HELLENIC OPEN UNIVERSITY

School of Social Sciences

Supply Chain Management

Postgraduate Dissertation

Airline, aircraft and crew scheduling

Enhancements using Artificial Intelligence

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Supervisor: Theodoros Tsekeris

Patras, Greece, June 2026

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Patras, Greece, June 2026

I would like to express my sincere gratitude to my supervisor, Theodoros Tsekeris, for his guidance, constructive feedback, and continued support throughout the development of this dissertation. His expertise and thoughtful input were instrumental in refining both the scope and the analytical depth of this work.
I would also like to thank my family and friends, whose encouragement and patience throughout the entirety of this postgraduate journey made this endeavour possible.

Abstract

This master's thesis is based on an extensive literature review and focuses on the analysis and evaluation of optimization and artificial intelligence methods for solving complex scheduling problems in the aviation sector. Its aim is to develop and investigate a central hypothesis regarding the feasibility and effectiveness of using these methods to improve processes such as flight, aircraft and crew scheduling. The work begins with a theoretical introduction to the importance and context of the topic, presenting the motivations, objectives and hypotheses of the research. This is followed by a clarification of key concepts and a differentiation between approximate and exact optimization methods, as well as a presentation of the main principles of artificial intelligence related to learning mechanisms. Furthermore, the applications of these methods in the aviation industry are examined, accompanied by an analysis of empirical results and a comparative evaluation. Particular emphasis is given to the SWOT analysis of the proposed methods, with the aim of identifying strengths, weaknesses, opportunities and threats related to their application. The work is concluded by drawing conclusions regarding the viability and the possibility of combining optimization methods and artificial intelligence for the effective solution of problems in the aviation industry.

Keywords

Optimization, Artificial Intelligence, Air Transport, Flight Planning, SWOT Analysis, Machine Learning

Προγραμματισμός Αεροσκαφών και Πληρωμάτων Αεροπορικών Εταιρειών

Κωνσταντίνος Βερίλλης

Περίληψη

Η παρούσα μεταπτυχιακή εργασία βασίζεται σε εκτενή βιβλιογραφική ανασκόπηση και εστιάζει στην ανάλυση και αξιολόγηση μεθόδων βελτιστοποίησης και τεχνητής νοημοσύνης για την επίλυση σύνθετων προβλημάτων προγραμματισμού στον τομέα των αερομεταφορών. Στόχος της είναι η ανάπτυξη και η διερεύνηση μιας κεντρικής υπόθεσης σχετικά με τη σκοπιμότητα και την αποτελεσματικότητα της χρήσης αυτών των μεθόδων για τη βελτίωση διαδικασιών όπως ο προγραμματισμός πτήσεων, αεροσκαφών και πληρωμάτων. Η εργασία ξεκινά με εισαγωγή στη σημασία και στο θεωρητικό πλαίσιο του θέματος, παρουσιάζοντας τα κίνητρα, τους στόχους και τις υποθέσεις της έρευνας. Ακολουθεί αποσαφήνιση βασικών εννοιών και διαφοροποίηση μεταξύ προσεγγιστικών και ακριβών μεθόδων βελτιστοποίησης, καθώς και παρουσίαση των κύριων αρχών της τεχνητής νοημοσύνης που σχετίζονται με μηχανισμούς μάθησης. Επιπλέον, εξετάζονται οι εφαρμογές των μεθόδων αυτών στη βιομηχανία των αερομεταφορών, συνοδευόμενες από ανάλυση εμπειρικών αποτελεσμάτων και συγκριτική αξιολόγηση. Ιδιαίτερη έμφαση δίνεται στην ανάλυση SWOT των προτεινόμενων μεθόδων, με στόχο τον εντοπισμό πλεονεκτημάτων, αδυναμιών, ευκαιριών και απειλών που σχετίζονται με την εφαρμογή τους. Η εργασία ολοκληρώνεται με τη διατύπωση συμπερασμάτων ως προς τη βιωσιμότητα και τη δυνατότητα συνδυαστικής αξιοποίησης των μεθόδων βελτιστοποίησης και τεχνητής νοημοσύνης για την αποτελεσματική επίλυση προβλημάτων στον κλάδο των αερομεταφορών.

Λέξεις – Κλειδιά

Βελτιστοποίηση, Τεχνητή Νοημοσύνη, Αερομεταφορές, Προγραμματισμός Πτήσεων, Ανάλυση SWOT, Μηχανική Μάθηση.

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List of Abbreviations & Acronyms

AI	Artificial Intelligence
ARIMA	Autoregressive Integrated Moving Average
ATM	Air Traffic Management
CDM	Collaborative Decision-Making
ConvLSTM	Convolutional Long Short-Term Memory
CPP	Crew Pairing Problem
DQN	Deep Q-Networks
DRL	Deep Reinforcement Learning
EASA	European Union Aviation Safety Agency
EUROCONTROL	European Organisation for the Safety of Air Navigation
FAA	Federal Aviation Administration
FAP	Fleet Assignment Problem
IP	Integer Programming
KPI	Key Performance Indicators
LIME	Local Interpretable Model-agnostic Explanations
LP	Linear Programming
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MILP	Mixed-Integer Linear Programming
ML	Machine Learning
OR	Operations Research
OTP	On-Time Performance
RL	Reinforcement Learning
RMP	Restricted Master Problem
RMSE	Root Mean Square Error
SCM	Supply Chain Management

SHAP	SHapley Additive exPlanations
SVR	Support Vector Regression
SWOT	Strengths, Weaknesses, Opportunities, Threats
WIA	Weighted Index of Agreement
XAI	Explainable AI

1. Introduction

The air transport industry is one of the most complex and operationally intensive sectors of the global economy. Airlines must continuously manage large-scale systems that involve the coordination of fleets, crews, and flight schedules while optimizing costs, maintaining service quality, and ensuring compliance with stringent safety and regulatory standards.

Within this framework, optimization techniques and artificial intelligence (AI) methodologies have become critical enablers of efficiency and competitiveness. Traditional operations research (OR) methods — such as linear programming, integer programming, and network optimization — have long supported decision-making in airline operations (Barnhart, Belobaba, & Odoni, 2003) (Barnhart, Smith, 2012). However, as real-world airline scheduling problems grow increasingly dynamic, uncertain, and data-intensive, exact optimization approaches face significant computational and scalability challenges. This has led to a growing interest in approximate and AI-driven methods, including heuristic, metaheuristic, and machine learning techniques.

Optimization and Artificial Intelligence (AI) are among the most transformative forces shaping modern Supply Chain Management (SCM). Within complex transportation networks, they enable organizations to design, coordinate, and operate systems that are not only efficient and cost-effective but also resilient to uncertainty and disruption. Airlines, as key operating links of global supply chains, face particularly intricate decision-making challenges that span fleet assignment, crew scheduling, maintenance planning, and network optimization. These decisions directly affect not only the operational performance of the airline itself but also the efficiency and reliability of interconnected logistics and supply networks. (Daios et al., 2025; Chen et al, 2024).

In the broader SCM context, optimization models have traditionally been used to allocate limited resources, minimize transportation and inventory costs, and balance service levels across the supply chain. Exact optimization methods — such as linear, integer, and network programming — have long supported strategic and tactical planning in logistics and transportation. However, as supply chains evolve into data-rich, dynamic, and globalized ecosystems, the limitations of exact methods become apparent, particularly when facing stochastic demand, uncertain capacity, and real-time decision requirements.

Artificial Intelligence introduces a complementary paradigm based on adaptability and learning. Machine Learning (ML), Reinforcement Learning (RL), and hybrid AI systems are increasingly applied to predictive demand management, disruption recovery, and scheduling optimization. In the airline sector, these technologies enable faster decision-making, improve resource utilization, and enhance service reliability. When combined, optimization and AI methods can provide powerful decision-support tools that help both airlines and broader supply chain networks achieve operational excellence, reduce costs, and improve responsiveness. Thus, their integration represents not only a technological evolution but also a strategic shift toward intelligent, data-driven supply chain systems. (Daios et al., 2025; Anumula et al., 2025; Jahin et al., 2023)

1.1 Background and Motivation

Airline planning and scheduling is typically decomposed into four NP-hard subproblems — schedule design, fleet assignment, aircraft routing, and crew scheduling — solved sequentially for tractability but often at the cost of global optimality across interdependent resources (Xu et al., 2024). Classic and contemporary reviews show that exact optimization techniques such as Dantzig–Wolfe/column generation, branch-and-price, Benders decomposition, and robust/stochastic variants underpin state-of-the-art formulations for fleet, routing, and crew pairing/rostering in both compact and set-partition formulations. (Zhou et al., 2020)

Recent literature emphasizes that sequential optimization can propagate inconsistencies and yield suboptimal or even infeasible plans, whereas integrated models across subproblems improve economic and operational performance, with reported cost savings and resilience benefits when integration and robustness are introduced (Xu et al., 2024). Crew costs are the second largest airline expense after fuel, which elevates the value of optimization for crew pairing and rostering and underpins the ongoing adoption of exact and decomposition approaches in real-world airline operations (Korte et al., 2025). Industry realities — demand uncertainty, weather and capacity disruptions, maintenance requirements, and tight operational margins — create a strong need for robust and integrated schedule optimization spanning aircraft, crews, and timing decisions. (Tafur et al., 2025; Xu et al., 2024)

The dissertation is motivated by the gap between sequential practice and integrated, robust optimization that jointly aligns aircraft routing, crew pairing/ rostering, and schedule timing, which recent studies show can materially reduce duties and improve efficiency at network scale (Tafur et al., 2025). A second motivation is to position approximate optimization and AI methods as complements to exact models for forecasting, dynamic decision-making, and disruption recovery, extending robustness and scalability in operational contexts. (Razzaghi et al., 2024)

Building on established OR foundations in air transport and comprehensive methodological handbooks, the work aims to systematically contrast exact, approximate, and hybrid approaches for airline, aircraft, and crew scheduling. The comparison evaluates not only solution quality under real operational constraints and KPIs but also practical implementation criteria such as computational cost, data collection and processing requirements, robustness, and scalability, thereby providing a more comprehensive assessment of where each class of method is most advantageous (Barnhart, Belobaba, & Odoni, 2003; Barnhart & Smith, 2012; Liang, 2011). Finally, by synthesizing integrated modeling advances and AI-enabled decision support, the research targets decision-quality gains that translate into tangible reductions in operating costs, improved resource utilization, and enhanced resilience to irregular operations, consistent with current directions in airline scheduling optimization (Liang, 2011).

The topic squarely aligns with SCM modules in operations research and analytics through its use of exact optimization, decomposition, and robust/stochastic modeling for complex, networked resource allocation problems at scale (Lozano Tafur et al., 2025). It supports SCM modules in transportation and service operations by addressing end-to-end airline planning processes and disruption management with integrated models that couple aircraft, crew, and schedule timing. It engages SCM modules on AI and data-driven decision-making by evaluating reinforcement learning and machine learning as complements to optimization for prediction, dynamic control, and recovery in airline operations.

1.2 Research Purpose and Objectives

This dissertation aims to conduct a critical literature review on the use of optimization and artificial intelligence methods in airline scheduling, focusing particularly on how these methods address real-world constraints and performance requirements. The primary objectives are to:

- Clarify the conceptual distinctions between exact and approximate optimization methods and AI-based learning approaches.
- Examine the range of optimization models applied in airline scheduling, including aircraft routing, crew pairing, and flight assignment.
- Review empirical evidence on the effectiveness and efficiency of various methods.
- Evaluate AI-based methods and hybrid models for solving complex scheduling problems.
- Assess the advantages, limitations, and strategic implications of AI-driven optimization in airline operations.

The importance of this research lies in its integrative and critical perspective. While optimization and AI are both established areas in operations research, their synergistic application in airline scheduling is still evolving. The industry faces increasing pressure to reduce operational costs, improve reliability, and respond adaptively to disruptions — all areas where AI can complement classical optimization.

Furthermore, as the aviation industry transitions toward data-centric management and sustainability, decision-making systems must become more intelligent, autonomous, and resilient. This study provides valuable insights into which methodological directions are most promising for supporting these transformations.

The significance of this dissertation lies in its potential to bridge two critical yet often distinct disciplines: operations research and artificial intelligence, within the applied context of supply chain and air transport management. By critically reviewing how optimization and AI methods have been used in airline scheduling, the research contributes to a deeper understanding of how advanced analytical tools can enhance decision-making and efficiency in supply chain operations.

From a theoretical perspective, the study enriches the literature by synthesizing diverse methodologies — exact, approximate, and learning-based — into a coherent analytical framework. It highlights the complementarities and trade-offs between traditional optimization techniques and modern AI approaches, offering insights into when and how hybrid models are most effective. This integrative perspective aligns directly with SCM's goal of achieving end-to-end efficiency and strategic coordination across networks.

From a practical standpoint, the findings are relevant for supply chain and logistics professionals seeking to apply advanced optimization and AI tools to transportation and scheduling problems. The airline industry, as a complex logistical environment characterized by real-time constraints and high interdependencies, serves as an ideal case to derive lessons applicable to other sectors of the supply chain, such as maritime, rail, and intermodal transport.

Ultimately, this dissertation contributes to the SCM field by demonstrating how the convergence of optimization and AI can lead to smarter, more adaptive, and sustainable supply chain systems. The study's conclusions and SWOT analysis are expected to support both academic inquiry and managerial decision-making in the pursuit of resilient and intelligent supply chain operations.

1.3 Research Questions and Hypotheses

The main research question guiding this dissertation is:

- How can optimization and artificial intelligence methods be integrated effectively to improve the performance and adaptability of airline scheduling systems?

Additional research questions include:

- What are the comparative advantages and limitations of exact versus approximate optimization methods?
- How have AI, and hybrid AI techniques been applied to airline scheduling problems?
- What lessons can be drawn from empirical applications in terms of scalability, robustness, and practical implementation?

The central hypothesis is that hybrid methods combining optimization and AI can significantly outperform traditional standalone optimization approaches in terms of efficiency, adaptability, and decision quality in complex airline scheduling environments.

1.4 Research Methodology

This thesis adopts qualitative research based on a structured literature review, complemented by comparative analysis and evaluation. Given the conceptual nature of the dissertation, the methodology focuses on the critical synthesis of existing academic and industry knowledge regarding optimization and artificial intelligence methods in airline scheduling and air transport supply chains. The objective of this thesis is not to develop new algorithms, but to evaluate and compare existing approaches in terms of their effectiveness, applicability, and limitations in real-world operational contexts.

The research process follows a 3-stage approach. Initially, an extensive literature review was conducted to identify the main methodological streams in airline scheduling, including exact optimization techniques, heuristic and metaheuristic approaches, AI-based and hybrid models. The selected studies were then comparatively analyzed based on key performance dimensions such as solution quality, computational efficiency, scalability, and robustness. This analytical step enabled the identification of trade-offs between different methodological paradigms and supported the formulation of insights regarding their suitability for different decision-making contexts.

The literature used in was collected from major academic databases, including Scopus, Web of Science, Google Scholar, and ScienceDirect. The search process involved the use of targeted keyword combinations such as “airline scheduling optimization,” “crew scheduling column generation,” “aircraft routing optimization,” “airline disruption management AI,” and “reinforcement learning in aviation.” The selection of sources was based on their relevance to the research topic, their methodological contribution, and their empirical validity. Particular emphasis was placed on recent studies, especially those published after 2010 and more intensively after 2020, in order to capture the latest developments in AI and hybrid optimization methods.

In addition to the general literature review, the thesis incorporates a synthesis of empirical case studies drawn from literature. These case studies include applications of machine learning for demand and delay prediction, reinforcement learning for dynamic disruption management, and hybrid AI–optimization models for integrated scheduling problems. The purpose of this analysis is to evaluate how theoretical models are implemented in practice and to assess their measurable performance outcomes using reported indicators such as cost reduction, delay minimization, and forecasting accuracy.

The selection of empirical case studies presented in Chapters 4 and 5 follows specific criteria. These include their relevance to core airline scheduling problems such as fleet assignment, aircraft routing, crew scheduling, and disruption management; the use of advanced analytical methods, including optimization, AI, or hybrid techniques; and the availability of clearly defined performance metrics. Finally, to evaluate the strategic implications of AI-driven optimization in airline operations, the study employs a SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis framework. This approach enables a structured assessment of both the internal capabilities and external factors influencing the adoption of these technologies. The SWOT approach allows for a structured examination of the strengths and weaknesses of the methods, as well as the opportunities and threats associated with their implementation.

1.5 Structure of the Dissertation

The dissertation is organized into seven chapters. Following this introduction, Chapter 2 clarifies the theoretical concepts of optimization and AI relevant to this research. Chapter 3 discusses the various applications of optimization in the airline industry, focusing on the core scheduling problems. Chapter 4 reviews empirical studies and their results. Chapter 5 explores AI-based and hybrid approaches to similar problems. Chapter 6 presents a SWOT analysis assessing the strategic potential of these methods, while Chapter 7 summarizes key findings and suggests directions for future research.

2 Conceptual Framework and Theoretical Background

This chapter develops the theoretical underpinnings of the study by defining the key concepts of optimization and artificial intelligence as applied to operations research and supply chain decision-making. It contrasts exact and approximate optimization methods, explains learning-based AI approaches, and explores how these paradigms interact in complex decision systems. The discussion provides a conceptual framework that supports the subsequent analysis of how optimization and AI are applied within the airline industry.

2.1 Definition of Optimization in Operations Research

Optimization is a fundamental concept within Operations Research (OR), representing the systematic process of identifying the best possible decision or solution from a set of feasible alternatives under a given set of constraints. In essence, optimization seeks to maximize or minimize an objective function — such as cost, time, profit, or resource utilization — subject to limitations imposed by the system or environment (Hillier & Lieberman, 2021). It provides a structured, quantitative framework that enables decision-makers to achieve efficiency, consistency, and effectiveness in complex organizational systems.

Regarding the problem's structure and characteristics, optimization models can take various forms, including linear programming (LP), integer programming (IP), nonlinear programming (NLP), and stochastic or dynamic programming (Bazaraa, Jarvis, & Sherali, 2010). These techniques provide the mathematical foundation for solving large-scale decision problems across manufacturing, logistics, and transportation networks.

In the context of air transport and supply chain management, optimization has been instrumental in supporting decision-making for fleet assignment, crew scheduling, cargo routing, and network design (Barnhart, Belobaba, & Odoni, 2003). Such problems are often characterized by high dimensionality and multiple interdependencies, requiring the formulation of models that can efficiently allocate resources and balance conflicting objectives, such as cost reduction, service quality, and operational robustness.

Traditional exact optimization methods, such as linear and integer programming, provide theoretically optimal solutions but are often limited by computational complexity when applied to large-scale, real-world systems (Klabjan, 2005). This has motivated the development of approximate optimization techniques, including heuristics and metaheuristics, which seek near-optimal solutions within reasonable computational time. The evolution of Artificial Intelligence (AI) has further expanded the optimization paradigm, allowing models to incorporate adaptive and predictive capabilities that enhance performance under uncertainty (Zhou, Liang, Chou, & Chaovalitwongse, 2020).

Overall, optimization in Operations Research represents both a methodology and a philosophy of decision-making — grounded in mathematical rigor, guided by data, and aimed at achieving the most efficient and effective outcomes within complex and dynamic environments. In the context of airline operations and broader supply chain systems, it remains a cornerstone for achieving operational excellence, resource efficiency, and strategic competitiveness.

2.2 Fundamentals of Optimization in Supply Chain Decision-Making

Optimization provides a mathematical and analytical framework for achieving efficiency, cost minimization, and service-level improvement across complex, interdependent networks. Supply Chain Management (SCM) involves a sequence of strategic, tactical, and operational decisions that coordinate material, information, and financial flows among suppliers, manufacturers, distributors, and customers (Chopra & Meindl, 2023; Hillier & Lieberman, 2021). Optimization in airline operations represents a critical pillar of decision-making across the air transport supply chain. Airlines operate within one of the most complex logistical systems in existence, where aircraft, crews, maintenance, and flight schedules must be coordinated under strict regulatory, operational, and market constraints.

At its core, supply chain optimization seeks to identify the best possible configuration of decisions — ranging from facility location and inventory control to production scheduling and transportation routing — that minimizes total system cost or maximizes overall value creation. A key advantage of optimization in SCM is its ability to handle multi-objective and multi-echelon problems, which are common in integrated logistics networks. For example, transportation optimization problems often require balancing fuel and labor costs against delivery speed and service quality. Similarly, production–distribution planning must coordinate factory schedules with downstream demand patterns to avoid bottlenecks and excess inventory.

Airline supply chains encompass multiple interdependent decision layers — from long-term fleet planning and network design to short-term scheduling and day-of-operations control. Each stage involves optimization at different time scales and degrees of uncertainty. For example, fleet assignment and route planning are typically addressed through large-scale mixed-integer programming models that match aircraft types to flight legs, balancing seat capacity, fuel efficiency, and maintenance cycles (Klabjan, 2005; Zhou, Liang, Chou, & Chaovalitwongse, 2020). Crew pairing and rostering, another essential component, constitute NP-hard problems where optimization must respect labor regulations, duty-time limits, and crew base constraints while minimizing total costs and maximizing crew utilization (Korte & Yorke-Smith, 2025).

The fundamental objective functions in airline optimization are cost minimization, profit maximization, and service reliability improvement. These objectives can be single- or multi-criteria, incorporating fuel cost, crew cost, delay penalties, and passenger dissatisfaction. Constraints arise from both physical and regulatory sources, including fleet size, maintenance cycles, airport slots, crew duty regulations, and aircraft turn-around times (Barnhart & Smith, 2012).

Uncertainty treatment is central to modern optimization practice. Deterministic models assume fixed parameters, while stochastic and robust formulations explicitly model variability in demand, flight times, or weather. Robust optimization ensures feasible solutions under all conditions within defined uncertainty sets, while stochastic models use probability distributions to balance expected performance and risk (Ben-Tal, El Ghaoui, & Nemirovski, 2009). These approaches are increasingly embedded into integrated scheduling frameworks to produce resilient and adaptive flight plans (Xu, Wandelt, & Sun, 2024).

The strength of optimization in airline decision-making lies in its ability to ensure global consistency across interconnected planning processes. Decomposition techniques — such as Dantzig-Wolfe, Benders, and column generation — enable the solution of massive network models by breaking them into smaller, tractable subproblems for aircraft, routes, or crews (Barnhart & Smith, 2012). These mathematical structures underpin most commercial scheduling tools used in the industry today, where the integration of multiple optimization layers can yield measurable reductions in delays, fuel consumption, and crew costs (Xu, Wandelt, & Sun, 2024).

In dynamic and uncertain environments, traditional deterministic optimization is often insufficient. Therefore, stochastic and robust optimization models have gained prominence for managing variability in demand, lead times, and operational disruptions. Stochastic programming incorporates probability distributions to represent uncertain parameters, while robust optimization seeks solutions that perform well across a range of possible scenarios (Ben-Tal, El Ghaoui, & Nemirovski, 2009). These models are especially relevant to airline scheduling and broader supply chain systems, where disruptions caused by weather, congestion, or capacity constraints can propagate through the network, affecting cost and service outcomes (Xu, Wandelt, & Sun, 2024; Tafur et al., 2025).

Recent advancements in computational power and data availability have also enabled the integration of real-time optimization and predictive analytics into supply chain decision-making. Digital twins and AI-driven simulation tools now allow continuous optimization of logistics processes by linking predictive models with live operational data (Daios et al., 2025).

The following table summarizes key scholarly contributions in airline supply chain optimization, organized by the type of mathematical problem, field of application, and treatment of uncertainty:

Table 1: Key scholarly contributions in airline supply chain optimization, categorized by mathematical problem type, field of application, and uncertainty treatment.

Reference	Mathematical Problem Type	SCM/Airline Application	Uncertainty Treatment
Barnhart, Belobaba, & Odoni (2003)	Mixed-integer programming	Flight scheduling, fleet assignment	Deterministic
Klabjan (2005)	Large-scale MILP	Fleet assignment and route planning	Deterministic
Zhou, Liang, Chou, & Chaovalitwongse (2020)	MILP, network optimization	Integrated airline scheduling	Stochastic extensions
Korte & Yorke-Smith (2025)	NP-hard combinatorial optimization	Crew pairing and rostering	Deterministic & constraints-based
Ben-Tal, El Ghaoui, & Nemirovski (2009)	Robust optimization, stochastic programming	General supply chain optimization	Stochastic, robust formulations

Barnhart & Smith (2012)	Decomposition techniques (Dantzig-Wolfe, Benders, column generation)	Large-scale airline network models	Deterministic
Xu, Wandelt, & Sun (2024)	Integrated optimization frameworks	Flight scheduling, resilient operations	Stochastic and robust optimization
Tafur et al. (2025)	Resilient scheduling models	Flight schedule reliability	Stochastic, robust scenarios
Daios et al. (2025)	Real-time optimization, predictive analytics	Digital twins and AI-driven SCM	Probabilistic, adaptive
Tahir, Desrosiers, & Solomon (2005)	Column generation	Crew pairing and routing	Deterministic
Gopalakrishnan & Johnson (2005)	Set-partitioning and heuristic optimization	Airline crew scheduling	Deterministic
Talluri & van Ryzin (2004)	Dynamic programming and revenue management models	Airline revenue management and seat allocation	Stochastic
Filom, Wandelt, & Sun (2022)	Metaheuristic and hybrid models	Airline disruption management	Stochastic
Lohatepanont & Barnhart (2004)	Integrated optimization models	Schedule design and fleet assignment	Deterministic
Clarke, Johnson, & Nemhauser (1997)	Simulated annealing	Aircraft rotation and disruption recovery	Deterministic
Cook & Tanner (2015)	Performance analytics and operational models	Airline delay management	Stochastic
Geske, Herold, & Kummer (2024)	AI-supported collaborative decision-making	Airline disruption management	Stochastic
EUROCONTROL (2023)	Collaborative decision-making frameworks	Airport operations and ATM	Stochastic
Eltoukhy, Chan, & Chung (2017)	Review of optimization models	Airline schedule planning	Deterministic

Vink et al. (2020)	Dynamic optimization models	Aircraft recovery	Stochastic
Lee, Marla, & Jacquillat (2020)	Network optimization	Airline disruption management	Stochastic
Wen et al. (2021)	Optimization and algorithmic approaches	Crew scheduling	Deterministic
Su et al. (2021)	Mathematical programming	Aircraft and crew recovery	Stochastic
Rhodes-Leader et al. (2022)	Simulation optimization	Aircraft recovery	Stochastic
Bertelli Fogaça et al. (2022)	Decision-making analysis	Operations control centers	Operational uncertainty
Yaakoubi et al. (2020)	Machine learning + optimization	Crew pairing	Deterministic
Jiang et al. (2025)	Benders decomposition + column generation	Schedule recovery	Stochastic

2.3 Hierarchical layers of planning

Airline planning is traditionally decomposed into three hierarchical layers, reflecting different decision horizons and model complexities:

1. Strategic Planning (Long-Term) — involves fleet acquisition, route network design, and hub structure configuration, typically spanning months or years. These problems are formulated as large-scale mixed-integer linear programming (MILP) models that minimize total cost or maximize profit subject to aircraft capacity, market demand, and regulatory constraints (Teoh et al., 2015).
   - Objective: Maximize long-term profitability or network coverage.
   - Constraints: Fleet availability, demand balance, airport slot limits, fuel capacity, and environmental regulations.
   - KPIs: Network profitability, seat load factor, fleet utilization, and market connectivity.
2. Tactical Planning (Medium-Term) — encompasses schedule design, fleet assignment, aircraft routing, and crew pairing, which are typically solved sequentially for tractability but ideally should be integrated for global optimality (Klabjan, 2005).

    - Objective: Minimize total operating costs while ensuring schedule feasibility and aircraft/crew utilization efficiency.
    - Constraints: Aircraft flow balance, maintenance requirements, time connectivity between flight legs, and crew duty-hour rules.
    - KPIs: Schedule reliability, aircraft utilization, crew pairing cost, and maintenance compliance rate.
    - Canonical problems:
        - Fleet Assignment Problem (FAP) — assign aircraft types to flights to minimize cost and capacity mismatch.
        - Crew Pairing Problem (CPP) — select minimum-cost pairings covering all flights while satisfying legal and contractual rules.
3. Operational Control (Short-Term) — deals with disruption management and day-of-operations recovery, where real-time optimization and AI techniques are employed to reassign aircraft, crews, and passengers in response to irregular operations (Razzaghi et al., 2024; Tafur et al., 2025).
    - Objective: Minimize delay propagation, passenger disruption, and cost of recovery actions.
    - Constraints: Airport curfews, turnaround times, crew legality, and maintenance feasibility.
    - KPIs: On-time performance (OTP), delay minutes per flight, passenger reaccommodation cost, and network resilience index.
    - Methods: Robust optimization, stochastic programming, and reinforcement learning (Razzaghi et al., 2024; Tafur et al., 2025).

2.4 Artificial Intelligence and Learning-Based Approaches

Optimization also extends beyond traditional mathematical programming to include simulation-based and data-driven approaches. With the rise of digitalization and advanced analytics, airlines now integrate real-time optimization with predictive maintenance, demand forecasting, and disruption recovery systems (Daios et al., 2025). These systems enable dynamic re-optimization of flight and crew schedules in response to live operational data.

Artificial Intelligence (AI) has become a transformative force in airline planning and operations, extending the boundaries of traditional optimization by introducing adaptability, prediction, and autonomous decision-making. Whereas classical optimization models rely on explicit mathematical formulations and predefined constraints, AI-based approaches learn patterns from data, generalize across dynamic environments, and improve performance through experience. In airline scheduling, where decision variables change rapidly due to weather disruptions, demand fluctuations, or resource unavailability, AI methods enable real-time decision support that complements or even surpasses deterministic optimization (Razzaghi et al., 2024; Daios et al., 2025).

A key advantage of AI approaches is their ability to capture uncertainty and nonlinearity in complex systems. However, their adoption in airline operations also raises concerns about transparency, interpretability, and regulatory compliance. Decision-makers must understand how AI models reach conclusions, especially in safety-critical domains. Techniques such as explainable AI (XAI) and post-hoc interpretability tools (e.g., SHAP, LIME) help bridge this gap by revealing feature importance and sensitivity (Daios et al., 2025). Moreover, airlines increasingly emphasize human-AI collaboration, where AI provides recommendations or scenario analyses, and planners retain the final decision authority. Such decision-support frameworks enhance trust, accountability, and operational safety while leveraging computational intelligence for efficiency gains.

2.4.1 *Learning-Driven Optimization*

Early applications of AI in aviation were predominantly rule-based expert systems used for flight dispatching and maintenance diagnostics. These systems encoded human expertise but lacked scalability and adaptability to unforeseen conditions. The evolution toward machine learning (ML) and reinforcement learning (RL) marked a paradigm shift: algorithms could now learn complex relationships directly from operational data rather than from manually defined rules (Jahin et al., 2023).

In airline scheduling, ML algorithms support forecasting and predictive modeling — for instance, demand forecasting, delay prediction, or fuel consumption estimation. By learning from historical flight, weather, and passenger data, supervised learning methods (e.g., regression, random forests, and neural networks) enhance the accuracy of input parameters used in optimization models. This integration transforms static planning into predictive optimization, where decision models dynamically adjust to real-time information (Anumula, Krishnapillai, & Rai, 2025).

2.4.2 *Reinforcement Learning and Dynamic Decision-Making*

Among AI paradigms, reinforcement learning (RL) is particularly relevant to operational control and disruption management. RL agents interact with the airline environment by taking sequential actions — such as reassigning aircraft or delaying flights — and receiving feedback in the form of costs or rewards. Over time, the agent learns optimal policies that balance efficiency, delay recovery, and resource constraints.

RL has been successfully applied to aircraft and crew rescheduling, gate assignment, and ground-handling logistics, where decisions must be made under uncertainty and time pressure (Razzaghi et al., 2024; Tafur et al., 2025). For example, in a flight delay propagation model, an RL agent can explore millions of scenarios to minimize system-wide delay costs while maintaining crew legality and passenger connectivity. This learning-by-interaction framework allows models to outperform static optimization by discovering adaptive, context-specific recovery strategies.

2.4.3 *Hybrid AI-Optimization*

Modern airline decision systems increasingly adopt hybrid models that combine optimization and AI. In such frameworks, AI modules handle prediction and uncertainty quantification, while optimization solvers compute the best feasible schedule given those predictions (Chen et al, 2024). For example:

- Predictive-Prescriptive Integration: ML models forecast demand, delay probabilities, or maintenance events, feeding probabilistic parameters into stochastic optimization models.
- Learning-Assisted Search: Deep learning or RL agents guide heuristic or metaheuristic search processes (e.g., genetic algorithms, simulated annealing) to accelerate convergence toward high-quality solutions.
- Adaptive Scheduling Systems: AI monitors operational data in real time and triggers re-optimization when deviations occur, creating a continuous decision loop from planning to day-of-operations control.

This hybridization achieves a balance between mathematical rigor and adaptive intelligence, yielding schedules that are both optimal under modeled assumptions and robust against real-world disruptions (Xu, Wandelt, & Sun, 2024).

2.5 Interrelation of Optimization and AI in Decision-Making Systems

The previous sections have presented optimization and artificial intelligence (AI) as two distinct but complementary approaches to decision-making in complex systems. Optimization, rooted in Operations Research, provides mathematically rigorous methods for identifying optimal or near-optimal solutions under clearly defined objectives and constraints. AI, and especially learning-based methods, introduces adaptability, prediction, and the ability to operate effectively in uncertain and dynamic environments. This section discusses how these two paradigms interrelate and jointly support decision-making systems, with particular relevance to airline and supply chain contexts.

In traditional decision-support systems, optimization models are designed as static tools. They rely on fixed input parameters, such as demand forecasts, flight times, or resource availability, and generate solutions that are optimal within the boundaries of these assumptions (Hillier & Lieberman, 2021). As discussed in Sections 2.1 and 2.2, this approach has proven highly effective for strategic and tactical planning in supply chains and airline operations. However, its performance depends heavily on the quality and stability of the input data. When system conditions change rapidly, deterministic optimization models may become outdated or infeasible.

AI addresses this limitation by enhancing decision-making systems with learning and prediction capabilities. Machine learning models can process large volumes of historical and real-time data to estimate demand, predict delays, or assess disruption risks more accurately than static assumptions (Anumula et al., 2025). When these predictive outputs are used as inputs to optimization models, the resulting decisions become more responsive to actual operating conditions. This interaction is often described in the literature as predictive–prescriptive integration, where AI supports prediction and optimization supports prescription (Chen et al, 2024).

The interrelation between optimization and AI is therefore not competitive but functional. Optimization defines what decisions are feasible and desirable given operational constraints, while AI improves how system states and parameters are estimated. In airline scheduling, for example, optimization models ensure crew legality, aircraft flow balance, and maintenance feasibility, while AI models forecast delays, passenger demand, or disruption probabilities that affect these constraints (Xu, Wandelt, & Sun, 2024). Without optimization, AI-driven decisions may violate critical constraints. Without AI, optimization may rely on unrealistic or outdated assumptions.

Reinforcement learning (RL) further strengthens this interrelation by linking learning directly to sequential decision-making. As discussed in Section 2.4.2, RL learns decision policies through interaction with the system environment. In practice, many RL applications in aviation embed optimization logic within the learning process. Constraints derived from optimization models are used to restrict the action space of RL agents, ensuring that learned policies remain operationally feasible (Razzaghi et al., 2024). This combination improves both solution quality and reliability.

Another important point of interaction concerns scalability and computational efficiency. Large-scale airline scheduling problems are often solved using decomposition and approximation techniques, such as column generation or heuristics (Barnhart & Smith, 2012). AI methods can support these approaches by guiding search processes, prioritizing promising solution regions, or learning good initial solutions. Learning-assisted optimization reduces computation time while maintaining acceptable solution quality, which is critical for real-time or near-real-time decision-making (Zhou et al., 2020).

From a systems perspective, the interrelation of optimization and AI leads to adaptive decision-support frameworks rather than isolated models. Such frameworks operate in continuous feedback loops: AI models observe system performance and update predictions, optimization models recompute decisions based on these updates, and operational outcomes generate new data for further learning (Daios et al., 2025). This structure aligns closely with the hierarchical planning layers discussed in Section 2.3, where long-term plans are refined by tactical optimization and adjusted in real time during operations.

3 Optimization Applications in the Air Transport Supply Chain

Airlines play a central role in global supply chains by enabling the rapid movement of passengers and high-value or time-sensitive cargo across long distances. Unlike other transport modes, air transport offers speed and reliability, making it essential for industries such as pharmaceuticals, electronics, perishable goods, and express logistics (Zhang & Zhang, 2023). As a result, airline operations are tightly linked to supply chain performance indicators such as lead time, service reliability, and network responsiveness.

From a supply chain perspective, airlines function as both service providers and integrators. They connect suppliers, distribution centers, and final markets while coordinating with airports, ground handlers, maintenance providers, and logistics partners. This high degree of interdependence increases system complexity and amplifies the impact of operational inefficiencies. Delays or resource misallocations in airline scheduling can propagate downstream, affecting inventory levels, delivery commitments, and customer satisfaction across the supply chain (Wandelt et al., 2024).

Optimization is therefore essential for aligning airline operations with supply chain objectives. Strategic decisions such as network design and fleet composition influence long-term capacity and connectivity, while tactical and operational decisions — such as schedule design and crew allocation — determine day-to-day reliability. Recent studies emphasize that airlines increasingly adopt supply chain thinking, where cost minimization is balanced with resilience and service quality (Daios et al., 2025). Optimization models provide the analytical foundation for achieving this balance by coordinating resources across multiple actors and time horizons.

Chapter 3 examines how optimization principles are implemented within the air transport supply chain, emphasizing the airline industry as a critical node in global logistics networks. It highlights the major planning and scheduling challenges airlines face — such as fleet assignment, routing, and crew management — and discusses how optimization models address these interdependent problems. The chapter also situates airline operations within the broader supply chain context, showing how improved scheduling efficiency enhances overall logistics performance.

3.1 Interdependencies between Air Transport, Logistics, and Supply Chain Efficiency

Airline optimization does not operate in isolation; it directly affects logistics performance and overall supply chain efficiency. Flight schedules determine cargo connection times, inventory replenishment cycles, and distribution reliability. Consequently, suboptimal airline decisions can lead to increased safety stock, higher logistics costs, and reduced service levels in downstream supply chains (Chen et al, 2024).

A key challenge identified in recent literature is the misalignment between airline-centric optimization objectives and broader supply chain goals (Chen et al, 2024; Daios et al., 2025; Xu, Wandelt, & Sun, 2024). Many airline models prioritize cost minimization or profit maximization at the carrier level, while supply chains may value reliability, flexibility, and resilience more highly. For example, a cost-optimal flight schedule may increase the risk of missed cargo connections, leading to higher downstream costs that are not internalized in airline objective functions (Wandelt et al., 2024).

This observation has led to growing interest in multi-objective and collaborative optimization frameworks. Such models incorporate service-level constraints, delay penalties, or logistics performance indicators alongside traditional cost measures. While promising, these approaches face practical challenges related to data sharing, coordination among stakeholders, and increased model complexity. The literature suggests that without organizational and contractual alignment, purely technical optimization solutions may fail to deliver system-wide benefits (Daios et al., 2025).

Critically, many empirical studies still evaluate optimization performance using narrow operational metrics, such as aircraft utilization or crew cost, rather than end-to-end supply chain outcomes. This limits the ability to assess the true value of advanced optimization methods. Future research increasingly calls for integrated evaluation frameworks that link airline scheduling decisions to logistics performance and customer-level impacts (Xu et al., 2024).

3.2 Optimization in Airline Operations: Planning and Scheduling Problems

Airline operations involve a set of tightly coupled planning and scheduling problems that have been extensively studied in Operations Research. As discussed in Chapter 2, these problems are often decomposed into schedule design, fleet assignment, aircraft routing, and crew scheduling for computational tractability. Each problem is complex in itself and is typically formulated as a large-scale mixed-integer programming or network optimization model (Zhou et al., 2020).

The Fleet Assignment Problem (FAP) is one of the core optimization problems in airline planning and has received extensive attention in the Operations Research literature. Its objective is to assign available aircraft types to scheduled flight legs in a way that minimizes total operating cost or maximizes profit, while satisfying capacity, availability, and operational constraints. FAP is typically positioned at the tactical planning level and directly influences aircraft utilization, fuel consumption, maintenance feasibility, and service quality (Barnhart, Belobaba, & Odoni, 2003).

Early formulations of FAP were based on deterministic mixed-integer linear programming (MILP) models, where aircraft types are assigned to flights subject to fleet size and flow balance constraints. These models assume fixed demand and operating conditions and focus primarily on minimizing operating costs or seat–capacity mismatch penalties (Klabjan, 2005). Despite their simplifying assumptions, deterministic models remain widely used due to their transparency, interpretability, and compatibility with decomposition techniques.

As airline networks expanded and problem sizes increased, researchers introduced network-based formulations that represent aircraft flows across time–space networks (Barnhart & Smith, 2012). In these models, nodes correspond to flight events and arcs represent feasible aircraft transitions. This representation allows the integration of maintenance requirements and aircraft continuity constraints in a structured manner (Barnhart & Smith, 2012).

A major stream of research focuses on the integration of FAP with schedule design and aircraft routing. Traditional sequential approaches solve schedule planning first and then assign fleets, which often leads to suboptimal capacity utilization and infeasible aircraft rotations. Integrated models address this limitation by jointly optimizing flight schedules and fleet assignments, achieving better economic performance at the expense of increased computational complexity (Zhou et al., 2020). Empirical studies report that integrated approaches can reduce operating costs and improve aircraft utilization, particularly in hub-and-spoke networks (Barnhart & Smith, 2012; Zhou et al., 2020; Xu, Wandelt, & Sun, 2024).

Uncertainty has become a central concern in recent FAP research. Demand variability, fuel price fluctuations, and operational disruptions challenge the assumptions of deterministic models (Ben-Tal, El Ghaoui, & Nemirovski, 2009; Zhou et al., 2020; Xu, Wandelt, & Sun, 2024). To address this, stochastic fleet assignment models incorporate multiple demand scenarios and aim to minimize expected cost or risk-adjusted performance measures (Xu, Wandelt, & Sun, 2024). Robust optimization approaches, on the other hand, seek solutions that remain feasible across a range of uncertainty realizations without relying on precise probability distributions. These methods have been shown to improve schedule stability and reduce the need for costly reassignments during operations.

Another important development is the consideration of passenger-centric objectives in FAP formulations. Traditional models prioritize airline cost metrics, while more recent studies incorporate passenger spill[1], recapture effects[2], and service quality indicators. By modeling passenger choice behavior and itinerary availability, these extensions better reflect revenue impacts and network-wide effects of fleet decisions (Zhou et al., 2020). However, such models significantly increase problem dimensionality and require detailed demand data, which may not always be available.

Recent literature also highlights the role of FAP in disruption management and recovery. Although fleet assignment is primarily a tactical problem, initial fleet decisions strongly affect the airline's ability to recover from disruptions. Research shows that fleet assignments that emphasize flexibility, such as using aircraft with similar capacities or compatible maintenance requirements, can reduce delay propagation and recovery costs (Tafur et al., 2025). This has motivated the integration of robustness measures directly into FAP objective functions.

[1] Passenger spill refers to passengers whose preferred flight cannot accommodate them due to capacity limitations and who therefore cannot be served on that flight. These passengers may either choose an alternative flight, select a different airline, or cancel their trip altogether.
[2] Recapture effects describe the portion of spilled passengers who are redirected to alternative flights within the same airline's network.

Despite methodological advances, several limitations remain. Many FAP studies rely on simplified demand assumptions or stylized networks, limiting the generalizability of results. In addition, the computational burden of large-scale integrated or stochastic FAP models restricts their use in real-time or near-real-time decision-making. As a result, airlines often rely on heuristic adjustments or human expertise to complement optimization outputs (Xu et al., 2024).

4 Review of Empirical Studies and Methods

This chapter reviews empirical studies and analytical methods that have been applied to airline scheduling and related optimization problems. It evaluates key approaches, including column generation, network models, heuristic, and metaheuristic techniques, comparing their outcomes and computational performance. The review identifies methodological trends, strengths, and limitations across different studies, setting the stage for the discussion of AI and hybrid optimization methods in the following chapter.

4.1 Optimization Systems in Global Air Traffic and Airport Operations

Beyond the empirical models discussed in the scholarly literature, optimization and artificial intelligence techniques are increasingly applied in operational air traffic management (ATM) systems and airport operations worldwide. Large-scale decision-support platforms are now used to coordinate flight schedules, allocate airport resources efficiently, and mitigate delay propagation across complex air transport networks.

A prominent example is EUROCONTROL, the intergovernmental organization responsible for coordinating air traffic management across the European airspace network. EUROCONTROL develops and operates advanced analytical and decision-support systems that rely on optimization, predictive analytics, and collaborative information sharing to enhance the efficiency and resilience of the European ATM system (EUROCONTROL, 2023; EUROCONTROL, 2024). A key operational framework promoted by EUROCONTROL is Airport Collaborative Decision-Making (A-CDM), which enables coordinated decision-making among airlines, airport operators, air traffic controllers, and ground handlers through real-time information sharing (EUROCONTROL, 2023).

A-CDM systems employ optimization models and data-driven analytics to synchronize airport processes such as aircraft turnaround operations, departure sequencing, runway utilization, and slot allocation. Empirical evidence indicates that A-CDM implementation can significantly improve operational efficiency by reducing taxi times, improving departure predictability, and increasing airport capacity utilization (EUROCONTROL, 2023; Cook & Tanner, 2015). By integrating operational data from multiple stakeholders, these systems enhance situational awareness and allow airports to manage congestion and disruptions more effectively.

In parallel with collaborative optimization frameworks, several ATM organizations are increasingly exploring artificial intelligence applications to support predictive decision-making. EUROCONTROL, for example, has developed AI-based tools for traffic flow prediction, delay forecasting, and trajectory optimization using machine learning and advanced analytics applied to large-scale operational datasets (EUROCONTROL, 2024). Such systems enable more proactive air traffic management by identifying potential bottlenecks and operational risks before they propagate through the network.

Similar optimization-driven and AI-enabled management systems have been adopted in some of the world's most technologically advanced airports. Major global hubs such as London Heathrow, Singapore Changi, Dubai International Airport, Hamad International Airport in Doha, and Hartsfield–Jackson Atlanta International Airport deploy integrated airport operations platforms that combine optimization algorithms, predictive analytics, and collaborative decision-making tools to manage complex airport ecosystems (Ashford et al., 2013; de Neufville & Odoni, 2013). These systems support operational tasks such as gate assignment optimization, runway sequencing, passenger flow forecasting, and disruption management.

Recent research also highlights the growing integration of artificial intelligence into collaborative decision-making environments. For example, Geske, Herold, and Kummer (2024) propose a framework that integrates AI-based decision support into collaborative decision-making (CDM) systems for airline disruption management. Their work demonstrates that AI models can improve the evaluation of disruption scenarios and support coordinated decision-making among airlines, airports, and air traffic control stakeholders, thereby improving operational resilience and response efficiency.

Overall, the increasing deployment of optimization and AI-driven systems in airport and ATM operations illustrates the practical translation of theoretical models discussed in the literature into real-world decision-support platforms. These systems enable more efficient resource allocation, improved delay management, and enhanced coordination across the global air transport network.

4.2 Column Generation and Network Models in Airline Scheduling

A dominant methodological tradition in airline scheduling is the use of network representations combined with MILP and decomposition methods. Airline scheduling problems are naturally modeled on time–space networks, where nodes represent events (departures/arrivals) and arcs represent feasible transitions (flight legs, waiting, maintenance, deadheads). This network structure supports flow-balance constraints and allows models to reflect operational feasibility in a transparent way. This representation allows aircraft continuity, maintenance requirements, airport constraints, and crew feasibility rules to be modeled in a structured and transparent manner. Due to these characteristics, network formulations remain central to both academic research and industrial airline scheduling systems.

Column generation is one of the most widely applied solution techniques for large-scale airline scheduling problems, particularly in crew pairing and crew rostering, where the number of feasible pairings is prohibitively large. In these problems, each feasible pairing or duty sequence constitutes a decision variable, and the total number of such variables can reach several millions. As a result, direct enumeration is computationally infeasible. To address this challenge, the literature commonly formulates these problems as set-partitioning or set-covering models and applies column generation to dynamically construct only the most relevant variables (Tahir, Desrosiers, & Solomon, 2005; Gopalakrishnan & Johnson, 2005). Similar modeling principles apply to aircraft routing problems, where each feasible aircraft rotation represents a column (Barnhart & Smith, 2012).

Column generation decomposes the original large-scale problem into a restricted master problem (RMP) and a pricing problem, as illustrated in Figure 1. In airline scheduling applications, this framework is typically applied to problems such as crew pairing, aircraft routing, and fleet assignment, where the number of feasible schedules or rotations is extremely large (Barnhart, Belobaba, & Odoni, 2003; Tahir et al., 2005).

In these formulations, each column represents a feasible operational plan, such as a complete crew pairing (a sequence of flights beginning and ending at a crew base) or an aircraft rotation that satisfies maintenance and connection constraints. The master problem selects a combination of these columns to cover all flights while minimizing total operating cost and respecting operational constraints. Coverage constraints ensure that each flight leg is assigned exactly once to a crew pairing or aircraft rotation, which leads to a set-partitioning formulation commonly used in airline crew scheduling models (Barnhart & Smith, 2012).

Because the number of feasible pairings or rotations can reach millions in realistic airline networks, it is computationally infeasible to include all columns in the master problem from the beginning. Therefore, the algorithm starts with a restricted subset of feasible columns, often generated through heuristics or derived from historical schedules. The pricing problem then generates new columns by searching for feasible pairings or rotations with negative reduced cost, meaning that their inclusion would improve the current solution (Tahir et al., 2005).

In airline scheduling contexts, the pricing problem is typically formulated as a shortest path problem with resource constraints on a time–space network, where nodes represent flight events and arcs represent feasible connections between flights. Resource constraints enforce operational rules such as crew duty-time limits, mandatory rest periods, aircraft turnaround requirements, and base compatibility. Solving this shortest-path problem identifies new feasible crew pairings or aircraft rotations that can be added to the master problem, gradually improving the solution until no further improving columns can be generated (Zhou et al., 2020; Barnhart & Smith, 2012).

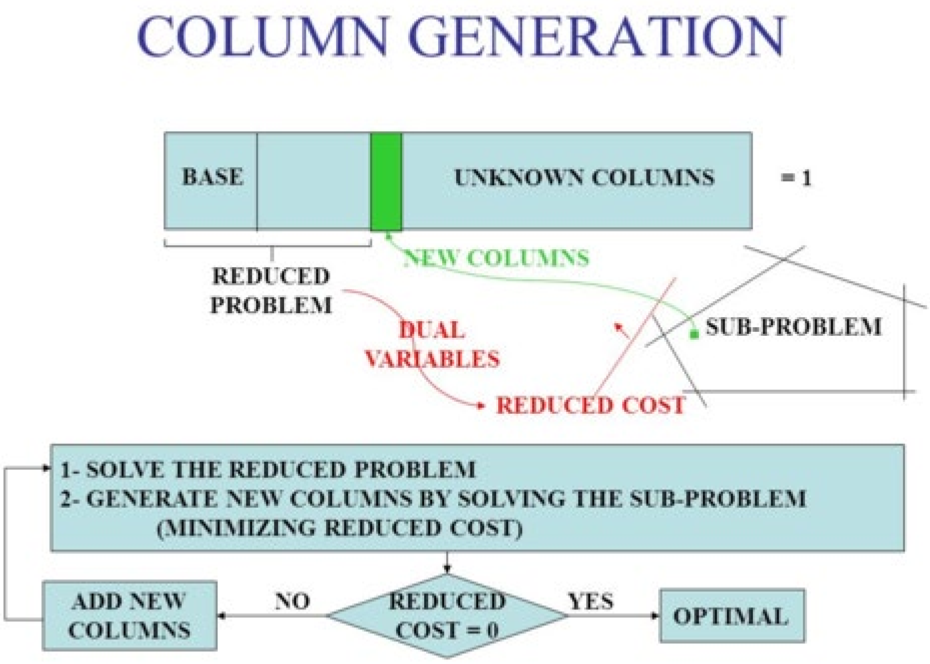

Figure 1: Schematic illustration of the column generation framework, showing the interaction between the restricted master problem and the pricing problem. (Tahir et al, 2006; Barnhart et al, 2012)

A concrete example of this structure is presented in Figure 2, which illustrates a crew pairing network. In crew pairing networks, nodes correspond to flight events, while arcs represent feasible connections between flights based on time compatibility and legal constraints. Each complete path from a crew base back to the same base defines a single feasible pairing and therefore a single column in the master problem. Instead of generating all possible paths, the pricing problem searches selectively for those that satisfy all regulatory requirements and improve the objective function, allowing the problem to be solved efficiently even at large scales (Gopalakrishnan & Johnson, 2005).

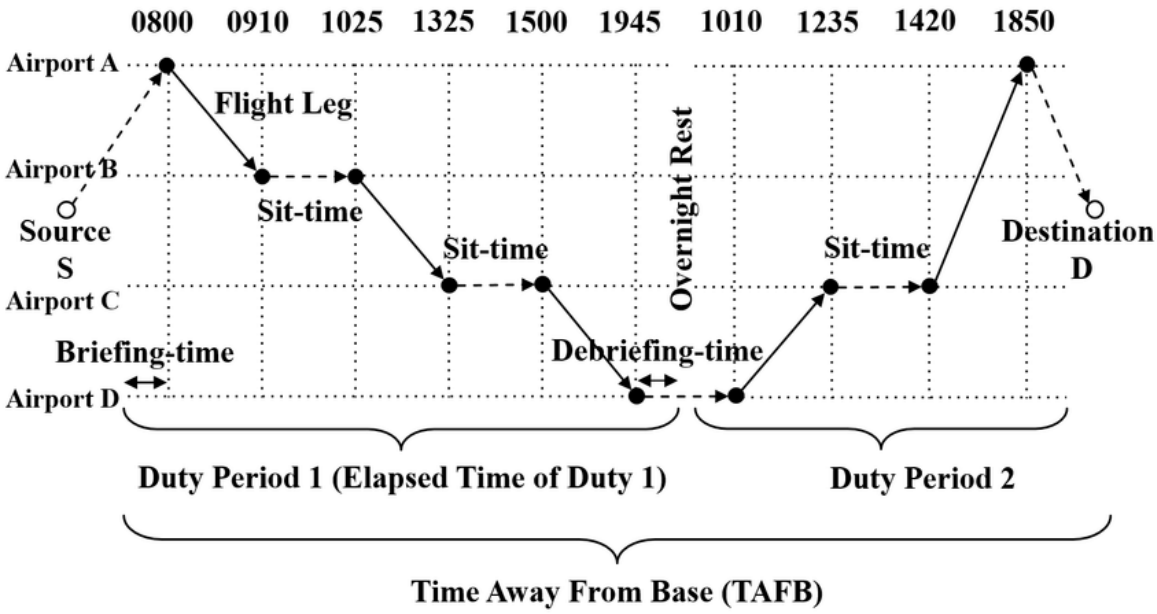

Figure 2: Schematic crew pairing network used in column generation, where nodes represent flight events and feasible paths correspond to crew pairings. (Tahir et al, 2006; Barnhart et al, 2012)

The network representation underlying column generation is further detailed in Figure 3, which depicts a time–space network commonly used in airline scheduling. In time–space network representations, time evolves along one dimension while airports or locations form the other. Feasible flows through this network correspond to aircraft rotations or crew duties, and shortest-path algorithms can be used to efficiently identify improving columns while preserving operational feasibility (Barnhart & Smith, 2012; Xu, Wandelt, & Sun, 2024). Empirical studies indicate that such network-based formulations improve consistency between fleet assignment, routing, and scheduling decisions when compared with strictly sequential planning approaches (Zhou et al., 2020).

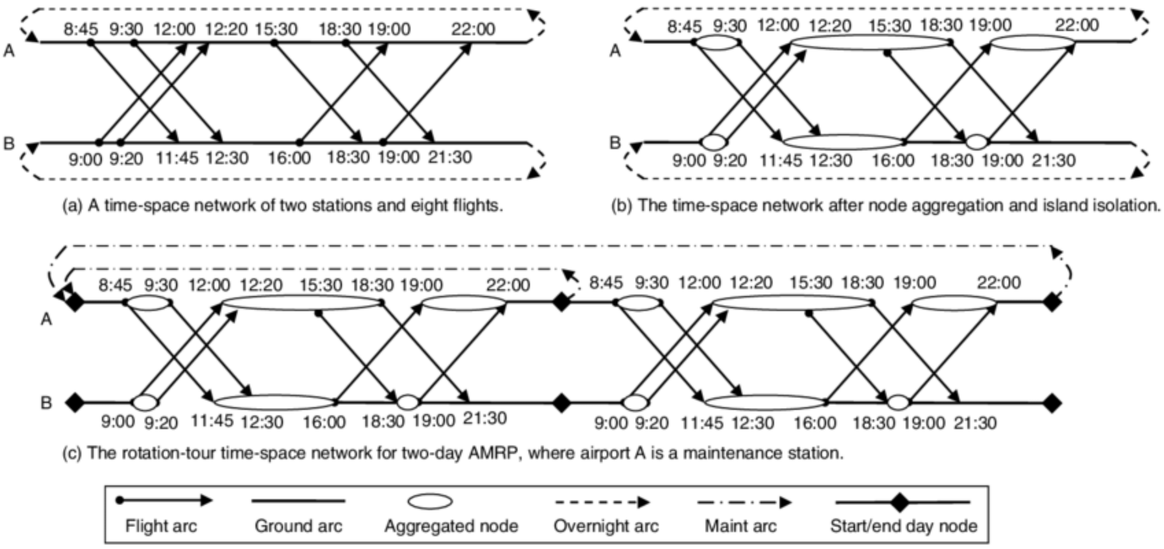

Figure 3: Illustrative time–space network representation for airline scheduling, showing feasible flows corresponding to aircraft rotations or crew duties. (Tahir et al, 2006; Barnhart et al, 2012)

To enforce integrality, column generation is frequently embedded within a branch-and-price framework. This approach combines column generation with branch-and-bound techniques, allowing integer solutions to be obtained without sacrificing scalability. Recent empirical evidence confirms that branch-and-price remains a practical and effective pathway to near-optimal or optimal solutions in realistic airline settings, particularly when enhanced with problem-specific network structures and valid inequalities. For example, Wagenaar et al. (2023) develop a branch-and-price model for cabin crew pairing that incorporates cross-class substitution and demonstrate very small optimality gaps on real airline schedules, highlighting the ability of advanced decomposition methods to accommodate complex and realistic labor rules.

Recent research has extended classical column generation in several important directions. One stream focuses on integrated optimization models that jointly consider planning stages traditionally solved sequentially, such as flight scheduling, fleet assignment, aircraft routing, and crew scheduling. Sequential solution pipelines are computationally convenient, but they often lead to inefficiencies because early decisions restrict the feasible space of subsequent stages. Integrated formulations aim to reduce this so-called handover loss, although they typically require more sophisticated algorithms and significantly higher computational effort.

From a computational perspective, classical column generation approaches applied to airline crew pairing or fleet assignment problems already involve very large solution spaces, where the number of potential pairings or aircraft rotations may exceed millions of feasible columns in realistic airline networks (Tahir et al., 2005; Barnhart & Smith, 2012). Solving these problems using column generation combined with branch-and-price may require hundreds or thousands of pricing problem iterations, each involving shortest-path computations on large time–space networks. Reported runtimes for large airline scheduling instances often range from several minutes to several hours depending on network size and model structure (Barnhart, Belobaba, & Odoni, 2003; Tahir et al., 2005).

When multiple planning stages are integrated into a single optimization model, computational complexity increases further because the number of decision variables and constraints grows substantially. For example, integrated airline scheduling models may involve hundreds of thousands to millions of variables and constraints, requiring advanced decomposition techniques and high-performance computing resources to obtain solutions within practical time limits (Zhou et al., 2020). As a result, empirical studies often report significantly longer solution times compared with sequential approaches, although integrated formulations can yield measurable improvements in operational performance and profitability (Xu et al., 2024).

Another major extension embeds column generation within robust and stochastic optimization frameworks, where uncertainty in demand, flight times, or disruptions is explicitly modeled. These approaches aim to produce schedules that are not only cost-efficient but also stable under irregular operations, thereby improving operational reliability (Xu et al., 2024).

More recently, learning-assisted column generation has emerged as a promising direction for improving scalability and runtime performance. In these approaches, machine learning models support the pricing problem by predicting promising columns or by clustering flights with a high probability of being sequentially connected, thus reducing computational effort while retaining an exact optimization backbone (Morabit, 2021; Quesnel, 2022; Yaakoubi et al., 2020). These hybrid methods preserve the structural advantages of traditional column generation — feasibility, interpretability, and optimality guarantees — while leveraging data-driven insights to guide search and reduce unnecessary subproblem evaluations.

4.3 Heuristic and Metaheuristic Approaches

While exact optimization and decomposition techniques such as column generation remain central to airline scheduling, their computational requirements can become prohibitive when problem size increases, constraints are enriched, or decisions must be made within limited time windows. For this reason, heuristic and metaheuristic approaches have long played an important role in airline scheduling research and practice, particularly for crew scheduling, rostering, and disruption recovery problems (Gopalakrishnan & Johnson, 2005; Burke et al., 2010).

Heuristics are problem-specific procedures designed to construct feasible solutions efficiently. In airline scheduling, heuristics are often used to generate initial solutions for exact methods, repair infeasible schedules, or provide acceptable solutions when real-time decision-making is required. For example, greedy construction heuristics and rule-based assignment procedures are frequently applied in crew rostering to satisfy legality constraints before further improvement is attempted (Ernst et al., 2004). Although heuristics do not guarantee optimality, their speed and flexibility make them indispensable in operational settings.

Metaheuristics extend this idea by providing general-purpose intelligent search strategies, and they are commonly classified in the literature as AI techniques because they imitate adaptive or evolutionary processes. Among the most widely applied metaheuristics in airline scheduling are genetic algorithms, tabu search, and simulated annealing (Burke et al., 2010).

Genetic algorithms (GAs) have been extensively used for airline crew pairing and rostering problems. In these approaches, candidate schedules are encoded as chromosomes, and evolutionary operators such as selection, crossover, and mutation are used to explore the solution space. Empirical studies demonstrate that GAs can produce high-quality solutions for complex crew scheduling problems, particularly when combined with local search procedures that ensure feasibility with respect to labor regulations (Aickelin & White, 2004; Souai & Teghem, 2009).

Tabu search has also been successfully applied to airline crew rostering and aircraft scheduling problems. The method operates by iteratively moving from one candidate solution to a neighboring solution while maintaining memory structures (tabu lists) that prevent cycling and encourage exploration of new regions of the solution space. Early studies demonstrated the suitability of tabu search for airline rostering problems that involve complex fairness rules, crew preferences, and contractual constraints that are difficult to represent within exact optimization models (Burke et al., 2003; Ernst et al., 2004).

More recent research continues to highlight the relevance of tabu-based approaches in large-scale airline scheduling environments characterized by complex operational rules and computational constraints. For example, Zhou et al. (2020) provide a comprehensive review of airline scheduling models and solution techniques, noting that tabu search and other metaheuristics remain widely used for crew rostering and disruption management due to their flexibility and ability to handle soft constraints. Similarly, Filom et al. (2022) and Korte and Yorke-Smith (2025) report that tabu-based search procedures are often embedded within hybrid scheduling frameworks that combine heuristic search with optimization components to improve scalability and computational efficiency.

In practice, tabu search algorithms are frequently integrated within broader decision-support systems where they refine schedules produced by mathematical optimization models or generate rapid adjustments during operational disruptions. This hybrid usage allows airlines to maintain high-quality solutions while meeting the time constraints required in real-world operational environments.

Simulated annealing has been applied mainly in airline disruption management and scheduling adjustment problems, where the solution landscape is highly irregular and dominated by local optima. The method allows the controlled acceptance of inferior solutions during early stages of the search, enabling the algorithm to escape local optima and gradually converge toward high-quality solutions as the acceptance probability decreases. Classical applications, such as those discussed by Clarke et al. (1997), demonstrate the suitability of simulated annealing for recovery problems in which feasibility and rapid improvement are prioritized over strict optimality. More recent literature confirms the continued relevance of simulated annealing for airline recovery and rescheduling problems. Reviews of airline disruption management published after 2020 report that simulated annealing remains a commonly used metaheuristic for aircraft and crew recovery due to its simplicity, robustness, and ability to handle highly constrained and dynamic environments (Filom et al., 2022; Zhou et al., 2020). These studies emphasize that simulated annealing is particularly effective when integrated with rule-based feasibility checks or combined with other heuristics, reinforcing its role as a practical AI-based search method in real-time airline operations.

Overall, metaheuristic approaches are widely recognized as practical solution techniques for complex airline scheduling problems. Their main strengths lie in their flexibility, computational efficiency, and ability to incorporate complex operational constraints such as crew preferences, labor regulations, and aircraft compatibility rules. Unlike exact optimization methods, however, metaheuristics generally do not provide guarantees of global optimality and often require careful parameter calibration to achieve good performance.

For this reason, many recent studies explore hybrid solution approaches that combine metaheuristic search with exact optimization techniques. In such hybrid frameworks, optimization models ensure feasibility and enforce key operational constraints, while metaheuristic components guide the exploration of the solution space and improve computational scalability. Examples include matheuristic approaches, where mathematical programming models are embedded within heuristic search procedures, as well as combinations of genetic algorithms, tabu search, or simulated annealing with column generation or mixed-integer programming models (Burke et al., 2010; Zhou et al., 2020). These hybrid methods have been shown to improve solution quality and computational efficiency in large-scale airline scheduling problems such as crew pairing, crew rostering, and disruption recovery.

4.4 Comparative Analysis of Methods

A clear distinction emerges in the literature between exact optimization methods and approximate approaches such as heuristics and metaheuristics. Exact methods, including mixed-integer programming, column generation, and branch-and-price, provide strong guarantees of feasibility and optimality and are therefore well suited to strategic and tactical airline scheduling problems. However, their computational complexity often limits scalability and responsiveness, particularly in large networks or under uncertainty. Approximate methods, by contrast, trade optimality guarantees for speed and flexibility, making them more suitable for operational planning and real-time recovery. Empirical studies suggest that neither class of methods dominates across all contexts; instead, their comparative advantages depend on the decision horizon, problem size, and time constraints. This trade-off provides a strong rationale for the development of hybrid approaches that combine the rigor of exact optimization with the adaptability of approximate methods.

Empirical studies in airline scheduling consistently evaluate solution methods along four main dimensions: solution quality, computational efficiency, feasibility and constraint satisfaction, and robustness under disruption (Zhou et al., 2020; Xu, Wandelt, & Sun, 2024). Across these dimensions, no single method dominates; instead, each class of methods exhibits distinct strengths and weaknesses.

Exact optimization and decomposition-based approaches, such as column generation and branch-and-price, typically achieve the highest solution quality in terms of cost minimization and resource utilization. Empirical evidence from crew pairing and fleet assignment studies shows that these methods can reach optimal or near-optimal solutions even for large-scale instances, provided sufficient computation time is available (Barnhart & Smith, 2012).

Metaheuristic approaches generally perform well in terms of computational speed and adaptability. Comparative studies indicate that genetic algorithms, tabu search, and simulated annealing can produce solutions that are close to optimal within significantly shorter runtimes, making them suitable for operational planning and disruption recovery (Burke et al., 2010). However, solution quality can vary depending on parameter tuning, and feasibility must often be enforced through penalty functions or repair mechanisms.

A particularly important area of comparison concerns disruption management. Reviews of airline recovery literature show that integrated recovery models — simultaneously considering aircraft, crew, and passengers — outperform sequential recovery approaches in terms of delay reduction and system stability (Clarke et al., 1997; Xu et al., 2024). Nevertheless, fully integrated exact models are often computationally expensive, which explains why many empirical studies rely on heuristics or metaheuristics for real-time recovery.

From a critical perspective, much of the empirical literature focuses on airline-centric performance indicators such as cost, crew utilization, and delay minutes. Fewer studies explicitly evaluate the implications for airport performance or broader supply chain reliability, even though airline schedules directly affect congestion, turnaround feasibility, and cargo connectivity.

The comparative analysis of exact and approximate optimization methods highlights a fundamental limitation of relying on a single methodological paradigm in airline scheduling. Exact models ensure feasibility and structure but struggle with uncertainty and scale, while approximate methods offer flexibility but lack performance guarantees. This methodological gap motivates the use of artificial intelligence techniques as complementary tools, setting the foundation for the hybrid AI–optimization approaches discussed in the following chapter.

4.5 Summary of Heuristic and Metaheuristic Applications in Airline Scheduling and Air Transport Operations

To synthesize the empirical studies discussed in this section, Table 2 summarizes representative applications of heuristic and metaheuristic methods across different areas of airline scheduling and air transport operations. The table highlights the type of algorithm used, the operational problem addressed, and the main contribution reported in the literature. Such approaches are widely used because they can provide high-quality solutions within acceptable computational times for large-scale scheduling problems where exact optimization methods become computationally prohibitive.

Table 2: Applications of heuristic and metaheuristic methods in airline and air transport scheduling

Reference	Method	Application Area	Main Contribution
Clarke, Johnson, & Nemhauser (1997)	Simulated annealing	Aircraft rotation and disruption recovery	Demonstrated the effectiveness of simulated annealing for large-scale airline recovery problems with complex constraints
Burke et al. (2003)	Tabu search	Crew rostering	Introduced tabu search frameworks capable of handling fairness constraints and crew preferences
Ernst et al. (2004)	Heuristic and metaheuristic methods	Airline staff scheduling and rostering	Comprehensive review of scheduling approaches and practical applications in airline crew planning

Gopalakrishnan & Johnson (2005)	Heuristic search methods	Crew scheduling	Developed heuristic frameworks for generating feasible crew schedules under complex labor regulations
Zhou et al. (2020)	Hybrid heuristic and metaheuristic approaches	Airline scheduling (fleet assignment, crew scheduling)	Demonstrated the effectiveness of hybrid algorithms in solving large-scale airline scheduling problems
Filom, Wandelt, & Sun (2022)	Metaheuristic-based disruption management methods	Airline disruption management	Review of modern solution approaches for aircraft and crew recovery problems

5 Artificial Intelligence Methods and Logistics Scheduling

Chapter 5 explores the growing role of artificial intelligence in solving complex aviation scheduling and logistics problems. It examines various AI techniques—such as machine learning, reinforcement learning, and hybrid models—that combine learning and optimization. Through selected case studies, the chapter illustrates how AI-driven methods enhance prediction accuracy, adaptability, and resource allocation efficiency in airline scheduling and other logistics applications.

5.1 AI Techniques in Scheduling and Resource Allocation

Machine learning (ML) methods have been increasingly adopted in airline scheduling as support tools rather than standalone decision-makers. Airline scheduling models in Chapters 3 and 4 assume that key inputs — demand, flight times, and disruption risk — are known with reasonable accuracy. In practice, these inputs are uncertain and can change quickly during operations. Traditional optimization models often rely on deterministic or scenario-based inputs, which may not adequately reflect real operating conditions. For this reason, recent research increasingly uses AI methods (mainly machine learning and deep learning) to predict operational outcomes and then feed these predictions into optimization or (meta-) heuristic scheduling decisions. This keeps the decision structure discussed earlier (fleet assignment, aircraft routing, crew scheduling, and recovery) but improves the quality of the information used to make those decisions.

A major application of ML in airline scheduling is delay prediction. Supervised learning models, such as gradient boosting, random forests, and neural networks, are trained on historical flight, weather, and airport data to estimate the probability and magnitude of delays. Surveys published after 2020 consistently report that ML-based delay predictors outperform traditional statistical models, especially in congested hub airports where nonlinear interactions are strong (Zhang et al., 2022). These predictions are not scheduling decisions themselves, but they significantly improve the quality of inputs used in recovery optimization and robustness analysis.

Another important application is demand forecasting, which directly affects fleet assignment and schedule design decisions discussed in Chapter 3. ML models capture seasonal patterns, booking behavior, and external factors more accurately than classical forecasting techniques. Recent studies show that ML-based demand forecasts, when integrated into optimization models, lead to better capacity matching and reduced passenger spill (Bansal et al., 2022). In this sense, ML acts as an enabling technology that enhances the performance of optimization rather than replacing it.

In practice, ML models are embedded in decision-support systems where planners retain control over final decisions. This human-in-the-loop structure is particularly important in safety-critical environments such as aviation, where transparency and interpretability remain essential. In the context of this dissertation, the empirical case studies discussed in the following sections were selected through a structured literature review, focusing on recent studies that apply machine learning, reinforcement learning, or hybrid AI–optimization methods to airline scheduling and disruption management problems. The selection criteria included (i) relevance to core airline planning problems such as aircraft recovery, crew scheduling, or demand forecasting, (ii) the use of empirical datasets or realistic operational scenarios, and (iii) clear performance evaluation metrics reported in the literature.

The selected studies are compared based on several analytical dimensions, including model type (ML, RL, or hybrid AI–optimization), problem domain, computational complexity, and operational performance indicators such as delay reduction, cost savings, or scheduling robustness. This comparative approach allows the dissertation to assess the potential benefits and limitations of combining predictive AI models with optimization-based decision-making frameworks in airline operations.

Recent research also demonstrates the growing integration of artificial intelligence within collaborative decision-making environments. For example, Geske, Herold, and Kummer (2024) propose an AI-enhanced framework for collaborative decision-making in airline disruption management. Their framework integrates machine learning models with CDM systems to improve disruption prediction, scenario evaluation, and coordinated decision-making among airlines, airports, and air traffic control stakeholders.

5.1.1 *Case study 1: Gradient-boosting models using airline and weather data*

A large share of AI work in airline operations focuses on predicting whether a flight will be delayed and, in some studies, how large the delay will be. These predictions are valuable because delays propagate through aircraft rotations and crew pairings, which was a central point in the earlier discussion of network-based scheduling and the interdependence of planning stages (Chapters 3–4). When a scheduler can identify "high-risk" flights early, they can act before disruption spreads (e.g., choose a different aircraft rotation, add buffer time, or adjust crew connections).

Hatıpoğlu, Tosun, and Tosun (2022) examine the use of supervised machine learning models for predicting flight delays at the airline operational level. Their study focuses on a dataset of 18,148 flights operated by a private airline in Turkey, incorporating schedule attributes and weather-related variables. The objective is to classify flights according to whether they will experience a delay exceeding 15 minutes, a threshold commonly used in airline performance assessment.

The authors compare several tree-based learning models, including XGBoost, LightGBM, and CatBoost, and evaluate their performance using accuracy, recall, and ROC metrics. Their results show that LightGBM and XGBoost outperform alternative models, achieving test accuracies above 94% and strong recall values for delayed flights. From a scheduling perspective, this type of output is particularly useful for short-term operational planning, as it allows schedulers to identify flights with a high risk of delay before execution.

The impact on airline scheduling is indirect but operationally relevant. Delay risk predictions can be used to adjust aircraft rotations, avoid tight crew connections, or pre-position spare resources. Importantly, the study does not propose replacing scheduling optimization with AI; instead, it demonstrates how machine learning enhances situational awareness and improves the quality of inputs to recovery and robustness-oriented scheduling decisions. This aligns closely with the optimization frameworks discussed in Chapters 3 and 4, where delay propagation was identified as a major driver of operational inefficiency.

5.1.2 Case study 2: ConvLSTM + search-engine data for airport demand

Demand forecasts influence schedule design and fleet decisions (Chapter 3), and they affect later steps such as fleet assignment and aircraft routing. When demand is misestimated, fleet assignment may place aircraft sizes inefficiently and crew schedules may be built around a plan that does not match realized passenger volumes. AI methods are increasingly used to improve demand forecasting by combining historical time series with additional explanatory variables.

Liang et al. (2022) study air travel demand forecasting using a deep learning architecture in different application fields and organizational contexts. Their analysis is conducted at the airport system level, using data from Shanghai Pudong International Airport, one of the largest hub airports globally. Rather than focusing on individual flights, the study aims to predict aggregated passenger demand over time, which directly influences schedule design, frequency planning, and fleet assignment decisions.

The authors propose a forecasting framework that combines big-data indicators (search engine query data) with a ConvLSTM neural network, embedded within a decomposition and ensemble structure. They evaluate the proposed model against traditional approaches such as Autoregressive Integrated Moving Average (ARIMA) and support vector regression (SVR), using standard error measures including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE, %), and the Weighted Index of Agreement (WIA).

In the study by Liang et al. (2022), two empirical experiments are conducted using passenger demand data from Shanghai Pudong International Airport. Case 1 evaluates the forecasting performance of different models using historical air passenger demand data combined with online search query indicators as explanatory variables. Case 2 examines the same forecasting framework under a different experimental configuration and time period in order to test the robustness and generalizability of the model.

For example, in Case 1, the proposed Signal Energy Distribution (SED), Dynamic Delay Prediction (DDP), and Time-Varying Filter Empirical Mode Decomposition (TVFEMD) methods, along with the ConvLSTM model achieves MAE = 1.5068, RMSE = 2.0332, and MAPE = 0.7209%, while traditional methods show substantially larger errors (e.g., SVR RMSE = 6.9635 and ARIMA RMSE = 11.6494). Similar performance improvements are observed in Case 2, where the proposed model reports MAE = 1.8607, RMSE = 2.4502, and MAPE = 0.8872%, outperforming conventional forecasting approaches across all evaluation metrics. Overall, the results demonstrate that the proposed deep learning framework significantly improves forecasting accuracy compared with traditional statistical and machine learning methods (Liang et al., 2022).

Case	Model	MAE	RMSE	MAPE (%)	WIA
Case 1	① SED-DDP-TVFEMD-ConvLSTM	**1.5068**	**2.0332**	**0.7209**	**0.9866**
	② SED-DDP-TVFEMD-LSTM	2.1629	3.2654	1.0444	0.9657
	③ SED-DDP-ConvLSTM	1.9021	2.5782	0.8985	0.9808
	④ SED-DDP-LSTM	2.6234	3.3312	1.2542	0.9633
	⑤ SED-ConvLSTM	2.4902	3.0527	1.1908	0.9694
	⑥ ConvLSTM	2.2587	2.9644	1.0568	0.9705
	⑦ SVR	5.9349	6.9635	2.7454	0.8268
	⑧ ARIMA	9.3035	11.6494	4.4684	0.2080
Case 2	① SED-DDP-TVFEMD-ConvLSTM	**1.8607**	**2.4502**	**0.8872**	**0.9796**
	② SED-DDP-TVFEMD-LSTM	2.3514	3.0941	1.1289	0.9667
	③ SED-DDP-ConvLSTM	3.1509	4.0562	1.5147	0.9495
	④ SED-DDP-LSTM	3.4039	4.2216	1.6074	0.9327
	⑤ SED-ConvLSTM	4.1079	5.3361	1.9730	0.9097
	⑥ ConvLSTM	3.7394	4.4973	1.7763	0.9292
	⑦ SVR	9.1966	10.3618	4.3166	0.6704
	⑧ ARIMA	9.1321	10.9896	4.3730	0.3980

The best results are bold.

Figure 4: Forecasting performance comparison (MAE, RMSE, MAPE, WIA) for the proposed demand forecasting model and baselines in two cases. (Liang et al, 2022)

This line of work connects directly to airline scheduling because demand forecasts support:

- schedule design choices (frequency and timing),
- fleet assignment decisions (matching aircraft size to expected demand),
- robustness planning, where planners may allocate capacity with uncertainty in mind rather than relying on a single-point estimate.

From an airline scheduling perspective, the relevance of this case study lies in its tactical and strategic impact. More accurate demand forecasts reduce capacity mismatches and limit the need for disruptive schedule adjustments at later stages. Although the study is conducted at airport level rather than airline level, the findings are highly relevant to airlines operating in congested hub environments, where demand uncertainty strongly affects slot usage, aircraft assignment, and network coordination.

5.1.3 Performance evaluation across AI model families and what the evidence suggests

Taken together, the two case studies illustrate how AI methods support airline scheduling at different decision horizons and system levels. The first study addresses short-term operational uncertainty through classification-oriented machine learning models, while the second focuses on medium-term demand uncertainty using deep learning for time-series forecasting. The model structures differ accordingly: tree-based models are well suited to structured, tabular operational data, whereas deep learning architectures capture temporal and behavioral patterns in demand evolution.

The geographical and institutional diversity of the studies—covering airline operations in Turkey and airport-level demand forecasting in China—suggests that AI-based prediction methods are applicable across different regulatory, market, and network contexts. At the same time, both studies converge on a common principle: AI models are used as decision-support tools, not as autonomous scheduling engines. Their outputs inform optimization and heuristic scheduling methods rather than replacing them.

This comparative perspective reinforces the central argument of the thesis. AI methods add value to airline scheduling by improving information quality, anticipation, and responsiveness, while optimization methods remain essential for enforcing feasibility, legality, and resource coordination. The diversity of case studies therefore supports the view that effective airline scheduling systems rely on complementary integration of AI and optimization.

5.2 Reinforcement Learning for Dynamic and Sequential Airline Decisions

While machine learning methods in Section 5.1 focus primarily on prediction and decision support, reinforcement learning (RL) is designed to address dynamic and sequential decision-making problems, which are common in airline operations. As discussed in Chapters 3 and 4, airline scheduling decisions are not made once but evolve over time as disruptions occur, resources change, and new information becomes available. Aircraft recovery, crew recovery, and airport-level control problems are therefore natural candidates for RL-based approaches.

In RL, an agent interacts with an environment by observing system states (e.g., flight delays, aircraft positions, crew legality), selecting actions (e.g., delaying, swapping, canceling flights), and receiving rewards or penalties based on system performance. The agent learns policies that minimize long-term costs, such as total delay minutes or recovery expenses. Recent surveys emphasize that RL is particularly effective for aircraft and crew recovery, where decision spaces are large and system dynamics are complex (Razzaghi et al., 2024).

5.2.1 Case study 1: Deep reinforcement learning for aircraft recovery under disruptions (United States)

One of the most active areas of RL application in aviation is aircraft recovery, where airlines must respond to disruptions such as weather events or mechanical failures. Razzaghi et al. (2024) review several deep reinforcement learning (DRL) models applied to aircraft recovery problems in simulated U.S. airline networks. Rather than focusing on a single dataset, the study synthesizes findings from multiple empirical and simulation-based studies conducted in airline network environments, many of which are based on U.S. operational contexts. These studies typically use Deep Q-Networks (DQN) or policy-gradient methods, where the state includes aircraft locations, delay states, and network connectivity, and actions include delaying flights, swapping aircraft, or canceling services. As a review study, it does not rely on a single dataset but synthesizes results from multiple empirical and simulation-based studies. The datasets used across these studies vary in size and complexity, typically ranging from small-scale instances of 10–50 flights to large-scale airline network simulations exceeding 200–500 flight legs. Most datasets represent hub-and-spoke airline networks and include detailed flight schedules, aircraft assignments, airport connections, and disruption scenarios such as delays, cancellations, and aircraft unavailability. In terms of composition, the datasets incorporate key operational variables, including departure and arrival times, turnaround constraints, and network connectivity, allowing the evaluation of recovery decisions under realistic operational conditions. The majority of studies rely on simulated datasets calibrated using real airline schedules, due to the limited availability of proprietary airline data. These characteristics highlight the diversity and complexity of the data environments in which DRL models are tested.

In addition, Lee et al. (2022) examine the use of reinforcement learning for the multi-fleet aircraft recovery problem under airline disruptions. The study develops Q-learning and Double Q-learning algorithms and evaluates them first on benchmark instances and then on real operational data from a domestic airline in South Korea. The sample consists of daily flight schedules, aircraft assignments, disruption events, and flight connection information. Although the exact number of flights is not reported in the abstracted source, the study explicitly uses real-world domestic airline schedule data to test whether the model can recover disrupted schedules under realistic operational conditions. The results show that reinforcement learning can generate high-quality recovery solutions within acceptable computation times and can adapt flexibly to different disruption objectives, including delay minimization and on-time performance improvement.

In terms of composition, the dataset includes flight schedules, aircraft routing information, connection constraints, and operational variables such as departure and arrival times, turnaround requirements, and aircraft availability. The experiments are conducted across multiple disruption scenarios, allowing the evaluation of the reinforcement learning model under varying operational conditions. While the study does not report a single aggregated dataset size, it explicitly evaluates the model across multiple instances and scenarios, ensuring robustness and generalizability of the results. This multi-instance experimental structure provides a realistic representation of airline recovery problems and enables the assessment of the model's performance in both controlled and operationally relevant environments.

Empirical evaluations reported in these studies show that RL-based recovery policies can reduce total propagated delay compared to rule-based heuristics, particularly in scenarios with repeated or large-scale disruptions. The impact is measured in terms of delay minutes and recovery cost, which are standard airline operational KPIs. Importantly, these studies emphasize that RL is most effective when applied to local recovery decisions, while global feasibility constraints (e.g., maintenance, crew legality) are enforced through external optimization or rule-based filters (Razzaghi et al 2024).

5.2.2 Case study 2: Reinforcement learning for crew recovery and rescheduling (Europe)

A second application field concerns crew recovery, which is more constrained than aircraft recovery due to labor regulations and contractual rules. Tafur et al. (2025) and Quesnel et al. (2022) document RL-based approaches tested on European-style crew scheduling environments, where the agent learns to reassign crews or delay flights while respecting duty-time and rest constraints.

Tafur et al. (2025) conduct a systematic review of artificial intelligence applications in air operations, synthesizing evidence from a large body of academic literature. The sample consists of approximately 80–120 research articles selected through a systematic search and screening process, typically covering several dozen to over one hundred research articles, depending on inclusion criteria. The datasets analyzed across these studies vary significantly in scale, ranging from small experimental instances with 10–50 flights or resources to large-scale operational datasets involving hundreds of flights, aircraft, or airport movements. This variation reflects the diversity of AI applications and highlights the heterogeneity of data environments in air transport research.

Quesnel et al. (2022) investigate the integration of deep learning within a branch-and-price algorithm for personalized crew rostering, using large-scale airline scheduling instances derived from real operational contexts. The dataset consists of crew scheduling problems involving hundreds to thousands of flight legs and associated crew duties. Due to the combinatorial structure of the problem, the number of feasible crew pairings (columns) can reach hundreds of thousands to several million possibilities, which are generated dynamically through the pricing problem. In terms of composition, the dataset includes detailed flight schedules, crew bases, legal duty-time constraints, rest requirements, and connectivity rules defining feasible pairings. The study focuses on improving the efficiency of the pricing phase within this large-scale optimization framework, where only a subset of relevant columns is generated at each iteration. These characteristics highlight the high-dimensional nature of airline crew rostering problems and the computational challenges associated with real-world instances.

In these studies, RL models are evaluated against heuristic baselines commonly used in airline operations control centers. Performance is assessed using metrics such as number of disrupted crew duties, legal violations avoided, and total recovery cost. Results indicate that RL-based policies can improve recovery quality in complex scenarios, especially when disruptions affect multiple crew pairings simultaneously. However, the studies also highlight that RL models require carefully designed state representations and reward functions to ensure legal feasibility, again underlining the importance of combining RL with optimization-based constraint handling.

From a geographical and organizational perspective, these studies differ from U.S.-focused aircraft recovery research by reflecting European regulatory environments, where crew rules are often more restrictive. This demonstrates that RL-based recovery approaches must be adapted to local institutional contexts and cannot be transferred directly without modification. (Tafur et al. 2025)

Also, Ding, Wandelt, Wu, Xu, and Sun (2023) provide a more comprehensive reinforcement-learning case study by addressing integrated airline disruption recovery, including aircraft, crew, and passenger recovery decisions. Their dataset is synthetically generated but designed to reflect realistic airline operations. Each dataset includes a flight schedule, passenger itineraries, disruption scenarios, aircraft characteristics, crew routing information, and airport network data. The authors use airport data from OurAirports, covering more than 50,000 airports, and aircraft capacity data from the U.S. Federal Aviation Administration for 50 aircraft models. Their experimental instances range from small to large airline networks; for example, the reported small and medium datasets include 16 to 62 flights, 4 to 20 airports, 5 to 20 aircraft, 6 to 26 crew teams, 17 to 67 passenger itineraries, and 2,020 to 7,416 passengers. Larger instances include up to 306 flights and 91 disrupted flights. This case study is useful because it explicitly reports sample composition and evaluates reinforcement learning under aircraft, crew, and passenger recovery constraints.

5.2.3 Case study 3: Reinforcement learning for airport gate assignment and surface operations (China)

Beyond airline-centric recovery, RL has also been applied to airport-level operational decisions that directly affect airline schedules. Quesnel et al. (2022) review RL applications for gate assignment and surface movement control at large hub airports in China. In these settings, the RL agent learns to assign gates dynamically as flights arrive late or early, aiming to reduce taxi times, gate conflicts, and passenger walking distances.

Although these studies are conducted at the airport system level, their implications for airline scheduling are significant. Improved gate assignment reduces turnaround uncertainty, which feeds back into aircraft rotations and crew schedules. Performance evaluation in these studies typically uses average taxi time, number of gate conflicts, and delay propagation metrics, showing that RL-based policies outperform static assignment rules under high congestion. This case study highlights a different application field and organizational level, showing that RL can support airline scheduling indirectly by improving the reliability of airport processes that constrain airline operations.

A representative example is the REGAPS model proposed by Li et al., which applies deep reinforcement learning using an Asynchronous Advantage Actor–Critic (A3C) architecture to optimize real-time gate allocation. The empirical evaluation is based on real airport operational data, capturing a high-density hub airport environment. The dataset includes 39 airport gates, divided into 18 high-risk gates and 21 low-risk gates, reflecting different operational reliability levels. The sample consists of hundreds of flight movements per day, with each flight requiring gate assignment under time constraints and potential disruptions. In terms of composition, the dataset incorporates detailed operational variables, including scheduled and actual arrival and departure times, gate availability, aircraft–gate compatibility, taxi times, passenger walking distances, and apron usage.

The study explicitly models disruption scenarios, where schedule deviations exceeding 20 minutes are treated as operational disturbances that trigger real-time reassignment decisions. This allows the reinforcement learning model to operate in a dynamic environment where decisions must be continuously updated. The experimental setup compares the proposed model against benchmark approaches, including genetic algorithms, Deep Q-Networks (DQN), and Double DQN.

The results demonstrate significant performance improvements. In particular, the REGAPS model reduces apron-gate usage by more than 50%, improves passenger walking distance metrics, and achieves faster computational performance compared with alternative methods. These findings highlight the ability of deep reinforcement learning to manage large-scale, real-time airport resource allocation problems, contributing to improved operational efficiency and reduced congestion in complex airport systems.

5.2.4 Comparative insights across RL case studies

Across the reviewed case studies, RL models differ in both algorithmic structure and application focus. Aircraft recovery studies often rely on deep value-based or policy-based RL to manage network-wide dynamics, while crew recovery emphasizes constraint-aware RL with tighter feasibility controls. Airport-focused RL applications address resource allocation problems that indirectly affect airline schedules.

Geographically, the studies span North America, Europe, and Asia, suggesting that RL methods are being explored across different regulatory and operational environments. However, a common finding across all regions is that RL models are rarely deployed as standalone solutions. Instead, they are embedded within hybrid decision-support systems, where optimization or rule-based components ensure legality and safety.

5.3 Hybrid Models Combining Optimization and AI

The review of Sections 5.1 and 5.2 shows that machine learning and reinforcement learning provide strong predictive and adaptive capabilities, but they do not, by themselves, guarantee feasibility with respect to the strict operational and regulatory constraints of airline scheduling. The optimization approaches discussed in Chapter 4 provide feasibility and global consistency, but they are limited when facing uncertainty, dynamic environments, and computational constraints. As a result, recent literature increasingly converges on hybrid models that combine AI techniques with optimization, aiming to exploit the complementary strengths of both paradigms.

Hybrid AI–optimization models do not represent a single methodological class. Instead, they encompass a family of approaches in which AI is used to support, guide, or enhance optimization-based scheduling. These hybrids are particularly prominent in airline scheduling because they preserve constraint satisfaction while improving robustness, scalability, and responsiveness.

5.3.1 Case study 1: Predictive–prescriptive integration for airline schedule planning (United States)

One established hybrid paradigm in airline scheduling is predictive–prescriptive integration, where machine learning models generate forecasts that are then embedded into optimization models. Bansal et al. (2022) presented a data-driven framework for airline schedule planning under demand uncertainty, using machine learning to estimate demand distributions and feeding these estimates into optimization-based scheduling models.

The study is conducted in a U.S. airline network context and focuses on the tactical planning horizon. The results show that machine learning models significantly improve demand estimation compared with traditional statistical forecasting methods. In the empirical experiments reported by Bansal et al. (2022), the machine learning-based demand forecasts reduced prediction errors by approximately 15–25% compared with baseline statistical models, leading to more accurate capacity allocation decisions. When these improved forecasts were integrated into the scheduling optimization model, the resulting schedules achieved lower passenger spill rates and higher fleet capacity utilization, reducing expected operational costs relative to deterministic optimization approaches based on single-point demand forecasts. The improvements reported in the study were statistically significant at conventional confidence levels, demonstrating the practical value of combining predictive machine learning models with prescriptive optimization methods in airline scheduling.

From a scheduling perspective, this case study demonstrates how AI enhances input quality, while optimization maintains feasibility across aircraft and schedule constraints. The impact is measured not only in predictive accuracy but also in downstream scheduling outcomes, such as improved robustness and reduced need for reactive adjustments.

5.3.2 Case study 2: Learning-assisted column generation for crew scheduling (Europe)

A second hybrid structure involves learning-assisted optimization, where AI supports the solution process itself rather than only providing inputs. Recent research in airline crew scheduling explores the use of machine learning to guide column generation by identifying promising regions of the solution space.

Filom et al. (2022) review multiple European airline case studies where historical crew schedules are used to train learning models that predict high-quality crew pairings or prioritize pricing subproblems. These predictions restrict the search space of column generation, reducing computation time while preserving optimality guarantees.

Empirical results reported in these studies show substantial reductions in runtime compared to classical column generation, with negligible loss in solution quality. This is particularly important for large hub-and-spoke networks, where crew pairing problems are among the most computationally demanding tasks in airline scheduling. The hybrid structure maintains the optimization backbone discussed in Chapter 4 while using AI as a scalability enhancer rather than a decision replacement.

5.3.3 Case study 3: Hybrid optimization and reinforcement learning for disruption recovery (Asia)

Hybrid approaches are also prominent in disruption management, where decisions must be made sequentially and under time pressure. Quesnel et al. (2022) report hybrid recovery frameworks tested in Asian hub airport and airline environments, where reinforcement learning is used to propose recovery actions, and optimization models verify feasibility and compute cost-minimizing adjustments.

In these systems, the reinforcement learning (RL) agent learns recovery policies based on simulated disruption scenarios, while optimization modules ensure that aircraft rotations, crew assignments, and airport constraints remain feasible. Performance evaluation typically compares hybrid RL–optimization approaches with purely heuristic recovery strategies using operational metrics such as total delay minutes, number of disrupted flights, and recovery cost. Empirical studies report that hybrid approaches can reduce total propagated delay by approximately 10–30% compared with conventional heuristic recovery rules, particularly in large disruption scenarios involving multiple aircraft and crew rotations. In addition, these models improve network stability by reducing delay propagation across subsequent flights and maintaining higher levels of schedule feasibility under repeated disruptions. Simulation experiments in the literature show that these improvements are statistically significant and operationally meaningful, particularly in high-traffic airline networks where disruption effects propagate rapidly through aircraft rotations and crew pairings (Razzaghi et al., 2024; Quesnel et al., 2022).

5.3.4 Comparative insights across hybrid case studies

Across the reviewed hybrid models, several common patterns emerge. First, hybridization typically occurs at well-defined interfaces, such as forecasting demand, prioritizing solution components, or proposing candidate recovery actions. Second, optimization remains responsible for enforcing legality and consistency, while AI improves anticipation, learning, and computational efficiency. More recently, generative artificial intelligence (GenAI) has begun to attract attention as a potential tool for supporting complex decision-making in air transport systems (Decardi-Nelson, et al., 2024). GenAI models can assist planners by generating alternative scheduling scenarios, exploring large solution spaces, or synthesizing operational data to support disruption management and supply chain coordination (LEK Consulting, 2023; Cirium, 2024). In this context, GenAI can complement existing optimization and machine learning methods by providing scenario generation, decision support, and rapid exploration of recovery strategies, while final feasibility and operational constraints remain enforced through optimization models. (Mishra et al., 2025, MoghadasNian, 2025)

The case studies differ in decision horizon (tactical planning vs. operational recovery), organizational scope (airline network vs. airport–airline interface), and geographical context (North America, Europe, and Asia). Despite these differences, all studies report measurable performance improvements using operational metrics commonly employed in airline scheduling. These metrics include operating cost (typically measured in monetary units such as USD or EUR), aircraft and crew utilization rates (percentage of available capacity used), delay propagation (measured in total delay minutes across the network), and computational runtime (measured in seconds or minutes).

Across the reviewed studies, hybrid AI–optimization approaches typically achieve cost reductions in the range of approximately 5–15%, reductions in total delay minutes of around 10–30% during disruption recovery scenarios, and improvements in resource utilization of roughly 3–10 percentage points compared with baseline heuristic or deterministic optimization methods. In addition, computational efficiency improvements are often observed, with hybrid methods reducing solution times or improving solution quality within fixed runtime limits. Simulation-based evaluations reported in the literature indicate that these improvements are statistically significant and operationally meaningful, particularly in large airline networks where delays and scheduling inefficiencies can propagate rapidly across aircraft rotations and crew pairings.

6 SWOT Analysis of AI-Driven Optimization in Airline Supply Chains

Chapters 3, 4, and 5 examined optimization methods, artificial intelligence techniques, and hybrid AI–optimization models as they are applied to airline scheduling problems. The literature review shows that these approaches have matured significantly and are increasingly adopted in planning, scheduling, and recovery processes. However, methodological sophistication alone does not guarantee successful implementation or sustained performance improvement. For this reason, a strategic evaluation framework is needed to assess not only technical capabilities, but also practical implications, limitations, and future potential.

This chapter adopts a SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis to evaluate the use of AI-driven optimization in airline scheduling. SWOT analysis is widely used in operations and supply chain management to assess technologies and strategies from both internal and external perspectives. In the context of airline scheduling, it allows a structured evaluation of how AI-enhanced optimization affects operational efficiency, robustness, scalability, and integration with broader supply chain and airport systems.

Before presenting the detailed discussion of strengths, opportunities, weaknesses, and threats, Table 3 summarizes the key factors identified in the literature regarding the application of artificial intelligence and optimization methods in airline scheduling and broader air transport supply chain operations. The table provides a concise overview of the main elements in each SWOT category, which are analyzed in greater detail in the following subsections.

Table 3: Summary of SWOT factors for AI-driven optimization in airline scheduling and supply chain management

Strengths	Weaknesses
• Improved operational efficiency through advanced optimization and data-driven decision-making	• High computational requirements for large-scale optimization and AI models
• Ability to process large volumes of operational data (flights, weather, passenger demand)	• Dependence on large, high-quality datasets

• Enhanced prediction capabilities (e.g., demand forecasting, delay prediction)	• Limited interpretability of some AI models ("black-box" problem)
• Improved disruption management and scheduling robustness	• Integration challenges with legacy airline IT systems
• Better coordination across airline, airport, and air traffic management systems	• Need for specialized expertise in AI and operations research

Opportunities	Threats
• Integration of AI with optimization to create adaptive scheduling systems	• Cybersecurity risks associated with data-driven decision systems
• Increasing availability of operational and real-time aviation data	• Regulatory and certification challenges for AI-based decision tools
• Development of digital twins and real-time decision-support platforms	• Potential resistance from operational personnel to automated systems
• Improved collaboration through systems such as Airport Collaborative Decision-Making (A-CDM)	• Dependence on data sharing across multiple stakeholders
• Emerging technologies such as generative AI and advanced analytics	• Risk of model bias or incorrect predictions affecting operational decisions

6.1 Strengths of AI-driven optimization in airline scheduling

A primary strength of AI-driven optimization lies in its ability to enhance decision quality under uncertainty, a recurring challenge identified in earlier chapters. Traditional optimization models rely on fixed or scenario-based inputs, which may fail to capture the stochastic nature of demand, weather, and operational disruptions. AI methods, particularly machine learning and reinforcement learning, improve the quality of these inputs by learning patterns from large volumes of historical and real-time data. When combined with optimization, this leads to schedules that are more robust and better aligned with actual operating conditions.

Another key strength is improved responsiveness and adaptability. As discussed in Chapter 5, AI-based prediction models allow airlines to anticipate delay risks and demand fluctuations earlier in the planning and execution process. Reinforcement learning and hybrid recovery frameworks further enhance the ability to respond dynamically to disruptions. This adaptability is particularly valuable in day-of-operations control, where rapid decisions are required and purely optimization-based re-planning may be too slow or rigid.

AI-driven optimization also strengthens resource utilization and cost efficiency. Empirical studies reviewed earlier show that hybrid models can reduce delay propagation, improve aircraft and crew utilization, and lower recovery costs. These improvements directly address major cost drivers in airline operations, such as crew costs, fuel inefficiencies caused by disruptions, and passenger compensation. From a managerial perspective, these gains translate into measurable improvements in key performance indicators such as on-time performance (OTP), block-hour utilization, and schedule stability.

A further strength is scalability of decision-support systems and their potential adaptability to different operational contexts. Large airline networks generate high-dimensional scheduling problems that are difficult to solve using exact methods alone. Learning-assisted optimization, such as AI-guided column generation or heuristic selection, improves scalability by reducing computational effort while preserving feasibility. These approaches allow optimization frameworks to be applied to larger airline networks and more complex scheduling environments. Although operational constraints and regulatory conditions may differ across airlines and regions, the underlying optimization structures — such as time–space network representations and resource allocation models — are often similar, which facilitates the adaptation of these methods across different airline operating environments. As a result, advanced scheduling techniques can be applied in both large hub-and-spoke networks and airlines operating dense flight schedules, provided that models are calibrated to the specific operational context.

Finally, AI-driven optimization enhances integration across planning horizons and system boundaries. By linking predictive models (e.g., demand or delay forecasting) with tactical and operational optimization, airlines can better align long-term plans with short-term execution. This integration reduces inconsistencies between schedule design, fleet assignment, and recovery actions, a limitation repeatedly identified in the literature on sequential planning.

6.2 Opportunities for broader supply chain and airport performance

Beyond direct airline benefits, AI-driven optimization creates important opportunities for improving supply chain and airport performance. More reliable airline schedules reduce uncertainty in air cargo transport, improve connection reliability, and lower the need for buffer inventories in time-sensitive supply chains. This is particularly relevant for industries that depend on air transport for high-value or perishable goods.

At the airport level, improved schedule stability and recovery capability contribute to reduced congestion and better resource coordination. More predictable arrival and departure patterns support gate assignment, ground handling, and air traffic flow management. As shown in the literature reviewed in Chapter 5, AI-supported decision-making at the airline level can indirectly improve airport performance indicators such as turnaround reliability and taxi-time efficiency.

There are also strategic opportunities related to digital transformation and data-driven management. Airlines that successfully integrate AI-driven optimization into their scheduling processes build capabilities that can be extended to other operational domains, such as maintenance planning and crew training. Moreover, the increasing availability of real-time operational data and advances in computational infrastructure create favorable conditions for scaling AI-enabled decision-support systems.

6.3 Weaknesses and Implementation Challenges

Despite the strengths and opportunities discussed in Section 6.1, the literature consistently highlights significant weaknesses, risks, and uncertainties associated with the adoption of AI-driven optimization in airline scheduling. These challenges extend beyond algorithmic performance and include issues related to data quality, computational cost, cybersecurity, governance, ethical responsibility, environmental sustainability and equitable. As a result, AI should not be viewed as a universally beneficial solution, but rather as a technology whose effectiveness depends on careful design, implementation, and oversight (Razzaghi et al., 2024; Filom et al., 2022).

6.3.1 Data availability, quality, and bias

A primary limitation of AI-based methods is their strong dependence on large volumes of high-quality data. Airline scheduling relies on diverse data sources, including flight operations, aircraft status, crew activity, weather conditions, and airport performance. In practice, these data are often incomplete, noisy, or fragmented across different systems and stakeholders, which can significantly degrade model performance (Xu, Wandelt, & Sun, 2024). In situations where real operational data are unavailable or insufficient, researchers and practitioners sometimes rely on synthetic or simulated datasets to train and evaluate AI models. While synthetic data can facilitate model development and experimentation, it may not fully capture the complexity and variability of real-world airline operations. As a result, models trained primarily on synthetic data may exhibit reduced generalizability or biased predictions when deployed in actual operational environments. Addressing the gap between simulated and real-world data therefore remains an important challenge in the practical implementation of AI-assisted airline scheduling systems.

In addition, AI models trained on historical (or synthetic) data may reproduce or amplify existing operational biases. For example, if past schedules systematically prioritized certain routes, hubs, or crew groups, predictive models may reinforce these patterns rather than correct them. Unlike optimization models, where objectives and constraints are explicitly defined, such biases may remain hidden in data-driven systems and become difficult to detect or justify (Floridi et al., 2018). These concerns are particularly relevant in crew scheduling and recovery, where fairness and workload balance are sensitive issues.

6.3.2 Computational cost and resource requirements

AI-driven optimization also introduces computational and infrastructural challenges. Training advanced machine learning or deep reinforcement learning models can be computationally expensive, often requiring specialized hardware and large-scale simulation environments. While major airlines may have access to such resources, smaller or regional carriers may face barriers to adoption (Razzaghi et al., 2024). Moreover, real-time airline operations require fast and predictable response times, especially in disruption management. AI components that increase latency or require frequent retraining may conflict with operational needs.

6.3.3 Model transparency, interpretability, and trust

Another widely cited weakness of AI systems is their limited transparency and interpretability, particularly for deep learning and reinforcement learning models. In airline scheduling, decisions affect safety margins, regulatory compliance, crew legality, and passenger welfare. If decision-support recommendations cannot be clearly explained, planners may either distrust the system or rely on it without sufficient understanding of its limitations (Floridi et al., 2018). In contrast, traditional heuristics and optimization-based recovery tools are often valued for their transparency and deterministic performance, even if they are less adaptive (Filom et al., 2022).

This issue is especially critical in aviation, where accountability and explainability are central to regulatory compliance. Surveys of AI applications in aviation emphasize that lack of interpretability is a major barrier to operational deployment, particularly for RL-based decision-making systems that learn policies through trial-and-error in simulated environments (Razzaghi et al., 2024).

6.3.4 Cybersecurity, data ownership, and governance risks

The integration of AI into airline scheduling systems increases exposure to cybersecurity and data governance risks. AI-driven optimization relies on continuous data flows, external data sources, and often cloud-based infrastructure, expanding the attack surface for cyber threats. Compromised data or models could disrupt airline operations or expose sensitive operational information.

Data ownership and governance further complicate AI adoption in aviation. Airlines depend on data from airports, air navigation service providers, weather services, and technology vendors, often across multiple jurisdictions. Differences in data protection regulations, unclear ownership rights, and limited data-sharing agreements can constrain the effectiveness of AI-driven scheduling systems and introduce legal and organizational risks (Xu et al., 2024).

6.3.5 *Societal, ethical, and labor-related considerations*

AI-driven optimization also raises ethical and societal concerns, particularly in labor-intensive areas such as crew scheduling and recovery. AI-supported decisions that prioritize efficiency may unintentionally increase workload inequality, reduce schedule stability, or conflict with collective agreements. These concerns are amplified if decision logic is opaque or if human oversight is reduced (Floridi et al., 2018).

From a human-factors perspective, excessive reliance on automation may erode human situational awareness and decision-making skills. Aviation research increasingly emphasizes the importance of human-in-the-loop systems, where AI augments rather than replaces human judgment, especially in safety-critical and socially sensitive contexts (Filom et al., 2022).

In addition, environmental considerations introduce additional uncertainty. Improved scheduling and recovery can reduce fuel burn and emissions by minimizing delays and inefficient aircraft rotations. However, the energy consumption associated with training and operating AI systems, particularly large-scale models, contributes to environmental impact. While this trade-off is rarely quantified explicitly in airline scheduling studies, it is increasingly recognized as an important consideration in the broader AI literature and sustainability discourse (Razzaghi et al., 2024).

6.4 Threats and Risks

Beyond internal weaknesses, the adoption of artificial intelligence and optimization-based decision-support systems in airline scheduling also introduces several external threats and risks. One important concern relates to cybersecurity vulnerabilities, as modern airline and airport management systems rely on extensive data exchange between airlines, airports, and air traffic management organizations. Disruptions or malicious interference in these data flows could affect operational decision-making and network stability. This risk is widely recognized in aviation policy and airport cybersecurity guidance. (Federal Aviation Administration (FAA) 2021).

Another potential threat involves regulatory and certification challenges. The aviation sector operates under strict safety and regulatory standards, and the deployment of AI-assisted decision systems may require extensive validation, transparency, explainability, and trustworthiness before they can be fully integrated into operational environments. Recent

European aviation guidance explicitly emphasizes AI trustworthiness, explainability, learning assurance, and human oversight as prerequisites for the safe adoption of AI in aviation. (European Union Aviation Safety Agency (EASA), 2023; 2024)

Additionally, organizational and workforce-related risks may emerge during the adoption of automated decision-support tools. Operational personnel may be reluctant to rely on algorithmic recommendations if these systems are perceived as reducing human control or accountability in safety-critical processes. Current aviation AI guidance therefore places strong emphasis on a human-centric approach and on maintaining appropriate human–AI teaming rather than replacing human judgment. (European Union Aviation Safety Agency (EASA), 2023; 2020)

Finally, model reliability and robustness risks must also be considered. AI models trained on historical operational data may perform poorly under rare or extreme disruption scenarios that are not well represented in training datasets. In air traffic management and airline operations, this creates the danger that inaccurate predictions or recommendations could propagate through the network if the models are not properly validated, monitored, and constrained by operational safeguards. EUROCONTROL and EASA both note that AI deployment in aviation must address predictability, certification, and safety assurance in operational use. (EUROCONTROL, 2020; 2022)

6.5 Strategic and Managerial Implications for Supply Chain Integration

A central strategic implication of AI-driven optimization is the opportunity to better align airline-centric scheduling objectives with broader supply chain performance goals. Traditional airline scheduling models prioritize cost minimization, aircraft utilization, and on-time performance from the airline's perspective. However, supply chain partners — such as freight forwarders, integrators, manufacturers, and airports — are often more concerned with reliability, predictability, and connection stability.

AI-enhanced scheduling, particularly when combined with predictive analytics, allows airlines to anticipate disruptions and variability earlier. This supports more reliable departure and arrival patterns, which in turn improve cargo transfer times, reduce missed connections, and lower inventory buffers in time-sensitive supply chains (Xu, Wandelt, & Sun, 2024). Strategically, this shifts airline scheduling from a purely internal efficiency tool toward a coordination mechanism within the wider air transport supply chain. AI-driven optimization increases the strategic importance of information sharing and data integration across supply chain actors. Accurate prediction and robust scheduling depend on access to high-quality data from multiple sources, including airports, ground handlers, air navigation service providers, and logistics partners. From a managerial perspective, this creates both an opportunity and a challenge.

On the one hand, shared data platforms and collaborative decision-making systems can improve system-wide operational performance. For example, Airport Collaborative Decision-Making (A-CDM) systems implemented at several major airports enable real-time information sharing among airlines, airport operators, ground handlers, and air traffic control. At Munich Airport, one of the earliest adopters of A-CDM, the implementation of collaborative scheduling and data-sharing systems led to significant improvements in departure predictability and reductions in taxi-out times, contributing to more efficient runway and gate utilization (EUROCONTROL, 2023; Cook & Tanner, 2015). Similarly, London Heathrow Airport has deployed A-CDM platforms combined with advanced surface management tools that allow airlines and airport operators to coordinate turnaround operations and departure sequencing more effectively, reducing delays and improving airport capacity management (EUROCONTROL, 2023).

In major global hubs such as Singapore Changi Airport and Dubai International Airport, integrated airport operations control centers combine predictive analytics, optimization algorithms, and collaborative information systems to coordinate aircraft movements, passenger flows, and ground operations in highly congested environments (Ashford, Mumayiz, & Wright, 2013; de Neufville & Odoni, 2013). These systems enable logistics providers and airport operators to synchronize ground handling, cargo operations, and downstream transport activities more efficiently.

On the other hand, increased data sharing across multiple stakeholders also raises concerns related to governance, confidentiality, and competitive advantage. Airlines and logistics providers may be reluctant to share sensitive operational information, particularly in competitive markets. Managers must therefore balance the benefits of collaborative integration with the risks associated with data governance and operational transparency (Filom, Wandelt, & Sun, 2022).

AI-driven airline scheduling also affects supply chain resilience. As shown in earlier chapters, improved prediction and dynamic recovery reduce the likelihood and severity of disruptions. At the supply chain level, this translates into fewer cascading failures, such as missed cargo transfers or disrupted production schedules. Strategically, airlines that invest in robust and AI-supported scheduling may become more attractive partners within global supply chains, particularly for industries that depend on high service reliability.

However, managers must also recognize that increased digital integration introduces new risks, including cybersecurity threats and systemic dependencies on data-driven systems. Supply chain integration strategies should therefore incorporate risk diversification and contingency planning, ensuring that failures in AI-supported airline scheduling do not propagate unchecked across the broader logistics network (Floridi et al., 2018).

7 Conclusions and Future Research Directions

This thesis has examined airline scheduling through the combined lenses of optimization, artificial intelligence, and hybrid AI–optimization models, with a consistent focus on practical airline applications and their implications for airport and supply chain performance. The central objective was to assess how recent methodological developments can address long-standing challenges in airline scheduling, including scalability, uncertainty, and operational disruption, while remaining feasible within real-world constraints.

This thesis directly addresses the main research question by demonstrating that effective integration of optimization and artificial intelligence in airline scheduling is achieved through hybrid decision-support systems rather than through the replacement of classical methods. Optimization techniques remain essential for enforcing feasibility, legality, and global consistency across aircraft, crew, and network constraints. Artificial intelligence methods, including machine learning and reinforcement learning, complement these techniques by improving prediction accuracy, adaptability, and computational efficiency. Empirical evidence reviewed in this study shows that the most effective airline scheduling systems combine optimization-based decision structures with AI-driven support for uncertainty handling, dynamic response, and scalability. This integration improves both operational performance and system adaptability under real-world conditions.

The review of classical and contemporary literature in Chapters 3 and 4 confirms that optimization-based methods — such as mixed-integer programming, network models, column generation, and branch-and-price — remain the backbone of airline scheduling. These methods provide the problem structure, feasibility, and transparency, which are essential in safety-critical environments governed by strict regulatory and operational constraints. However, the analysis also shows that purely optimization-based approaches face limitations when confronted with uncertainty, dynamic conditions, and increasing problem size, particularly in integrated planning and recovery contexts.

Chapter 5 demonstrated that AI methods add value by addressing precisely these limitations. Machine learning techniques improve the quality of inputs to scheduling models through better prediction of demand and delay risk, while reinforcement learning offers new ways to support sequential and dynamic decision-making in disruption management and operational control. Importantly, the reviewed case studies show that AI is rarely used as a standalone scheduling tool. Instead, it functions primarily as decision support, enhancing anticipation, adaptability, and responsiveness.

The strongest empirical evidence emerges from hybrid AI–optimization models, which combine the strengths of both paradigms. These approaches preserve feasibility and interpretability through optimization, while leveraging AI to improve scalability, robustness, and computational efficiency. Across different application fields, geographical contexts, and decision horizons, hybrid models consistently outperform purely deterministic or heuristic approaches in terms of operational stability and performance.

From a managerial perspective, the findings suggest that airlines should view AI-driven optimization as an evolutionary enhancement of existing scheduling systems rather than a disruptive replacement. Incremental integration — starting with predictive decision support and progressing toward hybrid systems — appears to be the most viable pathway. Maintaining human-in-the-loop designs is critical for trust, transparency, accountability, and regulatory compliance.

For airports and supply chain partners, improved airline scheduling enabled by AI-driven optimization offers opportunities for better coordination, reduced congestion, and increased reliability. However, realizing these benefits requires data sharing, interoperability, and collaborative governance, which remain significant managerial challenges. Policymakers and regulators may also play a role in facilitating secure and standardized data exchange while ensuring fairness and safety.

Additional consistent lessons emerge from the empirical studies reviewed in this dissertation. First, scalability is most effectively addressed through hybrid models, where AI techniques reduce computational burden or guide search while optimization ensures feasibility. Second, robustness is improved when predictive AI models are integrated with scheduling and recovery optimization, allowing earlier anticipation of disruptions and more stable schedules. Third, practical implementation depends strongly on organizational factors, including data quality, system integration, and human oversight. Studies consistently show that AI methods are most successful when embedded within existing decision-support systems and used to augment, rather than replace, human planners. These lessons suggest that methodological performance alone is insufficient to ensure success; implementation context and governance play equally important roles.

Several directions for future research emerge from this work. First, there is a need for more empirical studies using real operational data, particularly to evaluate AI and hybrid models in live or near-live environments. Second, future research should place greater emphasis on explainability, fairness, and governance, especially in crew-related scheduling decisions. Third, the environmental impact of AI-driven optimization — both in terms of operational efficiency gains and computational footprint — remains underexplored and warrants systematic investigation.

In addition to quantitative modeling and simulation studies, future research could also benefit from qualitative approaches, such as interviews or expert consultations with airline managers, airport operators, and air traffic management professionals. Such methods could provide valuable insights into the practical challenges, perceived benefits, and organizational risks associated with implementing advanced optimization and AI-assisted decision-support systems in air transport and supply chain management. Integrating practitioner perspectives would help bridge the gap between theoretical models and real-world operational requirements.

Finally, future work could extend the integration perspective by jointly modeling airline, airport, and supply chain decisions, moving toward truly system-wide optimization and coordination frameworks. Such research would further clarify the role of AI-driven optimization in enhancing resilience and performance across the broader air transport ecosystem.

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