

AIRCRAFT SEQUENCING UNDER UNCERTAINTY: GAME-THEORETIC OPTIMIZATION AND A COMPARATIVE ASSESSMENT OF GLOBAL AND INTRA-AIRLINE COOPERATIVE DECISION FRAMEWORKS

Sakura Tsuru[1] & Adriana Andreeva-Mori[1]

[1]Graduate School of Engineering, Osaka Metropolitan University, Japan

Abstract

This study proposes a comprehensive air traffic management framework that applies game-theoretic aircraft sequencing to multi-airline operations, validated using simulations involving eight aircraft from two airlines under both deterministic and stochastic conditions. Traditional First-Come, First-Served principles often result in asymmetric cost penalties or constrain the decision-making autonomy of airlines. To resolve these limitations, we evaluate the trade-off between system efficiency and airline flexibility across two arrival patterns: consecutive blocks (same-airline flights) and alternating configurations (mixed-airline flights). Deterministic analysis reveals that competing without coordination is highly inefficient for airlines. While working together keeps collective cost increases at a bare minimum (0.76%), uncoordinated competition causes costs to increase up to 4.42%. Establishing a rigid schedule deterministically without accounting for arrival perturbations exposes the system to maximum velocity constraints, leaving insufficient margins to handle delays and triggering an abrupt cost escalation. The analysis demonstrates that a robust schedule designed with temporal buffers can achieve up to a 60% cost reduction compared to the rigid deterministic schedule when the arrival standard deviation is 120 seconds. Furthermore, initial flight configurations within a schedule do not correlate with cost mitigation under uncertainty. Whether the baseline schedule is consecutive airline blocks or alternating configurations, arrival fluctuations inevitably necessitate tactical resequencing by ATC. As operational uncertainty escalates, the overall controller workload and the number of slot shifts increase rapidly, rendering pre-planned schedules equally ineffective under either configuration. To overcome these barriers, we introduce a multi-period cooperative credit mechanism. ATC establishes a privacy-preserving economic environment where airlines make strategic decisions based on internal cost structures. By allocating cooperative bonuses via the Shapley value, the system successfully compensates localized tactical sacrifices over time. Simulations show that adding an annual rollover feature keeps the entire system stable. When airlines successfully save fuel and reduce delays, those achievements are converted into extra starting capital for the next year. This rollover mechanism allows the starting credit pool to grow steadily over time, climbing from 200,000 units in the first year, to 220,000 in the second, and reaching 225,000 by the third. This steady growth demonstrates the long-term sustainability of our proposal.

Keywords: Aircraft Sequencing, Merging Traffic, Game Theory, Uncertainty

1. Introduction

1.1 Background and Fundamentals of Air Traffic Control

The safe, orderly, and efficient management of aircraft operating in poor visibility or severe weather conditions is the foundation of modern air traffic management (ATM). In daily operations, while aircraft depart from various airports across different regions, they naturally converge as they approach their common destination runway, funneled into specific arrival routes and predefined merging points. This

physical convergence creates a highly dynamic and high-density bottleneck. Unlike ground transportation, airplanes cannot halt or hover in mid-air to wait for their turn. Therefore, without active management and precise tactical adjustments from Air Traffic Control (ATC), aircraft arriving simultaneously at these merging points would fail to maintain the prescribed minimum separation standards, leading to severe airspace congestion and, critically, catastrophic mid-air collision risks. To prevent such hazards, ATC must intervene to ensure a safe buffer between aircraft. However, achieving this vital safety separation is not without economic and environmental consequences. Forcing aircraft to alter their trajectories or adjust their Estimated Time of Arrival (ETA) to absorb delays frequently translates into increased fuel consumption, elevated flight times, and compounding operational delays. Operational flexibility and economic efficiency must therefore be balanced with safety. From this perspective, arrival sequencing must be treated not merely as a problem of geometric distance separation, but as a complex decision-making process that directly impacts the competing economic interests of individual airspace users.

1.2 Limitations of Conventional ATC and the First-Come, First-Served Principle

In current ATC practices, spacing is predominantly managed through distance-based tactical control, where controllers rely on radar surveillance and employ vectoring or speed adjustments to maintain safe spacing [1]. The overarching sequencing philosophy relies heavily on the 'First-Come, First-Served' (FCFS) principle [2, 3]. FCFS is a transparent and straightforward rule where aircraft are granted priority based on the chronological order in which they reach a specific airspace boundary or metering fix. Although the FCFS method is simple, it suffers from systemic inefficiencies and economic imbalances. Under heavy traffic, FCFS forces trailing aircraft to absorb all delays and speed changes, completely ignoring their specific costs or operational priorities.

To overcome these reactive interventions, emerging paradigms such as 'Trajectory-Based Operations' (TBO) aim to introduce time as an explicit control dimension using four-dimensional (4D) trajectories [4, 5]. However, centralized optimization models often face practical hurdles. As noted by Ball et al.(2011) [6] and Jovanović et al. (2015) [7], centralized authorities face fundamental information gaps. Airlines regard their own operating cost profiles, such as their own "Cost Index" (CI) values, as highly confidential commercial secrets and are reluctant to share them. Without direct access to these private cost structures, centralized systems are forced to rely on sub-optimal default sequencing, failing to achieve true operational flexibility.

1.3 Game Theory and Uncertainty in Arrival Sequencing

To resolve the information asymmetry and privacy concerns inherent in traditional ATM, Park et al. (2017) [8] introduced a methodology utilizing game theory. Generally, game theory is a mathematical framework used to analyze situations where multiple independent participants, or players, make decisions that affect each other. In this paper, as explained in Section 2.3.3, each aircraft is modeled as a rational player whose strategy is the choice of an ETA, and whose goal is to minimize its own operational cost. Through this interaction, the system can derive a stable outcome known as a Nash Equilibrium (NE). A NE is a state where no single player has an incentive to change their strategy because doing so would increase their own cost, assuming all other players keep their strategies unchanged. Significantly, this approach allows airlines to achieve efficient sequencing without disclosing their sensitive CI data to competitors.

However, a major limitation of the foundational model by Park et al. was its strict reliance on a predictable, deterministic environment that ignored random disruptions. In actual aviation, operational uncertainty is unavoidable. Weather changes, departure delays, and orbital prediction errors cause probabilistic disruptions that delay arrival times. To address this gap, our past work [9, 10] incorporated stochastic operational conditions into this game-theoretic framework. Numerical simulations involving two aircraft revealed that optimal sequences calculated under fixed, deterministic assumptions become unstable under random delays. By optimizing expected costs under uncertainty, the stochastic approach identified robust sequences that reduced additional operational costs by 16% compared to the FCFS baseline and by 22% compared to deterministic algorithms. Yet, these studies only looked at isolated, two aircraft situations, failing to address how the system scales when multiple airlines compete.

1.4 Multi-Aircraft and Multi-Airline Dynamics

To bridge the gap between simplified theoretical models and dense, real-world airspace operations, this study significantly extends the previous two aircraft foundation into a comprehensive multi-aircraft and multi-airline framework under centralized ATC management. Specifically, the operational horizon is scaled up to an eight-aircraft, two-airline scenarios. Importantly, this expansion is not merely a technical exercise in managing computational scaling. In dense terminal airspaces, multiple arriving flights belong to different commercial carriers, creating a complex gaming structure where individual corporate choices interact under a centralized set of rules. To investigate these intra-airline and inter-airline competitive dynamics, three distinct operational structures across different fleet distributions were evaluated. As will be explained in Section 2.4.1 later, this analysis compares a baseline Global Optimum model against two distinct airline fleet configurations under ATC supervision: a sequential grouping where flights from the same airline arrive in consecutive blocks First/Last and an interleaved grouping Odd/Even where flights from different airlines alternate positions.

1.5 Research Questions and the Strategic Limitations of Self-Interest and Uncertainty

By scaling the environment to a more realistic eight-aircraft, two-airline scenario, this study seeks to answer a fundamental and urgent research question:

> *Does competition between airlines improve or worsen air traffic operations under uncertainty?*

To address this question, numerical analyses were conducted through two distinct approaches and identified the inefficiencies caused by airlines' self-interest.

1. **The Cost of Self Interest (Deterministic Analysis):** By analyzing a scenario involving eight aircraft under idealized conditions, this study quantitatively identifies the direct negative effects of competition. It demonstrates that when flights are allocated to two competing airlines, and each pursues its own interests within ATC system, total operating costs are systematically higher than under a globally optimal solution. This exposes the inevitable Price of Anarchy born from airline fragmentation.[11],[12]

2. **Strategic Rigidity (Probabilistic Analysis):** By incorporating stochastic delays into the multi-airline model, the resilience of the system under conditions of uncertainty is evaluated. The result shows that a pass sequence deemed optimal under deterministic conditions becomes highly sub-optimal as uncertainty increases, causing expected costs to spike. This exposes the weaknesses of deterministic approaches. Furthermore, as random perturbations intensify, the frequency and magnitude of necessary slot exchanges expand drastically, leading to a state of strategic rigidity where non-cooperative adjustments result in excessive system-wide friction and severe delay propagation.

1.6 Transforming Friction into Long Term Cooperation via Credits

The findings from the numerical analysis reveal that purely competitive optimization cannot withstand the combined forces of multi-airline competition and operational uncertainty. Under competitive conditions, airlines lack the immediate economic incentive to voluntarily absorb delays or yield preferred slots to a competitor, even if doing so would dramatically improve overall system efficiency.

To resolve this deadlock and bridge the gap between rational corporate behavior and the global optimum, the primary contribution of this study introduces an incentive mechanism based on a continuous dynamic credit economy managed by a central authority. Under this proposed framework, ATC gives airline companies rewards in the form of cooperation credits if they accept tactical penalties, like giving up priority slots, to help ease schedule congestion. Crucially, these credits are essentially backed by the physical fuel and time savings achieved through global optimization, preventing arbitrary economic inflation.

By simulating this credit-based framework over a multi-year timeline with an annual carryover mechanism, this paper demonstrates a practical pathway to transform short-term competitive friction into sustainable, long-term systemic cooperation under centralized guidance.

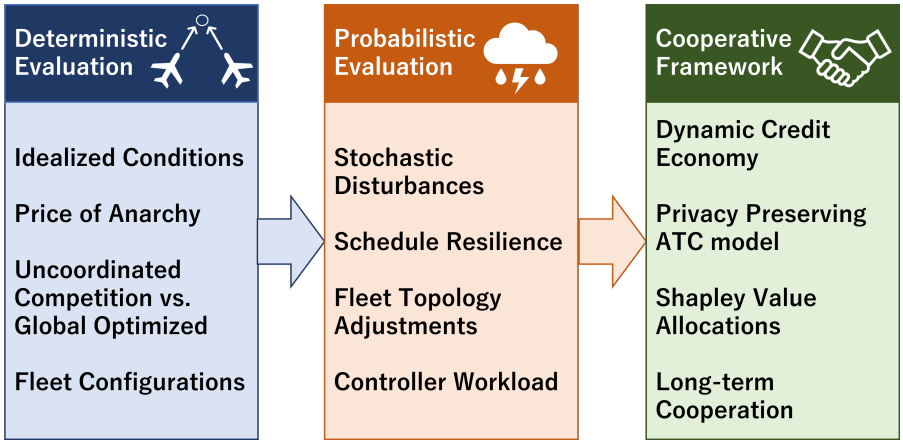


Figure 1 – Research flow.

1.7 Paper Organization and Research Flow

To systematically address the research questions posed above, this study is structured into a multi-stage analytical framework as shown in Figure 1. The logical progression of the research, from foundational cost modeling to the simulation of a multi-year cooperative economy, is outlined below.

- **Phase 1: Deterministic Evaluation (Section 3.1)**
  Operating under idealized conditions without uncertainty, this stage quantifies the "Price of Anarchy". It evaluates how uncoordinated competition between two airlines degrades system efficiency compared to a globally optimized baseline across different fleet configurations.
- **Phase 2: Probabilistic Evaluation (Section 3.2)**
  This phase introduces stochastic arrival disturbances to test the resilience of the schedules. It analyzes the nonlinear cost degradation of compressed schedules, the fundamental limits of fleet topology adjustments across consecutive and interleaved arrangements, and the escalation of tactical controller workload under uncertainty.
- **Phase 3: Cooperative Framework (Section 2.5, Section 3.3)**
  To resolve the strategic rigidities identified in Phase 2, the final phase introduces and evaluates a multi-year dynamic credit economy. Using a privacy-preserving ATC model and Shapley value allocations, it demonstrates how short-term competitive friction can be mathematically converted into long-term sustainable cooperation.

2. Methodology

2.1 Simulation Scenarios and Fleet Configuration

Illustrated in Figure 2, the operational environment assumes that all aircraft operate at a constant cruising altitude of 39,000 feet, denoted as 'Flight Level 390' (FL390), with the fleet consisting exclusively of Airbus A320 aircraft. The baseline characteristics for each flight, including individual CI values and initial temporal offsets (delays), are summarized in Table 1. The parameter "Delay" denotes the initial spatial displacement relative to AC1, which is the reference point for generating individual cost curves corresponding to distinct arrival slot allocations. In this study, for the sake of simplicity, the minimum interval between consecutive aircraft during a merge was set at 90 seconds.

2.2 Trajectory Optimization and Cost Modeling

2.2.1 Direct Operating Cost Formulation

Flight operating expenditures are primarily evaluated using the 'Direct Operating Cost' (DOC), which is modeled as a weighted linear sum of fuel consumption and elapsed flight time:

$$DOC = \text{Fuel} \times C_f + \text{Time} \times C_t \tag{1}$$

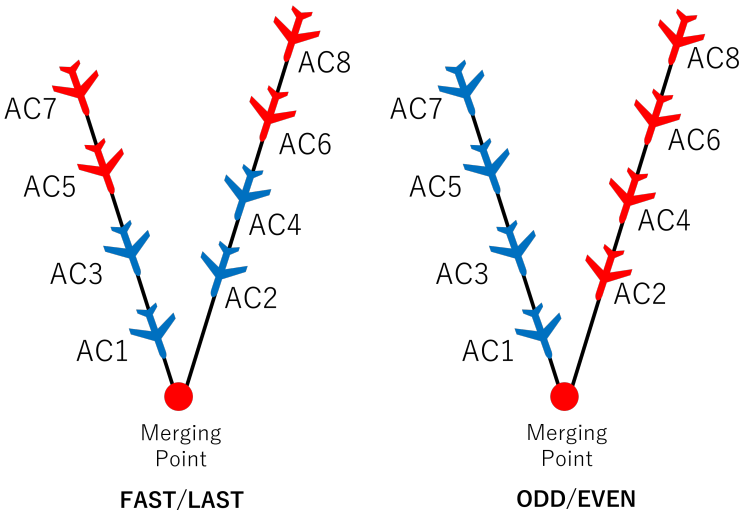


Figure 2 – Assignment of eight aircraft to two airlines.

Table 1 – Initial aircraft data for the eight aircraft scenario.

Aircraft	CI	Delay [s]	Aircraft	CI	Delay [s]
AC1	0.2	0	AC5	0.7	320
AC2	0.6	80	AC6	0.9	400
AC3	0.8	160	AC7	0.2	480
AC4	0.5	240	AC8	0.4	560

where C_f is the unit cost of fuel (\$/kg) and C_t is the unit cost of time (\$/s). These baseline unit costs represent highly sensitive, proprietary data that fluctuate based on fuel markets, aircraft variants, and payload configurations, directly reflecting individual airline revenue policies. By normalizing Eq.(1) with respect to the unit fuel cost C_f, the DOC is formulated in terms of equivalent fuel consumption, explicitly introducing the CI as a governing operational parameter:

$$DOC = \text{Fuel} + \text{Time} \times CI \tag{2}$$
$$CI = C_t / C_f$$

2.2.2 The Operational and Economic Significance of the Cost Index

Integrating the CI into the sequencing framework is essential because a simple temporal delay does not impact all flights equally. In real-world operations, the financial penalty of a one-minute delay varies significantly depending on the specific characteristics of each flight. For instance, a flight with a high CI places a heavy premium on time, meaning that airborne holding or speed reductions cause rapid cost escalation due to tight crew connections, passenger transfers, or strict schedule constraints. Conversely, a flight with a low CI prioritizes fuel efficiency, meaning it can absorb temporal adjustments with less financial damage by operating at a lower fuel flow rate. If ATC system manages arrivals using only temporal measurements, such as a strict FCFS sequence, it creates an asymmetric economic burden on airlines. A uniform delay applied to a high CI flight and a low CI flight causes highly unequal financial losses, leading to systemic inefficiency. Therefore, capturing the individual CI characteristics allows the framework to look beyond simple time increments and instead evaluate the true economic reality of airspace scheduling.

2.2.3 Privacy-Preserving Cost Metric: ΔDOC

Rather than mandating the direct sharing of raw CI data, the proposed coordination methodology utilizes the increase in Direct Operating Cost, denoted as 'ΔDOC'. This metric quantifies the penalty cost incurred when an aircraft is compelled to deviate from its economically optimal ETA. Crucially, this mechanism circumvents the requirement for operators to disclose confidential financial data. By

submitting only the processed ΔDOC arrays, airlines can work on decentralized sequence optimization, while the basic corporate strategy built into the CI remains completely private.

2.2.4 Baseline ETA and Aerodynamic Performance

The baseline, cost-minimizing ETA for each individual flight is governed by the aerodynamic relationship between the cruising Mach number and the 'Specific Range' (SR) (nm/kg). The SR is as a key performance indicator of fuel efficiency, mapping the distance traversed per unit mass of fuel consumed under varying parameters such as airspeed, altitude, and instantaneous aircraft mass. This framework incorporates empirical SR data for a standard mass Airbus A320 cruising at FL390 obtained from Xu et al.(2017)[13], as illustrated in Figure 3 and tabulated in Table 2. The permissible cruising speed is strictly bounded between Mach 0.74 and Mach 0.80.

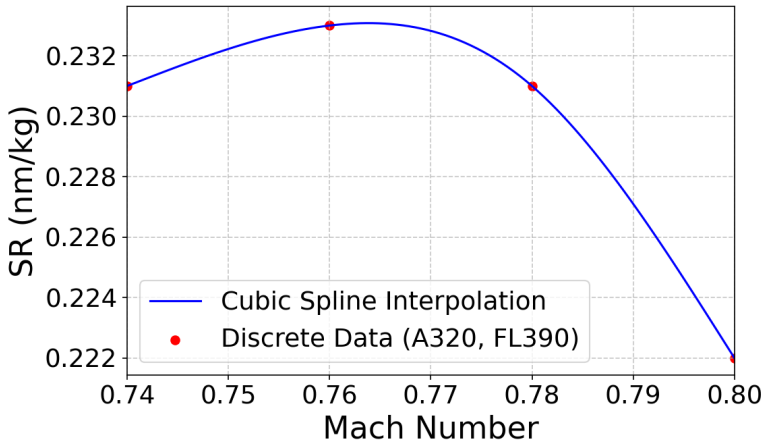


Figure 3 – Mach vs. SR (A320, FL390).

Table 2 – Specific Range and Mach number (A320, FL390).

Mach	0.74	0.76	0.78	0.80
SR (nm/kg)	0.231	0.233	0.231	0.222

2.2.5 Strategy Space Expansion via Path Stretching

The strategy space for each participant is generated by systematically changing the cost optimal standard ETA. Relying exclusively on airspeed modulations within the baseline nominal flight envelope (Mach 0.74-0.80) yields insufficient operational flexibility; multiple fixed slots would necessitate airspeed falling below the lower safe boundary of Mach 0.74. Consequently, without modification, only approximately three slots per aircraft would remain mathematically feasible, severely restricting the degree of freedom required for effective sequencing.

To resolve this limitation and define coherent cost penalties for significantly delayed slots, a 'path stretching' mechanism is integrated as illustrated in Figure 4. For any target arrival slot requiring a speed below Mach 0.74, the aircraft is modeled to maintain its minimum safe aerodynamic speed while lengthening the flight path, mathematically simulating linear vectoring or holding maneuvers. This framework models dynamic trajectory alterations during actual operations, permitting an expansion of the flight distance up to a maximum factor of 1.2 relative to the original path.

This modeling approach yields a distinct V-shaped profile of additional operating costs, where extensive arrival delays trigger substantial ΔDOC penalties driven by the compounded effects of extended flight duration and heightened fuel burn from path extension. For the subsequent multi-aircraft simulations, this mechanism provides each participant with a broader strategy space consisting of discrete options, thereby facilitating robust and practical sequence coordination.

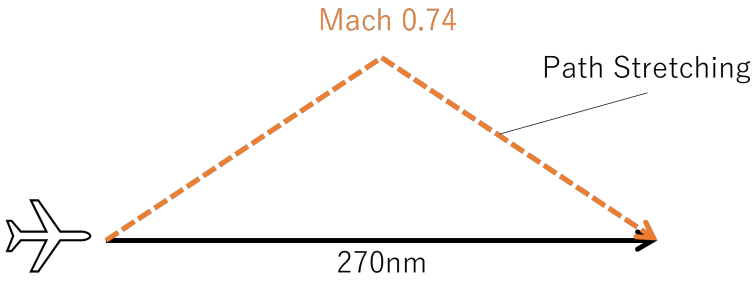


Figure 4 – Path stretching mechanism.

2.3 Optimization Framework: MILP and Game Theory

To enable the simulation of a vast number of aircraft, Mixed-Integer Linear Programming (MILP) was implemented as the computational engine. This architecture completely avoids heuristic methods and brute-force searches, ensuring high accuracy and computational efficiency in scenarios involving up to eight aircraft. In the game-theoretic analysis described below, the MILP framework is applied recursively as a subsolver embedded within an iterative algorithm to compute the locally optimal response to competing agents.

2.3.1 Foundational MILP Formulation (Base Constraints)

To preserve absolute mathematical consistency across all evaluated optimization scenarios, the foundational mathematical architecture is standardized using the following definitions:

- $I = \{1, 2, \ldots, N\}$: The set of participating aircraft ($N = 8$).
- $S = \{1, 2, \ldots, M\}$: The set of discrete 90-second arrival slots ($M = 15$).
- $x_{i,s} \in \{0, 1\}$: The binary slot assignment variable, where $x_{i,s} = 1$ if aircraft i is assigned to slot s, and 0 otherwise.

Every feasible scheduling solution must satisfy the following structural operational constraints:

$$\sum_{s \in S} x_{i,s} = 1 \quad \forall i \in I \tag{3}$$

$$\sum_{i \in I} x_{i,s} \leq 1 \quad \forall s \in S \tag{4}$$

Eq.(3) constitutes the assignment constraint, ensuring that each individual aircraft is allocated exactly one arrival slot. Eq.(4) is the capacity constraint, guaranteeing that each discrete arrival slot is occupied by at most one aircraft to satisfy safety separation standards at the merge point.

2.3.2 Centralized Approach: Global Optimization

In the centralized optimization model, the core MILP solver is executed to minimize the combined cost of the entire fleet simultaneously. This configuration identifies the absolute 'System Optimum', simulating a scenario where a single central coordinator commands all individual arrival vectors to yield the maximum possible system-wide fuel efficiency and minimal aggregate delay costs. The objective function is formulated as follows:

$$\text{Minimize} \sum_{i \in I} \sum_{s \in S} \Delta DOC_{i,s} \cdot x_{i,s} \tag{5}$$

2.3.3 Decentralized Approach: Game Theory and Best Response Dynamics

To model a competitive market environment, the problem of arriving flight conflicts is framed as a non-cooperative game among autonomous agents (airlines). The operational logic for sequence determination is outlined in Figure 5. In this competitive formulation, the game components are defined as follows:

- **Players:** The converging aircraft or airline fleet alliances (Airline Team A and Airline Team B).
- **Strategy:** The specific arrival slots selected by the players from their predefined strategy sets.
- **Loss Function:** The localized group or individual cost (ΔDOC) resulting from the combined strategy profile.

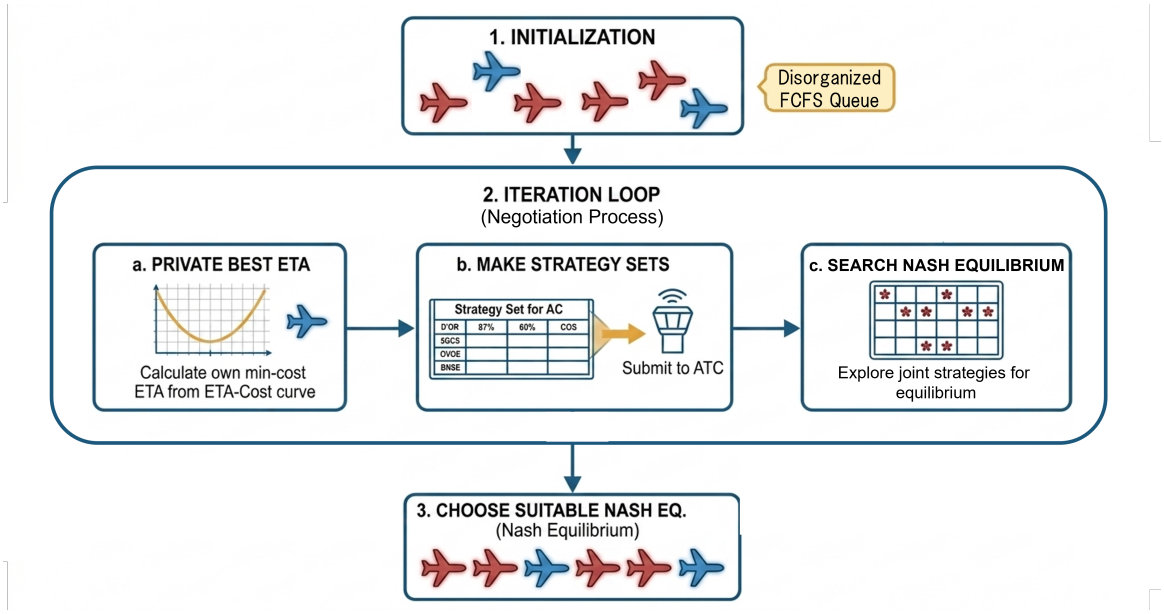


Figure 5 – Game-theoretic sequencing flow.

The primary analytical objective is to identify the 'Nash Equilibrium' (NE) [14], where no individual player can unilaterally deviate to reduce its own loss (ΔDOC), assuming the strategies of all other competitors remain fixed. Mathematically, a strategy pair (s_A^*, s_B^*) constitutes an NE if:

$$L_A(s_A^*, s_B^*) \leq L_A(s_A, s_B^*) \quad \text{and} \quad L_B(s_A^*, s_B^*) \leq L_B(s_A^*, s_B) \tag{6}$$

where L denotes the respective loss function. Competitive privacy is rigorously preserved during this mathematical sequencing process since operators only transmit their processed strategy sets (ΔDOC arrays) without disclosing underlying raw cost functions or commercial parameters.
In a dense multi-aircraft scenario ($N = 8$), if you try to find a NE by brute force, the combinations explode exponentially. The system has 15 candidate arrival slots, but as shown in Table 4 later, due to speed constraints, each aircraft can only evaluate about 7 or 8 slots. As a result, the search space increases to at least $7^8 = 5.76 \times 10^6$ possibilities, making it impractical for real-time operations. To circumvent this, the multi-aircraft NE is isolated through decentralized 'Best Response Dynamics' utilizing iterative MILP sub problems:

1. **Initialization (Monte Carlo Seed Generation):** A randomized, mathematically feasible initial slot assignment is generated. To guarantee structural stability and isolate true global equilibria, this process is repeated across 5,000 independent trials.
2. **Iterative MILP Sub-problems:** The competing entities alternately optimize their respective schedules. During the optimization cycle for Team A, the positions of all aircraft belonging to Team B are frozen and treated as rigid operational constraints. Team A then solves its local MILP sub problem to minimize its specific group cost, $J_{\text{Team A}}$.
3. **Convergence Verification:** This iterative "Best Response" loop alternates continuously until the MILP outputs for both airline groups achieve perfect stability and cease to change, mathematically confirming the attainment of an NE.
4. **Frequency Analysis:** The specific equilibrium pattern that exhibits the highest statistical frequency of occurrence across the 5,000 randomized Monte Carlo trials is isolated for the final operational analysis.

2.4 Modeling Operational Uncertainty and Tactical Resequencing

2.4.1 Deterministic Baseline and Multi-Airline Configurations

To evaluate scalability and team-based dynamics under idealized conditions without operational uncertainty, a deterministic baseline is first established. Based on the trajectory optimization and cost modeling framework described in Section 2.2, the fuel consumption and subsequent ΔDOC cost curves are rigorously computed for each aircraft relative to its target arrival times. To construct a standardized, discrete strategy space, a total of 15 common arrival slots spaced at 90 second intervals are extracted as the permissible ETA choices for all participants. In this multi-airline environment, two distinct grouping patterns, denoted as First/Last and Odd/Even, are defined to analyze competitive behavior when individual airlines independently search for a NE to achieve their optimal slot allocations:

- **First/Last:** Airline A operates the leading block, AC1–AC4; Airline B operates the trailing block, AC5–AC8.
- **Odd/Even:** Airline A operates the odd-indexed aircraft, AC1, AC3, AC5, and AC7; Airline B operates the even-indexed aircraft, AC2, AC4, AC6, and AC8.

By implementing the decentralized game-theoretic framework, the simulation examines how competing airlines negotiate for priority arrival slots. The final analysis directly compares the resulting optimal passing sequences and system-wide operational costs across three key configurations: the centralized 'Global Optimum', the non-cooperative First/Last fleet distribution, and the non-cooperative Odd/Even fleet distribution. This comparative structure isolates the systemic penalties triggered by localized self interest, quantifying how the uncoordinated scramble for slots among commercial rivals degrades global airspace efficiency.

2.4.2 Stochastic Disturbances and Tactical FCFS Resequencing Model

To evaluate the impact of real-world arrival disturbances, the performance of the deterministic approach is compared against a robust probabilistic framework that models arrival deviations via normal probability distributions.

Let ETA_i^{plan} denote the pre-calculated arrival time slot allocated to aircraft $i \in I$ under a specific coordination model (e.g., Global Optimization or a specific Nash Equilibrium). When subjected to unexpected stochastic operational disturbances during the cruise phase, the actual unadjusted arrival time, ETA_i^{stoch}, is formulated as follows:

$$ETA_i^{\text{stoch}} = ETA_i^{\text{plan}} + d_i \tag{7}$$

where $d_i \sim \mathcal{N}(0, \sigma^2)$ is the independent and identically distributed stochastic delay parameter governed by the standard deviation σ.

During tactical terminal operations, ATC must guarantee physical safety standards regardless of scheduling deviations. Consequently, the actual chronologically ordered realization sequence is established by sorting the stochastic arrival array such that $O = \text{sort}(ETA^{\text{stoch}})$, where $O(k)$ indicates the aircraft index holding the k-th position in the modified arrival flow via FCFS rule. To ensure that the minimum safety separation window ($\Delta t_{\text{sep}} = 90$ seconds) is continuously preserved at the merge point, a dynamic temporal recursion model is enforced. The final, control assured arrival time, $ETA_{O(k)}^{\text{realized}}$, is sequentially generated via the following mathematical relations:

$$ETA_{O(1)}^{\text{realized}} = ETA_{O(1)}^{\text{stoch}} \tag{8}$$

$$ETA_{O(k)}^{\text{realized}} = \max\left(ETA_{O(k)}^{\text{stoch}}, ETA_{O(k-1)}^{\text{realized}} + \Delta t_{\text{sep}}\right) \quad \forall k \in \{2, 3, \ldots, N\} \tag{9}$$

The total flight duration for each aircraft is subsequently updated based on this finalized $ETA_{O(k)}^{\text{realized}}$ to extract the effective operational cost under uncertainty.

2.4.3 Total Expected Cost Formulation

To quantify system performance under these dynamic tactical interventions, the 'Total Expected Cost' (TEC) is implemented as the primary performance benchmark. The TEC is the probabilistic mathematical expectation of total system costs aggregated across all potential delay realizations for a designated strategy profile. The workflow for this evaluation is illustrated in Figure 6.

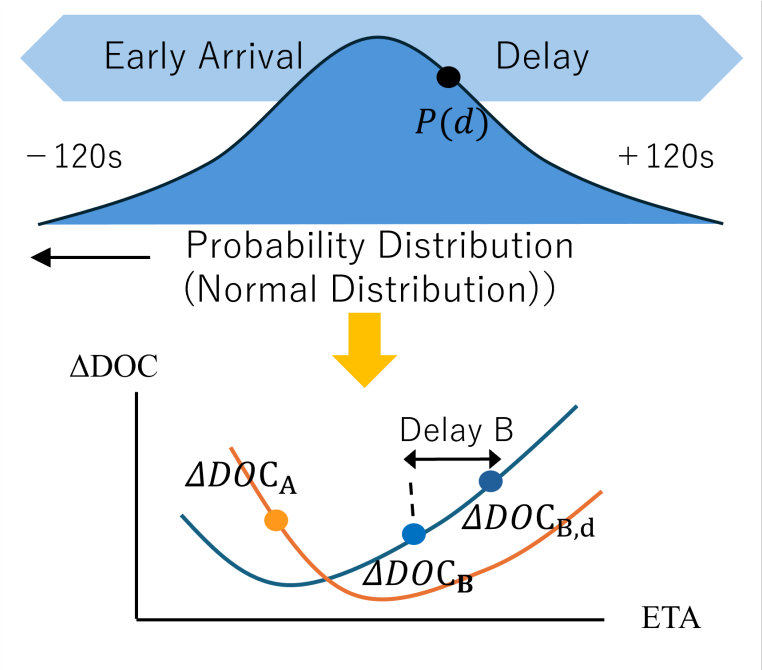


Figure 6 – Workflow for TEC calculation.

To execute this probabilistic evaluation, extensive Monte Carlo simulations are performed using robust sampling sizes ($N_{\text{sample}} = 5000$ for comprehensive Nash tracking, and $N_{\text{sample}} = 3000$ for rule-based competitive scenario evaluations). For each independent trial, randomized delay parameters are sampled across an incremental uncertainty spectrum ($\sigma \in [0, 120]$ seconds). The aggregate system performance metric is formalized as follows:

$$TEC = \frac{1}{N_{\text{sample}}} \sum_{m=1}^{N_{\text{sample}}} \left[\sum_{i \in I} \Delta DOC_{i,m} \right] \tag{10}$$

where $\Delta DOC_{i,m}$ is the realized normalized cost penalty of aircraft i during the m-th independent Monte Carlo trial, derived by mapping the finalized control-assured arrival time ETA_i^{realized} onto the aerodynamic SR datasets. To mathematically confirm that the sampling density provides sufficient precision and avoids stochastic noise, a formal convergence diagnostics protocol is integrated by tracking the running average of the collective costs across the simulation evolution.

2.5 Dynamic Framework for Long-Term Airline Cooperation

2.5.1 Transition from Single Wave Optimization to Long-Term Cooperation

Within the basic framework presented so far, one of the core findings derived from this baseline analysis is that competition among airlines under conditions of uncertainty leads to severe 'strategic rigidity', resulting in excessive competition for slots and a significant decline in the overall efficiency of the system. To overcome these local inefficiencies, this study proposes a systematic mechanism where airlines cooperate to exchange slots with one another when unexpected delays occur. Through this mechanism, efficiency is expected to improve as the overall air traffic system approaches a global optimum. However, in real-world operations, airlines will not voluntarily absorb delays or yield preferred slots to competitors without a sustainable, long-term incentive. This challenge served as the direct catalyst for developing a continuous, multi-year simulation framework. By establishing a dynamic

credit economy, this framework models how localized tactical sacrifices can be fairly compensated over time, transforming short-term competitive friction into long-term systemic cooperation.

2.5.2 Privacy Preserving ATC Model and Information Isolation

To reflect the highly competitive nature of commercial aviation, the simulation logic positions ATC as a strict, neutral coordinating body. In this architecture, airlines are modeled as independent and isolated decision-making entities. Direct accessing or exchanging competitor's cost structures, proprietary CI values, or internal credit balances is strictly prohibited. ATC computes the optimal slot allocations based solely on the submitted normalized relative cost matrices (ΔDOC). Following the execution of a daily schedule, airlines receive only their individual, private credit reports from ATC. This guarantees complete information privacy while enabling centralized global optimization.

2.5.3 Shapley Value Allocation and Economic Equivalence

The core mechanism for distributing the benefits of cooperative slot reallocation relies on a simplified Shapley value approach [15]. In game theory, the Shapley value is a classic method used to fairly allocate the total gains or costs generated by a coalition of players. It operates on the principle that the rewards given to each participant should be directly proportional to their marginal contribution to the group. In other words, if cooperation creates a certain amount of savings, the Shapley value looks at how much value each player added to the alliance and divides the profit in a way that respects everyone's role in achieving that outcome. In this study, this economic concept is applied to resolve the conflict between competing commercial airlines under centralized ATC supervision. When ATC identifies a new slot allocation that yields a system-wide cost reduction ΔC compared to the baseline Nash Equilibrium, the joint savings are fundamentally distributed based on the Shapley fairness concept:

$$\text{Shapley}_i = C_{\text{base},i} - \left(\frac{\Delta C}{2}\right) \tag{11}$$

$$\text{where } \Delta C = \sum C_{\text{base}} - \sum C_{\text{opt}}.$$

By subtracting half of the joint savings from the baseline cost of each airline, the mechanism ensures that the financial benefits of the swap are shared equally between the carrier that received the priority slot and the carrier that yielded it.

Importantly, the generation of new credits within the system is strictly bounded by physical reality. The credit authority, such as ATC, mints new cooperative bonus credits only in proportion to the actual physical fuel and time savings achieved through slot optimization. If an airline accepts a localized penalty ($C_{\text{opt},i} > C_{\text{base},i}$) to facilitate a global benefit ($\Delta C > 0$), a cooperative bonus is awarded:

$$\text{Bonus}_i = \Delta C \times \gamma \tag{12}$$

where $\gamma = 0.3$ is the incentive rate. While the standard Shapley value divides the savings evenly, this study introduces the cooperative bonus as an additional, customized incentive. This bonus is given exclusively to the airline that absorbed a delay, acting as a direct reward for its concession. This combined structure ensures that the credit economy is intrinsically backed by ecological and operational efficiency gains, preventing arbitrary inflation while actively encouraging cooperative behavior.

To clarify the mathematical and operational mechanisms of this incentive framework, a basic two aircraft slot exchange scenario, as shown in Table 3, is presented as an example. Consider Aircraft A, which operates with high fuel efficiency such that a one-minute delay incurs a cost penalty of only 20 units. Conversely, Aircraft B operates with low fuel efficiency, where a one-minute delay results in a cost penalty of 100 units. Aircraft A is scheduled to arrive slightly ahead of Aircraft B, but a minimum separation standard must be enforced at the merging point. Under the conventional non-cooperative FCFS baseline, Aircraft A lands first without any delay penalty, while Aircraft B is forced to wait for one-minute, incurring a cost of 100 units. This yields a total system cost of 100 units. If tactical cooperation is enforced via global optimization, ATC instructs Aircraft A to yield the right of way to Aircraft B. Consequently, Aircraft B lands first with zero delay cost, while Aircraft A absorbs a one-minute delay, incurring a localized penalty of 20 units. From a systemic perspective, the total cost

drops from 100 to 20 units, successfully generating a physical surplus of 80 units through collective value creation. On an individual corporate level, however, this optimal solution introduces severe asymmetry. Airline A suffers an uncompensated loss of 20 units, while Airline B enjoys a complete cost elimination from 100 to 0. To resolve this imbalance, the Shapley value allocation mathematically distributes the 80 units of systemic savings based on the structural contribution of each participant. Under the standard Shapley formulation, the 80 units surplus is divided equally, granting a 40 units dividend to each party. Furthermore, this study introduces an additional concession incentive, where a 30% bonus of the total systemic savings (24 units) is allocated exclusively to the yielding carrier. Thus, Airline A gains 64 credits, and the profit from participating in the coordination reaches 44 credits. Meanwhile, Airline B was supposed to suffer a loss of 100 units, but by participating in the coordination, they limited the loss to 40 units to compensate for A's loss. This is equivalent to gaining 60 units of profit through cooperation. This fundamental economic equilibrium demonstrates that localized tactical sacrifices can be seamlessly transformed into mutually beneficial corporate assets across multiple accounting periods.

Table 3 – Credit allocation for a two aircraft slot swap.

Economic Metric	**Airline A (Yielding)**	**Airline B (Beneficiary)**	**Total System**
1. Baseline Cost (C_{base})	0	100	100
2. Coordinated Cost (C_{opt})	20	0	20
Joint Savings (ΔC)			**80**
3. Shapley Value Allocation	+40	-40	0
4. Cooperative Bonus (Bonus)	+24	0	+24
Final Credit Balance Change (The Benefits of Cooperation)	**+64 (64-20=44)**	**-40 (-40-(-100)=60)**	**+24 (104)**

2.5.4 Multi Year Credit and Carryover Mechanism

To evaluate long-term financial sustainability, a multi-year simulation architecture spanning three years was established. To prevent unbounded credit accumulation or catastrophic insolvency, a year end carryover mechanism is enforced. At the conclusion of each 365-day fiscal cycle, an airline's 'surplus' credits exceeding the baseline initial credit ($B_{\text{base}} = 100,000$) are partially carried over to the subsequent year at a rate of $\alpha = 0.3$.

$$B_{\text{new}} = B_{\text{base}} + \alpha \times \max(0, B_{\text{end}} - B_{\text{base}}) \tag{13}$$

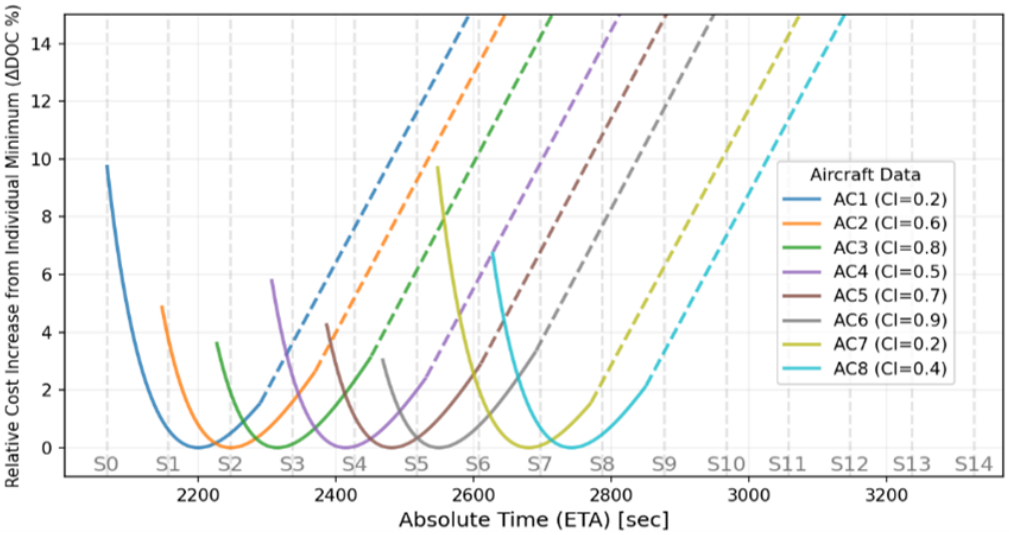


Figure 7 – ETA vs DOC for each aircraft and time of slots.

3. Results and Discussion

3.1 Deterministic Analysis: The Price of Uncoordinated Competition

3.1.1 Cost Curve Modeling and Strategy Mapping

To establish the baseline rules of competition, an eight-aircraft scenario as compiled in Table 1 was analyzed. Figure 7 illustrates the detailed cost structure for each individual aircraft. The solid lines represent the cost variations associated with speed adjustments within the nominal operating flight envelope (Mach 0.74 to 0.82). The dotted lines indicate the path stretching regime, where the aircraft is modeled to maintain its minimum safe aerodynamic speed of Mach 0.74 while extending the physical flight distance to absorb further delays. The gray vertical lines indicate the discrete temporal positions corresponding to each 90 second arrival slot. These continuous cost curves serve as the analytical foundation for extracting the discrete monetary penalties associated with each available landing slot allocation.

3.1.2 Slot Cost Matrix and Discrete Mapping Table

Table 4 presents the specific cost increments (ΔDOC) for each of the eight aircraft across the available terminal slots, S0 through S14. This discrete mapping is derived by evaluating the continuous cost profiles from Figure 7 at the scheduled arrival times of each slot. By quantifying the economic penalty for every possible slot assignment permutation, this matrix functions as the payoff table for each autonomous "player" in the game-theoretic analysis, directly dictating the baseline conditions for the resulting Nash equilibria.

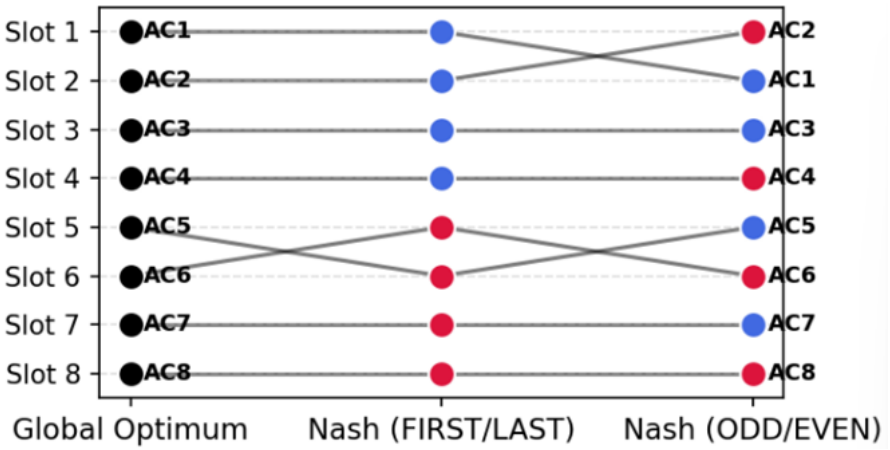


Figure 8 – Changes in slot assignment.

Table 4 – Relative cost slot (ΔDOC %).

	S0 2067s	S1 2157s	S2 2247s	S3 2337s	S4 2427s	S5 2517s	S6 2607s	S7 2697s	S8 2787s	S9 2877s	S10 2967s	S11 3057s	S12 3147s	S13 3237s	S14 3327s
AC1	INF	0.33	0.00	3.00	6.97	10.93	14.90	18.87	INF	INF	INF	INF	INF	INF	INF
AC2	INF	3.99	0.00	1.56	5.09	9.12	13.15	17.18	21.21	INF	INF	INF	INF	INF	INF
AC3	INF	INF	2.14	0.00	2.20	5.94	9.99	14.03	18.08	22.12	INF	INF	INF	INF	INF
AC4	INF	INF	INF	2.78	0.00	1.85	5.64	9.66	13.68	17.70	21.71	INF	INF	INF	INF
AC5	INF	INF	INF	INF	0.91	0.00	2.32	6.30	10.33	14.35	18.38	22.40	INF	INF	INF
AC6	INF	INF	INF	INF	INF	0.00	0.43	3.19	7.24	11.28	15.33	19.37	23.42	INF	INF
AC7	INF	INF	INF	INF	INF	INF	2.08	0.00	2.05	6.04	10.02	14.00	17.98	INF	INF
AC8	INF	INF	INF	INF	INF	INF	INF	0.49	0.00	2.80	6.80	10.79	14.79	18.78	INF

3.1.3 Comparative Visualization of Sequencing Frameworks

To reveal how organizational fleet structures dictate airspace efficiency, the optimal passing sequences generated under three distinct frameworks are compared in Figure 8. From left to right, the diagram displays the final slot assignments for the centralized Global Optimum, the decentralized Nash (First/Last), and the decentralized Nash (Odd/Even) arrangements. The lines connecting each aircraft to its respective arrival slot provide an intuitive visualization of sequence reversals driven by localized self interest. Aircraft are color coded to denote their corporate fleet affiliations: Airline A (blue) and Airline B (red). In all evaluated cases, the total operational time required for all eight aircraft to pass the merge point remained invariant (using S1 through S8). This comparison sets the stage for quantifying the systemic efficiency loss when centralized control is replaced by competitive slot capture.

3.1.4 Strategic Rigidity and the Price of Anarchy

A critical finding of this deterministic analysis is the manifestation of the 'Price of Anarchy', driven by the disparate CI values of competing aircraft. When airlines selfishly optimize their sequences without central coordination, severe sequence reversals occur:

- **AC5 vs. AC6 (First/Last Nash):** Within the internal coordination of Airline B under the First/Last arrangement, AC6 ($CI = 0.9$) overtakes AC5 ($CI = 0.7$). While self interest dictates this move to secure an earlier slot for the higher CI aircraft, it pushes AC5 to a highly sub-optimal slot (S6), inflating Airline B's aggregate cost.
- **AC1 vs. AC2 (Odd/Even Nash):** In the Global Optimum, AC1 ($CI = 0.2$) sacrifices its position, shifting to slot 1 to allow the time sensitive AC2 ($CI = 0.6$) to occupy slot 2, thereby minimizing system-wide costs. Conversely, in the Odd/Even equilibrium, AC1 (Airline A) aggressively captures the more favorable slot 2 to minimize its localized loss. This forces AC2 (Airline B) into the high-cost slot 1, heavily penalizing the high CI aircraft.

The quantitative results expose a stark efficiency disparity. The centralized Global Optimum restricts the collective cost increment (ΔDOC) to a mere 0.76%. In contrast, the decentralized Nash outcomes fluctuate drastically based on spatial grouping. In the First/Last arrangement, where aircraft are bundled sequentially by airline, total ΔDOC is 2.65%; the airlines can somewhat mitigate losses by internally swapping slots among their own fleet. However, in the interleaved Odd/Even arrangement, the collective cost jumps up to 4.42%. Because every adjacent slot is held by a competitor, a state of severe 'strategic rigidity' emerges yielding any slot immediately benefits a rival at the airline's own expense, preventing any cooperative concession. This proves that uncoordinated competition reduces global efficiency, and it provides the basis for the need for new cooperation mechanisms.

3.2 Probabilistic Analysis: The Collapse of Competitive Strategies

3.2.1 Nonlinear Cost Degradation and Slot Shift Buffer Effects

To evaluate whether the competitive strategy profiles formed under idealized deterministic conditions remain viable in realistic environments, stochastic arrival perturbations (σ) are introduced. Figure 9 illustrates the TEC across multiple Nash equilibria as a function of the uncertainty standard deviation. A critical mathematical and operational finding from this analysis is the distinct bifurcation between two primary Nash equilibria, denoted as N8(blue) and N18(light blue). Notably, both equilibria generate the same physical passing sequence, ordered chronologically from AC1 to AC8. The structural differentiation lies strictly in their temporal slot allocations; while N8 aggressively assigns flights to the earliest possible compressed block (slots 1 to 8), N18 uniformly shifts the entire allocation backward by one slot (slots 2 to 9). The N8 profile demonstrates a fundamental lack of operational flexibility, as it is anchored to the earliest possible arrival slots. In this configuration, Aircraft 1 is already assigned to the earliest feasible slot (slot 1); therefore, the system cannot move the schedule forward because any earlier arrival at slot 0 is physically impossible due to the aircraft's maximum velocity constraints. This extreme compression leaves N8 with zero margin to absorb incoming disturbances.

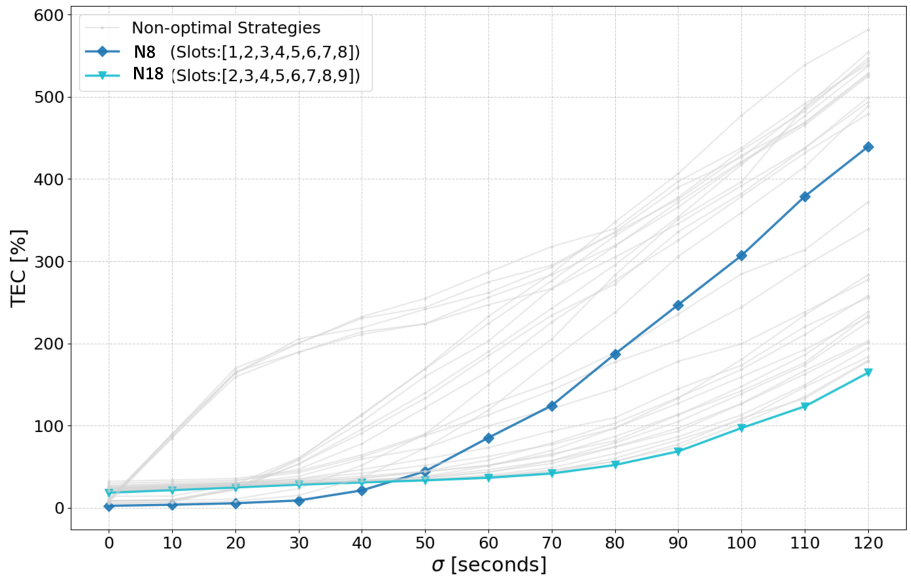


Figure 9 – TEC change for each equilibrium.

Consequently, despite possessing identical landing sequences, their economic resilience under uncertainty diverges nonlinearly. Under a near deterministic baseline ($\sigma \leq 30$ seconds), N8 achieves superior efficiency by minimizing absolute transit time. However, as operational uncertainty expands past $\sigma = 40$ seconds, the cost profile of N8 suffers severe degradation, skyrocketing to a TEC of over 400% at $\sigma = 120$ seconds. This rapid cost escalation is driven by a lack of temporal margins. Strategy profiles like N8, which are tightly compressed to optimize peak deterministic efficiency, trigger a cascading domino effect of delay propagation to all subsequent flights via tactical FCFS resequencing rules. This lack of buffer forces trailing aircraft into extensive path stretching maneuvers. Conversely, the shifted profile of N18 displays an extraordinarily stable, linear cost growth, maintaining a TEC of approximately 160% even under maximum uncertainty. By systematically shifting the schedule by one slot, N18 acts as an implicit temporal buffer at the terminal boundary, absorbing arrival deviations without triggering downstream delay propagation. This insight demonstrates that pursuing peak efficiency without accounting for uncertainty leads to highly fragile schedules. If the magnitude of operational variance can be estimated to be a priority, air traffic providers can selectively filter and enforce robust shifted equilibria to safeguard macroscopic airspace efficiency.

3.2.2 Limited Operational Efficiency Due to a Lack of Cooperation Among Airlines

The evaluation of the two airline allocation rules under stochastic conditions exposes a critical limitation of non-cooperative strategy variations. Figures 10 and 11 map the aggregated system-wide and localized TEC performance for both the First/Last and Odd/Even distribution models across the uncertainty spectrum. A primary observation from Figure 10 is that the structural configuration of the fleet provides remarkably little defense against growing operational disturbances. Under a deterministic baseline ($\sigma = 0$), the total system cost increments for both First/Last and Odd/Even are nearly identical. As the arrival standard deviation expands, the interleaved Odd/Even layout suffers a slightly steeper cost trajectory than the clustered First/Last framework. However, this system-wide efficiency gap remains highly marginal, never exceeding a difference of roughly 2.0%. Crucially, once uncertainty scales to $\sigma \geq 100$ seconds, the cost profiles of the two frameworks converge, tracking an identical systemic degradation ceiling of approximately 17%. This visual convergence signifies the fundamental breakdown of localized scheduling strategies. While First/Last is theoretically expected to shield operations by facilitating internal slot exchanges, such localized mechanisms are rapidly nullified in a highly stochastic environment. When random deviations past the inter slot separation threshold, delayed flights from the competing carrier inevitably penetrate the coordinated blocks. This interference from other airlines completely undermines local flexibility, thereby degrading the total cost trajectory of the First/Last model to the same level as that of a rigid Odd/Even framework.

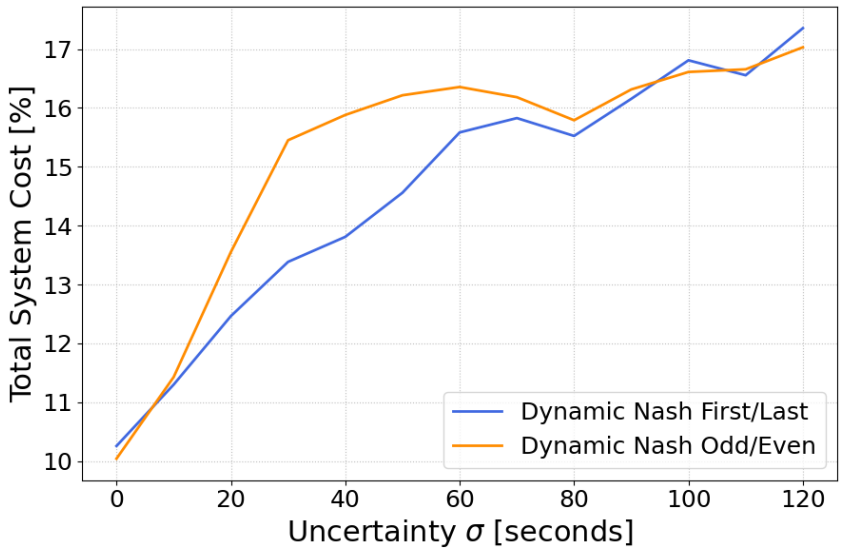


Figure 10 – TEC for eight aircraft when split into two airline.

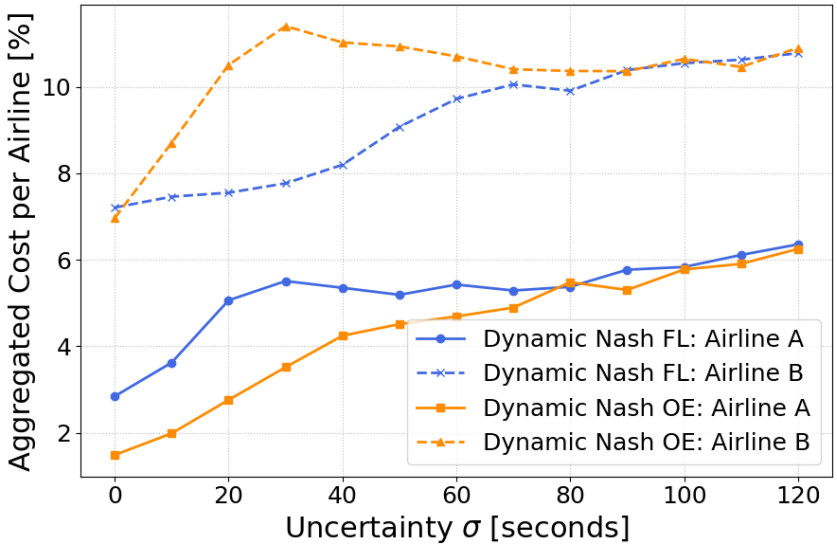


Figure 11 – TEC for each airline.

This systemic limitation is further illuminated by the individual airline cost trends in Figure 11. Regardless of whether First/Last or Odd/Even initial topology is applied, both configurations exhibit a nearly identical macroeconomic asymmetry between the two competing carriers. In both frameworks, the operating costs of Airline B (dashed lines) stayed steady at a high penalty level of 10% to 11%. Concurrently, the costs of Airline A (solid lines) remain locked to a much lower cost band between 3% and 6% across the entire uncertainty spectrum. The fact that the individual cost trajectories of both airlines under First/Last match those under Odd/Even so closely demonstrates that the initial spatial distribution of a fleet does not alter the underlying economic power balance or risk distribution within a decentralized game. Self-interested non-cooperative slot capture locks the system into a rigid, suboptimal state, with the result that neither carrier can escape the penalties imposed by uncertainty. This profound lack of divergence across both system-wide and localized metrics proves that scheduling adjustments alone are entirely insufficient to safeguard system resilience. Consequently, these findings establish compelling prerequisites for a structural paradigm shift and highlight the urgent need for a long-term, cross-carrier credit incentive framework, which will be discussed in detail in the following section.

3.2.3 Systemic Workload Trends and Structural Predictability

Beyond operating expenditures, the operational viability of sequencing frameworks depends on their predictability under uncertainty. Figure 12 quantifies this structural resilience by mapping both the cumulative slot shift magnitude (solid lines) and the unique count of disrupted aircraft (dashed lines) against the uncertainty spectrum.

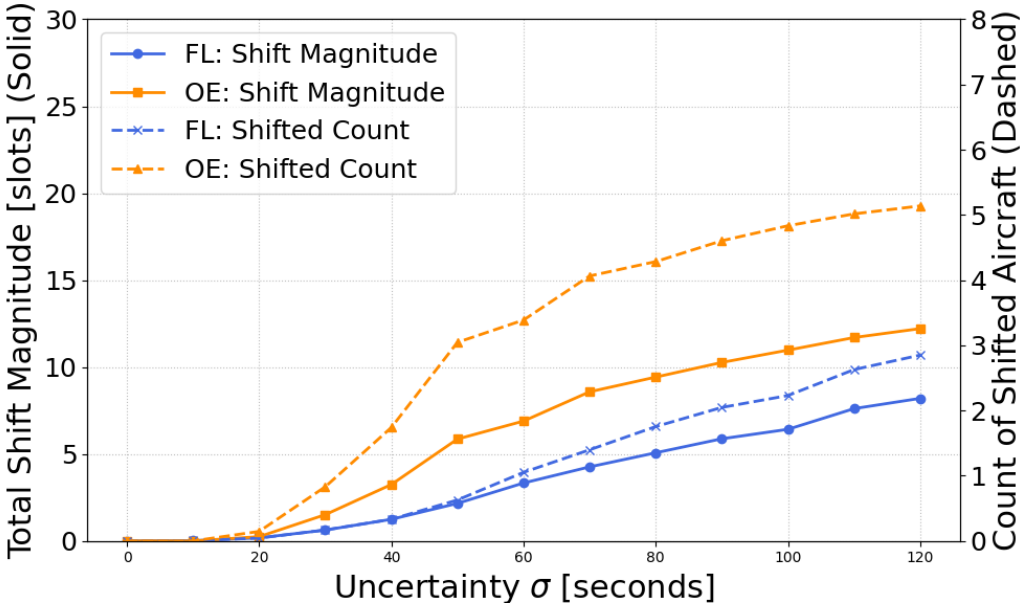


Figure 12 – Number and magnitude of slot shift.

As illustrated in Figure 12, the clustered First/Last framework consistently maintains a lower profile than the interleaved Odd/Even model for both metrics across the evaluated spectrum ($\sigma \geq 20$ seconds). This indicates that consecutive fleet bundling provides a localized geometric dampening effect, reducing slot inversions within a single carrier's block under minor perturbations. Crucially, while the First/Last rule offers a relative reduction in geometric disruption, both frameworks exhibit a rapid, monotonic escalation in total shift magnitude and disrupted aircraft count as a function of variance σ. Once cruise phase delays are introduced, the chronological arrival order at the terminal boundary becomes heavily randomized. Under tactical FCFS resequencing to preserve minimum separation, the progressive growth of these topological metrics indicates that the pre-planned scheduling grid becomes equally obsolete under both rules. While First/Last marginally insulates internal fleet interactions, it cannot flatten the upward workload trajectory induced by stochasticity. This absolute growth proves that competitive slot jockeying provides zero fundamental protection to ATC system against schedule degradation, reinforcing the urgent necessity for a unified, cooperative management paradigm.

3.3 Dynamic Framework for Long-Term Airline Cooperation

To resolve the inefficiency of non-cooperation and scheduling rigidities demonstrated in the previous sections, a long-term decentralized credit economy was evaluated. This mechanism aims to incentivize self-interested commercial rivals to voluntarily yield tactical landing priority to competitors whenever such local sacrifices minimize global operational costs. The dynamic macroeconomic and microeconomic trajectories of this mechanism over a continuous three-year simulation are illustrated in Figure 13.

Several important system-level behaviors can be deduced from the empirical trends in Figure 13. Importantly, a vital consideration of this framework is to gradually increase the total cost of entire system at the beginning of each accounting period. The simulation starts on the first day with a base total pool of 200,000 credits (100,000 credits per carrier), but at the beginning of each subsequent year, the threshold is significantly higher: about 220,000 credits and 225,000 credits. Because the carryover mechanism ($\alpha = 0.3$) compresses unbounded inflation while preserving a fixed ratio of

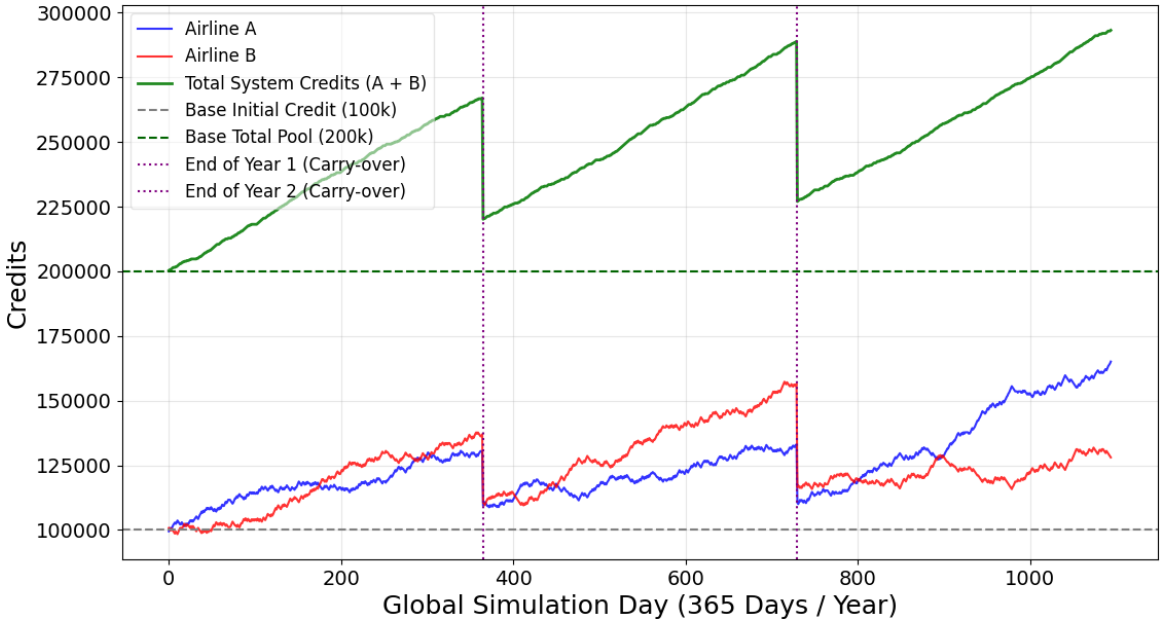


Figure 13 – A three-year simulation of airline alliances.

the accumulated wealth, this stepwise elevation of the starting capital empirically demonstrates a positive compounding effect of cooperative equity. The portion of the credit endowment carried over into the next fiscal year functions as an institutionalized reward directly proportional to each airline's cumulated contribution toward systemic delay and fuel reductions in the preceding year.

At the microeconomic level, the localized credit trajectories of Airline A (blue) and Airline B (red) expose a dynamic yet highly stable competitive equilibrium. Throughout the three-year timeline, the two carriers show a pattern of alternating dominance in a fluid way. Airline A captures a higher surplus in year 3, while Airline B achieves dominance in year 2. Remarkably, despite daily stochastic disruptions and intense competition for slots, neither airline diverges toward insolvency nor suffers unilateral exploitation. Both carriers consistently expand their individual asset reserves from the initial 100,000 credits. This cross-over behavior validates the long-term equity and reciprocity embedded in the Shapley-value bonus allocation framework, proving that carriers can confidently absorb localized delays on a given day, knowing they will be systematically compensated over time. Finally, this combined structure where individual operational sacrifices are converted into an enhanced starting capital for the following fiscal year confirms that localized tactical friction in high uncertainty terminal airspaces can be mathematically converted into a stable, sustainable cooperative economy. It offers a viable path forward for decentralized ATM without requiring the exposure of proprietary corporate cost data.

4. Conclusion and Future Work

This study proposed a comprehensive ATM framework, scaling game-theoretic aircraft sequencing to an eight-aircraft, two-airline scenarios to investigate the intersection of operational uncertainty, corporate competition, and airspace efficiency. To overcome the limitations of naive FCFS principles, a MILP framework was deployed. As a result of this analysis, three key conclusions were drawn that illustrate the need for a paradigm shift in ATM. First, it is demonstrated that uncoordinated inter-airline competition under deterministic conditions induces severe cost penalties. When airlines aggressively protect their individual flight slots, the Price of Anarchy manifests as a substantial inflation in total system operating costs. Second, probabilistic analysis reveals that these losses are independent of the initial flight configurations within a schedule. Under high uncertainty, arrival deviations inevitably necessitate tactical resequencing by ATC, triggering cost escalations and sharp increases in controller workload. These findings mathematically prove that without structured collaboration, ATM systems will remain trapped in sub-optimal stagnation. Finally, to overcome these barriers, this study introduced a privacy-preserving long-term cooperative credit economy. By utilizing a neutral central

authority, ATC, to allocate cooperative bonuses based on the Shapley value, a three-year simulation confirmed that the mechanism establishes sustained incentives for airlines to concede arrival slots to competitors when operationally beneficial. This framework successfully transforms localized tactical sacrifices into equitable, long-term credit growth rooted in actual fuel conservation and delay reductions, while an annual carryover mechanism guarantees macroeconomic stability within the system. The core significance of this research lies in demonstrating that the future of ATM cannot rely solely on superior delay predictability. Instead, incentive integration is indispensable to align individual corporate interests with global operational objectives.

Future research will focus on expanding this dynamic credit framework to account for network wide capacity constraints, moving beyond a single terminal boundary to encompass intersecting arrival routes and multi-node terminal airspaces with multi-runway hub configurations. Additionally, subsequent investigations will model advanced strategic behaviors within the credit economy using auction theory. This will include evaluating how airlines intelligently bid and invest surplus credits during seasonal peak periods to secure arrival priority, as well as designing regulatory rules for the central ATC to mitigate potential credit inflation or monopolization by dominant carriers.

5. Contact Author Email Address

mailto: sr22645l@st.omu.ac.jp

References

[1] Brooker P. *Air Traffic Control Separation Minima: Transition to a Trajectory-based System*. Journal of Navigation, 2011.

[2] *ATM Operational Concepts*. International Air Transport Association. Available: https://www.iata.org/en/programs/ops-infra/air-traffic-management/operational-concepts/

[3] Andreeva-Mori A, Suzuki S and Itoh E. *Rule derivation for arrival aircraft sequencing*. Aerospace Science and Technology, 2013.

[4] *Trajectory Based Operations (TBO) Vision*. Federal Aviation Administration. Available: https://www.faa.gov/air_traffic/technology/tbo

[5] *4D Trajectory Concept*. Skybrary. Available: https://skybrary.aero/articles/4d-trajectory-concept

[6] Ball M.O, Glover C and Lovell D.J. *Collaborative Approaches to the Application of Enroute Traffic Flow Management Optimization Models*. Ninth USA/Europe Air Traffic Management Research and Development Seminar (ATM2011), 2011.

[7] Jovanovi R, Babi O, ivanovi M and Toi V. *Efficiency vs. Flexibility in ATM: Can Pricing Help?*. SESAR Innovation Days (SIDs), 2015.

[8] Park S.G and Menon P.K. *Game-Theoretic Trajectory Negotiation Methodology for Merging Air Traffic Management*. Aerospace Research Central, 2017.

[9] Tsuru S and Andreeva-Mori A. *A Game-Theoretic Approach to Trajectory Negotiation in Merging Air Traffic: Adaptive Optimization Based on Dynamic Flight Conditions*. in proceedings of the 63rd Aircraft Symposium, Japan, 2025.

[10] Tsuru S and Andreeva-Mori A. *Aircraft Sequencing under Uncertainty: Game-Theoretic Optimization and a Comparative Assessment of Global and Intra-Airline Cooperative Decision Frameworks*. Bachelor's thesis, Osaka Metropolitan University, Osaka, Japan, 2026.

[11] Johari R. *The Price of Anarchy and the Design of Scalable Resource Allocation Mechanisms*. Cambridge University Press, 2011.

[12] Wang C, Doan X.V and Chen B. *Atomic congestion games with random players: network equilibrium and the price of anarchy*. Jornal of Combinatorial Optimization, 2020.

[13] Xu Y, Dalmau R and Prats X.*Maximizing airborne delay at no extra fuel cost by means of linear holding*. Transportation Research Part C, 2017.

[14] Taha W.M, Taha A.M and Thunberg J. *Game Theory. In: Cyber-Physical Systems: A Model-Based Approach*. Springer, 2021.

[15] Tripathy M. *MULTI-STAKEHOLDER AIRCRAFT SCHEDULING PROBLEM PERFORMANCE EVALUATION AND FAIRNESS ANALYSIS AT SCHIPHOL AIRPORT*. Delft University of Technology, 2015.

Acknowledgments

This research was supported by a Grant-in-Aid for Scientific Research (KAKENHI) from the Japan Society for the Promotion of Science (JSPS) (Grant Number: 24K07723).

6. Copyright Statement

The authors confirm that they, and/or their company or organization, hold copyright on all of the original material included in this paper. The authors also confirm that they have obtained permission, from the copyright holder of any third party material included in this paper, to publish it as part of their paper. The authors confirm that they give permission, or have obtained permission from the copyright holder of this paper, for the publication and distribution of this paper as part of the ICAS proceedings or as individual off-prints from the proceedings.