Robust airline scheduling with turnaround under uncertainty: towards collaborative airline scheduling

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Abstract

Robust airline scheduling fosters operational resilience in aviation by producing plans that remain feasible despite ensuing disruptions. This paper analyses the airline scheduling process, including flight scheduling, fleet assignment, aircraft routing, and crew pairing. It examines how previous studies optimise these decisions and deal with the influence of the aircraft ground handling (turnaround) process, an important aspect of airport operations that is known to often create havoc in flight timetables. The analysis of the literature focuses on how to harness turnaround resilience to improve airline schedule robustness and applies a framework of variables (characteristics) to support data collection and synthesis. The variables include levels of integration of multiple planning stages, uncertainty modelling, turnaround consideration, type of robustness sought, and type of optimisation method employed. Based on our review, we propose a comprehensive airline scheduling process that incorporates turnaround planning to enhance the estimation of aircraft turn time, crew sit time, and passenger connecting time under uncertainty. More precise estimates will enable models to produce robust schedules at a lower cost (shorter buffer times). Since third-party organisations typically operate turnarounds, this planning approach needs to involve multiple autonomous decision-makers. Therefore, we encourage a collaborative robust scheduling framework to be built on existing operations research theories and industry protocols.

Keywords: OR in airlines, turnaround operations, robust scheduling, collaborative scheduling

1. Introduction

Resilience in air transport systems has gained increasing attention from operational research (OR) scholars as it is a pressing need for the industry. The global air transportation system trans-

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ported over 5.0 billion passengers on more than 32.4 million flights worldwide in 2024 alone (ICAO, 2021; IATA, 2022; ICAO, 2024). Changes in planned departure or arrival time of flights — delays or cancellations— constitute irregular operations and may result in significant economic loss. For example, in the US, the costs of delays in 2019 were estimated at 33.5 billion dollars (FAA, 2020). The causes of irregular operations are varied, from unavoidable bad weather events to the pressure on capacity due to the industry's almost uninterrupted, steadfast growth. Since the latter is increasingly regarded as an important source of costly disruptions, it is imperative to factor in resilience in operations planning. The need for industry-specific planning models to develop profitable and resilient flight schedules has prompted relevant academic research.

Operational resilience has been defined in many contexts as the ability to withstand or rapidly recover from disruptions (Mattsson and Jenelius, 2015). Duchek (2020) identifies two approaches to foster resilience: active response and anticipation. The literature on airline scheduling is aligned with these views (Figure 1) as it recognises two types of resilience: disruption management (*responsiveness*) and schedule *robustness* (Hassan et al., 2021; Clausen et al., 2010). Disruption management leverages the responsiveness of the system by implementing *reactive* actions, e.g. swapping two aircraft when one becomes unavailable. Schedule robustness consists of foreseeing potential disruptions and proactively devising more *reliable* or *flexible* schedules. Reliable schedules absorb minor disturbances with virtually no changes needed, while flexible schedules facilitate the selection and implementation of recovery actions in the event of severe disruptions (Clausen et al., 2010).

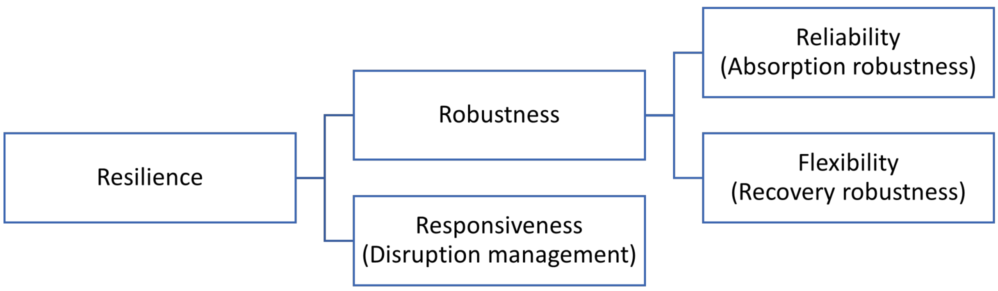


Figure 1: Taxonomy of airline scheduling resilience

The resilience of airline schedules and that of airport operations are mutually interdependent. However, each is controlled by separate organisations. Every scheduled flight requires airport facilities to land, take off, and handle aircraft (Schmidt, 2017). A significant portion of the uncertainty affecting airline operations stems from activities performed at airports, such as turnaround (De Neufville et al., 2013). Turnaround encompasses the services required by an aircraft before each outbound flight, e.g., cleaning, catering, and refuelling. This process significantly affects flight departure punctuality (De Neufville et al., 2013; Schmidt, 2017). The turnaround begins shortly after the aircraft arrives at the airport and must be completed before the scheduled departure time of its next flight. If disruptions affect the punctuality of inbound flights, the timing and efficiency of turnaround will also be affected (Wu and Caves, 2003). Similarly, delays in turnaround may propagate throughout the airline schedule. According to Eurocontrol (2023), overall arrival punctuality exceeded departure punctuality in 2022, which indicates the impact of airport operations, including turnaround, on delay propagation. Despite the interconnection between airline scheduling and turnaround resilience, they have mostly been studied individually. The reason may lie in the separation of decision makers; while airline schedules are developed by airline planners, the execution of aircraft turnaround is typically in the hands of ground handling service providers (GHSP), who subcontract from airlines directly.

We identified two gaps in the literature on airline schedule resilience. Firstly, to the best of the authors' knowledge, the way OR scholars have approached the interdependence between resilience in airline schedules and turnaround operations has not been surveyed yet. Secondly, with one exception (Ma et al., 2022), existing reviews have not discussed the two proactive resilience options each in its own right.

Existing literature surveys on airline and turnaround scheduling can be classified into three groups according to their approach to system resilience: no resilience, proactive resilience (robustness), and reactive resilience (responsiveness). Airline schedule planning involves decisions on flight scheduling, fleet assignment, aircraft routing, and crew scheduling (Barnhart et al., 2003a). Reviews focus on one or multiple of these decisions. Table 1 shows the scope of existing literature reviews and facilitates the classification of each group.

The first group of reviews does not apply resilience concepts. The studies surveyed by Wandelt et al. (2025); Kasirzadeh et al. (2017); Barnhart et al. (2003a) aim to plan schedules assuming that disruptions do not affect airline operations. As a consequence, uncertainty is not considered, and deterministic models are used to solve the scheduling problem. Schmidt (2017) examines studies that model and simulate the turnaround for various purposes, such as planning the operation and describing the impact of stochastic flight delays.

The proactive resilience group comprises reviews that examine the literature on airline schedule robustness. The objective of the reviewed articles is to plan robust schedules, recognising that uncertain events may disrupt the operation. Improving robustness demands modelling the inherent stochasticity of the system. Only Ma et al. (2022) appears to appreciate the conceptual difference

Study of resilience	Literature review paper	Decision					Type of resilience		
		FS	FA	AR	CP	TA	R	F	DM
No resilience	Wandelt et al. (2025)	✓	✓	✓	✓				
	Kasirzadeh et al. (2017)				✓				
	Schmidt (2017)					✓			
	Barnhart et al. (2003a)	✓	✓	✓	✓				
Reactive resilience	Wu et al. (2025)								✓
	Santana et al. (2023)								✓
	Hassan et al. (2021)								✓
	Su et al. (2021)								✓
	Clausen et al. (2010)								✓
	Ahmed and Poojari (2008)		✓						✓
	Filar et al. (2001)								✓
Proactive resilience	Xu et al. (2024)	✓	✓	✓	✓		$*$	$*$	
	Ma et al. (2022)			✓			✓	✓	✓
	Wen et al. (2021)				✓		$*$	$*$	✓
	Zhou et al. (2020)		✓	✓	✓		$*$	$*$	
	Deveci and Demirel (2018)				✓		$*$	$*$	
	Eltoukhy et al. (2017)	✓	✓	✓	✓		$*$	$*$	
	This review	✓	✓	✓	✓	✓	✓	✓	

FS: Flight schedule; FA: Fleet assignment; AR: Aircraft routing; CP: Crew pairing; TA: Turnaround
R: Reliability; F: Flexibility; DM: Disruption management; $*$: Do not differentiate between R and F

Table 1: Literature review papers grouped by scheduling decision and type of resilience

between reliability and flexibility. The authors analyse emerging technologies used to manage the uncertainty that affects aircraft routing. They primarily focus on smart technologies, e.g. big data, machine learning, and the internet of things. Other studies in this group do not differentiate the types of robustness (Xu et al., 2024; Wen et al., 2021; Zhou et al., 2020; Deveci and Demirel, 2018).

Reviews in the reactive resilience group analyse proposed models to recover a disrupted schedule in operational time rather than planning the schedule. Decisions in this case relate to the recovery of aircraft rotations, passenger itineraries, and crew itineraries post-disruption. Unlike proactive resilience, reactive resilience does not require uncertainty modelling because the disruption has already occurred.

Our review complements the proactive resilience group by examining the robustness of airline schedules considering all stages or decisions of the airline scheduling process, both types of schedule robustness— reliability and flexibility— , and how studies on airline schedule robustness model the influence of aircraft turnaround operations. The outcomes of our analysis will benefit the work of OR scholars in many directions. Firstly, the analysis will reveal patterns in the OR methods used to model uncertainty. Secondly, we discuss how the inclusion of turnaround operations may help researchers to identify new mechanisms to enhance the reliability and flexibility of airline schedules, such as where it may be most *cost-effective* to include a time buffer in the aircraft ground time. Cost-effectiveness depends on the trade-off between on-time performance and aircraft productivity (Wu and Caves, 2004). Thirdly, we will discuss the role of collaborative scheduling in enhancing robustness on turnaround.

This review complements the existing surveys on robust scheduling by examining the OR methods applied. Traditionally, airline scheduling has relied on deterministic, exact or heuristic optimisation models (Barnhart et al., 2003a). When the need for robust scheduling emerged more strongly in the early 2000s, simulation and stochastic optimisation models were also adopted (Barnhart et al., 2003a; Barnhart and Smith, 2012). Simulation models have been instrumental in evaluating schedule performance under uncertainty (Rosenberger et al., 2002; Lee et al., 2003), particularly when the schedule is planned using a deterministic optimisation model. However, the use of simulation in this context has not been surveyed (see Table A.1).

In summary, this paper outlines an approach to robust airline schedule planning that integrates turnaround resilience. By extending the airline scheduling process considering the turnaround planning, we offer a holistic scheduling perspective that is essential for enhancing the robustness of airline operations. We also propose a framework of definitions for robust airline scheduling from an OR standpoint. The developed framework is used to conduct a literature review and assess the current advancements in the topic. Based on a critical evaluation of the literature, we identify potential research directions to further develop the field.

This paper is organised as follows. Section 2 outlines the airline scheduling and turnaround planning processes, highlighting their interdependence. It also introduces our proposed framework for review, in all details. Section 3 discusses the methodology we followed in our survey, reporting the criteria used to identify and select the papers to be reviewed. Insights supported by descriptive statistics of our review findings are presented in section 4. Section 5 identifies open problems and discusses their impact on scholarship and practice. Section 6 offers guidelines for future work based on the OR methodologies applied in the literature. Finally, section 7 summarises our concluding remarks.

2. Evaluation framework for robustness approaches

The conceptual framework aims to describe the methodological and theoretical background that underpins this review by identifying the variables to be evaluated in the survey (Paul et al., 2024). The selection of the variables is based on relevant literature on airline and turnaround operations.

Particularly, we focused on research concerning airline schedule planning, as robustness is achieved during the planning process. The literature on airline scheduling, in turn, revealed the need to investigate the interactions between airline schedules and aircraft ground handling, or turnaround planning.

Section 2.1 analyses the airline planning process and its interrelation with turnaround. The analysis shapes the set of variables of our conceptual framework, presented in section 2.2.

2.1. Airline operations planning

During the airline planning process, planners design schedules based on strategic decisions about fleet acquisition and route coverage. Airline scheduling determines future operations, including details such as dates, times, and the allocation of resources to each flight (De Neufville et al., 2013; Belobaba et al., 2009). Airline schedule planning is typically formulated as an optimisation problem aimed at maximising profitability. This problem is commonly divided into four deterministic stages: flight scheduling, fleet assignment, aircraft routing, and crew pairing (Barnhart and Talluri, 1997; Barnhart et al., 2003a). Due to the complexity and large scale of the optimisation stages (Klabjan, 2005), these have been traditionally solved sequentially. In the traditional approach, the solution to one optimisation problem is an input for the subsequent stage. For instance, timetables obtained in flight scheduling constrain fleet assignment. Figure 2 illustrates the optimisation process and each of the stages, which are explained in the following sections.

2.1.1. Flight scheduling

During flight scheduling, airlines determine the markets to serve, the flight frequency on each route, and the scheduled departure and arrival times for each flight leg, i.e. the timetables. The decisions are driven by demand and seek to maximise overall profit and market share (Barnhart et al., 2003a; Barnhart and Talluri, 1997). A notable progress in algorithms developed for timetable planning involves the application of *incremental approaches*, which performs small changes to a published flight schedule by adding and removing flight legs from a predefined set (Barnhart et al., 2003a). These approaches solve the scheduling problem efficiently and set the foundation for flight *retiming* techniques (Barnhart et al., 2003a; Belobaba et al., 2009). Retiming adjusts flight departure times of a schedule within specified time windows after the optimisation of other subproblems. This technique improves the solution quality of subsequent subproblems, otherwise limited by the "optimal" flight schedule.

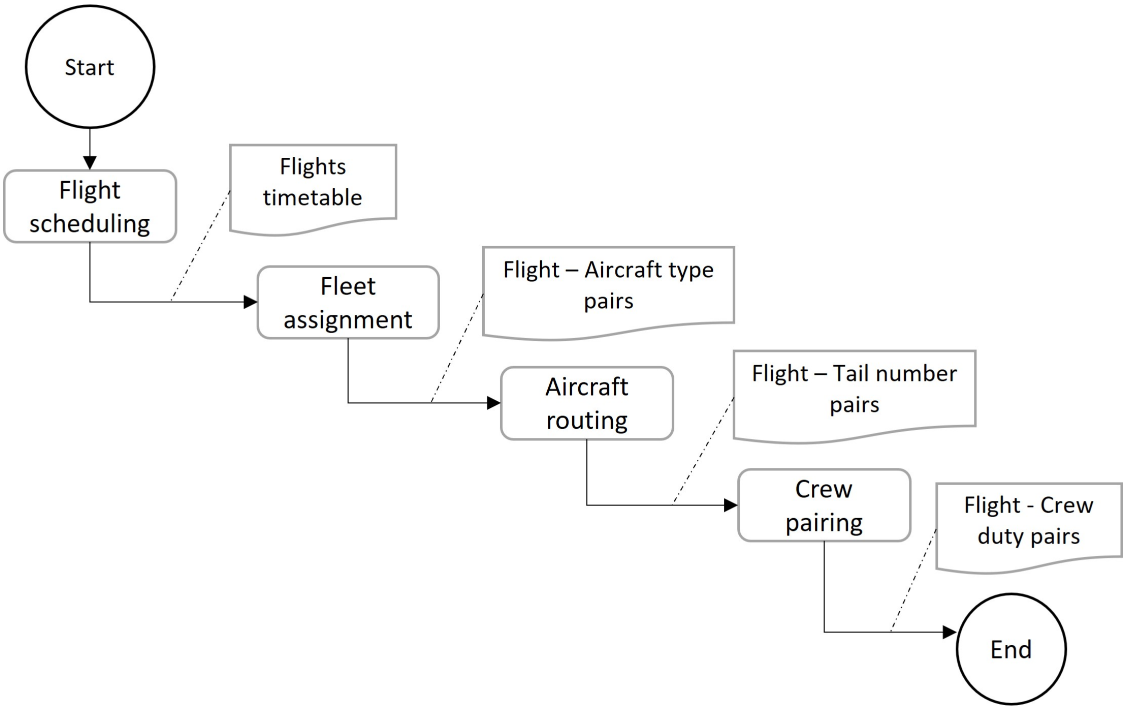


Figure 2: Airline schedule planning process

2.1.2. Fleet assignment

Fleet assignment allocates an aircraft type to each scheduled flight, aiming to meet market demand at minimal cost. Fleet assignment models (FAM) consider the technical characteristics and performance of the aircraft, e.g., size, range, etc. This typically results in maximising aircraft utilisation and keeping turnaround times at a minimum to reduce costs (De Neufville et al., 2013). The costs considered include the operating expenses of each flight leg and the passenger spill (unmet demand) costs.

The cost and productivity of the fleet are affected by both the airborne and ground time. Barnhart et al. (2003a) emphasise the importance of considering the stochastic nature of these times in fleet assignment models. Factors such as weather conditions, air traffic, and ground congestion contribute to variations in airborne and ground times. Ground time is heavily influenced by the uncertainty of turnaround operations, which are affected by the variability in sub-processes duration, the possible unavailability of required resources, and other factors.

2.1.3. Aircraft routing

Aircraft routing assigns specific aircraft to each flight leg in the timetable, based on the fleet allocations determined during the fleet assignment stage. This assignment provides the route that each aircraft will take across the network on the day of operations. To be more specific, the set of flights assigned to an aircraft is timed to form an ordered sequence where the destination of one flight is the origin of the subsequent one (Barnhart et al., 2003a; Wu, 2010). These routes must enable the aircraft to receive regular maintenance at specified airports; for that reason, this optimisation problem is often called aircraft maintenance routing problem.

Aircraft routing may generate disruptions that affect robustness. In schedules with insufficient time for airborne and ground operations, delays occur easily. Delays may propagate through the routes, potentially triggering flight cancellations and breaking crew and passenger connections.

2.1.4. Crew pairing

Crew scheduling assigns crew members to all flights in the timetable. To reduce complexity, it is broken down into two problems that are solved independently: crew pairing and crew assignment. Crew pairing generates multi-day work schedules for crews to cover all flights, aiming to minimise overall cost. Pairings are usually built by concatenating multiple duty periods, i.e. 24-hour sequence of flights separated by a certain connecting time, with mandatory rest time in between (Barnhart et al., 2003b). Each of these pairings is assigned to cockpit crew members and service attendants during crew assignment (Barnhart et al., 2003a), to form monthly schedules. In this paper, we analyse the crew pairing problem. Pairing considers constraints related to labour regulation, such as maximum duty time, minimum and maximum connection times (known as sit time), etc. (Barnhart et al., 2003a).

2.1.5. Aircraft ground handling or turnaround

The turnaround process prepares the aircraft for the next flight and takes place during its ground time. It encompasses various services, such as boarding and disembarking, baggage loading and unloading, refuelling, cabin cleaning, and others. Ideally, the turnaround starts at the Scheduled In-Block Time (SIBT) and ends at the Scheduled Off-Block Time (SOBT), corresponding to the time printed on passenger tickets for arrival and departure, respectively. Thus, the turnaround is aligned with the timetables produced by the flight scheduling. Additionally, there are precedence relations between certain pairs of turnaround activities, and some pairs cannot be executed at the same time, e.g. for most aircraft types, boarding cannot start until aircraft fuelling has finished. Therefore, efficient turnarounds are essential to ensure on-time departures.

The management of turnaround operations is inherently complex as it involves multiple actors and shared resources. Turnaround tasks are typically performed by third-party organisations subcontracted by airlines, the GHSP (Graham, 2018). There may be multiple GHSPs operating at each airport, meaning that they share physical space and equipment. An airport operator is responsible for coordinating the use of its facilities. Additionally, each GHSP team serves various turnarounds during the day, which implies travel times and replenishment of supplies. Hence, the visits of each team need to be planned through synchronised routing plans.

2.2. Framework variables

To support this review, we propose a framework that defines the characteristics considered essential in robust airline and turnaround scheduling studies, i.e. framework variables. The framework makes explicit prior knowledge and assumptions by supporting variables on fundamental topics (Tranfield et al., 2003), including non-resilient airline schedule planning and uncertainty management in comparable transportation systems, such as train timetable rescheduling (Zhan et al., 2024). To facilitate data extraction, synthesis, and explanation of the findings (Tranfield et al., 2003; Denyer and Tranfield, 2009; Paul et al., 2024), the framework also defines the values each variable can take. This enables the articles to be classified according to a predefined set of categories and analysed. Figure 3 offers a visual representation of the framework.

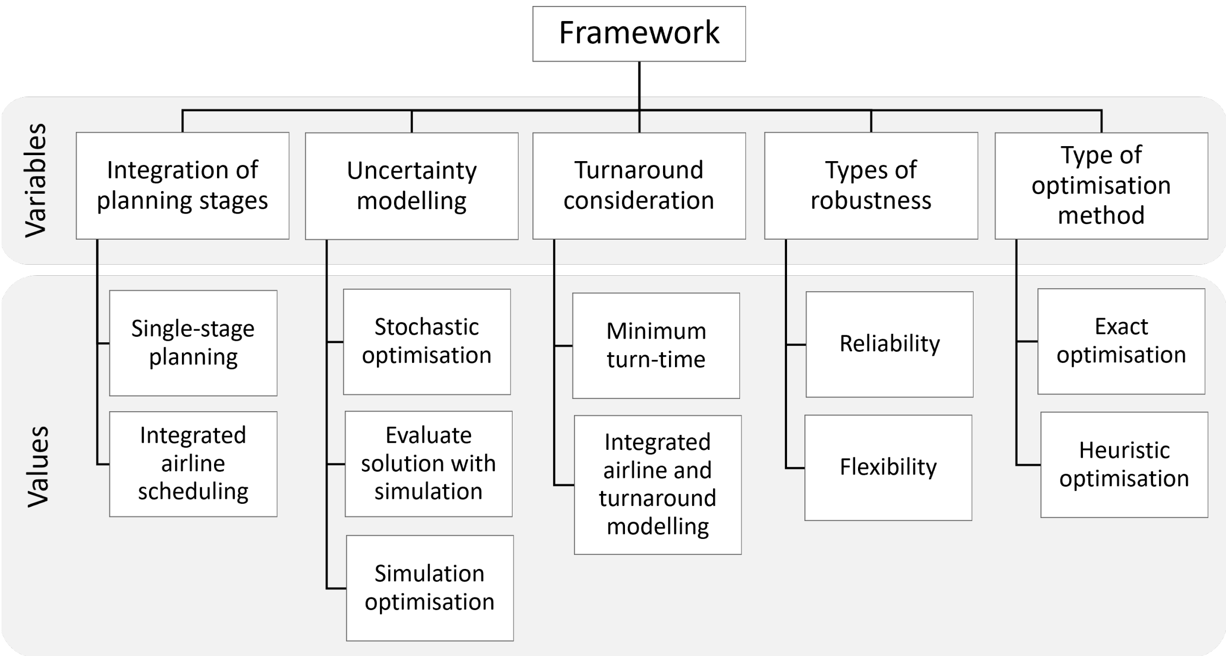


Figure 3: Framework variables and values

2.2.1. *Integration of planning stages*

The four airline scheduling subproblems had traditionally been addressed sequentially, taking the solution of one problem as input for the next one. The drawback of this approach is that the overall solution is often suboptimal because the solution of each stage constrains the feasible solutions of subsequent stages (Wu, 2010). The integration of planning stages variable describes the approaches that non-resilient airline scheduling literature, i.e. not concerned with robustness, has proposed to enhance the quality of the solution by integrally considering the airline scheduling subproblems.

Two strategies have been proposed to mitigate this adverse effect. The first widely used strategy replaces the exact flight times from the optimal schedule (first stage) with time windows in the formulation of the following subproblems. For example, a time window may start 10 minutes earlier than the optimal flight departure and finish 10 minutes later. This expands the search space in subsequent optimisation problems and enhances the quality of the overall solution. Various studies have employed this strategy to integrate flight scheduling with other stages, such as fleet assignment (Belanger et al., 2006; Rexing et al., 2000), aircraft routing (Desaulniers et al., 1997), and crew pairing (Klabjan et al., 2002). The second strategy formulates and solves a single optimisation model that addresses two or more planning problems. Barnhart et al. (1998) and Haouari et al. (2009) are examples that simultaneously solve fleet assignment and aircraft routing. This approach overcomes the limitation of the sequential approach, where the optimal fleet assignment may be infeasible for maintenance. The categories used to classify the papers according to this variable are:

***Single stage planning*:** Papers that solve one of the airline scheduling stages individually.

***Integrated airline scheduling*:** Articles that propose approaches to simultaneously address two or more airline schedule optimisation problems.

2.2.2. *Uncertainty modelling*

Airline operation planners aiming to plan robust schedules need to incorporate operational feedback into the decision-making process. The inherent stochasticity of airline operations often prevents optimal schedules from being operated as planned (Belobaba et al., 2009). Typically, the schedule planning process is completed months before the day of operations and assumes certain system conditions, e.g. specified flight block times and aircraft turn times. On the day of operations, however, the assumptions may not hold due to several factors and schedules derived from deterministic optimisation models may no longer be optimal. To address this, robust airline scheduling implements stochastic models to develop plans that remain effective despite potential operational disruptions.

The uncertainty modelling variable describes the OR methods that modellers can use to develop robust and cost-effective schedules in realistic operational settings. In the following, we present our selection of values for this variable, which is consistent with the categories that emerged from the literature on train scheduling under uncertainty (Zhan et al., 2024).

Stochastic optimisation: Multiple methods optimise the performance of the system under uncertain parameters, with the most typical being *two-stage stochastic programming*, *chance constraints* (Birge and Louveaux, 2011) and *robust optimisation* (Bertsimas and Sim, 2004).

***Evaluate deterministic solution with simulation*:** This approach produces an optimal solution using deterministic optimisation and evaluates its performance under uncertainty using simulation (Belobaba et al., 2009). Simulation may use different types of models such as *discrete-event simulation (DES)*, *agent-based simulation (ABS)*, or a hybrid model (Brailsford et al., 2019).

***Simulation optimisation*:** Method used to address large-scale optimisation problems, often referred to as optimisation via simulation (Petropoulos et al., 2023). It provides a framework for stochastic optimisation that uses simulation to estimate the stochastic variables (Fu, 2014). In particular, we refer to simulation optimisation as the approach where the random output of the simulation is used to guide the search process (Fu, 2014).

2.2.3. Turnaround consideration

In the review, we will analyse how airline scheduling models incorporate turnaround time.

***Minimum turnaround time*:** Studies that define the minimum turn time based on the technical specifications of each type of aircraft and a metric reflecting the congestion level of the airport where the turnaround is performed.

***Integrated airline and turnaround scheduling*:** The different services involved in the turnaround are modelled and integrated into algorithms to improve the resilience of airline schedules.

2.2.4. Types of robustness

We will review the following two types of robustness:

***Absorption robustness or reliability*:** The studies propose methods to include slacks into the schedule to absorb the effects of disruptions and remain feasible. These buffer times may be inserted in aircraft rotations, crew duties, or passenger itineraries, i.e. when developing the flight schedules according to the demand.

***Recovery robustness or flexibility*:** The approaches facilitate recovery actions to reduce the cost of resuming normal operations, e.g. injecting swap opportunities in aircraft rotations and crew pairings.

2.2.5. Optimisation methods

The values of this variable are ***exact optimisation*** and ***heuristic optimisation***.

3. Review Methodology

We review the contributions of published papers on the use of OR models to generate robust airline and turnaround schedules. The review evaluates relevant articles according to the variables of the framework introduced in Section 2.2 (Paul et al., 2024). The relevant articles were identified and screened following the procedure described in this section. The PRISMA flow diagram introduced in Moher et al. (2009) is used to visualise the process. The process includes four phases (see Figure 4). It starts with the identification phase, in which we searched the bibliographic database Scopus for terms describing two planning processes: airline scheduling and turnaround planning.

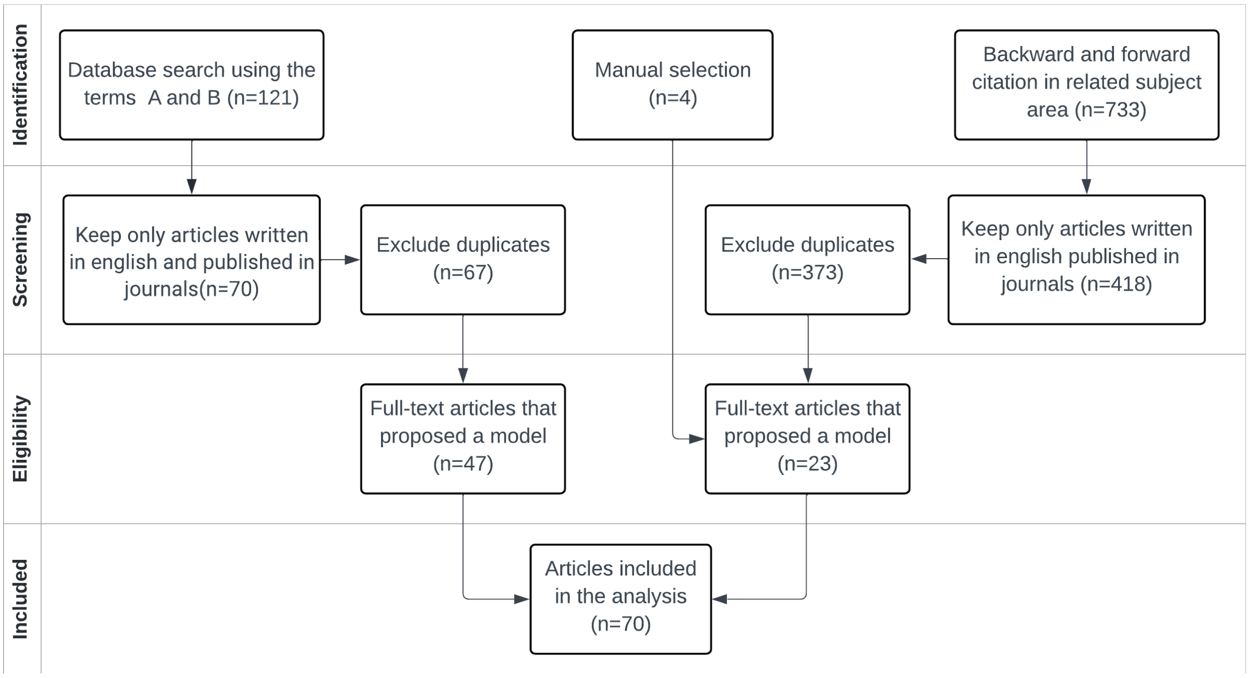


Figure 4: PRISMA workflow for paper selection

Table 2 shows the terms used. Term A contains keywords related to the development of robust airline schedules, considering the four stages of this process: flight scheduling and retiming, fleet assignment, aircraft routing, and crew pairing. Term B corresponds to the keywords related to the turnaround. Our review surveys turnaround resilience papers, i.e. robust planning and responsiveness, because we are interested in studying how resilient turnarounds can enhance airline scheduling. The identification phase used advanced searches with proximity operators to ensure the relevance of the majority of the selected documents. This step yielded 121 papers.

Code	Search Term
A	airline AND ((robust* OR resilien*) w/2 (((flight OR airline*) w/1 schedul*) OR ((fleet or tail) w/1 assignment) OR (aircraft w/1 (routing OR schedul*)) OR (crew w/1 (pairing OR schedul*)) OR (integrated w/1 (schedul* OR modeling))))
B	airport* AND ((robust* OR resilien* OR recover*) W/2 (plan*OR schedul*)) AND ((ground OR turnaround OR apron) AND operation*))

Table 2: Search terms per planning process

In the next phase, the identified papers were screened to keep only articles published in peer-reviewed journals, i.e. excluding conference papers, reviews and book chapters. Additionally, duplicates were eliminated at this stage. The publication date was not a screening criterion; hence, we considered all articles related to airline robustness and turnaround resilience. A corpus of 70 articles resulted from the screening step.

During the eligibility phase, we read the abstract of the screened papers to identify the research objectives. The eligibility criterion was to retain only articles that propose optimisation models; therefore, we excluded studies focused solely on modelling delay propagation. The reason is that the methods used to solve optimisation models are not comparable to those for delay modelling, e.g. queuing network models. The eligibility phase reduced the number of full-text reading papers to 47.

As a second identification step, we performed manual selection and citation analysis based on the bibliographies of the eligible papers. The backward and forward citation analyses identified 733 articles. These articles were screened using the same procedure described above, which reduced the dataset to 373 articles. Subsequently, the eligibility criteria described previously were applied. Together, the manual selection and citation analysis resulted in the selection of 23 new articles. In total, 70 papers were analysed as part of the literature review, 60 on airline schedule robustness, and 10 on turnaround resilience.

4. Descriptive statistics and insights

4.1. Emergence of robustness proxies

A classification that emerged from the review concerns the approach used to foster robustness. Some studies identify a specific characteristic of the schedule that arguably improves robustness and then optimise the schedule based on that feature. We refer to this approach as *proxy* robustness. An example of a proxy is penalising aircraft changes in crew pairing optimisation (Ben Ahmed et al., 2022). This proxy assumes that pairings where the crew stays in the same aircraft for consecutive flights are more robust than those where the crew must disembark and board a different aircraft because the requisite connecting time is shorter. Proxy robustness assumes that robustness can be improved in the planning stage without the need for feedback from the operational stage. In other words, the performance of solutions under operational uncertainty is not estimated during the optimisation process. In contrast, *feedback* robustness is driven by the capacity of the schedule to absorb or recover from disruptions, i.e. modellers estimate the future performance of the system. Typically, a feedback algorithm minimises a probabilistic delay measure, e.g., total propagated delay or the cost associated with delays. Our definition of feedback robustness differs from that of Froyland et al. (2014) and Maher et al. (2014) in that we consider feedback may occur even if performance assessment does not involve recovery actions. For example, Sanjeevi and Venkatachalam (2021) evaluates solutions to the flight retiming problem (which minimises delay propagation) using scenarios in the second stage of a two-stage stochastic programming formulation. In this case, operational feedback is derived from the primary delay scenarios.

Most authors opt for feedback approaches and limited attention has been given to proxies (see Table A.2). By analysing this under-researched approach, we identified promising opportunities to expand the research and practice on airline scheduling. Our analysis suggests that proxy approaches facilitate addressing complex problems with tractable formulations.
Firstly, proxies have enabled the optimisation of large networks (in terms of the number of flights). To simplify the comparison of approaches, Table 3 shows the optimisation problems that have been addressed using at least two approaches, with the corresponding maximum number of flights. For example, the first row (aircraft routing) says that the largest network addressed in feedback studies has 6,000 flights, while the figure for proxy studies is 9,036. According to the table, proxy approaches handled more flights than feedback approaches. The table also reveals that proxy and feedback approaches are not mutually exclusive. Their combination may produce robust schedules for realistic-sized networks, leading to significant cost savings for airlines.

Secondly, proxies have been instrumental in integrating crew pairing with other decision stages. Most of the crew scheduling studies (8 out of 11) apply a proxy. Integration entails challenges because crew pairing is a highly complex optimisation problem in itself. For example, a medium-sized fleet with 200 flights may result in billions of possible crew pairings (Klabjan, 2005). However, approaches that succeed in injecting robustness into crew pairings can yield higher profitability,

Optimisation problem	Feedback	Proxy	Proxy and Feedback	Other
Aircraft routing	6,000	**9,036**	3,370	667
Aircraft routing and flight retiming	1,278	1,278	**3,387**	
Crew scheduling	309	**3,300**	442	490
Aircraft routing and crew pairing	90	**1,130**	61	

Table 3: Maximum number of flights per approach reported in the literature

as the crew is the second-largest operative cost for airlines (after fuel). Thirdly, only five articles managed to integrate at least three optimisation problems for robust airline scheduling, with four relying on proxies. Table 4 lists all articles that apply a proxy and indicates whether they address single or integrated problems.

The previous analysis will hopefully motivate researchers to develop new proxies and improve existing ones by incorporating uncertainty modelling. Table 4 shows the method used to model uncertainty in each proxy study. Uncertainty management is crucial for proxy approaches because the effectiveness of the proxy is not certain. For example, Dück et al. (2012) evaluates the efficacy of the proxy that penalises crews changing aircraft using simulation. The study calculates the correlation between the indicator used in the optimisation (non-robustness penalties) and the robustness metric (reactionary delay) measured during the simulation. The results show a high correlation, which indicates that the proxy is effective. The analysis suggests that the proxy is as effective as optimising the expected reactionary delay. Dück et al. (2012) also examines the proxy efficiency and reports that reactionary delays can be decreased by up to 6.4% without increasing crew costs. Their analyses assume that simulation can accurately estimate schedule performance during operations because it can capture non-linear dependencies. The importance of evaluating robustness will be discussed further in section 4.3.

4.2. Integration of airline planning stages and type of optimisation method

The articles analysed in our review have contributed to scholarship and practice by i) innovating models to consider uncertainty and maintain tractability, ii) developing efficient algorithms to solve the models, iii) demonstrating how expanding the problem conceptualisation can enhance robustness, iv) analysing the relative advantages of specific modelling approaches, e.g. comparing robust optimisation versus chance constraints to address aircraft routing, v) proposing metrics and methodologies to evaluate robustness, and vi) introducing robustness proxies. Tables 5 - 9 classify the literature according to its main contributions or innovations. The tables also summarise the characteristics of the methods applied to solve the models and the size of the network addressed.

			Problem			App			
Citation	FS	FA	AR	CP	TA	P	F	Proxy	UM
Ben Ahmed et al. (2018)			x	x		x		Short crew connecting time Crew changing aircraft	ES
Ben Ahmed et al. (2022)		x	x	x		x		Short crew connecting time Crew changing aircraft	-
Cacchiani and Salazar-Gonzalez (2017)		x	x	x		x		Crew changing aircraft	-
Cacchiani and Salazar-Gonzalez (2020)	x	x	x	x		x		Short crew connecting time Crew changing aircraft	-
Dück et al. (2012)			x	x		x	x	Crew changing aircraft	TS
Gao et al. (2009)		x		x		x		Station purity Crew base purity	-
Ruther et al. (2017)			x	x		x		Crew changing aircraft	-
Weide et al. (2010)			x	x		x		Short crew connecting time Crew changing aircraft	-
López-Ramos et al. (2025)	x		x			x		Slack between flights	-
Ben Ahmed et al. (2017a)	x		x			x	x	Slack between flights	SB
Aloulou et al. (2013)	x		x			x		Slack between flights	ES
Ehrgott and Ryan (2002)				x		x		Short crew connecting time Crew changing aircraft	-
Schaefer et al. (2005)				x		x		Short crew connecting time	ES
Shebalov and Klabjan (2006)				x		x		Similar crew duty per base	-
Tam et al. (2011)				x		x	x	Short crew connecting time Crew changing aircraft	TS
Wei and Vaze (2018)				x		x		Crew changing aircraft Crew base purity	-
Diepen et al. (2013)					x	x		Idle time of boarding buses	ES
Lapp and Cohn (2012)			x			x		Maintenance misalignments	-
Maher et al. (2014)			x			x	x	Maintenance misalignments	TS
Zhang et al. (2024a)			x			x		Delay risk of maintenance tasks	-
Rosenberger et al. (2004)		x				x		Hub isolation & short cycles	ES
Smith and Johnson (2006)		x				x		Station purity	-

FS: Flight scheduling; FA: Fleet assignment; AR: Aircraft routing; CP: Crew pairing; TA: Turnaround
App: Robustness approach (P: Proxy; F: Feedback); UM: Uncertainty modelling (ES: Evaluate with simulation; TS: Two-stage stochastic programming; SB: Scenario-based optimisation); - No uncertainty modelling

Table 4: Summary of studies applying proxy approaches

This aims at giving a sense of the tractability of the models and efficiency of the approaches.

To develop new knowledge, researchers can extend these methodologies while addressing the limitations of specific approaches and modelling choices. From our analysis of these limitations, we derived four main recommendations for future research. Firstly, since robustness always comes at a cost, e.g. reduced aircraft utilisation or additional ground resources, these costs should be modelled either as variables or constraints. This becomes critical for robust optimisation approaches that may produce over-conservative and costly optimal solutions (Ball et al., 2007).

Secondly, the type of disruption addressed should be carefully considered when modelling un-

Paper reference	ToC	Main contribution or innovation	ToM	Method	Flights
Sanjeevi and Venkatachalam (2021)	i, ii	TS model that balances rescheduling and delay costs, and L-shaped algorithm	E	BD	324
Novianingsih and Hadianti (2016)	i	Scenario-based stochastic retiming approach	H	-	287
Duran et al. (2015)	i, iii	Pioneer in modelling airport congestion and cruise time as a controllable variable	E	CPLEX	114
Chiraphadhanakul and Barnhart (2013)	iv	Compare flight retiming with aircraft rerouting, optimising multiple objectives	E	CPLEX	268
Sohoni et al. (2011)	i, ii	First CC model with block-time uncertainty and efficient cutting algorithm	E	BD	1500
Ahmadbeygi et al. (2010)	i	Simple linear model that applies time windows to maintain revenue	E	CPLEX	500
Lee et al. (2007)	i, ii	Model crewing variables to balance planned and operational costs	H	MGA	441
Wu (2006)	iii	Pioneer in modelling turnaround and block-time uncertainties	H	-	-
Wu and Caves (2002)	v	Robustness metrics (expected delay and mean delay in rotation segments)	E	-	7

ToC: Type of contribution; i, ii, ii, iv, v: See main text; TS: Two-stage stochastic programming; CC: Chance constraints; ToM: Type of method; E: Exact method; H: Heuristic; BD: Benders decomposition; -: Not specified; CPLEX: Commercial solver

Table 5: Main contributions and innovations of flight scheduling and retiming papers

Paper reference	ToC	Main contribution or innovation	ToM	Method	Flights
Smith and Johnson (2006)	ii, vi	Limit the number of fleets or crew compatible families that can serve each station to facilitate swaps	H	CG-based	4182
Rosenberger et al. (2004)	vi	Creates partial rotations with many short cycles to mitigate the impact of cancellations	E	-	2558

ToC: Type of contribution; i, ii, ii, iv, v, vi: See main text; ToM: Type of Method; E: Exact method; H: Heuristic; CG: Column generation

Table 6: Main contributions and innovations of fleet assignment papers

certainty. For example, the recoverable robust approach addresses severe disruptions, i.e. cancellations and aircraft unavailability, and applies scenario-based optimisation (Glomb et al., 2024) or two-stage stochastic programming (Froyland et al., 2014). The variability of this type of disruption is typically high, and therefore, the scenarios should be rigorously defined to ensure that the solution is robust and close to the true optimum. Future research could expand these approaches by applying sample average approximation (SAA) to analyse the impact of this modelling choice in managing severe and highly variable disruptions (Birge and Louveaux, 2011).

Thirdly, while using deterministic functions to compute propagated delay (affected by scheduling decisions) can reduce model complexity and computation time, they may produce inaccurate estimations of delays and the associated costs. An interesting future stream of research is how these functions can be based on delay propagation models, for example, using delay multipliers as

Paper reference	ToC	Main contribution	ToM	Method	Flights
Akıncılar and Güner (2025)	v	Methodology to evaluate the performance of robust solutions	E	-	229
Zhang et al. (2024a)	vi	Introduce proxy based on fuzzy risk assesment of delays	H	MH	9036
Birolini and Jacquillat (2023)	i	Scenario-based model with sample average approximation	E	B&C	700
He et al. (2023)	iii	Pioneer to model disruptions caused by maintenance operations	E	CG	259
Eltoukhy et al. (2020)	iii	Pioneer to reduce turnaround duration to improve robustness	H	ACO	400
Cui et al. (2019)	ii	Solving algorithm that outperforms CPLEX	H	VNS	667
Marla et al. (2018)	iv	Compare RO and CC generic models (solution quality and tractability)	E	CPLEX	165
Yan and Kung (2018)	i	First RO approach that models correlation between flight delays	E	RG + CG	117
Liang et al. (2015)	i, ii	Model daily maintenance capacity and introduce a CG-based heuristic	H	CG-based	6000
Maher et al. (2014)	i	Detailed single-day AR and analyse connection cost functions (quality, runtime)	E	BD + CG	3370
Froyland et al. (2014)	i	Pioneer to model a recoverable robust AR based on TS	E	BD + B&P	53
Lapp and Cohn (2012)	i, vi	Pioneer to model MLOF and maintenance misalignment proxy	E	CPLEX	3353

ToC: Type of contribution; i, ii, ii, iv, v, vi: See main text; MO: Multi-objective model; GP: Goal programming; CPLEX: Commercial solver; RO: Robust optimisation; CC: Chance constraints; CG: Column generation AR: Aircraft maintenance routing model; TS: Two-stage stochastic programming; MLOF: Maintenance line-of-flight; ToM: Type of method; E: Exact method; H: Heuristic; -: Not specified; MH: Matheuristic; B&C: Branch and cut; CG: Column generation; ACO: Ant colony optimisation; VNS: Variable neighbourhood search; RG: Row generation; BD: Benders decomposition; B&P: Branch and price

Table 7: Main contributions and innovations of aircraft routing papers

introduced in Wu and Law (2019).

Fourthly, combining multiple scheduling problems does not always improve robustness or produce a useful approach to address the industry's needs. Therefore, this type of research should demonstrate the contributions to practice and scholarship. For example, Memarzadeh et al. (2024) attempts to integrate aircraft routing and crew rostering by building four-week pairings. Assigning individual crew members to aircraft rotations several months before operations may be simply impractical, even if a tractable model could be formulated while complying with all applicable regulations and business rules, e.g. holidays and fair workload (Barnhart et al., 2003b).

Paper reference	ToC	Main contribution or innovation	ToM	Method	Flights
Schrotenboer et al. (2023)	i	Model repairs crew assignments maintaining flexibility to address future disruptions	E	B&P	309
Wen et al. (2020)	v	Incorporate a robustness metric dependent on the cruise variable time	E	CG	98
Antunes et al. (2019)	i	RO model with crew delay propagation and the complex crew cost structure	E	CG	94
Wei and Vaze (2018)	iv	Estimate the extent of the crew-propagated delays and disruptions	H	CG & B&B	3300
Bayliss et al. (2017)	i	Schedule standby duties for reserve crews to minimise flight delays and cancellations	E	CPLEX	243
Chung et al. (2017)	iii	Crew pairing considering reserve crew planning	E	CG	447
Lu and Gzara (2015)	i, ii	RO model solved with an efficient algorithm based on LR for a larger instance	E	LR	184
Muter et al. (2013)	ii	Solves the extra flight problem with a more efficient algorithm for a larger network	H	RG & CG	490
Tam et al. (2011)	iv	Compares TS (Yen and Birge, 2006) and MO (Ehrgott and Ryan, 2002) using delay scenarios	E	DCG	442
Tekiner et al. (2009)	iii	Flexibility for extra flights by increasing swap opportunities and long connections	E	CG	96
Shebalov and Klabjan (2006)	i	Maximise swap opportunities within limited additional crew cost	H	LR	228
Yen and Birge (2006)	i, ii	Model relationships between crew pairings in the non-linear recourse component	E	B&B-based	79
Schaefer et al. (2005)	v	Introduces a measure for evaluating performance based on the FTC	H	LS	342
Ehrgott and Ryan (2002)	ii, vi	MO model that penalises aircraft changes, solved with e-constraint method	E	B&B	-

ToC: Type of contribution; i, ii, ii, iv, v, vi: See main text; RO: Robust optimisation; LR: Lagrangian relaxation; TS: Two-stage stochastic programming; MO: Multi-objective model; FTC: Flight time credit; ToM: Type of method; E: Exact method; H: Heuristic; B&P: Branch and price; CG: Column generation; B&B: Branch and bound; CPLEX: Commercial solver; RG: Row generation; DCG: Dynamic column generation; LS: Local search

Table 8: Main contributions and innovations of crew pairing papers

4.3. Uncertainty modelling

We have included two new subcategories under the stochastic optimisation group to classify papers that consider stochasticity but do not fit within the subcategories introduced in section 2.2. The *expected value* subcategory includes approaches that formulate and solve a deterministic model to optimise the expected value of a delay cost function. The *scenario-based* subcategory uses disruption scenarios to assign values to specific parameters within the optimization model or to evaluate the performance of the schedule. Scenario-based approaches either use historical data or realise a probability distribution. For a detailed explanation of the differences between these

Paper reference	FS	FA	AR	CP	ToC	Main contribution or innovation	ToM	Method	UM	Flights
López-Ramos et al. (2025)	x		x		ii	Address the MO model with lexicographic GP and e-constraint methods	E	CPLEX	-	-
Glomb et al. (2024)		x	x		i	Embeds a recovery optimiser into a planning model (similar recoverable robust AR)	H	Gurobi	SB	120
Memarzadeh et al. (2024)			x	x	iii	Tries to build crew parings that expand few weeks	H	RG & CG	SB	90
Ben Ahmed et al. (2022)		x	x	x	i, ii	Integrate three problems in a single model and propose a MH to solve it	H	MH	-	646
Deng et al. (2022)		x	x		ii	Heuristic algorithm combining VNS and CG	H	VNS & CG	-	-
Simsek and Akturk (2022)	x	x	x		ii	Introduces a MH to solve the integrated model	H	MH	CC	150
Xu et al. (2021)	x	x	x		i, ii	Consider demand recapture and solve the model with an efficient al VNS algorithm	H	VNS	EV	1607
Cacchiani and Salazar-Gonzalez (2020)	x	x	x	x	i	Retime an existing schedule considering aircraft maintenance and crewing constraints	H	CG-based	-	172
Ben Ahmed et al. (2018)			x	x	i	Integrate AR and CP problems in a model that can be solved with a commercial solver	E	CPLEX	ES	336
Ben Ahmed et al. (2017a)	x		x		ii	Solves the two problems sequentially for a weekly schedule and a large network	H	CPLEX	SB	3387
Ben Ahmed et al. (2017b)	x		x		ii	Introduce a heuristic that embeds simulation to solve the integrated problem efficiently	H	PSO & GA	SB	1278
Cacchiani and Salazar-Gonzalez (2017)		x	x	x	i, ii	Model three problems jointly and introduce an efficient heuristic that reaches optimality	H+	B&P	-	172
Jamili (2017)	x		x		ii	Efficient hybrid heuristic algorithm	H	PSO & SA	RO	-
Ruther et al. (2017)			x	x	ii	Model pricing problems for groups of resources with similar availability periods and base	H	B&P	-	1130
Liu et al. (2016)		x	x		i	MO model that minimises costs and propagated delay	E	B&P	EV	252
Dunbar et al. (2014)			x	x	ii	Iteratively solve AR and CR, considering interactions across resources in propagated delay	H	CG-based	SB	54
Aloulou et al. (2013)	x		x		vi	Model based on a proxy that quantifies passenger misconnections	E	CPLEX	ES	1278
Dück et al. (2012)			x	x	i	Pioneer in integrating AR and CP in a TS model	E	CG	TS	61
Dunbar et al. (2012)			x	x	i	Compute the propagated delay considering the interactions between aircraft and crew	E	CPLEX	EV	54
Burke et al. (2010)	x		x		ii, iv	Compare reliability vs flexibility approaches using MO and introduce hybridised GA with LS	H	GA & LS	SB	504
Weide et al. (2010)			x	x	ii	Improve cost and robustness progressively by iteratively solving AR and CP models	H	-	-	750
Gao et al. (2009)		x		x	i	Model crew connections explicitly and base robustness on FA proxy (station purity)	E	B&B	-	1388
Lan et al. (2006)	x		x		i	Seminal AR and FR (separate) models to improve integrated and single-problem approaches	E	B&P	EV	102/1067

FS: Flight scheduling; FA: Fleet assignment; AR: Aircraft routing; CP: Crew pairing; ToC: Type of contribution; MO: Multi-objective; MH: Matheuristic; VNS: Variable neighbourhood search; CG: Column generation; SA: Simulated annealing; TS: Two-stage stochastic programming; GA: Genetic algorithm; ToM: Type of method; E: Exact; H: Heuristic; RG: Row generation; PSO: Particle swarm optimisation; B&P: Branch and price; LS: Local search; B&B: Branch and bound; SB: scenario-based optimisation; CC: Chance constraints; EV: Expected value; ES: Evaluate with simulation; RO: Robust optimisation

Table 9: Main contributions and innovations of papers addressing multiple scheduling problems

two new subcategories and stochastic programming, refer to Birge and Louveaux (2011).

			Optimisation Problem					App	
Citation	UM	Int	FS	FA	AR	CP	TA	P	F
Dunbar et al. (2012)	EV	I			x	x			x
Lan et al. (2006)	EV	I	x		x				x
Liu et al. (2016)	EV	I		x	x				x
Xu et al. (2021)	EV	I	x	x	x				x
Liang et al. (2015)	EV	S			x				x
Wu and Caves (2002)	EV	S			x				x
He et al. (2023)	EV	S			x				x
Schrotenboer et al. (2023)	EV	S				x			x
Glomb et al. (2024)	SB	I		x	x				x
Memarzadeh et al. (2024)	SB	I			x	x			x
Ben Ahmed et al. (2017a)	SB	I	x		x			x	x
Ben Ahmed et al. (2017b)	SB	I	x		x				x
Burke et al. (2010)	SB	I	x		x				x
Dunbar et al. (2014)	SB	I			x	x			x
Evler et al. (2021a)	SB	I					x		x
Ahmadbeygi et al. (2010)	SB	S	x						x
Chiraphadhanakul and Barnhart (2013)	SB	S	x						x
Eltoukhy et al. (2020)	SB	S			x				x
Birolini and Jacquillat (2023)	SB	S			x				x
Bayliss et al. (2017)	SB	S				x			x
Lee et al. (2007)	SB	S	x						x
Novianingsih and Hadianti (2016)	SB	S	x						x
Wu (2006)	SB	S	x						x
Gök et al. (2023)	Sim-opt	S					x		x
Guimarans and Padrón (2022)	Sim-opt	S					x		x
Marla et al. (2018)	CC vs RO	S			x				x
Simsek and Akturk (2022)	CC	I	x	x	x				x
Duran et al. (2015)	CC	S	x						x
Sohoni et al. (2011)	CC	S	x						x
Zhu et al. (2022)	CC	S					x		x
Jamili (2017)	RO	I	x		x				x
Lu and Gzara (2015)	RO	S				x			x
Yan and Kung (2018)	RO	S			x				x
Zhang et al. (2024b)	RO	S					x		x
Antunes et al. (2019)	RO	S				x			x
Dück et al. (2012)	TS	I			x	x		x	x
Froyland et al. (2014)	TS	S			x				x
Han et al. (2023)	TS	S					x		x
Maher et al. (2014)	TS	S			x			x	x
Sanjeevi and Venkatachalam (2021)	TS	S	x						x
Tam et al. (2011)	TS	S				x		x	x
Yen and Birge (2006)	TS	S				x			x

UM: Uncertainty modelling (EV: Expected value; SB: Scenario-based optimisation; Sim-opt: Simulation optimisation; CC: Chance constraints; RO: Robust optimisation; TS: Two-stage stochastic programming; CC vs RO: compare CC with RO); Int: Integration (S: Single stage; I: Integrated); FS: Flight scheduling; FA: Fleet assignment; AR: Aircraft routing; CP: Crew pairing; TA: Turnaround; App: Robustness approach (P: Proxy; F: Feedback)

Table 10: Articles applying feedback during optimisation

Most authors (76%) recognise that modelling the inherent stochasticity of airline and turnaround operations is essential to developing robust schedules (see Table A.2). This is especially true for studies on turnaround resilient scheduling, as most papers (80%) use feedback from operations during optimisation or evaluate schedule robustness using simulation. This signals a higher awareness within the academic community of the multiple uncertainties in turnaround operations. The guideline for future research on airline and turnaround scheduling is to incorporate operations feedback in the optimisation models. This can be accomplished by applying stochastic programming, robust optimisation, simulation optimisation, expected values or scenarios-based approaches. Table 10 summarises the feedback approaches proposed in the literature to solve different optimisation problems.

As seen in Table 10, modellers prefer expected values and scenario-based optimisation to manage the uncertainty in integrated optimisation problems. Only two studies apply stochastic programming (Simsek and Akturk, 2022; Dück et al., 2012), and one uses robust optimisation (Jamili, 2017) for integrated formulations. This should not discourage research on the application of those methodologies. Drawing on existing literature, future research may study how Benders' decomposition can solve a two-stage stochastic programming model to address an integrated aircraft routing and crew pairing problem. Dück et al. (2012) decomposes and iteratively solves (using column generation) a two-stage recourse model for the integrated aircraft routing and crew pairing problem. Froyland et al. (2014) and Maher et al. (2014) decompose the aircraft routing problem in two stages. In the first (deterministic) stage, they formulate aircraft planning while considering maintenance constraints. The second stage uses stochastic recovery scenarios (aircraft rerouting, flight cancellation and delays) to guide the search towards solutions that perform better under uncertainty. Both studies use Benders' decomposition to solve the problem as it is "naturally fit" for two-stage stochastic programming.

For articles implementing a robustness proxy with a deterministic model, it is advisable to evaluate schedule robustness with simulations or scenarios. Besides demonstrating the effectiveness of the proxy, simulation can help demonstrate the value of robustness. For example, Rosenberger et al. (2004) proposes a proxy-based fleet assignment model to reduce the cost of recovering from disruptions. The proxy assumes that maximising the number of short cycles (sequence of flight legs that start and end at the same hub) facilitates aircraft reroutings, reducing the need for flight cancellation when a flight is delayed. The effectiveness of the proxy can only be measured by evaluating the schedule in the simulated operational setting. Rosenberger et al. (2004) uses a discrete-event simulation (DES) model (Rosenberger et al., 2002) to prove that their schedules outperform the minimum-cost schedule using robustness metrics, i.e. tardiness, cancellations, reroutings and swaps.

Since DES models can represent relevant aspects of the operational environment, including shared resources, they more accurately evaluate the future schedule performance. From Table 11, which lists all studies using simulation for schedule evaluation, we can learn that not only proxy approaches benefit from DES simulation. Five feedback studies use a DES model or Simair (Rosenberger et al., 2002; Lee et al., 2003) after the schedule has been optimised. Simair is a DES model that comprehensively emulates the airline operational system (airside), including the recovery actions implemented to mitigate disruptions. However, the turnaround duration in Simair is modelled using a single probability distribution. Further research can be conducted to integrate a detailed model of turnaround activities and resources in the simulation model to evaluate schedule performance.

Citation	Uncertainty Model		App		Int	Decision problem				
	Simulation	Feedback	P	F		FS	FA	AR	CP	TA
Burke et al. (2010)	DES	SB		x	I	x		x		
Ahmadbeygi et al. (2010)	DES	SB		x	S	x				
Novianingsih and Hadianti (2016)	DES	SB		x	S	x				
Diepen et al. (2013)	DES		x		S					x
Ben Ahmed et al. (2017b)	MC	SB		x	I	x		x		
Wu (2006)	MC	SB		x	S	x				
Guimarans and Padrón (2022)	MC	Sim-opt		x	S					x
Marla et al. (2018)	MC	CCvsRO		x	S			x		
Zhu et al. (2022)	MC	CC		x	S					x
Ben Ahmed et al. (2018)	MC		x		I			x	x	
Aloulou et al. (2013)	MC		x		I	x		x		
Gök et al. (2023)	MC+DES	Sim-opt		x	S					x
Akıncılar and Güner (2025)	∗				S		x			
Antunes et al. (2019)	∗	RO		x	S				x	
Evler et al. (2021b)	∗				I					x[b]
Chung et al. (2017)	∗				S				x[a]	
Lee et al. (2007)	Simair	SB		x	S	x				
Rosenberger et al. (2004)	Simair		x		S		x			
Schaefer et al. (2005)	Simair		x		S				x	
Wei and Vaze (2018)	Simair		x		S				x	
Ben Ahmed et al. (2017a)	Simair	SB	x	x	I	x		x		

DES: Discrete-event simulation; MC: Monte Carlo simulation; SB: Scenario-based optimisation; CC: Chance constraints; RO: Robust optimisation; CCvsRO: Compare CC with RO; Sim-opt: Simulation optimisation; App: Robustness approach (P: Proxy; F: Feedback); Int: Integration (I: Integrated, S: Single stage); FS: Flight Scheduling; FA: Fleet Assignment; AR: Aircraft Routing; CP: Crew pairing; TA: Turnaround; * Not specified; [a] Only for reserve crew; [b] Integrated with gate-reallocation

Table 11: Studies using simulation for schedule evaluation

4.4. Turnaround consideration

Only three studies modelled turnaround operations to enhance the resilience of aircraft rotations. Wu (2006) optimise the use of scheduled buffer times to maintain the balance between reliability and profitability. The optimisation model reallocates and resizes buffers in the aircraft rotations according to their vulnerability to delay propagation. The effectiveness of the allocated buffers is evaluated using simulation models: a Monte Carlo simulation module accounts for the uncertainty in en-route operations, and a semi-Markov chain model simulates ground operations. Besides demonstrating that efficient turnarounds can absorb delays in the airline network, Wu (2006) proves that considering turnaround uncertainty enables the appropriate use of costly buffer times. In Evler et al. (2022) and Glomb et al. (2023), the potential of ground operations to mitigate delay propagation was used to boost airline schedule recovery. These three studies demonstrate that modelling turnaround activities potentially improves the performance of airline robust schedules, revealing a gap in the literature. Existing research on turnaround scheduling provides valuable tools to address the complexity of turnaround modelling in future research, in particular, studies addressing the planning of multiple services simultaneously (Guimarans and Padrón, 2022; Gök et al., 2023; Zhu et al., 2022). This will be discussed in-depth in the section 6.

4.5. Type of robustness

Relatively limited research has been dedicated to flexibility compared to reliability (see Table A.2). To encourage further investigation of this under-researched strategy, we outline the main characteristics of the existing literature on schedule flexibility.

Flexible schedules facilitate strategies to manage disruptions aiming to reduce the realised cost, i.e. the cost of executing the schedule on the day of operations when disruptions occur. There exist two major flexibility approaches in the literature. The first approach increases the opportunities for aircraft and crew swaps (Burke et al., 2010; Maher et al., 2014), while the second reduces the impact of delaying and cancelling flights (Rosenberger et al., 2004; Simsek and Akturk, 2022). Similar to absorption robustness, there are costs associated with recovery robustness. Half of the studies that foster flexible schedules optimise a surrogate for robustness. Common proxies in the literature include: short aircraft cycles and hub isolation (Rosenberger et al., 2004), to reduce the cost of cancellations; station and crew base purity (Smith and Johnson, 2006; Gao et al., 2009), to facilitate aircraft and crew swaps, etc. In the case of proxies, an extra planned cost may result from competing objectives. For instance, short cycles and hub isolation imply reduced connectivity between hubs. Isolated hubs prevent disruptions at one hub from spreading to another. However, this assignment may prevent the schedule from capturing "throughs"—sequences of flights with demand from the first to the last flight leg that are operated by the same aircraft. There is revenue associated with the premium paid by passengers who avoid changing aircraft in their connections.

The scope of our review includes ten articles dedicated to turnaround resilience, i.e. robustness and responsiveness. Six articles promote reliability in turnaround operations (see Table A.2). The mechanisms applied by these studies are similar to those used to improve absorption robustness in airline schedules. Overall, in the six approaches, larger slacks are assigned to resources serving operations more susceptible to delays (Diepen et al., 2013; Guimarans and Padrón, 2022; Gök et al., 2023). The remaining four papers focus on the disruption management of apron operations and, therefore, are not included in the classification of studies per type of robustness. The excluded articles study the potential of ground operations (turnaround and gate assignment) to improve the resilience of airline operations. To be more specific, the authors optimise the recovery of turnaround schedules and gate assignments given airline schedule deviations considering passenger and crew connections (Evler et al., 2021a,b). The recovery options developed in these studies are incorporated into the aircraft recovery model introduced in Evler et al. (2022). Interestingly, these ten articles reveal growing recognition among scholars of the importance of airport processes, such as turnaround, to robust airline scheduling.

5. Discussion and open problems

The previous section synthesises the literature on robust airline scheduling by combining and evaluating the findings of individual studies. The insights derived from this process revealed open problems that will be discussed in this section to shape prospective research directions.

The most prominent problem is the need for a wider perspective on the airline scheduling process, incorporating aircraft turnaround. By considering the turnaround and its impact on airline operational resilience, i.e. delay creation and propagation, the academic community can innovate their approaches to robust scheduling. Optimisation models must consider that turnaround time varies depending on the aircraft type, airport congestion and availability of ground resources, e.g. staff, equipment, and stands. Overlooking this variability may result in under- (or over-)estimation of optimal connection times for aircraft rotations, crew duties, and passenger itineraries. Future research should aim to incorporate these three variability factors into robust scheduling decisions such as aircraft routing, crew pairing and flight retiming. Modelling turnaround activities and resources may be needed to capture the impact of ground-handling tasks on each specific scheduling problem. For example, the interaction between the deboarding and boarding of crews changing aircraft influences crew pairing decisions. Likewise, tight synchronisation between these two activities (deboarding and boarding) may result in broken passenger itineraries, affecting passenger spill and recapture, which concerns fleet assignment and flight retiming models.

To address this need, we propose the *comprehensive airline scheduling process*, illustrated in Figure 5. The figure expands Figure 2 by including a decision stage where the turnaround is planned. This decision takes the partial schedule as input (green arrow) to estimate the aircraft turn time and crew connecting time using a model of the ground handling operations in key airports (hubs). Then, the estimations can inform the aircraft routing, crew pairing, and flight retiming decisions (blue arrows). Partial examples of comprehensive scheduling process are in Wu and Law (2019) who characterise stochasticity of delay propagation across airline networks considering the turnaround activities; Evler et al. (2022) and Glomb et al. (2023) use variable minimum turn time to update aircraft routing and recover airline operations; Eltoukhy et al. (2020) address aircraft routing assuming that the minimum turnaround time in certain connections can be reduced with additional resources; and Wu (2006) retime a schedule based on future airborne and ground time estimated with simulation.

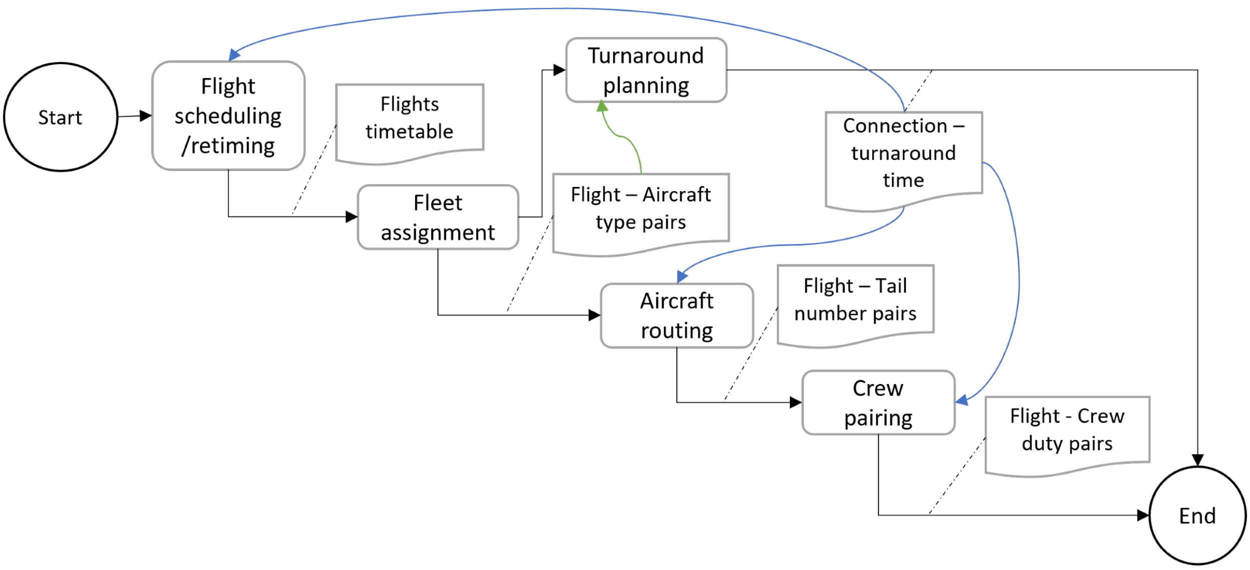


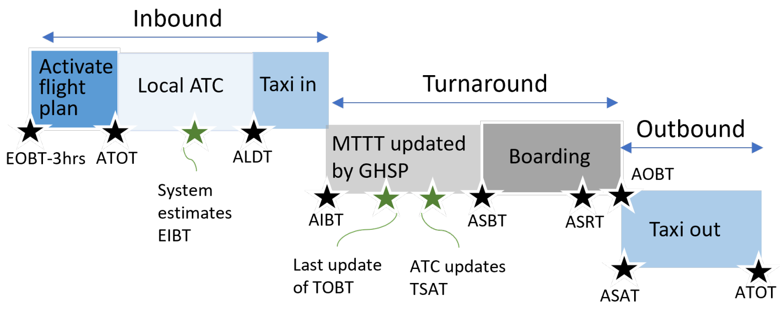
Figure 5: Comprehensive airline scheduling process

Another major open problem is the need for collaborative approaches to enhance the robustness of airline schedules. Although this review demonstrated that schedule robustness can be improved by leveraging turnaround resilience, most airline planners and researchers avoid modelling turnarounds in their decision-making models, with few exceptions, e.g. Wu (2006). This is not surprising because airlines have limited control over turnaround operations and, consequently, restricted access to the data required for modelling. Since the deregulation and liberalisation of the airline industry, competition has led the market, including ground handling services (De Neufville et al., 2013; Bazargan, 2010; Graham, 2018). Although the normative allows self-handling in certain circumstances, in most airports, the turnaround of multiple airlines is operated by third-party organisations, the GHSP (ECC, 1996). Therefore, informed planning decisions require the collaboration of various decision-makers.

All actors involved in the airline schedules operation (airlines, airports, GHSP, etc.) are impacted by disruptions and are interested in systemically improving resilience. However, individual business objectives determine the boundaries of practicable collaboration. OR scholarship may holistically study the robust scheduling problem and propose collaborative solutions that enhance individual businesses and achieve common goals. Studies on the value of collaboration in supply chain may theoretically support these efforts (Fu and Piplani, 2004; Wang et al., 2023).

Research on a *collaborative robust scheduling* framework may be of interest to practitioners and researchers. It could build on airport collaborative decision-making framework (A-CDM) (Eurocontrol, 2017). A-CDM is currently in place at some European airports to improve operational responsiveness by facilitating coordination and information sharing among actors involved in pre-departure processes. The success of A-CDM in facilitating disruption management signals the applicability of collaboration to robust scheduling. In particular, actors (airline planners, airport managers, and GHSP decision-makers) may be willing to cooperate to enhance the systemic resilience of operations from the planning stage. Policymakers may also be interested in fostering collaboration to support robust airline scheduling. Although scheduling is currently performed by airline planners autonomously, the resulting schedules affect the air transport industry as a whole, and policymakers are concerned with fostering seamless air traffic management.

To illustrate how collaborative scheduling can build on A-CDM, Figure 6 shows the main A-CDM milestones (stars in the image) in the operational plan of a busy airport (LHR, 2018). The flight plan is activated three hours before the estimated off-block time (EOBT) from the origin airport. After the network manager confirms the aircraft has taken off (ATOT), the estimated in-block time (EIBT) at the local airport is updated on the local A-CDM system. Discrepancies between EIBT and SIBT trigger messages to the airport operator (AO), the airline, and its GHSPs. The AO revisits the gate assignments, and the GHSPs reschedule and reroute their teams to accommodate the delayed flight. When the aircraft reaches its gate position (AIBT), the GHSP updates the target off-block time (TOBT), based on which the target start-up approval time (TSAT) is determined. The TSAT of all aircraft waiting to taxi out towards the runway is synchronised in the pre-departure sequence, and therefore, adherence to TOBT is essential to streamline airside operations. The consistency of the TOBT is checked when boarding starts (ASBT) and, if the check is successful (as depicted in Figure 6), permission to taxi out is requested (ASRT) shortly before its approval (ASAT) at AOBT.



Code	Description
EIBT/EOBT	Estimated in-block/off-block time
ATOT	Actiual take-off time
ALDT	Actual landing time
AIBT	Actual in-block time
MTTT	Minimum turnaround time
TOBT/AOBT	Target/actual off-block time
TSAT/ASAT	Target/actual start-up approval time
ASBT	Actual start of boarding time
ASRT	Actual start-up request time

Figure 6: Example flight operation based on Eurocontrol CDM (source: (LHR, 2018; Eurocontrol, 2025))

Methodologies to define the earliest, yet feasible, TOBT can underpin collaborative scheduling approaches. Evler et al. (2022) uses turnaround acceleration as a schedule recovery strategy in cases where the airline manages its handling services. The methodology reallocates available ground resources (staff and equipment) to delayed flights to minimise overall operational and recovery costs across concurrent turnarounds. Reassignment opportunities are limited by the number of resources available in each period of the turnaround daily schedule, i.e. shift design (Chew, 1991; Chu, 2007; Wu et al., 2023). To foster schedule flexibility, self-handling airlines can jointly retime the flight schedule and design ground shifts to facilitate turnaround acceleration. The approach can be extended to airlines that outsource turnaround services by developing mechanisms to enable partners (the airline and GHSPs) to share specific information to jointly solve the two planning problems, i.e. flight retiming and shift design (Dudek and Stadtler, 2005; Pibernik et al., 2011; Wang et al., 2023). These centralised approaches should evaluate the costs and benefits of collaboration and propose distribution mechanisms (Fu and Piplani, 2004; Aviv, 2007; Pérez-Perales et al., 2024). Another approach is decentralised collaborative scheduling, where partners iteratively negotiate and compromise to find a "Pareto optimal solution" for interdependent planning problems (Homberger and Fink, 2017).

The collaborative robust scheduling framework differs from other decision-making frameworks in many aspects. Firstly, the collaborative framework assumes that actors (an airline and GHSPs) cooperate to achieve a shared goal (resilience) while protecting their financial feasibility and competitiveness (Homberger and Fink, 2017). In contrast, Sun et al. (2025) and Eltoukhy et al. (2018) support the interaction between an airline planner and a maintenance service provider (MSP) to decide competing objectives, assuming the dominance of one of them. Both frameworks (Sun et al., 2025; Eltoukhy et al., 2018) apply a Stackelberg game approach where the follower provides feedback to the leader on their own planning decisions, which may strengthen dominance and make the approach impractical. Secondly, the operation and organisational structure underpinning maintenance services are different from those of turnaround. We analyse in more detail Sun et al. (2025) and Eltoukhy et al. (2018) to understand these differences.

Sun et al. (2025) aims to invert the status quo of the negotiation between the airline and the aircraft maintenance service providers (MSP), traditionally dominated by the airline. In Sun's framework, an MSP is the leading decision-maker interested in increasing its own profitability by using resources efficiently and innovating pricing strategies. To achieve this, the approach considers airlines' objective of minimising operational costs while maintaining the maintenance feasibility of most aircraft rotations. Therein, a deterministic aircraft maintenance routing model is adapted to support the optimal allocation of MSP resources, e.g. scheduled flights can be cancelled due to maintenance resource unavailability and the associated opportunity costs penalised. Our collaborative framework addresses operational resilience as a shared goal (not only profitability), affects various stages of the scheduling process (not only aircraft routing), integrates turnaround models (multiple interdependent services), and involves multiple actors (GHSPs).

In Eltoukhy et al. (2018), the airline leads the game by building aircraft rotations that minimise the costs of propagated delays. The MSP plans minimum-cost staff assignments to serve maintenance visits on the airline schedule, and informs the airline of delays caused by staff unavailability. The airline is supposed to adjust the rotations accordingly. However, since adjustments may result in unsatisfied demand, the airline may prefer to change its provider. Eltoukhy et al. (2018) modelled maintenance visits as a single task performed by a single service provider, and all causes of delay are aggregated except for staff unavailability. In contrast, the collaborative framework accounts for the stochasticities in the airline schedule and turnaround operations that can cause or amplify delays, including reactionary delay, availability of GHSP staff and equipment, variable duration of multiple turnaround services, and interactions of different services and resources, e.g. a crew disembarking late can delay various aircraft rotations and the teams servicing them. Since recent studies split maintenance service into multiple tasks of shorter and stochastic durations (Villafranca et al., 2025; Zhang et al., 2024a; He et al., 2023), the two processes (turnaround and maintenance) may seem similar. However, maintenance tasks are performed by a single MSP at the airport, which makes this operation less complex than turnaround.

Data collection may pose a major challenge for researchers aiming to develop a collaborative scheduling framework. Applying a case study research strategy may be difficult, as this demands sensitive data from two separate organisations with perceived conflicting interests. However, an experimental approach may be possible by building realistic data instances using freely available data. Aircraft rotations of real airlines can be obtained from Flightradar24 (2024) and BTS (2025). Crew assignments can be added using the mechanism applied in Wu and Law (2019) and the dataset provided in Kasirzadeh et al. (2017). A realistic configuration of turnaround operations can build on the literature. Dall'Olio and Kolisch (2023) combined the data (flight schedules, a map of the apron, and information on the loading and unloading process) provided by a hub airport in Europe (Munich) with the technical manuals of aircraft manufacturers (available online). The resulting data instances and the method used to build them are available in the supplementary material. In addition, Fricke and Schultz (2009); Oreschko et al. (2012) fitted probability distributions for the processing times of most turnaround services. The data sources collated in Li et al. (2024) could also provide insights for building realistic data instances.

6. Methodological background for future research

In this section, we introduce a range of OR methodologies that could form the basis for future investigations into the open challenges discussed earlier, drawing on the models and methods explored so far.

6.1. Integrating turnaround and airline scheduling models

Applying the comprehensive airline scheduling process, turnaround models can be incorporated into aircraft routing, crew pairing, and flight retiming (see blue arrows in Figure 5) to obtain more reliable aircraft rotations, crew duties, and passenger itineraries. We collate the existing advancements in integrating turnaround planning with these three decisions to facilitate future development.

Two approaches have been used to improve the responsiveness of airline schedules by supporting decisions made during (or shortly before) operations (Evler et al., 2022; Glomb et al., 2023). Both studies model turnaround activities in hub airports to decide simultaneously on aircraft rotations (*rerouting*) and turnaround schedules. Extending the idea introduced in Eltoukhy et al. (2020), they reduce the ground time of delayed aircraft to minimise the departure delay of downstream flights at the cost of allocating additional resources to turnaround activities. They also change some rotations if this is less costly than compensating passengers for broken itineraries. Changes to aircraft rotations are, in practice, aircraft swaps, which may make crew pairings and aircraft maintenance plans infeasible unless certain conditions are met. Therefore, disruption management models need to incorporate constraints to comply with predefined aircraft maintenance events and crew assignments. These rerouting approaches differ from robust aircraft routing in that the latter is concerned with satisfying the maintenance requirements during the entire planning horizon despite uncertainties affecting operations.

Glomb et al. (2023) can be extended to address robust aircraft routing with turnaround. Although it accounts for schedule deviations known one day ahead of operations, stochasticity is not modelled. Therefore, we recommend incorporating uncertainty modelling with a feedback mechanism to support planning decisions made weeks in advance. In some aspects, the optimisation model proposed by Glomb et al. (2023) is similar to those on robust aircraft routing reviewed in this paper (see Table 12). It is based on a connection network graph and minimises the cost of aircraft assignments along with the costs of delays and potential turnaround acceleration actions. Future research can propose a two-stage stochastic programming model drawing on Maher et al. (2014); Froyland et al. (2014), where planning decisions (aircraft assignments) are addressed in a deterministic stage and the recovery opportunities are evaluated under stochastic scenarios in a second stage. Alternatively, building on existing literature, Glomb's model can be extended by including constraints for maintenance requirements (Maher et al., 2018) and chance constraints to limit the probability of each flight being delayed more than a certain parameter, e.g. 15 minutes (Marla et al., 2018). Additionally, Marla et al. (2018); Yan and Kung (2018) can underpin robust optimisation models where the maximum cost of delay is incorporated in the objective function.

A closer look at the methodologies of these approaches (Evler et al., 2022; Glomb et al., 2023) provides insights for future research on integrated aircraft routing and turnaround planning. Evler et al. (2022) defines a rolling horizon over a day of operations to address the integrated recovery problem using multi-period optimisation (Glomb et al., 2022). Each period specifies scheduling constraints for turnaround activities in the next hub bank, while constraints on passenger itineraries and aircraft rotations are considered for the entire day. The objective function minimises the costs of aircraft assignments (planned operational cost) and recovery (accelerating turnaround activities, cancelling flights, and breaking passenger or crew connections) during the next period. The model encompasses a vehicle routing problem with time windows (VRPTW) to support aircraft routing and a resource-constrained project scheduling problem (RCPSP) to plan turnaround activities. Glomb et al. (2023) also combines RCPSP and VRPTW; the former calculates the costs of the optimal turnaround schedule, while the latter determines the availability of ground resources to accelerate critical turnarounds, i.e. it helps constrain the feasible space. Since VRPTW are

Citation	Model	Obj. function (min)	UM	Method
Lapp and Cohn (2012)	Assignment	MM	-	E
Froyland et al. (2014)	Network flow	PC + RC	TS	E
Maher et al. (2014)	Network flow	PC + MM + RC	TS	E
Liang et al. (2015)	Network flow	TPDC	EV	H
Marla et al. (2018)	Time-space network	TPD	CC vs RO	E
Yan and Kung (2018)	Integer programming	MTPD	RO	E
Cui et al. (2019)	Integer linear programming	NA + DC	-	H
Eltoukhy et al. (2020)	Multi-commodity network flow	PDC	SB	H
He et al. (2023)	Mathematical programming	DRS + NA + IAP	-	H
Birolini and Jacquillat (2023)	Set partitioning	TPD	SB	E
Zhang et al. (2024a)	Set partitioning	TPD	-	E
Akıncılar and Güner (2025)	Set partitioning	NA + DC	ES	E
Glomb et al. (2023)	Mixed-integer programming	PC + DC + TAC	-	E

* Not specified; PC: Planned costs; MM: Maintenance misalignments; RC: Recovery costs; TPDC: Total propagated delay costs; TPD: Total propagated delay; MTPD: Maximum total propagated delay; NA: Number of aircraft; DC: Delay cost; PDC: Propagated delay costs; DRS: Delay risk score; IAP: Idle aircraft penalty; TAC: Turnaround acceleration costs; UM; Uncertainty modelling; EV: Expected value; - No uncertainty modelling; TS: Two-stage stochastic programming; CC: Chance constraints; RO: Robust optimisation; SB: Scenario-based optimisation; E: Exact, H: Heuristic ES: Evaluate with simulation

Table 12: Models and methods per approach reported in the literature for aircraft routing

NP-hard combinatorial optimisation problems, modellers may need to develop compact formulations equivalent to network flow models (Leggieri and Haouari, 2017) in order to address realistic networks.

A study incorporating a turnaround simulation model within a flight retiming approach is introduced in Wu (2006). The model estimates the duration and delay of ground-handling activities under uncertainty, but it does not incorporate turnaround planning or recovery decisions because ground resources are not modelled. The objective function minimises ground delay and the estimated airborne delay. Wu (2006) can underpin future research to retime the airline and turnaround schedules simultaneously, using a simulation optimisation approach to consider the stochasticity of operations. The optimisation model can build on the reviewed studies on flight retiming shown in Table 13. Most objective functions minimise the delay or its associated costs, while Sohoni et al. (2011) also maximises the revenue from satisfied demand. Because schedule retiming may result in infeasible passenger and crew itineraries, Lee et al. (2007) and Sohoni et al. (2011) minimise total deviation from the original schedule.

The integration of turnaround planning with crew pairing has not been attempted, although the interdependence across crew duties via aircraft rotations has been recognised (Schaefer et al., 2005; Wei and Vaze, 2018). As Table 14 shows, crew pairing models minimise the delay costs or include penalty costs associated with violations of robustness features, such as aircraft changes and short sit

Citation	Model	Objective function	UM	Method
Wu and Caves (2002)	*	min PC	EV	E
Wu (2006)	MP	min ED	SB	H
Lee et al. (2007)	MOO	min DDT	SB	H
Ahmadbeygi et al. (2010)	LP	min EPD	SB	E
Sohoni et al. (2011)	Stochastic IP	max NR - DDT - OC	CC	E
Chiraphadhanakul and Barnhart (2013)	LP	min TEAD vs max TEES	SB	E
Duran et al. (2015)	NLP	min AIT + FC	CC	E
Novianingsih and Hadianti (2016)	NLIP	min TEPD	SB	H
Sanjeevi and Venkatachalam (2021)	LP	min TRC + EDC	TS	E

MP: Mathematical programming; MOO: Multi-objective optimisation; LP: Linear programming; IP: Integer programming; NLP: Nonlinear programming; NLIP: Nonlinear integer programming; ED: Estimated delay; DDT: Deviation from departure time; EPD: Expected propagated delay; NR: Net revenue; OC: Operational costs; TEAD: Total expected arrival delay; TEES: Total expected effective slack; AIT: Aircraft idle time; FC: Fuel cost; TEPD: Total expected propagated delay; TRC: Total reschedule costs; EDC: Expected delay costs; UM: Uncertainty modelling (SB: Scenario-based optimisation; CC: Chance constraints; TS: Two-stage stochastic programming); E: Exact, H: Heuristic

Table 13: Models and methods used in the flight retiming literature

times, i.e. connections shorter than the minimum connecting time (MCT) in the objective function. Together, this helps address the interdependence challenges to some extent (Wei and Vaze, 2018). However, the MCT variability and recovery potential of the turnaround have not been considered, and this depends on the physical and operational configuration of the airport terminal. Short crew sit times impact disembarking and boarding, which are a large proportion of turnaround. Since ground handling operations are also interdependent, these activities significantly influence the flight departure delay of multiple rotations (Neumann, 2019). In future research, objective functions may optimise turnaround and crew schedule decisions simultaneously, for example, adjusting turnaround resources to reduce boarding time. Such research would need to consider the collaboration of the different actors involved in ground handling.

6.2. Methodologies for airline scheduling with turnaround

Our review found extensive use of most modelling methodologies to apply feedback during optimisation, i.e. stochastic programming, robust optimisation and scenario-based approaches, but limited use of simulation optimisation (see Table 10). While this methodology has been under-researched in the robust airline scheduling literature, it has been applied to various problems in the aviation industry, such as turnaround planning (Guimarans and Padrón, 2022; Gök et al., 2023), runway scheduling (Shone et al., 2024), check-in counter allocation (Forbes et al., 2024), and airline disruption management (Rhodes-Leader et al., 2022). Next, we will discuss the potential adoption of these approaches in robust airline scheduling with turnaround.

Citation	Model	Objective function	UM	Method
Ehrgott and Ryan (2002)	Set partitioning	min PC + PRV	-	E
Schaefer et al. (2005)	Set partitioning	min PC + PRV	ES	H
Yen and Birge (2006)	Stochastic IP	min PC + RC	TS	E
Shebalov and Klabjan (2006)	IP	max CSO	ES	H
Tekiner et al. (2009)	Set partitioning	max CSO + BT	-	E
Tam et al. (2011)	Stochastic IP	min AD	TS	E
Muter et al. (2013)	Set covering	min PC + RC	-	H
Lu and Gzara (2015)	Multi-commodity flow	min TC + MTD	RO	E
Chung et al. (2017)	Set covering	min PC + PDC + RCC	ES	E
Bayliss et al. (2017)	MILP	min ENC	SB	E
Wei and Vaze (2018)	Set partitioning	min PC + PRV	ES	H
Antunes et al. (2019)	MILP	min PC + DC	RO	E
Wen et al. (2020)	Set partitioning	min PC, PRV	-	E
Schrotenboer et al. (2023)	Set covering	min PC + RC + RCC	EV	E

IP: Integer programming; PC: Planned cost; PRV: Penalties for robustness violation; RC: Recovery costs; CSO: Crew swap opportunities; BT: Buffer time; AD: Average delay; TC: Total cost; MTD: Maximum total delay; PDC: Propagated delay cost; RCC: Reserve crew cost; ENC: Estimated number of cancellations; UM: Uncertainty modelling (- No uncertainty modelling; ES: Evaluate with simulation; TS: Two-stage stochastic programming; RO: Robust optimisation; SB: Scenario-based optimisation; EV: Expected value); E: Exact, H: Heuristic

Table 14: Models and methods used in the crew pairing literature

The first approach, presented in Forbes et al. (2024), formulates the allocation problem as a stochastic integer programming model and solves it using logic-based Benders decomposition (LBBD). The delay is modelled as a function of the number of staff (single type) in multiple periods and, relying on the monotonicity property, the output of a DES simulation is used as Benders' cuts for the master problem. By doing this, the approach avoids simulating all candidate solutions, improving efficiency. The results report that LBBD outperforms a conventional solver and reaches the optima or insignificant optimality gaps. This work can motivate applications of LBBD to the network flow and set partitioning problems underlying the integration of turnaround with aircraft routing and crew paring, respectively. This entails methodological contributions to address various challenges, including the multivariate nature of the delay function and the existence of VRP or RCPSP constraints.

The second approach, called simheuristics, embeds a simulation model within a metaheuristic to search large solution spaces efficiently (Juan et al., 2015; Figueira and Almada-Lobo, 2014). Similar to airline schedule operations, the runway scheduling problem addressed by Shone et al. (2021) is characterised by multiple types of uncertainty (flight arrival times, sequence-dependent aircraft separation and weather conditions), which are accounted for by the simulation. The multi-objective model minimises schedule delays and operational delays using a complex cost function and is solved using a variable neighbourhood search (VNS) algorithm (Mladenovic and Hansen, 1997; Hansen et al., 2008). Simheuristics has been used to solve various NP-hard problems by implementing a variety of metaheuristics, such as random variable neighborhood descent (RVND) (Mecler et al., 2022) for the parallel machine scheduling problem (Abu-Marrul et al., 2023) and genetic algorithms for the integrated facility location and vehicle routing (Rabbani et al., 2019). The simulation models that capture the stochasticity of the turnaround system introduced in Gök et al. (2023) can be extended to consider the influence of the delay propagated across the airline schedule (aircraft rotations, crew duties and passenger itineraries) to address the complex cost functions and constraints that configure the robust airline scheduling with turnaround.

The third approach is multi-fidelity modelling, which reduces the computational budget spent in high-fidelity simulation by using a low-fidelity model, less computationally demanding, to drive the search towards near-optimum areas (Lin et al., 2021; Xu et al., 2016). Rhodes-Leader et al. (2022) applies multi-fidelity modelling to address the aircraft recovery problem using a deterministic mathematical programming model that finds initial solutions and a simulation optimisation algorithm that improves them considering uncertainty.

7. Conclusion and avenues for research

This paper presents a framework that encompasses essential characteristics of robust scheduling to support data extraction and synthesis (Paul et al., 2024; Tranfield et al., 2003). Each framework variable regards a unique viewpoint on the methodologies proposed by the papers, facilitating the analysis of their properties.

The literature confirmed that authors and airline operation planners are increasingly opting for stochastic models to develop robust schedules (Simsek and Akturk, 2022; Marla et al., 2018; Froyland et al., 2014). These studies have articulated stochastic optimisation approaches using the applicable OR methodologies, including stochastic programming, robust optimisation and scenario-based optimisation. The use of simulation optimisation has been limited, although simulation models have proven effective in providing high-fidelity estimation of future operations to evaluate the performance of planning decisions (Burke et al., 2010; Novianingsih and Hadianti, 2016; Ben Ahmed et al., 2018; Guimarans and Padrón, 2022; Gök et al., 2023).

This paper proposes a *comprehensive airline scheduling process*, which incorporates turnaround planning to improve robustness in aircraft routing, crew pairing, and flight retiming (revisits flight scheduling decisions). This wider perspective on the scheduling process, including the need to make decisions that involve various organisations with autonomous decision-makers, demands a *collaborative robust scheduling* framework to be built on existing OR theories and industry protocols (Eurocontrol, 2017; Fu and Piplani, 2004; Dudek and Stadtler, 2005).

For empirical validation, these two concepts can be progressively implemented. The comprehensive scheduling process can be readily adopted by a self-handling airline to streamline its operations in a hub airport, e.g. jointly planning timetables and turnaround shifts. Expectedly, the savings in recovery costs will be positively correlated with the airline's dominance in the hub (Calzada and Fageda, 2023), typically concentrated in one of the airport terminals. Learnings from this implementation can support the construction of a collaborative platform for other terminals, where ground handling services are provided by third parties. The airport is a natural candidate to lead such a transition because its competitiveness is determined by the on-time performance of all terminals. In addition, methodologies for the operational coordination of multiple GHSP indicate the decisive role of the airport operator (Padrón et al., 2016; Gök et al., 2023). Local initiatives, such as the airline operators committee (AOC) that operates at Heathrow, can also catalyse cooperation (LHRAOC, 2025).

A limitation of this study is not considering other airport processes that affect the resilience of the schedule in addition to turnaround, such as gate assignment (Dijk et al., 2019). Future research on the collaborative framework could overcome this limitation by studying airport decisions that affect the reliability of the schedule.

In addition to those presented in the discussion, the comprehensive process raises other interesting open questions. How can schedule robustness across the network be evaluated considering the propagation of delays through turnaround operations? What robustness proxies can improve airline schedule flexibility? Industry practitioners and scholars will benefit from fostering advancements in simulation and optimisation methodologies to address these questions.

Literature Review	OR Method			Approach to Uncertainty	
	EO	HO	Sim	Deterministic^{+}	Stochastic
Xu et al. (2024)	✓	✓			✓
Ma et al. (2022)	*	*	*		✓
Wen et al. (2021)	✓			✓	✓
Zhou et al. (2020)	✓	✓		✓	
Deveci and Demirel (2018)	✓				✓
Eltoukhy et al. (2017)	✓	✓		✓	✓
This review	✓	✓	✓	✓	✓

EO: Exact optimisation; HO: Heuristic optimisation; Sim: Simulation
*The methods are only mentioned
$^{+}$ Uncertainty is not considered

Table A.1: Methods analysed by previous literature reviews

Appendix A. Supplementary material

	Count of papers	
Robustness Approach	Airline schedule	Turnaround
Feedback	32	6
Proxy	17	1
Proxy and feedback	4	
Neither proxy or feedback	7	3
Total	60	10
Uncertainty Management		
Stochastic optimisation	36	4
Simulation optimisation		2
Evaluate solution with simulation	7	2
Evaluate solution with scenarios	3	2
No uncertainty modelling	14	
Total	60	10
Type of Robustness		
Reliability	41	6
Reliability and Flexibility	4	
Flexibility	15	
Total	60	6*

* Four articles on turnaround resilience that focus on responsiveness (disruption management) are not included in this table.

Table A.2: Number of studies by robustness approach, uncertainty management, and type of robustness

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