future transportation

Review

Towards Environmentally Sustainable Aviation: A Review on Operational Optimization

Laura Calvet

Telecommunications and Systems Engineering Department, Universitat Autònoma de Barcelona, 08202 Sabadell, Spain; laura.calvet.linan@uab.cat

Abstract: In recent years, the rapid growth of air traffic has intensified pressure on the air transport system, leading to congestion problems in airports and airspace. The projected increase in demand exacerbates these issues, necessitating immediate attention. Additionally, there is a growing concern regarding the environmental impact of the aviation sector. To tackle these challenges, the adoption of advanced methods and technologies shows promise in expanding current airspace capacity and improving its management. This paper presents an overview of sustainable aviation, drawing on publications from academia and industry. The emphasis is on optimizing both flight and ground operations. Specifically, the review delves into recent advancements in airline operations, airport operations, flight operations, and disruption management, analyzing their respective research objectives, problem formulations, methodologies, and computational experiments. Furthermore, the review identifies emerging trends, prevailing obstacles, and potential directions for future research.

Keywords: aviation; optimization; operations research; sustainability; environmental impacts

check for updates

Citation: Calvet, L. Towards Environmentally Sustainable Aviation: A Review on Operational Optimization. *Future Transp.* **2024**, *4*, 518–547. https://doi.org/10.3390/futuretransp4020025

Academic Editor: Laura Eboli

Received: 9 November 2023
Revised: 21 April 2024
Accepted: 14 May 2024
Published: 17 May 2024

1. Introduction

After a decline in air travel due to COVID-19, air passenger demand is now rebounding and is projected by the International Air Transport Association (IATA) [1] to return to pre-pandemic levels by 2024. This growth is expected to continue for the next two decades, presenting challenges in managing the increased demand and addressing environmental concerns. In 2021, the aviation sector accounted for more than 2% of global energy-related CO_2 emissions, with a faster growth rate compared to other transportation industries like road, rail, and shipping [2]. Additionally, the climate impact of aviation extends beyond CO_2 emissions, as it includes the release of nitrogen oxides, water vapor, sulphate, and soot particles at high altitudes, which can significantly affect the climate [3]. Numerous organizations have been actively advocating for solutions and roadmaps to mitigate these environmental impacts (e.g., IATA [4]). Sustainable aviation encompasses various research areas, such as sustainable aviation fuel [5], hydrogen energy systems [6], and electric aircraft [7]. In the systematic review by Afonso et al. (2023) [8], sustainability efforts in aviation are categorized into operations, energy sources, propulsive systems, aerodynamics, structures, materials, and manufacturing processes.

Certainly, the optimization of both flight and ground operations is an efficient and effective way to enhance aviation efficiency while reducing its environmental footprint. Operations Research (OR) models and methodologies play a practical role in air transport, providing a faster implementation compared to technological advancements. As a result, the discipline of OR has become essential for advancing the aviation industry [9].

The aviation operations optimization literature is extensive, covering a wide range of research topics, problem formulations, methodologies, and technologies. While traditionally focused on safety, economics, efficiency, and customer satisfaction, there is a growing emphasis on environmental and social factors. This paper aims to review environmentally sustainable aviation from an OR perspective, with a focus on recent publications from academia and industry. Based on the research topic, the reviewed works are categorized into four groups: airline operations, airport operations, flight operations, and disruption management. Many of these works directly address environmental concerns by incorporating indicators like CO_2 emissions into their objective functions or constraints. In other cases, the indicators that are used may relate more to economics, efficiency, customer satisfaction, or safety, but still positively impact environmental aspects. For example, optimizing crew assignments to reduce flight delays and cancellations also helps lower fuel consumption. To ensure a comprehensive review, works with indirect connections to environmental indicators have also been considered.

This paper offers several contributions: (i) a review of environmentally sustainable aviation from an OR perspective, including a detailed discussion of findings; (ii) an analysis of emerging trends in the literature; (iii) identification of key challenges; and (iv) suggestions for future research directions. The paper is structured as follows: Section 2 presents the research methodology. Works are categorized into airline operations, airport operations, flight operations, and disruption management, with key findings being discussed in Sections 3–6, respectively. Building on these insights, Section 7 highlights emerging trends and challenges, while Section 8 suggests future research directions. Finally, Section 9 provides conclusions.

2. Research Methodology

The literature review approach is crucial for advancing research and uncovering new opportunities. It systematically synthesizes and consolidates dispersed knowledge. The process began with an initial search on Google Scholar to find recent reviews on sustainable aviation [8,10,11]. These reviews, combined with the author′ expertise, were used to identify categories and subcategories for environmentally sustainable aviation operations. These categories are airline operations, airport operations, flight operations, and disruption management. The subcategory labels, which are described in the following sections, were used as keywords for further searches, sometimes with the addition of the keyword "review".

The selection of primary studies was based on inclusion and exclusion criteria described next. Rather than aiming for an exhaustive compilation, the review sought to provide a representative selection of recent works, offering valuable insights into the ways in which optimizing operations contributes to aviation's environmental sustainability. Additionally, it aimed to identify and discuss emerging trends, challenges, and potential areas for future research. Studies that met inclusion criteria were those that (i) optimize aviation operations with direct or indirect consideration of environmental sustainability; (ii) present literature reviews or proposal OR methodologies with computational experiments; (iii) are published in peer-reviewed journals or international conference proceedings; (iv) are in English; and (v) were published between January 2015 and May 2023. Studies that contained exclusion criteria were those that (i) do not focus on aviation operations and (ii) center on aviation infrastructure or airline revenue management.

Moreover, this search was broadened to include recent contributions from industry sources, such as company reports and websites.

3. Airline Operations

In this section, recent studies on airline operations are reviewed, highlighting the consideration of environmental impacts. Airline operations (Figure 1) refer to the core activities and processes involved in the daily functioning of an airline. It encompasses a range of tasks and functions required to operate flights and ensure the safe, efficient, and reliable transportation.

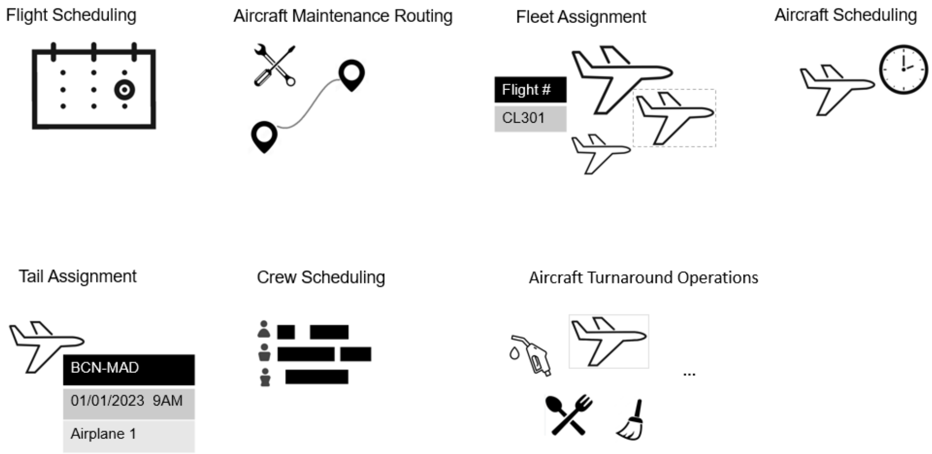

Figure 1. Representation of subcategories in airline operations.

3.1. Flight Scheduling

Flight scheduling encompasses the creation and optimization of flight itineraries, routes, and timetables for flights. It takes various factors into account, such as aircraft availability, airport slot availability, demand and profitability, crew scheduling, regulatory and airspace constraints, weather conditions, and aircraft turnaround time. By optimizing flight routes, aircraft utilization, and minimizing unnecessary idling and delays, airlines can reduce their carbon footprint. Additionally, scheduling flights during off-peak hours can alleviate congestion and reduce the environmental impact. Employing direct flight paths, optimizing altitude and speed profiles, and using advanced technologies for navigation and communication can help airlines reduce fuel consumption. Finally, minimizing delays, providing accurate and reliable schedules, and offering convenient connections can improve passenger satisfaction. An overview of airline schedule planning, including flight scheduling, is provided by Eltoukhy et al. (2017) [12]. The authors categorize flight scheduling models into those that consider market share and passenger demand fluctuations and those that prioritize the robustness of the timetable. The models exhibit variations in planning horizon, network type, model formulation, objective function, solution procedure, data used, airline, stochasticity, robustness, passenger demand (fixed or variable), and market share (fixed or variable). The review criticizes models that rely on assumptions like daily repeated flight schedules, fixed arrival and departure times, and deterministic passenger demand, arguing that these limitations hinder their real-life applicability. Furthermore, the authors emphasize the significance of integrated schedule planning models despite acknowledging the complexity they introduce. They do not prioritize sustainability considerations.

In the context of reducing CO_2 emissions, Mitici et al. (2022) [13] address challenges in short-range electric flights, focusing on fleet investment and efficient charging logistics. The authors propose a two-phase mixed-integer linear programming (MILP) model. The first phase develops a schedule for flight operations and battery recharge management. The second phase determines optimal charging times, station, and battery requirements. All parameters are assumed to be deterministic and known in advance. The model is applied in a European airport. Kenan et al. (2018) [14] tackle flight scheduling and fleet assignment challenges, which must be completed many weeks prior to the flight date. The authors propose a two-stage stochastic programming model to maximize profit under demand and fare uncertainties. The first stage assigns fleet families to each flight leg, while the second stage determines fleet types based on actual demand and fares. A sample average approximation algorithm is employed to solve the problem.

While the results show promise in terms of estimated optimality gap, the computational time may pose a challenge for medium- and large-sized companies, particularly when considering additional sources of uncertainties or integrating different problems.

Birolini et al. (2021) [15] address flight scheduling and fleet assignment, proposing a mixed integer nonlinear model to maximize operating profits while considering air travel demand generation and passenger allocation within markets. They employ least squares piecewise linearization for nonlinearities and a nested logit formulation to assess competitive dynamics. Computational experimentation indicates the model's capability to efficiently optimize mid-size hub-and-spoke networks within reasonable time. Nonetheless, the authors highlight the potential for further investigation into heuristic methods. The approach's benefits are showcased in a European carrier case study. Despite the absence of specific environmental indicators, fuel costs constitute a primary component of direct operating costs.

3.2. Aircraft Maintenance Routing

Aircraft maintenance routing is the process of determining the sequence of flight legs for individual aircraft to cover each flight once while meeting maintenance requirements. Regulatory bodies like the Federal Aviation Administration (in the US) and the European Union Aviation Safety Agency (EASA, in Europe) enforce these rules. Airlines add their own standards. A solution includes a generic route in a rolling time frame. Each aircraft undergoes many maintenance tasks in its life cycle. Tasks vary in scope, duration, and frequency, depending on aircraft type. Examples: walk-around inspections, light checks, emergency equipment inspections, engine oil servicing, and repairs if needed. In their 2009–2019 review, Temucin et al. (2021) [16] identify trends in aircraft maintenance. Short-term maintenance studies dominate, with more emphasis on scheduled vs. unscheduled maintenance. Daily and weekly studies are equally common. They emphasize the problem's NP-hard nature, leading to preference for heuristic and metaheuristic approaches. It is found that studies predominantly feature a single objective, while existing multi-objective models typically encompass certain operational cost elements like crew pairing cost, idle time cost, CO_2 emission cost, fuel consumption cost, or spill cost.

Ruan et al. (2021) [17] present a network flow-based integer linear programming (ILP) framework aiming to maximize profitability and considering three maintenance constraints: maximum cumulative flying hours, maximum number of take-offs between two maintenance checks, and workforce capacity. They propose a reinforcement learning (RL) algorithm, tested on real data from a Middle Eastern airline, and compare its performance against both CPLEX and various metaheuristic algorithms. The RL algorithm exhibits faster computational times and surpasses them in solution quality in large-scale datasets, where CPLEX struggles to deliver optimal solutions. Similarly, Bulbul and Kasimbeyli (2021) [18] address the aircraft maintenance routing problem on a connection network, treating it as an asymmetric traveling salesman problem with fleet size and maintenance constraints. Their hybrid solution combines Gasimov's modified subgradient algorithm with ant colony optimization (ACO). Test problems provide proof that the method can solve instances with 260 flights and 7982 connections in under three hours. Cui et al. (2019) [19] create an ILP model for aircraft maintenance routing, aiming to minimize aircraft count and remaining flying time. It is expanded for robustness via aircraft delay probability to cut delay costs. The variable neighborhood search (VNS) algorithm is used for solving the problem and it is validated through comparisons with CPLEX 12.6 software. While these works do not directly tackle environmental concerns, the emphasis on reducing delays carries positive implications for both economic and environmental factors.

3.3. Fleet Assignment

The fleet assignment problem involves optimizing aircraft allocation to flights, considering aircraft diversity and flight variations. It aims to maximize revenue, minimize costs, and ensure operational efficiency. Factors like fuel, crew, maintenance, and dynamic changes due to weather or demand are considered. By considering aircraft range, capacity, and fuel consumption, airlines can reduce emissions. Efficient fleet allocation enhances resource utilization, including crew and facilities. It also accounts for noise concerns and supports sustainable technology adoption.

Ma et al. (2018) [20] address the fleet assignment problem by proposing a multi-criteria approach taking into account random demand, fare price, and gasoline price. The model aims to maximize revenue while minimizing operational costs and emissions. A rounding algorithm is developed to handle the large-scale nature of the problem. Its effectiveness is evaluated by applying it to two test cases: Jetstar Asia and a major Chinese airline. When compared to the prevailing assignment strategy of the Chinese airline, the proposed model demonstrates superior performance in both profitability and emission reduction. Justin et al. (2022) [21] investigate the integrated fleet assignment and scheduling for environmentally friendly electrified regional air mobility. This problem is formulated as a half-leg half-itinerary MILP. A hierarchical multi-objective approach is proposed, which reveals the trade-offs between profitability and emissions. The approach is used to solve large fleet assignment and scheduling problems in the US Northeast Corridor using electric and hybrid-electric regional aircraft. Their method achieves near-optimal solutions, allowing for the service of twice as many communities as currently served while reducing carbon emissions per passenger by fifty percent. Glomb et al. (2023) [22] present a mixed-integer programming (MIP) model to address the combined challenges of fleet assignment, tail assignment, and turnaround handling. A decomposition algorithm is developed, which alternates between solving the combined assignment problems and the turnaround model. Through a study using realistic instances containing up to several hundred flights, it is demonstrated that this method outperforms comparable state-of-the-art exact approaches. Moreover, two strategies to scale up the results for large airlines are presented. Finally, Liu et al. (2023) [23] examine the problem from a risk-averse standpoint, taking into account both uncertain passenger demand and fuel prices. This problem is formulated as a two-stage stochastic programming model. In the first stage, aircraft families are assigned to flight legs, while the second stage determines the specific deployment of aircraft based on realized information. A sample average approximation approach and an efficient string-based heuristic are proposed to solve the problem. Future research is proposed to explore the integration of multimodal transportation and the inclusion of carbon emission costs.

3.4. Aircraft Scheduling

While the fleet assignment problem focuses on the strategic assignment of aircraft types and quantities to routes, aircraft scheduling deals with the operational assignment of specific aircraft to individual flights within a shorter time frame, considering factors such as flight timings, crew scheduling, and resource utilization. Ikli et al. (2021) [24] review aircraft scheduling, emphasizing key techniques: exact methods, metaheuristics, and RL. The most common objective functions are deviations from target times, delays, makespan, and emissions. The authors introduce a challenging dataset due to the ease of solving current benchmarks. Future prospects include aircraft categorization, air traffic control integration, broader air traffic context, surface operations, matheuristics, and uncertainty handling.

Samà et al. (2017) [25] tackle aircraft landing and take-off schedules and re-routing. Despite its MILP model potential, the problem's NP-hard nature demands heuristic algorithms. Their approach starts with an initial solution via a truncated branch-and-bound algorithm with fixed routes and known resources. A metaheuristic optimizes it by rerouting some aircraft within a terminal control area. Experiments in an Italian terminal control area test the framework, simulating disturbances like delays and runway disruptions. Zheng et al. (2020) [26] address aircraft scheduling and parking, determining take-off, landing times, wake vortex constraints, and apron space. The authors formulate it as an MILP model minimizing aircraft service time. Using a bottom-left/right strategy, they employ a hybrid approach with simulated annealing (SA) and reduced VNS to find near-optimal solutions. Experiments on random instances and reduced benchmarks showcase the method's effectiveness and efficiency in comparison to the CPLEX solver. Huo et al. (2021) [27] tackle aircraft scheduling under uncertainty, aiming for robust arrival flight schedules. They use a trajectory model with time as random variables, comparing it to two benchmarks: a deterministic model and one with separation buffers. For the Paris Charles de Gaulle airport case study, they employ an SA algorithm with a time decomposition sliding window. Solutions are evaluated using a Monte-Carlo-based simulation framework. Results show that the model with separation buffers is unstable under uncertainty, while the proposed model excels in stability and conflict management.

3.5. Tail Assignment Problem

The tail assignment problem assigns aircraft to flights using their unique tail numbers, optimizing efficiency, minimizing costs, and meeting constraints like aircraft type, maintenance, crew, and passenger demand. For example, Vikstål et al. (2020) [28] solve instances of up to 25 routes of the exact cover problem derived from reducing the tail assignment problem, where the goal is to find any solution satisfying all the constraints. They propose a quantum approximate optimization algorithm and assess its effectiveness using simulation techniques. A comprehensive comparison against classical methods is missing. Khaled et al. (2018) [29] present a compact mathematical programming formulation for the tail assignment problem with few, 0–1, decision variables and polynomial-sized constraints. Based on the results of solving randomly generated instances, state-of-the-art MIP solvers demonstrate efficient handling of large scenarios, such as 30-day flight schedules typically involving up to 40 airplanes. Khaled et al. (2018b) [30] emphasize tail assignment solutions for cost minimization and robustness but acknowledge the need for plan adjustments due to unforeseen events. They formulate a multi-objective ILP for repair and recovery, minimizing multiple repair criteria using an additive value function for solution selection. A test case example involving 111 flights, 10 airplanes, and 11 airports is solved and discussed. Jayaraj et al. (2020) [31] address robustness by integrating maintenance routing and tail assignment. This combines tactical and operational planning for a resilient schedule, using real-time aircraft data. The problem combines set partition and multi-commodity network models, efficiently solved with a restrict-and-relax strategy, proven effective in large-scale instances. Real-world tests validate the approach.

3.6. Crew Scheduling

Scheduling airline crews involves cockpit and cabin crews, split into tactical and operational planning stages. Tactical planning aims for cost efficiency but has shifted towards robust scheduling in response to unpredictable conditions. This aims to enhance robustness and reduce potential disruptions. The operational stage is discussed in Section 6.2.

The airline crew scheduling problem comprises two components: crew pairing and crew assignment/rostering. Crew pairing generates adequate anonymous feasible pairings to meet the personnel requirements for all flights. In the crew assignment/rostering stage, these pairings are combined into monthly assignments. To enhance crew and customer experiences, crew assignments consider qualifications, rest, and preferences. Crew pairing, being the initial stage, receives more attention and significantly impacts schedule quality. Optimizing crew assignments reduces flight disruptions, crew repositioning, fuel usage, and commuting, reducing environmental impact. In Wen et al. (2021) [32], airline crew scheduling literature is reviewed. Alongside set-covering and set-partitioning models, pure network models are suitable for smaller problems. Incorporating side constraints improves cabin crew pairing solutions. However, considering unique cabin crew characteristics, like mixed qualifications and crew substitution, escalates the problem's complexity, making column-generation approaches less suitable. Scheduling both cabin and cockpit crews often overlooks cabin crew's distinct features for simplicity. A rolling horizon approach is suggested, dividing the problem into daily, weekly, and monthly sub-problems.

Table 1 summarizes recent works on the crew pairing problem, outlining their objectives and solving methods. Main objectives include cost minimization, revenue maximization, robustness, and risk reduction. Crew preferences and penalty schemes are considered in some studies. Common methodologies are column generation algorithms and genetic algorithms (GAs). Table 2 compiles recent studies on the rostering problem, with two works addressing both crew pairing and rostering. The primary aim is cost reduction, but other objectives focus on crew-related aspects like equitable benefits, workload, and vacation requests. Most studies employ population-based metaheuristics, including ACO and particle swarm optimization (PSO) algorithms.

Table 1. List of recent works on the crew pairing problem.

Work	Objective(s)	Methodology
[33]	Min. costs.	GA.
[34]	Max. revenue—fleet assignment costs—non-robustness penalties.	Matheuristic: decomposition approach and proximity search algorithm.
[35]	Min. deadhead cost, crew cost and risk of COVID-19.	GA.
[36]	Min. cost of crew members, penalization for short or long connection times, cost for crew members changing aircraft along their routes, and penalty for the use of aircraft.	Four heuristic algorithms based on an MILP model.
[37]	Min. sum of pairing costs and penalties related to the base, monthly language, and daily language constraints.	Branch-and-price heuristic.
[38]	Min. adjusted costs. It considers crew preferences.	Column generation algorithm.

Table 2. List of recent works on the rostering problem. Note: [1] Integrated model for crew pairing and rostering problems.

Work	Objective(s)	Methodology
[39]	Max. crew satisfaction.	Deep learning-based partial pricing in a branch-and-price algorithm.
[40]	Min. difference between crew sit times.	PSO algorithm.
[41] [1]	Min. costs.	ACO algorithm.
[42]	Min. nautical mile cost, balance workload among cockpit crews, max. preferential requests from senior pilots and min. number of repeated flight patterns flown by individual pilots.	MOEA/D and HBMO metaheuristics.
[43] [1]	Max. number of satisfied vacation requests and preferred flights and PFs and min. cost of pairings and dissimilarity of pilot and copilot pairings.	Alternating Lagrangian decomposition.
[44]	Max. fairness and satisfaction of crew.	ACO algorithm.

3.7. Aircraft Turnaround Operations

Flight turnarounds involve vital tasks like baggage handling, refueling, and pushback, alongside passenger services like cleaning and catering. Ground handling providers strategically plan these operations to minimize delays. This planning occurs in advance and aims for robustness, considering uncertainties like task durations, aircraft arrival times, and equipment availability. Sustainable aircraft turnaround practices encompass optimizing fuel efficiency, waste management, energy use (e.g., using ground power units and efficient lighting, heating, and cooling systems), water conservation, noise reduction, and sustainable procurement.

In San Antonio et al. (2017) [45], a simulation estimates critical paths and survival functions in aircraft turnarounds, departing from deterministic time assumptions. This approach provides probabilities of completing operations before target times, validated through small numerical experiments. Saha et al. (2021) [46] focus on allocating ground handling teams to aircraft turnarounds, using a two-part approach: (i) simulation based on flight data and static rules and (ii) RL for dispatching rule selection. A case study at Luton Airport in the UK illustrates their methodology. With more aircraft needing service, ground handling operators encounter higher workloads that can result in delays. Gök et al.

(2020) [47] study aircraft turnaround scheduling and ground service team/equipment planning. They initially tackle the resource-constrained project scheduling problem to minimize delays. Then, they support decentralized team/vehicle allocation, using constraint programming and MIP solvers for tasks like multiple traveling salesman problems with time windows. To generate real-world solutions, they employ a matheuristic with large neighborhood search (LNS), emphasizing maximizing total slack time for robustness. The solutions' robustness is evaluated with a discrete-event simulation model, demonstrated in a case study at Barcelona Airport, in Spain.

3.8. Contributions from the Industry

The industry has taken steps to enhance the efficiency of airline operations with a focus on environmental considerations. The following examples illustrate these efforts.

- Flight Scheduling. In terms of route optimization, KLM Royal Dutch Airlines [48] (i) employ a flight plan computer system for calculating the most fuel-efficient routes, (ii) advocate for the establishment of a Single European Sky (SES) to enhance the capacity, safety, efficiency, and environmental impact of Europe's airspace, and (iii) support the necessary reform of the European Air Traffic Management System at institutional, operational, technological, and control and supervision levels. Another example involves Eurocontrol's promotion of continuous climb and descent operations [49], allowing for aircraft to follow a flexible, optimum flight path that brings significant environmental and economic benefits, including reduced fuel burn, emissions, noise, and fuel costs without compromising safety. Lastly, SAS [50] optimizes schedules and aircraft sizes to meet demand effectively, particularly on regional routes with lower demand. This approach allows for the optimization of fuel usage and emissions per seat kilometer.
- Aircraft Maintenance Routing. The industry is increasingly adopting physics-based modeling, statistical analysis, and machine learning for predictive maintenance recommendations. This shift aims to enhance dispatch reliability, reduce unplanned maintenance, and optimize schedules. Collins Aerospace [51] offers Ascentia, a service converting data into tailored, predictive insights. Jeppesen [52] provides decision support tools, including what-if simulations, for precise aircraft routing solutions, factoring in revenue forecasts, maintenance, and operational costs. Skywise [53], a collaboration between Airbus and Palantir Technologies, utilizes abnormal behavior analysis of aircraft sensor data for proactive component failure anticipation. It integrates reliability data, enabling fleet performance benchmarking and identifying root causes and solutions. This marks a significant advancement in proactive aircraft maintenance management, which reduces fuel consumption and emissions by ensuring optimal performance and reliability of aircraft systems.
- Fleet Management. Software solutions often overlook the distinctions between fleet assignment, aircraft scheduling, and tail assignment problems, with many companies offering integrated solutions for flight operations and fleet management. For instance, Ramco's flight operations [54] provides a comprehensive solution catering to aircraft professionals' needs, offering real-time operational readiness tracking for fleet availability. Matellio's aviation fleet management software [55] automates various aspects of the aviation industry, including fleet, fuel, and crew management. Veryon [56] offers its integrated flight operations software to optimize flight schedules and crew assignments for fleet utilization. Additionally, there is a notable industry focus on developing eco-friendly aircraft, such as hybrid-electric models and weight-saving measures, to minimize fuel consumption and emissions. In terms of fleet composition, the industry places significant emphasis on advancing eco-friendly aircraft, such as hybrid-electric models [57] and initiatives focused on weight reduction [58]. Lighter aircraft offer clear advantages as they require less fuel and produce lower emissions.
- Crew Scheduling. When selecting crew scheduling software, airlines take into account factors such as operational size, complexity, budget, and desired functionalities. So-

lutions typically feature a rule engine to handle intricate regulations on flight time limitations, duty hours, and rest periods. This software can integrate with existing bidding systems where pilots and crew members input preferences for routes, days off, and vacations. Additionally, optimization algorithms process extensive data on pilot qualifications, aircraft types, flight routes, and layover requirements to generate efficient schedules aimed at cost reduction. Notable examples of such software include PDC crew scheduling [59], ProDIGIQ's flight operations system—NAXOS [60], and Sabre schedule manager [61]. One aspect of cost optimization involves minimizing crew deadheading, which mitigates environmental impacts.

- Aircraft Turnaround Operations. Software solutions streamline processes, optimize resource allocation, and reduce turnaround times. This is achieved by collecting and integrating real-time data from diverse sources such as flight schedules, gate availability, maintenance requirements, weather conditions, and ground crew schedules. Employing advanced algorithms that analyze historical data and forecast potential delays or bottlenecks enables stakeholders to preempt issues and implement preventive measures, such as pre-positioning ground crew or conducting maintenance tasks proactively. Examples of such software include ADB SAFEGATE's AiPRON 360 [62] and FLYHT [63]. These software contribute to environmental sustainability, for example, by mitigating ground delays. Noteworthy initiatives in sustainable aviation include Turin Airport (TRN) in Italy [64], which transitioned to a 100% electric ground handling fleet in 2020, featuring electric tractors, baggage loaders, and pushback tugs for aircraft maneuvering. Similarly, dnata [65], an aviation services provider, has globally implemented electric ground support equipment, replacing traditional diesel-powered counterparts, with a focus on utilizing on-site renewable energy sources or clean electricity grids whenever feasible.

3.9. Discussion

Airline operations encompass a variety of tasks aimed at ensuring safety, efficiency, and reliability in daily airline functioning. Optimizing these operations directly mitigates environmental impact, particularly by reducing fuel consumption through minimizing resource idling, traffic congestion, flight delays, and cancellations.

- In flight scheduling, airlines can reduce environmental impact by scheduling flights during off-peak hours to alleviate congestion, employing direct flight paths, optimizing altitude and speed profiles to reduce fuel consumption, and providing reliable schedules to minimize delays.
- Efficient aircraft maintenance routing ensures peak performance, reducing fuel consumption and emissions associated with inefficient operations and unexpected maintenance delays. Minimizing last-minute maintenance also reduces environmental impact by preventing disruptions to flight schedules and unnecessary fuel consumption.
- Strategic fleet assignment facilitates the integration of sustainable aircraft and technologies. In fleet assignment, aircraft scheduling, and tail assignment, approaches that minimize fuel costs and maximize aircraft load factors correlate with emission reduction.
- Crew scheduling optimizes staffing to minimize inefficient flights, reducing fuel consumption and emissions. It prevents last-minute cancellations or delays and optimizes crew rotations, reducing the need for deadhead flights.
- Efficient turnaround operations minimize ground idle time between flights, reducing fuel consumption and emissions. They also contribute to on-time departures, decreasing fuel burn associated with holding patterns or inefficient routing.

Despite relatively few works directly addressing environmental aspects to quantify and reduce environmental impacts, the increasing availability of high-quality data, computing power, and hardware development, and focusing on efficiency, robustness, and resilience contribute to a more environmentally sustainable aviation industry.

4. Airport Operations

Airport operations (Figure 2) are the various activities and procedures involved in managing and running an airport efficiently and safely.

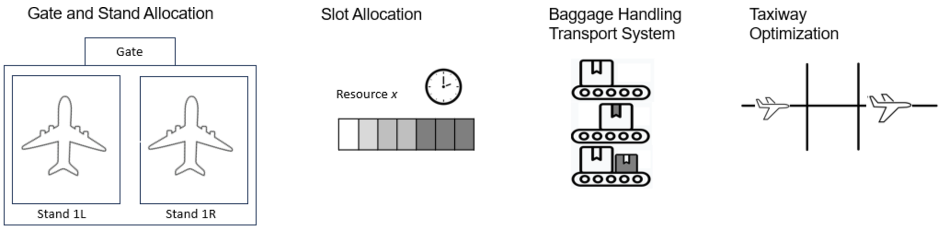

Figure 2. Representation of subcategories in airport operations.

4.1. Gate Allocation

The gate assignment problem allocates aircraft to gates, with two main strategies: common use and exclusive use. Common use optimizes gate utilization, while exclusive use involves leasing gates to airlines. Airlines prioritize access and efficient ground times, passengers want convenience, and airport operators aim for revenue by improving resource efficiency, reducing congestion, and minimizing disruptions. Gate schedules need robustness due to flight time uncertainty. Some models prioritize idle time between gate uses, enhancing schedule resilience. Airports may enforce minimum buffer times between flights for safety and delay accommodation. Other models focus on resolving gate conflicts, which occur when multiple aircraft request the same gate, impacting passenger delays, connections, and fuel consumption.

Daş et al. (2020) [66] survey the gate assignment problem, noting its lack of a standard formulation due to diverse stakeholders, feasibility criteria, and objectives. Common formulations use assignment and flow variables, with numerous heuristic and metaheuristic algorithms developed. Table 3 compiles recent studies on the gate assignment problem, emphasizing objectives and solving methods. Common objectives include minimizing walking distance, aircraft taxiing costs, and enhancing robustness. Metaheuristics are prevalent among the proposed methods. These studies do not directly address environmental impacts, and only one takes into account robustness, which, as mentioned earlier, leads to decreased delays and congestion, and consequently lower fuel consumption. Unfortunately, a fair comparison of the effectiveness of the proposed methods is not feasible, as each study presents a highly specific formulation and addresses instances that are neither accessible nor replicable.

Table 3. List of recent works on the gate assignment problem.

Work	Objective(s)	Methodology
[67]	Min. aircraft taxiing costs and passenger walking distance.	NSGA-II-LNS algorithm (builds upon the NSGA-II framework and LNS algorithm).
[68]	Max. sum of preference values.	Branch-and-price algorithm.
[69]	Max. operators' preferences (scores) and min. robustness cost caused by changes of flight schedule.	Monte Carlo based NSGA-II algorithm.
[70]	Min. number of aircraft assigned to apron and walking distance.	Branch-and-bound algorithm, beam search, and filtered beam search algorithms.
[71]	Penalty cost of remote stands, walking distance, and fuel consumption cost of taxiing.	Improved adaptive parallel GA.
[72]	Min. walking distance.	Quantum approximate optimization algorithm.

4.2. Stand Allocation

Stand allocation assigns parking positions to flights, aiming to minimize delays, reduce congestion, and optimize resource use while adhering to constraints. The common objectives are to enhance airport resource utilization, reduce delays, and improve the passenger experience. Real-time data integration and adjustments are vital for real-world implementation. Guépet et al. (2015) [73] show that allocating operations to airport stands is NP-hard. The authors create a MIP model with the aim of maximizing the utilization of contact stands by passengers/aircraft and minimizing towing movements, all while adhering to operational and commercial prerequisites. Additionally, they introduce two heuristic algorithms based on spatial and temporal decomposition. Realistic scenarios from two major European airports validate these methods. Zhao and Duan (2021) [74] introduce a multi-objective model for stand allocation at Lanzhou Zhongchuan Airport, targeting passenger distance, airline costs, and stand usage efficiency. They employ an SA algorithm and use actual flight data to validate the approach. These two papers concentrate on pre-departure position allocation, which occurs before early departures and involves arranging positions for the entire day in advance. Delays and other unforeseen circumstances necessitating position adjustments are not taken into account. Bagamanova and Mota (2020) [75] propose a method for stand assignment, considering airport environment uncertainties. They merge Bayesian modeling and metaheuristics for robust solutions against schedule disruptions. The elements comprising the multi-objective function include the number of flights designated for remote parking positions, the total taxi distance for the assigned schedule, the number of flights waiting for an available stand, and the average area per passenger at the boarding gate. It is noteworthy that reductions in both total taxi distances and the number of flights allocated to remote parking positions can result in substantial fuel savings. Combining this with simulation aids in assessing assignment robustness, illustrated in a Mexico City International Airport case study.

4.3. Slot Allocation

Airport capacity limits hinder global air travel growth. Congested airports use slot allocation to grant access to limited resources like runways, gates, and air traffic control. Katsigiannis and Zografos (2021) [76] offer a framework integrating airline flexibility preferences and dynamic and asynchronous total airport capacity constraints. The approach addresses multiple objectives, including rejected requests and displacement, aligning with IATA Guidelines. Airline preferences are represented by timing flexibility indicators, contributing to a weighted objective. Computational analysis, using Gurobi as a solver, demonstrates the approach's value with data obtained from a coordinated regional European airport. Wang and Zhao (2020) [77] propose a robust slot allocation model spanning multiple days, addressing uncertainties in airport capacity. It prioritizes minimizing scheduling conflicts in worst-case scenarios, ensuring resilience in allocation. This model connects strategic and pre-tactical decisions in air traffic management by balancing strategic cost and operational congestion. It harmonizes long-term planning with short-term efficiency. Validation employs the CPLEX solver and numerical analyses involving Level 3 airports in the South China Airport network. Androutsopoulos et al. (2020) [78] address the strategic airport slot allocation problem, treating it as a bi-objective resource-constrained project scheduling issue with partially renewable resources and non-regular objective functions. These non-regular criteria encompass total earliness–tardiness and a dispersion measure to manage overdisplaced requests. They propose a hybrid heuristic algorithm, combining the objective feasibility pump algorithm with the LNS metaheuristic. A new set of instances, based on real slot request patterns at a Greek Regional Airport, evaluates the algorithm, showing it provides reasonably accurate solutions.

4.4. Baggage Handling Transport System

The baggage handling transport system (BHTS) poses an optimization challenge, aiming to find optimal paths for baggage from check-in counters to departure gates. This entails choosing conveyor belts, sorting facilities, and transfer points. The main goal is to minimize operational costs, covering energy, maintenance, and labor expenses. Capacity, time, and security constraints apply. Metrics focus on throughput, efficiency, and resource use. Optimizing BHTS is vital for airport operation, requiring detailed modeling, precise data, and ongoing dynamic adjustments to adapt to changing conditions.

Lodewijks et al. (2021) [79] introduce a mathematical model addressing key costs in belt conveyor operations within a BHTS, covering capital, operational, and CO_2 emission offsetting costs. The authors employ three advanced PSO algorithms, demonstrating their effectiveness and efficiency. The self-regulation PSO algorithm excels, particularly in CPU time performance. The experiments, relying on artificial data, reveal that a BHTS with multiple shorter belt conveyors outperforms a single long conveyor system. However, practical applicability depends on factors like varying baggage throughput per hour. Thus, BHTS optimization requires customized, case-specific approaches. Volt et al. (2022) [80] develop a model to optimize the allocation of airport equipment for baggage loading and unloading. The study comprises two main phases. Initially, a thorough analysis investigates the existing baggage processes. Then, a mathematical model predicts equipment demand and computes the optimal number of carts required for efficient flight handling. Internal validation leverages operational data from Václav Havel Airport Prague. Allocating ground handling staff is considered a topic for future research.

4.5. Taxiway Optimization

The airport taxiway planning problem involves designing efficient and safe taxiway networks, connecting runways, terminals, hangars, and other facilities. Aircraft use taxiways for movement, including landing, take-off, and taxiing. The aim is to optimize layout, configuration, and connectivity to reduce taxiing times, congestion, enhance safety, and minimize fuel consumption and carbon emissions.

Deng et al. (2022) [81] propose a multi-strategy PSO and ACO algorithm to tackle taxiway conflicts and propagation, enhancing taxiway resource utilization. They introduce a conflict adjustment strategy based on speed priority and first-come-first-served principles to optimize airport taxiway paths. The authors aim to minimize flight taxiing time and flight delay time. An experiment considering 28 taxiing nodes, three gates and three runway entrances is carried out to illustrate their approach. Zhang et al. (2019) [82] aim for a Pareto-optimized taxiing plan, considering taxiing time, fuel usage, and emissions. Their work involves choosing waiting points and optimizing speed curves, utilizing parameters and fuel consumption data for various aircraft types. Validation occurs via a case study at Shanghai Pudong International Airport. Li et al. (2019) [83] consider factors like aircraft taxiing distance, steering times, and collision avoidance. They propose a path optimization model to minimize taxi time on airport surfaces, utilizing a GA for solution. Experiments based on Shanghai Hongqiao Airport show substantial improvements over pre-optimization scenarios.

In the field of airport taxiway planning, Guépet et al. (2016) [84] explore the ground routing problem, which involves efficiently scheduling aircraft movements on the ground between runways and parking positions, while adhering to operational and safety standards. The authors introduce an MIP model for this challenge. It encompasses traditional metrics like average taxi and completion times, along with aviation-specific punctuality indicators. Using real data from Copenhagen Airport, the authors explore the intricate relationship between these performance and punctuality metrics. The aviation industry's conventional punctuality measures often conflict with efforts to reduce taxi times and emissions. To address this, the authors propose new indicators that not only reflect sustainability, but also carry greater significance for stakeholders.

4.6. Contributions from the Industry

This subsection outlines industry-specific software utilized to improve airport operations, which have a primary focus on enhancing operational efficiency.

- Gate and Stand Allocation. Several software solutions exist for optimizing gate and stand allocation. One example is the PDC StandPlan [85], a decision support system guiding users through all planning stages, from long-term specification to last-minute revisions. It optimizes gate and stand utilization while considering various constraints like arrival patterns and airline rules. Another example is the CAST Stand and Gate Allocation [86], which efficiently allocates resources for long-term, medium-term, and operational planning tasks, including optimizing allocation for objectives and increasing peak hour capacity. Finally, AeroCloud [87] offers gate management with artificial intelligence and machine learning, making allocation easier and more efficient by automatically planning based on real-time flight data and allowing flexible gate ownership.

- Slot Allocation. Several software solutions are available for slot allocation in airports. PDC SCORE [88] is a widely used software designed specifically for this purpose, with over 30 years of development and global usage in over 50 countries. It offers features such as schedule data validation, visualization tools, historical data management, and task automation to streamline the slot allocation process. Sabre's Slot Manager [89] streamlines slot portfolio management for airlines by automating changes and facilitating efficient utilization, enabling them to compare historical slots with future schedule requirements to avoid losses and expedite slot requests. OneAlpha [90] provides a comprehensive airport slot coordination and capacity management solution, offering features such as a cloud-based platform, automated messaging, apron planning, dynamic reporting, and tailored customer support, ensuring efficient airport management and planning.
- Baggage Handling Transport System. Designing and improving baggage handling transport systems often involves utilizing either general simulation software like Arena [91], Simio [92], and FlexSim [93], or specialized solutions like Maxibas [94]. Maxibas, crafted by the Scarabee Aviation Group, is a comprehensive testing and training simulation tool tailored specifically for baggage handling systems.
- Taxiway Optimization. No dedicated software explicitly designed for taxiway optimization has been found. However, simulation software could prove beneficial in making such decisions, or alternatively, integrated solutions like INFORM's advanced software for aviation ground operations [95], which effectively balance costs, punctuality, and quality, may offer viable options. In this context, an interesting tactic aimed at diminishing fuel consumption, emissions, and engine wear during taxiing involves operating an aircraft on the ground with just one of its engines [58], necessitating meticulous coordination and adherence to safety protocols.

4.7. Discussion

The efficient and safe management of airports involves a variety of activities and procedures known as airport operations. By optimizing these operations, environmental impact can be directly mitigated, notably by decreasing fuel consumption through the reduction of distances, congestion, delays, and other inefficiencies.

- Optimizing gate and stand allocation reduces aircraft idle time, aircraft taxiing distances, and congestion, leading to lower fuel consumption and greenhouse gas emissions. Additionally, strategic gate assignments facilitate the adoption of sustainable practices and efficient use of infrastructure.
- Efficient slot allocation at airports optimizes aircraft schedules, minimizing waiting times and reducing fuel consumption. Strategic slot assignments also promote smoother operations, encouraging the adoption of sustainable practices.
- Optimizing the baggage handling transport system through energy-efficient technologies and streamlined processes reduces fuel consumption, emissions, and resource usage. These efforts enhance operational efficiency and minimize transportation distances.
- Strategic taxiwaylayouts and procedures at airports reduce aircraft taxiing distances and idle time, leading to decreased fuel consumption and emissions. Strategic taxiway planning also enhances operational efficiency, minimizing congestion and delays.

5. Flight Operations

Flight operations (Figure 3) can be defined as the set of activities and processes specifically focused on the planning, execution, and management of individual flights.

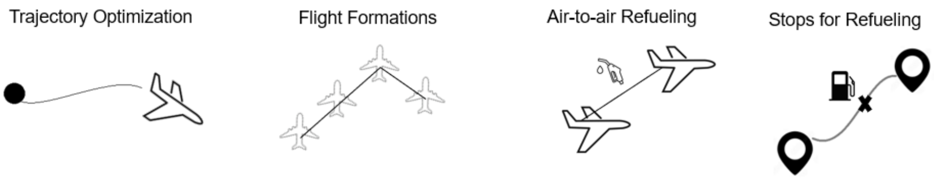

Figure 3. Representation of subcategories in flight operations.

5.1. Trajectory Optimization

Aircraft trajectory optimization involves adjusting speed and flight level on cruise routes to achieve predefined objectives while considering airspace, aircraft maneuverability, and control constraints. The literature covers optimal control methods (direct and indirect), as well as non-optimal methods like mathematical programming, metaheuristics, and path planning. Noteworthy reviews include Hammad et al. (2020) [96], who propose a classification framework considering modelization, objectives, and methods for sustainable fixed-wing aircraft trajectories. Simorgh et al. (2022) [97] survey operational strategies addressing aviation's climate impact, especially non-CO_2 emissions. These emissions significantly contribute to aviation radiative forcing, and their effects vary with location, altitude, and emission time. The study emphasizes the potential of climate-aware trajectory planning to reduce these effects.

In a recent study, Ma et al. (2021) [98] tackle sustainable trajectory optimization through a discretization approach. They introduce a method that combines forward recurrence and memoization to solve the problem. Real-world operational data, including meteorological conditions, aircraft type, and time horizon, are used for evaluation. The objective function comprises three components: (i) an economic benefit index (fuel- and time-related cost), (ii) a green benefit index (aviation pollutants and temperature change cost), and (iii) a passenger benefit index (travel time value and passenger loss). The flight route from Beijing Capital International Airport to Shanghai Hongqiao International Airport is considered to illustrate the approach. Murrieta-Mendoza et al. (2020) [99] utilize metaheuristic algorithms to improve the cost efficiency of the cruise flight phase, with a specific emphasis on reducing fuel consumption. These optimization techniques involve GAs, the artificial bee colony algorithm, and the ACO algorithm. The computational experiments, relying on a flight simulator, demonstrate that these algorithms effectively lower fuel consumption during flight.

Flight plans rely on static atmospheric forecasts. However, unforeseen changes in atmospheric conditions, such as shifts in wind speed and direction, are challenging to predict and are not factored into flight operations, except in cases of severe weather events. Lindner et al. (2020) [100] explore the benefits of providing in-flight weather updates and optimizing short-term trajectories. Evaluation criteria include fuel consumption, engine emissions, and controller workload. The analysis employs an air traffic simulation environment. Samà et al. (2019) [101] propose integrating aircraft scheduling and trajectory optimization for congested terminal maneuvering areas. The formulation considers various factors, such as trajectories, safety regulations, and decisions regarding timing and sequencing. The performance metrics involve minimizing delays, travel times, and fuel consumption. MILP solvers are used to tackle the problem and validate the approach through experiments using data from Milano Malpensa Airport.

5.2. Flight Formations

Formation flying, observed in both nature and human aviation, entails coordinated flight patterns. In military aviation, it fulfills tactical roles like mutual defense and concentrated firepower. In civil aviation, it has traditionally been associated with air shows and recreation. However, there is growing interest in exploring formation flying as a means to decrease fuel consumption and emissions. Researchers have explored extended flight formations for long-haul commercial aircraft, focusing on minimizing fuel consumption by flying in the upwash of the lead aircraft's wake. In two-aircraft formation flight, Dahlmann et al. (2020) [102] assess the potential of aircraft wake-surfing in efficient formation flights, accounting for CO_2, water vapor, ozone, methane, and contrail cirrus impacts on different flight paths. Case studies reveal an average 5% reduction in fuel consumption when implementing formation flights at the 50 busiest airports. Investigating various airline scenarios like long-haul, transatlantic, and low-cost carriers, Kent and Richards (2021) [103] explore the feasibility of two-aircraft formation flight. The study employs an analytical geometric approach to determine optimal route combinations and utilizes a MILP model to pair aircraft into formations. Their findings suggest substantial fuel savings and reductions in CO_2 emissions through scheduling adjustments.

Unterstrasser (2020) [104] studies how aircraft formation flight can mitigate contrail formation using detailed simulations. By employing advanced modeling techniques, the study demonstrates that contrail ice mass and total extinction are notably reduced behind a two-aircraft formation compared to a separate aircraft. This finding suggests that adopting formation flight strategies could significantly alleviate the climatic impact of contrails. Marks et al. (2021) [105] utilize an interdisciplinary approach merging aerodynamics, aircraft operations, and atmospheric physics to quantify flight formation effects. This approach employs an integrated model chain to evaluate climate impact based on flight plan data, aerodynamic interactions within the formation, detailed trajectory calculations, and a tailored climate model. Representative scenarios for major airports worldwide are derived by analyzing and assessing flight plans. Formations are recalculated using trajectory calculation tools, and emission inventories are generated for these scenarios. Quantitative estimation of climate impact, measured by average temperature response, reveals a relative change ranging between 22% and 24%, with fuel savings estimated at 5–6%.

5.3. Air-to-Air Refueling

Long-haul flights require carrying extra fuel, resulting in higher fuel consumption. However, refueling during the flight can help avoid the additional fuel consumption and potentially reduce aircraft emissions. Fezans and Jann (2018) [106] outline the modeling and simulation infrastructure used to assess novel functions for aerial refueling in piloted simulations, emphasizing the noteworthy aerodynamic interaction between tanker and receiver aircraft during these maneuvers. To maintain simplicity, the entirety of flight physics is encompassed within a single model. The authors intend to expand the simulation framework in future research to explore formation flight. Rong (2020) [107] introduces a Floating Aerial Refueling System (FARS). The study encompasses stakeholder analysis, system architecture, economic feasibility, mathematical simulation, and optimization. The optimization model incorporates design variables for every component: tanker aircraft (including wing-span, aspect ratio, sweep angle, maximum take-off weight, and thrust-to-weight ratio), refueling strategy (such as the number of refueling operations per tanker and per receiver), and mother ship (comprising class of ship, hull number, and mooring configuration). Through the case study of Singapore Airlines SQ21, the optimized FARS design indicates potential annual fuel savings of up to 39,415 tons over 25 years.

In a recent study, Hansknecht et al. (2023) [108] study the air-to-air refueling problem within the framework of a vehicle routing problem. Their focus is on a scenario where a fleet of feeder aircraft undertakes air-to-air refueling operations for a predetermined group of cruisers. The study introduces a comprehensive model detailing the feeder aircraft's fuel consumption during various flight phases. Additionally, it proposes two integer programming models and adapts a widely recognized labeling algorithm for solving the problem. The effectiveness of their methods is demonstrated on real-world and artificial instances. Zhang et al. (2023) [109] introduce the multi-dimensional improved NSGA-II algorithm for air-to-air refueling planning, with the objective of minimizing both total fuel consumption and refueling time. Their approach involves several notable assumptions, such as disregarding the impact of variables like wind direction, wind speed, and weather conditions. The optimization solution provided by their algorithm comprises the longitude and latitude coordinates of multiple aerial refueling points. Simulation experiments indicate that the improved NSGA-II variant displays enhanced convergence, uniformity, and universality when contrasted with the original version.

5.4. Stops for Refueling

When conducting long-range operations, considering refueling stops can decrease the total amount of fuel needed. However, refueling stops may reduce passenger comfort, worsen local air quality, stress flight crews, and lead to congestion in specific areas, affecting air traffic management. Deo et al. (2020) [110] propose two methodologies minimizing the cost index through intermediate refueling stops. They employ an ILP model and network strategy, reducing costs by 3% in a case connecting six airports and 17 refueling stops. Non-CO_2 emissions like water vapor, nitrogen oxides, and contrail cirrus significantly affect aviation's radiative forcing. In this context, Zengerling et al. (2022) [111] utilize simulations to compare reference cases with climate-optimized and fuel-optimized scenarios, taking into account stop operations in European long-haul flights. The findings highlight the potential for climate mitigation and a shift in flight trajectories towards lower latitudes and altitudes. Linke (2018) [112] employs an analysis workflow that integrates databases for aircraft movements, meteorology, and navigational information, along with models for trajectory calculation and optimization, leveraging advanced aircraft performance models. They assess fuel savings resulting from intermediate stops in global wide-body aircraft operations. Wind-optimized flight planning has demonstrated potential savings of up to 15%. In conclusion, further research is necessary to design realistic experiments that consider various indicators relevant to all stakeholders involved, including congestion, passenger comfort, local air quality, and more.

5.5. Contributions from the Industry

- Trajectory Optimization. Integrated flight operations software often includes features for trajectory optimization. For example, Pacelab Flight Profile Optimizer [113] provides crews with actionable recommendations throughout the flight, optimizing altitudes and speeds for the most cost-efficient journey under current conditions. It carefully balances operational needs with passenger comfort and on-time performance. Additionally, Veryon's software [56] tracks daily flights via an interactive map, displaying alerts and weather information in real time. It allows for swift updates directly within the map interface, including diversions or cancellations.
- Flight Formations. In 2020, Airbus conducted flight tests for formation flying and achieved the first long-haul demonstration in transatlantic airspace in 2021 [114]. The demonstration involved two A350s flying from France to Canada, resulting in over six tonnes of CO_2 emissions saved, equivalent to a more than 5% fuel saving rate on long-haul flights. The focus now is on concept maturation, with the aim of enabling controlled implementation by the mid-2020s.
  The EU SESAR-funded Geese initiative [115], spearheaded by Airbus, will conduct flight trials involving Air France and French Bee A350s from 2025 to 2026, with Boeing participating for interoperability. Geese also encompasses collaboration with Eurocontrol and air navigation service providers from Bulgaria (BULATSA), France (DNSA), Ireland (IAA), Lithuania (ON), and the UK (NATS), alongside ATM technology providers Indra and Frequentis.
- Air-to-air Refueling. The Airbus A330 Multi-Role Tanker Transport, certified for automatic air-to-air refueling since late 2020, marks a significant milestone in this technology [116]. Airbus is currently working on the Auto'Mate demonstrator project, focused on advancing autonomous air-to-air refueling. Several companies provide aerial refueling services. Omega [117], for instance, offers a variety of refueling solu-

tions to both the U.S. Armed Forces and global allies, boasting around 10,000 missions conducted since 2000. Metrea [118] delivers commercially owned, operated, and maintained aerial refueling aircraft, along with personnel and equipment to satisfy fleet training, operational, test and evaluation, and Foreign Military Sales requirements.
- Stops for Refueling. Flight planners are increasingly incorporating advanced fuel planning features, such as predictive fuel-warning systems [119], into their processes. There are companies, such as Flightworx [120], that handle every aspect from route planning to actual flight management. Should the initial flight plan suggest the aircraft cannot fly directly, they strategically arrange a fuel stop along the route.

5.6. Discussion

Flight operations encompass the planning, execution, and management of individual flights. Optimizing these operations directly reduces environmental impact by minimizing fuel consumption, distances traveled, emissions of CO_2, water vapor, ozone, methane, and contrail cirrus effects.

- Trajectory optimization can reduce fuel consumption by finding more efficient flight paths, thereby decreasing greenhouse gas emissions and minimizing the environmental footprint of each flight. By minimizing unnecessary deviations and optimizing altitude and speed profiles, trajectory optimization can also reduce the formation of contrails and their associated climate impacts.
- Flight formations can reduce aerodynamic drag and fuel consumption by allowing aircraft to fly in close proximity, benefiting from reduced air resistance. Additionally, coordinated formations enable more efficient routing and spacing, optimizing airspace usage and minimizing emissions from individual flights.
- Air-to-air refueling can extend the range and endurance of aircraft, allowing for them to fly more direct routes and avoid unnecessary fuel-consuming stops, thereby reducing overall fuel consumption and emissions. Additionally, by enabling aircraft to carry less fuel during take-off, air-to-air refueling reduces their weight, leading to improved fuel efficiency and lower environmental impact per mission.
- Stops for refueling can enable aircraft to carry less fuel during initial take-off, reducing their weight and improving fuel efficiency throughout the flight, thereby lowering overall emissions. Additionally, strategically located refueling stops can allow for aircraft to optimize routing, potentially minimizing the distance traveled and further reducing fuel consumption and environmental impact.

6. Disruption Management

Unforeseen factors like severe weather, airport closures, and maintenance disrupt aircraft and flight operations. Airline operation control centers respond by reallocating resources and accommodating passengers to restore schedules and minimize costs. Inability to address these disruptions can harm airlines economically, socially, and environmentally. High resource utilization exacerbates the impact of disruptions. Planning prioritizes optimization, while recovery aims for swift real-time solutions, even if they are suboptimal.

Flight disruptions fall into two categories: those originating from airline resources (like aircraft and crew) and those resulting from external environmental factors (such as weather). Recovery operations include addressing flight delays, cancellations, resource swaps (e.g., aircraft or crew), using reserved resources, deadheading (transporting crew as passengers), ferrying (relocating aircraft without passengers from one location to another), managing speed, and reassigning passengers. This section covers aircraft, crew, and passenger recovery (Figure 4). Aircraft recovery involves retrieving, repairing, and restoring immobilized or damaged aircraft, often due to accidents, technical issues, or weather. Crew recovery focuses on assisting flight crew members affected by disruptions, scheduling changes, or events impacting their duty schedules. Passenger recovery involves managing and assisting passengers affected by flight disruptions, cancellations, delays, overbookings, etc.

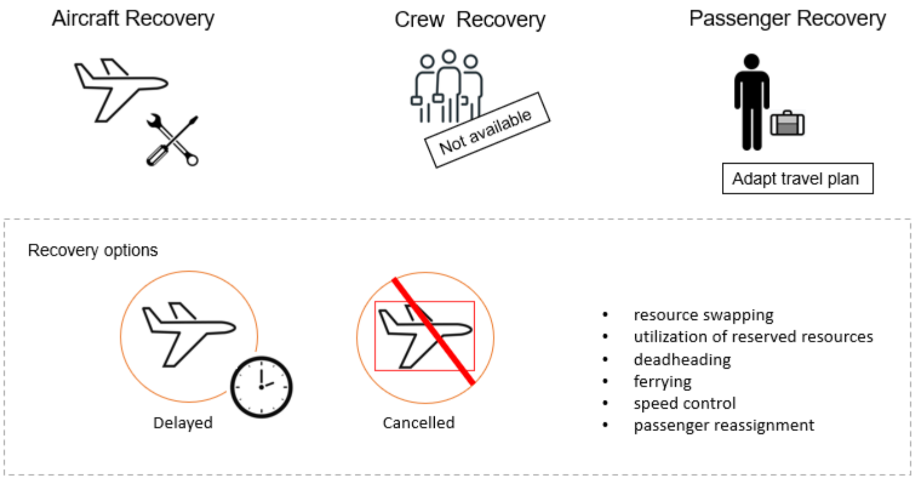

Figure 4. Representation of subcategories in disruption management.

6.1. Aircraft Recovery

Recent studies have explored different aspects of aircraft recovery. For instance, Wang et al. (2023) [121] analyze operational data from China South Airlines to comprehend delay causes and recovery patterns. The authors introduce a heuristic algorithm simulating dispatcher actions, involving two operations: flight tail number exchanges and departure time resets. Evaluations consider delay costs, adjustment costs, and an analytic hierarchy process scoring system, indicating the impact of irregular flights on the airline system. Zhao et al. (2023) [122] suggest a two-stage algorithm to mitigate the impact of daily disruptions on airline schedules. It deals with uncertainty in disruption duration and when its length is known. Network models pinpoint highly affected flights and adjust their schedules for system-wide optimization. The goal is to minimize delay costs, cancellation costs, curfew violations, and schedule deviations. Uncertainty is managed through scenario analysis, evaluating likely outcomes. A rolling horizon approach, mirroring existing airline procedures, serves as a benchmark for comparison. Lee et al. (2022) [123] use RL for aircraft recovery, allowing for aircraft swaps within subfleets to alleviate flight delays. The goals include reducing total delays and the count of delays exceeding 30 and 0 min. Q-learning and Double Q-learning algorithms are employed and validated with a domestic flight schedule from a South Korean airline. Rhodes-Leader et al. (2022) [124] propose an aircraft recovery approach involving an initial deterministic integer program and subsequent simulation optimization. It addresses uncertainties in solution evaluation, aiming to minimize recovery costs, aircraft allocation changes, and delays. The model focuses on a short-haul airline's homogeneous sub-fleet. The authors conduct an empirical assessment, resolving three problem instances involving up to 102 aircraft, yielding promising outcomes. They acknowledge that transitioning to real-world implementation hinges on overcoming the challenge of reducing computation time. Lee et al. (2020) [125] propose a dynamic approach for optimizing recovery decisions considering both realized and anticipated disruptions. The framework involves forecasting future disruptions by estimating systemic delays and employs a stochastic integer programming model to minimize expected costs. The model integrates a stochastic queuing model for airport congestion, flight planning, and airline disruption recovery. The approach's benefits are achieved by introducing departure holds strategically to reduce fuel costs, flight cancellations, and aircraft swaps. They examine Delta Air Lines' flight network, a prominent US hub-and-spoke carrier, conducting experimental studies. These experiments demonstrate that incorporating partial and probabilistic estimates of future disruptions can lead to a 1–2% reduction in expected recovery costs compared to a myopic baseline approach reliant solely on realized disruptions.

6.2. Aircraft and Crew Recovery

While crew scheduling has been extensively studied, crew recovery has received less attention. For example, Khiabani et al. (2022) [126] propose integrated aircraft and crew recovery plans to minimize delay and prevent its propagation in airline schedules. They use an MILP model considering various factors, efficiently solving it with Benders' decomposition and testing it on a 227-flight case. Another strategy involves scheduling reserve crew members to replace absent crew when needed. Bayliss et al. (2020) [127] address this by formulating the scheduling of reserve crew duties as a combinatorial optimization problem. They propose a mathematical model to assess different reserve crew schedules, considering factors like expected flight cancellations and delays due to reserve crew assignments. The experiments utilize problem instances derived from data supplied by KLM. This study specifically focuses on a single fleet, crew rank, and crew qualification scenario. Consequently, exploring more intricate examples and adapting the model into an online decision-making tool represents a future line of research.

6.3. Aircraft and Passenger Recovery

Yetimoglu and Akturk (2021) [128] address an integrated approach to aircraft and passenger recovery. It focuses on evaluating passenger itineraries to maximize airline profit while minimizing passenger dissatisfaction, considering options like cruise time control, aircraft exchange, and cancellation. They use a two-phased approach, presenting findings based on a U.S. airline's daily schedule. Similarly, Sun et al. (2021) [129] reduce problem complexity using a modified time-band network, introducing intermodal concepts for greater flexibility and passenger protection in aircraft recovery. Computational experiments with up to 144 flights are carried out. According to the results, considering a real-time intermodal network in disruption management drastically reduces the number of disrupted passengers and total disruption cost. In the future, the authors plan to develop a methodology of real-time intermodalism that integrates pre-scheduled ground transportation. Hu et al. (2021) [130] examine passenger willingness in optimizing aircraft rerouting and recovery, proposing an integer programming model with dual objectives of minimizing airline recovery cost and reducing passenger recovery loss. They employ a heuristic combining multi-directional and stochastic VNS for real-data experiments.

6.4. Aircraft, Crew, and Passenger Recovery

The integration of recovery decisions across all elements is crucial, as choices made for one element directly affect the others. However, given the vast scale of airline flight networks and the need for rapid recovery, this integration is complex. Evler et al. (2022) [131] propose an approach to enhance integrated recovery by incorporating aircraft turnaround considerations. This model combines a heterogeneous vehicle routing problem with time windows to assign aircraft to flight routes and a resource-constrained project schedule problem for allocating limited resources to turnarounds at the central hub airport. The model considers passenger and crew itineraries as connections between flights, influencing stand allocation and resource assignment while factoring in transfer times. However, these connections can only be disrupted if spare capacities exist and if rebooking and compensation costs outweigh the benefits of accepting departure delays to maintain transfers. The study employs a rolling horizon algorithm and case study evaluation, demonstrating that incorporating turnaround recovery options significantly enhances the airline network's resilience. Similarly, Arıkan et al. (2017) [132] propose a flight network-based representation for the problem, which supports recovery decisions such as departure delays, aircraft/crew rerouting, passenger reaccommodation, and ticket and flight cancellations. The model incorporates aircraft cruise speed decisions and uses a conic quadratic MIP formulation. Additionally, methods to address large airline networks are presented. They assess the viability of the proposed methods using actual data from a prominent U.S. airline's network in the year 2013.

6.5. Contributions from the Industry

Amadeus [133] is a report that delves into the evolving landscape of disruption management within airline IT systems. It highlights a notable shift in industry perspectives towards prioritizing the development of disruption mitigation tools. This change is evident in the industry's move towards automated backend processes and proactive passenger service solutions. The report underscores the increasing recognition of the return on investment in disruption management tools, with airlines demonstrating a greater willingness to collaborate with competitors and third parties for better responses to disruptions. As air travel continues to rise, effective disruption mitigation will become a critical aspect of customer service. Encouragingly, ongoing high levels of investment in IT system integration and tools suggest that significant progress is on the horizon.

In this context, Sabre introduces IROPS Reaccommodation [134], an advanced tool designed to assist airlines in managing irregular operations and devising reaccommodation strategies that enhance customer satisfaction. This system identifies passengers based on various criteria such as frequent flyer status, Special Service Requests (SSRs), and fare levels. By leveraging computerized decision support for swift and efficient issue resolution, airlines can deliver elevated service levels, often resulting in future revenue opportunities. The objective is to enhance customer satisfaction, boost agent productivity, optimize operational efficiency, and minimize passenger recovery expenses. Inform [135] provides advanced decision support for aviation disruption management, addressing the growing challenges faced by airports and airlines. Real-time operational decision-making software helps optimize staff and equipment scheduling, maximizing resource utilization and effectively managing disruptions such as understaffing.

6.6. Discussion

Disruption management encompasses the recovery of aircraft, crew, and passengers. Streamlining these operations directly mitigates environmental impact by minimizing fuel consumption associated with delays, congestion, ferrying, adjustments in speed away from the optimal rate, and more.

- Optimizing aircraft recovery streamlines operations, reducing idle time and unnecessary fuel consumption during disruptions, consequently lowering carbon emissions. By swiftly resolving disruptions, optimized aircraft recovery minimizes the need for additional flights or fuel-intensive repositioning, thus curbing environmental impact.
- Optimizing crew recovery ensures efficient utilization of workforce, minimizing the need for additional crew repositioning flights and reducing fuel consumption and emissions. By swiftly resolving crew disruptions, optimized crew recovery minimizes delays and operational inefficiencies, thereby mitigating environmental impact associated with extended flight durations and unnecessary resource consumption.
- Optimizing passenger recovery facilitates efficient rebooking and rerouting processes, minimizing the need for additional flights and reducing overall fuel consumption and emissions. By swiftly resolving passenger disruptions, optimized recovery procedures decrease flight delays and congestion, ultimately lowering carbon emissions and mitigating environmental impact.

7. Trends and Challenges

Drawing from the literature review presented in preceding sections, the objective of this section is to discern and elucidate emerging trends and pertinent challenges. Each trend and challenge is illustrated with an example to enhance clarity.

7.1. Trends

Below, we provide an overview of the key trends that have emerged.

- Multiple Optimization Problems. The aviation industry often models decisions as optimization problems, enabling the integration of diverse environmental indicators.

The literature shows a growing variety of problem formulations. This review encompasses 18 distinct optimization problems. Recent works for each problem have been introduced, each offering its unique formulation tailored to address specific nuances. Take, for instance, flight formations, where alongside traditional objectives like mutual defense and concentrated firepower recent studies have delved into considerations such as fuel consumption, CO_2 emissions, and the environmental impact of water vapor.

- Variety of Methodologies. The OR literature offers a range of methodologies to optimize and promote sustainability within the aviation industry. For example, in crew scheduling, various approaches including exact methods, heuristics, metaheuristics, hybrid methods like matheuristics, and deep learning have been identified. This diverse range of methodologies enables professionals to compare and select the most suitable one for their specific problem. Consequently, when environmental considerations are integrated into the problem formulation, it enhances the likelihood of discovering more environmentally sustainable solutions.
- Multi-objective. With the wide range of stakeholders and diverse impacts involved, multi-objective models are gaining prominence. For example, Stollenwerk et al. (2020) [72] tackle the gate assignment problem with a primary emphasis on minimizing passenger walking distances. Conversely, Liang et al. (2020) [71] not only prioritize minimizing walking distances, but also integrate a penalty cost for remote stands and minimize fuel consumption during taxiing. This holistic approach reduces passenger inconvenience and also contributes to mitigating emissions by optimizing fuel consumption.
- Robustness. Uncertainties are inevitable and pose challenges. Researchers are transitioning from cost-minimization planning to robustness-oriented planning. For example, neglecting robustness in flight scheduling can result in airport congestion and delays. Such delays not only inconvenience travelers but also escalate fuel consumption and emissions for aircraft waiting to take off or land [136].
- Disruption Management. Disruptions demand immediate and viable solutions for recovery, potentially inflicting costs, as well as social and environmental repercussions. Researchers are turning increased attention to this topic. To illustrate, flight delays and cancellations often result in increased fuel consumption if passengers must return home and then travel back to the airport via fuel-consuming transportation modes. The recovery option of relocating aircraft from other locations requires greater fuel consumption. Furthermore, adjusting aircraft speed can also contribute to heightened fuel consumption, as speeds are optimized to minimize fuel costs.

7.2. Challenges

Moreover, the literature underscores several pivotal challenges described below.

- Stochasticity, Uncertainty, and Incomplete Information. The industry necessitates methodologies capable of addressing this type of information.
  For example, random events like unexpected maintenance delays, bad weather, or passenger issues can disrupt aircraft schedules. Factors like wind speed or pilot availability can fluctuate, creating uncertainty in how long specific tasks take. Real-time data on aircraft position and landing times might be incomplete due to communication gaps. By considering these elements, aircraft scheduling can become more resilient, ultimately leading to smoother and more environmentally sustaiable operations.
- Integrated Approach. Authors often concentrate on individual optimization problems, making it easier to define and solve them. Yet, in practice, these problems are interconnected and interdependent. Isolated solutions may work for one problem but often fail to meet another's objective. In disruption management, an emerging trend is the simultaneous consideration of aircraft, crew, and passenger recovery. By adopting an integrated approach and incorporating environmental sustainability indicators

like CO_2 emissions, we can potentially achieve superior solutions to optimization problems in environmentally sustainable aviation.

- Realistic Formulations. Authors frequently simplify problem formulations to enhance manageability, but this simplification can result in unrealistic representations, limiting their effectiveness in real-life applications. Oversimplifying air-to-air refueling models by excluding variables like wind direction, wind speed, and weather conditions can produce misleading results. When implemented in real-life operations, these simplified solutions might lead to significantly higher fuel consumption than anticipated.
- Meteorological Information. Meteorological information is frequently disregarded, yet it can significantly affect operational performance. For instance, by avoiding adverse weather conditions such as thunderstorms, icing conditions, or strong crosswinds, airlines can minimize delays and disruptions while enhancing passenger safety. Moreover, headwinds can increase fuel burn during flight, while tailwinds can reduce it.
- Information Sharing. Vital data like landing time and aircraft position are dispersed among stakeholders with conflicting interests, usually not sharing information [137]. For instance, airlines might prioritize on-time arrivals over informing air traffic control of potential delays, leading to inefficiencies in the airspace.
- Problem Instances. A lack of standardized problem instances exists. Some authors create test cases with distribution properties instead of sharing actual data, while others use inaccessible real data. A diverse collection of problem instances encompassing various environmental indicators would empower researchers and practitioners to enhance the design, validation, and comparison of their approaches. It would facilitate the exploration of trade-offs between conflicting objectives and the effects of incorporating a broader range of constraints. Moreover, a diverse set of problem instances could spark increased interest from the academic community in addressing the challenges of environmentally sustainable aviation operational optimization.
- Code Sharing. Authors frequently describe their approaches but often do not share their code, hindering scientific progress. This lack of code transparency makes it difficult to replicate published findings, hinders collaboration, and ultimately slows the development and validation of new approaches. Therefore, encouraging code sharing among experts and practitioners engaged in operational optimization for environmentally sustainable aviation would facilitate the development of more sustainable solutions.

8. Future Research Directions

Drawing upon the insights gathered from the literature review, we discerned the promising lines for future research.

- Data Science and Big Data. Through data analytics and advanced algorithms, aviation stakeholders can boost operational efficiency while reducing environmental impact. This involves utilizing extensive datasets from sources. As an illustration, leveraging traffic data and weather conditions enables the construction of a model aimed at identifying optimal timeframes for air traffic controllers to facilitate continuous descent approaches for the majority of incoming aircraft [138]. This approach effectively mitigates noise, minimizes fuel consumption, and curtails pollution emissions.
- Simulation and Optimization. Simulation is a valuable tool allowing for stakeholders to model and assess scenarios without costly real-world experiments. When integrated with other OR techniques, simulations can effectively tackle complex challenges. For example, digital twins can incorporate dynamic information including environmental conditions and aircraft status to offer optimization recommendations for aircraft operations such as fuel optimization and flight route recommendations [139]. Moreover, they can forecast the remaining useful life of components, facilitating predictive maintenance and minimizing downtime.
- Reinforcement Learning. RL is gaining traction for its capacity to learn from dynamic and stochastic environments, enhancing decision-making processes. As an example,

deep multi-agent RL has been employed to tackle aircraft conflict resolution while optimizing trajectories [140]. This approach aims to resolve conflicts by optimizing solutions with regard to time, fuel consumption, and airspace complexity.

- Hybrid Algorithms. Integrating methodologies enables researchers to create more efficient algorithms for realistic problems. For example, Gök et al. (2020) [47] introduce a matheuristic approach, which combines heuristics with techniques from linear and integer programming, to efficiently obtain high-quality solutions within reasonable time for real-world aircraft turnaround scheduling instances.
- Parallel and Distributed Computing, and Quantum Computers. Problems frequently entail large-scale data, complex models, and high-dimensional search spaces. Advances in computing help researchers overcome computational constraints, enabling them to obtain better solutions [71].
- Electric and Hydrogen-Powered Aircraft. Electric and hydrogen-powered aircraft requires studies examining throughputs, capacities, and requirements. The use of electric and hydrogen-powered aircraft has the potential to significantly reduce emissions compared to the use of traditional aircraft, especially if the aircraft are powered by renewable energy sources. Nevertheless, optimizing operations, such as refining battery charging regimes, is necessary [141].
- Automation. Numerous opportunities exist for automating operations, e.g., for the docking process of ground support equipment with aircraft. For instance, Alonso Tabares and Mora-Camino (2019) [142] emphasize the potential for automating the docking process of ground support equipment with aircraft, implementing autonomous vehicles for maneuvering around aircraft, and incorporating automated systems within the aircraft.
- Aviation's Climate Impact. The existing literature focuses on indicators indirectly associated with environmental impacts and CO_2 emissions. Greater efforts are needed to comprehend and minimize other environmental indicators [3]. As an illustration, in flight formation, Dahlmann et al. (2020) [102] consider the effects of CO_2, water vapor, ozone, methane, and contrail cirrus.
- Climate Change Adaptation. Changes in storm and wind patterns, sea-level rise, and extreme temperatures pose significant risk factors. Climate change can have diverse impacts on aviation operations, such as alterations in aircraft performance [143,144]. The aviation sector must proactively prepare for climate change. Aircraft scheduling, turnaround operations, and disruption management are fields that require adaptation to mitigate the risks of accidents, congestion, delays, and cancellations.
- Open Data. The publication of open data attracts the attention of researchers, accelerating progress in optimizing aviation operations. The ROADEF 2009 challenge on disruption management (https://roadef.org/challenge/2009/en/, accessed on 1 April 2024) is a noteworthy example.
- Information Security. Cooperation among multiple agents requires preserving information security. Blockchain technology, for instance, can play a crucial role in safeguarding security and privacy during the exchange of information among various stakeholders, including crew members, flight manifests, and passenger data [32]. This technology can indirectly contribute to environmental sustainability by enhancing the efficiency and reliability of aviation operations.
- Infectious Diseases. The aviation industry saw major effects from the COVID-19 pandemic, leading to operational adaptations. For example, aircraft turnaround operations had to be streamlined to ensure thorough cleaning, disinfection, and sanitization of cabins and cockpits after each flight [145]. Additionally, new technologies and protocols, such as biometric boarding, were swiftly adopted to enhance bio-safety and security throughout travel [146]. These advancements hold potential to alleviate environmental impacts if they minimize congestion and delays. More research on disruption management can enhance preparedness and response strategies for future similar scenarios.

9. Conclusions

The projected trajectory indicates a return to pre-pandemic aviation levels by 2024, followed by substantial growth over two decades. Managing this demand surge and addressing environmental impacts is a significant challenge. Operations Research (OR) plays a key role in aviation offering efficient solutions. This paper reviews operational optimization in environmentally sustainable aviation, categorizing works into airline operations, airport operations, flight operations, and disruption management. The review contextualizes optimization problems, focusing on objectives and methodologies, and explores approaches to addressing environmental impact.

Several emerging trends are notable, such as the effective modeling of aviation decision-making as optimization problems, an expanding array of powerful methodologies in OR literature, the growing use of multi-objective models, and a shift toward robustness-oriented planning to address complex stakeholder interests and impacts during disruptions. Challenges persist, including dealing with stochasticity, uncertainty, and incomplete information, emphasizing integrated and realistic problem formulations, the influence of meteorological data on operational performance, fostering collaboration and data sharing among stakeholders, generating realistic problem instances, and promoting code sharing for reproducibility and reusability. Future research directions include leveraging data science and big data methods for insights, integrating simulation and optimization tools, exploring reinforcement learning, hybrid algorithms, distributed computing, and quantum computing, addressing the OR challenges of electric and hydrogen-powered aircraft, exploring automation in aviation operations, open data publication to stimulate research, and finding a balance between information security and cooperation among multiple agents. Further areas of study encompass the climate impact of aviation, climate change adaptation, infectious disease effects, and proactive disruption management.

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

ACO	Ant Colony Optimization
BHTS	Baggage Handling Transport System
CO_2	Carbon Dioxide
EASA	European Union Aviation Safety Agency
FARS	Floating Aerial Refueling System
GA	Genetic Algorithm
IATA	International Air Transport Association
ILP	Integer Linear Programming
LNS	Large Neighborhood Search
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
OR	Operations Research
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
SA	Simulated Annealing
VNS	Variable Neighborhood Search

References

1. IATA. *Global outlook for Air Transport. Sustained Recovery Amidst Strong Headwinds*; IATA: Geneva, Switzerland, 2022.
2. IEA. Aviation: Tracking Progress. 2022. Available online: http://www.iea.org/reports/aviation (accessed on 1 April 2024).
3. EASA. *Updated Analysis of the Non-CO2 Climate Impacts of Aviation and Potential Policy Measures Pursuant to EU Emissions Trading System Directive Article 30(4)*; European Aviation Safety Agency: Cologne, Germany, 2020.
4. IATA. International Air Transport Association's Annual Review. In Proceedings of the 78th Annual General Meeting and World Air Transport Summit, Doha, Qatar, 19–21 June 2022.

5. Bauen, A.; Bitossi, N.; German, L.; Harris, A.; Leow, K. Sustainable Aviation Fuels: Status, challenges and prospects of drop-in liquid fuels, hydrogen and electrification in aviation. *Johns. Matthey Technol. Rev.* **2020**, *64*, 263–278. [CrossRef]
6. Yusaf, T.; Fernandes, L.; Abu Talib, A.R.; Altarazi, Y.S.M.; Alrefae, W.; Kadirgama, K.; Ramasamy, D.; Jayasuriya, A.; Brown, G.; Mamat, R.; et al. Sustainable aviation: Hydrogen is the future. *Sustainability* **2022**, *14*, 548. [CrossRef]
7. Barzkar, A.; Ghassemi, M. Electric power systems in more and all electric aircraft: A review. *IEEE Access* **2020**, *8*, 169314–169332. [CrossRef]
8. Afonso, F.; Sohst, M.; Diogo, C.M.; Rodrigues, S.S.; Ferreira, A.; Ribeiro, I.; Marques, R.; Rego, F.F.; Sohouli, A.; Portugal-Pereira, J.; et al. Strategies towards a more sustainable aviation: A systematic review. *Prog. Aerosp. Sci.* **2023**, *137*, 100878.
9. Wu, C.L. *Airline Operations and Delay Management: Insights from Airline Economics, Networks and Strategic Schedule Planning*; Routledge: New York, NY, USA, 2016.
10. Guimarans, D.; Arias, P.; Tomasella, M.; Wu, C.L. Chapter 4—A Review of Sustainability in Aviation: A Multidimensional Perspective. In *Sustainable Transportation and Smart Logistics*; Faulin, J., Grasman, S.E., Juan, A.A., Hirsch, P., Eds.; Elsevier: Amsterdam, The Netherlands, 2019; pp. 91–121.
11. Ng, K.; Lee, C.K.; Chan, F.T.; Lv, Y. Review on meta-heuristics approaches for airside operation research. *Appl. Soft Comput.* **2018**, *66*, 104–133. [CrossRef]
12. Eltoukhy, A.E.; Chan, F.T.; Chung, S.H. Airline schedule planning: A review and future directions. *Ind. Manag. Data Syst.* **2017**, *117*, 1201–1243. [CrossRef]
13. Mitici, M.; Pereira, M.; Oliviero, F. Electric flight scheduling with battery-charging and battery-swapping opportunities. *EURO J. Transp. Logist.* **2022**, *11*, 100074. [CrossRef]
14. Kenan, N.; Jebali, A.; Diabat, A. An integrated flight scheduling and fleet assignment problem under uncertainty. *Comput. Oper. Res.* **2018**, *100*, 333–342. [CrossRef]
15. Birolini, S.; Antunes, A.P.; Cattaneo, M.; Malighetti, P.; Paleari, S. Integrated flight scheduling and fleet assignment with improved supply-demand interactions. *Transp. Res. Part B Methodol.* **2021**, *149*, 162–180. [CrossRef]
16. Temucin, T.; Tuzkaya, G.; Vayvay, O. Aircraft maintenance routing problem–A literature survey. *Promet-Traffic Transp.* **2021**, *33*, 491–503. [CrossRef]
17. Ruan, J.; Wang, Z.; Chan, F.T.; Patnaik, S.; Tiwari, M. A reinforcement learning-based algorithm for the aircraft maintenance routing problem. *Expert Syst. Appl.* **2021**, *169*, 114399. [CrossRef]
18. Bulbul, K.G.; Kasimbeyli, R. Augmented Lagrangian based hybrid subgradient method for solving aircraft maintenance routing problem. *Comput. Oper. Res.* **2021**, *132*, 105294. [CrossRef]
19. Cui, R.; Dong, X.; Lin, Y. Models for aircraft maintenance routing problem with consideration of remaining time and robustness. *Comput. Ind. Eng.* **2019**, *137*, 106045. [CrossRef]
20. Ma, Q.; Song, H.; Zhu, W. Low-carbon airline fleet assignment: A compromise approach. *J. Air Transp. Manag.* **2018**, *68*, 86–102. [CrossRef]
21. Justin, C.Y.; Payan, A.P.; Mavris, D.N. Integrated fleet assignment and scheduling for environmentally friendly electrified regional air mobility. *Transp. Res. Part C Emerg. Technol.* **2022**, *138*, 103567. [CrossRef]
22. Glomb, L.; Liers, F.; Rösel, F. Optimizing integrated aircraft assignment and turnaround handling. *Eur. J. Oper. Res.* **2023**, *310*, 1051–1071. [CrossRef]
23. Liu, M.; Ding, Y.; Sun, L.; Zhang, R.; Dong, Y.; Zhao, Z.; Wang, Y.; Liu, C. Green airline-fleet assignment with uncertain passenger demand and fuel price. *Sustainability* **2023**, *15*, 899. [CrossRef]
24. Ikli, S.; Mancel, C.; Mongeau, M.; Olive, X.; Rachelson, E. The aircraft runway scheduling problem: A survey. *Comput. Oper. Res.* **2021**, *132*, 105336. [CrossRef]
25. Samà, M.; D'Ariano, A.; Corman, F.; Pacciarelli, D. Metaheuristics for efficient aircraft scheduling and re-routing at busy terminal control areas. *Transp. Res. Part C Emerg. Technol.* **2017**, *80*, 485–511. [CrossRef]
26. Zheng, S.; Yang, Z.; He, Z.; Wang, N.; Chu, C.; Yu, H. Hybrid simulated annealing and reduced variable neighbourhood search for an aircraft scheduling and parking problem. *Int. J. Prod. Res.* **2020**, *58*, 2626–2646. [CrossRef]
27. Huo, Y.; Delahaye, D.; Sbihi, M. A probabilistic model based optimization for aircraft scheduling in terminal area under uncertainty. *Transp. Res. Part C: Emerg. Technol.* **2021**, *132*, 103374. [CrossRef]
28. Vikstål, P.; Grönkvist, M.; Svensson, M.; Andersson, M.; Johansson, G.; Ferrini, G. Applying the quantum approximate optimization algorithm to the tail-assignment problem. *Phys. Rev. Appl.* **2020**, *14*, 034009. [CrossRef]
29. Khaled, O.; Minoux, M.; Mousseau, V.; Michel, S.; Ceugniet, X. A compact optimization model for the tail assignment problem. *Eur. J. Oper. Res.* **2018**, *264*, 548–557. [CrossRef]
30. Khaled, O.; Minoux, M.; Mousseau, V.; Michel, S.; Ceugniet, X. A multi-criteria repair/recovery framework for the tail assignment problem in airlines. *J. Air Transp. Manag.* **2018**, *68*, 137–151. [CrossRef]
31. Jayaraj, A.; Panicker, V.V.; Sridharan, R. Large-scale model and solution for integrated maintenance routing and tail assignment problem in airline industry. *Int. J. Ind. Syst. Eng.* **2020**, *36*, 384–399. [CrossRef]
32. Wen, X.; Sun, X.; Sun, Y.; Yue, X. Airline crew scheduling: Models and algorithms. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *149*, 102304. [CrossRef]

33. Aggarwal, D.; Saxena, D.K.; Bäck, T.; Emmerich, M. Real-world airline crew pairing optimization: Customized genetic algorithm versus column generation method. In Proceedings of the Evolutionary Multi-Criterion Optimization: 12th International Conference, EMO 2023, Leiden, The Netherlands, 20–24 March 2023; Springer: Berlin/Heidelberg, Germany, 2023; pp. 518–531.
34. Ahmed, M.B.; Hryhoryeva, M.; Hvattum, L.M.; Haouari, M. A matheuristic for the robust integrated airline fleet assignment, aircraft routing, and crew pairing problem. *Comput. Oper. Res.* **2022**, *137*, 105551. [CrossRef]
35. Shafipour-Omrani, B.; Rashidi Komijan, A.; Sadjadi, S.J.; Khalili-Damghani, K.; Ghezavati, V. A flexible mathematical model for crew pairing optimization to generate n-day pairings considering the risk of COVID-19: A real case study. *Kybernetes* **2022**, *51*, 3545–3573. [CrossRef]
36. Cacchiani, V.; Salazar-González, J.J. Heuristic approaches for flight retiming in an integrated airline scheduling problem of a regional carrier. *Omega* **2020**, *91*, 102028. [CrossRef]
37. Quesnel, F.; Desaulniers, G.; Soumis, F. A branch-and-price heuristic for the crew pairing problem with language constraints. *Eur. J. Oper. Res.* **2020**, *283*, 1040–1054. [CrossRef]
38. Quesnel, F.; Desaulniers, G.; Soumis, F. Improving air crew rostering by considering crew preferences in the crew pairing problem. *Transp. Sci.* **2020**, *54*, 97–114. [CrossRef]
39. Quesnel, F.; Wu, A.; Desaulniers, G.; Soumis, F. Deep-learning-based partial pricing in a branch-and-price algorithm for personalized crew rostering. *Comput. Oper. Res.* **2022**, *138*, 105554. [CrossRef]
40. Mirjafari, M.; Komijan, A.R.; Shoja, A. An integrated model of aircraft routing and crew rostering problems to develop fair schedule for the crew under COVID-19 condition. *Int. J. Sustain. Aviat.* **2022**, *8*, 162–180. [CrossRef]
41. Saemi, S.; Komijan, A.R.; Tavakkoli-Moghaddam, R.; Fallah, M. Solving an integrated mathematical model for crew pairing and rostering problems by an ant colony optimisation algorithm. *Eur. J. Ind. Eng.* **2022**, *16*, 215–240. [CrossRef]
42. Chutima, P.; Arayikanon, K. Many-objective low-cost airline cockpit crew rostering optimisation. *Comput. Ind. Eng.* **2020**, *150*, 106844. [CrossRef]
43. Zeighami, V.; Saddoune, M.; Soumis, F. Alternating Lagrangian decomposition for integrated airline crew scheduling problem. *Eur. J. Oper. Res.* **2020**, *287*, 211–224. [CrossRef]
44. Zhou, S.Z.; Zhan, Z.H.; Chen, Z.G.; Kwong, S.; Zhang, J. A multi-objective ant colony system algorithm for airline crew rostering problem with fairness and satisfaction. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 6784–6798. [CrossRef]
45. San Antonio, A.; Juan, A.A.; Calvet, L.; i Casas, P.F.; Guimarans, D. Using simulation to estimate critical paths and survival functions in aircraft turnaround processes. In Proceedings of the 2017 Winter Simulation Conference (WSC), Las Vegas, NV, USA, 3–6 December 2017; IEEE: New York, NY, USA, 2017; pp. 3394–3403.
46. Saha, S.; Tomasella, M.; Cattaneo, G.; Matta, A.; Padrón, S. On static vs dynamic (switching of) operational policies in aircraft turnaround team allocation and management. In Proceedings of the 2021 Winter Simulation Conference (WSC), Phoenix, AZ, USA, 12–15 December 2021; IEEE: New York, NY, USA, 2021; pp. 1–12.
47. Gök, Y.S.; Guimarans, D.; Stuckey, P.J.; Tomasella, M.; Ozturk, C. Robust resource planning for aircraft ground operations. In Proceedings of the 17th International Conference, CPAIOR 2020, Vienna, Austria, 21–24 September 2020; Springer: Berlin/Heidelberg, Germany, 2020; pp. 222–238.
48. KLM. Climate Action Plan. Air France-KLM Group. 2023. Available online: http://img.static-kl.com/m/7b0b0f3946d5bb53/original/KLM-Climate-Action-Plan-2023.pdf (accessed on 1 April 2024).
49. Eurocontrol. European Continuous Climb and Descent Operations Action Plan. 2020. Available online: http://www.eurocontrol.int/publication/european-cco-cdo-action-plan (accessed on 1 April 2024).
50. SAS. SAS Annual and Sustainability Report Fiscal Year 2022. 2023. Available online: http://www.sasgroup.net/files/Main/290/3701838/sas-annual-and-sustainability-report-fy-2022.pdf (accessed on 1 April 2024).
51. Aerospace, C. Ascentia Analytics Services. 2022. Available online: http://www.collinsaerospace.com/what-we-do/capabilities/connected-ecosystem/power-to-predict (accessed on 1 April 2024).
52. Jeppesen. Jeppesen Aircraft Routing. 2024. Available online: http://ww2.jeppesen.com/network-and-operations-management/aircraft-routing/ (accessed on 1 April 2024).
53. Skywise. Skywise Digital Solutions. 2024. Available online: http://aircraft.airbus.com/en/services/enhance/skywise (accessed on 1 April 2024).
54. Ramco. Fleet Technical Management. 2024. Available online: http://www.ramco.com/products/aviation-software/fleet-technical-management/ (accessed on 1 April 2024).
55. Matellio. Aviation Fleet Management Software Development—Top Features, Cost, and Development Process. 2024. Available online: http://www.matellio.com/blog/aviation-fleet-management-software-development/ (accessed on 1 April 2024).
56. Veryon. Integrated Flight Operations Software. 2024. Available online: http://veryon.com/solutions/commercial-aviation/flight-operations (accessed on 1 April 2024).
57. Airbus. The EcoPulse Aircraft Demonstrator Makes First Hybrid-Electric Flight. 2023. Available online: http://www.airbus.com/en/newsroom/press-releases/2023-12-the-ecopulse-aircraft-demonstrator-makes-first-hybrid-electric (accessed on 1 April 2024).
58. United. Fuel Efficiency and Emissions Reduction. 2021. Available online: http://www.united.com/ual/en/us/fly/company/global-citizenship/environment/fuel-efficiency-and-emissions-reduction.html (accessed on 1 April 2024).

59. PDC. Airline Crew Scheduling—PDC FlightCrew. 2024. Available online: http://www.pdc.com/solution/planning-for-airlines/airline-crew-scheduling-flightcrew/ (accessed on 1 April 2024).
60. ProDIGIQ. ProDIGIQ's Flight Operations System, NAXOS. 2024. Available online: http://www.prodigiq.com/airlines/flight-operations-system/crew-scheduling-module/ (accessed on 1 April 2024).
61. Sabre. Schedule Manager—Airline Scheduling Software. 2024. Available online: http://www.sabre.com/products/suites/network-planning-and-optimization/schedule-manager/ (accessed on 1 April 2024).
62. AiPRON 360. ADB SAFEGATE's AiPRON 360. 2024. Available online: http://adbsafegate.com/products/apron/apron-management-system/aipron-360/ (accessed on 1 April 2024).
63. FLYHT. Turn Management—ClearPort. 2024. Available online: http://flyht.com/actionable-intelligence/turn-management/ (accessed on 1 April 2024).
64. Aeroporto di Torino. Torino Green Airport. 2024. Available online: http://www.aeroportoditorino.it/en/torinogreenairport/other-environmental-impact-mitigations/turnaround-green (accessed on 1 April 2024).
65. Aviation Pros. Dnata's Vision for Environmental Efficiency. 2024. Available online: http://www.aviationpros.com/ground-handling/ground-handlers-service-providers/article/21274646/environmental-efficiency (accessed on 1 April 2024).
66. Daş, G.S.; Gzara, F.; Stützle, T. A review on airport gate assignment problems: Single versus multi objective approaches. *Omega* **2020**, *92*, 102146. [CrossRef]
67. Jiang, Y.; Hu, Z.; Liu, Z.; Zhang, H. Optimization of multi-objective airport gate assignment problem: Considering fairness between airlines. *Transp. B Transp. Dyn.* **2023**, *11*, 196–210. [CrossRef]
68. Kim, J.; Goo, B.; Roh, Y.; Lee, C.; Lee, K. A branch-and-price approach for airport gate assignment problem with chance constraints. *Transp. Res. Part B Methodol.* **2023**, *168*, 1–26. [CrossRef]
69. She, Y.; Zhao, Q.; Guo, R.; Yu, X. A robust strategy to address the airport gate assignment problem considering operators' preferences. *Comput. Ind. Eng.* **2022**, *168*, 108100. [CrossRef]
70. Karsu, Ö.; Azizoğlu, M.; Alanlı, K. Exact and heuristic solution approaches for the airport gate assignment problem. *Omega* **2021**, *103*, 102422. [CrossRef]
71. Liang, B.; Li, Y.; Bi, J.; Ding, C.; Zhao, X. An improved adaptive parallel genetic algorithm for the airport gate assignment problem. *J. Adv. Transp.* **2020**, *2020*, 1–17. [CrossRef]
72. Stollenwerk, T.; Hadfield, S.; Wang, Z. Toward quantum gate-model heuristics for real-world planning problems. *IEEE Trans. Quantum Eng.* **2020**, *1*, 1–16. [CrossRef]
73. Guépet, J.; Acuna-Agost, R.; Briant, O.; Gayon, J.P. Exact and heuristic approaches to the airport stand allocation problem. *Eur. J. Oper. Res.* **2015**, *246*, 597–608. [CrossRef]
74. Zhao, N.; Duan, M. Research on airport multi-objective optimization of stand allocation based on simulated annealing algorithm. *Math. Biosci. Eng.* **2021**, *18*, 8314–8330. [CrossRef]
75. Bagamanova, M.; Mota, M.M. A multi-objective optimization with a delay-aware component for airport stand allocation. *J. Air Transp. Manag.* **2020**, *83*, 101757. [CrossRef]
76. Katsigiannis, F.A.; Zografos, K.G. Optimising airport slot allocation considering flight-scheduling flexibility and total airport capacity constraints. *Transp. Res. Part B Methodol.* **2021**, *146*, 50–87. [CrossRef]
77. Wang, D.; Zhao, Q. A simultaneous optimization model for airport network slot allocation under uncertain capacity. *Sustainability* **2020**, *12*, 5512. [CrossRef]
78. Androutsopoulos, K.N.; Manousakis, E.G.; Madas, M.A. Modeling and solving a bi-objective airport slot scheduling problem. *Eur. J. Oper. Res.* **2020**, *284*, 135–151. [CrossRef]
79. Lodewijks, G.; Cao, Y.; Zhao, N.; Zhang, H. Reducing CO_2 emissions of an airport baggage handling transport system using a particle swarm optimization algorithm. *IEEE Access* **2021**, *9*, 121894–121905. [CrossRef]
80. Volt, J.; Stojić, S.; Had, P. Optimization of the baggage loading and unloading equipment. *Transp. Res. Procedia* **2022**, *65*, 246–255. [CrossRef]
81. Deng, W.; Zhang, L.; Zhou, X.; Zhou, Y.; Sun, Y.; Zhu, W.; Chen, H.; Deng, W.; Chen, H.; Zhao, H. Multi-strategy particle swarm and ant colony hybrid optimization for airport taxiway planning problem. *Inf. Sci.* **2022**, *612*, 576–593. [CrossRef]
82. Zhang, M.; Huang, Q.; Liu, S.; Li, H. Multi-objective optimization of aircraft taxiing on the airport surface with consideration to taxiing conflicts and the airport environment. *Sustainability* **2019**, *11*, 6728. [CrossRef]
83. Li, N.; Sun, Y.; Yu, J.; Li, J.C.; Zhang, H.f.; Tsai, S. An empirical study on low emission taxiing path optimization of aircrafts on airport surfaces from the perspective of reducing carbon emissions. *Energies* **2019**, *12*, 1649. [CrossRef]
84. Guépet, J.; Briant, O.; Gayon, J.P.; Acuna-Agost, R. The aircraft ground routing problem: Analysis of industry punctuality indicators in a sustainable perspective. *Eur. J. Oper. Res.* **2016**, *248*, 827–839. [CrossRef]
85. PDC. Stand & Gate Management. 2024. Available online: http://www.pdc.com/solution/resource-planning-airports/airport-stand-gate-planning-standplan/ (accessed on 1 April 2024).
86. ARC. CAST Stand & Gate Allocation. 2024. Available online: http://arc.de/cast-simulation-software/cast-stand-gate-allocation/ (accessed on 1 April 2024).
87. AeroCloud. Gate Management. 2024. Available online: http://aerocloudsystems.com/airport-operations-system/gate-management/ (accessed on 1 April 2024).

88. PDC. Airport Slot Coordination and Reporting. 2024. Available online: http://www.pdc.com/solution/airport-slot-coordination-score/slot-coordination-score/ (accessed on 1 April 2024).
89. Sabre. Slot Manager. 2024. Available online: http://www.sabre.com/products/suites/network-planning-and-optimization/slot-manager-iata/ (accessed on 1 April 2024).
90. OneAplha. OneAlpha's Software Rising to Industry Challenges. 2024. Available online: http://onealphatech.com/onealphas-software-rising-to-industry-challenges/ (accessed on 1 April 2024).
91. Kelton, W.D. *Simulation with Arena*; McGraw-Hill: Boston, MA, USA, 2002.
92. Smith, J.S.; Sturrock, D.T. Simio and Simulation—Modeling, Analysis, Applications. 2023. Available online: http://textbook.simio.com/SASMAA/index.html (accessed on 1 April 2024).
93. Nordgren, W.B. FlexSim Simulation Environment. In *Proceedings of the Winter Simulation Conference*; Chick, S., Sánchez, P.J., Ferrin, D., Morrice, D.J., Eds.; Institute of Electrical and Electronics Engineers, Inc.: Orem, UT, USA, 2002; pp. 250–252.
94. Scarabee. Baggage Handling Systems. 2023. Available online: http://www.scarabee.com/baggage-handling-systems-2 (accessed on 1 April 2024).
95. INFORM. Fuel Efficiency and Emissions Reduction. 2024. Available online: http://www.inform-software.com/en/solutions/aviation-ground-operations (accessed on 1 April 2024).
96. Hammad, A.W.; Rey, D.; Bu-Qammaz, A.; Grzybowska, H.; Akbarnezhad, A. Mathematical optimization in enhancing the sustainability of aircraft trajectory: A review. *Int. J. Sustain. Transp.* **2020**, *14*, 413–436. [CrossRef]
97. Simorgh, A.; Soler, M.; González-Arribas, D.; Matthes, S.; Grewe, V.; Dietmüller, S.; Baumann, S.; Yamashita, H.; Yin, F.; Castino, F.; et al. A comprehensive survey on climate optimal aircraft trajectory planning. *Aerospace* **2022**, *9*, 146. [CrossRef]
98. Ma, L.; Tian, Y.; Yang, S.; Xu, C.; Hao, A. A scheme of sustainable trajectory optimization for aircraft cruise based on comprehensive social benefit. *Discret. Dyn. Nat. Soc.* **2021**, *2021*, 1–15. [CrossRef]
99. Murrieta-Mendoza, A.; Botez, R.M. Commercial Aircraft Trajectory Optimization to Reduce Flight Costs and Pollution: Metaheuristic Algorithms. In *Advances in Visualization and Optimization Techniques for Multidisciplinary Research: Trends in Modelling and Simulations for Engineering Applications*; Vucinic, D., Rodrigues Leta, F., Janardhanan, S., Eds.; Springer: Singapore, 2020; pp. 33–62.
100. Lindner, M.; Rosenow, J.; Fricke, H. Aircraft trajectory optimization with dynamic input variables. *CEAS Aeronaut. J.* **2020**, *11*, 321–331. [CrossRef]
101. Samà, M.; D'Ariano, A.; Palagachev, K.; Gerdts, M. Integration methods for aircraft scheduling and trajectory optimization at a busy terminal manoeuvring area. *OR Spectr.* **2019**, *41*, 641–681. [CrossRef]
102. Dahlmann, K.; Matthes, S.; Yamashita, H.; Unterstrasser, S.; Grewe, V.; Marks, T. Assessing the climate impact of formation flights. *Aerospace* **2020**, *7*, 172. [CrossRef]
103. Kent, T.E.; Richards, A.G. Potential of formation flight for commercial aviation: Three case studies. *J. Aircr.* **2021**, *58*, 320–333. [CrossRef]
104. Unterstrasser, S. The contrail mitigation potential of aircraft formation flight derived from high-resolution simulations. *Aerospace* **2020**, *7*, 170. [CrossRef]
105. Marks, T.; Dahlmann, K.; Grewe, V.; Gollnick, V.; Linke, F.; Matthes, S.; Stumpf, E.; Swaid, M.; Unterstrasser, S.; Yamashita, H.; et al. Climate impact mitigation potential of formation flight. *Aerospace* **2021**, *8*, 14. [CrossRef]
106. Fezans, N.; Jann, T. Towards automation of aerial refuelling manoeuvres with the probe-and-drogue system: Modelling and simulation. *Transp. Res. Procedia* **2018**, *29*, 116–134. [CrossRef]
107. Rong, K. System Design and Optimization of an Aerial Refueling System for Transcontinental Flights. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 2020.
108. Hansknecht, C.; Joormann, I.; Korn, B.; Morscheck, F.; Stiller, S. Feeder routing for air-to-air refueling operations. *Eur. J. Oper. Res.* **2023**, *304*, 779–796. [CrossRef]
109. Zhang, Z.; Huang, Z.; Liu, X.; Feng, B. Research on multiple air-to-air refueling planning based on multi-dimensional improved NSGA-II algorithm. *Electronics* **2023**, *12*, 3880. [CrossRef]
110. Deo, V.A.; Silvestre, F.J.; Morales, M. The benefits of tankering considering cost index flying and optional refuelling stops. *J. Air Transp. Manag.* **2020**, *82*, 101726. [CrossRef]
111. Zengerling, Z.L.; Linke, F.; Weder, C.M.; Dahlmann, K. Climate-optimised intermediate stop operations: Mitigation potential and differences from fuel-optimised configuration. *Appl. Sci.* **2022**, *12*, 12499. [CrossRef]
112. Linke, F. The Global Fuel Saving Potential of Intermediate Stop Operations Considering Meteorological and Operational Influences. In Proceedings of the 31st Congress of the International Council of the Aeronautical Sciences (ICAS), Belo Horizonte, Brazil, 9–14 September 2018.
113. Pace. Pacelab Flight Profile Optimizer. 2024. Available online: http://pace.txtgroup.com/products/flight-operations/pacelab-flight-profile-optimizer/ (accessed on 1 April 2024).
114. Airbus. *Fello'Fly: Airbus' Wake Energy Retrieval Concept Shows Promise for Operational Fuel Savings*; Chapter Climate Change Mitigation: Operations; International Civil Aviation Organization: Montreal, QBC, Canada, 2023; pp. 153–155.
115. Airbus. *Airbus to Continue Fello'Fly Flight Tests via SESAR-Backed Geese Project. Flight Global—Air Transport*; Flight Global: Sutton, London, 2023.

116. Airbus. Airbus A330 MRTT Becomes World's First Tanker Certified for Automatic Air-to-Air Refuelling Operations. Press Release. 2022. Available online: http://airbus.com/en/newsroom/press-releases/2022-07-airbus-a330-mrtt-becomes-worlds-first-tanker-certified-for (accessed on 1 April 2024).
117. Omega. Aerial Refueling Services. 2024. Available online: http://omegaairrefueling.com/ (accessed on 1 April 2024).
118. Metrea. Air-to-Air Refueling. 2024. Available online: http://metrea.aero/air/aar/ (accessed on 1 April 2024).
119. AOPA. Fuel Planning, EFB Integration Added to AOPA Flight Planner. 2024. Available online: http://aopa.org/news-and-media/all-news/2016/february/18/fuel-planning-efb-integration-added-to-aopa-flight-planner (accessed on 1 April 2024).
120. Flightworx. Flight Planning. 2024. Available online: http://flightworx.aero/solutions/flight-planning/ (accessed on 1 April 2024).
121. Wang, N.; Wang, H.; Pei, S.; Zhang, B. A data-driven heuristic method for irregular flight recovery. *Mathematics* **2023**, *11*, 2577. [CrossRef]
122. Zhao, A.; Bard, J.F.; Bickel, J.E. A two-stage approach to aircraft recovery under uncertainty. *J. Air Transp. Manag.* **2023**, *111*, 102421. [CrossRef]
123. Lee, J.; Lee, K.; Moon, I. A reinforcement learning approach for multi-fleet aircraft recovery under airline disruption. *Appl. Soft Comput.* **2022**, *129*, 109556. [CrossRef]
124. Rhodes-Leader, L.; Nelson, B.; Onggo, B.S.; Worthington, D. A multi-fidelity modelling approach for airline disruption management using simulation. *J. Oper. Res. Soc.* **2022**, *73*, 2228–2241. [CrossRef]
125. Lee, J.; Marla, L.; Jacquillat, A. Dynamic disruption management in airline networks under airport operating uncertainty. *Transp. Sci.* **2020**, *54*, 973–997. [CrossRef]
126. Khiabani, A.; Rashidi Komijan, A.; Ghezavati, V.; Mohammadi Bidhandi, H. A mathematical model for integrated aircraft and crew recovery after a disruption: A Benders' decomposition approach. *J. Model. Manag.* **2022**, *18*, 1740–1761. [CrossRef]
127. Bayliss, C.; De Maere, G.; Atkin, J.A.; Paelinck, M. Scheduling airline reserve crew using a probabilistic crew absence and recovery model. *J. Oper. Res. Soc.* **2020**, *71*, 543–565. [CrossRef]
128. Yetimoglu, Y.N.; Akturk, M.S. Aircraft and passenger recovery during an aircraft's unexpected unavailability. *J. Air Transp. Manag.* **2021**, *91*, 101991. [CrossRef]
129. Sun, F.; Liu, H.; Zhang, Y. Integrated aircraft and passenger recovery with enhancements in modeling, solution algorithm, and intermodalism. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 9046–9061. [CrossRef]
130. Hu, Y.; Zhang, P.; Fan, B.; Zhang, S.; Song, J. Integrated recovery of aircraft and passengers with passengers' willingness under various itinerary disruption situations. *Comput. Ind. Eng.* **2021**, *161*, 107664. [CrossRef]
131. Evler, J.; Lindner, M.; Fricke, H.; Schultz, M. Integration of turnaround and aircraft recovery to mitigate delay propagation in airline networks. *Comput. Oper. Res.* **2022**, *138*, 105602. [CrossRef]
132. Arıkan, U.; Gürel, S.; Aktürk, M.S. Flight network-based approach for integrated airline recovery with cruise speed control. *Transp. Sci.* **2017**, *51*, 1259–1287. [CrossRef]
133. Amadeus. Shaping the Future of Airline Disruption Management (IROPS). 2024. Available online: http://amadeus.com/documents/en/airlines/white-paper/shaping-the-future-of-airline-disruption-management.pdf (accessed on 1 April 2024).
134. Sabre. Airline Recovery with IROPS Reaccommodation. 2024. Available online: http://sabre.com/products/suites/departure-control/irops-reaccommodation/ (accessed on 1 April 2024).
135. INFORM. Advanced Decision Support for Aviation Disruption Management. 2024. Available online: http://inform-software.com/en/lp/aviation-disruption-management (accessed on 1 April 2024).
136. Hassan, T.H.; Sobaih, A.E.E.; Salem, A.E. Factors affecting the rate of fuel consumption in aircrafts. *Sustainability* **2021**, *13*, 8066. [CrossRef]
137. Eurocontrol. Performance Review Report (PRR) 2022. 2023. Available online: http://www.eurocontrol.int/publication/performance-review-report-prr-2022 (accessed on 1 April 2024).
138. Alharbi, E.A.; Abdel-Malek, L.L.; Milne, R.J.; Wali, A.M. Analytical model for enhancing the adoptability of continuous descent approach at airports. *Appl. Sci.* **2022**, *12*, 1506. [CrossRef]
139. Phanden, R.K.; Sharma, P.; Dubey, A. A review on simulation in digital twin for aerospace, manufacturing and robotics. *Mater. Today Proc.* **2021**, *38*, 174–178. [CrossRef]
140. Isufaj, R.; Aranega Sebastia, D.; Angel Piera, M. Toward conflict resolution with deep multi-agent reinforcement learning. *J. Air Transp.* **2022**, *30*, 71–80. [CrossRef]
141. Doctor, F.; Budd, T.; Williams, P.D.; Prescott, M.; Iqbal, R. Modelling the effect of electric aircraft on airport operations and infrastructure. *Technol. Forecast. Soc. Chang.* **2022**, *177*, 121553. [CrossRef]
142. Alonso Tabares, D.; Mora-Camino, F. Aircraft ground operations: Steps towards automation. *CEAS Aeronaut. J.* **2019**, *10*, 965–974. [CrossRef]
143. Burbidge, R. Adapting aviation to a changing climate: Key priorities for action. *J. Air Transp. Manag.* **2018**, *71*, 167–174. [CrossRef]
144. Gratton, G.B.; Williams, P.D.; Padhra, A.; Rapsomanikis, S. Reviewing the impacts of climate change on air transport operations. *Aeronaut. J.* **2022**, *126*, 209–221. [CrossRef]

145. Congressional Research Service. Addressing COVID-19 Pandemic Impacts on Civil Aviation Operations. 2020. Available online: http://crsreports.congress.gov/product/pdf/R/R46483 (accessed on 1 April 2024).
146. Lohmann, G.; Pereira, B.; Houghton, L. Creating a Safer Journey: Exploring Emerging Innovations in the Aviation Sector. In *Tourist Health, Safety and Wellbeing in the New Normal*; Wilks, J., Pendergast, D., Leggat, P.A., Morgan, D., Eds.; Springer: Singapore, 2021; pp. 467–487.