

Integrating Extended Arrival Management and Network Management for Demand and Capacity Balancing with User Preferences

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Abstract—Aiming at a more integrated and synchronised demand and capacity balancing (DCB), this paper proposes a framework that combines the User Driven Prioritisation Process (UDPP), system-wide optimization, and extended arrival management (E-AMAN). In this approach, airspace users (AUs) provide operational preferences, including flight protection, suspension, baseline keeping, or rerouting, which are incorporated into a centralized DCB optimization conducted by the Network Manager (NM). Linear holding bounds, derived from airline trajectory performance, are introduced as flexible delay-absorption measures alongside ground and limited airborne holding. Building on this, the E-AMAN model refines sequencing in the terminal-entry area by integrating both linear and airborne holding, enhancing predictability and fairness in arrival operations. The framework aims to minimize system cost while accommodating user preferences and reducing environmental impact. Numerical experiments with large-scale European traffic data demonstrate that the proposed framework substantially reduces delay and operational costs while improving equity among airlines. Moreover, the use of linear holding adds flexibility in handling uncertainty without additional fuel burn. These findings highlight a promising balance between efficiency, equity, and sustainability in future trajectory-based air traffic management (ATM).

Keywords—demand and capacity balancing, User Driven Prioritisation Process, extended AMAN, linear holding

NOMENCLATURE

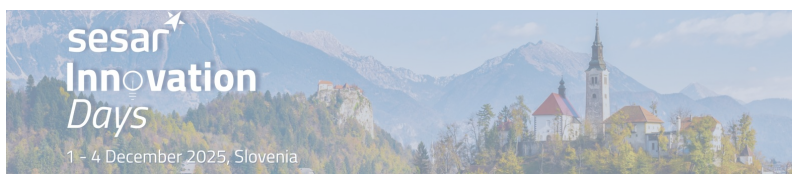
$\tau \in T$	set of time periods for unit capacity
$f \in F$	set of flights
F_h	subset of flights traversing hotspot h
$h \in H$	set of hotspots
$j \in J$	set of elementary sectors
$k \in K_f$	set of submitted trajectories for flight f
$l \in L$	set of operating sectors
M_f	penalty cost of flight f for AU
$t \in T$	set of time moments
$T_f^{k,j}$	subset of time feasible for flight f (trajectory k) entering
$z_f^{j,j'}$	scheduled operation time between j and j' for f

I. INTRODUCTION

With the rapid growth of global air traffic, the gap between increasing demand and limited airspace capacity has become a critical challenge for civil aviation. When traffic demand exceeds the available capacity within a certain airspace sector and time interval, congestion and excessive controller workload occur, leading to delays and reduced operational efficiency [1]. These situations, often referred to as hotspots, highlight the importance of demand and capacity balancing (DCB) as a key component of future air traffic management (ATM) [2]. According to the SESAR vision, DCB will play a central role in network management by mitigating the adverse impacts of demand–capacity mismatches and supporting a more resilient and sustainable ATM system [3].

Traditional DCB approaches generally rely on either capacity adjustments (e.g., sector reconfiguration) or demand adjustments (e.g., ground delay programs and rerouting) [1]. Ground delay adjusts a flight plan only along the temporal dimension, making it straightforward to apply and computationally less demanding, though its optimization potential is limited. In contrast, rerouting changes the spatial distribution of flights across the network, which can achieve greater efficiency but involves more complex coordination, may generate new hotspots, and often increases fuel consumption and emissions [4]. In practice, methods such as the Computer-Assisted Slot Allocation system in Europe have successfully applied delay assignment on a First-Come, First-Served (FCFS) basis, ensuring fairness but lacking formal optimization [5]. While more recent studies have explored algorithmic approaches to enhance efficiency and scalability [6], most existing research has paid limited attention to the seamless integration between pre-tactical trajectory planning (e.g., DCB at the network level) and tactical arrival management [7]. This gap underscores the need for solutions that bridge these layers, with particular emphasis on integrating extended arrival management (E-AMAN) with network-wide DCB.

To address these challenges, this paper introduces an in-



egrated framework that operates in two stages. In the first stage, airspace users (AUs) share operational preferences and reprioritize flights, while the Network Manager (NM) performs pre-tactical DCB optimization at the network level. In the second stage, AUs provide linear holding bounds to absorb tactical delays in a cost-efficient and environmentally friendly manner, complementing limited airborne holding. Then, E-AMAN is integrated with network management to support tactical sequencing and delay absorption in the terminal-entry area (making use as much as possible of linear holding), thereby improving predictability and resilience in arrival operations.

The main contributions of this work are as follows:

(1) Proposes a collaborative optimization framework that, to the best of our knowledge, is the first to jointly incorporate all three User Driven Prioritisation Process (UDPP) features into system-wide DCB, thereby bridging pre-tactical network planning with tactical arrival management and enhancing fairness and flexibility in delay allocation;

(2) Introduces a trajectory management mechanism combining rerouting and linear holding, which improves delay absorption while reducing fuel consumption and emissions;

(3) Develops an E-AMAN model integrated with network management, enabling dynamic pre-sequencing and delay distribution at the terminal-entry area, and achieving seamless coordination between en-route and terminal airspace while demonstrating significant benefits in alleviating congestion and operational delays.

The remainder of this paper is structured as follows: Section II introduces the proposed framework in detail, Section III describes the experimental setup and discusses the results, and Section IV summarizes the main findings of the research.

II. METHODOLOGY

The proposed framework addresses the DCB problem through a collaborative trajectory planning approach. Figure 1 illustrates its overall scheme, which operates in two stages. The first stage consists of: (1) the **scheduling of user-driven preferred greener trajectories**, enabling flexible trajectory choices according to AU preferences; and (2) the **system-wide optimization to balance demand and capacity**, initiated by the NM to minimize operating and environmental costs. The second stage includes: (3) the **computation of linear holding bounds for optimal trajectories** based on reference business trajectories and performance models; and (4) the **integrated optimization model for extended-arrival management**, which determines trajectory allocation, delay distribution, and optimal arrival sequencing.

A. Module I: Scheduling of User-driven preferred greener trajectories

In response to the need for greater flexibility and equity in ATM, the UDPP introduces mechanisms that allow AUs to exchange flight slots and redistribute delays among flights [8]. By reprioritizing delayed flights within capacity-constrained

planning, UDPP helps mitigate the overall cost and operational impact of delay. Its main features are outlined below.

1. Fleet Delay Reordering (FDR) allows an AU to reprioritise its flights by slot swapping within the UDPP measure, without advancing any flight before its original slot.

2. Selective Flight Protection (SFP) enables an AU to secure a specific flight's schedule by shifting another earlier flight, ensuring the protected flight retains its planned slot.

3. Margins with Priority Values (MPV) assign flexible time windows ("not before" and "not after") to flights, used alone or with FDR and SFP, to reflect AU constraints and maintain stable prioritisation under varying ATM conditions.

1) Problem statement: The UDPP optimization model addresses irregular operations by assigning a status to each flight crossing a hotspot. For such flights, the AU can choose among four options: protect, suspend, keep baseline delay, or rerouting. The decision variables are defined as follows:

$$\begin{aligned} p_f^h &= \begin{cases} 1, & \text{if flight } f \text{ is protected in hotspot } h \\ 0, & \text{otherwise} \end{cases} \\ s_f^h &= \begin{cases} 1, & \text{if flight } f \text{ is suspended in hotspot } h \\ 0, & \text{otherwise} \end{cases} \\ k_f^h &= \begin{cases} 1, & \text{if flight } f \text{ is keeps baseline in hotspot } h \\ 0, & \text{otherwise} \end{cases} \\ r_f^h &= \begin{cases} 1, & \text{if flight } f \text{ is rerouting in hotspot } h \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

2) Objective function: The objective function of the proposed model minimizes both delay costs and trajectory emission costs. The complete formulation is given as follows:

$$C_{delay}^s = \sum_{h \in H} \sum_{f \in F_h} s_f^h (t_{f_{md}}^h - (t_{f_{cat}}^h - t_{f_{eat}}^h)) D_f \quad (1)$$

$$C_{delay}^r = \sum_{h \in H} \sum_{f \in F_h} r_f^h (\gamma_{fuel} d_f + \gamma_{em} e_m f + e_f) \quad (2)$$

$$C_{protect} = \sum_{h \in H} \sum_{f \in F_h} p_f^h ((t_{f_{cat}}^h - t_{f_{eat}}^h) D_f + V_f) \quad (3)$$

$$C_{penalty} = \sum_{h \in H} \sum_{f \in F_h} (s_f^h + \xi r_f^h + k_f^h) M_f \quad (4)$$

$$\min (C_{delay}^s + C_{delay}^r - C_{protect} + C_{penalty}) \quad (5)$$

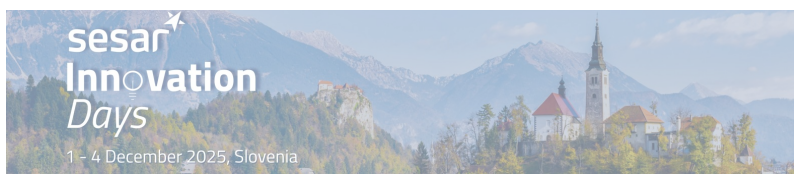
which consists of the delay cost of suspended flights (C_{delay}^s), the rerouting cost (C_{delay}^r), the gains from flight prioritization ($C_{protect}$), and the penalty cost for unpunctuality ($C_{penalty}$).

3) Constraints:

$$\sum_{h \in H} \sum_{f \in F_h} 100(p_f^h + s_f^h + \delta r_f^h) \geq \sum_{h \in H} \sum_{f \in F_h} O_h p_f^h \quad (6)$$

$$\sum_{h \in H} \sum_{f \in F_h} 100(s_f^h + \delta r_f^h) N_f^h C_h + \sum_{h \in H} \sum_{f \in F_h} 100 p_f^h \geq \sum_{h \in H} \sum_{f \in F_h} O_h p_f^h \quad (7)$$

$$\sum_{h \in H} \sum_{f \in F_h} [s_f^h (t_{f_{md}}^h - (t_{f_{cat}}^h - t_{f_{eat}}^h)) - p_f^h (t_{f_{cat}}^h - t_{f_{eat}}^h)] \leq 0 \quad (8)$$



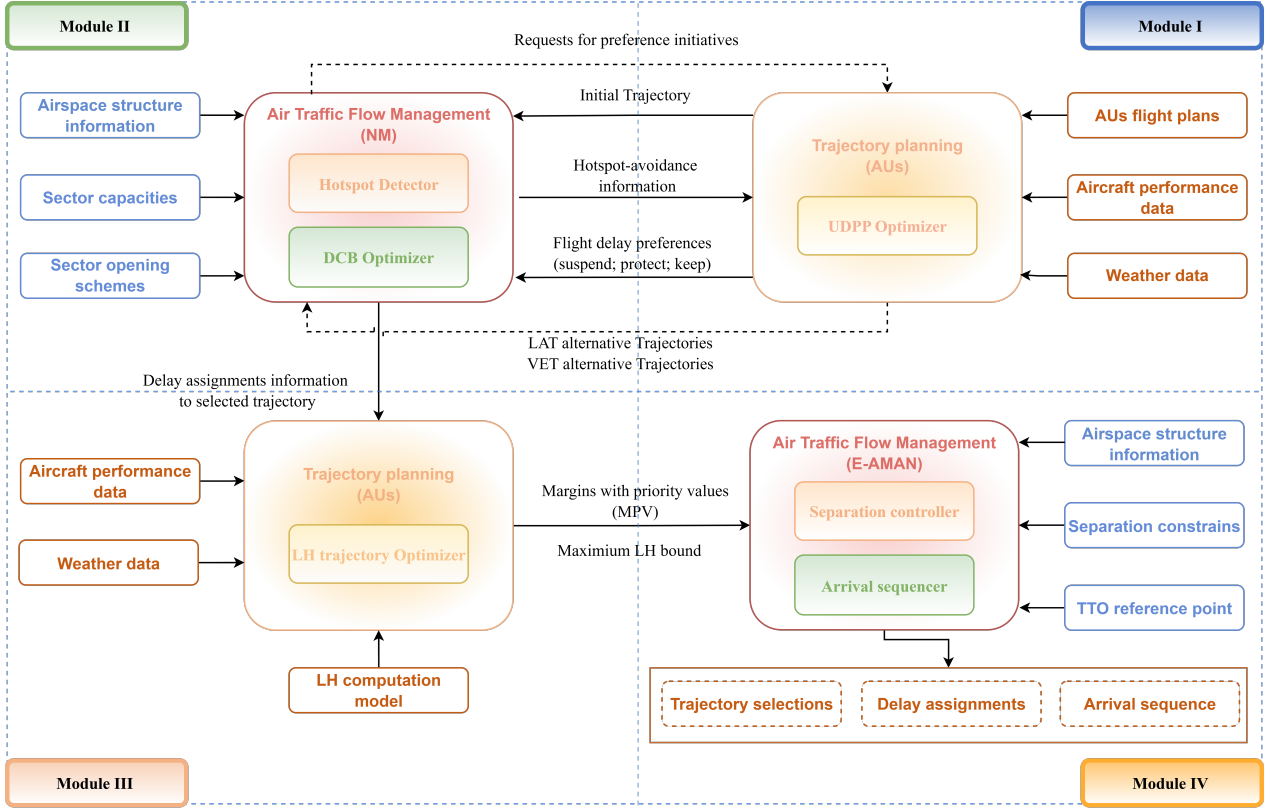


Figure 1. An overview of the architecture and workflow for the proposed model framework.

$$p_f^h + s_f^h + k_f^h + r_f^h = 1, \forall h \in H, \forall f \in F_h \quad (9)$$

$$r_f^h + (p_f^{h^*} + s_f^{h^*} + k_f^{h^*} + r_f^{h^*}) = 1, \forall h, h^* \in H, h \neq h^*, \forall f \in F_h \quad (10)$$

$$p_f^h \in \{0, 1\}, s_f^h \in \{0, 1\}, k_f^h \in \{0, 1\}, r_f^h \in \{0, 1\}, \forall h \in H, \forall f \in F_h \quad (11)$$

Constraint (6) preserves the consistency of an AU's operating credits (OC, O_h) after UDPP by requiring that its OC not exceed the initial value. Flights keeping their baseline delay retain their OC, whereas protected flights reduce their OC from 100 to the hotspot's operating index (OI), and suspended flights reduce theirs from 100 to 0. Constraint (7) defines the transformation of OC between suspended and protected flights: the OC of protected flights must not exceed the sum of the OC released by suspended flights and their original OC, with an equivalence factor accounting for different hotspots (C_h). Constraint (8) ensures that the use of the UDPP mechanism has a positive effect on flight delays, Constraint (9) enforces that each flight can take only one option, Constraint (10) guarantees uniqueness of the solution, and Constraint (11) specifies that all decision variables are binary. Detailed definitions of OI and OC can be found in [9].

B. Module II: System-wide optimization to balance demand and capacity

In this section, two types of delay measures are considered: **ground holding** and **alternative route selection**. The corresponding costs include (i) ground holding costs, covering fuel consumption and route charges, and (ii) alternative route costs, which also account for emission charges along the selected trajectories. For a detailed description of the cost calculation process, readers are referred to [10].

1) *Problem statement:* The DCB(i) model used in this study is based on [11], which considers only ground holding, while DCB(ii) extends it by incorporating both ground holding and alternative route selection. By incorporating the global cost of all flights into the objective function, the model seeks to maximize system efficiency. To integrate UDPP with the DCB model, this paper focuses on the UDPP-DCB(ii) formulation, while UDPP-DCB(i) is used only for comparative analysis. The outputs of the UDPP model are incorporated into the DCB framework through additional constraints and objectives, ensuring on-time arrivals for protected flights and delayed arrivals for suspended flights in hotspot areas.

In this model, controlled times of arrival (CTAs) are enforced at each control point along the trajectory, following the time-based operations defined at the entry of each elementary sector. The CTAs are assigned using a set of variables:

$$x_{f,t}^{k,j} = \begin{cases} 1, & \text{if flight } f\text{'s } k^{th} \text{ trajectory enters elementary sector } j \text{ by time } t, \\ 0, & \text{otherwise} \end{cases}$$

$$z_f^k = \begin{cases} 1, & \text{if flight } f \text{'s } k^{th} \text{ trajectory is chosen} \\ 0, & \text{otherwise} \end{cases}$$

2) *Objective function:* The objective function of the proposed model minimizes delay costs (C_d^k), rerouting costs (C_d^r), suspension costs (C_d^s), as well as additional fuel consumption, emissions, and route charges. The complete formulation is given as follows:

$$C_d^k = \sum_{f \in F} \sum_{k \in K_f} \sum_{j=J_f^k(1)} \sum_{t \in T_f^{k,j}} (t - r_f^{k,j})(x_{f,t}^{k,j} - x_{f,t-1}^{k,j})k_f^j \quad (12)$$

$$C_d^r = \sum_{f \in F} \sum_{k \in K_f} \sum_{j=J_f^k(1)} \sum_{t \in T_f^{k,j}} (t - r_f^{k,j})(x_{f,t}^{k,j} - x_{f,t-1}^{k,j})r_f^j \quad (13)$$

$$C_d^s = \sum_{f \in F} \sum_{k \in K_f} \sum_{j=J_f^k(1)} \sum_{t \in T_f^{k,j}} (t - r_f^{k,j})(x_{f,t}^{k,j} - x_{f,t-1}^{k,j})s_f^j \quad (14)$$

$$C_r = \sum_{f \in F} \sum_{k \in K_f} (\gamma_{fuel}u_f^k + \gamma_{em}em_f^k + e_f^k)z_f^k \quad (15)$$

$$\min \alpha(C_d^k + C_d^r) + \beta C_d^s + \delta C_r \quad (16)$$

3) *Constraints:*

$$\sum_{k \in K_f} z_f^k = 1, \forall f \in F \quad (17)$$

$$x_{f,\underline{T}_f^{k,j}-1}^{k,j} = 0, \quad x_{f,\overline{T}_f^{k,j}}^{k,j} = z_f^k, \quad \forall f \in F, \forall k \in K_f, \forall j \in J_f^k \quad (18)$$

$$x_{f,t}^{k,j} - x_{f,t-1}^{k,j} \geq 0, \forall f \in F, \forall k \in K_f, \forall j \in J_f^k, \forall t \in T_f^{k,j} \quad (19)$$

$$x_{f,t+i_f^{k,j,j^*}}^{k,j^*} - x_{f,t}^{k,j} = 0, \forall f \in F, \forall k \in K_f, \forall t \in T_f^{k,j}, \forall j \in J_f^k(i) \\ j^* = J_f^k(i+1) : \forall i \in [1, n_f] \quad (20)$$

$$\sum_{f \in F} \sum_{k \in K_f} \sum_{j=J_f^{k,\tau}} \sum_{t \in T_f^{k,j} \cap T(\tau)} (x_{f,t}^{k,j} - x_{f,t-1}^{k,j}) \leq c_l^\tau, \\ \forall l \in L_\tau, \forall \tau \in T \quad (21)$$

$$p_f^j(t - r_f^{k,j})(x_{f,t}^{k,j} - x_{f,t-1}^{k,j}) = 0, \forall f \in F_p, \forall j \in J_f^k, \forall t \in T_f^{k,j}, \\ \forall k \in K_f \quad (22)$$

$$x_{f,t}^{k,j} \in \{0, 1\}, \forall f \in F, \forall j \in J_f^k, \forall t \in T_f^{k,j} \quad (23)$$

$$z_f^k \in \{0, 1\}, \forall f \in F, \forall k \in K_f \quad (24)$$

Constraint (17) guarantees that each flight selects a unique trajectory from its submitted set of options (K_f), which may differ across flights. Constraint (18) defines the feasible CTA range at each control point for each flight (i.e., T_f^j), determined by its Estimated Time of Arrival (ETA). The upper bound

of this window ($\bar{T}_f^{k,j}$) depends on the selected trajectory (z_f^k). Constraint (19) enforces continuity of the decision variable timeline under the “by-time” concept. By allowing only ground delay, Constraint (20) ensures that segment flying times remain identical to those in the initial schedule. Constraint (21) requires that demand not exceed planned capacity. Constraint (22) ensures that protected flights are punctual within their designated hotspots. Constraints (23)–(24) restrict all decision variables to binary values.

C. Module III: Computation of linear holding bounds for optimal trajectories

The linear holding (LH) strategy allows aircraft to cruise at the lowest feasible speed within the aircraft performance envelope while keeping fuel consumption equal to that of the initially planned trajectory. Previous studies [12] have shown that LH can absorb airborne delays, but its effectiveness is constrained by factors (e.g., take-off weight). As airline-specific data are typically proprietary, only airlines can reliably assess the delay absorption capability of their flights. To incorporate AUs’ MPV (as defined in UDPP) into pre-arrival management, the LH bounds of planned trajectories are therefore provided as inputs to the E-AMAN model.

Aircraft trajectory optimization requires models of aircraft dynamics and atmospheric conditions (see [13]). In this study, the aircraft is represented by a three-degree-of-freedom point-mass model, the Base of aircraft data (BADA) performance model, and International standard atmosphere (ISA) conditions. For the nominal flight (i.e., AU’s initial plan), the objective is to minimize a composite cost function within the time window $[t_0^i, t_f^i]$, as defined in Eq. (25),

$$\min f(t) = \min \int_{t_0^i}^{t_f^i} (FF(t) + CI)dt \quad (25)$$

where $FF(t)$ and CI represent the fuel flow and the Cost Index, respectively.

D. Module IV: Integrated optimization model for extended-arrival management

1) *Problem statement:* After obtaining the aircraft adjustment plan time from the UDPP-DCB model, Model E-AMAN considers the margin conditions of the aircraft (i.e., MPV) and calculates the Target Time Over (TTO) for a corresponding waypoint, in addition to analyzing the airspace structure. It then optimizes the aircraft’s passing time by employing a combination of airborne holding and linear holding strategies, with the ultimate aim of minimizing flight conflicts between aircraft. The decision variables are as follows:

$$x_{f,t}^j = \begin{cases} 1, & \text{if flight } f \text{ departs from position } j \text{ by time } t \\ 0, & \text{otherwise} \end{cases} \\ y_{f,t}^j = \begin{cases} 1, & \text{if flight } f \text{ arrives at position } j \text{ by time } t \\ 0, & \text{otherwise} \end{cases} \\ h_{f,f'}^j = \begin{cases} 1, & \text{if flight } f \text{ arrives at position } j \text{ before flight } f' \\ 0, & \text{otherwise} \end{cases}$$

2) *Objective function:* The objective function of the proposed model aims to minimize the costs of airborne holding and linear holding delays. The complete formulation is as follows:

$$\min(\varphi AH + \eta LH) \quad (26)$$

where AH denotes airborne holding time, LH denotes linear holding time, and φ and η represent the cost coefficients associated with airborne and linear holding, respectively. To account for fairness in delay allocation, a coefficient $c_f = (t - r_f^k)^{1+\varepsilon}, \varepsilon > 0$ is introduced to distribute the total delay time, ensuring that delays are reasonably shared among all flights. Since the total delay time of an aircraft comprises both airborne and linear holding costs, substituting LH yields:

$$\min \sum_{f \in F} (\eta c_f h_f + (\varphi - \eta) a_f) \quad (27)$$

$$c_f h_f = \sum_{t \in T_f^a, P(f, n_f)} (t - r_f^a)^{1+\varepsilon} (y_{f,t}^a - y_{f,t-1}^a) \quad (28)$$

$$a_f = \sum_{t \in T_f^w, w \in P(f, i): 1 < i < n_f} t(x_{f,t}^w - x_{f,t-1}^w - y_{f,t}^w + y_{f,t-1}^w) \quad (29)$$

3) *Constraints:*

$$x_{f,t}^j - x_{f,t-1}^j \geq 0, \forall f \in F, \forall j \in P_f, \forall t \in T_f^j \quad (30)$$

$$y_{f,t}^j - y_{f,t-1}^j \geq 0, \forall f \in F, \forall j \in P_f, \forall t \in T_f^j \quad (31)$$

$$x_{f,t}^j - y_{f,t}^j \leq 0, \forall f \in F, \forall w \in W, \forall t \in T_f^w \quad (32)$$

$$y_{f,t'}^j - x_{f,t}^j \leq 0, \forall f \in F, \forall i \in [1, n_f - 1], P(f, i) = j, \\ P(f, i + 1) = j', \forall t \in T_f^j, t' = t + z_{f,f'}^{j,j'} \quad (33)$$

$$y_{f,t'}^j - x_{f,t}^j \geq 0, \forall f \in F, \forall i \in [1, n_f - 1], P(f, i) = j, \\ P(f, i + 1) = j', \forall t' \in T_f^{j'}, t' = t + z_{f,f'}^{j,j'} + v_{f,f'}^{j,j'} \quad (34)$$

$$\sum_{t \in T_f^j} t(y_{f',t}^j - y_{f',t-1}^j) - \sum_{t \in T_f^j} t(y_{f,t}^j - y_{f,t-1}^j) \geq S_{f,f'}^j, \\ \forall j \in J^A, \forall (f', f) \in F_j^c, f \neq f' \quad (35)$$

$$\left| \sum_{t \in T_f^j} t(y_{f',t}^j - y_{f',t-1}^j) - \sum_{t \in T_f^j} t(y_{f,t}^j - y_{f,t-1}^j) \right| \geq S_{f,f'}^j h_{f',f}^j, \\ + S_{f',f}^j (1 - h_{f',f}^j), \forall j \in J^B, \forall (f', f) \in F_j, f \neq f' \quad (36)$$

$$\begin{cases} \sum_{t \in T_f^j} t(y_{f',t}^j - y_{f',t-1}^j) - \sum_{t \in T_f^j} t(y_{f,t}^j - y_{f,t-1}^j) < M_0 h_{f',f}^j \\ \sum_{t \in T_f^j} t(y_{f',t}^j - y_{f',t-1}^j) - \sum_{t \in T_f^j} t(y_{f,t}^j - y_{f,t-1}^j) \geq M_0 (1 - h_{f',f}^j) \end{cases} \quad (37)$$

$$\begin{cases} \sum_{t \in T_f^j} t(y_{f',t}^j - y_{f',t-1}^j) - \sum_{t \in T_f^j} t(y_{f,t}^j - y_{f,t-1}^j) + M_1 a_{f',f}^j \geq \\ S_{f,f'}^j h_{f',f}^j + S_{f',f}^j (1 - h_{f',f}^j), \forall j \in J^B, \forall (f', f) \in F_j \\ \sum_{t \in T_f^j} t(y_{f',t}^j - y_{f',t-1}^j) - \sum_{t \in T_f^j} t(y_{f,t}^j - y_{f,t-1}^j) + M_1 a_{f',f}^j \leq \\ M_1 - (S_{f,f'}^j h_{f',f}^j + S_{f',f}^j (1 - h_{f',f}^j)), \forall j \in J^B, \forall (f', f) \in F_j \end{cases} \quad (38)$$

$$x_{f,t}^j \in \{0, 1\}, \forall f \in F, \forall j \in P_f, \forall t \in T_f^j \quad (39)$$

$$y_{f,t}^j \in \{0, 1\}, \forall f \in F, \forall j \in P_f, \forall t \in T_f^j \quad (40)$$

$$h_{f,f'}^j \in \{0, 1\}, \forall j \in J^B, \forall (f, f') \in F \quad (41)$$

$$a_{f,f'}^j \in \{0, 1\}, \forall j \in J^B, \forall (f, f') \in F \quad (42)$$

Constraints (30)–(31) ensure that each flight f is assigned one departure and one arrival slot at position j . Constraint (32) limits airborne holding time to a maximum value u^w at each designated position. Constraint (33) requires LH to be non-negative, meaning flying faster than planned is excluded from delay assignment. Constraint (34) ensures that LH between two consecutive positions of flight f does not exceed the maximum LH bound $v_{f,f'}^{j,j'}$ provided by airlines, with 0 as the default if unspecified. Constraint (35) enforces minimum time intervals at designated control points J^A .

Except at certain positions (e.g., terminal-entry points), aircraft are not allowed to change order and must follow the “first planned, first served” rule along the planned waypoint sequence. At other points, however, limited resequencing is allowed to improve efficiency, enabling a more flexible FCFS operation. As a result, an absolute value appears on the left-hand side of Eq. (35), complicating the use of dynamic spacing on the right-hand side. To address this, the auxiliary variable $h_{f,f'}^j$ is introduced, as defined in Eq. (36).

When aircraft pass the waypoints (f, f') in the original sequence ($h_{f,f'}^j = 1$), the spacing standard on the right-hand side of the inequality is $S_{f,f'}^j$. Conversely, if the sequence is changed to (f', f) ($h_{f,f'}^j = 0$), the right-hand side becomes $S_{f',f}^j$. This formulation enables sequence swapping while preserving the functionality of dynamic spacing.

Specifically, the decision variable $h_{f,f'}^j$ is defined using the constraint Eq. (37), which states that when, $\sum_{t \in T_f^j} t(y_{f',t}^j - y_{f',t-1}^j) - \sum_{t \in T_f^j} t(y_{f,t}^j - y_{f,t-1}^j) \geq 0$, $h_{f,f'}^j = 1$,

and conversely, $h_{f,f'}^j = 0$. Here, the artificial coefficient M_0 takes on any sufficiently large positive real number.

In addition, the inequality with absolute values in Eq. (36) is linearized by introducing a binary variable $a_{f,f'}^j$ and a large positive coefficient M_1 , yielding the equivalent formulation in Eq. (38). Finally, the ranges of the decision variables and the definitions of the binary variables are explicitly specified in Eqs. (39)–(42).

III. CASE STUDY AND RESULTS

Numerical experiments are conducted, and the results are presented in this section. The experimental setup is first described, including key assumptions. Then, the numerical results of the UDPP-DCB model are reported to demonstrate the potential benefits of the proposed integrated scheduling, followed by the results of the E-AMAN model.

A. Experimental setup

To assess the effectiveness of the proposed model, two-stage simulation experiments were conducted based on flight sequencing principles. The first stage focused on the pre-tactical phase, considering flight plan allocation on the day prior to operations. The experimental scenario was set in French airspace and encompassed 24-hour traffic data, including 6,255 scheduled flights, 164 elementary sectors, and 224 operating sectors. All source data used in the experiments are based on the EUROCONTROL's DDR2 database.

The second stage focused on tactical phases (-24h to execution, especially near real-time tactical), dealing with the pre-sequencing and separation of flights entering the terminal area of LFPG Airport. The experimental scenario targeted the adjacent area outside the terminal area of the airport and involved 24-hour arrival flight data, comprising 677 inbound flights and 8 terminal-entry points. Inspired by [7], the airspace is divided into concentric circles around the destination, ranging from 0 to 400 nautical miles with 50-nautical-mile intervals (the terminal area falls within the first 50-nautical-mile circle). Each of these circles is further subdivided into 60-degree segments, defining the fundamental units of airspace. In light of the aforementioned considerations, we have conceptualized the aircraft approach route into six discrete and autonomous approach trajectory flows. This conceptual representation is elucidated in Figure 2.

In addition, the integration of a management framework, especially within the context of UDPP and an E-AMAN horizon, represents a future scenario and does not reflect current operations. The model is based on a set of key assumptions that will be elaborated upon below:

(1) For the UDPP-DCB model, the unit time slot in the experiments is set to 1 min, while the time scale for matching demand and capacity is 60 min; (2) The default ground holding cost (D_f) for AUs follows [4], set at 100 €/min based on the European network average ATFM delay cost. The cost for airborne holding, including both standard and linear holding (assumed to incur no additional fuel consumption beyond the initial plan), is set at 90 €/min; (3) The upper bound

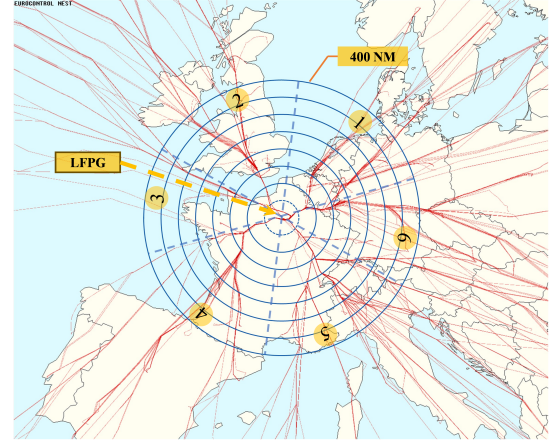


Figure 2. Schematic of airspace slices and approach trajectories near LFPG. for LH is set to 20% of the segment flight time for all flights, based on the statistical reported in [12]. Both values are rounded down to the nearest integer; (4) Only AUs with multiple flights through the relevant hotspots can participate in UDPP via the SFP mechanism. Certain hotspot volumes may lie near origin/destination airports or restricted areas, where trajectory alternatives for bypassing are not feasible; (5) The unit cost of fuel consumption (γ_{fuel}) is 0.5 €/kg; (6) The maximal allowance of capacity overload is set to 50%; (7) Rerouted flights may traverse other sectors to bypass hotspots, potentially impacting additional flights and even creating new hotspots. In the case studies, the penalty coefficient of operating credits for rerouted flights is set to $\delta = 0.3$; (8) Rerouted flights are more likely to be on time as they bypass hotspots. Accordingly, in the case studies, the unpunctuality coefficient for rerouted flights is set to $\xi = 0.2$.

In the E-AMAN model, segmenting the experimental data into time periods may disrupt the continuity of flight information across segment boundaries. To balance solution quality with computational efficiency, we adopted a sliding time window algorithm 1. The entry times of incoming aircraft into the terminal-entry area are divided into intervals, with an optimization horizon of 2 h. After each optimization, the window is shifted by 1 h (i.e., the optimization step is 1 h). Through this iterative process, an acceptable suboptimal solution is obtained.

For the numerical experiments, GAMS was used as the modeling tool, and Gurobi served as the Mixed-Integer Programming solver. The dimensions of the different problems are presented in Table I along with the computational time to solve them. The computations were executed on a computer equipped with a 64-bit Intel i7-4790@3.60 GHz quad-core CPU, with 16 GB of RAM, operating on the Linux OS.

B. Numerical results of UDPP-DCB model

As shown in Figure 3a, the initial demand of each operational sector is depicted across distinct time intervals. Over the 24 time periods of a day, a total of 1,098 operational sectors are generated within 1-hour slots. Figure 3b further reveals numerous instances of capacity overload, where demand exceeds capacity, in some cases reaching twice the available capacity.

Algorithm 1 Sliding Time-Window Based Arrival Pre-Sequencing Algorithm

Input: Flight plan F^{plan} ; optimization horizon O^{time} ; optimization step O^{step} ; airspace structure data D^{airspace}

- 1: Initialize time-window size $W \leftarrow O^{\text{time}}$ and the number of aircraft released per step $N^{\text{step}} \leftarrow O^{\text{step}}$
- 2: Sort the flights inside the initial window based on sequencing criteria determined by D^{airspace}
- 3: Initialize the final arrival sequence list $Q \leftarrow []$
- 4: **for** $k \leftarrow 1$ **to** N^{step} **do**
- 5: Remove the first aircraft from the current window (and from F^{plan})
- 6: Append this aircraft to the final sequence Q
- 7: **end for**
- 8: **while** $\text{len}(F^{\text{plan}}) > W$ **do**
- 9: Sort the flights inside the new window
- 10: **for** $k \leftarrow 1$ **to** N^{step} **do**
- 11: Remove the first aircraft from the current window (and from F^{plan})
- 12: Append this aircraft to the final sequence Q
- 13: **end for**
- 14: **end while**
- 15: **if** $\text{len}(F^{\text{plan}}) > 0$ **then**
- 16: Sort the remaining flights in the last window
- 17: **for** $k \leftarrow 1$ **to** $\text{len}(F^{\text{plan}})$ **do**
- 18: Remove the first aircraft from the current window (and from F^{plan})
- 19: Append this aircraft to the final sequence Q
- 20: **end for**
- 21: **end if**

Output: Final arrival sequence Q

TABLE I. PROBLEM DIMENSIONS AND COMPUTATIONAL TIMES.

Summary	Baseline (DCB)	UDPP-DCB(ii)	E-AMAN
Time window	360 min	120 min	6 min
Variables	12,392,347	16,002,524	275,483
Equations	22,459,267	21,580,388	707,498
Non-zeros	47,518,810	44,456,969	6,085,613
Presolved variables	147,048	69,627	2,004
Presolved equations	141,785	75,793	26,057
Presolved non-zeros	496,032	297,593	19,186
Generation time	2 min	1 min	5 sec
Solution time	4 min	2 min	7 sec

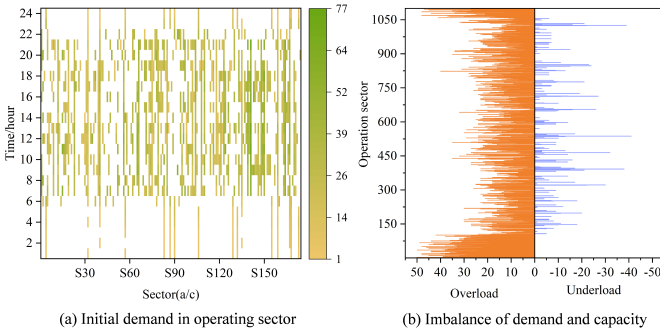


Figure 3. Initial traffic demand and imbalances with capacity for each operating sector during each time period.

By comparing demand with capacity, 15 hotspots were identified during the day and selected as the experimental scenario for the UDPP-DCB model. These hotspots involve 941 flights, of which 427 flights operated by 10 AUs are eligible to apply UDPP-DCB to improve irregular operations. According to AU operational specifications and the requirement that at least two flights pass through a hotspot (see Assumption (4)), 10 AUs are granted flexibility to participate in UDPP.

Table II provides information on the capacity and demand of the 15 operating sectors during the specified time periods mentioned earlier. Additionally, it presents the OI (recall Section II-A) and the maximum baseline delay (in minutes) assigned to each sector by the DCB model.

TABLE II. INFORMATION OF OPERATING SECTORS.

Time period	Sector	Capacity	Demand	OI	Max.delay(min)
8:00-9:00	LFMMZL	54	56	104	119
10:00-11:00	LFBBLM	50	55	110	119
	LFMMZL	54	66	122	119
11:00-12:00	LFMMSTAJ	48	53	110	92
	LFMMZL	54	74	137	119
12:00-13:00	LFMMZL	54	68	126	119
13:00-14:00	LFMMZL	54	77	143	119
15:00-16:00	LFMMZL	54	62	115	119
16:00-17:00	LFMMZL	54	63	117	119
17:00-18:00	LFMMZL	54	57	106	119
18:00-19:00	LFMMZL	54	60	111	119
	LFMMMFM	57	61	107	92
21:00-22:00	LFBBLM	50	55	110	119
	LFMMZL	54	75	139	119
	LFBBL4	57	59	104	118

Considering the operational cost profiles of flights for each AU, we categorize them into distinct cost scenarios. Table III lists the AU types, the corresponding number of flights, and their associated cost scenarios.

Figures 4 show the decision outcomes of AUs in the UDPP-DCB(ii) model: green denotes RF, blue denotes SF, orange denotes PF, and purple denotes KF. Figure 4a indicates that SF decisions are relatively few, mainly because rerouting is more cost-effective and also releases operating credits. In terms of hotspot distribution, Figure 4b shows that most SF decisions occur in hotspots 9, 10, 12, and 14, where lower operating indices make SF a more favorable option.

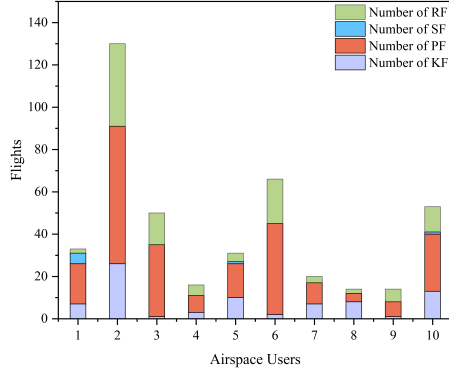
The key results and performance indicators are summarized in Table IV-V. In the baseline model, DCB solely through ground holding results in significant delays. This occurs because constraints are imposed on all operating sectors, creating an overly restrictive problem. In practice, however, only a subset of sectors is regulated at any given time.

For the UDPP-DCB(i) model, an interesting pattern emerges: although total delay rises by 16%, the number of delayed flights drops by 19%, and Table 6 shows lower delay costs for each AU. This suggests that most participating AUs accept slightly higher delays overall in order to protect their high-priority flights based on operational costs. Generally, AUs with more flights in UDPP achieve greater cost savings.

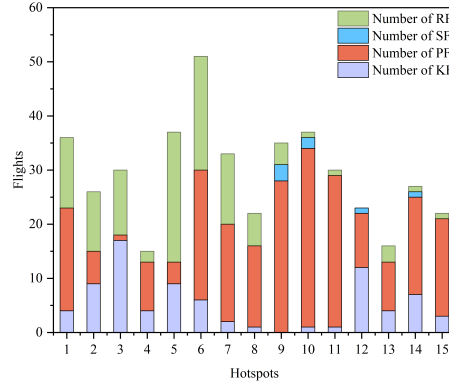
For the UDPP-DCB(ii) model, a promising finding is that total delays are reduced to 219 min through the use of alternative trajectories. Most flights (6,065, or 97%) retain their originally scheduled paths, while only 3% deviate to

TABLE III. INFORMATION OF AUs INVOLVED IN UDPP.

AU	Number of flights	Cost scenario	Type of operation	AU	Number of flights	Cost scenario	Type of operation
AU1	33	High	Full service	AU6	66	low	Low-cost
AU2	130	Low	Low-cost	AU7	20	High	Full service
AU3	50	High	Full service	AU8	14	Regional	Full service
AU4	16	High	Full service	AU9	14	High	Full service
AU5	31	High	Full service	AU10	53	High	Full service



(a) AU's decision results



(b) Flight states in each hotspot

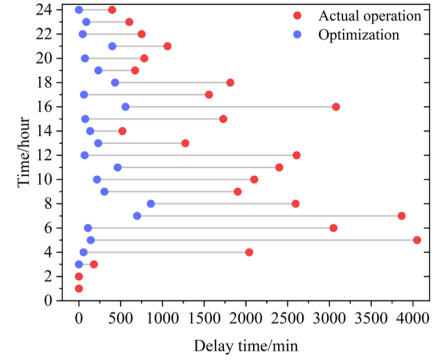
Figure 4. AU's decision results in UDPP optimisation model

preferred alternatives, yet these account for 99% of the total delay reduction. As Table V shows, UDPP-DCB(ii) further lowers each AU's total delay compared with both UDPP-DCB(i) and the baseline, with greater savings for AUs that include more flights. Notably, even non-participating AUs benefit, making this one of the most compelling results from an ATFM perspective.

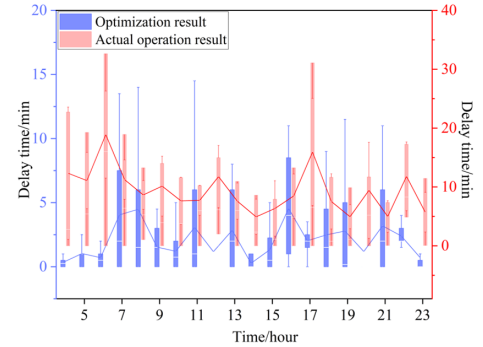
C. Numerical results of E-AMAN optimization model

Below are the optimized traffic delays compared with the actual operational delays, as summarized in Table VI. Figure 5 further illustrates the comparison between CTA optimization results and the actual time of arrival (ATA). As shown in Figure 5a, the CTA/ATA delays over a 24-hour period are presented. It can be observed that from 00:00 to 03:00, traffic volume is low and no delay occurs. During the remaining periods, ATA delays are significantly higher than CTA delays, with peak ATA delays reaching around 280 minutes per hour at 07:00. In addition, Figure 5b provides a statistical analysis of 670 flights at 350-400 nautical miles. The results indicate

that under the E-AMAN optimization model, CTA delays are virtually eliminated for 75% of flights, with the maximum delay not exceeding 150 seconds. By contrast, actual operational ATA delays are dispersed between 0 and 500 seconds for 75% of flights, with the maximum delay for a single flight exceeding 2000 seconds.



(a) Total delay time (actual and optimized)



(b) Distribution of actual and optimized delay times.

Figure 5. Comparison of delay outcomes between actual operation and the optimization model.

As shown in Table VI, the E-AMAN optimization model is compared against actual operations. The results indicate that total delay under E-AMAN is reduced to 113.83 minutes (158 delayed flights), far lower than the 2783.26 minutes (391 delayed flights) observed in actual operations. This corresponds to a 95.91% reduction in delay time and a 59.59% reduction in delayed flights. In addition, 208 flights adopted LH trajectories, accounting for 27.15 minutes of delay. These findings demonstrate that the proposed E-AMAN optimization model can substantially mitigate flight delays and is well-suited for improving pre-arrival and terminal-area traffic management.

To analyse delay distribution, the E-AMAN optimisation model was used to examine the 24-hour delay patterns of 670 inbound flights across eight control circles (Figure 6).

TABLE IV. OVERALL OPTIMIZATION RESULT COMPARISONS FOR THE BASELINE AND UDPP-DCB.

Indicators	Total delays(min)	Delayed flights(a/c)	Initial trajectory(a/c)	Lateral alternative(a/c)	Vertical alternative(a/c)
Baselines	23,780	548	6255	\	\
UDPP-DCB(i)	27,483	442	6255	\	\
UDPP-DCB(ii)	219	48	6065	39	151

TABLE V. AUs PARTICIPATE IN THE BENEFITS AFTER THE IMPLEMENTATION OF UDPP.

AU	Flights (a/c)	Baseline delay indicators		UDPP-DCB(i) delay indicators			UDPP-DCB(ii) delay indicators		
		Delay(min)	Flights(a/c)	Delay(min)	Flights(a/c)	Cost reduction(€)	Delay(min)	Flights(a/c)	Cost reduction(€)
AU1	33	675	14	995	4	40,495	3	1	64,042
AU2	130	1903	65	2024	26	118,040	24	3	192,526
AU3	50	596	16	729	6	41,160	13	2	63,364
AU4	16	302	7	387	2	18,370	2	1	29,973
AU5	31	402	9	426	3	27,495	8	2	39,605
AU6	66	771	30	952	13	39,870	11	2	76,284
AU7	20	236	7	320	2	16,770	3	1	28,422
AU8	14	104	3	138	2	1270	2	1	10,329
AU9	14	135	3	168	3	1,530	5	1	13,567
AU10	53	883	31	959	15	55,535	22	2	83,705

TABLE VI. COMPARISON OF DELAY INDICATORS: E-AMAN VS. ACTUAL

Indicator	Delay(min)	Flights(a/c)	LH(a/c)	LH Delay(min)
E-AMAN	113.83	158	208	27.15
Actual	2783.26	391	\	\

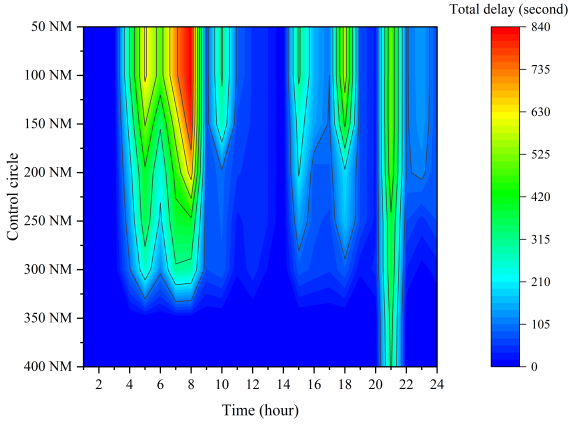


Figure 6. CTA delay results for flights corresponding to eight control circles. Temporally, delays peak between 04:00 and 09:00. Spatially, except near 21:00, delays are concentrated mainly within the three inner circles (50-150 nautical miles).

IV. CONCLUSION

This paper demonstrates, through simulation experiments, that the proposed integrated framework combining UDPP, DCB, and E-AMAN can effectively reduce delays and operational costs while improving fairness and environmental sustainability in ATM. The main findings are as follows:

(1) Integrating UDPP into the network-level DCB process expands decision scope and enables airlines to reprioritize flights, yielding substantial reductions in both delay and cost;

(2) Incorporating linear holding alongside limited airborne holding provides a more efficient and environmentally friendly means of absorbing delays compared with conventional airborne strategies;

(3) By seamlessly integrating with network management, the E-AMAN optimization achieves greater predictability and more effective mitigation of arrival congestion through dynamic sequencing in the terminal-entry area.

Future research will focus on extending the model by incorporating more realistic airline behavioral preferences, accounting for stochastic demand and weather uncertainty, and testing scalability in larger and more complex traffic networks.

ACKNOWLEDGMENT

The work presented in this paper was partially supported by the Fundamental Research Funds for the Central Universities, Ministry of Education of China (No.KJZ53420250004), and by a grant from the China Scholarship Council (No.202406830124).

REFERENCES

- [1] Marc Melgosa, Andrija Vidosavljevic, and Xavier Prats. Hybrid method for holistic air traffic demand and capacity balancing optimisation based on sector complexity. *Transportation Research Part C: Emerging Technologies*, 180:105306, 2025.
- [2] Luigi De Giovanni, Carlo Lancia, and Guglielmo Lulli. Data-driven optimization for air traffic flow management with trajectory preferences. *Transportation Science*, 58(2):540–556, 2024.
- [3] Bolić T, Ravenhill P. SESAR: The past, present, and future of European air traffic management research[J]. *Engineering*, 2021, 7(4): 448-451.
- [4] Zhang Q, Le M, Xu Y. Collaborative delay management towards demand-capacity balancing within User Driven Prioritisation Process[J]. *Journal of air transport management*, 2021, 91: 102017.
- [5] EUROCONTROL, *Atfcm operations manual-network manager*, Tech.rep., EUROCONTROL (2021).
- [6] Chen Y, Dalmau R, Alam S. Spatio-temporal graph-based demand and capacity balancing considering flight uncertainties[C]. *14th SESAR Innovation Days*, 2024.
- [7] Raphael C, Hoffman E, Zeghal K. Interaction between arrival management and network management when extending the arrival horizon[C]//*AIAA Aviation 2019 Forum*. 2019: 3406.
- [8] Pilon N, Guichard L, Cliff K. Reducing impact of delays using airspace user-driven flight prioritisation[C]. *9th SESAR Innovation Days*, 2019.
- [9] Pilon N, Cook A J, Ruiz S, et al. Improved flexibility and equity for airspace users during demand-capacity imbalance—an introduction to the user-driven prioritisation process[C]. *6th SESAR Innovation Days*, 2016.
- [10] Tian Y, He X, Xu Y, et al. 4D trajectory optimization of commercial flight for green civil aviation[J]. *IEEE Access*, 2020, 8: 62815-62829.
- [11] Xu Y, Prats X, Delahaye D. Synchronised demand-capacity balancing in collaborative air traffic flow management[J]. *Transportation Research Part C: Emerging Technologies*, 2020, 114: 359-376.
- [12] Xu Y, Prats X. Effects of linear holding for reducing additional flight delays without extra fuel consumption[J]. *Transportation Research Part D: Transport and Environment*, 2017, 53: 388-397.
- [13] Wan J, Zhang H, Liu F, et al. Optimization of aircraft climb trajectory considering environmental impact under RTA constraints[J]. *Journal of Advanced Transportation*, 2020, 1: 2738517.