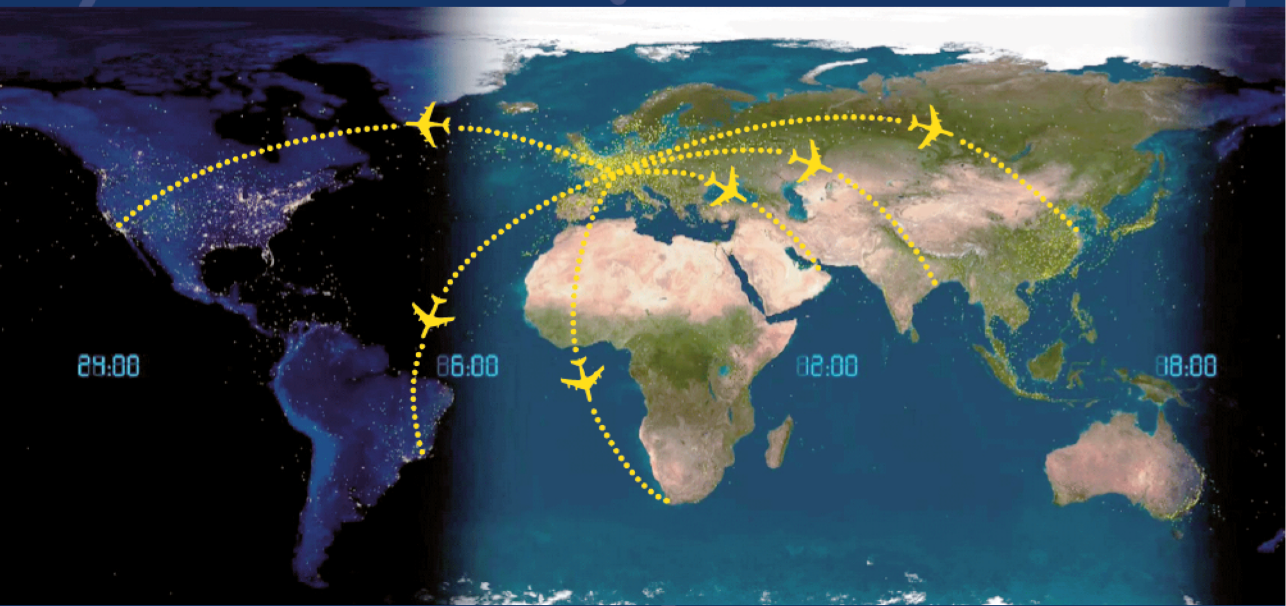
AARON B. SCHOLZ

Network Structures of Cargo Airlines

An Empirical and a Modelling Approach



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by
Aaron B. Scholz

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To my family

Preface

Air cargo transport is developing at high growth rates. Although the share of air cargo of total freight transport is low, measured in tonnes lifted or tonne-kilometres carried, the share of values transported is high, which underlines its importance for the functioning of supply chains for high valued goods in the economy. The development of air cargo networks was historically dominated by the air passenger hubs, because the major part of air cargo was transported in the bellies of passenger airplanes. With the extension of dedicated air cargo lines and the increasing environmental problems of big passenger hubs the development of efficient future air cargo networks is an upcoming challenge. Basically the network configurations of air cargo carriers can be developed towards pure cargo carriers, combined carriers or integrated service providers (integrators).

The modelling of airline network design includes four steps as there are schedule design, fleet assignment, maintenance routing and crew scheduling. Aaron Scholz focuses on the first two problems, and in particular on the hub location problem, because this will be an increasing challenge in particular for the integrators and cargo fleet operators. This results in a large-scale/non-linear optimization problem, which only can be solved by heuristic methods.

Aaron develops the model *AirTrafficSim*, which consists of graph theoretical components to model transport movements in space and optimal selection tools to reduce the combinatorial complexity of fixed charge problems. The main algorithm applied is based on the meta-heuristic “Simulated Annealing” which is a spin-off concept of thermodynamics. The innovative feature of this approach is its ability to jump from local search to other promising branches of the search tree. Aaron gives some impressive examples for the efficiency of this algorithm compared to widely applied methods like for instance the Greedy algorithm.

But the reader will not only find in this book a remarkable progress with the development of modelling tools for treating complex optimisation problems. Aaron has invested the same effort into the empirical analysis of the air cargo sector. In particular he has compiled available data on the demand and supply side of one important player in the market such that he is able to calibrate his model in a way that it reproduces the present structure of the air cargo branch of this company with remarkable accuracy. Starting from this baseline he constructs a scenario for the optimal adjustment of the air cargo branch of this company until the year 2029.

The results of this empirical exercise lead to the discussion to which extent the deviations of the model results from the actual behaviour of the firm is caused by the modeller’s ignorance or the firms missing ability to adjust to market challenges. The reader will not fail to notice that there are significant indicators for the latter interpretation. Insofar the book of Aaron Scholz provides both: A sophisticated analytical platform to design optimal network structures for the air cargo industry and an accurately constructed empirical demonstrator for the practical use of a theoretically well-founded instrument.

Werner Rothengatter

Acknowledgements

The present dissertation has been prepared during my time as researcher at the Institute for Economic Policy Research, Karlsruhe Institute of Technology and many people have inspired, assisted and promoted me during this time. To all of them I wish to express my deepest gratitude because without their encouragement the present work would not have been possible.

Special thanks go to Prof. Dr. Werner Rothengatter for giving me the opportunity to conduct my research at IWW, for his belief in me and in young researchers in general and for his supporting advices during my dissertation. I would like to thank Prof. Dr. Frank Schultmann (Karlsruhe Institute of Technology) and Prof. Dr. Eddy Van de Voorde (University of Antwerp) for co-refereeing my dissertation and for their interest in my work. Furthermore, Prof. Dr. Eddy Van de Voorde and his air cargo colleagues at the University of Antwerp inspired this work through fruitful discussions at conferences and workshops.

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Marcus Hammer and Thomas Ingold were irreplaceable in transferring my ideas into a model. Thanks also go to Petra Horlbeck and Christine Zarda for their creativity and lovely helpfulness in designing this book cover, to Prof. Dr. Karl Rege for allowing me to use the pictures of AirTraffic Worldwide as book cover, to Andreas Gärtner for proofreading my thesis and to Torben Wulf for supporting me with editing this book.

I would also like to thank Lufthansa Cargo AG and aviainform GmbH for providing me with data and information and therefore enabling the application of *AirTrafficSim* to a real world case-study.

The loving support of my entire family and especially of my wife and their unswerving belief in me has guided me throughout this work. Last but not least, the pleasant anticipation of Jona gave me the necessary effectiveness to finalize this dissertation. Words cannot express my feelings for them right!

Aaron B. Scholz

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Abstract

Air cargo has become a key element of global supply chains, and is expected to continue to grow because of increasing worldwide economic integration, shorter product life cycles, reductions in inventory stocks, and increasing competition between the airlines. A major constraint for future growth scenarios are capacity limitations at major airports. Airport investment plans exist, but in times of strained public budgets, airport investments directly compete with other public sectors. Therefore, profitable and from an air transport perspective necessary airport investments need to be selected.

The objective of this dissertation is based on the (long–term) vision to incorporate airlines' strategic behaviour into traffic forecasts. Hence, it is essential to understand the airlines' strategies to design and to configure their networks. The present dissertation approaches this problem for cargo airlines by developing a model for an airline's strategic network design.

In a first step, network structures of cargo airlines are analysed empirically. Concentration and centrality measures are applied which guarantee that the network's shape (morphology) and concentration is considered. The present dissertation has found out that airlines which combine passenger and cargo services, such as Lufthansa, are concentrated around a small number of airports. These airports are the airlines' passenger hubs. Network configurations of pure cargo airlines, such as Cargolux, which focus their services on freight only, are much more diverse. However, round–trip structures are their major network characteristic.

The acquired information is transferred into *AirTrafficSim*, which models the strategic network structure of cargo airlines. A three step approach is applied which differentiates between initialization, optimisation and finalization phase. The initialization phase requires a disaggregated demand structure as input. The output of the initialization phase is direct services between the airports which relates to a perfect point–to–point (P2P) network structure. The empirically observed behaviour of cargo airlines to achieve economies of scale by bundling and consolidating freight at dedicated airports suggests incorporating nonlinear elements into airline network modelling. In such cases, traditional linear programming models reach their limits, so that the combinatorial optimisation problem needs to be solved heuristically. The strong competition between cargo airlines results in cost being the primary decision parameter for an airline's network design. The cost minimal network structure is determined by *AirTrafficSim* by using the Simulated Annealing metaheuristic (optimisation phase). Total network cost consists of transport related operating cost as well as warehouse cost, and cost of capital. The variety of analysed network structures are finally compared with each other and the cost minimal structure is determined (finalization phase).

The case study of Lufthansa has shown that the developed model is able to replicate the status–quo network structure of Lufthansa. The above mentioned and empirically applied network measures are used for a comparison between real world and modelled networks, and suggest the correctness of the model.

Furthermore, scenario analyses, such as demand changes, cost changes, or changes in the airline's business model, are applicable with *AirTrafficSim*.

This dissertation enables researchers to develop an integrated model for an airline's network design including passenger and cargo services as well as an integrated demand and supply model for cargo airlines. The dissertation further provides policy–makers with a better understanding of cargo airlines' network design. In the long–run, policy–makers will benefit from behaviour based forecasts as a basis for future airport investments. Moreover, the dissertation allows practitioners to analyse the effectiveness of their current network structure, and allows airlines to configure their network structure for the future (e.g. jet fuel price, demand shifts).

1 Introduction

In the past decades air cargo volumes have strongly been linked to trade growth and have even outpaced the growth rate of worldwide GDP between 1.5 and 2 times. Reasons for this development are manifold and are exogenous as well as endogenous in nature: product life cycles are shortening, increasing worldwide economic integration, reductions in inventory stocks (including safety stocks), increase in competition in the air freight sector, and lower air freight tariffs are only some reasons for the recent air cargo boom. Things changed dramatically in 2008. The worldwide production halt in various industries and a strong reduction of international trade has hit the entire logistics business but especially the air cargo industry. In December 2008 worldwide air cargo plunged by 22.6% compared to the same month of 2007 which was a sharper reduction than in September 2001 where most of the fleet stayed on ground for days (IATA, 2009). In total, an 18–month decline was observed and the two years period (2008/2009) constitutes the first time that air cargo traffic has decreased in two consecutive years. Since November 2009 monthly air cargo statistics turned positive again and Boeing still expects a triple of cargo volumes over the next 20 years (Crabtree et al., 2010).

A major constraint for such growth scenarios are capacity limitations at airports. Expansion projects at airports (e.g. Amsterdam, Frankfurt, London, Munich, and Rome) are planned (or even completed) and are (mainly) driven by passenger considerations. The importance of air freight is often under–estimated, but already over one third of total revenue–tonne–kilometres is generated by air freight services (two third are passenger services). Even though the revenue contribution of freight is much smaller, it makes a significant contribution to the overall profitability of many flights, airlines and airports (Doganis, 2010).

Since deregulation of the air transport markets at the end of the 1970s in the US and at the end of the 1980s in Europe volatility of air traffic has increased steadily (Burghouwt, 2007). Free route entries and exits, airline bankruptcies as well as airline mergers and acquisitions impact current traffic numbers at airports and complicate the accuracy of traffic forecasts especially for the distant future. Traffic forecasts are however the basis for an efficient airport investment strategy especially as airport investments are long–term investments (Beria and Scholz, 2010). Forecasts have to deal with the flexibility of the airline industry and should represent airlines' strategic behaviour to design and to configure their networks.

An integrated model of demand and supply will finally be able to canalize public investments in airports effectively and avoids over–investments as well as inefficient subsidies in non–competitive airports. In particular, in times of strained public budgets and expenditure reductions public investments for transport infrastructures compete with investment needs of other public sectors (e.g. social system, health care, education) so that (long–term) profitable airport investments need to be selected.

1.1 Objectives

The present dissertation aims to add a mosaic to the ongoing discussion on air traffic forecasts. The objective is to understand and to model the network structure of cargo airlines. To achieve this overall objective the following milestones are aimed at:

- Identification of indicators that characterise network structures of airlines
- Application of these indicators to real world network structures of cargo airlines
- Development of a network design model that bases on an evolutionary approach where the network design emerges endogenously given that demand is transported to minimal cost by a single airline
- Application of the developed model to a cargo airline (case study)
- Comparison of real world and modelled network structures based on the identified indicators

1.2 Structure

Introductory remarks on the motivation for, the relevance and the objectives of this dissertation are given in chapter 1.

Chapter 2 specifies the transportation market under research, the air cargo sector, characterises the key players and especially the airlines as the focus of the present dissertation is on cargo airlines. Finally, these airlines are characterised to achieve a homogeneous research sample.

Chapter 3 develops indicators to characterise network structures of cargo airlines and applies these indicators to real world airline schedules. The indicators are used to compare the modelled network structures with existing real world structures of cargo airlines.

Chapter 4 reviews literature on airline network design modelling which is differentiated into schedule design and fleet assignment literature and literature on hub location modelling.

The core of the present dissertation is incorporated into chapter 5 which describes the developed model, called *AirTrafficSim*. A formal definition of *AirTrafficSim* is given which differentiates between its basic principles, its general structure, the initialization phase, the optimisation phase and the model calibration. The focus of chapter 5 is on the optimisation phase of *AirTrafficSim* as the core components of the model are the optimisation metaheuristic, the cost calculation approach (including economies of scale considerations) as well as the model's objective function (total network cost).

The case study of Lufthansa is included in chapter 6. Lufthansa's demand structure is incorporated into the model and results are compared with the real world network structure of Lufthansa.

Finally, the dissertation is summarised in chapter 7 pointing out its main contributions and argues for further research on airline network modelling

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2 The air cargo sector

The air cargo sector has developed from a pure by–product of passenger airlines to a self–contained business. Dedicated cargo airlines entered the market that provide either highly specialised or mass services and compete with traditional passenger airlines that combine passenger and cargo services. The understanding of these differences is essential to be able to model network structures of airlines close to reality. The objectives of this chapter are to understand

- the characteristics of the sector and its challenges
- the differences between air cargo and air passenger transport and
- the differences in the airlines' business models

2.1 Characteristics of the air cargo sector

Passenger transportation is mainly a one–dimensional business (one passenger = one seat) which is driven by the number of tickets sold. The decision rationale for cargo is three–dimensional, depending on weight (kg), size (m) and volume (m^3) (Spohr, 2007). All three dimensions have to be considered before deciding if cargo can be shipped on a specific route and by a specific aircraft[1].

The required air freight capacities can be provided in three different ways: Airlines can use the cargo capacities of passenger aircrafts (belly capacities), operate pure cargo flights (freighter aircrafts) or use other transport modes for their shipments (e.g. road feeder services). In total around half of worldwide air cargo is transported on passenger aircrafts as belly freight and half on pure freighter aircrafts (Bowen, 2004). The share has been shifted to pure freighter aircrafts in the last decade because of the following reasons (Schmeling, 2006b):

- air cargo increased over air passenger demand (belly capacities)
- more and more requirements appeared for air cargo (need for specialised aircrafts)
- new cargo airlines stepped into the market which only operate freighter aircrafts
- also combined airlines increasingly ordered pure freighter aircrafts

Besides transporting air cargo on aircrafts, a significant share of air freight is also transported by trucks (and very seldom also by train) (Vahrenkamp, 2005). The trucking is operated under an air waybill and is officially regarded as air freight. In particular, on short and medium distances (e.g. within Germany or Europe) road transport is more efficient for airlines (e.g. higher flexibility, lower cost, lower complexity) (Aberle, 2009).

A distinction must be made between scheduled services which are carried out regularly and charter services which are only carried out on demand. Airlines operate scheduled services on a specific day and at a specific time of the week with a dedicated aircraft that their customers can rely on. Non–regular services are

[1] Further decision parameters are the treatment of dangerous goods, live stocks, explosive goods, etc.

called charter services which are offered by airlines on an ad–hoc basis. Charter services are booked by the charterer for a certain time and route which are both determined by the charterer. Usually the entire aircraft capacity is sold to one charterer. In case of sufficient demand and an adequate willingness to pay, customers can book aircrafts for their dedicated services. On a worldwide scale scheduled services predominate by far the air cargo business but charter services are an important alternative for customers (Crabtree et al. 2006).

One–way trips (unidirectional) are standard because of the geographical concentration of cargo demand (e.g. China) and its consumption at the destination (e.g. textiles, perishables). In contrast, passenger trips are mostly planned in advance (especially leisure and holiday trips) and are mainly booked as return flights which lead to an almost equal utilization of both directions (Terhorst, 1992).

The decision of customers to choose air transport instead of other transport modes is usually based on its following advantages (Grandjot et al., 2007):

- very short transport times (which allow special goods to be transported also on long distances, such as spare parts, perishables and newspapers)
- low damage or loss risk (corresponds to low insurance rates as well as lower packaging cost)
- very high security criteria
- a high geographical coverage
- small warehousing cost because of its reliability, punctuality, flexibility and its very short transport times

On the other hand, air transport has much higher transport rates (in average more than ten times higher than maritime transport (Spohr, 2007)) and much lower overall transport capacities than maritime transport which are moreover extremely standardised depending on the operating aircraft and the fleet of the airline. Therefore, air cargo qualifies for very high value and sensitive goods that require high safety as well as high surveillance standards.

2.2 Air cargo logistics chain

The shipment of goods from origin to destination does not consist of one single and homogeneous service but of different service steps which are usually carried out one after another. The typical three main steps of the air freight logistics chain commences after transport capacities have been sold to the (end) customer either via the airline or in general via the freight forwarder. Goods are collected by a forwarder from the (end) customer or a dedicated assembly point and are transported (usually by truck) to a trans–shipment centre. In the trans–shipment centre goods are sorted, consolidated and pooled to larger units (e.g. pallets, containers). Such units are finally packaged according to their requirements, their destination and the aircraft operating on that specific route either at the trans–shipment centre or directly at the airport. Most air freight forwarders operate trans–shipment centre directly at the airport to minimise transport cost and to be more flexible concerning available aircraft capacities. However, also the direct delivery from a non–airport trans–shipment centre to the airline is possible. In case that the end customer books capacities directly via the airline a delivery to the airport is common, and the airline carries out sorting, consolidating and pooling of the goods. This first step of the air freight logistics chain usually takes 26% of total transport time (Helmig, 2005).

Ground handling agents load the aircraft and assure that all specific requirements of the transported goods are fulfilled. Afterwards, the core of the air freight logistics chain proceeds, the flight from origin to destination airport[2]. In average air freight is in the air for only 17% of total transport time (Helmig, 2005). This core step of the air freight logistics chain is the object of investigation for the present dissertation.

At the destination airport freight is unloaded by ground handling agents and cleared by customs. The transported units (e.g. pallets, containers) are unpooled, unconsolidated and shipped to their final destination usually by freight forwarders. The last step takes around 57% of total transport time (Helmig, 2005).

2.3 Business models of cargo airlines[3]

Network decisions are based on the business strategy of the airline as fleet composition, cost structure, core markets, customer segments, etc. are determined by the airline's business strategy. Therefore, a deeper look into the airlines' business models is needed. Kleiser (2010) developed an approach to classify airlines according to their business model which bases on three steps and finally differentiates eight independent business models. The three steps as well as the eight business models (dark–grey shaped) are illustrated in Figure 1, and the approach as well as the business models will be introduced in the following.

Step 1 – Coverage of the logistics chain

Cargo airlines are firstly examined by their coverage of the logistics chain. Vertically integrated carriers, the so–called Integrators (e.g. FedEx), offer door–to–door services (Grandjot et al., 2007) whereas airport–to–airport carriers (e.g. Lufthansa) focus on the core part of the air freight logistics chain (Jansen 2002). Apart from distinguishing between door–to–door and airport–to–airport providers, a third business philosophy can be differentiated the so–called Aircraft, Crew, Maintenance, Insurance Providers (ACMI Provider). ACMI providers (e.g. Atlas Air) lease their entire aircrafts (including crew) to air cargo airlines and do not offer transport services to (end) customers (DVZ, 2008). Integrators' main customers are end customers whereas airport–to–airport providers primarily serve freight forwarders.

[2] In some regions (e.g. Europe) the transport service is mainly realized by trucks. This strategic decision is taken by each carrier separately and is based on the total logistics cost (e.g. transport cost, warehousing cost) which are dependent on the general conditions of the specific market (e.g. geographical dimension of the region, road network, frequency, cargo quantities).

[3] In relation to this chapter, the following article has been published which has been supervised by the present author: Kleiser (2010).

At the end of step 1 two homogeneous business models are distinguished, namely Integrators and ACMI providers (see Figure 1) and their characteristics are explained in chapter 2.3.1 and 2.3.2 respectively. The third category of airport–to–airport operators is still heterogeneous and needs to be further differentiated based on their market positioning is needed.

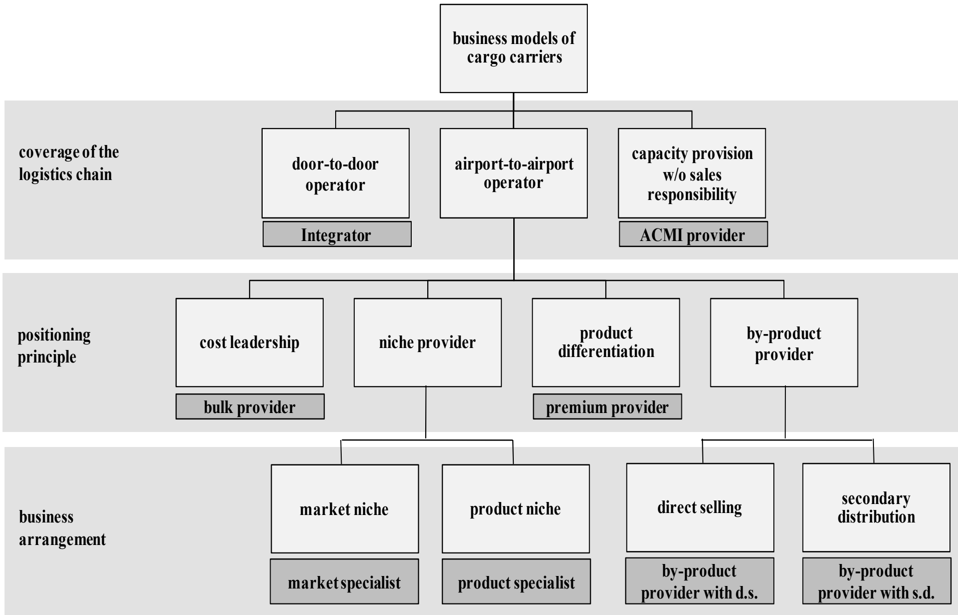


Figure 1: Classification scheme to characterise cargo airlines according to their business model (Source: author's own representation based on Kleiser, 2010)

Step 2 – Positioning principle

Michael E. Porter (1999) analysed competitive advantages of companies and identified three strategies to manage a strong market position in a competitive environment: cost leadership, differentiation strategy or niche strategy (Porter, 1999). The air freight market is highly competitive as entry barriers are negligible because of aircraft leasing opportunities and slots are available especially at secondary (uncongested) airports. Therefore, the approach of Porter (1999) is also applicable for the air cargo market and cost leadership, differentiation strategy and niche strategy further differentiate airport–to–airport operators.

Cost leadership in a competitive market implies a very lean service and it requires easily–manufactured products (standardised products), an efficient and inexpensive distribution system and a high output level (Porter, 1999; Grund–Ludwig, 2008). In the air cargo sector such properties are possessed by the so–called mass providers (cf. chapter 2.3.3.1 for further details).

The strategy of differentiation aims to achieve a clear distinction from competitors by concentrating on characteristics that assure an island position in the market (Porter 1999). The intention is to tie customers by the added value of the offered products. Premium providers emphasize on a differentiation strategy (cf. chapter 2.3.3.2 for details)

Niche providers concentrate on services for an explicit group of customers, for a special part of the logistics chain or/and for a geographically limited market. Niche providers “can achieve their strategically limited goal more effectively and efficiently than competitors who are situated in the broad competition” (Porter, 1999). Niche providers need to be further distinguished in the following as different niches exist in the market.

Step 3 – Market position arrangement

Geographical niche providers (market specialists: cf. chapter 2.3.3.3.2 for details) can be differentiated from product niche providers (product specialist, cf. chapter 2.3.3.3.1 for details) whereas airlines that do not follow a predominant positioning strategy consider freight transport only as a by–product. Their overall focus is on passenger transport. Freight is only shipped on existing routes when cargo does not constrain passenger services and conveniences (e.g. maximum payload of the aircraft) and when the necessary cargo load devices fit into the operating aircraft. Such airlines can be differentiated by means of their distribution system into providers with and without a corporate distribution unit (by–product provider with direct distribution versus by–product–provider with secondary distribution).

Based on these three steps eight core business models are distinguished and will be introduced in detail in the following:

- Integrators
- ACMI providers
- Mass providers
- Product specialist
- Market specialist
- Premium provider
- By–product provider with direct distribution
- By–product provider with secondary distribution

2.3.1 Integrators

Integrators are vertically integrated transport providers that cover and serve the complete air cargo logistics chain from the door of the shipper to the door of the recipient (consumer–to–consumer). The largest Integrators are FedEx, DHL, UPS and TNT.

Integrators are focused on freight transport only. Therefore, only pure cargo fleets (so–called freighter aircrafts) are used which are operated on scheduled services (Kleiser, 2010). Remaining capacities are sold to airport–to–airport providers which partially use these capacities to handle their own express products (Kleiser, 2010). Integrators operate an air cargo network of global coverage, and their worldwide network is organised as a multiregional hub–and–spoke system with dedicated departure and arrival waves. Cargo is mainly turned over at night by using automatic sorting machines to enable short transport times (Bachmeier, 1999). From the destination airport and to the origin airport Integrators use ground transportation (mainly trucks) to reach the final destination and the pick–up location of the freight. Integrators operate large fleets of trucks to be able to carry out the delivery transports independently. Therefore, Integrators achieve a majority of their added values by themselves. Only few activities are outsourced (Knyphausen–Aufseß and Meinhardt, 2002). Caused by the high added value, the continuous transport chain and the quality of their services, integrators are able to achieve higher prices from their customers (Doganis, 2010)[4].

2.3.2 ACMI providers

ACMI (Aircraft–Crew–Maintenance–Insurance) providers do their business by leasing aircrafts to airlines (Grandjot et al, 2007). ACMI providers do not sell cargo capacities to end customers but operate the transport service from the origin to the destination airport on behalf of their customer airline. The business risk of the cargo transport (e.g. utilization, rates) stays completely with the customer airline. ACMI providers bear the risk of sufficient leasing contracts for their aircrafts.

The network and routing of ACMI aircrafts solely depend on the customer airline's strategy. Hereby, the ACMI operated flights are fully integrated in the network concept of the customer airline. ACMI providers and cargo airlines are therefore no competitors (Bjelicic 2001). ACMI providers are e.g. ABX Air, ASTAR Air Cargo and Atlas Air.

2.3.3 Airport–to–Airport carriers

2.3.3.1 Mass providers

Mass providers are airport–to–airport operators with a corporate strategy of offering under–average priced services to achieve the cost leadership in the market (Kleiser, 2010). Cost leadership is achieved through economies of scale with scheduled services, high capacities, high frequencies, efficient distribution systems and standardized products and aircrafts (Grund–Ludwig, 2008). In order to achieve a competitive position as a mass provider, it is essential to have a simple business model with lean handling processes (no auxiliary services such as chilled/frozen transport products).

Mass providers offer services on the major global markets, but they do not aim at a full global coverage as Integrators do. A reason for that are the high capacities and frequencies offered for achieving economies of scale. Mass providers operate a homogeneous pure freighter fleet (usually B 747F), which concentrates on selected routes with a sufficiently large demand for mass cargo.

Mass providers' main customers are freight forwarders (Jansen 2002). The freight forwarder usually operates the feeder services to/from the airport whereas the airline focuses on the airport–to–airport transport. Mass providers mainly

[4] A detailed analysis on Integrators can be found in e.g. Onghena (2011).

transport standardized goods and determine their permitted sizes as well as the type of required packaging. Standardized freight does not need comprehensive customized handling activities, and lean services can be achieved by the carrier. A typical mass provider is the cargo airline Cargolux.

2.3.3.2 Premium providers

Premium providers differ from their competitors by emphasizing on quality and service in the segment of express, special and standardized cargo. Premium providers offer a broad, fast and attractive network to their customers which are mainly freight forwarders and the production sector (Kleiser, 2010).

Premium providers are globally acting passenger airlines that build their freight services on a comprehensive passenger network. Therefore, destinations can be offered with a low freight but sufficient passenger demand. The airports where freight is turned over are the passenger hubs of the airline.

Premium providers started as highly standardized freight providers that only considered freight as a by–product to their core passenger business. Nowadays, premium providers increasingly focus on express or special freight (e.g. perishables, very high value goods) to achieve higher added values which can be charged to their customers (Kleiser, 2010). Airlines following a premium strategy are e.g. Lufthansa Cargo, Air France Cargo, and Singapore Airlines Cargo.

2.3.3.3 Niche providers

2.3.3.3.1 Product specialists

Product specialists are airport–to–airport carriers which concentrate on specialised goods or specialised products (Kleiser, 2010). Goods that are transported very irregular or that need special treatment are the core business of product specialists. Product specialists need to be extremely flexible, operate pure freighter fleets only and offer services globally on–demand (charter flights). Product specialists generally do not operate a fully developed hub–and–spoke system but turn over the freight as required by their customers. Product specialists distribute their capacities via direct distribution or via chart broker (Schmeling, 2006a). An exemplary airline is Volga–Dnepr which concentrates on oversized goods.

2.3.3.3.2 Market specialists

Niche providers that focus on selected geographical markets are called market specialists. They transport goods from their core market which is in most cases their home market to non–home destinations. Freight is primarily turned over at the home basis of the carrier in case that the market specialist is a pure cargo carrier or at the passenger hub of the airline when the carrier is a combined airline.

Market specialists mainly transport standardized freight. The primary reason for this is either the objective to have lean handling processes (pure cargo carrier) or their low priority of the cargo business (combined carrier). Therefore, combined carriers only use their belly capacities for freight transport.

Market specialists are traditional airport–to–airport providers whose main customers are freight forwarders. Airlines such as Royal Jordanian Airlines (combined carrier) and Air India (combined carrier) are market specialists.

2.3.3.4 By–product provider

Airport–to–airport providers with only a little share of cargo revenues on their total turnover, and almost no focus on freight business are called by–product providers. Cargo is transported to achieve higher profit margins on existing flights with available cargo capacities as well as to utilize their aircrafts to full capacity.

Network structures of by–product providers are predetermined by their passenger business only. Their network contains a large number of destinations especially in passenger affine regions (Thuermer, 2007). All cargo is turned over at the passenger hub(s) of the airline because of the utmost priority of the by–product provider to fulfil passengers' service requirements (Bowen, 2004). Therefore, complex handling processes are avoided by by–product providers, and only standardized freight services which are delivered by freight forwarders directly to the origin airport are offered.

By–product providers can be separated into two categories; by–product providers with direct distribution and without direct distribution. Airlines that can be classified as by–product providers with direct distribution are Delta Air Lines and Thai Airways whereas for example TUIfly and Air Berlin are by–product providers with secondary distribution. By–product providers with secondary distribution outsource their capacity distribution to general sales agents or sell their total belly capacities to cargo focused airlines.

2.4 Alliances and cooperation

Strategic alliances, such as Star Alliance, oneworld or SkyTeam, have been founded for passenger transport since the 1990s. An international airline alliance is an agreement between all member airlines to cooperate in a commercial relationship (Hsu and Shih, 2008). Primary objectives of airline alliances are the creation of a comprehensive, high quality and online network, to strengthen customer loyalty by widespread frequent–flyer–programs, by accessing new markets and by extending the own network under air traffic rights and resource limitations (Oum et al., 2001).

Strategic alliances in passenger transport have generally worked well when they have been formed for network–based (strategic alliance) rather than for specific market reasons (tactical alliances) (Zhang and Zhang, 2002). In strategic alliances partner airlines combine their networks to gain access to further geographical markets, whereas market alliances refer to route–based alliances in which airlines only cooperate on specific routes. Oum et al. (2000) found that strategic alliances tend to increase partner airlines' productivity and profitability.

Strategic considerations as well as efficiency gains also promoted the foundation of cargo alliances which developed mainly from existing passenger alliances such as SkyTeam Cargo from SkyTeam (AeroMexico Cargo, Air France – KLM Cargo, Alitalia Cargo, Czech Airlines Cargo, Delta Cargo and Korean Air Cargo) and WOW from Star Alliance members (SAS Cargo Group, Singapore Airlines Cargo and Japan Airlines Cargo[5]).

The success of cargo alliances never really commenced, results stayed far behind airlines' expectations, and cargo alliances appear to have little bearing on air cargo carriers (Zhang and Zhang, 2002). Reasons for the failure are mainly driven by the air cargo market characteristics:

- Demand concentration: The air cargo market is internationally extremely concentrated on few profitable routes (e.g. China–>US, China–>Europe, US – Europe). Hence, airlines tend to use their own capacities and optimize their load factors instead of cooperating with the alliance partners (Doganis, 2010).
- Load factor consideration: Indirect services with en–route stops are very common in the cargo business. Thus, total transport times are much higher than in passenger transport. Additional waiting times were accepted by the airlines to ship freight with the corporate aircrafts instead of saving some hours and cooperating within the alliance especially on profitable routes. Cooperation between the alliance partners only occurred at secondary markets which usually bear high extra cost (e.g. handling, re–packing) for the carrier and might finally be less profitable.
- Uniform appearance: A uniform appearance was missing, such as internet, contact person, marketing, etc. A common and standardized system has never been promoted by the partners and bookings, inquiries, complaints, etc. have to be communicated directly with the airline and cannot be directed via an alliance administrative office (Vahrenkamp, 2007). The focus of each cargo airline is on its own business. Hence, alliances do not play a significant role in the air cargo market.
- Coordination/cooperation: A comprehensive need for coordination and cooperation exist for cargo alliances (e.g. empty container management, software/hardware adaptations) which is far higher than for passenger alliances (cargo needs to be electronically monitored at all time).
- Heterogeneity of goods and products: In the passenger market differentiations between customers are small (e.g. size, weight), and their consequences for the airlines are even smaller – one passenger fits on one seat[6]. In the air cargo market products, services and transported goods differ extremely from another (e.g. perishables, standardised freight, refrigerated goods, frozen goods, oversized goods). Therefore, creating, steering and administrating a cargo alliance is more challenging and difficult than for passenger alliances (Grandjot et al., 2007).
- Time sensitiveness: Freight is transported by air especially because of its short transport times. Compared to passenger services time sensitiveness is

[5] Lufthansa Cargo was one of the alliance's founding airlines but exited the alliance in 2009 because of non-realised efficiency gains between the alliance partners.

[6] The only relevant differentiation for airlines is the passenger's booking class (e.g. first, business, economy). Alliances guarantee a similar booking class standard for all alliance partners. Thus, transfers between alliance partners occur for customer and airline without complications.

much smaller, so that the advantages of code–share flights and an alliance membership are rather small.

Successful concepts of cooperation in the air cargo industry exist either as vertically integrated cooperations or as business participations between cargo carriers and freight forwarders. The objective is a closer tie between forwarder and carrier to offer optimized products and services to end customers. Moreover, combined forces of carriers and freight forwarders are more competitive to Integrators which offer worldwide express services (Grandjot et al., 2007). The market of express (mail) services is very profitable as much higher rates can be charged to the end customer caused by the urgency of the goods. Combined services of cargo carriers and freight forwarders may successfully participate in such markets. Lindstädt and Fauser (2004) analysed business concepts of network carriers for passenger services and found out that the integrator approach where airlines pool their different business streams within one company is both less efficient and effective and they argue that airlines should preferably operate with separate entities which do have different business focuses. Such tendencies are currently also observed for air freight services.

Further promising cooperations exist between airport–to–airport providers and Integrators[7]. Such cooperations are meant for optimal capacity utilization and to achieve worldwide network coverage. Furthermore, shared facilities for maintenance, handling and clearing as well as joint terminals reduce fixed costs and risks of each airline.

2.5 Recapitulation

Air freight has developed very rapidly during the last decades from a pure by–product of passenger airlines to a self–contained business. The air cargo sector can be characterised by short transport times on long distances, as a reliable and safe transport mode, by comparatively little transport capacities (compared to ship, train and road transport) and by high average transport rates (Grin, 1998). Depending on the general needs and the requirements of the customer different services are offered by cargo airlines. Such differences are also reflected in the design of the airlines' business models. Services range from door–to–door to airport–to–airport services. Only four worldwide operating door–to–door airlines, the so called Integrators (e.g. FedEx), exist. Airport–to–airport operators are a very heterogeneous category with different core markets and core products (e.g. premium segment, mass freight provider, geographical focus).

Airport–to–airport providers that combine belly capacities of passenger aircrafts with freighter capacities of pure freighter aircrafts are called combined airlines. Former flag carriers, such as Lufthansa and Air France, play a significant role in

[7] Lufthansa Cargo (airport-to-airport operator), for instance, cooperates with DHL (Integrator). Both companies jointly founded AeroLogic a pure cargo carrier (shares are divided 50:50). On workdays, the busiest days for Integrators, AeroLogic flies primarily for DHL whereas on the weekends, highest demand for airport-to-airport providers, AeroLogic's aircrafts operate for Lufthansa Cargo solely. In addition, Lufthansa Cargo also ships freight for DHL on long-distance routes.

the air freight market as combined carriers. In contrast, pure cargo airport–to–airport carriers focus on cargo services only and operate pure freighter fleets.

Strategic alliances that generally worked well for passenger services have not had an impact on the air cargo market so that a focus on the single airline's network design can be justified. The following chapter analyses network structures of airport–to–airport airlines.

3 Cargo airlines' network structures

The present work is about cargo airlines and their network structures. Therefore, it is fundamental to understand the principles of networks before assessing real world air cargo networks. The chapter is organized as follows: Firstly, an introduction to graph theory in aviation is provided. Secondly, existing studies on air transport networks are presented and reviewed. All of these studies analyse passenger airline structures. Thirdly, the applied measurements for assessing air cargo networks are introduced and critically reviewed. Fourthly, typical airline network structures are presented, and their structures are assessed with the applied measurements. Fifthly, the chosen real world cargo airlines as well as the used dataset are introduced and in section six, their network structures are assessed. Finally, the chapter on real world network structures is recapitulated.

3.1 Graph theory in aviation research

A graph G consists of a set of vertices V(G) and a set of edges E(G). If e is an edge which links the vertices u and v, then e is said to join u with v (Bondy and Murty, 2008). The edges of a directed graph have directions pointing from one vertex u to another vertex v and only allow interaction between u and v in this direction. A directed graph D consists of a set of vertices V(D) and a set of directed edges A(D) which are called arcs. Each arc of D links an ordered pair of vertices of D (Bondy and Murty, 2008). The arc a is said to join the vertex u to the vertex v if a runs from u (origin) to v (destination). Edges and arcs can also be labelled with a corresponding strength which is given by a real number called weight. If each edge e of G (or arc a of G, respectively) is labelled with a weight w the pair (G,w) defines a weighted graph (Newman, 2010). In airline networks airports are the vertices whereas the arcs represent the routes between the airports. Weights in airline networks can be operating costs, route capacities, route demand, etc.

Graph and network are usually used synonymously in literature because both are interpreted as a set of vertices and a set of edges/arcs (with/without weights). The present understanding of networks is based on the work of Liedtke and Friedrich (2010) who ascertain a predominant characteristic to networks which is not required for graphs. A network is subject to the planning process of an economic actor and did not emerge randomly. The economic actor decides on the structure of the network as well as its service characteristics (Liedtke and Friedrich, 2010). Random graphs as researched by Solomonoff and Rapoport (1951) which appear either in neural networks, in social networks or in networks rooted in genetics are according to this understanding graphs but not networks. Cargo airlines are managed by an economic actor, the airline management, which decides on the network configuration, the operated vertices (airports) and arcs (flight routes), flight frequencies, aircrafts, etc. and develops therewith the airline's network.

Despite the differences in the understanding between graph and network, graph theoretical measures can also be applied to networks[8] and were firstly introduced to aviation research in the 1970s to describe and to illustrate airline networks (James et al., 1970 and Tinkler, 1977). As arc weights transportation costs, amount of goods, flights, passengers and so on are applied making airline networks directed, weighted and (mostly) connected[9] networks. These characteristics enable the application of traditional graph theoretical methods also for aviation specific challenges, such as network capacity problems or a price–effective network design. In particular, two graph theoretical network models are applied, namely the shortest–path problem methods and the network flow problem models (Bazargan, 2010).

Flow problems are further differentiated into minimum cost and maximum flow problems. Minimum cost flow problems are defined as to send flows from vertices through the network to vertices at minimum cost and without violating the lower and upper bounds on the arcs or at the vertices (Bazargan, 2010). Its objective function minimises the total network cost whereas constraints impose the bound restrictions along the arcs and satisfy the requirements of each vertex. Airlines are interested in determining the best way to transport goods, passengers or both from their origin airports to their destinations at minimal cost and without violating the given basic conditions (e.g. number of slots at airports, maximum capacity on arcs or at airports). Such real world problems can be approached by minimum cost flow problems.

The maximum flow problem is a specialisation of the minimum cost flow problem where all costs are set equal to zero and only the amount of flow which can be directed through the network is requested. Therefore, costs are not considered in the problem statement that the methodology focuses on flows only (e.g. number of flights, amount of passengers, cargo). The high degree of competition in the aviation business and especially for cargo transport suggests incorporating cost into network design modelling. The following research problem considers this.

The shortest–path problem is another specification of the minimum cost flow problem which is achieved if the capacity constraint of the minimum cost flow problem is removed. The shortest–path problem and its solution algorithms identify a path between two airports such that the sum of the arc weights of its constituent arcs is minimised. Transportation times or transportation costs are used as arc weights to identify the fastest or cost minimal network configuration. In its simplest form the shortest–path problem is represented by a binary integer programming model (Bazargan, 2010):

8 Graph theory has become state-of-the-art in representing networks in general. A detailed overview on different application cases (incl. measures, techniques, etc.) can be found in Newman (2010) who differentiates between technological networks (incl. physical networks), social networks, information networks and biological networks.

9 In a connected network every two vertices are linked by at least one path (every vertex can be reached from every other vertex of the network).

Objective function:

$$\text{Min} \sum_{i \in M} \sum_{j \in M} c_{i,j} x_{i,j}$$

Subject to:

$\sum_{j \in M} x_{1,j} = 1$, $j \neq 1$

$\sum_{j \in M} x_{i,j} - \sum_{k \in M} x_{k,i} = 0$, for all i, i $\neq$1 and i $\neq$ m

$\sum_{i \in M} x_{i,m} = 1$

Where M is a set of vertices, i,j,k are indices for the vertices, $c_{i,j}$ is the cost of flow from i to j, m is the destination mode and $x_{i,j}$ is the decision variable with $x_{i,j}$=1 if arc (i,j) is part of the path and 0 otherwise.

The objective function minimises the flow cost between the vertices whereas the constraints guarantee that the flow is shipped from the origin vertex, that all other vertices are transhipment vertices only and that the flow is finally received at the destination vertex (airport).

The application cases show that graph theory provides powerful methods and algorithms for the study of airline networks. Therefore, literature on the study of airline networks is sighted first, and the measures that will be applied in the present dissertation are deduced from these observations afterwards.

3.2 Literature review on the study of airline networks

In academic literature two philosophies exist that aim to describe airline networks: the spatial approach and the temporal approach. The spatial configuration can be defined as the level of concentration of an airline network around one or a few central hub airports (concentration in space). The temporal concentration analyses how departure and arrival flights are coordinated at the main airport of the airline (usually its hub airport). Airlines operate synchronized waves of flights from their hub(s) with the aim to optimize the quantity and quality of connections offered and to increase aircraft utilization (Graham, 1995; Reynolds–Feighan, 2000).

The spatial approach was developed in the 1960s to research the spatial characteristics of networks and was recently applied to study airline networks in detail, such as line networks (Hanlon, 1996), fully connected versus hub–and–spoke networks (e.g. Shy, 1997) and linear versus hub–and–spoke networks (e.g. Oum et al., 1995). Furthermore, measurements (indices) were developed to distinguish quantitatively between the observed structures especially after the deregulation act of the US air transport market in 1978. All studies focus on the classification of air passenger networks whereas cargo services as well as cargo airlines are neglected. A summary of the introduced measures is presented in Table 1.

Table 1: Literature review on spatial network measurements (Source: author's own representation)

Measure	Publication in aviation research	Calculation basis
Number/percentage of transfer passengers	e.g. Kanafani and Ghobrial (1985)	Concentration measure
Percentage of traffic at the three busiest airports	e.g. McShan and Windle (1989)	Concentration measure
Number of outlying cities served from pre–defined hubs divided by the number of spokes radiating from the hub	e.g. Toh and Higgins (1985)	Concentration measure
Chou`s beta index of spatial concentration	e.g. Chou (1993a, 1993b)	Graph theory
Valued–graph index	e.g. Shaw (1993)	Graph theory
Topological hubbing index	e.g. Wojahn (2001)	Graph theory
Gross vertex connectivity	e.g. Ivy (1993)	Graph theory
Herfindahl index	e.g. McShan (1986)	Economic theory
Theil`s entropy measure	e.g. Reynolds–Feighan (1998)	Economic theory
Concentration ratio	e.g. Burghouwt (2007)	Economic theory
Gini index	e.g. Reynolds–Feighan (2001)	Economic theory

At first very simple measures were applied including the number and percentage of transfer passengers (e.g. Kanafani and Ghobrial, 1985), the percentage of traffic at the three busiest airports of the airline (e.g. McShan and Windle, 1989) and the number of outlying cities served from pre–defined hubs divided by the number of spokes radiating from the hub (e.g. Toh and Higgins, 1985). All of these measures focus on one (or few) airport(s) of the network and do not consider the total network structure of the airline.

More advanced measures include Chou`s beta index of spatial concentration (Chou, 1993a and Chou, 1993b), the valued–graph index (Shaw, 1993), the topological hubbing index (Wojahn, 2001) and the gross vertex connectivity (Ivy, 1993). The topological hubbing index, for instance, combines four independent indices, namely the normalized Gini–coefficient, the Theil index, the McShan–Windle index and the coefficient of variation whereas the valued–graph index sums up for each node (airport) the distances to all other nodes (airports).

Based on economic theory concentration measures have been applied to study the distribution of concentration within the airline network. Measures such as the coefficient of variance[10], the Herfindahl index[11], Theil`s entropy measure[12], the concentration ratio[13] and the Gini index[14] are published in literature as spatial concentration indices of airline network structures. All these indices have a long tradition as income inequality measures. Allison (1978) and Sen (1976) analysed their properties, compared their results and recommended their use: The concentration ratio (CRk) only reacts when the concentration of the largest k nodes (e.g. airports) changes. All other changes within the network distribution of the airline do not have any influence on the result of the measure. The Herfindahl index is only sensitive to distribution changes in the extremes as the index squares the relative shares of all nodes. The coefficient of variance reacts sensitive to changes in the network but is extremely sensitive to the underlying distribution. Reynolds–Feighan (2001) analysed the Gini index on the basis of axioms that were introduced by Sen (1976) and which should be satisfied by a concentration measure for airline traffic distribution:

- the concentration measure is increased if a lower ranked airport's traffic proportion is reduced (monotonicity axiom)
- a pure transfer of traffic from a low ranked airport to a high ranked airport will increase the concentration measure (transfer axiom)
- the weight on the traffic gap of airport i equals the number of airports in the network with at least the same traffic proportion as airport i (ordinal rank weight axiom)

Reynolds–Feighan (2001) recommended the use of the Gini index as it satisfies all of these axioms.

Alderighi et al. (2007) applied a famous concept of social network analysis to airline network structures, the concept of centrality. Centrality measures the shape of the network rather than the network concentration. Three main concepts of centrality have been developed by Freeman in the late 1970s, the concept of degree centrality, closeness centrality and betweenness centrality (Freeman, 1978). Degree is the number of nodes that one vertex (e.g. airport) is connected to but it does not take into account the global structure of the total network (Opsahl et al., 2010). Closeness centrality is the inverse sum of shortest distances to all other nodes from one vertex and is generally restricted to nodes within the largest component of a network. The last of the three measures, betweenness centrality, assesses the degree to which a vertex lies on the shortest path between two other nodes (Freeman, 1978). Nodes with a high betweenness value are able to control the flows within

[10] The coefficient of variation is a normalized measure of dispersion of a probability distribution. It is defined as the ratio of the standard deviation to the mean value of the sample.

[11] The Herfindahl index is a measure of the size of firms (or airports) in relation to the size of the total industry (network).

[12] Theil`s entropy measure is used to quantify economic inequality and is superior to the Gini index when analysing concentrations within clusters of grouped agents (Conceicao and Ferreira, 2000). The present analysis based on disaggregated (non-grouped) data (e.g. freight volumes at single airports, departures/landings at single airports) so that the superior characteristic of the Theil's measure is not required.

[13] The concentration ratio measures the output of a number of firms in relation to the total market size.

[14] The Gini Coefficient is the area between Lorenz curve (real distribution within the network) and the bisectrix (representing an equal distribution within the network).

the network and are therefore extremely important for the overall airline network. In contrast to concentration measures which focus on the spatial concentration within the network, centrality measures assess the network's structural configuration.

3.3 Measurements for the study of cargo airline networks

The objective of the present work is to model cargo airlines' networks close to reality. Therefore, two families of measurements are applied for comparisons between modelled and real world network structures, namely concentration and centrality measures. Based on recommendations of Reynolds–Feighan (2001) the Gini index has been considered as the primary concentrations measure. Furthermore, the Herfindahl–Index (HI) and the concentration ratio (CRk) are calculated as supporting measures and to compare the results of the Gini index with other concentration measures. In analogy to Alderighi et al. (2007) betweenness centrality is applied as the measurement for network configuration. The chosen measurements are introduced and defined in the following:

The Gini index (GI) as a measure for spatial concentration can be defined as

$$\mathrm{GI} = \left(\frac{2 * \sum_{i=1}^{n} i * x_i}{n * \sum_{i=1}^{n} x_i} - \frac{(n+1)}{n}\right)$$

where x_i is the absolute traffic of the analysed airline at airport i, with x_i is increasing in i according to its annual cargo capacities and n is the number of airports.

In the context of this research GI can be interpreted as follows: The smaller the GI of an airline's network, the more equal the airline distributes its traffic to all airports. In other words, a large index express that the airline focuses on one or a few airports only (Scholz, 2011).

The GI increases with the number of airports in a network and is therefore size dependent. To be able to compare airline networks of different sizes GI needs to be standardized. The maximum value for GI of airlines is dependent on the market size and can be computed as (Burghouwt et al., 2003):

$$\mathrm{GI}_{max} = \frac{(n-2)}{n}$$

The maximum Gini index can be observed in a single–hub network where traffic is concentrated on one route (feeder flights from hub to spoke airport) (Burghouwt, 2007).

The standardized Gini–coefficient[15] (GI*) equals the observed Gini index (GI) divided by its maximum value (GI_{max}). GI* guarantees that the spatial concentration is independent of network size and that networks of different sizes

[15] Burghouwt (2007) entitles the introduced standardized GI* as NC (network concentration).

can be compared comprehensively. For that reason, GI* is used as the primary concentration measure.

The Herfindahl–Index (HI) of an airline's network is computed as

$$HI=\sum_{i=1}^{n} s_i^2$$

where s_i is the share of air traffic at airport i in relation to the total traffic of the airline and n is the number of airports in the network.

The HI takes into account the relative size and distribution of the nodes (e.g. airports) in the network. It is size dependent and its minimum for a fixed number of actors is achieved in case of equal shares resulting in a value of 1/n. Furthermore, the HI is primarily sensitive to changes in the extremes which is a property of the square–function which gives high weights to the largest airports. The HI is the most frequently used measure of market concentration. Since 1982, the index plays a central role in the US Justice Department's merger guidelines (e.g. Rhoades, 1993).

The concentration ratio CRk is the fraction of the airline's network held by the largest k airports.

$$CRk=\sum_{i=1}^{k} s_i$$

The CR is a single point on the concentration curve and has a range between 0 and 1 (Hall and Tideman, 1967). Its value only changes when the largest k airports are affected. CR1 and CR3 are calculated to analyse the concentration of the major airports and their importance for the entire network.

Betweenness centrality (CB) is a measurement for the network shape, and it is based on geodesic distances (Freeman, 1978). In graph theory, the geodesic distance between two nodes is defined as the length of the shortest path between them whereas its length is defined as the number of intermediate stops (Alderighi et al., 2007). The betweenness centrality CB of airport i requires the evaluation of all geodesic paths within the network and is calculated as follows (Alderighi et al., 2007):

$$CB(i)=\sum_{j<k}^{k}\sum_{j<k}^{n} b_{jk}(i)$$

With

$$b_{jk}(i) = \frac{g_{jk}(i)}{g_{jk}}$$

where g_{jk} is the number of geodesics linking airport j with airport k, and $g_{jk}(i)$ is the number of geodesics that pass by airport i (transfer airport). The centrality of airport i CB(i) is the sum of all b_{jk} values for all unordered pairs of points where $j < k$ and $i \neq j \neq k$.

Freeman's centrality index of a network is defined as the average difference between the relative centrality of the most central airport CB(i*) and that of all other airports within the network (i*: CB(i*) ≥ CB(i) for all i).

$$CB=\frac{\sum_{i=1}^{n} CB\left(i^{*}\right)-CB(i)}{(n^{3}-4n^{2}+5n-2)}$$

where CB(i) is the centrality score of airport i and i* is the most central airport (highest CB value).

Betweenness centrality measures the network configuration as a percentage of a perfect star network which is found in aviation by a perfect hub–and–spoke (H&S) network configuration (Alderighi et al., 2007). Therefore, the concept of betweenness has been chosen for analysis to measure the similarity of the airline's network to a perfect H&S configuration.

3.4 Network types of cargo airlines

Since deregulation of the US airline industry in 1978, hub–and–spoke networks (H&S) emerged as the major network configuration of full–service passenger airlines in deregulated markets (Reynolds–Feighan, 2001). The advantage of H&S structures is its efficiency for operating large networks by maximizing the number of destinations under the restrictions of the airline's capacity (TRB, 1991). The advantages of H&S operations for airlines are the achievement of regional market dominance as well as economies of scale[16], scope[17] and density[18] (Burghouwt, 2007). Customers benefit from a wider range of destinations (via indirect connections at the hub airport) at higher frequencies that otherwise could not be afforded by the airline with the same number of routes (Pels, 2001). The more central an airline's network the greater these advantages to customers as well as the airline. Nevertheless, centralised network structures do not come without drawbacks. Hub congestion is a major challenge to the airlines and delays may spread over the entire network (Lederer and Nambimadom, 1998). Network duplication and network complexity issues are further disadvantages of large H&S structures that can be observed in real world airline networks.

Point–to–Point (P2P) network configurations are focussing on direct traffic (non–hub traffic) which became widespread with the entrant of low–cost carriers (e.g. Southwest Airlines, Ryanair). Only direct services are offered to passengers to

[16] The concept of economies of scale means that cost per unit decrease if output increase.

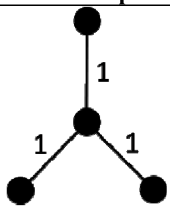
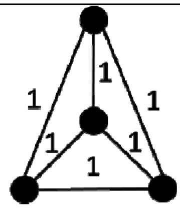
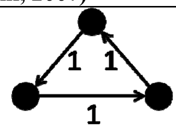
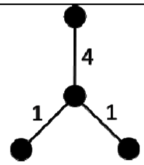
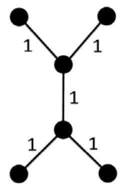
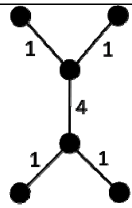
[17] The concept of economies of scope means that cost per unit decrease if output variety is increased by similar products (services).

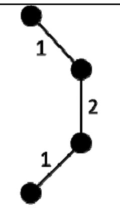
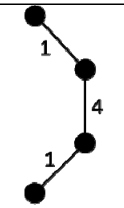
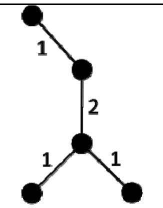
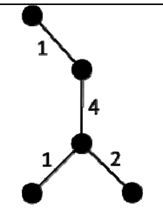
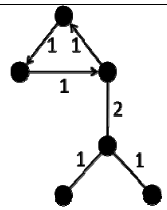
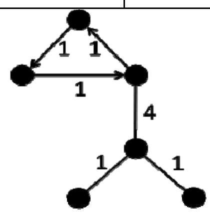
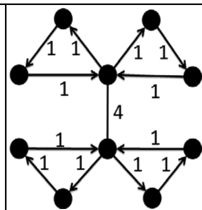
[18] The concept of economies of density means that cost per unit decrease if density (e.g. traffic on a route) is increased.

reduce their total travel time and to be more convenient without transferring at hub airports. Furthermore, decentralised networks are less vulnerable to delays which only affect single routes instead of whole network components. Hence, a high schedule reliability can be achieved (Lederer and Nambimadom, 1998).

Beside these two perfect network structures, a large number of mixed structures exist (e.g. Air Berlin's hybrid network). Table 2 illustrates selected idealized network structures and summarises their performances concerning the chosen concentration and centrality measures. The illustrated network structures are classified based on their core network configuration and are introduced in detail afterwards.

Table 2: Selected spatial network types
(Source: author's own representation based on Alderighi, 2007)

1. Category: Perfect configurations	 **A**: Perfect H&S GI*=0.5 HI=0.33 CB=1.0	 **B**: Perfect P2P GI*=0.0 HI=0.25 CB=0.0	 **C**: Perfect Round–trip GI*=0.0 HI=0.33 CB=0.0
2. Category: H&S configurations	 **D**: H&S w concentration at one spoke GI*=0.75 HI=0.38 CB=1.0	 **E**: Multi–H&S GI*=0.4 HI=0.22 CB=0.56	 **F**: Multi–H&S w concentration between hubs GI*=0.63 HI=0.3 CB=0.56

<table>
<tr>
<td>3. Category: Linear network configurations</td>
<td>
G: Linear network
GI*=0.5 HI=0.31
CB=0.44</td>
<td colspan="2">
H: Linear network w concentration between hubs
GI*=0.67 HI=0.36
CB=0.44</td>
</tr>
<tr>
<td>4. Category: Mixed configurations of H&S and linear configurations</td>
<td>
I: H&S w linear component
GI*=0.53 HI=0.28
CB=0.71</td>
<td colspan="2">
K: H&S w linear component and concentration at one spoke
GI*=0.67 HI=0.31
CB=0.71</td>
</tr>
<tr>
<td>5. Category: Mixed configuration of H&S and round–trip configurations</td>
<td>
L: H&S w round–trip at one hub
GI*=0.48
HI=0.24
CB=0.49</td>
<td>
M: H&S w round–trip at one hub and concentration between hubs
GI*=0.62
HI=0.29
CB=0.49</td>
<td>
N: H&S w round–trips at all spokes
GI*=0.5
HI=0.2
CB=0.47</td>
</tr>
</table>

GI* and CB range from zero to one whereas HI ranges from 1/n to one with n being the number of serviced airports. In general, the greater the index, the more concentrated, respectively centralised is the network configuration of the airline. The first observations of the selected networks illustrate the challenges of network classification because similar values result for different network types. However, the combination of measures allows general conclusions on the classification of airline networks which always need to be enriched with corporate in–depth information.

GI* and CB takes value zero in case of a perfect P2P or in case of a perfect round–trip structure where all destinations are served equally. With a perfect H&S structure, GI* takes 0.5 and betweenness centrality takes 1.0 indicating a supreme central airport within the airline network, i.e. the hub airport. Operating an H&S scheme around a hub airport allows an airline to take advantage of higher freight/passenger volumes by using larger aircrafts including the scale economy it creates, a characteristic common to all scheduled transport systems (Kanafani and Ghobrial, 1985). The preference of customers for higher frequencies can be complied by the airline via its hub strategy. Airlines are able to achieve relatively high load factors by consolidating flights at major connecting hubs. Therefore, H&S configurations have higher GI* concentrations and also comparatively high HI values whereas the centrality score varies significantly between one hub and multi–hub configurations. In case of a pure single hub network all routes pass by the hub airport whereas for a multi hub network, shortest paths exist where only one of the two hubs is used as transfer point within the network which leads to much lower centrality scores for multi–hub network structures. Both concentration indices prove the importance of the hub airport in an H&S network scheme with high concentration values.

Linear network configurations are characterised by smaller centrality scores than for the other network structures except the perfect P2P and the perfect round–trip structures. No hubbing activities are offered that concentrate and centralise flight activities at one airport resulting in lower scores than for most other network configurations.

Mixed configurations based on H&S configurations with linear elements show their mixed natures also in the index scores. Centrality is less distinct than for most other H&S configurations because of the linear component of the network configuration whereas concentration measures signalize higher importance of major airports for the entire network.

Round–trip configurations can be characterised by comparatively low centrality as well as concentration scores. The higher the importance of a single link within the network, the higher is the concentration level for the entire network (GI* and HI). Centrality measure identifies the round–trip configuration but does not serve as a valuable indicator for detecting differences within the category.

Summarising the observations from the examples, some general conclusions can be drawn:

- both concentration indices (Gini and Herfindahl index) can be applied to measure the flight frequency concentration of the network
- the Gini index is much more volatile than the Herfindahl index making the index sensitive to changes in the network traffic distribution
- the Gini and the Herfindahl index are affected by the frequencies and their distribution within the network (see network G versus network H)
- the Gini index fulfils the axioms of monotonicity, of transfer and of ordinal weight axiom as shown by Reynolds–Feighan (2001) but the index fails to detect the spatial morphology of the network (see network B versus network C)

- betweenness centrality measures the shape of the network (morphology) (Alderighi, 2007)
- reference configurations are the perfect P2P (CB=0) and the perfect H&S (CB=1) structure
- all other configurations are measured as the degree of inequality with respect to the pure H&S network structure (Alderighi, 2007)
- betweenness centrality fails to measure the concentration of frequencies
- only the combination of centrality and concentration measures assesses network configuration as well as network concentration.

3.5 Data and selection of real world cargo airlines

Data of the Official Airline Guide (OAG) for the year 2007 have been chosen for analysis. The database contains variables based on published information on planned scheduled flights of participating airlines for the coming twelve months. Each flight within the OAG database is characterised among others by its flight number, departure airport, destination airport, aircraft type, cargo and seat capacity and its number of en–route stops. The considered database is of April 2007. Limitations of the OAG database are (Burghouwt, 2007)[19]:

- data are based on planned scheduled flights (future perspective) instead of realized services
- data only include scheduled services (no charter services)
- road feeder services are not incorporated into the database by every airline

In contrast to other studies, flights of the whole year instead of one representative week are considered. Air cargo has very high demand volatility over the year with demand peaks in November and December as well as before Easter and less demand in summer. To avoid data tilts flights of the entire year are selected for analysis.

Burghouwt et al. (2003) suggest analysing the number of seats (capacity) instead of flight frequencies per time to characterise airline networks. In contrast, Alderighi et al. (2007) recommend using the number of flights to reduce the impacts of short–term aircraft changes. The present analysis follows Burghouwt's suggestion by applying capacities instead of frequencies to be able to incorporate aircraft size into the calculations. In particular, in cargo transport the impact of aircraft size is substantial and ranges from few tonnes (e.g. A320 family) to more than hundred tonnes of cargo payload per aircraft (e.g. B747–400 freighter). An entire consideration of economies of scale can only be achieved by applying a capacity dependent indicator. As indicator the annual available freight capacities (annual maximum payload) is used.

The analysis focuses on routes operated under the International Air Transport Association (IATA). This means that every flight with an official flight number is included in the sample. Flights with one (or more) en–route stops are recorded for

[19] These limitations are known to the author, but in order to be able to use this comprehensive and best developed dataset, the limitations needed to be accepted. However, interpretations of the results as well as general conclusions need to consider these shortcomings.

each of the sector separately (e.g. LH8370 from FRA to ICN via TSE is recorded as FRA–TSE, TSE–ICN). Code–share flights have only been assigned to the operating airline (no double–counting), and Road Feeder Services (RFS) were excluded from analysis because data on RFS have been incomplete in the database for some analysed airlines which would lead to biased conclusions.

The selection of airlines is based on the business model classification of chapter 2, and only airport–to–airport airlines are considered for analysis. Out of the eight business models two major categories have been created for analysis, namely combined airlines and pure freighter airlines. Combined airlines are premium providers that build their networks on a comprehensive passenger network. Lufthansa is a representative of this category. Category two incorporates airlines that focus on freight transportation only. The corresponding business models are mass providers as well as pure cargo niche providers, and Cargolux is a representative of this category. Finally, a sub–category of combined airlines, their pure freighter operation, is analysed separately (e.g. Lufthansa Cargo). Table 3 displays the characteristics of the three airline categories.

Table 3: Analysed groups of air cargo carriers
(Source: author's own representation)

Airline category	Primary business	Cargo capacity from	Selected carriers for analysis
Combined carriers	Passenger services	Belly capacity and pure freighter capacities (optionally)	Air France (AF), China Airlines (CI), Cathay Pacific (CX), Korean Air (KE), Lufthansa (LH), Singapore Airlines (SQ).
Cargo brands (Freighter fleet of combined carriers)	Cargo services	Freighter fleet	Air France Cargo, China Airlines Cargo, Cathay Pacific Cargo, Korean Air Cargo, Lufthansa Cargo, Singapore Airlines Cargo.
Pure cargo airlines	Cargo services	Freighter fleet	China Cargo Airlines (CK), Cargolux (CV), ABX Air (GB), Nippon Air Cargo (KZ), Varig Logistica (LC), Polar Air (PO).

The distinction between the three airline categories has been made, so that the following questions can be answered: How do structural differences in the business models impact network configuration of cargo airlines? Is the network structure of combined carriers also reflected in the network configuration of their cargo brands? Is the network structure of the cargo brands similar to the network configuration of pure freighter airlines?

3.6 Network configurations of real world cargo airlines

The results of the network structure analysis will be discussed in the following section[20]. In the beginning the network structures of combined airlines are introduced. The chosen airlines follow the business model of premium airport–to–airport providers. Next, the pure freighter fleet of the previously discussed combined carriers are presented, and their results are compared with the network structures of the whole airline. Finally, the networks of airlines that focus on cargo transport exclusively are acquainted.

3.6.1 Combined airlines

Six combined airlines are chosen for analysis: Air France (AF), China Airlines (CI), Cathay Pacific (CX), Korean Air (KE), Lufthansa (LH) and Singapore Airlines (SQ). The primary focus of combined carriers is on their passenger business but cargo service plays an increasing role for their corporate success. The overall results are displayed in Figure 2.

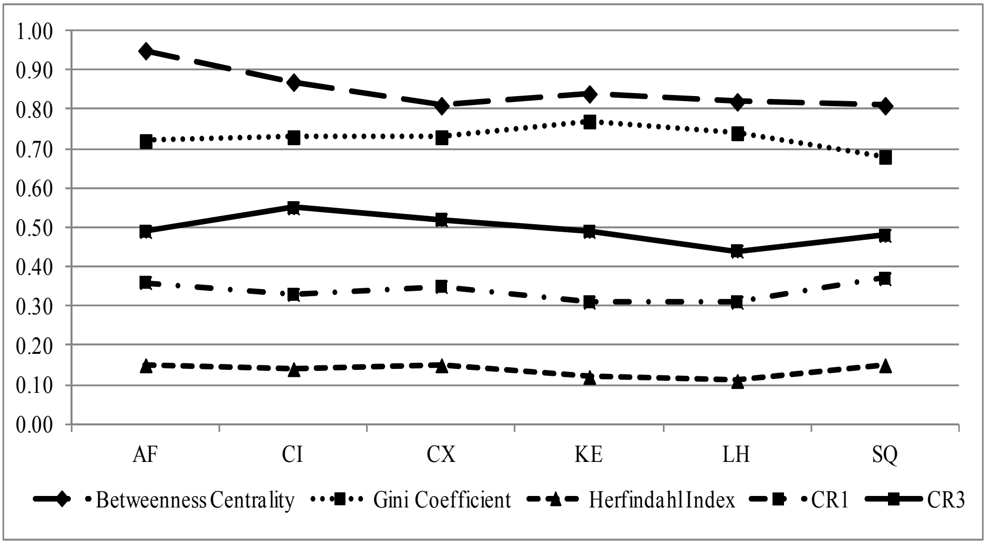


Figure 2: Results of the spatial network analysis for combined carriers (Source: author's own representation)

[20] In relation to this chapter the following article has been published: Scholz and von Cossel (2011).

The Gini index (GI*) for combined carriers varies slightly between 0.68 (SQ) and 0.77 (KE) resulting in a mean value of 0.73. A high GI* as discovered for the analysed airlines indicates an unequal spread of traffic in the network and can be observed for hub–and–spoke schemes (H&S) with one (or a few) major airports plus a large number of spoke airports connected to the hub.

The highest concentration of cargo capacities (CR1) accumulates at the carriers' passenger hubs (e.g. SQ: 0.37 at SIN[21], AF: 0.36 at CDG[22], CX: 0.35 at HKG[23]). More than half of total air freight is still transported as belly freight in passenger aircrafts which explains the importance of the passenger hub also for freight services. The average fraction of the three largest airports (CR3) for combined carriers is 0.50 which denotes that 50% of cargo capacities are bundled at the three largest airports. The highest fraction can be observed for China Airlines (0.55) with its three major airports Taipei (TPE), Hong Kong (HKG) and Anchorage (ANC) whereas Lufthansa has the lowest fraction with 0.44 (FRA[24], MUC[25], CGN[26]). The marginal difference between the largest (CR1) and the three largest airports (CR3) show that the focus for combined airlines is on their hub airport, and much lower fractions can be observed for the second and third largest airport.

The betweenness approach expresses the degree of centrality of the network. This measure takes its maximum value of one for a perfect star structure which can be interpreted for airlines as a pure H&S scheme. Its minimum of zero is achieved for a complete graph which stands for a perfect P2P configuration. The betweenness centrality measure underlines the observation of the concentration indices: combined carriers operate H&S networks also for freight transport.

AF scores highest with 0.95 and detects CDG as its most central airport. CDG also scores 0.95, followed by much smaller centrality value for ORY[27] (0.13) and BKK[28] (0.04). It becomes obvious that Paris with its two major airports, CDG and ORY, is the primary destination for AF. BKK serves as a regional connecting airport for Air France with high frequencies to CDG and to further South–East Asian countries (e.g. Vietnam). The range of the betweenness centrality index for combined carriers varies from 0.95 (AF) to 0.81 (SQ and CX). Lufthansa as a carrier with a low centrality level (0.82) operates two passenger hubs, namely FRA and MUC. Both airports serve as hubs with different key markets for LH which results in a lower network centrality value (the network is less compact).

The overall results show homogeneous tendencies for combined airport–to–airport operators. For all carriers H&S networks are identified (high concentration of cargo capacities at selected airports). In particular, the network configuration of AF is depicted as a clear H&S structure. A very high betweenness centrality combined with a high concentration measure (Gini and Herfindahl) characterises

[21] SIN: Singapore Changi Airport
[22] CDG: Paris Charles-de-Gaulle
[23] HKG: Hong Kong International Airport
[24] FRA: Frankfurt Airport (Germany)
[25] MUC: Franz Josef Strauss Airport Munich (Germany)
[26] CGN: Cologne/Bonn International Airport (Germany)
[27] ORY: Paris-Orly Airport (Germany)
[28] BKK: Bangkok Suvarnabhumi Airport (Thailand)

H&S schemes with concentrations on some major destinations and on one hub airport.

3.6.2 Freighter fleets of combined airlines

The cargo fleets of the previously analysed combined carriers are evaluated separately. The overall results are displayed in Figure 3.

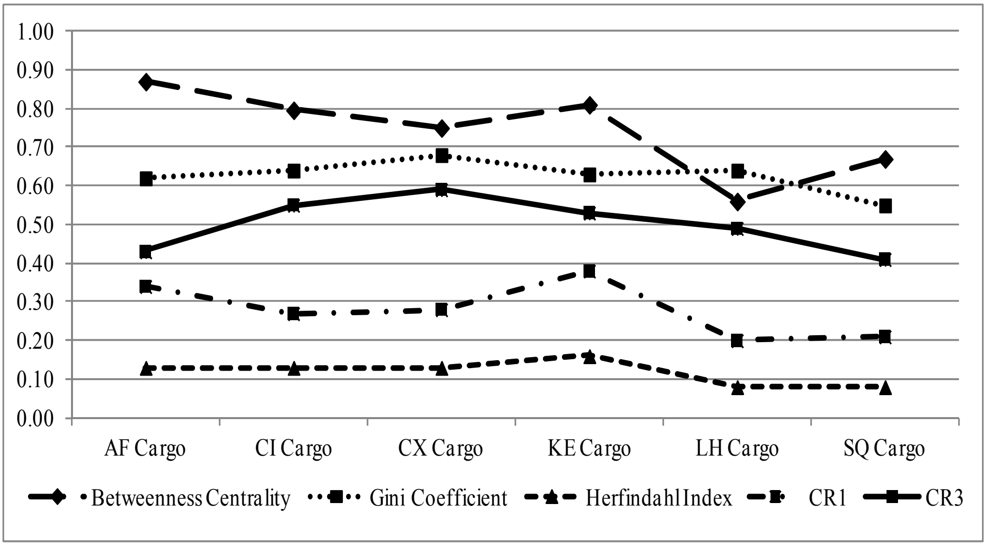


Figure 3: Results of the spatial network analysis for the cargo brands of combined carriers (Source: author's own representation)

The results show similar tendencies for the network structures of the freighter fleet compared to the entire combined carrier: GI* detects concentrated network structures but with lower absolute concentration values (0.63). A homogeneous category of airlines exists with small differences between the carriers concerning GI* (min. 0.55 for SQC, max. 0.68 for CXC). As for the entire carrier, the passenger hubs are also the main airports in the networks of the freighter fleets but with lower concentrations, and secondary airports play a significant role for cargo carriers.

For all analysed Asian airlines, Anchorage (ANC) was ranked second in their networks. Anchorage plays an unusual role for the cargo industry. It is solely important because of intermediary rather than for any local origin and destination traffic. Anchorage is used as transfer hub for the Asia–North America route that is fed by domestic traffic from North America (Bowen, 2004). This characteristic is also retrieved by the present results.

Betweenness centrality is in average lower for the freighter fleets (CB=0.74) compared to the entire carrier (CB=0.85). Based on betweenness centrality Air France Cargo (AFC) operates the most central network (CB=0.87) with CDG as its most central airport. In contrast to AFC is the network of Lufthansa Cargo (LHC) with a betweenness centrality of only 0.58 indicating moderate H&S activities.

Beside FRA as its major (passenger and cargo) hub, further airports exist in the network with lower but still important freighter capacities, namely CGN[29], TSE[30], EMA[31], SHJ[32], NBO[33] and DKR[34]. In particular, SHJ, NBO and DKR serve as major airports for their regions where either freight is bundled and shipped to the core markets of LHC or where intermediate stops are carried out to refuel aircrafts and to replace crews. Such characteristics lead to lower centrality scores.

Summarising the findings for the freighter fleets it becomes obvious that H&S structures are the dominant network configurations. Particularly AFC, as AF, operates a one hub network strategy. The network structure of LHC differs therefrom. Betweenness centrality is much lower (CB=0.56) which points towards a multi–hub network configuration with FRA (CB=0.58) and CGN (CB=0.23) serve as primary cargo hubs for LHC in 2007. Based on these results the network configuration of LH Cargo can be classified as a multi–hub–and–spoke structure with a concentration of flight activities at few destinations (e.g. FRA–TSE).

3.6.3 Pure cargo airlines

Pure cargo airlines focus their business entirely on cargo transport and do not operate passenger services. Six pure cargo airlines are analysed: China Cargo Airlines (CK), Cargolux (CV), ABX Air (GB), Nippon Air Cargo (KZ), Varig Logistica (LC) and Polar Air (PO). The results are summarised in Figure 4.

Pure cargo carriers have the lowest Gini coefficients (average value of 0.52) and therefore the highest flight equalities between the airports. A homogeneous business category exists concerning flight concentrations with a GI* ranging from 0.42 (PO) to 0.57 (GB).

Concerning the routing behaviour of pure cargo airlines significant differences can be observed (e.g. round–trip structures are observed to cope with imbalances of demand). For example, PO operates the route PVG[35]–ANC–LAX[36]–PVG and scores 0.42 in GI*. Caused by en–route stops and one–way traffic flows, less concentration can be observed for single airports resulting in a minor overall network concentration. Similar characteristics are found for other cargo airlines. KZ has a business focus on inter–continental flights connecting the major cargo markets (North America and Europe) with Asia and especially with Japan, its country of origin. NRT[37] serves as its major airport (traffic share 27%) closely followed by ANC (18%) which shows a concentration level of a second major airport for KZ. The traffic shares of the succeeding airports, such as KIX[38] (9%),

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[29] CGN: Konrad-Adenauer International Airport Cologne/Bonn (Germany)
[30] TSE: Astana International Airport (Kazakhstan)
[31] EMA: East Midlands (United Kingdom)
[32] SHJ: Sharjah International Airport (United Arab Emirates)
[33] NBO: Jomo Kenyatta International Airport Nairobi (Kenya)
[34] DKR: Dakar Léopold Sédar Senghor International Airport (Senegal)
[35] PVG: Shanghai Pudong International Airport (China)
[36] LAX: Los Angeles International Airport (USA)
[37] NRT: Narita International Airport (Japan)
[38] KIX: Kansai International Airport (Japan)

AMS[39] (6%) and SFO[40] (6%) underline the importance of inter–continental connections for KZ.

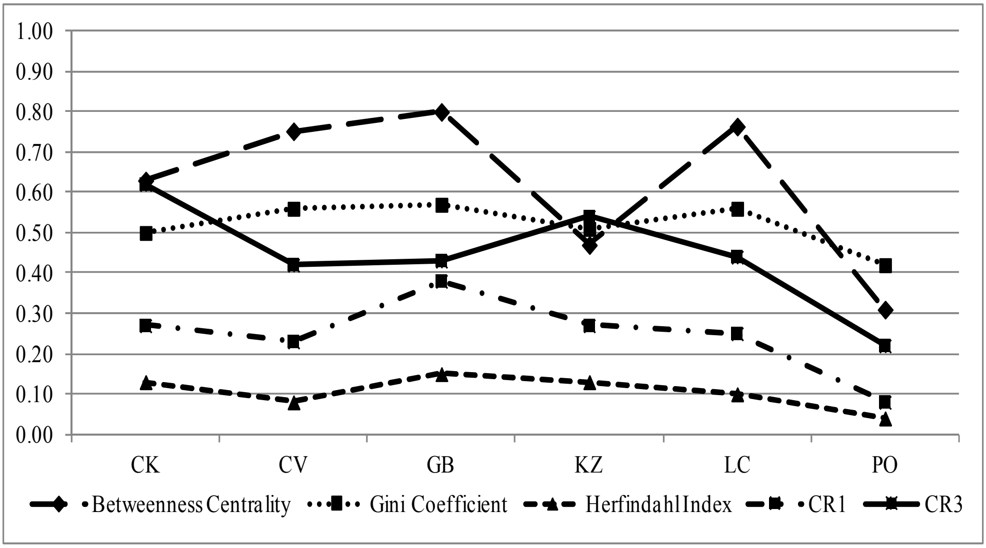

Figure 4: Results of the spatial network analysis for pure freighter airlines (Source: author's own representation)

CK focuses more than half of its business on three airports with PVG (27%) being the largest airport in its network followed by PEK[41] (17%) and ANC (12%). This leads to a concentration ratio (CR3) of 56%. In total, only 14 airports are operated by CK but other airports than the three largest only play minor roles (< 6%).

In contrast to the small network size of CK is the network of Cargolux (CV) with around 60 destinations. Flights are distributed more equally among the airports with most airports having traffic shares smaller than 2.5%. The three largest airports (CR3) combine 42% of traffic (LUX[42]=23%, GYD[43]=14% and HKG=5%) which leads to a much smaller HI compared to the other carriers within the pure cargo carrier category and especially compared to the other business models of combined carriers and their freighter fleets.

Analysing the results of betweenness centrality, the observations of the former indices are validated. Pure cargo carriers operate less compact and more equal distributed networks. Betweenness centrality of pure cargo carriers is in average 0.62 compared to 0.74 (freighter fleets of combined airlines) and 0.85 (combined airlines).

In particular, the heterogeneity of centrality values within the pure cargo category indicates that different network configurations are operated by the airlines

39 AMS: Schiphol Airport Amsterdam (The Netherlands)
40 SFO: San Francisco International Airport (USA)
41 PEK: Beijing Capital International Airport (China)
42 LUX: Luxembourg Findel International Airport (Luxembourg)
43 GYD: Heydar Aliyev International Airport of Baku (Azerbaijan)

(0.31<CB<0.8). GI* detects KZ as having a low concentrated network amongst the pure cargo carriers (GI*=0.51). In combination with a low centrality value (CB=0.47) the network can be characterised as a H&S network with round–trips originating from the two major airports (NRT and ANC). Flights are concentrated on one major route NRT – ANC that combines 15% of total traffic. Round–trips are operated from NRT (e.g. NRT–KIX–SIN–BKK–NRT) as well as from ANC (e.g. ANC–ORD–JFK–ANC) to feed the inter–continental flights of KZ.

The network shape of Cargolux (CV) differs significantly from the KZ network with a GI*=0.56 and CB=0.75 that indicates a more concentrated and centralised network. Such characteristics exist for mixed networks of linear and H&S configurations. CV operates two hubs which are LUX and GYD. More than 10% of total traffic is operated between these two hubs, and other routes are operated less frequently. Connections to the spokes airports are serviced through bi–directional flights as well as through round–trips whereas the most important spoke airports are connected directly to the hubs, such as LUX–MXP[44], LUX–PIK[45], GYD–PVG and GYD–HKG and account for 17% of the remaining flights (excluding LUX–GYD).

The case of ABX Air (GB) shows some interesting characteristics. While its primary airport ILN[46] has traffic share of 38% (CR1), CR3 is only 43%. In total, more than 90 destinations have shares of up to 2.5% which results in an unconcentrated network configuration, even though a major airport for GB exists. The high betweenness score underlines the importance of the major airport for the entire network. 80% of all connections run through ILN. In combination with a moderate Gini index (GI*=0.57), the premises for a pure H&S configuration are fulfilled.

Comparing the results of pure cargo airlines with the two other airline categories we see that network configurations of pure cargo carriers are much more diverse than the ones of combined airlines (and their freighter fleets). In particular, the round–trip structure is a major network characteristic of pure cargo airlines (and to lesser extend also of the freighter fleets of combined carriers) which is not applied in passenger transport. This structure can also be observed in road freight transport where trips are organized and operated as round–trips to cope with imbalances of demand (efficient resource allocation) (Liedtke, 2006). The importance of single airports (hubs) for pure cargo airlines is much smaller than these for passenger airlines. In average CR1 is 25% and CR3 45% indicating a greater importance of the remaining airports, and a less concentrated network configuration. This result can also be underlined by smaller average concentration levels (GI* and HI) and less centralised network configurations.

[44] MXP: Milan Malpensa Airport (Italy)
[45] PIK: Glasgow Prestwick International Airport (Scotland)
[46] ILN: Airborne Park Wilmington, Ohio (USA)

3.7 Recapitulation

The objective of the present chapter was to introduce the network perspective to air transport studies and to assess real world network structures of cargo airlines with appropriate measurements. Later, the results of this chapter are used to compare the endogenously modelled with the existing network structures of cargo airlines. Therefore, above observations serve as a quality criterion for the modelled network structures. The results can be summarised as follows:

More than eighty percent of worldwide air freight is shipped between the core markets of Asia, North America and Europe with Asia being the most important freight market based on tonne–miles transported as well as the monetary value of the goods (Crabtree et al., 2006). These characteristics are also reflected in the network structure of cargo airlines (supply side).

In total, twelve cargo airlines are analysed based on concentration and centrality measures. Six combined carriers which are airport–to–airport operators that focus mainly on passenger services are examined, such as Lufthansa and Air France. Furthermore, the freighter fleets of combined carriers are analysed separately to understand their network structures. Finally, six pure cargo airlines, such as Cargolux, are analysed. Concentration measures, such as an adapted Gini coefficient, are applied to assess the geographical concentration (inequality of services) of the airlines' networks. The shape (structure) of the networks is analysed based on betweenness centrality. Results are summarised in Figure 5.

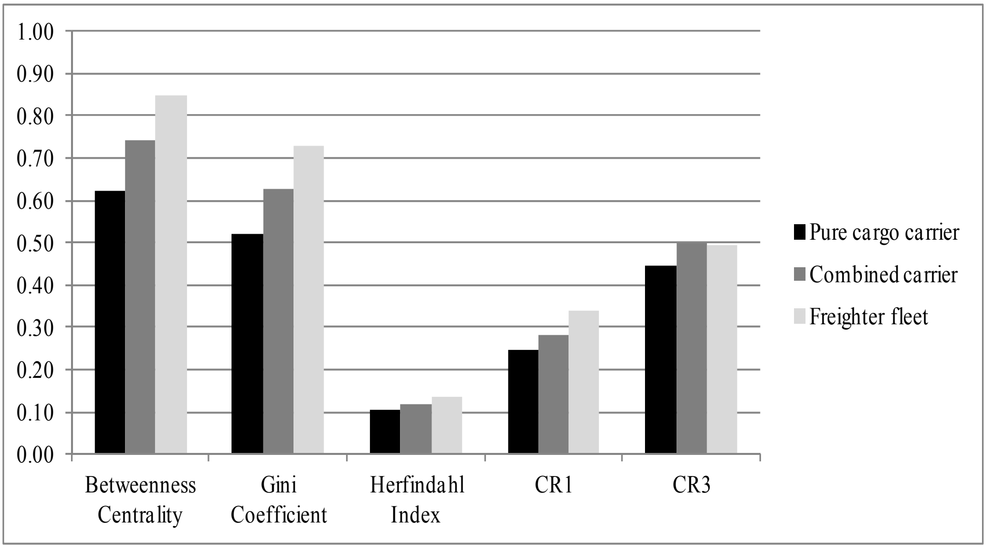

Figure 5: Comparison of results for the spatial network analysis (Source: author's own representation)

Combined carriers operate networks of similar configuration. Single H&S schemes are the predominant network configurations. A very high betweenness centrality value combined with high concentrations characterises H&S schemes with one hub airport (the passenger hub) and with high flight concentrations on selected routes.

The combined carriers’ freighter fleets primarily operate H&S structures with lower concentration and centrality values than the entire airline. The characteristics of air freight transport (e.g. imbalances of demand, independence of passenger behaviour) are directly integrated into the network design of the freighter fleets. Network configurations of pure cargo carriers are much more diverse than of combined carriers (and their freighter fleets). In particular, the round–trip structure is a major network characteristic of pure cargo carriers. The importance of single airports (hubs) for pure cargo airlines is much smaller than for combined airlines indicating a greater importance of the remaining airports and a less concentrated network configuration. This result is also underlined by smaller average concentration levels and less centralised network configurations.

4 Airline network design modelling

The study of airline networks has always been an inter–disciplinary challenge. Economists, operations researchers as well as transport engineers have studied airline networks from different point of views. Major research questions dealt with the cost structure of passenger airlines (e.g. Bailey et al., 1985; Wei and Hansen, 2003; Swan and Adler, 2006), with pricing strategies (e.g. Chi and Koo, 2009; Forbes, 2008; Hofer et al., 2008; Vowles, 2006), with demand modelling (e.g. Abdelghany and Abdelghany, 2009; Garrow, 2009; Jorge–Calderón, 1997; Wei and Hansen, 2005) and with schedule design and fleet assignment modelling (see below). So far, research on airline networks has been focused on passenger transport.

This dissertation has the objective to model cargo airline networks. Thus, the theoretical framework on airline network modelling is provided in the following chapter. The chapter begins by introducing the traditional four step airline network design approach and by describing the four steps, namely schedule design (step one), fleet assignment (step two), maintenance routing (step three) and crew scheduling (step four). Next, existing modelling approaches for schedule design (step one) and fleet assignment (step two) are surveyed. Then, literature on the hub location problem is presented because hub airports emerge endogenously in the developed model. Finally, lessons–learned of this chapter are summarised.

4.1 The traditional airline network design approach

The development of an airline's flight schedule is subdivided into four core problems (Schön, 2008):

- Schedule design: starting from a strategic view point and usually from an existing (former) flight schedule, the airline decides which markets to serve at which frequencies
- Fleet assignment: the available equipment (e.g. aircraft categories) is assigned to markets such that expected demand is served at minimal cost
- Maintenance routing: aircrafts are assigned to routes (and sequences of flights) so that regulations (e.g. maintenance) are fulfilled
- Crew scheduling: the required crew is assigned to each flight.

So far no single optimisation model exists that covers all four core problems of airline schedule planning. A single and disaggregated model would contain billions of decision variables as well as many constraints. With every further step that is included in an overall model additional constraints emerge (e.g. slot availability, maintenance requirements, labour time restrictions) which cannot be solved by the preceding objective function. Therefore, sequential approaches are applied in practice (Barnhart and Cohn, 2004).

The present work models the strategic level of the schedule planning approach and analyses the network structures of cargo airlines. Therefore, the schedule design problem is the core of the present dissertation including applications of the fleet assignment problem. For this reason, literature on the two core problems schedule design and fleet assignment is reviewed in detail in the following.

Schedule design

The primary objective of the schedule design problem is to define a feasible schedule of transport services for a dedicated future period. Parameters which represent the airline's environment are inputs for schedule design, such as forecasts of available resources (e.g. fleet size, aircrafts), demand forecasts (e.g. origin–destination traffic expectations) and planned market initiatives (e.g. new market entries or exists) (Mathaisel, 1997). The outcome of the schedule design process is a generic schedule that consists of a feasible set of services without aircraft and crew assignment.

Practitioners (and scientists) have so far not fully met the challenges of the schedule design problem. In reality, schedule design is still a manual process with limited optimisation procedures. Schedules are usually based on preceding schedules which are improved incrementally by applying a limited number of changes (e.g. demand changes, market entries/exists). Main reasons for an incremental approach are (Barnhart and Cohn, 2004):

- complexity/problem size: an all–in–one model (including crew, fleet assignment and schedule design) includes numerous flight–leg options, constraints and interdependencies. The combinatorial complexity makes such a model (currently) intractable
- risk reduction: an existing schedule is a feasible solution of the complex network design problem. Selected and comparatively few changes at a feasible schedule reduces overall risk and makes the network design problem manageable.

Fleet Assignment

Based on the developed generic schedule, the question on how to efficiently allocate the airline's fleet needs to be answered. Aircraft categories are assigned to every flight leg so that capacity matches demand at lowest cost (Gopalan and Talluri, 1998).

Existing models for the schedule design and the fleet assignment problem are reviewed in the following with a focus on schedule design problems as they are the core of the present work. Fleet assignment is only considered on an aggregated level ensuring that the present model represents real world cases accurately.

4.2 Literature review on schedule design and fleet assignment modelling

Solving the schedule design problem is the key requisite for a successful airline operation and a profitable network structure. A variety of publications exist which deal with schedule design modelling, schedule design optimisation or the integration of schedule design into fleet assignment models. To the author's best knowledge, all but three of these publications deal with air passenger network modelling where air freight is excluded from network design determination. An overview on academic publications is displayed in Table 4, and all non–survey publications are discussed in the following. Three approaches are presented in detail, namely Marsten and Muller (1980) and Derigs, Friederichs and Schäfer (2009) as their works are the most comprehensive literature on air cargo network planning which can be compared with the present work as well as the publications of Schön (2007, 2008) since these are the most recent and very comprehensive publications on airline network design.

Table 4: Schedule design literature
(Source: author's own representation)

Year	Author(s)	Description	Scope of publication		
			I[47]	II[48]	III[49]
1980	Soumis, Ferland and Rousseau	Mathematical programming model for flight scheduling which maximise company profits and passenger satisfaction (air passenger transport)	Y	N	N
1980	Marsten and Muller	Mathematical programming approach to schedule design and fleet assignment (air cargo planning)	Y	Y	N
1985	Etschmaier and Mathaisel	Survey on Airline Scheduling (air passenger transport)			
1989	Teodorovic and Krcmar–Nozic	Heuristic approach to determine frequencies on a route network (maximizing profit, maximizing number of passengers, minimizing schedule delay) (air passenger transport)	Y	N	N
1993	Dobson and Lederer	Mathematical programming heuristic to determine flight frequencies and route prices by airlines (hub–and–spoke networks) (air passenger transport)	Y	N	N

47 Scope I: airports fixed and given
48 Scope II: cargo considered
49 Scope III: eonomies of scale considered

Year	Author(s)	Description	Scope of publication		
			I[47]	II[48]	III[49]
1993	Kuby and Gray	Hub network design (air express carrier)	Y	Y	Y*
1995	Hane et al.	Fleet assignment problem with large–scale integer program (air passenger transport)	Y	N	N
1998	Lederer and Nambimadom	Influence of structural parameters on optimal airline network (air passenger transport).	Y	N	N
1998	Gopalan and Talluri	Survey on mathematical models in airline schedule planning (traffic forecast and allocation, fleet assignment, equipment swapping, through flight selection, maintenance routing) (air passenger transport)			
2004	Barnhart and Cohn	Survey on Scheduling Planning Approaches (Schedule Design, Fleet Assignment, Aircraft Maintenance and Crew Scheduling) (air passenger transport)			
2004	Lohatepanont and Barnhart	Simultaneous optimisation of schedule design and fleet assignment (air passenger transport)	Y	N	N
2004	Lin and Chen	Hub network schedule and fleet size (air express carrier)	Y	Y	Y*
2007	Schön	Simultaneous optimisation of schedule design, fleet assignment and strategic pricing (air passenger transport)	Y	N	Y*
2009	Derigs, Friederichs and Schäfer	Schedule optimisation to maximise network–wide profit by determining the best combination from a given set of mandatory and optional flights, assigning flights to aircrafts, identifying optimal cargo flows.	Y	Y	Y*

(N) not considered, (Y) considered, (Y*) partly considered (e.g. as fixed cost degression)

Soumis et al. (1980) developed a model to maximise airline's profit and simultaneously maximise passengers' service satisfaction. Passengers' service satisfaction is quantified by minimizing passengers' dissatisfaction cost. The starting point of the algorithm is an initial solution (e.g. actual flight schedule), and an iterative optimisation approach is applied where single flights are added or deleted from the schedule.

The aircraft routing and the scheduling problem is solved by an adapted Frank–Wolfe algorithm50. A heuristic recalculates demand on the itineraries based on passenger's dissatisfaction and the capacity constraints of the aircraft on the route. Soumis et al. (1980) assume fixed prices, a fixed number of airports, focus on passenger transport and do not allow feedbacks between passenger dissatisfaction, fare prices and route demand. The inclusion of passengers' dissatisfaction into the network design problem is an innovative approach which enables the model to counterbalance between customers' and airline's optimisation principles.

A first comprehensive air cargo fleet and schedule planning approach was published by Marsten and Muller (1980). Marsten and Muller (1980) developed a mathematical program to design an air cargo carrier's route and plane assignment for spider–shaped networks. Marsten and Muller distinct between three network design problems: (1) a single–hub model for night delivery, (2) a multiple–hub model for night delivery and (3) a multiple–hub model for day and night deliveries. For all three network design schedules the objective function is to maximise profit by subtracting total operating cost from the corresponding revenues. The following equation introduces the objective function of the basic single–hub model:

$$\text{Profit} = \sum_{i} \sum_{j \neq i} \text{Revenue}(i,j)\, x_{ij} - \sum_{s} \sum_{k \in \text{MIX}(s)} \text{Cost}(s,k) z_{sk}$$

With:

$$\begin{aligned}\mathbf{Cost(s,k)} &= \mathbf{2(Fixcost(k) + Opcost(k) * Dist\big((hub, city(s,1)\big)\big)} \\ &\quad + \mathbf{2} \sum_{\mathbf{t=1}}^{\mathbf{m_s-1}} \mathbf{(Fixcost(k) + Opcost(k) * Dist\big(city(s,t), city(s,t+1)\big))}\end{aligned}$$

Where:

s = 1, …, S (spider leg: combination of at least one link)
k = aircraft type
MIX(s) = available aircraft fleet for leg s
Revenue(i,j) = the revenue received for carrying cargo from city i to city j
Cost(s,k) = cost for leg s and aircraft type k

[50] The Frank-Wolfe algorithm solves quadratic programming problems with linear constraints. At each sequence the objective function (minimization problem) is linearized and then a step is taken in a direction that reduces the objective while maintaining feasibility (Bobzin, 2006).

Fixcost(k) = the cost of one take–off and landing for an aircraft of type k
Opcost(k) = the operating cost for an aircraft of type k
Dist = distance
Capacity(k) = the capacity of an aircraft of type k

The demand coefficient is an aggregation over several freight categories, so that revenue is therefore a weighted average of the prices charged for the different categories.

The decision variables and the outcome of the optimisation model are continuous freight flows (x_{ij}) and aircraft selections (integer variable z_{sk}). Results are achieved by applying a branch–and–bound technique[51] in combination with linear programming[52] computations. The approach of Marsten and Muller (1980) assumes and requires a given and fixed network structure (hub and spoke scheme) to maximise profitability of the analysed cargo carrier.

Teodorovic and Krcmar–Nozic (1989) introduced competition between airlines in modelling flight schedules. A multi–criteria model was set up to determine frequencies on a route level with the simultaneous objective to maximise profit, to maximise the number of passengers flown and to minimise total passenger schedule delay. The comprehensive combinatorial problem (here: nonlinear integer problem[53]) in determining flight frequencies on a route network is solved heuristically. Therefore, Teodorovic and Krcmar–Nozic apply Monte Carlo techniques which randomly generate solutions whose feasibility is finally examined. After several iterations, the best solution (best objective function result) is interpreted as an approximation of the optimum. The model is limited to passenger services and to nonstop flights only (no hubbing activities allowed). Competition between carriers only exists on flight frequencies and not on fares, service quality, etc. Finally, economies of scale are not incorporated into the model.

Dobson and Lederer (1993) focus their analysis of airline scheduling and routing on hub–and–spoke networks. A nonlinear model for the competitive choice of flight schedule and route prices in order to maximise airline's profit is presented. Passengers are modelled with homogeneous behaviour and static competition between airlines is assumed. Demand for each route is calculated by an aggregated multinomial logit choice model based on service quality (departure time and travel duration) and the route price. A three level hierarchical approach is implemented:

51 Branch-and-bound is a search method. The feasible solution space is partitioned into smaller subsets. A lower bound (in the case of minimization) is calculated for each subset. Subsets with a bound that exceeds the cost of an already known feasible solution are excluded from further calculations. The partitioning continues until a feasible solution is found such that its cost is no greater than the bound for any subset to find a best solution for a given optimisation problem. The final result presents a feasible but not necessarily an optimal solution for the optimisation problem (Lawler and Wood, 1966).

52 Linear programming solves optimisation problems of a linear objective function (minimizing or maximizing functions) under restrictions of linear equality and/or inequality constraints (Bazaraa et al., 2010). The simplex method is the best known linear programming algorithm.

53 Nonlinear programming solves a system of objective function (maximization or minimization problem) and constraints (equalities and/or inequalities) where at least one function (objective function and/or constraint) is nonlinear (Sun and Li, 2006).

The lowest level (level three) determines optimal route prices that satisfy capacity constraints, consumer choice behaviour and airline's total revenue for the route. Level two determines routes from a set of flights chosen by the airline and based on the results of the lowest level. Finally, level one search for the profit maximizing set of flights (minimum cost circulation problem[54]). Dobson and Lederer reduce complexity by assuming a given and fixed network structure (hub–and–spoke system), only one aircraft size and service class, by excluding cargo transport, by allowing through traffic only via the airline's hubs and by neglecting economies of scale.

Kuby and Grey (1993) discussed the hub network design problem with stopovers and feeders. Thus, direct flights between spokes are allowed. Furthermore, multiple stops along routes as well as different aircraft types are incorporated into the model. Starting from the network of Federal Express where most flights to and from the hub airport make at least one stopover and where many cities are served by feeder flights which are only connected to larger non–hub cities, Kuby and Grey develop a mixed–integer (linear) program[55] to design least–cost single–hub air networks. The cost function (objective function) includes line–haul cost for links, fixed cost for routes, fuel cost, maintenance cost, labour cost and aircraft depreciation. Kuby and Grey's approach assumes that the hub location and the set of airports is fixed, that only one hub exists and that line haul cost are not a function of the respective cargo volumes and independent of the aircraft chosen.

Hane et al. (1995) focus on the fleet assignment problem when a flight schedule and a set of aircraft is given and the type of aircraft for each flight segment is determined. Hane et al. developed a model based on a large multi–commodity flow problem with side constraints. A combination of methods[56] is used to find appropriate solutions in a faster time than standard linear programming techniques.

The understanding of the choices of network structure (routing) and schedules (frequency) is the primary objective of Lederer and Nambimadom (1998). Therefore, an airline economics model that includes airline cost (fixed aircraft cost plus variable aircraft cost) as well as passenger cost (travel cost plus schedule delay cost) is applied. Lederer and Nambimadom conclude that direct services have the lowest frequencies and highest schedule reliability whereas hub–and–spoke networks have high optimal schedule frequencies but low schedule reliability. Assumptions include symmetric demand between origin and destination, fixed network design and no scale effects at airports.

Another operations research approach for an integrated schedule design and fleet assignment is provided by Lohatepanont and Barnhart (2004). A mixed integer

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[54] Minimum cost circulation algorithm: Create a graph with one node for each city. Place directed arcs in the graph corresponding to all possible flights. Set one for the flights which are in the current schedule. Impose variable cost to the arcs and for each arc leaving a node at the first period add the fixed cost of the operating plane. A minimum cost assignment of the flights to planes is the solution of a minimum cost circulation algorithm (Dobson and Lederer, 1993).

[55] Linear programming solves optimisation problems of a linear objective function (minimizing or maximizing functions) under restrictions of linear equality and/or inequality constraints. A mixed-integer problem requires only some of the unknown variables to be integers.

[56] Hane et al. (1995) apply a method that consists of an interior-point algorithm, dual steepest edge simplex, cost perturbation, model aggregation, branching on set-partitioning constraints and prioritizing the order of branching.

linear model with the objective to maximise schedule profitability based on an incremental approach (list of mandatory and optional flights) is developed. The models simultaneously optimize the selection of flight legs for and the assignment of aircraft types to the flight legs. Lohatepanont and Barnhart limit their contributions to passenger transport and assume constant returns to scale.

The problem to determine the fleet size for a time constraint hierarchical hub–and–spoke network, such as an express freight carrier network, was studied by Lin and Chen (2004). The time–constraint hierarchical hub–and–spoke network design problem involves determining the fleet size and fleet schedules on the primary as well as secondary routes of the network to minimise the total operating cost. Cost are composed of fixed cost and operating cost. The minimal cost approach was transferred into a 0–1 binary problem. The problem was faced by an implicit enumeration method with an embedded least time path sub problem. Lin and Chen (2004) use as input a given network structure (hub–and–spoke network), fixed primary and secondary routes, fixed hub airports and do not consider scale economics at secondary airports.

Schön (2007 and 2008) developed a simultaneous model for airline schedule design, fleet assignment and strategic pricing. A period length of one day is applied to keep data effort and the size of the optimisation problem in real world applications at a reasonable level. The model bases on an incremental approach. Hence, an existing schedule or a set of mandatory and optional flights is needed. Customers are passengers that are segmented by their service characteristics (e.g. leisure versus business travellers). Each customer segment s has a multi–dimensional demand function $d_{js}(p_s)$ at fare level j depending explicitly on the price of the service. The objective function maximises profit overall customer segments by determining the fare products with the corresponding prices and by assigning the flights to dedicated aircrafts (Schön, 2008).

$$\text{Max} \sum_{s \in S} \sum_{j \in J} (p_{sj}(d_s) - c_{sj}) d_{sj} - \sum_{k \in K} \sum_{l \in L} f_{kl} C_{kl}$$

Where:

S = set of customer segments (s is one segment)
K = set of aircraft types (k is one aircraft type)
J = set of potential fare products (j is one special fare product)
L = set of flight legs (l is one specific flight leg)
$p_{sj}(d_{sj})$ = inverse price–demand function for segment s and fare product j
d_{sj} = demand of segment s for fare type j (variable)
f_{kl} = 1 if flight leg l is assigned to fleet type k, 0 otherwise (variable)
c_{sj} = variable cost for one passenger of segment s with fare product j
C_{kl} = fixed cost for assigning aircraft type k to flight leg l

The underlying assumptions are that all mandatory (optional) flights must be operated exactly (at most) by one aircraft type, that total demand does not exceed capacity, that a fare product can only be offered when all flight legs in the underlying itinerary are operated and that all inbound flights equal all outbound flights (including grounding aircrafts) (Schön, 2007). A mixed–binary maximization problem with a concave objective function and linear constraints is applied. The algorithm requires pre–decisions as inputs, namely a list of mandatory and optional flights which are exogenously determined (no evolutionary approach) as well as a set of given airports. Furthermore, economies of scale are only incorporated into the model as fixed cost degression and variable cost are only dependent on customer segment and fare product but independent of aircraft type and aircraft size. Finally, the optimisation problem is defined for passenger service design.

Derigs, Friederichs and Schäfer (2009) developed two integrated models that combine the three planning stages flight selection, aircraft rotation planning and cargo routing. The overall objective of both models is to maximise the network–wide profit by determining the optimal combination from a given set of mandatory and optional flights. Furthermore, Derigs, Friederichs and Schäfer (2009) assigned the selected flights to aircrafts and identified optimal cargo flows. The first model, INT–A, is a flight–based optimisation model. A flight is defined as a single execution of a route on a specific operating day (e.g. flight from FRA to MUC on Wednesday). Therefore, the flight–based airline rotation problem[57] is combined with the leg–based network evaluation problem[58]. The focus of the second model, INT–B, is on paths instead of flights. Paths (rotations) are predefined as a number of flights that are operated by a single aircraft. Both models lead to the same results when the given set of feasible paths (rotations) which are input of INT–B contains exactly those paths that are considered feasible endogenously by the model INT–A. In the following INT–A will be introduced as its scope is closer to *AirTrafficSim*.

The objective function of INT–A maximises the network–wide profit. Therefore, for each path the flow on this path is multiplied by the respective margin (revenue minus variable transportation cost) minus the fixed cost for operating the path (e.g. crew, landing fees) and minus the fixed cost of each aeroplane used (e.g. depreciation). Constraints restrict leg capacities (volume and weight), flight allocation, aircraft allocation[59] and rotation duration[60]. Furthermore, constraints are introduced to control that all mandatory flights are incorporated into the schedule. The objective of the model is to optimize air cargo network planning by operating pure freighter aircrafts only (e.g. constant fixed cost, no belly capacities, uniform fleet).Therefore, a homogeneous supply market (including a given one hub network structure) is assumed which avoids aircraft choice decisions and predefines the network structure of the operating airline. Economies of scale are focused in the model on decreasing fixed cost and are applied on all network links (no limitation to inter–hub connections) whereas variable cost are fixed and independent of aircraft utilization and traffic flows on the links.

[57] The objective of the aeroplane rotation problem is to minimise the number of aeroplanes necessary to operate all flights.

[58] The objective of the network evaluation problem is to maximise the contribution of each route to the overall profit of the airline.

[59] The flight allocation constraint enforces that every flight is assigned to exactly one aircraft.

[60] The duration of one rotation is fixed to one week. After one week the initial situation (e.g. location of aircrafts) must be achieved again.

The presented models determine airline network structures based on given assumptions (and in most cases also a given demand). In case that a network structure (e.g. hub–and–spoke structure) is predetermined, the optimal distribution of traffic is modelled by schedule design and fleet assignment models. A different research question is the hub location problem where the best location for a hub airport is requested and where the decision on the network structure is already carried out. Models that decide on the hub location are surveyed in the following section.

4.3 Literature review on hub location modelling

In most cases and in practice hub location and schedule design decisions are treated successively. The present work optimizes total network structures and hubs (may) emerge from the optimisation process by taking advantage of economies of scale. Therefore, the state–of–the–art in hub location modelling is introduced in the following[61]. Research on the hub location problem often assumes three fundamentals (Alumur and Kara, 2008):

- the hub network is complete with a link between every hub pair
- no direct services are allowed
- economies of scale are incorporated by a discount factor

Based on these assumptions four sub–problems are differentiated for the hub location problem:

- the **p–hub median problem** minimises the total transportation cost by determining p hubs from a number of potential nodes:
    - Single allocation: non–hub nodes are only connected to one hub
    - Multiple allocation: non–hub nodes can be connected to more than one hub
- the **hub location with fixed cost**: the p–hub median problem is extended, so that fixed cost of opening facilities are incorporated into the decision
- the **p–hub centre problem** is a minmax problem which
    - minimises the maximum cost for any origin–destination pair or
    - minimises the maximum cost for movements on any single link or
    - minimises the maximum cost of movements between a hub and an origin/destination
- the **hub covering problem** minimises the number of hubs under the constraint, so that demand is met within a given threshold (e.g. at maximal cost).

The problem formulation which is closest to the present work is the multiple allocation approach of the p–hub median problem. Nodes (airports) can be

[61] The hub location problem is a specification of the general location problem as surveyed by e.g. Brandeau and Chiu (1989).

connected to more than one hub, and a total cost minimization optimisation is applied (see chapter 5 for further details). The assumption that p hubs need to be allocated is invalid for the present dissertation because the number of hubs is determined endogenously by *AirTrafficSim* and is not restricted to a given and fixed number. Table 5 summarises the relevant studies on the multiple allocation p–hub median problem.

Table 5: Multiple allocation p–hub median literature
(Source: author's own representation based on Alumur and Kara, 2008)

Year	Author(s)	Description	Scope of publication		
			I[62]	II[63]	III[64]
1992	Campbell	First linear integer program	N	N	N
1994	Campbell	New formulation, flow thresholds, fixed cost	N	N	N
1996	Jaillet et al.	First that did not assume an explicit p–hub network, hub location endogenously.	Y	N	Y*
1998	O'Kelly and Bryan	Flow economies of scale with a piece–wise linear approximation of a nonlinear cost function.	Y	N	Y*
1998	Bryan	Capacities and minimum flows on interhub links, flow–dependent cost in all network links.	Y	N	Y*
1998a	Ernst and Krishnamoorthy	New formulation, Branch and Bound method, two heuristics	N	N	N
1998b	Ernst and Krishnamoorthy	Shortest paths based Branch and Bound algorithm	N	N	N
2006	Kimms	Economies of scale on all network links, fixed cost, quantity discounts.	Y	N	Y

(N) not considered, (Y) considered, (Y*) partly considered (e.g. as fixed cost degression)

Campbell (1992) firstly formulated the multiple allocation problem as a linear integer problem which minimises total transportation cost.

[62] Scope I: hubs endogenous
[63] Scope II: cargo considered
[64] Scope III: economies of scale

$$\text{Min} \sum_{i}\sum_{j}\sum_{k}\sum_{m} W_{ij}X_{ijkm}C_{ijkm}$$

Where:

W_{ij} = total amount of flow from origin airport i to destination airport j,

X_{ijkm} = fraction of flow from airport i to airport j that is routed via hubs k and m,

C_{ijkm} = transportation cost of one unit of flow between airport i and airport j via hubs k and m.

Campbell (1994) found out that in the absence of capacity constraints on the routes, there is an optimal solution where all X_{ijkm} are set either to zero or to one. In such a case total flows between origin and destination airport are routed via the least–cost hubs. Further studies formulated the hub location problem as mixed integer problems (Skorin–Kapov, 1996) or as a one–stop multiple allocation p–hub median problem (Sasaki et al., 1999).

Jaillet et al. (1996) were the first who did not assume an explicit p–hub network and make hub location endogenously. Passengers are routed within the network by given aircraft sizes and given demand on the routes. Restrictions are placed on the number of stops that an aircraft is allowed to make. The output of the model is the number of departing aircrafts, number of originating/destinating passengers and the number of transfer passengers. Hubs airports are the airports that fulfil the airline's business objectives best.

O'Kelly and Bryan (1998) show that traditional hub location models miscalculate total network cost and erroneously select hub locations because of assuming flow–independent cost and by not considering economies of scale entirely. Traditionally, economies of scale are only incorporated into hub location models by an interhub discount factor. The discount factor is defined for all interhub connections jointly regardless of the amount of flows on the links. O'Kelly and Bryan (1998) applied a nonlinear cost function. Thus, costs are increasing at a decreasing rate as flows increase. The discount (Φ) increases with increasing interhub flows.

$$\Phi = \Theta\left[\frac{\sum_i \sum_j W_{ij}X_{ijkm}}{\sum_i \sum_j W_{ij}}\right]^{\beta}$$

Where:

Φ = interhub discount factor,

W_{ij} = amount of flow between airport i and airport j,

X_{ijkm} = 1 if the flow between airport i and airport j is routed via hub k and hub m; 0 otherwise,

$\sum_i \sum_j W_{ij}X_{ijkm}$= total amout of flow travelling across the interhub link (k,m),

$\sum_i \sum_j W_{ij}$ = total network flow,

Θ, β = parameter for varying the cost function.

The discount factor ranges from zero to one, with zero being the discount earned when no flow is routed across the interhub connection and one being the largest possible discount. Because of the complexity of the traditional multiple hub location problem the nonlinear cost function is approximated as a piece–wise linear function to minimise computational time and to be able to use linear optimisation techniques. O'Kelly and Bryan (1998) predefine the network structure as well as the number of hub airports within the airline network. This information is input into the multiple hub location model. Furthermore, O'Kelly and Bryan (1998) require that hubs must utilize their interhub connections, that hubs maintain their relevance and that economies of scale only occur at interhub connections.

Bryan (1998) published an enhancement of the formulation presented in O'Kelly and Bryan (1998) by considering capacities and minimum flows on interhub links, as well as flow–dependent cost in all network links. Hubs are determined from a list of known candidate airports. Any number of airports can be ascertained as hubs as long as connections between the hub airports hold the required minimum flows.

Ernst and Krishnamoorthy (1998a and 1998b) developed a linear programming method based on branch–and–bound techniques as well as two heuristics (one based on shortest–paths and the second based on an explicit enumeration approach). In case of fixed hub locations, each pair of nodes sends flows through their shortest paths via the given hubs (Alumur and Kara, 2008). The heuristics are extremely (time and memory) efficient and deliver solutions close to optimum in most of the problems that Ernst and Krishnamoorthy (1998) tested. Economies of scale are excluded from analysis by Ernst and Krishnamoorthy (1998) and assume a fixed and given network structure (e.g. number of hub airports).

Kimms (2006) stated that even though economies of scale are the major driver for hub–and–spoke networks, they are mostly incorporated into network models incorrectly. Therefore, Kimms (2006) assumed that economies of scale may occur on all network links instead of on interhub connections only. A piecewise linear cost function which incurs a fixed cost for using (opening) a (new) node (airport) is proposed. Hence, quantitative discounts can be achieved. The developed models can be extended to incorporate further assumptions (side constraints).

4.4 Recapitulation

Strategic airline network design is usually solved sequentially because of complexity reasons and missing models which combine the four main steps of airline network design, namely schedule design (strategic decision which markets to serve at which frequencies), fleet assignment (which aircraft categories are assigned to which routes), maintenance routing (assignment of each aircraft to each flight) and crew scheduling (required crew is assigned to each flight). The present dissertation focuses on the strategic level by modelling the schedule design decision including the general fleet assignment problem. Existing models mainly accrue from operations research. Based on graph theory, airports are interpreted as nodes and connections between airports are modelled as edges (or arcs). Solution algorithms stem in most cases from linear programming to achieve an efficient network design for the airline (e.g. cost minimizing, profit maximizing) under business assumptions (e.g. fleet size, airports). Very few publications release the optimisation principle of a linear objective function by solving a nonlinear model with (meta–) heuristics. The behaviour of airlines especially of cargo airlines to bundle freight at (hub) airports to achieve economies of scale and to operate aircrafts at high capacities as well as to be able to allocate larger aircrafts to routes with high capacities suggest the incorporation of nonlinear elements to airline network design modelling. In particular, cost concavity appears appropriate for the airline business as cost is increasing at a decreasing rate as flows increase (O'Kelly and Bryan, 1998).

The determination of the number of airports, and particularly of the number of hubs, is predefined and fixed in most models (exogenous variable). In operations research such problems are called p–hub location problems. Exactly p hubs are allocated to serve the given demand by minimizing the total transportation cost. A given set of airports and a given set of hubs is required as input to such an optimisation problem. More recently an innovative approach to the network design and location problem emerged that does not assume a–priori a given and fixed network structure. The network design in such evolutionary approaches emerges as an output from the model. The present dissertation follows this approach.

Nearly all reviewed models focus on air passenger transport. Network design and hub location is determined by the behaviour of passengers whereas cargo flows and freight characteristics are neglected. The increasing importance of air freight transport in a globalized world and the need for fast, reliable and cost effective inter–continental transports and in particular between the major trade markets, has motivated this dissertation. The developed approach to model airlines' network structures endogenously is presented in the following chapter.

5 *AirTrafficSim*: Model description

AirTrafficSim has been developed to model the network structure of cargo airlines. The model is introduced in the following by

- presenting its basic principles (chapter 5.1) as well as its general structure (chapter 5.2)
- introducing the initialization phase of *AirTrafficSim* (chapter 5.3)
- presenting the core component of *AirTrafficSim,* the optimisation phase (chapter 5.4) which consists of the applied optimisation algorithm (chapter 5.4.1), the underlying cost calculation procedure (chapter 5.4.2), the incorporation of economies of scale into *AirTrafficSim* (chapter 5.4.3), the determination of the optimal aircraft size (chapter 5.4.4) as well as the objective function of *AirTrafficSim* (chapter 5.4.5)
- defining and conducting the calibration procedure (chapter 5.5)
- recapitulating the major findings of the chapter (chapter 5.6)

5.1 Basic principles

AirTrafficSim models the cost minimizing network structure of a single airline that serves the given freight demand with being absent other competitors. Such problems are known as partial network design problems. *AirTrafficSim* addresses this research question for air freight carriers by applying an evolutionary approach. "Evolutionary" suggests that a network structure is not assumed a priori but emerges from the model. Therefore, the following basic principles can be formulated for *AirTrafficSim*:

- air freight focus (passenger services are disregarded from network design considerations)
- supply side model (based on given freight demand)
- one airline approach (no competition, no cooperations, no alliances)
- economies of scale are applied on all network links and are not restricted to interhub links
- the level of link discounts is endogenously determined
- *AirTrafficSim* is an optimisation model that is network cost driven (cost minimization approach)

Besides these basic principles of *AirTrafficSim* its spatial scope as well as the applied aircraft categorization is introduced in the following.

5.1.1 Spatial scope

Air cargo is mainly an inter–continental business with Asia, Europe and North America being the primary markets. Therefore, a worldwide research scope is adequate and applied in *AirTrafficSim*. Regions are determined based on the WORLDNET research project (2009). Six "continents" (Africa, Asia/Pacific, Europe, Near East, North America and South America) are further subdivided into 29 regions (see Annex for details). Only the region “United States of America” has been further disaggregated in *AirTrafficSim* for the purpose of the present research into West Coast (NAOW), Central (NAOC) and East Cost (NAOE) to be able to differentiate the US air freight market properly.

5.1.2 Aircraft categorization

More than hundred different commercial aircraft types exist which differ by their characteristics, such as maximum payload, maximum takeoff weight, seat capacities, etc. The reduction of complexity and the creation of a manageable model is the primary reason for categorizing these aircrafts into groups. Based on the elaborations of chapter 2.1 a first distinction is made between aircrafts which are pure freighter aircrafts and aircrafts that transport freight as a by–product (belly freight).

Pure freighter aircrafts are further differentiated based on the Boeing freighter segmentation into standard–body (< 45 tonnes), medium wide–body (40–80 tonnes) and large body (> 80 tonnes) aircrafts (Crabtree et al., 2008). Because of the very few aircrafts in operation of the standard–body segment and the expectations of Boeing that the number of aircrafts of medium–wide bodies will dominate the standard–body segment, both categories are grouped together to a small freighter category. The representative aircraft for the class of small freighters is the Airbus 330–200F whereas the Boeing 747–400F represents the class of large freighters. Characteristics of the representative aircraft are interpreted as a proxy for the whole aircraft category. Thus, *AirTrafficSim* focuses on the aircraft category’s representative aircraft.

Belly–hold aircrafts are differentiated based on maximum payload and maximum stage length into four aircraft categories, namely small, medium, large and very large belly aircrafts. *AirTrafficSim* focuses on the strategic network configuration of scheduled cargo services and does not consider singular and short–term charter operations. Hence, only aircrafts of the two largest aircraft manufacturers Airbus and Boeing are incorporated into the model. Regional jets are operated for passenger services and are usually not considered for regular cargo services. Therefore, regional jets are not interpreted as alternatives for cargo transport. Table 6 summarises the characteristics of the representative aircraft of every aircraft category.

Table 6: Aircraft categories[65]
(Source: author's own representation)

Aircraft category	**I[66]**	**II[67]**	**III[68]**	**IV[69]**	**V[70]**	**VI[71]**
Aircraft	733[72]	321[73]	343[74]	744[75]	332F[76]	74Y[77]
Max. range [km]	2,990	5,300	13,100	13,430	7,400	8,230
Max. payload[78] [t]	14	23	50	69	69	112
Avg. PAX[79]	141	185	295	416	0	0
Max. cargo capacity[80] [t]	4	10	29	39	69	112

5.2 Structure of *AirTrafficSim*

A three step approach is implemented into the programming language JAVA which differentiates between the initialization, the optimisation and the finalization phase (Figure 6). The three steps of *AirTrafficSim* will be introduced in the following.

[65] Aircraft data are taken from the technical information manual of the aircraft manufacturers (last visited July 15, 2011).
[66] Category I: small belly
[67] Category II: medium belly
[68] Category III. large belly
[69] Category IV: very large belly
[70] Category V: small freighter
[71] Category VII: large freighter
[72] B737-700
[73] A321
[74] A340-300
[75] B747-400
[76] A330-200 Freighter
[77] B747-400 Freighter
[78] Maximum payload = maximum design zero fuel weight (maximum weight allowed before usable fuel and other specified usable agents are loaded) minus operational empty weight (weight of operational standard aircraft).
[79] PAX = number of passengers
[80] The average cargo capacity is calculated as follows: cargo capacity = maximum payload – (load factor*PAX*weight per PAX). The following assumptions are applied: Average load factor for passenger utilisation is 0.7. Each person (incl. baggage) weights 100kg (Doganis, 2010).

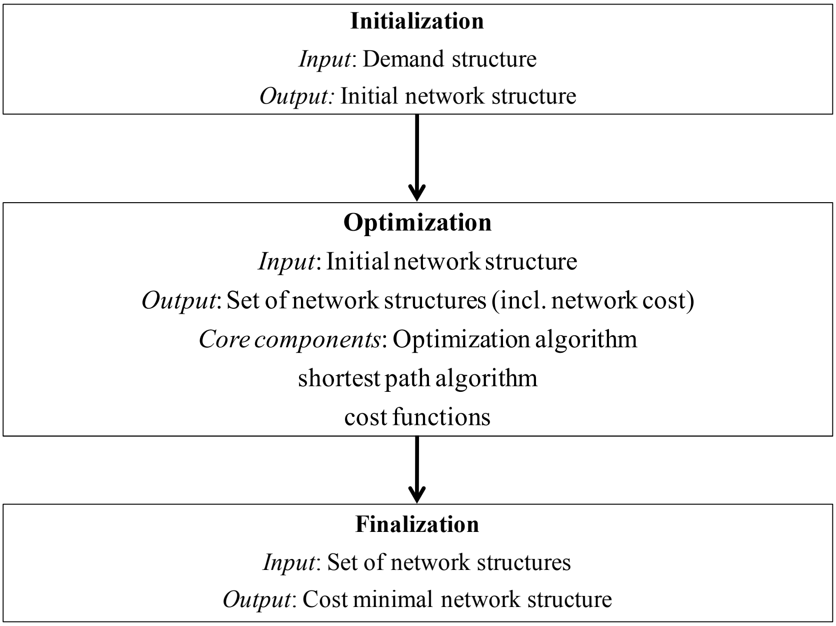

Figure 6: General structure of *AirTrafficSim*
(Source: author's own representation)

Initialization

The initialization step of *AirTrafficSim* prepares the required input data for the core step of the model, the optimisation phase. As input to the initialization phase a demand structure is required which consists of annual tonnages from origin to destination airport (OD tonnages). Direct services are conveyed from the demand data which will be evaluated in the following step of *AirTrafficSim*.

Optimisation

The optimisation procedure applies a Simulated Annealing technique which belongs to combinatorial optimisation methods. Simulated Annealing allows nonlinear components, avoids becoming trapped in local minima and is in general a very effective algorithm for combinatorial optimisation problems. Simulated Annealing and its components are introduced in detail in chapter 5.4.1. As objective function total network cost is chosen which consist of transport related operating cost (including opportunity cost of capital) (see chapter 5.4.2 for further details).

The decision which route to operate is solved by a shortest path algorithm (Dijkstra algorithm) based on unit cost as link weights[81]. Therefore, it is assumed that if comparable routing options exist, the option with the lowest cost is chosen by the airline. Link weights are determined by an average cost function (see

[81] Air Transport Agreements are considered in the optimisation phase that only flights can be operated where a legal foundation exist.

chapter 5.4.2) which depends on the business framework of the airline as well as economies of scale as introduced in chapter 5.4.3.

The unit cost for every link (per tonne and per mile) is conveyed into the optimal aircraft size decision (see chapter 5.4.4). The outcome of the aircraft size calculation is a cost optimal aircraft size for the respective flight leg as well as the service frequency to fully serve the route demand. Finally, the total network cost (fitness function) is determined based on the developed objective function (see chapter 5.4.5).

Finalization

The last step of *AirTrafficSim* (finalization phase) compares the different feasible network structures which resulted within the optimisation procedure and selects the structure with the lowest overall network cost. This structure is defined as best and is interpreted as the network which the airline will operate and which can be compared with a real airline network structure. The finalization phase of *AirTrafficSim* terminates the model run.

5.3 Initialization phase

The initialization step of *AirTrafficSim* prepares the required input data for the optimisation phase. Therefore, the design of the input data as well as the creation of a first feasible network structure is defined below.

Input data for AirTrafficSim

A demand structure is the prerequisite for *AirTrafficSim* which consists of annual demand from origin airport where the freight is affiliated by the airline to its destination airport. Demand data are ascertained for one cargo airline as the algorithm optimizes total network cost from an airline's perspective.

Initial network structure

An initial and feasible network structure is then applied for the set of airports and routes by allocating direct services to every defined route. Furthermore, Air Transport Agreements which determine landing rights, enplaning or deplaning opportunities as well as cabotage rights for the airline are considered within *AirTrafficSim*. Based on the demand structure and the allowed operations, direct services are allocated to each route which relates to a point–to–point (P2P) network structure. In case that direct services are not allowed by Air Transport Agreements a shortest–path analysis is carried out and determines a feasible path. The P2P network structure is a practical solution for the airline but most likely not a cost minimal network structure. The finding of the lowest cost network structure is part of the second step, the optimisation phase of *AirTrafficSim*.

5.4 Optimisation phase

Optimisation deals with determining the best alternative from a set of possible alternatives on the basis of a given objective function. The underlying objective function measures the quality of a feasible solution. The optimisation problem of *AirTrafficSim* relates to the subset of combinatorial optimisation problems where the set of possible alternatives is finite but of exponential size depending on the number of nodes (airports). In general, two solution techniques are available, exact methods and heuristics (Morlock and Neumann, 2002).

The branch–and–bound technique is the most widespread technique for exact methods. Thereby the overall optimisation problem is decomposed into several sub problems which are either solved or proved not to yield an optimal solution for the initial optimisation problem (Pardalos and Resende, 2002). Though exact methods have developed rapidly during the last decades, still in many instances exact methods are unable to efficiently achieve optimal solutions of combinatorial optimisation problems. In particular, the exponentially growing decision tree which results from increasing problem sizes as occurring in real world applications tend to degenerate to complete enumeration (Pardalos and Resende, 2002). Such techniques are therefore very time consuming and unfeasible for scenario analyses as intended by *AirTrafficSim*.

Heuristics and especially metaheuristics determine the most appropriate solution in an acceptable time period but do not guarantee to achieve the optimal solution. The general advantage of metaheuristics in particular is that not only solutions are selected that decrease the objective function (minimizing problem) but that also local minima can be leaved by them. In particular, this property has been the reason for the choice of a metaheuristic in *AirTrafficSim*[82].

Since the 1980s researchers have developed a wide variety of metaheuristics for several optimisation problems, such as the tabu search[83], the ant colony optimisation algorithm or Simulated Annealing[84]. Thereof, Simulated Annealing (SA) has been chosen as optimisation algorithm because of the following experiences with SA as well as its advantageous properties:

- Very satisfactory experiences exist with SA in aviation research as well as on the vehicle routing problem that prove an efficient application of SA for i.e. hub–and–spoke network decisions (e.g. Breedam van, 1995; Daniel and Pahwa, 2005; Martin, 2010)
- SA overcomes local optima (Vidal, 1993)
- SA is able to improve the performance of local search by replacing the deterministic acceptance criterion by a stochastic criterion (Aarts and Eikelder, 2002)
- SA finds global minimum definitely if the annealing process is applied infinitely slow (Granville et al., 1994)
- SA is a transparent approach which can easily be understood by policy makers and practitioners (Vidal, 1993)

The general Simulated Annealing approach as well as its implementation into *AirTrafficSim* is presented in the following.

[82] Search strategies without this property are local search strategies. Further information on these algorithms is found in Pardalos and Resende, 2002.

[83] Tabu search has been proving to cope sufficiently with different vehicle routing problems (e.g. Fiechter, 1994, Gendreau et al., 1994 and Schultman et al, 2006)

[84] Information on other metaheuristics is found in e.g. Horst and Pardalos, 1995 and Du and Pardalos, 1999.

5.4.1 General concept of Simulated Annealing

Metropolis et al. (1953) developed an algorithm to model the process by which molecules align themselves during the slow cooling of metals which is called annealing in thermodynamics. The annealing process consists of the following two steps: first, temperature is increased to the value at which solid melts, and second, temperature is decreased slowly until the molecules of the melted solid arrange themselves in the ground state of the solid. Whilst all particles in the liquid phase arrange themselves randomly, they are in a highly structured lattice (minimal energy system) in the ground state (Aarts and Eikelder, 2002).

Kirkpatrick et al. (1983) and Cerny (1985) transferred the general approach of Metropolis et al. (1953) to combinatorial optimisation problems by adapting the following characteristics (Sixt, 1995):

- The **variables** of the optimisation problem are interpreted as **molecules** in thermodynamics
- A **feasible solution** of the optimisation problem corresponds to a **state situation** of a solid
- The **objective function** is regarded as the **energy** of the system (that is to be minimised)
- The transition to a **neighbouring** solution relates to a **change of state**
- The search for an **optimal solution** replaces the determination of the **ground state**

5.4.1.1 Procedure of the Simulated Annealing algorithm

The Simulated Annealing algorithm determines the least cost network structure out of the set of possible alternatives in *AirTrafficSim*. Its implementation in *AirTrafficSim* is introduced as pseudo–code in the following (based on Aarts and Eikelder, 2002):

procedure Simulated Annealing;
begin
  INITIALIZE (x_0, T_0, L_0);
  k:=0;
  x_a:=x_0;
  repeat
    for l:=1 **to** L_k **do**
    begin

      GENERATE (x_{a+1} from $N(x_a)$);
      if ($f(x_{a+1}) <= f(x_a)$ **then** a:=a+1
      else
      if $\exp(-(f(x_{a+1})-f(x_a))/f(x_a)) >$ random[0;1] **then** a:=a+1

    end;

    k:=k+1;

CALCULATE_LENGTH (L_k),
CALCULATE_TEMPERATURE (T_k);

until stop criterion
end;

Where:
x_a = current solution of the optimisation problem
x_0 = initial solution
T = temperature of the annealing process
T_0 = initial temperature
T_k = temperature at step k
L_k = length of Markov chain[85] k
k = local parameter that defines the iteration number of the Markov chain
l = local parameter for the inner–Markov chain loop
$f(x_a)$ = evaluation of the current solution x_a according to the objective function f
$N(x_a)$ = neighbour function that generates a neighbour solution x_{a+1} from the current solution x_a

The general description of the Simulated Annealing algorithm as pseudo–code is now transferred into a flowchart for a better understanding of the model steps and their applied methodologies.

85 A Markov chain is a set of states where the future state is only dependent on the present state and independent of the past states.

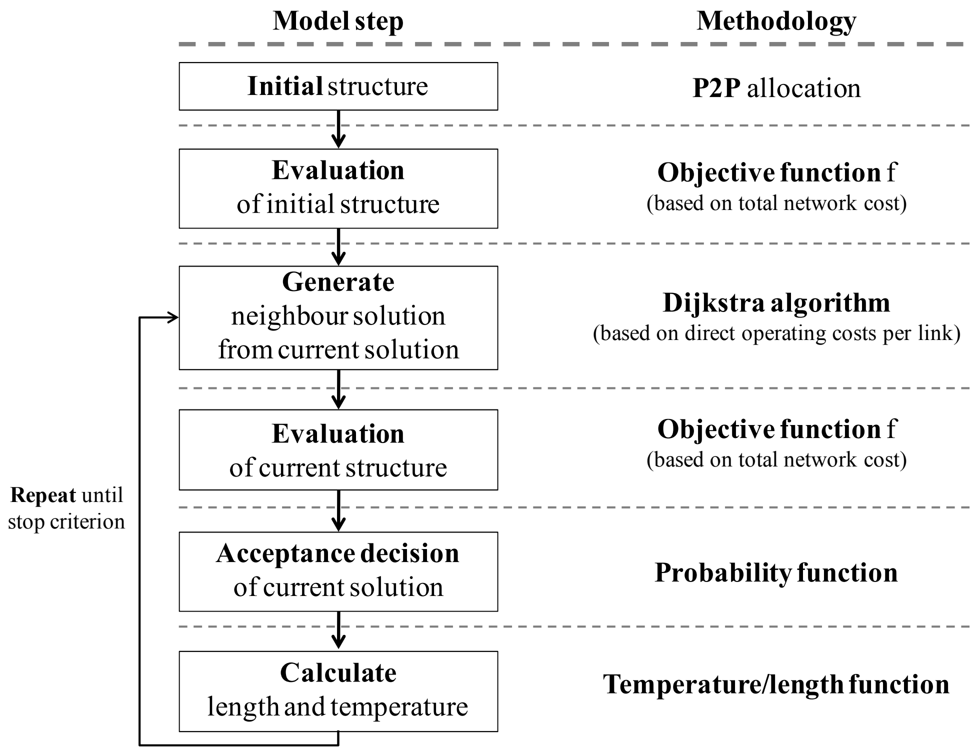

Figure 7: Flowchart of *AirTrafficSim*
(Source: author's own representation)

In a first step, the initial solution which is based on a P2P adaptation of the demand structure is evaluated based on the objective function (see chapter 5.4.5 for further details). Second, a neighbour solution of the P2P structure is determined by a Dijkstra shortest–path algorithm which is based on the links' operating costs. The neighbour solution is interpreted as a new network configuration which emerges from the current solution and which is evaluated likewise to see if a lower cost solution is achieved. If network cost are lower for the neighbour solution, the algorithm moves to the new state (solution). If cost is higher, the algorithm either reverts back to the former state or stays in the higher state depending on a predefined probability function. The possibility of moving to a higher cost state allows escaping local minima. New neighbour solutions are created as long as the stop criterion is achieved (see 5.4.1.2 for further details). With decreasing temperature, the probability of accepting a higher cost state decreases. Ideally, the network terminates where cost is minimal (global minimum). The comparison between two states (solutions) terminates one model iteration whereas at the end of Simulated Annealing one model run is conducted.

The concrete design of the different model steps and their parameter choice for *AirTrafficSim* is introduced in the following chapter.

5.4.1.2 Design of the Simulated Annealing algorithm in *AirTrafficSim*

The SA algorithm consists of parameters which are presented in Table 7 and which are predetermined for the use in *AirTrafficSim* afterwards.

Table 7: Main Simulated Annealing parameters
(Source: Vidal, 1993)

Algorithm predeterminations	
Generic (cooling scheme)	**Problem specific**
▪ T_0 (initial temperature) ▪ L_k (number of iterations) ▪ Temperature function for the determination of T_k ▪ Stop criteria	▪ x_0 (initial solution) ▪ Evaluation of result ▪ Neighbour solution generation

x_0 (initial solution)

The initial solution in most Simulated Annealing applications is determined by random selection because no detailed information is available on a feasible solution (state). *AirTrafficSim* requires demand data as input to the optimisation phase. Based on these information a possible solution can be ascertained which assumes that all routes are directly operated without transferring at dedicated hub airports. Such a network structure is called point–to–point (P2P) network. Thus, the Simulated Annealing algorithm initiates with this P2P network structure.

T_0 (initial temperature) [86]

The traditional concept of Simulated Annealing envisages a rather high initial temperature to overcome the randomized initial solution as well as neighbouring local minima (Vidal, 1993). Therefore, the temperature should be high enough to accept nearly all changes at the beginning of the algorithm. In case of uncertainty about an adequate initial solution, it has been shown that an initial temperature (T_0) of 500 provides sufficiently good optimisation results (Foidl, 2009). The determination of T_0 for *AirTrafficSim* is presented in the model calibration chapter 5.5.

Evaluation of results based on $f(x_a)$

The evaluation function of each solution is the objective function as introduced in chapter 5.4.5. The objective function calculates the total network cost which is determined by the ascertained network structure.

Neighbour generation x_{a+1}

AirTrafficSim commences as illustrated in Figure 7 with a real world point–to–point network structure (initial solution (x_0)). The network structure contains information on the operated airports and links as well as on the tonnes at each airport and on each link. Link specific cost for transporting one tonne of cargo on this link is then ascertained based on this information. Starting therefrom a first neighbouring solution (x_{a+1}) is calculated by Dijkstra's shortest–path algorithm. The Dijkstra algorithm[87] is a graph search algorithm that solves the single–source shortest path problem for a graph with nonnegative link weights (Morlock and Neumann, 2002). As link weights total aircraft operating cost (TAOC) are implemented in *AirTrafficSim* which are by definition nonnegative (see chapter 5.4.2 for further details on TAOC). An error term which is directly dependent on the current temperature T_k is added to the operating cost which is interpreted as an exogenous shock to the present network to break open the current structure for overcoming local minima. The following equation displays the link weight determination for the Dijkstra algorithm:

$$C_{ij}=\left(1+\varepsilon_{ij}\right)*c_{ij}*d_{ij}$$

Where:

C_{ij} = cost of flight leg ij [USD[88] per tonne]

ε_{ij} = error term: random number between $[-T_k/T_0;+T_k/T_0]$

c_{ij} = unit cost of flight leg ij [USD per RTM]

d_{ij} = distance between origin airport i and destination airport j

[86] Temperature is interpreted in *AirTrafficSim* as a parameter that rearranges the present network structure randomly to overcome local minima. Therefore, an exogenous shock to the current network structure is accomplished as temperature directly impacts the error term (ε_{ij}) (cf. chapter 5.4.1.2).

[87] The Dijkstra algorithm is implemented based on the open-source library JUNG (Java Universal Network Graph) (O'Madadhain et al., 2005).

[88] USD=United States dollar

The structure of the equation has been applied for the following reasons:

- The impact of the error term needs to be significant to escape local minima
- Bonus (e.g. subsidies) as well as malus (e.g. slot restrictions) should be considered by the error term
- The error term should follow the Simulated Annealing philosophy that the global minimum is achievable (high error term at the beginning of the algorithm which decreases with the number of performed iterations)

It is assumed that if comparable routing options exist within the network of the airline, the option with the lowest cost (shortest–path) is chosen by the airline. The neighbouring solution is a new network structure which contains the updated information on the operated airports and links as well as the tonnes at the airports and on the links. Figure 8 displays the procedure of the neighbour generation.

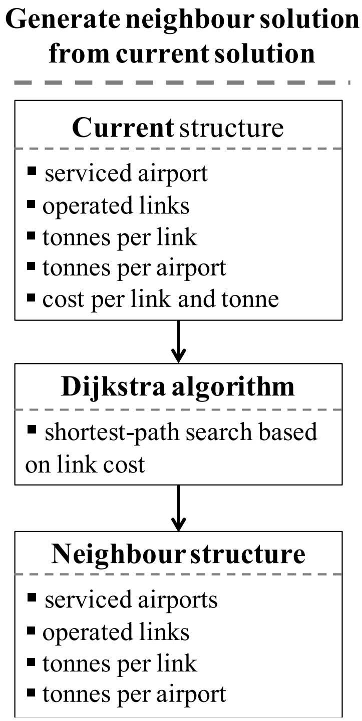

Figure 8: Flowchart of the neighbour solution generation (Source: author's own representation)

L_k (number of iterations)

L_k defines the length of the k–th Markov chain which indicates the number of neighbouring solutions which are analysed for a constant temperature (T_k). Markov chains can be differentiated into homogeneous and inhomogeneous chains. Inhomogeneous chains decrease temperature based on a decision function which rules whether or not leaving the current temperature on the basis of the present and preceding solutions whereas homogeneous chains decrease temperature after a number of transitions that is predefined and fix.

The concept of inhomogeneous Markov chains is incorporated into *AirTrafficSim*. Every solution that worsens the objective function and is not accepted by the probability function results in an adaptation of the temperature from T_k to T_{k+1}. Additionally, at most five solutions are considered with a constant temperature T_k. By weighting up running times (including the ability of *AirTrafficSim* to be scenario sensitive) with effectiveness criteria (quality of results) the presented approach is chosen.

T_k (temperature function)

The temperature function, also known as the cooling schedule, specifies the finite sequence of temperature values. High temperature values at the beginning of the algorithm avoid being locked in local minima whereas at the end of the algorithm only small deteriorations should be accepted by the Simulated Annealing philosophy. Two classes of cooling schedules can be differentiated, namely static and dynamic schedules (Aarts and Eikelder, 2002). In a static cooling schedule all relevant parameters are predetermined, fix and cannot be adjusted during the algorithm whereas dynamic schedules adaptively change parameters during the execution of the algorithm (Aarts and Eikelder, 2002).

Different temperature functions have been applied and tested for the objectives of *AirTrafficSim* and will be presented in the model calibration chapter (chapter 5.5).

Stop criteria

An appropriate stopping criterion is needed to prevent the algorithm from endlessly repeating in search of improved solutions. Therefore, two categories of stopping criteria are required:

- Local constraint to restrict iterations of Markov chain: Stopping criteria for each (inhomogeneous) Markov chain in case that no transition occurs,
- Global constraint: Stopping criteria for the entire algorithm in case that a (most likely) optimal solution is achieved.

Local constraint

Each Markov chain k is terminated if one of the following two constraints arrives:

- Acceptance constraint: to overcome local minima, Simulated Annealing accepts less efficient solutions under certain circumstances. Such circumstances are evaluated based on a so called acceptance function that applies a random experiment. The acceptance of a solution grounds on Metropolis et al. (1953) and the following probability characterises the acceptance of the situation x_{a+1} (state) compared to the former situation x_a.

$$p(x_{a+1}) = \begin{cases} 1 & \text{if } f(x_{a+1}) < f(x_a) \\ e^{-\frac{f(x_{a+1}) - f(x_a)}{f(x_a)}} & \text{else} \end{cases}$$

The "else–case" is decided on the basis of a random experiment which compares the above introduced exponential value with a random number which is generated from a uniform distribution within the interval [0,1]. A lower random number than the exponential value implies that the algorithm is continued with the situation x_{a+1} otherwise with the former situation x_a.

- Duration constraint: An algorithm path (Markov chain) is regarded as exhausted if more than five iterations have already been tested during the current Markov chain k and no best solution appeared. Test runs with this constraint achieved good results.

Global constraint

The algorithm quits when it fails to pass from a current level (T_k) to the next level (T_{k+1}) because the predefined number of annealing iterations have already been achieved (see chapter 5.5 for the determination of the maximum number of annealing iterations). Another global constraint which is common in other publications such as a stopping criterion in case of two successive Markov chains which do not improve the objective function (e.g. Sixt (1996)) is not applied in *AirTrafficSim*. It is argued that the advantages of Simulated Annealing should be fully exploited to increase probability of finding the optimal solution and not limiting the algorithms ahead of schedule. The best determined situation (state) at the end of the Simulated Annealing algorithm is interpreted as the cost minimal network configuration by *AirTrafficSim*.

5.4.2 Cost calculation

The creation of feasible neighbourhood solutions is a prerequisite for the applied Simulated Annealing algorithm. A neighbourhood solution is defined in *AirTrafficSim* as a network structure which is determined based on the current network by applying a shortest–path algorithm (Dijkstra algorithm) based on operating cost. The following chapter presents the development of the average cost function that considers the airline's market environment and defines average cost per revenue–tonne–mile[89] for the investigated airline.

Studies on the relationship between cost drivers (i.e. fuel price) and an airline's unit cost has so far been focused on passenger services only. Therefore, the starting point of *AirTrafficSim*'s network cost calculation is the development of an average cost function for cargo airlines that integrates airline specifics into unit cost.

Like many other studies, such as Caves et al. (1984), Gillen et al. (1990) Oum and Zhang (1997), Wei and Hansen (2003), Swan and Adler (2006) and Tsoukalas et al. (2008), the present study runs regression analyses to understand the relationship between airline's unit cost and its major cost components. The

[89] One revenue-tonne-mile (RTM) is achieved if one freight tonne is transported for one mile.

comprehensive database on which the analysis grounds is introduced in the following before the regression analysis for the average cost function is presented.

5.4.2.1 Cost components of airlines

The US Department of Transportation (US DOT) publishes airline specific financial and traffic data of large certified airlines (US DOT, 2010). Large certified airlines hold Certificates of Public Convenience and Necessity with annual operating revenues of at least 20 MUSD. Such airlines are obliged to report information. Thus, the database is the only database that offers disaggregated and comparable airline cost data sufficient for statistical analyses.

Form 41 of this database consists of financial information of large US certified air carriers which includes balance sheet, income statement, cash flow, aircraft inventory and aircraft operating costs. Airline cost is classified into two main functional groups: direct operating cost and indirect operating cost. Direct operating cost includes all cost components which are necessary for operating flights (e.g. fuel, aircraft, flight crew) whereas indirect operating cost includes all other cost components for airlines which are not directly flight–related (e.g. management, marketing). *AirTrafficSim* models the network structure of cargo airlines. Hence, the direct operating cost determines the network structure of the airline (ceteris paribus). Table 8 summarises the distribution of direct operating costs in 2000 and 2007[90] and proves that fuel (incl. oil) is by far the most significant cost component for airlines.

Table 8: Distribution of direct operating cost of major US carrier (Source: author's own representation based on US DOT, 2010)

Direct operating cost	2000 [%]	2007 [%]
Flying operations costs (total)	68,4	76,3
Flight crew	25,1	15,2
Aircraft fuel and oil	30,0	53,2
Insurance	0,2	0,2
Rentals	11,0	6,0
Others	2,1	1,7
Flight equipment maintenance	22,9	17,5
Flight equipment depreciation	8,7	6,2

A comparison between the US DOT data and analyses of Doganis (2010) who compiled the distribution of direct operating cost for ICAO[91] member airlines

[90] The year 2007 has been chosen for analysis as it is the base year of *AirTrafficSim*. The development of direct operating cost becomes apparent against the background of the year 2000 (the year 2000 is regarded as a "normal" year for the airline industry).

[91] The International Civil Aviation Organization (ICAO) is an agency of the United Nations which focuses on aviation issues, such as standard setting and the facilitation of border-crossing procedures.

(international sample) showed similar results[92]. Thus, the US DOT data are interpreted as representative also for Non–US carriers and can be considered for the present dissertation.

Doganis (2010) ascertained that in 2007 flying operations costs are around 75% of direct operating cost whereas flight equipment maintenance are approx. 17% and depreciation approx. 8% of total direct operating cost. The flying operations are further differentiated into flight crew (16% of flying operations costs), fuel and oil (55%), airport and en–route charges (14%) and aircraft rental and insurances (15%). In both analyses aircraft fuel (including oil) is by far the most influencing cost component for flying operations followed by maintenance, crew and airport costs.

Airport and en–route charges are roughly 14% of overall direct operating cost of ICAO certified carriers (Doganis, 2010). The impact of aircraft size and aircraft category on airport charges is analysed in detail in chapter 5.4.3.2.

Maintenance cost for aeroplanes compose around 10% of total airline operating cost in 2007 (Doganis, 2010). Materials for maintenance works as well as labour cost are included in this percentage. The US Federal Aviation Administration (FAA) as well as most international operating airlines differentiates the major maintenance checks into four categories, commonly referred to as A–, B–, C–, and D–checks. A–checks which involve a visual inspection of all major systems is mandated by FAA approx. every 60 flight hours whereas B–checks are carried out every 300 to 600 hours and C– as well as D–checks every one to four years (Bazargan, 2010). These guidelines prove that maintenance checks primarily accrue based on block hours of the aircraft and are independent of the transported payload.

Fuel (including oil) was over 50% of total aeroplane operating cost in 2007 making fuel the most important single airline cost component (Doganis, 2010). Aviation fuel price has been tripled between 2002 (67.8 US cents per US gallon) and 2006 (195 cents per US gallon) and is expected to remain at a high level[93]. It can be doubted that fuel efficiency gains of new aircrafts fully compensate the expected fuel price development. Thus, fuel price and fuel efficiency of aircrafts will remain a key component of airline's operating cost.

5.4.2.2 Average cost function

The objective of constructing an average cost function is to relate the primary cost components of air cargo services to the industry's standard cost unit. As standard cost unit (dependent variable) total aircraft operating cost (TAOC) in US Dollar per revenue–tonne–mile has been used. TAOC incorporates all cost categories in real terms that are directly associated with the operation of an airline's own air service

[92] The valuation that similar results are existent is based on the distribution of costs and their overall share on direct operating cost.

[93] Fuel price declined to 140 US cents per US gallon at the end of 2008 because of the global economic crises. Many airlines had bought fuel hedges when prices were high and rising (especially in 2006/7). Thus, most airlines were paying fuel prices well above the market price in 2009 (Doganis, 2010).

which is common practice by airlines (Doganis, 2010). In other words, TAOC is the airline's total average cost for carrying out its air services.

In total 146 observations could be generated for the present statistical analysis. One observation relates to annual cost data of one airline, and data of ten cargo transporting airlines could be considered for analysis (see Table 9). The sample presents a representation of the industry as Integrators, pure cargo carriers and combined carriers are included for the time period between 1990 and 2007.

Table 9: Cargo airlines considered for average cost function analysis (Source: author's own representation based on Mayer and Scholz, 2010)

Airline	IATA Code	Business model	Reporting period
ABX Air	ABX	Pure Cargo Airline	2005–2008
American Airlines	AA	Combined Carrier	1990–2008
AStar Air Cargo	ER	Pure Cargo Airline	1997–2008
Continental Airlines	CO	Combined Carrier	1990–2008
Delta Airlines	DL	Combined Carrier	1990–2008
FedEx	FX	Integrator	1990–2008
Northwest Airlines	NW	Combined Carrier	1990–2008
United Airlines	UA	Combined Carrier	1990–2008
UPS	5X	Integrator	1990–2008
World Airways	WO	Pure Cargo Airline	1990–2008

Cost data of combined carriers which operate passenger and cargo services had to be fairly allocated to the responsible service class. Cost components that could be explicitly allocated to one specific service type (e.g. catering for passenger services, cargo handling for freight transport) are entirely allocated to that specific service. Combined costs, such as fuel cost or flight crew, are allocated based on the revenue–tonne–miles travelled share between cargo and passenger services. Data for pure cargo carriers as well as for Integrators which only operate cargo services kept unchanged.

All data have been analysed on an annual basis, and currency fluctuations could be avoided by using US Dollar as currency in *AirTrafficSim*. All cost components have been inflation–adjusted by the use of the industry specific Airline Cost Index of the Air Transport Association of America (ATA).

The starting point for the regression was the aforementioned analyses on cost components for airlines (see chapter 5.4.2.1). The average cost function is represented by a multiple log linear regression model. As independent variables fuel prize, load factor, average distance, depreciation, landing fees and flight related labour cost were selected as these variables properly represent the airlines' direct operating cost composition[94]. The model has the following regression equation (Mayer and Scholz, 2010):

[94] Further information can be found in Mayer and Scholz (2010).

$$\ln(TAOC_n) = a_0 + a_{Dep} * \ln(Dep_n) + a_{avgDist} * \ln(avgDist_n) + a_{LF} * \ln(LF_n) + a_{Land} * \ln(Land_n) + a_{Fuel} * \ln(Fuel_n) + a_{Sal} * \ln(Sal_n) + \zeta$$

Where:

n = (analysed) airline n
$TAOC_n$ = total aircraft operating cost of airline n [USD2000/RTM)
Dep_n = aircraft depreciation of airline n [USD2000/RTM]
$avgDist_n$ = average distance of airline n's network [miles]
LF_n = average load factor of airline n [%]
$Land_n$ = average landing fee of airline n [USD2000/per landing]
Fuel = market jet fuel price [USD2000/gallon]
Sal_n = Flight related labour cost of airline n [USD2000/RTM]
ζ = normal distributed error term

The 146 observations[95] achieved a coefficient of determination (R^2) of 67.4%. The consistency of the model is supported by a Durbin Watson coefficient of 2.220 and an insignificant f–test (see Table 10).

Table 10: General quality of the average cost model (Source: Mayer and Scholz, 2010)

Number of observations	146
Coefficient of determination (R^2)	0.674
Durbin–Watson coefficient	2.220
significance F–Test	0.000

Besides the overall fit of the model, detailed analyses of co–linearity between the cost components have been conducted. Results did not find any significant correlations to be concerned (Mayer and Scholz, 2010). Coefficients as well as their significances are displayed in Table 11.

[95] As indicated in Table 9 some airlines have only reported their financial data in selected years. Thus, in total 146 observations could be used for analysis.

Table 11: Detailed results of the average cost model (Source: Mayer and Scholz, 2010)

Variable	Coefficient	Std. Error	Significance
Constant	–9.156	0.577	0.000
ln (Dep)	0.082	0.020	0.000
ln (avgDist)	0.276	0.074	0.000
ln (LF)	–0.418	0.132	0.002
ln (Land)	0.049	0.028	0.086
ln (Fuel)	1.364	0.738	0.067
ln (Sal)	0.544	0.039	0.000

Table 11 statistically shows the importance of the fuel price for the TAOC as already indicated in Table 8. The disproportionately high impact of the fuel price is explained by variables which also impact TAOC and which are not directly incorporated into the average cost function because of correlation issues and which are therefore integrated among others indirectly via the fuel price development, such as costs for aircraft oil, spare parts, etc.

The variable average distance of the airline can be considered as a measure for the network strategy of the airline (short– vs. long–haul). The positive relationship of average distance and TAOC can be explained by:

- the fact that airlines that operate long–haul destinations (higher average distance) usually operate a heterogeneous aircraft fleet (short–haul, medium–haul and long–haul aircrafts) which increase complexity for instance for maintenance services, crew, etc. (higher TAOC)
- the possibility of short–haul airlines to efficiently allocate crew and aircraft utilization (Doganis, 2010)

The parameter flight related labour cost is noteworthy as it shows great impact on the TAOC. The positive prefix specifies that the higher the labour cost per RTM, the higher the TAOC per RTM for the analysed airline.

The predominant performance indicator on a flight leg level is the load factor (capacity utilization). The negative prefix in the developed model approves the impact of the load factor on TAOC as with decreasing load factor cost per unit increase.

Therefore, the resulted average cost function for the airline's total aircraft operating cost in *AirTrafficSim* is:

$$\ln(TAOC_n) = -9.156 + 0.082 * \ln(Dep_n) + 0.276 * \ln(avgDist_n) - 0.418 * \ln(LF_n) + 0.049 * \ln(Land_n) + 1.364 * \ln(Fuel_n) + 0.544 * \ln(Sal_n) + \zeta$$

While the average cost function was developed and estimated for the air cargo industry in general, differences in cost occurrence between the introduced business models were determined. However, the small number of observations for some business models does not allow detailed business model specific analyses. Hence, deviations from the industry wide cost function could only be applied and statistically estimated for pure cargo carriers where results were statistically significant. Therefore, two well–founded cost functions are incorporated into *AirTrafficSim*, namely one specific average cost function for pure cargo carriers and a general average cost function for all remaining airlines. The influence of economies of scale to the operating cost of an airline is analysed in the following.

5.4.3 Economies of scale in *AirTrafficSim*

Economies of scale are a motivation, especially for freight transport operators, to establish concentrated and centralised hub and spoke networks. Thus, it is surprising that transportation cost is usually modelled without including economies of scale into the models (Kimms, 2006). In this section the incorporation of economies of scale into the network design modelling of *AirTrafficSim* is presented.

In general, economies of scale exist if the long–term average cost curve decreases as output increases (Blauwens et al., 2006). Of course, they cannot be realized infinitely as i.e. the maximum cargo capacity of each aircraft as well as the overall maximum capacity of cargo aircrafts is limited[96]. The concept of economies of scale is extremely multifaceted and is applied in freight transportation and especially in aviation research at least in three different ways (cf. Blauwens et al., 2006):

- aircraft specific economies of scale: How does the chosen aircraft (e.g. A319, A321, A330) and its utilization influence average transport cost[97]?
- route specific economies of scale: Do route specific traffic volumes influence the airline's average operating cost on this route?[98],
- company specific economies of scale: Does the size of the airline (e.g. turnover, employees, airports served) influence airline's average operating cost?[99]

Few existing models, as introduced in chapter 4, incorporate route specific economies of scale by assuming that economies of scale can be achieved on

[96] Currently, the Boeing 747-400F has the largest freight capacities of conventional scheduled cargo aircrafts with 112.67 tonnes. Larger cargo aircrafts exist but are only in service for charter flight which are operated for special purposes only (e.g. Antonov 124-100: 230 tonnes payload) (Grandjot et al., 2007).

[97] Research on aircraft specific economies of scale are published in e.g. Miller and Sawers (1970), Bailey et al. (1985), Wei and Hansen (2003), Swan and Adler (2006). The mentioned publications focus on the first research question (inter-aircraft comparison) and do not consider cost developments for different load factors (intra-aircraft comparison).

[98] Research on route specific economies of scale are published in e.g. Aykin and Brown (1992), O'Kelly and Bryan (1998) and Horner and O'Kelly (2001). Alumur and Kara (2008) surveyed publications on the network hub location problem (includes economies of scale).

[99] Research on company specific economies of scale are published in e.g. Caves, Christensen and Tretheway (1984), Kirby (1986), Oum and Zhang (1997) and Tsoukalas, Belobaba and Swelbar (2008).

interhub connections. In such cases, an exogenous and fixed discount factor is applied to interhub connections only (e.g. Ernst and Krishnamoorthy (1998)). The present work follows the more recent philosophy of e.g. Bryan (1998) and Kimms (2006) which allows that economies of scale can be realized on every network connection. Network optimisation decisions of airlines justify this approach.

The relevant research questions for the implementation of economies of scale into *AirTrafficSim* are:

- aircraft specific economies of scale:
    - how does average operating cost develop with increasing load factor (intra–aircraft comparison)?
    - how does average operating cost differentiate between aircraft categories (inter–aircraft comparison)?
    - how does landing fees develop with increasing aircraft size?
- Route specific economies of scale:
    - how does average operating cost develop with increasing freight quantities at the involved airports (bundling opportunities)?

Available analyses compare the average transportation cost between different aircrafts only (inter–aircraft comparison). Studies of e.g. Wei and Hansen (2003) and Swan and Adler (2006) found out that operating cost on long distances flown by large aircrafts are up to 20–25% less than on short–haul distances flown by small aircrafts (Doganis, 2010). The overall assumption behind such analyses is a given load factor that is usually fixed to the maximum payload capacity of the aircraft (full loading).

Intra–aircraft comparisons which analyse the development of operating cost with increasing aircraft utilization are scientifically not ascertained and comprehensive approaches are missing. The following approach has been developed for the objective of the present dissertation:

The previous chapter introduced the importance of fuel cost on direct aircraft operating cost (>50%) making fuel the most important single airline cost component. Therefore, the development of fuel consumption with increasing load factor as well as for different aircrafts is used as proxy for the overall aircraft specific economies of scale.

5.4.3.1 Aircraft specific economies of scale (fuel consumption calculation of aircrafts)

The relationship between aircraft type, load factor and stage length is crucial for an efficient assignment of aircrafts to flight legs. Therefore, an engineering approach is conducted which uses aircraft specific data to compare operating cost of different aircraft categories for various load factor configurations.

The basic model for describing the physics of aircrafts is the Breguet range equation[100] (Lee et al., 2001). The Breguet range equation determines the maximum flight distance (range) under aircraft specific characteristics and the current payload. Engine, aerodynamic and structural technologies are represented by three aircraft specific parameters, namely its specific fuel consumption, its lift–to–drag ratio, and its structural weight. The following equation illustrates the basic form of the Breguet range equation.

$$Range\ [m] = \frac{\sqrt{\theta} * M * a_0 * L/_D}{g * SFC} * \ln\left(\frac{w_{initial}}{w_{final}}\right)$$

Where:

a_0 = Speed of sound [340.294 m/s],
M = Mach number [],
L/D = Lift–to–drag ratio [],
g = Gravitation [9.8065 m/s²],
SFC = Specific fuel consumption [kg/s*N],
T = Temperature at cruise altitude (11,000 feet) [K],
T_0 = Temperature on ground [K],
$\Theta = T/T_0$ [],
$w_{initial} = w_{fuel}+w_{payload}+w_{structure}+w_{reserve}$ [t],
$w_{final} = w_{payload}+w_{structure}+w_{reserve}$ [t],
w_{fuel} = weight of fuel [t],
$w_{payload}$ = weight of payload [t],
$w_{structure}$ = weight of structure ($w_{MTOW} - w_{OEW}$) [t],
w_{MTOW} = maximum take–off weight [t],
w_{OEW} = operating empty weight [t],
$w_{reserve}$ = security fuel reserve [t].

The relevant parameter for the aircraft specific economies of scale consideration is the development of the fuel weight. Fuel weight directly influences the initial weight of the aircraft and can be solved by the following equation:

$$w_{fuel} = \left(w_{payload} + w_{structure} + w_{reserve}\right) * \left(e^{Range * \frac{SFC*g}{L/_D * M * a_0 * \sqrt{\theta}}} - 1\right)$$

Figure 9 displays the fuel consumption of the six different aircraft categories, namely small belly, medium belly, large belly and very large belly aircrafts as well as small freighter and large freighter aircrafts, for a stage length of 1,000sm (approx. 1,609km).

100 The key assumptions of the Breguet range equation are: specific fuel consumption (SFC), lift-to-drag ration (L/D) and flight speed (M) are constant during the whole flight. Therefore, take-off-, climb- and descend-phase of a flight are modelled under steady cruise flight conditions.

It becomes obvious that for a given aircraft (e.g. B744F) and a given stage length fuel consumption increases linear with payload which is due to the structure of the Breguet range equation. Once the aircraft characteristics are determined, such as specific fuel consumption, lift–to–drag–ratio and structural weight, only the payload influences fuel consumption. The fixed fuel consumption characterises the fuel needed for hauling the aircraft without loading. A similar result was found by Swan and Adler (2006) who analysed seat capacities of aircrafts against their respective trip cost (including fuel cost). Swan and Adler (2006) observed that for short–haul as well as long–haul transports linear correlations between seat capacity and trip cost exist.

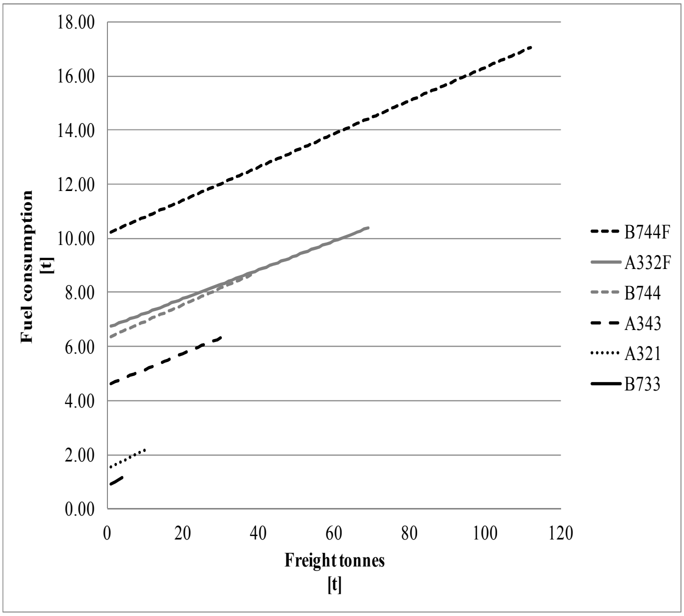

Figure 9: Fuel consumption for different aircraft categories (stage length: 1,000 sm[101])
(Source: author's own representation)

The airline's decision which aircraft category to chose for a given stage length and a given demand considers the specific characteristics of each of the six aircraft categories. For a stage length of 1,000sm and only little freight demand, small aircrafts are most efficient and therefore the economically optimal aircraft choice. The more freight tonnes per flight need to be transported, the larger the aircrafts should be chosen by the airline. Figure 10 and Figure 11 display the development of fuel consumption with increasing freight tonnes for a stage length of 1,000sm (1,609km) respectively 4,000sm (6,327km).

[101] sm = statute mile (1.609 km)

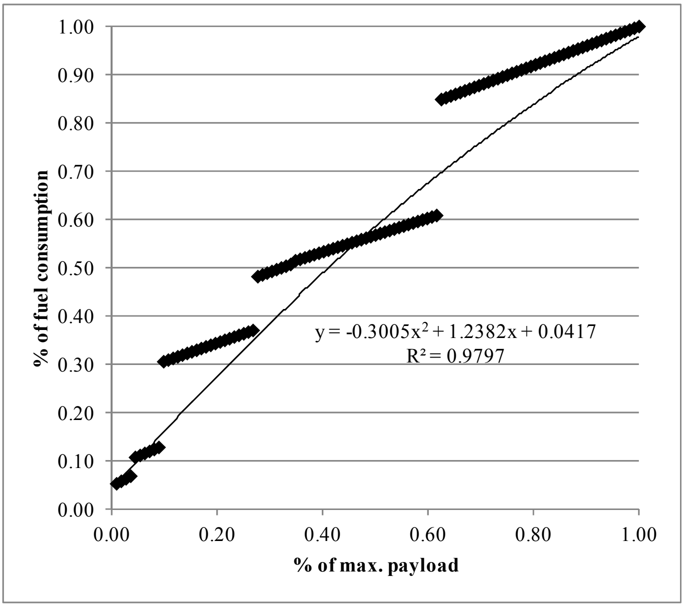

Figure 10: Aircraft–specific economies of scale (stage length: 1,000sm) (Source: author's own representation)

Two airline decisions are displayed in the figures: First, a short–term decision in case that a respective aircraft is predetermined and that the airline can only ascertain the loading of the aircraft (degree of freedom: aircraft loading). Second, a medium–term decision in case that aircraft alternatives exist (heterogeneous fleet) and that the airline can chose the most efficient aircraft category for the respective flight leg (degree of freedom: aircraft category and aircraft loading). Long–term decisions would also comprehend investment decisions which are out of scope of the present analysis which assumes a given fleet structure.

Both figures prove that aircraft specific economies of scale do exist and that on a medium–term economies of scale do not develop linearly with cargo payload because aircraft category and aircraft loading are determinable. For six distance belts[102] functions representing aircraft specific economies of scale are developed and incorporated into *AirTrafficSim*. Each function considers the aircraft alternatives for the specific distance and their respective fuel consumption with increasing payload. The optimal aircraft category choice for each flight leg which reverts to the economies of scale functions is presented in chapter 5.4.4.

102 The six distance belts are: (0 - 1,000sm], (1,000 - 2,000sm], (2,000 - 3,000sm], (3,000 - 4,000sm], (4,000 - 5,000sm], (>5,000sm].

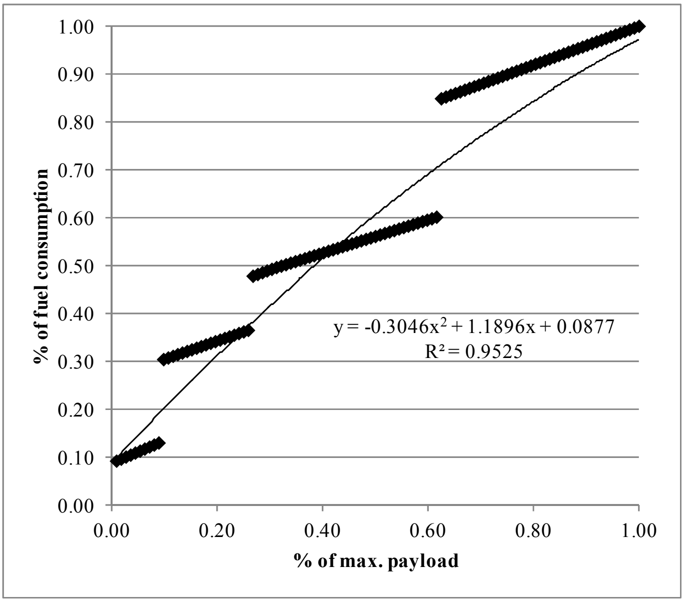

Figure 11: Aircraft–specific economies of scale (stage length: 4,000sm) (Source: author's own representation)

5.4.3.2 Aircraft specific economies of scale (landing fee calculation)

Airport and en–route charges contribute roughly 14% to overall direct operating cost. Gardiner et al. (2005) concludes that airport charges (and overall cost minimisation) are one of the most influential factors for cargo airlines when choosing airports. In contrast to flight crew or maintenance cost which are directly dependent on the number of flights (or flight hours), airport charges need to be further analysed to comprehend their occurrence. Airlines are charged by the airports for landing (use of runway, etc.) and terminal use. Terminal charges are generally levied per passenger (or per payload tonne). Hence, they do not influence the airline's decision which aircraft to assign on which flight leg because terminal charges accrue anyway. Therefore, the dependence between landing fee and the respective payload will be analysed in the following based on airport specific data from the Global Airport Benchmarking Report 2006 of the Air Transport Research Society (ATRS, 2006).

The airport sample includes 135 airports of different sizes and ownership structures (ATRS, 2006). These airports are located across the regions Asia–Pacific, Europe and North America which are the major markets for air cargo services. Furthermore, data of few airports in Africa and South America have additionally been analysed to be able to draw general conclusions also on these two world regions.

The two research questions that will be answered in the following are:

- what is the average landing fee per tonne in the analysed regions and do they differ significantly from another

- how do landing fees develop with increasing aircraft size (in terms of payload) in the analysed regions

The Global Benchmarking Report (ATRS, 2006) differentiates four aircraft types reflecting different aircraft categories (including weight classes). These aircrafts are: Boeing 747–400 (2–class configuration, MTOW[103] 396,900kg, 524 seats), Airbus A320 (2–class configuration, MTOW 73,474kg, 150 seats), Boeing 767–400 (1–class configuration, MTOW 204,120kg, 304 seats), Canadian Regional Jetliner CRJ200–LR (1–class configuration, MTOW 24,041kg, 50 seats).

Landing charges include (ATRS, 2006):

- the use of air traffic control facilities during approach and landing/take–off
- runways, taxiways, etc.
- parking of the aircraft on a stand or apron for some clearly specified time
- the use of facilities for disembarking passengers of aircraft gates, air bridges and other facilities in the terminal building

The database focuses on international transports (international charges), reports all charges in USD and does not include taxes which vary significantly across the analysed regions (ATRS, 2006). These assumptions guarantee an unbiased comparison of the different landing fees. Table 12 illustrates the landing charges of selected airports for the year 2006 where data have been available.

Table 12: Airport charges in USD at selected airports (Source: ATRS, 2006)

Airport	Airport charges per aircraft [USD]			
	CRJ200	A320–100	B764	B744
ATL[104]	11	65	94	290
CDG[105]	195	530	1,927	3,988
DXB[106]	76	254	706	1,373
FRA[107]	86	262	727	1,413
ICN[108]	211	646	1,772	3,391
JFK[109]	297	907	2,520	4,900
LAX[110]	65	383	549	1,695
LHR[111]	455	773	773	1,160
SIN[112]	117	376	1,183	2,399

[103] Maximum take-off weight (MTOW)
[104] Hartsfield-Jackon Atlanta Airport
[105] Paris Charles de Gaulle Airport
[106] Dubai Airport
[107] Frankfurt am Main Airport
[108] Incheon Airport
[109] New York John F. Kennedy Airport
[110] Los Angeles Airport
[111] London Heathrow Airport
[112] Singapore Changi Airport

The airport specific landing fees were aggregated to airport clusters which are chosen based on the regional classification of *AirTrafficSim* (see chapter 5.1.1). Because only dedicated airports are reported in the Airport Benchmarking Report, the clustering of airports allows the determination of average values which can also be allocated to airports that are not directly covered by the Airport Benchmarking Report. The underlying assumption grounds on the understanding that airports of a region compete for air services and are influenced by the surrounded airports. The following approach has been developed to be able to answer the above mentioned research questions:

- calculate the landing charges per payload–ton (l) and per aircraft class (f) at every airport (p) ($\dot{l}_{pf}$)

$$\dot{l}_{pf} = \frac{l_{pf}}{t_f}$$

- disaggregate the total aircraft movements at each airport to the four aircraft categories[113] (ω_{pf})
- calculate the average landing fee per payload–ton at every airport ($\hat{l}_p$)

$$\hat{l}_p = \sum_{f \in F} \omega_{pf} * \dot{l}_{pf}$$

- sum up the average landing fees for every region by weighting them with the total movements of every airport ($\tilde{l}_r$).

$$\tilde{l}_r = \sum_{p \in P(r)} \omega_p * \hat{l}_p$$

Where
l_{pf} = total landing fee for aircraft class f at airport p (Source: ATRS 2006)
t_f = maximum payload of aircraft class f (in tons)
$\dot{l}_{pf}$ = landing fee per payload–ton for aircraft class f at airport p
ω_{pf} = flight movements of aircraft class f at airport p
F = set of all aircraft classes
$\hat{l}_p$ = average landing fee at airport p
ω_p = total flight movements at airport p
$P(r)$ = set of all airports p which are located in region r
$\tilde{l}_r$ = average landing fee of region r

[113] The total movements at each airport have been allocated to the four categories so that the average cargo tonnage per movement is achieved at the airport.

The introduced approach enables to answer the first research question on the average landing fee per payload–tonne and region which are summarised in Table 13 for the 17 regions which are covered by data from the Global Benchmarking Report (ATRS, 2006). It becomes obvious that:

- landing fees in Asia–Pacific and in Europe are significantly higher (per payload–tonne) than in North America
- landing fees in Asia–Pacific and Europe decrease per payload–tonne with increasing maximum payload
- landing fees per payload–tonne are independent of the maximum payload in North America and in the Near East
- landing fees are the lowest in the Near East for all aircraft classes and
- the region with the highest landing fee is dependent on the aircraft class (e.g. B747–400 in East Europe, A320–100 in North–West Europe)

Table 13: Average landing fee per payload–tonne (in USD) per region and aircraft class (Source: author's own representation)

Region	Total movements	Average Landing Fee [USD/payload–tonne]			
		CRJ200	A320	B764	B744
APA	785.735	141	127	104	98
APO	1.682.299	175	136	137	128
APS	1.050.047	305	141	99	86
EUA	2.070.797	194	156	135	127
EUB	26.501	157	149	143	142
EUE	5.544.980	240	192	142	131
EUG	378.535	148	142	136	117
EUI	810.411	105	101	99	100
EUN	656.213	164	157	142	136
EUO	315.709	197	180	164	159
EUS	600.763	103	100	92	90
EUW	1.369.105	167	151	143	137
NAOC	6.090.861	25	35	23	33
NAOE	6.948.649	34	37	31	35
NAOW	4.204.521	25	32	22	29
NAW	1.529.906	73	74	77	79
NOG	195.820	76	73	66	64

The second research question which deals with economies of scale in landing charges and how landing fees develop with increasing aircraft size also bases on the above introduced results. The results evidence that:

- in North America landing fees per payload–tonne are independent of the maximum payload of the aircraft. No economies of scale can be achieved by operating larger aircrafts. These results are in line with the observations of Wei and Hansen (2003) who concluded that the US domestic airline industry favours more flights rather than larger planes. Even though the analysis of Wei and Hansen was focused on domestic passenger flights only and considered total operating cost as the dependent variable instead of landing fees only, the behaviour of US airlines for domestic services is provided by the landing fee incentives of the US airports.

- A different picture can be observed for Europe, Asia–Pacific and the Near East where economies of scale exist in landing fee structures. High landing fees per payload–tonne are levied within all sub–regions of Europe, Asia–Pacific and the Near East for the smallest aircraft class (CRJ200–LR: maximum payload 5 tonnes) whereas the largest aircraft class (B747–400: maximum payload 72 tonnes) is charged less per payload–tonne.
  Differences exist in the distribution of economies of scale between the sub–regions. Thus, *AirTrafficSim* applies a distinct landing fee distribution for every sub–region. Figure 12 illustrates the distribution of landing fees in the Asia–Pacific region subdivided into APA (Australian continent), APO (East–Asia) and APS (South–East–Asia) and in Figure 13 the distribution for Europe is displayed (EUA: Central–Europe/Alps, EUE: North–West–Europe, EUN: North–Europe/Scandinavia, EUW: West–Europe).

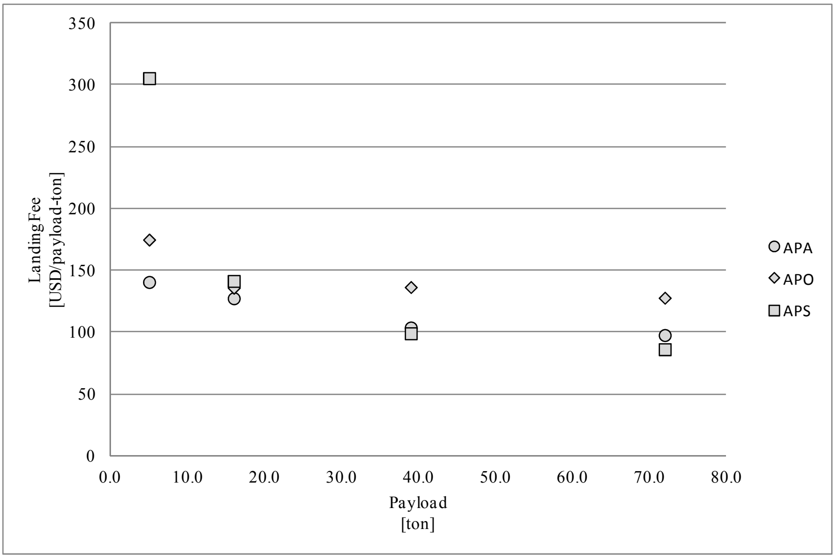

Figure 12: Landing fee economies of scale (Asia–Pacific)
(Source: author's own representation)

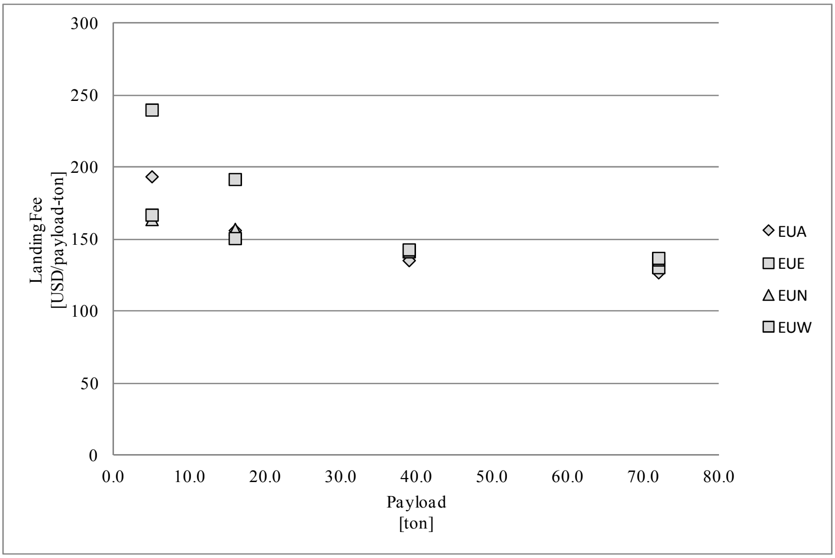

Figure 13: Landing fee economies of scale (Europe)
(Source: author's own representation)

Concave functions can be observed with different gradients for every region. A sufficient trend line for each region which equates the landing fees economies of scale has been developed based on its coefficient of determination (R^2). Therefore, it had to be weighted between completeness of trend lines (that all sub–regions are covered by a landing fee equation) and an adequate R–squared. In case of no sufficient data (e.g. Africa, South America) for judging on the existence of landing fee economies of scale, a constant average landing fee has been applied for these regions. This procedure grounds on the assumption that landing fee economies of scale are especially applied to overcome congestion at major airports (especially European and Asian) by providing incentives for operating larger aircrafts. The results that are applied in *AirTrafficSim* are displayed in Table 14.

Table 14: Average landing fee per payload–tonne (in USD) per region and aircraft class (Source: author's own representation)

Region	#airports	Avg. landing fee [USD/payload–ton]	Landing fee function	R²
APA	7	134.84	$y = 181.21 * x^{-0.144}$	0.959
API[114]		168.90	$y = 263.66 * x^{-0.174}$	0.989
APO	10	145.27	$y = 200.01 * x^{-0.11}$	0.838
APS	8	234.00	$y = -82.37 \ln(x) + 411.81$	0.893
AFN[115]	1	17.00	constant	
AFO[116]	2	23.00	constant	
AFS[117]	3	41.00	constant	
AFZ[118]	1	46.00	constant	
EUA	9	184.62	$y = -25.39 \ln(x) + 231.3$	0.978
EUB	1	157.07	$y = 167.37 * x^{-0.041}$	0.970
EUE	6	235.87	$y = -11.03 \ln(x) + 183.62$	0.953
EUF[119]		193.49	$y = 272.05 * x^{-0.239}$	0.946
EUG	2	144.18	$y = -0.4487x + 150.58$	0.983
EUI	3	104.60	$y = -5.057 \ln(x) + 85.436$	0.949
EUN	4	161.41	$y = -43.01 \ln(x) + 308.51$	0.983
EUO	4	195.70	$y = -14.88 \ln(x) + 220.87$	0.992
EUS	4	101.62	$y = -5.156 \ln(x) + 111.87$	0.941
EUU[120]		193.49	$y = 272.05 * x^{-0.239}$	0.946
EUW	4	157.15	$y = -11.17 \ln(x) + 183.84$	0.987

114 Comprehensive data for the region are not available in ATRS (2006). Hence, an average value of the remaining AP regions has been applied for API.
115 The analysed airport is CAI (Cairo, Egypt).
116 The analysed airports are ADD (Addis Ababa, Ethiopia) and NBO (Nairobi, Kenya)
117 The analysed airports are CPT (Cape Town, South Africa), DUR (Durban, South Africa) and JNB (Johannesburg, South Africa).
118 The analysed airport is LOS (Lagos, Nigeria).
119 Comprehensive data for the region are not available in ATRS (2006) so that an average value of the remaining EU regions has been applied for EUF.
120 Comprehensive data for the region are not available in ATRS (2006) so that an average value of the remaining EU regions has been applied for EUU.

Region	#airports	Avg. landing fee [USD/payload–ton]	Landing fee function	R²
NAOC	16	26.24	constant	
NAOE	22	34.00	constant	
NAOW	15	26.05	constant	
NAW	8	15.28	constant	
NAS[121]	2	171.00	constant	
NOG	1	70.39	$y = 167.37 * x^{-0.041}$	0.970
NOM[122]		70.39	$y = 167.37 * x^{-0.041}$	0.970
SAK[123]		34.00	constant	
SAO[124]	1	28.00	constant	
SAW[125]	1	40.00	constant	
SAZ[126]		34.00	constant	

5.4.3.3 Leg specific economies of scale

Many airline network models assume bundling effects only on interhub links with an exogenous discount factor (e.g. Aykin and Brown, 1992). *AirTrafficSim* makes link discounts endogenously by rewarding the airline for greater volumes. In the following the approach of Horner and O'Kelly (2001) is further developed for *AirTrafficSim*.

Starting from link performance functions (LPFs) which are applied in urban transportation planning and which penalize links for high volume–to–capacity ratios, Horner and O'Kelly (2001) argue that in hub–and–spoke networks the mirror opposite is true. In urban transportation planning cost are increasing with link flows (convex cost function) caused by congestion on the link whereas in hub–and–spoke networks decreasing cost can be observed (concave cost function). One of the most common LPFs is the Bureau of Public Roads (BPR) link performance function (Sheffi, 1985):

$$P_l = (1 + \Theta_r \left(\frac{x_l}{K_l}\right)^{\beta_r})$$

[121] The analysed airports are MEX (Mexico City, Mexico) and CUN (Cancun, Mexico).

[122] Comprehensive data for the region are not available in ATRS (2006). Thus, the values of NOG have also been applied for NOM.

[123] Comprehensive data for the region are not available in ATRS (2006) so that an average value of the remaining regions has been applied for SAK.

[124] The analysed airport is GRU (Sao Paolo, Brazil).

[125] The analysed airport is LIM (Lima, Peru).

[126] Comprehensive data for the region are not available in ATRS (2006) so that an average value of the remaining regions has been applied for SAZ.

Where
P_l = penalty on link l
x_l = link flow on link l
K_l = maximum link capacity
Θ_r, β_r = economies of scale constants

A cost function that benefits higher link flows can be derived from the introduced BPR function by simply changing the sign.

$$D_{ij} = (1 - \Theta_r \left(\frac{x_{ij}}{K_{ij}}\right)^{\beta_r})$$

Where
D_{ij} = discount on link ij
x_{ij} = link flow from origin airport i to destination airport j
K_{ij} = maximum link capacity
Θ, β = economies of scale constants

x_{ij} is applied in *AirTrafficSim* as the ratio between all outgoing cargo flows of airport i plus all ingoing cargo flows of airport j and the total network tonnages. The more traffic (e.g. cargo tonnages) is bundled at airport i and j, the higher the discounts for all links that are operated from the airport. Such economies of scale discounts emerge through i.e. cost efficient handling activities, high capacity utilization of cargo terminals, efficient bundling of cargo, higher routing flexibilities, better aircraft utilization, a more effective labour allocation, etc. As these economies of scale are not covered by the aircraft specific economies of scale a double–counting is avoided.

The capacity term K_{ij} is set to 1 which assumes uncapacitated links and reflects the characteristic that links but airports are the limiting factors in aviation. Therefore, the changed LPF is rewritten as follows and discounts are only determined by the relative link flows x_{ij} as well as the calibration parameters θ and β.

$$D_{ij} = (1 - \Theta_r {x_{ij}}^{\beta_r})$$

Horner and O'Kelly (2001) concluded that such an approach is well suited for delivery systems (e.g. air cargo) which allow multiple stops but would not be feasible for an air passenger carrier. A strong evidence of flow collectivization was achieved with Θ=0.75 and β=0.25 which is applied in *AirTrafficSim*.

5.4.4 Optimal aircraft choice

Airline's decision which aircraft to allocate to which flight leg is fundamental within the network design process and especially for airlines that operate mixed aircraft fleets. The optimal aircraft choice is incorporated as an economic order quantity (EOQ) decision where the economic order quantity is defined as the optimal payload (measured in tonnes) that minimises total transportation cost of the flight leg under consideration. The optimal payload directly determines the aircraft category based on the principle that always the smallest possible aircraft which is able to transport this payload is chosen. The reasons for this approach are the lower fixed cost and a higher load factor by allocating the smallest possible aircraft to the flight leg (see chapter 5.4.3).

The traditional EOQ model was developed by F. W. Harris (1913)[127] and consists of variable and fixed cost. Variable cost occurs by warehousing the products and by purchasing them whereas fixed cost occur per ordering (independent of the order quantity q). The following equation displays the total order cost per time period (Harris, 1913):

$$C_{total} = p * Q + C_{fix} * \frac{Q}{q} + \frac{q}{2} * \frac{p * h}{100}$$

Where:
- C_{total} = total order cost per time [USD]
- p = purchase price per unit [USD]
- Q = order quantity per time [e.g. tonnes]
- q_{EOQ} = order quantity per order [e.g. tonnes]
- C_{fix} = fixed cost per order (including transportation cost) [USD]
- h = annual holding cost per unit (incl. warehousing) [%]

The optimal order quantity (q_{EOQ}*) is determined from the total cost equation by setting the derivate equal to zero and solving the equation for q_{EOQ}*:

$$q_{EOQ}^{*} = \sqrt{\frac{200 * C_{fix} * Q}{h * p}}$$

The transformation of the traditional Harris model to the present research question is illustrated in Figure 14 and can be explained as follows: In aviation the optimal order quantity (q*) can be interpreted as the optimal shipment size per flight (payload). The optimal shipment size which directly configures the operating aircraft determines the point in time t when the shipment is carried out and the flight leg specific stocks are depleted. At the starting point of *AirTrafficSim* flight leg specific stocks are empty. Deliveries for every destination arrive at the airport by e.g. aircraft, road feeder service or direct deliveries that stocks increase. For the sake of simplicity *AirTrafficSim* assumes a continuous delivery of freight which allows the application of the above mentioned optimal payload equation.

[127] The EOQ model is also known as the Wilson EOQ Model because R.H. Wilson was the first who applied the formula extensively.

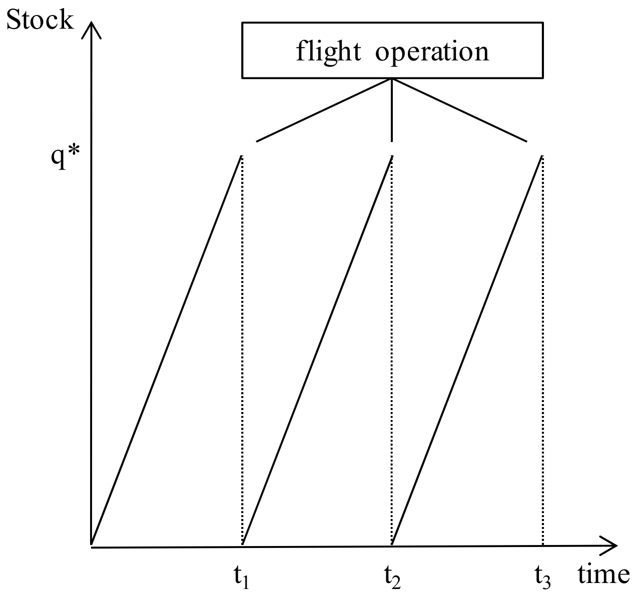

Figure 14: Stock level development (including optimal departure time) (Source: author's own representation)

The Harris–Model grounds on the following assumptions and their practicability for the present dissertation is evaluated afterwards (Friedrich, 2010):

- Static model
- Constant demand
- Constant lead time
- Constant cost parameters
- Constant price
- One product
- Unlimited resources (storage capacity)

Static model:

The Harris model is a static model which does not allow adaptations during the modelling horizon and does not provide feedbacks between inputs and outputs. *AirTrafficSim* is aimed at simulating network structures of cargo airlines on a strategic time horizon including the development of hub airports, the emergence/expiration of routs and the optimal aircraft assignment. These objectives can be achieved sufficiently with a static model.

Constant demand:

Demand modelling and demand forecasting are out of scope of the present work. The point of origin of *AirTrafficSim* is a given demand structure. It is abstracted from demand fluctuations, either deterministically or stochastically, so that a constant demand distribution is assumed for the considered time horizon. Air cargo has annual demand peaks in late autumn and in early spring which mainly influence load factors and tariffs on the flights. Strategic network decisions as modelled in *AirTrafficSim* are not affected by such seasonal demand fluctuations and are geared on long–term average demand developing.

Constant lead time:
Lead time in *AirTrafficSim* defines the time needed from departure to arrival of a service. Compared to the time horizon of *AirTrafficSim* which grounds on annual input data, the lead time can be neglected (instantaneous receipt).

Constant price:
The original Harris model comes from the corporate decision how many parts (inputs) should be ordered at once to minimise total ordering cost (including purchase cost, transportation cost and warehousing cost). An important cost item for that decision is price p which directly influences total order cost as well as cost of capital. For the present dissertation the interpretation of p needs to be adapted as the objective of *AirTrafficSim* is on a transport decision than on an order quantity decision.

Cost of capital is a driver for customers to choose air transport instead of other transport modes (e.g. maritime transport). Therefore, airlines have to balance carefully their aircraft choice and the corresponding flight frequency against the customers' requirements for short transport times, high flexibility (high frequencies) and for low tariffs. To simulate this weighting between frequency and aircraft size the customer perspective needs to be included in the aircraft choice decision.

The last summand of the EOQ model ($\frac{q}{2} * \frac{p*h}{100}$) considers this perspective: q/2 characterises the average stock size which is the average tonnage in warehouse (see Figure 14). p is defined in *AirTrafficSim* as the average value of goods which are transported by air and h defines the annual holding cost per year.

The value of goods (p) is determined as the average value of goods transported by air in 2007 (base year of *AirTrafficSim*). Data are taken from Eurostat and are displayed in Table 15[128].

The development of goods values fluctuates over time which is driven by market characteristics as well as currency deviations (original values are provided in Euro but base currency in *AirTrafficSim* is USD). As default value for the base year 91,304 USD/tonne is incorporated into *AirTrafficSim*.

[128] Analyses with *AirTrafficSim* for non-European airlines should critically review these values and if required adjust them to market values.

Table 15: Value of goods in air freight transport[129]
(Source: Eurostat, 2010)

Year	**Value of goods [USD/tonne]**	
	EU27 – Extra EU27	**D – Extra EU27**
2000	64,278	78,774
2001	60,225	53,983
2002	59,089	48,318
2003	70,962	99,148
2004	59,903	106,757
2005	62,959	96,381
2006	54,113	94,096
2007	**50,996**	**91,304**
2008	53,190	101,999

Definition of the annual holding cost parameter h:

Total warehouse costs which are the basis of the annual holding parameter h consist in its simplest form of fixed (WC_{fix}) and variable costs (WC_{Var}) (Gudehus, 2004).

$$WC_{ij} = WC_{fix} + WC_{Var,ij}$$

Where:

ij = link from airport i to airport j
WC = warehouse costs
WC_{fix} = fixed warehouse costs
WC_{Var} = total variable warehouse costs

Variable costs (WC_{Var}) can be further differentiated into handling costs (HC) (e.g. loading and unloading of the aircraft) and other variable warehouse costs (WC_{OVar}) (incl. cost of capital and standard warehouse costs).

$$WC_{Var,ij} = WC_{OVar,ij} + HC_{ij}$$

With:

$$HC_{ij} = hc * q_{ij}^*$$

$$WC_{OVar,ij} = wc_{Var} * \frac{q_{ij}^*}{2}$$

129 The value of goods is calculated as a weighted average of imports and exports from/to Extra EU27 countries to/from EU27 (respectively Germany).

Where:
ij = link from airport i to airport j
q^*_{ij} = optimal payload on link ij
WC_{OVar} = other variable warehouse costs
HC = handling costs
hc = handling costs per unit
wc_{Var} = variable warehouse costs per unit (incl. h_{var} and wacc)
h_{var} = variable standard warehouse costs per unit
wacc = weighted average cost of capital

Finally, variable warehouse costs per unit (wc_{Var}) are differentiated into cost of capital (wacc) and variable standard warehouse costs[130] (h_{var}) which are independent of the value of transported goods (p).

The optimal aircraft choice decision (incl. optimal payload) is impacted by the variable cost components whereas fixed cost as well as handling cost influence the overall cost but can be neglected in the aircraft choice procedure.

Friedrich (2010) estimates the variable standard warehouse cost per unit (h_{var}) on the basis of expert interviews to annually 50 Euro per pallet. Breaking this value down to metric scale leads to 71.43 Euro per tonne and year (in average 0.7 tonnes are carried on a pallet).

Cost of capital (wacc) is defined as the weighted average cost of capital which defines the cost associated with the company's capital structure. It is important to notice that the owner's perspective is needed for the cost of capital estimation and not the airline's perspective because the longer the transport lasts, the higher the cost of capital for the owner (and not for the airline).

The calculation of the customers' average wacc grounds on the major customer segments of cargo airlines (see Crabtree et al., 2008) and calculates an average wacc for them (see NYU, 2010). The incorporated default value for the weighted average cost of capital in *AirTrafficSim* is 8.33% (see Table 16).

[130] Standard warehouse costs are e.g. warehouse rentals, depreciations.

Table 16: Weighted Average Cost of Capital of air cargo customers (Source: Crabtree et al. (2008) and NYU (2010))

Commodity group[131]	Share of commodity group[132]	Assigned commodity group (NYU classification)	WACC[133] [%]
Chemical products	0.01	Chemical (Basic)	8,70
Transportation	0.01	Auto & Truck	8,58
Specialised equipment	0.03	Precision Instrument	8,94
Telephone equipment	0.03	Telecom. Equipment	8,63
Manufactured goods	0.04	Machinery	8,53
Perishables	0.04	Food processing	7,16
Computer products	0.05	Computers/Peripherals	9,23
Textiles	0.06	Apparel/Shoe	8,95
Small packages	0.08	Air Transport	7,64
Intermediate manufacturers	0.20	Machinery	8,53
Others	0.45	Total Market	8,20

The air cargo specific annual holding cost parameter h is finally determined to 8.41% which proves the importance of wacc (8.33%) for the annual variable warehouse costs.

One product:

Air freight products are very heterogeneous and they come in all shapes, densities and weights. In 2007, high tech products accounted for 27%, capital equipment for 19%, apparel for 17%, consumer products for 16%, intermediate materials for 12%, food for 6% and others for 2% of worldwide air freight (measured in FEU–km) (Doganis, 2010). This heterogeneity poses numerous challenges for the industry (e.g. handling issues, treatment of goods, security, aircraft loading) but influences medium– to long–term network structure decisions only slightly. Network structures are primarily determined by the airline's business model (e.g. fleet structure, core markets) as well as the respective worldwide demand distribution. Therefore, multiple products are simplified by modelling a one product flow with a standardized unit that represents the air freight business. The chosen unit are metric tonnes.

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131 Based on Crabtree et al. (2010)

132 Shares are based on Crabtree et al. (2008) for the base year 2007.

133 WACC are taken from NYU (2010)

Unlimited resources (storage capacity):

Limited warehouse capacities at airports are not incorporated into *AirTrafficSim*. Medium– to long–term network decisions which are the primary objective of the model assume that warehouse capacities are flexible and can be adapted on such a time horizon.

Constant cost parameters:

The traditional Harris model uses fixed transportation cost that accrues per order and independent of the order quantity. In chapter 5.4.3 the concept of economies of scale was introduced and it was proved that aircraft specific economies of scale do exist in the air freight market. Economies of scale cause transportation cost to decrease with increasing aircraft size. Thus, the assumption of the Harris model of fixed transportation cost cannot be sustained in *AirTrafficSim*. The same holds true for the distance dependency of transportation cost that is not considered in the traditional Harris model. Therefore, the Harris model needs to be further developed to fulfil the objectives of *AirTrafficSim*.

The following approach is leaned on the procedure of Friedrich (2010) who simulated the logistics in food retailing for freight transportation analysis: The fixed cost (C_{fix}) of the traditional Harris model are converted into two cost components: first, a scalable component which represents the maximum load cost[134] for a given distance ($C_{total}(d_D)$) and second a component that represents the cost degression for increasing loading (ε). Friedrich (2010) applies a general power function for the economies of scale and calibrates the full load cost according to real transport cost structures of road transport operators.

The share of fixed operating cost for airlines (see chapter 5.4.3) advices to transfer the general power function into a function with a dedicated fixed cost share. Therefore, and in analogy of the results of chapter 5.4.3 a quadratic equation is applied in *AirTrafficSim*. The scalable component ascertains the maximum operating cost for a given flight leg which are dependent on the flight leg distance (d_{ij}), the overall maximum loading of cargo aircrafts ($q^*_{max,cargo}$[135]) and the average cost (per rtm) of the operating airline (c_{ij}[136]). The following equation represents the distance and payload dependent operating cost:

$$C_{op,ij}(q_{ij}) = \left(\alpha(d_D) + \beta(d_D) * q_{ij} + \gamma(d_D) * q_{ij}{}^2\right) * C_{full,ij}(d_D)$$

Where:

$C_{op,ij}$ = operating cost on flight leg ij
q_{ij} = payload on link ij (tonnes per flight on link ij)
$C_{full,ij}$ = maximum operating cost for the flight
d_D = distance class
α, β, γ = economies of scale parameters (with $\alpha > 0$, $\beta > 0$, $\gamma < 0$)

[134] Maximum load cost reflects the shipment cost for a Boeing 747-400F which is currently the largest scheduled freighter (112.67 tonnes).

[135] $q^*_{max,cargo}$ = 112.67 tonnes

[136] c_{ij} are introduced in chapter 5.4.2.

The total costs per flight leg which include economies of scale finally compose of the following:

$$C_{total,ij}(q_{ij}) = \left(\alpha(d_D) + \beta(d_D) * q_{ij} + \gamma(d_D) * {q_{ij}}^2\right) * C_{full,ij}(d_D) * \frac{Q_{ij}}{q_{ij}} + \frac{q_{ij}}{2} * \frac{p * h}{100}$$

The optimal payload per flight leg (q_{ij}*) is determined by setting the derivative of the total cost equation equal to zero and solving the equation for q_{ij}*:

$$q_{ij}^* = \sqrt{\frac{\alpha(d_D) * C_{full,ij}(d_D) * Q_{ij}}{\gamma(d_D) * Q_{ij} * C_{full,ij}(d_D) + \frac{p * h}{200}}}$$

The results of the economies of scale analyses (see chapter5.4.3) prove the negative nature of γ (degressive cost function) and the positive nature of α and β. Therefore, the domain of definition is limited to the following constraint:

$$\gamma(d_D) * Q_{ij} * C_{full,ij}(d_D) + \frac{p * h}{200} > 0$$

The limit of the function close to its constraint (=0) continues for q_{ij}* to infinite. Such behaviour can be interpreted so that flight legs exist which are ideally operated by infinitely large aircrafts. Engineering limitations for aircrafts lead to the application of the largest aircraft category in case of violations in the domain of definition.

5.4.5 Objective function

The findings of the previous chapters are now merged together to develop an overall cost function which serves as the fitness function for the optimisation algorithm of *AirTrafficSim*. The complexity of the different influencing factors that determine the cost is simplified for an illustrative example first. Cost for a specific flight leg (FRA–DUB) are ascertained and analysed. Afterwards the overall objective function (fitness function) is introduced and discussed.

5.4.5.1 Compilation of flight leg specific operating cost

The multifaceted relationships between the different cost components (including the economies of scale considerations) are illustrated in the following based on an exemplarily flight leg. A flight leg is assumed which originate at airport i (i.e. Frankfurt International – FRA). The destination airport j is assumed to be located in North–West Europe which consists of Ireland and the United Kingdom, so that

Dublin International (DUB) is chosen for analysis. Flight–related labour cost are determined to 0.2 US Dollar per RTM and the depreciations for flight equipment amount to 0.015 US Dollar per RTM. Depreciation is determined by the airline's cost for flight equipment (exogenous) but total revenue–tonne–miles (RTM) are endogenously calculated. Hence, the above mentioned value is only fixed for one iteration of *AirTrafficSim*. The average distance of all flight legs for the airline is 1,500 sm (endogenous) and a fuel price of 0.785 US Dollar per gallon (exogenous) is assumed.

The optimal aircraft size (payload) is determined to aircraft category 6 which has a maximum cargo capacity of 112.7 tonnes (Boeing 747–400 Freighter). Loading is kept variable and directly impacts total landing fees. In North–West Europe economies of scale are incorporated for landing fee calculations (see chapter 5.4.3.2 for further elaborations). Finally, flight leg distance (676 sm) and loading determines the average cost to operate one flight from airport i to airport j.

Figure 15 illustrates the developments of operating cost (y–axis) for different payloads (x–axis) and for different airport concentration levels (for the leg specific economies of scale). As concentration indicator the share of cargo tonnes at the airports (outbound freight at FRA plus inbound freight at DUB) to the overall network size (tonnes at all airports) is applied. This indicator benefits a higher concentration level at the participating airports which accrues from e.g. cost efficient handling activities, efficient bundling of cargo, higher routing flexibilities, a more effective labour allocation. In Figure 15 concentration level between 0 (no concentration at these airports) and 0.5 (50% of all tonnes are either originating at FRA or terminating at DUB) are illustrated. In reality much smaller concentration levels are observed. Therefore, the applied range serves as a didactic representation of the leg specific economies of scale mechanism.

If almost no cargo concentration exists at airport i and j (only feeder airports) the topmost graph (w/o concentration) is applied. In case that concentration is available at these two airports (airport i and airport j) further cost advantages (economies of scale) are present for the airline which are determined endogenously. Such discounts may emerge through cost efficient handling activities, high capacity utilization of cargo terminals, efficient bundling of cargo, higher routing flexibilities, better aircraft utilization, a more effective labour allocation, etc and which are determined by the adapted link performance functions. Significant discounts are applied within *AirTrafficSim* to encourage bundling of flows (θ=0.75, β=0.25).

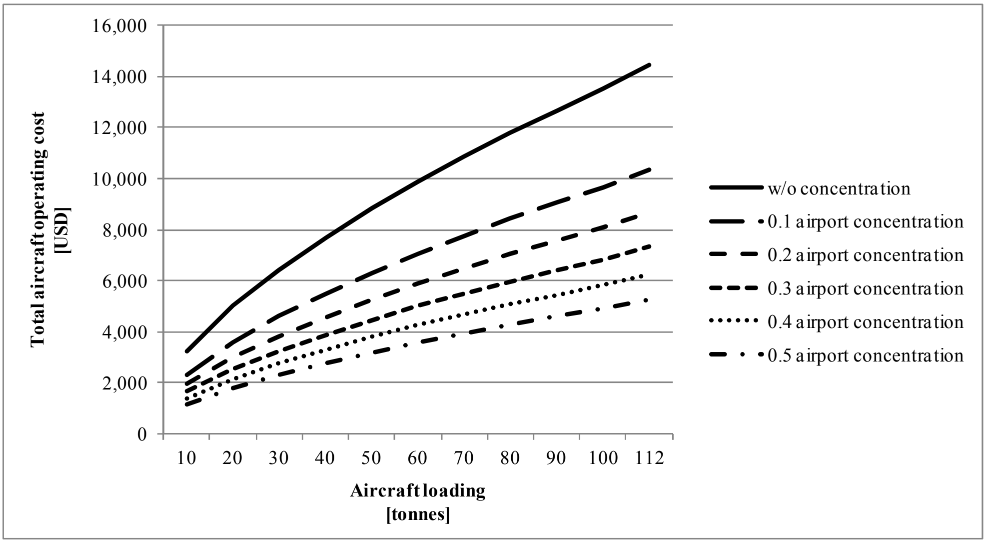

Figure 15: Compilation of flight leg specific operating cost (Source: author's own representation)

Concave cost functions can be observed for every concentration level which means that cost decrease as loading increases. Higher loading implies a better utilization of the aircraft which leads to lower average cost. The cost level is mainly determined by the airline specific cost components as well as the market environment, such as depreciation, fuel price, etc. which enter into the average cost function. The shape of each graph is however impacted by aircraft specific economies of scale, such as landing fee discounts for larger aircrafts (per payload–tonne) and cost efficient shipments with larger aircrafts (per payload–tonne). Finally, the differences between the airport concentration graphs are determined by flight leg specific economies of scale and especially by the link discounts θ and β. These three levels allow the application of concave cost structures on a network design problem which is the case for air cargo carriers. Total network cost is the objective function of the network design problem and it is introduced in the following section.

5.4.5.2 Total network cost

The objective of the present model is to determine the cost minimal network structure which serves the given demand. It is assumed that an endogenously modelled network structure based on cost equals airline networks. Therefore, the overall optimisation problem can be formulated as:

$$\text{Min } C_{Network}$$

$$C_{Network} = \sum_{i \in I} \sum_{j \in J} [\left(\alpha(d_D) + \beta(d_D) * q^*_{ij} + \gamma(d_D) * q^{*^2}_{ij}\right) * (\frac{Q_{ij}}{q^*_{ij}} * q_{max} * d_{ij} * \left(1 - D_{ij}\right) * c_{ij})]$$

s.t.

- Demand for flight leg ij (from airport i to airport j) is given by the input data and must be fulfilled by the airline
- Aircraft fleet is given and fix (further aircrafts can be leased on a shot–term at higher average cost)
- Each flight leg ij is operated by exactly one aircraft category
- Number of flights per aircraft and per year is limited (depending on aircraft category)
- Capacity per aircraft is limited to its maximum payload
- Flight distance per aircraft is limited to its maximum range.

$$0 \leq q^*_{ij} \leq 112.7, 0 \leq D_{ij} \leq 1, c_{ij} > 0, i \in I, j \in J$$

Where:

$C_{Network}$ = total network cost
I = Set of origin airports, indexed by i
J = Set of destination airports, indexed by j
ij = flight leg from airport i to airport j
q^*_{ij} = optimal payload on flight leg ij
d_D = distance class of flight leg ij
d_{ij} = distance between airport i and airport j
Q_{ij} = total quantity on flight leg ij per time
D_{ij} = flight leg specific economies of scale discount
p = average value of goods [USD]
h = annual holding cost per unit [%]
α, β, γ = aircraft specific economies of scale parameters

Total network cost consist of two cost components as shown in the aforementioned equation: transport operating cost and warehousing cost (including cost of capital). Transport operating cost reflects the total flight leg cost for shipping the annual quantity of freight from origin airport i to destination airport j. This cost includes aircraft as well as flight leg specific economies of scale as introduced in chapter 5.4.3 and implemented in the optimal aircraft choice decision in chapter 5.4.4. Warehousing cost is mainly cost of capital for the end customer of airlines because the longer the transport lasts, the higher the cost of capital for the end customer (and not for the airline). This cost is incorporated into *AirTrafficSim* as the second cost component in the equation. Both cost components are needed to be able to balance the airline's decision between optimal flight frequency and optimal aircraft size. Higher frequencies are associated with higher operating cost. Hence, customer's satisfaction is achieved through higher flexibility whereas larger aircrafts enable airlines to exploit economies of scale through the optimal bundling of the freight. Both issues are reflected in the objective function.

Based on the overall objective function (total network cost) the optimisation procedure of Simulated Annealing is accomplished. The determination of *AirTrafficSim's* essential parameters for the Simulated Annealing algorithm is introduced in the following chapter.

5.5 Model calibration

The presented model uses a disaggregated and close–to–reality approach. Essential parameters are determined based on real world data, such as the average cost function (including its independent variables for the case study application), the aircraft economies of scale functions, the weighted average cost of capital or the value of transported goods which are not open for calibration. In contrast, the parameters which set the framework for the optimisation procedure, the Simulated Annealing metaheuristic, need to be adapted to the current research question (calibration).

The objective of the calibration procedure is to set parameters in a way that the advantages of Simulated Annealing are fully exploited. In particular, its property to overcome local optima is essential for the present analysis and need to be guaranteed by the parameters' choice. Therefore, two initial network structures are applied for calibration purpose which fulfils the same transportation request. First, a point–to–point network structure (P2P) is integrated in *AirTrafficSim* where direct services between all airports are operated (Figure 16). Second, a one hub network structure (1H) is used where only indirect services via the hub airport are initially allowed (Figure 17). The final outcome of both initial networks is aimed around the same minima which would prove the independence of the cost minimal solution from the initial network structure.

In total nine airports exist for both initial networks. The home market is Europe that four airports are located there whereas the other five airports are equally distributed around the world. The market volumes are identical and 100 tonnes need to be transported between all airports. Based on this framework *AirTrafficSim* is searching for the optimal network structure.

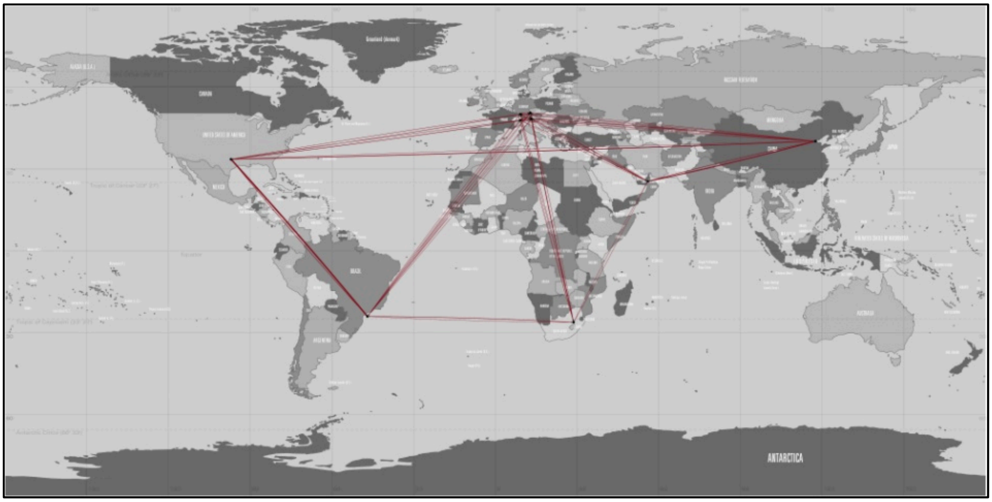

Figure 16: Point–to–point calibration network (initial structure)
(Source: author's own representation)

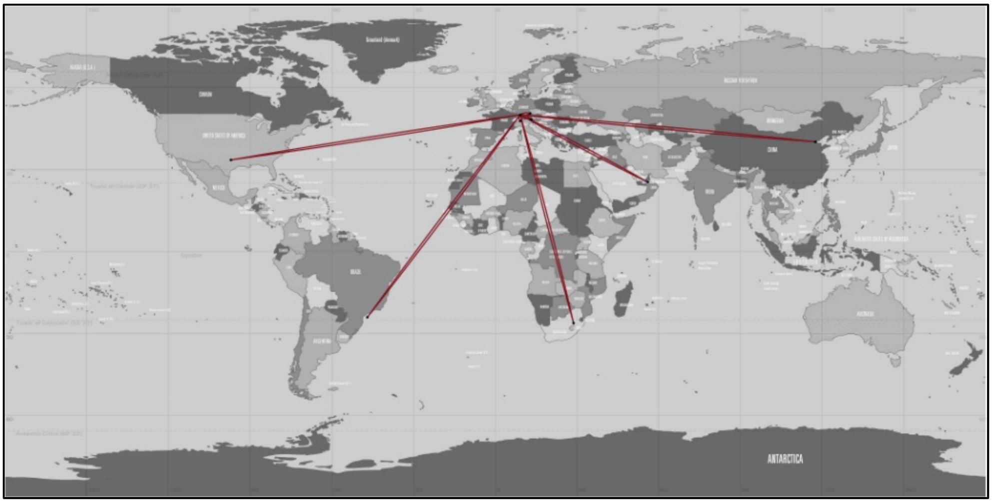

Figure 17: One hub calibration network (initial structure)
(Source: author's own representation)

The essential parameters of the Simulated Annealing algorithm as well as their choice range are introduced in the following:

- Initial temperature (T_0)
- Number of iterations (L_k)
- Temperature function (T_k)

Initial temperature (T_0)

AirTrafficSim starts with a given initial solution which is not randomly created. The comprised information of this initial solution suggests the application of an initial temperature which is able to destroy the initial structure (to avoid becoming trapped in local minima) but which also allows to further use the information of the initial network structure. Temperatures between 0 and 1000 have therefore been tested based on literature suggestions (e.g. Sixt, 1996, Foidl, 2009).

Number of iterations (L_k)

The advantage of Simulated Annealing is to screen miscellaneous structures and then deciding whether to change this structure slightly to have a chance to receive an even better network structure. Therefore, an appropriate large number of iterations is necessary to be able to analyse a sufficiently large part of the sample space. For calibration purpose the number of iterations has been varied between 10 and 100. Good results concerning effectiveness and efficiency were achieved with 50 iterations. Results of L_k=50 are discussed below in detail.

Temperature function (T_k)

The temperature function specifies the finite sequence of temperature values. High temperature values at the beginning of the algorithm avoid being locked in local minima whereas at the end of the algorithm only small deteriorations are accepted by the Simulated Annealing philosophy. Several static temperature functions have been tested starting from linear to trigonometric functions. The present approach finally uses a static temperature function (cooling schedule) which is leant on the specifications of the traditional annealing process in metallurgy (Foidl, 2009):

$$T_k = T_0 * (1 - \frac{k}{L_k})$$

Where:

L_k = predefined number of annealing iterations (L_k=50)
T_0 = initial temperature
T_k = temperature at step k
k = iteration number

Table 17 summarises the parameter ranges which have been applied for model calibration purposes.

Table 17: Parameter range for model calibration (Source: author's own representation)

Parameter	$\mathbf{T_0}$	$\mathbf{L_k}$	$\mathbf{T_k}$
Range	0 – 1000	10 – 100	static temperature functions

A large number of model runs has been conducted for each calibration network (n=50).

Table 18 displays the best results (based on minimal network cost) for two different temperature levels. Without the error term which is directly dependent on

T_0, a Greedy[137] search algorithm is applied (T_0=0). Compared to the model application with a high temperature (T_0=100), the Simulated Annealing metaheuristic, much higher network costs are achieved for both calibration networks for the Greedy application (see Table 18). The differences between Greedy and the Simulated Annealing algorithm suggest that the Greedy algorithm finds the nearby (local) minimum dependent on the initial network structure, but it fails to overcome this structure for a global search. Up to 16% in cost reduction can be achieved by a broader search algorithm as intended by the Simulated Annealing application.

Table 18: Best results for Greedy versus Simulated Annealing application (Source: author's own representation)

Network cost [USD]	P2P	1H	Deviation
Greedy application (T_0 = 0)	34,459,386	36,974,510	–7%
Simulated Annealing application (T_0 = 100)	30,221,583	31,956,089	–6%
Deviation	–14%	–16%	

A primary objective of the calibration step is to set parameters in a way that local minima can be overcome by the algorithm. As indicator for the variety of analysed network structures, and therefore for a broad minimum search betweenness centrality has been chosen (see chapter 3.3 for further information on the indicator). Betweenness centrality measures the shape of the network and a variety of betweenness centrality scores guarantee that several structures have been analysed and tested.

Figure 18 shows the development of betweenness centrality values for the best P2P run (T_0=100).

137 According to Greedy algorithm's properties a locally optimal choice is conducted at each stage of the algorithm. Greedy algorithms build up a solution step by step, and they always choose the next step that offers the most obvious and immediate benefit. Greedy algorithms are part of local search algorithms which cannot overcome local minima. Therefore, the comparison between Greedy and Simulated Annealing is suitable for parameter choice and especially for setting parameters for global minima search right.

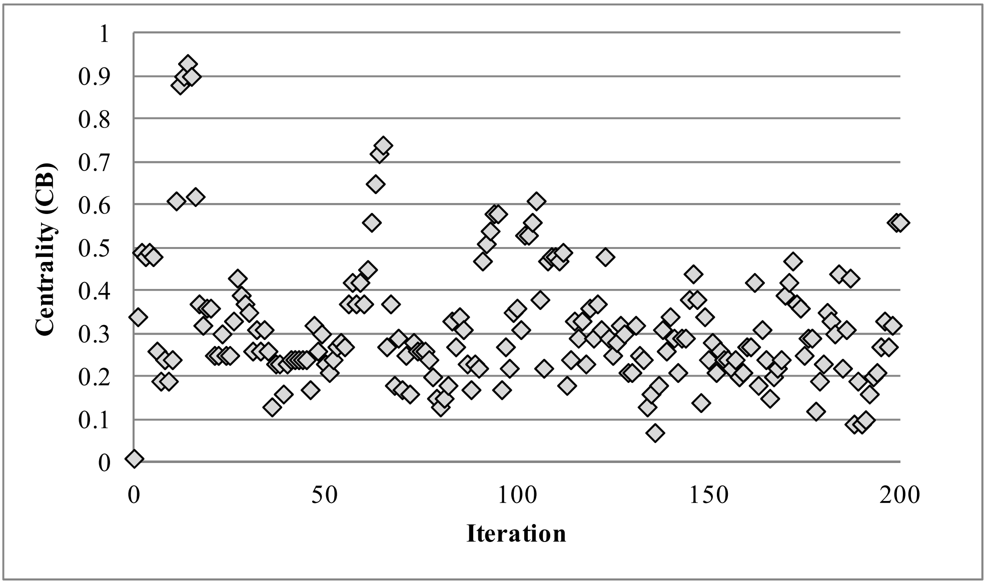

Figure 18: Analysed network shapes based on betweenness centrality values of one P2P calibration network run
(Source: author's own representation)

It becomes obvious that the chosen temperature (T0=100) as well as the chosen number of iterations (Lk) ensure a wide search area as intended by the Simulated Annealing metaheuristic. This behaviour has been observed for both calibration networks. Based on these parameters the following best results are achieved for the calibration networks.

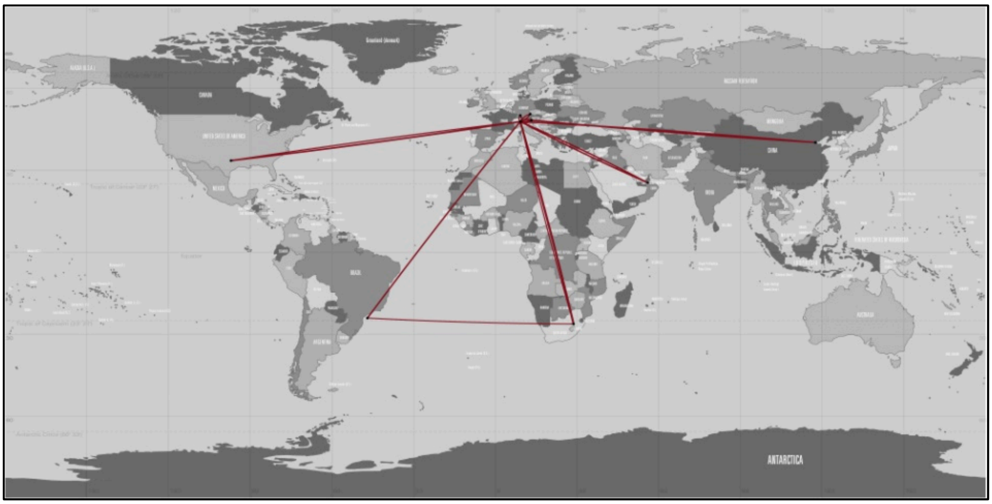

Figure 19: Point–to–point calibration network (best structure)
(Source: author's own representation)

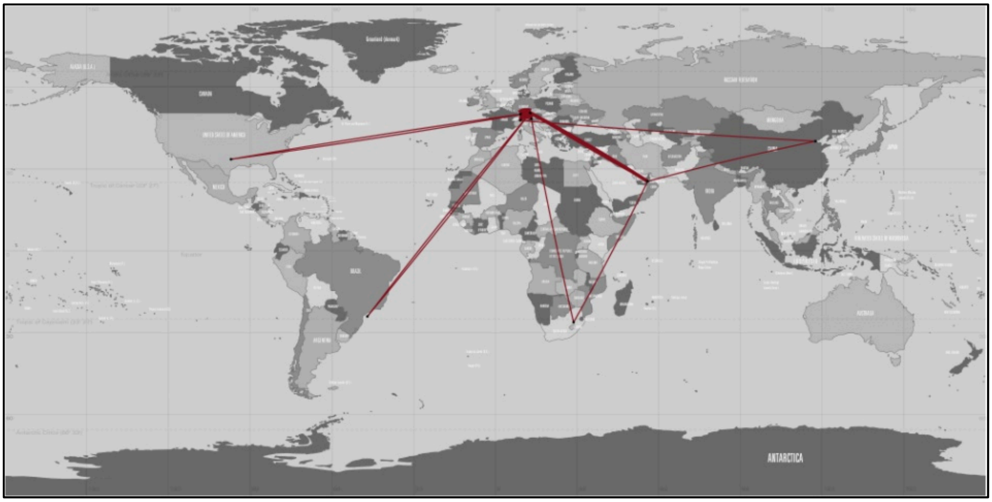

Figure 20: One hub calibration network (best structure)
(Source: author's own representation)

Despite their different initial structures (Figure 16 and Figure 17) a one hub airport structure emerges as best network structure for both calibration networks. The hub airport is located in Europe whereas one secondary hub airport exists (either in the Near East for routes from Asia and Africa to Europe or in Africa). Out of the (possible) 72 routes which represent the P2P network structure only around one fifth of these routes are operated directly whereas all other routes are operated through the hub airport(s). The analogy of results between the best (cost minimal) structures (see Figure 19 and Figure 20) proves the present parameter choice because independent of the initial structure similar network structures emerge as best structures. Therefore, the following parameters are implemented as default values in *AirTrafficSim*.

Table 19: Default values for the Simulated Annealing parameters of *AirTrafficSim*
(Source: author's own representation)

Parameter	**T_0**	**L_k**	**T_k**
Range	100	50	linear temperature function

5.6 Recapitulation

AirTrafficSim has been developed to model the strategic network structures of cargo airlines (supply side) based on a given demand structure. A three step approach is applied which differentiates between initialization, optimisation and finalization phase. The initialization phase requires a disaggregated demand structure as input (annual origin–destination tonnages). The output of the initialization phase is direct services between the airports which relate to a perfect point–to–point (P2P) network structure.

The optimisation phase analyses several network structures by applying the metaheuristic Simulated Annealing. Based on total network cost (objective function) which consists of transport related operating cost as well as warehouse cost and cost of capital various structures are analysed. Transport related cost are based on total aircraft operating cost and incorporate economies of scale. Optimal aircraft size, the required service frequencies as well as the operating cost are the outcome for every flight leg. A shortest path algorithm (Dijkstra algorithm) based on the operating cost searches for the cost minimal routes. Finally, total network cost (objective function) is achieved by adding up the operating cost of all routes.

The variety of analysed network structures are finally compared with each other and the cost minimal structure is determined (finalization phase). In the following chapter *AirTrafficSim* is run for a real world case of a leading cargo airline.

6 *AirTrafficSim:* Case study application

The present chapter demonstrates the applicability of *AirTrafficSim* to model real world airline networks. The indicators which have been developed for classifying airline networks are summarised first and applied to the real world network of Lufthansa (chapter 6.1). In a first step, the primary input to *AirTrafficSim*, the demand structure, is generated and introduced (chapter 6.2). Thereafter, results of the status–quo application (base scenario) are presented and compared with the real world network structure of Lufthansa (chapter 6.3). If future network adaptations on Lufthansa's present network structure are required, is analysed in the demand scenario 2029 (chapter 6.3.2). Finally, the overall results of the case study application are summarised (chapter 6.4).

6.1 Assessment indicators and its application to the real world network structure of Lufthansa[138]

Networks in general and airline networks in particular are complex structures. Comparisons between different networks of the same typology are only effective if their specific characteristics are considered in the assessment framework. The present dissertation compares real world with modelled airline networks and chooses several indicators for comparison. These indicators are classified into network shape (centrality measures) and network concentration (concentration measures)[139]. The indicators are summarised and briefly described in Table 20 (see chapter 3.3 for a detailed discussion of the indicators).

[138] A detailed discussion on the network structure of cargo airlines is found in chapter 3.

[139] Other indicators especially indicators of network size (e.g. number of airports, routes) have not been considered in the present analysis for the following reasons: (1) demand structure (from origin to destination airport) has been determined based on secondary sources (no real data) (2) country demand is allocated to one randomly chosen airport of the country whereas airlines are mainly operating to several airports of a country (3) no information on the final destination (city, region, etc.) exist (4) no airport choice model is implemented and freight terminates at the airport instead of at the final destination (5) real world data are supply side data (available-tonne-miles) whereas the present analysis bases on demand data. These reasons suggest focusing on network concentration as well as network shape indicators for comparisons between real world and modelled network structures.

Table 20: Assessment indicators for comparison between real world and modelled network structures
(Source: author's own representation)

Indicator class	Indicator	Description of indicator
Network shape	Betweenness centrality	Measures the network configuration as a percentage of a perfect star network (perfect H&S network)
Network concentration	Gini index	Measures the inequality of traffic distribution within the network.
	Herfindahl–index	Measures the concentration within the network
	Concentration ratio	Measures the importance of the major airports for the entire network

The network structure of Lufthansa is illustrated in Figure 21. It becomes obvious that the major markets for Lufthansa are Europe, Asia/Pacific and North America. In particular, on the routes between Europe and Asia/Pacific as well as between Europe and North America the highest air freight capacities are offered by Lufthansa. Besides the comprehensive belly capacities that are operated on these routes further pure freighter capacities are added to cope with the demand.

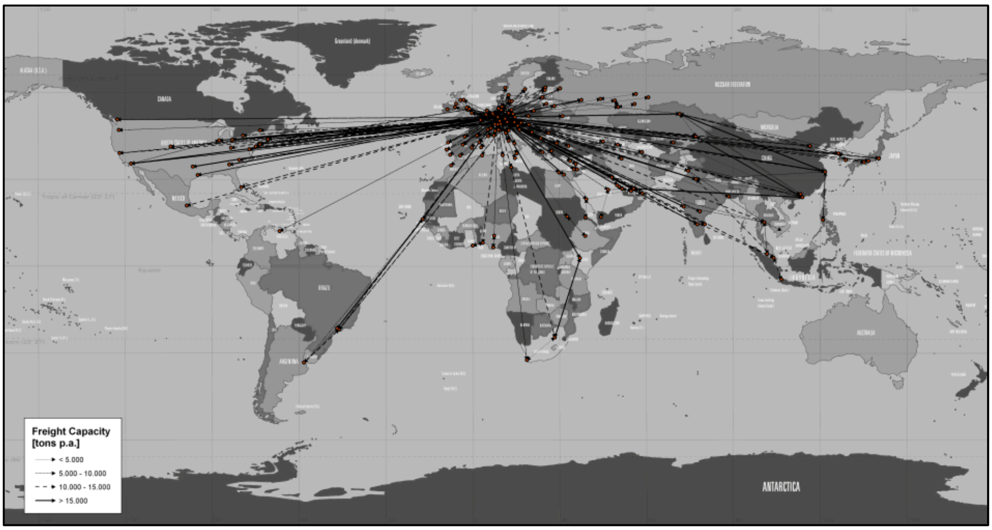

Figure 21: Network structure of Lufthansa
(Source: author's own representation based on OAG data for 2007)

Lufthansa's primary focus is still on its passenger business even though cargo services play an increasing role for the corporate success. Therefore, the traditional H&S network structure of combined carriers is also observed for Lufthansa (high concentration of cargo capacities at the hub airports). A high betweenness centrality combined with a high concentration measure (Gini and Herfindahl) characterises the H&S scheme with concentrations on selected destinations.

The highest concentration of flights accumulates at the airline's passenger hub(s). Lufthansa operates two hub airports for its passenger service (FRA and MUC) which is also reflected in the network structure for cargo because slightly lower values are observed than for other combined carriers, such as Air France (dedicated focus on CDG as hub airport). Because of its two passenger hubs Lufthansa also operates a slightly less central network (CB=0.82). Both airports serve as hubs with different key markets for LH, freight is also transferred at these hubs which results in a lower overall centrality value. More than half of total air freight is still transported as belly freight in passenger aircrafts which explains the importance of the passenger hubs also for freight services. The network shape and network concentration indicators are summarised in

Table 21.

Table 21: Network shape and network concentration data of Lufthansa (source: author`s calculations based on OAG, 2007)

Assessment indicators	Lufthansa
Fitness [MUSD[140] p.a.]	–
Gini index	0.74
Herfindahl–index	0.11
Concentration ratio CR1	0.31
Concentration ratio CR3	0.44
Betweenness centrality (CB)	0.82

6.2 Demand generation for Lufthansa

The primary input for *AirTrafficSim* is an airline's demand structure. Because such corporate data is highly confidential four different sources have been merged to replicate Lufthansa's demand structure adequately. Table 22 specifies the data sources and their contents.

[140] MUSD refers to millions of US dollar

Table 22: Demand generation data sources and their content (Source: author's own representation)

Data source	Content	Level of detail[141] [unit]	Example
Lufthansa (CASS data)	Air freight tonnages for German exports/imports	German airport –> world region [annual tonnes] World region –> German airport [annual tonnes]	FRA –> Africa: 100 tonnes
MergeGlobal	Air freight traffic flows between world regions	World region –> world region [annual tonnes]	Asia/Pacific –> North America: 100 tonnes
Lufthansa	Market share of Lufthansa between world regions	World region –> world region [%]	Asia/Pacific –> North America: 1%
aviainform	Air freight import/export data Germany	Germany –> country [annual tonnes]	Germany –> China: 100 tonnes

The main contribution relates to aggregated import/export data to/from Germany of the Cargo Account Settlement System of Lufthansa which are further introduced in chapter 6.2.1. Transfer freight is determined on the basis of data of MergeGlobal and of Lufthansa (chapter 6.2.2) and finally all data are further disaggregated to the country level based on data of aviainform (chapter 6.2.3). In a final step a randomly chosen airport per country is determined to achieve the required level of detail for *AirTrafficSim*.

6.2.1 Generation of export/import tonnages from/to Germany

The basis of the present demand generation model is data of the international Cargo Account Settlement System (CASS). CASS data of 2007[142] have been provided by Lufthansa and are classified into seven spatial markets, such as Africa, Asia/Pacific, Europe, Germany, North Atlantic, Near East and South Atlantic. Furthermore, export and import data are differentiated and the region's market shares are illustrated in Figure 22.

[141] The stated level of detail relates to its application in the present demand generation model. Data might even be more detailed, but this information is not considered here.

[142] The year 2007 has been chosen as base year for analysis because 2007 is interpreted as an average year for cargo airlines without significant shocks, such as September 11, 2001, the economic crises in 2008/2009 or the ash cloud in 2010. It is assumed that strategic decisions such as network structure considerations are decided on the demand situation of such an average year.

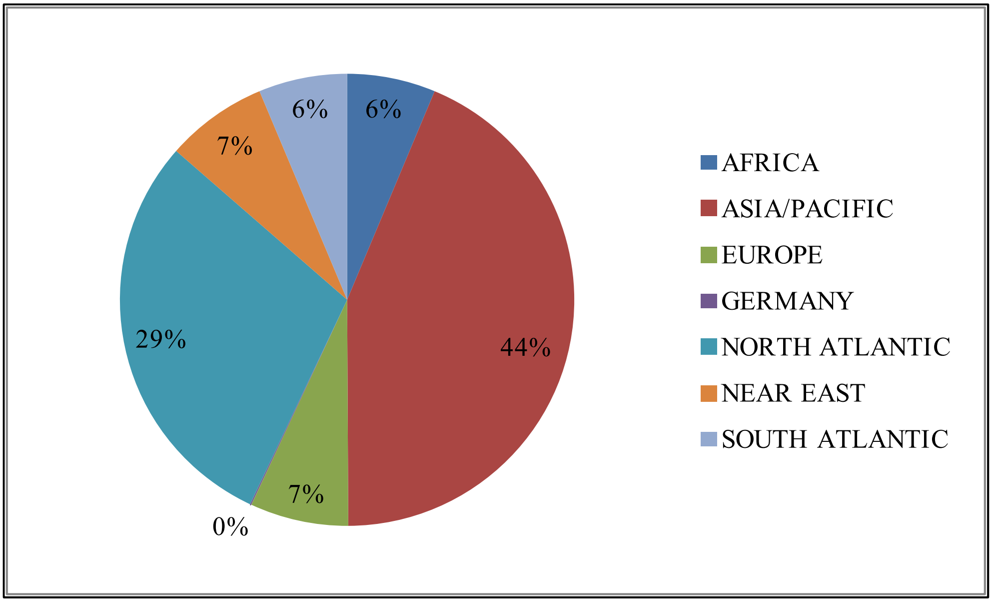

Figure 22: Regional market shares of Lufthansa Cargo based on export data (Source: Lufthansa, 2010)

For Germany data are provided on an airport level and thirty airports are differentiated. Table 23 displays the data structure of the CASS database for FRA.

Table 23: Annual tonnages between FRA and destination regions (Source: Lufthansa, 2010)

Origin Airport	Destination Region	Tonnage in 2007 [tonnes]
FRA	Africa	42,165
FRA	Asia/Pacific	329,600
FRA	Europe	43,578
FRA	Germany	366
FRA	North Atlantic	210,494
FRA	Near East	52,106
FRA	South Atlantic	53,329

In a second step air freight which is only transferred at German airports by Lufthansa is reproduced because CASS data are only considering import and export to/from Germany.

6.2.2 Transfer freight generation

Data of MergeGlobal (2007) are considered and displayed in Figure 23. MergeGlobal determines worldwide air freight traffic flows, and it becomes obvious that freight flows from Europe to Asia/Pacific (and vice versa) as well as from North America to Asia/Pacific (and vice versa) are the leading inter–

continental air freight markets whereas Africa and South America only play secondary roles.

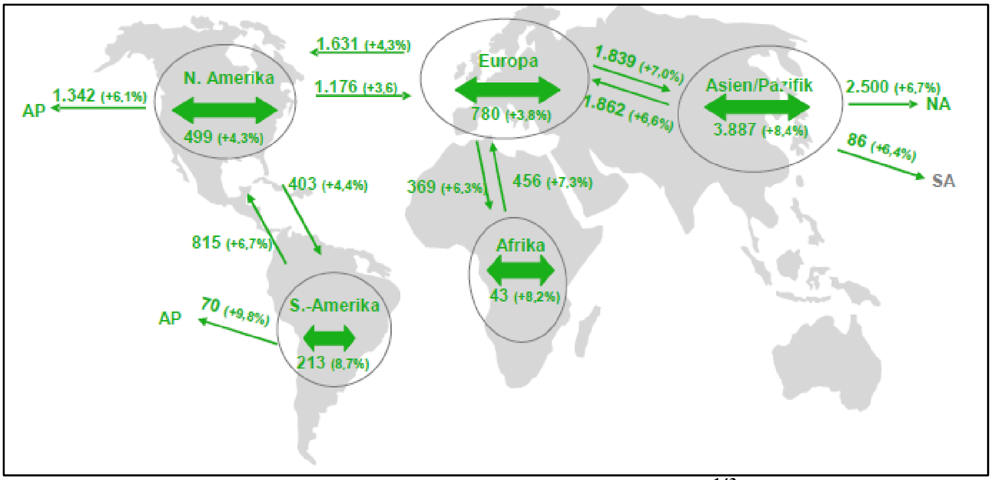

Figure 23: Worldwide air freight traffic flows[143]
(Source: Lufthansa Cargo, 2008 based on MergeGlobal, 2007)

The aggregated market data are further disaggregated to the company level of Lufthansa by the use of Lufthansa's market shares (see Figure 24).

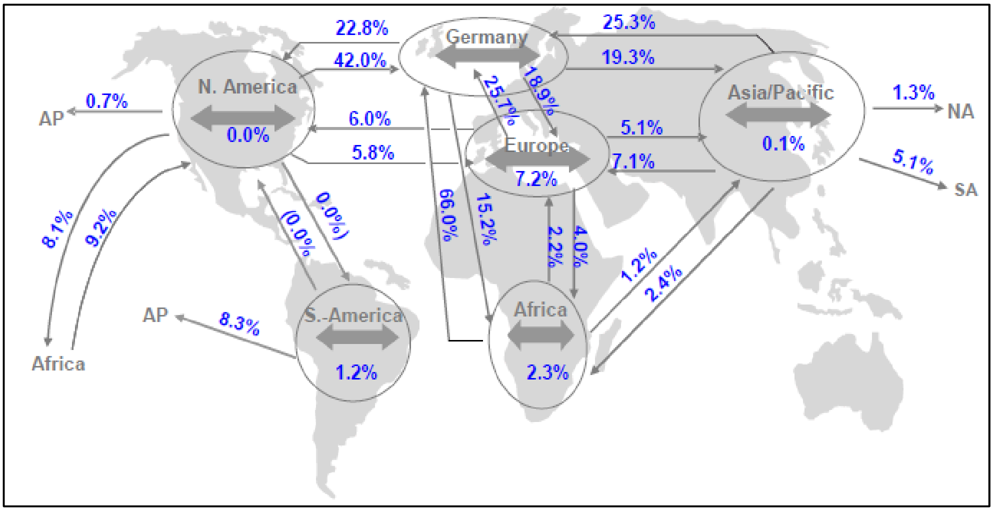

Figure 24: Market share of Lufthansa
(Source: Lufthansa Cargo, 2008)

The outcome of the second step is annual tonnages between German airports and the world regions (e.g. FRA–>Asia/Pacific) as well as between all world regions

143 Data are of 2006 and stated in thousand tonnes. In brackets the growth rate between 2005 and 2006 is displayed.

(North America–>Asia/Pacific). In the last step the ascertained traffic flows are allocated to the country level and respectively the airport level which is the level of detail of *AirTrafficSim*'s inputs and will be introduced in the following.

6.2.3 Allocation of traffic flows to the airport level

The last step of the demand generation model disaggregates air traffic flows of the CASS system and of MergeGlobal to achieve airport to airport tonnages. Therefore, air freight import/export data for whole Germany have been provided by aviainform an aviation consultancy specialised in market data and especially in maintaining traffic data. It is assumed that the spatial distribution of air freight from/to Germany also represents Lufthansa's spatial distribution. This approach is justified by the importance of Lufthansa for Germany's air freight shipments. The top 10 export countries for Germany are displayed in Table 24.

Table 24: Top 10 of the German air freight export countries (Source: aviainform, 2010)

Rank	Destination country	Air freight exports [tonnes]	Market share of total air freight export [%]
1	United States	296,261	24.9
2	China (incl. Hong Kong)	190,090	16.0
3	Japan	71,807	6.0
4	India	58,667	4.9
5	Korea (Republic of)	55,732	4.7
6	Brazil	43,060	3.6
7	South Africa	42,807	3.6
8	United Arab Emirates	41,157	3.5
9	Singapore	31,449	2.6
10	Canada	29,684	2.5

Finally, one randomly selected airport per country is chosen and cargo tonnes are allocated to this airport. The final output of the demand generation model for the present case study is therefore a disaggregated demand structure for Lufthansa (annual airport to airport tonnages for 2007). The airline's network structure emerges from *AirTrafficSim* given that demand is transported to minimal cost by the airline. The cost minimal network that serves the entire demand is the outcome of *AirTrafficSim* and will be presented and compared to the existing airline network in the following.

6.3 Model results

The following chapter presents the model results for the Lufthansa applications based on *AirTrafficSim*. Model procedure and the choice of the required parameters are applied in the following as determined in chapter 5. *AirTrafficSim* grounds on cost as decision variable, and the network structure is chosen and defined as best with the lowest overall cost. First, the results of the modelled network structure are introduced and critically compared with the real world network of Lufthansa. Afterwards, a demand scenario 2029 is modelled and presented.

6.3.1 Base scenario

The initial point for *AirTrafficSim* is a given demand structure which is then transferred into a point–to–point (P2P) network structure as illustrated for Lufthansa in Figure 25[144].

Figure 25: Initial network structure of Lufthansa
(Source: author's own representation)

The core markets of Lufthansa are becoming obvious already by the initial network structure. A large number of freight is transported from the core market of Lufthansa, namely from Europe to North America (and vice versa) and to Asia (and vice versa) as well as within Europe. Africa and South America (as well as Australia) are playing minor roles (no role) for Lufthansa and are also in their overall market size much smaller than the foresaid air freight markets (Crabtree et al., 2010). The initial network structure consists of 90 airports and 3,893 routes which are chosen based on the demand generation model's assumptions (see

[144] The thickness of each route (arc) is proportional to its tonnage.

chapter 6.2 for further details). Table 25 summarises the results of the assessment indicators of the initial network structure.

Table 25: Network shape and network concentration of Lufthansa's initial network structure (Source: author`s calculations)

Assessment indicators	Initial network structure
Fitness [MUSD[145] p.a.]	9,210
Gini index	0.78
Herfindahl–index	0.08
Concentration ratio CR1	0.23
Concentration ratio CR3	0.37
Betweenness centrality (CB)	0.02

The initial network structure of Lufthansa has a significant concentration level (e.g. Gini index). FRA serves as major airport within the initial network structure because Lufthansa receives a large amount of cargo from air freight forwarders at its hub airport which makes FRA its major airport already before the optimisation phase of *AirTrafficSim*. The CR1 value is also explained by the above mentioned characteristics of the initial network configuration whereas the increase to CR3 documents that other airports of the network are of much smaller importance for the initial network of Lufthansa.

The difference in betweenness centrality between a perfect point–to–point (P2P) network structure (CB=0.00) and Lufthansa's value (CB=0.02) can be explained by limitations in the maximum range of aircrafts. *AirTrafficSim* assumes that each aircraft category has a maximum range (maximum stage length) which is derived from the aeroplane characteristics handbook. An overall maximum range of 7,000 sm is therefore defined[146]. Flights with a longer non–stop distance are not operable and are therefore allocated to their shortest–paths. Thus, the overall tonnage of the entire network is retained. This reallocation increases the betweenness centrality value of the airports which are on the shortest–paths and leads to a slightly larger centrality value for the initial network configuration than for a perfect P2P network structure.

In a first step a Greedy optimisation algorithm has been applied for the present case study which is a local search algorithm and which follows the solving heuristic of making the locally optimal choice at each stage of the algorithm. The application of a Greedy algorithm has been chosen to evaluate the effectiveness of the global search algorithm (Simulated Annealing) compared to the local search of the Greedy application. Figure 30 displays the cost minimal network structure of the Greedy application whereas Table 26 presents the assessment indicators' results and compares them with the initial network structure of Lufthansa.

[145] MUSD refers to millions of US dollar

[146] Payload-range diagrams which depends the maximum range of a flight on the present aircraft's payload are currently not applied in *AirTrafficSim*.

Figure 26: Cost minimal network structure of Lufthansa based on a Greedy algorithm (Source: author's own representation)

Results demonstrate that cost savings can be achieved by the application of a local search algorithm and amount to more than 50% compared to the P2P network (initial network structure). In particular, betweenness centrality (CB=0.91) indicates the shift in network structure (compared to 0.02 in the initial network). Additionally, the Herfindahl index which is especially sensitive to changes in the extremes and CR1 (concentration of the largest airport) as well as CR3 (concentration of the three largest airports) underline the increased importance of dedicated airports for the Lufthansa network. Most inter–continental routes are operated via the hub airport FRA which achieves a betweenness centrality of 0.92 (CB=0.92). The following airport based on its betweenness centrality value is the Greece airport (CB=0.03) which serves as intermediate airport to Mediterranean countries. The difference between FRA and the Greece airports proves that FRA is the only hub airport for Lufthansa based on the Greedy application.

The comparison between the Greedy application and the real world network structure of Lufthansa (named as "Lufthansa" in Table 26) indicates a considerable market concentration (and centrality) which is even more distinctive than for the real world network structure. The Simulated Annealing application is now analysed to see if network cost can be further reduced as well as if the assessment indicators are getting closer to the real world network of Lufthansa.

Table 26: Network shape and network concentration of Lufthansa's Greedy application (Source: author's own representation)

Assessment indicators	Lufthansa	Initial network structure	Greedy result
Fitness [MUSD p.a.]	–	9,210	4,061
Gini index	0.74	0.78	0.85
Herfindahl–index	0.11	0.08	0.24
Concentration ratio CR1	0.31	0.23	0.47
Concentration ratio CR3	0.44	0.37	0.58
Betweenness centrality (CB)	0.82	0.02	0.91

The application of the Simulated Annealing metaheuristic within *AirTrafficSim* is firstly analysed based on the results of one run which is defined as one completed model run consisting of the initialization, the optimisation and the finalization phase (see chapter 5 for further details). Within one model run several configurations (network structures), hereinafter referred to as iterations[147], are tested and assessed by their overall network costs (fitness) which serve as decision variable. Figure 27 displays exemplarily the results of one model run by illustrating the first 200 iterations. The overall fitness (network cost) is indicated on the primary y–axis whereas the iteration's network centrality (network shape) is showed on the secondary y–axis.

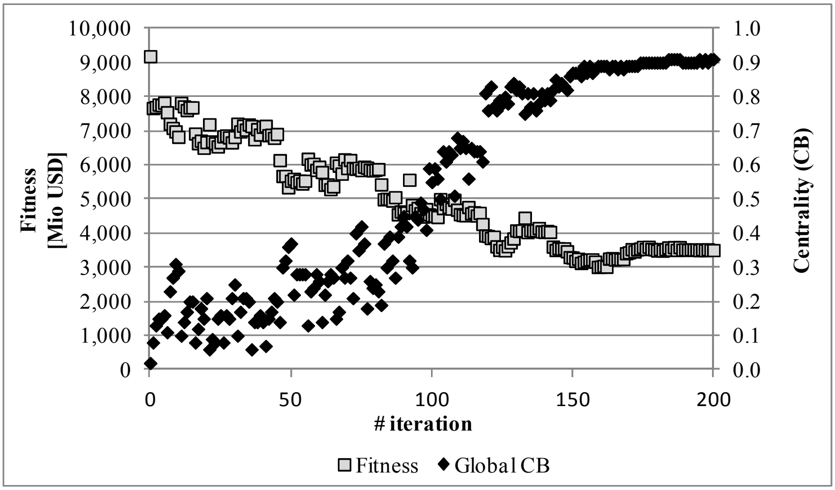

Figure 27: Development of the network's fitness and centrality values of one model run for Lufthansa
(Source: author's own representation)

[147] Simulated Annealing literature refers to as neighbour solutions or neighbour states.

The strength of the Simulated Annealing metaheuristic as illustrated in Figure 27 is that steady state structures (network configurations) can also be released. Thus, completely new structures emerge and can be assessed for the search of the global minimum. The different network configurations are identified in Figure 27 based on betweenness centrality (secondary y–axis) which is an indicator for network shape. Almost perfect network structures, such as a point–to–point network (CB=0.00) are compared with hybrid structures and (nearly) perfect hub–and–spoke structure (CB=0.9) and are assessed concerning their overall network cost (fitness). With increasing running time of the algorithm the external shocks of the Simulated Annealing algorithm are reduced as intended by the algorithm which leads to a rather stable situation and results in a reduction of centrality's variability. The characteristic of the wide search domain privileges Simulated Annealing over Greedy algorithms which perform a locally optimal choice at each stage of the algorithm (local search algorithm). The iteration which is defined as best is the iteration with the lowest fitness level (network cost) because demand is served at lowest cost by the airline.

In total 50 model runs are carried out for the search of the best (cost minimal) network configuration. Because of the stochastic component of the algorithm a large number of runs is performed to increase probability of achieving network's global minimum. Figure 28 illustrates the results of the 50 model runs by displaying the overall network cost (fitness) and centrality values of the Lufthansa base scenario on the primary respectively secondary y–axis.

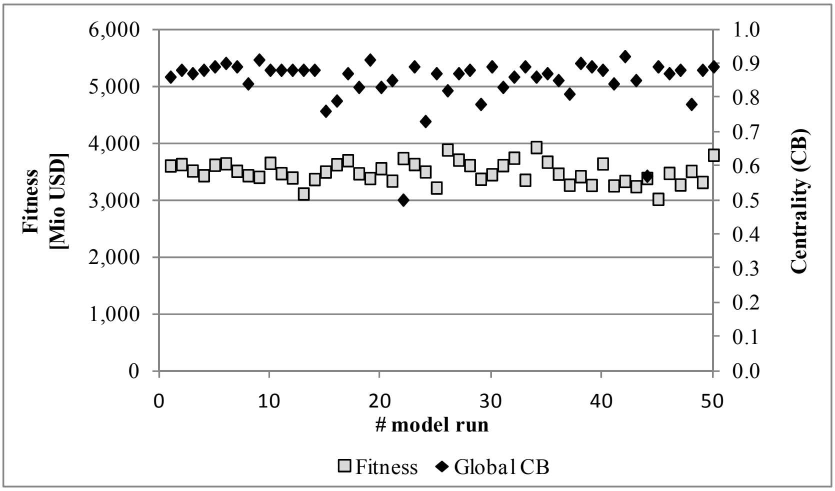

Figure 28: Results of the 50 model runs for Lufthansa
(Source: author's own representation)

Overall fitness amounts between 3 and 4 billion US Dollar per annum with an average annual fitness of 3.48 billion US Dollar (standard deviation: 0.19 billion US Dollar). In other words, Lufthansa may serve annual demand in average for 3.48 billion US Dollar per annum. The coefficient of variation is 0.05 which implies a small volatility in relation to the average fitness of the networks and indicates stable results. Analysing the centrality values of the 50 runs a variation between 0.5 and 0.92 was calculated by *AirTrafficSim* with an average value of 0.82 and a standard deviation of 0.08 (coefficient of variation: 0.09). Standard deviation as well as the coefficient of variation for centrality (CB) present that results are stable and are around the same values with very few outliers (which are however intended by the Simulated Annealing approach). Out of the 50 model runs the network structure which fits best with the real world network of Lufthansa is introduced and discussed first. Afterwards the network structure with the lowest cost which differs from the best–fit network structure is presented.

Table 27 compares the assessment indicators of the modelled network structures with Lufthansa's real world network.

Table 27: Network shape and network concentration values of the best–fit network structure (source: author's own representation)

Assessment indicators	Lufthansa	Initial network structure	Greedy result	Simulated Annealing (best–fit)
Fitness [MUSD p.a.]	–	9,210	4,061	3,879
Gini index	0.74	0.78	0.85	0.84
Herfindahl–index	0.11	0.08	0.24	0.12
Concentration ratio CR1	0.31	0.23	0.47	0.30
Concentration ratio CR3	0.44	0.37	0.58	0.49
Betweenness centrality (CB)	0.82	0.02	0.91	0.82

The best–fit application achieves a high degree of similarity with the real world network structure of Lufthansa. Network shape based on betweenness centrality is identical (CB = 0.82) for both network structures which proves that most routes run through the airline's hub airport. Also the Herfindahl index as a measure of network concentration as well as CR1 achieves very high level of similarity to the real world network of Lufthansa. Both indicators are based on or are very sensitive to the importance of the largest airport(s). Hence, the high degree of fitness between modelled and real world network proves the model's accuracy for the determination of the number of hub airports. A slightly higher CR3 value of the modelled network structure implies that a higher importance is assigned to the second and third largest airport compared to the real world network. Finally, the difference in the Gini index indicates a more unequal spread of freight for the modelled network compared to the real world network structure. Differences between the real world and the best–fit modelled structure of Lufthansa can be explained by the following reasons:

- demand data are synthetically replicated based on secondary sources and are allocated to one airport in the destination country which cannot always be observed in reality (e.g. China, Japan, USA)
- real world network structures are based on supplied capacities whereas modelled structures are demand driven
- simplified assumptions

Figure 29 displays the best–fit modelled network structure.

Figure 29: Best–fit network structure of Lufthansa based on *AirTrafficSim*
(Source: author's own representation)

The best–fit network structure achieves a very high degree of similarity as shown in Table 27 and illustrated in Figure 29, but the best–fit network structure does not serve demand at lowest cost. More than 20% of cost savings can be achieved by transferring the best–fit network structure into the cost–minimal network structure which is introduced in the following and displayed in Figure 30. The assessment indicators are summarised in Table 28.

Figure 30: Cost minimal network structure of Lufthansa based on *AirTrafficSim*
(Source: author's own representation)

Similarities between the real world and the cost–minimal modelled network structure are still visible and the major markets of Lufthansa (Europe, Asia/Pacific and North America) are also the ones with the highest tonnages in the modelled network. A two European hub structure is carved out to fit best for Lufthansa plus one secondary hub airport in China. Hub airports combine significant centrality as well as concentration levels and are observed best for the two European hub airports which are both located in Germany. FRA is ranked second with a betweenness centrality value of 0.11 and 12% of freight is handled at the airport whereas a smaller airport, MHG (Mannheim, Germany), is ranked first (CB=0.90) with 40% of freight. The achievement of *AirTrafficSim* is the determination of the cost minimal network structure rather than the hub airport choice. Therefore, further analyses are needed to prove the efficiency of the hubs for Lufthansa's network.

The Chinese airport also has a high importance for origin/destination traffic from/to China but also serves as gateway to/from East Asia (e.g. South Korea and Japan)[148]. The Chinese airport scores a CB value of 0.07 indicating that 7% of all routes run through the airport and it is ranked third after the two global hub airports of Lufthansa located in Europe, the home market of the airline. Furthermore, 10% of total freight is handled at the airport which underlines its importance for the network structure of Lufthansa. Furthermore, a transfer airport located in Canada can also be observed which serves as gateway for selected routes to North America

[148] Bilateral air transport agreements regulate international air transport and define which services are allowed for which airlines. The fifth freedom which is signed by the European Union with China as well as with North America allows a European airline to carry traffic (passenger and freight) between foreign countries as a part of services connecting the airline's own country. Therefore, Lufthansa is allowed to carry freight from China to East Asian countries as part of a service from Germany and vice versa.

but with a much smaller importance for the entire network (based on betweenness centrality). The importance of the Chinese airport as well as the Canadian gateway to North America are neither existent in the initial network structure of Lufthansa (Figure 25) nor in the structure of the Greedy application (Figure 26). Such behaviour is modelled by *AirTrafficSim* as a cost saving structure to serve the East Asian market as well as selected North American routes at lower cost.

Table 28: Network shape and network concentration values of Lufthansa's cost minimal network structure (source: author's own representation)

Assessment indicators	Lufthansa	Greedy result	Simulated Annealing (best–fit)	Simulated Annealing (lowest–cost)
Fitness [MUSD p.a.]	–	4,061	3,879	3,015
Gini index	0.74	0.85	0.84	0.88
Herfindahl–index	0.11	0.24	0.12	0.19
Concentration ratio CR1	0.31	0.47	0.30	0.40
Concentration ratio CR3	0.44	0.58	0.49	0.62
Betweenness centrality (CB)	0.82	0.91	0.82	0.89

The Simulated Annealing algorithm in general and especially the lowest–cost network structure outperforms Greedy as well as the initial network structure concerning the overall fitness and therefore guarantees that demand is served by Lufthansa at lower cost. In contrast to the Greedy application a lower betweenness centrality is achieved which is explained by the gained importance of the secondary hub in China as well as by the reduced concentration at the hub airport (CR1) and the increased importance of the following airports (CR3). Additionally, the reduced Herfindahl index which is especially sensitive to changes in the extremes further emphasises these observations. Savings which transfer the best–fit network into the lowest cost network structure are achieved by further reducing the number of direct services and by implementing distinctive hub structures in Asia. In particular, the betweenness centrality value of the Chinese airport in the cost minimal network structure is double the value of the best–fit structure.

The present network configuration of Lufthansa is analysed against the background of future demand which grounds on forecasts for 2029. The following chapter will present these results.

6.3.2 Demand scenario 2029

The demand scenario 2029 assumes a shift in the core air freight markets towards Asia and analyses its implications on the network structure for a leading cargo airline (Lufthansa). The air cargo scenario 2029 is based on Boeing's World Air Cargo Forecast 2010–2011 (Crabtree et al., 2010). The biennial assessment forecasts the future performance of the industry within a twenty year time horizon and analyses market developments of the world's major air freight markets. The primary objective of the air cargo scenario 2029 is to determine and analyse necessary network adaptations for a leading cargo airline based on the world's expected demand development. Therefore, the expected demand development is introduced first.

After an 18–month decline of world's air freight which was caused by the economic crisis in 2008/2009 air cargo traffic already rebounded in 2010. In spite of this downturn, Boeing expects the world air cargo traffic to almost triple over the next 20 years. The 166.8 billion RTKs[149] in 2009 are expected to increase to 526.5 billion RTKs in 2029 resulting in an average annual growth rate of 5.9% (Crabtree et al., 2010).

Different developments are forecasted for the world regions with Asia will continue with the highest growth rates worldwide. In contrast, the markets of North America and Europe (and especially their home markets) reflect lower–than–average air freight growth rates. Markets like Latin America–North America, Latin America–Europe, as well as between the Middle East and Europe, will grow at approximately the world average growth rate (Crabtree et al., 2010). Table 29 summarises the expectations for selected air cargo markets, and it becomes obvious that forecasts are for all but one market above the historic 10 years trend. Boeing valuates the past ten years as extremely fragile especially for the air freight industry because of internal as well as external shocks (e.g. September 11, war against terrorism, economic crisis of 2008/2009, high average oil price) which will reduce in the coming twenty years (Crabtree et al., 2010). Such a valuation is extremely optimistic as regional and global conflicts still swell, oil price is expected to further increase and economic cycles will also be volatile in future. Thus, the applied growth rates are construed as an upper bound. It is argued that if the current network configuration of Lufthansa also persists for such an optimistic scenario no comprehensive actions are required for less optimistic and therefore more likely developments. In such a case the network structure of Lufthansa is regarded as well positioned for the future.

[149] RTK: revenue-tonne-kilometre

Table 29: Selected historical and forecasted air cargo annual growth rates (Source: Crabtree et al., 2010)

Annual growth rates	Historic 10 years (1999–2009)	Forecast 20 years (2009–2029)
World	1.9%	5.9%
Africa–Europe	3.3%	5.1%
Asia–North America	1.4%	6.7%
Europe–Asia	4.1%	6.6%
Europe–North America	–1.5%	4.2%
Latin America–Europe	2.5%	5.6%
Latin America–North America	–0.7%	5.7%
Middle East–Europe	6.5%	6.0%

The above mentioned growth rates are applied to the demand generation model as introduced in chapter 6.1. Demand data which are mainly based on Lufthansa's cargo account settlement system (base year 2007) are then extrapolated to the year 2029. Overall network size increases from 2.4 million tonnes (2007) to 7.1 million tonnes in 2029. The different growth rates for the world regions determine a shift in Lufthansa's core markets and Asian routes will still gain importance. The outcome of the demand generation model is a disaggregated demand structure for Lufthansa for the year 2029. Annual tonnes per route (from origin to destination airport) are generated as input for *AirTrafficSim* and direct services are allocated. Figure 31 displays the initial network structure of the demand scenario 2029.

Figure 31: Initial network structure of Lufthansa's scenario 2029 (source: author's own representation)

The expected worldwide air freight growth rates as forecasted by Boeing (Crabtree et al., 2010) and applied here are also observed in Figure 31 as tonnages for all markets are increasing (thickness of routes increases). The same route scaling has been applied as for the base scenario to allow visual comparisons between base scenario and scenario 2029. The cost minimal network that serves the entire demand is the outcome of *AirTrafficSim* and is illustrated in Figure 32.

Figure 32: Cost minimal network structure of Lufthansa's scenario 2029 based on *AirTrafficSim*
(Source: author's own representation)

As for the base scenario a two European hub structure fits best for Lufthansa's 2029 network. The Chinese airport gains importance because of China's market growth as well as its central location for shipments to East Asia (e.g. South Korea and Japan). The same can be observed for India which serves as distribution airport for Thailand and Malaysia. Such differences between base scenario and scenario 2029 are due to the above–average growth rates of India which enable cost efficient transfer flights also to South–East Asia. North America develops under–average but still with positive growth rates. Overall tonnages to North America are increasing and direct services from Europe to North America (and vice versa) can be operated efficiently. Markets such as Africa and South America are still not of utmost importance for Lufthansa and mainly direct services from the European hubs are operated.

The visible changes between base scenario and scenario 2029 are now analysed in detail based on the in–depth assessment indicators (Table 28). Overall network cost increase to USD 4,743 million per annum which is caused by the increase in demand in all parts of the world. The triple of network size to 7.1 million tonnes in 2029 leads to an increase in network cost of only 60%. Efficiency gains can be realized by Lufthansa as follows: Besides the dominating European hub airports which are both located in central Germany which is in analogy to the base scenario further European airports play an increasing role for Lufthansa's freight network. Such airports are not rising to hub airports but their concentration as well as centrality values increase. Furthermore, from Asian airports direct services are now efficiently operated to other Asian destinations which are presently financially ineffective (e.g. China–India, China–India). Such behaviour becomes effective because the critical air freight mass is achieved in 2029 between these routes. A decreasing overall betweenness centrality level underlines this development as well as a slight decrease of CR1 combined with an increase in CR3. Concentration levels are exactly the same for both scenarios. The results of the assessment indicators detect a hub–and–spoke network structure with dedicated direct services also for Lufthansa's network in 2029.

Table 30: Network shape and network concentration values of Lufthansa's scenario 2029 (Source: author's own representation)

Assessment indicators	**Scenario 2029: Simulated Annealing (lowest cost)**	**Base scenario: Simulated Annealing (lowest cost)**
Gini index	0.89	0.88
Herfindahl–index	0.19	0.19
Concentration ratio CR1	0.39	0.40
Concentration ratio CR3	0.66	0.62
Betweenness centrality (CB)	0.80	0.89

6.4 Recapitulation

AirTrafficSim has been developed to replicate the network structure of real world airlines. It was shown that the model which was calibrated based on synthetical networks is also applicable for real world cases. A high degree of similarity between the network of Lufthansa (2007) and the modelled network was achieved for the base scenario (best–fit network structure). In both cases hub–and–spoke networks are observed with high concentrations on selected airports and routes and a high degree of centrality. Differences between the structures are mainly due to the synthetical demand generation of the modelled network and because real world network structures are based on supplied capacities (available tonnes) whereas modelled structures are demand driven (revenue tonnes). The cost minimal network structure which was modelled for the base scenario by *AirTrafficSim* even further concentrates and centralises the network of Lufthansa. Thus, demand is served at even lower cost. This cost level is achieved by optimizing the routes from Europe to Asia and vice versa.

The future scenario 2029 examines the influence of future demand on Lufthansa's network structure. Asia will gain importance for Lufthansa as origin and destination market but also for strategic airport decisions. *AirTrafficSim* supports decision–making on the basis of the overall network cost of an airline.

7 Conclusions

Air cargo is a key element of global supply chains. It makes the difference between profit and loss of many long–haul flights (Morrell, 2011). The present dissertation approaches the air freight market from an airline's perspective and aims at better understanding market behaviour, decision making and network design of cargo airlines. Such an understanding is crucial for efficient airport infrastructure investments which are based on passenger and freight traffic forecasts.

Previous research on network structures of airlines has been focused on passenger services and has shown that airlines' networks are concentrated around a limited number of airports. In particular, former flag carriers, such as Air France and Lufthansa, operate very concentrated networks. The present dissertation has found out that these observations are also valid for cargo networks. Combined airlines which provide passenger and cargo services operate concentrated and centralised hub–and–spoke networks. The airlines' passenger hubs also serve as cargo hubs for the airlines. The extensive belly capacities of passenger aircrafts are the major reason behind this strategy. Network configurations of pure cargo airlines are much more diverse but round–trip structures are a common network characteristic of pure cargo airlines.

The software–based replication of an airline's network structure is the primary objective of the present dissertation and of *AirTrafficSim* which has been developed therefore. The merit of *AirTrafficSim* is that a network structure is not assumed a priori but emerges endogenously from the least cost operation. The strong competition between cargo airlines results in cost being the primary decision parameter for an airline's network structure. Therefore, total network cost is applied as objective function in *AirTrafficSim* which composes of the costs of all operated routes. An average cost function has been developed as basis for total network cost which guarantees that an airline's characteristics, such as its business model, its fleet structure, its labour costs, etc. are considered for network design. The empirically observed behaviour of cargo airlines to bundle and to consolidate freight at dedicated airports suggests incorporating economies of scale into airline network modelling. Aircraft as well as airport specific economies of scale are applied in *AirTrafficSim*. A developed aircraft choice model assigns the optimal aircraft to each flight leg based on transport related operating cost as well as warehouse cost (including cost of capital). The Simulated Annealing metaheuristic is implemented into *AirTrafficSim* and is based on total network cost. The network structure with the minimal cost is regarded as the structure which is operated by the airline as demand is fulfilled at lowest cost.

The application of *AirTrafficSim* to a real world case, the case of Lufthansa, has shown its ability for network design modelling. High concentrations at few airports as well as high centrality values at these airports have been observed for real world as well as for the modelled network structure of Lufthansa. Most routes are operated via the hub airport(s) which underlines the importance of the hub airport(s) for the entire network.

A future scenario, the demand scenario 2029, analyses Lufthansa's cost minimal network structure for the year 2029. In general, Lufthansa's present network structure with two European hub airports located in Germany can also be maintained in future. The Asian market will gain importance as origin and destination market. Furthermore, Asian airports will become more important for Lufthansa to bundle air freight for shipments to Europe and to North America as well as for direct services within Asia. In particular, direct services within Asia represent a modification of Lufthansa's present network structure.

The dissertation at hand adds a mosaic to the ongoing development towards an integrated demand and supply model. Therefore, a supply side model for cargo airlines is presented. Future research can build on the elaborations of this dissertation by developing an integrated supply–side model for passenger and freight services and by incorporating an airport choice model into *AirTrafficSim*.

The integration of a joint air passenger and air cargo model would present an essential enhancement of existing models which either focus on passenger or, as *AirTrafficSim,* on cargo airlines. The importance of combined airlines for worldwide cargo as well as passenger services necessitates such a model. Thus, an integrated model would constitute a break–through for practitioners and researchers.

A further research direction deals with linking the present model, *AirTrafficSim*, with an airport choice model. Therefore, *AirTrafficSim* needs to be regionalised and expanded by an airport choice model. The knowledge about origin and destination of freight gives the airline a higher flexibility of developing an efficient network structure. In a further step, such an approach can be combined with existing air freight demand models to achieve accurate forecasts on an airport level.

The mentioned expansions of *AirTrafficSim* are further mosaics on the way towards an overall aviation model which is based on the activity patterns of the involved actors. *AirTrafficSim* serves as a starting point for modelling the thriving air cargo business.

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Annex A: Regions in *AirTrafficSim*

Table 31: Regions in *AirTrafficSim*
(Source: WORLDNET, 2009)

Continent	WORLDNET region	Region name	Exemplary countries
AF	AFN	North–Africa	Egypt, Morocco
	AFO	East–Africa	Ethiopia, Kenya
	AFS	South–Africa	Namibia, South Africa
	AFZ	Central–Africa	Cameroon, Nigeria
AP	APA	Australia	Australia, New Zealand
	API	Indian–Subcontinent	India, Pakistan
	APO	East–Asia	China, Japan, Korea
	APS	South–East–Asia	Indonesia, Malaysia, Singapore, Thailand
EU	EUA	Central–Europe/Alps	Austria, Germany, Switzerland
	EUB	North–East–Europe/Baltic	Estonia, Latvia, Lithuania
	EUE	North–West–Europe	Ireland, UK
	EUF	East–Europe	Bulgaria, Romania, Ukraine
	EUG	South–East–Europe	Greece, Turkey
	EUI	South–West–Europe	Portugal, Spain
	EUN	North–Europe/ Scandinavia	Denmark, Sweden
	EUO	East–Europe	Croatia, Hungary, Poland
	EUS	South–Europe	Italy
	EUU	Central–Asia	Russian Federation
	EUW	West–Europe	Belgium, France, Netherlands
NA	NAOC	North America–East (Central)	USA (Central)
	NAOE	North America–East (East)	USA (East)

Continent	WORLDNET region	Region name	Exemplary countries
	NAOW	North America–East (West)	USA (West)
	NAS	North America–South	Mexico
	NAW	North America–West	Canada
NO	NOG	Near–East/Gulf	Iran, Saudi Arabia, United Arab Emirates
	NOM	Near–East/Mediterranean	Israel, Syrian
SA	SAK	Caribbean	Cuba, Dominican Republic
	SAO	South America–East	Argentina, Brazil, Chile
	SAW	South America–West	Bolivia, Colombia, Peru
	SAZ	Central–America	Costa Rica, Panama

Annex B: Case study application (detailed results)

B.1 Base scenario: Initial network structure

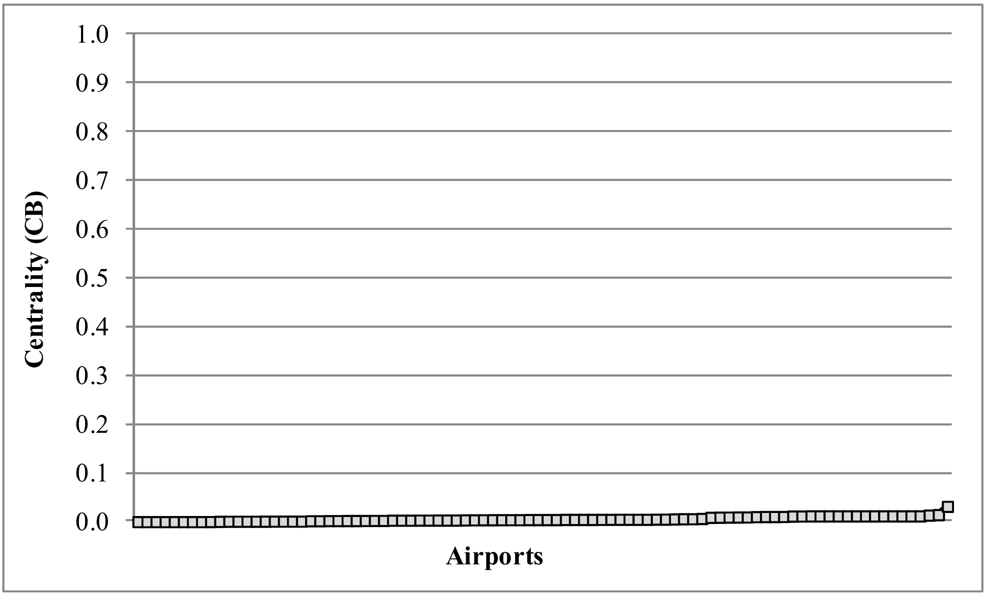


Figure 33: Base scenario: Initial network structure – Distribution of centrality values at the airports
(Source: author's own representation)

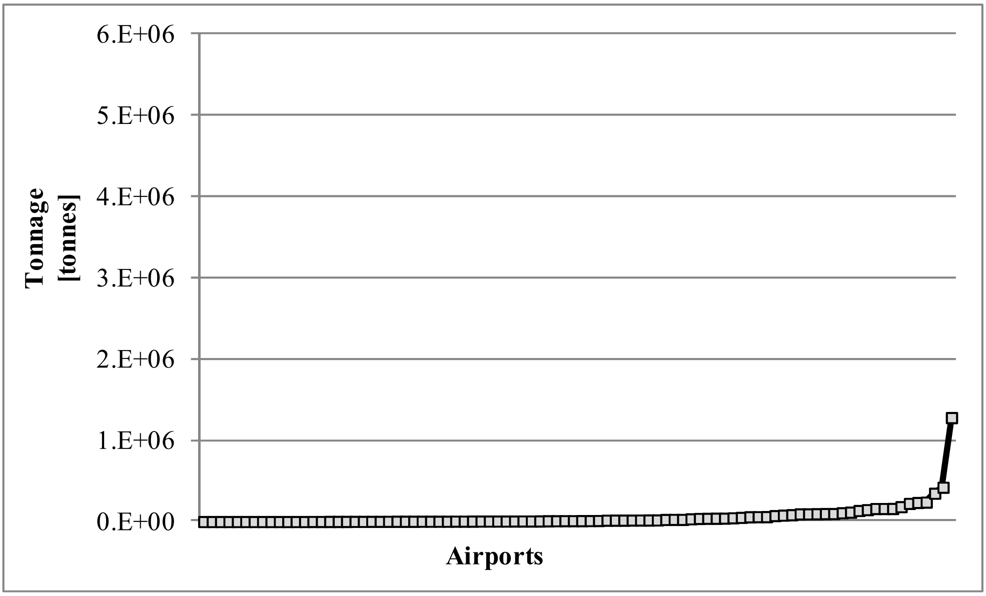


Figure 34: Base scenario: Initial network structure – Distribution of tonnages at the airports
(Source: author's own representation)

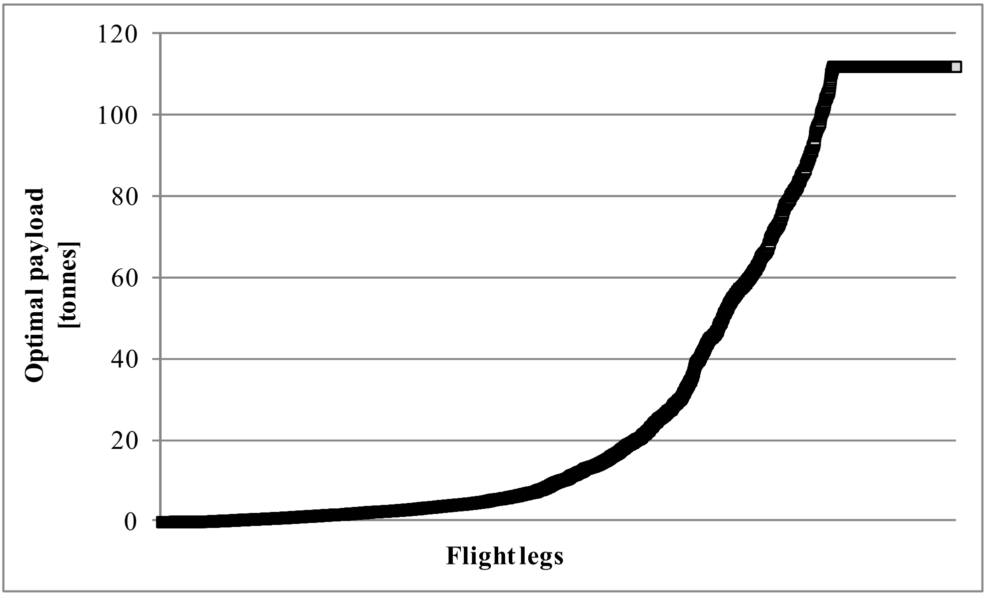


Figure 35: Base scenario: Initial network structure – Distribution of the optimal payload for the flight legs
(Source: author's own representation)

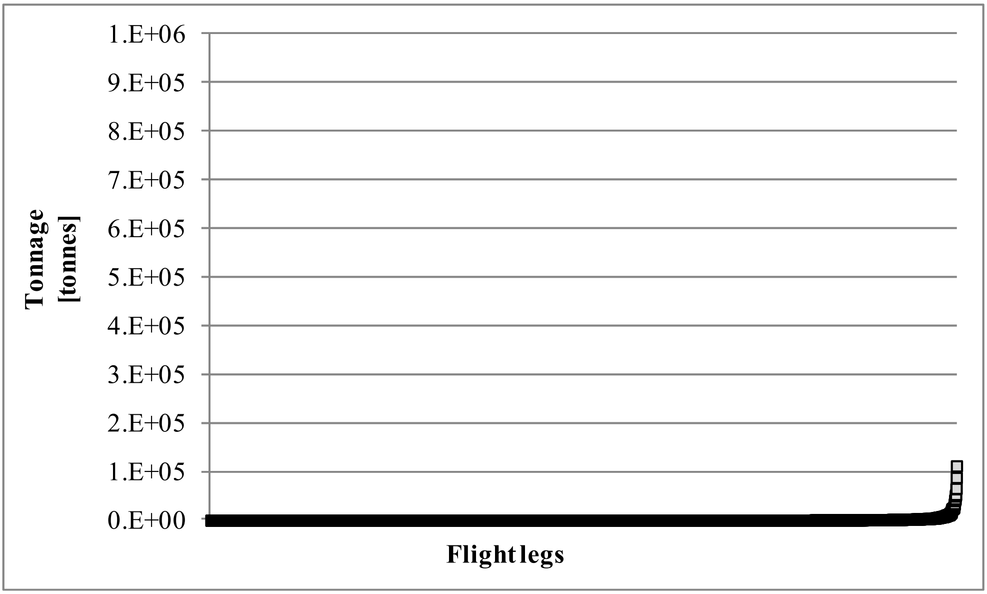


Figure 36: Base scenario: Initial network structure – Distribution of tonnages at the flight legs
(Source: author's own representation)

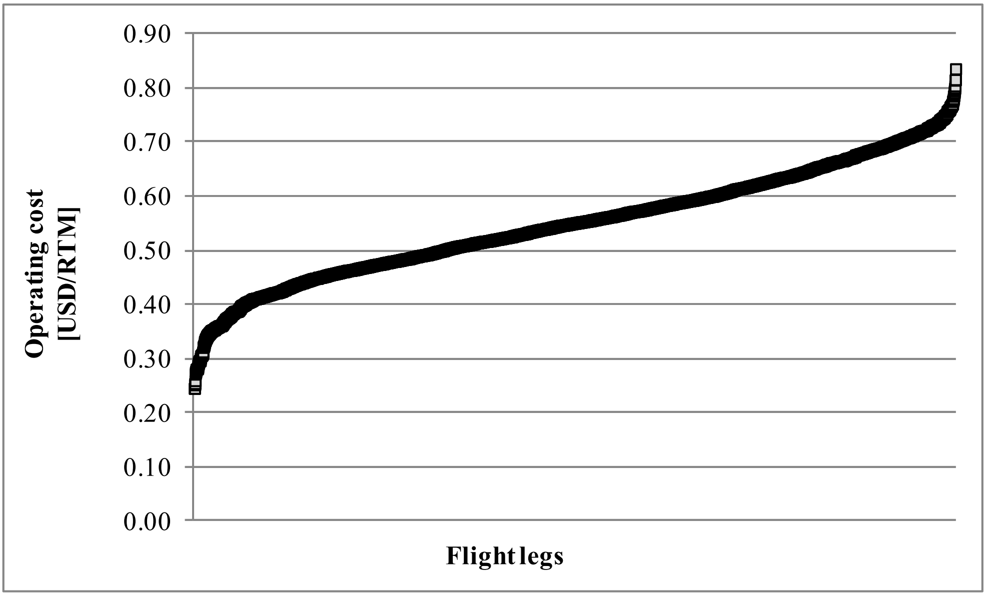


Figure 37: Base scenario: Initial network structure – Distribution of flight leg specific operating cost
(Source: author's own representation)

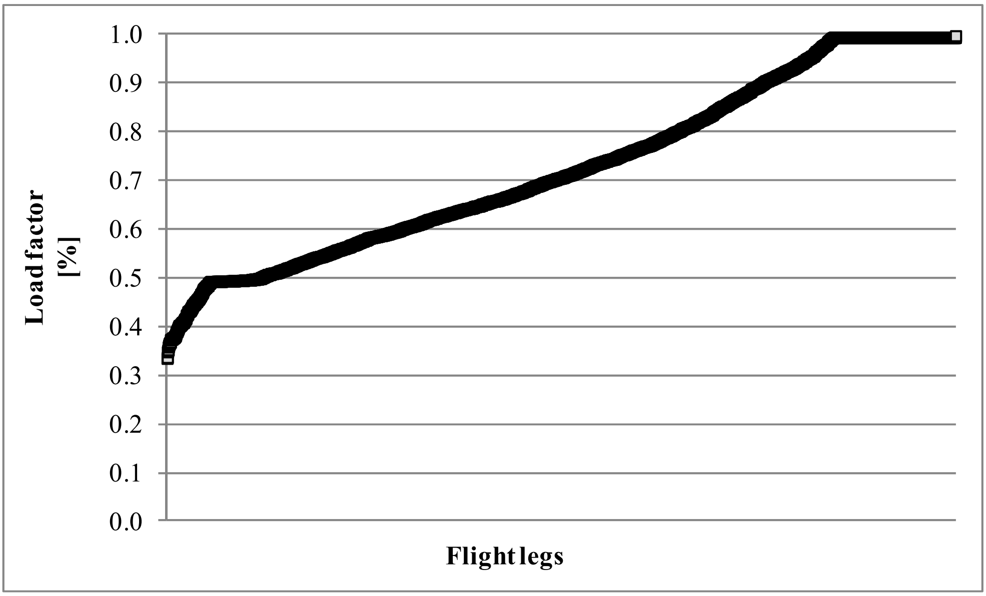


Figure 38: Base scenario: Initial network structure – Distribution of the flight leg specific load factor
(Source: author's own representation)

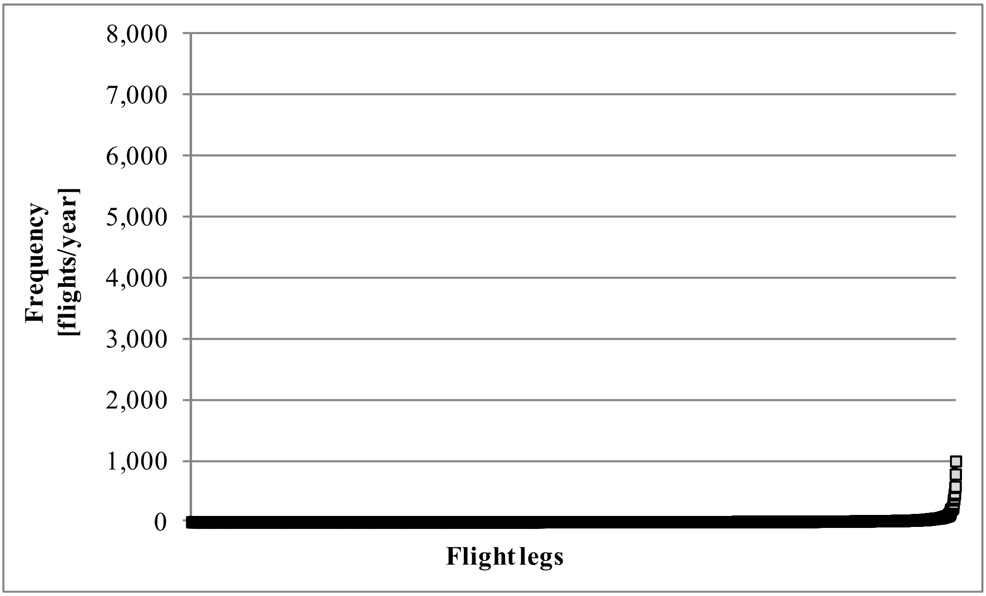


Figure 39: Base scenario: Initial network structure – Distribution of flight frequencies (Source: author's own representation)

B.2 Base scenario: Greedy algorithm

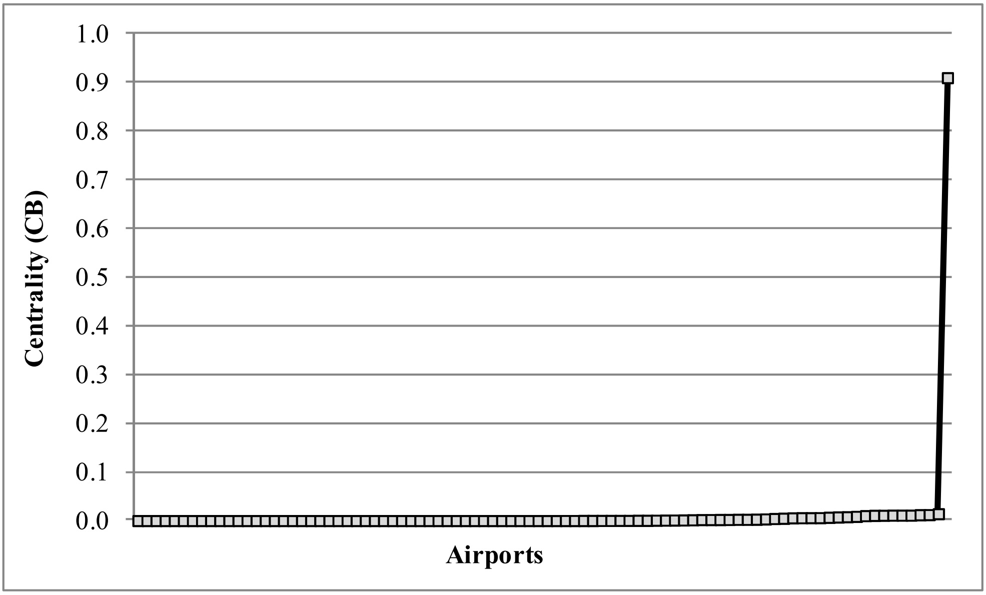


Figure 40: Base scenario: Greedy algorithm – Distribution of centrality values at the airports (Source: author's own representation)

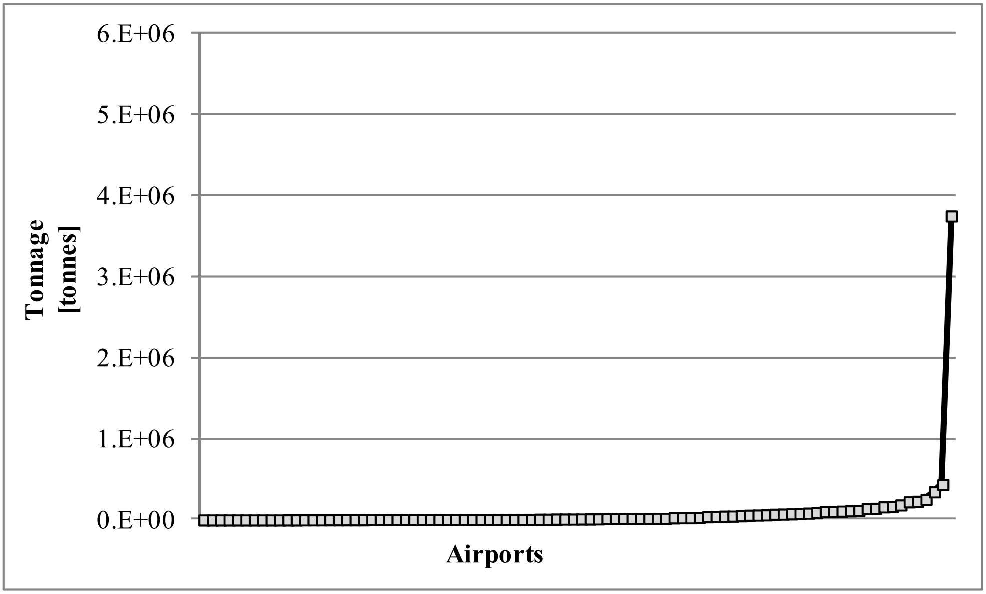


Figure 41: Base scenario: Greedy algorithm – Distribution of tonnages at the airports (Source: author's own representation)

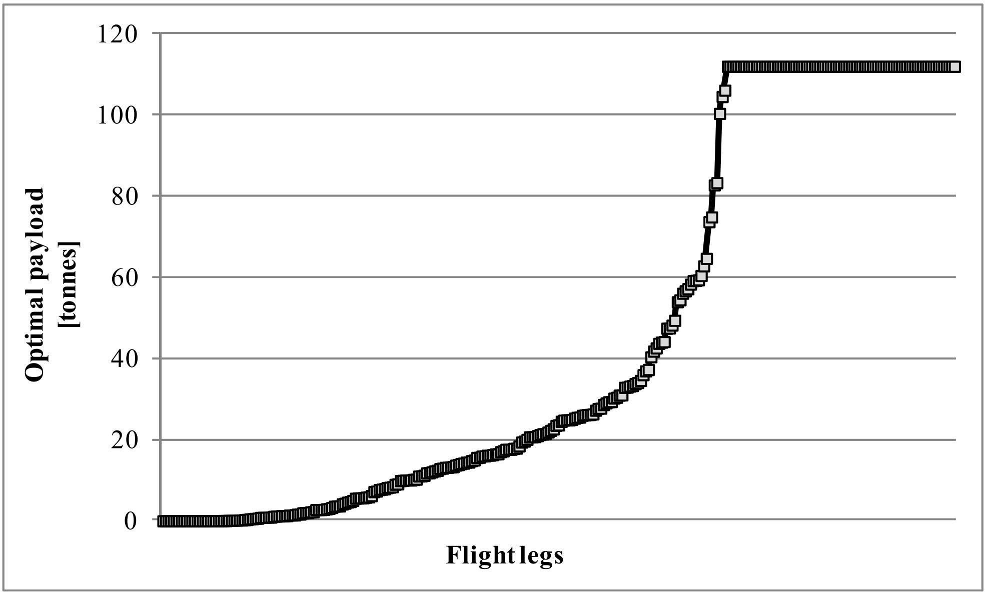


Figure 42: Base scenario: Greedy algorithm – Distribution of the optimal payload for the flight legs
(Source: author's own representation)

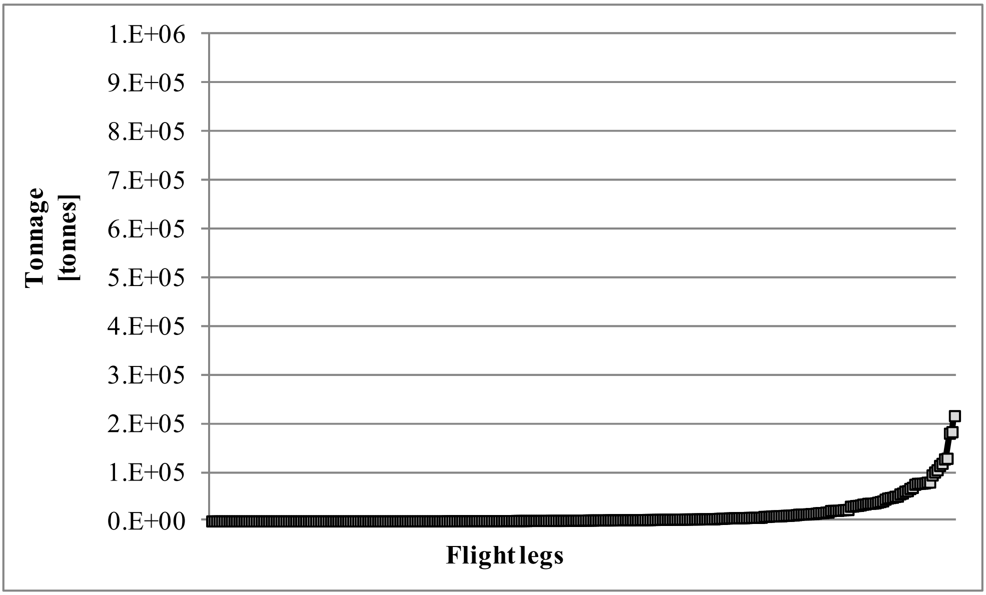


Figure 43: Base scenario: Greedy algorithm – Distribution of tonnages at the flight legs
(Source: author's own representation)

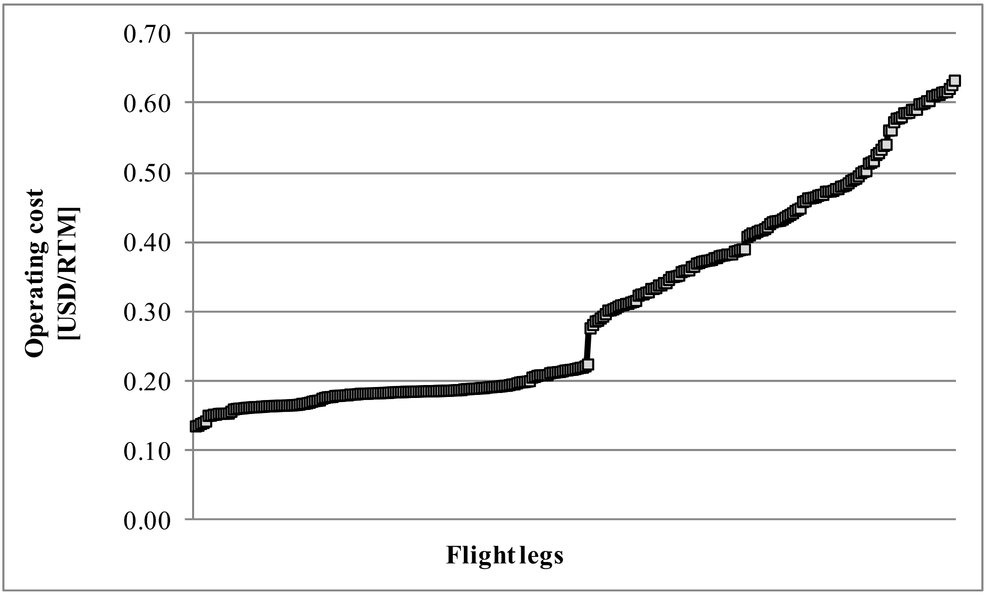


Figure 44: Base scenario: Greedy algorithm – Distribution of flight leg specific operating cost (Source: author's own representation)

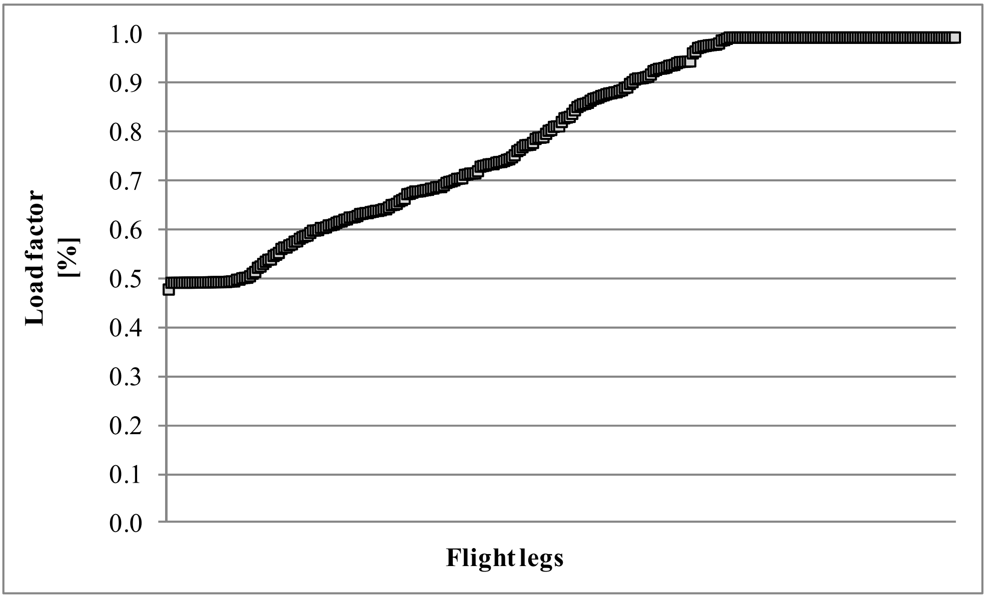


Figure 45: Base scenario: Greedy algorithm – Distribution of the flight leg specific load factor (Source: author's own representation)

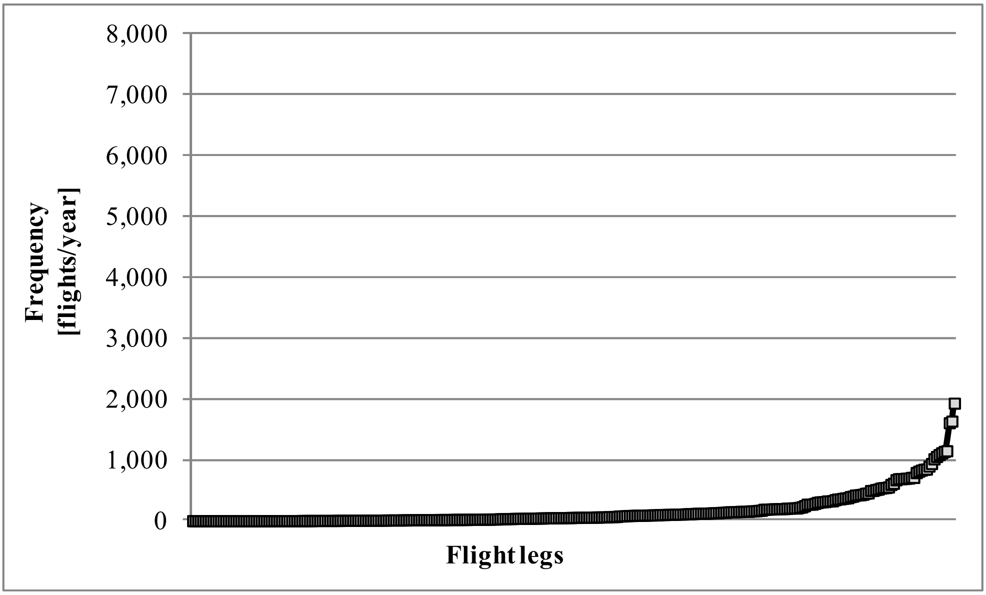


Figure 46: Base scenario: Greedy algorithm – Distribution of flight frequencies (Source: author's own representation)

B.3 Base scenario: Simulated Annealing (best–fit run)

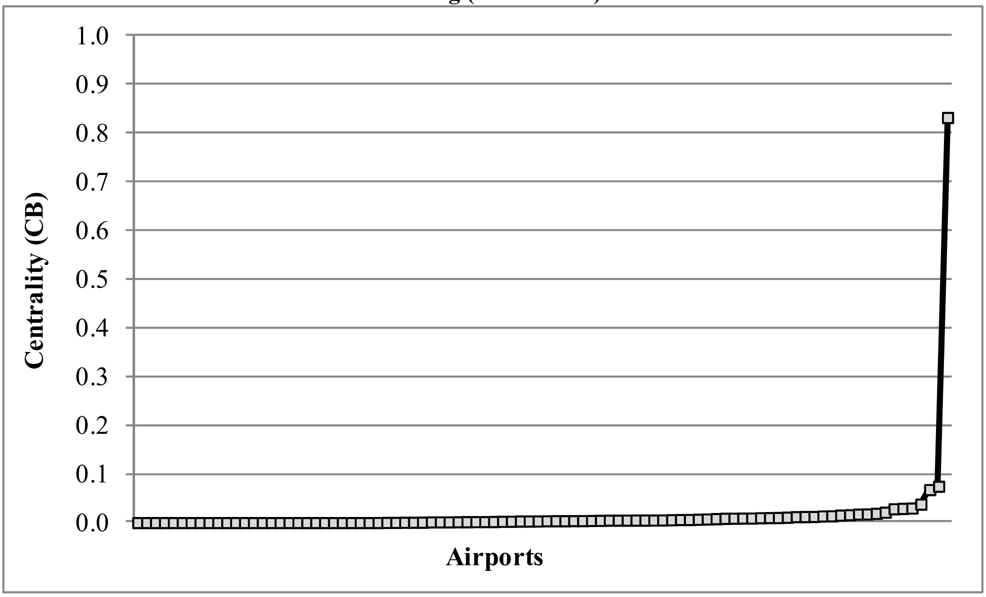


Figure 47: Base scenario: Simulated Annealing (best–fit run) – Distribution of centrality values at the airports
(Source: author's own representation)

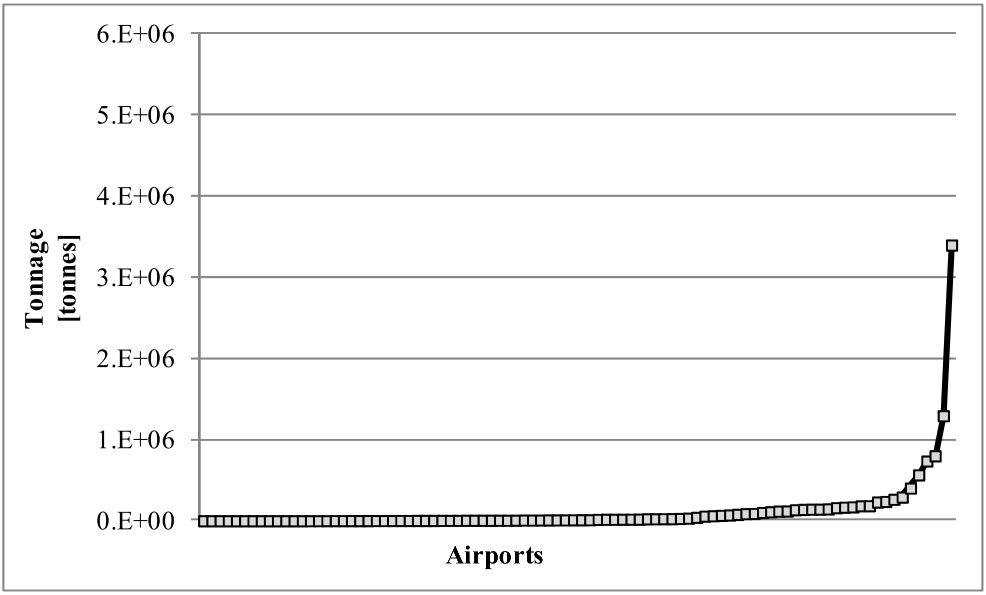


Figure 48: Base scenario: Simulated Annealing (best–fit run) – Distribution of tonnages at the airports
(Source: author's own representation)

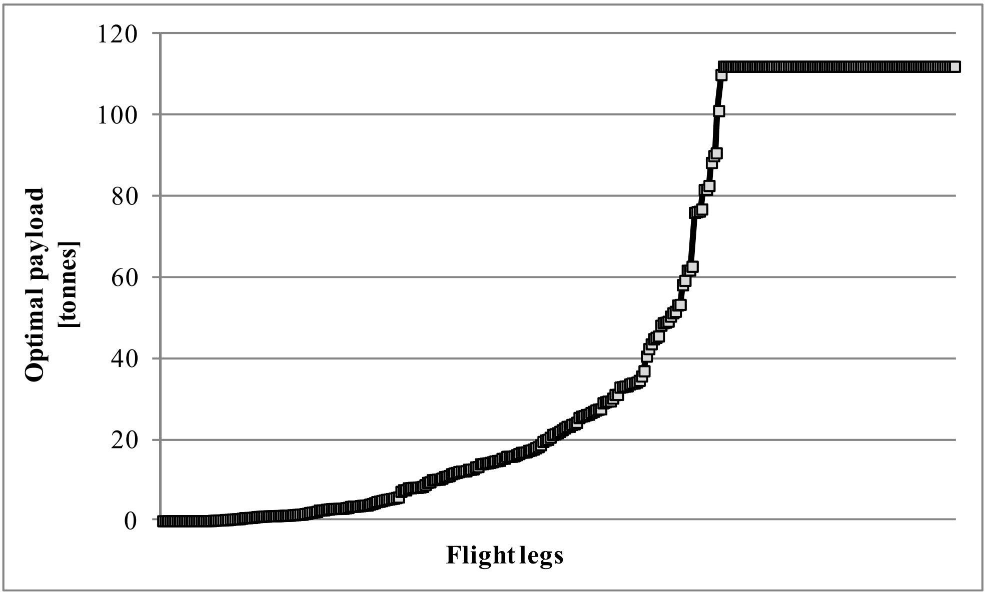


Figure 49: Base scenario: Simulated Annealing (best–fit run) – Distribution of the optimal payload for the flight legs
(Source: author’s own representation)

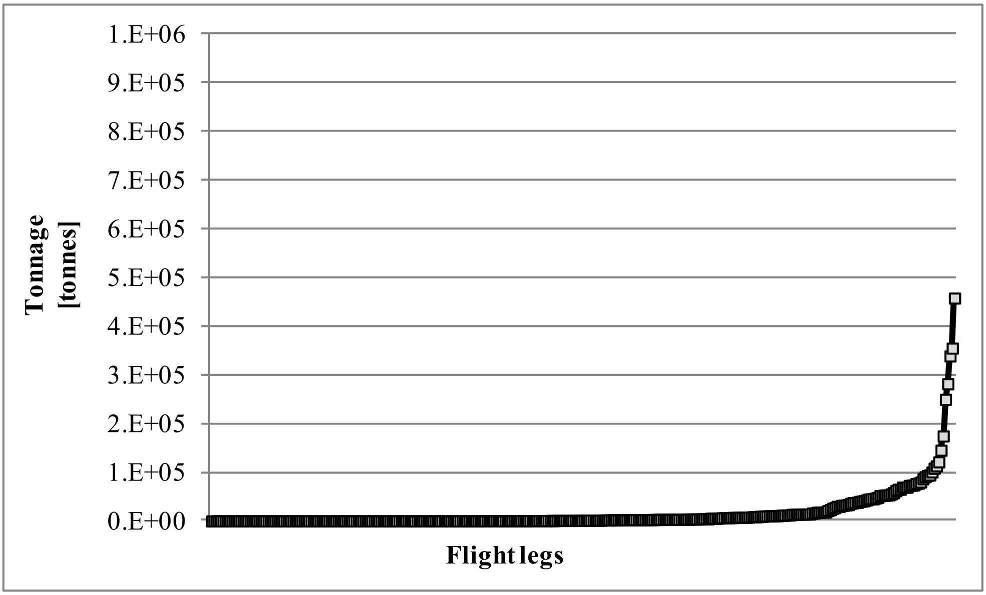


Figure 50: Base scenario: Simulated Annealing (best–fit run) – Distribution of tonnages at the flight legs
(Source: author’s own representation)

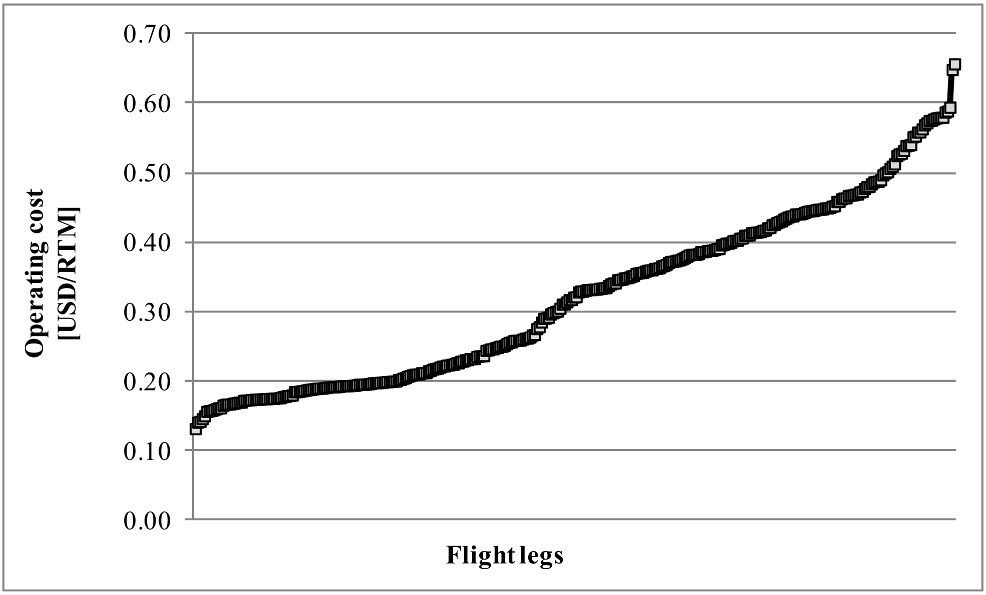


Figure 51: Base scenario: Simulated Annealing (best–fit run) – Distribution of flight leg specific operating cost (Source: author's own representation)

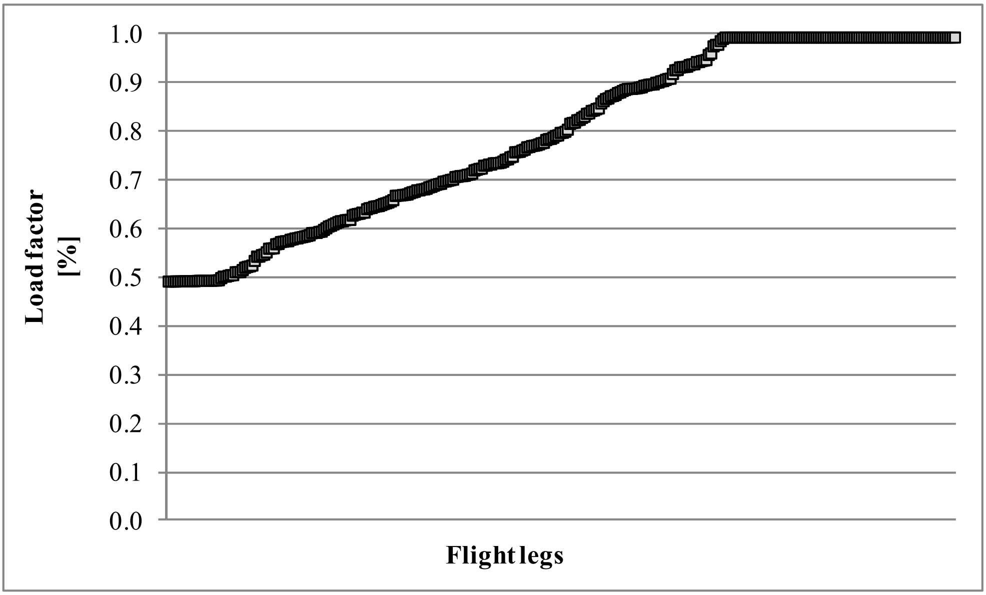


Figure 52: Base scenario: Simulated Annealing (best–fit run) – Distribution of the flight leg specific load factor (Source: author's own representation)

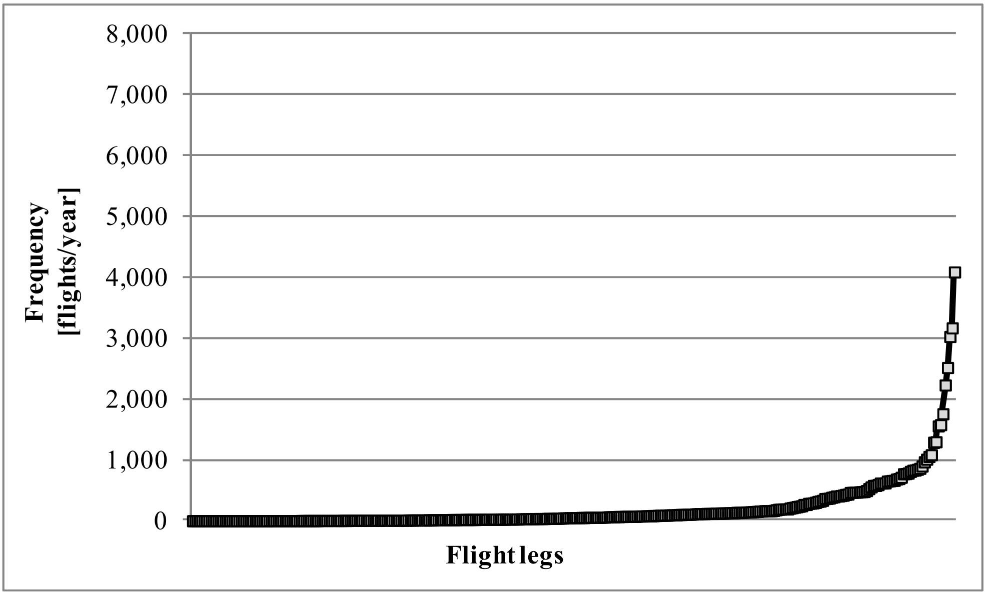


Figure 53: Base scenario: Simulated Annealing (best–fit run) – Distribution of flight frequencies (Source: author's own representation)

B.4 Base scenario: Simulated Annealing (lowest–cost run)

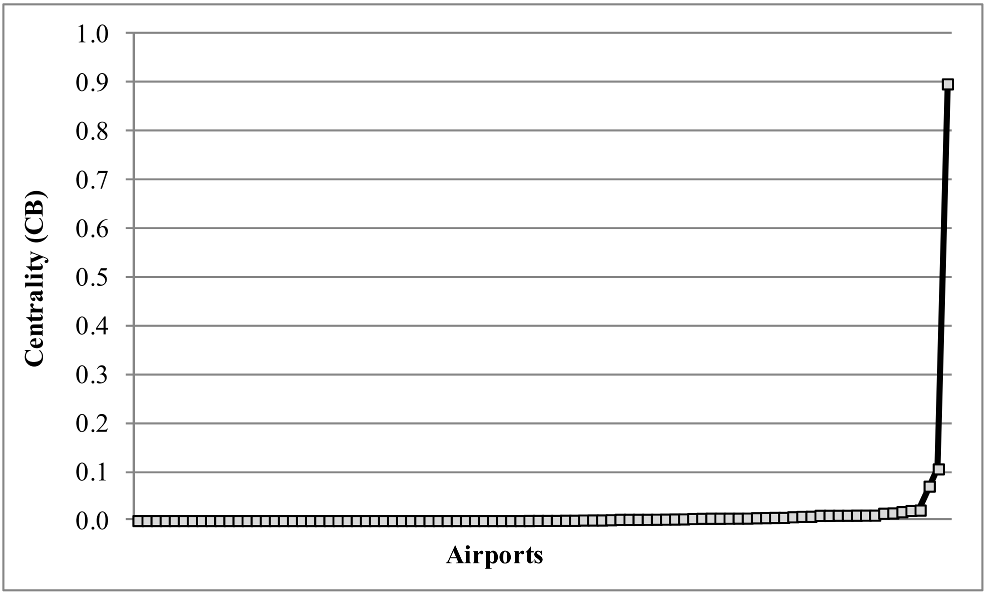


Figure 54: Base scenario: Simulated Annealing (lowest–cost run) – Distribution of centrality values at the airports
(Source: author's own representation)

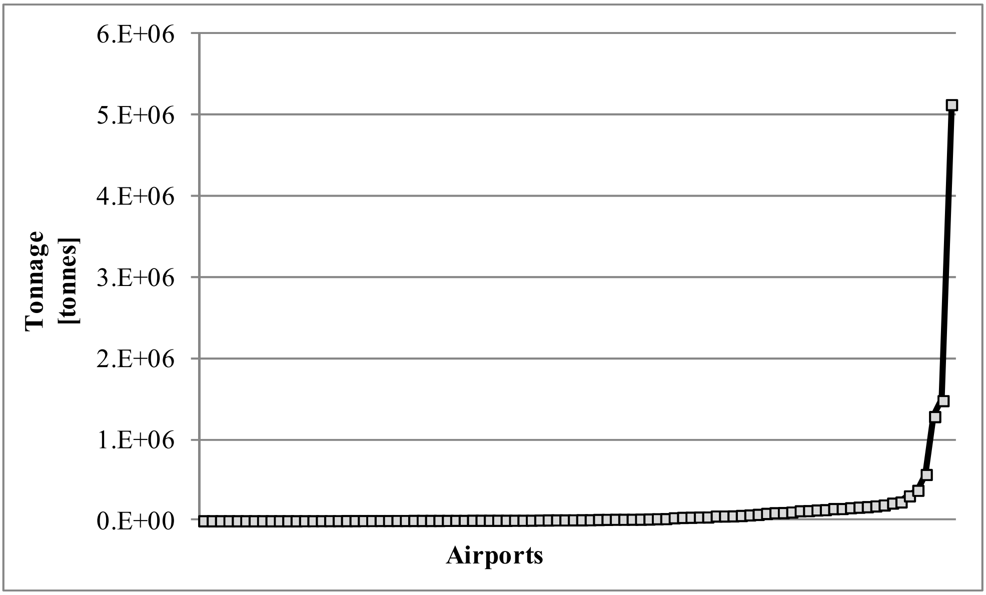


Figure 55: Base scenario: Simulated Annealing (lowest–cost run) – Distribution of tonnages at the airports
(Source: author's own representation)

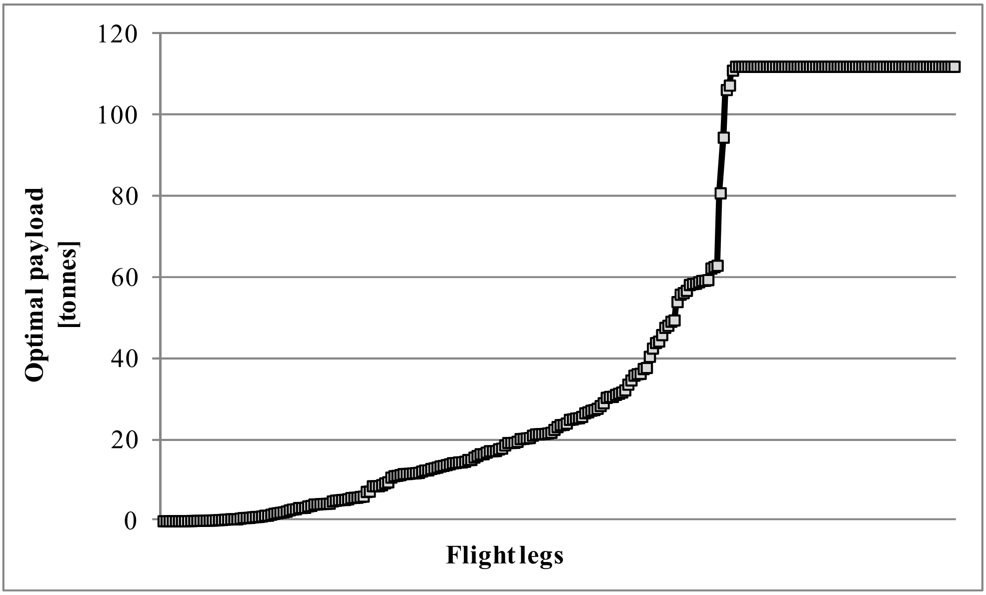


Figure 56: Base scenario: Simulated Annealing (lowest–cost run) – Distribution of the optimal payload for the flight legs
(Source: author’s own representation)

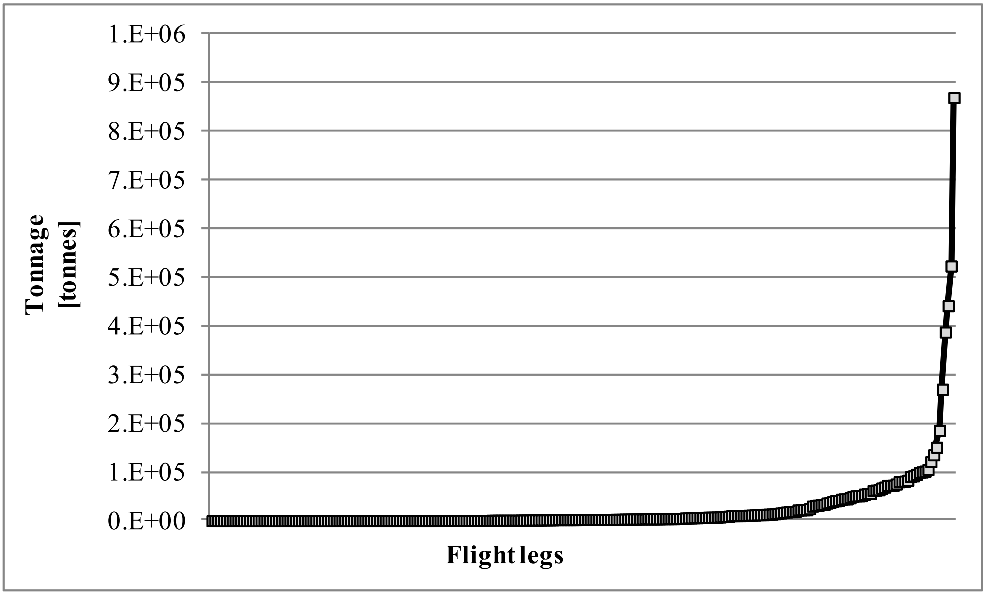


Figure 57: Base scenario: Simulated Annealing (lowest–cost run) – Distribution of tonnages at the flight legs
(Source: author’s own representation)

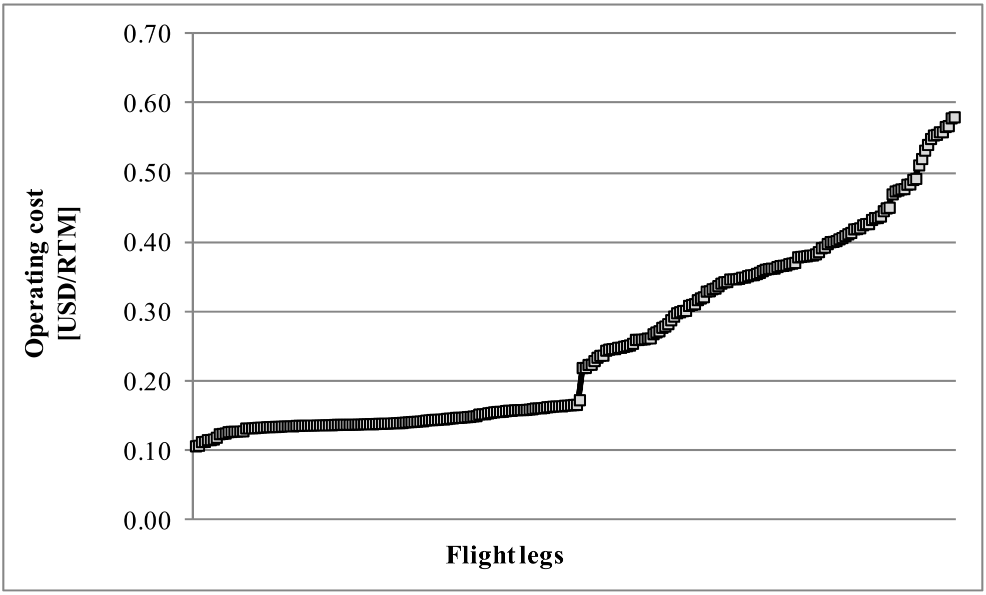


Figure 58: Base scenario: Simulated Annealing (lowest–cost run) – Distribution of flight leg specific operating cost
(Source: author's own representation)

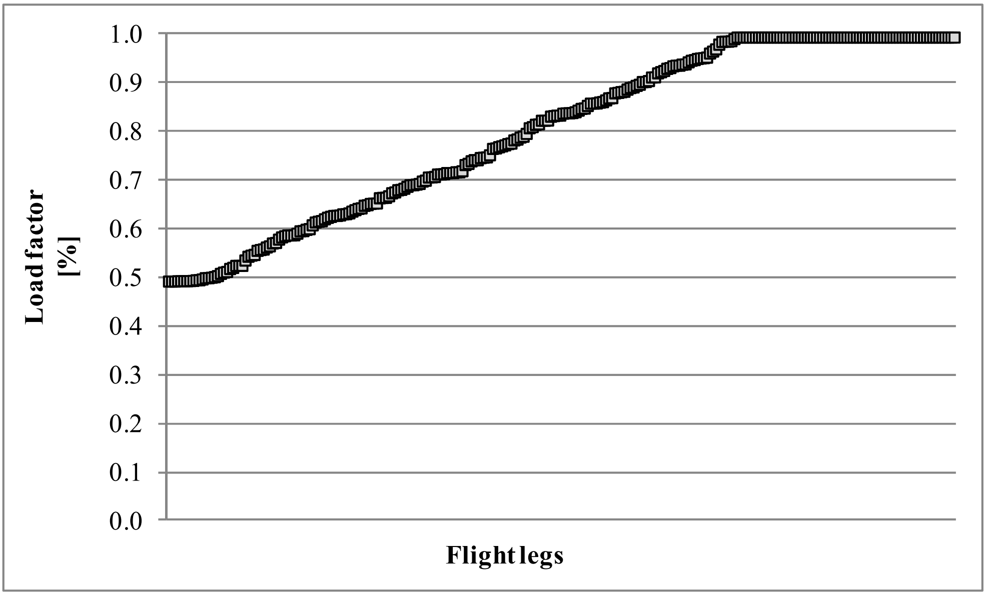


Figure 59: Base scenario: Simulated Annealing (lowest–cost run) – Distribution of the flight leg specific load factor
(Source: author's own representation)

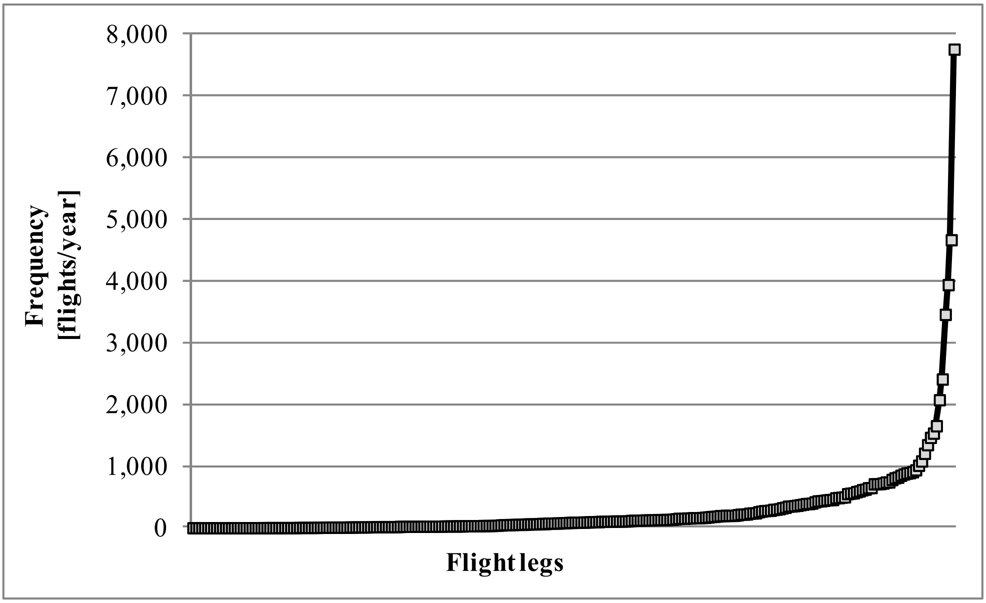
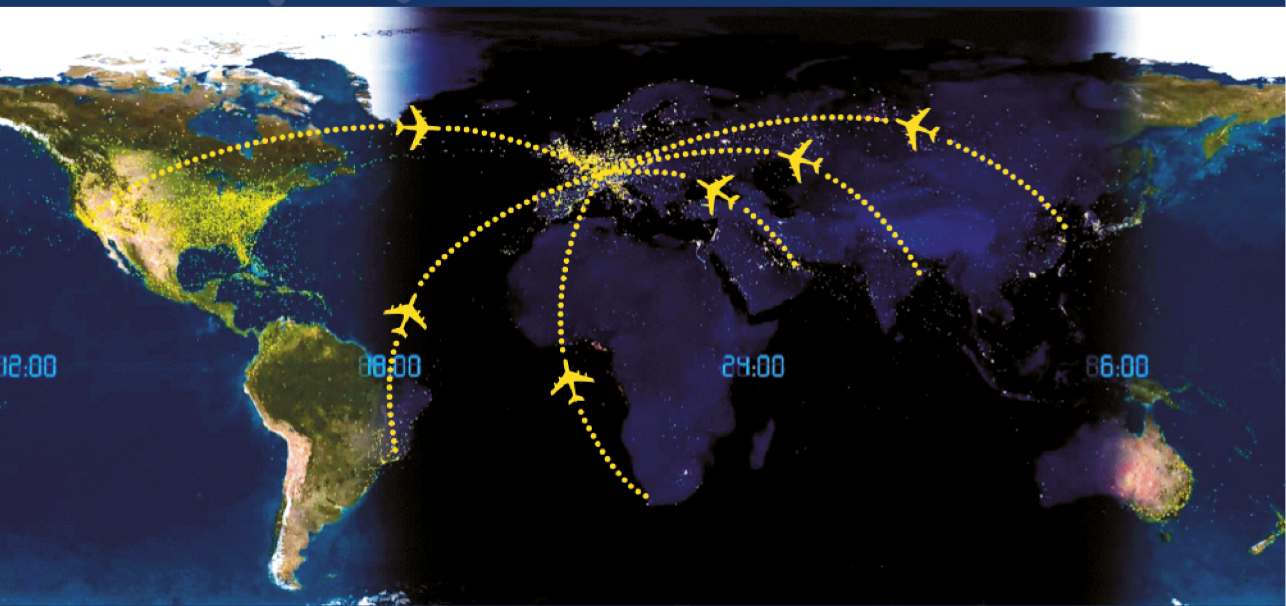


Figure 60: Base scenario: Simulated Annealing (lowest–cost run) – Distribution of flight frequencies (Source: author's own representation)

Air cargo has become a key element of global supply chains, and is expected to continue to grow. A constraint for future growth scenarios are capacity limitations at major airports. Airport investment plans exist, but in times of strained public budgets, airport investments directly compete with other public sectors. Therefore, profitable and from an air transport perspective necessary airport investments need to be selected.

The objective of this book is based on the (long-term) vision to understand airlines' strategic behaviour to design and to configure their networks and to convey this understanding into traffic forecasts. The present book approaches this problem for cargo airlines by characterising and classifying their network structures and by developing a model for an airline's strategic network design.
This book enables researchers to develop an integrated model for an airline's network design including passenger and cargo services as well as demand and supply. The dissertation further provides a tool for policy assessment by determining the impacts of future policies on airlines' networks. Moreover, the work allows practitioners to analyse the effectiveness of their current network structure, and allows cargo airlines to (re-) configure their networks for future developments effectively.



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