Integrated Hub Location and Schedule Design of Multi-Hub Airline Networks

A Case Study on India's International Connectivity

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Thesis report

by

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Preface

With the conclusion of my thesis project, my academic journey at TU Delft comes to an end. The last years have been a truly enriching experience, both academically and personally.

I would like to express my sincere gratitude to my supervisors Dr. Marta Ribeiro and Marco van Vliet. Their support, critical insights, and encouragement have been instrumental throughout this journey. I am especially thankful for the opportunity to align the project with my interests and explore a topic at the intersection of theory and real-world application.

Moreover, I would like to express my appreciation to the friends who have accompanied me during these years and brought joy and perspective into my life. Your support and companionship have played a vital role in shaping both this thesis and the person I am today.

Finally, I am incredibly grateful to my family for their unwavering support, belief, and love. Thank you for standing by me throughout this journey, your encouragement has meant more than I can express.

Wouter Sougé
Delft, June 2025

Contents

Part I

Scientific Article

Abstract

The Europe-Asia-Oceania air route is experiencing rapid growth, traditionally served by direct legacy flights but increasingly dominated by hub-based carriers. These airlines leverage large, single-hub models to capture transfer traffic. However, limited research exists on how to efficiently design and operate multi-hub networks for international connectivity. Existing models either oversimplify hub capacities or focus solely on fleet planning and re-timing, lacking an integrated, schedule-based approach. This research develops an integrated decision support model that combines a capacitated multi-allocation p-hub location problem with airline schedule design under operational constraints and competitive dynamics. A multi-step iterative method connects hub assignment and scheduling using a genetic algorithm to ensure feasibility, connectivity, and profitability. The findings reveal that adding hubs initially boosts network efficiency and profitability, though marginal benefits diminish after a certain number of hubs. The integrated model significantly narrows the gap between theoretical and actualized profitability, showing a 7.6% increase in daily profit for the scheduling model over iterations. This research offers a crucial decision-support tool for long-term airline network planning, particularly in rapidly expanding aviation markets. Its ability to jointly optimize hub locations and flight schedules under operational constraints provides substantial utility for diverse airline network planning scenarios, leading to more viable and profitable network configurations.

1 Introduction

The route from Europe to Asia, and even further to Oceania, is on the rise (EUROCONTROL, 2025). This has long been served by legacy airlines with, mostly, direct flights. However, this trend has started to shift in recent years. Major airlines strategically placed themselves to serve this route, mainly the Gulf carriers (Emirates, Qatar and Etihad) and Turkish Airlines at the expense of European airlines with direct flights (Georgiadis, 2024). These airlines position themselves with large hubs and dedicated connection banks to connect as many passenger as possible. For example, around two-thirds of Turkish Airlines' passengers use Istanbul as a transfer hub, highlighting its role in connecting traffic (OAG Aviation Worldwide, 2025).

These airlines all operate from a single hub airport and there is limited research on how to utilize multi-hub network efficiently to serve international to international traffic flow. (Yang, Delahaye, et al., 2024) is the only paper to focus on increasing the efficiency of multi-hub network from an airline planning perspective. Looking at it from a hub location problem ("HLP") perspective, (Mohri et al., 2022) and (Nasrollahi & Kordani, 2023) are the only papers on integrating the HLP with airline planning, but limited to the integration of fleet planning.

Existing literature on multi-hub airline network design primarily focuses on re-timing individual flight legs, lacking a comprehensive approach to constructing full flight schedules for multi-hub systems from a zero starting point. Furthermore, competitive hub location models often rely on simplified assumptions such as uncapacitated hubs and fixed connection times, which limit their applicability to real-world operations. There remains a clear gap in integrated models that jointly optimize hub locations and flight schedules while accounting for competitive dynamics and operational constraints across multiple hubs.

This research paper aims to develop an integrated framework for multi-hub allocation and schedule design ("SD"), incorporating geographical and demand information as well as airline capacity constraints. To achieve this, two existing models, a HLP model and a SD model, are combined into a multi-step iterative approach. The HLP model determines which spokes are allocated to specific hubs, while the SD model checks the viability of the allocated flow and creates a timetable from the ground up.

The paper starts with the problem statement in Section 2. Section 3 presents a literature review on hub networks and airline planning models. In Section 4, the methodology outlines the approach and models used. Section 5 introduces the hypotheses guiding this research. The application of this framework to IndiGo's possible expansion strategy is detailed in Section 6, followed by the results in Section 7. Section 8 validates the findings through sensitivity analysis, assessing the robustness of the proposed model. Finally, Section 9 discusses the implications of these results and potential future research directions, leading to the conclusions in Section 10.

2 Problem Statement

In network planning, there are two distinct network configurations, namely a point-to-point network and a hub-and-spoke network. The point-to-point network is mostly favored by low-cost carriers operating between secondary airports. This is due to only direct flights, which enable reduced operational complexity, costs, and total travel time (Cook & Goodwin, 2008; Martí et al., 2015; Zgodavová et al., 2018). This model also enhances airline flexibility, especially in dynamic markets, and offers environmental benefits through

[0] AI tools were used to assist with coding and academic writing throughout the research process.

reduced emissions (Morrell & Lu, 2007). A point-to-point network has generally its limitations in lower load factors, connectivity, and reduced frequency, making it less suitable for routes with limited demand (Alderighi et al., 2005; Martí et al., 2015). In contrast, the hub-and-spoke model enables higher connectivity and frequency by routing passengers through a hub, enabling economies of scale and increased flexibility in uncertain and limiting markets (Barla & Constantatos, 2000; Brueckner & Spiller, 1994; Wheeler, 1989). This model also has its vulnerabilities such as reliance on a single airport which results in hub congestion and negatively impacts travel time and sustainability (Pels, 2021; Wheeler, 1989). A Multi-hub network could overcome these drawbacks by extending market reach, reducing delays and less travel time (Chou, 1990; Goedeking, 2010; Karaman, 2018). While the added complexity may reduce density economies (Düdden, 2006), frequency gains and regional adaptability often outweigh the downsides in thinner markets (Burghouwt, 2014).

Currently, multi-hub systems are present in the aviation industry. Good examples are Delta, Lufthansa and China Southern Airlines. (Burghouwt, 2014) shows a distinction in types of multi-hub systems: the complementary system, the overflow system, and the regional systems. Firstly, the complementary multi-hub system can be seen in two or more evenly distributed hubs that serve both long-haul flights. This results in a high-yield local market at both hubs at the same time. The hubs are complementary on smaller (international) destinations. Secondly, the overflow system contains a primary hub and smaller hubs, which do not have any natural advantages. The smaller intercontinental destinations are served from the primary hub. Lastly, the regional system, when the local geographical market cannot be covered by the primary hubs. In most cases, multi-hub networks were created through mergers & acquisition. The acquired hubs are by default downgraded to less of importance hubs without empirical evidence. None have gone from mostly domestic flight to long-haul flight overnight. So for these instances, how many hubs do you need to serve the demand? How do you decide which hub will have which role? What should be the location of these hubs? And what influences these decisions?

Although multi-hub systems are becoming increasingly common, there is a notable lack of decision-support models that provide guidance on where hubs should be located and how their roles should be defined. This gap is especially critical in rapidly growing aviation markets such as India, where carriers like IndiGo are expanding their international presence amid growing capacity constraints at major airports like Delhi and Mumbai. Most existing literature on multi-hub network design focuses narrowly on re-timing individual flight legs, rather than developing comprehensive flight schedules from the ground up. Moreover, many competitive hub location models rely on assumptions, such as unlimited hub capacity and fixed connection times, that undermine their practical relevance. As a result, there is a clear need for integrated models that can jointly optimize hub location, role assignment, and schedule design, while incorporating operational constraints and competitive dynamics across multiple hubs.

This research addresses that gap by developing an integrated optimization model for multi-hub airline network planning. The model assigns airports to hubs and designs corresponding flight schedules under operational constraints, such as hub capacity, aircraft availability, and minimum connection times. The objective is to maximize overall network profitability by optimizing both direct and transfer passenger flows, while simultaneously minimizing transfer times to enhance connectivity and passenger experience. The model serves as a strategic decision-support tool. It does not attempt to model detailed demand forecasting or short-term operational disruptions, but instead focuses on long-term, high-level network design.

3 Related Work

This section outlines the related work relevant to multi-hub airline planning. Section 3.1 focuses on the work within airline planning, such as Schedule Design, Fleet Assignment and Aircraft Routing. Section 3.2 goes more in-depth into the HLP. At last, the research gaps and main research objective are described in Section 3.3.

3.1. Airline Planning

Airline planning is a complex and multi-layered process, and it involves decisions at strategic, tactical, and operational levels. At a strategic level, fleet planning decides on the types and numbers of aircraft to be operated, while network development addresses the choice of destinations and the overall network design. This study specifically focuses on frequency and schedule planning, which involves evaluating destination demand, setting flight frequencies, and creating preliminary schedules. At a tactical- and operational level, resource allocation assigns specific aircraft and crew to each flight, a topic that is outside the scope of this study. Similarly, while maintenance planning and financial optimization are critical aspects of airline planning, they also lie beyond the scope of this research. Although the planning components are categorized, they are intricately connected in practice, adding to the complexity of the planning process.

To start with the fleet assignment model (”FAM”), the FAM focuses on allocating different types of aircraft to scheduled flights. In most cases with the aim to maximize profits (Abara, 1989; Hane et al., 1995). The two main structures within the FAM are the connection network (Abara, 1989) and the time-space network (Hane et al., 1995). The connection network captures aircraft transitions between flights with explicit connection arcs and turn-time constraints, and the time-space network, which simplifies variable counts by modeling flight legs through time and space but lacks aircraft-specific detail (H. D. Sherali et al., 2006). (Barnhart et al., 2002) introduced the itinerary-based fleet assignment model, which integrated a Passenger Mix Model into the FAM to better reflect passenger dynamics such as spill and recapture. The integration of schedule design and fleet assignment was further advanced by (Lohatepanont & Barnhart, 2004), who proposed the Integrated Schedule Design and Fleet Assignment Model (ISD-FAM) building upon the IFAM framework to optimize both flight leg selection and aircraft assignment while incorporating demand correction terms for a dynamic market.

To improve flexibility in an integrated airline scheduling and fleet assignment model, (H. Sherali et al., 2013) introduced optional flight legs, itinerary-based demand with multiple fare classes, and balance constraints to ensure an even distribution of flights across the day. This model already presents a well-rounded solution approach with various real-world considerations. However, it requires a predefined set of mandatory flight legs. A further extension to airline planning with airport congestion was proposed by (Pita et al., 2013), who integrated delay costs and congestion effects within a multi-hub setting. It shows improvements in profitability and operational efficiency.

Within airline planning, most of the time the objective is to maximize profit. One of the key drivers for profitability is whether passengers opt to fly with the airline. (Abdelghany et al., 2017) included passengers' choice into an optimization framework that integrates scheduling decisions within competitive markets, surpassing previous models by adopting a more dynamic and comprehensive approach and solving it using a genetic algorithm. In a similar way, (Wei & Jacquillat, 2019) underscored the importance of incorporating passenger preferences into the scheduling process as opposed to modifying pre-existing timetables. (Ciftci & Özkır, 2020) focused on minimizing passenger connection times at hubs by employing meta-heuristic approaches, enhancing convenience for passengers and alleviating congestion.

At a strategic level, (Birolini, Jacquillat, et al., 2021) introduced a model that captures long-term supply and demand interactions, resolved through an innovative gradient-based algorithm. (Birolini, Pais Antunes, et al., 2021) addressed this issue by introducing a new advanced optimization model that simultaneously plans the flight schedule and aircraft use while also estimating and distributing passenger demand. (Yang, Buire, et al., 2024) developed a multi-objective model intended to optimize hub connectivity by employing a Quality of Connectivity Index metric, effectively balancing detour distances and connection times.

To the best knowledge of the author, (Yang, Delahaye, et al., 2024) are the first and only authors focusing on improving efficiency specifically focused on a multi-hub network. Previous research has included multiple hubs within their network for a case study, but never the focus on utilizing the hubs as efficiently as possible. (Yang, Delahaye, et al., 2024) proposed a model to re-time flight legs in order to increase the total connectivity of the network measured by a modified Hub Connectivity Index. It showed significant results, but the scope was limited to re-timing and therefore not applicable to building a network from the ground up.

An overview of the important research done in this field is presented in Table 3.1.

Table 3.1: Literature Overview Airline Planning

Paper	Network Type			Problem			Focus						Algorithm
	P2P	H&S	multi-hub	SDP	FAP	ARP	Demand	Connectivity	Competition	Passenger Choice	Fares	Airport Congestion	
(Abara, 1989)					x		x	x					ILP
(Hane et al., 1995)		x			x		x	x			x		B&B
(Barnhart et al., 2002)		x				x		x					CRG
(Lohatepanont & Barnhart, 2004)		x		x	x								CRG, B&B
(H. D. Sherali et al., 2006)		x		x	x	x		x	x		x		N/A
(Yan et al., 2008)	x			x	x			x		x			HA
(H. Sherali et al., 2013)		x			x		x			x		x	BD
(Pita et al., 2013)		x	x		x	x			x			x	XS
(Abdelghany et al., 2017)		x		x			x		x	x			GA
(Wei & Jacquillat, 2019)			x	x	x			x	x	x			RBH
(Ciftci & Özkır, 2020)		x		x				x					TS & SA
(Birolini, Pais Antunes, et al., 2021)		x		x	x		x		x				PLT
(Birolini, Jacquillat, et al., 2021)		x	x	x	x		x	x					CPA
(Yang, Delahaye, et al., 2024)			x	x				x					SSA
(Yang, Buire, et al., 2024)		x	x	x				x					SA

Algorithm Abbreviations:
ILP = Integer Linear Programming, B&B = Branch and Bound, CRG = Column-and-row generation, HA = Heuristic Algorithms, BD = Bender Decomposition,
XS = Xpress (Commercial Solver), GA: Genetic Algorithm, RBH: Rule-Based Heuristics, TS: Tabu Search, SA: Simulated Annealing, CPA: Cutting-Plane Algorithm

3.2. Hub Location Problem

There is limited research on optimizing airline planning using multiple hubs, so it is useful to examine the more general HLP. The HLP focuses on strategically placing hubs to maximize overall network efficiency, which can be measured in various ways (Farahani et al., 2013). (O'Kelly, 1987) was the first to explore the HLP and presented the first optimization-based formulation. Since then, the number of variants has increased. These variants can be classified based on the hub node capacity, the assignment of non-hub nodes to hubs, the objective, and the number of hubs. Table 3.3 provides a concise summary of these classifications.

Table 3.3: Classification of HLP Models (Farahani et al., 2013)

Capacity of hub node	Assignment of non-hub node to hub nodes
Capacitated (C)	Single allocation (SA)
Uncapacitated (U)	Multiple allocation (MA)

Type of the HLP	Number of hub nodes
Median (M, min cost)	Single (1)
Center (T, min distance)	More than one (P)
Covering (V, # nodes)	

In the context of the airline industry, the HLP typically takes the form of a C-MA-…-P problem. Although, the objective is more complex as it may involve dynamic demand or competitive factors. Several studies have extended the traditional HLP to capture competitive settings and operational nuances. (Eiselt & Marianov, 2009) developed a competitive hub location framework that incorporates an attractiveness function based on travel time and fares. This is later extended by (Tiwari et al., 2021a) and (Tiwari et al., 2021b) to handle large-scale instances using approaches like Kelley's cutting plane method within Lagrangian relaxation. (Soylu & Katip, 2019) proposed a bi-objective uncapacitated multiple allocation p-hub median problem to enhance customer satisfaction by increasing direct and one-stop routes.(Yin & Zhao, 2021) introduced a data-driven robust mean-CVaR hub interdiction model accounting for uncertainty in travel times. In the recent years, research on integrating fleet planning with hub location has emerged, with (Mohri et al., 2022) pioneering an integrated approach and (Nasrollahi & Kordani, 2023) further incorporating passenger preferences and time valuation. (Hatipoğlu et al., 2024) focused on selecting secondary hubs under connectivity and green airport criteria. An overview of the HLP can be seen in Table 3.2.

3.3. Research Gap & Research Objective

Substantial progress has been made in various facets of airline planning and the hub location problem. However, the literature review reveals existing opportunities for further development, particularly concerning their integration. Focusing on airline planning, it can be observed that a lot of research has been conducted on schedule design and fleet assignment, primarily focusing on demand, connectivity, and re-timing flight legs. Only one study focused on the optimization of a multi-hub network while that was also only on re-timing flight legs rather then building a timetable (Yang, Delahaye, et al., 2024). Furthermore, airport congestion has been scarce in research, with (Pita et al., 2013) being the only study that incorporates congestion and competition. However, their model did not fully account for time costs like in-flight and connecting time. At the HLP, competitive models have used uncapacitated hubs most of the time with fixed connecting time (Eiselt & Marianov, 2009; Tiwari et al., 2021b). Some studies have integrated hub location with fleet planning (Mohri et al., 2022; Nasrollahi & Kordani, 2023), however they fail to capture the complexities introduced by capacitated hubs and schedule design.

Given the research gaps provided, this research focuses on developing an integrated model that combines the capacitated multi-allocation p-hub location problem with airline schedule design under competitive and operational conditions. The proposed approach aims to optimize for profitability and connectivity. This results in the research objective:

To develop a robust integrated hub location and schedule design model that accounts for operational constraints and competition, with the goal of creating an airline network optimized for maximum profitability.

This highlights the opportunity to enhance existing models by incorporating the complexity of multi-hub airline network planning under competitive pressures and operational limitations.

Table 3.2: Literature Overview Hub Location Problem

Title	Capacity		Allocation		Number of hubs		Algorithm	Relation to airline industry
	Uncapacitated	Capacitated	Single	Multiple	1	p		
(Eiselt & Marianov, 2009)	x			x		x	Heuristic concentration procedure	Competition / attractiveness of hubs
(Soylu & Katip, 2019)	x			x		x	Variable Neighborhood Search	Minimize transportation cost & 2-stop journey
(Tiwari et al., 2021a)	x			x		x	LR-CPA	Competition / attractiveness of hubs
(Tiwari et al., 2021b)	x		x	x		x	LR-CPA	Competition
(Yin & Zhao, 2021)	x		x			x	Sample Average Approximation	Minimize transportation cost
(Mohri et al., 2022)	x			x		x	Commercial solver (exact, GAMS)	Minimize cost
(Nasrollahi & Kordani, 2023)	x		x			x		Passengers choice

4 Methodology

There are several benefits of an integrated model. The first benefit is that an integrated approach improves consistency between hub allocation and scheduling by ensuring that the hubs used can actually support a feasible and profitable schedule, avoiding mismatches between strategic and operational decisions. The second benefit; it reduces the risk of suboptimal outcomes that often arise when models operate in isolation, as joint optimization prevents locally optimal solutions that fail when combined. The last benefit is by coordinating decisions across the models, the approach minimizes passenger transfer times, ensuring that the final schedule not only meets operational constraints but also delivers an optimized passenger experience.

The following chapter outlines the methodology used. In Section 4.1, a high-level overview is given of the methodology and how the different models interact. Section 4.2 focuses on the first model, namely the HLP model. Section 4.3 consists of the SD models. Section 4.4 provides basic functions needed to process the data.

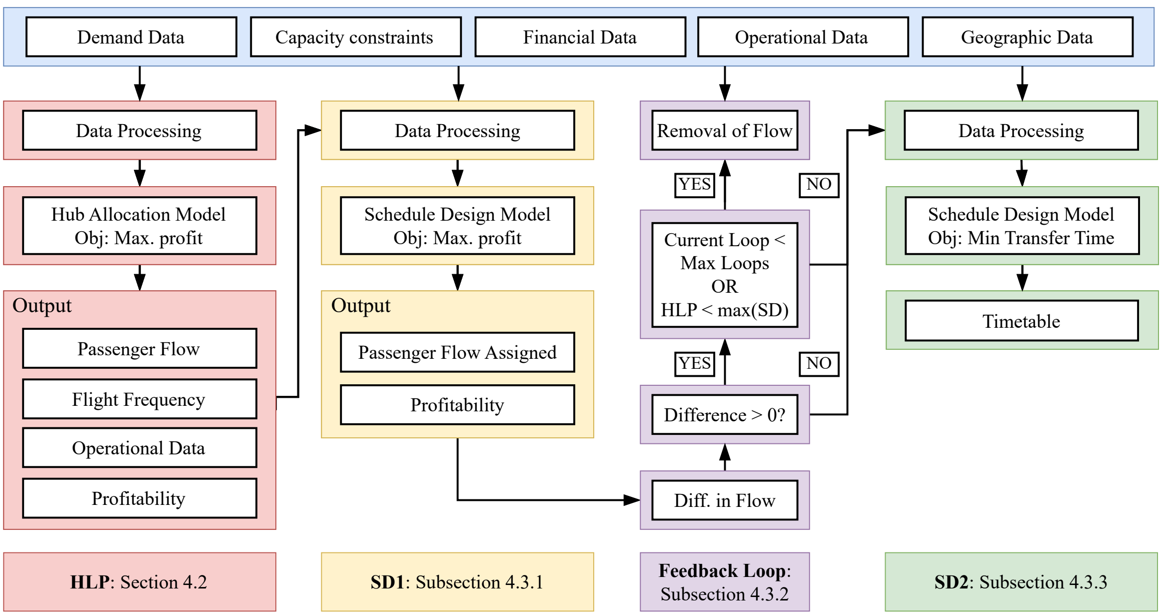
4.1. Overview

Figure 4.1 provides a high-level overview of the research methodology workflow. The diagram is divided in a top-level row with the input data. Below this top level row, the three different models and feedback loop are positioned in four columns. Each model is displayed with a different color. The first model is the HLP model (red color) and is used for two reasons. The first is to evaluate how many and which hubs are necessary to get a theoretically optimal multi-hub network. The second reason is to get input data for the subsequent model. The objective of this model is to maximize the daily profitability. The second model ("SD1") is the schedule design model using a genetic algorithm, which is displayed in yellow. This intermediate step is taken to check if the theoretical passenger flow can be assigned given (mainly) time constraints. The objective is in essence to maximize profitability and maximize the assigned flow. This will be further explained in Section 4.3.1. The third column, in purple, of the figure shows the feedback loop. As it is not likely that the flow determined by the HLP model can all be scheduled. However, unscheduled capacity leaves room for opportunity. The passenger flow that cannot be scheduled will be removed from the model and the HLP model and SD1 model will run again until there is no difference between passenger flow and assigned passenger flow, the maximum value in the SD1 model exceeds the new value of the HLP model, or the maximum number of loops is met. The third and last model (green color) is again, a schedule design model ("SD2"), however there is one major difference with the previous model. The passenger flow inserted into this model can be assigned within certain time constraints and therefore the objective is minimizing transfer time as maximum profitability is guaranteed. In the following sections, an in-depth analysis is given of each model.

4.2. Hub Location Problem Model

For this research, a capacitated, multi-assignment, profit-maximizing p-hub model (C-MA-Profit-P) is used. This variant includes upper bounds on hub capacity (capacitated), allows each spoke to connect to multiple hubs (multi-assignment), aims to maximize total

Figure 4.1: High-level overview of the research methodology workflow.



network profitability, and there are P number of hubs. This framework will allow for evaluating hub-spoke structures under realistic constraints such as aircraft utilization and airport capacities (Farahani et al., 2013). The model is inspired by (Nasrollahi & Kordani, 2023) and (Sharma et al., 2021). In Table 4.1 and Table 4.2, the decision variables and parameters of the model can be found.

Table 4.1: Decision variables (HLP Model)

Variable	Meaning
d_{ij}	Direct flow from $i \to j$
t_{ijh}	Transfer flow $i \to j$ via h
f_{ij}	Flights from $i \to j$
u_{ij}	1 if long-haul aircraft used from $i \to j$

Table 4.2: Model parameters (HLP Model

Parameter	Meaning
C_h	Capacity of hub h
AC_{Long}	Seats per long-haul a/c
AC_{Short}	Seats per short-haul a/c
R_l, R_s	Distance thresholds
$Dist_{ij}$	Distance i–j
α	Min. load factor
D_{ij}	Demand i–j
TC_{ijh}	Transfer cost i–j via h
TF_{ijh}	Transfer fare i–j via h
DC_{ij}	Direct cost i–j
DF_{ij}	Direct fare i–j
T_{ij}	Flight time i–j
TaT	Turnaround time
T_{day}	Daily flight time
A^{long}	Long-haul a/c available
A^{Short}	Short-haul a/c available
RF	Reverse-flow factor
N	All nodes
H	Hub nodes
S	Spoke nodes ($N \setminus H$)

The objective function and constraints of the HLP are defined as follows:

$$\max \sum_{\substack{i,j,h \in N \\ h \in H}} (TF_{ijh} - TC_{ijh}) \cdot t_{ijh} \tag{4.1}$$

$$+ \sum_{\substack{i,j \in N \\ i \in H \vee j \in H}} (DF_{ij} - DC_{ij}) \cdot d_{ij} \tag{4.2}$$

Subject to

$$\sum_{i \in N} f_{ih} + \sum_{i \in N} f_{hi} \leq C_h \qquad \forall h \in H \tag{4.3}$$

$$\sum_{i,j \in N} f_{ij} \cdot (t_{ij} + TaT) \cdot u_{ij} \leq A^{\text{long}} \cdot T_{\text{day}} \tag{4.4}$$

$$\sum_{i,j \in N} f_{ij} \cdot (t_{ij} + TaT) \cdot (1 - u_{ij}) \leq A^{\text{short}} \cdot T_{\text{day}} \tag{4.5}$$

$$\sum_{j \in N} t_{ijh} + \sum_{j \in N} t_{jhi} + d_{ih} \leq f_{ih} \cdot (u_{ih} AC_{\text{Long}} + (1 - u_{ih}) AC_{\text{Short}}) \quad \forall i \in N,\, h \in H \tag{4.6}$$

$$\sum_{i \in N} t_{ijh} + \sum_{i \in N} t_{hij} + d_{hj} \leq f_{hj} \cdot (u_{hj} AC_{\text{Long}} + (1 - u_{hj}) AC_{\text{Short}}) \quad \forall j \in N,\, h \in H \tag{4.7}$$

$$\sum_{j \in N} t_{ijh} + \sum_{\substack{j \in N \\ i \in H}} t_{jhi} + d_{ih} \geq \alpha \cdot f_{ih} \cdot (u_{ih} AC_{\text{Long}} + (1 - u_{ih}) AC_{\text{Short}}) \quad \forall i \in N,\, h \in H \tag{4.8}$$

$$\sum_{i \in N} t_{ijh} + \sum_{\substack{i \in N \\ j \in H}} t_{hij} + d_{hj} \geq \alpha \cdot f_{hj} \cdot (u_{hj} AC_{\text{Long}} + (1 - u_{hj}) AC_{\text{Short}}) \quad \forall j \in N,\, h \in H \tag{4.9}$$

$$u_{ij} = 0 \qquad \forall i,j \in N : Dist_{ij} < R_s \tag{4.10}$$

$$u_{ij} = 1 \qquad \forall i,j \in N : Dist_{ij} > R_l \tag{4.11}$$

$$\sum_{i \in N} f_{ij} \cdot u_{ij} = \sum_{k \in N} f_{jk} \cdot u_{jk} \qquad \forall j \in N \tag{4.12}$$

$$\sum_{i \in N} f_{ij} \cdot (1 - u_{ij}) = \sum_{k \in N} f_{jk} \cdot (1 - u_{jk}) \quad \forall j \in N \tag{4.13}$$

$$\sum_{h \in H} t_{ijh} + d_{ij} \leq D_{ij} \qquad \forall i,j \in N \tag{4.14}$$

$$d_{ij} = 0 \qquad \forall i,j \in S \tag{4.15}$$

$$\sum_{h \in H} t_{jih} + d_{ji} \;\geq\; RF \cdot \left(\sum_{h \in H} t_{ijh} + d_{ij} \right) \quad \forall i,j \in N \tag{4.16}$$

The first constraint (4.3) ensures that the total number of incoming and outgoing flights at each hub does not exceed its capacity. Constraints (4.4) and (4.5) limit the total aircraft time used by long-haul and short-haul aircraft, respectively, ensuring that the total time (including turnaround time) does not exceed the available fleet hours per day. Constraints (4.6) and (4.7) ensure that the total passenger flow (direct and transfer) on each node pair does not exceed the available seat capacity, which depends on the aircraft type (short- or long-haul). Constraints (4.8) and (4.9) enforce a minimum load factor for each operated flight. Constraints (4.10) and (4.11) enforce aircraft type based on distance. Constraints (4.12) and (4.13) ensure that the number of aircraft entering and exiting each airport is balanced, for both long-haul and short-haul aircraft separately. Constraint (4.14) caps total passenger flows between origin-destination pairs by the respective demand. Direct flights between spokes are disallowed by constraint (4.15). Finally, constraint (4.16) enforces a minimum level of reverse passenger flow to ensure realistic two-way connectivity between city pairs.

4.3. Schedule Design Model

The second model (Figure 4.1: yellow) and third model (Figure 4.1: green) are, as mentioned, the schedule design model. The SD1 model has as objective to assign as much passenger as possible or as much profit as possible using a genetic algorithm. This is explained in Subsection 4.3.1. The feedback loop (Figure 4.1: purple) is discussed in Subsection 4.3.2. The SD2 model is the schedule model with the focus on minimizing transfer time, which is described in Subsection 4.3.3.

4.3.1. Maximize profitability: Genetic Algorithm

Genetic Algorithm Design

After the optimal number of hubs and assigned spokes are determined by the HLP Model in Section 4.2, the SD model is the next step in the workflow seen in Figure 4.1. In short, the SD model assigns flights to a specific time in the day in order to capture the most profit and/or passenger flow. In this research, this also happens, but with a slightly different purpose.

The objective of scheduling flights is to maximize the passenger flow and/or profitability while having minimal transfer time in order to stay competitive. In theory, the first part is taken care of in the first model, so the only objective should be minimizing transfer time. However, it might not be possible to schedule a flight within a certain time-frame resulting in a large transfer time which is competitively not advantageous. To mitigate this problem, the SD1 model is introduced to assign flights and passenger flows within certain time constraints. This allows for the passengers that cannot be assigned, to be removed. The passengers that can be assigned will be moved to the third model to optimize for transfer time.

The SD1 model is optimized using a genetic algorithm instead of exact methods due to the limitations of time and computing power in the time available for this research. Heuristic algorithms aim to find good and feasible solutions within a desirable timeframe, but not the optimal solution. These methods focus on efficiency and practical usage. There is a difference between heuristics and metaheuristics. Heuristics has no local optimum escape mechanism while metaheuristics does. Partially, this results in heuristics finding a feasible solution quickly while metaheuristics are better in finding a near-optimal solution. Genetic algorithm is an example of a metaheuristic algorithm. Genetic algorithms were chosen over Simulated Annealing and Tabu Search because their population-based approach allows for broader exploration of the solution space. Compared to Tabu Search, which focuses on improving a single solution through local search, Genetic algorithms are better suited to exploring diverse regions of the solution space simultaneously, making them more effective for handling the complexity and multiple constraints of the SD problem.

The genetic algorithm starts with an initial population of the size of x times the total number of time steps. This ensures that every flight is assigned to every viable time step at least once, and up to x times. This results in a solution space where every possibility is available. The chromosomes are formatted in (Flight, Departure Time), and the departure time is variable. After the first iteration of the integrated model, the initial population contains partially the schedule of the best solution of the previous best iteration, which is a warm start. This is done as flights in iteration one have a high chance of being in the subsequent iteration.

The chromosomes of the initial population are evaluated using a fitness function with an alternating objective. Before the fitness function, two checks are performed. The first check is which routes are possible to fly by the aircraft. This means that an aircraft arriving at a spoke needs to depart within a specific time frame. This can be to the original hub, but it is also possible to return to another hub, which is one of the benefits of a multi-hub network. The second check is to compute all the transfer connections possible. So if a flight arrives at the hub, which outbound flight can passengers take within a maximum transfer time window. It should be also noted that transfer flow can occur from hub A to spoke B via hub C.

The passenger assignment and fitness evaluation involves three steps. The first step is an assignment of the passengers based on their unit profitability, e.g. profitability per passenger. The problem is that some flights may be filled with direct passengers with a high profitability while there is also the need to get transfer passengers on that flight so they can connect to their next flight on time. This is solved in the second step, which is a spill and recapture model. The model looks if some of the initially assigned passengers can be spilled and recaptured on other flights. This again happens based on the unit profitability. The last step is to compile the objective of the fitness function, which can be maximizing profit or maximizing passenger flow. It starts to optimize for maximizing profitability, but when the solution converges, it switches to optimizing for maximizing flow. This allows for the genetic algorithm to escape local optima. In essence, maximizing flow also increases profitability; however, sometimes passengers are taken at a loss to satisfy the load factor constraint. The fitness function is a percentage of the profit or passenger flow determined in the HLP Model.

Elitism is integrated into the model as the flights within the chromosomes are highly dependent on each other in terms of connections and routes possibilities. So it is beneficial to keep the top performing schedules. Parents are selected with a probability based on their fitness function, so it is not automatically the highest rated chromosomes. Crossover and mutation are applied to the parents and a new population is formed. If the genetic algorithm is above a threshold or has not improved by toggling the objective function, the genetic algorithm will be terminated.

This genetic algorithm is inspired by (Abdelghany et al., 2017). The outline of the genetic algorithm can be found in algorithm 1.

Algorithm 1: Genetic Algorithm for Assigning Passenger Flow

```
if Iteration > 1 then
    Warm-start population;
population ← InitializePopulation;
for generation in generations do
    if fitness improvement < convergence gap then
        Toggle objective;
    // Evaluate population fitness
    fitnesses ← [];
    foreach individual in population do
        fitness ← Evaluate Fitness;
        Append fitness to fitnesses;
    // Check stopping conditions
    if max(fitnesses) ≥ cutoff optimal or no improvement for x generations then
        break;
    // Select new population based on fitness
    Elite ← top individuals by fitness;
    Selected ← Selection();
    // Preserve elite, then refill with offspring
    New population ← top (elite) ;
    while size of new population < population size do
        for each pair (parent1, parent2) in selected do
            (child1, child2) ← Crossover;
            Mutate;
            Add child1 and child2 to new population;
Best Individual ← individual with highest fitness;
return Best Individual and associated outputs;
```

Genetic Algorithm Tuning and Objective Evaluation

To determine a suitable configuration for the genetic algorithm, hyperparameter tuning was conducted using the One-Factor-At-a-Time principle. This method involves varying one parameter at a time while keeping all others fixed, allowing the isolated impact of each parameter on the performance score to be measured. The objective was to identify which parameter settings yield the highest solution quality for both small and large instances of the problem. To account for the stochastic nature of the algorithm, each configuration was evaluated by running the genetic algorithm three times, and the average score of those runs was used to determine the best-performing value for each parameter.

Table A.1, in the appendix, presents the results of parameter tuning for the genetic algorithm across both small and large datasets. The large dataset consists of 146 flights, generating a total of 10,626 transfer passengers and 10,264 direct passengers. These transfer passengers are spread out over 236 itineraries. The small dataset includes 76 flights, with 6,052 direct passengers and 5,095 transfer passengers over 75 itineraries.

The data structure determines the ordering of flights within each chromosome, which directly influences how crossover is performed. Since the child inherits flight sequences from both parents, this structure shapes how information is combined and passed on. Three structures were tested: hub-focused, spoke-focused, and random. In the hub-focused structure, outbound - and inbound flights are placed after each other. This enables the crossover cut to more effectively explore new hub-based connection patterns. The spoke-focused structure groups flights by spoke, maintaining routing consistency. The random structure shuffles all flights, maximizing diversity. Each structure affects how effectively genetic operations explore and exploit the solution space.

For the small dataset, the algorithm performed best with a relatively high mutation rate of 0.01 and a large selection size of 0.75, indicating a need for greater diversity during the search process. A hub-focused data structure and a higher elitism rate of 0.2 further improved performance. In contrast, the large dataset favored a lower mutation rate of 0.005 and a more balanced selection size of 0.5, suggesting a stronger emphasis on convergence stability. Interestingly, a random data structure (slightly) outperformed the other options, and a standard elitism rate of 0.1 provided the best results. As expected, increasing the population size and number of generations consistently enhanced solution quality. These findings highlight the sensitivity of the algorithm to hyperparameter settings and were used to guide the final configuration in the main experiments.

In addition to tuning parameters, different optimization objectives were tested. These included maximizing total passenger flow, maximizing profit, or using a combined objective that balances both. Table A.2, in the appendix, presents an overview of the tested objectives and their corresponding performance scores. The table shows that while optimizing solely for flow or profit yields good results, combining both objectives performs best. Especially the dynamic combined objective, which switches between flow and profit, achieves the highest average profit (91.9%) and flow (87.3%), indicating that a balanced approach leads to superior overall network performance.

Figure A.1, in the appendix, visualizes the evolution of the objective function throughout the generations of the genetic algorithm. Notably, it captures the moment the objective switches from profit maximization to flow maximization and how this has a positive effect.

4.3.2. Feedback loop

After each iteration of the genetic algorithm, certain flows cannot be scheduled due to various reasons, such as operational constraints. This could be that there is no connecting flight or the aircraft exceed the maximum ground time at a spoke. These flows are stored in a list (FNP) and excluded from the optimization in the subsequent iterations of the HLP model. To account for this, an additional constraint is added to the HLP, as shown below:

$$\sum_{i,j,h \in \mathrm{FNP}} t_{ijh} = 0 \tag{4.17}$$

It should be clarified that if spoke i via hub h_1 to spoke j is not possible, it is still possible to transfer through a different hub ($h_{2,3,..}$).

4.3.3. Minimize Transfer Time: Exact Method

The third and last step in the process is the SD2 model focused on minimizing the transfer time. In the SD1 model, it is already proven that it can take the passenger within a certain transfer time. This is the maximum allowable transfer time. In the SD2 model, it is going to optimize the schedule to make the most competitive schedule possible. The following model is inspired by (Wei & Jacquillat, 2019). The decision variables and input parameters used in the SD model are summarized in Tables 4.3 and 4.4, respectively. The decision variables define the scheduling and flow decisions, while the input parameters specify the sets, time definitions, demand limits, and aircraft availability used throughout the formulation.

Table 4.3: Decision variables (SD Model)

Variable	Meaning
$t^{dep}_{f,t}$	1 if flight f departs at time t
$t^{arr}_{f,t}$	1 if flight f arrives at time t
$z^{dep}_{i,t}$	Itinerary i departs at hub at t
$z^{arr}_{i,t}$	Itinerary i arrives at hub at t
$q^{dep}_{r,t}$	Route r departs at time t
$q^{arr}_{r,t}$	Route r arrives at time t
$FIA_{f,t}$	1 if flight f is airborne at t
TF_i	Transfer flow on itinerary i
DF_f	Direct flow on flight f
R_r	1 if route r is used
IT_i	1 if itinerary i is used

Table 4.4: Input parameters (SD Model)

Parameter	Meaning
F	Set of flights (o, d)
TS	Discrete time steps
N	Network nodes
S	Max dep./arr. per node/time
FT_{ij}	Flight time $i \to j$
PI, PR	Possible itineraries/routes
HB	Hour buckets
FS_s	Flights to spoke s
BT, ET	Start/end of schedule horizon
SH	Time steps per hour
$MaxTF_i$	Max demand for itinerary i
$MaxDF_d$	Max demand for OD pair d
TP, DP	Transfer and direct pairs
FC_f	Flight seat capacity
$MinTF$	Minimum transfer time
$MaxTF$	Maximum transfer time
TaT	Turnaround time
$MaxGT$	Max ground time at spokes
A^{short}	Available short-haul aircraft
A^{long}	Available long-haul aircraft

Based on these parameters, the following constraints ensure feasible scheduling, capacity adherence, and operational consistency. The objective function is defined at the flight level rather than the passenger level, as individual passenger itineraries are not yet determined. Modeling at the passenger level would require a quadratic objective function, which is computationally impractical for this application.

$$\min \sum_{i\in PI}\sum_{t\in TS}\left(z_{i,t}^{dep} - z_{i,t}^{arr}\right) \tag{4.18}$$

Subject to

$$\sum_{t\in TS} t_{f,t}^{dep} = 1 \qquad \forall f\in F \tag{4.19}$$
$$\sum_{t\in TS} t_{f,t}^{arr} = 1 \qquad \forall f\in F \tag{4.20}$$

$$\sum_{\substack{f\in F\\ o_f=i}} t_{f,t}^{dep} \le S \qquad \forall i\in N,\ t\in TS \tag{4.21}$$
$$\sum_{\substack{f\in F\\ d_f=i}} t_{f,t}^{arr} \le S \qquad \forall i\in N,\ t\in TS \tag{4.22}$$

$$\sum_{\substack{f\in F\\ (o_f,d_f)=p}} \sum_{t\in h} t_{f,t}^{dep} \le 1 \qquad \forall p\in F,\ h\in HB \tag{4.23}$$

$$t_{f,(t+FT_f)}^{arr} = t_{f,t}^{dep} \qquad {\scriptstyle \forall f,\forall t:\ (t+FT_f)\in TS} \tag{4.24}$$
$$t_{f,(t+FT_f-24\cdot SH)}^{arr} = t_{f,t}^{dep} \qquad {\scriptstyle \forall f,\forall t:\ (t+FT_f)\ge ET} \tag{4.25}$$
$$t_{f,t}^{dep} = 0 \qquad {\scriptstyle \forall f,\forall t:\ (t+FT_f-24\cdot SH)<BT} \tag{4.26}$$

$$\sum_{\substack{i\in PI\\ i_3=t}} TF_i = MaxTF_{tp} \qquad \forall tp\in TP \tag{4.27}$$
$$\sum_{\substack{f\in F\\ (o_f,d_f)=d}} DF_f = MaxDF_d \qquad \forall d\in DP \tag{4.28}$$

$$\sum_{\substack{i\in PI\\ o_i=f}} TF_i + DF_f \le FC_f \qquad \forall f\in F \tag{4.29}$$

$$IT_i = 1 \qquad \forall i\in PI: TF_i>0 \tag{4.30}$$

$$z_{i,t}^{dep} = t_{i_2,t}^{dep}\cdot t \quad \forall i\in PI,\ t\in TS; IT_i=1 \tag{4.31}$$
$$z_{i,t}^{arr} = t_{i_1,t}^{arr}\cdot t \quad \forall i\in PI,\ t\in TS; IT_i=1 \tag{4.32}$$

$$\sum_{t\in TS} z_{i,t}^{dep} \ge \sum_{t\in TS} z_{i,t}^{arr} + MinTF \quad \forall i\in PI \tag{4.33}$$
$$\sum_{t\in TS} z_{i,t}^{dep} \le \sum_{t\in TS} z_{i,t}^{arr} + MaxTF \quad \forall i\in PI \tag{4.34}$$

$$\sum_{\substack{r\in PR\\ f\in r}} R_r = 1 \qquad \forall f\in F \tag{4.35}$$

$$q_{r,t}^{dep} = t_{r_2,t}^{dep}\cdot t \quad \forall r\in PR,\ t\in TS; R_r=1 \tag{4.36}$$
$$q_{r,t}^{arr} = t_{r_1,t}^{arr}\cdot t \quad \forall r\in PR,\ t\in TS; R_r=1 \tag{4.37}$$

$$\sum_{t\in TS} q_{r,t}^{dep} - \sum_{t\in TS} q_{r,t}^{arr} \le MaxGT \qquad \forall r\in PR \tag{4.38}$$
$$\sum_{t\in TS} q_{r,t}^{dep} - \Big(\sum_{t\in TS} q_{r,t}^{arr} + TaT\Big) \ge 0 \qquad \forall r\in PR \tag{4.39}$$

$$FIA_{f,t} = FIA_{f,t-1} + t_{f,t}^{dep} - t_{f,t-1}^{arr} \qquad {\scriptstyle \forall f\in F,\forall t:\ t>BT} \tag{4.40}$$

$$\sum_{f\in F} FIA_{f,t} \le A^{short} \qquad \forall t\in TS \tag{4.41}$$
$$\sum_{f\in F} FIA_{f,t} \le A^{long} \qquad \forall t\in TS \tag{4.42}$$

The first constraints (4.19) and (4.20) ensure that each flight has at most one departure and one arrival slot. Constraints (4.21) and (4.22) allow a maximum number of movements at a airport during one time step. (4.23) ensures no more than one departure per origin–destination pair in each hour. The timing constraints (4.24) to (4.26) link departures and arrivals by flight duration, including wrap-around at the day boundary, and forbid infeasible assignments outside the daily window (i.e. no departures or arrivals during the night). Flow conservation constraints (4.27) and (4.28) match transfer and direct passenger volumes to their demands. Constraint (4.29) caps the sum of those flows on each flight by its seat capacity. (4.30) indicates if an itinerary is used. Constraints (4.31) and (4.32) transform the arrival and departure times of the two flights in the itinerary from binary to integers. Which constraints (4.33) and (4.34) use to enforce minimum and maximum transfer times. Constraint (4.35) ensures that each flight is assigned to exactly one route. Constraint (4.36) and (4.37) compute the linearized departure and arrival times of each route in order to monitor maximum ground time limits. Groundtime constraints (4.38) and (4.39) similarly bound the connection interval between legs of each route of the aircraft. Finally, the flight-in-air balance (4.40) and fleet-size constraints (4.41) and (4.42) track in-flight aircraft over time and ensure that the total number of short- and long-haul aircraft never exceeds the available fleet.

4.4. Support Functions

In order for the HLP Model to work properly, multiple functions need to be explained. The functions outlined in this section will cover fare prices, cost functions and detour factor including the incorporation of competition.

The ticket prices will be modeled as follows; the direct fare between every Origin-Destination (”OD”) pair will be determined using equation (4.43). If the itinerary has a connection through a hub airport, a detour factor is implied. However, if the itinerary goes directly over a hub, a minimum reduction of the transfer fare is implemented as can be seen in equation (4.44).

$$DF_{i,j} = r \cdot 45 \cdot d_{i,j}^{0.7} \cdot c \qquad (4.43)$$

where:

$r \in [0.95, 1.05]$ (randomness factor)
$d_{i,j}$ distance in km
$c = 0.011$ (INR to EUR conversion)

$$TF_{i,j,h} = \text{min}\left(DF_{i,j} \cdot \left(\frac{1}{D_{i,j,h}}\right)^{\alpha}, DF_{i,j} \cdot (1-\delta)\right) \qquad (4.44)$$

where:

$D_{i,j,h}$ Detour factor
α detour penalty based on competition (e.g. 1.0)
δ minimum discount factor (e.g. 0.1)

The detour factor is calculated by dividing the distance flown via a specific hub by the direct distance of each OD pair. Figure 4.2 shows the effect of different alphas on the transfer fare. A higher alpha implies more competition which would result in passengers less likely to accept a higher price. The alpha is determined using the population and GDP of each city. This data was obtained from the United Nations and World Data Bank, respectively (United Nations, Department of Economic and Social Affairs, Population Division, 2024) (World Bank, 2024).

The cost functions are stated in equation (4.45) and equation (4.46). The cost functions are both on a passenger level. To compensate for ignoring fixed costs, a minimum load factor will be implied into the HLP model. This has been showed in constraints (4.8) and (4.9). This ensures that flights are not operated below a certain threshold, and therefore mitigating the effects of ignoring the fixed costs. The transfer costs are almost the same the direct costs; however, a small discount factor is inserted to account for costs that only occur once, like overhead and administrative cost.

$$\text{DC}_{i,j} = r \cdot 50 \cdot d_{i,j}^{0.675} \cdot c \qquad (4.45)$$

where:

$r \in [0.95, 1.05]$ (randomness factor)
$d_{i,j}$ distance from i to j in km
$c = 0.011$ (INR to EUR conversion)

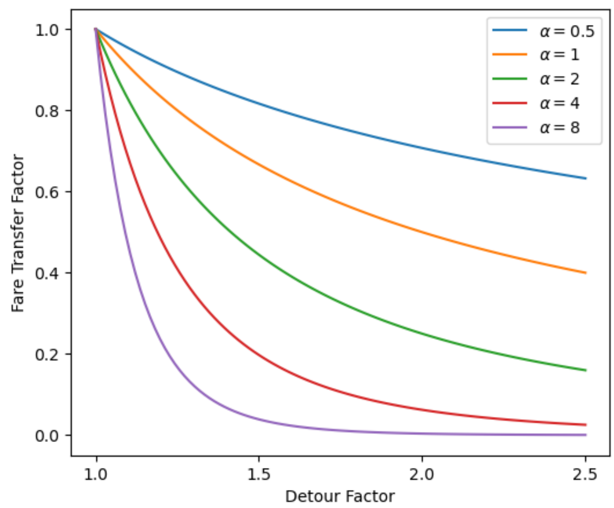
$$\text{TC}_{i,j,h} = (1-\delta) \cdot r \cdot 50 \cdot d_{i,j,h}^{0.675} \cdot c \qquad (4.46)$$

where:

$d_{i,j,h}$ total distance via hub h
δ transfer discount (e.g. 0.1)
other variables as in Eq. (4.45)

The last input data that need to be processed is the demand data. This is not within the scope of this paper and will be elaborated on in chapter 6.

Figure 4.2: Transfer Fare Factor for different α



5 Hypotheses

This section outlines the hypotheses formulated to address the research objectives and guide the development of our modeling approach. Each hypothesis is further illustrated with a practical example, grounded in the context of the airline network design problem.

- **H1: The incremental value of each new hub decreases with the number of existing hubs.** *Example:* After a certain number of hubs, the addition of an extra hub would only increase the network profitability by y%. This suggests that not every additional hub contributes meaningfully to profit, supporting H1.

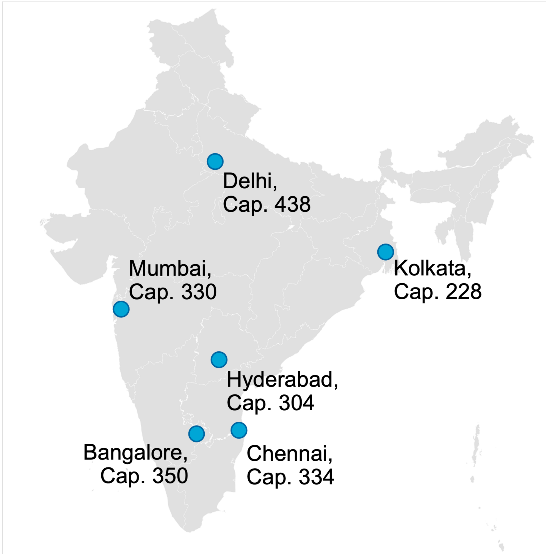
- **H2: An integrated Hub Location Problem and Schedule Design model has advantages over separated models.**
  Example: A two-step approach (first solving HLP, then SD) is compared to a fully integrated model. The integrated approach yields x% higher total profitability of the schedule design model. This demonstrates that considering hub selection and scheduling jointly can lead to better network efficiency.
- **H3: The network progressively shifts its focus from direct service to optimizing transfer connectivity.**
  Example: With the addition of hubs, the proportion of transfer passengers grows significantly, while the share of direct passengers stabilizes or decreases. This would suggests that the primary role of additional hubs is to enhance transfer connectivity rather than direct routes, supporting the hypothesis that multi-hub networks shift towards prioritizing transfer flow.
- **H4:Competition and capacity constraints influence the profitability of the network.**
  Example: A comparison between unconstrained and different competition-constrained models shows that the profitability of the network decreases when competition increases. This illustrates how market competition can alter hub viability and supports H4.

6 IndiGo Case Study

This research is applied to a case study of IndiGo. IndiGo has ordered 30 Airbus A350-900 in April 2024 (IndiGo, 2024). Subsequently, in June 2025, the airline announced an additional order for 30 more A350-900 aircraft (The Economic Times, 2025). Besides these wide-body aircraft, IndiGo has also ordered 40 Airbus A321 XLR (extra long-range). These are narrow-body aircraft that will also be able to fly to Central/Eastern Europe The case study results presented here are based on a subset of these aircraft. These aircraft have the range to connect Europe with India and therefore Europe with East Asia and Oceania. In addition to this future route, IndiGo already serves international areas at closer distances, like the Middle East and Central Asia. IndiGo operates six major hubs across India, as shown in Figure 6.1. These hubs vary in size based on their total flight slots, which includes both arrivals and departures. The largest hub is Delhi, with a total capacity of 438 flight movements per day, followed by Bangalore with 350, and Mumbai with 330. Hyderabad handles 304 movements daily, while Chennai and Kolkata have capacities of 234 and 228 flight movements, respectively.

Due to India's promising geographic location between Europe and East Asia, it is an excellent candidate to serve this route. The competition on this route is however fierce. Firstly, the legacy carriers that fly direct, like Air France - KLM and Singapore Airlines. Secondly, the connecting carriers between Europe and Asia, like Turkish Airlines and the Gulf (Emirates, Qatar and Etihad). The latter will most likely be the biggest competition. The question, therefore, is whether IndiGo can effectively utilize its six hubs to design an attractive and efficient network offering. Within this question, it will become clear what the optimal number of hubs is for international - international traffic flow.

Figure 6.1: Location and number of daily departures per hub



Given the scope of this research, complex demand modeling is simplified, with assumptions being used instead of real-world data. A demand factor matrix has been designed in which a base factor is multiplied by such a factors. The matrix includes the six hubs and the spokes are divided into five categories (S1, ... , S5). The factor of the six hubs is based on their current size, so Delhi has the highest factor and Chennai and Kolkata have the lowest factor. An S1 spoke has the highest factor (i.e. high demand spoke) and an S5 spoke has the lowest factor (i.e. low demand spoke). The classification of spokes is done by evaluating their respective city population and GDP per city. The combined factor of each OD-pair is multiplied by a base demand and a random factor ($r \in [0.95, 1.05]$). The demand between Delhi and an S1 Spoke (e.g. London) is $F_D \cdot F_1 \cdot BaseDemand \cdot r$.

Table 6.1: Demand factor matrix

		S1	**S2**	$\cdots$
	Factor	F_1	F_2	$\cdots$
Delhi	F_D	$F_D \cdot F_1$	$F_D \cdot F_2$	$\cdots$
Mumbai	F_M	$F_M \cdot F_1$	$F_M \cdot F_2$	$\cdots$
S1	F_1	$F_1 \cdot F_1$	$F_1 \cdot F_2$	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$

An example of the transfer fare (equation (4.44)) is showcased in Figure 6.2 of the transfer fare from Dubai to Kathmandu. As expected, the detour factor via Delhi is the lowest and via Chennai the highest. The graph should be interpreted that passengers would accept a ticket price of ~ 80 EUR when flying through Delhi. The max fare is equal to the direct fare using equation (4.43).

Figure 6.2: Example Transfer Fare Dubai to Kathmandu

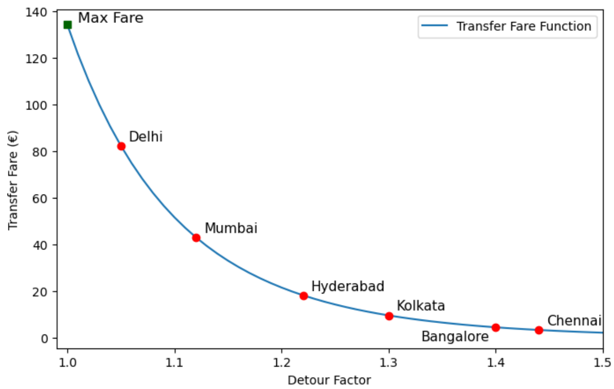


Table 6.2 shows the number of destinations selected by spoke category (S1 through S5). The distribution across spoke categories reflects a deliberate effort to ensure a representative mix of market types, ranging from high-demand routes to thinner, more peripheral destinations. This classification impacts model outcomes by shaping demand patterns. A more balanced category distribution supports generalizable insights, while the heavier concentration in categories S1 and S5 highlights areas of potential strategic interest, such as growing connectivity (S1) and serving underserved regions (S5).

Table 6.2: Number of selected destinations by spoke category

	S1	S2	S3	S4	S5
Current	4	5	4	5	16
New	11	8	9	2	0
Total	15	13	13	7	16

The parameters in Table 6.3 define the operational parameters and market conditions for the HLP Model. The parameters include C_h for hub capacity, AC_{Short} and AC_{Long} for short and long-haul aircraft capacities, A^{short} and A^{long} for aircraft availability, α for minimum load factor, T_{day} for daily flying hours, TaT for turnaround time, R_s and R_l for aircraft range cutoffs, RV for reverse flow constraint, base demand, and competition factor α. There are also fare and cost decreases for transfer flow.

Table 6.3: Key Parameters for the HLP Model

Symbol	**Value**
Int. Allocation	0.33
C_h	Delhi: 438, Bangalore: 350, Mumbai: 330, Hyderabad: 304, Chennai: 234, Kolkata: 228
AC_{Short}	200 seats
AC_{Long}	400 seats
A^{short}	170
A^{long}	30
α (Load Factor)	80%
T_{day}	14 hours
TaT	1 hour
R_s	6000 km
R_l	7000 km
RF	80%
Base Demand	100
α (competition)	{0.5, 1, 2, 4, 8}
δ (fare)	5%
δ (cost)	10%

The parameters in Table 6.4 govern the SD model's structure and constraints. These include TS for discrete time steps, OH for operational hours per day, and S for the number of simultaneous departures or arrivals allowed per hub. $MinTF$ and $MaxTF$ define the allowable transfer time window, while $MaxGT$ limits ground time between flights, and TaT represents the turnaround time per flight. Genetic algorithm settings include population size, number of generations, mutation rate, selection size, and elitism percentage.

Table 6.4: Key Parameters for the SD Model

Symbol	**Value**
TS	10 minutes
OH	19 hours
S	2 (Dep. or Arr.)
$MinTF$	30 minutes
$MaxTF$	3 hours
$MaxGT$	5 hours
TaT	1 hour
GA Specific	
Pop. Size	456 $(4 \cdot \#TS)$
Generations	1500
Mutation Rate	0.005
Selection Size	50%
Elitism	10%
Data Structure	hub-focused
Convergence Gap	0.1%
Objective Switch	75 generations

7 Results

The results of this research are shown in this section, using the methodology provided. Section 7.1 described the experimental setup. Section 7.2 shows the results of the Hub Location Problem, and Section 7.3 presents the results of the schedule design model and also the integrated model. A detailed interpretation of the outcomes will be provided in Chapter 9.

7.1. Experimental Setup

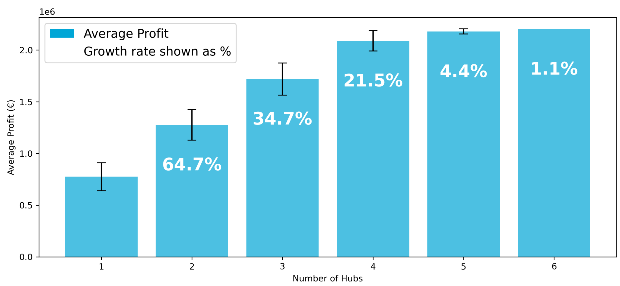
The test instances are based on the network of IndiGo. IndiGo currently operates six hubs and serves 30 international destinations. In the results section, we evaluate a scenario that includes IndiGo's current network, extended with thirty additional spokes. These spokes are selected based on their classification, as described in Section 6.

The HLP experiments were all run on a local device: a MacBook Pro M1 Pro with 16GB of RAM and 8 CPU cores, using Gurobi Optimizer version 11.0.3. The HLP results were generated with a 1% optimality gap. The Integrated Model experiments were run on an external server with a 64-core processor, supporting 256 logical processors, using up to 32 threads.

7.2. Hub Location Problem

Figure 7.1 depicts the mean profitability in relation to the number of hubs. For each configuration, every possible combination of hubs within the network of six hubs is assessed, and the outcomes are averaged. The growth percentages are shown in the bars of the chart, it can be noted that the growth decreases over time. This is not strange as the effect of a single hub addition becomes less when the number of existing hubs increases. Summary statistics for each configuration are shown in Table A.3, in the appendix. From this table, it can be noted that in some configuration, lesser (well chosen) hubs could be more profitable than more hubs. In theory, the maximum objective should increase as the number of hubs increase, because at least the same hubs are available.

Figure 7.1: Evolution of Profit by Number of Hubs



The numbers in Figure 7.1 are all averages, however in the optimal configuration for each number of hubs is shown in Table 7.1. The network structure for each hub configuration is shown in Figure A.2, illustrating how spokes are assigned to hubs. In the six-hub configuration, northern European spokes are primarily connected via Delhi and Kolkata, while southern European cities are mainly routed through Mumbai and Bangalore, as expected.

Table 7.1: Optimal hub combinations and objective value growth

# Hubs	Optimal Hub Combination	Profit Growth Rate (%)
1	Bangalore	–
2	Bangalore, Delhi	+71.3
3	Bangalore, Delhi, Mumbai	+30.0
4	Bangalore, Delhi, Mumbai, Hyderabad	+8.4
5	Bangalore, Delhi, Mumbai, Hyderabad, Kolkata	+0.9
6	Bangalore, Delhi, Mumbai, Hyderabad, Kolkata, Chennai	+0.0

The trend in average profit per passenger is shown in Figure 7.2, with detailed statistics presented in Table A.4. Overall, the profit per passenger decreases as the number of hubs increases from one to four, dropping from €47.60 with one hub to €40.24 with four hubs. This downward trend is largely driven by demand cannibalization between hubs and the dilution of high-yield routes. The sharpest decline occurs between one and three hubs, with average profit per passenger falling by approximately 13.5% during that interval. Interestingly, the decline slows between three and four hubs and reverses beyond that. At five hubs, profit per passenger slightly increases with 2.1%, and at six hubs, it further rises with 3.6%, nearly recovering the earlier losses. This late-stage rebound suggests that once a sufficiently large network is established, the airline can capture additional efficiencies, possibly by leveraging better connectivity. It should be noted that this decline is not a major concern, as overall profit still increases. Adding more hubs enables the network to capture less profitable routes, which can enhance market share and strengthen global presence.

Figure 7.2: Average profit per passenger per number of hubs

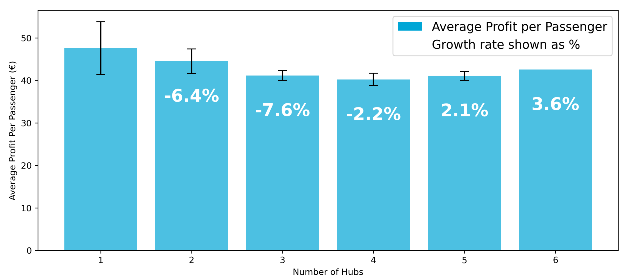
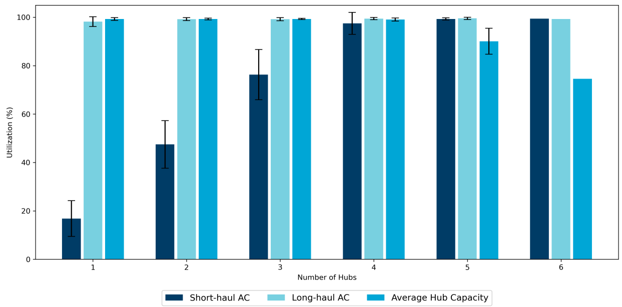


Figure 7.3 presents average hub capacity and aircraft utilization across network configurations with one to six hubs. For one to three hubs, average hub utilization remains consistently high at 99.3%, indicating uniform usage levels in these smaller networks. For four hubs, the average value drops slightly to 99.1%, and for five and six hubs, the values drop to 90.1% and 74.6%, respectively. This reflects a more dispersed allocation of capacity across a greater number of hubs.

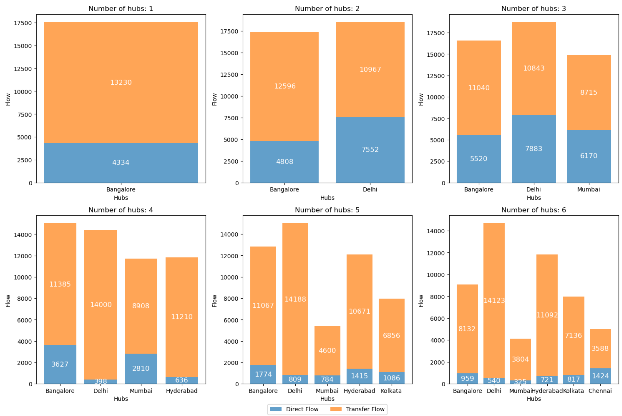
Short-haul aircraft utilization shows a progressive increase as the number of hubs rises. It starts at 16.8% in the one-hub scenario, climbs to 47.5% with two hubs, and reaches 76.3% with three hubs. With four or more hubs, short-haul utilization exceeds 97.5%. For five and six hubs, it reaches 99.3% and 99.5%, respectively. Long-haul aircraft utilization, by contrast, remains relatively stable and high across all configurations. It starts at 98.2% with one hub and gradually varies between 99.2% and 99.5% for the other scenarios, showing minimal variation over the different cases. Long-haul aircraft show high utilization from the start because they serve the most profitable international routes.

Figure 7.3: Capacity Utilization across different hub configurations



A critical metric is the network's evolution in terms of flow type and the number of destinations as additional hubs are integrated. Table 7.1 outlines the optimal scenarios used to examine how flow types evolve with each hub addition. Figure 7.4 shows the progression of direct and transfer flows with the incorporation of each additional hub. The data show that transfer passengers increasingly dominate the network as more hubs are added. While their share initially drops from 75% to 61% with three hubs, it rises sharply thereafter, reaching 89% with six hubs. Table A.5 summarizes the total number and proportion of transfer and direct passengers across different hub configurations. While direct traffic is still being accommodated, the model increasingly favors transfer flows as hubs are added. This suggests that each additional hub enhances connectivity by unlocking more efficient transfer opportunities.

Figure 7.4: Flow development after addition of hubs



As the number of hubs increases, the network expands significantly in reach (Table 7.2). Unique destinations grow from 34 to 58, and the share of destinations served by multiple hubs increases from 0 to 43, indicating greater connectivity. At the same time, the average flight distance drops from 6,257 km with one hub to 4,396 km with six hubs, suggesting a shift toward more regional connections. The load factors remain consistently high, reflecting efficient use of capacity despite the network's expansion. These numbers are for only one scenario in this specific case of IndiGo, but they illustrate dynamics that are likely to apply more broadly. The four-hub network shows only an 8.4% increase in profitability despite a 23.9% increase in the number of flights (Table 7.1). This limited gain, especially in the absence of fixed cost considerations, might be problematic.

Table 7.3 shows that the additional hubs particularly benefit medium and smaller cities (S2–S5), with

Table 7.2: Destination statistics

# Hubs	Unique Dest.	Dest. with multiple hubs	Avg Flights/Dest.	Total Flights	Avg Load Factor	Avg. Distance (km)
1	34	0	3.4	116	99.98	6,257
2	45	27	5.8	260	99.59	5,668
3	51	36	7.2	368	99.93	5,468
4	59	45	7.7	456	99.55	4,460
5	60	44	7.7	462	99.71	4,358
6	58	43	7.9	461	99.81	4,396

rising frequencies and declining average distances. This implies that multi-hub structures allow for better short- and medium-haul connectivity, especially to non-primary markets.

This shift toward shorter average flight distances can also be attributed to capacity saturation in the three-hub configuration. As shown in Figure 7.3, with three hubs, both the average hub utilization and aircraft utilization are already near maximum levels. The introduction of a fourth hub (Hyderabad) adds a significant amount of new capacity to the network, roughly 100 additional flights. To effectively absorb and utilize this added capacity, the model compensates by increasing the total number of flights. However, given operational constraints such as daily aircraft flying hours, these additional flights must cover shorter distances to remain feasible within a day. Consequently, the network begins to emphasize more regional or medium-haul routes, which better match the utilization needs of the expanded hub infrastructure.

Table 7.3: Average distance and daily frequency to city categories across hub configurations

# Hubs	Metric	S1	S2	S3	S4	S5
1	Freq.	27	15	14	1	1
	Dist (km)	6364	5720	5537	4672	4801
2	Freq.	51	43	29	4	3
	Dist (km)	6024	4863	5826	5250	4201
3	Freq.	72	61	42	5	4
	Dist (km)	5976	4676	5340	4867	4005
4	Freq.	71	84	49	16	7
	Dist (km)	5756	4404	4461	3392	2310
5	Freq.	73	81	46	17	7
	Dist (km)	5786	4426	4368	3499	2844
6	Freq.	77	84	49	14	4
	Dist (km)	5604	4258	4376	3179	3168

7.3. Schedule Design Model

In this section of the results of the SD model and integrated model are shown. Subsection 7.3.1 shows the results of the SD1 model with the focus on maximizing profitability using a genetic algorithm. Subsection 7.3.2 shows the SD2 model, which has as objective to minimize the transfer time of connecting passengers.

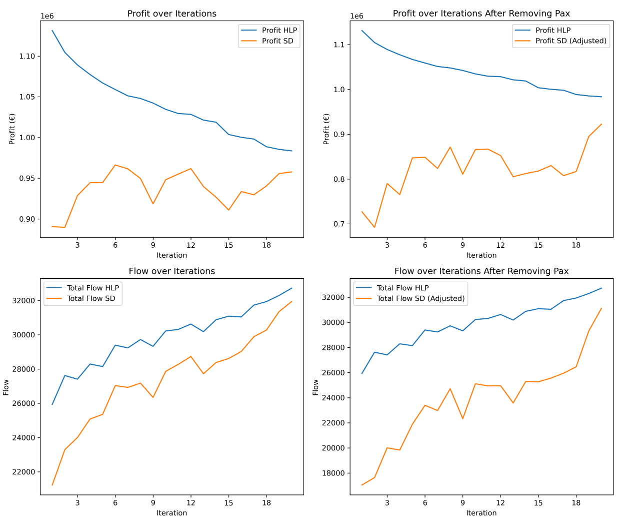
7.3.1. Maximize Profitability: Genetic Algorithm

In this section, The results of the integrated SD model are presented, which aims to maximize profitability using a genetic algorithm. This model combines the HLP and the SD component in an iterative process.

Figure 7.5 illustrates the interaction between the HLP model and the SD1 model over the course of 20 iteration of the genetic algorithm. The left subplots show the raw output of the optimization process, while the right subplots account for the practical constraint of a minimum load factor threshold of 80%. Flights falling below this threshold are excluded from both profit and flow calculations. Due to time and computational constraints, the integrated model is applied to a subset of the ideal solution by lowering the international allocation factor to 0.15. Also by focusing only on three hubs (Bangalore, Delhi, and Mumbai). However, as seen in the results section of the HLP, more hubs won't increase the profitability significantly while drastically increase complexity. This results in a total of 162 scheduled flights. The number of iterations was limited to 20 due to time constraints, with each iteration taking approximately 40 minutes.

The top left plot in Figure 7.5 illustrates convergence between the HLP and SD1 model, although with some fluctuations. Notable dips in SD1 profit after certain iterations may stem from challenging schedule configurations or instability within the genetic algorithm. The gradual decline in the HLP benchmark reflects capacity limitations as no additional passengers can be allocated in the optimal scenario, as explained in Subsection 4.3.2. Ultimately, the SD1 model reaches 97.4% of the HLP profit, representing a profit increase of 7.5% compared to the initial iteration. The top right plot, which includes only flights with load factors above 80%, shows a more pronounced initial gap, but the schedule improves considerably across iterations. In this case, the SD1 model improves by 26.9% from its starting point, reaching over 93% of the HLP profit. These improvements highlight the model's ability to generate increasingly efficient and profitable schedules. Even relatively modest percentage gains can translate into substantial operational and financial impact for airlines over the course of a year.

Figure 7.5: Profit and Flow Evolution Across Iterations



The bottom left plot in Figure 7.5 shows a steady increase in total passenger flow across iterations for both the HLP and SD1 models, while the profit decreases. This shows that over the iterations, passengers are captured with a lesser unit profitability. After excluding underperforming flights with load factors below 80%, the bottom-right plot shows the SD1 model's convergence. Initially, the adjusted SD1 flow accounts for only 65.7% of HLP flow. However, it reaches an adjusted flow of 95.1% of the HLP levels by the final iteration.

Overall, these plots demonstrate the iterative convergence of the SD1 model toward the HLP benchmark. Early iterations are marked by inefficient scheduling, resulting in many low load factor flights and underperforming routes. As the optimization progresses, the model learns to favor better-utilized connections, ultimately approaching the performance of the ideal HLP scenario in both total profit and flow.

The final configuration includes 33 unique destinations, excluding the hubs. Of these, 13 are located in Europe, 12 in Asia, 4 in the Middle East, 2 in Africa, and 2 in Oceania. Compared to earlier iterations, the passenger flow has shifted from a relatively balanced mix of direct and transfer passengers to a composition of 80% direct and only 20% transfer passengers. This shift highlights the increasing difficulty of efficiently scheduling transfer connections within the network.

7.3.2. Minimize Transfer Time: Exact

To evaluate the performance in minimizing passenger transfer times of the different scheduling models, we compare the outcomes of the Genetic algorithm and the Exact Method. Table 7.4 presents the average transfer time achieved by each approach. The Exact Method is the third and last model (SD2) in the integrated model. The exact method obtains a average transfer time of 34 minutes, which is 4 minutes higher that the minimal transfer time of 30 minutes. The SD2 model ran for two hours and cutoff at a optimality gap of 10.8%. The incorporation of the exact method shows a great improvement compared to the genetic algorithm, which is not strange as the genetic algortihm had a different objective, namely maximizing profit and passenger flow within a certain transfer time.

Table 7.4: Comparison of Minimum Transfer Time: Genetic Algorithm vs. Exact Method

Method	Avg. Transfer Time (min.)
Genetic Algorithm	107
Exact Method	34

To illustrate the output of the optimized schedule, a snippet is included of the flight schedule generated. It displays arrivals and departures at Delhi. It can be observed that flights originating from the northwest of India arrive between 16:00 and 17:00 with transfer passengers who are later connected to Australia.

Table 7.5: Flight Schedule with Passenger Composition

From	To	Dep. Time	Arr. Time	% Direct Passengers	% Transfer Passengers
St. Petersburg	Delhi	10:30	16:10	15.5%	84.5%
Vienna	Delhi	10:20	16:40	58.5%	41.5%
Copenhagen	Delhi	10:10	16:50	51.8%	48.2%
Delhi	Melbourne	17:20	05:00	7.7%	92.3%
Delhi	Sydney	17:20	05:20	45.7%	54.3%

8 Sensitivity Analysis & Validation

This chapter presents a sensitivity analysis of the HLP model and integrated model. The goal is to assess how variations in key input parameters affect model outcomes and to validate the model's robustness under different scenarios.

8.1. Hub Location Problem

The results in the sensitivity analysis of the HLP model are computed using the parameters of table 6.3, unless stated otherwise. The sensitivity analysis results were obtained using a 3% optimality gap and may therefore differ slightly from those presented in Chapter 7. The three hub configuration consists of the Bangalore, Delhi and Mumbai, which is the same as the results in Figure 7.4, Table 7.2, Table 7.3, and Table A.5.

Table 8.1 shows the performance of the HLP under varying levels of base demand. As base demand increases, both total profit and profit per flight improve. Especially in the three hub configuration where profit per flight rises from €4,627 to €5,824. This is likely due to a stronger focus on high-profit spokes, as the number of unique destinations decreases while the average number of flights per destination increases. Despite a fairly constant number of total flights at 366, the network becomes more efficient in terms of profitability and density. In the six hub configuration, more destinations are served, ranging from 54 to 58, with a moderate increase in total flights and a slightly lower profit per flight compared to the three hub setup. Although total profit increases with higher demand, the other metrics show no consistent trend. This makes it harder to interpret the effect of base demand on network structure and efficiency.

In Figure 6.1 in Section 6 the total number of airport slots are shown, covering both domestic and international routes. The allocation percentages, such as those referenced in Table 8.2, represent the portion of these flights dedicated to international flights. For example, an allocation percentage of 33% means that approximately one-third of the total capacity is used for international flights, while the remaining flights serve domestic routes.

Table 8.2 evaluates how different allocations of available hub capacity affect network performance. A higher allocation of 50% yields the highest profits for both the three- and six-hub configurations (€2,158,386 and €2,171,423, respectively). However, the increase in profit over the 33% allocation is relatively modest, while average hub utilization drops substantially, especially in the six-hub setup, where it falls to just 45.7%. This suggests that although higher capacity enables more flights, it may lead to underutilized hubs and diminishing efficiency. It should also be noted that the extra capacity allocated to international flights, removes profit from the domestic operations. This is a consideration to be made. Aircraft utilization remains consistently high across all scenarios, particularly for long-haul aircraft. This might also be the limiting factor why allocating more capacity does not improve the objective function significantly. The last interesting metric of the table is the percentages of transfer and direct flow, which favors transfer flow drastically when increasing the allocation factor. This is mainly due to the reason that connection to unique destination is around 30 for a 10% allocation and increased to 54 for the three hub configuration and 58 for the six hub network at 50% allocation. This creates the opportunity to serve more transfer passengers.

Table 8.3 investigates how varying aircraft availability influences profit and aircraft utilization. As fleet availability changes (from 90% to 110% of the base fleet), profit also rises consistently, indicating that additional aircraft capacity enables greater revenue generation. However, this comes with a noticeable decline in short-range aircraft utilization in the three-hub configuration: from 100% at 90% availability to 86.4% at 110%. This suggests that as more aircraft become available, scheduling inefficiencies emerge for short-haul operations and extra aircraft become redundant. In contrast, long-range aircraft utilization remains very high across all scenarios, with only a minor drop in the three hub case. For the six hub setup, both short- and long-haul aircraft show consistently high utilization, even at increased availability levels. This implies that a larger network better absorbs additional fleet capacity.

The parameter α represents the penalization of transfer flows. A higher α effectively means more competition within the market. When α is set to 0, transfer flows are treated as if there is no competition. Table 8.4 analyzes how varying α values affect profitability and flow distribution across different hub configurations. As α increases from 0 to 3, profitability drops by 8.1% for the three-hub case and 3.8% for the six-hub case. This decline is partly offset by a rise in direct flows: 21.3% for three hubs and 238.9% for six hubs. However, profit per passenger still falls by 12.4% and 15.0% respectively. The low detour factor (1.002 to 1.013) observed across all settings is largely due to India's geographical location, minimizing the impact of penalizing transfer flows.

The parameter α represents the penalization of transfer flows. A higher α effectively means more competition within the market. When α is set to 0, transfer flows are treated as if there is no competition. Table 8.4 analyzes how varying α values affect profitability and flow distribution across different hub configurations. As α increases from 0 to 3, profitability drops by 7.9% for the three-hub case and 3.5% for the six-hub case. This decline is partly offset by a rise in direct flows: 107.2% for three hubs and 8.4% for six hubs. However, profit per passenger still falls by 18.7% and 11.0% respectively. The low detour factor (1.002 to 1.012) observed across all settings is largely due to India's geographical location, minimizing the impact of penalizing transfer flows. The transfer fare formula, which depends on the detour factor, further explains the limited effect on profitability. The transfer fare is calculated as shown in Equation (4.44). Since the detour factor remains low, the penalization of transfer fares has a limited impact on the overall flow and profitability, despite the shift towards more direct connections.

Table 8.1: HLP performance for different base demand

Number of Hubs	Base Demand	Profit (€)	Unique Destinations	Avg Flights/Dest	Total Flights	Profit per Flight (€)
	50	1,693,543	51	7.2	366	4,627
3	100	2,003,786	48	7.7	368	5,445
	200	2,131,531	46	8.0	366	5,824
	50	2,000,467	54	8.7	468	4,275
6	100	2,159,823	58	8.0	464	4,655
	200	2,233,800	54	8.8	474	4,713

Table 8.2: HLP performance under varying hub capacity constraints.

Number of Hubs	Allocation (%)	Profit (€)	Hub Util. (%)	Flights	Hubs Unique Destinations	Short AC Util. (%)	Long AC Util. (%)	Transfer Flow (%)	Direct Flow (%)
3	10	892,566	98.0	110	28	23.9	98.6	52.5	47.5
	33	2,003,786	99.5	368	48	95.8	98.5	60.2	39.8
	50	2,158,376	81.5	459	54	99.7	99.4	90.0	10.0
6	10	1,249,809	97.6	184	38	46.6	97.3	51.6	48.4
	33	2,159,823	72.9	464	58	99.7	98.0	90.5	9.5
	50	2,171,423	45.7	464	58	99.7	96.9	93.3	6.7

Table 8.3: HLP performance under varying aircraft availability.

# Hubs	# Short Range	# Long Range	Profit (€)	Short Range Utilization (%)	Long Range Utilization (%)
3	153	27	1,926,686	100.0	98.9
	170	30	2,003,786	95.8	98.5
	187	33	2,040,293	86.4	98.4
6	153	27	1,956,127	100.0	100.0
	170	30	2,159,823	99.7	98.0
	187	33	2,379,169	99.2	99.3

Table 8.4: HLP performance under varying alpha factor.

# Hubs	Alpha Factor	Profit (€)	Transfer Flow	Direct Flow	Total Flow	Detour Factor	Profit / Pax (€)
3	0	2,048,940	34,692	10,337	45,029	1.012	45.50
	1	2,003,786	30,416	19,087	49,503	1.005	40.48
	3	1,888,258	29,701	21,417	51,118	1.002	36.94
6	0	2,190,614	43,256	11,994	55,250	1.009	39.65
	1	2,159,823	45,854	7,367	53,221	1.005	40.58
	3	2,114,247	48,864	11,002	59,866	1.002	35.32

Table 8.5 examines the impact of varying spoke network sizes on both profitability and the percentage of transfer flow in different hub configurations. For reference, in a six hub and thirty spoke network, there are 5,220 connections between the spokes, while a sixty spoke network has 21,240 spoke-to-spoke connections. This has been calculated by S × (S - 1) × H. The results indicate a clear trend: as the number of spokes increases, both the profit and the proportion of transfer flow rise significantly. For instance, when the number of spokes increases from 30 to 60 in the three-hub configuration, profit increases by 264.6% and the transfer flow percentage rises from 37.5% to 61.4%. Similarly, in the six-hub configuration, profit increases by 168.3% and the transfer flow percentage escalating from 51.4% to 86.2%. This data suggests that increasing the number of spokes significantly enhances network performance, both in terms of profit and transfer flow efficiency. This is most likely due to the increased access to high value spokes.

Table 8.5: Impact of spoke network size on profit and transfer flow.

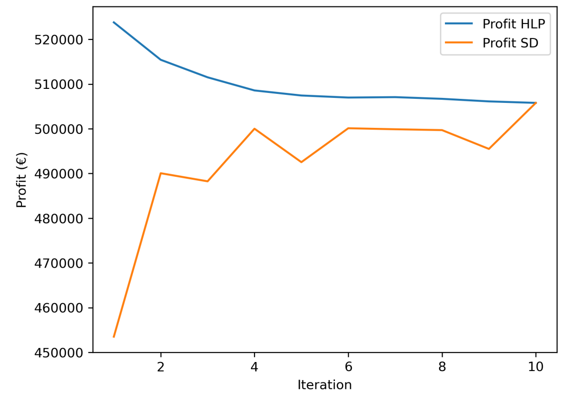
# Hubs	# Spokes	**Profit (€)**	**Transfer Flow (%)**
3	30	549,509	37.5%
	40	1,600,105	54.3%
	60	2,003,786	61.4%
6	30	804,615	51.4%
	40	1,972,409	54.5%
	60	2,159,823	86.2%

An important final observation concerns the difference in profitability between configurations with three and six hubs. As shown in Figure 7.1, the marginal profit gain diminishes beyond three or four hubs. However, this conclusion is highly dependent on the underlying parameters. Again, for the sensitivity analysis, the three hub network consisted of the biggest hubs, namely Delhi, Bangalore and Mumbai. In the base scenario, the profit increases from €2,003,786 with three hubs to €2,159,823 with six hubs which is an increase of 7.8%. Yet, when adjusting parameters, this difference can become much more pronounced. For instance, when only 10% of hub capacity is allocated to international flights, the profit increase from three to six hubs rises to 40.0%. Similarly, in a network with only 30 spokes, the increase in profit from three to six hubs is as high as 46.4%. These cases clearly demonstrate that the optimal number of hubs is highly sensitive to assumptions about hub capacity utilization and network size.

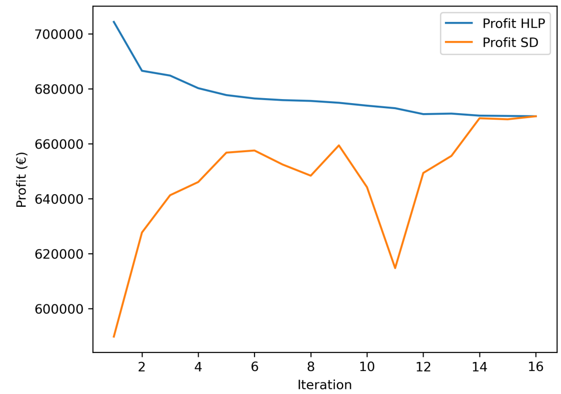
8.2. Integrated Model

The integrated model, and more specifically the genetic algorithm, is quite sensitive to the input size. Figure 8.1 illustrates the iterative profit evolution for two datasets: (a) displays results for a smaller instance with 50 flights, while (b) presents a medium-sized instance with 76 flights.

Figure 8.1: Profit Evolution Across Iterations for Two Dataset Sizes



(a) Profit Evolution - Small Dataset



(b) Profit Evolution - Medium Dataset

For the small dataset, the difference between the HLP model and SD model is in the first iteration just over €70,000 (-13.4%). Over 10 iteration, when the model convergence, the profit drops slightly to €505,797 (-3.4% of initial HLP). Which is a €52,290 (+11.5%) increase for the SD results of the first iteration. The composition of type of passengers does not change significantly, the passenger mix of the first iteration consisted of 38% transfer passenger. This only drops to 36% in the last iteration.

The medium dataset shows similar results, but slightly different. As expected, the initial daily profit of the HLP is higher at €704,396 and this drops with a rate of 16.3% for the SD model to €589,813. The integrated model converges at the 16th iteration with a profit of €670,044 this is only a €34,351 (-4.9%) drop in comparison to the first iteration and an increase of

€80,231 (+13.6%) compared to the first SD results. However, the passenger mix is quite effected as the transfer passenger account for 49% of the flow in the first iteration and this drops significant to 32% in the last iteration. The decrease in performance at iterations 10 and 11 is probably caused by a change in the network configuration, limiting the effectiveness of the genetic algorithm's warm start and reducing its optimization capability temporarily.

Comparing this to the results of Figure 7.5, which were 162 flights, the smaller dateset converge within 20 iterations. The difference between the first and last iteration of the SD model is just over €62,000, which is less of an improvement than the medium dataset. The respective increase of the larger data set is 7.5%, while this is 13.6% for the medium dataset. Looking at the HLP, for the larger set, the difference between the first iteration of the HLP and the last has a decrease of 13.1%, while at the small - and medium dataset those are 3.4% and 4.9%, respectively.

The smaller datasets show overall better performance with lower HLP drop off over the iteration and a higher increase in the SD model resulting in a quicker and more optimal convergence of the integrated model. This is driven by the decrease in the solution space which resulted in an increased performance of the genetic algorithm.

9 Discussion & Future Work

This chapter presents a critical reflection on the model's performance and outcomes. The discussion begins in Section 9.1 with an evaluation of the methodology, followed by a review of the hypotheses. Finally, in Section 9.2, key assumptions and limitations are addressed, and suggestions for potential improvements are outlined to guide future work.

9.1. Discussion

The discussion section is divided into two subsections, with the first subsection focusing on the overall performance of the method and in the hypotheses are discussed in the second subsection.

9.1.1. Method Evaluation

The methodology developed in this research presents a robust and comprehensive approach to network design and scheduling, effectively bridging the traditional gap between strategic planning and operational execution.

A key strength of this integrated method lies in its holistic optimization. It allows the strategic decisions regarding hub placement and network structure (from the HLP) to be continuously validated and refined by the operational realities of scheduling (captured by the SD model). This iterative feedback loop is crucial; it ensures that insights from the operational layer, such as unassignable demand due to schedule constraints, directly adjust the strategic network design. This dynamic interaction drives the system towards a more realistic and globally optimal solution that considers both financial objectives and operational viability.

A notable aspect of the SD component is the combination of a genetic algorithm in SD1 model with an Exact Method for final refinement in the SD2 model. The genetic algorithm effectively tackles the inherent computational complexity of large-scale scheduling problems, providing near-optimal solutions efficiently. Its ability to handle dynamic objective functions (profit or flow) and adapt iteratively enhances its robustness. Subsequently, using an exact method to minimize passenger transfer times allows for a precise optimization of customer experience, demonstrating the model's flexibility to address specific service quality objectives once a profitable and feasible schedule is established.

Ultimately, this integrated framework offers significant advantages for complex network-based operations across various industries. While this case study focuses on IndiGo, the underlying principles are broadly applicable to other airlines and regions worldwide, as well as any system where strategic location decisions interact with tactical resource allocation and scheduling. This could include logistics and supply chain management, where warehouse locations affect delivery schedules or public transportation, where hub design influences bus or train timetables.

9.1.2. Hypotheses Validation

Hypothesis 1

The results presented in Figure 7.1 and Table A.3 provide strong support for Hypothesis 1: the marginal benefit of adding hubs decreases beyond a certain point. The transition from one to two hubs yields a substantial profit increase of 64.7%, as the network begins to capture more demand and improve connectivity. However, this gain drops to 34.7% with the third hub, 21.5% with the fourth hub and declines further to just 4.4% and 1.1% for the fifth and sixth hubs, respectively. This clear trend of diminishing returns in total profit, despite the growing size and complexity of the network, confirms the plateauing value of further hub expansion. For the scenario in Table 7.1, the profitability of the four hub network only increases by 8.4% given 88 extra flights, which is a 23.9% increase (Table 7.2). As fixed costs are ignored, this might be problematic.

This is further illustrated by average profit per passenger, as shown in Figure 7.2 and Table A.4. While the network earns €47.60 per passenger with a single hub, this steadily declines to €42.57 with six hubs.

Underlying these profitability dynamics is the network's ability to manage capacity constraints and utilization. As shown in Figure 7.3, the hubs are nearly fully saturated when one to four hubs are active Once additional hubs are introduced, demand is more evenly distributed, reducing the average hub utilization load to 90.1% for five hubs and eventually to 74.6% for six hubs.

Due to the increase of hub capacity after each introduction, more flights are added to the network—most of which are short-haul flights, as can be seen in Table 7.2. These flights are generally less profitable, and this helps explain the trend in profitability per passenger in Figure 7.2. This redistribution to more frequent shorter flights is also reflected in Figure 7.3: short-haul flight utilization rises from 16.8% (1 hub) to over 97.5% (4+ hubs), while long-haul utilization remains consistently high (above 98%) across all scenarios. This shows that long-haul demand is saturated early, while short-haul operations benefit from added hub capacity.

Additionally, the expansion from three to six hubs leads to a noticeable shift in network structure. As shown in Table 7.3, average flight distances to lower-demand cities (S4–S5) drop significantly, from 4801 km at one hub to as low as 2221 km at five hubs. Flight frequencies to these low demand cities also increase steadily, even though they likely contribute less to overall profitability. This supports the observation that later stage hub additions enable connectivity to thinner markets, but yield diminishing returns due to the lower revenue potential and shorter trip distances.

Additionally, the expansion from three to six hubs leads to a noticeable shift in network structure. As shown in Table 7.3, average flight distances to lower-demand cities (S4–S5) drop significantly, from 4672-4801 km at one hub to as low as 3179-3168 km at five hubs. Flight frequencies to these low-demand cities also increase steadily, even though they likely contribute less to overall profitability. This supports the observation that later stage hub additions enable connectivity to thinner markets, but yield diminishing returns due to the lower revenue potential and shorter trip distances.

Lastly, the profitability dynamics are influenced by parameter variations. When considering a three-hub configuration of Delhi, Bangalore and Mumbai, the following data can be observed. In the base scenario, moving from three to six hubs yields a 7.8% profit increase. However, under more constrained conditions, such as limiting international flight capacity to 10% or reducing the network to just 30 spokes, the profit increase rises to 40% (Table 8.2) and 46.4% (Table 8.5), respectively. These findings underscore that the optimal number of hubs is not fixed but sensitive to assumptions about hub capacity allocation and network size.

In summary, while initial hub additions significantly improve network efficiency and profitability, the marginal benefits decline rapidly beyond three to four hubs. Additional hubs help resolve capacity bottlenecks and improve aircraft utilization, especially for short-haul services, but also introduce complexity, reduce per-passenger profitability, and lead to reliance on lower-margin traffic. These dynamics collectively confirm Hypothesis 1.

Hypothesis 2

The results presented in Figure 7.5 strongly support Hypothesis 2: An integrated Hub Location Problem and Schedule Design model has advantages over separated models. In the initial iteration, which effectively represents a separated, sequential approach, the HLP suggests a theoretical profit benchmark. However, the SD model, when exposed to practical scheduling constraints, achieved only about 78.7% of that theoretical HLP profit. This significant initial gap highlights the inherent challenge of translating strategic plans into feasible operations without tight integration.

Throughout the 20 iterations, the integration of HLP and SD via a genetic algorithm facilitated a strong convergence between these ideal and realistic solutions. From its first to its final iteration, the SD model's daily profit increased by approximately 7.6%.

When applying a minimum load factor threshold of 80%, the initial SD profit saw a sharp reduction. However, the model quickly adapted. This ”corrected” SD profit then rose by nearly 26.9% by the final iteration, demonstrating a substantial recovery and efficiency gain through the integrated process. This robust improvement ultimately reduced the gap with the HLP benchmark to less than 7%, proving the model's ability to approach theoretical profitability while maintaining practical feasibility.

A sensitivity analysis further reveals that the performance of the integrated model depends significantly on input size. For smaller datasets (50 and 76 flights), the model converges faster and shows higher relative improvements in SD profit, 13.6% for the medium dataset compared to 7.5% for the original larger one. Additionally, the HLP drop-off is less severe in smaller cases (-3.4% and -4.9%) than in the large case (-13.1%), suggesting that the genetic algorithm is more stable and effective with fewer variables. Furthermore, the share of transfer passengers remains more consistent in smaller cases, while larger datasets show a marked decline in transfer traffic, indicating increased scheduling complexity. These findings imply that although the integrated model scales to larger problems, its efficiency and convergence quality diminish with size.

Overall, these results confirm that iteratively integrating hub selection and schedule design leads to a more feasible and profitable network. The process reduces the gap between theoretical and actualized performance by continuously adapting to operational constraints. In doing so, the model validates Hypothesis 2.

Hypothesis 3

The results in Figure 7.4 and Table A.5 provide clear empirical support for Hypothesis 3: the inclusion of multiple hubs significantly shifts the network's focus toward transfer flow. The table shows the distribution of direct and transfer passengers across different hub configurations, revealing that as hubs are added, the share of transfer passengers increases, reflecting the growing importance of transfer connectivity in multi-hub networks.

When there is only one hub in the network, transfer passengers account for 75% of total traffic. As additional hubs are introduced, this share steadily increases, reaching 89% by the time six hubs are in place. Also, the focus goes from only highly profitable spokes (mostly S1) to a more regional network of more secondary spokes. This shift in flow type indicates that the network's primary objective evolves from serving direct connections to optimizing the flow of passengers between hubs, as more opportunities for connecting flights are created.

However, it is important to note that this trend is sensitive to the allocation factor and number of spokes in the network. Table 8.2 shows that the share of transfer flow increases significantly with higher hub capacity allocations, driven by the greater number of unique destination pairs that can be served, rising from around 30 at 10% allocation to over 50 in higher capacity scenarios. As shown in Table 8.5, the number of spokes strongly influence the share of transfer traffic. A larger spoke network increases spoke-to-spoke connection opportunities, boosting transfer flows. Thus, although multi-hub networks tend to favor transfer based traffic, this effect depends heavily on the network structure.

In conclusion, the data supports H3 by showing that the inclusion of multiple hubs increasingly emphasizes transfer flow, although the effect is influenced by the base demand and the number of spokes in the network.

Hypothesis 4
The results in Table 8.4 provide support for Hypothesis 4: competition constraints significantly impact hub profitability. The competition parameter α penalizes transfer flows to simulate competitive market conditions. As α increases from 0 to 3, profitability declines in both hub configurations: by over €160,000 in the three hub case and around €76,000 in the six hub case. This is partially offset by a rise in direct flows from 10,337 to 21,417 for three hubs. The efficiency loss is further illustrated by the decline in profit per passenger from €45.50 to €36.94 (three hubs) and from €39.65 to €35.32 (six hubs). Interestingly, the detour factor is and remains low (1.002 - 1.012) across all scenarios due to India's central location. However, it declines slightly when α increases, meaning that the network starts to favor low detour routes to offer the most compelling product.

In conclusion, the data support H4 by showing a decline in profit as competition increases as expected. However, competition is oversimplified in this research so the real effects are still unknown.

9.2. Future Work

This section outlines the main assumptions and limitations of the current model (Subsection 9.2.1) and presents potential enhancements to improve its practical applicability (Subsection 9.2.2).

9.2.1. Model Assumptions and Limitations

The current model operates under a number of simplifying assumptions to ensure computational tractability and clarity of results. First, it assumes that demand is static and entirely fabricated for the purposes of model development and testing. The demand data used does not reflect observed passenger volumes or patterns from real-world airline operations. While this assumption allows for controlled experimentation, it significantly limits the model's external validity and its ability to provide actionable insights.

Second, the model applies a single average fare per OD pair. This assumption simplifies the revenue calculation but neglects the complexities of airline revenue management, including the existence of multiple fare classes, OD market specific prices and passenger segmentation. As a result, the model may misestimate route profitability and fail to capture the full impact of pricing strategies on network design.

Third, competitive effects are modeled only indirectly, via a penalization factor on transfer flows. This simplification overlooks the strategic role of competitor schedules. Without this information, the model cannot simulate demand diversion.

Lastly, fixed and capital costs are not explicitly included in the objective function of the hub location problem. This exclusion could lead to an overestimation of the benefits of opening new hubs or operating new flights, as the cost of establishing and maintaining additional infrastructure is not factored into the decision making process.

While these assumptions were necessary to integrate the HLP model with the SD model, they also limit the model's realism and direct applicability. Understanding these limitations is essential for interpreting the model's outcomes and setting directions for future improvements.

9.2.2. Potential Enhancements

Several promising directions can be pursued to enhance the model's accuracy and practical relevance. A key improvement would be to replace fabricated demand with real-world data derived from historical passenger volumes. This would provide a more realistic basis for network design. To account for variability, stochastic optimization techniques could then be applied to capture fluctuations due to seasonality, economic shifts, or competitor actions.

Another extension involves modeling fare segmentation and revenue management practices more explicitly. Rather than relying on a single average fare, the model could integrate multiple fare classes. This would lead to more accurate profitability estimates and more targeted route development. A further enhancement lies in the explicit modeling of competition. Incorporating actual schedules, capacities, and prices of competing airlines would allow for more realistic assessments of market share and route viability.

Additionally, the genetic algorithm could be improved by focusing primarily on transfer passengers, assuming direct passengers serve to fill remaining seat capacity. This simplification may improve scalability and performance in larger solution spaces.

Finally, the model could be extended by the aircraft routing problem to ensure feasible aircraft transitions between scheduled flights.

Together, these enhancements would transform the model from a high-level strategic tool into a comprehensive framework capable of addressing the multifaceted challenges of modern airline network planning.

10 Conclusion

As demand keeps exceeding supply in the aviation sector, and airports are increasingly getting more congested. New players and new solutions need to be found. One of those solutions is the introduction of a multi-hub network focusing on international - international traffic flow. This study set out to explore how an airline network can be efficiently scheduled by utilizing multiple hubs, accounting for competition and operational constraints.

This research contributes theoretically by introducing an integrated model that aligns hub location and schedule design through a feedback loop, bridging the gap between strategic planning and operational feasibility in airline networks. It extends existing theory by quantifying diminishing returns from hub expansion, modeling competitive effects on transfer traffic, and showing how capacity constraints shape network structure. Practically, the model provides airline planners with a realistic, data-driven tool for designing multi-hub networks.

This research shows that an integrated approach to hub location and schedule design significantly enhances network efficiency by effectively leveraging multiple hubs within operational constraints. The study confirms that while initial hub additions lead to substantial improvements in connectivity, aircraft utilization, and profitability, the marginal benefits decline beyond a certain number of hubs due to saturation effects and lower per passenger profitability. The integration of hub selection and scheduling through an iterative model proves more effective than a sequential approach, reducing the gap between theoretical and feasible outcomes. Additionally, the inclusion of multiple hubs shifts the network toward transfer dominant flows and emphasizes the importance of short haul connectivity. These findings underscore the importance of integrated, constraint-aware optimization in designing robust and realistic multi-hub airline networks.

Future research could enhance this integrated multi-hub network model by incorporating real-world demand data, modeling demand uncertainty, and including fare class segmentation and explicit competitor schedules. These improvements would allow the model to better reflect market dynamics, passenger behavior, and strategic responses in a competitive airline environment.

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A Appendix

Table A.1: Parameter tuning Genetic Algorithm

Parameter	Values Tested	Small Dataset Best Value	Small Dataset Best Score	Large Dataset Best Value	Large Dataset Best Score
Population Size	114, 228, 342, 456	456	89.2	456	89.3
Generations	500, 1000, 2000, 3000	3000	88.7	3000	89.4
Mutation Rate	0.001, 0.005, 0.01, 0.015	0.01	90.1	0.005	88.0
Selection Size	0.1, 0.25, 0.49, 0.75	0.75	89.7	0.49	88.3
Data Structure	hub_focused, spoke_focused, random	hub_focused	87.1	random	89.4
Elitism Rate	0.05, 0.1, 0.15, 0.2	0.2	90.0	0.1	88.0
Objective Switch	25, 50, 75, 100	100	86.9	75	89.0

Table A.2: Performance of different optimization objectives in the genetic algorithm.

Objective	Description	Avg Profit (%)	Avg Flow (%)
Flow	Maximize total passenger flow	83.7	81.9
Profit	Maximize net profit	90.1	85.0
Combined	Weighted balance of flow and profit	91.7	85.8
Combined	Switch between flow and profit	91.9	87.3

Figure A.1: Evolution of Genetic Algorithm Objective Function

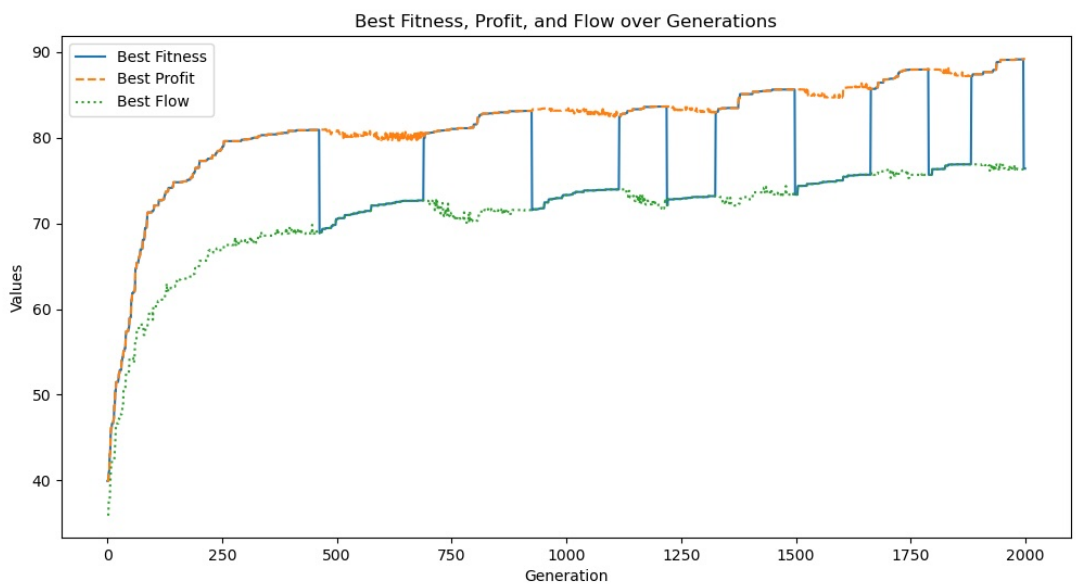


Table A.3: Profit statistics by number of hubs

# Hubs	Unique Combinations	Mean Profit (€)	Std. Dev.	Min Obj.	Max Obj.	Growth Rate (%)
1	6	775,177	135,610	534,023	904,399	–
2	15	1,276,790	148,190	1,017,313	1,547,772	64.7
3	20	1,719,683	155,289	1,448,181	2,014,352	34.7
4	15	2,088,826	97,823	1,891,402	2,183,265	21.5
5	6	2,179,919	24,880	2,130,888	2,201,706	4.4
6	1	2,204,464	–	2,204,464	2,204,464	1.1

Table A.4: Profit per passenger statistics by number of hubs

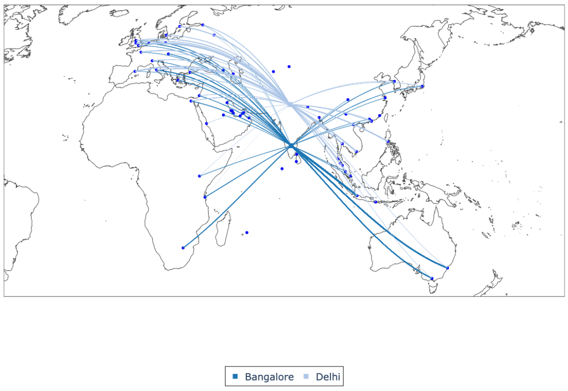
# Hubs	Unique Comb.	Avg. Profit (€)	Std. Dev.	Min Profit (€)	Max Profit (€)	Growth Rate (%)
1	6	47.60	6.22	38.50	54.59	–
2	15	44.53	2.88	36.65	48.61	-6.4
3	20	41.16	1.15	39.24	43.71	-7.6
4	15	40.24	1.43	37.11	42.73	-2.2
5	6	41.10	1.05	39.06	41.94	2.1
6	1	42.57	–	42.57	42.57	3.6

Table A.5: Daily passengers based on type

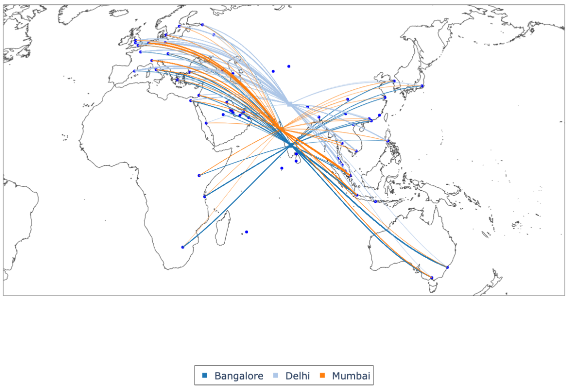
# Hubs	Direct	Transfer
1	4,334 (25%)	13,230 (75%)
2	12,360 (34%)	23,563 (66%)
3	19,573 (39%)	30,598 (61%)
4	7,471 (14%)	45,503 (86%)
5	4,972 (9%)	47,413 (91%)
6	5,636 (11%)	47,002 (89%)

Figure A.2: Hub-and-spoke networks for 1 to 6 hubs

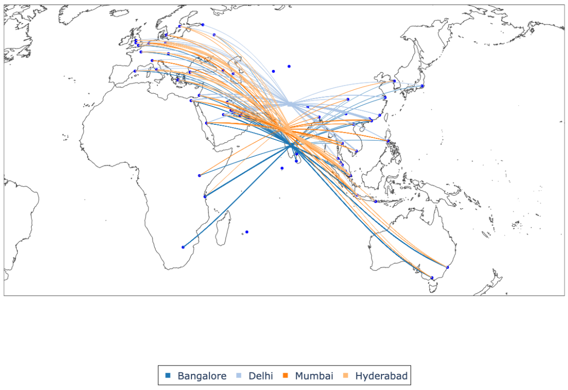
(a) 1 hub



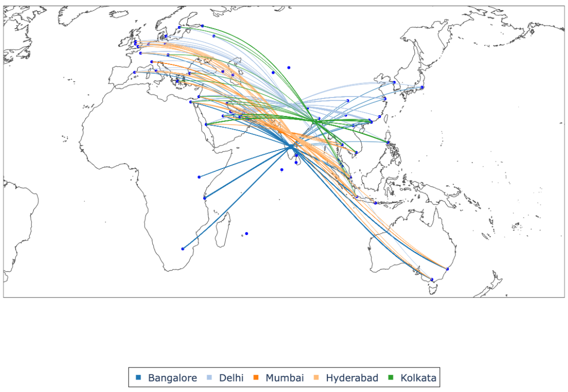
(b) 2 hubs



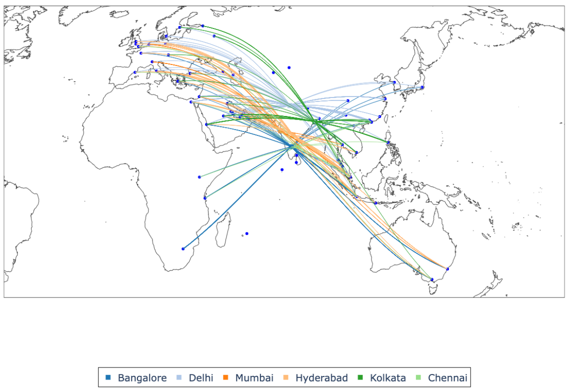
(c) 3 hubs



(d) 4 hubs



(e) 5 hubs



(f) 6 hubs

Part II

Literature Review & Research Definition

Contents

List of Figures

List of Tables

Abbreviations

ARP	Aircraft Routing Problem
ASD-FAM	Approximate Schedule Design and Fleet Assignment Model
BD	Bender Decomposition
B&B	Branch & Bound
CN	Connection Network
FAM	Fleet Assignment Model
GA	Genetic Algorithm
HLP	Hub Location Problem
HS	Hub-and-Spoke
IFAM	Itinerary Fleet Assignment Model
ISD-FAM	Integrated Schedule Design and Fleet Assignment Model
OD	Origin-Destination
PMM	Passenger Mix Model
P2P	Point-to-Point
SDP	Schedule Design Problem
SA	Simulated Annealing
TSN	Time-Space Network

1

Introduction

The aviation sector is growing every year, and forecasts do not expect this growth to slow down anytime soon. During the COVID-19 shock, the Revenue Passenger Kilometers (RPK) dropped by 93%. In the spring of 2023, domestic travel bounced back to the pre-COVID level, and a year later the international demand bounced back IATA (2024). The same report shows incredible growth projections in terms of total passengers number for the upcoming year, with an expected global growth in 2024 of 10.4%. This number will decrease due to the end of the recovery period to 4.7% Y-o-Y growth in 2028. In a press release of August 2024, IATA showed a RPK YoY% growth of 20.1% on the Europe - Asia route. Major airlines strategically positioned themselves to serve this route, mostly the Gulf carriers [1] and Turkish Airlines at the expense of European airlines with direct flights Georgiadis, P. (2024).

The demand continues to exceed supply, both at the airport and for the airlines. Istanbul opened in 2019 a new airport and Dubai is also planning to build a new airport, which would be the largest in the world Ros, M. (2024). This excess demand results in opportunities for other carriers to compete for passengers from Europe to (Southeast) Asia. Geographically India could be an exciting opportunity to serve as a hub for this connection. The two leading airlines in India are IndiGo and Air India, with a combined domestic market share of over 80%. In addition to this route, India also presents it as an ideal hub for other east-west and north-south flows. IndiGo already has flights to the Middle East, Central Asia, and South East Asia.

Currently, IndiGo serves European cities under the auspices of a codeshare partnership with Turkish Airlines and Air India serves limited European countries directly. Both airlines are expanding their operations to get ready to gain more market share in this route. Air India just recently added its third hub in Bangalore to attract more international destinations. IndiGo announced at the beginning of 2024 the purchase of 30 Airbus A350-900 aircraft to offer non-stop flights to Europe, the UK, the US, and Australia from India. Both these Airlines operate using a multi-hub network, with Air India operating from three hubs and IndiGo from six hubs. Air India's main hub is in Delhi, with additional hubs in Mumbai and Bangalore. In addition to these three, IndiGo has hubs in Hyderabad, Chennai, and Kolkata. The location of these hubs can be seen in figure 1.1.

[1] Emirates, Qatar and Etihad

Figure 1.1: Map of India including hub locations

One of the challenges that will arise is efficiently scheduling these flights over multiple hubs. The Gulf carriers and Turkish Airlines, among other carriers, only connect flights through one hub. When used efficiently, multiple hubs can have advantages over single hubs. Firstly, increased flexibility for passengers by offering more connecting possibilities between origin-destination pairs. Secondly, shorter flight times as the connection can take place at the optimal airport with the least detour between the origin and destination. However, it makes scheduling efficiently also more difficult. First of all, a decision needs to be made which hubs need to be considered for this connection and secondly, if multiple hubs are attractive between origin-destination pairs, the passengers could transfer at all these hubs both ways. To clarify this even more when all six hubs are considered, it can be that a passenger can transfer at each of these hubs on both ways. A passenger can fly to its destination with a connection in Delhi, but back to their original location transferring through Mumbai.

Therefore, this research aims to investigate how to schedule international-to-international traffic flow using six hubs given a multi-objective criteria of efficiency, maximize revenue, and connectivity.

This literature review will provide an overview of the state-of-the-art existing research on airline network planning. This includes, but not limited to, network development, frequency planning, and schedule planning. The objective of this review is to identify research gaps in multi-hub systems and to propose specific research questions for future the subsequent master thesis.

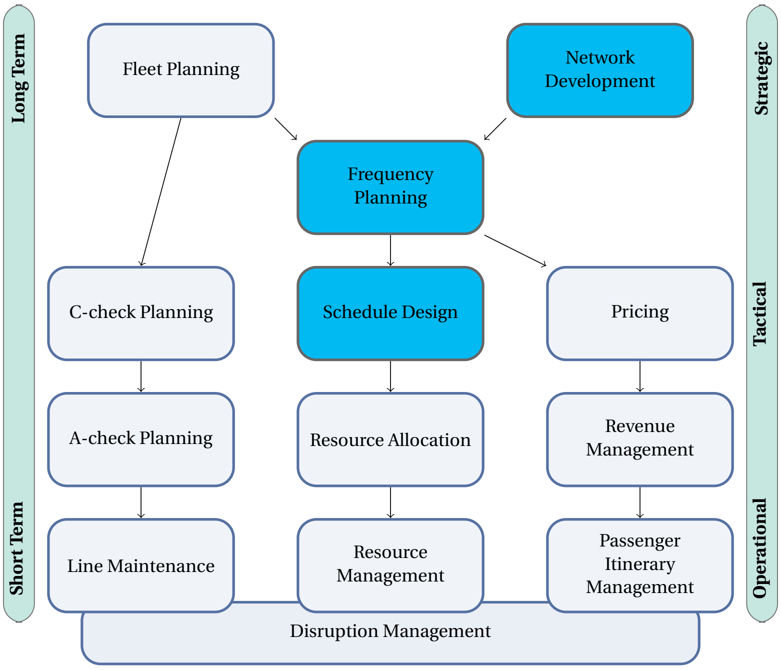
Chapter 2 provides background information on airline planning, including recent research and key considerations for effective planning. Chapter 3 provides an overview of the state-of-the-art research done in airline planning and the hub location problem. Subsequently, relevant and frequently used algorithms are explained in chapter 4. In chapter 5, the case study on IndiGo is introduced. Chapter 6 shows the research gap including opportunity. In the last chapter, chapter 7, the approach is presented.

2 Background

In this chapter, a brief introduction is given to the aspects that contribute to the scheduling problem. At the beginning of this chapter, an overview is given of all the decisions that are involved in airline planning, ranging from short to long-term and from operational to strategic. In section 2.1, a deep dive is done into different network models to give a better understanding of the advantages and limitations of a multi-hub network. Section 2.2 discusses destination and frequency modeling. In section 2.3, connectivity and connection banks are reviewed. A timetable example is given in section 2.4.

Airline planning is a complex process and it involves lots of stakeholders. In Figure 2.1 an overview is given of the framework from the long-term decision at the top to the short-term decision at the bottom. This can be connected with strategic, tactical, and operational decisions.

Figure 2.1: Overview of the Planning Framework, derived from Santos, B. (2023)



The top layer shows the most strategic decisions. Fleet planning determines the quantity of certain types of aircraft to acquire and operate. Network development evolves around which destinations should be served and what kind of network model needs to be adopted. To summarize, this top layer answers the question; Which pool of different aircraft can be used to serve which destination?

The last block within the strategic domain is frequency planning and consequentially schedule planning. This research will mostly focus on this part of the airline planning as highlighted in figure 2.1. Within frequency planning, the demand of the destinations is determined, and, of course, the frequency of flights to these destinations. Schedule design decides which aircraft could potentially serve a destination at what time. The following block of this column is resource allocation in which crew and one specific aircraft are assigned to a flight leg.

The other two pillars, focused on maintenance and optimizing financial gain are both important within airline planning, but these are out of the scope of this research. These will be not discussed in depth during the literature review. Although this figure shows three pillars, in the real world everything is connected. This makes airline planning a very complex process and therefore it will be simplified in the subsequent research.

2.1. Network Models

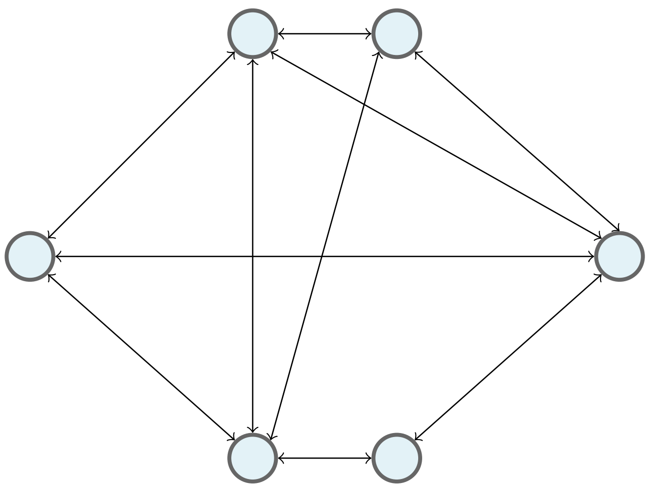
An airline needs to strategically determine its network structure, which outlines how city pairs are served and how flights are scheduled to offer attractive itineraries. Two main models are used; a Point-to-Point model and a Hub-and-Spoke model. In the most basic definition the former connects the origin directly with the destination and the latter allows transfers through the centrally located hub Abdelghany, A. F., and Abdelghany, K. (2018). These systems are widely used over decades, and over the years combinations and variations have emerged to try to mitigate the downside of each model.

Point-to-Point

The Point-to-Point model was initially used due to low demand for more complex networks like a hub-and-spoke model Martí, L., (2015). Thereafter it was opted by low-cost carriers who serve mainly secondary airports within a smaller region. As explained in the introduction the main idea of the point-to-point model is that the flight goes directly from city A to city B without a connection. An example framework can be seen in figure 2.2 with each node representing an airport and the arrows indicating flight legs and direction.

The Point-to-Point model is generally cheaper to operate for airlines Zgodavová, Z., (2018). Martí, L., (2015) finds that low-cost and private flight operators, which typically use the Point-to-Point system, manage their resources more efficiently than those using hubs. The efficiency score is calculated based on the relationship between the weighted sum of outputs (operating income) and the weighted sum of inputs (tangible and intangible assets, supplies, and labor costs). One of the reasons is the reduction in operational complexity and time. Cook, G., and Goodwin, J. (2008) also highlights that low-cost carriers, often associated with Point-to-Point systems, have been more successful and have grown more compared to network carriers using the Hub-and-Spoke system. Another advantage stated by Cook, G., and Goodwin, J. (2008) is the duration of flying: Point-to-point flights reduce the total travel time which is valued by passengers. In addition, an advantage of point-to-point is limiting congestion at one single airport. Airlines adopting the point-to-point model often increase the agility and flexibility of adding or adjusting the routes based on demand, this was especially seen during COVID-19. Morrell, P., and Lu, C. (2007) shows also the sustainable benefits of direct routes. It generates significant savings in noise and engine emissions costs. The environmental (social) cost difference ranged from 25% to 71%, depending on population density and extra mileage involved in hub routing.

Figure 2.2: Illustration of Point-to-Point Network

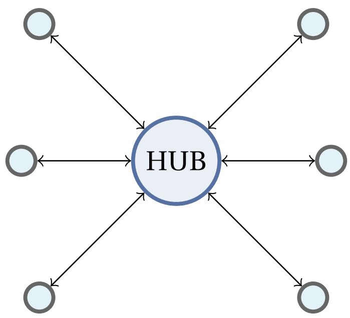


Martí, L., (2015) and Alderighi, M., (2005) state that scheduling a direct flight between two cities is only feasible if the demand is high enough between the cities. This is one of the biggest drawbacks of a point-to-point network as it limits origin-destination pairs. The load factor is generally lower due to point-to-point operations being sensitive to demand fluctuations. Point-to-point offers limited connectivity, as no connection is possible. Flight frequency is found important by customers and in general, flight frequency is low in point-to-point.

HUB-AND-SPOKE

The hub-and-spoke model has increased in popularity over the recent decades. It offers passengers a substantial increase in origin-destination pairs by connecting cities through a hub. A hub is a central airport where all flights either depart to or arrive from various spoke airports. A spoke is a non-hub airport in the airline network. See figure 2.3 for an illustration.

Figure 2.3: Illustrations of Hub-and-Spoke Network



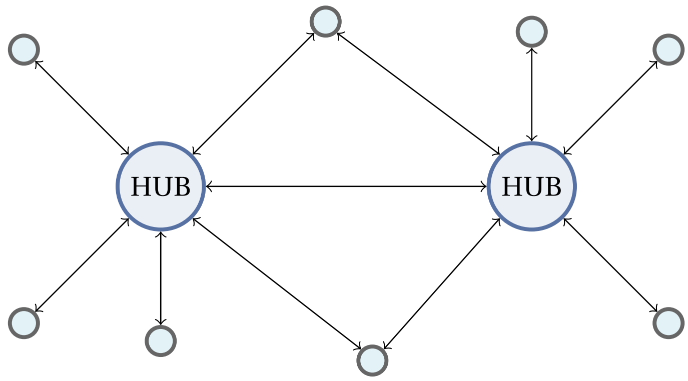
Wheeler, C. F. (1989) notes that a hub-and-spoke network provides high-frequency flight routes between low-density city pairs. A hub-and-spoke network model offers, when designed efficiently, a wide variety of origin-destination pairs via a connection through the hub. Having not only direct passengers but also connecting passengers allows the airlines to use bigger planes which are cheaper per seat Brueckner, J. K., and Spiller, P. T. (1994). Using a hub-and-spoke model allows airlines to increase the flight frequency between the hub and a spoke, which ultimately gives the passenger more flexibility on the time of departure. Due to the large number of routing possibilities and always returning to the hub, a hub-and-spoke can utilize its resources better, which increases operational efficiency Wheeler, C. F. (1989). Barla, P., and Constantatos, C. (2000) shows that hubbing provides airlines with increased flexibility in demand-uncertain markets, by reallocating its capacity.

The hub-and-spoke model increases traffic at the hub, especially during peak demand. This results in congestion at the hub airport, which most likely leads to more delays. On top of this, a drawback of this model is the dependency on one single airport. If the airport is nonoperational due to weather or strikes, the whole network collapses. This would result in lots of claims from passengers and operational problems Wheeler, C. F. (1989). In the previous subsection, it is already mentioned that point-to-point is better for the environment. This is confirmed by Pels, E. (2021), who gave an overview of several studies assessing the sustainability of a hub-and-spoke network.

Multi-hub Model

Quickly after the introduction of hub-and-spoke networks, networks with multiple hubs emerged. This is strengthened by mergers and partnerships between airlines, like Air France-KLM. Naturally, a single hub network reaches a maximum in growth in the form of airport capacity or origin-destination routes to be logically flown through the hub. A Dutch airline with a hub in Amsterdam, would not be able to capture passengers flying from Barcelona to Rome without excessive detours Goedeking, P. (2010). It could be advantageous for this airline to add a second hub to gain access to new regions while being competitive. Even when overlapping some O-D routes, airlines found it to be highly beneficial and yield enormous benefits.

Figure 2.4: Illustrations of Multi-Hub Network



Chou, Y.-H. (1990) mentions that major airlines upgrade to hub-and-spoke networks with multiple hubs to remain competitive. If the duration of the route gets too long, customers will move to other airlines. One of the downsides of a hub-and-spoke network is congestion at a hub airport, which can lead to delays. When transforming from a single hub to multi-hub, delays can be decreased and passenger satisfaction increased as shown by Karaman, A. (2018).

The strategic advantages of utilizing multiple hubs within a network, as opposed to a single hub, are still uncertain, since the primary benefit — density economies — declines with the addition of each new hub Düdden, J.-C. (2006). However, in this stage, the frequency development outweighs the loss in density economies in most of the thin markets Burghouwt, G. (2014).

Burghouwt, G. (2014) shows a distinction in types of multihubs: the complementary, overflow, and regional systems. The complementary multihub system can be seen in two or more evenly distributed hubs that serve both long-haul flights. This results in a high-yield local market at both hubs at the same time. The hubs are complementary on smaller (international) destinations. A great example is the Air France-KLM dual hub system. The overflow system contains a primary hub and smaller hubs, which don't have any natural advantages. The smaller intercontinental destinations are served from the primary hub. Lastly, the regional system, when the local geographical market cannot be covered by the primary hubs. Lyon is a regional hub in the Air France-KLM multi-hub system.

2.2. DESTINATION AND FREQUENCY MODELING

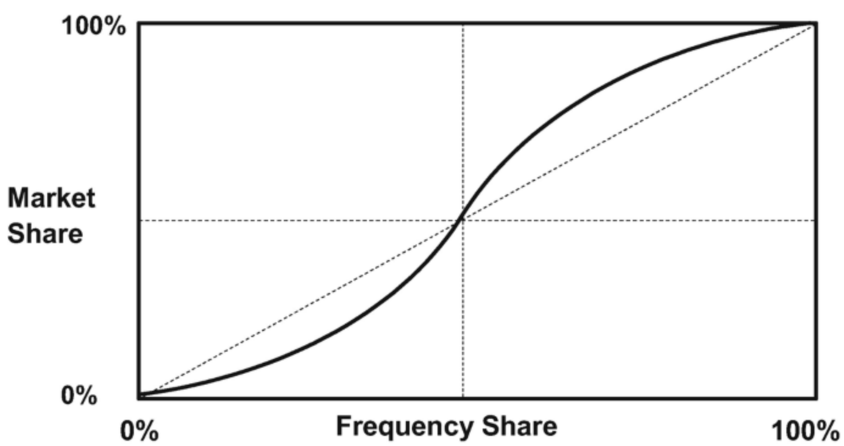
When airlines choose new destinations to operate, several factors are at stake. These factors could be, among other things, market demand, network strategy, competitive dynamics, operational restrictions, and regulatory considerations Wong, C. W., (2023). Airlines also prioritize destinations that complement their current network, considering both direct demand, as well as connecting demand.

Demand forecasting is a major topic within airline planning. As the objective for any airline is to maximize profits in the long run, the best match needs to be found between demand and supply. Demand is however uncertain. Basic models used to predict demand are based on historical data, economic trends, and passenger booking patterns. More advanced models often incorporate seasonality, demographic factors, and competitive pricing. Sherali, H., and Zhu, X. (2008), Kenan, N., (2017), Birolini, S., Jacquillat, A., (2021), and Birolini, S., Pais Antunes, A., (2021) are all focused on the integration of (stochastic or uncertain) demand in airline planning.

To model demand with respect to airline planning, two approaches can be taken. A static or dynamic demand model can be implemented Enki, Y., (2024). Static demand refers to a product or service that remains constant over a period of time. In the context of the airline industry, static demand assumes that passenger demand for flights is predictable and does not change significantly due to external factors. Dynamic demand adapts to these external factors, such as competitors, economic conditions, and unexpected events (e.g. pandemic). Therefore dynamic demand models often incorporate real-time data to better capture these variations. This allows for more responsive planning.

Market share, which can be variously measured in terms of passengers, seats, or flights between origin-destination markets, is always a function of the frequency of flights Vogel, H. L. (2021). Frequent flights lead to increased market share as the flexibility of the airline increases and therefore the service to passengers. The theoretical relationship between flight frequency and market share can be seen in figure 2.5 as an elongated forward slanted "S"-curve. This is only theoretical as operationally more factors are at play such as departure times and airline reputation.

Figure 2.5: Flight Frequency in relation to Market Share Belobaba, P., (2015).



2.3. CONNECTIVITY AND CONNECTION BANK

Hub connectivity refers to the number and efficiency of connecting flights available to passengers through an airline hub Bootsma, P. (1997).

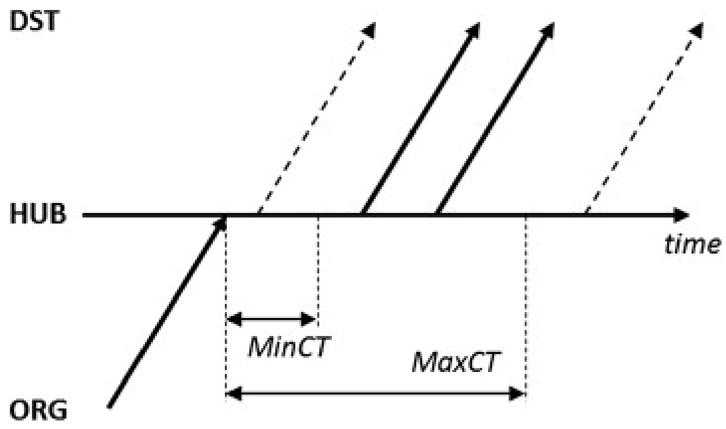
The choice for an airline includes numerous factors: fares, airline reputation, in-flight services, and frequent flyer programs among other things. Another factor is scheduling convenience, this would include the total duration of the flight and the number of destinations. IATA (2015) showed the three most influential metrics for ticket purchases. For most passengers, the ticket price (41%) is the most important factor, followed by schedule and convenient flight time (21%) and frequent flyer program (13%). The second factor is especially present for business passengers as they are more time-sensitive and less price-sensitive Nenem, S., (2020). This is also proved by Milioti, C., (2015), who used multivariate probit models to analyze airline choice by passengers. The model showed business travelers are less price-sensitive and consider the flight schedule to be important, they have also a higher tendency to direct non-stop flights. Burghouwt, G., and De Wit, J. (2005), Huang, J., and Wang, J. (2017) and Jiang, Y., (2020) model the duration of the connection with respect to the total duration of the route in choosing flights. These models show the behavior of passengers who seek the quickest and most convenient routes. In addition, passengers tend to accept a one-stop route, but this acceptance decreases drastically when it is a multi-stop route. Multistop routes attract only about 2–3% of the total passenger demand Seredyński, A., (2014).

Another factor considered in deciding if a connection is valid is the degree of geographical detour, which is also known as circuitry or detour factor. It is calculated by the sum of the distances of all legs divided by the origin-destination distance. Research has shown acceptable maximum detour factors are between 1.25 and 1.7, however in most cases not more than 1.5 Seredyński, A., (2014). So if the detour factor is 2, the total distance flown by the route with a connection is twice as much a direct flight.

Logothetis, M., and Miyoshi, C. (2018) developed a new model (The Hub Connectivity Performance Analyser (HCPA)) to evaluate the connectivity of indirect flights, in which schedule- and comfort-related attributes are both assessed. The paper conducts a case study on Emirates and Turkish Airlines. It shows that for Emirates almost 85% of the connecting flight is perceived by passengers as the same value as direct flights between the O-D market. For Turkish Airlines, this drops to an efficiency of only 70.7%. It needs to be noted that the presence of a large local market for Turkish Airlines influences the strategy to not only focus on optimal connecting flights or that it is simply not possible.

A connection bank is a core feature of a hub-and-spoke. A connection bank is a cluster of closely timed arrivals and departures at a hub airport, designed to maximize feasible connections for passengers transferring between flights. Feasible solutions entail as many origin-destination pairs within a specific time frame. In figure 2.6 a connection bank can be seen from a passenger's point of view Seredyński, A., (2014). It also shows the minimum connecting time (MinCT) and maximum connecting time (MaxCT). The MinCT in this case is the time needed for passengers and their baggage to change flights. This number is set by the airport and usually depends on the type of connection. The value of this number is derived from several hundreds of rules and therefore simplified within research. By applying MaxCT limits, strongly unattractive connections are removed by restricting the maximum time transfer passengers have to wait between flights at a hub airport. This can be distinguished between continental and intercontinental flights and proposed 180 min for continental, 300 min for continental-to-intercontinental, and 720 min for intercontinental connections Burghouwt, G., and De Wit, J. (2005).

Figure 2.6: Connection Bank including minimum and maximum connecting time.



On frequently served routes, multiple flight-legs can be done in one day. Seredyński, A., (2014) analyzed that 85% of the passengers book the fastest connection, 13% the second fastest, and the rest book slower connections.

From an aircraft point of view, there is also a minimum time during a connection, this is called the minimum Turnaround Time. This is the time needed between arriving and departure to reload the aircraft and switch crew.

2.4. TIMETABLE DESIGN

Combining all above would result in a timetable as seen in table 2.1. In this case, passengers from using F5 can be connected at Airport A to F6. This creates an attractive origin-destination pair between airports B and C.

Table 2.1: Airline Timetable derived from Xu, Y., (2023)

Flight	Dep. Airport	Arr Air.	Dep. time	Arr. time
F1	Airport A	Airport B	08:00	09:30
F2	Airport B	Airport A	10:10	11:40
F2	Airport C	Airport A	10:20	12:20
F4	Airport A	Airport B	07:30	09:00
F5	Airport B	Airport A	10:15	11:45
F6	Airport A	Airport C	13:00	16:00
F7	Airport C	Airport A	16:45	19:45
F8	Airport A	Airport C	20:30	22:30

3

Literature Review

As already discussed in chapter 2, airline planning involves many different stakeholders and one bucket cannot be solved independently without influencing other areas. For example, it is possible to develop an extremely efficient schedule, but if maintenance checks are not accounted for, the schedule is basically useless. Said this, to solve the whole picture is impossible for this research. In section 3.1, a closer look is taken into efficient scheduling with a focus on the airline scheduling problem and the fleet assignment problem. Section 3.2 provides an overview of the state-of-the-art research of the hub location problem with a focus on the airline industry.

3.1. Airline Planning Problem

The fleet assignment model (FAM) involves allocating aircraft types to scheduled flights to maximize profit, while scheduling determines flight timetables. The fleet assignment problem and airline schedule planning problem have been researched over decades. Abara, J. (1989) was one of the first to solve the fleet assignment problem, but with a fixed daily schedule. In addition to Abara, J. (1989), Hane, C. A., (1995) also discussed the fleet network problem at an early stage, both with a daily fixed schedule. Abara, J. (1989) point out that the objective is free to choose based on the preference of the user, but generally it is to maximize the benefit contribution of the flights less the cost. Since then, research has shown fleet assignment and scheduling as an integrated problem to find the optimal solution for both.

In the airline industry, two mathematical types of networks are mostly used to solve problems within airline planning. The first is a connection network, an illustration of this network van be seen in figure 3.1. This network was first introduced by Abara, J. (1989). The second is a time space network which can been seen in figure 3.2. Hane, C. A., (1995) was among the first to discuss this type of network.

In a connection network, the nodes represent a point in time when flight arrive or depart. The arcs in the network represent flight connection arcs who link arrival nodes to departure nodes. It also includes master source and master sink nodes to model the beginning and end of the day. This structure ensures that the model adheres to constraints such as minimum turn-times between flights and allows for the assignment of fleet types to these connections. The decision variable x_{ijf} in this network is a binary variable that takes 1 if there is a connection between flight leg i and flight leg j by fleet type f, and otherwise 0 Sherali, H. D., (2006).

Figure 3.1: Connection Network

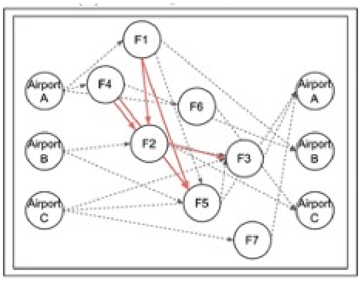
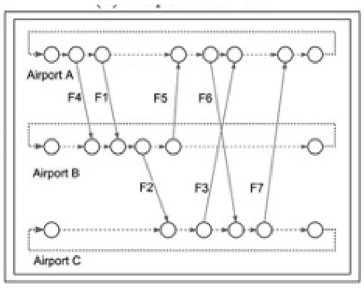


Figure 3.2: Time Space Network



In contrast, a time-space network focuses on representing flight legs directly. This allows the model to determine feasible connections based on time and space. The nodes represent the departure and arrival of a flight leg. The arcs represent ground arcs, flight arcs, or wrap-around arcs. This representation provides greater flexibility in establishing connections and reduces the number of decision variables since it does not require specifying all possible connections in advance. However, it does not distinguish among specific aircraft on the ground, which can limit its application in the subsequent routing problem. The decision variable x_{fi} in this network is a binary variable that takes 1 if fleet type f covers flight leg i, and otherwise 0. Additionally, it includes flow variables $x_{fstt'}$ that represent the flow over the ground arcs by fleet type f at station s between a specific time Sherali, H. D., (2006).

Desaulniers, G., (1997) build upon the work of Hane, C. A., (1995) by incorporating time windows into the arrival and departure of flight legs. This concept allows for greater flexibility by allowing airlines to shift between departure times within the time window to better match passenger demand, optimize resource usage, and mitigate delays. The increase in flexibility comes with its limitation as the bigger the time windows, the bigger the problem. Also, aircraft utilization decreased, and subsequently the airline's profit. The needed time window should be observed case by case.

In addition to the fleet assignment model, Barnhart, C., (2002) introduced the itinerary-based fleet assignment model (IFAM). They combine the FAM with the Passenger Mix Model (PMM). The PMM is a framework designed to optimize the allocation of passengers across different flight legs in an airline's schedule, with the goal of maximizing revenue or minimizing costs associated with carrying passengers. It improves the FAM model by more effectively capturing network effects and handling spill and recapture dynamics. While FAM treats each flight leg independently, IFAM integrated the flight legs for increased efficiency. IFAM explicitly models spill and recapture, optimizing capacity across the network. Barnhart, C., (2002) used the model of Hane, C. A., (1995) as the basis of the IFAM.

Previous research was focused solely on daily schedules. Bélanger, N., (2006) was the first to research to develop a weekly schedule with homogeneity, meaning using the same aircraft for each flight. The used an edited version of the model proposed by Hane, C. A., (1995), which includes additional variables and constraints. The advantages of a weekly schedule are differentiating between weekdays and weekend days.

Till this time the fleet assignment model and scheduling problem were solved independently. To the best of the author's knowledge Lohatepanont, M., and Barnhart, C. (2004) was the first to introduce an Integrated Schedule Design and Fleet Assignment Model (ISD-FAM). Lohatepanont, M., and Barnhart, C. (2004) used the IFAM framework developed by Barnhart, C., (2002) as the core of the integrated model. The ISD-FAM can optimize both the selection of flight legs and the assignment of the different types of aircraft. ISD-FAM incorporated demand correction terms to account for a dynamic market. However, at that time, this model is not suitable to find solutions to large problem sizes within a desired timeframe. Therefore the Approximate Schedule Design and Fleet Assignment Model (ASD-FAM) was proposed. The ASD-FAM removes the demand correction terms and applies modified recapture rates for interaction between demand and supply. The ASD-FAM demonstrated improved performance by quick and feasible solutions.

Sherali, H., and Zhu, X. (2008) present a two-stage stochastic mixed-integer approach to address the FAM. The primary focus is assigning aircraft to flight legs while demand is uncertain. In the first stage, the model makes a high-level family assignment decision based on different scenarios. The second stage involves a detailed assignment of the different fleet types within the chosen families, taking into account the uncertain demand. This allows for greater flexibility during the decision-making process. Yan, S., (2008) also addresses the complexity of demand uncertainty during the scheduling process. The authors highlight that the traditional approach at that time often relied on average demand. The paper introduced a two-stage stochastic framework that incorporates stochastic demand and variable market shares. The results of the stochastic-demand flight scheduling model show improvements over the deterministic-demand flight scheduling model.

To add flexibility to an integrated airline schedule design and fleet assignment problem optional flight legs can be included in the model Sherali, H., (2013). The model also includes utilization of itinerary-based demand and multiple fare classes. In addition, it incorporates balance constraints to ensure even distribution of flights over the day to 1) accommodate passengers and 2) less congestion at major hubs. This is in addition to more features already mentioned in the research above. The model of Sherali, H., (2013) shows a well-rounded solution for the problem. One of the limitations of this model is that it uses mandatory flight legs as input, so it does not build a network schedule from scratch. This could however be due to the limited computer power at the time, as the proposed model had already out-of-memory difficulties.

The first model focused on integrated airline scheduling and fleet assignment in combination with airport congestion was proposed by Pita, J., (2013). The model significantly improves airline modeling by incorporating delay cost and airport congestion using an origin-destination based framework. The case study of TAP Portugal, a multi-hub network with the main hub in Lisbon and a secondary hub in Porto, showed great results. The model showed an increase in profits, a reduction of total flights and a decrease in delay cost. However, the average connecting time increased slightly.

Zhang, D., (2016) propose a two-mixed integer programming model, with the first stage solving the integrated airline schedule and fleet assignment based on a discrete choice model. The second model includes price elasticity on an itinerary base level. The focus on price elasticity and passenger preferences, provides a more nuanced understanding of how these factors influence flight scheduling and fleet assignment decisions in a competitive airline market. The authors use a heuristic algorithm to solve the second model efficiently and they demonstrate that the proposed models can significantly improve airline profits by optimizing flight schedules and fleet assignments, particularly in competitive markets where passenger preferences and market share dynamics are crucial.

Previous research showed integrated flight scheduling and fleet assignment under stochastic demand Yan, S., (2008) and Sherali, H., and Zhu, X. (2008). In addition, Kenan, N., (2017) proposed an integrated model in combination with stochastic demand and stochastic fares. The authors developed a similar two-stage stochastic programming model as Sherali, H., and Zhu, X. (2008), but including stochastic fares in the second stage. A Sample Average Approximation algorithm was used, which was the first time within the airline industry, resulting in a near-optimal solution. Although the paper focused on stochastic demand, the model does not account for demand spill and recapture.

Abdelghany, A., (2017) presents a comprehensive model to optimize airline scheduling in a competitive environment. The focus of the paper is developing an operational flight timetable that maximizes revenue while ensuring enough possibilities to utilize its resources like aircraft and crew. The framework explicitly focuses on demand shift due to competition among airlines by integrating a network competition analysis model. This model captures the interaction between the scheduling decisions of the target airline and the responses of passengers to these decisions, particularly in terms of their itinerary choices. It uses a bi-level optimization model, with the upper level focusing on the initial schedule and the lower level focusing on passenger choice on the attractiveness of the itinerary. Genetic Algorithm is used to solve the problem in combination with a passenger assignment-simulation model, and a resource-tracking model. Previous research already incorporates competition into their model Yan, S., (2008), Sherali, H., (2013) and Pita, J., (2013). However, Abdelghany, A., (2017) advances by providing a more holistic and dynamic approach that incorporates competition.

Wei, K., and Jacquillat, A. (2019) focused on integrating passenger choice into timetable development and the fleet assignment model. The authors argue passengers booking decisions depend on airline planning decisions. This model captures the attractiveness of each itinerary based on various factors, including the departure and arrival times of flights, connection opportunities, and ticket prices. Specifically, the model allows for the calculation of the probability that a passenger will choose a particular itinerary based on its attractiveness relative to other available options, including itineraries offered by competing airlines and the no-fly alternative. The model includes a comprehensive approach to timetabling that starts from scratch rather than making incremental adjustments to existing schedules. Due to the size of the model, commercial solvers and state-of-the-art integer programming approaches were not possible. They proposed a multiphase solution framework including a rule-based heuristic strategy.

Ciftci, M. E., and Özkır, V. (2020) presented a model to minimize connection time for passengers at hub airports. The study examines the bank structure at hub airports. Bank structures try to minimize the connection time between flight legs by passengers. The model showed enhanced passenger convenience and operational efficiency by reducing the connection time and airport congestion. Given the nature of the NP-hard problem, they employ two meta-heuristic algorithms, Simulated Annealing and Tabu Search, to derive near-optimal solutions efficiently.

Over recent years, the supply-demand interaction has gained a lot of attention. Birolini, S., Pais Antunes, A., (2021) proposed a mixed integer nonlinear flight scheduling and fleet assignment optimization model. The paper overcomes the limitation of Zhang, D., (2016), where the model suffers from unrealistic substitution patterns due to the assumption that the odds ratios between pairs of alternatives are unaffected by other choices. This limitation was already addressed by Cadarso, L., (2017). The model proposed by Pita, J., (2013) lacks advanced market demand representation where service attributes such as flight frequency and travel time are ignored. To overcome these limitations, the paper integrates a hierarchical demand model based on nested logit formulation, which results in nonlinearity. The benefit of this model is the continuous integration of demand and allocation of individual itineraries. To solve this model a tailored piecewise linearization scheme is introduced followed by tightening constraints. The case study of Alitalia showed an improvement in profits of 6.9% in comparison to the baseline scenario.

In the same year, another paper was published by partially the same authors. Birolini, S., Jacquillat, A., (2021) similarly proposed a model to capture the interactions between demand and supply. This paper indeed recognizes also the interdependencies between supply and demand (i.e. demand changes on the service/products provided). However the major difference in this paper focuses on strategic planning, so long-term planning decisions. Birolini, S., Pais Antunes, A., (2021) focuses more on tactical planning, medium-term planning decisions. Birolini, S., Jacquillat, A.,

(2021) present a mixed-integer non-convex optimization model known as Airline Network Planning with Supply and Demand Interactions (ANPSD). To solve this model they introduce 2αECP: An exact gradient-based cutting plane algorithm. This algorithm develops a linear outer approximation of the nonlinear, nonconvex function. In the case study, a multihub network system is present. The hubs are randomly chosen among the ten largest hubs in Europe. This could limit the efficiency.

Yang, H., Buire, C., (2024) focused on optimizing connectivity through bank structure via a multi-objective framework. The authors use a hub connectivity index to quantify the attractiveness of a connection. First, it evaluates all feasible connections and secondly it ranks these connections using the Quality of Connectivity Index. The Quality of Connectivity consists of two components, with the first focusing on detours in terms of distance and the second focusing on the extra time by connecting instead of a direct flight. To solve this a Selective Simulated Annealing is adopted which resulted in time-efficient results.

Enki, Y., (2024) proposed a two-phase methodology aimed at capacity optimization and the fleet assignment problem. The first phase is focused on demand projection with three different scenarios (low, base, and high) as output. These outputs consist of flight frequency to which destination and an acceptable range for the fleet size of the FAP model. This methodology allows for Network Contribution at a strategic level, which results in increased coverage and subsequently increase in revenue. Network Contribution refers to the revenue generated by specific routes or flight legs within the overall flight network.

To the best knowledge of the author, Yang, H., Delahaye, D., (2024) are the first and only authors focusing on improving efficiency specifically focused on a multi-hub network. Previous research has included multiple hubs within their network for a case study, but never the focus on utilizing the hubs as efficiently as possible. Yang, H., Delahaye, D., (2024) proposed a model to re-time flight legs in order to increase the total connectivity of the network measured by a modified Hub Connectivity Index. It showed great results, but the scope was limited to re-timing and therefore not applicable to building a network from scratch.

Table 3.1: Literature Overview Airline Planning

Paper	Network Type			Network model		Problem				Focus						Algorithm
	P2P	H&S	MultiHub	CN	TSN	SDP	Timetable	FAP	ARP	Demand	Connectivity	Competition	Passenger Choice	Fares	Airport Congestion	
Abara, J. (1989)				x				x		x	x					ILP
Hane, C. A., (1995)		x			x			x		x	x				x	B&B
Desaulniers, G., (1997)	?	?			x	x		x		x	x					B&B
Barnhart, C., (2002)		x			x			x			x					CRG
Bélanger, N., (2006)	?	?			x			x								TPH
Lohatepanont, M., and Barnhart, C. (2004)		x														CRG, B&B
Sherali, H. D., (2006)		x			x	x	x	x		x	x		x			N/A
Yan, S., (2008)	x				x	x	x			x		x	x			HA
Sherali, H., and Zhu, X. (2008)	?	?			x			x		x						BD
Sherali, H., (2013)		x			x	x		x		x		x		x	x	BD
Sherali, H., (2013)		x	x		x	x	x	x			x	x			x	XS
Zhang, D., (2016)		x			x	x		x					x	x		HCPR
Kenan, N., (2017)		x			x					x				x		SAA

Algorithm Abbreviations:
ILP = Integer Linear Programming, B&B = Branch and Bound, CRG = Column-and-row generation, TPH = Two-phase heuristics, HA = Heuristic Algorithms, BD = Bender Decomposition, XS = Xpress (Commercial Solver), HCPR = Heuristic (Clique Partition, Relaxation), SAA = Sample Average Approximation.

Table 3.1 continued: Literature Overview Airline Planning

Paper	Network Type			Network model		Problem				Focus						Algorithm
	P2P	H&S	MultiHub	CN	TSN	SDP	Timetable	FAP	ARP	Demand	Connectivity	Competition	Passenger Choice	Fares	Airport Congestion	
Abdelghany, A., (2017)		x			x	x	x			x		x	x			GA
Kenan, N., (2018)		x	x	x		x		x	x	x	x					SMP, CG
Wei, K., and Jacquillat, A. (2019)			x		x	x	x	x			x	x	x			RBH
Ciftci, M. E., and Özkır, V. (2020)		x		N/A	N/A	x	x				x					TS & SA
Birolini, S., Pais Antunes, A., (2021)		x			x	x		x		x		x				PLT
Birolini, S., Jacquillat, A., (2021)		x	x		x	x	x	x		x	x					CPA
Xu, Y., (2021)		x		x		x		x	x		x					VNS, CG
Yang, H., Delahaye, D., (2024)			x	-	-	x	x				x					SSA
Enki, Y., (2024)		x		x				x		x						MILP
Yang, H., Buire, C., (2024)		x	x	N/A	N/A	x	x				x					SA

Algorithm Abbreviations:
GA: Genetic Algorithm, SMP: Stochastic Mixed-Integer Programming, CG: Column Generation,RBH: Rule-Based Heuristics, TS: Tabu Search, SA: Simulated Annealing,
PLT: Piecewise Linearization and Tightening Constraints, CPA: Cutting-Plane Algorithm, VNS: Variable Neighbourhood Search, MILP: Mixed-Integer Linear Programming

3.2. HUB LOCATION PROBLEM

As there is limited research on optimizing airline planning utilizing multiple hubs, a closer look is taken into a more general problem. This problem is the Hub Location Problem (HLP). The hub location problem is a specific area in the location theory focused on the strategic placement of the hubs to maximize the efficiency of the total network Farahani, R. Z., (2013). The efficiency can be measured in several ways, and this will be discussed later in this section. The first HLP to be addressed using optimization models was proposed by O'Kelly, M. (1987). The hub location problem has several variants and can be summarized in table 3.2.

Table 3.2: Classification of Hub Location Problem (HLP) Models Farahani, R. Z., (2013)

Capacity of hub node	Assignment of non-hub node to hub nodes	Type of the HLP	Number of hub nodes
Capacitated (C)	Single allocation (SA)	Median (M)	Single (1)
Uncapacitated (U)	Multiple allocation (MA)	Center (T)	More than one (P)
		Covering (V)	
		Set covering (SV)	
		Maximum covering (MV)	

Firstly, A hub node can be capacitated (C) or uncapacitated (U), identifying whether a hub has capacity constraints like maximum traffic flow. Secondly, a spoke can be allocated to a single hub (SA) or allocated to multiple hubs (MA). Thirdly, what is the type of HLP, this can also be observed as the objective of the HLP. This can be seen in table 3.3. Lastly, the decision on how many hubs are being used.

Table 3.3: Hub Location Problem Types Farahani, R. Z., (2013)

Type of the HLP	Objective
Median (M)	Minimize total transportation cost
Center (T)	Minimize maximum distance
Covering (V)	Cover all nodes within a threshold
Set Covering (SV)	Ensure all nodes within range
Maximum Covering (MV)	Maximize coverage of nodes

In the case of the airline industry and the focus of this research; it should be a **C-MA-...-P** HLP. The airline industry is in terms of the objective somewhat more complicated as the objective is not as straightforward as in table 3.3. The objective could involve dynamic demand or competition.

Eiselt, H. A., and Marianov, V. (2009) addresses the competitive hub location problem. The authors incorporate an attractiveness function based on flying time (including connection time) and fares. This model is proposed to capture the preferences of the passengers. The authors relax the "winner-takes-all" assumption, resulting in a more realistic model. The model uses three factors to decide the attractiveness of each route; The basic attractiveness of an airline, travel time, and fare. The model incorporates non-elastic demand to calculate the market share. The case study used only one competitor and was based on Australian Post data. Tiwari, R., (2021a) extends the work of Eiselt, H. A., and Marianov, V. (2009) by introducing four alternative approaches to solve large-scale instances. The findings indicate that Kelley's cutting plane method within Lagrangian relaxation (LR-CPA) is the most effective approach, successfully solving all tested instances with up to 50 nodes within a 1% optimality gap in less than 10 minutes of CPU time. Tiwari, R., (2021b) extends the work of Eiselt, H. A., and Marianov, V. (2009) by proposing a single allocation and multiple allocation model in which only one path is allowed between any origin and destination pair through the hubs. It claims that this preserves the economy of scale benefit of a hub and spoke network. Due to this added constraint, the market share is lower than the model of Eiselt, H. A., and Marianov, V. (2009), but the authors mentioned that the network is also more likely to be costlier to operate. The difference between market share between single allocation and multiple allocations is negligible, however, CPU time is drastically different (120 minutes for SA and 10 minutes for MA).

Soylu, B., and Katip, H. (2019) proposed a bi-objective uncapacitated multiple allocation p-hub median problem to minimize the transportation cost and 2-stop journey. The argument is that this will increase the direct and 1-stop routes. This results in higher customer satisfaction. The authors propose both exact and heuristic (Variable Neighborhood Search) algorithms to find the Pareto frontier, which represents the set of optimal solutions balancing the two objectives.

Yin, F., and Zhao, Y. (2021) introduce a mean-CVaR (Conditional Value-at-Risk) hub interdiction median model that considers travel time as a random variable with finite sample observations. It develops a data-driven robust model with integration of statistical hypothesis testing. The model accounts for uncertainty in travel time based on finite sample data, which has not been previously applied to hub interdiction problems.

The first step in airline planning is fleet planning. So for a new airline, deciding which hubs to operate is closely related to fleet planning. Mohri, S. S., (2022) is the first with an integrated approach to the hub location problem and fleet planning. Nasrollahi, M., and Kordani, A. A. (2023) extends this work by incorporating passengers' preferences and the value of time. It uses a bi-objective uncapacitated single allocation HLP.

ExtHatipoğlu, S., (2024) focuses on the selection of a secondary hub using the HLP. The objective is to maximize connectivity and green airport solutions. The model incorporates social, economic, and environmental factors affecting airport connectivity.

Table 3.4: Literature Overview Hub Location Problem

Title	Capacity		Allocation		Number of hubs		Algorithm	Relation to airline industry
	Uncapacitated	**Capacitated**	**Single**	**Multiple**	**1**	**p**		
Eiselt, H. A., and Marianov, V. (2009)	x			x		x	Heuristic concentration procedure	Competition / attractiveness of hubs
Soylu, B., and Katip, H. (2019)	x			x		x	Variable Neighborhood Search	Minimize transportation cost & 2-stop journey
Sharma, A., (2021)	x			x		x	MIP (CPLEX)	Cooperation
Tiwari, R., (2021a)	x			x		x	LR-CPA	Competition / attractiveness of hubs
Tiwari, R., (2021b)	x		x	x		x	LR-CPA	Competition
Yin, F., and Zhao, Y. (2021)	x		x			x	Sample Average Approximation	Minimize transportation cost
Mohri, S. S., (2022)	x			x		x	Commercial solver (exact, GAMS)	Minimize cost
Nasrollahi, M., and Kordani, A. A. (2023)	x		x			x		Passengers choice

4

Solution Algorithms

The problems described in chapter 3 are very complex and need to be solved in a clever way. These problems are all (mixed) integer programming problems. Commercial solvers, like Gurobi, are very advanced. However, in most of the literature unique algorithms were used to obtain a faster reasonable result. In this section, four algorithms are highlighted that were often found in recent research. These four are not exhaustive. In section 4.1 an overview will be given of exact methods. In section 4.2 a deep dive will be done into metaheuristic methods. Section 4.3 provides an overview of the models.

4.1. Exact solution models

It is possible to solve these problems by just trying every option. Due to the complexity of the problem, this is not reasonable as runtime would be enormous. Different algorithms have been developed and used to mitigate this problem. These algorithms create several smaller subproblems or relax a constraint (i.e. ignore a constraint).

Benders Decomposition

Sherali, H., (2013) used a bender decomposition algorithm to solve the integrated schedule design and fleet assignment problem. Bender composition split the problem into several smaller, more manageable problems. This method works particularly well if the decision variable consists of integer and continuous variables.

This algorithm was first introduced by BENDERS, J. (1962/63). The problem is first divided into two parts. The first one is the master problem. The master problem is the main problem that includes the decision variables that are difficult to handle directly. This would be integer or binary decision variables. The second part is the subproblem. the subproblem evaluates the feasibility and optimality of the master problem. It usually involves continuous variables and can be solved more easily than the master problem.

It is an iterative process. After the initial solution by the master problem and the evaluation of the subproblem, **Bender's cuts** (additional constraints) based on the sub problem's solution or dual values are introduced to the master problem. This is done to narrow the search space in the master problem. These steps are repeated until the master and subproblem solutions converge.

Potential drawbacks of Bender Decomposition are slow convergence if the cuts are poor and the setup requirements to use this algorithm.

Algorithm 1 Benders Decomposition

Inputs:
P: Original problem formulation
ϵ: Tolerance for optimality
Outputs:
x^*: Optimal solution of the master problem
y^*: Optimal solution of the subproblem

Initialize $x^{(0)}$ — *Start with an initial feasible solution*
Set $LB = -\infty$ — *Initialize lower bound*
Set $UB = +\infty$ — *Initialize upper bound*
while $UB - LB > \epsilon$ **do** — *Continue until within tolerance*
  Solve the master problem with current $x^{(k)}$ — *Find feasible solution*
  if optimal master problem solution is found **then**
    $x^{(k+1)} = x^*$ — *Update solution*
    Solve the subproblem with $x^{(k+1)}$ — *Check feasibility of the master solution*
    if subproblem is feasible **then**
      $LB = f(x^{(k+1)})$ — *Update lower bound*
    else
      Generate Benders cuts — *Create cuts for infeasibility*
      Add cuts to the master problem — *Update master problem with cuts*
    end if
  end if
  Update upper bound UB — *Modify if necessary*
end while
return x^*, y^* — *Return optimal solutions*

Branch and Bound

Although Branch and Bound is a fairly old algorithm, it is still being used today. Abara, J. (1989) used this method when first introducing the fleet assignment problem more than three decades ago.

The algorithm starts by relaxing a constraint, most likely an integer or binary constraint. Solving this relaxed version gives an upper bound for a maximization problem and a lower bound for a minimization problem for the original integer problem. The objective is to find a minimum optimality gap.

After an initial solution is found for the relaxed version. A **branch** is created at the non-integer variable in the solution. If decision variable $x_1 = 3.7$ in the relaxed solution, two branches are created: 1) $x_1 \leq 3$ or 2) $x_1 \geq 4$. Each subproblem is solved as a relaxed version.

If a solution yields only integers, it is a candidate for the best solution. If the solution is worse than the best feasible solution, the solution gets **discarded** as it can not improve anymore. If the solution is non-integer and better than the current best solution, continue branching and creating further subproblems.

The limitation of branch and bound is that it is computationally intensive as the number of branches grows exponentially. This is especially true if the branches are not effective.

A pseudo-code derived from Martins, J. R. R. A., and Ning, A. (2021) can be found in algorithm 2.

Algorithm 2 Branch-and-Bound Algorithm

Inputs:
S: Set of binary constrained design variables
f_{best}: Best known solution, if any; otherwise $f_{\text{best}} = \infty$
Outputs:
x^*: Optimal point
$f(x^*)$: Optimal function value

```
while branches remain do
    Solve relaxed problem for x̂, f̂
    if relaxed problem is infeasible then
        Prune this branch, back up tree
    else
        if x̂_i ∈ {0,1} for all i ∈ S then                A solution is found
            f_best = min(f_best, f̂), back up tree
        else
            if f̂ > f_best then
                Prune this branch, back up tree
            else                                  A better solution might exist
                Branch further
            end if
        end if
    end if
end while
```

4.2. METAHEURISTIC MODELS

Heuristic algorithms aim to find good and feasible solutions within a desirable timeframe, but not the optimal solution. These methods focus on efficiency and practical usage. There is a difference between heuristics and metaheuristics. Heuristics has no local optimum escape mechanism while metaheuristics does. Partially, this results in heuristics finding a feasible solution quickly while metaheuristics are better in finding a near-optimal solution. As time is not relevant in this case and a better result is more desirable. The focus is on metaheuristics.

GENETIC ALGORITHM

A Genetic Algorithm (GA) is an optimization technique inspired by the principle of natural selection and genetics. It is particularly useful in large search spaces or highly nonlinear structures. Abdelghany, A., (2017) used GA to solve the airline planning problem under competition.

First, the algorithm creates **an initial population** (i.e. an initial set of solutions). Each solution will be evaluated by **the fitness function**, which scores how well it solves the optimization problem. The last step of this part is selecting a set of **parents** from the initial population. Higher-fitness solutions are more likely to be chosen, but low-rated fitness scores can also be chosen allowing for genetic diversity.

After the parents are selected multiple actions can happen but it is all probabilistic. The first is a crossover. For each of the selected parents, a crossover is done to create offspring. So a part of the solution space of one parent merges with the other half of the solution space of another parent. The second is the mutation. Mutation entails randomly altering genes based on a small probability. For example, flipping a binary bit. This helps to maintain diversity and not get stuck in a local optimum.

These steps are repeated for several generations until the algorithm is terminated. The algorithm is terminated when certain conditions are met, which could be a number of generations or minimum fitness level.

The limitations of the Genetic Algorithm are there is no guarantee of finding a global optimum. Also, the Genetic Algorithm is sensitive to parameters like mutation rate, crossover rate, and population size, often requiring fine-tuning.

A pseudo-code derived from Martins, J. R. R. A., and Ning, A. (2021) can be found in algorithm 3.

Algorithm 3 Genetic Algorithm

Inputs:

$\underline{x}$, $\bar{x}$: Lower and upper bounds

Outputs:

x^*: Best point

f^*: Corresponding function value

$k = 0$

$P_k = \{x^{(1)}, x^{(2)}, \ldots, x^{(n_p)}\}$ — *Generate initial population*

while $k < k_{\max}$ **do**

  Compute $f(x)$ for all $x \in P_k$ — *Evaluate objective function*

  Select $n_p/2$ parent pairs from P_k for crossover — *Selection*

  Generate a new population of n_p offspring (P_{k+1}) — *Crossover*

  Randomly mutate some points in the population — *Mutation*

  $k = k + 1$

end while

SIMULATED ANNEALING

Simulated Annealing (SA) is a probabilistic optimization technique. It finds a good approximation of the global optimum by allowing the algorithm to accept a worse solution. This allows the possibility to escape a local optimum. Yang, H., Delahaye, D., (2024) used SA to address the re-timing of flight for an optimal bank structure.

The algorithm starts with an initial solution and sets an initial temperature. The temperature parameter is used to determine the probability of accepting a worse solution. A high temperature allows for greater exploration of the solution space due to the increase in the probability of accepting a worse solution. The temperature decreases over time by a factor of α, making it more likely for worse solutions to be rejected in the later stages of the algorithm.

After the initial solution, a neighboring solution is generated by making small random changes to the solution space. The energy (i.e. objective function) is calculated for each solution. A better solution is always accepted. A worse solution could be accepted or rejected.

The algorithm terminates by setting up a stopping criterion. This could be the number of iterations or a threshold for the temperature. The final solution is the best solution found so far, it does not have to be the last solution found.

The limitations of Simulated Annealing are there is no guarantee of finding a global optimum. Also, Simulated Annealing is sensitive to parameters like the initial temperature, cooling schedule, and stopping criteria.

A pseudo-code derived from Martins, J. R. R. A., and Ning, A. (2021) can be found in algorithm 4.

Algorithm 4 Simulated Annealing

Inputs:
x_0: Starting point
T_0: Initial temperature
Outputs:
x^*: Optimal point

```
for k = 0 to k_max do                                   ▷ Simple iteration; convergence metrics can be used instead
    x_new = neighbor(x^(k))                             ▷ Randomly generate from neighbors
    if f(x_new) ≤ f(x^(k)) then                         ▷ Energy decreased; jump to new state
        x^(k+1) = x_new
    else
        r ∈ U[0,1]                                      ▷ Randomly draw from uniform distribution
        P = exp(−(f(x_new) − f(x^(k)))/T)               ▷ Probability high enough to jump
        if P ≥ r then
            x^(k+1) = x_new
        else
            x^(k+1) = x^(k)                             ▷ Otherwise remain at current state
        end if
    end if
    T = αT                                              ▷ Reduce temperature
end for
```

4.3. OVERVIEW

Several algorithms have been discussed above. It comes down to a trade-off between accuracy and speed between the exact methods and metaheuristics. In the case of this problem, accuracy is more important than speed as this model tackles long-term problems. However, there are limitations on the duration of the algorithm for practicality.

As a lot is still unknown at this point of the research, not a single algorithm can be chosen that guarantees the best result. This should be a process. Most likely to start with a metaheuristics approach to find quickly a feasible and near-optimal solution. If the model shows quick convergences using these algorithms, it could be that exact algorithms will be possible to implement. Based on the weighted score table 4.1, the Genetic Algorithm stands out as a strong initial candidate for implementation due to its high score in speed, scalability, and ease of implementation. It lacks however in robustness and interoperability, so this needs to be looked into.

Table 4.1: Weighted score table of the algorithms

	Weight	**Benders Decomposition**	**Brand and Bound**	**Genetic Algorithm**	**Simulated Annealing**
Accuracy	3	5	5	3	3
Speed	2	2	2	5	4
Implementation	2	2	2	4	4
Scalability	3	3	2	5	4
Robustness	2	5	4	3	3
Interpretability	1	4	3	2	2
Total Score		46	40	50	45

5

Case Study: IndiGo

This research is done in collaboration with IndiGo. In the end, a case study will be performed using IndiGo's network. As mentioned in the introduction, IndiGo recently purchased a new set of Airbus A300-900. This aircraft has the range to connect Europe with India and therefore Europe with East Asia. In addition to this future route, IndiGo already serves international areas at closer distances, like the Middle East and Central Asia. IndiGo is operating from six hubs in India. See table 5.1 below which six hubs are used including the current daily departures indicating the size of each hub.

Table 5.1: Hubs of IndiGo in India, including daily departures

City	Daily Departures
Delhi	219
Bengaluru	175
Mumbai	165
Hyderabad	152
Chennai	117
Kolkata	114

Due to India's promising geographic location between Europe and East Asia, it is an excellent candidate to serve this route. The competition on this route is however fierce. Firstly, the legacy carriers that fly direct, like Air France - KLM and Lufthansa. Secondly, the connecting carriers between Europe and Asia, like Turkish Airlines and the Gulf carriers[1]. The latter will most likely be the biggest competition. The question therefore is whether IndiGo can utilize its six hubs to gain an edge over the single hub networks of the competitors. Within this question, it will become clear if all the current six hubs, presented in table 5.1, are being used for international - international traffic flow.

[1] Emirates, Qatar and Etihad

6

Research Gap

This short chapter states the research gap in section 6.1, which identifies gaps in the reviewed literature. Section 6.2 identifies the opportunity presented by these gaps and which the focus would be for further research. Section 6.3 shows how this research will be divided into sub-problems by introducing the main research question and sub-questions.

6.1. Research Gap

In this literature study, an overview has been given of airline planning and the hub location problem. As it can be understood by the previous chapters, a great work of research has already been done on the problems individually and the integration of the different problems. Within airline planning, the main focus was on the schedule design problem and the fleet assignment problem with the most focus on demand and connectivity. However, within this literature, only one paper was dedicated to optimizing a multi-hub network Yang, H., Delahaye, D., (2024). This research only focused on re-timing the flight legs, and not designing a flight schedule from scratch. Another area where research has been lacking is mitigating airport congestion. Pita, J., (2013) is the only research focused on airport congestion. Their model also includes competition, however, one major area is missing in this research and that is time costs. Time costs include in-flight time and connecting time costs. Therefore the demand captured is simplified and therefore unpractical in the real world.

The hub location problem is a far broader problem than only in the airline industry. Previous Research focused on the competitive hub location problem showing its limitation as the hubs are uncapacitated Eiselt, H. A., and Marianov, V. (2009) and Tiwari, R., (2021b). The competition analysis is relatively basic as limited factors are used and/or simplified. The most notable simplified factor is the flight time, including connection time. This means that connection times are assumed to be fixed, however, this is not practical as connection time depends on the schedule design problem. Mohri, S. S., (2022) and Nasrollahi, M., and Kordani, A. A. (2023) focused on incorporating airline planning into the hub location problem, but only limited to fleet planning. In addition, all the reviewed literature on the hub location problem used uncapacitated hubs.

To combine the two research areas with their respective limitations, the following research gaps can be identified:

- The design of a complete flight schedule for multi-hub networks from scratch, as current studies focus only on re-timing flight legs rather than a full integrated schedule design that considers multiple hubs.

- There is a lack of research addressing airport congestion combined with the detailed modeling of time costs (in-flight and connecting times), which would provide more realistic and practical insights into passenger behavior and network efficiency.
- Existing studies on competitive hub location models are limited by the assumption of uncapacitated hubs and fixed connection times.

Addressing all of these research gaps is not feasible within the scope of this study. Therefore, the focus will be on the integration of the capacitated multi-allocation p-hub location problem and airline planning (especially the schedule design problem) under competition that could optimize for revenue, connectivity, and market share among focus areas. Such integration would enable airlines to make strategic decisions on which hubs to operate for a (sub)network or evaluate the current hub efficiency. This could lead to the closing or opening of hubs.

6.2. RESEARCH OPPORTUNITY

Given the research gaps identified, the thesis project focuses on the following research objective:

To develop a robust integrated hub location and schedule design model that accounts for operational hub constraints, with the goal of creating an airline network optimized for maximum revenue.

Revenue has been chosen as a metric to distinguish different point-to-point pairs and the reason for choosing one pair above another. Otherwise, there would be no incentive to connect in one particular hub. The fares will most likely be simplified as the average between point-to-point pairs. This adds robustness to the model, as in the real world, this could be linked to the revenue management system, but this is out of the scope of this research. It is also acknowledged that costs are ignored in the research objective, and therefore it is not to maximize profit. This has also been done out of simplicity and assumed that the cost of all hubs is roughly the same.

In a later stage, and if time allows, the fleet assignment model and/or aircraft routing problem could also be integrated. Due to time and complexity constraints, this is not the initial focus.

6.3. RESEARCH QUESTIONS

The research objective described in section 6.2 is still a big problem to grasp at once. This has been divided into multiple areas. Starting with the main research questions.

Main Research Question

How can an integrated model for hub location and schedule design enhance network efficiency by leveraging multiple hubs, while accounting for hub constraints?

Sub-questions

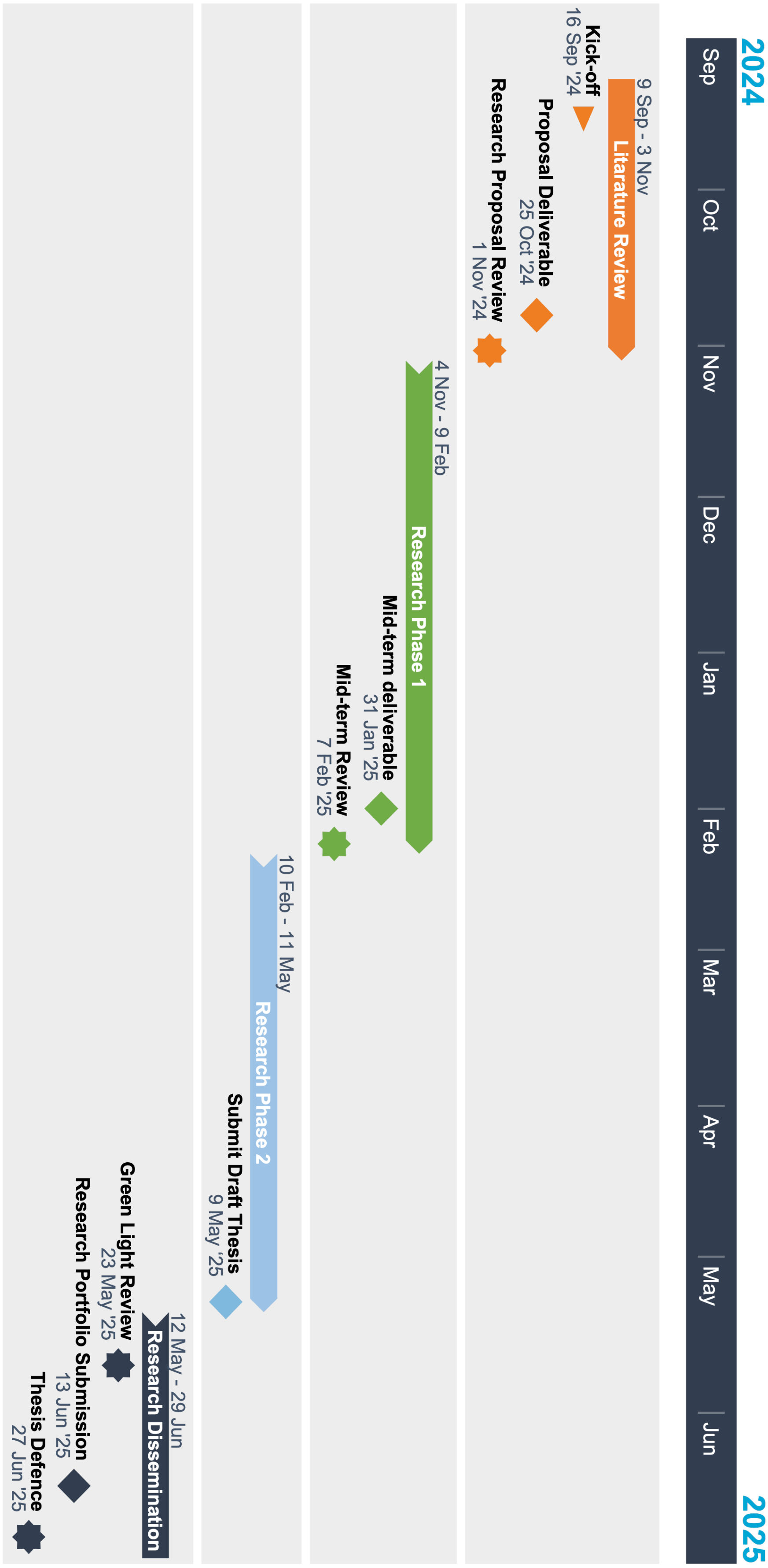
1. How can hub location and airline schedule design be effectively integrated into a single optimization model?
2. How can we determine the optimal number and location of hubs in a multi-hub airline network?
3. What is the effect of hub and fleet constraints and competition on the profitability of the hub location problem?

7 Approach

In this chapter, an overview is given of the approach of the subsequent research. The approach is divided into five buckets, namely literature review, research phase 1, research phase 2, results and discussion, and finalization. The detailed Gannt chart can be found in figure 7.1.

- **Literature Review:** This section is almost finished. The objective of this part is to identify the research gap that is going to be researched in the next two phases.
- **Research Phase 1:** Validating the two separate models/problems (hub location problem and airline scheduling). Also, a basic integration of the two models should be in place.
- **Research Phase 2:** Firstly, to finalize or add to models and secondly, validation of the model. Complete data analyses and interpret the results. Major steps into writing the body of the thesis should be done in this phase.
- **Research Dissemination** Finalize writing thesis and prepare for submission.

Figure 7.1: Gantt chart



8

CONCLUSION

In conclusion, this literature study explored the different aspects of network planning, starting with the background on the topic. This included network structures, passenger preferences, bank structure, and market capture. It delved deeper in into the advantages and complexities of multi-hub airline network planning. A multi-hub network can potentially provide advantages, such as increased connectivity, enhanced passenger flexibility, and greater operational efficiency. By distributing traffic flow across the different hubs, airlines can expand their product offerings and increase flight frequency. However these advantages come at a price, and this price is increased complexity. Within the literature, multi-hub models remain underexplored compared to single-hub and point-to-point networks.

The literature study reveals several key research gaps: 1) the need for complete flight schedule design for multi-hub networks from scratch, as current studies only focus on re-timing flight legs rather than developing a fully integrated schedule; 2) limited research on airport congestion that models time costs, including in-flight and connection times, which would yield more practical insights into passenger behavior; and 3) a lack of competitive hub location models that incorporate capacitated hubs and variable connection times, which would better reflect real-world constraints.

To address these gaps, the subsequent study aims to:

To develop a robust integrated hub location and schedule design model that accounts for operational hub constraints, with the goal of creating an airline network optimized for maximum revenue.

This objective focuses on creating a model capable of efficiently managing multi-hub operations while maximizing revenue.

A case study of IndiGo, India's leading airline, will provide valuable insights into the practical application of a multi-hub network. IndiGo's six hubs allow it to optimize connectivity, with this study focused on international routes. This will highlight the importance of an integrated model to fully realize the benefits of multi-hub operations in a competitive airline industry.

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