REPUBLIC OF TURKEY

YILDIZ TECHNICAL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

FLEET ASSIGNMENT AND BANK STRUCTURE INTEGRATION IN AIRLINE SCHEDULING PROBLEM

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DOCTOR OF PHILOSOPHY THESIS

Department of Industrial Engineering

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February, 2021

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A thesis submitted by Muharrem Enis ÇİFTÇİ in partial fulfillment of the requirements for the degree of **DOCTOR OF PHILOSOPHY** is approved by the committee on 18.02.2021 in Department of Industrial Engineering, Program of Industrial Engineering.

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Signature

This study was supported by the Scientific and Technological Research Council of Turkey (TUBITAK) Grant No: 2211.

Dedicated to Evre, Defne, Yiğit

ACKNOWLEDGEMENTS

Undertaking this PhD has been a long process for me, and it would not have been possible to do without the support and guidance that I received from many people.

Firstly, I express sincere appreciation to Assoc. Prof. Dr. Vildan ÖZKIR for his guidance and insight throughout the research. Without her guidance and constant feedback, this PhD would not have been achievable.

I also would like to thank my thesis committee members, Prof. İlker BİRBİL, Assoc. Prof. Nezir AYDIN for their valuable contribution and advice during the thesis monitoring committee meetings.

I gratefully acknowledge the funding received from The Scientific and Technological Research Council of Turkey (TUBITAK) towards my PhD.

My thanks also go out to the support that I received from a very good friend of mine, Mohammed-Amine HADDI, for his technical support while coding the algorithm on R program. Many thanks also to Assoc. Prof. Muhammet DEVECİ who was always so helpful and provided me with his assistance throughout my dissertation.

I express my thanks and appreciation to my wife, my mother and my father for their understanding, motivation and patience.

A special thanks to my wife Evre for her patience and understanding, to my daughter, lovely Defne, for being such a good little baby that past 3.5 years and making it possible for me to complete what I started.

Lastly, but in no sense the least, I am thankful to all colleagues at Turkish Airlines and friends in Yıldız Technical University who made my Ph.D. at the university a memorable and valuable experience.

Muharrem Enis ÇİFTÇİ

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LIST OF SYMBOLS

$\propto$	Cooling rate of simulated annealing
E(s)	State of the evaluation for annealing
niter	number of iterations
T_0	Initial temperature

LIST OF ABBREVIATIONS

ACI	Airport Council International
ANP	Analytic Network Process
ASK	Available Seat Kilometer
ASM	Available Seat Mile
CASK	Cost per Available Seat Kilometer
CASM	Cost per Available Seat Mile
DHMI	Devlet Hava Meydanları İşletmesi
DL	Delta Airlines
E.G	Exempli Gratia
EK	Emirates Airlines
ESB	Ankara Esenboğa Airport
EU	European Union
FAM	Fleet Assignment Model
FAP	Fleet Assignment Problem
FR	Ryanair
GAMS	General Algebraic Modeling System
HS	Hub and Spoke
IATA	International Air Transport Association
IST	Istanbul Airport
IOCC	Integrated Operations Control Center
L/F	Load Factor
LCC	Low Cost Carrier
LH	Lufthansa Airlines

MARS	Multivariable Adaptive Regression Splines
MIP	Mixed Integer Programming
NEOS	Network-Enabled Optimization System
NP	Nondeterministic Polynomial Time
OCC	Operations Control Center
O&D	Origin and Destination Market
PC	Pegasus Airlines
PGS	Pegasus Havayolları
QSI	Quality Service Index
RASK	Revenue per Available Seat Kilometer
RASM	Revenue per Available Seat Mile
RPK	Revenue Passenger Kilometer
RPM	Revenue Passenger Mile
R/Y	Revenue Yield
SA	Simulated Annealing
SAW	Sabiha Gökçen Airport
STA	Scheduled Time of Arrival
STD	Scheduled Time of Departure
SQ	Singapore Airlines
SWOT	Strengths, Weaknesses, Opportunities, Threats
TS	Tabu Search
THY	Turk Hava Yolları
TK	Turkish Airlines
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
U2	Easyjet
US	United States

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ABSTRACT

Fleet Assignment and Bank Structure Integration in Airline Scheduling Problem

Muharrem Enis ÇİFTÇİ

Department of Industrial Engineering

Doctor of Philosophy Thesis

Advisor: Assoc. Prof. Dr. Vildan OZKIR

In hub and spoke airline networks, flight arrivals and departures generally have a bank structure to increase connections among spoke cities through a hub airport in order to provide cheaper service for higher volumes of air traffic. Main objective of this thesis is to determine that routes in the banks are planned with the correct aircraft type, right departure and arrival time so as to maximize the passenger flow and the revenue flow of all destinations across the network and to fit the slot capacity of hub airport. In the first part of this thesis, Airline planning process and its subproblems are defined. Airline bank optimization problem which is a particular flight scheduling problem is introduced. A mathematical model is formulated for improving connection times among connecting flights by changing departure or arrival times of flights in a bank structure. The mathematical model aims to minimise the total waiting times for transfer passengers and generates flight schedules regarding slot constraints in the hub airports. Since the problem is NP-hard, Simulated annealing and the tabu search algorithms are adopted to solve the bank optimization problem. A real-world application with a major Turkish carrier dataset which has a bank structure that connects Middle East and Europe flights is presented. The comparative results are promising for the airlines bank structure optimization. In the second part of this thesis, airline bank optimization problem is integrated with fleet assignment problem. A particular flight scheduling problem is combined with a strategic airline planning problem concurrently in the airline industry. It has been aimed to provide clean-state schedules instead of providing incremental update. Lastly, real-world case study is repeated using the same dataset for bank optimization to exhibit the competence of the integrated model on generating schedules that outperform existing schedules.

Keywords: Airline scheduling problem, bank optimization, fleet assignment, integrated approach, metaheuristic algorithms

ÖZET

Havayolu Tarife Planlama Probleminde Bank Yapısı ve Filo Atama Entegrasyonu

Muharrem Enis ÇİFTÇİ

Endüstri Mühendisliği Bölümü

Doktora Tezi

Danışman: Doç Dr. Vildan ÖZKIR

Göbek ve ispit (hub and spoke) uçuş modeline sahip havayollarında, uçuşların varış ve kalkışları genellikle, daha yüksek hacimli hava trafiğine daha düşük maliyetli hizmet sağlamak amacıyla şehir grupları halinde planlanmaktadır. Uçuş tarifelerindeki bu grup yapısına bank yapısı da denilmektedir. Bu tezin ana amacı bank yapısı içerisindeki uçuşların bağlantısallıklarını maksimize ederken optimal kalkış ve varış saatlerini havayolu slot kapasitelerine uygun olarak belirlemek ve karlılığı da maksimize etmek için optimum filo atamasının birlikte sağlanmasıdır. Bu tezin ilk bölümünde öncelikli olarak havayolu planlama sürecini ve alt problemleri detaylı bir şekilde tanımlanmıştır. Ayrıca özel bir uçuş planlama problemi olan havayolu bank optimizasyon problem de literature eklenmiştir. Bir bank yapısında uçuşların kalkış veya varış saatlerini değiştirerek bağlantılı uçuşlar arasındaki bağlantı sürelerini iyileştirmek için matematiksel bir model oluşturulmuştur. Oluşturulan matematiksel model, transfer yolcular için toplam bekleme sürelerini en aza indirmeyi amaçlar ve ana havalimanlarındaki slot kısıtlamalarına uygun uçuş tarifeleri oluşturur. Problem NP-hard olduğundan, benzetilmiş tavlama ve tabu search algoritmaları bank optimizasyonu problemini çözmek için uyarlanmıştır. Ayrıca Orta Doğu ve Avrupa uçuşlarını birbirine bağlayan bir bank yapısına sahip Türkiye merkezli büyük bir havayolunun veri setiyle vaka uygulaması sunulmuştur. Karşılaştırmalı sonuçlar, havayolları bank yapısı optimizasyonu için matematiksel modelin ve benzetilmiş tavlama algoritmasının kullanımı açısından umut vaat edicidir. Bu tezin ikinci bölümünde, havayolu bank optimizasyon problem ile filo ataması problemi entegre edilmiştir. Kurulan entegre matematiksel model ile, tarifede ilave güncellemeler yerine sıfırdan düzenli bir uçuş tarifesi üretilebilmektedir. Son olarak, entegre modelin mevcut tarifelerden daha iyi performans gösteren tarifeler oluşturma konusundaki yeterliliğini kanıtlamak için bank optimizasyon probleminde kullanılan veri setini tekrar kullanarak gerçek dünya vaka çalışması sunulmuştur.

Anahtar Kelimeler: Havayolu tarife planlama problemi, Dalga yapısı optimizasyonu, filo ataması, entegre matematiksel model, sezgisel algoritmalar

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YILDIZ TEKNİK ÜNİVERSİTESİ

FEN BİLİMLERİ ENSTİTÜSÜ

1
INTRODUCTION

Commercial airlines use optimization methods to efficiently allocate their resources in order to compete in the growing air transportation industry. An airline's most important assets are its aircraft, and its most important product is its schedule. Full-service carriers have changed their business models and schedules from 'point to point' to 'hub and spoke' (HS) in order to serve growing passenger demand and to achieve higher levels of profit and resource utilisation, depending on global liberalisation developments in the last 30 years. Even though some airlines currently operate through the point-to-point business model, major airlines such as Delta, Lufthansa, Turkish Airlines, Emirates and Singapore Airlines work on a HS system with flights through hub airports and transfer passengers from spoke cities to their final destinations. In order to manage the passenger transfer flow, these airline companies create flight clusters in a so-called bank structure in their hub airports.

1.1 Literature Review

Number of hubs, location of the hub, local traffic of hub city, airport resources, meteorological conditions and strategy of other airlines are the factors that has influence on the network structure of an airline (Martin and Román, 2004).

As it can be seen below in Figure 1.1 Emirates flight network map and associated wave structure of this network in Figure 1.2, arrivals to Dubai airport, which is the hub of Emirates (EK), are from Asia points between 1 am and 4 am. After the passengers on these arriving flights are de-boarded, the planes are cleaned and refueled. Local passengers from Dubai and Asian destinations are transferred to their desired Europe and America flights on the first departure bank of this hub. During the day there are 3 waves like this. (O'Connell and Bueno, 2018)

Figure 1.1 Emirates flight network map.

Table 1.1 summarizes EK wave structure. Thus, it is possible to carry passengers significantly on the east / west axis.

Table 1.1 Emirates wave structure

Wave	Inbound	Outbound
Morning	Asia, Middle East	Europe, North America
Noon	Europe, Africa	Asia, Middle East
Night	Asia	Europe

Wave structures are essential part of hub and spoke networks. They have provided rapid growth for the airlines who utilize hub and spoke on their network (Gillen & Morrison, 2005).

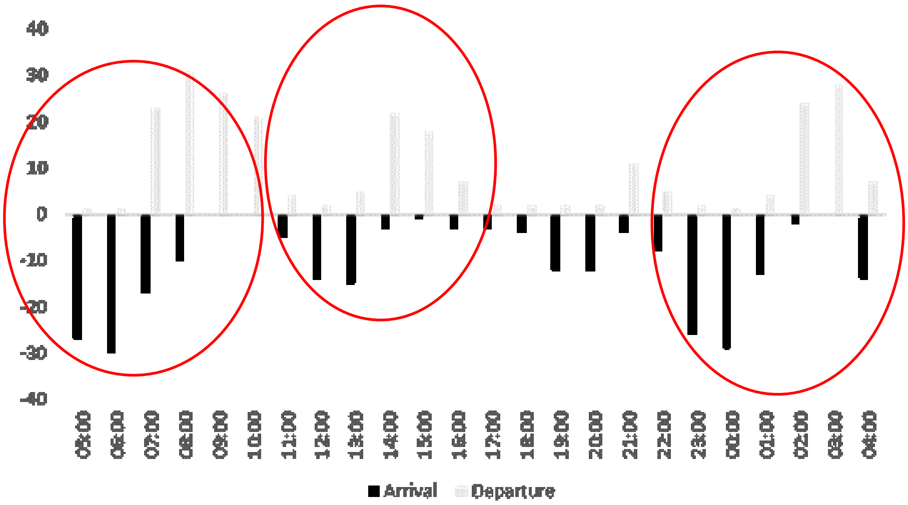


Figure 1.2 A representative example for airline bank structure.

Wave structures increase connectivity of spoke cities, increase traffic demand, lower the prices, increase asset utilization by decreasing the number of routes that are required to connect city pairs. They allow operational robustness for the crew, maintenance, routine checks of aircrafts. In contrast, bank structures cause the escalation of slot problems in limited time ranges. They increase congestion at the hub airport; runways, taxiways and gates are busy during the arrival and departure bank timings. This situation also leads to inefficient use of airport resources. Lastly, wave structures are highly vulnerable for the delays. Delay in one of the incoming segments could affect all segments in the outgoing bank cluster because there could be many different outgoing passengers in an incoming segment. Recovering the schedule for the passengers and having a normal operation for the crew and aircraft rotation could take more than one day.

1.2 Objective of the Thesis

The main purpose of this study is to design a new flight bank with the optimal flight distribution at the base airport with shortening transfer passengers' connection times based on their demand and revenue, satisfying the available slot capacity at the hub airport. Therefore, having less congested operation would be possible.

The scale of the problem to be investigated in this doctoral dissertation is quite large, aims to cover rotation of about more than 20 aircraft and more than 100 flights per day of a network carrier. Figure 1.3 represents the daily morning bank structure of the airline that has been investigated. Flights that are above the timeline are departures and below the timeline are arrivals. An arrival is connected to departure flights which are on top itself or right positioned above the timeline. As a research topic following questions will be modelled;

- Are the flights positioned in the right place on each wave?
- In case of half-hour shifting, what is the potential revenue, passenger increase?
- Is it possible for an airline to transport more passengers, is there a potential for more revenue generation when the aircraft types of flights at similar times are changed?
- Is the fleet assignment maximize passengers and revenue on transfer itineraries?

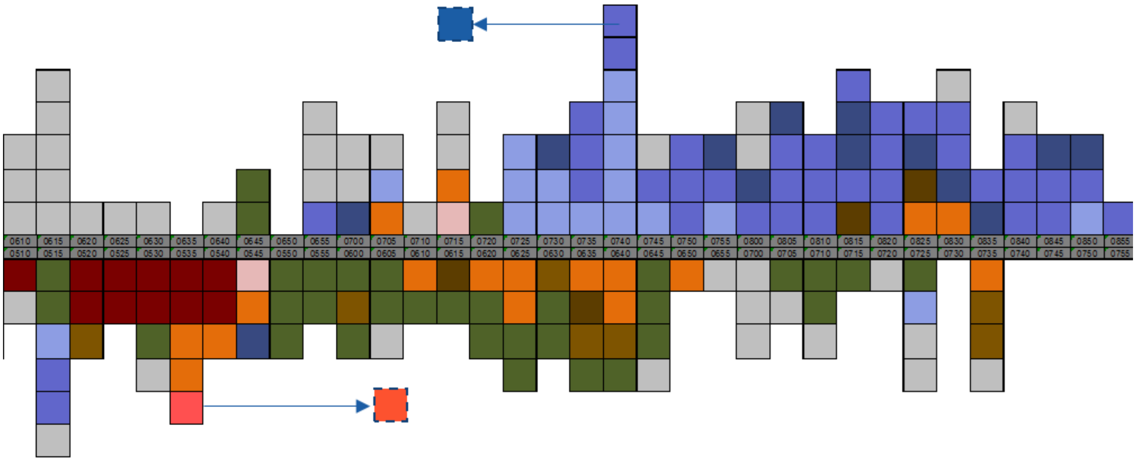


Figure 1.3 Example of shifting flights in a bank structure.

It is aimed to construct a mathematical model to represent the current wave structure. Model is going to be validated on a small sample and a solution is going to be provided on sample then it will be moved on the real-life case study with fleet assignment. Main objective of the thesis is to determine that routes in the banks are planned with the correct aircraft type, right departure and arrival time so as to maximize the passenger flow and the revenue flow of all destinations across the network and to fit the slot capacity of hub airport.

1.3 Contribution to the Literature

Contribution to the literature is to address a variation of the network and business models of airlines, Turkey's aviation industry, slot applications and its implications in the aviation business. Specifically, in the present study, the demand and passenger flow between spoke cities of a hub are associated with the connection times of those cities at the hub. My key research topic is a real-world problem faced by a carrier on Sabiha Gökçen Airport (SAW) which is operating on the edge of its limits. As a result of this, flight delays occur, passengers miss their connections, congestion increases. Therefore, mathematical model will help airlines to fit the slot capacity without losing connection and passengers.

Our goal in this thesis is to design the optimal departure and arrival times of the flight bank for connecting passengers while assigning routes to the most suitable aircrafts in terms of route profitability. Our model formulation extends bank optimization approach with fleet assignment constraints and objective. To our knowledge, ours is the first research study to integrate the fleet assignment problem with airline's bank structure under airport slot constraints with connectivity focuses.

Exact algorithms typically take more time than heuristic methods to execute, as they are mathematically difficult to solve. Due to the complex, dynamic, competitive, and highly regulated environment in the airline industry, complex operational issues require fast, efficient, and responsive solutions. Therefore, we adapt two well-known meta-heuristic algorithms, tabu search (TS) and simulated annealing (SA), in order to obtain near-optimal solutions in a desirable runtime. Based on our empirical results, the proposed approach has the following advantages:

- It minimises flight connection times between departures and arrivals.
- It decreases congestion for the respective slots.
- It increases passenger convenience.
- It provides fast, efficient, and executable solutions.

Our contribution to the literature could be summarized in five major way. First, we introduce bank optimization problem to the literature. Second, we combine a specific flight scheduling problem with another major problem in the airline industry to solve simultaneously. Third, our models do not involve only incremental scheduling decisions using a schedule as a basis. Instead, it provides completely new schedules from clean state. Four, we perform a real-world case study using a major Turkish carrier's data to demonstrate integrated model's capability on generating schedules that outperform existing schedules. Finally, we adapt two metaheuristic algorithms for the airline related problems which are used rarely.

1.4 Organization of the Thesis

The remainder of the thesis is organized as follows: Section 2 introduces typical airline planning process to the reader including terminology, a brief literature review of the airline business models and networks, fleet planning, network and schedule planning and crew planning. Section 3 consists of a detailed literature survey regarding bank optimization, capacity management at the congested airports and the fleet assignment problem (FAP). Section 4 then presents a methodology process for bank optimization problem and fleet assignment problem including mathematical formulations of the problems, metaheuristics - simulated annealing and tabu search algorithm that is modelled specifically for this problem. In Section 5, experimental case studies and a real-world case study of SAW (Sabiha Gökçen Airport) is presented together with comparative results of the exact solution and metaheuristic algorithms. In section 6, an integrated mathematical model is provided in order to combine bank optimization and fleet assignment problem. Finally, in section 7, the study is concluded with the results of the cases and discusses the benefits and limitations in terms of revenue, cost and planning effort for the hub and spoke airlines' operations research departments, network, and schedule planners.

2
AIRLINE PLANNING PROCESS

2.1 Introduction and Chapter Outline

Objective of this chapter is to provide an overview about the airline business planning process, its terminology, airline business models. As shown in Figure 2.1, the airline business planning processes begin with strategic level decisions followed by medium level and short term tactical commercial actions. From left to right, it goes from strategic level and long term to the tactical level and short term.

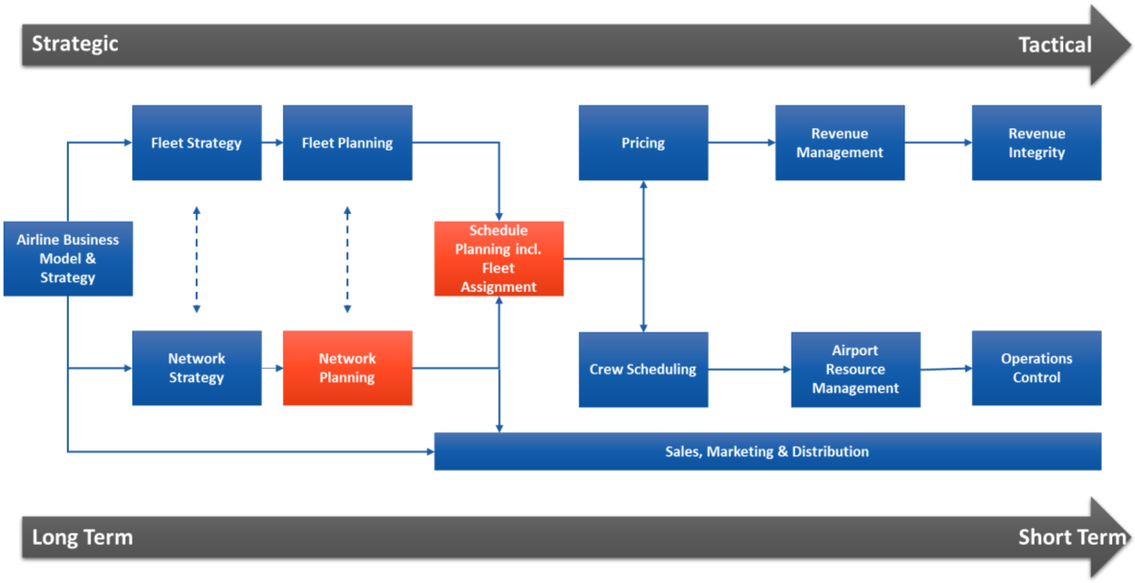


Figure 2.1 Airline planning process

Airline planning process is a complex process consisting of complex sub-problems. Each problem considers a specific resource and time horizon. With increasing competition each year, airlines are forced to solve problems on a larger scale. In order to cope with this, six relevant problems can be identified, as follows (Mancel and Mora-Camino, 2006)

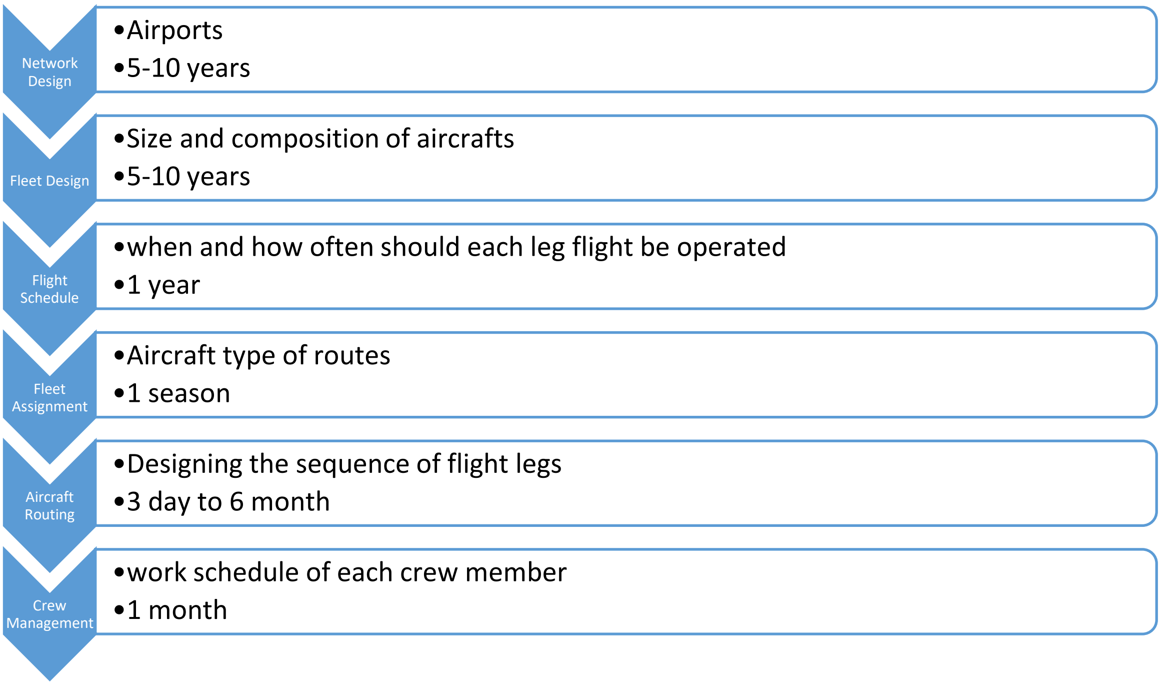


Figure 2.2 Airline related problems

Problems are related to each other, the solution of one problem can depend on the solution of the previous problem and affects the solution of the next problem

In this chapter, firstly, commonly used terminology in the airline industry is provided. Secondly, different types of airline business models are explained in the second section. Third focus of this chapter is a general overview of the airline planning problems which are fleet planning, network and schedule development, fleet assignment and crew planning problems. These problems are defined and explained in the rest of subsections of this chapter.

2.2 Terminology

Origin: it is defined as the true starting point of the passengers' trip.

Destination: it is defined as the final destination or point of the passengers' trip

O&D Market: combination of origin and destination of a single trip.

Leg: A cycle considering one take off and one landing. It reflects the movement of the aircraft

Segment: A segment is an arbitrary series of legs having the same flight number. It reflects the movement of the passengers.

Itinerary: airports that a passenger uses through his/her trip. It is a combination of segments for going and coming back throughout the trip.

Non-stop itinerary: Direct markets without intermediate stops

Connect market: Markets where more than a flight number and a stop are required.

Through market: A flight where passengers travel from origin points to the destination ones without any change in flight numbers, which may involve a stop-over at an intermediate point

Single connection: A single connection is a connection that has one flight change in the itinerary.

Double connection: A double connection is a connection that has two or more flight changes in the itinerary.

Online connection: An online connection is a connection that has no carrier change but a flight changes in the itinerary.

Interline connection: An interline connection is a connection that has at least a carrier change and a flight change in the itinerary.

Inbound: The points that are feeding the connection of the specified point as passenger.

Outbound: The points that are fed their connection by the specified point as passenger.

Fleet type or subtype: Group of aircrafts which are the same in terms of capacity, configuration of cockpit and crew requirements.

Fleet family or aircraft family: A set of fleet types that are requirements are same in terms of cockpit configuration and crew requirements. Thus, the same crew can fly any aircraft type of the same family. Capacity could be different across the subtype.

Fleet type and fleet family examples are given in the table 2.1

Table 2.1 Fleet type and family examples

Fleet Family (Aircraft Family)	Fleet Type (subtype)
A320	A32A
A320	A32B
A320	A32C
A320	A319
A320	A321
B777	B77K
B777	B77C
B777	B77B
B777	B77A

Narrow body aircraft: A single aisle aircraft which has typically 6-hour ranges, optimum for short and medium haul flights. Examples are Boeing 737-800, Airbus 320-200 etc.

Wide body aircraft: A twin aisle aircraft which has typically 10-to-16-hour ranges optimum for long haul flights. They are mostly used for intercontinental flights. Examples are Boeing 787-900, Airbus 350-900 etc.

Scheduled time of departure (STD): departure time of a flight which shows the doors closing time at the gate before leaving the gate, off-block time.

Scheduled time of arrival (STA): arrival time of a flight which shows the doors opening time at the gate, on block time.

Block time: total amount of time that is calculated from departure gate to arrival gate, including taxi-out time, flying time and taxi-in time.

Ground time or turnaround time: Aircraft needs time after landing and before next take-off for cleaning, refueling, disembarking, and embarking passengers. Turnaround time is the minimum time between landing and take-off. Turnaround time is aircraft and airport dependent, and typically between 30 and 60 minutes for domestic flights with narrow body aircrafts**.** It is typically 60 for international flights with narrow body aircrafts and 90 minutes with wide body aircrafts.

Hub and spoke: It is an airline network model which has a center airport that connects many different flights that are incoming or outgoing: passengers and cargo are transported from origin to their final destination via hub. Typically, passengers and cargo change aircrafts at the hub if they have connected flights.

Full-service carrier (network carrier): usually operates on hub and spoke model and offers a wide range of services on flights without extra fees.

Low-cost carrier: usually operates a point-to-point network model and offers lower prices than full-service carriers that reflects limited-service provision. Unlike full-service carriers, they charge additional fees for on-flight and airport services.

Available Seat: The total number of seats offered for sale on a flight.

Revenue Passenger Kilometer/Mile: It is multiplication of the number of passengers and flown distance in kilometer or mile. It represents the passenger traffic of an airline. It is abbreviated as RPK or RPM.

Available Seat Kilometer/Mile: It is multiplication of the available seat and flown distance in kilometer or mile. It represents the capacity of an airline. It is abbreviated as ASK or ASM.

Load Factor: The occupancy rate of the flights for the specified period. It is calculated as RPK divided by ASK. It is abbreviated as L/F. Formula is shown below.

$$L/F = RPK \div ASK \tag{2.1}$$

Revenue Yield: It is calculated as total passenger revenue divided by RPK. Revenue yield is generally shown in US cents per mile or kilometer. It is a useful unit revenue to analyze changes in prices over time. Abbreviation is R/Y. It is mostly analyzed in US Cents. Therefore, it is multiplied by 100.

Revenue Yield = Net Passenger Revenue ÷ RPK * 100 (2.2)

Revenue per Available Seat Kilometer/Mile: It is calculated as total passenger and cargo revenue divided by ASK or ASM. It is abbreviated as RASK or RASM. It is mostly analyzed in US Cents. Therefore, it is multiplied by 100.

RASK = Total Operating Revenue ÷ ASK * 100 (2.3)

Unit Passenger Revenue: is the total passenger revenue divided by the total number of passengers.

Belly Cargo Revenue: is obtained by the cargo transported in the belly of the aircraft increasing the total revenue on a route.

Airline cost structure can be classified as direct and indirect costs. The indirect costs include marketing, salary, general management etc. costs that are not directly related with the operation on the specific route. The direct costs can be divided into two sub groups, namely, variable and fixed costs.

• **Fixed Costs of Operation** are the ownership cost of an aircraft, crew costs, maintenance cost of the aircraft and insurance costs.

• **Variable Costs of Operation** are directly related with the operation output. The important variable costs of the airlines include the fuel costs, handling, passenger service costs, airport service charges, commissions etc.

A general airline cost breakdown is summarized in Table 2.2

Table 2.2 Airline cost breakdown

Direct		**Indirect**
Variable (Operating)	**Fixed**	
Fuel	Aircraft Ownership	General Management
Commision	Crew	Marketing
Handling	Maintenance	Distribution

Table 2.2 Airline cost breakdown (continued)

Passenger Service Cost	Insurance	
Airport Fees		
Overflight Fees		
Carbon Emissions		

Contribution 1: Total revenue - direct operating cost.

Contribution 2: Total revenue – (direct operating cost + direct fixed costs).

Profit and Loss: Total revenue - (direct operating cost + direct fixed cost + indirect costs).

Cost per Available Seat Kilometer/Mile: Unit cost value in the airline industry. It is calculated as total operating expenses divided by available seat kilometer or mile. Abbreviation is CASK or CASM which depends on the distance unit. In general, it is analyzed in US Cents. Therefore, it is multiplied by 100.

$$CASK = \text{Total Operating Cost} \div ASK * 100 \qquad (2.4)$$

Utilization: It is the measure for aircraft productivity. It shows the average usage of an aircraft in a day. For a specific period of the time, it can be calculated as total block times divided by total aircraft inventory in that period.

Cycle: each departure in a flight operation is considered a cycle.

Figure 2.3 Example of connecting passenger itinerary.

Figure 2.3 shows an example of connecting itinerary for a passenger who wants to travel from London to Dubai via Istanbul. Below there are exemplary calculations of route metrics that have been explained previously.

Available Seat for London – Istanbul : 180

Available Seat for Istanbul – Dubai : 180

Passenger Revenue : 30,000 + 20,000 = 50,000 $

Belly Cargo Revenue : 5,000 + 1,0000 = 15,000 $

Total Revenue : 50,000 + 15,000 = 65,000 $

Total Cost : 45,000 $

Cycle : 2

RPK : (150*2,494) + (100*3,030) = 677,100

ASK : (180*2,494) + (180*3,030) = 994,320

L/F : 677,100/ 994,320 = %68

R/Y : 50,000 / 677,100 * 100 = 7.38 $ Cent

Passenger Revenue per ASK: 50,000 / 994,320 * 100 = 5.03 $ Cent

CASK : 45,000 / 994,320 * 100 = 4.53 $ Cent

Table 2.3 Profitability summary of the example aircraft routing

Orig	Dest	Available Seat	Km	Pax	Revenue	Cost	ASK	RPK	CASK (US Cent)	RASK (US Cent)	RY (US Cent)	LF	Profit
LHR	**IST**	180	2,494	150	30,000	25,000	448,920	374,100	5.57	6.68	8.02	83%	5,000
IST	**DXB**	180	3,030	100	20,000	20,000	545,400	303,000	3.67	3.67	6.60	56%	0
Itinerary			5,524	250	50.000	45,000	994,320	677,100	4.53	5.03	7.38	68%	5,000

Table 2.3 provides an example of calculations with an exemplary itinerary which has two legs from London to Dubai via Istanbul. Total profit in this example is 5.000 USD.

2.3 Airline Business Models

2.3.1 Network Carriers

HS network systems provide following advantages for network airlines (Brueckner & Spiller, 1994; Caves, Christensen, & Tretheway, 1984). HS systems decrease costs by creating economies of scale for the passenger demand, consolidating personnel, operations, and maintenance costs at the base city, decreasing the number of routes. It also increases passenger loyalty thanks to airport dominance. Network carriers have the advantage of hub domination. Thanks to domination, they can also control the slots and to keep Low-Cost Carriers (LCCs) out of primary airports and their hubs (Dennis, 2007).

The number of hubs, location of the hub(s), local traffic of hub city, airport resources, meteorological conditions and strategy of other airlines are the factors that have influence on the network structure of an airline (Martıin and Roman, 2004).

Discussions about network strategies in a hub and spoke system can be found in (Adler, 2001; Hansen, 1990; Hong & Harker, 1992). Burghouwt and De Wit (2005) mentions that HS networks in the European Union (EU) are different from the ones in the US. HS carriers in EU operate their networks under a bank structure.

Figure 2.4 Turkish Airlines network map.

Figure 2.4 shows the Turkish Airlines (TK) network map as of Jan 2020. Network of Turkish Airlines is balanced on the east and west axis. Network includes both short haul and long-haul flights together. Turkish Airlines have three main bases, namely, IST, SAW and ESB. IST is the main domestic and international hub of Turkish Airlines. ESB is dominated by its sub brand AnadoluJET and it is used for mostly domestic flights except for Turkish Republic of Northern Cyprus flights. SAW is the secondary base of Turkish airlines in the Istanbul city and flights are operated by both Turkish Airlines brand and AnadoluJET brand. It can be concluded that Turkish Airlines is operating a multi – hub strategy.

Figure 2.5 Emirates Airlines network map.

Figure 2.5 shows the Emirates Airlines (EK) network map as of Jan 2020. Network of Emirates Airlines is also balanced on the east and west axis. However, it is different from the Turkish Airlines network in terms of stage length of the flights. Most of the flights are long haul flights. Emirates Airlines operates a single hub strategy. EK is focused on the passenger traffic between Europe – South Asia, Europe – Far East and Europe – Asia Pacific.

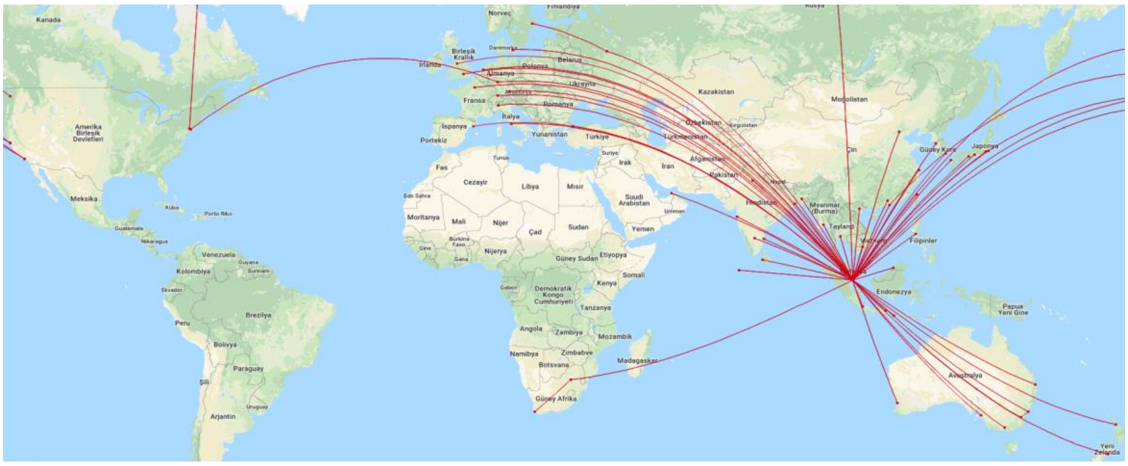


Figure 2.6 Singapore Airlines network map.

Figure 2.6 shows the Singapore Airlines (SQ) network map as of Jan 2020. Network of Singapore Airlines is also balanced on the east and west axis. It is similar to the EK network in terms of stage length of the flights. Most of the flights are long haul flights. SQ also operates a single hub strategy.

Figure 2.7 Lufthansa Airlines network map.

Figure 2.7 shows the Lufthansa Airlines (LH) network map as of Jan 2020. It is also very similar to Turkish Airlines network. Main differences are while TK has more African flights, LH has more North America services. TK has three hub; LH has two hubs namely FRA and MUC.

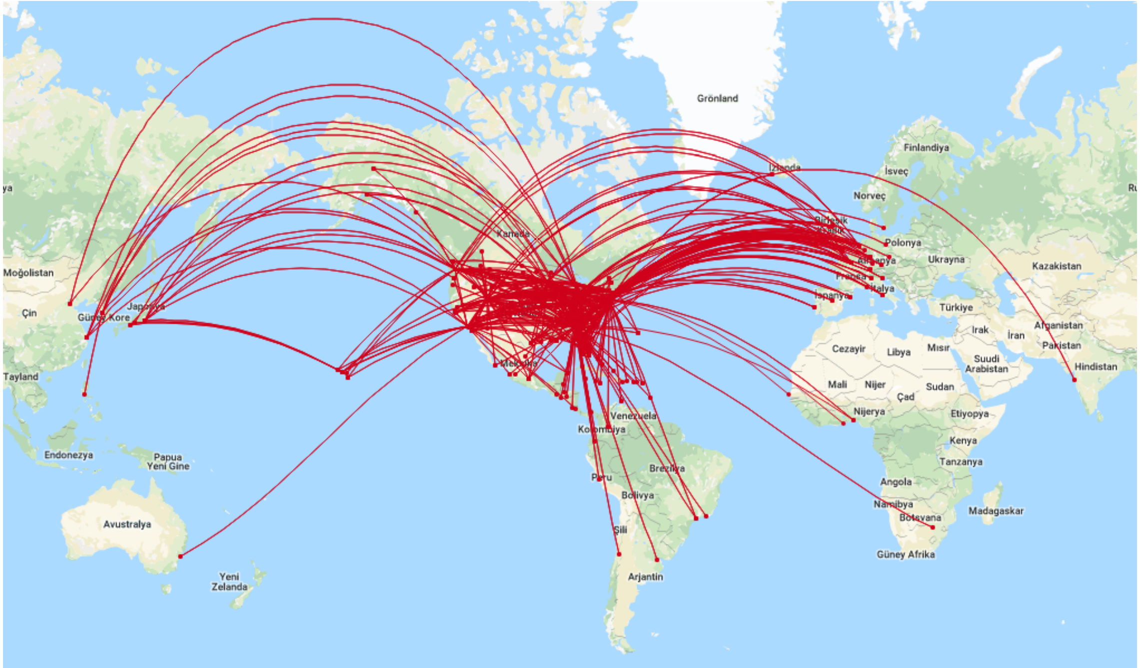


Figure 2.8 Delta Airlines network map.

North American carriers' network strategy is different from the European and Asian counterparts. Their networks are more complicated. For example, Delta Airlines (DL) has 5 hubs for international flights. Figure 2.8 shows the DL international network map as of Jan 2020.

2.3.2 Low-Cost Carriers

Thanks to liberalization and deregulation LCCs gained market and become profitable. LCC's offer lower prices with more direct travel options on big markets. Providing point to point direct short haul service is the main strategy of the LCC's. (Gillen and Lall, 2004).

Southwest Airlines has started its operations with low-cost carrier model for first time in the world in 1971. Ryanair and easyJet was the follower airlines in the Europe for the low cost busines model. They have launched their operations on

Ireland and U.K, respectively. WizzAir in Europe, Air Asia in Asia and Pacific are good successful example airlines of these kind of business model.

Figure 2.9 Ryanair network map.

Ryanair (FR) network map and route structure in the Figure 2.9 shows that it is operating a point-to-point network structure.

Figure 2.10 Easyjet network map.

Same network structure in Figure 2.10 is also valid for the Easyjet (U2) which is main rival of Ryanair. Both carriers operate intra-Europe and connect secondary airports on the point-to-point traffic.

LCCs focus on traffic flow between key, big and dense markets. These markets has influence on the LCCs point-to-point network system and aircraft utilization. (Reynolds-Feighan, 2001)

There are also other examples of LCCs such as JetStar from Australia and Norwegian from Europe are flying long-haul markets. Forsyth (2007) mentioned that it is more likely that long-haul LCCs will be in the competition for the future.

Major issue for a successful long-haul low-cost model is to find right markets where lower prices become profitable while the distance and operating cost increases. Important characteristics of these markets are: strong local point to point traffic, low seasonality, slot availability. (Wensveen and Leick, 2009).

Low-cost carriers provide unrestricted fares and low prices. They operate on a point-to-point network. Fares are distrubited by websites or call centers not by travel agencies. Generally, they provide short haul flights with high frequencies. Networks consist of secondary airports in the cities because of low price structure of secondary airports. Their turnaround times are short, aircraft utilization is higher than the full-service carriers. They operate on a single aircraft type in the fleet. Salaries are competitive and staff should be productive to earn profit sharing (Alamdari and Fagan, 2005).

2.3.3 Hybrid Carriers

Due to the complex, dynamic, competitive, and highly regulated environment in airline industry, many of the airlines are looking for market niches and adopting business models that do not exactly fit the typical business models described above. Air Berlin was a carrier that has changed its business model from a holiday charter business model to a hybrid one. Beside the most of the LCCs focus on short haul point-to-point flights however some European low-cost carriers are changing their business model towards a hybrid strategy using a HS network system and adopting other characteristics of full-service network airlines. (Klophaus et al., 2012).

Aer Lingus was an example for a hybrid type carrier. In the past, Aer Lingus was providing full service both transatlantic flights and Europe flights from Dublin and Shannon. However, the effect of increasing competition in aviation industry forced Aer Lingus to offer low-cost services from Dublin in short haul services and provide full-service in long-haul flights to North America (Klophaus et al., 2012).

Pegasus Airlines (PC) of Turkey is another example of a hybrid model (Stimac et al., 2012). Pegasus Airlines has the following characteristic of a hybrid carrier:

- Operates on the Sabiha Gokcen Airport with hub and spoke model.
- Operates as a low-cost airline with high densitiy aircrafts.
- Most of the ticket revenue comes from its website, but also utilizes agencies for ticketing.
- Has a loyalty program with credit card providers.
- Has code share flights.
- offers extra services with additional fees, such as: onboard meal service, travel insurance, choosing seats in aircraft, car booking, hotel booking, extra baggage.

Figure 2.11 Pegasus Airlines network map.

As it can be seen in the Figure 2.11, PC operates a hub and spoke network on SAW flights however it also has direct flights in the domestic operation especially from Adana, Ankara, Antalya, İzmir and Trabzon bases. PC also has direct flights from Central Europe to Turkey. These network structure makes PC as an example of hybrid carrier with low-cost business model.

2.3.4 Charter Carriers

Travel to sunny destinations, holiday travels can be defined as leisure traffic. These types of travels are main revenue sources of the charter airlines' consumer segments. Leisure traffic includes ease times transportation, relaxing activities, and religious visits. Charter airlines are very important elements of the tourism economies.

Charter carriers are owned by tour operators and their primary focus is tourism destinations. Their tickets are not sold by distribution channels, they have irregular schedules and most of the time departure and arrival times are not convenient for the passengers. Flights are operated to the secondary airports in the cities to reduce the airport costs and fees. They provide point to point no-frill services. They are pioneers of the low-cost airline business model. Charter airlines are primary transportation source for leisure holiday destinations in Caribbean, Spain, Turkey, and Egypt (Papatheodorou and Lei, 2006).

Most of the charter carriers are owned by tour operators and have tiny operating margins. These tour operators sell hotel service and air transportation tickets as packages (Williams, 2002).

Charter airlines are usually small airlines which have small market sizes and shares compared to network carriers and low-cost carriers.

2.4 Fleet Planning

After the decision of the airline business model, fleet planning is the first step for the airline planning process. Fleet planning decisions are strategically important for the airline. Effects and results could be seen in the long term and needs huge amount of capital investments. Fleet planning decisions answers following questions. (Belobaba et al., 2015)

- Which type of the aircraft is going to acquire?
- How many aircraft is going to be in the airline's fleet?
- When is it planned to phase in or phase out (retirement etc) aircrafts?
- What type of payment method is utilized (buy, financial lease, wet lease, dry lease etc)?

Type of the aircraft is one of the crucial decisions in the fleet planning. Making a wrong decision effects the airlines' cash flow for long years. Sometimes, even choosing the right engine provides competitive advantage or, just the opposite, choosing a type of aircraft engine that is constantly deteriorating will affect the daily operation of the airline. Therefore, it can be concluded that not only fleet decisions but also engine decisions have significant effect on the airlines long term goals and future daily life.

Every aircraft has different characteristics in terms of fuel economics, seat capacity, range and financial cost to acquire. Range can be defined as the maximum distance that aircraft can fly nonstop, while still transporting reasonable number of passengers and/or tonnes of the cargo (Belobaba et al., 2015).

Narrow body aircrafts, e.g Boeing 737-800 or Airbus 320-232 typically have 6–7-hour range and average capacity between 120 seat and 180 seat. They are single aisle and have twin engine. Narrow body aircrafts are utilized in the short and medium haul routes. Wide body aircrafts, e.g Boeing 777-300ER or Airbus 350-900 have 15-18 range and average capacity is between 250 seat and 400 seats. They are also known as twin aisle aircrafts. In general, wide body aircrafts have twin engine, however there are also four engine versions of wide body aircrafts, namely, Airbus 340, Boeing 747, and Airbus 380. Wide body aircrafts are generally utilized in the long-haul routes. However, they are also utilized in some short or medium haul routes that has slot constraints but has high demand of passenger.

Figure 2.12 shows the Boeing and Airbus aircraft types and their respective range capability and passenger seat capacity. It can be clearly seen from the graphic that widebody aircrafts have long range and high passenger seat capacity (Tak, 2015).

Within all these different characteristics, fleet decisions have significant effects not only on airlines financial payment positions and debt structures but also have effects on the route, network structure and profitability.

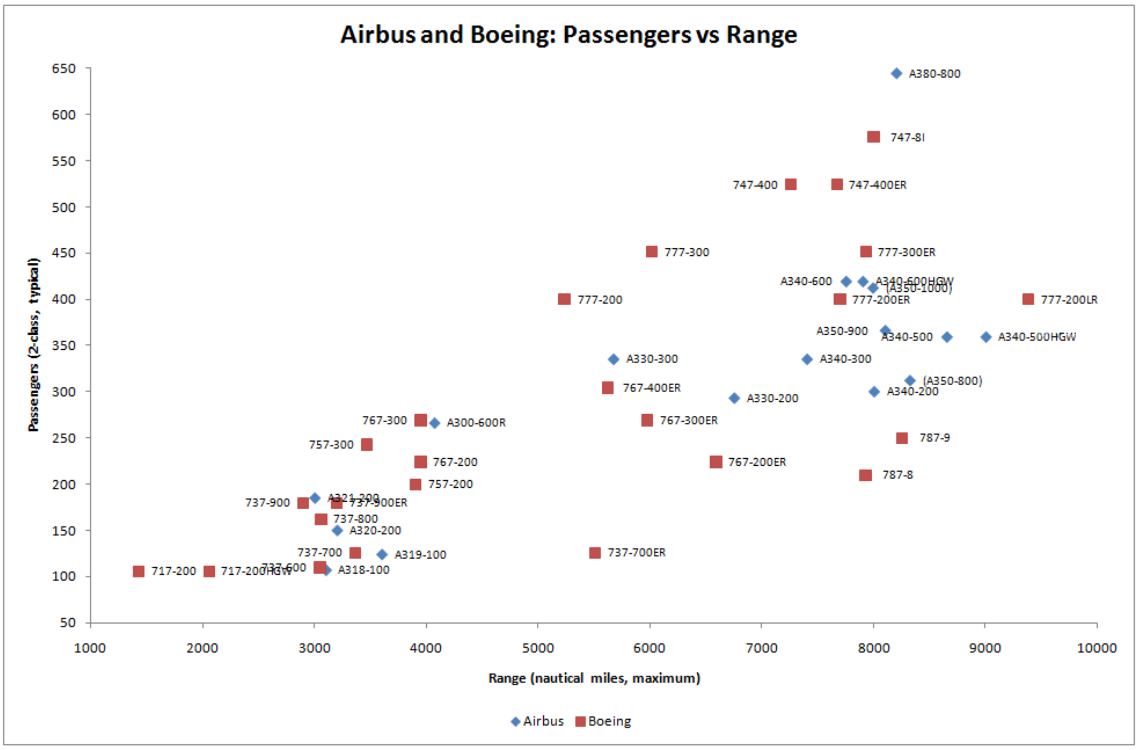


Figure 2.12 Aircraft seat capacity and range characteristics (Tak, 2015)

Although the airlines have option to buy directly from the manufacturers, e.g Boeing or Airbus, this is not common in the industry. Mostly, airlines prefer to acquire aircrafts from a leasing company (lessor) which has a large number of aircrafts. This type of leasing is named as financial leasing. Payment terms are generally long term such as 10-15 years. At the end of payment terms, airlines could have option to send back to lessor or to buy with a pre-determined amount at the beginning of the agreement. Financial leasing can be seen as more costly in terms of monthly lease payments, but most of the carriers prefer this methodology. It gives the flexibility, allows more frequent fleet renewal, and needs less advance capital investment. (Belobaba et al., 2015)

Another option of the acquiring method is medium term leasing of the aircraft from another carrier or lessor. Medium term should be understood as for 5-8 years. There are two type of these methods.

Dry Lease: means that renting the aircraft without crew, maintenance, and insurance. In dry lease operations; crew, maintenance and insurance is provided by commercial (who sells tickets) airline company and operates the flights itself. Lessor airline Company does not interfere any of the operational or commercial activities of the lessee airline company in wet lease cases.

Wet Lease: renting the aircraft (A) with crew (C), maintenance (M) and insurance (I), in short with ACMI. Lessee pays all the fixed cost of the operations to the lessor airline company. Lessor provides crew, maintenance services to the commercial airline and operates the flights on behalf of the commercial airline. In Wet-Lease operations, the technical, operational, and other administrative responsibilities of the flight activities carried out throughout the rental period belong to the lessor company who has rented the aircraft, and the commercial responsibility belongs to the lessee. Operational (lessor) and commercial (lessee of the aircraft and selling tickets) airlines are different in wet lease cases.

Adding a new aircraft type to the current fleet has other costs than the ownership costs. Airlines needs inventory for the spare engines and other parts of the aircrafts. New ground handling equipment could be necessary depending on the physical and operational characteristics of the new aircraft type. Another important issue is that training of the pilots, cabin crew, technicians, and ground handling personnel. Also, updating the IT systems, company standards, procedures and manuals should be carefully considered.

Another important dimension of fleet planning is that protecting the fleet commonality while the fleet is evolving. Fleet commonality does not refer to have one single aircraft type in the fleet but also having similar aircrafts from the fleet family of same manufacturer. This will bring seat capacity flexibility on network scheduling and crew scheduling as well as decrease the training efforts of the engineering, cabin and cockpit staff. Having high fleet commonality also decreases required spare inventory for different families.

2.5 Network and Schedule Planning

Network planning can be defined as the managing passenger flow and flight connections at the hub and spoke system. Network planners are responsible for preparation of the economic and financial evaluation of various new route studies while analyzing different business risks such as demand, competition, cost, and financial results. They also consistently review the performance of the overall route portfolio in order to identify profitability issues and provides alerts to the senior management and executive teams along with detailed recommendations to improve route profitability and strategy going forward.

Network planning includes evaluation of the strategic opportunities in the product planning, such as aircraft redeployment scenarios and new schedule design by providing improvements in network (fleet, schedule, and routing) deployment to maximize network profitability (cost efficiencies and revenue potential). A typical network planner starts with the analyzing the market data and identifying patterns for potential routes in order to optimize airline schedule and network profitability.

Main target is not to have profit on a single route but total HS system profitability. There could be some routes that is not profitable in the network, but they can still keep alive in the network because of the fact that they are feeding other routes in the hub and spoke system. In case this route is removed from the system, other routes may suffer due to dependency on the passenger who are travelling to/from unprofitable route. This dependency can be defined as network contribution of the unprofitable route. This route is not profitable by itself however it contributes the total network profitability significantly. Therefore, it makes sense to keep it in the HS network.

Another important dimension of the network planning is design and analysis of the hub structure in order to maximize profit while satisfying all operational constraints and business restrictions.

They evaluate the schedules and forecast its market shares while developing and calibrating models which quantifies the passenger choice on the picking up the airline for their itinerary. These models are generally called quality service index (QSI) models. It is a method to evaluate different options (airlines and flights) in front of the consumer (passenger). It starts with determining the factors that affect passengers' choice when choosing a flight among the others.

General factors that have been used in the industry are explained as follows; (Belobaba et al., 2015)

Number of stops: How many stops/connections are occurred in the itinerary? Some lucky city pairs in the world have direct flights (IST-JFK, LAX-DXB etc), however given 10K airport, there are many more indirectly connected city pairs (ADB-BCN, ESB-LHR etc) at least 1 or more stop. Passenger utility decreases while providing an increase of the number of stops in the travel.

Aircraft type: Which aircraft type is going to operate the flights? This factor is important especially for the jet and turboprop aircraft types. There is less preference on the turboprops over the jet aircrafts. In most cases, passengers are not aware of different aircraft types involved in a given itinerary. However, with help of the advertisement, airlines can make more revenues; becoming the first airline to operate the newest aircraft type (e.g., Airbus 380, Boeing 787) or the being the airline with the youngest fleet.

Aircraft type also important in terms of the capacity (available seat) provided to route. High capacity attracts more market share.

Flight frequency: just like aircraft type, more frequent services provide more capacity and attract more market share. It is also important to have at least daily services (one flight per each day in a week) in order to cover all the demand around the week.

Detour: Comparison (ratio) of the direct routing and indirect routing in terms of distance. Nonstop itineraries detour is 1. In general, detour factor up to 1.4 is acceptable for the itineraries that have intermediate stops. Although, passengers do not prefer high detours, they are obliged in some cases due to insufficient itinerary options. There can be only one flight to some airports, and they do not have any other option to select.

Travel time: Elapse time or travel time can be defined as total trip time that is required from origin city to destination city of itinerary including connection times at the intermediate stops. Longer itineraries are less attractive compared to shorter ones.

Time of day: morning and evening times are important for business travelers. It is also important to match hotel check-in and check-out timings for group travelers.

Night schedules, especially after the midnight, are less preferable due to less transportation opportunities between airports and city centers, inconvenient departure, and arrival times of the flight. Destinations with high local share are scheduled according to their time-of-day preferences in order to ensure market acceptance and exploit market potential.

Day of week: Mondays and Fridays are important for business travelers in general. It is important to have schedule on weekends due to high demand for leisure travelers. In some Muslim countries in the Middle East, Friday and Saturday are weekends, therefore airlines should be careful and aware of this fact while they plan their schedule to these destinations.

After deciding the factors, coefficients are applied to each factor for each schedule alternative. Then QSI scores are calculated. At the final step, QSI model scores of each alternative schedule is compared to forecast market share and to estimate the profitability of airline schedules (Barnhart and Smith, 2012).

Table 2.4 provides a typical schedule example which consists of the following information: airline code, flight number, departure time, arrival time, aircraft type, block time and departure day.

Table 2.4 Example of an airline schedule

Flight Number	Start Date	End Date	Pattern	Orig	STD	STA		Dest	Aircraft Type	Block Time
TK 1	25 July 2019	31 July 2019	1234567	IST	13:30	17:20		JFK	77B	10:50
TK 2	25 July 2019	31 July 2019	1234567	JFK	19:00	12:00	+1	IST	77B	10:00

A schedule is assumed feasible both operational and commercial constraints are satisfied. **Operational constraints** are explained as follows;

Ground times at the stations should be higher than the minimum ground time. Block times of the legs should be determined by dispatchers and schedulers that are analyzing the historical enroute flight times and taxi times at the stations. For existing destinations analysis is done by scheduling team. For new destinations, Integrated Operations Control Center (IOCC) departments are generally responsible for the block time input for the schedule.

Departure and arrival times of the schedule should be inline with the meteorological analysis. Destinations which have airport curfews and do not allow night operations should be planned their respective airport curfews.

Minimum connection time between flights that is required for transferring passengers at the hub station must be considered when the schedule is planned. Departure and arrival slots at the congested spoke airports must be satisfied. Crew planning teams should validate the duty times of the crews.

Commercial constraints are explained as follows;

Fleet should be available and should rotated for given schedule.

Local departure and arrival times should be reasonable for passengers.

Market potentials are used to identify the ideal capacity allocation for the destinations. Historical market data, growth rates and the level of competition are used determine the market potential for each destination. Together with passenger demand, belly potential cargo contribution of the destinations should be considered when feasilibity studies are evaluated.

Fleet assignment should be inline with the market potential and passenger preference. Passenger spill is minimized by re-distributing aircraft capacity in order to capture full potential of passengers.

The number of frequencies for seasonal destinations should be adjusted through the year in order to reflect demand variability.

A minimum service level of 3 times per week is defined in order to guarantee product quality.

Frequency rights should be utilized however frequency or capacity cannot exceed the defined right in the bilateral agreement between countries.

Schedule of the codeshare partner airlines should be considered for interline connecting passengers.

2.6 Fleet Assignment

Increase in the demand of airline transportation has led the airline companies to use their resources more effectively. Due to a sector with low profitability and high costs, the desire and competition of companies to meet the demands increases. The fleet assignment problem generally aims to generate the maximum profit to achieve the assignment of aircraft of different characteristics to predetermined flight schedules.

The fleet assignment problem (FAP) is the problem of assigning aircraft with predetermined flights, each with different capacities, material and fuel requirements, and operating costs (Akay, 2009).

The assignment problem directly affects the profitability of the airline. Assigning a plane smaller than the required passenger capacity to a flight directly leads to loss of customer due to lack of capacity, while assigning a plane larger than the required passenger capacity to a flight causes the seats not to be sold and a higher operating cost as well as the seats cannot be sold. Therefore, FAP is the one of the most important part of an airline's planning strategy and process.

When the aircraft assigned to a flight departure is too small and potential demand and revenue of flight revenues are lost to airline. It means that revenue and passenger spill occur. Spill is the loss of bookings due to the fact that the flight has been fully booked to capacity. In summary spill is the rejected of demand.

Objective of the fleet assignment is to minimize the spill and aircraft operating costs (Sherali et al., 2006). In other words, the problem of fleet assignment, which causes a significant increase in cost, means the assignment of the correct plane to the correct flight (Sarsenov, 2011). With the correct solution of fleet assignment problems, it is possible to increase the utilization rates of aircraft on air and to reduce the time they stay on the ground, to decrease costs and to provide new opportunities, thus profitability increases. Fleet assignment problems are not easy to solve because they are dynamic and can be affected by the change of environmental factors such as, fuel prices, demand shocks, revenue changes. Detailed literature review is provided on the section 3.5 of this thesis.

2.7 Crew Planning

Crew planning or scheduling is the final process for the airline planning process. Generally, it is solved by monthly and in two phases, namely crew pairing and crew rostering. Crew scheduling is done after the fleet assignment process. Since crew scheduling is not the focus of this thesis, only a brief summary of the crew scheduling process is provided in this part of the thesis.

Crew pairing is to find the mini schedules that are sequence of flight legs, pairings, typically spanning from 1 to 5 days. Objective of the problem is to minimize the crew related costs while covering all flights. Crew related costs are salaries and benefits, per diem, hotels and other expenses that crew were at a city other than their home base (Bazargan, 2010).

Crew pairings must satisfy the government regulations, union and labor collective agreements and airline's set of rules. In crew pairing phase of the crew scheduling, individual crew members are not addressed. Assignment of the each spesific crew member to pairings is the crew rostering phase (Belobaba et al., 2015).

Home base is defined as the home city/hub city where the crew actually lives.

Duty is defined as a crew that is going to operate combined flight legs in a working day. Length of the duty in a day is limited by regulators and individual airline rules. For example, in United States, airline pilots cannot fly more than 8 hours in 24 hours. (Bazargan, 2010).

Rest is defined as time between two consecutive duties.

Sit connection is defined as time between two consecutive flight in a duty. This time is required for waiting times between flights, changing the aircrafts for the next leg in the duty.

Duty time starts with sign (clock) in, generally 1 hour before the first flight's departure time and ends with sign (clock) out 15 minutes after last flight's arrival time. General rule settings of crew pairing for an examplary airline is shown as follow;

- Each duty cannot exceed 7 hours of flight time.

- Home base for the crew is IST.
- Minimum sit-connection time is 30 minutes and maximum sit-connection time is 3 hours.
- There should be at least 24-hour rest after the long haul flights.

When crew pairing problem is done, second stage of the crew scheduling is rostering. It can be defined as assigning crew members to crew pairings. In this stage, individual crew members are assigned to flights. Requests from the crew members are concerned in this phase. These requests are off-days, holidays, work-load balance, annual leaves etc. Methods that are taken into consideration varies among the airlines. Some of the examples are

- Assigning, firstly, senior employees to their biddings for the crew pairings.
- Minimizing total or average unmet bidding/demand for the individual crew members.
- Developing rosters without considering the requests.

Crew rostering for cabin crew and cockpit crew is different. While Cockpit crew members (pilots and captains) require license or type rating to fly on specific fleet family, cabin crew members can be assigned more than one fleet types (Bazargan, 2010).

2.8 Conclusion

Second chapter of this thesis starts with providing the information on the commercial terminology of the aviation. Terminology includes origin and destination (OD), fleet types, connection types, schedule information, calculations of the metrics and examples. In the second part of this chapter, airline business models are explained in detail. Network carriers and low-cost carriers are compared to each other in terms of network structure, service offering and pricing. Thirdly, airline planning process and its subproblems are explained. In the next chapter, a detailed literature review will be provided about bank structures, fleet assignment problems and airport capacity management problems.

3
LITERATURE REVIEW

3.1 Introduction and Chapter Outline

In this chapter, a comprehensive literature survey will be provided about airline fleet assignment problem, bank optimization and capacity management at the congested airports.

Literature review is built on three main pillars. First of all, theoretical background of airline bank structures will be provided. Secondly, previous works in the literature about capacity management applications in the congested airport industry will be presented. Finally, fleet assignment problem, solution approaches and its integration with other airline problems will be detailed.

3.2 Bank Structure

A bank is a group of incoming and outgoing segments, whereby the incoming flights all arrive at a hub within a short time period, and the connecting outgoing segments depart from the hub within a short time period once most or all of the incoming flights have arrived. A bank structure allows the connection of many incoming and outgoing flights with a low detour factor, which is the in-flight time for an indirect flight compared with the direct flight time (Burghouwt, 2016). Mostly, segments in the incoming banks are similar to each other in terms of passenger behaviour, geography and economy. This is also true for the outgoing segments in the bank (Goedeking, 2010).

Moreover, since the resources are scarce in an airport, within a bank, there could be overlaps and misconnections between incoming and outgoing flights in terms of arrival and departure time due to less connection than minimum connection time at the hub (Goedeking, 2010). Additionally, there could be long connection times between flights because of:

• Unavailable arrival or departure slots at the hub/spoke airport for creating connection.

• Unavailable equipment, required workforce, terminal facility at the desired timings.

• Aircraft availability at the hub airport.

These factors negatively affect both satisfaction of passengers and revenue of airline companies. Airlines cannot sell transfer tickets because of misconnected arrival and destination city pairs. Passengers spends more time at the airports than actually needed time for the transfer process from one flight to another.

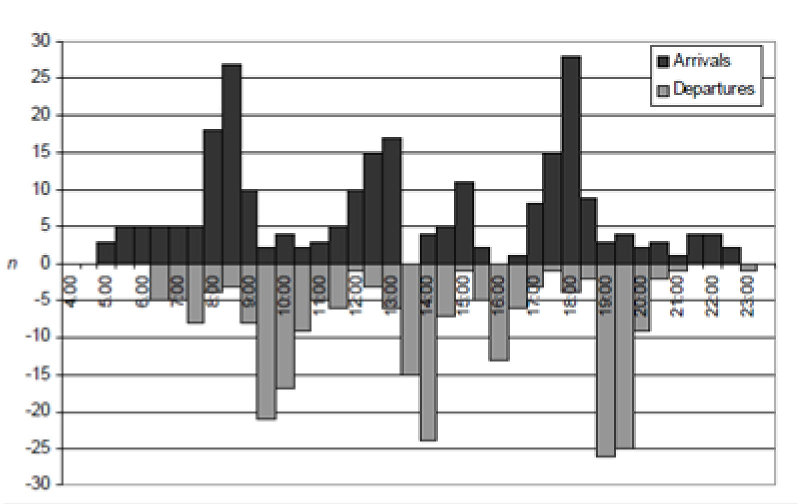


Figure 3.1 Wave structure of KLM Airlines (Danesi, 2006)

Entire bank structure on the hub is is combination of all feeder and de-feeder banks. Figure 3.1 shows the bank structure of KLM Airlines on its' hub Amsterdam Schiphol Airport (Danesi, 2006).

3.3 Capacity Management at the Congested Airports

Airport capacity can be defined as maximum number of operations that can take place in one hour (Ates and Uzulmez, 2016). Slot is a permission given by a coordinator for a planned operation to use the full range of airport infrastructure necessary to arrive or depart at a Level 3 airport on a specific date and time (IATA Worldwide Slot Guidelines, 2015). Basically, airport capacities are managed by slot allocations at the level 3 coordinated airports. Runway capacity, airport plan and design, terminal capacity, apron capacity, airside capacity, accessibility between apron and terminal are the factors that have influence on the airport capacity (ACI, 2013).

A detailed literature review of mathematical models for Air Traffic Flow Management can be found in study of Agustin et al. (2010). Barnhart et al. (2012) provides a summary of research trends and future opportunities in the area of air transportation demand and capacity. Potential research areas with significant impact includes integrated schedule solutions, dynamic decision making and inter-airline capacity exchange mechanisms. It has also been suggested to develop novel methods for allocating capacity to the airlines that value it most and will best use it to transport passengers. Lastly, I would like to address some of the papers about slot allocation mechanism and modelling among many studies. Corolli et al. (2014) presents mathematical models to assign and to optimize the allocation of air traffic time slots under uncertain capacity. Madas and Zografos, (2008) has developed a methodological framework for the multi-criteria evaluation and selection of the most compatible slot allocation strategy. Jiang and Barnhart (2013) proposed a robust scheduling approach which modifies current de-banked schedule according to feasible itineraries' weighted revenue and creates new flight schedule while satisfying the limit of the number of flight departures and arrivals per unit time at the hub. They have suggested to define additional metrics and measure their effectiveness for generating flight schedules for future research directions. Avenali et al. (2015) provides and builds incentive pricing in order to measure the best allocation and use of airport slots.

3.4 Fleet Assignment

The airline fleet assignment problem has been an important topic for academic and industrial studies. Modern aviation operations performed manually in the early years, the scale of the problem grows, it entered the field of operations research and new tools and methods have been developed.

The first model in this area was developed by Ferguson and Dantzig (1955). In 1956, the probabilistic nature of the demand was added. The model basically provides profit maximization by doing fleet assignment and aircraft rotation. Simpson (1978) developed a model that satisfies the demand and performed fleet assignment by minimizing operational costs.

With the increase of competition, the importance of schedule and fleet assignment has also increased. When the fleet assignment is done correctly, the costs will decrease, and the profitability will increase. Computer, innovations in hardware and operations research has enabled better methods to be introduced for the use of airlines and solving problems.

Abara (1989), introduced a basic framework for the Fleet Assignment problem using a connection network structure for solving a realistic fleet assignment problem and formulated as an integer programming model for the first time in the literature. The model solves the problem with an aim of profit maximization, while taking into account the following limitations. All flights should be covered exactly with one aircraft type. Connection network and schedule should be balanced, and the fleet inventory should be available. For the Abara (1989) model, all connections in the network are built and all possible connections are taken into consideration during the solution phase of the model. As a result, because of the too many possible flight connections, connection network becomes too large to be solved in a reasonable time. Figure 3.2 shows the feasible connection in one station for connection network model (Sherali et al., 2006). Abara (1989) model is missing the point of time in order to determine the planes that can be assigned at an airport.

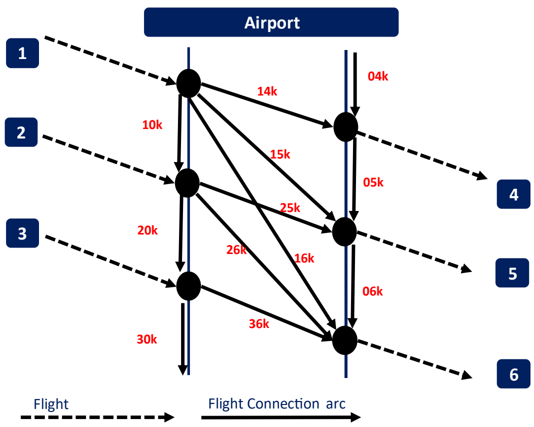


Figure 3.2 Feasible connection in one station

Subramanian et al. (1994) successfully applied a similar model to the Delta Air Lines Fleet Assignment problem. In this study, it is stated that the proposed method provides a profit improvement of 100 million dollars per year. The Coldstart model is a large-scale mixed-integer linear program that assigns fleet types to flight legs with an aim of minimization of the operating cost and passenger spill costs, subject to following constraints, cover, balance and aircraft availability. The model deals with a single day, which is assumed to be part of a repeating cyclic schedule.

El Sakkout (1996) proposed a solution using British Airways short haul flight list on ECLiPSE platform which is the academic Constraint Logic Programming platform. Götz et al. (1999) proposed a simulated annealing approach based on a local neighborhood search to improve the existing solution. They could reduce the calculation time to 75% for major problem sizes compared to classical methods.

Hane et al. (1995), proposed a novel model of the fleet assignment problem that is large multi commodity flow problem on a time-space network. Hane et al. (1995) solved the deficiency in the model of Abara (1989) by the time-space network model which is a frequently used model today. In this article, they describe a basic daily domestic network, fleet assignment problem, and then chronologically presented steps to solve it. Figure 3.3 shows an example of a time space network which consists of two fleet type and two station (Sherali et al., 2006).

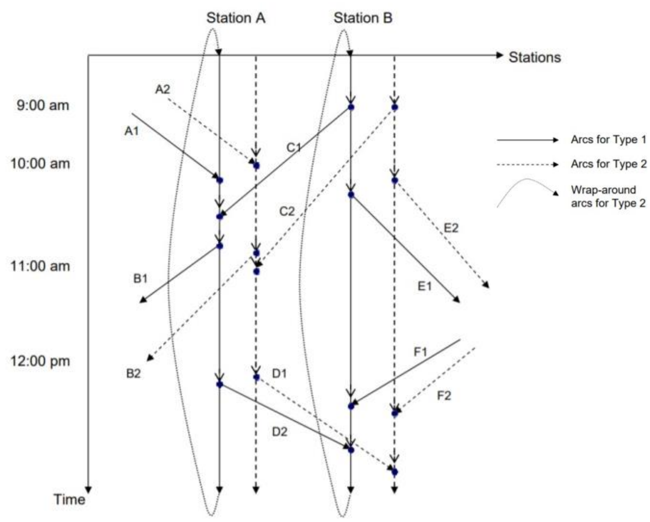


Figure 3.3 A two-type, two-station time–space network (Sherali et al., 2006)

Most important contribution of this study in the literature is aggregation of flights. It dramatically reduces computation times. The most important advantage of the model is that in the network created for each fleet type, each arrival and departure event at a given time is associated with a node. To allow appropriate aircraft connections, an arrival node is placed at the time of flight, depending on the flight time and the required return time. Figure 3.4 shows the pre-processing and node aggregation techniques for the time-space network model (Sherali et al., 2006). Hane et al. (1995) proved that the presented mathematical model was NP-hard and proposed a series of pre-processing techniques in order to reduce problem complexity. i.e. node aggregation and isolated islands at stations.

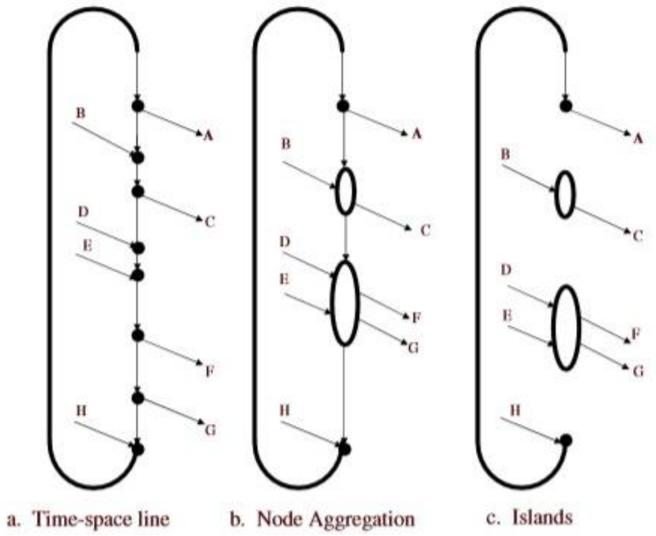


Figure 3.4 Node aggregation techniques (Sherali et al., 2006)

Pilla et al. (2008) formulated the fleet assignment problem as an integer multiple commodity flow problem in a timeline network similar to that of Hane et al. (1995). They use a two-stage stochastic programming model for fleet assignment. In the first stage, the model assigns flight legs to fleet families. In the second stage, the model assigns the types of aircraft to the flight legs. An experiment on a real airline showed the resulting Multivariable Adaptive Regression Splines (MARS), which provided nearly perfect fit. Revenue and operating costs, passenger demand and aircraft capacity are considered implicitly in each model. Estimation of expected revenue is determined on average according to scenarios.

Yan et al. (2008) uses a two-stage stochastic programming concept to develop the stochastic demanded flight planning model. The authors develop two different heuristic algorithms and compare their results with the most appropriate solution of the model. In the general two-stage stochastic programming process, decision variables are divided into two groups. In the first stage, a number of decisions such as passenger demand need to be determined before random variables are known to occur. In the second stage, a number of decisions can be determined after the values of the random variables are realized. The second stage decision variables are the passenger flow variables. The model and intuitive scanning were tested on a real-life case from the Taiwan airline's operation. The results show the good performance of the model and solution algorithms. In addition, it shows that the results obtained by stochastic approach are an improvement compared to the results obtained from the deterministic one.

Other authors also contributed the time-space network method. Grothklags et al. (2009) also used the time space network like Pilla et al. (2008) and Hane et al. (1995). In their study mixed integer programming (MIP) and 2 local heuristic method used to solve the uncertainty in demand. They have developed a ground-based fleet assignment model which utilizes both time-space and network connection concepts.

Cadarso and Marin (2013) developed a different perspective in addition to the above-mentioned fleet assignment problems. The importance of passengers in fleet assignment is mentioned in this article, and it is attempted to reduce the number of disconnected passengers in fleet assignment and flight planning. In their articles, they have shown that the probability of missing flight is dependent on the exponential distribution and connection time. GAMS / CPLEX was used to solve the models. In the model, it was found that the number of unconnected passengers decreased.

Rexing et al. (2000) proposed a model in which departure and arrival times could change during a certain time period. The purpose of which was to create a schedule with the minimum number of aircraft. They proceeded on a feasible solution using heuristic methods over an existing flight schedule to accomplish this. When they tested the algorithm on a major US carrier schedule, the algorithm made a time change of 8 percent of the flights and generated a profit of $ 65,000 per day. Belanger et al. (2003) proposed branch-and-price algorithm based on Hane et al.

(1995) model and tested on US carrier schedule. This method also reduced number of aircraft required compared to branch and bound problem.

In fleet assignment problem studies, there are some deficiencies in some area. These areas are increasing usage rate of aircraft reduction of difference in the usage rates between aircrafts, and uncertainty in airway planning. Also, the problem that may occur due to the operations of the aircraft have been ignored. Thereafter, the development of models and solution approaches that take uncertainty into account is a promising avenue for future research in this field (Kenan et al., 2018).

Fleet assignment process is not one time only in a year process for an airline. It is a continuous process that needs to be tackled very carefully and adopt the fleet assignment process for the changing of the cost and revenue structure of the airline Therefore, this optimization period can be done both for long term (strategic levet) and short term (tactical level).

3.4.1 Long Term Fleet Assignment

Long term fleet assignment is the process of the assigning next season flights to appropriate aircraft types depending on the of availability and technical performances, aircraft rotations and route profitability (Mancel and Mora-Camino, 2006). It is mostly done for one week of the schedule. It is assumed that it reflects the typical schedule of the season. It is done by network planners and schedulers together 6 months before the flights. Main targets are

- Creating a homogenous schedule in terms of the assigned aircrafts seven day in week as much as possible
- Optimizing the profit; not only to decrease cost or to increase revenue
- Testing the different commercial scenarios. (e.g., increase in the fuel price, change in the fleet plan)

However, 6 months is very long period for airline demand and revenue. Also, other assumptions are likely to be change between the fleet assignment processes are run and the time when the flights are operated. In order to manage this limitation of long-term fleet assignment in advance, short term fleet assignment runs are necessary in the airline scheduling departments as explained in the next section of this chapter.

3.4.2 Short Term Fleet Assignment

Short term fleet assignment has the same logic and parameters like the long-term fleet assignment. However, it differs from the time horizon point view of the schedulers. Airlines also needs to solve short term fleet assignment problem 8-10 week because of the crew planning reasons however demand is mostly not booked in this period. Demand forecasts are better 4-6 weeks in advance of the flights to catch the right aircraft capacity for each flight. (Sherali and Zhu, 2008). As a result, schedule that is optimal for previous fleet assignment runs could be infeasible at the operational level or not optimal at the commercial level (Mancel and Mora-Camino, 2006). Reasons for the different time windows are summarized as follow;

- Grounding of an aircraft in the inventory.
- Extension of the planned maintenance period.
- Change in the demand in the live schedule period.
- Crew planning reasons
- Delay of the planned phase-in delivery of the new aircraft to the fleet

Short term fleet assignment can be done one day, one week or one month of the schedule. Like time of interval of flights, it can be done one day, one week or one month before the scheduled time of departure of the flights. All these reasons require to change in the aircraft rotations and fleet assignments of the flights. This problem is sometimes referred as re-fleeting of the schedule.

3.5 Conclusion

As our knowledge, bank optimization problem has not directly been addressed in the literature. Despite the flight scheduling problem and airport slot capacity management are widely studied in the literature, previous work considering bank structure optimization is inadequate. Then, an overview of the existing fleet assignment models is provided. Regarding the financial importance, the most important problems among airline planning problems are aircraft and crew related problems due to high ownership costs. Due to high profitability effects, scheduling and fleet assignment problems have been an important topic for academicaş and industrial studies. Aviation related problems solved manually in the early years, as the scale of the industry grows, it entered the field of operations research and new tools and methods have been developed.

Next chapter will define the bank optimization problem. Then, a novel mathematical model for bank optimization, two existing mathematical model for the fleet assignment, and two metaheuristic algorithms for the bank optimization will be provided.

4
METHODOLOGY PROCESS

4.1 Introduction and Chapter Outline

Resolving the bank optimization problem involves determining the arrival and departure times of flights within a predefined bank, subject to available airport capacity, in order to minimise connection times between arrival and departure flights. Therefore, the problem can be modelled as an assignment problem that allocates flights to time slots in a bank.

In this chapter, a novel mathematical model and solution approach will be provided for the removing congestion and optimizing bank structures at the airports. Since the proposed assignment model is NP-hard, we examine two meta-heuristic search algorithms to yield better results in a reasonable time. Simulated annealing and tabu search algorithms are also defined and modelled in this chapter. Finally, two basic mathematical model, namely, connection network and time-space network, and their extensions in the literature is shown regarding the fleet assignment problem.

4.2 Mathematical Model for Bank Optimization

An integer programming model has been proposed in order to assign flights to available slots to increase the connectivity at the hub airport. It is also aimed to construct a new schedule that decreases connection times by considering the demand and revenue in the network. The model includes the following assumptions and limitations:

- Slot capacity at the spoke cities is assumed to be infinite.
- Belly cargo revenue of passenger aircraft is not considered.
- The frequency of flights is considered as one per day per city.
- The revenue from business and economy passengers are aggregated to a single passenger type as a weighted average.

Sets

F	Set of flights
S	Set of slots

Index

i	Arrival flights
k	Departure flights
j	Arrival slots
l	Departure slots

Parameters

C_{ijkl}	Connection value of flight i arrives at slot j and flight k departs at slot l.
K_{jl}	Binary minimum connection time feasibility parameter between arrival and departure slots. it has value of 1 if time difference between arrival slot j and departure slot k is higher than minimum connection time; 0 otherwise.
A_j, D_l	Number of available slots for arrival/departure flights.
P	Penalty cost for exceeding slot capacity.
h	Upper limit for exceeding slot capacity.
M	Big number

Decision variables

α_j, δ_l	Exceeding slot capacity for arrivals/departures.
x_{ij}	=1 if flight i is assigned to slot j; 0, otherwise.
y_{kl}	=1 if flight k is assigned to slot l; 0, otherwise.
z_{ijkl}	=1 if flight i arrives at slot j and flight k departs from slot l, provided that the connection time value between these flights is higher than the minimum connection time.

$$\max \quad \sum_{i\in F}\sum_{j\in S}\sum_{k\in F}\sum_{l\in S} C_{ijkl}\, z_{ijkl} - \sum_{j\in S} P\,\alpha_j \; - \sum_{l\in S} P\,\delta_l \qquad (4.1)$$

$$st. \quad \sum_{j\in S} x_{ij} = 1 \qquad \forall i \in F \qquad (4.2)$$

$$\sum_{l\in S} y_{kl} = 1 \qquad \forall k \in F \qquad (4.3)$$

$$M\left(K_{jl}\right) \geq \sum_{i\in F}\sum_{k\in F} z_{ijkl} \qquad \forall j, l \in S \qquad (4.4)$$

$$x_{ij} + y_{kl} \geq 2\, z_{ijkl} \qquad \forall i, k \in F, \forall j, l \in S \qquad (4.5)$$

$$\sum_{i\in F} x_{ij} \leq A_j + \alpha_j \qquad \forall j \in S \qquad (4.6)$$

$$\sum_{k\in F} y_{kl} \leq D_l + \delta_l \qquad \forall l \in S \qquad (4.7)$$

$$x_{ij}, y_{kl}, z_{ijkl} \in \{0,1\} \qquad (4.8)$$

$$0 \leq \alpha_j, \delta_l \; \leq h \text{ and integer} \qquad (4.9)$$

In the mathematical model, the objective function, Eq. 4.1, maximizes passenger revenue with shorter connection times and minimizes the exceeding slot capacity penalty cost. The parameter C_{ijkl}, which denotes the connection value of arriving flight i at slot j to departure flight k departing at slot l, is calculated as in Eq. 4.10.

$$C_{ijkl} = \frac{D_{ik} R_{ik}}{T_{jl}} \qquad (4.10)$$

Where D_{ik} represents passenger demand from city i to city k, R_{ik} denotes revenue per passenger from city i to city k, and T_{jl} is the connection time between arrival slot j and departure slot l. The parameter C_{ijkl} encourages shorter connection times by generating high values. Equation 4.2 ensures that each arrival flight is assigned to one arrival slot. Equation 4.3 assigns each departure flight to one departure slot. Equation 4.4 connects an incoming and an outgoing flight if the minimum connection time limit is satisfied. Equation 4.5 ensures that z_{ijkl} is 1 if an incoming flight i is connected to an outgoing flight k. Equations 4.6 and 4.7 ensure that the number of assigned flights to the slots cannot exceed the maximum slot capacity, which is the sum of slot capacity and the slot capacity allowance. These allowances are employed to allow flexibility for the planning period since other carriers that uses the same airport could change or cancel their schedule. Any change in the other carriers' schedules may result in a free slot capacity that should be taken into consideration. We define x_{ij}, y_{kl} and z_{ijkl} as binary variables in Equation 4.8. Finally, we introduce the decision variables α_j and δ_l as integer variables and there is an upper limit for exceeding the slot capacity, as in Equation 4.9.

4.3 Simulated Annealing

Simulated Annealing (SA), which was developed by Kirkpatrick et al. (1983), is an iterative and probabilistic meta-heuristic for global combinatorial optimization problems inspired by the annealing process of metals. SA starts with a feasible solution as an initial solution and improves it iteratively in the solution space according to certain acceptance rules. Uphill moves are accepted probabilistically to avoid becoming trapped in the local optimum and to explore the search space by an annealing process from high temperature to low temperature. The SA algorithm has also been utilized for solving many combinatorial optimization problems in recent decades. Recently, Franzin and Stützle (2019) investigated the advantages of SA algorithms for three well-known combinatorial optimization problems.

SA has been used to solve airline business-related problems in the literature. For instance, Hadianti et al. (2013) and Emden-Weinert and Proksch (1999) adapted the SA algorithm to solve crew scheduling and rostering problems. Kliewer and Tschoke (2000) used SA to solve the weekly fleet assignment problem in an internationally operating airline as a real-world application. Sosnowska (2000) reported that SA provides slightly lower cost than the greedy randomized adaptive search procedure algorithm for the fleet assignment problem. Abdinnour-Helm (2001) utilized the SA algorithm to solve the p-hub median problem and compared the results with TS using the data set of airline passenger flow in the United States of America. Lastly, Mashford and Marksjö (2001) applied SA to the airline scheduling problem.

The objective function in the SA algorithm is given in Equation 4.1. T represents the temperature in the SA process. Generally, four parameters are used to control the annealing process: the initial temperature (T_0), the number of iterations (n), the cooling rate ($\propto < 1$) and the number of iterations for each temperature value (θ).

Algorithm 1: Simulated Annealing Pseudo Code

(Initialise)
  Set SA parameters (T_0, α)
  Generate initial solution S
  Set $T = T_0$
Repeat
(Generate candidate solution)
  Apply a random change on state $S' = S + \Delta s$
  Evaluate $\Delta E(s) = E(S') - E(S)$:
    if *$\Delta E(s) < 0$* ***then*** *keep new state* S',
    else
    generate random threshold level $r \in [0,1]$
      if $r > \exp(-\Delta s/T)$ ***then*** *accept the new state* S'
      endif
    endif
    if *the T = 0 (mod θ)* ***then***
    decrease temperature $T = T \times \alpha$
    else *temperature is unchanged T = T*
    endif
until *timeLimit or maximum number of iterations reached.*

In SA algorithm, given in Algorithm 1, we swap the current solution if new solution is better, otherwise it will be accepted with probability P. The termination criteria of the SA algorithm is the maximum iteration number.

4.4 Tabu Search

The Tabu Search (TS) algorithm was first proposed by Glover (1989). It is a meta-heuristic search method whose iterations start with an initial solution that is either random or a given feasible solution. At each iteration, a number of neighbor solutions are created, from which the best neighbor is selected for the next iteration. In order to avoid revisiting the best solutions, a so-called tabu list is used as the short-term memory of the algorithm. In this way, accepted moves should always be the best one that has not been previously visited. Over the years, the algorithm has been improved and adapted for solving many combinatorial optimization problems.

In the airline industry, the TS algorithm has been applied for the airline crew scheduling problem by Caserta (2005) and Gamache et al. (2007). Büdenbender et al. (2000) proposed a hybrid TS/Branch-and-Bound algorithm for solving a direct flight network design problem. Xu and Bailey (2001) used a TS algorithm to solve a gate assignment problem to decrease the walking time between gates for transfer passengers. Their objective was to increase the customer service level by minimizing the required transfer distance between flights without changing the arrival and departure times of flights. Lumbanraja et al. (2017) applied the TS algorithm for selecting new routes to improve the robustness of an existing air transportation network.

In this study, we adapt the TS algorithm (as summarized in Algorithm 2) to solve the bank optimization problem.

Algorithm 2: Tabu Search Pseudo Code

The algorithm generates feasible solutions and evaluates these solutions with the

(Initialise)
Generate initial solution S
Set SBest := S
Set TabuList := ∅
Repeat
Generate candidate solutions
Evaluate candidate solutions
Pick the best the candidate solution as S′
If *the candidate solution S′ is better than S and is not in the TabuList* ***then***
update the TabuList, enqueue the S′ into the TabuList
endif
If *the length of the TabuList is longer than the maximum_list_length* ***then***
Remove the first element in the TabuList
endif
Set S as best solution S'
until *time_limit or max_number_of_iterations reached.*

TS procedure and the objective function given in Equation 4.1. The algorithm terminates when the maximum iteration number criterion is satisfied.

4.5 Mathematical Models for Fleet Assignment

Fleet assignment problem has been represented one of the most important and many times studied in the airline optimization problems. The aim of fleet assignment is to match most appropriate fleet type to flights while minimizing the cost (Özdemir et al., 2012).

The problem is described by Lohatepanont (2002) as follows: "Given a flight schedule with fixed departure times and costs (fleet and flights specific operating costs and spill costs), find the minimum cost assignment of aircraft types to flights, such that: each flight is covered exactly once by an aircraft, flow balance of aircraft by type is conserved at each airport, and only the available number of aircraft of each type are used.

4.5.1 Basic Models

There are two types of basic models in literature. Abara (1989) describes the first fleet assignment problem using connection network structure. Sherali et al. (2006) describes the following model as the basic fleet assignment model (FAM) using connection network structure, is a similar version of FAM proposed by Hane et al. (1995) and Abara (1989). Objective function could be minimizing cost (including spill cost, operating cost) or maximizing revenue (profit). In this thesis, we have utilized the objective function by using unit cost and revenue values of each route and specific fleet type.

Mathematical model for basic fleet assignment model using a connection network

Sets

L	Set of flights
F	Set of fleet types
S	Set of stations
A_s	Set of arrival legs for station s
D_s	Set of departure legs for station s

Index

i, j	Index for flights
f	Index for fleet type
s	Index for stations

Parameters

Rask_j	Revenue per available seat kilometer (unit revenue) of leg j.
$Cask_f$	Cost per available seat kilometer (unit cost) of fleet type f.

A_f	Number of available aircraft for fleet type f.
D_j	Distance of flight j.
Cap_f	Capacity of fleet type f.

Decision variables

x_{ijf}	=1 if connection is feasible between leg i to leg j by using fleet type f; else 0.

$$revenue = \sum_{i \in L \cup \{0\}} \sum_{j \in L} \sum_{f \in F} Cap_F * x_{ijf} * d_j * Rask_j$$

$$cost = \sum_{i \in L \cup \{0\}} \sum_{j \in L} \sum_{f \in F} Cap_F * x_{ijf} * d_j * Cask_f$$

$$max \quad revenue - cost \tag{4.11}$$

$$st. \quad \sum_{i \in L \cup \{0\}} \sum_{f \in F} x_{ijf} = 1 \qquad \forall j \in L \tag{4.12}$$

$$\sum_{i \in L \cup \{0\}} x_{ilf} = \sum_{j \in L \cup \{0\}} x_{ljf} \qquad \forall l \in L, \forall f \in F \tag{4.13}$$

$$\sum_{i \in D_s} x_{0if} = \sum_{i \in A_s} x_{i0f} \qquad \forall s \in S, \forall f \in F \tag{4.14}$$

$$\sum_{i \in L} x_{0if} \leq A_f \qquad \forall f \in F \tag{4.15}$$

$$x_{ijf} \in \{0,1\} \tag{4.16}$$

In the above model, the objective function in Eq 4.11 seeks to maximize the total profit of assigning the various fleet types to all the flights in the schedule. Eq 4.12 is the flight-cover constraints to ensure that each flight is flown by one type of fleet. Eq 4.13 is aircraft rotation balance constraint at each leg in the network for each fleet type. Eq 4.14 is the schedule balance constraint that "satisfies the same number of aircraft of each aircraft type remain at each station every night so that the same assignment can repeat daily". Eq 4.15 represents the available fleet size constraints. The number of aircraft in fleet type f, should not exceed the available number of aircraft in that fleet (A_f). Eq 4.16 represent the binary and integer status of the decision variable, (Sherali et al., 2006).

Mathematical model for basic fleet assignment model using a time–space network structure

Hane et al. (1995) are the first researchers who describes the time-space network approach for the fleet assignment problem. It has been discussed and showed the in the literature review part of thesis chapter 3.5. In this part, basic mathematical model which is adopted from Sherali et al. (2006) will be provided as follow;

Sets

S	Set of stations in the network
F	Set of fleet types
L	Set of legs scheduled
N	Set of nodes in the network
O_f	Set of arcs for fleet type f that cross the aircraft count timeline

Index

$l\ , odt$	Index for flight legs, where o,d ∈ S and t denotes the time when the flight takes off from o or is ready at d for the next take-off
f	Index for fleet type
s, o, d	Index for stations, origins, destinations
fst	Index for nodes in the network where f ∈ F, s ∈ S, and t denotes the event time

Parameters

c_{fl}	Cost of assigning fleet type f to leg l.
A_f	Number of available aircraft for each fleet types.

Decision variables

x_{fl}	=1 f fleet type f covers leg l; else 0.
$y_{fstt'}$	flow of aircraft on the ground arc from node {fst} ∈ N to node {fst'} ∈ N at station s ∈ S in fleet type f's network, for f ∈ F, where t' > t in general, and t' ≤ t for wrap-around arcs
t^-, t^+	the time preceding and succeeding t, respectively, in the timeline

---

$$
\begin{aligned}
& min \quad \sum_{l\in L}\sum_{f\in F} c_{fl} * x_{fl} && && (4.17)\\
& st. \quad \sum_{f\in F} x_{fl} = 1 && \forall l \in L && (4.18)\\
& \sum_{o\in S} x_{fost} + y_{fst^{-}t} - \sum_{d\in S} x_{fsdt} - y_{fstt^{+}} = 0 && \forall \{fst\} \in N && (4.19)\\
& \sum_{l\in O(f)} x_{fl} + \sum_{s\in S} y_{fst_n} t_1 \leq A_f && \forall f \in F && (4.20)\\
& x_{fl} \in \{0,1\}, y \geq 0 && && (4.21)
\end{aligned}
$$

Mathematical model objective function, equation 4.17, minimizes the total assignment cost. Like first basic model; constraints are cover, balance and availability of the fleet size Eq 4.18, Eq 4.19 and Eq 4.20, respectively.

4.5.2 Extended Models

Several extensions and integration of the fleet assignment model with other problems in the airline industry are studied in the literature. In this part of the thesis, additional constraints, and different objective function for the basic FAM in provided. Homogeneity model is proposed by Belanger et al. (2006). Main contribution is that assigning different sub fleets for different weekday of the schedule is penalized. Additional to cover, balance and availability constraints following constraints are added to model.

$$
\begin{aligned}
& \sum_{f\in F} d_{fn} = 1 && \forall n \in \varphi && (4.22)\\
& x_{fl} - d_{fn(l)} - p_{fl} \leq 0 && \forall f \in F, \forall l \in L && (4.23)\\
& x_{fl}, d_{fn(l)} \in \{0,1\}, y, p \geq 0 && && (4.24)
\end{aligned}
$$

Eq. 4.22 is deals with assigning a dominant fleet type for each flight in a period of one week. Eq. 4.23 satisfies that if a different fleet assigned than the dominant type then it is penalized.

Another integration of the FAM is the required maintenance check in the schedule. It has been modelled as follows Sherali et al. (2006).

Sets

PL	Long maintenance activities
J(p)	"set of eligible leapfrog arcs"
Parameters	
M_p	Number of aircraft required for long maintenance
Index	
p	Index for maintenance
j	Index for leapfrog arc

Additional constraint

$$\sum_{j \in J(p)} m_{pj} = M_p \qquad \forall p \in PL \qquad (4.25)$$

Rexing et al. (2000) and Desaulniers et al. (1997) introduced schedule design in the fleet assignment problem by adding following constraints to Abara's (1989) model which using a connection network.

$$a_{if} \leq T_{if} \leq b_{if} \qquad \forall f \in F, \forall i \in L \qquad (4.26)$$

$$x_{ijf}(T_{if} + d_{ijf} - T_{jf}) \leq 0 \qquad \forall f \in F, \forall i, j \in L \qquad (4.27)$$

4.6 Conclusion

In this chapter, a novel mathematical model is introduced to optimise the flight schedule of an airline at its hub airport regarding the bank structure. The goal is to design the flight bank with the optimal departure and arrival times of the flights in the predefined bank structure while shortening transfer passengers' connection times and decrease the congestion level in the hub airport. Integer programming model considers the available slot capacity of the hub airport as well as the demand and the revenue of spoke cities.

Simulated Annealing and Tabu Search algorithms are defined and their applications in the aviation literature is provided. There are very few applications in the field of aviation literature and these applications are generally old.

Finally, fleet assignment literature and two major mathematical models are reviewed in a detailed way. Extensions, examples and additional consraints from different areas of the aviation, such as maintenance, crew planning, flight scheduling, network planning, are provided.

Next chapter will address the Sabiha Gokcen case study for the bank optimization problem and metaheuristic algorithms.

5
CASE STUDY OF BANK OPTIMIZATION

5.1 Introduction and Chapter Outline

Sabiha Gökçen Airport (SAW) has been selected by airline network planning experts as hub in order to apply the model and evaluation. Morning arrival flights comes from Middle East, Central Asia; considered as "East Arrival" in the bank structure and departure flights goes to Europe, considered as "West Departure" in the bank structure. Current flights and their arrival and departure orders in the cluster could be re-evaluated according to their values of connecting passenger inside the planes and available slots at the airports in order to increase passenger utility and decrease congestion.

Figure 5.1 Current wave structure of the examined airline

Figure 5.1 illustrates the current wave structure of the examined airline which has hub and spoke system at Sabiha Gokcen Airport. Figure 5.2 shows the network map of these east and west flight clusters. In the current structure arrival flights are distributed among between 8:00 am to 10:00 am in the morning and departure flights are between 11:00 am and 1:00 pm.

Figure 5.2 Network map of case study airline at SAW airport.

Network consists of 23 destinations and 13 of these destinations are European cities and 10 of them are located in the Middle East.

Figure 5.3 shows the current capacity usage entire day of operations bank structure at SAW. Blue lines are number of the arrival flights per 10 minutes and orange lines are the departure flights per 10 minutes. Capacity is 4 for arrival and 4 for departure per 10 minutes. There are capacity exceeds both for arrival and departure slots in the initial planned flight schedule.

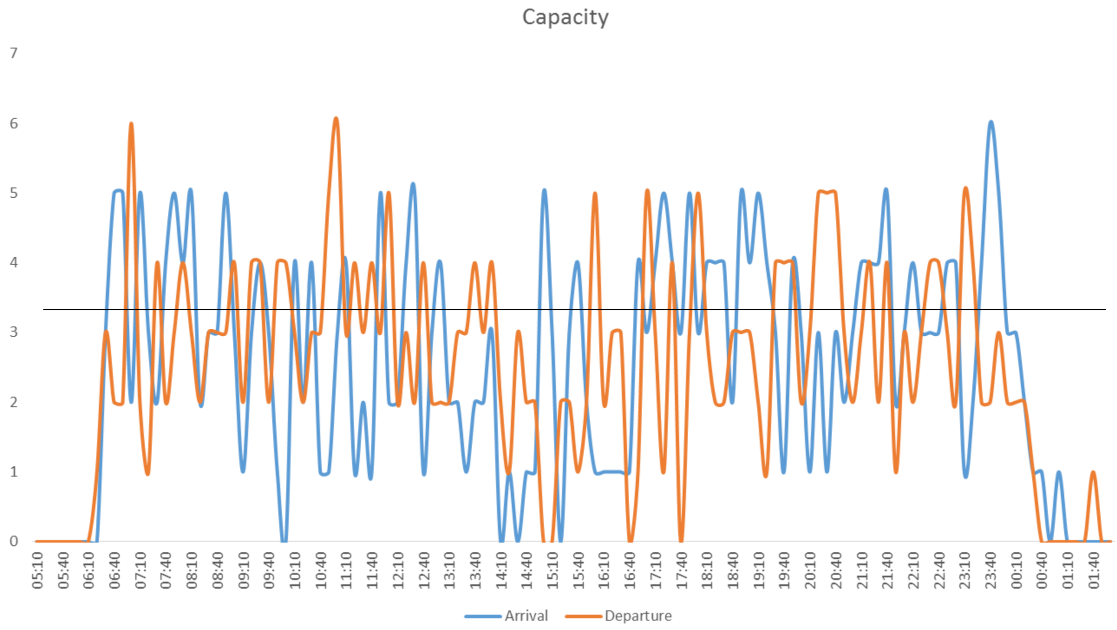


Figure 5.3 Ten minutes slot capacity and usage at SAW airport

Rest of this chapter is organized as follows, general overview about the Turkish aviation industry is provided in three sub section of this chapter. Firstly, deregulation and its effects are discussed, growth of the industry is provided summary of the academic literature and studies about Turkey's aviation industry is provided in three sub sections.

5.2 Turkish Aviation Industry

Turkish airlines is national carrier of Turkey and it was the only carrier until 1983. (Korul and Küçükönal, 2003). Domestic market has been deregulated since 2003 and from that year, passenger numbers, number of airlines and number of airports in the country are increasing. Turkish Airlines (THY) (59%), Pegasus Airlines (PGS)

(28.6%), Onur Air (7.9%), and Atlasjet (4.4%) has capacity share in the domestic market Dursun et al. (2014).

Torlak et al. (2011) analyzed Turkish domestic airline industry from a management perspective using fuzzy TOPSIS approach. Another fuzzy approach is provided by Şevkli et al. (2012) utilizing fuzzy ANP-based SWOT analysis for Turkish aviation industry. Karagülle (2012) presented strategic fleet decisions of Turkish airline companies and their fleet structures. Dursun et al. (2014) showed the transformation of Turkish Airlines from a regional player to a global network carrier. Çiftçi and Şevkli (2015) proposed a new hub and spoke system for Antalya because of the slot capacity constraints of Ataturk Airport and Sabiha Gokcen Airport in İstanbul. Acar and Karabulak (2015) analyzed the competition in Turkey between Turkish Airlines and Pegasus Airlines. They also provide a SWOT analysis for Pegasus Airlines. In 2017, Deveci et al. (2017) developed an interval type-2 fuzzy TOPSIS for new long haul route oppurtunity from Turkey. Logothetis and Miyoshi (2018) introduced a new model for hub connectivity and compared Turkish Airlines' hub Istanbul Atatürk Airport and Emirates' Hub Dubai International airport.

5.3 Growth of the Turkish Aviation Industry

Figure 5.4 is produced by owner of this thesis from the information derived from DHMI website. Industry is growing constantly in last 10 years both for domestic and international market (DHMI, 2019). There is only one year decrease in the figure which is during the 2016 demand crisis. Growth of the industry continues 2017 and recovers very quickly and has even better figures than the 2015.

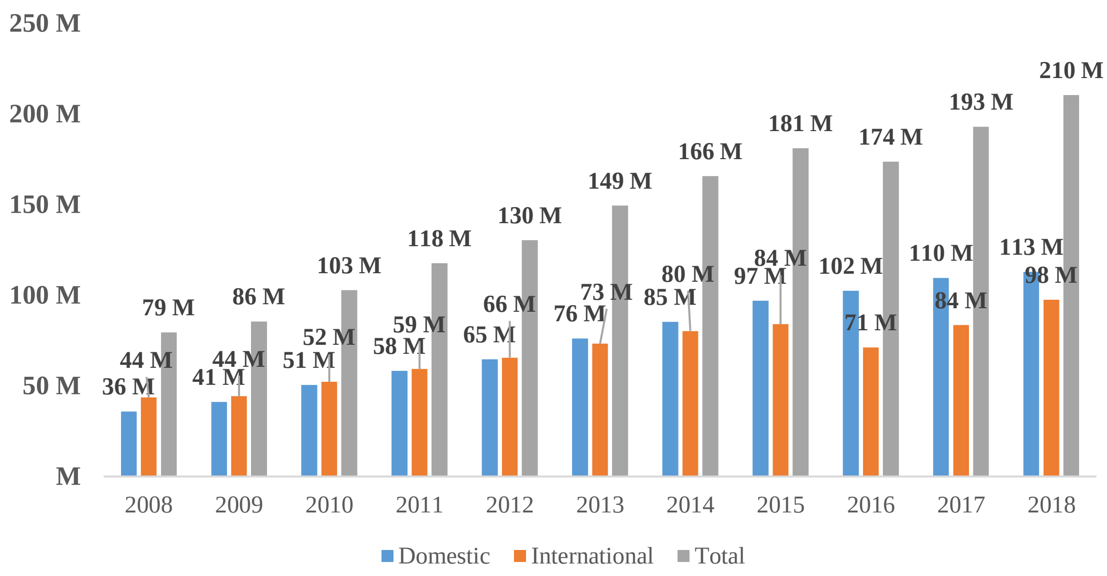


Figure 5.4 Number of passengers who are using Turkish Airports

5.4 Sabiha Gokcen Airport (SAW)

SAW International Airport is a hub airport of one of the biggest flag carriers in Turkey. SAW faces many operational problems due to its capacity limitations. It has only one runway and serves three hub carrier operations for Pegasus Airlines, Turkish Airlines and AnadoluJET. It is one of the fastest-growing airports among the members of Airports Council International (ACI) Europe and has reached its capacity limit.

General overview about Sabiha Gökçen (SAW) airport as follows;

- Has one runway (06/24) with limited capacity
- Two base carrier operations PGS and Turkish Airlines (also sub brand AnadoluJET),
- One of the fastest growing airports in the Europe and reached the limits;
- Level 3 airport (fully coordinated) demand exceeds the airport capacity supply
- Runway is closed temporarily to departure and arrival traffic at the midnights due to maintenance and repairs.

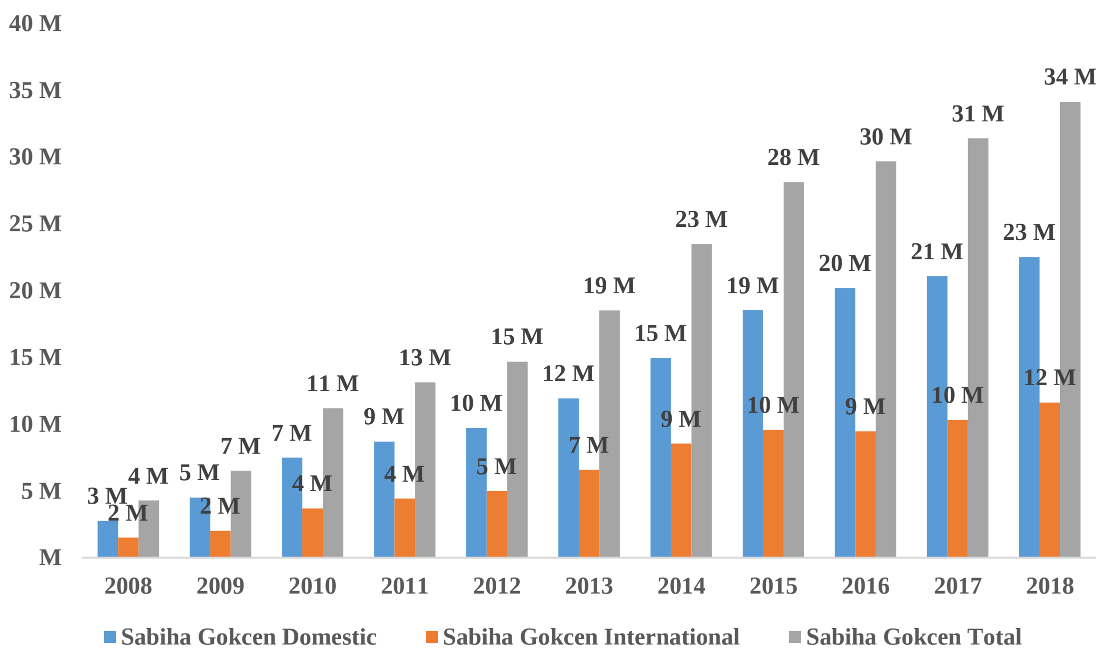


Figure 5.5 Number of passenger who are using Sabiha Gökçen Airport

Starting from 2016 IATA winter season, SAW became level 3 airport that slots are fully coordinated. Until then, airport was attracting too many carriers around the Europe and Middle East and Turkey, but due to high demand from the airlines, it quickly reached its capacity limit. Figure 5.5 shows the passenger demand growth of the SAW Airport. It is also important to note that even 2016 demand decrease of Turkey which can be seen at the Figure 5.4, SAW Airport has increased the passenger numbers.

Runway maintenance limits the airport usage and total available number of slots at the SAW Airport. To summarize, all of these factors cause congestion at the airport; flight delays, deterioration in customer service and misconnected flights, as well as increasing costs at SAW.

5.5 Experimental Results with Sample Problems

In order to solve the bank optimization problem five problem instances as subsets of the real-world problem are generated. These problems are coded in GAMS using a CPLEX solver for a mathematical model and in R for the SA and TS algorithms. Current flight schedule is used as an initial solution in the SA and TS algorithms. The sub-problems are solved on an Intel(R) Core(TM) i5-3317U CPU @ 1.70GHz and 12.0 GB RAM computer.

Extra capacity per slot is assumed 1 in each case. Three datasets, namely, schedule, capacity and demand, are utilized in these experimental runs. Table 5.1 shows the current arrival and departure times (schedule) of flights in the bank structure.

Table 5.1. Current arrival and departure times in experimental sub-problems.

Arrival Flight Number	Arrival Slot	Departure Flight Number	Departure Slot
101	2	201	19
102	5	202	23
103	9	203	21
104	1	204	18
105	8	205	26
106	4	206	31

Table 5.2 shows the first for 4 rows of number of available slots in the bank structure.

Table 5.2. Number of available slots in the bank.

Slot Time	Available Arrival Slot	Available Departure Slot
1	4	4
2	4	4
3	4	4
4	4	3

Table 5.3 shows the example of the passenger demand for a summer season and average unit passenger revenue information between arrival and departure flights on origin-destination (OD) pairs.

Table 5.3. OD demand and unit passenger revenue.

Arrival Flight Number	Departure Flight Number	Demand	Unit Revenue
104	204	14.614	229
104	201	11.581	200
103	204	7.285	164
104	203	6.222	200
104	205	5.461	190
106	204	4.227	218
104	202	4.193	259
103	203	3.866	183
103	201	3.464	232
106	201	3.001	217
103	205	2.929	165
104	206	2.326	262
103	202	2.282	232
106	202	2.232	261
105	204	2.200	321
103	206	1.816	186

It has been summarized the run times and results for each sub-problem in Table 5.4. Both the GAMS/CPLEX and SA algorithms improve the current solution in a range between 100% and 179%.

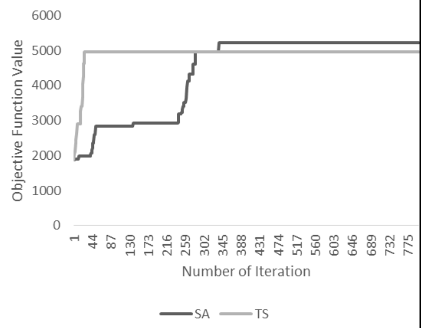
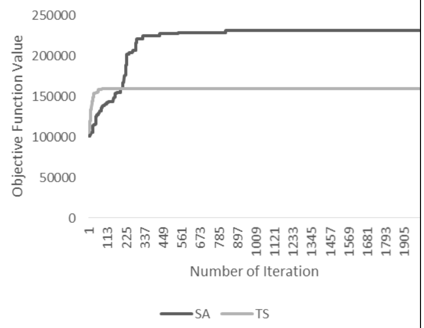
Table 5.4 Run times and results for the exact and meta-heuristic solutions

Problem Size				**Result**				**Run Time (seconds)**		
# of Arr. Flight	**# of Dep. Flight**	**# of Arr. Slot**	**# of Dep. Slot**	**Initial**	**GAMS**	**TS**	**SA**	**GAMS**	**TS**	**SA**
2	2	33	33	1,869	5,217	4,964	5,217	219	40	12
3	3	33	33	19,774	39,721	36,820	39,721	3,068	58	13
4	4	33	33	78,871	192,497	120,577	192,497	10,790	237	15
5	5	33	33	100,799	231,280	159,796	231,280	86,400+	144	31
6	6	33	33	123,769	303,634	193,881	297,931	86,400+	500	100

The TS algorithm also increases the solution quality; however, it does not perform as well as SA in terms of runtime and objective function value. As the problem size becomes larger, the improvement in the solution quality of the TS algorithm decreases (from 166% to 54%). Both meta-heuristic algorithms terminate in a very short time compared to the GAMS/CPLEX runtimes for each sub-problem. When we increase the problem dimension to 5x5 flight networks and higher, the exact solution calculation takes longer than one day. We stop the GAMS/CPLEX solver since the runtimes for such small problems are not acceptable in real-world airline operational planning.

The SA algorithm finds the optimal solution up to a 5x5 flight network. For a problem size of 6x6, the difference between the solution quality of the GAMS/CPLEX and SA algorithm is less than 2%. When the runtimes of the GAMS/CPLEX and SA algorithm are compared, the performance of SA considerably outperforms GAMS/CPLEX for each sub-problem. Since the solution speed is critical in the dynamic airline environment, we realize the advantage of using the SA algorithm by means of obtaining near-optimal solutions in a very short time period.

We illustrate the performance of the TS and SA algorithms for each sub-problem in Figure 5.6. The results demonstrate that the SA algorithm is superior to the TS algorithm in terms of solution quality and computation time. For solving the real-world bank optimization problem in SAW, we employ the SA algorithm regarding the computational study in this section.

<table>
<tr><th>Problem Size</th><th>Simulated Annealing vs Tabu Search</th><th>Problem Size</th><th>Simulated Annealing vs Tabu Search</th></tr>
<tr><td>2x2</td><td>
</td><td>5x5</td><td>
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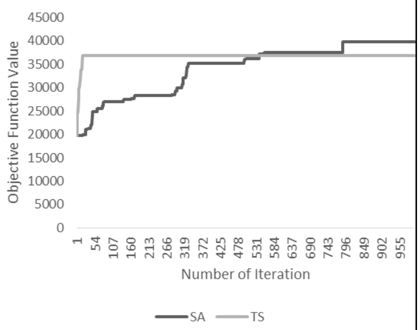
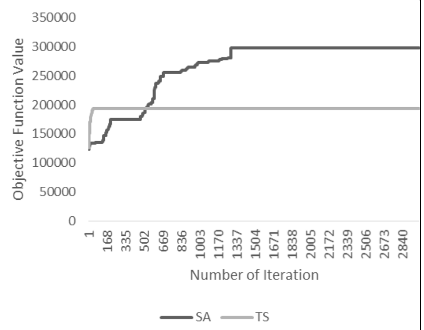
<tr><td>3x3</td><td>
</td><td>6x6</td><td>
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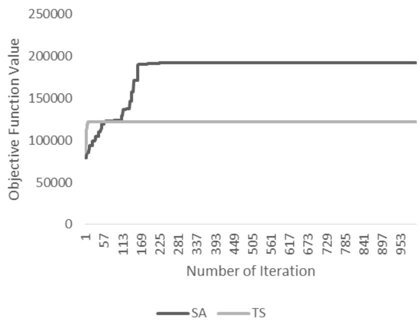
<tr><td>4x4</td><td colspan="3">
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</table>

Figure 5.6 Comparison of results obtained by the TS and SA algorithms

The final step with the experimental data is to adjust the parameters of the SA for real world case study. Table 5.5 shows the average and best fitness values obtained by SA over 10 runs of sample problem on 25 experiments, with the best average given in bold and best fitness underlined.

Table 5.5 Parameter fine tuning of SA

Experiment	Initial Temperature (T_0)	Maximum Number of Iteration	θ	Cooling Rate (α)	Run	6x6 Problem	
						average	best
1	10,000	1,000	2	0.92	10	283,073	291,120
2	10,000	2,000	4	0.94	10	268,201	282,327
3	10,000	3,000	6	0.96	10	261,819	280,721
4	10,000	4,000	8	0.98	10	284,063	293,468
5	10,000	5,000	10	0.99	10	285,707	297,203
6	20,000	1,000	2	0.92	10	285,373	292,738
7	20,000	2,000	4	0.94	10	281,098	295,053
8	20,000	3,000	6	0.96	10	265,679	289,610
9	20,000	4,000	8	0.98	10	278,445	285,109
10	20,000	5,000	10	0.99	10	287,136	295,451
11	30,000	1,000	2	0.92	10	280,924	290,992
12	30,000	2,000	4	0.94	10	282,462	287,922
13	30,000	3,000	6	0.96	10	280,375	290,532
14	30,000	4,000	8	0.98	10	280,366	292,739
15	30,000	5,000	10	0.99	10	288,561	297,527
16	40,000	1,000	2	0.92	10	268,259	279,927
17	40,000	2,000	4	0.94	10	276,603	293,117
18	40,000	3,000	6	0.96	10	276,565	282,327
19	40,000	4,000	8	0.98	10	281,061	295,053
20	40,000	5,000	10	0.99	10	289,021	296,674
21	50,000	1,000	2	0.92	10	265,786	279,345
22	50,000	2,000	4	0.94	10	278,513	281,929
23	50,000	3,000	6	0.96	10	275,251	285,655
24	50,000	4,000	8	0.98	10	281,069	290,513
25	50,000	5,000	10	0.99	10	**289,165**	<u>**297,931**</u>

Figure 5.7 shows the objective function value and its change for one slot earlier or later assignment for Flight 205 in the data. Horizontal axis represents the time slots and vertical axis represents the current value of objective function.

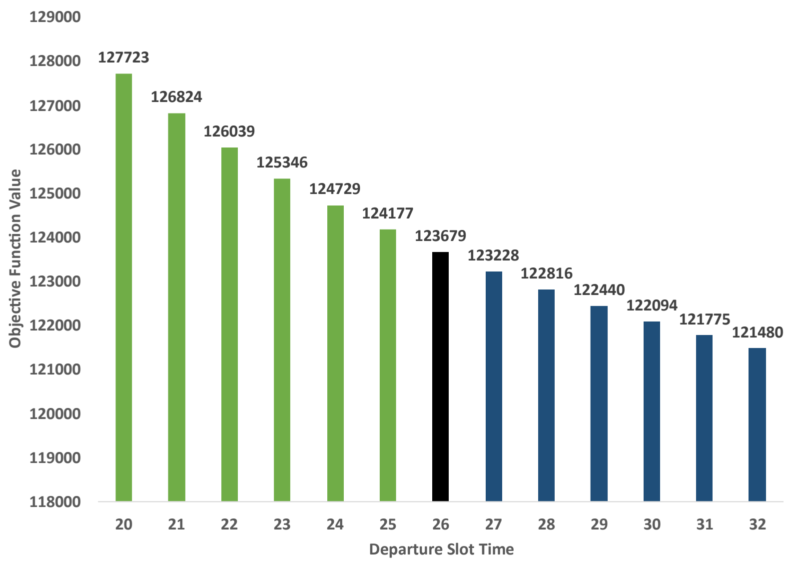

Figure 5.7 Sensitivity analysis of objective function

The black column represents the objective function's value when Flight 205 is assigned to its current (initial) slot. The green columns represent the assignments to earlier slots which gives shorter connection times and their objective function values, respectively. The blue columns represent the assignments with longer connection times and their objective function values, respectively. Earlier (closer departure to the arrival flights) slot times of departure flights create higher values for the objective function and vice versa.

5.6 Case Study of SAW Airport Real-World Data for Bank Optimization

The current arrival and departure times are given as an initial solution and the SA algorithm is run for 5.000 iterations with an initial temperature of 50.000. The temperature decreases with $\alpha = 0.99$ after every 10 iterations.

Initial solution of the problem had an objective function value of 322.806 and final solution after iterations is 583.421. The SA algorithm improves the solution quality by 81% in 10 minutes of runtime by a computer which has Intel(R) Core(TM) i5-3317U CPU @ 1.70GHz and 12,0 GB RAM. It has been illustrated the best solution, average results of the 10 different SA runs and minimum result over the iterations in Figure 5.8.

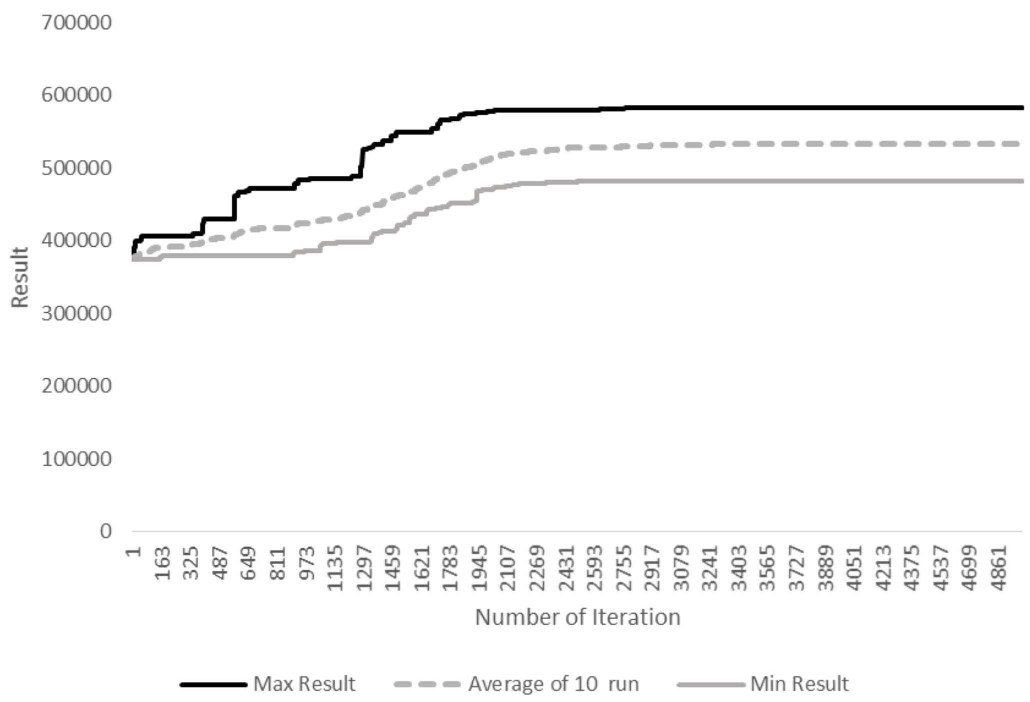

Figure 5.8 Graphical representation of SA solution quality

Mathematical model is also coded for General Algebraic Modeling System (GAMS) and code can be found in Appendix A. A comparison between the GAMS/CPLEX and SA results for the SAW problem can be found in Figure 5.9.

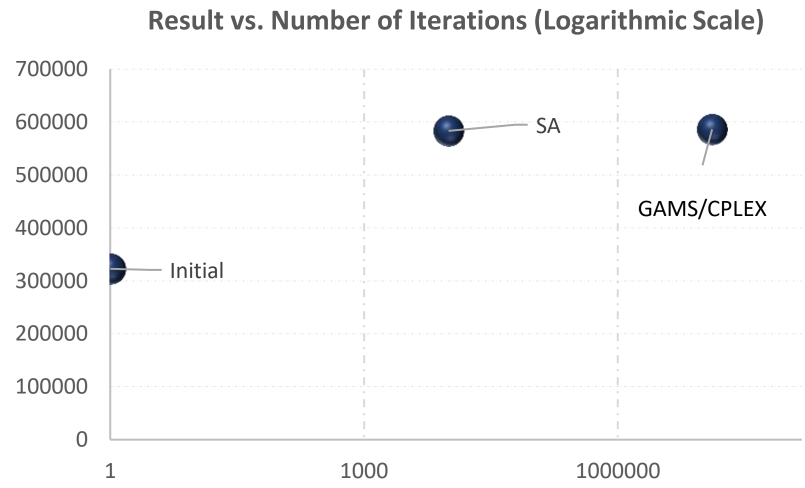

Figure 5.9 Comparison of the GAMS/CPLEX and SA runs for the SAW problem

While the best solution that we achieve in GAMS/CPLEX is 586,161; the SA algorithm provides near-optimal results (less than -0.5%) for almost 1,300 times shorter runtime.

5.7 Conclusion

Airlines utilise the HS system in order to serve not only the direct connections to spoke cities but also indirect connections between spoke cities. The HS system creates outbound and inbound peaks – or bank structures – to shorten connection times at the hub airport. Due to the high utilisation of resources along a bank, gates, runways, taxiways, landing, and departure slots become congested. Section 5 of this thesis proposed a novel mathematical model to answer the following research question: 'Is there an optimum arrival and departure time for a flight in the bank in order to increase passenger convenience and decrease the congestion level in the hub airport?'

In practice, the inefficient use of capacity in hub airports creates high costs for passengers, airlines, and airports. Our motivation was to present a mathematical model to limit the losses for all parties by achieving the objective of minimising connection times within a bank while satisfying problem-specific constraints. Since the integer programming formulation of the bank optimization problem takes long time to solve, we also adapted SA and TS algorithms to solve real-world bank optimization problems. Furthermore, we analysed the performance of these meta-heuristics in a comparative manner. Convergence rate of the SA algorithm was higher than the TS algorithm. Therefore, the SA algorithm is selected for a real-world case study and yielded favourable results by providing 81% increase in the objective function compared to the current schedule.

In the next chapter, a mathematical model will be provided for integration of bank optimization problem and fleet assignment problem. Also, a detailed literature review about integrated airlines problems and our motivation will be presented.

6
INTEGRATED OPTIMIZATION MODEL

6.1 Introduction and Chapter Outline

Airline planning process begins with strategic level decisions followed by medium level and short term tactical commercial actions. Examples of the strategic level decisions are business model decisions, fleet structure and network composition. These kinds of activities have long term effects on the airline in terms of cost, productivity, profitability, and they are generally required to be approved by board of directors of the company. Planning of the next summer season is an example of medium level decision process. An approval from CEO of the company could be enough for this decision. Long term and strategic decisions are followed by medium and short-term tactical decisions in order to reach the company targets. Figure 6.1 summarises the complex airline planning framework, its' effect on the airline lifetime and the answers for the business questions. This framework consists of complex sub-problems which needs to optimize the usage of specific resource on a particular time horizon.

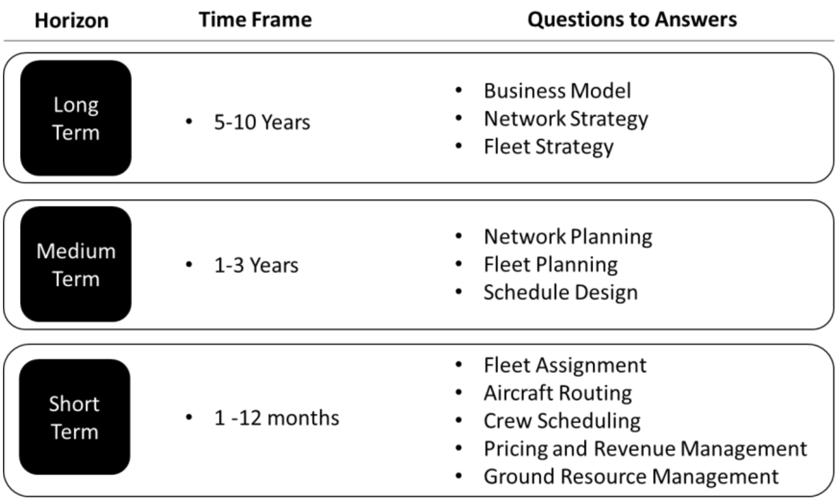

Figure 6.1 Airline planning framework and respective time horizons

Network and fleet decisions are long term decision which has very much relation with the business model of the airline. For instance, low-cost carriers prefer to fly secondary airports in the cities, and they have one type of aircraft in their fleet. On the contrary, network carriers have different kind of aircrafts in their fleet and they operate primary airports in their network. Schedule design is to decide which destination is going to operate how many frequencies per week and when to depart and arrive. Moreover, scheduling can be described as a planning activity that requires information from internal and external sources of the airline companies. Internal sources can be classified as historic slot timings, fleet composition, revenue and cost structure of the planned routes, standard flight times and ground times. External information can be classified as flight and frequency rights, airport slot capacities, market demand, oil prices, government incentives etc. All of this information is melted and translated into business know-how in the scheduling process by network planners and schedulers.

6.2 Integrated Problems in Airline Scheduling Process

Several studies have been done in order to combine fleet assignment with other problems of airline planning process. Desaulnier et al. (1997), Barnhart et al. (1998) integrated fleet assignment with aircraft rotation. Rushmeier and Kontogiorgis (1997) relaxed some constraints and introduced non-linear penalties to reduce aircraft costs. Their primary goal was to create more robust schedules and solutions at the operational level. Rushmeier and Kontogiorgis (1997) also reports an annual benefit of at least $15 million at US Airways, and the network processing techniques by Hane et al. (1995) have been widely applied in the industry.

Clarke et al. (1996) combined crew, maintenance, and fleet assignment model. Also, El Moudani and Mora-Camino (2000) extended the problem and provided a dynamic approach which combines a dynamic programming algorithm and heuristic method to solve fleet assignment and maintenance operations scheduling for a medium charter airline. Lohatepanont and Barnhart (2004) integrated the flight scheduling and fleet assignment problem with assumption of the flight schedule has optional flight legs.

Ahuja et al. (2004) proposed a multi-criteria optimization model in order to solve integrated problem of aircraft routing and crew scheduling by extending the fleet assignment problem. Yan et al. (2006) proposed a heuristic algorithm to solve three problem in an integrated way, namely, airport selection, fleet routing and scheduling problem.

Papadakos (2009) introduces several integrated approaches to solve crew scheduling, aircraft routing and fleet assignment problems. Ruther (2010) developed a mathematical formulation for the integration of aircraft routing, crew pairing, and fleet assignment problems. Cadarso and Marin (2013) integrated fleet assignment and flight planning problem in order to reduce the number of disconnected passengers in the operations. Sherali et al. (2013) introduced the integration of flight scheduling, fleet assignment and aircraft maintenance routing problems. Jiang and Barnhart (2013) have provided two mathematical models to incorporate schedule design and fleet assignment in the banked hub structure. Main aim is to respond the demand variability while increasing the potentially connecting more itineraries in a dynamic scheduling environment.

Different examples of integration between schedule design and fleet assignment problems can be found in Dong et al. (2016) and Gürkan et al. (2016). Jamili (2017) proposed a mathematical model to integrate the aircraft routing and scheduling problem with fleet assignment problem. He also introduced two heuristic algorithms in which one is based on simulated annealing and other is hybrid one. Cadarso and de Celis (2017) proposed integrated robust planning model in order to update base schedules in terms of timing and fleet assignment while considering the uncertainty in the demand and operational environment. Özener et al. (2017) proposed an optimization-based algorithm to solve integrated fleet assignment and crew pairing problem.

Khanmirza et al. (2020) developed a heuristic approach to combine schedule design and fleet assignment problem. They have utilised a parallel master–slave Genetic Algorithm (PMS-GA) for solving the problem. They have reported 1.8% less optimal solutions while achieving results five times shorter run times. For a detailed recent literature review regarding the integrated airline scheduling problems, we refer the readers to Eltoukhy et al. (2017).

Although there is a rich set of literature on that combines airline fleet assignment with other problems, integration with bank structures is adequate. Barnhart et al.

(2012) emphasize the importance of the integrated schedule solutions for potential research studies in the airline industry.

Integration with network planning process starts with Farkas (1996), he proposed an itinerary-based fleet assignment model with two methods. Firstly, assignment of complete network has been done thanks to column generation. Second method, breaking the flight schedule down into a different subproblems which has limited or no interaction with the rest of the network. Kniker and Barnhart (1998) studied "passenger mix model" with a given flight schedule, demand, and price. They have developed optimal traffic and revenue based on assumption that demand is deterministic and spilled passengers on one itinerary is recaptured on another itinerary. Kliewer (2000) proposed an iterative algorithm based on simulated annealing. His model integrated market modeling and fleet assignment; which calculates passenger flow on the network at each step of iteration. He also proposed a second approach that connects simulated annealing with itinerary based linear model to increase overall network profit. There are several academic works focuses on re-fleeting on operational level and taking into account of robustness, uncertainty of demand and operations, such as Etschmaier and Mathaisel (1984), Berge and Hopperstad (1993) and Winterer (2004).

6.3 Classical Approach

Scheduling process is complex process including information from internal and external sources of the airline companies. Internal sources can be classified as flight and frequency rights, historic slot timings, fleet composition, block times and ground times. External information can be classified as flight and frequency rights, historic slot timings, market demand. All of this information should be evaluated and all of the constraints must be satisfied in the scheduling process by network planners and schedulers.

In theory, solution methods are available for integrated problems of network modelling, scheduling and fleet assignment. However, this is not possible in business practise (Belobaba et al., 2015). Challenges are as follows;

- Data could not be available in order to optimize the entire schedule.
- Building a new schedule from scratch/zero is operationally impractical.

- Incremental schedules could have significant changes in the schedule; however, planners would like to have consistency over the seasons.

Incremental approaches are able to overcome multiple objectives and constraints in the schedule design process. Process starts with building the initial candidate schedule. In order to create initial schedule, previous year schedule is copied from the historical databases. Block times and ground times are adjusted if necessary. According to financial results of the routes, frequencies and capacities are adjusted. Frequencies of the routes are increased based on following logic;

- There should be high demand from the market.
- Routes should be profitable, and network contributed.
- There should be enough frequency right for the airline in terms of the traffic rights between countries.
- Airport slots and terminals should be available for both hub airport and spoke destination.
- Fleet should be available to execute the proposed frequency increase.

6.4 Problem Definition and Motivation

The advances in technology and deeper understanding of the airline planning problems have allowed operations researchers to develop integrated solutions (Lohatepanont and Barnhart, 2004). Also, real-life airline planning problems are more complex due to dynamic external factors such as, fuel prices, demand shocks, epidemics and pandemics. The airline schedule planning problem has generally been addressed with smaller scale sub-problems that are sequentially solved, since the problem is highly challenging to completely formulate and solve simultaneously. The bank optimization problem determines the arrival and departure times of flights within a predefined bank, subject to available slot capacities, in order to minimise connection times between arrival and departure flights. With the motivation of prior studies, we broaden the airline schedule design problem within a bank structure by incorporating fleet assignment decisions.

The demand, revenue and profitability of the hub carriers are directly influenced by bank and schedule design. In the bank structure, any change in flight timings may cause a breakdown on an existing connection in the passenger flow and it may trigger substantial revenue and demand losses (Goedeking, 2010). Therefore, given the projected demand and revenue for the itineraries, reducing the connection time of the itineraries may cause imbalanced utilization of slots, aircrafts and airport resources. (Goedeking, 2010) stated that forcing all possible connections to be built for the best connectivity causes the decrease in the aircraft productivity due to different stage length of the arrivals or departures in the banks. Therefore, there are two conflicting concerns to be considered simultaneously: (i) profit maximising fleet assignment, and (ii) maximising demand by providing lower connection times on available itineraries.

There are two flows that are connected in every bank. One is the aircraft flow in the physical network. Second one is the passenger flows that are using flight legs to travel. Figure 6.2 presents an exemplary bank structure of a hub airport. Horizontal axis represents time. Orange boxes that are below the axis represent arrival flights. Blue boxes above the axis represent departure flights. There are two banks in this example which are marked on the figure. The difference between aircraft flow and the passenger flow can be explained as follows: An aircraft that is arriving to hub could connect only one departure in the flow. Example of the aircraft flows are shown as green arrows on the second bank. There are four connections in terms of aircraft rotations (a_{10}-d_7, a_9-d_8, a_8-d_9, a_7-d_{10}). However, passengers in one of the arriving flights could make connections to the different departures. Possible passenger flow examples are shown in purple arrows on the first bank. For instance, passengers in the flight a1 could make connections to d_1, d_2, d_3, d_4 flights. Also, passengers could make connections outside of the banks which is shown as a_4-d_5.

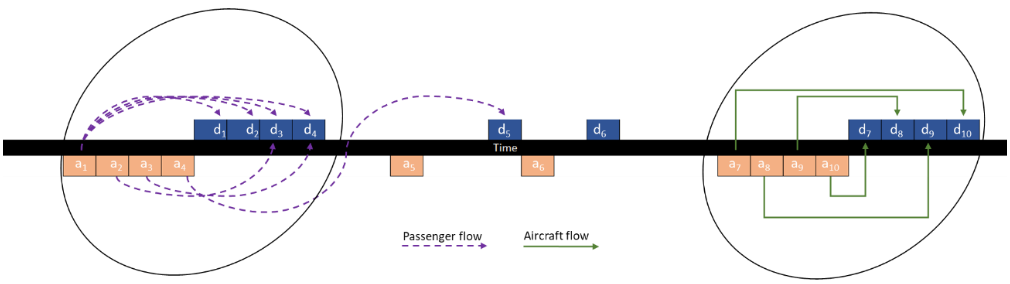

Figure 6.2 An example of connections inside the bank structure.

In this study, we explore the potential advantages of integrating fleet assignment and bank optimization problem. In order to integrate the complete hub and spoke operations and fleet assignment decisions under airport slot considerations, we introduce a mixed-integer linear program (MILP) that optimizes the flight schedule of an airline at its hub airport regarding the bank structure.

6.5 Integrated Mathematical Model

Integrated mathematical model has additional set and index for fleet, additional parameters for revenue and cost calculations, additional decision variable for rotation. Additional notation to bank optimizer model is highlighted as red;

Sets

F	Set of flights
S	Set of slots
G	Set of fleet

Index

i	Arrival flights
k	Departure flights
j	Arrival slots
l	Departure slots
f	Index for fleet

Parameters

C_{ijkl}	Connection value of flight i arrives at slot j and flight k departs at slot l.
K_{jl}	Binary minimum connection time feasibility parameter between arrival and departure slots. it has value of 1 if time difference between arrival slot j and departure slot k is higher than minimum connection time; 0 otherwise.
A_j, D_l	Number of available slots for arrival/departure flights.
P	Penalty cost for exceeding slot capacity.
h	Upper limit for exceeding slot capacity.
M	Big number
L_i	Leg distance for flight i, k.

J_i	Revenue per available seat per km for flight i, k.
U_f	Cost per available seat per km for fleet type f.
Y_f	Seat capacity for fleet type f.
N_f	Number of aircraft in each fleet type f
O_{ikf}	Cost of assigning a rotation pair of flight i and flight k to fleet type f
E_{ikf}	Revenue of assigning a rotation pair of flight i and flight k to fleet type f

Decision variables

α_j, δ_l	Exceeding slot capacity for arrivals/departures.
x_{ij}	=1 if flight i is assigned to slot j; 0, otherwise.
y_{kl}	=1 if flight k is assigned to slot l; 0, otherwise.
z_{ijkl}	=1 if flight i arrives at slot j and flight k departs from slot l, provided that the connection time value between these flights is higher than the minimum connection time.
rot_{ikf}	=1 if rotation pair of flight i and flight k assigned to fleet type f.

$$max \quad \sum_{i\in F}\sum_{j\in S}\sum_{k\in F}\sum_{l\in S} C_{ijkl}\, z_{ijkl} - \sum_{j\in S} P\,\alpha_j - \sum_{l\in S} P\,\delta_l + \sum_{i\in F}\sum_{k\in F}\sum_{f\in G} rot_{ikf} * (E_{ikf} - O_{ikf}) \qquad (6.1)$$

$$st. \quad \sum_{j\in S} x_{ij} = 1 \qquad \forall i \in F \qquad (6.2)$$

$$\sum_{l\in S} y_{kl} = 1 \qquad \forall k \in F \qquad (6.3)$$

$$M\,(K_{jl}) \geq \sum_{i\in F}\sum_{k\in F} z_{ijkl} \qquad \forall j,l \in S \qquad (6.4)$$

$$x_{ij} + y_{kl} \geq 2\, z_{ijkl} \qquad \forall i,k \in F, \forall j,l \in S \qquad (6.5)$$

$$\sum_{i\in F} x_{ij} \leq A_j + \alpha_j \qquad \forall j \in S \qquad (6.6)$$

$$\sum_{k\in F} y_{kl} \leq D_l + \delta_l \qquad \forall l \in S \qquad (6.7)$$

$$\sum_{k\in F}\sum_{f\in G} rot_{ikf} = 1 \qquad \forall i \in F \qquad (6.8)$$

$$\sum_{i\in F}\sum_{f\in G} rot_{ikf} = 1 \qquad \forall k \in F \qquad (6.9)$$

$$\sum_{i\in F}\sum_{k\in F} rot_{ikf} \leq \mathrm{N}_f \qquad \forall f \in G \qquad (6.10)$$

$$x_{ij}, y_{kl}, z_{ijkl}, rot_{ikf} \in \{0,1\} \qquad (6.11)$$

$$0 \leq \alpha_j, \delta_l \leq h \text{ and integer} \qquad (6.12)$$

$$\mathrm{rev}_{ikf} = \left(\mathrm{Distance}_i * Capacity_f * Rask_i\right) + \left(\mathrm{Distance}_k * Capacity_f * Rask_k\right) \qquad (6.13)$$

$$\mathrm{cost}_{ikf} = (\mathrm{Distance}_i * Capacity_f * Cask_f) + (\mathrm{Distance}_k * Capacity_f * Cask_f) \qquad (6.14)$$

or

$$\mathrm{E}_{ikf} = (\mathrm{L}_i * Y_f * J_i) + (\mathrm{L}_k * Y_f * J_k) \qquad (6.15)$$

$$\mathrm{O}_{ikf} = (\mathrm{L}_i * Y_f * U_f) + (\mathrm{L}_k * Y_f * U_f) \qquad (6.15)$$

The objective function of the model maximises the total worth of passenger connections and route profits, also penalizes exceeding slot capacity in Equation 6.1. The cover constraints are provided in Equation 6.8 and 6.9 that ensure all flights arriving at the hub must be connected to a departure flight in terms of aircraft rotation and vice versa. The availability constraint ensures that number of rotations cannot exceed the number of available aircrafts in each fleet type as given in Equation 6.10. Eq 6.11 has additional definition for binary decision variable rot_{ikf}. Since rotation continuity is satisfied with the rotation decision variable on the hub airport, balance constraint is not defined.

In summary, integrated mathematical model is designed to satisfy the desired network and frequency with available fleet and maximizes profitability on routes by fleet assignment. It also decreases connection times on connected itineraries to increase passenger preference for the airline

6.6 Problem Data

Table 6.1 and Table 6.2, a small set of current arrival and departure times of the flights in the morning bank are provided. Tables shows the flight number, slot timing, existing fleet assignment, RASK, and distance from hub information. Slot is a specific permission which has certain time limits that is given to airlines to use the airport, runway, and navigation services. There exists 144 slot times per day and slot times represent 10-minute time intervals in each hour clock time.

Table 6.1 Sample of current arrival schedule

Arrival Flight Number	Arrival Slot Time	Fleet	RASK (US cents)	Distance (km)
101	2	B78D	5.24	2.547
102	5	B738	5.82	2.473
103	9	B738	4.97	2.969

Table 6.2 Sample of current departure schedule

Departure Flight Number	Departure Slot Time	Fleet	RASK (US Cents)	Distance (km)
201	19	B738	6.18	2,251
202	23	B78D	5.97	2,279
203	21	B78D	5.85	2,209
204	18	A321	6.44	2,281

205	26	B78D	5.76	2,078
206	31	A320	5,51	1,429

There are 33 slot timings has been defined in the morning bank. A sample data for number of available slots is shown in the Table 6.3.

Table 6.3 Slot capacity data sample**.**

Slot Time	Available Arrival Slot	Available Departure Slot
1	4	4
2	4	4
3	4	4
4	4	3

Table 6.4 shows first 4 line of the data which includes passenger demand for a summer season and average unit passenger revenue information between arrival and departure flights on origin-destination (OD) pairs.

Table 6.4 OD demand and unit passenger revenue.

Arrival Flight Number	Departure Flight Number	Demand	Unit Revenue
104	204	14,614	229
104	201	11,581	200
103	204	7,285	164
104	203	6,222	200

Minimum connection time is defined as 60 minutes which is modelled as 6 slot difference between an arrival and departure in our data.

Additional data for the fleet assignment problem is described as follows: There are available four types of aircraft. Table 6.5 summarizes the capacity and CASK information of the fleet based at the SAW airport.

Table 6.5 Aircraft inventory which are based at the SAW

Fleet Type	Capacity	Inventory	CASK
A321	180	5	7.30
A320	159	2	7.51
B738	165	3	6.16
B78D	151	3	7.03

6.7 Bank Optimization Results of the Proposed Method

Mathematical model is coded in GAMS using a CPLEX solver for a mathematical model and solved on an Intel(R) Core(TM) i5-3317U CPU @ 1.70GHz and 12.0 GB RAM computer utilized 4 core processor. Extra capacity per slot is assumed 1 in each case. Maximum runtime limit is adjusted as 3,600 second and iteration count limit is 2,000,000,000. Initial schedule is given as starting point for the optimizer. Model has run 2,495 second and after 13,485,089 iteration optimal solution is found.

Table 6.6 shows the bank structure and flights' connection times prior to model run. There are 4 mis-connected OD's which are shown orange. Average connection time within the bank is 178 minutes, approximately 3 hours.

Table 6.6 Current bank structure and connection times

	DEST	AMS	BCN	BRU	CDG	DUS	FCO	FRA	LGW	MUC	MXP	STR	TXL	VIE
ORIG	**SLOT**	**19**	**23**	**21**	**18**	**26**	**31**	**27**	**17**	**27**	**25**	**29**	**22**	**28**
BAH	**2**	170	210	190	160	240	290	250	150	250	230	270	200	260
DMM	**5**	140	180	160	130	210	260	220	120	220	200	240	170	230
DXB	**9**	100	140	120	90	170	220	180	80	180	160	200	130	190
IKA	**1**	180	220	200	170	250	300	260	160	260	240	280	210	270
JED	**8**	110	150	130	100	180	230	190	90	190	170	210	140	200
KWI	**4**	150	190	170	140	220	270	230	130	230	210	250	180	240
MED	**3**	160	200	180	150	230	280	240	140	240	220	260	190	250
RUH	**8**	110	150	130	100	180	230	190	90	190	170	210	140	200
TBS	**11**	80	120	100	70	150	200	160	60	160	140	180	110	170
TLV	**16**	n/a	70	n/a	n/a	100	150	110	n/a	110	90	130	60	120

Table 6.7 provides the proposed bank structure which is result of the integrated model. Average connection time is 86 minutes in the proposed bank structure which is almost half of the previous schedule. Mathematical model has improved connection times between 60 and 120 minutes. Also, there are 4 new connections that does not exist in the previous structure.

Table 6.7 Proposed bank structure and connection times

	DEST	AMS	BCN	BRU	CDG	DUS	FCO	FRA	LGW	MUC	MXP	STR	TXL	VIE
ORIG	**SLOT**	**9**	**10**	**10**	**9**	**12**	**9**	**11**	**9**	**12**	**10**	**12**	**11**	**11**
BAH	**3**	60	70	70	60	90	60	80	60	90	70	90	80	80
DMM	**1**	80	90	90	80	110	80	100	80	110	90	110	100	100
DXB	**2**	70	80	80	70	100	70	90	70	100	80	100	90	90
IKA	**2**	70	80	80	70	100	70	90	70	100	80	100	90	90
JED	**1**	80	90	90	80	110	80	100	80	110	90	110	100	100
KWI	**2**	70	80	80	70	100	70	90	70	100	80	100	90	90
MED	**1**	80	90	90	80	110	80	100	80	110	90	110	100	100
RUH	**1**	80	90	90	80	110	80	100	80	110	90	110	100	100
TBS	**2**	70	80	80	70	100	70	90	70	100	80	100	90	90
TLV	**2**	70	80	80	70	100	70	90	70	100	80	100	90	90

Table 6.8 shows the connection time difference between existing bank structure and proposed bank structure. There are 4 new connection, 3 deteriorated connection time and 123 improved connection time. Average improvement is 91 minutes.

Table 6.8 Change in the connection times

	AMS	BCN	BRU	CDG	DUS	FCO	FRA	LGW	MUC	MXP	STR	TXL	VIE
BAH	110	140	120	100	150	230	170	90	160	160	180	120	180
DMM	60	90	70	50	100	180	120	40	110	110	130	70	130
DXB	30	60	40	20	70	150	90	10	80	80	100	40	100
IKA	110	140	120	100	150	230	170	90	160	160	180	120	180
JED	30	60	40	20	70	150	90	10	80	80	100	40	100
KWI	80	110	90	70	120	200	140	60	130	130	150	90	150
MED	80	110	90	70	120	200	140	60	130	130	150	90	150
RUH	30	60	40	20	70	150	90	10	80	80	100	40	100
TBS	10	40	20	0	50	130	70	-10	60	60	80	20	80
TLV	New	-10	New	New	0	80	20	New	10	10	30	-30	30

6.8 Fleet Assignment Results of the Proposed Method

Table 6.9 shows the input schedule and its' current fleet assignment. Flights are assumed daily one.

Table 6.9 Current Schedule at SAW Airport

Orig	STD	STA	STD	Distance	Fleet	Rask
SAW	22:05	1:40	MED	2,055	B78D-1	5.17
SAW	21:25	1:30	RUH	2,393	B78D-2	7.15
SAW	21:40	1:35	DMM	2,473	B78D-3	5.82
SAW	22:25	2:15	JED	2,324	A321-1	5.95
SAW	19:30	22:45	TBS	1,312	A320-1	5.90

Table 6.9 Current Schedule at SAW Airport (continued)

SAW	21:10	0:55	BAH	2,547	A320-2	5.24
SAW	20:35	2:00	DXB	2,969	A321-2	4.97
SAW	19:00	21:00	TLV	1,105	A321-3	8.42
SAW	19:15	23:45	IKA	2,003	A321-4	5.85
SAW	22:10	1:50	KWI	2,132	A321-5	7.15
SAW	10:00	12:20	DUS	2,078	A321-1	5.76
SAW	10:10	12:30	FRA	1,904	A321-2	6.01
SAW	10:15	12:00	MUC	1,613	A320-2	6.67
SAW	09:25	11:20	TXL	1,775	A320-2	6.38
SAW	10:35	12:35	STR	1,802	B738-1	6.06
SAW	08:40	11:35	CDG	2,281	A321-3	6.44
SAW	09:30	12:20	BCN	2,279	B78D-1	5.97
SAW	11:05	12:45	FCO	1,429	B78D-2	5.51
SAW	10:25	11:45	VIE	1,289	B738-2	6.65
SAW	09:50	11:45	MXP	1,746	B738-3	6.94
SAW	09:20	11:50	BRU	2,209	B78D-3	5.85
SAW	08:50	11:35	AMS	2,251	A321-4	6.18
SAW	08:40	10:50	LGW	2,529	A321-5	5.52
STR	13:35	17:25	SAW	1,802	B738-1	6.06

Table 6.9 Current Schedule at SAW Airport (continued)

TBS	06:05	7:30	SAW	1,312	A320-1	5.90
TLV	06:20	8:25	SAW	1,105	A321-3	8,42
TXL	12:20	16:05	SAW	1,775	A320-2	6.38
VIE	12:40	15:50	SAW	1,289	B738-2	6.65
AMS	12:30	16:50	SAW	2,251	A321-4	6.18
BAH	01:55	6:05	SAW	2,547	A320-2	5.24
BCN	13:15	17:40	SAW	2,279	B78D-1	5.97
BRU	12:45	17:00	SAW	2,209	B78D-3	5.85
CDG	12:30	16:55	SAW	2,281	A321-3	6.44
DMM	02:30	6:35	SAW	2,473	B78D-3	5.82
DUS	13:15	17:25	SAW	2,078	A321-1	5.76
DXB	03:15	7:10	SAW	2,969	A321-2	4.97
FCO	13:45	17:10	SAW	1,429	B78D-2	5.51
FRA	14:05	18:05	SAW	1,904	A321-2	6.01
IKA	04:10	5:55	SAW	2,003	A321-4	5.85
JED	03:15	7:00	SAW	2,324	A321-1	5.95
KWI	02:50	6:40	SAW	2,132	A321-5	7.15
LGW	11:50	17:40	SAW	2,529	A321-5	5.52
MED	02:40	6:15	SAW	2,055	B78D-1	5.17

Table 6.9 Current Schedule at SAW Airport (continued)

MUC	13:00	16:35	SAW	1,613	A320-2	6.67
MXP	12:45	16:30	SAW	1,746	B738-3	6.94
RUH	02:40	6:55	SAW	2,393	B78D-2	7.15

Table 6.10 shows the optimum fleet assignment of the bank optimized schedule.

Table 6.10 Output schedule at the SAW airport

Orig	**STD**	**STA**	**STD**	**Distance**	**Fleet**	**Rask**
SAW	22:05	1:40	MED	2.055	B78D-3	5.17
SAW	21:25	1:30	RUH	2.393	A321-3	7.15
SAW	21:40	1:35	DMM	2.473	B738-2	5.82
SAW	22:25	2:15	JED	2.324	B78D-2	5.95
SAW	19:30	22:45	TBS	1.312	A321-1	5.90
SAW	21:10	0:55	BAH	2.547	B738-1	5.24
SAW	20:35	2:00	DXB	2.969	B738-3	4.97
SAW	19:00	21:00	TLV	1.105	A321-2	8.42
SAW	19:15	23:45	IKA	2.003	B78D-1	5.85
SAW	22:10	1:50	KWI	2.132	A321-5	7.15
SAW	10:00	12:20	DUS	2.078	B78D-1	5.76
SAW	10:10	12:30	FRA	1.904	A320-1	6.01

Table 6.10 Output schedule at the SAW airport (continued)

SAW	10:15	12:00	MUC	1.613	A321-2	6.67
SAW	09:25	11:20	TXL	1.775	A321-1	6.38
SAW	10:35	12:35	STR	1.802	A321-3	6.06
SAW	08:40	11:35	CDG	2.281	B738-1	6.44
SAW	09:30	12:20	BCN	2.279	B78D-3	5.97
SAW	11:05	12:45	FCO	1.429	A320-2	5.51
SAW	10:25	11:45	VIE	1.289	A321-5	6.65
SAW	09:50	11:45	MXP	1.746	A321-4	6.94
SAW	09:20	11:50	BRU	2.209	B78D-2	5.85
SAW	08:50	11:35	AMS	2.251	B738-2	6.18
SAW	08:40	10:50	LGW	2.529	B738-3	5.52
STR	13:35	17:25	SAW	1.802	A321-3	6.06
TBS	06:05	7:30	SAW	1.312	A321-1	5.90
TLV	06:20	8:25	SAW	1.105	A321-2	8.42
TXL	12:20	16:05	SAW	1.775	A321-1	6.38
VIE	12:40	15:50	SAW	1.289	A321-5	6.65
AMS	12:30	16:50	SAW	2.251	B738-2	6.18
BAH	01:55	6:05	SAW	2.547	B738-1	5.24
BCN	13:15	17:40	SAW	2.279	B78D-3	5.97

Table 6.10 Output schedule at the SAW airport (continued)

BRU	12:45	17:00	SAW	2.209	B78D-2	5.85
CDG	12:30	16:55	SAW	2.281	B738-1	6.44
DMM	02:30	6:35	SAW	2.473	B738-2	5.82
DUS	13:15	17:25	SAW	2.078	B78D-1	5.76
DXB	03:15	7:10	SAW	2.969	B738-3	4.97
FCO	13:45	17:10	SAW	1.429	A320-2	5.51
FRA	14:05	18:05	SAW	1.904	A320-1	6.01
IKA	04:10	5:55	SAW	2.003	B78D-1	5.85
JED	03:15	7:00	SAW	2.324	B78D-2	5.95
KWI	02:50	6:40	SAW	2.132	A321-5	7.15
LGW	11:50	17:40	SAW	2.529	B738-3	5.52
MED	02:40	6:15	SAW	2.055	B78D-3	5.17
MUC	13:00	16:35	SAW	1.613	A321-2	6.67
MXP	12:45	16:30	SAW	1.746	A321-4	6.94

6.9 Conclusion

A comparison between previous fleet assignment and integrated mathematical model results could be find in Figure 6.3 Figure numbers are weekly and in terms of million USDs. Although there is very slightly decrease in the revenue side, there has been a significant cost reduction thanks to new fleet assignment. Figure shows that there is a potential of 4,5% for cost saving. This also affects profit and loss side as well. Saving in the loss is even more than the cost side with a 27% decrease.

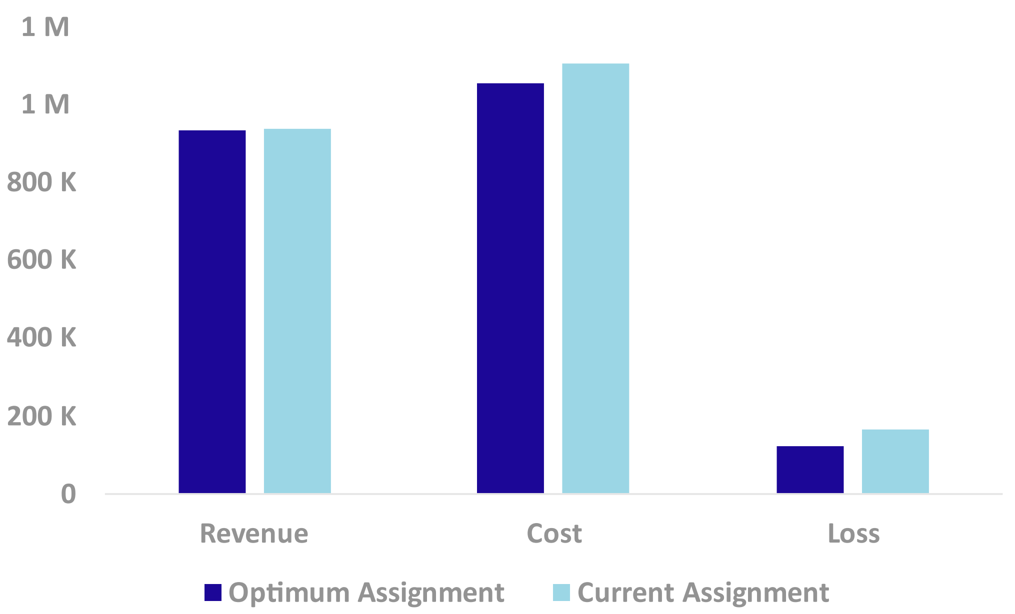

Figure 6.3 Comparison of the current assignment and optimized assignments.

Figure 6.4 compares the results of the integrated model and classical approaches in terms of objective function value.

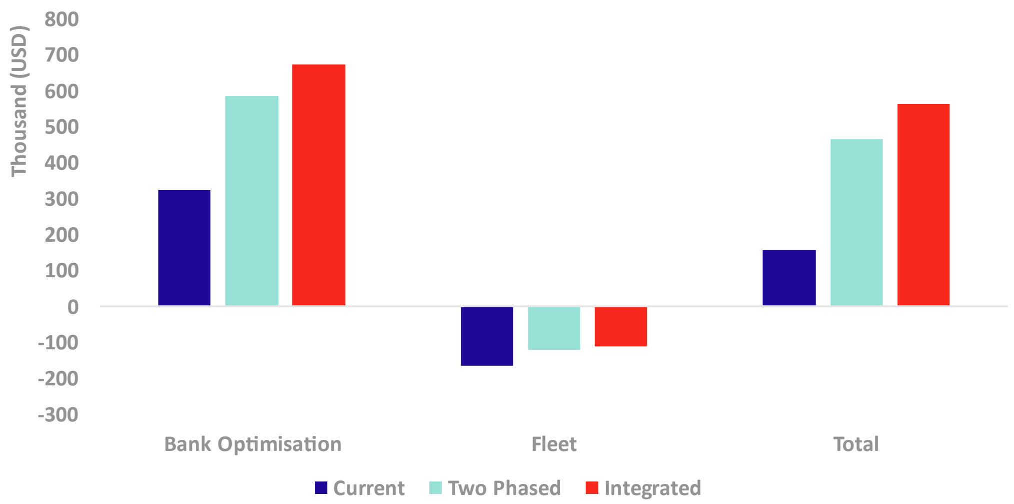

Figure 6.4 Comparison of the exact methods.

Integrated mathematical model performs better than the two phased classical approach. It provides better results both for the bank optimization and fleet assignment problems.

In chapter seven, thesis will be summarized with results and findings of the study.

7
RESULTS AND DISCUSSION

7.1 Summary of the Airline Optimisation Process

Airline planning process is a complex process with long-term results. It starts with defining the companies' mission, vision, corporate strategy and the business model.

Figure 7.1 summarizes the planning horizon and the responsible departments in a full service network carrier.

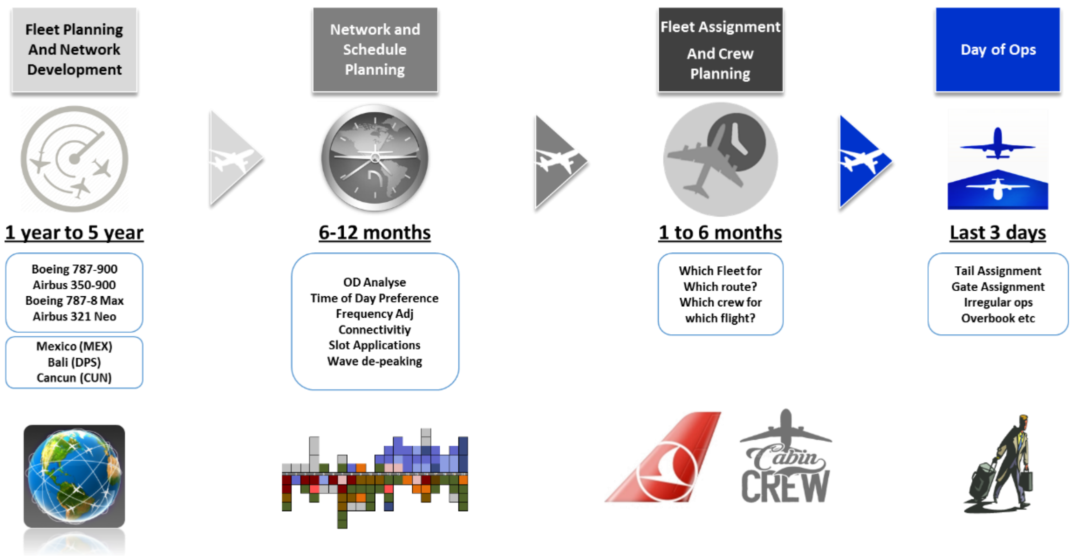

Figure 7.1 Airline planning problems and respective departments.

Fleet strategy and the acquisition planning is the initial step of the planning processes. Fleet planning studies have significant effect on the cash flow of the airline in the medium and long term. Medium and long term are defined as 1 year to 5 year. Since macro studies, the type of aircraft to be added to the fleet and the destinations to be opened, are conducted during this period of the planning processes, results of these studies affect the route and the network structure of the airline company. Fleet planning and network development works should be continuing jobs in order to have younger fleet and to adapt the changing business environment.

Second step is the network and schedule planning. After fleet is determined, next step is to utilize the fleet in order to generate money. This phase consists of scheduling of the fleet, decision on the weekly frequency of the routes, departure and arrival times of the flights, slot applications process and hub airport slot capacity management. Typical schedule planning consists of two seasons in a year. Summer season covers the months between April and October. Winter season covers the months between November and next year March. Time horizon of the planning efforts is between 6 month and 1 year.

Third step is fleet assignment and crew assignment. Fleet assignment determines which aircraft type is going to operate which leg. It is done in master period of the planning at which 2-3 months before the day of operation. It is also done in the live schedule (3 days and 1 month) of the planning period. Main target is to optimize the capacity of legs according to their demand and revenue potential as well as the minimize spill and operating cost of the operations. Crew assignment is done by monthly and daily. An aircraft change or departure time change is subject to agreement of the crew planning department. In other words, schedule is frozen, and no changes can be made unless the crew planning agrees.

Finally, schedule is delivered to the operations control center (OCC) 3 days before the day of operation. Operations control departments are generally integrated departments, and they are like a small model of the company. They have staff from diverse backgrounds. For example, there are schedulers, crew planners, revenue management teams, reservation officers, meteorological analysts, dispatchers, pilots, technicians, ground handlers. In most airlines, they are called integrated operations control center (OCC). Main target is to operate the schedule in a safe and secure manner. Specific tails in subfleets are assigned by IOCC to each flight. Gate assignment, which flights are going to use which gates for boarding and deboarding of the passengers is also done by IOCC. Main commercial responsibility is to operate the schedule as planned with minimum change. Another important responsibility is having high ratio of on-time departure/arrival ratio of the operations. They also deal with the schedule recovery irregular operations including political crisis, health problems, technical problems, diverts, meteorological events like heavy snow or wind etc.

7.2 Research questions

Airlines utilise the HS system in order to serve not only the direct connections to spoke cities but also indirect connections between spoke cities. The HS system creates outbound and inbound peaks – or bank structures – to shorten connection times at the hub airport. Due to the high utilisation of resources along a bank, gates, runways, taxiways, landing, and departure slots become congested. In this dissertation, a new mathematical model was proposed that changes in arrival and departure times of flights in a wave in order to answer: “Is there an optimum arrival and departure time for a flight in the bank in order to increase passenger convenience and decrease the congestion level in the hub airport.”

Motivation of this research was to present a mathematical model to limit the losses for all parties by achieving the objective of minimising connection times within a bank while satisfying problem-specific constraints. Since the integer programming formulation of the bank optimization problem is NP-hard, we also adapted SA and TS algorithms to solve real-world bank optimization problems.

7.3 Main Contributions of the study

First contribution of this study is that a detailed explanation of airline's planning process, airline business terminology, airline business models, calculations are provided in the chapter two and chapter three. We also provided a detailed literature review about the airline fleet assignment problem, airline bank structure optimization problems, airport slot capacity managements and Turkish airline industry.

Methodological contributions of this dissertation are in two directions of scheduling activities in the airline companies. A new mathematical model is presented which includes connection time as a penalty for the utility of passenger, which has high importance in terms of the choices of connecting passengers. First part of this study could assist airline network planning managers by providing an efficient solution method to optimize their flight schedules within short period of time.

Third contribution is that two metaheuristic algorithms, namely tabu search and simulated annealing, are applied for the bank optimization problem and results are compared both for mathematical model and metaheuristics.

Thanks to mathematical model and developed algorithms an airline could;

- Increase revenue and demand
- Improve connectivity at the hub airport
- Decrease planning efforts by automating retiming of the hub services
- Reduce operational costs
- Increase on time performance
- Satisfying all the slot and capacity constraints of the hub airport by shifting, retiming the flight banks

Our integrated approach contributes to the literature by providing opportunity to solve two major airline industry problem simultaneously. We combine a particular flight scheduling problem with a strategic airline planning problem concurrently in the airline industry. Next, the proposed model provides a clean-state schedule rather than a schedule update. Lastly, we present a real-world case study using data from a major Turkish carrier to exhibit the competence of the integrated model in generating schedules that outperform existing schedules.

7.4 Main findings of the study

According to the results of the sub-problems of the bank optimization, simulated annealing algorithm provided very fast and optimal results for all of the sub problems. Tabu search also provided fast results however the comvergance rates to the optimal solution were low. Mathematical model was also able to provide optimal solutions for the sub problems in very long computation time. Furthermore, we analysed the performance of these meta-heuristics in a comparative manner. The SA algorithm yielded favourable results for a real-world case study by providing 81% increase in the objective function compared to the current schedule.

Regarding the fleet assignment study, there were room for decreasing cost of the operations while losing too limited revenue by assigning the flights to optimal aircrafts depending on their RASK and CASK.

7.5 Limitations of the study

This research has several shortcomings including following aspects.

When we change a flights' arrival time to the hub, we also need to change it's departure time an departure slot from the spoke city. We assume that there is not any slot capacity constraints which is limiting to the change of departure. Same situation is also valid vice versa for departure flights from the hub.

Another important limitation of this study that we did not differentiate the business and economy passengers which may have different perceptions for the connection time at the hub airport. Figures are aggregated and studied only one type of passenger.

Third limitation is that we have assumed all flight frequencies in the schedule are one per day per destination and repeating each day of the week. This was done for the simplicity of the mathematical model however it is known that there could be different day patterns in the schedule for each destination.

7.6 Future research directions

Future research into bank optimization problem might usefully to focus particular on not only on one bank in a bank optimization problem but also on all banks in an entire day of operation in a hub airport and to create new schedules, including feasible aircraft rotations. Another important potential research topic for future studies could be to formulate the integrated model as a multi objective optimization problem and to develop new heuristics to decrease the computation times.

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A
BANK OPTIMIZER GAMS MODEL

```
Sets
        i   Arrival Flights   /TBS,TLV,BAH,DMM,DXB,IKA,JED,KWI,MED,RUH/
        k                                              Departure                  Flights
/DUS,FRA,MUC,TXL,STR,CDG,BCN,FCO,VIE,MXP,BRU,AMS,LGW/
        j   Arrival Slots     /1 * 33/
;
alias (j,l);
Scalar   BigM   /99999999/
        SP  /10000/
;

Parameters  c(i,j,k,l)  Connection value of flight i  slot j and flight k slot l
          p(j,l);
Parameter ASA(j) arrival slot capacity each 10 minute    /;

Parameter ASD(l) departures slot capacity each 10 minute  /;

Table    D(i,k) Demand of city i to k;

Table    R(i,k) Unit Revenue of city i to k;

Table    CT(j,l) Connection Time between slot j and l  ;

c(i,j,k,l) = D(i,k)*R(i,k)/CT(j,l);
P(j,l) =yes$(ord(l) lt (ord(j)+6));

Binary Variables
    x(i,j)  flight i to assign slot j in cases
    y(k,l)  flight k to assign slot l in cases
    t(i,j,k,l) connection control binary variable ;
Integer Variables
    a(j)
    b(l) ;
Free Variable z;

Equations
        Obj
        Assignment(i)
        Assignment2(k)
        ConnectionTime(i,k,j)
        ConnectedFlights(i,j,k,l)
        SlotCapacity(j)
```

```
        SlotCapacity2(l)
        Penalty(j)
        Penalty2(l);

obj                   .. z =e= sum((i,j,k,l), c(i,j,k,l)*t(i,j,k,l)) - sum(j,a(j)*SP) - sum(l, b(l)*SP)
;

Assignment(i)              ..      sum(j, x(i,j)) =e= 1 ;
Assignment2(k)             ..      sum(l, y(k,l)) =e= 1 ;
ConnectionTime(i,k,j)      ..      BigM*(1-x(i,j)) =g= sum(l, P(j,l)*y(k,l));
ConnectedFlights(i,j,k,l)  ..      x(i,j) + y(k,l) =g= 2*t(i,j,k,l);
SlotCapacity(j)            ..      sum(i, x(i,j)) =l=ASA(j)+a(j);
SlotCapacity2(l)           ..      sum(k, y(k,l)) =l=ASD(l)+b(l);
Penalty(j)                 ..      a(j) =l= 0   ;
Penalty2(l)                ..      b(l) =l= 0   ;

Model BankStructure /all/;
Solve BankStructure using MIP maximizing z;
Display  x.l, y.l, z.l;
```

B
INTEGRATED GAMS MODEL

```
Sets
        i   Arrival Flights   /TBS,TLV,BAH,DMM,DXB,IKA,JED,KWI,MED,RUH/
        k Departure Flights
 /DUS,FRA,MUC,TXL,STR,CDG,BCN,FCO,VIE,MXP,BRU,AMS,LGW/
        j   Arrival Slots     /1 * 33/
        f   Fleet  Index     /A321,B78D, A320, B738/
;
alias (j,l);
Scalar   BigM   /99999999/
        SP  /10000/
;

Parameters  c(i,j,k,l)  Connection value of flight i  slot j and flight k slot l
          p(j,l);
Parameter ASA(j) arrival slot capacity each 10 minute    /;

Parameter ASD(l) departures slot capacity each 10 minute  /;

Table    D(i,k) Demand of city i to k;

Table    R(i,k) Unit Revenue of city i to k;

Table    CT(j,l) Connection Time between slot j and l  ;

Parameter Distance(i) Flight distance of each flight i / ;
Parameter Distance2(k) Flight distance of each flight k /;
Parameter RASK(i)    Revenue per passenger per km of flight i     /;
Parameter RASK2(k) Revenue per passenger per km of flight k /;
Parameter CASK(f) Cost per Available Seat Kilometer of fleet f/;
Parameter Capacity(f) Available seat capacity of fleet f/  ;
Parameter n(f)   Number of available aircraft in fleet type f      /;

Parameter cost(i,k,f)  Cost of assigning fleet type j to flight i;
cost(i,k,f)=CASK(f)*Capacity(f)*(Distance(i)+Distance2(k))/100;
display cost;

Parameter rev(i,k,f)  Revenue of assigning fleet type j to flight i;
rev(i,k,f)=RASK(i)*Capacity(f)*Distance(i)/100+RASK2(k)*Capacity(f)*Distance2(k)/
100;
display rev;

c(i,j,k,l) = D(i,k)*R(i,k)/CT(j,l);
```

```
P(j,l) =yes$(ord(l) lt (ord(j)+6));

Binary Variables
    x(i,j)  flight i to assign slot j in cases
    y(k,l)  flight k to assign slot l in cases
    t(i,j,k,l) connection control binary variable
    Rot(i,k,f)    if rotation ik is  ;
Integer Variables
    a(j)
    b(l) ;
Free Variable z;

Equations
        Obj
        Assignment(i)
        Assignment2(k)
        Assignment3 (i)
        Assignment4 (k)
        Assignment5 (f)
        ConnectionTime(i,k,j)
        ConnectedFlights(i,j,k,l)
        SlotCapacity(j)
        SlotCapacity2(l)
        Penalty(j)
        Penalty2(l);

obj                   .. z =e= sum((i,j,k,l), c(i,j,k,l)*t(i,j,k,l)) - sum(j,a(j)*SP) - sum(l, b(l)*SP)
+ sum((i,k,f),Rot(i,k,f)*(rev(i,k,f)-cost(i,k,f)));

Assignment(i)            ..     sum(j, x(i,j)) =e= 1 ;
Assignment2(k)           ..     sum(l, y(k,l)) =e= 1 ;
Assignment3(i)           ..     sum((k,f), Rot(i,k,f)) =e=1;
Assignment4(k)           ..     sum((i,f), Rot(i,k,f)) =e=1;
Assignment5(f)           ..     sum((i,k), Rot(i,k,f)) =l=n(f);
ConnectionTime(j,l)      ..     BigM*P(j,l) =g= sum((i,k), t(i,j,k,l));
ConnectedFlights(i,j,k,l) ..    x(i,j) + y(k,l) =g= 2*t(i,j,k,l);
SlotCapacity(j)          ..     sum(i, x(i,j)) =l=ASA(j)+a(j);
SlotCapacity2(l)         ..     sum(k, y(k,l)) =l=ASD(l)+b(l);
Penalty(j)               ..     a(j) =l= 1   ;
Penalty2(l)              ..     b(l) =l= 1   ;

option resLim=3600;
option MIP=CPLEX;

Model BankStructure /all/;
Solve BankStructure using MIP maximizing z;
Display  x.l, y.l, z.l, Rot.l;
```

C
BANK OPTIMIZER SIMULATED ANNEALING R CODE

```
# Start the clock!
counter <- proc.time()

library(readxl)
First_Solution <- read_excel("F:/doktora/Tez/R SA/Wave Structure.xlsx",
   sheet = "initial solution",    col_names = TRUE)
Demand <- read_excel("F:/doktora/Tez/R SA/Wave Structure.xlsx",
   sheet = "demand", col_names = TRUE)


#Cleanin the data & naming the variables
First_Solution$N_Arrivals  <- 1:nrow(First_Solution)
First_Solution$N_Departures  <- 1:nrow(First_Solution)
First_Solution$X__3 <- NULL

First_Solution <- First_Solution[c("N_Arrivals", "Arrivals", "Arrivals_time", "N_Depar
tures", "Departures", "Departures_time")]

Demand <- Demand[c("Origin", "Destination", "Demand", "Unit Revenue")]
Demand$prod <- Demand$Demand * Demand$`Unit Revenue`
#View(Demand)
#View(First_Solution)

Bank_Structure  <- First_Solution
#View(Bank_Structure)

library(data.table)
ArrSlotCapacityTable <- data.table(arrslot  = c("1", "2", "3", "4", "5", "6", "7", "8", "9"
, "10", "11", "12", "13", "14", "15", "16", "17", "18", "19", "20", "21", "22", "23", "24",
"25", "26", "27", "28", "29", "30", "31", "32", "33"),
              capacity = c("4", "4", "4", "4", "2", "2", "2", "2", "2", "2",  "3",  "2",  "2",  "2
", "2",  "2",  "2",  "2",  "2",  "2",  "4",  "2",  "3",  "2",  "4", "4",  "2",  "3",  "2",  "4", "4",
"2",  "2")
              )
#View(ArrSlotCapacityTable)

DepSlotCapacityTable <- data.table(depslot  = c("1", "2", "3", "4", "5", "6", "7", "8", "
9", "10", "11", "12", "13", "14", "15", "16", "17", "18", "19", "20", "21", "22", "23", "24
", "25", "26", "27", "28", "29", "30", "31", "32", "33"),
              capacity = c("4", "4", "4", "3", "2", "2", "2", "2", "3", "3",  "3",  "3",  "2",  "2
", "2",  "2",  "3",  "2",  "2",  "2",  "3",  "2",  "2",  "2",  "2", "2",  "2",  "2",  "2",  "2", "2",
"2",  "2")
              )
#View(DepSlotCapacityTable)
```

```
BankOptimizer <- function(Bank_Structure)
{
i <- 1
j <- 1
k <- 0


data <- data.frame()

mydata <- matrix()
data_dest <- matrix()
data_Arri <- matrix()

for (i in 1:nrow(Bank_Structure)) {
 for (j in 1:nrow(Bank_Structure)) {
   if(is.na(Bank_Structure$Arrivals_time[i])){
    i <- i+1
    }
   else{

 a <- Bank_Structure$Departures_time[j] - Bank_Structure$Arrivals_time[i]
 if (a < 6){
   a <- 1000000
 }

   k <- k+1
   mydata[k] <- a
   data_dest[i] <- Bank_Structure$Arrivals[i]
   data_Arri[j] <- Bank_Structure$Departures[j]

   data[k,1] <- Bank_Structure$Arrivals[i]
   data[k,2] <- Bank_Structure$Departures[j]
   data[k,3] <- a
   }
   }
 }

names(data)[1] <- 'Origin'
names(data)[2] <- 'Destination'
names(data)[3] <- 'Connection Time'
#View(data)

Combined <- merge(data, Demand, by = c("Origin", "Destination"), all.x = TRUE)
Combined$b <- Combined$prod/Combined$`Connection Time`/-10
#calculation <- as.numeric(Combined$b)

ArrSlotCount <- data.frame()
```

```
ArrSlotCount <- as.data.frame(table(Bank_Structure$Arrivals_time))
names(ArrSlotCount)[1] <- 'arrslot'
ArrSlotCount <- (merge(ArrSlotCount, ArrSlotCapacityTable, by="arrslot"))
ArrSlotCount$Freq <- as.numeric(ArrSlotCount$Freq)
ArrSlotCount$capacity <- as.numeric(ArrSlotCount$capacity)
ArrSlotCount$arrexceed <- ArrSlotCount$Freq - ArrSlotCount$capacity
ArrSlotCount$arrexceed[ArrSlotCount$arrexceed < 0] <- 0
ArrSlotCount[c("arrslot", "Freq", "capacity", "arrexceed")]
#View(ArrSlotCount)

DepSlotCount <- data.frame()
DepSlotCount <- as.data.frame(table(Bank_Structure$Departures_time))
names(DepSlotCount)[1] <- 'depslot'
DepSlotCount <- (merge(DepSlotCount, DepSlotCapacityTable, by="depslot"))
DepSlotCount$Freq <- as.numeric(DepSlotCount$Freq)
DepSlotCount$capacity <- as.numeric(DepSlotCount$capacity)
DepSlotCount$depexceed <- DepSlotCount$Freq - DepSlotCount$capacity
DepSlotCount$depexceed[DepSlotCount$depexceed < 0] <- 0
DepSlotCount[c("depslot", "Freq","capacity", "depexceed")]
#View(DepSlotCount)
y <-
#names(calculation)[1] <- 'Departure'
#names(calculation)[2] <- 'Arrival'
#names(calculation)[1] <- 'calculation'
#y <- sum(Combined$b)+10000*sum(ArrSlotCount$arrexceed)+10000*sum(DepSlotC
ount$depexceed)


#d <- DepSlotCount$depexceed > 1
#any(d)
#a <- ArrSlotCount$arrexceed > 1
#any(a)
#any(d) || any(a)
#if (any(d) || any(a)) {y <- 0}
#else
#{y <- sum(Combined$b)+60000*sum(ArrSlotCount$arrexceed)+60000*sum(DepSlot
Count$depexceed)}
#y

y <- sum(Combined$b)+10000*sum(ArrSlotCount$arrexceed)+10000*sum(DepSlotC
ount$depexceed)
y
return(y)
}


    #Arrivals_time <- as.matrix( sample(1:33, 2, replace=T))
```

```
    #Departures_time <- as.matrix( sample(1:33, 2, replace=T))
    #s_n12 <-s_c[c("Departures_time")]

    #s_n13 <- First_Solution[c("N_Arrivals", "Arrivals","N_Departures", "Departures
")]
    #RandomInitial<- data.frame(Arrivals_time,Departures_time,s_n13)


simulated_annealing <- function(func, s0, niter = 100, step = 0.99) {

  # Initialize
  ## s stands for state
  ## f stands for function value
  ## b stands for best
  ## c stands for current
  ## n stands for neighbor

  s_b <- s_c <- s_n <- s0 <- RandomInitial <- First_Solution
  f_b <- f_c <- f_n <- func(s_n)
  result <-
  result_n <-
  iterationcount <-
  s_n1 <-
  s_n2 <-
  s_n3 <-
  Tempgraph <-
  #message("It\tBest\tCurrent\tNeigh\tTemp")
  #message(sprintf("%i\t%.4f\t%.4f\t%.4f\t%.4f", 0L, f_b, f_c, f_n, 1))
  Temp <- 500000

  pb <- winProgressBar(title = "Progress Bar", label="0% done", min = 0, max =niter ,
width = 300,  initial=0)

  for (k in 1:niter) {
    setWinProgressBar(pb, k,label=paste( k/niter*100,"% done"))
    #progress(k)


     if  ( k %% 10  < 1){
       Temp <- (Temp)*step
       } else
         {
          Temp <- Temp*1
          }

    #Temp <-(Temp)*step
```

```
    #consider a random neighbor with integer sample
    # modify elements less than 1 and greater than 33

    s_n1 <-s_c[c("Arrivals_time", "Departures_time")]

    random.row <- sample(1:nrow(s_n1),1)
    random.col <- sample(1:ncol(s_n1),1)

    s_n2<-s_n1
    add <- sample(-1:1, 1, replace=T)
    s_n2[random.row, random.col] <- (add + s_n2[random.row, random.col])
    s_n2[s_n2 < 1] <- 1
    s_n2[s_n2 > 33] <- 33
    s_n3 <- s_c[c("N_Arrivals", "Arrivals","N_Departures", "Departures")]
    s_n  <- data.frame(s_n2,s_n3)


    f_n <- func(s_n)
    # update current state
    if (f_n < f_c || runif(1, 0, 1) < exp(-(f_n - f_c) / Temp)) {
      s_c <- s_n
      f_c <- f_n
    }
    # update best state
    if (f_n < f_b) {
      s_b <- s_n
      f_b <- f_n
    }
    #message(sprintf("%i\t%.0f\t%.3f\t%.3f\t%.3f\t%.0f      ", k, Temp, f_b, f_n, f_c, s_c)
)
    result[k]<- -1*f_b
    iterationcount[k]<- k
    result_n[k]<- -1*f_n
    Tempgraph[k]<-Temp


  }
  library(ggplot2)
  abc <- plot(iterationcount,result_n,type="b", col="red")
  lines(iterationcount,result,type="b", col="green" )
  #lines(iterationcount,Tempgraph,type="b", col="blue" )
  title("Best, Current and Iteration Count")
  legend(5, 5, c("Current","Best"), lwd=c(1,1), col=c("red","green"), pch=c(14,19), y.in
tersp=1.5)
  print(abc)

  def <- data.frame(Tempgraph, result,result_n)
```

```
  library(xlsx)
  write.xlsx(def, "F:/doktora/Tez/R SA/Result.xlsx", sheetName="Sheet1")
  file <- "F:/doktora/Tez/R SA/Result.xlsx"


  return(list(iterations = niter, best_value = f_b, best_state = s_b, Temp,result[1]))


}


sol <- simulated_annealing(BankOptimizer, s0 = data.frame(First_Solution))



# Stop the clock
proc.time() - counter

##    user  system elapsed
##    8.75    0.53    8.26

library(beepr)
beep()
```

D
BANK OPTIMIZER TABU SEARCH R CODE

```
# Start the clock!
counter <- proc.time()

library(readxl)
First_Solution <- read_excel("F:/doktora/Tez/R SA/Wave Structure.xlsx",
   sheet = "initial solution 6x6",    col_names = TRUE)
Demand <- read_excel("F:/doktora/Tez/R SA/Wave Structure.xlsx",
   sheet = "demand", col_names = TRUE)


#Cleaning the data & naming the variables
First_Solution$N_Arrivals  <- 1:nrow(First_Solution)
First_Solution$N_Departures  <- 1:nrow(First_Solution)
First_Solution$X__3 <- NULL

First_Solution <- First_Solution[c("N_Arrivals", "Arrivals", "Arrivals_time", "N_Depar
tures", "Departures", "Departures_time")]

Demand <- Demand[c("Origin", "Destination", "Demand", "Unit Revenue")]
Demand$prod <- Demand$Demand * Demand$`Unit Revenue`
#View(Demand)
#View(First_Solution)

Bank_Structure  <- First_Solution
#View(Bank_Structure)

library(data.table)
ArrSlotCapacityTable <- data.table(arrslot  = c("1", "2", "3", "4", "5", "6", "7", "8", "9"
, "10", "11", "12", "13", "14", "15", "16", "17", "18", "19", "20", "21", "22", "23", "24",
"25", "26", "27", "28", "29", "30", "31", "32", "33"),
              capacity = c("4", "4", "4", "4", "1", "0", "0", "2", "1", "1",  "3",  "2",  "0",  "1
", "2",  "2",  "2",  "2",  "0",  "2",  "4",  "2",  "3",  "1",  "4", "4",  "2",  "3",  "1",  "4", "4",
"2",  "2")
              )
#View(ArrSlotCapacityTable)

DepSlotCapacityTable <- data.table(depslot  = c("1", "2", "3", "4", "5", "6", "7", "8", "
9", "10", "11", "12", "13", "14", "15", "16", "17", "18", "19", "20", "21", "22", "23", "24
", "25", "26", "27", "28", "29", "30", "31", "32", "33"),
              capacity = c("4", "4", "4", "3", "2", "2", "2", "2", "3", "3",  "3",  "3",  "2",  "1
", "1",  "2",  "3",  "1",  "2",  "2",  "3",  "1",  "1",  "2",  "1", "1",  "2",  "2",  "1",  "1", "1",
"0",  "1")
              )
#View(DepSlotCapacityTable)
```

```r
BankOptimizer <- function(Bank_Structure)
{
i <- 1
j <- 1
k <- 0


data <- data.frame()

mydata <- matrix()
data_dest <- matrix()
data_Arri <- matrix()

for (i in 1:nrow(Bank_Structure)) {
 for (j in 1:nrow(Bank_Structure)) {
   if(is.na(Bank_Structure$Arrivals_time[i])){
    i <- i+1
    }
   else{

 a <- Bank_Structure$Departures_time[j] - Bank_Structure$Arrivals_time[i]
 if (a < 6){
   a <- 1000000
 }

   k <- k+1
   mydata[k] <- a
   data_dest[i] <- Bank_Structure$Arrivals[i]
   data_Arri[j] <- Bank_Structure$Departures[j]

   data[k,1] <- Bank_Structure$Arrivals[i]
   data[k,2] <- Bank_Structure$Departures[j]
   data[k,3] <- a
   }
   }
 }

names(data)[1] <- 'Origin'
names(data)[2] <- 'Destination'
names(data)[3] <- 'Connection Time'
#View(data)

Combined <- merge(data, Demand, by = c("Origin", "Destination"), all.x = TRUE)
Combined$b <- Combined$prod/Combined$`Connection Time`/-10
#calculation <- as.numeric(Combined$b)

ArrSlotCount <- data.frame()
```

```
ArrSlotCount <- as.data.frame(table(Bank_Structure$Arrivals_time))
names(ArrSlotCount)[1] <- 'arrslot'
ArrSlotCount <- (merge(ArrSlotCount, ArrSlotCapacityTable, by="arrslot"))
ArrSlotCount$Freq <- as.numeric(ArrSlotCount$Freq)
ArrSlotCount$capacity <- as.numeric(ArrSlotCount$capacity)
ArrSlotCount$arrexceed <- ArrSlotCount$Freq - ArrSlotCount$capacity
ArrSlotCount$arrexceed[ArrSlotCount$arrexceed < 0] <- 0
ArrSlotCount[c("arrslot", "Freq", "capacity", "arrexceed")]
#View(ArrSlotCount)

DepSlotCount <- data.frame()
DepSlotCount <- as.data.frame(table(Bank_Structure$Departures_time))
names(DepSlotCount)[1] <- 'depslot'
DepSlotCount <- (merge(DepSlotCount, DepSlotCapacityTable, by="depslot"))
DepSlotCount$Freq <- as.numeric(DepSlotCount$Freq)
DepSlotCount$capacity <- as.numeric(DepSlotCount$capacity)
DepSlotCount$depexceed <- DepSlotCount$Freq - DepSlotCount$capacity
DepSlotCount$depexceed[DepSlotCount$depexceed < 0] <- 0
DepSlotCount[c("depslot", "Freq","capacity", "depexceed")]
#View(DepSlotCount)
y <-
#names(calculation)[1] <- 'Departure'
#names(calculation)[2] <- 'Arrival'
#names(calculation)[1] <- 'calculation'
#y <- sum(Combined$b)+10000*sum(ArrSlotCount$arrexceed)+10000*sum(DepSlotC
ount$depexceed)
d <- DepSlotCount$depexceed > 1
any(d)
a <- ArrSlotCount$arrexceed > 1
any(a)
any(d) || any(a)
if (any(d) || any(a)) {y <- 0}
else
{y <- sum(Combined$b)+10000*sum(ArrSlotCount$arrexceed)+10000*sum(DepSlot
Count$depexceed)}
y
return(y)
}



tabu_search <- function(BankOptimizer, s0, maxit = 30, max_row= 30, N = 10){

#max_row <- 130 #max tabu length
#maxit <- 100
#N <- 10 #number of neighbor configuration to check at each iteration
solution <- First_Solution
best_solution <- solution
```

```
tabu_list <- c()
tabu_list <- c(tabu_list,best_solution)
i <- 1
j <- 1

s_b <- s_c <- s_n <- s0 <- First_Solution
f_b <- f_c <- f_n <- BankOptimizer(s_n)

result <-
result_n <-
iterationcount <-
s_n1 <-
s_n2 <-
s_n3 <-
pb <- winProgressBar(title = "Progress Bar", label="0% done", min = 0, max =maxit ,
width = 300,  initial=0)

for (i in 1:maxit) {
    setWinProgressBar(pb, i,label=paste( i/maxit*100,"% done"))
    #progress(i)



  for (j in 1:N) {

      s_n1 <-s_c[c("Arrivals_time", "Departures_time")]
      random.row <- sample(1:nrow(s_n1),1)
      random.col <- sample(1:ncol(s_n1),1)
      s_n2<-s_n1
      add <- sample(-1:1, 1, replace=T)
      s_n2[random.row, random.col] <- (add + s_n2[random.row, random.col])
      s_n2[s_n2 < 1] <- 1
      s_n2[s_n2 > 40] <- 40
      s_n3 <- s_c[c("N_Arrivals", "Arrivals","N_Departures", "Departures")]
      s_n  <- data.frame(s_n2,s_n3)

      c_list <- c()

      if (!(setequal(intersect(s_n, tabu_list),s_n))){
        c_list <- rbind(c_list, s_n)

      f_n <- BankOptimizer(s_n)
      # update current state
      if (f_n < f_c ) {
        s_c <- s_n
        f_c <- f_n
      }
```

```
    # update best state
    if (f_n < f_b) {
      s_b <- s_n
      f_b <- f_n
      tabu_list<- rbind(tabu_list,s_n)

           if (nrow(tabu_list) > max_row){
           #tabu_list <-tabu_list[-(1:13), , drop = FALSE] # we eliminate the first 13 ele
ments.
           tabu_list <-tail(tabu_list,-6) # we eliminate the first 13 elements.
           }

    }
   }




  }

  #if (f_n < f_b) {
  #
  #s_b <- s_n
  #}

  result[i]<- -1*f_b
  iterationcount[i]<- i
  result_n[i]<- -1*f_n


}

library(ggplot2)
  abc <- plot(iterationcount,result_n,type="b", col="red")
  lines(iterationcount,result,type="b", col="green" )
  title("Best, Current and Iteration Count")
  legend(5, 5, c("Current","Best"), lwd=c(1,1), col=c("red","green"), pch=c(14,19), y.in
tersp=1.5)



  def <- data.table(iterationcount,result,result_n)

  library(xlsx)
  write.xlsx(def, "F:/doktora/Tez/R SA/Result_IST_Tabu.xlsx", sheetName="Sheet1")
  file <- "F:/doktora/Tez/R SA/Result_IST_Tabu.xlsx"

  write.xlsx(s_b, "F:/doktora/Tez/R SA/Best_Result_IST_Tabu.xlsx", sheetName="She
```

```r
et1")
  file <- "F:/doktora/Tez/R SA/Best_Result_IST_Tabu.xlsx"

 return(list(iterations = maxit, best_value = f_b, best_state = s_b))

}

sol <- tabu_search(BankOptimizer, s0 = data.frame(First_Solution))


# Stop the clock
proc.time() - counter

##    user  system elapsed
##    8.61    0.37    7.83

library(beepr)
beep()
```

E
FLEET ASSIGNMENT CPLEX CODE

```
{string} Legs = ...;                              // i, j, l
{string} Legs0 = {"0"} union Legs;                // i, j, l

{string} Fleets = ...;                            // f
{string} Stations = ...;                          // s
{string} Arrivals[Stations] = ...;
{string} Departures[Stations] = ...;

float RASK[Legs] = ...;
float CASK[Fleets] = ...;
float Distance[Legs] = ...;
float Capacity[Fleets] = ...;
float AvailableAircrafts[Fleets] = ...;
int ArrivalTimes[Legs] = ...;
int DepartureTimes[Legs] = ...;

dvar boolean x[Legs0][Legs0][Fleets];

dexpr float revenue = sum (i in Legs0, j in Legs, f in Fleets) RASK[j]
* Capacity[f] * Distance[j] * x[i,j,f];
dexpr float cost = sum (i in Legs0, j in Legs, f in Fleets) CASK[f] *
Capacity[f] * Distance[j] * x[i,j,f];

maximize revenue - cost;

subject to {
        cover:                          forall (j in Legs)
                                                sum (i in Legs0,
f in Fleets) x[i,j,f] == 1;

        balance:                        forall (l in Legs, f in Fleets)
                                                sum (i in Legs0)
x[i,l,f] == sum (j in Legs0) x[l,j,f];

        scheduleBalance:        forall (s in Stations, f in Fleets)
                                                sum (i in
Departures[s]) x["0",i,f] == sum (i in Arrivals[s]) x[i,"0",f];

        availability:           forall (f in Fleets)
                                                sum (i in Legs)
x["0",i,f] <= AvailableAircrafts[f];

        forall (f in Fleets) x["0","0",f] == 0;
        forall (s in Stations, a in Arrivals[s], f in Fleets) {
//              forall (s2 in Stations, a2 in Arrivals[s2]) {
//                      x[a,a2,f] == 0;
//              }
                forall (s2 in Stations : s2 != s, d2 in Departures[s2])
{
```

```
                        x[a,d2,f] == 0;
                }
                forall (d in Departures[s]) {
                        if (DepartureTimes[d] < ArrivalTimes[a]) {
                                x[a,d,f] == 0;
                        }
                }
        }
}

execute {
        // head of solution table
        writeln('key\t\t\tori\tdes\ttype');
        for (var l in Legs) {
                // flight key
                write(l + '\t');

                // origin
                for (var s in Stations) {
                        for (var d in Departures[s]) {
                                if (l == d) {
                                        write(s + '\t');
                                }
                        }
                }

                // destination
                for (s in Stations) {
                        for (var a in Arrivals[s]) {
                                if (l == a) {
                                        write(s + '\t');
                                }
                        }
                }

                // fleet type
                for (var i in Legs0) {
                        for (var f in Fleets) {
                                if (x[i][l][f] == 1) {
                                        write(f + '\t');
                                }
                        }
                }
                writeln();
        }
}

execute {

}
```

F
DATA

Table D.1 Demand and revenue data between OD city pairs

OriginKey	DestinationKey	Demand	Unit Revenue
AMS	TLV	20,023	88
TLV	AMS	17,758	75
CDG	IKA	16,191	233
IKA	CDG	14,614	229
AMS	IKA	12,619	215
CDG	TLV	12,376	75
IKA	AMS	11,581	200
CDG	TBS	10,558	169
TBS	TXL	10,255	124
LGW	TBS	9,914	193
BCN	TLV	9,855	127
TLV	MXP	9,384	101
MXP	IKA	8,815	245
TLV	MUC	8,388	78
VIE	IKA	8,385	214

OriginKey	DestinationKey	Demand	Unit Revenue
MUC	IKA	8,209	175
TLV	BCN	8,167	124
TXL	TBS	8,021	117
TBS	CDG	7,839	147
IKA	LGW	7,665	184
AMS	TBS	7,659	137
MXP	TLV	7,648	111
BRU	IKA	7,644	208
LGW	IKA	7,622	190
VIE	TBS	7,578	135
BCN	TBS	7,569	139
TBS	FRA	7,479	124
DXB	CDG	7,285	164
TLV	FCO	7,281	121
FRA	TBS	7,118	125
BRU	TBS	7,086	139
TBS	AMS	7,084	128
MXP	TBS	7,073	121
FRA	IKA	6,998	196

OriginKey	DestinationKey	Demand	Unit Revenue
MUC	TLV	6,869	77
TLV	CDG	6,811	70
TBS	BRU	6,790	143
TBS	VIE	6,754	126
IKA	MXP	6,652	240
TBS	BCN	6,588	128
TBS	MUC	6,571	96
MUC	TBS	6,482	105
TBS	LGW	6,436	167
IKA	FRA	6,234	177
IKA	BRU	6,222	200
CDG	DXB	6,202	143
LGW	TLV	6,106	80
BCN	IKA	6,065	271
TXL	IKA	5,972	219
IKA	VIE	5,931	195
FCO	TBS	5,825	121
TBS	FCO	5,822	120
DUS	IKA	5,775	209

OriginKey	DestinationKey	Demand	Unit Revenue
IKA	MUC	5,759	133
TBS	MXP	5,731	109
IKA	DUS	5,461	190
FCO	TLV	5,342	134
TLV	FRA	5,275	96
CDG	KWI	5,235	242
DXB	LGW	5,000	139
MUC	KWI	4,765	245
TLV	LGW	4,693	60
IKA	TXL	4,618	186
TXL	TLV	4,546	114
TLV	DUS	4,327	123
MXP	KWI	4,304	265
TLV	TXL	4,266	98
KWI	CDG	4,227	218
IKA	BCN	4,193	259
LGW	DXB	4,169	119
VIE	KWI	3,868	242
DXB	BRU	3,866	183

OriginKey	DestinationKey	Demand	Unit Revenue
DXB	TXL	3,831	171
AMS	KWI	3,532	245
FRA	TLV	3,491	89
TXL	DXB	3,470	152
DXB	AMS	3,464	232
TBS	DUS	3,291	104
DUS	DXB	3,163	139
FCO	IKA	3,151	243
MUC	DXB	3,114	137
DXB	MUC	3,083	148
KWI	AMS	3,001	217
LGW	KWI	2,974	193
KWI	LGW	2,947	187
DXB	DUS	2,929	165
DUS	TLV	2,925	111
KWI	MUC	2,921	227
DUS	TBS	2,912	103
STR	TLV	2,674	115
BCN	KWI	2,624	284

OriginKey	DestinationKey	Demand	Unit Revenue
STR	IKA	2,612	219
BRU	DXB	2,581	173
TBS	STR	2,536	153
KWI	VIE	2,368	219
DXB	STR	2,359	178
IKA	FCO	2,326	262
STR	TBS	2,316	124
BRU	TLV	2,293	100
DXB	FRA	2,291	152
DXB	BCN	2,282	232
AMS	DXB	2,254	189
KWI	BCN	2,232	261
JED	CDG	2,200	321
TLV	VIE	2,198	89
BCN	DXB	2,175	205
TLV	BRU	2,058	92
KWI	MXP	2,035	237
FCO	DXB	1,880	171
MXP	DXB	1,872	199

OriginKey	DestinationKey	Demand	Unit Revenue
IKA	STR	1,844	215
STR	DXB	1,823	144
DXB	FCO	1,816	186
FRA	KWI	1,801	238
FRA	DXB	1,782	176
DXB	MXP	1,777	224
TLV	STR	1,756	106
VIE	TLV	1,714	88
KWI	FRA	1,676	208
KWI	DUS	1,642	294
TXL	KWI	1,496	342
DUS	KWI	1,303	261
CDG	MED	1,233	359
JED	AMS	1,100	366
DXB	VIE	1,097	187
KWI	TXL	1,018	259
BRU	KWI	925	381
JED	LGW	910	275
CDG	JED	909	434

OriginKey	DestinationKey	Demand	Unit Revenue
JED	BRU	874	375
FCO	KWI	848	297
LGW	JED	826	272
DMM	CDG	782	263
KWI	FCO	773	269
KWI	BRU	697	277
BCN	RUH	602	505
VIE	DXB	599	165
BRU	JED	580	532
DMM	MUC	579	233
MED	CDG	571	386
AMS	JED	487	466
MUC	DMM	431	252
LGW	RUH	429	279
AMS	MED	420	283
RUH	AMS	407	387
RUH	BCN	406	380
JED	MXP	394	271
DMM	BCN	383	288

OriginKey	DestinationKey	Demand	Unit Revenue
MED	AMS	376	449
JED	BCN	361	381
CDG	DMM	347	246
BAH	MUC	329	238
RUH	CDG	327	364
BRU	MED	326	483
DMM	MXP	321	315
LGW	MED	320	281
JED	DUS	311	358
TBS	TLV	293	113
RUH	VIE	289	486
STR	KWI	286	421
BAH	CDG	282	300
MED	LGW	278	269
BCN	DMM	276	325
JED	MUC	274	310
MXP	RUH	273	427
RUH	LGW	273	252
DMM	AMS	268	365

OriginKey	DestinationKey	Demand	Unit Revenue
JED	VIE	262	351
TLV	TBS	256	94
DMM	LGW	236	295
RUH	MXP	235	399
MXP	DMM	233	320
DMM	VIE	228	293
JED	FRA	224	256
JED	TXL	224	397
KWI	STR	222	402
BCN	JED	217	353
RUH	TXL	217	444
CDG	RUH	208	475
AMS	BAH	199	240
BAH	AMS	196	272
DMM	FCO	192	284
FRA	JED	190	336
LGW	DMM	183	292
AMS	RUH	182	425
BAH	BCN	181	285

OriginKey	DestinationKey	Demand	Unit Revenue
FRA	RUH	180	447
FCO	RUH	174	405
BAH	MXP	163	286
MED	BRU	157	373
TXL	RUH	157	411
RUH	MUC	152	327
MUC	JED	147	311
BAH	LGW	142	210
RUH	FRA	142	358
DMM	FRA	140	288
JED	FCO	140	277
MED	MUC	139	287
VIE	DMM	139	272
BAH	FCO	138	246
MED	STR	136	302
BCN	BAH	134	306
AMS	DMM	132	320
MED	VIE	132	397
MUC	RUH	131	520

OriginKey	DestinationKey	Demand	Unit Revenue
BAH	VIE	130	253
VIE	RUH	125	332
MED	TXL	117	373
MED	BCN	114	323
FCO	DMM	107	287
RUH	BRU	107	418
DUS	RUH	105	460
MXP	JED	105	264
RUH	DUS	103	492
BAH	DUS	101	211
BAH	FRA	98	189
LGW	BAH	98	183
JED	STR	96	363
MED	FRA	96	281
MUC	BAH	94	224
CDG	BAH	90	204
RUH	FCO	88	374
DMM	TXL	83	350
FRA	MED	77	292

OriginKey	DestinationKey	Demand	Unit Revenue
DUS	JED	74	546
MED	MXP	73	256
BRU	RUH	71	552
TXL	MED	70	304
MUC	MED	69	231
TBS	DXB	69	185
FCO	BAH	64	273
VIE	BAH	64	197
BAH	TXL	63	331
DUS	MED	62	332
MXP	BAH	61	203
FCO	JED	60	246
TXL	JED	58	312
FRA	DMM	57	290
STR	JED	56	379
MED	DUS	51	414
DMM	BRU	49	366
RUH	STR	49	399
BRU	DMM	48	403

OriginKey	**DestinationKey**	**Demand**	**Unit Revenue**
DUS	BAH	45	213
BAH	BRU	41	287
BCN	MED	41	279
MXP	MED	41	246
TLV	DXB	41	298
VIE	JED	41	254
DMM	DUS	34	339
DUS	DMM	33	328
TXL	DMM	31	375
FRA	BAH	27	181
STR	RUH	26	623
TBS	RUH	26	170
DMM	STR	24	387
BAH	IKA	23	39
BRU	BAH	23	254
DXB	TBS	21	190
BAH	STR	19	475
DMM	TBS	19	314
KWI	TBS	19	296

OriginKey	DestinationKey	Demand	Unit Revenue
STR	MED	18	276
RUH	DXB	17	490
MED	FCO	16	209
DXB	TLV	15	282
IKA	TBS	15	268
TBS	IKA	14	289
JED	TBS	11	302
TXL	BAH	11	255
TBS	KWI	10	213
TLV	IKA	9	185
RUH	TBS	8	164
STR	BAH	8	267
TLV	KWI	7	170
FCO	MED	6	380
JED	DXB	6	215
JED	TLV	6	275
STR	DMM	6	417
TBS	JED	6	310
IKA	TLV	5	108

OriginKey	DestinationKey	Demand	Unit Revenue
KWI	DXB	5	448
AMS	DUS	4	238
JED	IKA	4	423
TBS	DMM	4	522
DXB	IKA	3	381
IKA	MED	3	517
BAH	DXB	2	414
CDG	FCO	2	158
DUS	BRU	2	164
FCO	TXL	2	121
KWI	TLV	2	132
VIE	MED	2	205
AMS	BRU	1	561
BAH	TBS	1	490
BRU	DUS	1	133
CDG	DUS	1	365
DUS	MXP	1	162
DXB	JED	1	296
FCO	FRA	1	142

OriginKey	DestinationKey	Demand	Unit Revenue
IKA	KWI	1	202
LGW	MXP	1	325
MED	KWI	1	425
MUC	CDG	1	246
MXP	BCN	1	118
MXP	CDG	1	359
MXP	STR	1	327
RUH	TLV	1	372
STR	CDG	1	750
TBS	BAH	1	225
VIE	FCO	1	75
VIE	MUC	1	725

Table D.2 Initial schedule of arrivals for TS and SA

Arrival Flight from	Arrival Slot
BAH	2
DMM	5
DXB	9
IKA	1
JED	8
KWI	6
MED	3
RUH	7
TBS	11
TLV	16

Table D.3 Initial schedule of departures for TS and SA

Departure Flight	Departure Slot
AMS	19
BCN	23
BRU	22
CDG	18
DUS	26

Departure Flight	**Departure Slot**
FRA	27
LGW	18
MUC	27
MXP	25
STR	29
TXL	22
VIE	28

Table D.4 Number of available slots at the hub airport

Slot Time	Number of Available Arrival Slot	Number of Available Departure Slot
1	4	4
2	4	4
3,	4	4
4	4	3
5	1	2
6	0	2
7	0	2
8	2	2
9	1	3
10	1	3
11	3	3
12	2	3
13	0	2
14	1	1
15	2	1
16	2	2
17	2	3

Slot Time	Number of Available Arrival Slot	Number of Available Departure Slot
18	2	1
19	0	2
20	2	2
21	4	3
22	2	1
23	3	1
24	1	2
25	4	1
26	4	1
27	2	2
28	3	2
29	1	1
30	4	1
31	4	1
32	2	0
33	2	1
26	4	1
27	2	2

Slot Time	Number of Available Arrival Slot	Number of Available Departure Slot
29	1	1
30	4	1
31	4	1
32	2	0
33	2	1

PUBLICATIONS FROM THE THESIS

Papers

1. Çiftçi, M. E., & Özkır, V. (2020). Optimising flight connection times in airline bank structure through Simulated Annealing and Tabu Search algorithms. Journal of Air Transport Management, 87, 101858.