-to-failure, remaining useful life, and maintenance costs. The probabilities are then used to create a mixed-integer program (using the *Branch & Cut algorithm*) that finds the best way to assign and schedule tasks while keeping operational constraints (like task dependencies and resource limits) in mind. Predicted failure probabilities weigh the cost of delaying tasks within the objective function of the optimization model.

We did not use deep learning (like convolutional neural networks for sensor analysis and recurrent neural networks for time series prediction) yet in this work, nor reinforcement learning (like dynamic scheduling). We are aware that new research on aviation maintenance is exploring these techniques.

ETTAPS uses *Random Forest* for prediction and mixed-integer programming for optimization. Unlike deep learning, ETTAPS effectively handles limited datasets. Unlike reinforcement learning, which often relies on simulations, ETTAPS leverages real-world maintenance data directly.

4.3 Historical records

This work uses a case of an aircraft under development to test the solution proposed. This approach was chosen because of its complexity, which will permit a broad diversity of intricacies that characterize aircraft development.

We chose important components used in aircraft under development that are commercially off-the-shelf components used in many other aircraft on the market. It is also significant that part of the maintenance history records is available: ejection pump; engine; fuel pump; hydraulic pump; starter generator and main battery. Another 80 aircraft repairable components, with some known attribute values, were added to the tests.

The general approach to the estimated parameter values for these 80 items' attributes was based on making a random choice in the range $[x_{min},\ x_{max}]$ according to the engineers' experience, where x is the parameter average considered.

As to the failure rates, we adopted what was proposed by Smith and Hinchcliffe [(36)]), that defines the observed ranges for a wide number of industry components.

The historical records generated for this work comprised: maintenance date; PM costs; man-hours spent; material consumed; operating hours; and failure probability.

Each time the operations and maintenance schedule block in Figure 1 sends a record, the learning mechanism is run to generate new slopes and bias. If a certain threshold is surpassed, the IP solver is triggered, and a new optimized maintenance plan is generated.

4.4 The TAPP Solver

This section presents the mathematical model for the *Efficient Task Allocating and Packing Problem Solver* (ETTAPS) presented in the doctoral thesis of the prime author.

This section provides the rules for any solution method to be adopted, a mathematical description of a system for maintenance planning that accounts for flight and labour times, resource availabilities, and due times.

As all variables are expected to be integer and the constraints and objective function are linear, we model TAPP as an *Integer Linear Programming* formulation.

Let $C = \{c_1, c_2, c_3, ..., c_{|C|}\}$ be a set of aircraft components, being $|C|$ the size of set C, with the following attributes each:

. $name_t$: a defining name for component c_t
. η_t: the Weibull characteristic life, the time at which 63.2% of the units are likely to fail. More details are available on *www.weibull.com*
. β_t: the Weibull shape parameter, which denotes the degradation rate if it exceeds 1.0
. $usage_t$: the usage parameter of component c_t

A component may have some usage parameters: FH (if the component is controlled by flight hour), FC (by flight cycles), or MO (monthly preventive tasks).

Let $M = \{General,\ Airframe,\ Powerplant,\ Avionics\ Inspection\}$ be a set of aviation mechanics qualifications ($qualif_r$) to be properly allocated as needed by the task, and a number of available ($available_r$) mechanics for each technical qualification. Each qualification ($qualif_r$) has the attribute $wage_r$ expressed in US$/h.

Let $Z = \{z_1, z_2, z_3, ..., z_{|Z|}\}$ be a set of aircraft zones according to the ATA-100 Specification, with the following attributes: id_x (zone z_x identifier); $area_x$ (zone area); and $limit_x$ (the maximum number of people to remain simultaneously in the zone z_x). Zones are designated physical areas of an aircraft that identify where maintenance activities occur. A maintenance task can span multiple zones.

Let $P = \{p_1, p_2, p_3, ..., p_{|P|}\}$ be a set of maintenance preparations sub-tasks, that must be performed before or after a maintenance task, to be efficiently allocated with the task to the set of packages, and not duplicated, as multiple tasks may use the same preparations.

Each preparation p_k has the following attributes:

- $name_k$: a defining name for preparation p_k, e.g., 141BL $\rightarrow$ in zone 141, open door BL
- $cost_k$: preparation p_k overall cost
- mh_k: estimated preparation p_k man-hours
- $qualif_k$: mechanic qualification needed
- $qualif_k^r$: numbers of mechanics for each qualification needed to execute the preparation task p_k
- $type_k$: a preparation or a follow-on task
- $nmec_k$: number of mechanics needed
- dt_k: estimated preparation p_k downtime

The cost for each preparation task p_k is calculated through Equation 1.

$$cost_k = mh_k \cdot wage_{qualif_k^r} + mat_k + \frac{mh_k}{nmec_k} \cdot HOC,\ for\ k \in \{1, 2, 3, \ldots, |P|\}. \quad (1)$$

Where, HOC is the hourly opportunity cost relative to revenue's losses, mh_k is the number of man-hour required, and $nmec_k$ is the quantity of mechanics necessary to accomplish the preparation p_k,.

Let $T = \{t_1, t_2, t_3, ..., t_{|T|}\}$ be a set of maintenance tasks to be efficiently allocated to one of the S packages.

By "flight time limit", we mean the maximum amount of time an aircraft can fly before it requires major maintenance or overhaul. This limit is set based on the *Hard Time* maintenance strategy, which focuses on scheduled maintenance at specific intervals, rather than relying on monitoring the aircraft's actual condition.

Each task t_j, has the following attributes:

- cid_j: component identifier
- lim_j: the flight time limits to accomplished task t_j
- pmc_j: PM cost of t_j
- $pmdt_j$: PM downtime of t_j
- $pmoc_j$: PM opportunity cost associated to $pmdt_j$
- cmc_j: CM cost associated to corrective maintenance of t_j
- $cmdt_j$: CM downtime associated to t_j
- $cmoc_j$: CM opportunity cost associated to $cmdt_j$
- $ztime_j^{xr}$: time required for each qualification m_r needed for task t_j to be executed in zone z_x
- $znum_j^{xr}$: number of mechanics of each qualification m_r needed for task t_j to be executed in zone z_x
- $zone_j$: aircraft zones where the task will be executed
- $qualif_j$: mechanic qualification needed
- $nmec_j^r$: number of mechanics of qualification (m_r) needed
- $preps_j$: list of preparations necessary to be accomplished prior or after task t_j

A task t_j may be subject to certain constraints if it is included in the same package as another task t_q. These constraints establish the relationship between the execution of tasks t_j and t_q. In this study, we used, $afterStart_q$ which implies only start task t_j after a relative task t_q finishes and $incompatible_q$ implying that task t_j must not be executed at the same time as task t_q.

Constraints of task t_j are identified according to the Table 1

Table 1: Task Relationship Codes

Task	Identification	Definition
t_j	$afterStart_q$	end t_j after starting a relative task t_q
	$beforeEnd_q$	end t_j before ending a relative task t_q
	$afterEnd_q$	end t_j after a relative task t_q finishes
	$startAfter_q$	start t_j after a relative task t_q finishes
	$incompatible_q$	task t_j must not be executed at the same time of task t_q

An important concept for this chapter is the *Opportunity Cost (OC)*. According to Wieser[(42)], OC represents the potential benefits an individual, investor, or business misses out on when choosing one alternative over another. Depending on the operating hours per day characteristic of an airline, we may establish the hourly opportunity cost (HOC) according to its *Revenue per Available Seat Mile (RASM)*.

While flying, the expenses are relative to fuel consumption and other administrative costs. While in AOG, the expenses are due to maintenance wages and supply. The cost difference: maintenance wages plus supply minus fuel consumption and uptime administrative costs may also be added to the HOC.

The equation 2 gives the reliability of a component c_t included in task t_j planned to stoppage s_i occurring at each $stop_i$ interval:

$$R_t^i = e^{-(\frac{stop_i}{\eta_t})^{\beta_t}},\ for\ t \in \{1, 2, 3, \ldots |C|\}\ ,\ for\ i \in \{1, 2, 3, \ldots |S|\} \tag{2}$$

The equation 3 gives the reliability of a component c_t included in a task t_j classified as an *Out of Phase* task to be executed in o_p stoppage at $stop_p$ interval:

$$R_t^o = e^{-(\frac{stop_p}{\eta_t})^{\beta_t}},\ for\ t \in \{1,2,3,\dots|C|\}\ ,\ for\ o \in \{1,2,3,\dots|O|\} \tag{3}$$

Let A_j be a set of P containing the preparations necessary to accomplish the task t_j.

Let D_{ij} be a set of preparations necessary to accomplish the task t_j whenever it is part of a package s_i.

$$D_{ij} = \begin{cases} A_j\ , & \text{if } x_{ij} = 1 \\ 0, & \text{if } x_{ij} = 0 \end{cases}$$

A task may seize preparations if it is included in a package, so its costs and time must be accounted for only once per package s_i.

The total number of preparations of a package s_i is defined by the set B_i, and is calculated as shown in the 4:

$$B_i = \bigcup_{j=1}^{m} D_{ij} \tag{4}$$

The preventive maintenance cost related to labour and material for each task t_j allocated in a package is calculated through Equation 5.

$$pmc_j = \sum_{r=1}^{|M|} mh_j^r \cdot wage^r + mat_j,\ for\ t,j \in \{1,2,\dots,|T|\} \tag{5}$$

The preventive maintenance opportunity cost for each task t_j is calculated through Equation 6.

$$pmoc_j = \sum_{r=1}^{|M|} \frac{mh_j^r}{nmec_j^r} \cdot HOC,\ for\ t,j \in \{1,2,\dots,|T|\} \tag{6}$$

Expression $\sum_{r=1}^{|M|} \frac{mh_j^r}{nmec_j^r}$ represents the PM downtime $pmdt_j$.

The total preventive maintenance cost for each task t_j is given by Equation 7

$$pmtc_j = pmc_j + pmoc_j,\ for\ j \in\ \{1,2,\dots,|T|\} \tag{7}$$

The equations 8 to 10 below give the task t_j inherent corrective maintenance (CM) cost calculations:

The corrective maintenance labour and material cost for each task t_j is calculated through Equation 8.

$$cmc_j = \sum_{r=1}^{|M|} mh_j^r \cdot CMCF \cdot wage^r + mat_j,\ for\ t,j \in \{1,2,3,\dots,|T|\} \tag{8}$$

The corrective maintenance opportunity cost for each task t_j is calculated through Equation 9.

$$cmoc_j = \sum_{r=1}^{|M|} \frac{mh_j^r}{nmec_j^r} \cdot CMTF \cdot HOC,\ for\ j \in \{1,2,3,\dots,|T|\} \tag{9}$$

Where, $CMCF$ is a cost factor for corrective maintenance that corresponds to the high-complexity of corrective maintenance in comparison to the preventive maintenance. $CMTF$ is the corrective maintenance time factor, which represents the increase in downtime caused by unexpected contingencies and unanticipated logistics demands, HOC is the hourly opportunity cost relative to revenue's losses, and mh_j^r is the number of man-hour of mechanics with qualification $qualif_r$ mechanic required, $wage^{qualif_r}$ is the man-hour cost of a mechanic with qualification $qualif_r$ required for task t_j.

The total corrective maintenance cost is given by Equation 10

$$cmtc_j = cmc_j + cmoc_j \tag{10}$$

Let $S = \{s_1, s_2, s_3, ..., s_{|S|}\}$ be a set of maintenance stoppages (or work packages), each with the attribute $stop_i$, the aircraft maintenance stoppage, and some other parameters to be updated after optimization:

- $cost_i$: overall work package maintenance cost
- dt_i: overall work package maintenance downtime
- $preps_i$: the set of unique subtasks associated to the work package

Let $O = \{o_1, o_2, o_3, ..., o_{|O|}\}$ be a set of *out-of-phase (OP)* stoppages for some tasks that are anti-economical to fit in the preceding regular work package s_i. o_p stays between s_i and s_{i+1} (the next stoppage). It cannot be allocated to s_{i+1} because the component would fly after it's due FH.

The individual task executed as *out-of-phase* has the same inherent costs described by the equation 10.

The calculation of the overall maintenance cost of an *out-of-phase* stoppage o_p is similar to that one used for a standard work package, s_i except for the considerations below:

- Estimation of the anticipated number of failures between two *out-of-phase* stoppages. o_p where the *out-of-phase* limit lim_p is used instead of the package $stop_i$ interval;
- There is no preparation cost savings, since each *out-of-phase* stoppage o_p has only one task t_j.
- The computation considers an *out-of-phase* factor $OPfactor$, which defines how important it is to the operator to include out-of-phase stoppages in the maintenance plan.

Let $B^i = \{b^i_1, b^i_2, b^i_3, ..., b^i_{|B^i|}\}$ be a set of maintenance bins which are partitions of maintenance work packages (Figure 4). I.e., each package is composed of subsets of tasks grouped by bins of concurrent tasks. These bins hold as many tasks as the number of mechanics of each qualification available or the limit of personnel for the task zone, whichever is less. If this number is exceeded, a new *Bin* must be used to hold other tasks for the same mechanics (or for the same zone) from the previous *Bin*.

As to the *Bin* downtime (dt^i_b), it may be accounted as the longest task and the overall bins downtime may be minimized by minimizing the number of bins.

In general, the task constraints defined in the Table 1 that refer to related tasks in the same *Bin* would be applied; however, only the $startAfter_j$ and $incompatible_j$ is

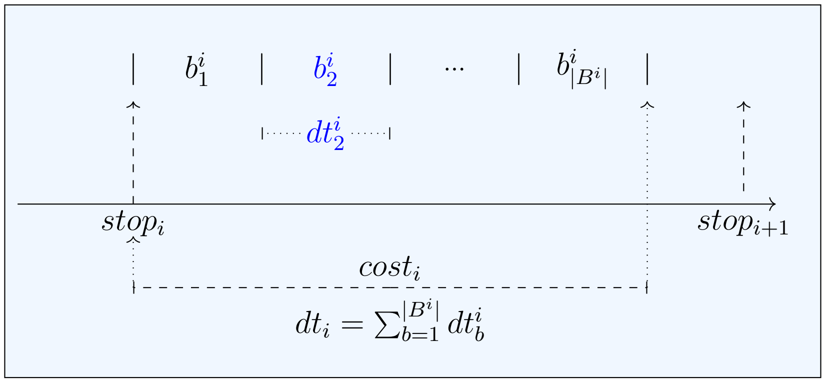

Figure 4: Work package bins

managed in this work, as the referred task must be in one of the previous bins and tasks that are not compatible must not be in the same bin.

Any resolution method to be used will output an optimal (or close to optimal) solution that expresses the allocations of tasks and their preparation works to regular packages or to *out-of-phase* stoppages, and tasks in packages to bins.

To permit this, we define 3 vectors of binary decision variables: (1) X_{ij}, to allocate task t_j and its preparations $preps_j$ to work package s_i; (2) O_{pj}, to allocate task t_j its preparations $preps_j$, not included in the regular work packages, to out-of-phase stoppage o_p; (3) W_{jb} to allocate task t_j to bin b_b.

- The binary variables $X_{ij} = 1$ if task t_j is assigned to maintenance package s_i, and 0 otherwise.
- The binary variables $O_{pj} = 1$ if the task t_j is assigned to an *out-of-phase* stoppage o_p, and 0 otherwise.
- The binary variables $W_{jb} = 1$ if task t_j is allocated to the bin b_b, and 0 otherwise.

Equation 19 states the Objective Function with four parcels:

• The equation 11 corresponds to the package preventive maintenance costs parcel, including the amount relative to the costs of the preparations after respective savings

$$pmc_j^i = R_t^i \cdot \left[pmc_j + pmoc_j + \sum_{q=1}^{n(B_i)} prepc_q \right] \tag{11}$$

• The equation 12 corresponds to the expected corrective maintenance costs if the task t_j is included in the package, s_i

$$cmc_j^i = \left(1 - R_t^i\right) \cdot (cmc_j + cmoc_j) \tag{12}$$

• The equation 13 corresponds to the *out-of-phase* stoppage preventive maintenance cost. In this case, there are no savings as regarding the preparations.

$$pmc_j^p = R_t^i \cdot \left[pmc_j + pmoc_j + \sum_{q=1}^{n(A_i)} prepc_m \right] \tag{13}$$

• The equation 14 corresponds to the expected corrective maintenance costs if the task t_j is included in the *out-of-phase* stoppage O_p

$$cmc_j^p = \left(1 - R_t^i\right) \cdot (cmc_j + cmoc_j) \tag{14}$$

Equations 15 and 16calculates the flight hour unused. I.e., how much flight hours the aircraft did not fly for being stopped before its flight limit.

$$unusedP_i^j = \lceil \frac{stop_i}{lim_j} \rceil - \frac{stop_i}{lim_j},\ for\ j \in \{1,2,3,...,|T|\}\ and\ for\ i \in \{1,2,3,...,|S|\} \tag{15}$$

$$unusedO_p^j = \lceil \frac{stop_p}{lim_j} \rceil - \frac{stop_p}{lim_j},\ for\ j \in \{1,2,3,...,|T|\}\ and\ for\ i \in \{1,2,3,...,|S|\} \tag{16}$$

Equation 19 states the first Objective Function that minimizes the maintenance cost of all tasks $|T|$ and preparation $|P|$ in the defined horizon $|S|$, if tasks and preparations are allocated to work packages. It also attempts to minimize the unused hours costs.

$$task\_costs = \sum_{i=1}^{|S|} \sum_{j=1}^{|T|} X_{ij} * \left(cmp_j^i + cmc_j^i + unusedP_i^j \cdot HOC\right) \tag{17}$$

$$prep\_costs = \sum_{p=1}^{|O|} \sum_{j=1}^{|T|} O_{pj} * \left(cmp_j^p + cmc_j^p + unusedo_p^j \cdot HOC\right) \tag{18}$$

$$Min\,\{task\_costs + prep\_costs\} \tag{19}$$

Subject to:

$$X_{ij} \cdot unusedP_i^j >= 0,\ for\ j \in \{1,2,3,...,|T|\}\ and\ for\ i \in \{1,2,3,...,|S|\} \tag{20}$$

$$O_{pj} \cdot unusedO_p^j >= 0,\ for\ j \in \{1,2,3,...,|T|\}\ and\ for\ o \in \{1,2,3,...,|O|\} \tag{21}$$

Equations 20 and 21 hinder a component from flying beyond its time limit.

$$\sum_{i=1}^{|S|} X_{ij} + \sum_{p=1}^{|O|} O_{pj} >= \lfloor \frac{stop_{|S|}}{lim_j} \rfloor,\ for\ j \in \{1,2,...,|T|\} \tag{22}$$

Equation 22 guarantees that the task t_j is executed at least $\lfloor \frac{stop_{|S|}}{lim_j} \rfloor$ times in planned horizon.

$$last_t = last_t \cdot (1 - X_{aj}) + stop_a \cdot X_{aj},\ for\ t \in \{1,2,...,|C|\} \tag{23}$$

For $i \in \{1,2,...,|S|\},\ a \in \{1,2,...,i-1\}$, the last component stoppage is calculated (Equation 23).

$$\sum_{k=1}^{|P|} |B_i| = X_{ij} \tag{24}$$

For $i \in \{1, 2, ..., |S|\},\ k \in \{1, 2, ..., |P|\}$, if the task is associated to the work package ($X_{ij} = 1$), the preparation p_k will be unique (Equation 24). I.e., the same door will not be opened or closed more than once.

$$\sum_{r=1}^{|M|} \sum_{x=1}^{|Z|} X_{ij} \cdot znum_j^{xr} > 0,\ for\ j \in \{1, 2, ..., |T|\} \tag{25}$$

For $x \in \{1, 2, ..., |Z|\}$ and $i \in \{1, 2, ..., |S|\}$, the number of mechanics of task zones must be greater than zero or the task will not be included (Equation 25).

The TAPP is solved at this point; tasks are associated with work packages, but their sequence and packing are not defined. So, we solve a *Bin Packing Problem* by minimizing the number of bins through packing tasks as efficiently as possible.

$$minimize\ |B^i| \tag{26}$$

Equation 26 states the second Objective Function that minimizes the number of bins. This minimization also minimizes the overall downtime.

Subject to:

$$\sum_{b=1}^{|B^i|} W_{jb} = 1,\ for\ j \in \{1, 2, ..., |T|\} \tag{27}$$

Each task must be in exactly one *Bin*, if it is associated to the *Bin* (27).

$$\sum_{j=1}^{|T|} \sum_{r=1}^{|M|} W_{jb} \cdot znum_j^{xr} <= limit_x \tag{28}$$

For each $b \in \{1, 2, ..., |B^i|\}$ and for each $x \in \{1, 2, ..., |Z|\}$, the number of mechanics cannot exceed the zone limit (Equation 28).

$$\sum_{j=1}^{|T|} \sum_{x=1}^{|Z|} W_{jb} \cdot znum_j^{xr} <= available_r \tag{29}$$

For each $b \in \{1, 2, ..., |B^i|\}$ and for each $r \in \{1, 2, ..., |M|\}$, the number of mechanics cannot exceed the available for each qualification (Equation 29).

$$W_{t1,b1} \cdot b1 < W_{t2,b2} \cdot b2,\ for\ (b1, b2) \in \{1, 2, 3, ..., |B^i|\},\ for\ (t1, t2) \in \{1, 2, 3, ..., |T|\} \tag{30}$$

Equation 30 guarantees that task $t2$ will be put in bin $b2$, which is posterior to bin $b1$ because task $t2$ must start after $t1$ is finished ($t1 = StartAfter_{t2}$).

$$X_{ic}^b = 1 - X_{id}^b \tag{31}$$

For $c, d \in \{1, 2, ..., |T|\}$, $i \in \{1, 2, ..., |S|\}$, and $b \in \{1, 2, ..., |B^i|\}$; and for $c \in incompatible_d$ or $d \in incompatible_c$, as c and d are segregated tasks, Equation 31 guarantees that they will not be executed in the same bin.

5.0 Results and discussions

To evaluate the performance of the ETTAPS framework proposed in Section 3, we conducted a series of computational experiments. We built the framework for these tests using Python, the CBC solver, and the scikit-learn library. We then tested the framework in various scenarios, varying the number of tasks, task dependencies, maintenance intervals, and data availability. The goal of these experiments was to assess the effectiveness of ETTAPS in optimizing maintenance plans and improving cost-effectiveness, resource utilization, and system availability, as well as to analyze the impact of the learning mechanism on the optimization process.

5.1 Optimization with Branch-and-Cut and FFD

Following the work of Almgren et al.[2] who utilized the *Branch-and-Cut* framework and observed a reduction in *Branch-and-Bound* nodes and simplex iterations for most problem instances with time-dependent costs, we also adopted this approach to solve the integer programming portion of the *Task Allocation and Packing problem.* Their work aimed to find optimal opportunistic maintenance schedules that maximize the replacement interval, similar to our goals. The mathematical formulation used in this context can be found in subsection 4.4.

This approach is particularly suited for ETTAPS, as it effectively handles the combinatorial complexity of maintenance task allocation by reducing the solution space through intelligent branching.

To enhance the gains in the availability, we implement the use of the *First-Fit Decreasing (FFD)* proposed by Johnson[22].

FFD was selected due to its computational efficiency in solving bin-packing-like problems, as opposed to alternative heuristics like Best-Fit or Next-Fit, which do not prioritize larger tasks for earlier allocation.

We also ran simulations to mimic the process depicted in Figure 1.

5.2 Simulation Results

Tests with different steps were conducted to verify the influence of the value of the step in optimization of grouping tasks around common preparations.

Figure 5 shows the results of simulations involving 85 maintenance tasks scheduled at intervals ranging in [20, 50, 100, 150, 200] flight hours. We analysed these different intervals to understand the potential advantages and disadvantages of using shorter intervals over three years, with a total flight time of 4,500 hours.

These maintenance intervals were selected through a trial-and-error experimental approach, starting at 10-hour intervals with 1-hour increments. This process aimed to identify potential improvements in overall cost and availability. We observed significant variations in the performance of different intervals, leading us to continue experiments with the selected values, which showed meaningful impacts on optimization outcomes.

Extensive simulations were performed for each interval to assess the impact. The maximum interval (200 hours) was chosen because some components have shorter lifespans and require more frequent maintenance.

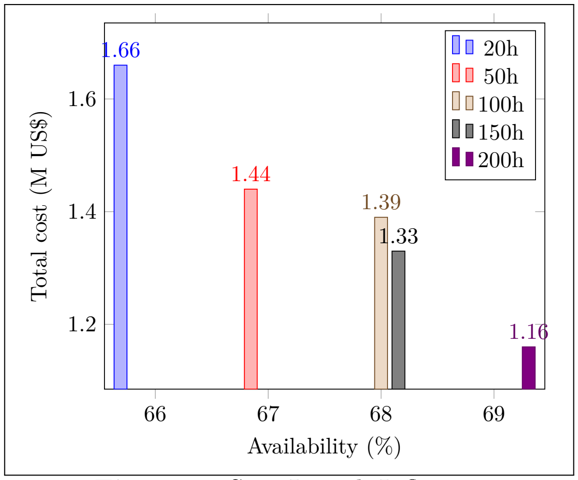

Figure 5: Step Length Influence

Our experiments revealed that increasing the maintenance interval generally leads to improved cost-effectiveness and equipment availability. However, it's important to note that 200 hours is the minimum interval considered for the tasks in our sample. This minimum interval is often determined by market demands during the initial development phase of a new product. Therefore, all generated maintenance requirements must adhere to these minimum interval limitations.

Table 2 summarizes the results of 20 experiments comparing two maintenance scheduling methods: a simple heuristic method and the ETAPPS+FFD optimization method. Each experiment considered a fixed maintenance interval of 200 hours and a total annual flight time of 1,500 hours.

Table 2: 200-hour Steps Tasks Distribution

Opt	A_o	**Cost** (M$)
No	0.80	14.7
Yes	0.87	11.6

The simple heuristic method mimics the existing practice of assigning tasks solely based on engineering expertise. In contrast, the ETAPPS+FFD optimization method utilizes both *Branch-and-Cut* and *FFD* algorithms to achieve optimal scheduling. The effectiveness of the proposed optimization model is evident, consistently demonstrating similar levels of improvement across various experiments involving different task numbers and operational profiles.

We also conducted tests with a sample of tasks that are common in commercial transport aircraft. We used the intervals shown in the MPD as the maximum permitted interval for the systems, structures, and zonal tasks. We simulated task allocation in packages using the present technique and compared it to the optimized results supplied by ETTAPS. Table 3 shows the results:

Table 3: Experiments results: 700 tasks and standard profile

Method	FFD	Availability	Total cost ($)	CM cost ($)	FH cost ($/FH)	Runtime (ms)
Simple	no	0.7639	22,815,444.79	1,576,749.96	912.62	7.71
ETAPPS	yes	0.8248	20,096,094.56	1,418,235.53	803.84	80.726

The findings consistently showed that using the ETAPPS resulted in an optimized task distribution. The ETTAPS capitalizes on the economic benefits of joining tasks that share the same preparations and access. There is also a gain in cost and availability associated with a lower likelihood of system failure.

The worst-case results expected from this work are an optimized maintenance plan, with tasks being allocated to maintenance packages in the most efficient schedule.

The best-case results are the long-term optimization of costs and improved resilience of the maintenance system, as new data is constantly included in the learning and optimization process and the task schedule is fine-tuned at each maintenance cycle.

5.3 Predictive Modeling with Random Forest

The Random Forest regression included in the Scikit-learn Pedregosa et al. [(31)] package was used to explore the dataset and select the best fit mapping function. Part of the data is dedicated to training the prediction model.

The main results of tests are presented together with the influence of the learning mechanism after some cycles of tests.

At this time, the historical records have not affected optimization; ML still forecasts a cost increase, but optimized maintenance plan records will feed the learning mechanism, which will probably result in an overall cost reduction.

We extract features such as the time since last maintenance and sensor readings from historical maintenance logs. The Random Forest model is retrained monthly using a rolling 24-month data window. Retraining improves predictive accuracy (e.g., AUC increases from 0.77 to 0.85), resulting in 27.4% lower maintenance costs and 1.0% increase in availability in five operations/maintenance cycles, according to Table 4.

Features were selected using recursive feature elimination (RFE) to identify the most influential predictors of maintenance needs. The predictive model used 1500 maintenance records. Limited data availability constrained the sample size. 5-fold cross-validation achieved an average AUC of 0.85, suggesting sufficient generalization for this application.

Table 4 depicts the effects of using the learning capability on the optimization process (A_a is the achieved availability). The resilient planner learned after exploring historical data during the maintenance cycles. This confirms the hypothesis.

Table 4: Influence of ML on optimization

	Operations/Maintenance Cycles				
	First	**Second**	**Third**	**Fourth**	**Fifth**
A_a	0.965	0.970	0.973	0.974	0.975
Cost (M$)	2.15	1.77	1.61	1.58	1.56

These results demonstrate ETTAPS' advantages in cost and availability compared to a baseline scenario. Due to space limitations, detailed cost distributions and task allocations are not included but are available upon request. ETTAPS achieves cost reductions by intelligently grouping tasks based on dependencies and predicted failure probabilities, minimizing redundant preparation efforts and overall maintenance downtime. This is reflected in the lower mean costs and improved availability metrics presented in the tables.

5.4 Limitations

As a limitation, the immediate reaction capacity of the resilient maintenance planner was not considered in this work, as the number of records produced during experimentation was not enough to guarantee an acceptable level of confidence. However, with new operating and maintenance records, we believe that soon lower maintenance costs will be observed.

Future work will explore integrating real-time anomaly detection into ETTAPS, enhancing its ability to dynamically adapt to unexpected component failures.

5.5 Qualitative Analysis of Results

While a comprehensive quantitative validation with real-world data is a subject for future research, we can offer some qualitative insights based on observed trends and expert knowledge. For instance, the model's tendency to group related tasks within the same maintenance package aligns with established maintenance practices, which aim to minimize aircraft downtime by coordinating maintenance activities. Furthermore, task prioritization based on predicted failure probabilities is consistent with expert knowledge in risk management for aircraft maintenance, where components with a higher risk of failure are often given priority. These qualitative observations, while not definitive, provide initial support for the practical applicability of the ETTAPS framework.

5.6 Conclusion

The ETTAPS framework, combining Branch-and-Cut optimization with First-Fit Decreasing task grouping and a Random Forest predictive model, effectively optimizes aircraft maintenance plans, improving cost-effectiveness, resource utilization, and system availability. While further validation with real-world data is needed, the results demonstrate ETTAPS' potential for achieving resilient and sustainable aviation maintenance practices.

The framework's modular design makes it adaptable for integration into existing airline maintenance management systems, facilitating deployment without major infrastructural changes.

6.0 Conclusions

This article introduces the Efficient Task Allocation and Packing Problem Solver (ETTAPS), a novel framework that integrates predictive analytics and optimization to enhance cost efficiency, resource utilization, and system availability in the maintenance of highly complex aircraft systems.

Our findings demonstrate that the integer programming step of ETTAPS, when combined with task grouping via the First-Fit Decreasing algorithm, significantly improves maintenance efficiency and system resilience. By addressing factors such as mechanic skills, physical capacity constraints, and task relationships, ETTAPS broadens the traditional scope of maintenance planning to meet the dynamic demands of modern aviation operations.

The integration of data-driven learning ensures continuous improvement by incorporating new maintenance data and fine-tuning plans with each maintenance cycle. This approach bridges critical gaps in the MSG-3 and certification analysis processes, enabling the development of robust maintenance plans that reduce downtime, optimize costs, and enhance operational readiness.

Furthermore, our experiments confirmed that leveraging a rolling 24-month data window for retraining the predictive model improves forecasting accuracy, leading to an overall reduction in maintenance costs and an increase in availability. The combination of machine learning and mixed-integer programming within ETTAPS ensures that task allocation remains both adaptive and economically efficient over successive operational cycles.

While ETTAPS demonstrates clear advantages in optimizing maintenance schedules, limitations remain regarding its immediate reaction capability to unforeseen failures. Future improvements should integrate real-time anomaly detection and explore reinforcement learning-based approaches for dynamic decision-making.

Looking forward, future research should investigate the integration of ETTAPS with advanced technologies such as digital twins and flight planning systems, fostering real-time maintenance decision-making. Collaboration with regulatory bodies and industry stakeholders could further refine the framework for broader adoption. Additionally, exploring the potential for commercialization and scalability across diverse aircraft models offers promising opportunities for practical implementation.

This research establishes a foundation for transforming aircraft maintenance planning by combining optimization models with data-driven learning. ETTAPS aligns with Industry 4.0 and aviation sustainability goals, representing a significant step toward an intelligent, proactive maintenance ecosystem that optimizes processes and enhances aircraft operational efficiency and resilience.

CRediT authorship contribution statement

José N. M. Filho: Conceptualization, Methodology, Software, Writing - original draft preparation, Investigation, Validation. **Antonio C. P. Mesquita:** Methodology, Software, Writing - reviewing & editing. **Fernando T. M. Abrahão:** Conceptualization, Methodology, and Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Algorithms availability

The algorithms developed in this work are available at:
`www.aerologlab.ita.br/datafiles/nogueira_algorithms.pdf`

Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work the authors used *ChatGPT 4o* and *QuillBot* in the writing process only to improve the readability and language of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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