Disruption Management in Airline Operations: A Solver-based Approach using Time-Space Network Optimization

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Abstract

This paper presents AIRS, a day-of-operations disruption-recovery system. AIRS.ACR models integrated aircraft–crew recovery on a Time–Space Network (TSN) and solves a mixed-integer linear program (MILP) that enforces rotation continuity, crew legality, maintenance windows, slot capacities, and multi-leg integrity via flow-balance constraints; disruption-aware search-space construction and warm starts control combinatorial growth. A companion module, AIRS.PaxR, performs rapid passenger re-accommodation using greedy assignment and lightweight evolutionary search while preserving aircraft–crew feasibility. Across realistic evaluations, AIRS meets operational decision windows and reduces recovery costs relative to manual or sequential methods, providing a scalable, extensible decision-support capability for operations control centers.

1. Introduction

The global airline industry, a cornerstone of modern economic activity and global connectivity, has demonstrated considerable resilience, with recovery and projected growth post-pandemic. As passenger demand rebounds and the industry resumes a trajectory toward long-term expansion, the operational complexities inherent in managing this large-scale system intensify. Operationally, day-to-day management requires coordinated control of schedules, resources, and external factors. Despite airline schedules planned months in advance, they are still highly vulnerable to "day-of" disruptions — adverse weather, unplanned aircraft maintenance, air traffic control (ATC) restrictions, and crew unavailability. Such events propagate cascading delays and cancellations, with ripple effects across the tightly interconnected network.

The economic impacts of such disruptions are substantial, costing the industry billions of dollars annually and eroding passenger satisfaction and trust [Ball et al., 2007, Hassan et al.,

2021, Lee et al., 2022]. Today, the task of managing these irregular operations (IROPs) falls to Airline Operations Control Centers (AOCCs). AOOC teams, often rely on manual adjustments, sequential decision-making, and institutional experience, work under intense time pressure to mitigate disruption impacts. As operations scale and disruptions become larger (and thus inherently more complex), traditional methods exhibit inherent limitations: a propensity for suboptimal, siloed recovery; inability to explore the combinatorial solution space within operational time limits; and lack of integrated decision-making across critical resources such as aircraft, crew, maintenance, and airport slots.

This paper addresses the imperative for robust, integrated, and mathematically rigorous approaches to airline disruption management. We argue that the combinatorial complexity of modern airline operations, particularly under disruption, necessitates optimization-based tools that systematically evaluate trade-offs and compute globally (or provably near-) optimal recovery solutions within operational time limits. To this end, we introduce AIRS.ACR (Airline Itinerary Recovery System – Aircraft & Crew Recovery), an integrated solver-based architecture for Airline Operations Control Centers (AOCCs). AIRS.ACR employs a Time-Space Network (TSN) formulation and mixed-integer linear programming (MILP) to jointly model aircraft rotations, flights, maintenance windows, crew pairings, and airport slot capacities with multi-leg integrity and flow-balance constraints. Our primary contribution is a system that supersedes reactive, heuristic-based decision-making to provide automated, feasible, and cost-efficient recovery schedules, enabling airlines to enhance operational resilience and precision — particularly in scenarios where manual recovery is infeasible during irregular operations (IROPs). We detail the AIRS.ACR methodology and present empirical evidence on real-world–sized instances indicating substantial improvements in solution quality and computational efficiency, with implications for transforming disruption management in the dynamic airline industry.

2. Executive Summary

Airline disruptions impose substantial and recurring costs. Fragmented, step-by-step decision making exacerbates these losses by overlooking interdependencies among aircraft, crews, maintenance, and airport capacity. This study introduces an end-to-end recovery planning system that optimizes these elements jointly and, when disruptions occur, rapidly produces a concise set of executable options with the trade-offs made explicit. The approach improves decision speed and quality, reducing secondary delays and cancellations, lowering overtime and compensation outlays, and enhancing the customer experience. It enables automation and operational precision in scenarios where manual recovery becomes ineffective or simply infeasible.

3. Background and Motivation

3.1. The Resilient Yet Fragile Airline Industry

The global airline industry, a critical engine for economic activity and connectivity, has demonstrated remarkable resilience. Following the unprecedented shock of the pandemic, domestic markets had fully recovered by early 2023, with long-haul travel largely restored by year-end. According to the latest IATA Annual Review (June 2024), passenger traffic in 2024 is expected to surpass 2019 levels, resuming a trajectory of sustained long-term growth projected at nearly 4% annually through 2043. This resurgence underscores the vital role of air transport but also amplifies the challenges inherent in managing the industry's complex operations.

Airline scheduling is the cornerstone of the industry, underpinning profitability, resource utilization, and customer service [Zhang et al., 2015]. Airlines invest heavily in developing sophisticated schedules months in advance [Clausen et al., 2010, Kohl et al., 2007]. However, the operational reality on the day of departure often diverges from these plans. The tightly interconnected nature of airline networks – a reality experienced daily by flight crews, ground

staff, and operations controllers – makes them inherently vulnerable to disruptions [Hassan et al., 2021, Su et al., 2021b]. Events such as adverse weather, unexpected aircraft maintenance, ATC restrictions, or crew unavailability can rapidly cascade through the system, causing delays, cancellations, and significant downstream impacts [Bratu and Barnhart, 2006, Kohl et al., 2007].

The economic consequences are substantial, costing the industry billions annually [Ball et al., 2007, Lee et al., 2022], while disruptions also erode passenger satisfaction and airline reputation [Hassan et al., 2021].

3.2. Current Disruption Management Practices and Limitations

The responsibility for managing operational irregularities falls primarily on the Airline Operations Control Center (AOCC) [Clarke, 1998, Fogaça et al., 2022, Kohl et al., 2007]. AOCC teams monitor operations in real-time and implement recovery actions such as delays, cancellations, resource swaps, and passenger reaccommodation [Clausen et al., 2010, Zhang et al., 2015].

Despite the critical role of the AOCC, current disruption management often relies heavily on manual adjustments, sequential decision-making, and the hard-earned experience of controllers and pilots navigating dynamic situations – sometimes aided by basic heuristics or limited decision support tools [Clausen et al., 2010, Kohl et al., 2007, Hassan et al., 2021]. This traditional approach faces several significant limitations:

- **Suboptimality:** Recovery decisions are typically made sequentially – often addressing aircraft first, then crew, and finally passengers [Su et al., 2021b, Zhang et al., 2015]. This siloed approach fails to capture the complex interdependencies between resources, potentially leading to solutions that are feasible but far from optimal [Lettovsky, 1997, Petersen, 2012].

- **Complexity and Scale:** The scale of modern airline operations makes it virtually impossible for human controllers to manually assess the full impact of a disruption and evaluate a wide range of recovery options comprehensively [Clausen et al., 2010, Zhang et al., 2016].

- **Time Pressure:** Recovery decisions must often be made under extreme time constraints, limiting the ability to explore multiple alternatives and favoring the first identified feasible solution [Hassan et al., 2021, Kohl et al., 2007].

- **Lack of Integration:** Existing decision-support tools often focus on specific aspects of the recovery problem and lack seamless integration across all affected resources [Clausen et al., 2010, Su et al., 2021b].

3.3. Literature review

Airline operations are prone to various forms of disruption that differ in scope, duration, and impact [Hu et al., 2024, Hassan et al., 2021]. These are broadly classified into:

- **Aircraft-related:** Mechanical failures and unexpected maintenance.

- **Crew-related:** Unavailability, misconnections, labor actions, and fatigue regulations.

- **Passenger-related:** No-shows, overbooking, and missed connections.

- **Airport and airspace:** Slot shortages, weather closures, and ATC capacity restrictions.

- **Systemic disruptions:** Epidemics (e.g., COVID-19), large-scale IT outages, and geopolitical crises.

Disruptions are further categorized as tactical (short-term, e.g., weather) or strategic (long-term, e.g., strikes). Models such as delay propagation networks [Wu and Law, 2019] and flight phase resilience frameworks [Zhang et al., 2023] are used to analyze their system-level effects.

Several recovery strategies have been identified in the literature [Su et al., 2021a, Clausen et al., 2010]:

- **Operational:** Flight delays, cancellations, swaps, and rerouting.

- **Resource-based:** Crew deadheading, reserve aircraft or crew, and cruise speed adjustments.

- **Passenger-centric:** Rerouting via interline or multimodal transport, flexible ticketing, and compensation policies.

- **Innovative:** Dynamic fare classes [Long and Belobaba, 2024] and proactive recovery using AI.

Strategic combinations of these actions are selected based on feasibility, cost, and regulatory constraints.

Objective functions capture the performance criteria of disruption recovery models. Common formulations include:

- **Cost minimization:** Operating costs and passenger compensation [Arıkan et al., 2017, Su et al., 2021a].

- **Delay minimization:** Total propagated or passenger-weighted delays [AhmadBeygi et al., 2008].

- **Satisfaction/utility:** Passenger dissatisfaction penalties [Khiabani et al., 2023a].

- **Environmental objectives:** Emission trade-offs under speed control [Aktürk et al., 2014, Arıkan et al., 2017, Zhang et al., 2023, Marla et al., 2012].

- **Robustness:** Minimizing infeasibility risks under uncertainty [Eikelenboom and Santos, 2023].

The disruption management problem has been modelled using a wide range of techniques:

- **Exact Optimization:** MIP [Hassan et al., 2021], set partitioning [Stojković et al., 1998], and Benders decomposition [McCarty and Cohn, 2018, Khiabani et al., 2023b].

- **Heuristics and Metaheuristics:** Genetic algorithms [Liu et al., 2010], ant colony optimization [Sousa et al., 2015, Zhang et al., 2023], tabu search [Yang, 2007], NSGA-II [Chen and Wu, 2024], and hybrid GRASP [Hu et al., 2016].

- **Simulation and Stochastic Models:** Stochastic programming [Petersen, 2012], delay simulations [Guimarans et al., 2017], hybrid reinforcement learning [Ding et al., 2023], and scenario sampling [Zhu et al., 2016].

- **Machine Learning and AI:** RL-PPO [Ding et al., 2023], ranker-based crew recovery [Eikelenboom and Santos, 2023], and supervised models for delay forecasting [Lee and Jacquillat, 2020].

Despite the richness of the modeling literature, adoption in AOCCs remains limited. Key implementation barriers include:

- **Data integration:** Incompatibilities in IT systems and the need for manual overrides [Castro and Oliveira, 2009].

- **Scalability:** The real-time demands and complexity of integrated recovery [Maher, 2015].

- **Explainability:** The need to maintain human-in-the-loop decision making [Eikelenboom and Santos, 2023].

- **Adaptability:** Limited availability of dynamic, scenario-driven planning tools.

Disruption management in airline operations constitutes a time-critical optimization problem characterized by network coupling, capacity and legality constraints, and uncertainty, requiring coordinated rerouting and reallocation of aircraft, crew, and passengers. Recent surveys [Hassan et al., 2021, Su et al., 2021a, Clausen et al., 2010, Hu et al., 2024] synthesize advances in algorithms and deployment. The literature coalesces around four domains: aircraft recovery, crew recovery, passenger reaccommodation, and integrated recovery systems. Across these domains, methods include time-space network formulations, mixed-integer models, decomposition, metaheuristics, stochastic/simulation planning, and data-driven approaches. We review representative models and strategies in the sections that follow.

3.3.1 Aircraft Recovery

The aircraft recovery problem (ARP) is a combinatorial optimization problem concerned with adjusting aircraft rotations in response to disruptions such as departure/arrival delays, cancellations, and aircraft unavailability, subject to routing continuity, fleet compatibility, turnaround, maintenance, and airport capacity constraints. Given a disrupted schedule and associated operational constraints, the goal is to select delay, cancellation, resequencing, swap, ferrying, and (where modeled) speed-control actions, and reassign aircraft across the network in a way that minimizes the total disruption cost.

These costs typically include operational expenses within the airline's control at the time of disruption – such as additional fuel use, aircraft repositioning, and passenger compensation. The ARP is commonly modeled as a cost-minimization problem, employing optimization techniques to balance feasibility and efficiency.

Aircraft recovery is typically the first step in disruption management. Key disruption types include aircraft unavailability and airport capacity constraints. The ARP focuses on restoring disrupted aircraft rotations by adjusting flight schedules and aircraft assignments. It has been widely studied because aircraft are among the most critical and costly resources to reposition.

The literature on ARP considers a variety of disruption types:

- **Flight delays**, the most common disruption type [Guardo-Martinez et al., 2026, Aktürk et al., 2014].

- **Flight cancellations**, addressed in most models [Liu et al., 2010].

- **Aircraft unavailability**, due to mechanical issues or grounding [Guardo-Martinez et al., 2026, Sousa et al., 2015] .

- **Airport disruptions**, modeled as binary constraints or degraded capacity [Liang et al., 2018].

ARP is modeled using several network representations:

- **Flight string networks**, often used in heuristic models [Barnhart et al., 1998].

- **Time-space networks**, capturing temporal and spatial dynamics [Guardo-Martinez et al., 2026, Aktürk et al., 2014, Vos et al., 2015].

- **Connection-based networks**, allowing flexible aircraft assignment [Sousa et al., 2015, Liu et al., 2010].

- **Time-band networks**, providing computational efficiency [He, 2024].

Typical recovery actions in ARP include:

- **Flight delays** [Sousa et al., 2015].

- **Flight cancellations** [Vos et al., 2015].

- **Aircraft swaps**, often combined with delay decisions [Liu et al., 2010, Aktürk et al., 2014].

- **Cruise speed control**, proposed for delay absorption [Aktürk et al., 2014].

- **Aircraft ferrying** and use of **reserve aircraft** [Guardo-Martinez et al., 2026, Gao et al., 2010].

- **New flight creation** and **multi-fleet management**, though rarely modeled [Xiuli and Yanchi, 2012].

Solution methods for ARP include:

- **Exact Approaches:** MIP and conic optimization to assign aircraft under time-space constraints [Arıkan et al., 2017]; column generation for capacity-constrained routing [Liang et al., 2018].

- **Metaheuristics:** Multi-objective genetic algorithms [Liu et al., 2010], ACO-based scheduling [Sousa et al., 2015, Zhang et al., 2023], and GRASP [Hu et al., 2016].

- **Hybrid and Stochastic Models:** Constraint programming combined with simulation [Guimarans et al., 2017]; robustness modeling via delay propagation; speed control optimization integrating fuel and delay trade-offs [Marla et al., 2012].

While exact methods like conic MILP offer optimality [Aktürk et al., 2014], they often suffer from scalability issues. Most models also overlook multiple fleet types and maintenance integration, which limit their practical applicability.

Recent hybrid approaches aim to address these gaps:

- [Eggenberg et al., 2007] use dynamic programming with column generation, achieving promising CPU times on real-world datasets.

- [Hu et al., 2016] apply GRASP for efficient yet realistic recovery.

- [Vos et al., 2015] propose MILP-based heuristics that incorporate maintenance considerations.

3.3.2   Crew Recovery

The crew recovery problem (CRP) focuses on restoring disrupted crew assignments by reallocating available pilots and cabin crew within a recovered flight schedule. Given a set of flight disruptions and operational constraints, the objective is to ensure that every flight has the required crew while minimizing overall disruption costs.

These costs may include direct expenditures, such as crew wages, overtime pay, and allowances, as well as indirect costs, such as crew positioning via deadheading – transporting crew as passengers to another airport to operate a scheduled flight.

Crew recovery involves rescheduling crews while adhering to regulatory, contractual, and operational constraints. The problem is combinatorially complex due to legality rules, pairing feasibility, and multi-crew coordination requirements.

Studies address a variety of disruption types:

- **Flight delays**, e.g., [Novianingsih et al., 2015, Chang, 2012].

- **Crew unavailability**, explicitly modeled in [Castro and Oliveira, 2009].

- **Combined disruptions** (delay + unavailability), addressed in [Liu et al., 2013, Zhu et al., 2014].

Network representations used for modeling include:

- **Connection networks**, commonly used with set-covering models [Liu et al., 2013].

- **Graph-based crew pairing networks**, suitable for constraint programming [Zhu et al., 2014].

Common recovery actions include:

- **Crew deadheading** [Novianingsih et al., 2015, Chang, 2012].

- **Crew swaps** [Zhu et al., 2014, Lettovský et al., 2000].

- **Flight cancellations**, when no legal crew is available.

- **New duty generation or partial re-planning**, though rarely considered [Lettovský et al., 2000].

Legal, regulatory, and fatigue-related constraints are central to CRP formulation. Various solution approaches have been proposed:

- **Exact and Decomposition Methods:** Set partitioning formulations have been applied in [Gamache et al., 1999, Stojković et al., 1998, Hu et al., 2024].

- **Metaheuristics:** [Chang, 2012] applied a genetic algorithm with constraint-aware mutation. [Liu et al., 2013] used interfleet and intrafleet set covering models. [Novianingsih et al., 2015] proposed a three-stage heuristic based on legal pairing rules.

- **Multi-agent Systems:** [Castro and Oliveira, 2009] modeled AOCC operations using agent-based simulation, where agents represent aircraft and crew managers negotiating recovery solutions.

Some selected contributions further illustrate the diversity of methods:

- [Chang, 2012] used a genetic algorithm that explicitly enforces legality rules.

- [Novianingsih et al., 2015] introduced a three-stage heuristic that simulates real AOCC crew planning.

- [Zhu et al., 2014] employed constraint programming to manage multi-crew assignments within recovery time windows.

3.3.3 Passenger Recovery

The Passenger Recovery Problem (PRP) is among the most critical challenges in airline disruption management. Prolonged delays and repeated disruptions significantly increase recovery costs and severely undermine passenger satisfaction, potentially leading to a loss of customer trust and long-term damage to brand reputation.

The core task of passenger recovery involves re-optimizing disrupted passenger itineraries on a recovered flight schedule, previously stabilized for aircraft and crew feasibility. Given a set of disrupted passenger itineraries and available seat-capacity vectors, the objective is to

assign passengers to feasible paths from their current locations to their intended destinations within the planning horizon while minimizing a total disruption-cost function (e.g., arrival delay, cancellations, downgrades, misconnections, and compensation) subject to capacity, minimum-connection-time, and product/fare-class constraints. Recent work emphasizes time-critical, cost-aware reaccommodation via network-based assignment models and preference-aware objectives.

Selected approaches for PRP include:

- **Stochastic Optimization:** [McCarty and Cohn, 2018] propose a two-stage stochastic model with Benders decomposition for proactive rerouting. [Cadarso and Vaze, 2023] incorporate passenger preferences and class-based delay penalties.

- **Cost Modeling:** [Cook et al., 2012] propose nonlinear delay cost functions. Other studies use linear or piecewise-linear approximations to ensure computational tractability.

Passenger recovery focuses on reaccommodating disrupted passengers by modifying itineraries, rerouting, or upgrading service. The following types of disruptions are commonly addressed:

- **Flight delays**, modeled in many works [Bratu and Barnhart, 2006].

- **Flight cancellations**, also widely considered [Sinclair et al., 2016, Lu et al., 2025].

- **Airport and aircraft disruptions**, less commonly incorporated in passenger-only models [Hu et al., 2016].

Network representations used in PRP include:

- **Time-space networks**, which dominate the literature due to their ability to capture rerouting options [Arıkan et al., 2017, Marla et al., 2012].

- **Connection graphs**, used for routing-based optimization [Niu et al., 2021].

Recovery actions implemented in PRP include:

- **Passenger itinerary changes**, the most common form of reaccommodation [Marla et al., 2012].

- **Delays and cancellations**, typically modeled as secondary effects [Sinclair et al., 2016].

- **Seat upgrades or overbooking adjustments**, rarely addressed explicitly [Nazifi et al., 2021].

3.3.4 Integrated Recovery Approaches

Integrated models better reflect real-world AOCC operations by capturing interdependencies among resources. Integrated Recovery simultaneously optimizes aircraft, crew, and passenger schedules to minimize total disruption costs. While offering the most realistic modeling approach, integrated recovery is also computationally demanding.

Different types of disruptions are considered in the literature:

- **Flight delays** [Arıkan et al., 2017, Zhu et al., 2016, Petersen, 2012].

- **Flight cancellations** and **airport disruptions**, often modeled using flow-based representations [Lettovsky, 1997, Castro et al., 2014].

- **Aircraft unavailability** [Arıkan et al., 2017].

- **Crew unavailability** [Castro et al., 2014].

Various network representations have been used:

- **Entity-flow networks**, introduced by [Arıkan et al., 2017], to represent all resource types.

- **Time-space networks**, commonly used in IRP models [Zhu et al., 2016, Marla et al., 2012].

- **Decomposed hierarchical models** [Lettovsky, 1997, Petersen, 2012].

A range of recovery actions are modeled:

- **Flight delays, cancellations, aircraft swaps, crew swaps**, and **crew deadheading** [Zhu et al., 2016, Petersen, 2012].

- **Passenger itinerary changes**, sometimes with service quality cost estimation [Castro et al., 2014].

- **Cruise speed control**, introduced to IRP in [Arıkan et al., 2017].

Selected integrated approaches include:

- **Exact and Network-based Models:** [Petersen, 2012, Arıkan et al., 2017, Maher, 2015] develop formulations that jointly optimize aircraft, crew, and passenger flows.

- **Hybrid Approaches:** [Zhu et al., 2016] propose a sampling-based strategy combining MIP with metaheuristics. [Sinclair et al., 2016] apply column generation with post-optimization heuristics.

- **Multi-Agent Systems:** [Castro and Oliveira, 2009] create decentralized systems with autonomous agents for each recovery stage, simulating AOCC decision-making.

Few studies address the interdependence between aircraft and crew recovery specifically:

- [Zhang et al., 2015] propose a two-stage heuristic with mutual feedback between aircraft and crew schedules.

- [Wang et al., 2024] apply coordinated rescheduling of flights, aircraft, and crew for robust disruption management.

- [de Bruin et al., 2025] present simulated annealing approach for integrated recovery using real airline data.

3.3.5 Research gap

Disruptions in airline operations cause significant economic and reputational damage. While the literature offers a range of recovery models, most studies adopt segmented approaches, focusing separately on aircraft, crew, or passengers. Although recent research increasingly favors integrated recovery frameworks, challenges remain regarding scalability, interpretability, and operational deployment.

Key directions for future research include:

- Development of scalable and interpretable real-time algorithms.

- Adaptive hybrid systems with human-in-the-loop decision making.

- Incorporation of behavioral modeling of passengers in recovery algorithms.

- Real-time disruption forecasting using deep learning.

- Interoperability between airline and airport decision-support systems.

This work contributes to these research directions by introducing AIRS, a solver-based system that integrates aircraft and crew recovery using a time-space network formulation. Unlike segmented or sequential approaches, AIRS addresses interdependencies directly while remaining computationally efficient and interpretable. By incorporating practical constraints – such as fixed decision time windows, flexible maintenance, and slot preservation incentives – AIRS bridges the gap between theoretical models and operational deployment in real-world AOCC settings.

3.4. Motivation for a Solver-Based Optimization Approach

The inherent limitations of current practices underscore the need for robust, integrated, and mathematically rigorous approaches to airline disruption management. The complexity and interconnectedness of the problem demand solutions that systematically assess trade-offs and identify globally or near-globally optimal recovery plans within operational time limits. Mathematical optimization, particularly via computational solvers, offers a powerful paradigm to address this challenge [Hassan et al., 2021, Su et al., 2021b].

This study is motivated by the significant potential of optimization-based solvers to transform airline disruption management. We specifically focus on the use of Time-Space Network (TSN) models, which offer a natural and effective framework for representing the movement and interaction of airline resources – aircraft, and potentially crew and passengers – across space and time [Thengvall et al., 2000, Yan and Young, 1996, Yan and Yang, 1996, Zhang et al., 2015, Rhodes-Leader et al., 2022]. TSNs enable the explicit modeling of flight activities, delays, ground operations, resource flows, capacity constraints, and a range of recovery actions.

By formulating the disruption recovery problem as a TSN-based optimization model and leveraging the capabilities of modern mathematical programming solvers (e.g., CPLEX, Gurobi), airlines can move beyond reactive, heuristic-based decision-making. This solver-based approach enables the rapid generation and evaluation of integrated recovery plans that explicitly minimize operational costs while adhering to complex regulatory and logistical constraints. It provides a systematic method to automate high-stakes decisions, support AOCC teams and flight crews, and ultimately enhance the efficiency and resilience of airline operations in the face of inevitable disruptions.

This paper presents solver-based approach and demonstrates its feasibility and potential benefits for a recovering, rapidly evolving airline industry. A key innovation of the proposed approach lies in its integrated solver architecture, which departs from the traditional sequential recovery paradigm. By jointly optimizing aircraft and crew assignments within a unified Time-Space Network framework, the system captures critical interdependencies that are often overlooked in decoupled models. This simultaneous treatment not only improves solution feasibility – especially in large-scale, disruption-heavy scenarios – but also enhances the realism and operational applicability of the recovery plans. The integrated MILP formulation ensures that aircraft and crew availability are synchronized, reducing infeasibility risks and enabling more robust and cost-effective recovery strategies.

4. System Overview: AIRS

AIRS (Airline Itinerary Recovery System) is an optimization-based algorithm designed to support airline decision-making in the event of disruptions to scheduled itineraries. The problem AIRS addresses is commonly referred to as the "Integrated Aircraft Recovery Problem" (Integrated ARP), which involves determining the adjustments necessary to restore operations following a disruption. This problem typically includes aircraft reassignment and may also extend to crew and passenger recovery.

Many existing approaches adopt a sequential recovery structure – aircraft are rescheduled first, followed by crew and then passengers. While simpler to implement, this strategy often overlooks the strong interdependencies between resources. Simultaneous recovery approaches tend to produce better solutions but face scalability challenges, especially on large, real-world instances, due to high computational and memory demands.

To address these limitations, AIRS introduces a scalable strategy that mitigates the complexity of solving large, integrated recovery problems. It employs a classical MILP formulation augmented with physics-inspired algorithms, probabilistic methods, and dynamic programming techniques. The highly interdependent problems of aircraft and crew reassignment are solved jointly, yielding a feasible schedule that remains as close as possible to the original while minimizing additional disruptions. In a subsequent phase, passengers are reallocated to the recovered schedule, with the aim of preserving original itineraries wherever possible.

Details of the AIRS methodology, including its optimization models and algorithmic workflow, are presented in the subsequent sections.

4.1. Problem Scenario

During a given airline's service day, one or more disruptions may occur. Such disruptions may include:

- delays in flights;
- flight cancellations;
- unforeseen maintenance required for an aircraft;
- changes in airport slots;
- airport closures;
- any sudden change in schedule necessary.

The AOCC (Airline Operations Control Centre) needs to decide, in response to disruptions, which flights to delay or cancel, whether to execute aircraft swaps, and how to reassign crews and other operational resources. Let us define **Current Time** as the decision epoch at which the AOCC issues recovery instructions. Events strictly prior to **Current Time** are treated as fixed (non-modifiable), and implementation may require a short operational lead time; accordingly, AIRS constrains changes to take effect at or after this decision epoch.

The following assumptions are important for the current version of AIRS:

1. There is a known time when the AOCC must send instructions to the rest of the airline in order to apply the necessary changes. This time we call **Current Time**, because the model considers this time to be the present, and everything before that point to be past – thus fixed and unchangeable.

2. The AOCC is able to send data to an instance of AIRS detailing the current itinerary and the reported disruptions.

3. There is a globally defined maximum amount of acceptable delay on takeoff for the flights.

4. Delaying flights shouldn't change their duration (time from takeoff to landing) in a provided solution.

5. **Recovery Start** means the earliest time after Current Time when schedule changes may take effect. Between Current Time and Recovery Start, flights either remain as planned, are canceled, or are moved to Recovery Start or later. Flights originally scheduled at or after Recovery Start may be delayed, but not advanced.

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6. Aircraft Maintenance may or may not be flexible in terms of where and when they can occur. Their duration, however, is relatively predictable and therefore can be perceived as fixed.

7. Some airport slots, if left non-utilized too many times, might be lost by the airline. It is important for the AOCC to add an artificial cost value to influence AIRS to assign some flight to the critical slot.

8. **Recovery Finish** means the latest time after Current Time to which any flight may be rescheduled. AIRS treats all flights departing after Recovery Finish as fixed and leaves subsequent itinerary segments unchanged.

Figure 1: Approximate problem timeline, such that "C.T." is Current Time, "R.S." is Recovery Start, and "R.F." is Recovery Finish. Not in scale.

4.2. The AIRS method

The AIRS method is composed of 2 main stages:

1. The **AIRS.ACR** module finds a feasible schedule considering mainly Aircraft and Crew, but not considering Passenger Itineraries directly.

2. The **AIRS.PaxR** module adjust the schedule generated by the previous module, keeping feasible the assignment of Aircraft & Crew, and re-assigning passengers to the flights in the new itinerary.
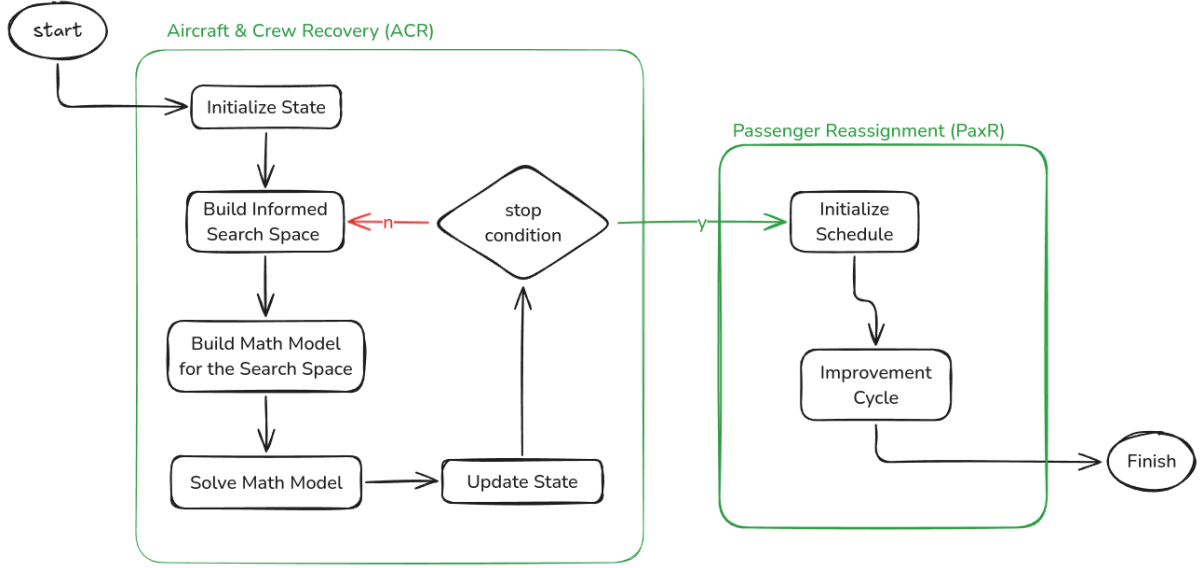
Figure 2: Flow diagram: top level view of solution steps in the AIRS solver.

Splitting the solution into a sequential two-part method reduces the time-to-solution and the required computational resources significantly (by reducing the combinatorial scaling in the number of variables and constraints). However, there are trade-offs involved. In particular, the division of Aircraft and Crew scheduling is usually the most critical.

Previous experiments showed that it is often very hard to reach feasible solutions in larger problem instances when the stages of aircraft rescheduling and crew rescheduling are split apart. This is not a cost issue, but rather a feasibility issue. A flight requires crew and aircraft to be available simultaneously and in accordance with many business rules. Computing both in the same mathematical model, in turn, tends to cause explosive growth in the constraint and variable counts, which means the model runs for much longer and uses much more memory. There is a trade-off between feasibility at larger problem sizes and computational complexity.

The approach adopted in **AIRS.ACR** focuses on containing the combinatorial growth of model size while still building an integrated model for aircraft and crew. The method can consider both resources at once, yielding a feasible schedule right in the first iteration, reducing cost over time. It has been shown to find feasible solutions within practical time limits even at larger problem sizes, and there remains scope for performance improvements. Empirically, this design achieves first-iteration feasibility with progressive cost reduction while maintaining tractable runtimes on large instances. The size of some tested problems is presented in Table 2.

On the other hand, splitting these critical resources from the passenger reassignment may yield solutions that disrupt passenger itineraries more than necessary. To handle this issue, the **AIRS.PaxR** module was designed to assign itineraries to flights while adjusting the results from **AIRS.ACR** to route more itineraries to their destinations, while maintaining schedule feasibility with respect to all constraints. Additional cost components are also considered at this stage.

4.3. ACR: Aircraft & Crew Recovery

AIRS.ACR is composed of the following high-level modules:

- Data Preprocessing (Flights, Maintenance, Crews, Slots)
- Search Space Construction
- MILP Model Generation

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- Solver Execution
- Output Interpretation and Visualization

4.3.1 Mathematical Model Overview

The core model is a MILP, in which each operational decision is represented by one or more binary variables. Higher-level structures are used to control the creation and retrieval of such variables. The main abstraction used for this representation is the **Choice**, of which there are two types:

- **OptionChoice**: represents state for flight or maintenance, such as Scheduled, Canceled, Succeeding Maintenance, Failing Maintenance;
- **SlotChoice**: represents airport slot usage with associated penalties for underutilization.

Each Choice is associated with a linear "cost expression", calculated based on specific rules for each type of Choice. Using this abstraction, the optimization objective is defined as follows:

$$\min \sum_{\text{choice}} \text{cost\_expr(choice)}$$

Costs in this objective will reflect:

- Delay minutes
- Cancelations
- Infeasible maintenances
- Slot underutilization when a penalty is specified

And the optimization will be subject to the following constraints:

- Flow balance across the Time Space Network:

$$\forall\ node \in \textbf{each\_node}(tsn), \text{ where "}tsn\text{" is the Time Space Network:}$$

$$
\begin{cases}
\displaystyle\sum_{\substack{arc\ \in \\ \textbf{outputs}(node)}} \textbf{decision}(arc) = \sum_{\substack{arc\ \in \\ \textbf{inputs}(node)}} \textbf{decision}(arc) & \text{if multileg node} \\[2em]
\displaystyle\sum_{\substack{arc\ \in \\ \textbf{outputs}(node)}} \textbf{decision}(arc) \leq \sum_{\substack{arc\ \in \\ \textbf{inputs}(node)}} \textbf{decision}(arc) & \text{otherwise}
\end{cases}
\tag{1}
$$

Multi-leg connections are handled in a different virtual position than usual connections, and the strict flow constraint guarantees that either all legs or none are performed.

- Unique decision per flight/maintenance group (ensures that no flight is assigned to more than one combination of aircraft, crew, and time, or is cancelled):

$$\forall\ choice\_group \in tsn.option\_choices\_by\_entity \atop \text{(grouped by maint or flight)} \quad \sum_{\substack{choice\ \in \\ choice\_group}} \textbf{decision\_expr}(choice) = 1 \tag{2}$$

- Slot capacity preservation (ensures that each slot is not used more than its capacity and makes sure the nonuse_var of the **Slot Choice** has the correct value):

$$\forall\ choice \in tsn.slot\_choices \text{ and associated } slot: \tag{3}$$

$$\textbf{decision\_expr}(choice) + \textbf{nonuse\_var}(choice) = \textbf{capacity}(slot)$$

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- Crew flight time limits (ensures that each crew group isn't assigned to fly more than its set limit):

$$\forall \; crew \in \textbf{crew\_groups}(tsn):$$

$$\sum_{\substack{choice \; \in \\ \textbf{flight\_choices}(crew)}} \textbf{decision}(choice)\textbf{duration}(choice) \; \leq \; \textbf{flight\_time\_limit}(crew) \qquad (4)$$

To take advantage of the constraints and costs presented above, the Time-Space Network **Nodes** and **Arcs** must be built following the rules detailed further.

4.3.2 Time-Space Network Construction

The **TSN** models resources (aircraft, crew) over time and space. **Nodes** represent possible states of a resource; **Arcs** represent state transitions, usually associated with actions over time such as flight legs or boarding a plane. There are several different rules on how to add **Arcs** to the networks, depending on the available **Choices**, as detailed in this section.

Option Choices: Depending on the kind of **Option** being considered in the **Choice**, a different algorithm is needed for choosing **Arcs**:

Scheduled Flight Option: When the **Option** being considered is to **Schedule** the flight, it's necessary to add **Arcs** that represent the flow between the airports for the aircraft and for the crew, as well as special **Arcs** to allow embarking the crew onto the aircraft in case they are not already embarked, and disembarking **Arcs** at the destination so that the crew has the chance to leave the flight. The embarking/disembarking **Arc** is not added in case the corresponding connection is a multi-leg transit. The minimum turnaround or transit is enforced by an extension on the tail of the aircraft's **Arc**, while the connection time for the crew is handled by the embarking **Arc** in case the crew needs to change aircraft.

The **Arc** associated with performing the flight on the aircraft's network will share the same decision variable as the one from the crew's network, and this variable is the only variable in the **Option Choice**'s decision expression. On the other hand, there are **Arcs** associated with embarking and disembarking crew, each with their own independent variables to account for crew movement that is not completely linked to the execution of the flight. Thus, if both **Arcs** can carry sufficient flow, the **Option** is feasible.

A simple example of the required **Arcs** is shown in Figures 3 and 4. Note that **Arc 3** and **Node 5** will not be created for this flight if it is part of a multi-leg and not the first leg, while **Arc 4** and **Node 6** will not be created for this flight if it is part of a multi-leg which does not conclude at that point. In the first case, the minimum transit would be used instead of the minimum turnaround.
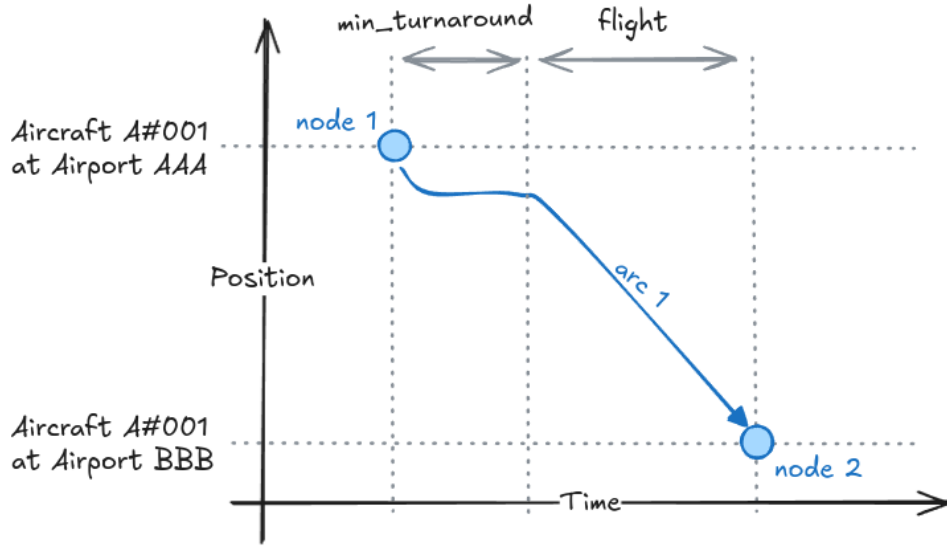
Figure 3: Required **Arcs** for representing the **Option** of scheduling a flight in the **aircraft** network.
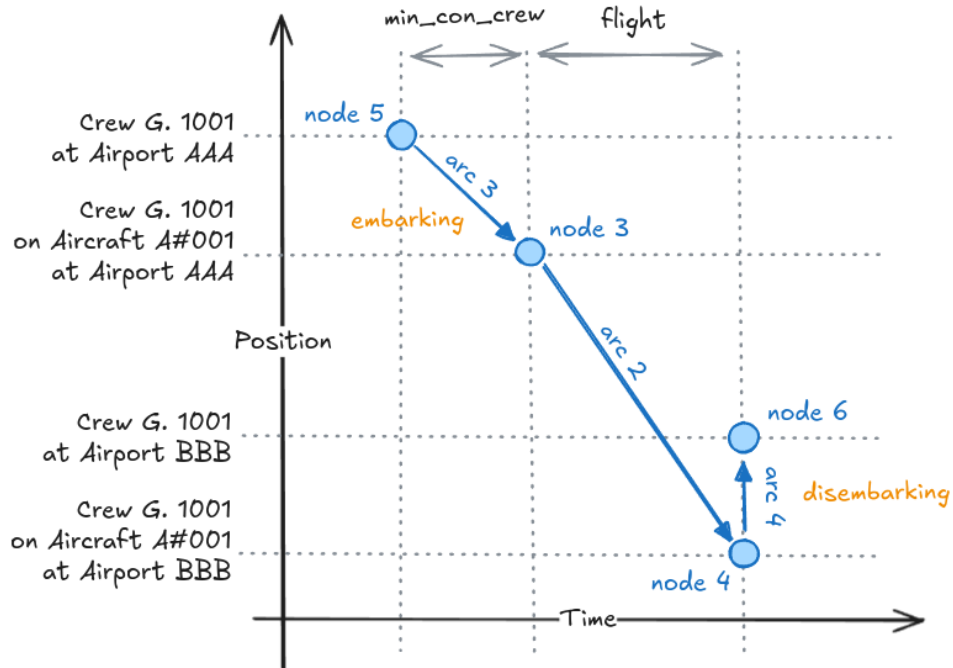

Figure 4: Required **Arcs** for representing the **Option** of scheduling a flight in the **crew** network.

To ensure that, for example, an aircraft performs only the first leg of a multi-leg flight and then proceeds to operate a completely different flight, there are special positions to describe being at a particular airport during the transit between two specific legs of a multi-leg flight. We refer to these virtually separate positions as *sub-threads*". These are treated as completely separate places when adding the **Ground Arcs** later. At those positions, the flow balance constraint is also more rigid" (= instead of ≤), which means that every unit of flow that goes in

must go out. This guarantees that either all the legs of a multi-leg flight are canceled, or they are all assigned to the same aircraft and crew. Figure 5 shows an example with a two-leg flight and a single-leg flight.
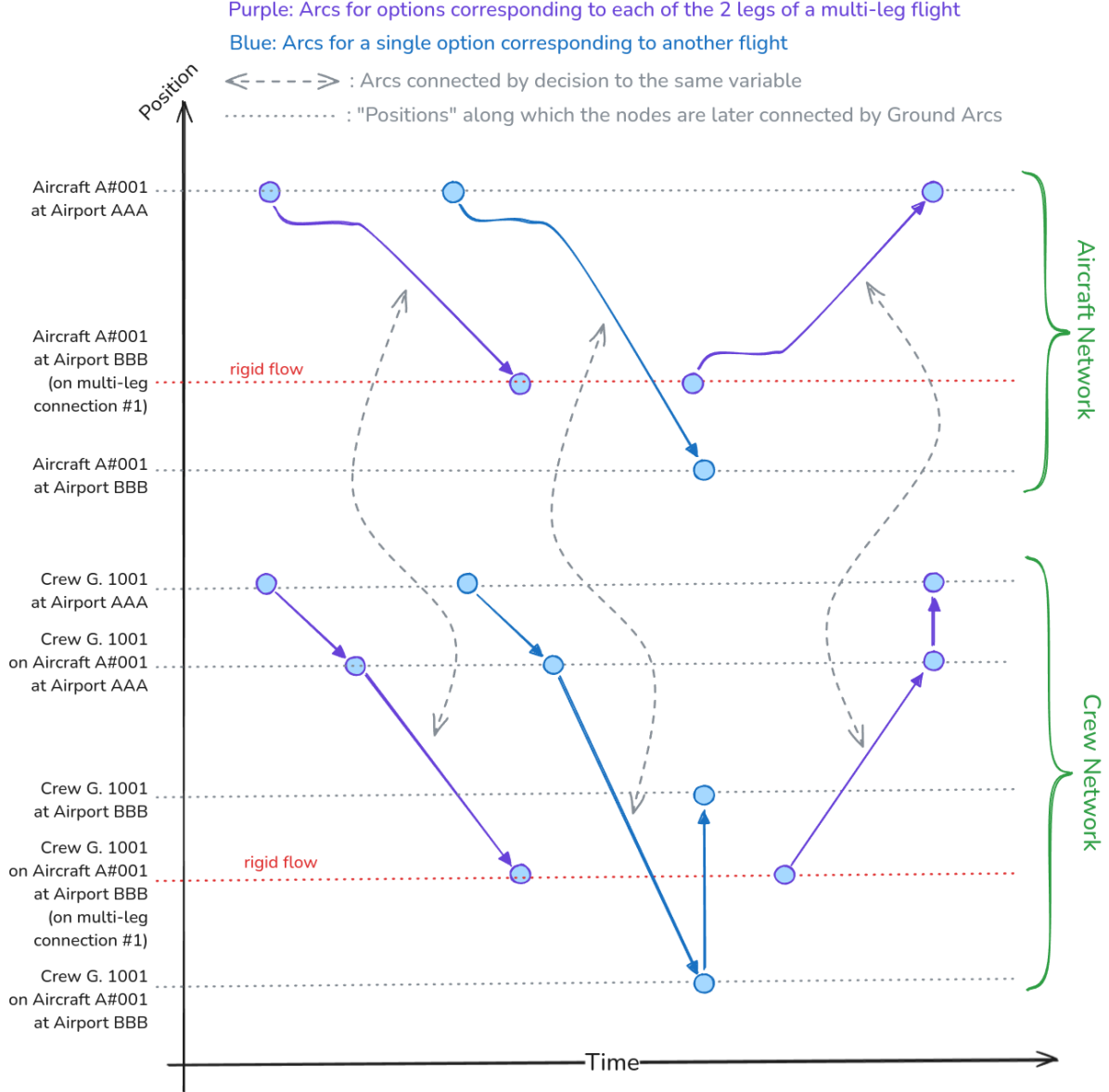

Figure 5: Example scheme of **Arcs** for one 2-leg flight and one single-leg flight.

Also, note how the disembarking **Arcs** are vertical in Figures 3 and 5. In practice, they connect at the same time on the main thread. Consequently, this model requires the crew's minimum connection time to be greater than zero.

Succeeding Maintenance: The **Succeeding** state holds information about the location and time for this maintenance. Within a single iteration of the ACR method, each maintenance will be associated with many **Options** with a different **Succeeding** states, each with distinct times and locations, representing different ways for that maintenance to be performed successfully. In the previous stage, the search space construction, the **Maintenance Options** are chosen based on the set of **Flight Options** under consideration. It is possible to represent each of these individual **Options** with a single **Arc** in the aircraft network, as shown in Figure
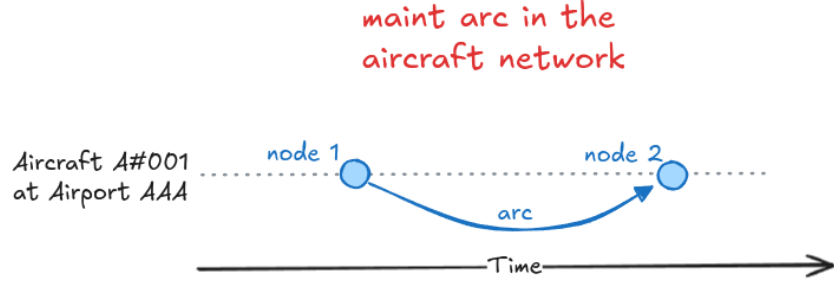
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6.

Figure 6: **Arc** representation of the **Option** of successfully performing a maintenance at a given time and airport.

Failing Maintenance: While omission of required maintenance is undesirable and would ideally be prohibited, strict enforcement can render the problem infeasible under severe disruption conditions; therefore, a soft-constraint mechanism is employed. Specifically, we assign a high penalty to the **Option** of failing maintenance and represent it via a set of **Sink Arcs**, as illustrated in Figure 7. These sink **Arcs** impose no flow-conservation constraint at the terminal **Node** by terminating at a **Void Node**; this prevents further assignments while recording the violation as a penalized choice. The **Void Node** serves as an origin and/or destination wherever unconstrained flow is required and is likewise used for the next two categories of **Arcs**.
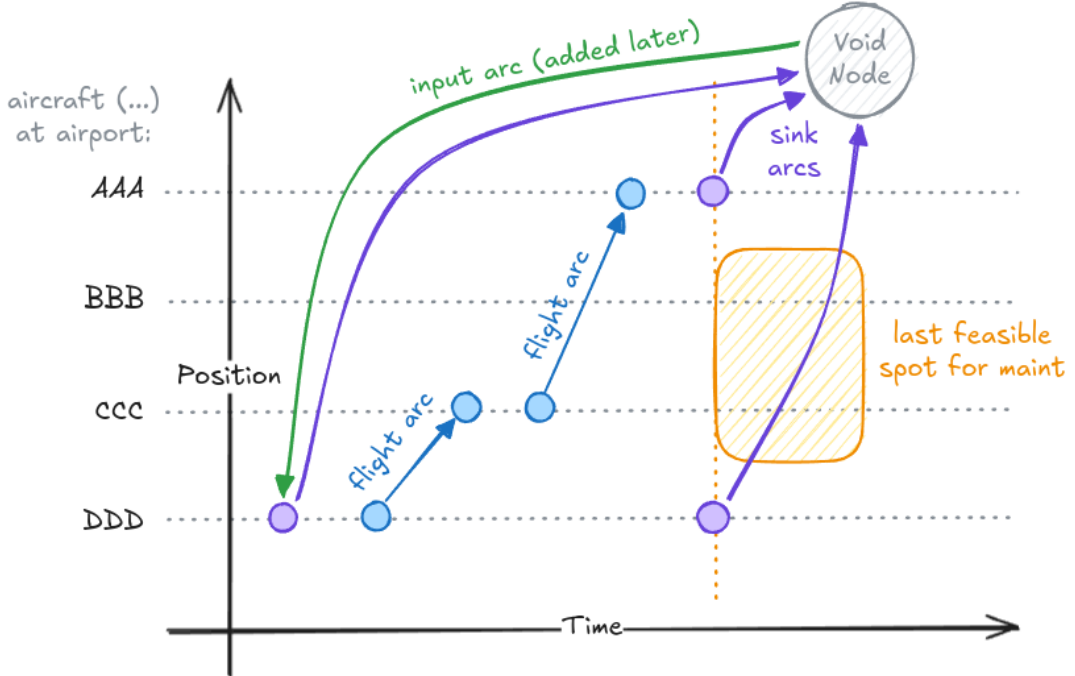

Figure 7: Required sink **Arcs** required to represent the **Option** of failing to perform a maintenance in a given aircraft, excluding the possibility of performing further flights with this vehicle.

Canceling Flight: This is the simplest case among the **Option Choices**, as it does not require any flow restriction. Thus, no **Arc** is required in any network, and free variables may

be used instead. For debugging and data analysis, it may be useful to generate **Arcs** that start and finish at the **Void Node**, so as to retain those **Options** represented in the network data.

Input Arcs: We represent the initial position for an Aircraft or Crew with an **Arc** that starts at the **Void Node**, ends at the position/time at which the input is given, and has a fixed decision (flow) of 1. Figure 8 presents an example input **Arc** (in green). These arcs work exactly the same way for both Aircraft and Crew. If the resource is reported as present at that airport but no previous history of flights is given, it will be assumed to have been there for an arbitrarily long time before **Current Time**. Otherwise it will be placed at the finishing position/time of its last flight starting before **Current Time**.

Ground Arcs: These are added after all the others to connect the timelines in each posi- tion" in the network. For example, consider the network presented earlier for the maintenance failure case. Its generated **Ground Arcs** are shown in Figure 8. To generate such **Arcs**, the program groups the **Nodes** by their positions", sorts the groups by time, and connects each pair of consecutive **Nodes** with a new **Arc** that has an independent variable.
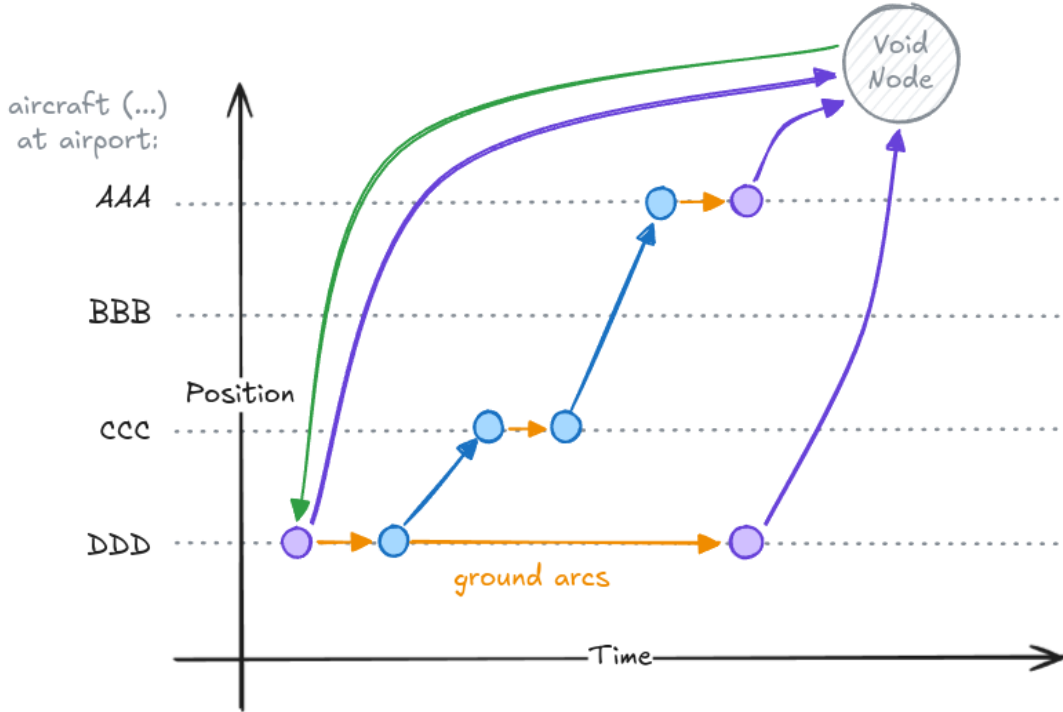

Figure 8: Generated **Ground Arcs** (in orange) and **Input Arc** (in green) for the network shown in figure 7.

4.4. PaxR: Passenger Reassignment and Schedule Improvement

The **AIRS.PaxR** module is responsible for reassigning passengers to flights. After finding a feasible flight schedule with the ACR module, the PaxR module uses a custom greedy algorithm to fix infeasible itineraries, thereby modifying the schedule to reduce costs associated with itinerary disruptions without violating already satisfied constraints.

The schedule provided by the ACR module may render some itineraries infeasible, but, in general, this is not expected to occur for the majority of itineraries. Other existing methods apply greedy algorithms Bisaillon et al. [2010], evaluating itineraries in priority order, keeping as many as possible unchanged and reassigning when needed to other routes. Algorithms 1, 2, 3, and 4 present pseudocode that provides a high-level view of how the algorithm operates.

Algorithm 1 displays the order in which the main operations are performed, and the others give additional detail on the operation of those procedures. The main procedure initializes flight capacities and assigns passengers in three passes–first preserving fixed portions of itineraries, then filling feasible original paths, and finally routing remaining demand along the earliest viable alternatives–updating capacities after each step. The subroutines prioritize earliest arrival and minimal downgrades while respecting remaining capacity, thereby reducing cancellations and preserving service where possible.

Algorithm 1 Assign Itineraries (Main Procedure)

1: **procedure** ASSIGNITINERARIES
2:     initialize $Flights$ with max capacity
3:     AssignFixedItineraries($flights$, $itineraries$, ...)
4:     AssignFeasibleItineraries($flights$, $itineraries$, ...)
5:     AssignInfeasibleItineraries($flights$, $itineraries$, ...)
6: **end procedure**

Algorithm 2 Assign Fixed Itineraries

1: **procedure** ASSIGNFIXEDITINERARIES($flights$, $itineraries$, ...)
2:     **for all** $itinerary$ starting before RP **do**
3:         $path \leftarrow$ original pre-RP flights assigned up to the last feasible (no downgrade)
4:         $capacity \leftarrow$ minimum capacity of flights in $path$ (original cabin classes)
5:         **if** $path$ not empty and $capacity$ non-zero **then**
6:             assign $itinerary$ to all flights in $path$ (original cabin classes)
7:             subtract $capacity$ from all flights in $path$ (original cabin classes)
8:         **end if**
9:     **end for**

10:     $partiallyAssigned \leftarrow$ itineraries assigned to parts of their original trips on the loop above
11:     Sort $partiallyAssigned$ by estimated remaining trip time (ascending)

12:     **for all** $itinerary$ in $partiallyAssigned$ **do**
13:         $remainingPath \leftarrow$ rest of the original flights up to the last feasible (no downgrade)
14:         $capacity \leftarrow$ minimum capacity of flights in $remainingPath$ (original cabin classes)
15:         **if** $remainingPath$ not empty and $capacity$ non-zero **then**
16:             assign $itinerary$ to all flights in $remainingPath$
17:             subtract $capacity$ from all flights in $remainingPath$
18:         **end if**

19:         **while** $itinerary$ has unassigned passengers **do**
20:             $bestPath \leftarrow$ path of earliest arrival to destination (least downgrade possible)
21:             $capacity \leftarrow$ minimum capacity of flight assignments in $bestPath$
22:             **if** $bestPath$ is not found **then**
23:                 **break**
24:             **end if**
25:             apply all assignments in $bestPath$ to $itinerary$
26:             subtract $capacity$ from all flights in $bestPath$ accordingly to the cabin class
27:         **end while**
28:     **end for**
29: **end procedure**

Algorithm 3 Assign Feasible Itineraries

1: **procedure** ASSIGNFEASIBLEITINERARIES(*flights*, *itineraries*, ...)
2:     *itineraries* ← itineraries not treated by AssignFixedItineraries
3:     **for all** *itinerary* in decreasing order of estimated cancellation costs **do**
4:         Determine how many can be scheduled on original flights without downgrading
5:         **if** any can be scheduled **then**
6:             Assign them and update *flight capacities*
7:         **end if**
8:     **end for**
9: **end procedure**

Algorithm 4 Assign Infeasible Itineraries

1: **procedure** ASSIGNINFEASIBLEITINERARIES(*flights*, *itineraries*, ...)
2:     *itineraries* ← itineraries not treated by Assign(Fixed/Feasible)Itineraries
3:     **for all** *itinerary* in decreasing order of estimated cancellation costs **do**
4:         *best_path* ← find earliest arrival path with remaining capacity
5:         **if** *best_path* is found **then**
6:             Assign as many passengers as possible to *best_path*, minimizing downgrades
7:             Update *flight capacities*
8:         **end if**
9:     **end for**
10: **end procedure**

At the same time, some evolutionary method may be applied to change the schedule progressively in order to allow more passengers to complete their trips and further reduce costs. As the greedy algorithm is very fast to execute, thousands of possible schedules may be evaluated in a few minutes. PaxR applies a custom genetic algorithm that evaluates individuals in each generation in parallel. Given a baseline schedule taken from the solution obtained by the ACR module, the internal representation of each individual to be evolved is a pair of two elements:

1. **ScheduleCandidate**: a data structure that contains a set of modifications to the baseline schedule

2. **PaxAssignmentCandidate**: a different data structure that contains passenger assignment compatible withe baseline schedule after the modifications specified in **ScheduleCandidate** are applied.

The only references shared among different individuals are the associated problem and baseline schedule, stored in the *PaxR* structure, which is not mutated after construction. Effectively, this means we can safely work with these individuals in a multithreaded environment with shared memory without race conditions.

Due to the heavy use of structs, careful memory management is important for this algorithm. Julia's built-in garbage collector caused crashes when it was not explicitly called in the evolution loop, due to not correctly handling the cleanup of the large number of leftover structs removed from the population during the iterations.

Other than that, the evolutionary algorithm applied was a very simple non-crossover genetic algorithm:

Algorithm 5 PaxR (non-crossover GA)

1: $\mathcal{P} \leftarrow$ {baseline schedule with passenger assignment}
2: Generate 49 mutated schedules; $\quad \mathcal{P} \leftarrow \mathcal{P} \cup$ {mutations}
3: **for all** $x \in \mathcal{P}$ **do**
4: $\quad f(x) \leftarrow \text{Cost}(x)$
5: **end for**
6: **while** termination criterion not met **do**
7: $\quad$ Select 30 schedules from $\mathcal{P}$ with probability biased toward lower cost
8: $\quad$ **for all** p in selected set **do** $\qquad\qquad\qquad$ ▷ can execute in parallel
9: $\quad\quad c \leftarrow \text{MUTATE}(p)$ $\qquad\qquad\qquad\qquad$ ▷ respect all constraints
10: $\quad\quad \text{ASSIGNPASSENGERS}(c)$
11: $\quad\quad f(c) \leftarrow \text{Cost}(c)$
12: $\quad\quad \mathcal{C} \leftarrow \mathcal{C} \cup \{c\}$
13: $\quad$ **end for**
14: $\quad \mathcal{P} \leftarrow \text{Best}_{50}(\mathcal{P} \cup \mathcal{C})$ $\qquad\qquad\qquad\qquad\qquad$ ▷ ascending cost
15: **end while**

---

1. starts with a population of 1 (no change to the baseline, and the associated passenger assignment);
2. creates 49 mutated schedules to compose an initial population of 50 individuals;
3. calculates the estimated costs of every individual;
4. finally, on each evolution iteration:
   (a) choose 30 schedules from the current population from a distribution that favors lower costs;
   (b) the following is done in multithreading for each of the 30 schedules chosen:
      i. create a mutated version of the schedule, keeping all constraints respected;
      ii. create the associated passenger assignment;
      iii. calculate the associated cost;
   (c) next population will be the 50 individuals with lower costs among all the 80 composed by the previous population and the new mutations.

The size of the population, the allowed optimization time, as well as the choice of evolutionary method can be changed in order to better utilize available hardware and to better suit user requirements.

5. Business Constraints and Data Integration

This family of constraints consists mainly of the following:

- Aircraft rotation consistency
- Crew legality and duty limits
- Airport slot capacity and overlapping
- Maintenance location/time constraints

These constraints are injected during search space and TSN construction phases.

6. Solver Strategy and Implementation

The solver builds the TSN, encodes decisions as symbolic variables, and uses MILP solvers (e.g., Gurobi or CBC). Key strategies:

- Warm start from current schedule
- Penalty tuning for preference control
- Layered constraint enforcement

7.   An Example Problem on AIRS.ACR

In this section, a small problem is visualized to ilustrate the sequence of steps executed by the ACR module. This example problem consists of a short schedule, illustrated in Figure 9 with:

- 7 airports
- 3 aircraft
- 5 crew groups
- 14 flights
- 2 initial flight delays
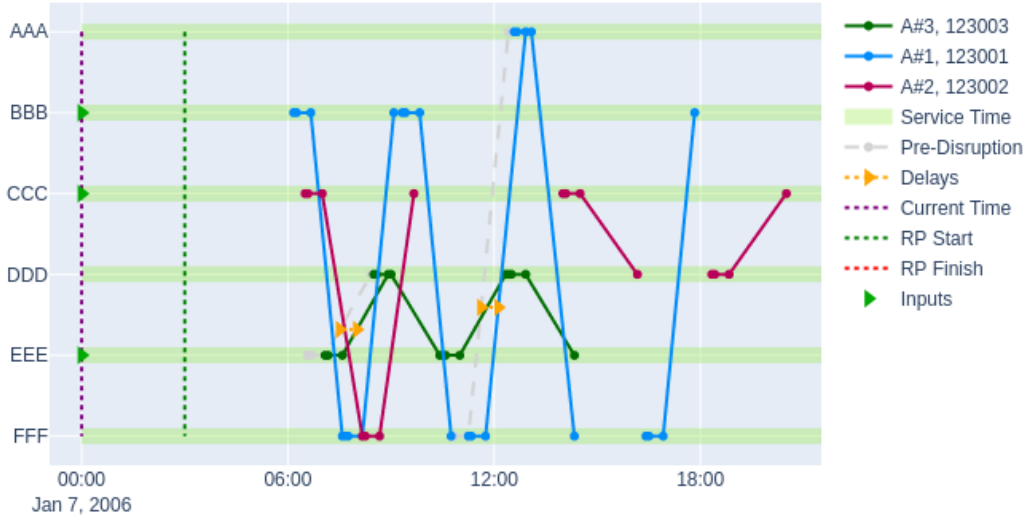- everything happening after Recovery Start, for simplicity

Figure 9: Example aircraft & crew rescheduling problem, split by the original aircraft assigned to each flight (A#1, A#2 and A#3), and by the original crew groups (123001, 123002 and 123003). Recovery Finish is ahead of all the events in this problem and is not shown in this plot.

The method applied in the ACR module is iterative, and at each iteration, a Time-Space Network is built. The network is divided into subnetworks associated with each aircraft and each crew, linked to the set of associated **Options** in the search space. Figures 10 and 11 show the time-space generated for, respectively, a given aircraft and a given crew group, specifically in the first iteration.
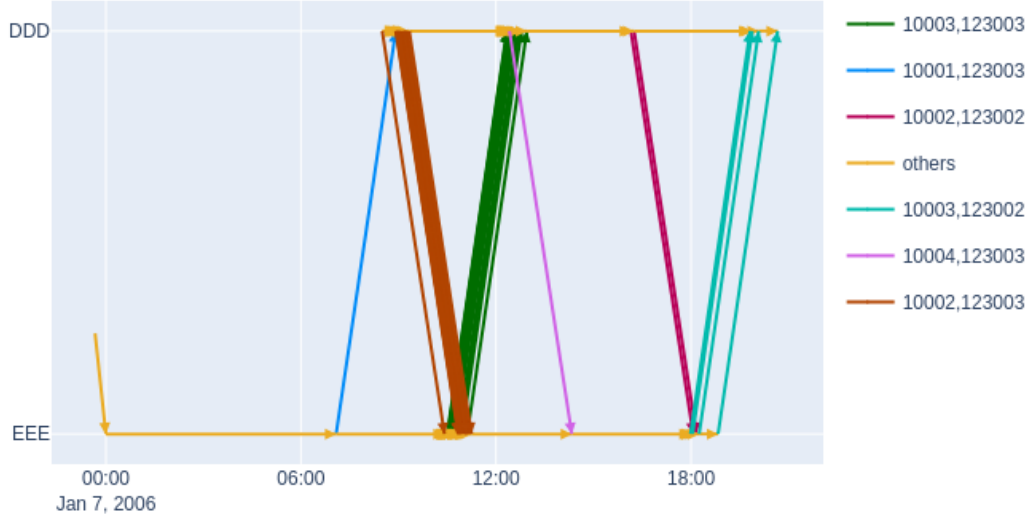
Figure 10: Time-Space Network segment generated for aircraft A#3 in the first iteration of the ACR method. The related problem is the one ilustrated in Figure 9. In the legend, the first number is the identifier of the flight leg, while the second number is the identifier of a crew group. Each arrow represents an **Option** for performing a given flight with a given crew group on aircraft A#3. The "others" label refers to **Arcs** that do not represent **Options** directly linked to flights, such as **Ground Arcs** and the **Input Arc** in the bottom-left. Other aircraft have their own parts in the overall Time-Space Network.
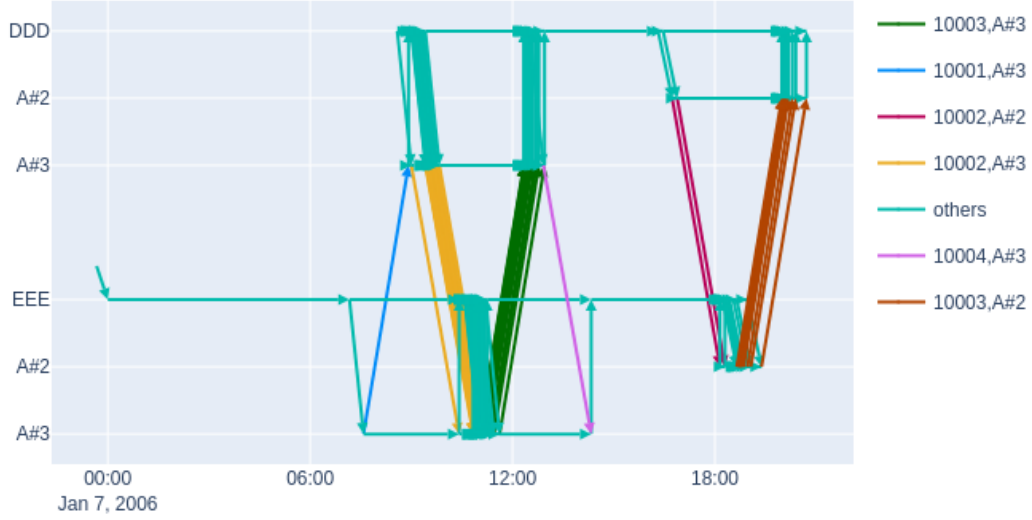
Figure 11: The Time-Space Network part generated for crew 123003 in the first iteration of the ACR method. The related problem is the one illustrated in Figure 9. In the legend, the first number is the identifier of the flight leg, while the second number is the identifier of an aircraft. Each arrow represents one **Option** for performing a given flight with a given aircraft and crew 123003. The "others" label refers to **Arcs** that do not represent **Options** directly linked to flights, such as ground **Arcs**, the input **Arc** on the far left, and the embark/disembark **Arcs** under each airport. It is worth noting the inclusion of vertical positions for the aircraft under each airport, which allows skipping connection time when staying on the same aircraft. Other crew groups will have their own parts in the overall Time-Space Network.

To contain the rapid growth in the number of variables, the method avoids enumerating all flight–crew–time combinations and instead activates **Options**, represented as arrows, concentrated around observed irregularities. In the figures, the disruptions depicted are those detectable from the baseline schedule; the first iteration therefore targets these visible events. In subsequent iterations, solver feedback reveals additional disruptions – such as large delays, flight cancellations, and maintenance infeasibilities – these events guide the injection of new **Options**, focusing computation on decisions that drive feasibility and cost.

This small problem can be solved to a satisfactory level in about 2 iterations, adding as few as 100 change **Options** to the system, in around 10 seconds on our test hardware, which is specified in Section 8. Solving larger problems with more disruptions requires a larger number of change **Options** per iteration, as well as more iterations. Figure 12 shows the solution reached for this specific problem, which requires a small number of delays.
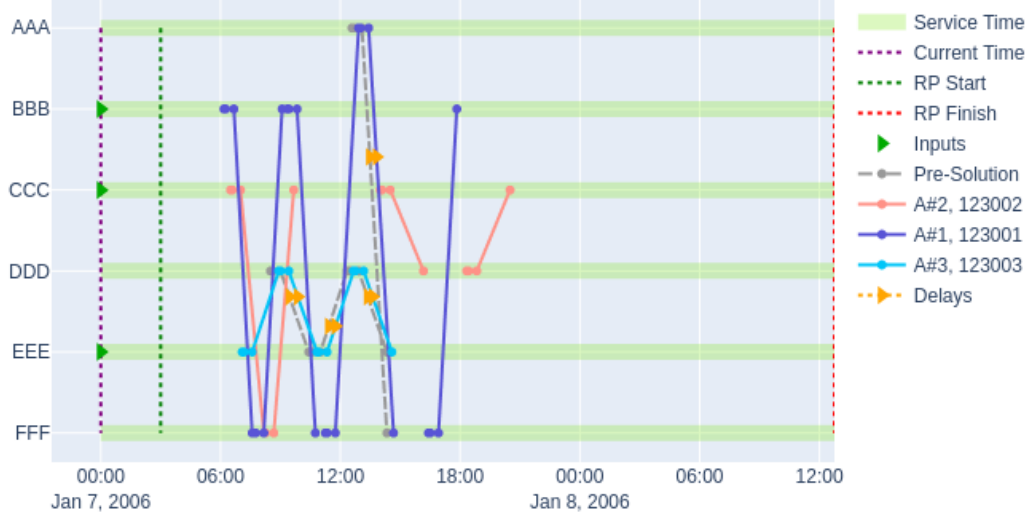
Figure 12: Solution achieved by the ACR method for the problem illustrated in Figure 9. No cancellations or swaps are required, although alternative crews are available. Some delays are needed to account for those in the original problem. This solution is reached in the second iteration because of the chain of delays on aircraft A#3, the initial iteration usually cancels the last flight. This cancellation is then solved in the second iteration.

8. Experimental Results

This section presents statistics on the execution of AIRS on 5 distinct test instances sized similarly to real-world problems. The recovery time windows are approximately one day. Detailed information on the nature of each instance is presented in Table 2. Tables 3, 4, and 5 contain information on time-to-solution for several different parts of the solver. The tables do not include statistics for feasibility, as the solver achieved feasible solutions for all the tested instances.

Note that AIRS is highly configurable in terms of cost and required TTS. This benchmark was executed using the current default parameters, targeting an execution time of around 10 minutes, as reflected in the third column of Table 5. The stopping conditions for ACR and PaxR adhere to this time target, seeking the best solution reachable within the available time. Therefore, the sub-step times are generally more informative.

It is also worth noting that the last column in Table 4 reports the number of generations for the evolutionary algorithm applied to the schedule. This evolutionary algorithm uses, by default, a population size of 50 schedules per generation, with 30 mutations per iteration. These settings are adjustable, and alternative heuristic strategies can also be employed (e.g., simulated annealing and other derivative-free methods). In practice, the population size and mutation rate can be tuned to balance runtime and solution quality.

The computational experiments were performed on a system with the specifications detailed below:

Table 1: System configuration used in computational experiments

Component	Specification
Processor	Intel Core i9-9960X
System memory	125.48 GiB
Operating system	Ubuntu 22.04.5 LTS
Software	Julia 1.11.5
Parallelism	Up to 12 threads
GPU	Not used (no acceleration required)

Table 2: Entity counts for Instances A01-A07

Instance	Airports	Slotted Airp.	Aircraft	Crew Groups	Flights	Pass. Tickets	Multileg Conn.	Flight Disrup.	Maint.	Airp. Slots
A01	35	25	85	162	608	43964	4	63	3	1478
A02	35	29	85	162	608	43965	4	107	3	1478
A04	35	32	85	162	608	43963	4	41	3	1478
A06	35	29	85	162	608	54687	4	63	3	1478
A07	35	30	85	162	608	54687	4	107	3	1478

Table 3: ACR Performance Averages (Sub-step times are per ACR iteration)

Avg. TTS→ ↰Instance	Prox. (s)	S.S. Gen. (s)	TSN Const. (ms)	TSN Optim. (s)	Entire Iteration (s)
A01	6.20	22.50	466.00	8.60	37.80
A02	6.20	22.30	428.60	5.30	34.20
A04	17.90	24.00	442.30	11.90	54.20
A06	16.50	23.30	430.90	8.60	48.80
A07	16.60	23.10	431.40	5.00	45.10

Table 4: PAXR Performance Averages (Times are per run)

Avgs→ ↰Instance	Sched. Improv. TTS (s)	Evolution Generations
A01	240.10	1156.60
A02	240.10	1146.20
A04	240.10	816.70
A06	240.20	808.50
A07	240.20	733.30

Table 5: Benchmark Summary (Averages are per run)

Instance	Avgs→ Runs	Full TTS (s)	ACR Iters/Run	Initial PaxR Cost	Final PaxR Cost
A01	10.00	555.60	8.30	1242860	1095620
A02	10.00	551.90	9.10	11247100	8556800
A04	9.00	559.70	5.90	6330020	5561000
A06	10.00	567.70	6.70	5942130	3652770
A07	10.00	556.30	7.00	22047600	10678000

9. Conclusion

This paper presents AIRS.ACR, a novel solver-based engine for integrated disruption recovery in airline operations. By leveraging a Time-Space Network formulation and mixed-integer linear programming, AIRS.ACR enables simultaneous optimization of aircraft and crew schedules, addressing a long-standing challenge in airline operations control. Unlike traditional sequential methods, which often yield suboptimal or infeasible solutions due to resource decoupling, AIRS.ACR captures the complex interdependencies between aircraft and crew, producing more realistic and operationally viable recovery plans.

The system demonstrates strong scalability and computational efficiency, solving real-world-sized instances within practical timeframes. Its modular architecture – separating aircraft and crew recovery (ACR) from passenger reassignment (PaxR) – balances feasibility and performance, while allowing further refinement through evolutionary algorithms.

Experimental results confirm the system's ability to generate high-quality solutions under diverse disruption scenarios, with significant reductions in total disruption costs. Moreover, the solver's flexibility to incorporate business constraints (e.g., maintenance, slot penalties, crew legality) makes it adaptable to real-world AOCC environments.

Future work will explore deeper integration of passenger-centric objectives, real-time data assimilation, and hybrid AI optimization strategies to further enhance responsiveness and decision support capabilities. Overall, AIRS.ACR represents a significant step toward more resilient, automated, and intelligent airline disruption management.

Acknowledgements

A. Input/Output Data Formats

- JSON or CSV inputs for flights, crews, slots, maintenance;
- Output: List of prescribed changes to the aircraft/crew/passenger schedule.

References

S. AhmadBeygi, A. Cohn, Y. Guan, and P. Belobaba. Analysis of the potential for delay propagation in passenger airline networks. Journal of Air Transport Management, 14(5): 221–236, 2008. ISSN 0969-6997. doi: https://doi.org/10.1016/j.jairtraman.2008.04.010. URL https://www.sciencedirect.com/science/article/pii/S0969699708000550.

M.S. Aktürk, A. Atamtürk, and S. Gürel. Aircraft rescheduling with cruise speed control. Operations Research, 62(4):829–845, 2014. doi: 10.1287/opre.2014.1279. URL https://doi.org/10.1287/opre.2014.1279.

U. Arıkan, S. Gürel, and M.S. Aktürk. Flight network-based approach for integrated airline recovery with cruise speed control. Transportation Science, 51(4):1259–1287, 2017. doi: 10.1287/trsc.2016.0716.

M. Ball, C. Barnhart, G. Nemhauser, and A. Odoni. Chapter 1 air transportation: Irregular operations and control. In C. Barnhart and G. Laporte, editors, Transportation, volume 14 of Handbooks in Operations Research and Management Science, pages 1–67. Elsevier, 2007. doi: https://doi.org/10.1016/S0927-0507(06)14001-3. URL https://www.sciencedirect.com/science/article/pii/S0927050706140013.

C. Barnhart, N. Boland, L. Clarke, E. Johnson, G. Nemhauser, and R. Shenoi. Flight string models for aircraft fleeting and routing. Transportation Science, 32(3):208–220, 1998. doi: 10.1287/trsc.32.3.208.

S. Bisaillon, J.-F. Cordeau, G. Laporte, and F. Pasin. A large neighbourhood search heuristic for the aircraft and passenger recovery problem. 4OR, 9(2):139–157, 2010. doi: 10.1007/s10288-010-0145-5.

S. Bratu and C. Barnhart. Flight operations recovery: New approaches considering passenger recovery. Journal of Scheduling, 9:279–298, 2006. doi: 10.1007/s10951-006-6781-0.

L. Cadarso and V. Vaze. Passenger-centric integrated airline schedule and aircraft recovery. Transportation Science, 57(3):813–837, 2023. doi: 10.1287/trsc.2022.1174.

A. Castro and E. Oliveira. A multi-agent system for airline operations control. In 7th International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS 2009), pages 159–168. Springer, 2009. doi: 10.1007/978-3-642-00487-2_17.

A. Castro, A.P. Rocha, and E. Oliveira. A New Approach for Disruption Management in Airline Operations Control, volume 562 of Studies in Computational Intelligence. Springer, Berlin, Heidelberg, 2014. ISBN 978-3-662-43372-0. doi: 10.1007/978-3-662-43373-7. URL https://link.springer.com/book/10.1007/978-3-662-43373-7.

S.-C. Chang. A duty based approach in solving the aircrew recovery problem. Journal of Air Transport Management, 19:16–20, 03 2012. doi: 10.1016/j.jairtraman.2011.12.001.

K. Chen and J. Wu. Improved nsga2 algorithm for recovery of interrupted departure flights. Scientific Insights and Discoveries Review, 4:88–100, Oct. 2024. doi: 10.59782/sidr.v4i1.83.

M.D.D. Clarke. Irregular airline operations: a review of the state-of-the-practice in airline operations control centers. Journal of Air Transport Management, 4(2):67–76, 1998. doi: https://doi.org/10.1016/S0969-6997(98)00012-X.

J. Clausen, A. Larsen, J. Larsen, and N.J. Rezanova. Disruption management in the airline industry – concepts, models and methods. Computers & Operations Research, 37(5):809–821, 2010. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2009.03.027. URL https://www.sciencedirect.com/science/article/pii/S0305054809000914. Disruption Management.

A. Cook, G. Tanner, and A. Lawes. The hidden cost of airline unpunctuality. Journal of Transport Economics and Policy, 46, 05 2012.

P. de Bruin, M. van den Akker, K. Kumar, L. Heuseveldt, and M. Paelinck. Integrated airline fleet and crew recovery through local search, 2025. URL `https://arxiv.org/abs/2505.04274`.

Y. Ding, S. Wandelt, G. Wu, Y. Xu, and X. Sun. Towards efficient airline disruption recovery with reinforcement learning. Transportation Research Part E: Logistics and Transportation Review, 179:103295, 2023. doi: 10.1016/j.tre.2023.103295.

N. Eggenberg, M. Bierlaire, and M. Salani. A column generation algorithm for disrupted airline schedules, 2007. URL `https://infoscience.epfl.ch/handle/20.500.14299/18732`.

B. Eikelenboom and B.F. Santos. A Decision-Support Tool for the Integrated Airline Recovery Using a Machine Learning Resources Selection Approach. SSRN, 2023. URL `https://books.google.pl/books?id=mkdMOAEACAAJ`.

L.B. Fogaça, E. Henriqson, G.C. Junior, and Lando F. Airline disruption management: A naturalistic decision-making perspective in an operational control centre. Journal of Cognitive Engineering and Decision Making, 16(1):3–28, 2022. doi: 10.1177/15553434211061024. URL `https://doi.org/10.1177/15553434211061024`.

M. Gamache, F. Soumis, G. Marquis, and J. Desrosiers. A column generation approach for large-scale aircrew rostering problems. Operations Research, 47(2):247–263, 1999. doi: 10.1287/opre.47.2.247.

Q. Gao, X. Tang, and J. Zhu. Research on Greedy Simulated Annealing Algorithm for Irregular Flight Schedule Recovery Model, pages 503–513. Springer Berlin Heidelberg, Berlin, Heidelberg, 2010. doi: 10.1007/978-3-642-13938-3_44.

E. Guardo-Martinez, S. Onggo, M. Kunc, S. Padrón, and M. Tomasella. Robust airline scheduling with turnaround under uncertainty: towards collaborative airline scheduling. Transportation Research Part E: Logistics and Transportation Review, 205:104440, 2026. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2025.104440. URL `https://www.sciencedirect.com/science/article/pii/S1366554525004818`.

D. Guimarans, P. Arias, and W. Zhao. A simheuristic approach for solving the aircraft recovery problem with stochastic delays. Metaheuristics: Proceeding of the MIC and MAEB, pages 48–50, 2017.

L.K. Hassan, B.F. Santos, and J. Vink. Airline disruption management: A literature review and practical challenges. Computers & Operations Research, 127:105137, 2021. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2020.105137. URL `https://www.sciencedirect.com/science/article/pii/S0305054820302549`.

P. He. Time-band network model and binary tree algorithm for multimodal irregular flight recovery. Scientific Reports, 14(5242), 2024. doi: https://doi.org/10.1038/s41598-024-56000-w.

Y. Hu, Y. Song, K. Zhao, and B. Xu. Integrated recovery of aircraft and passengers after airline operation disruption based on a grasp algorithm. Transportation Research Part E: Logistics and Transportation Review, 87:97–112, 2016. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2016.01.002. URL `https://www.sciencedirect.com/science/article/pii/S1366554516000028`.

Y. Hu, S. Wang, S. Zhang, and Z. Li. Review of optimization problems, models and methods for airline disruption management from 2010 to 2024. Digital Transportation and Safety, 3 (dts-0024-0022):246, 2024. ISSN 2837-7842. doi: 10.48130/dts-0024-0022.

A. Khiabani, A. Komijan, V. Ghezavati, and H. Mohammadi Bidhandi. An integrated model for crew, aircraft and passenger recovery problem: A real case study. Advances in Industrial Engineering, 57(1):75–95, 06 2023a. doi: 10.22059/AIE.2022.346585.1848.

A. Khiabani, A. Rashidi Komijan, V. Ghezavati, and H. Mohammadi Bidhandi. A mathematical model for integrated aircraft and crew recovery after a disruption: A benders' decomposition approach. Journal of Modelling in Management, 18(6):1740–1761, 2023b. doi: 10.1108/JM2-02-2022-0046. URL https://doi.org/10.1108/JM2-02-2022-0046.

N. Kohl, A. Larsen, J. Larsen, A. Ross, and S. Tiourine. Airline disruption management—perspectives, experiences and outlook. Journal of Air Transport Management, 13 (3):149–162, 2007. ISSN 0969-6997. doi: https://doi.org/10.1016/j.jairtraman.2007.01.001. URL https://www.sciencedirect.com/science/article/pii/S0969699707000038.

J. Lee, K. Lee, and I. Moon. A reinforcement learning approach for multi-fleet aircraft recovery under airline disruption. Applied Soft Computing, 129:109556, 2022. ISSN 1568-4946. doi: https://doi.org/10.1016/j.asoc.2022.109556. URL https://www.sciencedirect.com/science/article/pii/S1568494622006226.

L. Lee, J.and Marla and A. Jacquillat. Dynamic disruption management in airline networks under airport operating uncertainty. Transportation Science, 54(4):973–997, 2020. doi: 10.1287/trsc.2020.0983. URL https://doi.org/10.1287/trsc.2020.0983.

L. Lettovsky. Airline operations recovery: an optimization approach. Ph.d. thesis, Georgia Institute of Technology, 1997. URL https://api.semanticscholar.org/CorpusID:108184791.

L. Lettovský, E. Johnson, and G. Nemhauser. Airline crew recovery. Transportation Science, 34:337–, 11 2000. doi: 10.1287/trsc.34.4.337.12316.

Z. Liang, F. Xiao, X. Qian, L. Zhou, X. Jin, X. Lu, and S. Karichery. A column generation-based heuristic for aircraft recovery problem with airport capacity constraints and maintenance flexibility. Transportation Research Part B: Methodological, 113:70–90, 2018. ISSN 0191-2615. doi: https://doi.org/10.1016/j.trb.2018.05.007. URL https://www.sciencedirect.com/science/article/pii/S0191261517310421.

Q. Liu, X. Zhang, X. Chen, and Xi. Chen. Interfleet and intrafleet models for crew recovery problems. Transportation Research Record: Journal of the Transportation Research Board, 2336:75–82, 12 2013. doi: 10.3141/2336-09.

T.K. Liu, C.H. Chen, and J.H. Chou. Optimization of short-haul aircraft schedule recovery problems using a hybrid multiobjective genetic algorithm. Expert Systems with Applications, 37(3):2307–2315, 2010. ISSN 0957-4174. doi: https://doi.org/10.1016/j.eswa.2009.07.068. URL https://www.sciencedirect.com/science/article/pii/S0957417409007106.

Y. Long and P. Belobaba. Airline revenue management with segmented continuous pricing: methods and competitive effects. Journal of Revenue and Pricing Management, 23:14–27, 2024. doi: https://doi.org/10.1057/s41272-023-00462-6.

L. Lu, Y. Xu, W. Fan, H. Pan, W. Ip, and K.L. Yung. Research on the recovery method of disrupted flights considering passenger transfer and cancellation costs. Operations Management Research, 18:691–717, 2025. doi: https://doi.org/10.1007/s12063-024-00530-z.

S.J. Maher. A novel passenger recovery approach for the integrated airline recovery problem. Computers & Operations Research, 57:123–137, 2015. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2014.11.005. URL https://www.sciencedirect.com/science/article/pii/S0305054814002998.

L. Marla, B. Vaaben, and C. Barnhart. Integrated disruption management and flight planning to trade off delays and fuel burn. 51st AGIFORS Annual Proceedings - Annual Symposium and Study Group Meeting, AGIFORS 2011, 1, 01 2012. doi: 10.1287/trsc.2015.0609.

L. McCarty and A. Cohn. Preemptive rerouting of airline passengers under uncertain delays. Computers & Operations Research, 90:1–11, 2018. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2017.09.001. URL https://www.sciencedirect.com/science/article/pii/S0305054817302253.

A. Nazifi, K. Gelbrich, Y. Grégoire, S. Koch, D. El-Manstrly, and J. Wirtz. Proactive handling of flight overbooking: How to reduce negative ewom and the costs of bumping customers. Journal of Service Research, 24(2):206–225, 2021. doi: 10.1177/1094670520933683.

X. Niu, C. Jiang, J. Gao, G. Korniss, and B. Szymanski. From data to complex network control of airline flight delays. Scientific Reports, 11(18715), 2021. doi: https://doi.org/10.1038/s41598-021-98112-7.

K. Novianingsih, R. Hadianti, S. Uttunggadewa, and E. Soewono. A solution method for airline crew recovery problems. International Journal of Applied Mathematics & Statistics, 53(4): 137–149, 2015.

J.D. Petersen. Large-scale mixed integer optimization approaches for scheduling airline operations under irregularity. Georgia Institute of Technology, 2012.

L.A. Rhodes-Leader, B.L. Nelson, B.S. Onggo, and D.J Worthington. A multi-fidelity modelling approach for airline disruption management using simulation. Journal of the Operational Research Society, 73(10):2228–2241, 2022. doi: 10.1080/01605682.2021.1971574. URL https://doi.org/10.1080/01605682.2021.1971574.

K. Sinclair, J-F. Cordeau, and G. Laporte. A column generation post-optimization heuristic for the integrated aircraft and passenger recovery problem. Computers & Operations Research, 65:42–52, 2016. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2015.06.014. URL https://www.sciencedirect.com/science/article/pii/S0305054815001653.

H. Sousa, R. Teixeira, C. Lopes, and E. Oliveira. Airline disruption management - dynamic aircraft scheduling with ant colony optimization. In ICAART 2015 - 7th International Conference on Agents and Artificial Intelligence, Proceedings, volume 2, pages 398–405, 01 2015.

M. Stojković, F. Soumis, and J. Desrosiers. The operational airline crew scheduling problem. Transportation Science, 32(3):232–245, 1998. doi: 10.1287/trsc.32.3.232.

Y. Su, K. Xie, h. Wang, Z. Liang, W.A. Chaovalitwongse, and P.M. Pardalos. Airline disruption management: A review of models and solution methods. Engineering, 7(4): 435–447, 2021a. ISSN 2095-8099. doi: https://doi.org/10.1016/j.eng.2020.08.021. URL https://www.sciencedirect.com/science/article/pii/S2095809921000175.

Y. Su, K. Xie, H. Wang, Z. Liang, W.A. Chaovalitwongse, and P.M. Pardalos. Airline disruption management: A review of models and solution methods. Engineering, 7(4): 435–447, 2021b. ISSN 2095-8099. doi: https://doi.org/10.1016/j.eng.2020.08.021. URL https://www.sciencedirect.com/science/article/pii/S2095809921000175.

B.G. Thengvall, J.F. Bard, and G. Yu. Balancing user preferences for aircraft schedule recovery during irregular operations. IIE Transactions, 32(3):181–193, 2000. doi: https://doi.org/10.1023/A:1007618928820.

H.-W. Vos, B. Santos, and T. Omondi. Aircraft schedule recovery problem – a dynamic modeling framework for daily operations. Transportation Research Procedia, 10, 07 2015. doi: 10.1016/j.trpro.2015.09.047.

Q. Wang, J. Mao, X. Wen, S. Wallace, and M. Deveci. Flight, aircraft, and crew integrated recovery policies for airlines - a deep reinforcement learning approach. Transport Policy, 160, 11 2024. doi: 10.1016/j.tranpol.2024.11.011.

C.L. Wu and K. Law. Modelling the delay propagation effects of multiple resource connections in an airline network using a bayesian network model. Transportation Research Part E: Logistics and Transportation Review, 122:62–77, 2019. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2018.11.004. URL https://www.sciencedirect.com/science/article/pii/S1366554517309857.

Z. Xiuli and G. Yanchi. Study on graps-aco algorithm for irregular flight rescheduling. In 2012 International Conference on Computer Science and Service System, pages 266–269, 2012. URL https://api.semanticscholar.org/CorpusID:18890644.

S. Yan and D.H. Yang. A decision support framework for handling schedule perturbation. Transportation Research Part B: Methodological, 30(6):405–419, 1996. ISSN 0191-2615. doi: https://doi.org/10.1016/0191-2615(96)00013-6. URL https://www.sciencedirect.com/science/article/pii/0191261596000136.

S. Yan and H.-F. Young. A decision support framework for multi-fleet routing and multi-stop flight scheduling. Transportation Research Part A: Policy and Practice, 30(5):379–398, 1996. ISSN 0965-8564. doi: https://doi.org/10.1016/0965-8564(95)00029-1. URL https://www.sciencedirect.com/science/article/pii/0965856495000291.

M. Yang. Using Advanced Tabu Search Techniques to Solve Airline Disruption Management Problems. University of Texas, 2007. URL https://books.google.pl/books?id=dSGZDAEACAAJ.

D Zhang, H Lau, and C Yu. A two stage heuristic algorithm for the integrated aircraft and crew schedule recovery problems. Computers & Industrial Engineering, 87: 436–453, 2015. ISSN 0360-8352. doi: https://doi.org/10.1016/j.cie.2015.05.033. URL https://www.sciencedirect.com/science/article/pii/S0360835215002569.

D. Zhang, C. Yu, J. Desai, and H. Lau. A math-heuristic algorithm for the integrated air service recovery. Transportation Research Part B: Methodological, 84:211–236, 2016. ISSN 0191-2615. doi: https://doi.org/10.1016/j.trb.2015.11.016. URL https://www.sciencedirect.com/science/article/pii/S019126151500260X.

Q. Zhang, F.T.S. Chan, and X. Fu. Improved ant colony optimization for the operational aircraft maintenance routing problem with cruise speed control. Journal of Advanced Transportation, 2023(1):8390619, 2023. doi: https://doi.org/10.1155/2023/8390619. URL https://onlinelibrary.wiley.com/doi/abs/10.1155/2023/8390619.

B. Zhu, X. Cao, Y. Wang, and Q. Gao. Constraint programming method for crew schedule recovery. Applied Mechanics and Materials, 496-500:1788 – 1791, 2014. URL https://api.semanticscholar.org/CorpusID:109852546.

B. Zhu, J.-P. Clarke, and J. Zhu. Real-time integrated flight schedule recovery problem using sampling-based approach. Journal of Computational and Theoretical Nanoscience, 13(2): 1458–1467, 2016. doi: doi:10.1166/jctn.2016.5068.