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# Unleashing the potential of operations research in air transport: A review of applications, methods, and challenges

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ABSTRACT

Operations research (OR) has been applied in air transportation since the post-war period, starting from relatively simple static models and classical linear optimization techniques. Recent advancements in operations research, computational intelligence, and data management have significantly transformed the landscape of OR applications, addressing the growing complexity and demands of the modern aviation industry. This study explores the latest developments of OR applications within air transportation, focusing on key areas such as airline management, airport management, and air traffic management. We delve into the integration of big data, artificial intelligence and sustainability aspects, which has enabled unprecedented precision in, e.g., flight scheduling, air traffic control, and predictive maintenance. The adoption of modern heuristics based on machine learning algorithms and advanced solution techniques has facilitated to solve an increasingly larger and more complex set of mathematical models for improved resource allocation. This paper also highlights the shift towards holistic and integrated OR models that encompass the entire air transportation ecosystem, from airline operations to airport management. By analyzing these recent developments, we underscore the critical role of OR in driving efficiency, safety, and sustainability in air transportation, offering insights into future trends and potential research directions in this rapidly evolving field.

## 1. Introduction

The first applications of Operations Research (OR) in aviation can be traced back until World War II, at that time mostly referred to as Operational Research in the British military sphere, when OR was used to optimize the allocation of resources and the effectiveness of various operations, including air combat and logistics (Kittel, 1947; McCloskey, 1987; Thomas, 2024). According to Milkman (1968), the careful analysis of the outnumbering operations from the German Air Force enabled British scientists to *'set up a nearly perfect plan which included location of the radar sites, communication between stations and fighter bases, as well as methods for upkeep and repair'*. Following the war period, the fundamental principles of OR were gradually applied to non-operational aspects and inside commercial aviation, *e.g.*, to air traffic control (Bell, 1949), airline system simulation (Gunn, 1964), and airport operations (Killip, 1969). These applications were relatively simple - compared to modern applications, relying on static models as well as classical optimization, including linear programming and basic simulation / network flows. The major limiting factors at that time were the requirement to manually collect, aggregate data and the presence of mechanical/early electronical computers with limited computational resources (Bonder, 1979). Accordingly, while the complexity of these first OR applications is not comparable with nowadays application they have one thing in common: by avoiding human-based trial-and-error methods, significant advances in (operational) efficiency became possible. In the 1980s and 1990s, the increasing competition and pressure for airline efficiency, laid the foundation for developing hub-and-spoke networks, revenue management systems, crew scheduling, and security systems (Barnhart and Talluri, 1997; Barnhart et al., 2003; Martonosi, 2005; McLay et al., 2005; Sun et al., 2024b). Nowadays, with advancements in technology and data analytics (Li and Ryerson, 2019), modern OR applications in air transportation include optimizing fuel consumption, improving maintenance scheduling, managing disruptions, and enhancing passenger experience through better planning and resource allocation (Yu, 2012; Ng et al., 2018); particularly in light of the post-COVID-19 times (Sun et al., 2021; Paraschi et al., 2024; Yimga, 2024; Sun et al., 2024c) and in combination with modern artificial intelligence techniques (Geske et al., 2024a,b; Liu, 2024; Wandelt et al., 2024b,c). For instance, OR has optimized gate assignment at

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London Heathrow, reducing passenger delays by dynamically adjusting gates to real-time changes. Airlines such as Southwest have used OR in crew scheduling, minimizing disruptions and costs during irregular operations. In COVID-19 recovery, OR models helped Japan's airports balance capacity and safety by simulating social distancing in passenger flows. Additionally, Delta Airlines applied OR to fuel optimization, achieving significant cost reductions. These applications demonstrate OR's growing role in enhancing flexibility, safety, and cost-effectiveness in aviation operations. Accordingly, it can be said that OR has become a fundamental tool in the aviation industry, driving improvements in efficiency, safety, and profitability along the entire air transportation value chain Wen et al. (2024), Chen et al. (2024a).

In this study, we review the recent developments of OR applications in air transportation. Given the seminal paper by Barnhart et al. (2003), which was published more than 20 years ago, our review mainly focuses on developments in the 21st century; earlier applications and methods are mostly mentioned for historical reference and to create an adequate context. Inspired by the categorization in Barnhart et al. (2003), our review is structured into three major categories: airline management, airport management, and air traffic management. Within the airline management category, we review research on the entire workflow of an airline, from demand forecasting / analysis, over hub location and network design, to airline scheduling. Within the airport management category, we cover research on slot allocation, gate assignment, and ground handling/passenger flow optimization. For the category air traffic management, we review extant works on air traffic flow management, trajectory planning, and airspace optimization. Our literature review on OR applications in air transportation helps to identify and synthesize existing methodologies, highlighting their effectiveness and areas for improvement. We also reveal several gaps in the extant research landscape, suggesting opportunities for new studies and innovations, ultimately enhancing the efficiency, safety, and sustainability of air transport.

To collect and categorize papers for this review on the applications of operations research in air transport, a systematic approach was adopted to ensure comprehensiveness and relevance. The search began with a literature review conducted across multiple academic databases, including Web of Science, Scopus, and Google Scholar, to capture a wide range of studies published in peer-reviewed journals, conference proceedings, and relevant books. The keywords we used included "operations research", "air transportation", and "management", combined with specific techniques like "optimization", "simulation", "network design", and "decision support systems" to refine the search. Advanced filters were applied to focus on English-language publications from the last two decades, ensuring the inclusion of both foundational works and cutting-edge research. Additional sources were identified through backward and forward citation searches, allowing the inclusion of highly cited works and relevant emerging studies. Industry reports and government publications were also reviewed to provide context and identify practical applications. Studies were categorized based on their primary focus area, and duplicate studies were eliminated. Throughout the process, a thematic coding scheme was developed iteratively to identify recurring topics and trends in the literature. To sum up, the three major categories were derived by recognizing the natural division of operational challenges and stakeholder objectives within the air transport system; as well as the structure of the seminal review by Barnhart et al. (2003).

The remainder of this study is structured as follows. Section 2 reviews OR applications in the domain of airline management, covering aspects of demand forecasting, hub location/network design, and airline scheduling. Section 3 surveys OR applications in the domain of airport management, focusing on the problems of slot allocation, gate assignment, ground handling, and passenger flow optimization. Section 4 discusses OR applications in the domain of air traffic management, including air traffic flow management, trajectory planning/optimization, airspace design, and conflict detection/resolution. Section 5 concludes this study and summarizes important directions for future work.

## 2. Airline management

Airline management addresses all strategic and operational aspects of managing and operating an airline, while coordinating distinct airline activities. From an operational research perspective, this process usually begins with strategic planning for growth, partnerships, and competitive positioning, followed by route planning and network development to optimize the airline's network for profitability and efficiency. Operational activities include managing daily flight operations, ensuring on-time performance, and scheduling crews. Our review of OR aspects covers the following steps: demand forecasting (Section 2.1), airline network design (Section 2.2), and airline scheduling (Section 2.3).

### 2.1. Demand modeling

Demand modeling plays a critical role in OR framework within the aviation industry, as it enables airlines, airports, and policymakers to make informed decisions about capacity planning, resource allocation, and infrastructure development. Accurate demand forecasts are essential for optimizing flight schedules, network design, and pricing strategies, ensuring that services align with passenger needs and market conditions. By incorporating demand modeling into OR approaches, stakeholders can better predict passenger behavior, anticipate market shifts, and efficiently allocate resources. This results in improved operational efficiency, cost-effectiveness, and service quality, making demand modeling a cornerstone for strategic planning and decision-making in the aviation sector. Through the application of advanced OR techniques, demand modeling becomes a key tool in maximizing the performance of the aviation system, contributing to more sustainable and responsive operations.

In the extant literature, the air travel demand problem is predominantly divided the problem into two sub-problems: demand generation.[1] and demand allocation[2] Both subproblems are described below, in Section 2.1.1 (demand generation) and Section 2.1.2 (demand allocation), respectively.

#### 2.1.1. Demand generation

Air demand generation is commonly modeled using gravity-based approaches, where demand between city pairs is proportional to the cities' mutual attraction and inversely related to the generalized cost of travel (Wojahn, 2001; de Grange et al., 2011; Adler et al., 2018; Banerjee et al., 2020; Kaya et al., 2023). It usually incorporates various demand-side (attractors) factors such as income and population (Grosche et al., 2007; Alexander and Merkert, 2021; Alam et al., 2024), and supply-side (push) factors including distance, frequency, travel time and price (Jorge-Calderón, 1997; Boonekamp et al., 2018; Albayrak et al., 2020; Li et al., 2023a; Tirtha et al., 2023). Table 1 provides an overview in the extant literature[3].

Common methods for demand generation forecasting in air transportation include SARIMA and ARIMA, which have been used to estimate origin–destination demand and predict annual air demand Tsui et al. (2014), Li (2019), Li et al. (2023a), Madhavan et al. (2023). While

[1] It refers to estimating total air traffic flows between two markets.

[2] It refers to examine the factors that influence the distribution of passengers over available travel itineraries within a specific market.

[3] Tables in this study are grouped and sorted by column "Methodology" (usually the last column in each table), unless stated otherwise. As summarized in the table, traditional methodologies for modeling air travel demand have relied on time series (Li et al., 2022b) or causal models (Wang and Gao, 2021), focusing on historical data and deterministic relationships between variables. Time series models usually aim to forecast the demand through the changes over time periods (*i.e.*, yearly, quarterly, monthly, and hourly), while causal models are used to estimate a relationship function between explanatory variables and the demand that needs to be forecasted.

**Table 1**
Overview on variables and methodologies used for demand generation (AI: Artificial Intelligence, ALC: Airline count, APC: Airport connectivity, CFL: Competing flow, DIS: Distance, FAR: Fare, FRQ: Frequency, GDP: Gross Domestic Product, GM: Gravity model, HFL: Historical flow, LOS: Level of service, POP: Population, RG: Regression, TOD: Time of day, SEA: Seasonality, TRD: Trade, TS: Time series analysis).

| Reference | Socio-economic | Demand | Supply | Time | Other | Methodology |
|---|---|---|---|---|---|---|
| Alam et al. (2024) | GDP,POP,TRD | | FRQ | | | AI |
| Chen et al. (2020) | GDP | | FRQ | SEA | | AI |
| Stanulov and Yassine (2024) | GDP | | FRQ | SEA | | AI |
| Adler et al. (2018) | GDP,POP | HFL | APC,ALC,LOS | | DIS | GM |
| de Grange et al. (2011) | GDP,POP | CFL | | | DIS | GM |
| Grosche et al. (2007) | GDP,POP,TRD | | APC,FRQ | | DIS | GM |
| Tillmann et al. (2023) | GDP | | | SEA | | GM |
| Albayrak et al. (2020) | GDP,POP | | APC,FRQ | | DIS | RG |
| Alexander and Merkert (2021) | GDP,POP,TRD | | FLC,ALC | | | RG |
| Boonekamp et al. (2018) | GDP,POP | | FLC,FRQ | | DIS | RG |
| Kaya et al. (2023) | GDP,POP,TRD | | FLC,APC,FRQ | | DIS | RG |
| Tirtha et al. (2023) | GDP | | ALC,FRQ | | DIS | RG |
| Banerjee et al. (2020) | GDP,POP | CFL | LOS,FRQ | TOD,SEA | FAR | TS |
| Li et al. (2023b) | GDP | | FRQ | | | TS |
| Madhavan et al. (2023) | GDP,TRD | | FRQ | SEA | | TS |
| Nwaogbe et al. (2023) | GDP,TRD | | | SEA | | TS |
| Tsui et al. (2014) | GDP | | FRQ | SEA | | TS |

time series models handle seasonality, they struggle with non-linear changes like economic crises and may overfit data. Causal models, often used for regional demand forecasting, face challenges in accounting for volatile factors like economic conditions and demographic shifts. Recent advancements include more complex models, such as the SG-GOP model (Tirtha et al., 2024) and modified radiation models (Wang and Zhang, 2024), which aim to capture spatio-temporal dependencies and network disruptions but face issues with non-linearity and multi-collinearity. Machine learning techniques (Chen et al., 2020; Stanulov and Yassine, 2024; Alam et al., 2024), are emerging as promising alternatives, offering greater flexibility in capturing intricate data patterns and improving forecasting accuracy.

Integrating demand generation models with OR frameworks significantly enhances their effectiveness in air transportation by optimizing resource allocation, improving forecasting accuracy, and enabling more dynamic decision-making. By incorporating techniques such as optimization algorithms, network modeling, and scenario planning, airlines and airports can better match supply with predicted demand, ensuring cost-efficient operations and improved service quality. Additionally, OR methods like multi-stage decision-making and stochastic programming can address the non-linearity and complexity inherent in demand generation, capturing intricate relationships between variables and optimizing them within operational constraints. However, this integration presents challenges, including data complexity, quality issues, and increased model complexity. Additionally, ensuring model robustness amid data uncertainties and maintaining scalability for resource-intensive machine learning techniques, such as deep learning, poses significant hurdles. Balancing flexibility and stability in these models is crucial for effective decision-making and strategic planning.

#### *2.1.2. Demand allocation*

Demand allocation models, particularly itinerary choice models, focus on how passengers select between air travel options within a city-pair market. These models examine various factors that influence choice, highlighting the importance of service level, connection quality, and carrier attributes (Coldren et al., 2003; Gallego and Font, 2021; Fuyane et al., 2023), punctuality (Freund-Feinstein and Bekhor, 2017; Bachmat et al., 2023), and time-of-day preference (Koppelman et al., 2008; Lurkin et al., 2017; Üzülmez and Sarılgan, 2024). Specific aspects of demand allocation have been further examined, considering not only air travel itinerary features but also the presence of alternative transport modes (Adler et al., 2018; Nurhidayat et al., 2023; Mizutani and Sakai, 2023), competition between neighboring airports (Başar and Bhat, 2004; Hess and Polak, 2005; Üzülmez and Sarılgan, 2024), and the ground access and egress portions of the air passenger trip (Pels et al., 2003; Ekbote and Laferriere, 2020). These factors highlight the complexity of demand allocation and the importance of incorporating multiple elements to better understand passenger behavior and optimize resource allocation.

As summarized in Table 2, traditional methods for modeling itinerary choices in air travel often use discrete choice models like the multinomial logit (MNL), which estimate the likelihood of passengers choosing an itinerary based on factors such as price, flight duration, and departure time (Qu et al., 2024; Cordera et al., 2024). However, due to the independence from irrelevant alternatives (IIA) assumption, more advanced models like nested logit (NL) and mixed logit (ML) are used to capture more complex decision-making, accounting for correlations between alternatives and individual preferences (Saljoqi et al., 2024). Recently, machine learning methods have gained attention for choice modeling in aviation, offering greater flexibility and accuracy. These techniques can model complex interactions between variables and passenger characteristics, with random forests and decision trees segmenting passengers effectively (Rajendran et al., 2021; Stanulov and Yassine, 2024), and SVMs and neural networks capturing non-linear patterns in choice data (Zhang et al., 2018; García-Alonso et al., 2020). Additionally, ensemble methods like gradient boosting machines (GBM) enhance prediction accuracy by combining multiple models (Wang and Ross, 2018; Ren et al., 2024).

Integrating discrete choice models into OR for demand allocation involves several challenges. The MNL model's assumption of independence from IIA can lead to inaccuracies, as it does not capture correlations between similar alternatives. While more advanced models like NL and ML address these issues by allowing correlations, they introduce additional complexity and require high-quality data for accurate parameter estimation. Furthermore, accounting for heterogeneity in passenger preferences complicates system-level optimization, as mixed logit models capture individual variations but add complexity. Integrating static choice models into dynamic OR frameworks is also challenging, as it requires managing changes in passenger preferences over time. Additionally, machine learning models face scalability challenges when applied to large and complex OR models, making their integration into real-time decision-making systems difficult. Addressing these challenges is crucial for improving demand allocation and optimizing operations in air transportation.

### *2.2. Network design*

Given the results of demand modeling, the first task on the strategic planning horizon for an airline involves locating the hub/base airports and designing the route network. The location of hubs and network design have a tremendous influence on efficiency, connectivity, and profitability of an airline's operation. Hubs serve as central points for

**Table 2**
Overview on variables and methodologies used for demand allocation (COM: Competitors, DIS: Distance, FAR: Fare, FRQ: Frequency, GB: Gradient boosing, MNL: Multinomial logit, SIZ: Size, STS: Seats, SVM: Support vector machines, TOU: Tourism, TRT: Travel time).

| Reference | Itinerary | Market | Methodology |
|---|---|---|---|
| Pels et al. (2003) | FAR,TRT,FRQ | SIZ,COM | Choice model |
| Bachmat et al. (2023) | TRT,STS | TOU | Discrete choice model |
| Ekbote and Laferriere (2020) | FAR,TRT,FRQ,STS | SIZ,TOU,COM | Discrete choice model |
| Mizutani and Sakai (2023) | FAR,TRT,STS | DIS,SIZ,COM | Discrete choice model |
| Nurhidayat et al. (2023) | FAR,TRT | DIS,SIZ,COM | Discrete choice model |
| Rajendran et al. (2021) | FAR,TRT,FRQ | SIZ,TOU | GB + SVM |
| Fuyane et al. (2023) | FAR,TRT,FRQ | SIZ | Logit |
| Qu et al. (2024) | FAR,TRT,FRQ | SIZ,TOU | Logit + NL |
| Freund-Feinstein and Bekhor (2017) | FAR,TRT,FRQ | SIZ,COM | ML |
| Hess and Polak (2005) | FAR,TRT,FRQ | SIZ,COM | ML |
| Coldren et al. (2003) | FAR,TRT,FRQ | DIS,SIZ,COM | MNL |
| Koppelman et al. (2008) | FAR,TRT,FRQ | SIZ,TOU | MNL |
| Üzülmez and Sarılgan (2024) | FAR,TRT,FRQ | SIZ | MNL |
| Başar and Bhat (2004) | FAR,TRT,FRQ | SIZ,COM | MNL + NL |
| Saljoqi et al. (2024) | FAR,TRT,FRQ | SIZ,TOU | MNL + NL |
| Cordera et al. (2024) | FAR,TRT,FRQ | SIZ | MSLE |
| Gallego and Font (2021) | FRQ,STS | SIZ,TOU | Multinomial OLS |
| Lurkin et al. (2017) | FAR,TRT,FRQ | SIZ,TOU | Random utility model |
| García-Alonso et al. (2020) | FAR,TRT,FRQ | SIZ | SVM |

consolidating flights, allowing for more efficient use of resources and increased frequency of service to various destinations. Additionally, a well-designed airline network and usage of fleets ensures optimal route coverage, reduces travel time, increases aircraft utilization, and improves the overall passenger experience. From an OR perspective, the involved aspects can mainly be formulated and solved through the hub location problem (Section 2.2.1) and fleet planning problem (Section 2.2.2).

### 2.2.1. Hub location problem

(O'Kelly, 1986) pioneered the work on hub location problems (HLP), optimizing the location of hub airports and the allocation strategy of spoke airports, achieving a service-based or cost-based airline network topology; see the following seminal reviews: (Alumur and Kara, 2008; Campbell and O'Kelly, 2012; Farahani et al., 2013; Contreras and O'Kelly, 2019; Alumur et al., 2021; Wandelt et al., 2022). Compared to the (fully-connected) point-to-point network, the hub-and-spoke network consists of two types of nodes (hub airports and spoke airports) and links (inter-hub flight legs and distribution/collection flight legs). Table 3 summarizes a series of HLPs with various objective functions and constraints regarding the network structure. The extant literature mostly focuses on minimizing the cost or maximizing the profit as classical objective functions. With cost minimization, the $p$-hub median problem considers only the transportation cost for the predefined number of hubs $p$ (Kratica et al., 2007; Ghaffarinasab, 2022), while the hub location problem with fixed costs involves both the transportation cost and setup cost to determine the hub set (Silva and Cunha, 2009; Espejo et al., 2023). On the other hand, under profit-maximization, unprofitable OD demand pairs will not be served (Taherkhani and Alumur, 2019; Taherkhani et al., 2021; Oliveira et al., 2022). Moreover, multiple objectives to balance the cost and service have been considered for more realistic applications (Makui et al., 2002; Kahag et al., 2019; Khaleghi and Eydi, 2023; Bordeaux and Couto, 2024).

There exists a variety of different allocation strategies, inter-hub connections as well as capacity limitations. Single or multiple allocation strategies denote how the spokes are assigned to the hubs, where single-allocation HLP allocates each spoke to a single hub (Mohammadi et al., 2019; Hu et al., 2021a; Rostami et al., 2021; Andaryan et al., 2024), while a non-hub node can be allocated to several hubs in the multiple-allocation constraint (de Sá et al., 2018; Ghaffarinasab et al., 2018). Physical constraints with completeness (An et al., 2015; Abyazi-Sani and Ghanbari, 2016) and incompleteness (Lin et al., 2012; O'Kelly et al., 2015; De Camargo et al., 2017) are implemented to restrict the inter-hub connections. Additionally, hub capacity limits the incoming traffic flow through the corresponding hub (Rodriguez-Martin and Salazar-Gonzalez, 2008; Meraklı and Yaman, 2017). HLP can be solved by the exact methods, heuristics/metaheuristics, and machine learning-based algorithms in recent years. Specifically, row generation (Meier and Clausen, 2018), Benders decomposition (Contreras et al., 2011; Rahmati et al., 2023), and variable neighborhood search (Ilić et al., 2010; Dai et al., 2019; Chen et al., 2022; Wandelt et al., 2021; Dai et al., 2022; Wang et al., 2024b) are commonly-used solution methods.

Several research topics regarding solution techniques for HLPs and applying HLPs into real-world applications can still be further explored. Future directions should consider realistic characteristics such as the multi-period planning horizon and incomplete networks; both leading to a significant increase in computational challenges when solving HLPs. Solving large-scale hub location problems is imperative and related studies solved to optimality are very rare. Accordingly, development of exact and heuristic methods for solving large-scale problems is a must, especially heuristics and machine learning-oriented / - driven algorithms; particularly in the context of ever-increasing logistic networks. Finally, more sophisticated models covering location and routing aspects are required (Wandelt et al., 2025).

### 2.2.2. Fleet planning problem

With an adequate network being designed, the fleet planning problem has a significant effect on the profitability of the airline industry, which aims at selecting the specific aircraft types for the route network. Earlier studies have emphasized on the macro-fleet planning problem to determine the fleet size with the predicted air-traffic demand Belobaba et al. (2015), Clark (2017). However, this macroscale planning might result in resource waste and incompatibility of the aircraft types. Accordingly, the micro-fleet planning strategy has become popular in recent years to optimize the fleet size on each flight leg (Sun et al., 2010; Dožić and Kalić, 2015; Repko and Santos, 2017). Table 4 summarizes the recent literature about the fleet planning problems from macro/micro perspectives.

Fleet size (Gomes et al., 2014; Dožić et al., 2019; Csereklyei and Stern, 2020) and route-based fleet composition (Pai, 2010; Carreira et al., 2017; Sa et al., 2020) are the crucial aspects of the micro-fleet planning problem. Researchers and industry practitioners have emphasized the importance of statistics-based methods to deal with the fleet size problem. For instance, Givoni and Rietveld (2006) utilized regression analysis to investigate the effect of route features on the aircraft size and a nested logit model was presented in Wei and Hansen (2005) to analyze how the airline flight frequencies and fleet size had an influence on the passenger demand. Moreover, some recent studies focus on the fleet sizing for urban air mobility operations (Sieb et al.,

**Table 3**
Literature concerning hub location problems.

| Features | | References |
|---|---|---|
| Objective function | Cost minimization | Kratica et al. (2007), Silva and Cunha (2009); Ghaffarinasab (2022), Espejo et al. (2023) |
| | Profit maximization | Taherkhani and Alumur (2019), Taherkhani et al. (2021); Oliveira et al. (2022) |
| Constraint | Allocation strategy | de Sá et al. (2018), Ghaffarinasab et al. (2018); Mohammadi et al. (2019), Hu et al. (2021a), Rostami et al. (2021) Ghaffarinasab et al. (2023), Andaryan et al. (2024) |
| | Inter-hub connection | Lin et al. (2012), An et al. (2015), O'Kelly et al. (2015); Abyazi-Sani and Ghanbari (2016), De Camargo et al. (2017) |
| | Hub capacity | Rodriguez-Martin and Salazar-Gonzalez (2008); Meraklı and Yaman (2017) |

**Table 4**
Literature concerning fleet planning problems.

| Features | | References |
|---|---|---|
| Macro-fleet planning | | Belobaba et al. (2015), Clark (2017) |
| Micro-fleet planning | Fleet size | Wei and Hansen (2005), Givoni and Rietveld (2006); Gomes et al. (2014), Dožić et al. (2019); Csereklyei and Stern (2020), Sieb et al. (2023); Cao et al. (2024), Kotwicz Herniczek et al. (2024) |
| | Route-based fleet composition | Pai (2010), Khoo and Teoh (2014), Rosskopf et al. (2014); Wang et al. (2015), Carreira et al. (2017), Sa et al. (2020) |

2023; Cao et al., 2024; Kotwicz Herniczek et al., 2024). For the flight leg-centric fleet planning, some relevant studies have made decisions about the optimal aircraft type for each route with the maximization of operational profit or the minimization of the aircraft-focused costs. It should be noted that the route-based fleet composition during the strategic planning differs from the fleet assignment with flight schedules in the tactical or operational planning. Moreover, some realistic characteristics such as green fleets (Khoo and Teoh, 2014; Rosskopf et al., 2014) and multi-airline competitive environment (Wang et al., 2015) can be introduced in the fleet planning problem. In addition, as this problem is an essential process of airline management, the integration with other decision-making components like HLPs is an interesting and promising research topic in the future to get the optimal airline network (Mohri et al., 2022; Wu et al., 2022).

Future directions related to fleet planning problem need to incorporate environmental concerns in objective functions, technological advancements for solution methods, and market share for different types of aircraft. Although the extant research has adopted profit maximization as the first priority, green performance is another explicit objective for airlines to implement the fleet planning task. Additionally, considering the integration with other decision-making components is a promising trend, solving such complex and integrated problems is more computationally-challenging. It is required for a deeper understanding of the integration with several subproblems when designing an efficient solution technique. Moreover, the introduction of electric and hybrid aircraft might lead to additional increases in modeling and solution complexities of fleet planning problems.

### 2.3. Airline scheduling

Efficient airline scheduling ensures that resources, *e.g.*, aircraft and crew, are allocated in a way that maximizes profitability while meeting operational requirements and satisfying passengers demand. By optimizing schedules, airlines can minimize costs, increase capacity utilization, and improve service delivery, which are all essential for maintaining competitiveness in a cost-sensitive industry. Typically, the airline scheduling problem is divided into four subproblems that can be solved sequentially or using integrated approaches: flight scheduling (FS, Section 2.3.1), fleet assignment (FA, Section 2.3.2), aircraft routing (AR, Section 2.3.3), and crew scheduling (CS, Section 2.3.4). Table 5 provides an aggregated overview on the literature regarding the four subproblems.

#### 2.3.1. Flight scheduling

Flight scheduling, generally completed about six months before a flight's operation, primarily focuses on determining the itineraries to be operated in terms of frequency and timetable. This includes specifying airports for departure and arrival, along with departure and arrival times. The consideration of market share and demand is essential for airlines to translate theoretical solutions into practical applications. Traditionally, the scheduling process was done manually and without integrating sequential stages: it begins with drafting a tentative schedule, which is then evaluated by operations personnel who consider various factors such as costs and performance. The evaluation is fed back into the planning phase, leading to further adjustments. This loop can be repeated until a satisfactory final schedule is obtained (Etschmaier and Mathaisel, 1984). Various heuristic algorithms are designed based on this manual experience, with considerations of market share and demand Yan and Tseng (2002), Yan et al. (2007), Kepir et al. (2016).

Given that airlines want to solve increasingly larger problem instances while aiming to maximize revenues, numerous modern studies in the literature concern the development of more advanced solution algorithms and metaheuristic/hybrid algorithms, *e.g.*, based on tabu search (Kiarashrad et al., 2021), branch and bound (B&B) (Hou et al., 2023), and Benders decomposition (BD) (Cadarso and de Celis, 2017). One widely used method is column generation (CG), which often allows to solve instances with significantly less resources (Xu et al., 2020; Ding et al., 2023; Xu et al., 2024). During the optimization process, new routes can be added by the subproblems to escape local optima, all routes can be quickly selected using the main problem. Recent research has frequently utilized sampling average approximation to simplify demand uncertainty or employ machine learning techniques for prediction (Kenan et al., 2018; Birolini et al., 2023a). Machine learning (ML) methods have not only the potential to enhance predictions, but can also accelerate the resolution of complex combinatorial problems by narrowing the solution space, replacing intensive computations with quick approximations, or assisting

**Table 5**
Summary of the literature on airline scheduling.

| Problem | Topic | Reference & Method |
|---|---|---|
| FS | Passenger demand | Yan and Young (1996), LR; Kepir et al. (2016), heuristic algorithm; Kenan et al. (2018), CG; Birolini et al. (2023a), LNS; Cadarso and Vaze (2023), CPLEX; Xu et al. (2024), CG&LNS |
| | Market share | Yan et al. (2008), heuristic algorithm; Kiarashrad et al. (2021), tabu search metaheuristic method |
| | Robustness | Lee et al. (2007), CG; Jiang and Barnhart (2013), decomposition approach; Lee et al. (2020), SAA |
| FA | Develop model | Hane et al. (1995), B&B; Rushmeier and Kontogiorgis (1997), B&B; Ioachim et al. (1999), CG; Wei et al. (2020), heuristic algorithm; Yan et al. (2022), fare decomposition heuristics |
| | Different operational constraints | Barnhart et al. (2002), C&RG; Belanger et al. (2006), Dantzig–Wolfe decomposition; Pilla et al. (2012), Benders decomposition; Liu et al. (2018), SAA; Unal et al. (2021), Xpress optimization suite; Jing and Zhe (2024), B&B |
| | Robustness | Rosenberger et al. (2004), B&B; Smith and Johnson (2006), CG; Xu et al. (2021a), VNS&CG; Birolini et al. (2021), CG; Ahmed et al. (2022), proximity search, B&B; Glomb et al. (2024), Gurobi |
| AR | Regulatory compliance | Eltoukhy et al. (2019), ACO; Sanchez et al. (2020), iterative algorithm |
| | Machine learning | Baptista et al. (2018), data-driven technique; Yu et al. (2019), deep learning; Olive and Basora (2020), neural networks; Gui et al. (2020), machine learning; He et al. (2023), reinforcement learning; Birolini and Jacquillat (2023), ensemble machine learning; Ding et al. (2023), VNS, Deep learning |
| | Robustness | Hou et al. (2023), CG; Zhang et al. (2023a), matheuristic approach |
| CS | Crew Pairing Problem | Lavoie et al. (1988), CG; Hoffman and Padberg (1993), B&P; Haouari et al. (2019), commercial solvers; Quesnel et al. (2020a), CG; Quesnel et al. (2020a), B&P, heuristic algorithm; Tahir et al. (2021), integer CG, neural networks; Aggarwal et al. (2023), CG, genetic algorithm; Wen et al. (2023), CG |
| | Crew Rostering Problem | Day and Ryan (1997), CG; Maenhout and Vanhoucke (2010), scatter search heuristic; Quesnel et al. (2022), CG, deep neural networks |
| | Integrate | Zeighami et al. (2020), CG, alternative Lagrangian decomposition; Wen et al. (2022), CG, genetic algorithms; Saemi et al. (2022), ACO, Schrotenboer et al. (2023), B&P; Lin et al. (2024), CG |

LR: lagrangian relaxation; CG: column generation; LNS: Large Neighborhood Search; B&B: branch and bound; ACO: ant colony optimization; C&RG: column and row generation; SAA: sample average approximation; VNS: variable neighborhood search; B&P: branch and price.

in algorithm configuration (Ding et al., 2023). Additionally, ML can offer prescriptive insights by providing alternative approaches to tackle repetitive scheduling tasks (Razzaghi et al., 2024).

Various challenges exist regarding further advancements of flight scheduling. To push the integration of ML and optimization, focusing on model interpretability and effective mathematical integration is considered an important research direction (Xu, 2024; Wandelt et al., 2024a). In the view of various real-world disruptions, robustness and recovery flight schedules must be included as another important dimension (Lee et al., 2007, 2020; Cadarso and Vaze, 2023) as well as leasing aspects, given the increasing number of leased aircraft worldwide (Wandelt et al., 2023; Marintseva and Athousaki, 2024). Finally, while separate models are easier to solve, they often fail to fully account for the interdependencies between related decisions. For instance, most approaches focus on redistributing passenger flows among fixed market share (demand allocation) but often neglect the potential for demand stimulation from an attractive flight schedule (demand generation), or they handle it using overly simplified aggregate models. Consequently, these models tend to perform well in scenarios with limited schedule changes and dense markets but may fall short in identifying realistic growth opportunities in situations where demand is significantly induced rather than captured from existing competition.

### 2.3.2. Fleet assignment

Fleet assignment aims to assign appropriate fleet types to each flight leg such that seat capacity optimally matches the expected demand, subject to resource balance constraints. The objective function typically seeks to maximize total profit minus allocation costs. Two fundamental modeling techniques are used: connection networks (Abara, 1989) and time-space networks (Berge and Hopperstad, 1993). Subsequent research, building upon these two paradigms, differs mostly in terms of simplification / reformulation (Hane et al., 1995; Rushmeier and Kontogiorgis, 1997) or considering more complex application scenarios using different constraints (Barnhart et al., 2002; Belanger et al., 2006; Pilla et al., 2012). Modifying the model is an effective strategy for solving problems. For example, extensive networks can be partitioned into smaller sub-networks based on weak dependencies (Yan et al., 2022); pseudo aircraft can be introduced into the model to explore potential connections (Enki et al., 2024); availability constraints and flight overlap limitations can also decrease the size of the model (Unal et al., 2021; Glomb et al., 2024). A detailed summary of studies concerning fleet assignment are shown in Table 6.

Recently, more complex models have been developed, and various solution algorithms have been introduced to handle the large scale of real-world airline operations. Beginning with itinerary-based demand fleet assignment models (IFAM) (Kniker, 1998; Jacobs et al., 2008), advanced models have gained wider acceptance among airlines by incorporating additional features of real-world airline networks, such as robustness (Rosenberger et al., 2004; Smith and Johnson, 2006), stochasticity (Sherali and Zhu, 2008), and sustainability (Ma et al., 2018). Moreover, researchers have focused on developing integrated flight scheduling and fleet assignment models, which involve the simultaneous selection of flight legs for the schedule and the allocation of aircraft types to these legs (Zhou et al., 2020; Kızıloğlu and Sakallı, 2023), leading to more beneficial, integrated solutions. In particular, Birolini et al. (2021) proposed a novel mixed integer nonlinear flight scheduling and fleet assignment optimization model, where air travel demand generation and allocation are simultaneously endogeneized. Justin et al. (2022) posits that the convergence of electric propulsion and autonomy promises significant improvements

**Table 6**
Overview on studies regarding the fleet assignment problem.

| Reference | Novelty | Network | Flight | Time |
|---|---|---|---|---|
| Abara (1989) | Pioneer to use time-space network | TSN | 400 | 3600 s |
| Berge and Hopperstad (1993) | Pioneer to use connection network | CN | 8310 | 221 s |
| Pilla et al. (2012) | Stochastic demand driven; reallocation | TSN | 2358 | 3838 s |
| Liu et al. (2018) | Risk aversion | TSN | 72 | 57120 s |
| Kenan et al. (2018) | First using Sample Average Approximation to simplify demand | CN | 228 | 1692 s |
| Wei et al. (2020) | Combining and comparing seven heuristic algorithms | TSN | 390 | 2 h |
| Xu et al. (2021a) | Rapid computation of high-precision approximate optimal solutions | TSN | 1607 | 3460 s |
| Yan et al. (2022) | Partition flight into partly separable subnetworks | TSN | 815 | 10 h |
| Ahmed et al. (2022) | Accelerate computation | TSN | 646 | 5 h |
| Jing and Zhe (2024) | Integrate strategic planning and daily operating processes | TSN | – | 747 s |

TSN: time-space network CN: connection network.

in both operational efficiency and sustainability, formulating a half-leg half-itinerary mixed-integer linear program (MILP). Concerning robustness, Xu et al. (2021a) focuses on factors such as delay propagation, passenger recapture, and optional flights, developing an approach can get the approximate optimal solution for a network with 1,600 flights within two hours. The primary advantage of using such integrated models over a sequential approach is that they enable better decision-making and improved scheduling plans.

The requirement for precise demand information, increasing market share by utilizing appropriate aircraft types to enhance flight attractiveness, as well as global optimality of the solution, presents several challenges. The integrated problem leads to more complex models, and there is a lack of efficient and scalable solution algorithms for medium to large-scale issues. The application of machine learning is also affected by multidimensionality and constraint coupling, making it challenging to utilize its advanced data analysis and predictive modeling capabilities. Additionally, the literature on the seamless integration of air travel with other transportation modes (*e.g.*, high-speed rail and regional buses), which would provide travelers with higher connectivity and flexibility in their itineraries, can be developed further (Sun et al., 2024a). This integration could offer airlines more market opportunities, passengers better connectivity, and also improve resource utilization for airlines.

### 2.3.3. *Aircraft routing*

After assigning fleets to flights, airlines must devise effective routes for each aircraft, a problem known as aircraft routing (AR). Early research in the area focused on aircraft rotation problems or flight sequences (Clarke et al., 1997; Talluri, 1998). Later, more practical factors were incorporated, particularly maintenance requirements (Sriram and Haghani, 2003; Başdere and Bilge, 2014). Please refer to the following overview studies regarding maintenance path solutions (Eltoukhy et al., 2017), quantitative analysis (Ma et al., 2022), customer centricity (Thakkar and Palaniappan, 2024), and the evolution of network models and solutions (Chung et al., 2020; Xu et al., 2024). Table 7 summarizes extant studies in AR.

Existing solution techniques include CG (Hou et al., 2023) and ACO (Eltoukhy et al., 2019). However, the development of machine learning has recently introduced new perspectives in the filed (Yu et al., 2019; Olive and Basora, 2020; Gui et al., 2020), enabling end-to-end decision-making for the long-term operation of aircraft (Hu et al., 2021b), predicting the impact of flight delays on flight routes (Birolini and Jacquillat, 2023), and guiding heuristic methods to converge more effectively (Ding et al., 2023). Nonetheless, it can be observed that various studies overlook the randomness inherent in maintenance time, merely incorporating maintenance as a fixed time period into the flight schedule (He et al., 2023). Zhang et al. (2023a) addressed the issue by applying a fuzzy risk assessment to allocate adequate buffer times for each inspection package. The model and approach are shown in Fig. 1. This strategy aimed to mitigate the resulting disruptions. Subsequently, a metaheuristic approach was employed to solve 500 scenarios, leading to a notable reduction in flight delays.

The integration of AR with other airline scheduling components such as crew scheduling, passenger demand, and maintenance requirements introduces significant complexity and necessitates sophisticated algorithms and computational resources to handle large-scale problems. Uncertainty due to weather, operational disruptions, and demand variability further complicates routing, demanding robust algorithms that can adapt in real-time. Sustainability concerns, including the reduction of carbon emissions and noise pollution, require the incorporation of environmental objectives into routing models. Technological advancements, such as the integration of new aircraft technologies and air traffic management systems, necessitate continual updates to routing algorithms, while data-driven approaches leveraging big data and AI present both opportunities and challenges in real-time application. Additionally, resilience and rapid recovery from disruptions, along with preparedness for large-scale crises, demand resilient routing strategies.

### 2.3.4. *Crew scheduling*

The fourth step of airline scheduling typically involves crew assignment to flights, generally dissected into two subproblems: the Crew Pairing Problem (CPP) and the Crew Rostering Problem (CRP). Initially, the CPP problem was addressed using a model based on linear cost approximation (Lavoie et al., 1988); with more precise cost functions (Desaulniers et al., 1997) and a collection partition model for handling large-scale problems were developed (Hoffman and Padberg, 1993). CRP focused on achieving fair scheduling among crew members (Ryan, 1992; Day and Ryan, 1997). Recent research has increasingly focused on incorporating employee preferences (Maenhout and Vanhoucke, 2010), crew language qualifications (Quesnel et al., 2020b), sustainability (Wen et al., 2023), personnel unavailability (Schrotenboer et al., 2023), and pilot fatigue (Lin et al., 2024). Addressing CRP and CPP individually presents certain limitations. Accordingly, an increasing number of researchers have proposed to integrate these two problems, seeking solutions that hold greater practical significance (Zeighami et al., 2020; Wen et al., 2022).

In terms of solution methods, while commercial solvers are a good choice and there are even network flow models improved for commercial solvers (Haouari et al., 2019), heuristic algorithms remain the mainstream approach. Instances including the ACO metaheuristic algorithm (Saemi et al., 2022), genetic algorithm (Wen et al., 2022) and CG (Aggarwal et al., 2023). Methods based on neural networks have also been adapted recently, which can be used to predict the exploration direction of heuristic algorithm integer solution schemes (Tahir et al., 2021), as well as to select and pair the solution sets generated by heuristic algorithms (Quesnel et al., 2022). Details of extant papers are shown in Table 8.

**Table 7**
Overview on the aircraft routing problem.

| Reference | Novelty | Objective | Flight | Time |
|---|---|---|---|---|
| Clarke et al. (1997) | Pioneer of aircraft rotation problem | Max through value | – | 39 s |
| Sriram and Haghani (2003) | Maintenance requirement | Min maintenance and reassignment cost | 58 | 300 s |
| Başdere and Bilge (2014) | Maximizing utilization of the total remaining flying time of fleet | Min unused flying hours | 354 | 8514 s |
| Sanchez et al. (2020) | Multi-objective mixed integer linear programming | Min violations, max resource level, min tail reassignments, min maintenance interventions, max resource usage, and min maintenance | 16 000 | 1777 s |
| He et al. (2023) | Uncertainties of heterogeneous maintenance tasks | Maximizing robustness | 259 | 2767 s |
| Birolini and Jacquillat (2023) | Day-ahead aircraft routing; | Min delay | 700 | – |
| Ding et al. (2023) | Deep learning guide heuristic algorithm | Min cost due to disruptions | 931 | 14 s |
| Zhang et al. (2023a) | Optimization of cruise time | Min cost | 613 | 796 s |

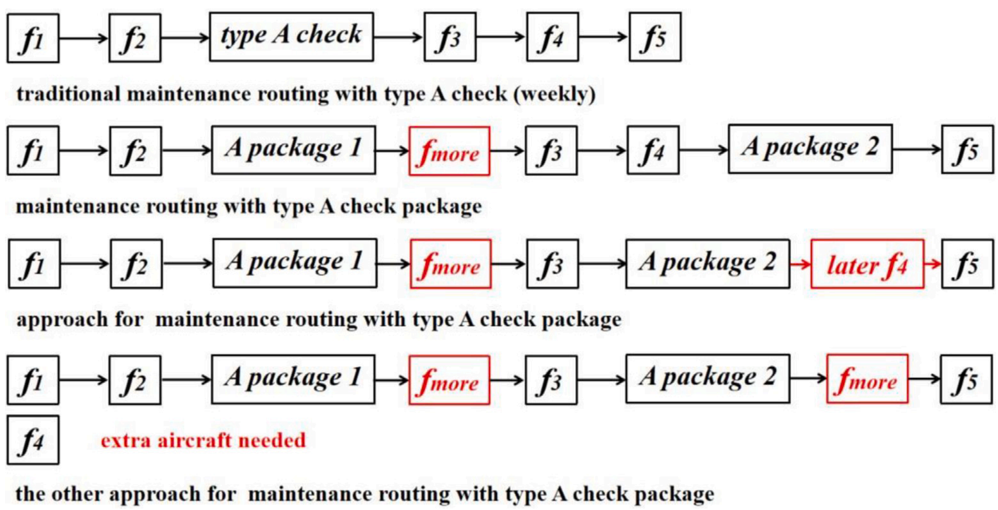


**Fig. 1.** Example for type A maintenance routing. Here, “extra aircraft needed” indicates that flight $f_4$ will be rerouted to an alternative aircraft. If no alternative aircraft is available, the flight will be cancelled.

**Table 8**
Overview on crew scheduling problem literature.

| Reference | Novelty | Objective | Flight | Time |
|---|---|---|---|---|
| Lavoie et al. (1988) | Model pairings as decision variables, using OR method in crew pairing problem | Min pairing cost | 1113 | 1250 s |
| Day and Ryan (1997) | Fair crew scheduling | Min cost of roster | – | 1.1 s |
| Quesnel et al. (2020b) | Crew menbers’ preference | Min cost | 7765 | 16267 s |
| Zeighami et al. (2020) | Integrated CPP and CRP | Max crew requests, min pairing cost, min dissimilarity of pilot and co-pilot | 5613 | 1944 s |
| Tahir et al. (2021) | Predict probabilities of integer solution leap with deep neural network | Min work time, deadhead, short connection and short rest | 1694 | 696 s |
| Saemi et al. (2022) | One or more days off in a pairing assignment | Min crew cost, deadhead and hotel cost | 134 | 34 min |
| Wen et al. (2022) | Individual cabin crew pairing | Min cost and substitution penalty | 2050 | 10 s |
| Wen et al. (2023) | Sustainability cost factors | Min basic cost, fuel consumptions, greenhouse gas emissions and the robustness cost | 98 | 226 s |
| Schrotenboer et al. (2023) | Repair a robust strategy for crew and reserve-crew | Min cost of basic operation, reserve-crew, deadhead and canceling | 309 | 161 s |
| Lin et al. (2024) | Balance the scheduling cost and crew fatigue working duration | Min cost of basic operation and crew fatigue working duration | – | - |

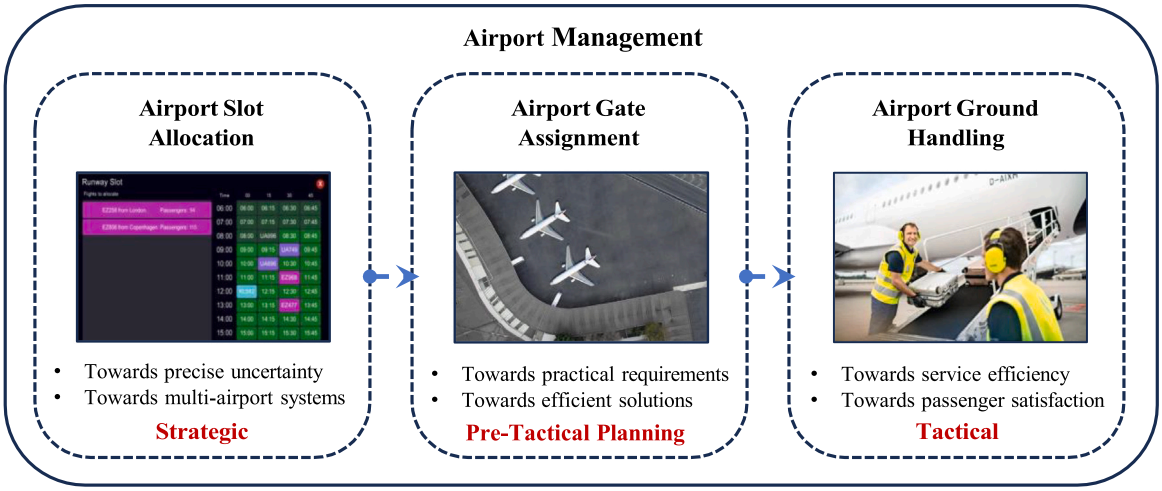


**Fig. 2.** The most three significant research topics in airport management.

One of the biggest challenges in research on crew scheduling is the unavailability of public data. While for the other airline scheduling sub-problems, relevant aircraft and market data can obtained from various global data providers, crew data seems to be one of the most protected business secrets by airlines. Accordingly, researchers have to rely on data obtained from airlines directly, which is usually not allowed to be published and leads to significant challenges in reproducibility as well as reduced innovation potential in the field. We believe there is an urgent need for a coordinated work on either developing realistic simulated data or finding ways to publish crew data from airlines - even historical data, as baseline for research purposes and benchmarks.

### 2.3.5. *Summary of airline scheduling*

To further advance the integration of ML and optimization in aviation scheduling problems, investigating model interpretability and effective mathematical integration is a particularly important avenue for future research. Particularly, researchers should focus on developing more scalable integrated models that accommodate a wider range of constraints and sub-problems, incorporate more realistic uncertainty-based forecasting, and utilize efficient heuristic or machine learning-guided algorithms. Additionally, exploring models and solution algorithms that leverage highly parallelized architectures, such as those in Graphics Processing Units (GPUs), could further enhance the effectiveness of airline management systems.

## 3. Airport management

This section provides a general review of operations research in airport management, which aims to coordinating the operations, services, safety, and overall functioning of an airport to ensure efficient and effective service to passengers, airlines, and other stakeholders (Fernandes and Pacheco, 2007; Graham, 2020; Dixit and Jakhar, 2021; Chen et al., 2024a). We cover the most three most prominent research topics in the airport management literature, namely, airport slot allocation (Section 3.1), gate assignments (Section 3.2), and ground handling (Section 3.3), with an emphasis on the usage of OR techniques. Fig. 2 provides an overview of these three topics and their temporal relationship.

### 3.1. *Airport slot allocation*

When increasing demands for air transportation meet limited airport/infrastructure capacity, airport slot allocation becomes a key factor in maximizing operational efficiency while ensuring the resilience of the system (Milioti and Odoni, 2024). This section dissects mathematical modeling techniques for airport slot allocation and corresponding solution approaches. Table 9 provides a summary of the extant literature.

Studies on airport slot allocation widely use a binary variables series $(x_{i1}, \ldots, x_{ij})$ for flight $i$ in the planning horizon $j$, where $x_{ij} = 1$ represent the flight $i$ is scheduled no later than slot $j$. The mathematical model ensures that each flight is assigned a slot and incorporates constraints on airport capacity and minimum/maximum turnaround time. Regarding the objectives airport slot allocation, existing literature mainly focuses on minimizing total/maximum schedule displacement (Katsigiannis et al., 2021; Liu et al., 2022; Wang et al., 2023b; Birolini et al., 2023b), dispersion of displacement (Androutsopoulos et al., 2020), flight numbers of displacement (Cheung et al., 2021), number of rejected slots (Katsigiannis and Zografos, 2021) as well as congestion (Wang and Zhao, 2020), while catering to airlines fairness (Castelli et al., 2011; Ribeiro et al., 2018; Zografos et al., 2018; Androutsopoulos and Madas, 2019; Zografos and Jiang, 2019; Fairbrother et al., 2019; Jiang and Zografos, 2021; Katsigiannis et al., 2021), preferences (Katsigiannis and Zografos, 2021; Jiang and Zografos, 2021), and priorities (Zografos et al., 2012; Ribeiro et al., 2018; Benlic, 2018; Ribeiro et al., 2019b; Wang et al., 2019; Zografos and Jiang, 2019; Ribeiro et al., 2019a; Katsigiannis et al., 2021; Katsigiannis and Zografos, 2021; Cheung et al., 2021; Jiang and Zografos, 2021). Recent studies also formulate the problem from passengers' perspectives, where available itineraries are maximized and connecting times minimized (Birolini et al., 2023b).

Given that disruptions are a common in real-world operations, research on slot allocation has seen a paradigm shift from deterministic slot allocation (Castelli et al., 2011; Zografos et al., 2012; Pellegrini et al., 2017; Benlic, 2018) to robust slot allocation (Wang and Zhao, 2020; Liu et al., 2022) in recent years. The robust slot allocation often considers airport capacity as a main factor of uncertainty (Corolli et al., 2014; Wang and Zhao, 2020; Wang and Jacquillat, 2020; Cheung et al., 2021; Liu et al., 2022; Wang et al., 2023b), as the airport capacity has a strong correlation to weather conditions and the capacity would decline desperately under bad weathers. To handle extreme capacity reductions, a robust optimization is used to identify the worst case of uncertain parameters and simultaneously find the best decisions under such conditions (Wang and Zhao, 2020; Liu et al., 2022). In reality, however, the probability of worst-case scenarios is relatively low, and therefore current research focus gradually shifts to stochastic programming, which is capable of obtaining a more reasonable slot allocation balancing the efficiency and robustness. The two dominant approaches are the chance constraint method - where the capacity

**Table 9**
Overview of literature in airport slot allocation. Displacement is omitted from the objective column as it is utilized in every study.

| Reference | MAP | Objective | | | UC | Methods |
|---|---|---|---|---|---|---|
| | | F | P | PAX | | |
| Katsigiannis and Zografos (2024) | | | ✓ | | | GA & clustering |
| Wang et al. (2024a) | | | | | | ALNS hyper-heuristic |
| Liu et al. (2024) | ✓ | | | | ✓ | Gurobi |
| Wang et al. (2023b) | ✓ | | | | ✓ | Gurobi |
| Birolini et al. (2023b) | | | | ✓ | ✓ | LNS |
| Liu et al. (2022) | ✓ | | | | ✓ | Gurobi |
| Katsigiannis et al. (2021) | | ✓ | ✓ | | | Gurobi & heuristic |
| Katsigiannis and Zografos (2021) | | ✓ | ✓ | | | Gurobi & problem specific cuts |
| Jorge et al. (2021) | | ✓ | | | | CPLEX & $\varepsilon$-constraint |
| Jiang and Zografos (2021) | | ✓ | ✓ | | | CPLEX |
| Cheung et al. (2021) | | ✓ | | | ✓ | CPLEX |
| Wang and Jacquillat (2020) | ✓ | | | | ✓ | CPLEX & problem specific cuts |
| Wang and Zhao (2020) | | | | | ✓ | CPLEX |
| Androutsopoulos et al. (2020) | | ✓ | | | | LNS |
| Zografos and Jiang (2019) | | ✓ | ✓ | | | CPLEX, $\varepsilon$-constraint & row generation |
| Wang et al. (2019) | | | ✓ | | | Heuristics |
| Ribeiro et al. (2019b) | | | ✓ | | | CPLEX |
| Ribeiro et al. (2019a) | | | ✓ | | | Heuristics |
| Fairbrother et al. (2019) | | ✓ | | | | Gurobi & $\varepsilon$-constraint |
| Androutsopoulos and Madas (2019) | | ✓ | | | | CPLEX |
| Zografos et al. (2018) | | ✓ | ✓ | | | CPLEX & $\varepsilon$-constraint |
| Ribeiro et al. (2018) | | ✓ | ✓ | | | CPLEX, $\varepsilon$-constraint & problem specific cuts |
| Benlic (2018) | ✓ | | ✓ | | | Heuristics |
| Pellegrini et al. (2017) | ✓ | | | | | CPLEX |
| Corolli et al. (2014) | ✓ | | | | ✓ | CPLEX & SAA |
| Zografos et al. (2012) | | | ✓ | | | Row generation |
| Castelli et al. (2011) | ✓ | ✓ | | | | XPRESS |

MAP: multiple airports, F: fairness, P: priority, PAX: passenger, UC: uncertainty,GA: Genetic Algorithm, ALNS: Adaptive Large Neighborhood Search.

constraint is probabilistic - and modeling the airport capacity as a random variable (Corolli et al., 2014; Wang and Jacquillat, 2020; Wang et al., 2023b).

CPLEX and Gurobi are the two most frequently used commercial solvers for obtaining exact solutions for slot allocation problems, especially for small / medium-scale instances (Katsigiannis et al., 2021; Katsigiannis and Zografos, 2021; Jorge et al., 2021; Jiang and Zografos, 2021; Cheung et al., 2021; Wang et al., 2023b). As the scale of instances increases, it is arduous to even find feasible solution since the slot allocation problem is NP-hard. Therefore, many recent studies on large, realistic instances have designed problem-specific acceleration tricks to reduce searching space and thus improve computational efficiency. For instance, Wang and Jacquillat (2020) added dual integer cuts which significantly tighten traditional Benders cuts and neighborhood constraints to overcome a long-tail effect during convergence. In addition, heuristic algorithms are often used; especially large-scale neighborhood search (LNS) is a frequently used (Androutsopoulos et al., 2020; Birolini et al., 2023b). Concerning multi-objective optimization, strategies such as the $\varepsilon$-constraint method are employed to transform multiple objectives into a single objective framework (Zografos et al., 2018; Fairbrother et al., 2019; Androutsopoulos et al., 2020; Jorge et al., 2021). Alternatively, a lexicographic optimization strategy can be implemented for a sequential optimization approach (Pellegrini et al., 2017; Androutsopoulos and Madas, 2019; Katsigiannis et al., 2021).

One of the major challenges is that stochastic programming often requires accurate knowledge of the probability distributions of uncertainties. The challenge lies in the fact that these distributions are ambiguous or change over time. This calls for the adoption of distributionally robust optimization (DRO), which does not only rely on a single distribution. Instead, DRO works on a set of possible distributions, providing a more robust and flexible framework for slot allocation under multiple sources of uncertainty. Addressing chance constraints in stochastic programming involves innovative approaches to effectively manage uncertainties. Moreover, current literature often discretizes time slots into 5 or 15-minute intervals. Achieving finer granularity in airport slots could significantly enhance the utilization of airport and airspace capacities, thereby highlighting the need for efficient solution algorithms. Consequently, the pivotal challenge in airport slot allocation is to design algorithms capable of effectively managing large-scale, real-world scenarios with comprehensive uncertainty considerations. Finally, the assignment of slots and timings in multiple airports regions is seen as increasingly important (Wandelt et al., 2024).

### 3.2. Airport gate assignment

Another crucial problem in airport management is airport gate assignment, involving multiple stakeholders' interests, while aiming to enhance operational efficiency and improve passenger satisfaction. A typical gate assignment plan is shown in Fig. 3. This subsection offers a concise overview of the modeling for the airport gate assignment problem including its basic modeling, objectives, and uncertainty considerations, and then summarizes the solution approaches presented in the literature. Readers are referred to Table 10 for an overview of extant studies.

Typically, there are two fundamental constraints in the airport gate assignment. The first constraint ensures that each aircraft is allocated exactly one parking spot, while the second constraint guarantees that the parking schedules of different aircraft at the same gate do not overlap in time. In addition to the basic constraints, a shadow constraint is often used to split a large gate for small aircraft (Daş et al., 2020). The objectives of the airport gate assignment problem need to satisfy a variety of stakeholders. Regarding passengers, it is generally assumed that they prefer shorted walking distances and enjoy convenience accessing airport services (Daş, 2017; Dell'Orco et al., 2017; Karsu et al., 2021; Li et al., 2022a; Jiang et al., 2023a); alternate objectives include maximizing the number of passengers using contact gate or jetways (Bi et al., 2022, 2020). Airlines are mostly interested in reducing taxi times and parking at nearby gates (Jiang et al., 2023a). Airports not only care about operational efficiency but also gate safety, including aspects of gate idle/blockage time (Xu et al., 2017; Jiang et al., 2023c), fairness (Jiang et al., 2023a), towing cost (Yu et al., 2017), conflict cost (also known as robustness cost) (Yu et al., 2017; Dorndorf et al.,

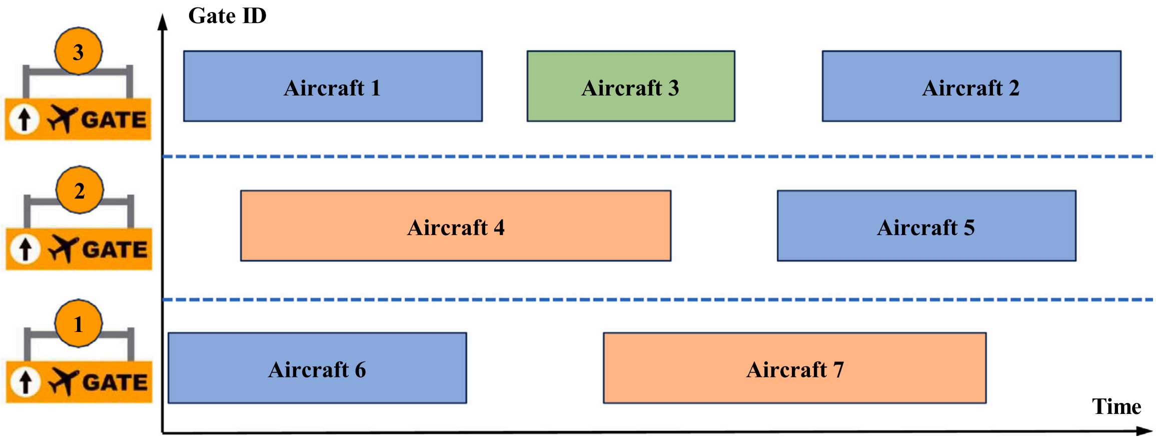


**Fig. 3.** Airport gate assignment plan example; the length of a bar visualizes an aircraft's turn around time.

**Table 10**
Overview of objectives and methods for airport gate assignment problem in recent literature.

| Reference | Objectives | | | | | | | | Methods |
|---|---|---|---|---|---|---|---|---|---|
| | PAX | R | T | G | P | TOW | R | C | |
| Nikolić et al. (2024) | ✓ | | | ✓ | | | | | BCO |
| Jiang et al. (2024) | | ✓ | | ✓ | ✓ | | | ✓ | B&P & CG |
| Li et al. (2024) | ✓ | | | ✓ | | | | | CG & LS |
| Liu and Xiang (2023) | | ✓ | ✓ | | | | | | B&P & CG |
| Kim et al. (2023) | | ✓ | | ✓ | | | | | B&P & CG |
| Jiang et al. (2023c) | | | ✓ | ✓ | | | | | B&P, $\varepsilon$-constraint & CG |
| Jiang et al. (2023b) | ✓ | | | | | | | | VNS |
| Jiang et al. (2023a) | ✓ | | | | | | | ✓ | NSGA-II & LNS |
| She et al. (2022) | ✓ | ✓ | | | ✓ | ✓ | | | NSGA-II |
| Li et al. (2022a) | ✓ | | | | | | | | TS & RL |
| Bi et al. (2022) | ✓ | | | | | | | | B&P, CG & TS |
| Karsu et al. (2021) | ✓ | | | ✓ | | | | | B&B & BS |
| Liang et al. (2020) | ✓ | | | ✓ | | | | ✓ | GA |
| Bi et al. (2020) | ✓ | | | | | | | | TS |
| Mokhtarimousavi et al. (2018) | ✓ | ✓ | | | | ✓ | | | NSGA-II |
| Yu et al. (2017) | ✓ | ✓ | | | | ✓ | | | LNS |
| Xu et al. (2017) | | ✓ | ✓ | | | | | | Heuristic |
| Schaijk and Visser (2017) | | ✓ | | | ✓ | | | | / |
| Dorndorf et al. (2017) | | ✓ | | | ✓ | ✓ | | | MECA |
| Dell'Orco et al. (2017) | ✓ | | | ✓ | | | | | FBCA |
| Daş (2017) | ✓ | | | | | | ✓ | | LS |

PAX: Passenger, R: Robustness, T: Gate Idle Time, G: Remote/Contact Gate, P: Preference, TOW: Towing Cost, R: Airport Revenue, C: Taxing Cost, BCO: Bee Colony Optimization,B&P: Branch-and-Price, CG: Column Generation, VNS: Variable Neighbourhood Search, NSGA-II: Non-dominated Sorting Genetic Algorithm II, TS: Tabu Search, RL: Reinforcement Learning, GA: Genetic Algorithm, LNS: Large Neighborhood Search, B&B: Branch-and-Bound, BS: Beam Search, MECA: Modified Ejection Chain Algorithm, FBCA: Fuzzy Bee Colony Algorithm, LS: Local Search.

2017; Liu and Xiang, 2023), use of remote gates (Dell'Orco et al., 2017; Jiang et al., 2023c) and also shopping revenues (Daş, 2017). These multiple and potentially conflicting objectives from each stakeholder combined with safety requirements and restricted sources of gates make the gate assignment problem intrinsically difficult to solve towards optimality for real-world instances. In recent years, the robustness of gate assignment solutions is seen as increasingly important. Aside from previous uncertainty modeling for slot allocations, where uncertain parameters are often shown in the constraints side (Xu et al., 2017; Schaijk and Visser, 2017), uncertainty modeling in gate assignment is often reflected in its objective function (She et al., 2022; Yu et al., 2017). For instance, a mapping function can be embedded into the objective to convert gate idle time into the expected gate conflict duration, where the parameters could be obtained through historical data (Liu and Xiang, 2023).

Most solution approaches for airport gate assignment problems are focused on designing customized algorithms, compared to using commercial solvers directly. Meta-heuristics including Fuzzy Bee Colony Optimization (Dell'Orco et al., 2017), Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Mokhtarimousavi et al., 2018; Jiang et al., 2023a), variable neighborhood search (VNS) (Jiang et al., 2023b), tabu search (Bi et al., 2020; Li et al., 2022a), adaptive parallel genetic algorithm (APGA) (Liang et al., 2020). Hybrid methods were well proposed as well, *e.g.* Daş (2017) utilized a combination of Two-Phase Local Search (TPLS) and Pareto Local Search (PLS) algorithms to tackle multi-objective optimization problems. Li et al. (2022a) proposed a mixed search strategy exploring both feasible and infeasible solutions with the tabu search method and employed a reinforcement learning mechanism to guide the search towards new promising regions. Besides metaheuristics, exact solution frameworks based on branch-and-bound (B&B) and branch-and-price (B&C) shows high potential to derive the global optimal solutions, because of its capability to incorporate a variety of acceleration techniques (Karsu et al., 2021; Jiang et al., 2023c).

Although the extant literature has explored the gate assignment problem from various perspectives, future research directions should focus on more practical and real-world modeling aspects like differences among gates due to airport layout, fairness, and preferences among airlines, as well as more passenger-centric objectives aimed at enhancing passenger satisfaction (Eshaghi et al., 2024). Moreover, incorporating uncertainty together with a prediction model into the modeling

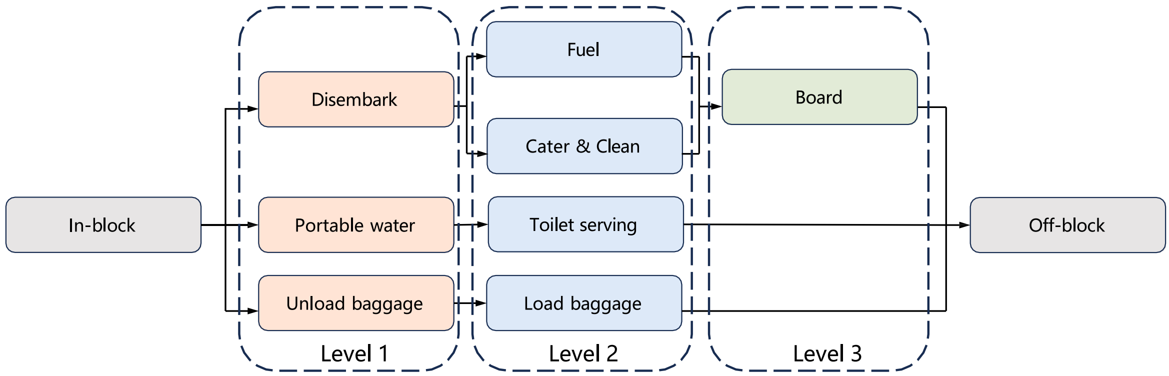


**Fig. 4.** Typical workflow for an airport ground handling procedure.

**Table 11**
Literature on service vehicle dispatching.

| Reference | Vehicles | Objectives | Methods |
|---|---|---|---|
| Du et al. (2008) | Refuelers | Service & start time | ACO |
| Norin et al. (2012) | De-icing | Flight delay & distance | GRAS |
| Du et al. (2014) | Towing tractors | Service time & delay | CG |
| Padrón et al. (2016) | Multiple | Completion & waiting time | Heuristic |
| Guo et al. (2020) | Baggage transport | Vehicles number & distance | GA |
| Han et al. (2022) | Ferry | Number of vehicle & flights serving | Heuristic |
| Zhang et al. (2022) | Apron support | Completion time | GA |
| Zhu et al. (2022) | Refuellers & buses | Completion time & service costs | CPLEX |
| Zhou et al. (2023) | Multiple | Distance | IL, GCN & LNS |

GRAS: Greedy Randomised Adaptive Search, GA: Genetic Algorithm, IL: Imitation Learning, ACO: Ant Colony Optimization, CG: Column Generation, GCN: Graph Convolutional Network, LNS: Large Neighborhood Search.

process is also a promising direction for future studies. In addition, existing heuristics on the subject are extremely diverse and complex; and there is room for comprehensive experimental benchmarks that identify strengths and weaknesses of these different heuristics and their components.

### 3.3. Airport ground handling

Airport ground handling is a critical component of aviation logistics, ensuring the swift and orderly transition of flights through the terminal. As shown in Fig. 4, the process encompasses a range of activities, from disembarking passengers to refueling aircraft, all of which must be executed with precision to maintain the integrity of the flight schedule. The optimization of ground handling operations has become increasingly sophisticated, with a focus on the deployment of service vehicles and the management of baggage handling systems.

Another important operational problem for airports is the dispatching of ground service vehicles. In recent years, research has shifted from single-type service vehicles, including de-icing vehicles (Norin et al., 2012), apron support vehicle (Zhang et al., 2022), refuelers (Du et al., 2008), towing tractors (Du et al., 2014), baggage transport vehicles (Guo et al., 2020) to multiple-type service vehicle integrated scheduling. Common objectives include the fleet size (Zhu et al., 2022) and routing distance (Zhou et al., 2023). In presence of variable flight arrival times, the punctuality of service vehicle arrival has emerged as a primary concern in the literature. Zhu et al. (2022) proposed a chance constraint method to describe the uncertainty of the flight's actual arrival time and transform it into a deterministic equivalent by fitting a normal distribution and applying a reverse probability density function. Recent studies have incorporated learning-based techniques. For instance, Zhou et al. (2023) proposed a learning-assisted LNS method, where imitation learning and graph convolutional network (GCN) were integrated to learn a destroy operator to automatically select variables. An overview of the literature is shown in Table 11.

Baggage handling is another pivotal aspect of ground operations, where research has focused on optimizing transfer baggage, inbound baggage, and the loading/unloading processes. Barth et al. (2021) considered arrival time uncertainty and modeled this problem as semi-stochastic programming and solved the model using CPLEX. For the inbound baggage handling, Frey et al. (2017) proposed a two-stage assignment framework including two subprocesses: the baggage infeed process at the airport's airside and the claiming process at the airport's landside. The target is to balance the load across baggage carousels and guarantee a high level of service for passengers. The last kind of problem shows some similarity with the vehicle routing problem. In this problem, a team of workers needs to load and unload baggage around the apron. Dall'Olio and Kolisch (2023) proposed a branch-and-price-and-check method incorporating Dantzig–Wolfe (DW) decomposition and showed its superiority.

Considering challenges in current research of airport ground handling, most articles only involved one or two types of vehicles for studying the dispatching problem, which would lead to over-simplified solutions that were not practical enough for realistic operations. Future studies are expected to consider broader types of vehicles as a whole. In addition to this, methods adopted to solve the problem were mostly heuristic algorithms, which leaves a huge gap to be bridged by cultivating acceleration techniques for exact algorithms. As for the baggage handling problem, the literature mainly split the problem into three sub-problems and solved them independently. However, these sub-problems are not fully decoupled actually, which also stipulates the necessity for developing integrated solutions to the whole baggage handling process.

### 3.4. Summary of airport management

To delve deeper into operation research applications in airport management, more practical modeling techniques to address specific layouts of an airport or set the finer granularity of airport time slots are necessary; special considerations for multiple stakeholders' preferences should be also given. Furthermore, as researchers gradually recognize the importance of aviation big data, machined learning-assisted operation research is becoming prevailing, where the range of a parameter could be predicted to reduce redundant space of uncertainty, which is beneficial to the data-driven optimization paradigm. Finally, the integrated optimization for handling coupled sub-problems simultaneously are promising to output more satisfactory solutions when managing airport operations.

## 4. Air traffic management

Air Traffic Management (ATM) aims to ensure the safe and efficient operation of aircraft in a constrained airspace (Wu and Caves, 2002; Kistan et al., 2017; Chen et al., 2024b). In this section, we focus on three widely adopted ATM problems that have been addressed using OR methods: Air Traffic Flow Management (Section 4.1), trajectory planning and optimization (Section 4.2), and airspace sectorization (Section 4.3).

### 4.1. Air Traffic Flow Management

The goal of Air Traffic Flow Management (ATFM) is to minimize delays and maximizing resource utilization, by balancing the capacity and demand while adjusting the flow of aircraft within a given region/sector. Traditionally, ATFM is formulated through a tactical flow plan designed to match the demand with real-time capacity based on existing information for an upcoming time window, *e.g.*, the next few hours. Typical causes of imbalance between capacity and demand include airport capacity constraints, traffic control restrictions, and weather disruptions.

Attwooll (1977), Odoni (1987) pioneered the formulation of ATFM in a mathematical optimization model. With the onset of collaborative decision-making programs, the field went away from relying on a single decision maker for large-scale operations. Over time, the models evolved to become dynamic decision-making supporters (Ball et al., 2003; Barnhart et al., 2003). Given the increase in computing power and the expansion of airline fleets, the ATFM considerations have gradually shifted towards large-scale flight networks, with a greater variety of realistic issues/constraints being considered. Examples of some features include robustness considering two-stage stochastic integer model (Pien et al., 2015), equity weighting between airlines (Hamdan et al., 2022a), sustainability considerations (Finke et al., 2021; Hamdan et al., 2022b), and user-preferences /prioritization (Qian et al., 2023; Gurtner and Bolić, 2023). A common problem for model formulations nowadays is the incorporation of uncertainty, including safety and operational adverse factors (Sandamali et al., 2020) as well as uncertainty in airspace sector capacity (Fadil et al., 2021).

In response to the more efficient computation and wider applicability to large-scale instances, scholars have increasingly focused on heuristic approaches (Xiao et al., 2018; Zhang et al., 2018b) and machine learning (Zhao et al., 2023, 2024; Mas-Pujol and Delgado, 2024) for solving AFTM problems. The advantage of machine learning lies in shifting a larger portion of the computational effort to the training phase by - intuitively speaking - enumerating previously seen adverse conditions and incorporating them into the model directly. Recent studies including the combination of Fuzzy C-Means and Graph Convolutional Networks (Zhang et al., 2023c), Multi-Aspect Spatio-Temporal Graph Convolutional Networks which is outperforming traditional machine learning and deep learning methods (Cai et al., 2024), as well as Multi-Agent Reinforcement Learning in unknown ATFM scenarios (Yutong et al., 2023). In order to efficiently apply machine learning in the field, Wang et al. (2023a) considered the impact of a large state space, combined action space, and coupled constraint action set on the effectiveness of reinforcement learning, proposing reinforcement learning-informed policy analysis, which can provide a 10-fold increase in computational efficiency compared to directly using reinforcement learning when solving ATFM problems. Table 12 summarizes the literature related to these developments in ATFM.

**Table 12**
Recent literature on ATFM.

| Topic | Reference |
|---|---|
| Diversity | Pien et al. (2015); Xiao et al. (2018); Zhang et al. (2018b) |
| Uncertainty | Starita et al. (2020); Sandamali et al. (2020); Fadil et al. (2021); Finke et al. (2021); Hamdan et al. (2022a); Hamdan et al. (2022b); Qian et al. (2023); Gurtner and Bolić (2023) |
| Prediction | Zhao et al. (2023); Yutong et al. (2023); Zhang et al. (2023c); Zhao et al. (2024); Mas-Pujol and Delgado (2024); Cai et al. (2024) |

### 4.2. Trajectory planning and optimization

Aircraft trajectories are influenced by a combination of strategic (trajectory planning) and operational (*e.g.*, air traffic control) aspects. Generally speaking, the objective of aircraft trajectory planning is to determine a flight path that meets the requirements of each stage of the flight, including altitude adjustments to ensure the most fuel-efficient and least emissions (Zhang et al., 2016; Gardi et al., 2016; Bouttier et al., 2017), climbing to ensure minimal social influence (Morrell and Lu, 2000; Khardi et al., 2010), and yawing to ensure safety (Nahayo et al., 2011; Rey et al., 2016), as illustrated in Fig. 5. Given a very early, seminal work of Rutowski (1954), various studies have investigated aircraft trajectory optimization through the kinetic models solved by integral-differential equations (Sorensen and Waters, 1981; Garcia-Heras et al., 2016). Rather than the kinetic model, the operational model is solved by non-linear programming (Nahayo et al., 2011; Bonami et al., 2013) and heuristic algorithms (Yu et al., 2016; Bouttier et al., 2017), facing complex aircraft trajectories. Recent advances include fixed arrival time analysis of the best cruise (García-Heras et al., 2014; Franco and Rivas, 2014), maximum unpowered descent range with height-related wind (Vormer et al., 2006), integrate the trajectory and sequence problems of approaching aircraft (Kamo et al., 2023), uncertainty on aircraft performance (Simorgh et al., 2024), the utilization of wind fields (Wells et al., 2023), evaluation of multi-criteria based on multi-trajectory (Guitart et al., 2024), integration of novel fuel/power technologies (Rau et al., 2024), micro-trajectories planning using dynamic window algorithm (Lu and Liu, 2022); see Table 13 for an overview.

In recent years, scholars have gradually explored the integration and application of machine learning algorithms. (Xu et al., 2023) studies how to combine machine learning with the heuristic algorithm by guiding the convergence of the A* algorithm under constraints of weather, aircraft performance, and complex real-world limitations. In this context, trajectory prediction has become an increasingly import research topic as well, given the abundant amount of historical trajectory data (Zeng et al., 2022). Past trajectory information can be used for prediction, making it suitable for machine learning especially without real-time information. Lin et al. (2019), Tran et al. (2022), *e.g.*, through a generative adversarial network approach (Pang and Liu, 2020) and improved LSTM (Xu et al., 2021b). (Jia et al., 2022) conducted a large-scale comparison of machine learning models, using a model combining attention and LSTM, compared to LSTM, support vector machines, backpropagation neural networks, hidden Markov models, and convolutional LSTM, and revealed that the combined model showed the best performance.

### 4.3. Airspace sectorization

Compared to ATFM (Section 4.1), which focuses on adjusting the demand, airspace sectorization pays more attention to the capacity, balancing air traffic distribution and controller workload; see Table 14.

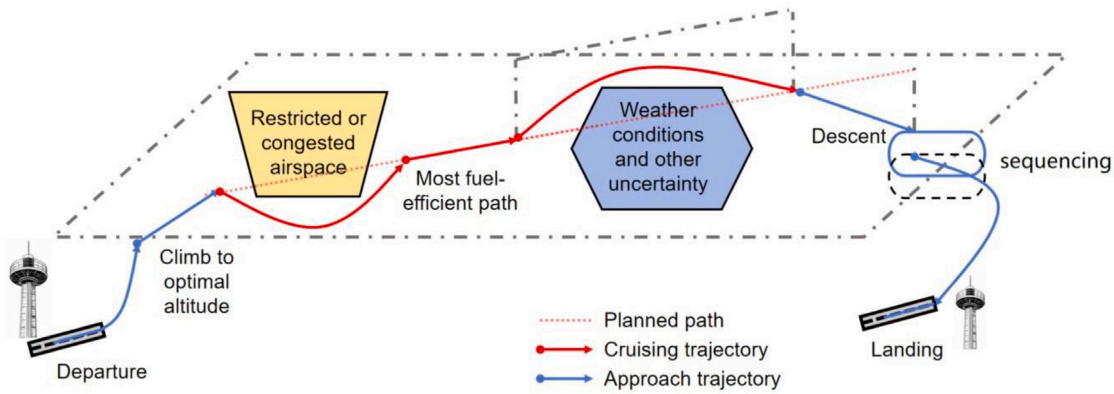


**Fig. 5.** Aircraft trajectory planning and interference.

**Table 13**
Extant literature on trajectory planning.

| Method | Reference |
|---|---|
| Mathematical programming | Nahayo et al. (2011); Bonami et al. (2013); Lu and Liu (2022); Kamo et al. (2023) |
| Heuristics algorithm | Yu et al. (2016); Bouttier et al. (2017); Gui et al. (2024) |
| Machine Learning | Lin et al. (2019); Pang and Liu (2020); Xu et al. (2021b); Tran et al. (2022); Jia et al. (2022); Xu et al. (2023) |

The goal of airspace sectorization is to partition the airspace into distinct sectors, each managed by an individual air traffic controller group. Traditionally, the methods of solving the problem include Voronoi diagrams, graph-based methods, and trajectory clustering (Zelinski and Lai, 2011; Chandra et al., 2024). Voronoi diagram is currently the most prevalent and fundamental approach and can generate sectors that conform to the requirements of connectivity and convexity. In the seminal work of Delahaye et al. (1994), the genetic algorithm and Voronoi diagram were first combined to partition airspace, and served as a landmark in the evolution of airspace partitioning, marking the transition from empirical method to automated methods. Although this work is not comprehensive, even in subsequent improvements, workload constraints were not adequately considered, leading to results that are not practical (Delahaye et al., 1995). In 1998, taking this constraint into account, evolutionary algorithms were used to improve the generator, yielding referential sectors (Delahaye et al., 1998). Despite being a method from 30 years ago, Voronoi diagram remains frequently used through the adaptation of more efficient evolutionary algorithms, the refinement of better generator generation, and migrating to the third dimension (Xue, 2009; Zou et al., 2016; Zhang et al., 2023b).

Graph-based methods do not refer to a specific technique but rather encompass a category of heuristic approaches that are based on the notion of graphs. Initially proposed by Trandac and Duong (2002) in the context of the dynamic airspace sectorization problem, a graph partitioning method based on peak traffic weighting was proposed, that reconfigures the sectorizations by calculating the weights of subgraph cuts and correlating them with sector associations (Martinez et al., 2007). This weighted subgraph pattern has inspired various follow-up studies (Li et al., 2009; Chen and Zhang, 2014). In addition, the use of Genetic Algorithms (Chen et al., 2013), the embedding of meme local search within the constrained evolutionary algorithm (Zou et al., 2016), and the partitioning of predefined 3D airspace blocks (Sergeeva et al., 2017) can be found in the literature. Brinton and Pledgie (2008) was the first to recommend trajectory clustering such that the sector boundaries are generated with geometry-based constraints, and the number of sectors can be adjusted according to the specified sector traffic capacity. Later research including heuristic gradient descent with the objective of dynamic density was described (Brinton et al., 2009) and the mean shift clustering algorithm was applied to cluster air traffic during both busy and idle periods (Peng et al., 2023). In addition to the three widely used methods mentioned above, scholars have employed various approaches to conduct airspace sectorization. For example, to satisfy connectivity constraints and convex constraints, a MIP method based on mathematical modeling was employed (Yousefi and Donohue, 2004; Schmidt et al., 2017; Oktal et al., 2020). Considering the fair distribution of workload and work quality, a constraint programming model was proposed (Trandac et al., 2005; Mogtit et al., 2020) and neural networks and single-layer state task networks have been utilized as well (Gianazza, 2010; Lema-Esposto et al., 2021).

To achieve the most reasonable airspace configuration, scholars generally adopt a combined approach of three methods. This process begins with trajectory clustering to identify cluster points, which are used as generator of Voronoi diagram to formulate an initial sector scheme. Graph-based method is used to refine the generators or boundaries, or heuristic algorithms, ultimately leading to the optimal sectorization (Wan et al., 2023). A schematic illustration of this process is provided in Fig. 6. Other combinations exist as well, such as using Voronoi diagram to enhance the non-smooth boundaries of the MIP solution or employing reinforcement learning to improve trajectory clustering (Zelinski, 2010; Wang et al., 2023c) (see Table 14).

While early studies on this subject mostly use a simplified two-dimensional representation, there is a shift towards higher dimensions, *e.g.*, three (including altitude) and four (including altitude and time). With each of these dimensional extensions increases the underlying computational complexity significantly, requiring the design of more effective approaches for sectorization. A common solution is to dividing the airspace into smaller blocks before generating actual sectorizations (Kicinger and Yousefi, 2009), artificially dividing the altitude into three layers for optimization (Yousefi and Donohue, 2004), and treating areas with significant altitude change as separate airspace for further division (Wei et al., 2014). Concerning the dynamic airspace sectorization, which entails balancing traffic among sectors during peak traffic periods or significant fluctuations in flow, Wong et al. (2018) explored the concept of rolling sectors over time, reporting that the development is impeded by the speed of air traffic control transitions and the accuracy of traffic forecasting.

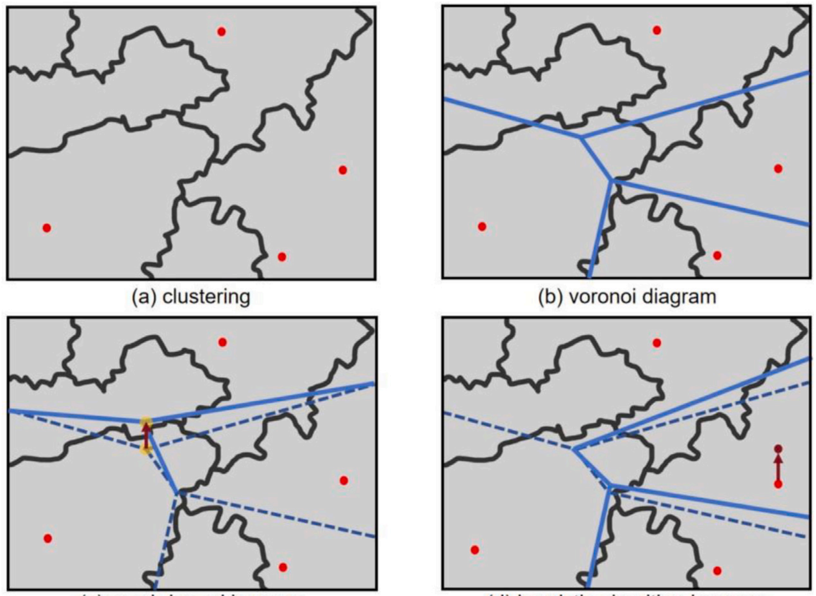


**Fig. 6.** Process of airspace sectorization.

**Table 14**
Extant literature on airspace sectorization.

| Method | Reference |
|---|---|
| Voronoi diagram | Delahaye et al. (1994, 1995, 1998), Xue (2009), Zou et al. (2016) |
| Graph-based method | Trandac and Duong (2002), Martinez et al. (2007), Li et al. (2009), Chen et al. (2013), Chen and Zhang (2014), Sergeeva et al. (2017) |
| Trajectory clustering | Brinton and Pledgie (2008), Brinton et al. (2009), Peng et al. (2023) |
| Integrated | Zhang et al. (2023b), Wan et al. (2023), Wang et al. (2023c) |

### 4.4. Summary of air traffic management

With the expansion of air traffic network scales, the complexity of ATM problems has gradually increased, prompting the incorporation of more effective modeling and solution approaches. From the OR perspective, traditional solver-based methods and heuristic techniques remain the primary means of addressing these issues. However, the role of machine learning has become increasingly significant, particularly in predicting uncertain information. Future developments should focus on the integration of ATFM and airspace sectorization, as addressing the imbalance in capacity demand through simultaneous adjustments of both may present a better option. In addition, one can envision a more effective integration of graph theory with OR algorithms and the exploration of machine learning methods for end-to-end problem-solving.

## 5. Conclusions

The purpose of our study was survey and dissect the extensive range of applications for operations research across three key domains of air transportation, namely airline management, airport management, and air traffic management. The breadth of literature reviewed demonstrates the pivotal role of operations research in optimizing processes, improving efficiency, and addressing complex challenges within the aviation industry. From route optimization and scheduling in airline management to capacity planning and congestion management in airports, and finally, to enhancing the safety and efficiency of air traffic management systems, the contributions of operations research are both diverse and profound. Furthermore, our study has identified several key research directions, listed individually in each subsection. These emerging avenues not only promise to enhance existing frameworks but also to pave the way for future innovations in air transportation management. Below, we list some of the recurring and most important directions/challenges across the three investigates air transportation domains.

Operations research has the goal to derive optimal results, heavily relying on accurate and comprehensive data, which is essential for constructing and refining models. The unavailability of data poses a significant obstacle to the further development of operations research in air transportation, especially in airline management and crew-related problems. Such hard-to-obtain data includes, fuel (hedging) strategies, maintenance, detailed data concerning crew availability, work hours, preferences, legal constraints, and fatigue levels. However, the lack of access to such crucial data - whether due to privacy concerns, proprietary restrictions, fragmented data storage, or issues with data integration - severely limits the potential of operations research to deliver effective solutions. This data scarcity leads to a large of group of potential researchers being excluded from this task. This gap not only restricts the current effectiveness of operations research but also stifles innovation, preventing researchers from exploring new methodologies presently used in other areas, *e.g.*, modern machine learning methods. The research community needs to provide more efforts for achieving open data availability.

Benchmarks are essential tools for advancing OR in air transportation, providing a standardized, objective means of evaluating and refining various methodologies. Such benchmarks were extremely successful in early OR challenges like the Traveling Salesman Problem (TSP) and the Knapsack Problem, offer a structured approach to assessing algorithmic performance when solving complex, real-world

**Table A.15**
Abbreviations used in this study.

| Abbreviation | Term |
|---|---|
| ACO | Ant Colony Optimization |
| AI | Artificial Intelligence |
| ALC | Airline count |
| ALNS | Adaptive Large Neighborhood Search |
| APC | Airport connectivity |
| ATFM | Air Traffic Flow Management |
| B\&B | Branch-and-Bound |
| B\&P | branch and price |
| BCO | Bee Colony Optimization |
| BS | Beam Search |
| C | Cost for taxiing |
| C\&RG | Column and row generation |
| CFL | Competing flow |
| CG | Column Generation |
| CN | connection network |
| COM | Competitors |
| DIS | Distance |
| F | Fairness |
| FAR | Fare |
| FBCA | Fuzzy Bee Colony Algorithm |
| FRQ | Frequency |
| G | Gate |
| GA | Genetic Algorithm |
| GB | Gradient boosing |
| GCN | Graph Convolutional Network |
| GDP | Gross Domestic Product |
| GM | Gravity model |
| GRAS | Greedy Randomised Adaptive Search |
| HFL | Historical flow |
| IL | Imitation Learning |

| Abbreviation | Term |
|---|---|
| LNS | Large Neighborhood Search |
| LOS | Level of service |
| LR | Lagrangian relaxation |
| LS | Local Search |
| MAP | Multiple airports |
| MECA | Modified Ejection Chain Algorithm |
| MNL | Multinomial logit |
| NSGA-II | Non-dominated Sorting Genetic Algorithm II |
| OR | Operations Research |
| P | Priority / Preference |
| PAX | Passenger |
| POP | Population |
| R | Robustness / Revenue |
| RG | Regression |
| RL | Reinforcement Learning |
| SAA | Sample average approximation |
| SEA | Seasonality |
| SIZ | Size |
| STS | Seats |
| SVM | Support vector machines |
| T | Gate Idle Time |
| TOD | Time of day |
| TOU | Tourism |
| TOW | Towing Cost |
| TRD | Trade |
| TRT | Travel time |
| TS | Tabu Search / Time series analysis |
| TSN | time-space network |
| UC | Uncertainty |
| VNS | Variable Neighbourhood Search |

problems of variable sizes. They enable to objectively assess the efficacy of models in a controlled environment, ensuring that solutions are not only theoretically sound but also practically applicable. Moreover, experimental benchmarks encourage consistency and transparency in research by providing a common framework that the OR community can use to share results and collaborate effectively. This shared platform promotes innovation, as researchers can build upon each other's work, refining algorithms and methodologies to achieve increasingly sophisticated solutions as well working towards reproducible research.

The highly complex and unpredictable environment of the air transport industry, where various factors - such as fluctuating passenger demand, adverse weather conditions, mechanical failures, crew availability, and unforeseen delays - can significantly impact operations. Traditional deterministic models, which assume a fixed set of conditions, often fail to account for the inherent variability and randomness that characterize real-world scenarios. This limitation can lead to suboptimal decisions, inefficiencies, and increased operational risks. By integrating uncertainty into OR models for air transport through advanced techniques such as stochastic programming, robust optimization, and Monte Carlo simulations, researchers and industry professionals can develop more adaptive and resilient strategies. For instance, in airline management, this approach enables the creation of more flexible scheduling, fleet management, and crew rostering systems that can dynamically adjust to disruptions and variability in demand, thereby minimizing delays and improving overall service reliability. For airport management, incorporating uncertainty helps in optimizing resource allocation, such as gate assignments and ground handling services, under varying conditions, ensuring smooth passenger flow and minimizing congestion even during peak times or unexpected disruptions. The incorporation of uncertainties will lead to the development of more resilient and adaptable systems, enabling for sophisticated and safe air transport operations.

Historically, OR models often focused on isolated aspects of these air transport operations; such isolated models are no longer sufficient to capture the full scope of these interdependencies. Therefore, there is a critical need for integrated models that can simultaneously consider multiple factors - such as scheduling, resource allocation, passenger flow, airspace management, and even environmental impacts—to enable more coordinated and efficient decision-making across the entire air transportation system. Along the incorporation of integrative aspects, scalability is becoming increasingly crucial to solve complex, large-scale, integrated optimization problems without compromising on accuracy or computational efficiency. Techniques such as machine learning, parallel computing, and big data analytics are becoming more important in this context, enabling researchers and industry professionals to develop models that can handle the scale and complexity of modern air transportation systems.

Finally, we would like to emphasize that the purpose of our work is not to provide an exhaustive list of pointers into the extant literature; instead, our work is intended to provide an overview to newcomers as well as expert, providing key references to seminal works and identifying recent trends of applications, methods and challenges for fully unleashing the potential of operations research in air transport.

## CRediT authorship contribution statement

**Sebastian Wandelt:** Writing – review & editing, Writing – original draft, Conceptualization. **Andrea Signori:** Writing – review & editing, Writing – original draft. **Shuming Chang:** Writing – review & editing, Writing – original draft. **Shuang Wang:** Writing – review & editing, Writing – original draft. **Zhuoming Du:** Writing – review & editing, Writing – original draft, Conceptualization. **Xiaoqian Sun:** Writing – review & editing, Writing – original draft.

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## Appendix A. Abbreviations

See Table A.15.

## Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jairtraman.2025.102747.

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