

Integrated Optimization of Aircraft Line Maintenance: Scheduling under Uncertainty and Predictive Part Failure Modelling

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Abstract

Growing demand for fast, reliable, and cost-effective transportation continues to drive innovation in the aviation sector. However, existing research has largely focused on routing and staffing, often overlooking line maintenance scheduling. This study addresses this gap by proposing an integrated framework for the Line Maintenance Scheduling Problem (LMSP). A stochastic mixed-integer linear programming (MILP) model is developed to generate optimal weekly maintenance schedules with embedded deferral planning, enabling efficient resource allocation under operational uncertainty. The model minimizes total maintenance cost while reducing deferrals of non-critical tasks and ensuring high resource utilization. In parallel, a probabilistic model is introduced to predict component failures. Using Weibull and Bernoulli distributions, aircraft parts are classified based on failure patterns, and their time to failure is estimated to support preemptive maintenance decisions. The integration of predictive failure modeling with optimization enhances scheduling accuracy and operational resilience. Results demonstrate that the proposed approach produces cost-efficient and robust maintenance schedules, with minimal deviation from theoretical optimality. The framework is scalable and adaptable across airlines and other industries requiring reliable scheduling under uncertainty, while maintaining high safety standards through proactive maintenance planning.

Keywords: Aviation Operations; Part Failure Prediction; Stochastics; Maintenance Scheduling; Optimization

1. Introduction and Background

The late 20th century saw a substantial rise in commercial air transport, driven by steadily growing demand as travel became increasingly affordable over time. According to a joint report from the Airports Council International (ACI) World and the International Civil Aviation Organization (ICAO), by the year 2050, global passenger traffic is projected to grow at a Compound Annual Growth Rate of 3.6%, eventually 244% of 2019 levels, as the strong and steady growth of emerging markets in Asia has become the driving force behind this increase (ACI World, 2025). However, most commercial airlines possess aging fleets that are not being replenished with new aircrafts (McKinsey, 2024). Hence, several of them will experience increasing needs for adequate maintenance services to adapt to growing multigenerational fleets and the increased demand for commercial transport (Aerospace and Defense Review, 2025). These facts indicate that existing standards of airline maintenance may not be able to overcome the challenges posed to the aviation industry and thus a set of solutions needs to be developed in order to enhance the efficiency of the maintenance process.

A key, post-COVID challenge in airline maintenance is the sharp rise in task deferrals. Maintenance-related delays have doubled or tripled, while technical dispatch reliability has dropped by up to 50% compared to pre-COVID levels. A study by BCG (BCG, 2025) attributes this to compounding pressures, including aging fleets and the prioritization of overdue MEL items over scheduled non-critical tasks. These factors place additional pressure on already limited maintenance windows. Each deferral or delay accelerates system degradation and raises future restoration costs. As a result, planners increasingly operate reactively, addressing immediate issues instead of following a structured long-term strategy (Kinnison & Siddiqui, 2013).

High-quality maintenance is essential for preventing part failures and ensuring aviation safety, where even a single accident can result in catastrophic loss (Guo et al., 2025). The foundational 1978 study by Nowlan

and Heap introduced six failure patterns based on United Airlines data, revealing that 68% of components followed an infant mortality failure mode, challenging the assumption that most parts degrade with age (Nowlan & Heap, 1978). Despite further research, their framework remains central to Reliability Centered Maintenance (RCM). Given these patterns, there is a clear need for models that estimate failure probabilities and predict time to failure based on part characteristics. Integrating such models into line maintenance can enhance scheduling precision, optimize MEL deferrals, and reduce maintenance backlog.

Although several studies have addressed related areas such as aircraft maintenance routing, fleet assignment and staffing, the literature related to line maintenance scheduling remains limited. One of the few focused contributions proposes a comprehensive framework using MILP and heuristic methods to solve the Line Maintenance Scheduling Problem (LMSP), offering a structured approach to optimize daily task allocation under operational constraints (Shaukat et al., 2020). Additional research has explored long-term maintenance planning, including a model that optimizes integrated ‘A’ and ‘C’ check schedules. For instance, one of the models aimed to reduce the number of checks by minimizing unused flight hours, ultimately improving aircraft availability and lowering maintenance costs. It accounted for aircraft type, maintenance capacity, and various operational constraints (Deng et al., 2020). Furthermore, discrete event simulation (DES) has been used to study line maintenance planning, focusing on task timing, workload and uncertainty, particularly issues such as missing tools and unmet safety requirements. These studies emphasize the importance of managing unplanned work and deferred tasks in line maintenance (Albakkoush et al., 2021). More general research on optimization under uncertainty has also provided helpful methodologies, such as stochastic scheduling frameworks that classify uncertainty types and propose practical solutions based on financial objectives and variable demand (Hegyháti et al., 2023).

Research on aircraft maintenance planning has increasingly focused on optimization-based approaches that consider workforce availability and uncertain operational conditions. More specifically, workforce planning models have been developed that jointly optimize workforce schedules, skill allocation and

training decisions in aircraft maintenance operations (De Bruecker et al., 2018). Stochastic optimization models have also been proposed to incorporate uncertainty in maintenance task durations and evaluate the resulting impact on operational performance (Villafranca et al., 2025). Also, hybrid simulation–optimization frameworks combining Monte Carlo simulation with optimization techniques have further been introduced to generate maintenance schedules that remain feasible across a wide range of operational scenarios (Shahmoradi-Moghadam et al., 2021). This progression led to the exploration of dynamic scheduling approaches, where maintenance decisions are continuously updated as new information becomes available through approximate dynamic programming and Markov decision processes (Lagos et al., 2020). In this context, decision-support frameworks integrating work-progress monitoring with maintenance planning have demonstrated how real-time operational data can improve responsiveness in airline maintenance scheduling (Callewaert et al., 2018).

Building on prior research in line maintenance optimization, methods from production and maintenance scheduling provide valuable analogies. Multi-objective optimization frameworks developed for low-volume production systems show how complex schedules can balance cost, service level and robustness, a logic directly transferable to maintenance planning (Russell & Taghipour, 2019). Similarly, recent advances in deep reinforcement learning (DRL) and hybrid metaheuristics, such as DQN-based scheduling for distributed job-shop systems (Du & Li, 2024) and rule-guided genetic algorithms for complex batch scheduling (Wang et al., 2025), illustrate how adaptive and hybrid decision-making can enhance flexibility and responsiveness under uncertainty.

Beyond aviation-focused studies, a large body of literature has examined integrated maintenance and scheduling problems in industrial systems. Unrelated parallel machine scheduling models capture assignment decisions under heterogeneous resources and sequence-dependent constraints, providing a strong analogue to workstation-based maintenance scheduling (Moser et al., 2022). Also, integrated maintenance scheduling models have addressed the joint optimization of component replacement and repair

flows under capacity and contractual constraints, highlighting the importance of linking operational scheduling with system availability (Obradović et al., 2024). Rolling-horizon rescheduling frameworks have been shown to improve performance in stochastic environments by dynamically updating schedules based on system load, disruptions, and operational objectives (Stevenson et al., 2020). Integrated scheduling approaches combining assignment and rescheduling decisions within a rolling horizon have demonstrated improved resource utilization and robustness in complex operational settings (Spratt & Kozan, 2021). Dynamic scheduling models that explicitly consider machine failures emphasize the importance of robust and adaptive rescheduling strategies to maintain stability under disruptions (Peng et al., 2025). Scheduling models incorporating workload-dependent maintenance highlight the interaction between system usage and maintenance timing, reinforcing the need for integrated planning approaches (P. Liu et al., 2025). In the aviation domain, resource-constrained scheduling problems such as airport slot allocation further illustrate the complexity of coordinating limited capacity under operational constraints (Zografos et al., 2017).

Selective maintenance models have been proposed to support decision-making when maintenance actions have uncertain effectiveness and systems must perform sequential missions (Duan et al., 2018). Joint optimization of production and preventive maintenance tasks has also been studied in job-shop environments using multi-objective genetic algorithms (Ben Ali et al., 2011). More recent work has introduced resilience-oriented scheduling frameworks that integrate system degradation and operational uncertainty into reinforcement learning scheduling models (Cai et al., 2024). Scenario-based robust optimization approaches have also been proposed to address manufacturing scheduling problems with uncertain processing times (J. Liu et al., 2019).

Predictive maintenance planning frameworks combining failure prediction with scheduling and rescheduling mechanisms have also been developed to improve schedule stability (Paprocka, 2019). Maintenance integration in multi-factory production environments has been studied through mixed-integer programming models that incorporate preventive and corrective maintenance activities (Kazemi et al.,

2025). Maintenance scheduling has also been investigated in logistics systems where maintenance and transportation operations must be coordinated across supply networks (Tsadikovich et al., 2016). Furthermore, research has explored the interaction between production workload and equipment deterioration in flexible manufacturing systems under uncertain demand conditions (Zhou et al., 2021).

In addition, several studies emphasize incorporating operational and contextual factors. Energy-aware optimization has coupled production scheduling with carbon and power-cost objectives, providing insights for maintenance operations where facilities or ground equipment consume significant energy (An et al., 2025). Capacity-planning research in the aircraft MRO sector highlights the stochastic nature of unscheduled work, reinforcing the need to embed robustness in any practical line-maintenance scheduler (Dinis et al., 2019). Furthermore, accounting for human factors and technician learning can improve long-term service levels by explicitly modeling on-the-job skill acquisition in routing and scheduling frameworks (Chen et al., 2024).

Finally, simulation-based approaches offer a pragmatic way to validate scheduling rules before implementation. Studies in aircraft engine maintenance demonstrate how simulation experiments can identify robust dispatching strategies under realistic operational variability (Reményi & Staudacher, 2014).

This study builds on these prior efforts by directly addressing the need for a targeted solution in line maintenance scheduling. It develops a MILP-based model for constructing daily maintenance task schedules and integrates uncertainty management into the planning process, an area previously identified as a gap in the literature. Specifically, the proposed model incorporates stochastic optimization techniques within a rolling horizon framework and introduces a dynamic approach to the LMSP to better respond to operational disruptions and emergency events. These contributions aim to enhance the efficiency, reliability and resilience of line maintenance operations, while demonstrating how production-scheduling principles can be operationalized in the highly constrained, safety-critical environment of aircraft maintenance,

aligning with recommendations from earlier research and extending the capabilities of existing models (Shaukat et al., 2020).

In detail, this study addresses the Line Maintenance Scheduling Problem (LMSP) by developing a Mixed-Integer Linear Programming (MILP) model designed to generate optimal daily maintenance schedules for a representative facility operating within a typical six-hour overnight line maintenance window (Shaukat et al., 2020). The model assumes a known number of available workstations and resources, which serve as the basis for task assignment decisions. Inevitably, some tasks may exceed the available capacity and must be deferred, and their deferral times are explicitly calculated and incorporated into subsequent schedules. Task criticality is determined through a Bernoulli-based classification, which assigns a binary status, i.e. critical or non-critical, to each task, to prepare and structure the input data for the MILP model. The final output includes a cost-minimized maintenance schedule and a corresponding Gantt chart detailing task allocation across workstations in a realistic operational setting.

It should be noted that due to the lack of publication in the field of line maintenance in aviation, the scheduling model was based primarily on past work that analyzed issues such as the aircraft maintenance routing problem (Al-Thani et al., 2016; Ben Ahmed et al., 2017; Cui et al., 2019; Ruan et al., 2021; Safaei & Jardine, 2018) or a proposed solution to the tail assignment problem that resembles the LMSP (Khaled et al., 2018; Sanchez et al., 2020). The formulation of the algorithm was also influenced by various heuristic approaches that tackle scheduling and maintenance problems with stochastic processes (Cacchiani & Salazar-González, 2020; De Bruecker et al., 2015). Also, the task assignment constraints were informed by discrete choice modeling approaches, commonly used in flight scheduling and fleet assignment problems (Dong et al., 2016).

The remainder of the paper is structured as follows: The next section outlines the methodology used to formulate the MILP model for solving the Line Maintenance Scheduling Problem (LMSP), including

schedule generation. It also introduces the auxiliary classification model, which leverages MMEL data from EASA (EASA, 2021) to categorize parts focusing on the Airbus A320 wing section. The results section presents the cost-optimal schedule, task durations, deferrals and a sensitivity analysis under varying cost coefficient assumptions. The final sections summarize key findings and offer recommendations for future research in line maintenance optimization.

2. Methodology

Two complementary models were developed as part of this study; the first is the formulated LMSP (primary model) while the second (auxiliary) is a probabilistic model that determines the time when each part presents the maximum probability of failure. The primary model minimizes total costs by incorporating earliness, tardiness, deferral, rescheduling, and resource utilization costs. The auxiliary model classifies wing parts by RCM curves and estimates their time to failure using the Weibull distribution.

2.1. Optimization Model

The Line Maintenance Scheduling Problem (LMSP) is set up for addressing two types of scheduling decisions: job assignments (tasks) and timetable design (Shaukat et al., 2020). In the job assignment component, the LMSP involves allocating specific maintenance tasks to available maintenance opportunities, as determined by the aircraft schedules. In the timetable problem, the model must define the time each job begins within its assigned workstation. Each job has a due time when it should be ideally performed, so the objective of the job assignment is to minimize the total deviation from these due times (Shaukat et al., 2020). While the conceptual definition of the Line Maintenance Scheduling Problem (LMSP) remains consistent across this paper and other studies, the mathematical formulation developed in

this work introduces several critical enhancements, most notably, the explicit consideration of deferred tasks and task criticality classification. To address these requirements, a Mixed-Integer Linear Programming (MILP) approach is employed. This methodology is deemed appropriate given that all model equations are linear, and this structure ensures the feasibility of generating optimal and practically actionable solutions. Below is the complete set of model components—sets, parameters, and decision variables—used in the MILP formulation for solving the LMSP.

Sets:

J_c : Set of critical tasks, $J_c = \{i \mid \text{task } i \text{ is critical}\}$

J_n : Set of non – critical tasks, $J_n = \{j \mid \text{task } j \text{ is non – critical}\}$

J : Set of all tasks (i.e. $J = J_c \cup J_n$)

M : Set of maintenance workstations

K : Set of resource types

S : Set of scenarios

Parameters:

$T_{s,i}$: Duration of task $i \in J$ in scenario $s \in S$

$T_{s,j}$: Duration of task $j \in J$ in scenario $s \in S$

E_i : Due date for task $i \in J_c$

a_i : Cost per unit of earliness for critical task $i \in J_c$

b_i : Cost per unit of tardiness for critical task $i \in J_c$

c_j : Cost coefficient for deferral of non – critical task $j \in J_n$

d_j : Additional cost coefficient for deferral of non – critical task $j \in J_n$

e_k : Cost per unit of resource $k \in K$ used

$r_{i,k}$: Number of resources of type $k \in K$ required by critical task $i \in J_c$

$r_{j,k}$: Number of resources of type $k \in K$ required by non – critical task $j \in J_n$

$R_{s,m,k}$: Availability of resource type $k \in K$ in workstation $m \in M$ under scenario $s \in S$

W_m : Maximum number of tasks that can be assigned to workstation $m \in M$

D_j : Deferral penalty for non – critical task $j \in J_n$ if not scheduled

λ_m : Penalty coefficient for assigning tasks to workstation $m \in M$

M_{big} : A large positive constant (e.g. 100)

Decision Variables:

$x_{i,m} \in \{0,1\}$: 1 if task $i \in J$ is assigned to workstation $m \in M$, 0 otherwise

$x_{j,m} \in \{0,1\}$: 1 if task $j \in J$ is assigned to workstation $m \in M$, 0 otherwise

$S_i \geq 0$: Start time of task $i \in J$ within its assigned workstation

$\Delta_j \geq 0$: Deferral cost for non – critical task $j \in J_n$

$Z_i \geq 0$: Earliness measure for critical task $i \in J_c$

$L_{i,s} \geq 0$: Lateness of critical task $i \in J_c$ in scenario $s \in S$.

$y_{i,j,m} \in \{0,1\}$: 1 if task $i \in J$ precedes task $j \in J$ (where $i < j$) in workstation $m \in M$, 0 otherwise.

The formulation of the LMSP as a MILP problem begins with the definition of the objective function, followed by the complete set of constraints, as presented below.

$$\min Z = \frac{1}{|S|} \cdot \left[\sum_{s \in S} \left(\sum_{i \in J_c} (a_i Z_i + b_i L_{i,s}) + \sum_{j \in J_n} (c_j \Delta_j + d_j \Delta_j) + \sum_{m \in M} \sum_{k \in K} e_k \left(\sum_{i \in J_c} x_{i,m} r_{i,k} + \sum_{j \in J_n} x_{j,m} r_{j,k} \right) \right) + \sum_{m \in M} \lambda_m \sum_{i \in J_c} x_{i,m} \right] \quad (1)$$

$$\sum_{m \in M} x_{i,m} = 1 \quad \forall i \in J_c \quad (2)$$

$$\sum_{m \in M} x_{j,m} \leq 1 \quad \forall j \in J_n \quad (3)$$

$$L_{i,s} \geq S_i + T_{s,i} - E_i \quad \forall i \in Jc, \quad \forall s \in S \quad (4)$$

$$S_i + T_{s,i} \leq E_i + Z_i \quad \forall i \in Jc, \quad \forall s \in S \quad (5)$$

$$S_i + T_{s,i} \leq 6 \quad \forall i \in Jc, \quad \forall s \in S \quad (6)$$

$$S_j \geq \sum_{m \in M} m \cdot x_{j,m} \quad \forall j \in Jn \quad (7)$$

$$S_j + T_{s,j} \leq 6 + M_{big}(1 - x_{j,m}) \quad \forall j \in Jn, \quad \forall m \in M, \quad \forall s \in S \quad (8)$$

$$\Delta_j = \left(1 - \sum_{m \in M} x_{j,m}\right) \cdot D_j \quad \forall j \in Jn \quad (9)$$

$$\sum_{i \in Jc} x_{i,m} r_{i,k} + \sum_{j \in Jn} x_{j,m} r_{j,k} \leq R_{s,m,k} \quad \forall s \in S, \quad \forall m \in M, \quad \forall k \in K \quad (10)$$

$$\sum_{i \in Jc} x_{i,m} T_{s,i} + \sum_{j \in Jn} x_{j,m} T_{s,j} \leq 6 \quad \forall s \in S, \quad \forall m \in M \quad (11)$$

$$Z_i \geq E_i - S_i \quad \forall i \in Jc \quad (12)$$

$$S_i + T_{s,i} \leq S_j + M_{big}(1 - y_{i,j,m}) + M_{big}(1 - x_{i,m}) + M_{big}(1 - x_{j,m}) \quad \forall i, j \in J, \quad i < j, \quad \forall m \in M, \quad \forall s \in S \quad (13)$$

$$S_j + T_{s,j} \leq S_i + M_{big}y_{i,j,m} + M_{big}(1 - x_{i,m}) + M_{big}(1 - x_{j,m}) \quad \forall i, j \in J, \quad i < j, \quad \forall m \in M, \quad \forall s \in S \quad (14)$$

$$\sum_{i \in Jc} x_{i,m} + \sum_{j \in Jn} x_{j,m} \leq W_m \quad \forall m \in M \quad (15)$$

The objective function (1) consists of 4 main components all of which convert certain quantities to costs in monetary units: the first component captures the earliness and tardiness associated with the completion of critical tasks; the second quantifies the cost and time impact of deferrals for non-critical tasks; the third reflects the utilization of available resources across all task types; and the fourth introduces an incentive mechanism to prioritize the scheduling of non-critical tasks, minimizing overall deferrals without compromising the execution of critical ones. As outlined, the objective function aims to minimize total cost, which implies timely completion of scheduled tasks (i.e. as close as possible to their due dates), strict limitation of deferrals to only those that are essential, full utilization of available resources and scheduling

the maximum feasible number of tasks each day within the typical six-hour overnight line maintenance window.

In terms of model structure, constraints serve to enforce feasibility and operational logic across the scheduling process. Equation (2) ensures that every critical task is assigned to a workstation within a maintenance window. Constraint (3) ensures that non-critical tasks are assigned to at most one workstation, thus allowing deferrals. Constraint (4) states that tardiness occurs when critical tasks are completed after their designated completion time. Constraints (5) and (6) link the completion time of critical tasks to their corresponding due date and earliness respectively, forcing them to be completed within a (usually 6-hour) overnight line maintenance window. Constraint (7) sets the start time for non-critical tasks based on the workstation they are assigned to, if assigned. Constraint (8) ensures that all scheduled non-critical tasks are fully completed within the designated 6-hour maintenance window, as tasks cannot be partially executed and carried over to the following day—each task must start and finish within the same operational period. Equation (9) calculates the deferral cost for non-critical tasks. Constraints (10) and (11) ensure that resource utilization remains within the available capacity and that the total working time at each individual workstation does not exceed the 6-hour maintenance window. Constraint (12) defines earliness for critical tasks, indicating that a task is considered early when it is completed before its designated completion time. Constraints (13) and (14) prevent task overlapping within the same workstation. Finally, constraint (15) restricts the number of tasks assigned to each workstation, ensuring that workstation capacity is not exceeded.

The optimization model was developed and executed on a standard computing machine equipped with 8 GB of RAM and an 11th Generation Intel Core i5-1135G7 processor (4 cores, 8 threads). This demonstrates that the model can be efficiently run on commonly available hardware, without the need for high-performance computing resources, ensuring broad accessibility and ease of implementation. Furthermore, the python libraries used in this model include the following: The random library is used for pseudo number

generation, implementing the Mersenne Twister algorithm. The pandas library is used for data manipulation and analysis, relying on the Quicksort algorithm, typically accessed via NumPy, which follows a divide-and-conquer strategy. The optimization problem is formulated using the PuLP modeling interface, which utilizes the FICO developed solver known as Xpress Optimizer. For visualization, matplotlib.pyplot and matplotlib.patches are used to generate plots and geometric elements, incorporating rendering algorithms such as rasterization and geometric simplification techniques like the Ramer–Douglas–Peucker algorithm. Finally, the datetime library is applied for handling date and time data using basic arithmetic and calendar-based logic.

2.2. Part Failure Prediction Model

As part of this study, a rule-based classification and simulation framework was designed, developed, and evaluated to characterize the failure behavior of aircraft wing components and quantify their risk of early failure. The methodology comprises four principal stages: textual pattern recognition, stochastic failure-time generation, exploratory visualization, and logistic modeling of criticality. First, a dataset of wing-part records was compiled, each annotated with a free-text description of its physical attributes and operating context. Drawing on established reliability-engineering archetypes, six keyword sets were defined corresponding to standardized failure-rate “patterns” (e.g., infant mortality, wear-out, constant rate). For each part description, a pattern score was computed by counting exact keyword occurrences in a lowercase transcript. Each part was then assigned to the pattern with the highest score, with ties and zero-match cases defaulting to a conservative baseline category. This procedure produced a labeled dataset in which each component is associated with one of six empirically inferred hazard archetypes (Bengtsson et al., 2004).

Second, a “time to failure” was simulated for each part by sampling from the distribution corresponding to its assigned pattern. For five of the patterns, Weibull distributions—whose shape and scale parameters

reflect early-life failures, transitional stability, or end-of-life wear-out behaviors—were utilized. For the remaining pattern, an exponential distribution was employed to model a constant hazard rate. This Monte Carlo approach yielded a numerical failure-time realization (in flight hours) for every component, enabling subsequent risk analysis.

Third, the simulated failure times were subjected to exploratory visualization to verify that the random draws conform to theoretical expectations. A faceted histogram displays the frequency distribution of failure times within each pattern, while a ridgeline density plot overlays smoothed hazard-rate shapes across categories. These visualizations confirmed the alignment between the keyword-driven classification and the intended failure-rate behavior of each pattern (Guo et al., 2025).

Finally, a binary “criticality” indicator was introduced, flagging components whose simulated failure time falls below a preselected threshold (e.g. 500 flight hours, based on the typical A-check interval of 600 hours as stated in the MPD). A logistic regression model was then fitted to predict this critical-failure status as a function of the categorical failure pattern. The resulting coefficients quantify the relative odds of early failure for each pattern, thereby closing the analytical loop from text-based classification through stochastic simulation to risk-ranking via statistical inference. This integrated pipeline offers both a theoretically grounded methodology for modeling part reliability and a practical tool for maintenance prioritization. The equations used for the creation of this auxiliary model are listed below.

$$f(t; \lambda, k) = \frac{k}{\lambda} \left(\frac{t}{\lambda}\right)^{k-1} e^{-(t/\lambda)^k}, t > 0 \quad (16)$$

$$R(t) = e^{-(t/\lambda)^k} \quad (17)$$

- $k < 1$: Displays decreasing initial failure rate (infant mortality).
- $k = 1$: Displays constant failure rate (random failures).
- $k > 1$: Displays increasing failure rate (wear-out).

$$h(t) = \frac{f(t)}{R(t)} = \frac{k}{\lambda} \left(\frac{t}{\lambda} \right)^{k-1} \quad (18)$$

$$Is_critical_i = \begin{cases} 1, & \text{if Possible_failure_time}_i < T = 500 \text{ h} \\ 0, & \text{if Possible_failure_time}_i \geq T = 500 \text{ h} \end{cases} \quad (19)$$

$$\log \left(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)} \right) = \beta_0 + \beta_1 \cdot \mathbf{1}_B + \beta_2 \cdot \mathbf{1}_C + \dots + \beta_5 \cdot \mathbf{1}_F \quad (20)$$

$$P_A = \frac{1}{1 + e^{-(\beta_v)}} \quad (21)$$

The probability density function (16) of the Weibull distribution uses 2 parameters λ and k where λ denotes the scale parameter which determines the spread of the distribution and k represents the shape parameter which is used to determine the shape. The reliability function (17) of the Weibull distribution was used to properly define and classify each failure category in accordance with the value of parameter k . The rate of failure is calculated through the Hazard function (18). This concludes the first part of the failure modeling process. The second part focuses on assessing the criticality of the classified wing components, based on their assigned failure pattern and estimated time to failure. As previously stated, a 500-flight hour threshold has been used to separate critical from non-critical parts, adhering to the maintenance routine set by the A320 Maintenance Planning Document and Maintenance Review Board which clearly mandate a 600-flight hour limit for A – checks. Therefore, as outlined in equation (19), a part is deemed to be critical if its estimated failure time is below 500 hours. A logistic regression model was subsequently developed, with the failure pattern as the independent variable and the binary criticality indicator (critical vs. non-critical) as the dependent variable. Equation (20) formalizes the model’s logic: it “learns” how each failure pattern affects the likelihood that a given part will be classified as critical.

Since the failure pattern is a categorical variable, dummy variables were created, designating one category, Category A, as a reference. The remaining categories are interpreted relative to this baseline. Ultimately, the model produces log-odds for the criticality of parts in the baseline category and log-odds differences

for all other categories, thus quantifying the relative likelihood of critical failure in comparison to Category A. Finally, equation (21) calculates the probability of parts belonging to each category to be critical through the use of the log – odds ($\beta_A, \beta_B, \beta_C, \beta_D, \beta_E, \beta_F$) and eventually shows which categories are more likely to include critical parts. The corresponding part failure categories, i.e. RCM curves, are shown below (**Fig. 1**).

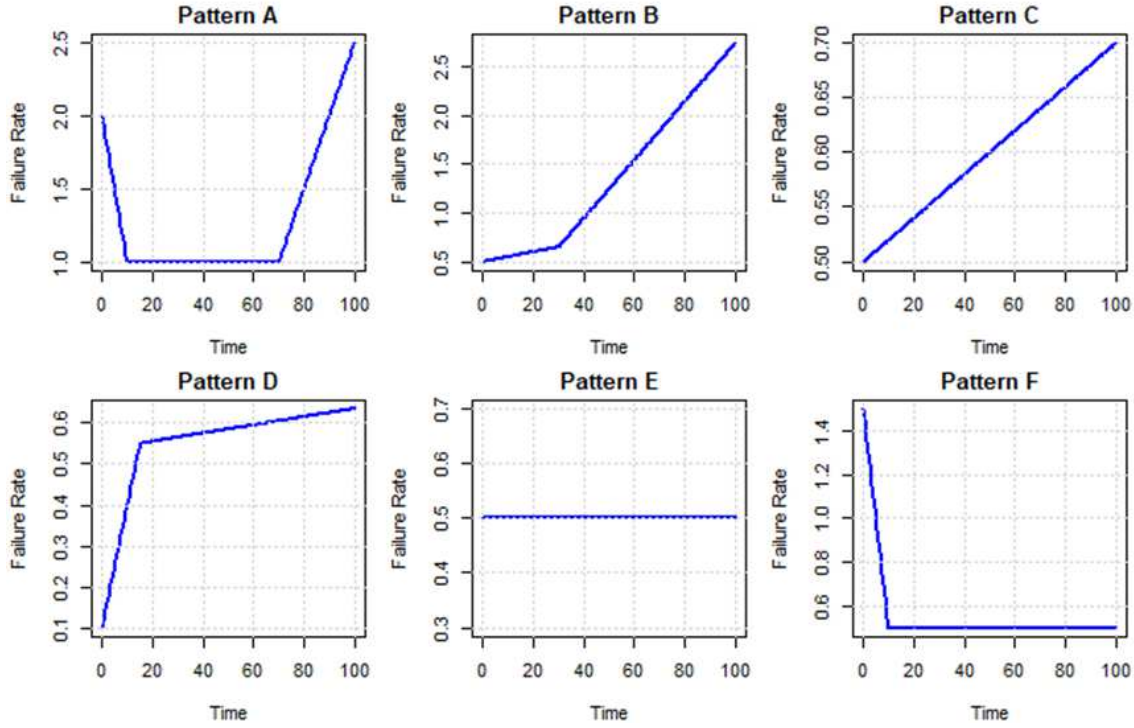


Fig. 1. Failure Rate Patterns.

While the part failure model is a standalone tool serving an important role in the predictive maintenance process, it also functions as an auxiliary model to the main scheduler. The part failure model predicts the failure time of different parts of the aircraft and identifies which parts are critical; these classifications can be utilized as data for the main scheduler embedded in the sets J_c set of critical tasks and J_n set of non-critical tasks. Specifically, the critical parts are identified through the part failure model and their corresponding tasks can be determined through the MPD. Tasks that are performed on the critical parts (or

zones) are predicted to fail early and require inspections that cannot be deferred. Furthermore, the output of the auxiliary model could serve as a database including predicted failure times (flight hours) for all aircraft parts and this could be useful information for long term planning of maintenance activities beyond one week. Ultimately, this integration allows the operators to proactively identify and schedule critical tasks through the scheduler, mitigating uncertainty and improving operational efficiency and safety (**Fig. 2**).

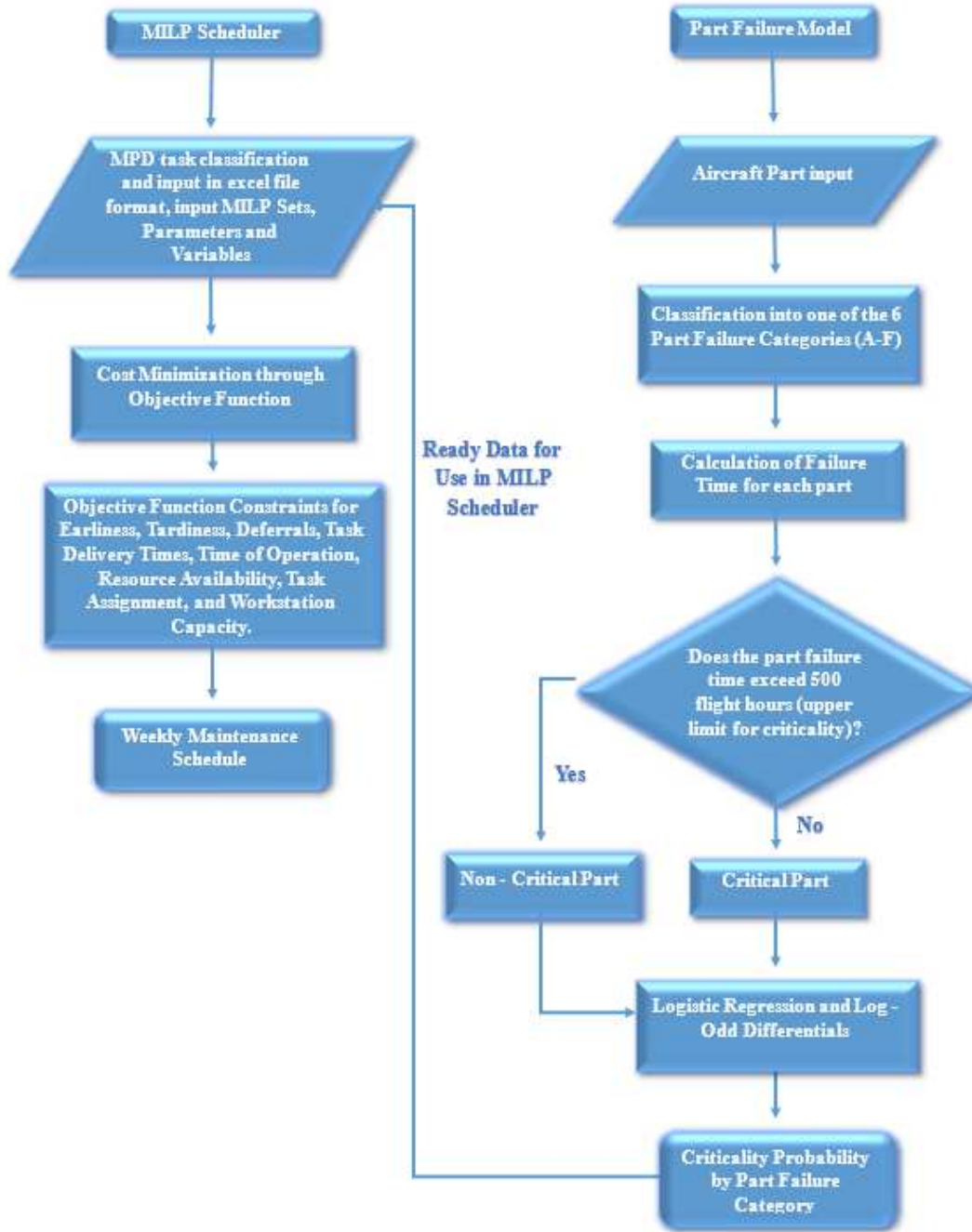


Fig. 2. Optimization Model Flowchart.

The part failure model was developed and executed on the same computing machine as mentioned above, with a recorded runtime of 1.89 seconds. The libraries used for this model are the following: The readxl library is employed for processing Excel files and relies on file parsing algorithms to perform this function. The dplyr library is utilized for data wrangling and manipulation, utilizing algorithms and methods such as

the split-apply-combine strategy, lazy evaluation, joins and filtering algorithms. This library is specifically designed to optimize tabular data operations, rather than to support advanced machine learning or statistical modeling. The ggplot2 library is used for data visualization, incorporating faceting and scaling algorithms as well as optional statistical transformations such as LOESS (locally estimated scatterplot smoothing). These algorithms are optional and serve as enhancements layered over the core visual aesthetics. The underlying rendering is handled by the grid graphics engine, which is the foundational graphics system used by the R programming language. Finally, the ggrridges library is used to generate ridge plots (stacked density plots), applying Kernel Density Estimation (with a default Gaussian Kernel) to smooth continuous data distributions and employing stacking algorithms to vertically offset each density, creating the characteristic “ridge” effect. This library inherits the full functionality and algorithms of ggplot2, with a primary emphasis on density estimation and geometric stacking.

3. Results

3.1. Optimization Model

To validate the developed model, a set of maintenance tasks was selected from the Maintenance Planning Document (MPD), as provided by the Hellenic Civil Aviation Authority (HCAA) (Airbus, 2024). In addition, the Master Minimum Equipment List (MMEL) (EASA, 2021), authored and approved by EASA, was also utilized. Based on the provisions of these two documents and the descriptions of the selected tasks, each task was mapped to a specific skill set required for completion by appropriately qualified personnel. The criticality of each task was determined according to the criteria outlined in the MPD, including task descriptions, maintenance thresholds and intervals. Similarly, the Rectification Interval Category for each task was assigned in alignment with the definitions and guidelines set forth in the MMEL.

The final output includes two Gantt charts: one illustrating the workload allocated to each workstation during the 6-hour overnight line maintenance window and another depicting the distribution of tasks across

available maintenance opportunities/ workstations. The model also incorporates deferred tasks, documenting non-critical deferrals along with their permissible deferral periods and rescheduling them to appropriate future maintenance opportunities/ workstations. What is ultimately produced is the daily line maintenance schedule for a representative facility over the course of a week. The results of the line maintenance schedule optimization model for the entire week are presented below (**Table 1**), along with indicative results for the first day of operations (**Table 2**) and the model's detailed cost output, showing the minimized daily costs and their proximity to the theoretical lowest bound (**Table 3**). It is noted that while an optimal solution was achieved in all days of the week, there have been cases where the theoretical lowest bound differs from the optimal solution found. This gap, however, does not exceed 0.81% over the entire work week, while in some cases it is equal to or approaches zero up to four decimal places. In certain cases, the solver's theoretical lowest bound cannot be fully attained due to real-world constraints and practical limitations; however, it can be approximated with negligible deviation.

Table 1 Optimized Maintenance Task Schedule Statistics

	DAY 1	DAY 2	DAY 3	DAY 4	DAY 5	DAY 6	DAY 7
Critical Tasks	20	20	19	20	20	20	20
Non-Critical Tasks	12	11	10	8	9	10	9
Task Deferral Percentage	3,13%	6,45%	6,90%	10,71%	6,90%	10,00%	3,45%
Deferred Tasks Scheduled	0	1	2	2	3	2	3

Table 2 Indicative Optimized Maintenance Task Schedule for Day 1

DAY 1					
Task	Type	Workstation	Start Time	End Time	Deferral
5	Critical	3	5.38	5.96	-
31	Critical	5	3.86	4.37	-
3	Critical	2	1.03	2.51	-
1	Critical	1	2.56	4.14	-
22	Critical	5	4.37	5.91	-
23	Critical	4	0.71	2.53	-
15	Critical	1	4.14	5.91	-
8	Critical	2	3.74	5.00	-
24	Critical	3	2.57	3.28	-
11	Critical	4	0.00	0.71	-
28	Critical	1	1.30	2.56	-
30	Critical	2	5.00	5.88	-
6	Critical	2	0.00	1.03	-
7	Critical	1	0.50	1.30	-
25	Critical	5	1.92	3.36	-
10	Critical	4	4.61	5.98	-
19	Critical	2	2.51	3.16	-
16	Critical	5	0.00	0.74	-
4	Critical	5	1.24	1.92	-
14	Critical	4	4.11	4.61	-

18	Non-Critical	3	4.88	5.38	0.0
9	Non-Critical	3	2.07	2.57	0.0
12	Non-Critical	3	3.28	4.88	0.0
32	Non-Critical	1	0.00	0.50	0.0
13	Non-Critical	3	1.57	2.07	0.0
17	Non-Critical	5	3.36	3.86	0.0
2	Non-Critical	2	3.16	3.66	0.0
20	Non-Critical	5	0.74	1.24	0.0
26	Non-Critical	4	2.53	4.11	0.0
27	Non-Critical	3	0.00	1.57	0.0
29	Non-Critical	Deferred	-	-	9.00
21	Non-Critical	Deferred	-	-	7.00

Table 3 Cost Minimization Model Output

Day	Solver	Status	Objective Value	Lowest Bound	Gap (%)	Nodes	Runtime (sec)
1	XPRESS_PY	Optimal	288,042406	288,042406	0	1122	0,22
2	XPRESS_PY	Optimal	343,556055	343,555712	0,0001	57	0,15
3	XPRESS_PY	Optimal	349,376631	346,54779	0,809682	2744	0,31
4	XPRESS_PY	Optimal	377,957035	376,586003	0,362748	6799	0,75
5	XPRESS_PY	Optimal	347,193199	347,192852	0,0001	1	0,17
6	XPRESS_PY	Optimal	415,243942	415,243526	0,0001	1886	0,27
7	XPRESS_PY	Optimal	332,250386	332,250054	0,0001	1	0,13

Weekly results show fluctuations in total cost, primarily driven by the accumulation of deferred non-critical tasks. On Day 1, the facility operates at peak productivity, with full workstation utilization and minimal cooldowns, resulting in a low total cost. One non-critical task is deferred to Day 2, but its incorporation has minimal impact on that day's scheduling, which again achieves high utilization. Day 3, with two deferrals, demonstrates a slight cost increase. On Day 4, the growing volume of deferred tasks increases the operational load, leading to the second-highest cost of the week. As illustrated in the Gantt chart (**Fig. 3**), task allocation is efficient, with sufficient transition time. Day 5 maintains a low cost, practically matching the theoretical minimum, while Day 6 records the highest cost due to accumulated deferrals and increased task volume. Nonetheless, the model effectively contains the impact of deferrals and prevents further disruption. Day 7 proceeds without major issues, completing the weekly schedule.

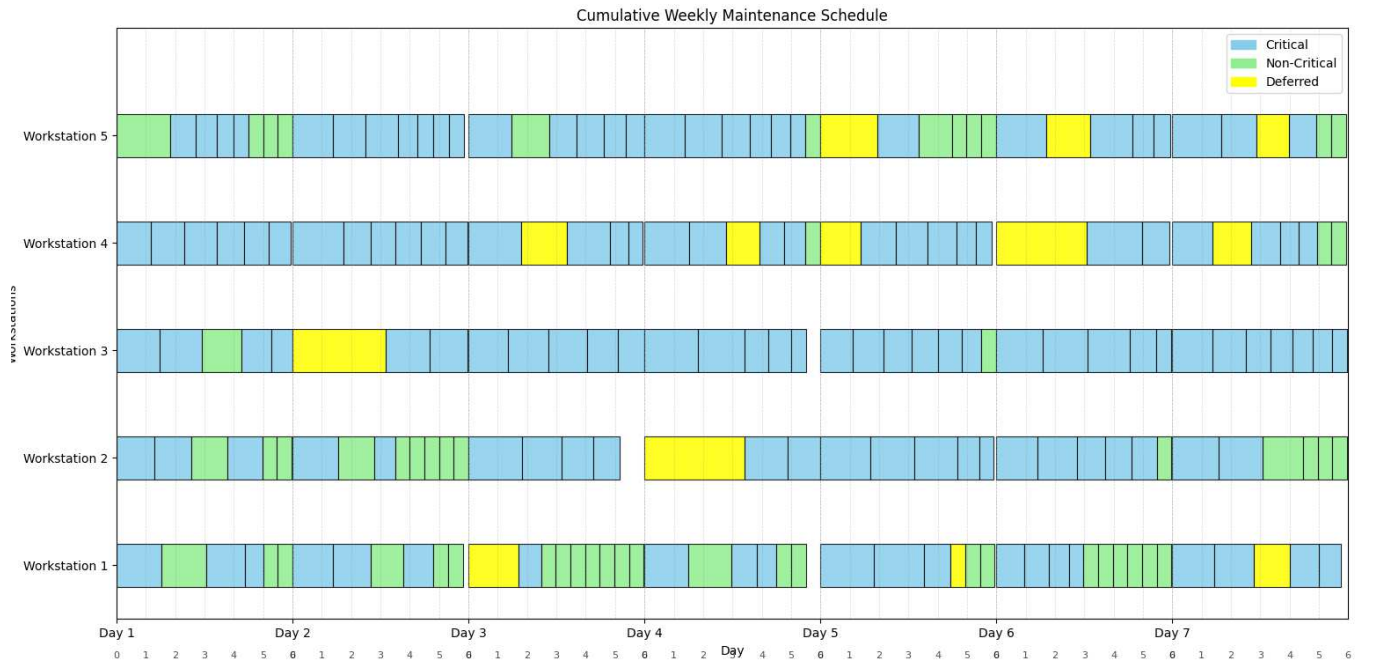


Fig. 3. Weekly Line Maintenance Task Schedule.

A sensitivity analysis was conducted to evaluate the model's robustness to changes in key parameters, including earliness and tardiness costs, resource utilization costs and workstation assignment penalties.

Parameter ranges were derived from empirical data and multiple iterations were performed to identify values yielding optimal model performance. This analysis demonstrates the model's adaptability to real-world variations in cost and resource conditions.

The first stage of the analysis examined the impact of earliness and tardiness cost coefficients on task completion (**Fig. 4** and **Fig. 5**). The total number of task deferrals over the week was used as the evaluation metric. Reducing the earliness cost coefficient a_i by half slightly increases deferrals, as the model prioritizes early scheduling of critical tasks to ensure timely completion, limiting available time for longer non-critical tasks. This trend persists in subsequent days as deferred tasks accumulate, increasing scheduling pressure. Conversely, a sharp increase in earliness cost produces a similar outcome. To avoid early completion penalties, critical tasks are spread across the shift, fragmenting the schedule and leaving insufficient continuous slots for long non-critical tasks, which are then deferred.

A similar pattern is observed in the analysis of tardiness cost b_i with the underlying rationale being the opposite of the previously discussed case. Specifically, when tardiness is severely penalized, critical tasks are scheduled as early as possible to ensure that there are no delays. As a result, non-critical tasks tend to be scheduled later in the day, while those with longer durations are deferred due to the constraints of the fixed maintenance window. This outcome mirrors the scheduling behavior observed in scenarios with low earliness completion costs. The results of the sensitivity analysis are summarized below (**Fig. 4** and **Fig. 5**).

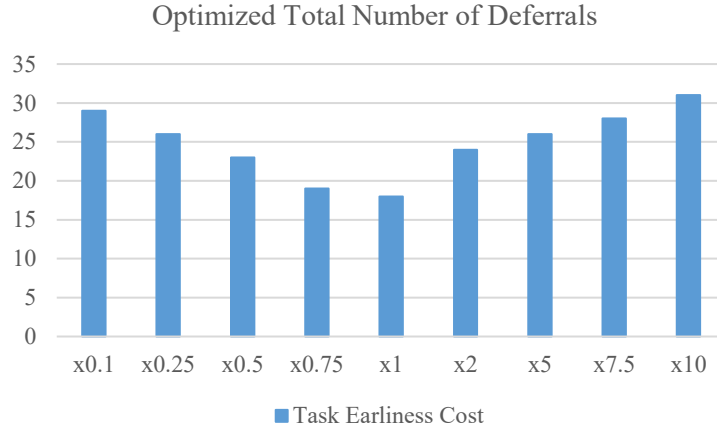


Fig. 4. Sensitivity Analysis: Impact of Earliness Cost.

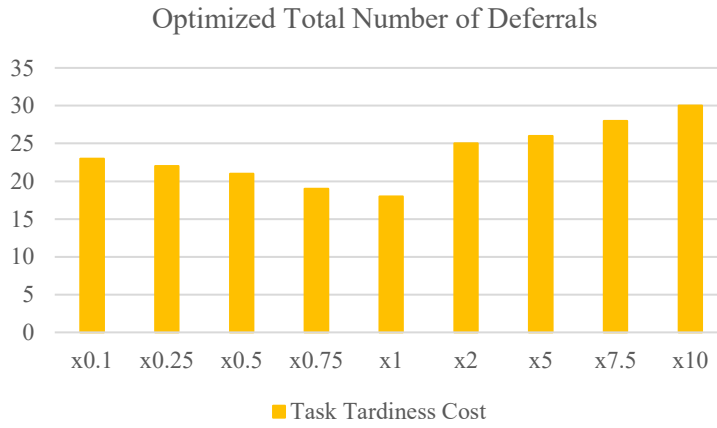


Fig. 5. Sensitivity Analysis: Impact of Tardiness Cost.

In addition to the primary parameters, two additional factors, namely e_k (cost per unit of resource k) and λ_m (penalty coefficient for assigning tasks to slot m), were included in the sensitivity analysis. The model exhibited a high level of sensitivity to changes in these parameters and a limited number of iterations was sufficient to draw clear conclusions. Both parameters were scaled by factors of 2, 5, 7.5, and 10 to observe the resulting effects. In the case of resource cost e_k , a clear pattern emerged: as the cost increased, the total number of task deferrals and the overall operational cost rose significantly. This outcome is expected, as

higher resource costs restrict the use of available resources, reducing scheduling flexibility and increasing the likelihood of deferrals. Similarly, increasing the assignment cost λ_m , intended to discourage overloading specific workstations, also led to a rise in task deferrals, though less significantly. A consistent upward trend was observed, indicating a moderate yet significant linear relationship. This behavior can be attributed to the model's effort to distribute tasks more evenly across workstations, which reduces the available time slots for scheduling longer non-critical tasks. Consequently, these tasks are more likely to be deferred, adding to the workload of subsequent days.

3.2. Part Failure Prediction Model

The results of the auxiliary part failure model are based on the analysis of 100 representative wing components, each of which was classified into one of the six defined failure pattern categories (**Fig. 1**). For each pattern category, the model also estimates the probability that a given part will be critical. Each probability estimate is accompanied by the corresponding log-odds value and its associated standard deviation. Additionally, an estimated time to failure was computed for each component. A summary of the results is shown below (**Table 4**).

Table 4 Cost Minimization Model Output

Failure Pattern	Number of Parts	Estimate	Standard Deviation	z value	Pr(> z)	Criticality Probability
A	15	-1,0116	0,58387	-1,733	0,0832	26,67%
B	6	-0,59784	1,24133	-0,482	0,6301	16,67%
C	4	-0,08701	1,29392	-0,067	0,9464	25,00%
D	7	1,29928	0,96137	1,351	0,1765	57,14%
E	7	0,09531	1,02025	0,093	0,9256	28,57%
F	61	1,58412	0,64188	2,468	0,0136	63,93%

According to the results, parts classified under Category F and Category D exhibit the highest likelihood of being deemed critical based on their failure patterns. On the contrary, the least probable parts to be critical belong in Category B. Thus, wing parts that demonstrate a failure rate that is similar to the RCM Curves F and D should be closely monitored within the first 500 hours of use upon acquisition.

4. Discussion

The MILP-based line maintenance scheduler follows safety rules and creates a reliable weekly plan that handles changing workloads without affecting flight schedules. In parallel, the auxiliary model classifies aircraft components according to their respective RCM curves, estimates failure times, and evaluates the probability of each part being deemed critical. Together, these models offer a rigorous framework for addressing the largely unresolved Line Maintenance Scheduling Problem and provide a foundation for advancing research in predictive maintenance and operational safety. At its foundation, the model fills a critical gap in the literature related to line-maintenance scheduling by embedding a “memory” of deferred jobs directly into the optimization framework. Each day’s critical maintenance directives are guaranteed placement within the fixed six-hour overnight maintenance window, while non-critical tasks that cannot fit are carried forward and re-balanced in subsequent days. This rolling-horizon deferral mechanism ensures that, regardless of how many unexpected tasks emerge, the schedule remains stable and predictable, an improvement over previous static or heuristic approaches.

A key strength of the framework lies in its automation. Users input the daily or weekly task list, and the system autonomously manages prioritization, deferral tracking and workstation allocation. This reduces the need for manual scheduling, freeing planners to focus on higher-value activities such as predictive analytics and innovation. Because all parameters, such as resources, thresholds and penalty weights, are fully customizable, the model can be easily adapted to various airline policies and operational environments. The part failure prediction model enhances aviation safety by enabling early identification of components at risk of failure and supporting proactive maintenance planning. One of the main challenges in aviation

maintenance has been managing the uncertainty surrounding part failures, which often leads to emergency inspections and unscheduled repairs. When combined with historical failure and maintenance data, this approach enables grouping of components by their projected failure horizon, allowing for more targeted and timely maintenance interventions such as inspections and preventive checks.

Finally, the proposed framework is also highly scalable and can be tailored to airlines of varying fleet sizes, operational structures and regulatory environments. Beyond aviation, its core principles, optimized scheduling, deferral tracking and risk-based task prioritization, are applicable to other industries that rely on asset availability and maintenance compliance, such as rail transport, maritime operations and manufacturing. This flexibility makes the model a valuable foundation for broader industrial deployment.

5. Conclusions

This study introduced an optimization framework for automated line maintenance scheduling in aviation, using a mixed-integer linear programming (MILP) model that incorporates operational constraints, safety requirements and dynamic task deferral. The model efficiently schedules daily maintenance within a strict six-hour window, prioritizes critical tasks and includes a “memory” mechanism to reassign deferred work, ensuring continuity and schedule stability. An auxiliary model estimates part failure times based on design characteristics, enhancing preemptive maintenance and addressing uncertainty in scheduling.

Given the limited academic focus on line maintenance scheduling, several paths exist for advancing this field. A key direction is the development of real-time, adaptive frameworks that incorporate rolling-horizon logic and respond dynamically to operational disruptions. Integrating live data streams, such as Aircraft on Ground (AOG) alerts, technician availability and spare parts inventory forecasts, can enable a responsive scheduling engine capable of minimizing downtime and improving reliability. In addition, the core logic of the deferral memory paradigm and risk-based scheduling is applicable beyond aviation. Validating this

approach in other compliance-driven sectors, such as rail, maritime and manufacturing can demonstrate its generalizability and reveal new operational efficiencies. Together, these enhancements position line maintenance not as a static planning task but as a dynamic, data-driven process that supports safety, efficiency and profitability.

In summary, the proposed framework delivers a practical and scalable solution for modern maintenance planning, combining safety, efficiency and flexibility in a way that is directly applicable to real-world operations. Its ability to integrate with diverse systems and adapt to various industry needs, positions it as a potential asset for organizations aiming to transform maintenance into a driver of operational excellence.

Author Contributions

The authors confirm contribution to the paper as follows: conception and design: D. Peteinatos, K. Kontodimou, V. Andronis, K. Kepaptsoglou; data collection: D. Peteinatos, V. Andronis, K. Kontodimou; analysis and interpretation of results: D. Peteinatos, K. Kontodimou, V. Andronis, K. Kepaptsoglou; draft manuscript preparation: D. Peteinatos, K. Kontodimou. All authors read and approved the final manuscript.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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