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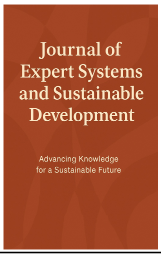

Workload Balancing in Periodic Aircraft Maintenance Checks: A Lexicographic Heuristic Approach Under Zone Constraints

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ABSTRACT

This study aims to provide solution approach to the task allocation problem for periodic aircraft maintenance checks with a flexible and parametric model, which is capable of adapting to various set of constraints. The primary goal is to minimize the fluctuations in workload (man-hour) along the planning period regarding maintenance packages in order to ensure the efficient use of resources and manage aircraft ground times. The problem is formulated as a packing problem while incorporating spatial conflict rules and periodicity requirements. The contribution of the proposed solution approach relies on its dynamic input structure, which can incorporate task lists and constraints without being dependent on a specific aircraft type or maintenance program. A lexicographic optimization structure is adopted to sequentially minimize workload imbalance, maximize interval utilization for tasks with high labor requirements, and minimize active zone diversity within maintenance checks. The proposed algorithm iteratively improves the solution using local search method after the greedy assignments. Computational experiments conducted on both narrow-body and wide-body fleet scenarios show that the proposed method achieves a substantially smoother workload profile across maintenance checks while successfully managing defined spatial conflicts. Although a controlled reduction in task interval utilization is observed, this trade-off is shown to be operationally acceptable when equalized workload demand are prioritized. The methodology proposed in this study can serve as a Decision Support System for airline operators and maintenance organizations, thanks to its speed and capability in generating feasible solutions.

Keywords:
Aircraft maintenance planning; Equalized check; Multiple objectives; Packing problem; Lexicographic optimization; Task allocation

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1. Introduction

The aviation industry operates with low profit margins due to high operating costs and intense competition among airlines [1]. Under these conditions, controlling cost-intensive operational activities becomes critical. One of these is maintenance operations. Maintenance activities account for a significant share of an airline's direct operating costs. Maintenance expenses typically represent 10% to 15% of an airline's total operating costs, which are influenced by fleet age and operational elements [2]. As a result, maintenance planning goes beyond a purely airworthiness requirement and becomes a strategic factor in sustaining financial performance.

Efficient maintenance planning supports airworthiness compliance while reducing aircraft ground time and improving the utilization of maintenance resources [3]. However, achieving efficiency is far from straightforward in practice. One of the main issues in maintenance planning is converting the Maintenance Planning Document (MPD) into a proper working schedule. Although maintenance requirements are formally defined in MPD, deciding how individual tasks should be grouped into operationally feasible maintenance visits is left to the operators [4]. This process, commonly referred to as the "Maintenance Packing Problem," requires organizing thousands of separate maintenance tasks—each with unique intervals, locations, and skill needs—into manageable work packages [5]. The difficulty of this process is increased by the diversity of airline fleets, as standard planning solutions often fail to meet operator-specific fleet configurations, utilization profiles, and resource constraints [6].

Mathematically, the maintenance packing is frequently modeled as an extension of the Bin Packing Problem (BPP). Although the classical BPP is well known to be NP-hard [7], its application to aircraft maintenance introduces additional structural constraints. In particular, spatial conflicts among tasks and the requirement to preserve strict periodicity significantly complicate the problem formulation [5].

Recent studies have attempted to address these problems through heuristic and meta-heuristic solution approaches. However, in current maintenance packing models, man-hour balance among maintenance packages[*] is generally not the top priority. This suggests that fluctuations in total man-hours across maintenance packages have not been adequately addressed in the current literature [8].

In operational practice, uneven man-hour profiles are a major source of planning instability and can lead to inefficiencies [9, 10]. The modeling approach presented here is motivated by the need to address, firstly, these workload fluctuation issues in maintenance packages. In this context, the model we have developed establishes a balance of total man-hours between packages while also considering the spatial constraints introduced to the system. Furthermore, secondary and tertiary objectives have been integrated into the model during this balancing process. As a result, lexicographic multi-objective framework is adopted, decision priorities within the model are handled as hierarchical. The primary priority is placed on limiting variations in required man-hours across maintenance packages, thereby supporting stable and predictable resource utilization. Additional objectives are introduced at lower priority levels to reduce the waste of interval utilization of high labor tasks and to try to minimize total active aircraft zone in the packages. In addition, the defined spatial constraint is considered throughout this process. A fallback mechanism is also included within the model to prevent tasks from being left unattended if these spatial constraints cannot be met. Thus, each valid task will continue to be assigned to maintenance packages without exceeding its interval and without disrupting the man-hour balance in the packages. Finally, unlike static models, our proposed model uses a dynamic input structure that can handle external task lists and constraint matrices.

[*] In this study, the terms of "package" and "check" are used interchangeably to refer to a grouped set of maintenance tasks.

2. Literature Review

2.1 Maintenance Routing and Scheduling

Although not the focus of this study, the routing or scheduling aspect of aircraft maintenance planning is extensively covered in the literature. In particular, significant research focuses on integrating maintenance decisions into flight scheduling. The study by Sarac *et al.* [11] can be cited as an example. Using the branch-and-price method, their research demonstrated that maintenance routing should be considered in conjunction with flight assignments. On this topic, Haouari *et al.* [12] further developed it by using network flow-based approaches to handle flight route changes and maintenance operations simultaneously. More recently, Başdere *et al.* [13] addressed the operational aspect of maintenance routing, focusing particularly on the remaining time factor, which directly influences how maintenance packages are generated and Eltoukhy *et al.* [14] highlighted the need for robust models capable of handling stochastic operational disruptions in flight scheduling.

2.2 Maintenance Packing (Task Allocation)

Maintenance packing is different from routing or scheduling, even though they are essentially sequential processes that support each other. When examining studies focusing more on maintenance packing, study made by Witteman *et al.* [5] is noticeable: They explicitly modeled the maintenance task allocation problem as a BPP. Their work demonstrated that advanced packing heuristics can effectively handle the clustering of tasks with varying periodicities. Furthermore, Vu *et al.* [15] proposed dynamic models for grouping maintenance tasks in multi-component systems. Their approach targeted to update the maintenance planning in dynamic contexts, which aligns closely with the parametric objectives of this study.

2.3 Workload Balancing and Workforce Management

Performing maintenance checks in a predictable and balanced (equalized) manner is highly beneficial not only for maintenance operations but also for flight operations [16]. For aircraft, especially those operating long-haul flights, there is limited time available per day for maintenance procedures. This generally means the aircraft needs to be grounded for a period to fulfill maintenance requirements [4]. However, by adopting a phased and equalized maintenance approach when needed, downtime due to maintenance can be minimized, and it may even be possible to perform maintenance procedures without affecting the flight schedule at all [17].

Beyond its primary objective of workload balancing, our study also aims to contribute to workforce management due to its spatial constraint-first structure. Regarding workforce management, Safaei *et al.* [8] addressed this by formulating a workforce-constrained maintenance scheduling problem. Their study, which focused on maximizing operational availability for military aircraft, demonstrated that workforce management is critical in aircraft maintenance planning. Yan *et al.* [18] specifically focused on short-term maintenance manpower supply planning, stated that the composition of maintenance plans is the primary driver of workforce requirements. This is supported by Van den Bergh *et al.* [19], whose review on personnel scheduling confirms the link between task packing and workforce efficiency.

2.4 *Heuristic Approaches and Existing Research Gaps*

The inherent computational complexity of the maintenance packing problem, classified as NP-Hard, often renders deterministic methods ineffective for large-scale, real-world scenarios. Consequently, researchers have shifted their focus towards heuristic strategies. For instance, the disconnect between theoretical planning and operational execution was addressed by Samaranayake *et al.* [9] through integrated heuristic frameworks. In the military domain, where operational availability is highly important, Kozanidis [20] prioritized mission readiness over cost within a multi-objective heuristic model. Furthermore, the necessity of heuristic approaches in handling the high dimensionality of airline operations was validated by Jamili [21], while Liang *et al.* [22] utilized rotation tour network models to navigate complex routing constraints.

However, integrated approaches are limited in the current literature, although packing and workload aspects of maintenance planning have been examined individually. This study fills this gap by introducing a parametric model capable of simultaneously managing workload balancing, spatial zone conflicts and dynamic input structures within a lexicographic framework.

3. Methodology

3.1 *Problem Definition*

This study deals with the assignment of repetitive maintenance tasks to scheduled maintenance checks. Each task has a specific interval, based on flight hours (FH), flight cycles (FC), or calendar days (DY). When a task depends on multiple parameters simultaneously, the limiting parameter is determined by the aircraft's daily utilization profile. In such cases, the "whichever comes first" rule applies, and the task is assigned based on the most restrictive parameter.

Tasks must be performed within their defined intervals. Although early applications are operationally feasible, exceeding the limit (overdue) is not permitted. Early applications in our model are used only in the initial phase in order to balance the workload and are only possible with the first assignments. In this initial phase, the Interval Utilization Rate (IUR) for tasks with low labor requirements is not a primary concern; however, for all subsequent repetitions, the objective is to maximize the IUR.

Similar to individual tasks, maintenance checks are also repetitive and must be performed without exceeding their respective intervals. The number of maintenance checks to which tasks can be assigned is dynamic and varies depending on maintenance interval, planning horizon and package multiplier (Section 3.2.1), which all can be determined as needed in accordance with the operator's maintenance strategy.

On an aircraft, tasks are performed in different areas (zones) such as the wings, engines, landing gear, tail, etc. These areas can differ in terms of physical access, safety space, workload, and required equipment during maintenance. Working on multiple areas at once can cause mechanical conflicts or access issues. For example, opening engine cowls on some aircraft might block access to nearby wing sections, delaying the work.

In this study, the problem is formulated and referred to as the "Constrained Periodic Aircraft Maintenance Packing Problem". It involves assigning maintenance tasks, which must be performed within a specific planning horizon, to maintenance packages (checks) subject to technical requirements and workforce constraints. The primary objective is to minimize workload (man-hour) fluctuations between packages to ensure the efficient utilization of maintenance resources. Simultaneously, the model aims to separate tasks involving predefined conflicting zones. Thus, the problem is formulated as a variation of the BPP within combinatorial optimization, characterized by periodic repetitions and spatial constraints.

The proposed methodology transforms the maintenance requirements defined in the MPD into an optimized operational schedule. The model is constructed upon a dynamic parameter set, a multi-objective lexicographic function and a set of operational constraints.

3.2 Parameter Normalization and System Configuration

In aviation, intervals are typically defined in three different units: FH, FC and DY [23]. **FH** is selected as the base parameter of this study.

The process begins by providing the values I_a, which indicates the interval for performing maintenance checks (packages), and I_b, which indicates the total planning horizon. These two defined intervals, I_a and I_b are converted into the same format (FH) using aircraft daily utilization values:

$$I_a = \min\left\{ I_a^{fh}, \quad I_a^{fc} \times \frac{U_{fh}}{U_{fc}}, \quad I_a^{dy} \times U_{fh} \right\} \tag{1}$$

$$I_b = \min\left\{ I_b^{fh}, \quad I_b^{fc} \times \frac{U_{fh}}{U_{fc}}, \quad I_b^{dy} \times U_{fh} \right\} \tag{2}$$

Here, U_{fh} and U_{fc} represent the aircraft daily utilization values in terms of FH and FC, respectively. It is assumed that $I_a < I_b$. Undefined components are treated as $+\infty$ to ensure it does not affect the minimization function.

3.2.1 Package Multiplier and Total Slots

To provide flexibility in planning, the model incorporates a *Package Multiplier* (P). This coefficient determines the granularity of the maintenance checks.

- If $P = 1$, the maintenance strategy follows a standard block approach where checks occur at I_a intervals.
- If $P > 1$, a phased approach is adopted to divide the work into smaller packages in order to reduce the workload per package and better satisfy zonal constraints. Accordingly, number of P package series are generated, where consecutive packages within each series follow each other at an interval of I_a

Consequently, the total number of maintenance packages (N) available within the planning horizon is calculated as:

$$N = \left\lfloor \frac{I_b}{I_a} \right\rfloor \times P \tag{3}$$

Here, N represents the discrete time slots (bins) available for task assignment.

3.3 Task Characterization and Pre-processing

The set of maintenance tasks to be scheduled is denoted by $T = \{1, 2, \ldots, n\}$. Each task $t \in T$ is characterized by its workload (mh_t), its physical location on the aircraft (zone set z_t), and its specific repetitive interval (I_t). It is important to note that I_t acts as a maximum limit. While performing a task earlier than scheduled is always an option, exceeding this interval is never allowed due to airworthiness regulations.

Similar to the system parameters, the raw interval of each task is normalized to FH to ensure consistency:

$$I_t = \min\left\{ I_t^{fh}, \quad I_t^{fc} \times \frac{U_{fh}}{U_{fc}}, \quad I_t^{dy} \times U_{fh} \right\} \tag{4}$$

3.3.1 *Validity and Repetition Logic*

Before the optimization phase, a pre-processing algorithm filters the tasks and calculates their periodicity.

Validity Check (v_t): Tasks with intervals shorter than the base interval ($I_t < I_a$) are considered ”Line Maintenance” tasks and are excluded from this model. Similarly, tasks with intervals exceeding the horizon ($I_t \geq I_b$) are out of scope. A binary parameter v_t is assigned:

$$v_t = \begin{cases} 1, & \text{if } I_a \leq I_t < I_b \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Repetition Period (r_t): For valid tasks, the repetition period r_t defines the frequency of the task in terms of ”number of packages”. It is calculated as the integer ratio of the task interval to the base package interval:

$$r_t = \left\lfloor \frac{I_t}{I_a} \right\rfloor \times P \tag{6}$$

The value of r_t serves two purposes: First, it defines the deadline for the **first assignment** (the task must be assigned to a package $k \leq r_t$). Second, it defines the **step size** for subsequent repetitions. For example, if $r_t = 4$ and the task is first assigned to package 2, it will automatically recur in packages $2 \rightarrow 6 \rightarrow 10 \rightarrow \dots$, ensuring that the maintenance interval is never exceeded. Additionally, with this pattern, the interval utilization of tasks (except for the first assignments) are maximized.

3.4 *Mathematical Formulation*

The problem is formulated as a multi-objective binary integer programming model. The definitions of sets, parameters, and decision variables are summarized in Table 1.

3.4.1 *Decision Variables and Periodicity*

The primary decision variable $f_{t,k}$ determines the first package to be assigned for each task. It is a binary variable and defined as:

$$f_{t,k} \in \{0, 1\}, \quad \forall t \in T, \quad 1 \leq k \leq r_t \tag{7}$$

$f_{t,k}$ takes the value 1 when package k is selected as the starting point for task t

Table 1
Sets, Parameters, and Variables

Symbol	**Description**
Sets	
K	Set of maintenance packages, $K = \{1, \ldots, N\}$.
T	Set of maintenance tasks, $T = \{1, \ldots, n\}$.
Z	Set of aircraft zones (e.g., Fuselage, Wing, Engine), $Z = \{\delta_1, \ldots, \delta_m\}$.
F	Set of Forbidden Zone Pairs, $F \subseteq Z \times Z$. Represents pairs of zones where simultaneous work is prohibited.
R	Set of unique repetition periods in the valid task list.
Input Parameters	
I_a	Defined maintenance interval.
I_b	Planning horizon.
U_{fh}	Aircraft daily flight hours utilization.
U_{fc}	Aircraft daily flight cycle utilization.
P	Package Multiplier (Granularity Coefficient).
I_t	Repetitive interval for task t.
mh_t	Workload required to complete task t (man-hours).
z_t	Subset of zones occupied by task t, $z_t \subseteq Z$.
Derived Parameters	
N	Total number of maintenance packages.
v_t	Binary validity parameter: 1 if task t is valid, 0 otherwise.
r_t	Calculated repetition period (frequency) for task t.
Decision Variables	
$f_{t,k}$	Binary variable: 1 if the first occurrence of task t is assigned to package k.
$y_{t,k}$	Binary derived variable: 1 if task t is present in package k (includes all repetitions).

To capture the periodic nature of maintenance, a derived variable, $y_{t,k}$, is introduced to indicate the packages to which the task is assigned throughout the entire planning horizon ($1 \dots N$). The relationship between the first assignment and subsequent repetitions is governed by the modulo operator:

$$y_{t,k} = \sum_{j=1}^{r_t} f_{t,j} \cdot \mathbb{I}(k \equiv j \pmod{r_t}) \tag{8}$$

where $\mathbb{I}(\cdot)$ is an indicator function returning 1 if the condition holds, and 0 otherwise. This equation ensures that once a start package j is selected, all corresponding slots ($j, j + r_t, j + 2r_t \dots$) are automatically reserved.

3.4.2 Lexicographic Objective Function

The problem seeks to satisfy multiple conflicting goals. A **Lexicographic Optimization** approach is employed, where objectives are strictly ordered by priority.

Priority 1 - Workload Balancing (θ_1): Primary objective targets the efficient use of maintenance resources via workload leveling. Volatility in cumulative workload (man-hours) can cause operational waste, manifesting as costly overtime in peaks and wasted capacity in valleys. To address this, our formulation aims to flatten the workload profile by reducing the aggregate absolute deviation from the ideal average.

Instead of balancing (leveling) the workload globally, the proposed method applies a stratified approach based on repetition groups (r_t). This distinction is critical to avoid "masking effect," a phenomenon where a surplus in one task category might obscure a deficit in another. By executing the balancing process independently for each repetition group $R = \{r_t \mid t \in T\}$, the algorithm guarantees a consistent and uniform distribution throughout the planning horizon.

The objective function for this primary objective is formulated as follows:

$$\theta_1 = \sum_{r \in R} \sum_{k=1}^{r} \left| L_{r,k} - L_r^{target} \right| \tag{9}$$

Here, $L_{r,k}$ represents the actual accumulated workload of group r in package k, and L_r^{target} is the ideal average load of group r. These components are mathematically defined as:

$$L_{r,k} = \sum_{t \in T_r} mh_t \cdot f_{t,k} \tag{10}$$

$$L_r^{target} = \frac{\sum_{t \in T_r} mh_t}{r} \tag{11}$$

In these equations, $T_r = \{t \in T \mid v_t = 1, r_t = r\}$ denotes the subset of valid tasks characterized by the specific repetition period r, ensuring that the aggregation is strictly confined to tasks sharing the same frequency.

Priority 2 - Maximizing Interval Utilization (θ_2): Secondary objective targets the efficient use of task intervals during task assignment (allocation) process. To increase operational efficiency and minimize the loss of remaining useful interval, tasks should be assigned as late as possible within their valid interval. This prevents *overmaintenance*.

The objective function for this secondary objective is formulated as follows:

$$\theta_2 = \sum_{t \in T} \sum_{k=1}^{r_t} (-k) \cdot f_{t,k} \tag{12}$$

Since k represents the package number, minimizing the negative sum is mathematically equivalent to maximizing the assignment index k.

However, strictly assigning every task to its latest possible package may contradict the primary workload balancing objective (θ_1). Therefore, the model adopts a strategic approach where tasks with higher workloads are prioritized for late assignment. This ensures that resource-intensive tasks maximize their interval utilization, while smaller tasks may be scheduled earlier to fill workload gaps and satisfy the balancing requirement.

Priority 3 - Minimizing Zone Diversity (θ_3): While the first two objectives address labor resources and time efficiency, the tertiary objective focuses on the spatial logistics of the maintenance operation. High diversity of active zones within a single package increases logistical complexity, as technicians and equipment must constantly move between distant parts of the aircraft (e.g., from the cockpit to the tail). Rather than enforcing strict spatial clustering, zone diversity is treated as a soft objective to preserve solution feasibility under tight periodicity constraints.

Therefore, the tertiary objective aims to minimize the number of distinct active zones per package, encouraging the spatial clustering of tasks. This is calculated by summing the cardinality of the union of zone sets for all active tasks across all packages:

$$\theta_3 = \sum_{k=1}^{N} \left| \bigcup_{t: y_{t,k}=1} z_t \right| \tag{13}$$

Here, the union operator $\bigcup$ merges the zone sets of all tasks assigned to package k, and the cardinality operator $|\cdot|$ counts the number of unique zones in that merged set. Minimizing this value ensures that maintenance activities in a given package are concentrated in fewer physical locations.

Finally, the general multi-objective function is expressed as a lexicographic minimization vector, strictly enforcing the hierarchy of these three priorities:

$$\text{lex min } \langle \theta_1, \theta_2, \theta_3 \rangle \tag{14}$$

3.4.3 Constraints

The optimization is subject to the following operational and zonal constraints.

1. Single Assignment Constraint: Every valid task ($v_t = 1$) must be assigned to only one first package within its repetition period r_t. This ensures no valid task is left unassigned or duplicated.

$$\sum_{k=1}^{r_t} f_{t,k} = 1, \quad \forall t \in T \text{ s.t. } v_t = 1 \tag{15}$$

Conversely, invalid tasks must not be assigned:

$$\sum_{k=1}^{r_t} f_{t,k} = 0, \quad \forall t \in T \text{ s.t. } v_t = 0 \tag{16}$$

2. Forbidden Zone Constraint (Spatial Conflict):

This is the critical constraint of the model, which prevents tasks from incompatible zones (as defined in set F) from being assigned to the same package. For every package k and every forbidden pair $(i, j) \in F$, the simultaneous presence of both zones is prohibited.

This logic is modeled using set intersection:

$$\forall k \in K,\ \forall (i,j) \in F : \quad \left| \{i,j\} \cap \left(\bigcup_{t: y_{t,k}=1} z_t \right) \right| \leq 1 \tag{17}$$

If the union of active zones in package k contains both i and j, the intersection size becomes 2, which violates the inequality (≤ 1). This constraint forces the algorithm to separate spatially conflicting tasks into different time slots.

3.5 Heuristic Solution Algorithm

The mathematical model defined in the previous sections belongs to the NP-Hard complexity class due to the combination of bin packing and spatial conflict constraints. For large-scale real-world datasets (e.g., thousands of maintenance tasks), exact solution methods are computationally infeasible. Therefore, a multi-stage *Constraint-First Heuristic Algorithm* has been developed to solve the problem efficiently.

The proposed algorithm consists of three main phases: (1) Data Pre-processing, (2) Initial Assignment Construction and (3) Repetitive Assignment Construction.

3.5.1 Phase 1: Pre-processing

The first phase involves importing data from the MPD and converting it into model-compatible parameters. In this step, heterogeneous task intervals (FH, FC, DY) are converted (normalized) to a single base unit (FH), and the specific repetition period (r_t) for each task is calculated. Tasks that fall outside the planning horizon or violate minimum frequency requirements are filtered out. The detailed pseudo-code for the first phase is presented in Table 2.

3.5.2 Phase 2: Constraint-First Initial Assignments

Since all assignments made after the initial assignments are already automated and subject to a specific rule (Eq. 8), the one and only decision-making phase of the model is the initial assignments phase. This phase employs a "hardest-first" strategy, where tasks are prioritized based on their constraints and man-hour requirements (mh_t).

To meet the lexicographic objectives, the algorithm sorts the tasks from highest to lowest man-hour and attempts to assign them iteratively to the latest possible package that does not violate the defined forbidden zone constraints. This greedy approach ensures that the most difficult tasks are assigned first, minimizing the risk of infeasibility.

Additionally, the proposed algorithm includes a **Fallback Mechanism** to ensure robustness under spatially constrained conditions. Due to the complex nature of the problem, a task may not always find a suitable package to meet the defined spatial constraint within their calculated repetition period. For instance, especially in a block maintenance structure ($P = 1$), tasks with a repetition period of one interval ($r_t = 1$) are naturally required to be performed in every check, even if they violate the defined spatial constraint when they are simultaneously in the same package. In these cases, the fallback

Table 2
Pseudo-code for Task Pre-processing

Procedure	
Input: Set of tasks T, Utilization (U_{fh}, U_{fc}), Planning parameters (I_a, I_b, P)	
For each task $t \in T$ **do**	
$I_t \leftarrow$ Eq. (4)	▷ *calculate normalized task interval*
If $I_a \leq I_t < I_b$ **then**	
$v_t \leftarrow 1$	▷ *task is valid*
$r_t \leftarrow$ Eq. (6)	▷ *calculate task repetition*
Else	
$v_t \leftarrow 0$	▷ *task excluded*
$r_t \leftarrow 0$	
End If	
End For	
Output: Final set of valid tasks T with v_t, r_t	

mechanism in the algorithm is activated, the strict spatial constraint is temporarily relaxed, and the task is assigned to the package that minimizes the instantaneous workload deviation, considering only the primary objective function (θ_1). Assignments made through the fallback mechanism are marked as ”Zone Violations” for subsequent manual review by planners. The step-by-step pseudo-code for the second phase is presented in Table 3.

Upon completion of the initial assignments, the algorithm employs a swap-based local search mechanism to address inherent structural limitations. Although the initial assignment algorithm prioritizes the primary objective (θ_1) for selecting the package among the feasible candidates, it is greedy by nature and may get trapped in local optima. Additionally, secondary objective (θ_2) creates a tendency for workload accumulation in the final packages. Consequently, the swap procedure serves as a necessary refinement step, optimizing global workload balance by transferring tasks between overloaded and underloaded packages without compromising zone constraints.

3.5.3 *Phase 3: Repetitive Assignments*

The initial assignment matrix ($f_{t,k}$) establishes only the start point of each task within its interval. Since maintenance tasks are repetitive by nature, defined by fixed intervals, assignments are projected across the full planning horizon to capture the true workload distribution. Consequently, this phase of the model implements a deterministic propagation routine. For any task t in package k_{start}, the algorithm populates the global binary variable $y_{t,k}$ across the sequence $k_{start}, k_{start}+r_t, k_{start}+2r_t, \ldots$ until the last package N is reached. This expansion converts local variables into a comprehensive plan, revealing the cumulative workload (L_k) for every package. The pseudo-code for this expansion procedure is presented in Table 4.

4. Results

To demonstrate the practical viability of the proposed methodology, a comprehensive evaluation was conducted using realistic maintenance data obtained from commercial fleets. The analyses fo-

Table 3
Pseudo-code for Constraint-First Initial Assignment (with Fallback Mechanism)

Line	Procedure
1:	**Input:** Set of tasks T, Set of packages K, Forbidden Zones F, Target Loads L_r^{target}
2:	**Initialize:** $f_{t,k} \leftarrow 0, \quad Z_k \leftarrow \emptyset, \quad L_k \leftarrow 0 \quad \forall t, k$
3:	**For** each valid task $t \in T$ **do** ▷ *tasks sorted by mh_t descending*
4:	$C \leftarrow \emptyset$ ▷ *C: set of feasible candidate packages*
5:	**For** $k = 1$ **to** r_t **do**
6:	**If** Eq. (17) ≤ 1 **then** ▷ *feasibility (zone conflict) check*
7:	Add k to C
8:	**End If**
9:	**End For**
10:	**If** $C \neq \emptyset$ **then** ▷ *normal assignment*
11:	**Select** $k^* \in C$ minimizing the lexicographic objective in Eq. (14)
12:	$f_{t,k^*} \leftarrow 1$
13:	Update L_{k^*} and Z_{k^*}
14:	**Else** ▷ *fallback mechanism*
15:	**Relax** Zone Constraint.
16:	**Select** $k_{fallback} \in \{1, \ldots, r_t\}$ minimizing Eq. (9)
17:	$f_{t,k_{fallback}} \leftarrow 1$
18:	**Log** Warning: "Forced assignment with Zone Violation"
19:	**End If**
20:	**End For**
21:	**Output** Initial assignments $f_{t,k}$

Table 4
Pseudo-code for Full Horizon Expansion (Repetitive Assignment)

Line	Procedure
1:	**Input:** Initial assignments $f_{t,k}$, Repetition periods r_t, Last package N
2:	**Initialize:** $y_{t,k} \leftarrow 0 \quad \forall t, k$
3:	**For** each valid task $t \in T$ **do**
4:	**Find** start package k_{start}
6:	$k \leftarrow k_{start}$
7:	**While** $k \leq N$ **do**
8:	$y_{t,k} \leftarrow 1$ ▷ *mark task as active*
9:	$k \leftarrow k + r_t$ ▷ *jump to next occurrence*
10:	**End While**
12:	**End For**
13:	**Output:** Global assignments $y_{t,k}$

cused on case studies designed to illustrate how shifting from traditional planning to the developed lexicographic heuristic approach influences workload balance and constraint compliance. All computational experiments were carried out using Python 3.13 on a computer equipped with an Intel i7-9750H processor and 16 GB of RAM.

4.1 Definition of Zones (Z) and Forbidden Zone Pairs (F)

Before moving on to case studies, it is necessary to determine the spatial level of detail of the model. The aircraft is divided into a series of major zones (Z) that conform to standard industry classification. This study encompasses the entire fuselage, including the lower and upper fuselage (100, 200), empennage (300), wings (500, 600), landing gears (700), and doors (800). A critical separation was applied to the power plants (400); this zone was divided into two parts, 400LH and 400RH, representing the left and right positions. This separation was carried out specifically to identify particular positional conflicts between the engines and their corresponding wing structures. Consequently, the study includes a total of 9 distinct major regions. Forbidden Zone Pairs (F) were selected from among these major zones.

In our study, forbidden zone pairs were configured to reduce physical conflicts during maintenance. These conflicts arise from the engine cowlings; when deployed, they create a physical barrier that completely or partially blocks access to the wing edges. This prevents simultaneous work in these zones. Consequently, the proposed model is designed to enforce a restriction on the simultaneous assignment of tasks involving the engine and wing pair in the same position.

4.2 Case Study I

The source data for this experiment originate from the MPD of a standard narrow-body commercial aircraft. For confidentiality purposes, the man-hour (MH) values reported here were normalized by a constant multiplier, a step that preserves the statistical integrity of the dataset while obscuring potentially sensitive operational details.

In its unprocessed form, the MPD dataset encompasses 1352 distinct effective maintenance tasks for the selected fleet (737-800). To align the data with the operational scope of the proposed methodology, a strategic filtering process was applied based on the task intervals (I_t). Tasks with high frequencies falling below the base interval ($I_t < I_a$) were classified as ”Line Maintenance” activities and were excluded, as these are typically performed on the apron during short turnarounds [24]. On the other end of the spectrum, tasks with intervals exceeding the planning horizon ($I_t \geq I_b$) are generally associated with ”Heavy Structural Maintenance” (e.g., D-Checks) and were also excluded from this specific case study. It is important to note that the proposed model is primarily constructed with the objective of balancing routine light maintenance packages (e.g., A-Checks) and intermediate visits. This strategic scoping was adopted because heavy maintenance visits are often dominated by stochastic ”non-routine” findings rather than routine task lists, rendering deterministic workload leveling less effective. Furthermore, the current model optimizes man-hour distribution but does not explicitly constrain aircraft ”Ground Time” (downtime), which is the primary driver for heavy checks. Consequently, a subset of 329 valid tasks (n_{valid}) representing the routine maintenance workload was identified for the optimization process.

To configure the experimental setup, the maintenance interval (I_a) and the planning horizon (I_b) were defined as 120 DY and 1095 DY (3 years), respectively. Simultaneously, daily utilization rates were set to constant values of 9 FH and 6 FC. These numerical inputs were chosen solely to reflect a representative commercial airline environment and are fully customizable. By design, the proposed algorithm is fully parametric and independent of hard-coded constants. This architecture enables the system to operate as a versatile Decision Support System; it can ingest arbitrary planning horizons, interval definitions, or fleet utilization profiles to align with diverse operator strategies without necessitating any algorithmic modification.

Table 5 provides a summary of the fixed parameters employed in Case Study I.

Table 5
Fixed Parameters for the Case Study I

Parameter	Symbol	Value
Aircraft Type	—	737-800
Total Tasks (Raw)	n_{raw}	1352
Valid Tasks	n_{valid}	329
Maintenance Interval	I_a	120 DY
Planning Horizon	I_b	1095 DY
Aircraft Daily Utilization	U_{fh}/U_{fc}	9 FH / 6 FC

In Case Study I, the experimental evaluation was structured around three different operational configurations to compare the performance of the proposed model. **Configuration A** was established as the control group, mirroring the traditional industry standard. In contrast, **Configuration B** and **Configuration C** implemented the proposed **Lexicographic Heuristic Algorithm**, exploring its performance under varying strategic conditions. Other parameters used in the configurations, in addition to the fixed parameters, are shown in the Table 6.

Table 6
Configuration-specific Parameters for the Case Study I

Parameter	Symbol	Config A	Config B	Config C
Package Multiplier	P	1	1	2
Forbidden Zone Pairs	F	—	{400LH, 500} {400RH, 600}	{400LH, 500} {400RH, 600}

4.2.1 *Configuration A: Traditional Block Maintenance*

This configuration demonstrated the traditional block maintenance methodology in its unoptimized form. Within this baseline framework, forbidden zone pairs (F) were ignored, as the task assignment logic was governed exclusively by due-date compliance. Tasks were typically clustered within defined maintenance interval unless their due-dates coincide with or are after the next scheduled maintenance date, regardless of the package size (workload). Consequently, the operational focus remained solely on satisfying deadlines, neglecting physical conflict risks and workload of packages. The workload profile, which highlights the instability caused by traditional block approach is visualized in Figure 1.

The quantitative outcome presented in Figure 1 reveals the inherent imbalance of this unoptimized approach. Without an active balancing mechanism, significant fluctuations were observed across the entire planning horizon. The workload varied considerably between 101.5 MH (Package K1) and 827.4 MH (Package K8). This extreme disparity, representing an approximately eight-fold difference between

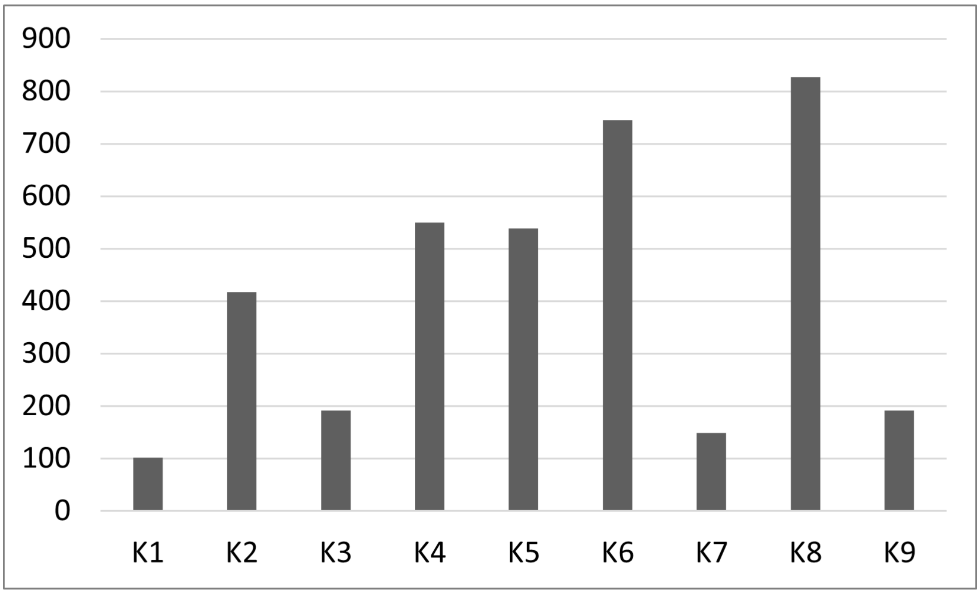

Fig. 1. Workload profile resulting from the traditional block maintenance strategy (Configuration A)

the lightest and heaviest checks, highlighted a critical operational inefficiency. Such peaks typically necessitates extensive overtime labor, while the valleys result in underutilized workforce capacity, thereby validating the need for the proposed optimization.

4.2.2 *Configuration B: Equalized-Block Maintenance*

In this configuration, the proposed **Lexicographic Heuristic Algorithm (LHA)** was applied, but the maintenance strategy was kept as block maintenance ($P = 1$). The model attempts to assign tasks with forbidden zones (F) to distinct packages and balance the workload within the packages to conform to the lexicographic objective function.

Fig. 2. Workload profile resulting from the equalized-block maintenance strategy (Configuration B)

The quantitative outcome (Figure 2) demonstrated a marked improvement in workload stability relative to the traditional block approach. The algorithm successfully converged the package loads toward the target mean, restricting fluctuations to a narrower band between 484.1 MH and 511 MH. However, this experiment also revealed a fundamental structural deficiency inherent in the block concept. Tasks with a repetition period of one interval $(r_t = 1)$, even if they cause forbidden zone conflicts, must be included in the sole available package to meet deadline requirements. Consequently, although man-hour balance was achieved with Configuration B, it failed to resolve spatial constraints. This finding confirmed that static block planning, even when driven by an optimization model, lacks the flexibility necessary to manage spatial constraints.

4.2.3 Configuration C: Equalized-Phased Maintenance

This final configuration of Case Study I also employed the proposed **Lexicographic Heuristic Algorithm** and represented the fully optimized state of the maintenance plan. The package multiplier was increased to $P = 2$, doubling the total number of assignable packages to $N = 18$ (Eq. 3). Therefore, this phased maintenance approach provided the algorithm with greater flexibility to segregate spatially conflicting tasks while also minimizing workload fluctuations between packages.

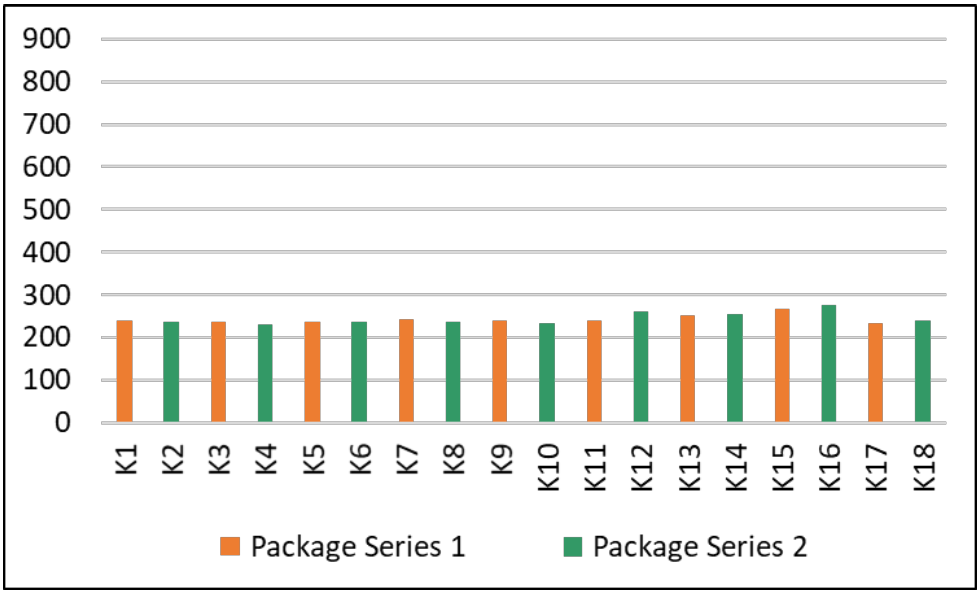

Fig. 3. Workload profile resulting from the equalized-phased maintenance strategy (Configuration C)

In Configuration C, as shown in Figure 3, since the total workload is distributed across twice as many packages, the average load per package naturally decreased and stabilized within a narrower range between 231.5 MH and 276.9 MH. Furthermore, the increase in the number of assignable packages allowed the algorithm to solve spatially conflicting tasks, which could not be solved in Configuration B, by placing them in adjacent but separate series. Consequently, no zone violations were recorded, and all constraints were met while achieving workload balancing.

The working principle of maintenance granularity, briefly explained in Section 3.2.1, can be exemplified in this configuration. In this phased configuration, a series of parallel checks equal to the package multiplier (P) is generated, and the interval between any two consecutive checks within the same series is limited by a defined maintenance interval (I_a). Thus, I_a acts as a rigid constraint, creating a "chain link" mechanism between checks in the same series. For example, if an earlier check in a series (e.g., K1) is scheduled before its due date, the due date of the subsequent checks in that series (e.g., K3, K5, K7, . . .) will need to be brought forward by the same amount to ensure that the elapsed time never exceeds the defined maintenance interval.

4.2.4 *Comparative Results*

The comparative results of all three configurations of Case Study I are summarized in Table 7.

Table 7
Results Across Configurations in Case Study I

Metric	**Config A**	**Config B**	**Config C**
Methodology	Traditional	Proposed LHA	Proposed LHA
Strategy	Block	Equalized-Block	Equalized-Phased
Multiplier (P)	1	1	2
Total Packages (N)	9	9	18
Operational Metrics			
Workload Range (MH)	101,5 - 827,4	484,1 - 511,0	231,5 - 276,9
Zone Violations	Ignored	Failed	Satisfied
Objective Function Scores			
θ_1: Workload Std. Dev. (MH)	254,1	8,1	12,7
θ_2: Avg. Task IUR	86%*	74%	74%
θ_3: Max. Active Zones	9/9	9/9	7/9

*Traditional block maintenance strategy tries to maximize task IUR by default within defined maintenance interval (I_a) but ignores capacity limits.

The comparative data summarized in Table 7 highlight an inverse relationship (trade-off) between workload balance (θ_1) and IUR (θ_2). In Configuration A, tasks naturally fall into their latest possible packages, resulting in a higher interval utilization of 86%. However, this comes at the cost of significant operational instability, as demonstrated by a larger workload deviation range of 254.1 MH and the ignored zone conflicts. In contrast, both optimized configurations (B and C) accept a reduction in utilization to 74% as a strategic necessity for balancing work packages. This drop is mitigated by the "Hardest-First" heuristic, which prioritizes heavy tasks for late assignment to maximize their economic value, while restricting early assignments—which cause the utilization drop—primarily to smaller tasks. Thus, the model achieves controlled stability where operational predictability takes precedence over theoretical interval utilization.

Beyond workload metrics, the phased approach (Configuration C) yields a critical operational benefit by minimizing concurrent active zones (θ_3). While the block-based strategies result in a maximum density of 9/9 active zones—implying simultaneous activity in every section of the aircraft—the proposed Equalized-Phased solution reduces this peak to 7/9. This reduction effectively alleviates congestion on the maintenance floor. By ensuring that at least two zones remain inactive during any given check, the system not only eliminates the spatial violations observed in Configurations A and B but also reduces competition for shared resources (such as stands, jacks, and test equipment), thereby streamlining logistics and enhancing safety.

Finally, it is worth noting the strategic position of Configuration B. Although it fails to satisfy defined spatial constraints due to the structure of the block concept, it remains a pragmatic alternative for specific contexts. This is because Configuration B offers a significant upgrade in workload stability over the traditional block approach. In scenarios where zone conflicts are accepted as a manageable logistical burden to be handled manually, it offers a middle ground between the workload instability of the traditional approach and the increased number of checks in the phased approach.

4.3 Case Study II

The second phase of the experimental evaluation demonstrates the system's versatility by operating under a different operational profile. Unlike, the previous analysis, which focused on a standard narrow-body fleet, Case Study II simulates a wide-body fleet environment defined by intensive daily utilization and distinct planning parameters.

The input parameter for this second case study, detailed in Table 8, were selected to demonstrate the model's "input-agnostic" architecture by introducing significant operational variances. To mirror typical long-haul operations, the daily aircraft utilization was elevated to 16 FH and 2 FC, contrasting with the shot-haul profile of the previous case. Accordingly, the planning parameters were adjusted to a horizon of 2 years, governed by a utilization-based maintenance interval of 1500 FH. In term of workload, a targeted subset of 157 valid repetitive tasks was derived from the MPD. Furthermore, a highly fragmented maintenance structure was enforced by increasing the package multiplier to $P = 3$. Finally, regarding spatial constraints, the configuration of forbidden zone pairs (F) was maintained identical to that of Case Study I.

Table 8
Input Parameters for the Case Study II

Parameter	Symbol	Value
Aircraft Type	—	787-9
Total Tasks (Raw)	n_{raw}	894
Valid Tasks	n_{valid}	157
Maintenance Interval	I_a	1500 FH
Planning Horizon	I_b	730 DY
Aircraft Daily Utilization	U_{fh}/U_{fc}	16 FH / 2 FC
Package Multiplier	P	3
Forbidden Zone Pairs	F	$\{$400LH, 500$\}$ & $\{$400RH, 600$\}$

4.3.1 Comparative Results

The optimization process, executed under these new utilization and planning parameters, reveals a sharp contrast between the traditional block and the proposed LHA strategy. As visualized in Figure 4, the traditional block planning results in severe instability, characterized by workload peaks approaching 700 MH (specifically in package K6). Conversely, the proposed equalized-phased model successfully dampens this volatility. By extending the package series, the algorithm maintains a highly stable workload profile, effectively flattening the curve despite the high-frequency $(N = 21)$ maintenance requirements.

Parallel improvements are observed in spatial management, as illustrated in Figure 5. While the traditional approach consistently reaches the maximum density of 9 zones in every check, the phased

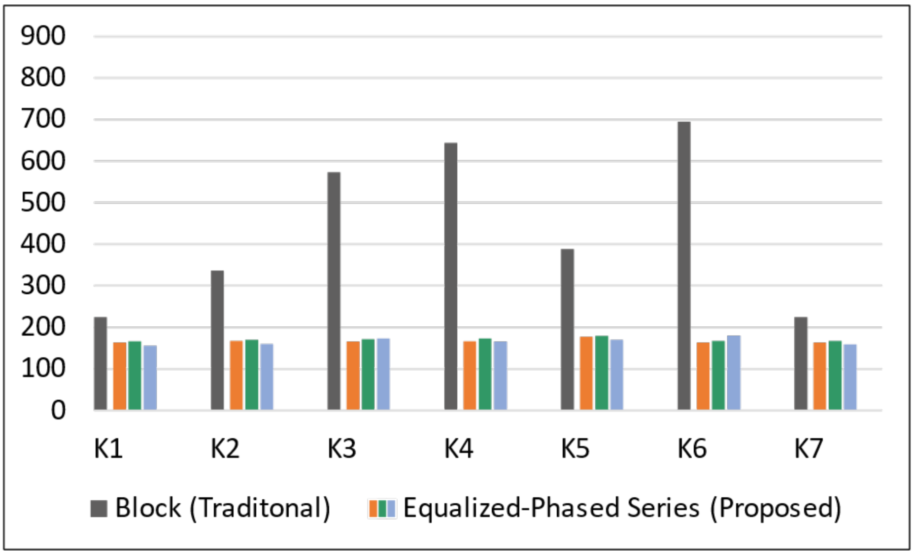

Fig. 4. Workload profiles resulting from the different maintenance strategies)

strategy effectively distributes this spatial impact. The algorithm reduces the active zone count to a manageable average ranging from 4 to 7 zones per check. A comprehensive summary of these performance metrics, which highlights the model's capacity to resolve zone conflicts even under high-utilization conditions, is provided in Table 9.

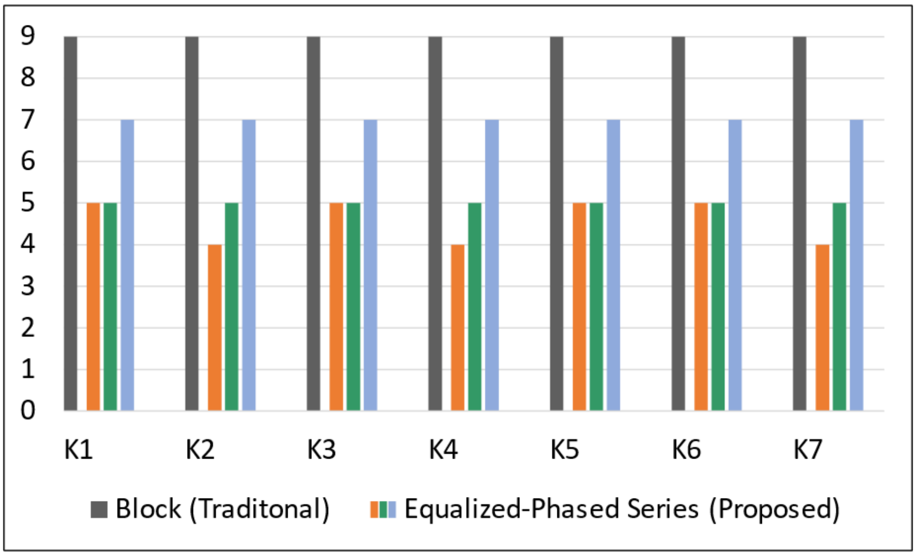

Fig. 5. Zonal density profiles resulting from the different maintenance strategies

Ultimately, this experiment validates the system's adaptability to high-intensity operational environments. By leveraging a higher package multiplier ($P = 3$), the algorithm effectively decomposes the checks of the wide-body fleet—which typically has less time for maintenance—into smaller, operationally feasible phases. As observed in the previous case study, the model eliminates all forbidden zone violations and achieves a consistent workload balance, thereby proving that the methodology is scalable across different aircraft types and maintenance strategies.

Table 9
Performance Comparison Summary for Case Study II

Metric	**Traditional Block**	**Proposed LHA**
Multiplier (P)	1	3
Total Packages (N)	7	21
Zone Violations	Ignored	Satisfied
Avg. Package Load	Unstable	Stable
Avg. Active Zones	High Density	Reduced Density

5. Conclusion

This research addressed the ”Constrained Periodic Aircraft Maintenance Packing Problem” by shifting the aircraft maintenance planning paradigm from a purely temporal focus to a constraint-first approach. Unlike traditional methods, the developed Lexicographic Heuristic Algorithm places physical spatial constraints, along with workload balancing, at the center of the optimization process. The application of this model (in both narrow-body and wide-body fleet scenarios) demonstrated that prioritizing logistic simplicity and workload balance does not necessarily require a compromise on feasibility. Conversely, the proposed methodology successfully eliminated the risks associated with simultaneous zone access while restricting man-hour fluctuations to a stable operational band.

A notable finding from the comparative experiments is the operational value of the ”balance vs. IUR” trade-off. While traditional block-based plan exhibited severe workload volatility and frequent spatial violations, the proposed phased configuration demonstrated that a controlled reduction in theoretical interval utilization yields substantial gains in execution predictability. This sacrifice is operationally reasonable, as it allows for the decomposition of heavier maintenance visits into smaller, manageable phases that strictly adhere to access limitations. Furthermore, the parametric nature of the model functions effectively as an adaptable Decision Support System, capable of reconfiguring for diverse fleet structures and strategic preferences without algorithmic modification.

The architectural flexibility of the proposed framework extends beyond the specific aircraft-zone interpretation presented in the case studies. With minor transformations, the same modeling layer can represent alternative operational connections such as access panel groupings, limited shared tooling or equipment dependencies, hangar resource conflicts, or technician skill compatibility constraints. In this sense, forbidden pairs can be interpreted as any set of simultaneous assignment prohibitions, enabling the approach to be tailored to operator-specific practices without modifying the core periodicity logic. This flexibility supports the development of configurable decision-support tools where the conflict model is updated to reflect the dominant execution bottlenecks.

In conclusion, although the case studies focus on aircraft maintenance planning, the suggested lexicographic and constraint-first packing method can be used in other fields that need regular task assignments under limited execution chances and incompatibility rules. This includes maintenance for rolling stock and rail fleets, shipyard and maritime maintenance packing, outage planning for power plants and refineries, as well as large-scale industrial inspection programs where access, safety, or resource conflicts must be taken into account. The shared feature in these situations is the necessity to assign recurring tasks to specific opportunities while managing workload and preventing incompatible co-locations or co-assignments.

Future work can build upon the suggested framework in various ways. Adding random task durations and uncertainty in usage patterns would make daily operations more realistic. Workforce availability, shift designs, and multi-skill technician assignments can be combined to optimize task grouping and labor scheduling together. Additionally, hybrid solution methods that merge the suggested heuristic with local improvement techniques or exact optimization in limited areas may further improve solution quality for large-scale fleet situations. Ultimately, this work provides a scalable methodology that transforms periodic maintenance packing from a static scheduling task into a dynamic, constraint-responsive process, ensuring operational viability across varying execution scenarios.

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Conflicts of Interest

The authors declare no conflicts of interest.

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