A Novel Aircraft Market Assessment Model under Flexible Passenger Demand

In the context of the ParsifalProject
MSc Thesis - Final Report

R.C. Wink

Technische Universiteit Delft

TU Delft

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MSc Thesis - Final Report

by

R.C. Wink

to obtain the degree of Master of Science

at the Delft University of Technology,

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TU Delft

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Preface

Dear reader,

It is with the submission of this report containing my MSc thesis that my time studying in Delft has come to an end. This period of five years at Delft University of Technology has taught me valuable lessons which I will definitely carry with me for the rest of my life. I was presented with excellent learning opportunities and met some truly fantastic people which made my time at the university a great one.

First of all I would like to sincerely thank my thesis supervisor Paul Roling for his excellent guidance during this project. It is beyond reasonable doubt that your input and helpful insights have significantly contributed to the quality of my research. Furthermore, I always enjoyed and will definitely miss the approximately biweekly meetings in which we elaborately discussed the race results and latest developments in Formula 1. It was clear from the start that we shared a mutual passion in the field of motorsports which has resulted in a pleasant working atmosphere throughout this research.

I would also like to thank all colleagues and my specifically my group of friends from the aerospace engineering community. Over the course of multiple years we have managed to get the best out of ourselves from an academic point of view but have also conducted multiple extracurricular activities or random trips centered around our shared passion we call aviation. Specifically I'll never forget our trip in which we took four flights in a day just to fly the new Air France Dreamliner which just entered service and our trip to the 2017 Paris Airshow.

Last but not least I would also like to thank my family and friends outside the aerospace engineering community. Specifically my parents and sister who have expressed unconditional support from day one. Also the group of friends from high-school which have always stayed in touch deserve special mentioning. I'm eternally grateful that you were there along the way.

Even though I would have loved to present my work to family and friends at my graduation ceremony, the current developments regarding the SARS-CoV-2 virus outbreak do not make it possible to celebrate the closing of the final chapter of my student life in Delft. However, I am confident that postponement will not lead to cancellation. For now stay in good health and I am very much looking forward to what an undoubtedly exciting future will bring.

R.C. Wink
Delft, October 2020

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List of Acronyms

ANN	Artificial Neural Network
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
DCP	Data Collection Point
DDD	Demand Driven Dispatch
DV	Decision Variable
FAA	Federal Aviation Administration
FAM	Fleet Allocation Model
FAR	Federal Aviation Regulations
FWO	Fair Work Ombudsman
GDP	Gross Domestic Product
GMF	Global Market Forecast
IATA	International Air Transport Association
ICAO	International Civil Aviation Organisation
LP	Linear Programming
LSSVM	Least Squares Support Vector Machine
MA	Moving Average
MTOW	Maximum Take-Off Weight
MZFW	Maximum Zero-Fuel weight
NATS	National Air Traffic Services
OAG	Official Airline Guide
OEW	Operating Empty Weight
PMM	Passenger Mix Model
SARIMA	Seasonal Autoregressive Integrated Moving Average
USD	United States Dollar

List of Symbols

Due to the very large amount of symbols and context-dependency of their meaning, all symbols are further explained in their relevant sections of this report

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Introduction and Reading Guide

Under the strong and continued growth of air traffic demand, more and more airports are facing capacity constraints. Estimates from IATA (2015) show that 45 out of the 100 busiest airports were already heavily congested and this problem was only expected to get worse in the following decades. New aircraft designs such as Prandtl-wing or blended-wing-body designs provide interesting opportunities to decongest these airports and assist them in coping with continued passenger growth because of their capabilities to carry higher passenger numbers at increased efficiency compared to conventional aircraft designs. Whether the aircraft design can actually make these promises true is difficult to assess, especially given that these aircraft concepts are often in a preliminary design phase with limited available performance data.

The aim of this project is to tackle this issue and construct a market assessment framework for novel aircraft designs by analysing their top-level design parameters and solving a fleet allocation problem to determine the most efficient aircraft type per route considering future, time-of-day sensitive passenger demand. In this model, novel aircraft concepts will compete with currently existing aircraft types in terms of efficiency and operational opportunities in such a way that conclusions can be drawn on the current cost-competitiveness of the novel design as well as the potential market impact and demand for such a new airliner. The developed model is used in a case study to determine the market opportunities of a novel Prandtl-wing aircraft in the context of the *ParsifalProject*. The model however could easily be generalised to applications beyond this project such as assessing the impact of engine retrofitting or development of a smaller or larger aircraft in an already existing aircraft family.

This overarching document comprises three different sections and should be interpreted as follows. The first section, section I, contains the scientific article which is the main deliverable of this thesis work. It contains all key information for this research in a concise manner and can be read as a standalone document. Next, section II contains background information to the paper presented in section I. It discusses in further detail some of the underlying assumptions made in the model and provides a more complete overview of the input data which was used for the generation of the case study results. Last but not least, section III contains the literature study which was conducted before the start of this research. This deliverable has been previously graded under the literature study course coded AE4020 and provides an extensive overview of the key research questions at the focus of this research and foundation of literature on which this research builds on. As conducting research is an effort in which new insights are gathered at a swift pace, not all information in the literature study made its way into the final paper. Conversely, some information may be present in the final paper which was no yet included in the literature review but originated from these new insights. All three segments merged into this document hence provide a complete overview of all work conducted for the completion of this MSc degree.

I

Thesis Paper

A Novel Aircraft Market Assessment Model under Flexible Passenger Demand

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***Abstract* - Due to strong demand for air travel, major airports are already constrained in capacity. Considering the expected growth of air travel demand in the coming decades, this issue is only expected to worsen. Novel aircraft or aircraft concepts could help to alleviate these capacity constraints but the exact market impact of such aircraft is often challenging to assess especially when the concept is in an early design phase. The purpose of this research is to construct a market demand model which uses basic aircraft design parameters and expected air travel demand growth scenarios as input to subsequently solve a fleet allocation problem under flexible passenger demand. This model can subsequently be used to assess the market competitiveness of the novel aircraft designs compared to existing aircraft in both the current and future aviation landscape. The *ParsifalProject*, which aims to further develop a PrandtlPlane aircraft designed with the purpose of alleviating capacity-constrained airports, serves as a case study for the developed model. Results show that the PrandtlPlane offers strong competition to both narrowbody and widebody aircraft with multiple operational opportunities for a long-range version of the current design.**

***Index Terms* - Aircraft Demand, Aircraft Performance, Market Forecast, Flexible Passenger Demand, Integer Linear Programming (ILP), Fleet Allocation Problem**

I. Nomenclature

$A(a, t_n)$	:	Set of flight arcs arriving at airport a on node time t_n
$D(a, t_n)$	:	Set of flight arcs departing at airport a on node time t_n
F	:	Set of available fleets
H	:	Set of airports
L	:	Set of flights in schedule as *(i,j)* combinations
N	:	Set of network nodes as (a, t_n) combinations
T	:	Set of times
X	:	Set of flight arcs
Y	:	Set of ground arcs
a	:	Airport
i	:	Origin airport
j	:	Destination airport
f	:	Fleet type
t	:	Time
t_n	:	Time of network node n
t^-	:	Time preceding time of network node n
t^+	:	Time following time of network node n
t_0	:	Time of first network node n
t_{start}	:	Startup network node before t_0
c^f_{ijt}	:	Total cost associated with operating fleet f on a flight from i to j at time t
$cflex_{ij}$	:	Total cost associated with not bringing a flexible passenger from i to j

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$cfix_{ijt}$: Total cost associated with not bringing a fixed passenger from i to j at time t

DC^f : Daily cost for making use of one aircraft of type f
$DFlex_{ij}$: Total daily flexible demand for route i to j
$DFix_{ijt}$: Total fixed demand for route i to j at time t

FH^f : Maximum number of flight hours per day for aircraft of type f
FM : Maximum number of aircraft movements per hour
FT_{ij}^f : Total flight time for aircraft of type f from i to j
GAC : Maximum number of simultaneous aircraft on ground at the start of the day

$PFlex_{ijt}^f$: Decision variable for number of flexible demand passengers travelling from i to j at time t on fleet f
$PFix_{ijt}^f$: Decision variable for number of fixed demand passengers travelling from i to j at time t on fleet f

$RFlex_{ij}$: Decision variable for number of not transported flexible passengers travelling from i to j
$RFix_{ijt}$: Decision variable for number of not transported fixed passengers travelling from i to j at time t
$RSeat_{ijt}^f$: Decision variable for number of empty seats on a flight from i to j at time t with fleet f

S_{ij}^f : Number of available seats on aircraft type of fleet f for a flight from i to j

X_{ijt}^f : Decision variable for number of aircraft of fleet f operating route i to j at time t
$Y_{at^-t_n}^f$: Decision variable for number of aircraft of fleet f on ground arc inbound of node n
$Y_{at_nt^+}^f$: Decision variable for number of aircraft of fleet f on ground arc outbond of node n
$Y_{at_{start}t_0}^f$: Decision variable for number of aircraft of fleet f on introduction ground arc at airport a

II. Introduction

Under the strong and continued growth of air traffic demand, an increasing number of airports are facing capacity constraints. Estimates from IATA (2015) show that 45 out of the 100 busiest airports are already heavily congested and this problem is only expected to worsen in the following decades. New aircraft designs such as Prandtl-wing or blended-wing-body designs provide interesting opportunities to decongest these airports and assist them in coping with continued passenger growth because of their capabilities to carry higher passenger numbers at increased fuel efficiency compared to conventional aircraft designs. Even though such concepts appear to be extremely promising from both an operational as well as an engineering point of view, these new visions still remain theoretical concepts and are far from being implemented on a medium to large scale airliner.

In light of a lack of concrete development on a larger scale for these concepts, the *ParsifalProject* was started. *ParsifalProject* aims to further develop the concept of a Prandtl-wing aircraft, the PrandtlPlane, by tackling the most common engineering and scientific issues with the concept. The newly developed airliner has wingspan, fuel consumption and mission range equal to a Boeing 737 or Airbus A320 and a payload capacity equal to that of a Boeing 767 or Airbus A330. These design characteristics make the aircraft specifically targeted to provide efficient decongestion at slot-constrained airports. However, before continuing with the detailed design and eventual manufacturing of the aircraft it is key to assess how the concept competes with current existing aircraft on the market and whether it can actually add value to the global aviation network.

In academic literature a significant research gap exists in the field of modelling competitiveness of novel aircraft designs which are in the preliminary design phase. This research aims to bridge the gap between the technological design of new airliners and the market position of such an aircraft and simultaneously contribute to the field of aircraft market demand modelling. This is done by analysing optimal novel aircraft utilisation strategies whilst taking into account their performance characteristics and time-of-day sensitive passenger demand. Several theoretical concepts are merged to achieve this goal. First of all, a market demand model will be constructed in order to analyse future passenger demand on routes between airports, taking into account time-of-day flexibility. Next, basic aircraft design parameters are used to model the operational capabilities and limitations of both the novel and 45 currently existing aircraft. This modelling framework is subsequently applied to different networks in which an integer linear programming (ILP) fleet allocation problem establishes a competitive environment which allow aircraft to compete with each other for utilisation on various routes and market share. The results provide information on the threats and weaknesses of the aircraft design, its main competitors, the best suited operational role and suggestions for favourable design improvements. The PrandtlPlane under development by the *ParsifalProject* provides an interesting case study to assess the quality of such a model.

This paper is structured as follows. First of all, in section III, the current state of art with respect to academic literature in similar research fields will be explored. The academic basis and research gap derived in this section will subsequently be used as a starting point to develop a methodology for this research in section IV. Section V will elaborate on the results of two case studies which have been performed using described methodology and section VI places these results in context with respect to its strengths and limitations. In conjunction, recommendations for potential future work in this field of research will be also be provided. Section VII concludes this paper by providing a concise overview of the work performed, key results, and their implications for the developed aircraft concept and field of research.

III. Literature Review

Literature on novel aircraft demand and performance modelling can be found in both the public domain as well as the academic domain. In the public domain modelling the strengths, weaknesses and future demand for novel products or services is essential in order make successful business decisions. The airline industry, with fierce competition and a wide variety of available aircraft, is no exception to this rule. Large aircraft manufacturers often release annual market forecasts to inform their investors on what they expect future aircraft sales to be and where they see key opportunities and threats. Lange (2019) of Airbus for example state in their 2018 global market forecast that they expect over 38.500 new aircraft will be delivered between 2019 and 2038, with world annual traffic growth (in revenue passenger kilometers) increasing by 4.3% per year. Main competitor Boeing (2020) expects total passenger aircraft deliveries between 2020 and 2039 to equal little over 42.500 jets with global revenue passenger kilometer growth equal to 4.0% for the period under consideration. How these businesses manage to come to these conclusions, assess how much market share they are able to take with their aircraft and how their aircraft hold up to the competition is a well kept industry secret. Even though importance of such tools is evident, the public domain fails to provide an available solution to the problems posed in this research.

Academic literature does provide several starting points which touch upon the essentials of this paper. For example, a key starting point for trading off aircraft performance in a network context is research on the fleet allocation problem. The problem seeks to assign a fleet of aircraft with different operational strengths to a network of passengers such that the total cost of moving the passengers is minimised. This problem has an extensive foundation in academic literature dating with an initial formulation provided by Ferguson and Dantzig (1954). Research in this field gained significant traction after research by Berge and Hopperstad (1993), which turned the model from a connection-based formulation to an arc-based formulation based on time-space networks. This resulted in significant improvements in computational efficiency and increased interest by airlines, as shown by Subramanian et al. (1994) who applied the model at Delta Air Lines. Whereas earlier papers considered research which was mostly tailored to case studies at airlines, the first general description of the arc-based fleet allocation problem is provided by Hane et al. (1995). Their paper serves as a cornerstone for a wide variety of existing research into the fleet allocation problem and subsequent variations. These variations involve most notably the ability to incorporate stochastic passenger demand (Barnhart et al. (2002) and Sherali and Zhu (2008)), integration of passenger itineraries instead of independent passenger demand per route (Barnhart et al. (2002), Atasoy et al. (2014) and Wang et al. (2014)) as well modelling flexible flight departure times (Rexing et al. (2000)). Almost all research regarding the fleet allocation problem concerns operational cases for airlines which are characterised by a small-scale network, a low number of incorporated aircraft, availability of good aircraft performance and network data as well as a limited timeframe. These network characteristics fall short of the objectives defined for this research.

When combining the fleet allocation with novel aircraft performance modelling, the number of available literature shrinks significantly. Closest to this research objective is the field of simultaneous aircraft design optimisation and fleet integration, which seeks to optimise aircraft design for a given network on which the aircraft should perform. Davendralingam and Crossley (2009) allow aircraft take-off weight, aspect ratio, thrust-to-weight ratio and wing loading to change from a reference design case under the condition that requirements on take-off and landing distances are satisfied to tailor aircraft design to the provided network. In their model they only trade-off the design with two other aircraft on a three-route network which is a significant limitation in scale. Jansen and Perez (2013) solve the simultaneous aircraft design and fleet allocation problem by simultaneously optimising aircraft seating capacity, wingspan, wing sweep angle, horizontal and vertical tail sizing, cruise speed and engine sizing. These researchers use two aircraft in the model on a network spanning 24 routes in the United States without operational constraints. Next to the fact that this research is not centered around aircraft optimisation, just modelling, research in this field falls short of our objectives due to the small network scale and a small number of considered aircraft which makes a competitive global analysis impossible. Furthermore, their modelling of new aircraft depends on detailed design data which is not available in our case.

Summarising, there is a significant research gap which seeks to provide a global competitive analysis of a novel aircraft concept compared to aircraft which are currently in service. Even though the fleet allocation model discussed in this section provides a good starting point for our research, to the best knowledge of the author no current research exists which is tailored to forecasting market share and operational strengths for a novel aircraft with limited available design data. This research aims to build on and add to a broad overview of academic literature regarding the fleet allocation problem and provide one of the first academic market assessment models for aircraft under development. The presented model in this paper furthermore provides the first academic alternative to aircraft competitive analyses conducted by businesses which enables a wide variety of novel aircraft concepts which are currently under development to be evaluated in terms of market attractiveness.

IV. Methodology

This section describes the theoretical concepts by which the modelling framework for this research has been constructed. Subsection IV.A will briefly state the means by which the future passenger demand has been estimated. Next, subsection IV.B elaborates on the approach to integrate aircraft performance characteristics in the model under the limitation of limited available aircraft performance data. Subsection IV.C integrates the learnings from these two fields into a modified integer linear programming (ILP) fleet allocation problem which is at the center of this research. Due to the vast scale of the problem under the original formulation, subsection IV.D provides a relaxed version of the problem which allows the problem to scale up to a global level which will be used in conjunction to the main formulation. Last, subsection IV.E will elaborate on the means by which the problems have been solved and relevant details on the generation of the results presented in this paper.

A. Passenger Demand Forecasts

In order to forecast future demand it is first required to obtain an accurate estimate of passenger numbers in present time. In order to achieve this the choice has been made to make use of data provided by OAG, which is a large travel data analyst located in the United Kingdom. The dataset contains elaborate timetable information on airline flight frequencies, arrival and departure times, aircraft type, the number of available seats on those flights and much more for the year 2018 on a global level. As the analysis will represent one day of operation, the busiest day in the annual 2018 dataset has been selected as a base case. A data cleaning step was performed first by only taking into account routes in the network with a total daily seat offering of 200 seats, which results in a smaller network by eliminating very low-density routes from the network and provides relief in terms of computational complexity. This cleaned data is analysed which results in a total number of aircraft seats offered between origin-destination pairs for every hour of the day, which will be assumed to be equal to the seat demand on a given route. Even though it is clear that this data is censored, as for every flight the load factor is unknown, it provides an as accurate as possible overview of the base situation of passenger transport demand in 2018.

The 2018 data from OAG will subsequently be used to make forecasts for the years 2032 and 2050, which have been selected as milestones for evaluation as aligned with the objectives defined in the *ParsifalProject*. A broad consultation of existing demand forecasting techniques, which involved both stochastic forecasting techniques as well as deterministic forecasting techniques, has been performed. For model simplicity and reproducibility, a simple annual average growth time series projection with a fixed rate of growth has been chosen to forecast the passenger numbers. Due to the resulting inherent sensitivity of the forecast with respect to the selected growth rate and large time scale under consideration, several measures have been taken in order to assure that the forecasts are as accurate as possible. First of all, the growth rates have been derived using data from the "20-year Air Passenger Growth Forecast Analysis" report by IATA (2018). Due to the large uncertainty with respect to growth scenarios beyond the 20-year time window used in the IATA report, these growth percentages will be assumed to be valid in a perpetual framework which means that these growth rates will be used for forecast years beyond this 20-year time window as well. Furthermore, the data provided by IATA differentiates on a regional basis which should also enhance forecast accuracy. These exact growth rates from the report can be found in table 9 in the Appendix. For flights within a sub-region highlighted in table 9 the growth rate from the table is used. For flights between two sub-regions, the average growth rate of the two regions is used.

A further distinction is made between passengers who are considered to be flexible in demand and passengers who are considered to be fixed in demand. Whereas flexible demand passengers can be allocated on flights departing at any time of the day, fixed demand passengers are only willing to travel on a predetermined departure time. The split between fixed demand passengers and flexible demand passengers is made in accordance with table 1 below. As can be observed the percentage of fixed demand passengers increases during both morning and evening rush hours to mimic business travellers who are more likely to depart on any of these times and less willing to accept other departure times. On the off-peak hours leisure travellers are assumed to be the dominant group of travellers. For leisure travellers, ticket price is a more significant driver for demand than for business travellers and they are more willing to accept unfavourable departure times if ticket prices are lower.

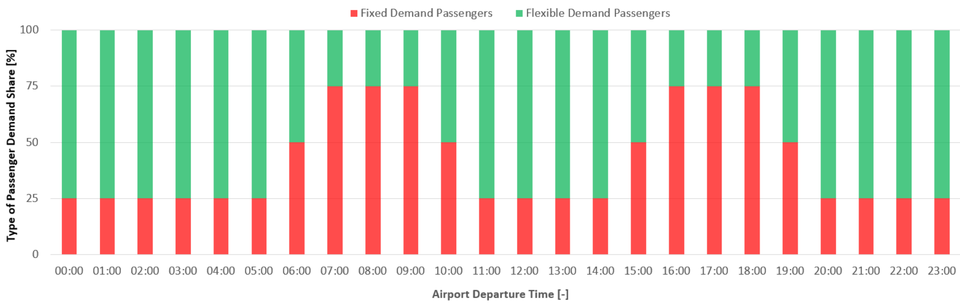

Fig. 1 Distribution rates for fixed demand and flexible demand passengers for different flight departure hours

B. Aircraft Performance Computations

One of the main limitations for this research is that limited design data is available for novel aircraft concept which is to be modelled. This section highlights the fuel consumption modelling strategy which calculates aircraft fuel consumption based on the combination of mission range and number of passengers. Inputs for these computations are limited to simple payload-range diagrams and high-level aircraft weights and performance characteristics. Such a typical payload-range diagram, which depicts the possible feasible combinations of fuel weight, payload weight and mission range for an aircraft, is shown below in figure 2.

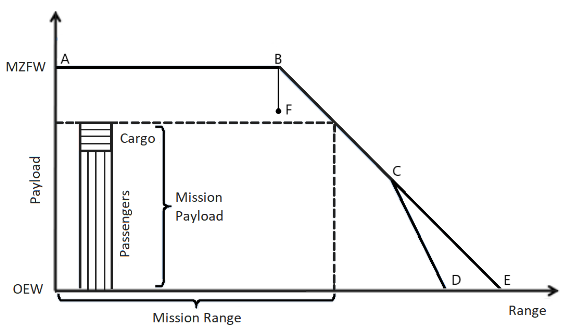

Fig. 2 A typical aircraft payload-range diagram. Adapted from Baxter et al. (2018)

In figure 2, the mission range is on the x-axis and the total payload on the y-axis. This total payload comprises of a combination of passengers with their luggage and possible cargo. At the bottom of the y-axis is the aircraft operating empty weight (OEW), which is the weight of the aircraft without any fuel or payload, but soley aircraft structure and items required for operation such as seats, galleys and toilets. When looking at point A, which is at a fictitious zero range, maximum payload can be added to the OEW until the maximum allowed weight with zero fuel (MZFW). From this point on, fuel can continuously be added to increase the aircraft range without having to sacrifice on the maximum payload capacity. This is possible until point B in the graph is reached, at which the operating empty weight, maximum payload weight and fuel weight combined reaches the maximum take-off weight (MTOW). As the MTOW can not be exceeded, from point B to point C in the graph payload has to be traded for additional fuel to make additional range possible. This can theoretically be continued until no payload remains, after which point E in the graph is reached. If there is a technical limit to the maximum amount of fuel an aircraft can carry, the segment from point C to point D represents the area where the maximum amount of fuel is reached and the only option is to further remove payload without adding extra fuel in return. For modelling purposes this segment of the payload-range diagram is not taken into account which entails that the assumption is made that aircraft can trade payload fuel fuel indefinitely. It is worth noting that these lines present the operating limits, and that any combination of fuel, payload and range in the area enclosed by these lines is also feasible.

From a mathematical point of view this relationship between payload weight, fuel weight and range can be modelled using the Breguet range equation. The Breguet range equation is derived by integrating the change in aircraft weight over time using a constant speed and fuel flow rate and is shown in equation 1 below.

$$R = \frac{VC_L}{C_D C_T} \ln\left(\frac{W_{Start}}{W_{End}}\right) = \frac{VC_L}{C_D C_T} \ln\left(\frac{W_0 + W_p + W_{fuel}}{W_0 + W_p}\right) \tag{1}$$

In which R is the aircraft range, V the cruise speed, C_L the lift coefficient, C_D the drag coefficient, C_T the thrust coefficient, W_{Start} the aircraft weight at the start of the flight, W_{End} the aircraft weight at the end of the flight, W_0 the operating empty weight of the aircraft, W_p the payload weight of the aircraft and W_{fuel} the fuel weight of the aircraft. As it is hard to estimate the parameters C_L, C_D and C_T for all aircraft due to the fact that this data is often classified and dependent on operational conditions such as altitude and mach number, an alternative approach was taken. For a typical mission with known range, aircraft empty weight, payload capacity and fuel capacity the aircraft constant C can be reverse engineered by following equation 2.

$$C = \frac{VC_L}{C_D C_T} = \frac{R}{\ln\left(\frac{W_0+W_p+W_{fuel}}{W_0+W_p}\right)} = \frac{TPR}{\ln\left(\frac{W_{MTOW}}{W_0+W_p}\right)} \tag{2}$$

The data which was used to calculate the constant C is included in table 11 in the Appendix of this paper for a selected number of aircraft. For all aircraft the typical mission selected operates at MTOW such that this parameter can be used in equation 2. The maximum aircraft range at MTOW was subsequently looked up, which is labelled the typical range (TPR) corresponding to this mission. For all aircraft in the model a reserve range requirement of 1325km plus a landing and take-off range surcharge of 250 kilometer have been incorporated. Furthermore, data was collected on the number of seats which were filled when performing this mission and the aircraft OEW. This allowed to calculate the payload weight of this specific mission by multiplying this value by the weight per passenger set at 95 kilograms. With all parameters now known the constant C can be calculated for each aircraft in the model. As for some aircraft the number of filled seats on this typical mission mismatches with the most common seating densities of these aircraft, the maximum number of seats used in the model may be different resulting in slightly different ranges at MTOW in the model compared to the TPR.

The coefficient C is a key parameter on which all aircraft fuel computations in the model are based on. This can subsequently be achieved as follows: The first assumption made is that when operating at MTOW, W_{MTOW}, equation 1 can be rewritten as equation 3 in which $W_{fuel_{MTOW}}$ is the fuel weight at MTOW.

$$R = \frac{VC_L}{C_D C_T} \ln\left(\frac{W_{MTOW}}{W_{MTOW} - W_{fuel_{MTOW}}}\right) \tag{3}$$

Equation 3 can subsequently be solved for the fuel weight at maximum take off weight $W_{fuel_{MTOW}}$ for a variety of theoretical ranges R. The result is shown in equation 4.

$$W_{fuel_{MTOW}} = W_{MTOW}\left(1 - \frac{1}{e^{\frac{RC_D C_T}{VC_L}}}\right) = W_{MTOW}\left(1 - e^{-\frac{RC_D C_T}{VC_L}}\right) \tag{4}$$

As the maximum possible aircraft weight will always be constrained by the MTOW, it is now possible to assess the total theoretical payload capacity for a variety of ranges under the condition that the aircraft is operating at MTOW. This can be achieved by subtracting the OEW and fuel weight at maximum take-off weight for a given range from the design maximum take-off weight of the aircraft as shown in equation 5.

$$W_p = W_{MTOW} - W_0 - W_{fuel_{MTOW}} \tag{5}$$

This equation returns the total possible payload capacity at MTOW. Two different scenarios are now possible. If the total remaining payload capacity is larger than the total weight of the possible payload on an aircraft, which is set equal to the number of seats in the aircraft multiplied by the weight per passenger, then it is possible for the aircraft to carry the maximum number of passengers. The point of operation is equal to anywhere between points A and B on the payload range diagram as shown in figure 2. As the total weight of all passengers is now smaller than the total possible payload capacity, this also entails that not all fuel is required to be taken on board of the aircraft. In other words, as the aircraft is not flying at maximum take-off weight for that range, the amount of fuel required is now smaller than the previously calculated fuel weight at maximum take-off weight. The actual required amount of fuel can now be calculated by solving equation 1 for the fuel weight W_{fuel} as shown in equation 6 using the maximum payload capacity of the aircraft for W_p.

$$W_{fuel} = \left(W_0 + W_p\right)\left(e^{\frac{RC_DC_T}{VC_L}} - 1\right) \tag{6}$$

On the other hand, if the total remaining payload capacity is smaller than the maximum possible payload weight of the aircraft, this entails that payload has to be sacrificed for additional fuel. This corresponds to segment B to C and segment C to E on the payload range diagram in figure 2. As the aircraft will now for sure operate at MTOW, the total amount of fuel required for the given range is subsequently provided by equation 4. The total amount of passengers which are able to be taken on this range can last but not least be calculated by dividing the total remaining payload capacity from equation 5 by the weight per passenger. These results are visually depicted in figure 3 and shows that the PrandtlPlane is able to carry the maximum number of 280 aircraft seats up to a range of 5162 kilometers.

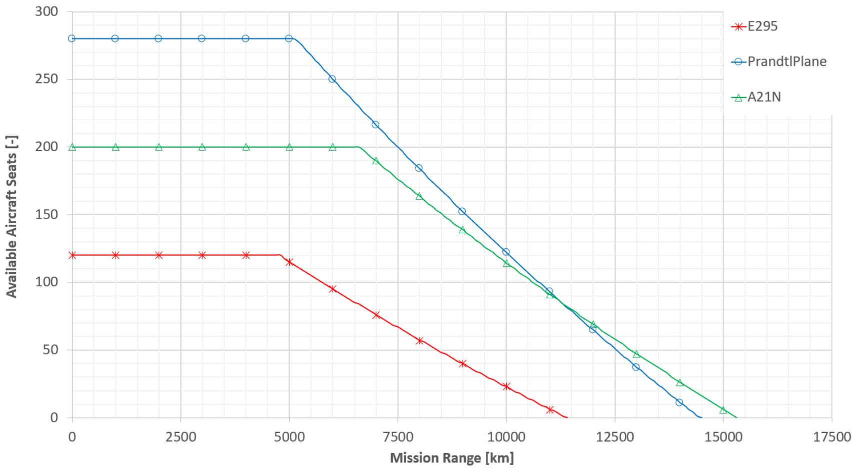

Fig. 3 Number of available aircraft seats for a given mission range for the PrandtlPlane and two reference aircraft

Using this methodology it is possible to calculate the required fuel weight and maximum number of passengers for any point on the edges of the payload range diagram. However, a lot of possible combinations of payload and range which are not located at the edges of the payload range diagram exist as well which is indicated by point F in figure 2. The reduction in associated payload of point F compared to point B also results in the fact that less fuel is required to transport the mission cargo over the same mission range. The relationship between reduction in payload weight and subsequent reduction in required mission fuel can be mathematically formulated by taking the partial derivative of equation 6 with respect to the payload weight, which is shown in equation 7 below.

$$\frac{\partial W_{fuel}}{\partial W_p} = \left(\left(\frac{W_0 + W_p + W_{fuel}}{W_0 + W_p}\right) - 1\right) = \left(e^{\frac{RC_DC_T}{VC_L}} - 1\right) \tag{7}$$

The partial derivative in equation 7 indicates how much fuel needs to be added or removed with a corresponding change in payload weight and shows that this value is constant for a given mission range. This characteristic can be exploited such that for all points on the interior of the payload-range diagram the required fuel weight can be determined by first calculating the required fuel and payload weights for the most limiting case for that particular range and subsequently subtracting the multiplication of this partial derivative with the reduction in payload. By adopting this strategy it is possible to now calculate the required fuel consumption for multiple aircraft based on their basic performance parameters, weights and mission characteristics. It is worth noting that in all fuel calculations a further contingency is built in by adding a 5% en-route reserve fuel buffer to handle possible en-route delays or detours. This is in addition to the earlier mentioned contingency range increases for operational reserve and landing and take-off fuel. The methodology in this section forms an essential part of the model which enables accurate fuel calculations of aircraft based on basic design parameters.

C. Fleet Allocation Model

The fleet allocation formulation provided by Hane et al. (1995) served as a staring point for the problem formulation but was significantly adjusted to meet the specific requirements for this research. Multiple different subsets of the problem will be explained in detail, starting of with the objective function of the model. Next, two different sets of constraints will be elaborated on. First, operational constraints which ensure that aircraft seat capacity and both fixed and flexible passenger demand are not violated. Second, operational constraints related to aircraft routing and utilisation such as the preservation of aircraft flow in the network and hourly flight movement restrictions. Last but not least, mathematical constraints are highlighted which are essential for the functioning of the model.

1. Objective Function

The objective function of the market assessment model follows a cost minimisation framework with the objective to as efficiently as possible transport passengers from their origin to their destination using the PrandtlPlane and 45 competing aircraft in the model which are included in table 10 in the Appendix. Its mathematical formulation is shown below in equation 8.

$$
\begin{aligned}
\min \quad Z = & \sum_{(i,j)\in L} \sum_{f\in F} \sum_{t\in T} c^f_{ijt} \cdot X^f_{ijt} \\
& + \sum_{(i,j)\in L} cflex_{ij} \cdot RFlex_{ij} \\
& + \sum_{(i,j)\in L} \sum_{t\in T} cfix_{ijt} \cdot RFix_{ijt} \\
& - \sum_{(i,j)\in L} \sum_{f\in F} \sum_{t\in T} \left(\frac{\partial W_{fuel}}{\partial W_p}\right)^f_{ij} \cdot W_{pax} \cdot RSeat^f_{ijt} \\
& + \sum_{a\in H} \sum_{f\in F} DC^f \cdot Y^f_{at_{start}t_0}
\end{aligned} \tag{8}
$$

The objective function above consists of five terms. The first term of the objective function calculates the total cost associated with performing a specific flight which is part of the network under consideration, c^f_{ijt}. Perhaps the most essential part of this coefficient in the model is the fuel quantity of the flight, which has been elaborated on in subsection IV.B and converted to euros with a fuel price of €623 per tonne. Furthermore, it contains a fixed cost parameter per flight which can be tuned to represent the slot cost of operating at an airport plus a weight-dependent charge of €10 per tonne MTOW to represent the airport handling costs. Incorporated hourly costs for both flight- and cabin crew are dependent on the requirements of each specific aircraft where flight crew costs are assumed to be equal to €200 per hour for all aircraft and cabin crew costs equal to €50 per hour per 50 passengers. The flight time of the aircraft is calculated by taking the range of the flight calculated through the great-circle equation and dividing by the speed of the aircraft. A complete overview of all involved terms is shown in equation 9.

$$c^f_{ijt} = FuelCost + SlotCost + WeightCost + \left(\frac{Range}{Speed}\right)(FlightCrewCost + CabinCrewCost) \tag{9}$$

The second term of the objective function is the total cost associated with not transporting a passenger who was flexible in demand in the network. As the flexible demand passengers can be considered a 'pool' of passengers on a route and are not constrained to any departure time, this term must be evaluated over the different routes in the network. Following similar reasoning, the third term in the objective function calculates the total cost for not bringing a passenger who is considered to be fixed in demand to his or her destination. As for fixed passengers the departure time is of importance, the total number of spilled fixed passengers must be calculated for all the departure times for a given route. Following the reasoning that fixed demand "business" travellers bring in higher revenue than flexible demand "leisure" passengers, the penalty for spilling a fixed demand passenger is higher than the penalty for spilling a flexible demand passenger. To spill a fixed demand passenger, the penalty cost $cfix_{ijt}$ is a flat €20 plus €0.02 per flight distance kilometer. For flexible demand passengers, the penalty cost $cflex_{ij}$ is a flat €10 plus €0.01 per flight distance kilometer.

The fourth term in equation 8 represents the fuel savings associated with flying with one or more empty seats compared to the full aircraft. This term has been discussed in subsection IV.B and results in improved realism as aircraft rarely fly with a load factor of 100%. This enables aircraft fuel consumption to be adjusted in line with the number of passengers on the flight which significantly enhances model accuracy. The fifth and final term represents the introduction cost of an aircraft at the starting node of an airport after which the aircraft can be used to perform flights in the model for the given day. This cost can be seen as a depreciation term for one day of operation, which is equal to the list price of the aircraft divided by an assumed operational life of 7500 days.

2. Operational Constraints - Passenger Allocation

Three further operational constraints have been added in order to ensure that the allocation of passengers to the flights which are or are not being operated works successfully. They are mathematically formulated as follows:

$$S^f_{ij} \cdot X^f_{ijt} - PFix^f_{ijt} - PFlex^f_{ijt} - RSeat^f_{ijt} = 0 \qquad \text{for all} \quad f \in F, \quad (i,j) \in L \quad \text{and} \quad t \in T \tag{10}$$

$$\sum_{f \in F} PFix^f_{ijt} - DFix_{ijt} + RFix_{ijt} = 0 \qquad \text{for all} \quad (i,j) \in L \quad \text{and} \quad t \in T \tag{11}$$

$$\sum_{t \in T} \sum_{f \in F} PFlex^f_{ijt} - DFlex_{ij} + RFlex_{ij} = 0 \qquad \text{for all} \quad \text{and} \quad (i,j) \in L \tag{12}$$

The constraint in equation 10 is present to ensure that the total number of available seats on a flight is not exceeded. This is done by ensuring that the total available seats on the flight, which is equal to the left hand side term, is taken by either a fixed demand passenger, a flexible demand passenger, or left empty. The parameter S^f_{ij} in this equation indicates the maximum number of available seats which can be filled on the aircraft for a specific mission in line with the fuel calculations performed in section IV.B. This constraint needs to be evaluated for every combination of fleet, route and departure time.

Next, equation 11 ensures that the total amount of fixed demand passengers allocated to flights does not exceed the total demand for the route at that point in time. The constraint sums all fixed demand passengers departing at a set time to a set destination over the different fleets which may operate the flights. This gives the total amount of departing passengers, from which subsequently the total market demand for this specific combination of route and time is subtracted. When all passengers are taken, the residual of the fixed demand passengers is equal to zero. However, if the model does not transport all the passengers to their destination, the value of the fixed demand residual will be positive and used in the objective function to assign penalty costs for leaving these passengers behind. Following a similar reasoning, equation 12 performs the same analysis for the flexible demand passengers. However, as for the flexible demand passengers the residuals need to be considered on a route basis only (their departure time does not matter, as long as they are transported), the summation sign for this constraint also runs over their different departure times and the constraint is applied on a route-basis only.

3. Operational Constraints - Aircraft Routing and Utilisation

The third set of constraints are related to aircraft routing and utilisation with the purpose to enhance network realism to match the real world scenario. Four of these constraints have been added to the model, which are mathematically formulated as follows.

$$\sum_{(i,j)\in A(a,t_n)} X_{ijt}^{f} + Y_{at^{-}t_n}^{f} - \sum_{(i,j)\in D(a,t_n)} X_{ijt}^{f} - Y_{at_n t^{+}}^{f} = 0 \qquad \text{for all} \quad (a,t_n) \quad \in N \quad \text{and} \quad f \in F \tag{13}$$

$$\sum_{a\in H} FH^{f} \cdot Y_{at_{start}t_0}^{f} - \sum_{(i,j)\in L} \sum_{t\in T} FT_{ij}^{f} \cdot X_{ijt}^{f} \geq 0 \qquad \text{for all} \quad f \in F \tag{14}$$

$$\sum_{(i,j)\in A(t_n)} X_{ijt}^{f} + \sum_{(i,j)\in D(t_n)} X_{ijt}^{f} \leq FM \qquad \text{for all} \quad (a,t_n) \in N \tag{15}$$

$$\sum_{f\in F} Y_{at_{start}t_0}^{f} \leq GAC \qquad \text{for all} \quad a \in H \tag{16}$$

The first constraint, listed as equation 13, has the largest impact on the function of the model. This constraint is called the "flow" constraint and ensures that aircraft are physically present at the airport before it can be assigned to a flight. The concept is depicted graphically in figure 4. At the start of the day, the model can decide which and how many of each aircraft type to incur a fixed daily cost for and at which airport to do so. These aircraft are placed on a ground arc, which means that they are parked at the airport. At the first time of the day where a flight arrives or departs the airport, in this case at 8:00 am, the first node can be seen. Nodes are placed at every hour of the day at which an aircraft arrives at or departs from the airport. At each node in the network, constraint 13 is evaluated and four terms have to be balanced. The first two terms of equation 13 are all inbound terms, with the first term equating to the number of arriving aircraft of a certain type on flights at the airport. The second term is the number of aircraft of a certain type which are parked on the ground arc inbound to that node. The second two terms are all outbound terms, with the third term being all departing aircraft of the same type from the airport and the fourth and last term all aircraft which remain parked on the ground arc outbound of that node. When this constraint is satisfied for all nodes on all airports during the time of operation it can be ensured that aircraft do not "appear out of nowhere" to complete a flight when they were not at that physical location and ready to complete the flight. Furthermore it causes flights to be dependent on each other as the decision on which aircraft to operate on an inbound flight affects the decision of which aircraft to operate on an outbound flight an hour later. This requirement enhances network accuracy at the cost of significant increases in model complexity.

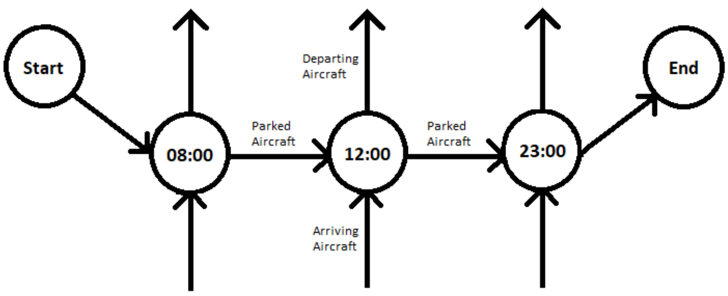

Fig. 4 Visualisation of network flow at an airport. Horizontal and diagonal arrows indicate ground arcs and vertical arrows indicate inbound and outbound flights. All four terms have to be balanced.

The second constraint related to aircraft utilisation is listed in equation 14 and is designed to ensure that that aircraft are not utilised an excessive amount of time over the day. This especially occurs when aircraft fly against the clock to the west, effectively increasing daily operational use. The constraint sums the number of acquired aircraft and multiplies this by the allowed daily flight time per aircraft. This creates a flight hour budget which can be used to operate flights. For each flight in the network, the travel time of that route is multiplied with the number of aircraft of that type which fly the route. This way the total airborne hours of the aircraft type can be calculated which can never exceed the total flight hours available for that aircraft type. Equation 15 limits the total number of movements of aircraft per hour by summing the total number arriving and departing flights for each node in the network and ensuring that these movements do not exceed the maximum capacity of the airport. The final constraint in equation 16 sets a limit on the total number of aircraft which can be acquired at the start of the day for each airport in the network in order to not violate the parking space capacity of the airport under consideration.

4. Mathematical Constraints

A number of mathematical constraints need to be added to the model in order to ensure that the solution to the model makes sense. For example, the constraint in equation 17 ensures that there is always a positive amount of aircraft on a ground arc. Allowing negative aircraft on a ground arc does not make sense from a modelling point of view as it allows aircraft to travel back in time. Following similar reasoning, constraint 18 ensures that negative flights can not be conducted either. The model is also free to choose whether it prefers to operate multiple aircraft to replace a single flight if that would be a more favourable combination. Last but not least, constraints 19 through 21 ensure that the total amount of passengers transported and the total amount of passengers who are spilled is at least greater than zero, because negative passengers should be avoided as well.

$$Y^f_{at^-t_n}, \quad Y^f_{at_nt^+} \geq 0 \qquad \text{for all} \quad (a, t_n) \in N \quad \text{and} \quad f \in F \tag{17}$$

$$X^f_{ijt} \geq 0 \qquad \text{for all} \quad f \in F, \quad (i, j) \in L \quad \text{and} \quad t \in T \tag{18}$$

$$PFlex^f_{ijt}, \quad PFix^f_{ijt}, \quad RSeat^f_{ijt} \geq 0 \qquad \text{for all} \quad f \in F, \quad (i, j) \in L \quad \text{and} \quad t \in T \tag{19}$$

$$RFix_{ijt} \geq 0 \qquad \text{for all} \quad (i, j) \in L \quad \text{and} \quad t \in T \tag{20}$$

$$RFlex_{ij} \geq 0 \qquad \text{for all} \quad (i, j) \in L \tag{21}$$

D. Relaxing the Formulation

The formulation of the problem presented in the previous section provides a realistic framework suitable for assessment of the capabilities and limitations of the PrandtlPlane. There is however one fundamental limitation with this formulation. In order to accurately determine market share for the aircraft, a global evaluation is required as different regions of the world have vastly different network characteristics in terms of passenger demand growth rates as well as the proximity and scale of major hub airports in metropolitan areas. This would entail that the entire problem has to be developed at a full scale global level where all flights on the network are either directly or indirectly dependent on each other. Next to the fact that this is not a realistic approach it is also an infeasible approach as the problem size scales up exponentially when adding more flights to the network and reaches computational limitations. Furthermore, operational constraints would have to be tailored for all airports in the global dataset which is a very challenging task. This fact, combined with the requirement to solve a significant number of variations to the problem introduces the need for a relaxed formulation compared to the formulation in subsection IV.C.

In the relaxed formulation the aircraft flow constraint of equation 13 plus the related routing and utilisation constraints of equations 14, 15 and 16 are omitted. By relaxing these constraints the optimisation of the route from Amsterdam to New York is now independent of the optimisation of the route from New York to Los Angeles and vice versa. As these routes are now independent from each other it is possible to split the global network into different subsets which can be solved in parallel, resulting in significant reductions in computational complexity. A further consequence of this formulation is that aircraft can no longer acquired at the start of the day which omits the depreciation factor in the relaxed model formulation. This has been solved by increasing the flight cost coefficient c^{f}_{ijt} of the objective function in equation 8 to include a hourly depreciation cost multiplied by the total duration of the flight which ensures that aircraft depreciation is still included in the model. All other model parameters including the flexible allocation of passengers and passenger-dependent fuel consumption based on payload-range characteristics remain valid in this new formulation.

E. Problem Solving Strategy

In order to solve the ILP problems described in the previous sections, the decision was made to make use of the *IBM ILOG CPLEX 12.10* solver which was made available under an academic license. The LP-problem files required as solver input have been created using *Python 3.6* on an ASUS notebook with a quad-core, eight-thread i7-4700HQ processor with 8GB of RAM. Due to the large scale of the problem and complex formulation combined with the need to solve a large number of subproblems, the optimisation of the LP-files and subsequent post-processing was performed on a dual AMD EPYC 7551 server with 64 cores, 128 threads and 256 GB of RAM. This server, made available by TU Delft, allowed for parallel solving of multiple subproblems which significantly reduced the total computational time required for this research.

V. Results

This section will elaborate on the results of two different case studies. First of all, in subsection V.A, the relaxed formulation of the market assessment model as described in section IV.D will be used to evaluate the performance of the PrandtlPlane with respect to competing aircraft on the global dataset, but without the preservation of aircraft flow. After the global potential of the aircraft has been evaluated, subsection V.B will discuss the results of the complete formulation of the problem from section IV.C for the smaller case of all flights in the daily dataset arriving at or departing from Amsterdam Schiphol Airport (AMS) which is known for its capacity constraints. For both case studies the networks with baseline 2018 demand and forecasted demand levels for 2032 and 2050 will be evaluated both with and without the PrandtlPlane available. Furthermore, slot costs will be varying with increments of €5000 per flight starting at €0 and increasing to a maximum of €50000 to assess the impact of a higher fixed cost per flight on aircraft utilisation.

A. Relaxed Global Network

The first case results will be discussed in the following structure. Subsection V.A.1 will elaborate on the network differences which arise when the PrandtlPlane is made available for operation. The total number of flights, passenger demand satisfaction and other key performance indicators such as aircraft market share and network fuel efficiency will be discussed. Subsection V.A.2 then zooms in on PrandtlPlane utilisation by analysing the market share in different regions of the world plus the airports and routes which suit the novel aircraft best. As it is still possible for the final design of the aircraft to change, a robustness analysis with respect to the aircraft design OEW is conducted which should give insight in the sensitivity of the aircraft design to its competitiveness on the market. This is discussed in the final subsection V.A.3.

1. PrandtlPlane Network Impact

The first important parameter to look at is the total number of flights which take place in the network. As can be observed in figure 5, the total number of flights in the network increases significantly over time. At a slot cost of €0,- per flight, over 180.000 flights per day are performed in 2050 without the PrandtlPlane in service which is almost triple that of the same situation in 2018. With increasing slot costs this number gradually decreases as more and more flights are no longer financially attractive. At low slot costs the introduction of the PrandtlPlane significantly decreases the total number of flights achieving the goal of decongesting airports due to the larger jet replacing a combination of smaller narrowbody aircraft on shorter routes. When slot costs start to increase a cross-over point is reached at which the introduction of the PrandtlPlane actually increases the total number of flights in the network, especially with higher passenger demand. This can be explained by the fact that the higher efficiency of the PrandtlPlane can make a flight financially attractive at higher level of slot costs whereas with conventional aircraft this flight would not be financially viable. When slot costs increase further to even higher levels the impact of the PrandtlPlane significantly decreases where the total number of network flights is only slightly above the baseline case without PrandtlPlane availability.

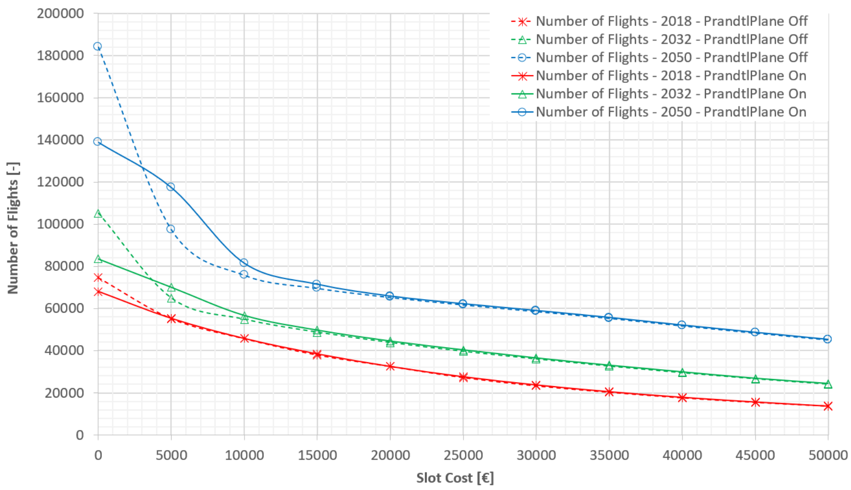

Fig. 5 Total number of flights in the network with and without the PrandtlPlane for various slot costs

The total number of conducted flights alone however does not tell the complete picture. Also important is the total number of passengers which are not transported in the network, or "spilled" as the introduction of the larger PrandtlPlane could result in more passengers being transported in the network with the same number of flights. When looking at figure 6, this does seem to be the case. With increasing slot costs less flights become financially attractive and more passengers are spilled. With the PrandtlPlane in service however, the percentage of spilled passengers is consistently lower than the same network without this aircraft available. Another interesting observation is that in the lower slot cost region, more passengers get spilled with higher demand in 2032 and 2050, but this relationship eventually reverses when slot costs increase significantly. This can be explained due to the fact that aircraft up to the very large Airbus A380 increasingly operate on high-density, short range routes as well which reduces the incentive to spill passengers as higher capacity is made available. Because slot costs are charged on a per-flight basis, larger aircraft become more attractive due to the fact that these slot costs can now be spread over a larger number of passengers.

A further metric which is closely related to the percentage of passengers spilled is the percentage of passenger kilometers spilled. This metric, which is obtained by multiplying the passenger demand on a certain route with the flight distance, provides an indication of the total distance flight distance demand in the model. As can be seen in figure 7 the percentage of spilled passengers in the model is consistently lower with the PrandtlPlane in service compared to the situation without, When combined with the percentage of passengers spilled it can be used to assess the type of flight on which these passengers are spilled. For example, when comparing figure 6 figure with figure 7, the percentage of passengers spilled at a slot cost of €0,- is lower than the percentage of passenger kilometers spilled at the same slot cost. When the slot costs per flight starts to increase, the percentage of spilled passengers increases faster than the percentage of spilled passenger kilometers. This indicates that passengers with shorter trip lengths are spilled disproportionally compared to long-distance travellers which is to be expected given the fact that spill costs are dependent on the length of the passenger trip.

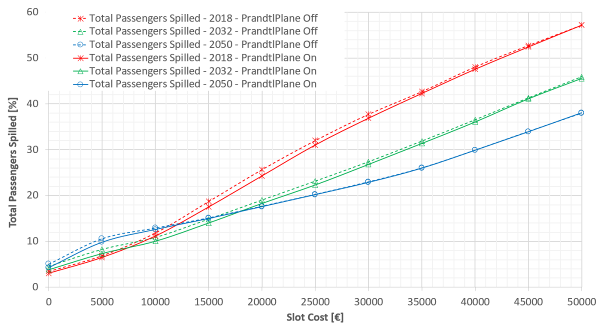

Fig. 6 Percentage of passengers spilled with and without the PrandtlPlane for various slot costs

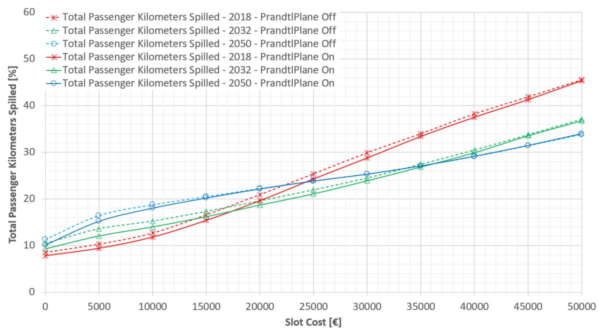

Fig. 7 Percentage of passenger kilometers spilled with and without the PrandtlPlane for various slot costs

Perhaps one of the most important questions which to be answered in this paper is to which extent the novel PrandtlPlane can obtain market share in the currently competitive mix of existing aircraft types. Figure 8 provides an overview of the market share of the Prandtlplane as a proportion of total flights conducted in the network. As can be observed, there is plenty of potential for the novel aircraft to be successful. Under the condition that there are no slot costs per flight, market share of the aircraft ranges from approximately 40% on the 2018 network demand up to a very high share of 85% on the 2050 network. Zooming in on the 2050 scenario, increasing slot costs cause the Airbus A380 to rapidly take market share from the PrandtlPlane on both medium- to short-haul routes as it is the most attractive option to cope with the booming passenger demand figures. For the years 2018 and 2032 a minor increase in slot costs helps the PrandtlPlane to gain market share, most dominantly from the Airbus A321neo and Embraer E195E2 on shorter range flights due the PrandtlPlane's advantage in size. When slot costs increase further, market share is once again lost to the Airbus A380 but much less rapidly compared to the forecasted network for 2050. It is worth expressing that in this scenario no restriction on the total number of flights in the network is present and that network effects are not taken into account.

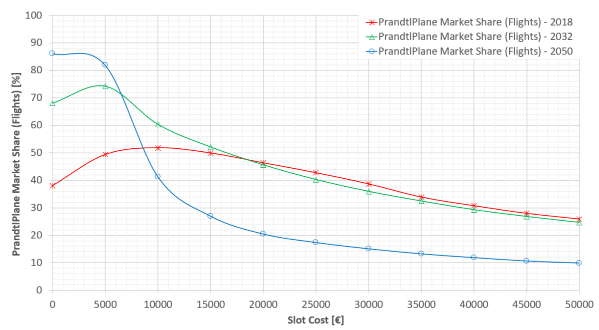

Fig. 8 PrandtlPlane market share as proportion of total conducted flights in network

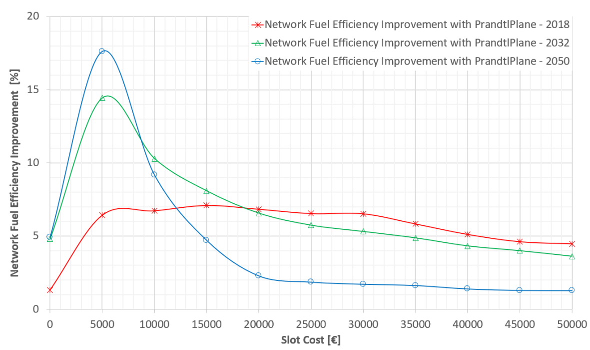

Fig. 9 Network Fuel Efficiency improvement per passenger kilometer with introduction of the PrandtlPlane

The Prandtl-wing design of the PrandtlPlane makes the novel aircraft more fuel efficient compared to its direct peers. Next to direct advantages in fuel efficiency however, network advantages in fuel efficiency may also be present due to the fact that a combination of the larger PrandtlPlane plus a smaller regional jet may result in additional fuel savings compared to two conventional narrowbody aircraft such as an Airbus A320 on the same route. Figure 9 shows the percentage of network fuel efficiency improvement per passenger kilometer when the PrandtlPlane is available for operation. The fuel savings range from 6% and 16% with maximum PrandtlPlane utilisation and drop to the range of 2% to 4% when slot costs increase further and less PrandtlPlanes are in operation. These results contribute to a strong incentive to operate PrandtlPlanes due to large additional savings in fuel cost and decreased carbon emissions whilst making no concessions in transported passengers.

2. PrandtlPlane Utilisation Characteristics

Even though a single percentage of global market share gives a good general indication into the qualities and potential of the PrandtlPlane, further analysis into the strengths and weaknesses of the novel aircraft are required paint a more complete picture and highlight potential areas of opportunity or caveats. For example, different regions of the world experience different growth rates in air travel demand and distances between key metropolitan areas may differ significantly over geographical regions. As all of these factors influence the choice of most appropriate aircraft to fulfil demand, figures 10 and 11 provide insight into the intra-continental market share for all five continents and derived global average with €0 and €50000 slot cost per flight respectively. Several interesting findings can be concluded from these figures. Figure 10 shows that, for the €0 slot cost scenario, PrandtlPlane utilisation in the intra-Asian market is much higher than the global average. The same intra-Asian market however significantly falls behind the global average when slot costs per flight are increased to €50000, as can be seen in figure 11. This significant reduction in market share can once again be explained by the fact that, for very high demand routes and high fixed costs per flight, the Airbus A380 starts to become financially more attractive even for very short-range flights. Due to the smaller growth rates expected for other intra-continental regions, this "tipping point" where Airbus A380's dominate short-range flights does not fully materialise. The intra-Americas and intra-European market shares for the PrandtlPlane are more robust to both passenger demand and fixed cost increases and are hence still a prime target for PrandtlPlane sales. The intra-Oceania market may not be as interesting other other regions due to its moderate size and growth forecasts compared to the other regions. Inter-African demand however is expected to grow significantly and behaves similar to the intra-Asian market, albeit at a much smaller absolute level.

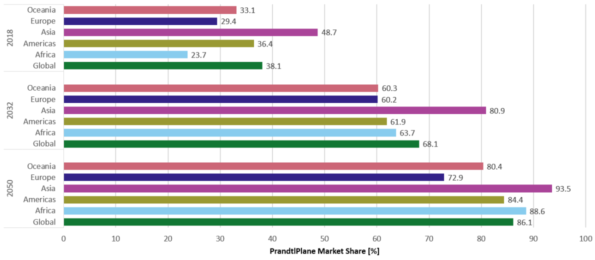

Fig. 10 Intra-continental PrandtlPlane market share with €0 slot cost per flight

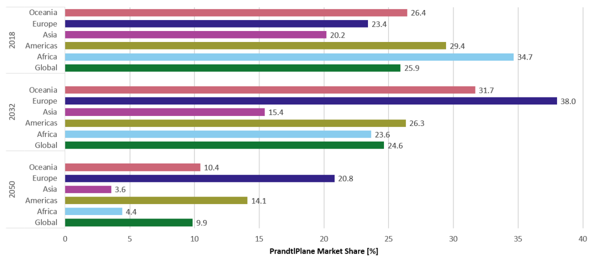

Fig. 11 Intra-continental PrandtlPlane market share with €50000 slot cost per flight

The final level of depth for the market analysis is to evaluate the most flown routes and visited airports by the PrandtlPlane for various network types. Table 1 below provides an overview of the routes which are most often performed by the PrandtlPlane under the condition of €0,- slot cost. All routes, with the exception of Las Vegas (LAS) to Los Angeles (LAX) in 2018, are located in Asia which is in line with the large market share for this region observed in figure 10. The most commonly flown route, Gimpo (GMP) to Jeju (CJU) in Korea is generally recognised to be the busiest route for passenger air travel in the world. With the exception of Las Vegas (LAS) to Los Angeles (LAX) and Jakarta (CGK) to Densapar (DPS), all other routes are listed amongst the top 5 busiest routes for passenger air travel which shows that the PrandtlPlane suits operation on the busiest routes in the world best. As these routes are forecasted to growt further in line with their regional growth rates and no operational constraints are present, the total number of flights on these routes scales exponentially as well.

Table 1 Most popular daily PrandtlPlane routes - €0 Slot Cost

2018				2032				2050			
Route		Flights	Distance	Route		Flights	Distance	Route		Flights	Distance
GMP	CJU	146	451 km	GMP	CJU	282	451 km	GMP	CJU	656	451 km
CTS	HND	125	820 km	CTS	HND	140	820 km	CTS	HND	561	820 km
FUK	HND	95	881 km	FUK	HND	183	881 km	FUK	HND	430	881 km
BOM	DEL	84	1138 km	BOM	DEL	163	1138 km	BOM	DEL	381	1138 km
LAS	LAX	75	380 km	CGK	DPS	136	983 km	CGK	DPS	317	983 km

As shown earlier in figure 8, increasing slot costs to high values cause the market share of the PrandtlPlane to decrease. The most popular routes for the most extreme scenario, that of €50000 slot cost, are shown in table 2. In line with the strongly decreasing market share in Asia with higher fixed costs per flight, the most commonly served routes are now no longer in Asia but domestic flights in the United States. Furthermore, the average length of the most common routes has increased significantly as well, indicating that with increasing slot costs, the main focus of the PrandtlPlane shifts from short-range, high-density operations to medium-range, medium-density operations.

Table 2 Most popular daily PrandtlPlane routes - €50000 Slot Cost

2018[1]				2032				2050[3]			
Route		**Flights**	**Distance**	**Route**		**Flights**	**Distance**	**Route**		**Flights**	**Distance**
ATL	LAX	16	3126 km	LAX	MDW	17	2812 km	BOS	PHX	14	3694 km
PHX	PHL	15	3333 km	BNA	LAX	15	2886 km	LAX	MDW	13	2812 km
LAX	EWR	15	3941 km	ATL	LAX	15	3126 km	BNA	LAX	13	2886 km
BOS	DEN	14	2816 km	PHX	PHL	15	3333 km	PHX	JFK	13	3458 km
BNA	LAX	14	2886 km	DFW	LGA	14	2231 km	LAX	FLL	13	3736 km

[1] Not complete: 3 other routes also have 14 daily PrandtlPlane flights
[2] Not complete: 1 other route also has 13 daily PrandtlPlane flights

Next to routes which are flown commonly with PrandtlPlanes, table 3 shows exactly the airports with most daily PrandtlPlane movements under the condition of no slot costs per flight. As can be observed, the most commonly visited airports are located in the United States, with a strong presence at the hub airports of Atlanta (ATL), Los Angeles (LAX) and Denver (DEN). With increasing demand, especially in the Asian region, major hub airports in this region such as Tokyo (HND) and Delhi (DEL) are identified as prime targets for PrandtlPlane operation in this scenario as well.

Table 3 Airports with most PrandtlPlane movements per day - €0 Slot Cost

2018			2032			2050		
Airport	**Country**	**Movements**	**Airport**	**Country**	**Movements**	**Airport**	**Country**	**Movements**
ATL	United States	1063	ATL	United States	1743	HND	Japan	3482
LAX	United States	905	HND	Japan	1476	DEL	India	3123
DEN	United States	848	LAX	United States	1403	ATL	United States	2931
PHX	United States	806	DEN	United States	1383	CGK	Indonesia	2827
HND	Japan	728	DEL	India	1312	PEK	China	2613

When fixed slot costs per flight increase, the market position of the PrandtlPlane moves away from the very high-density, short-range operations to medium-density, medium-range operations. This can also be observed in table 4, the PrandtlPlane still operates from hub airports in the United States such as Los Angeles (LAX) and Las Vegas (LAS) but significantly less on the very busy routes in Asia where the Airbus A380 starts to dominate.

Table 4 Airports with Most PrandtlPlane Movements - €50000 Slot Cost

2018			2032			2050		
Airport	**Country**	**Movements**	**Airport**	**Country**	**Movements**	**Airport**	**Country**	**Movements**
LAX	United States	298	LAX	United States	306	LAX	United States	327
PHX	United States	170	PHX	United States	198	LAS	United States	210
JFK	United States	165	LAS	United States	156	PHX	United States	159
LAS	United States	133	JFK	United States	148	BOS	United States	135
DEN	United States	118	BOS	United States	142	MIA	United States	131

3. Sensitivity Analysis

As the PrandtlPlane is still in development there is a possibility that the current design parameters are subject to change, especially when dealing with innovative aircraft design concepts. The question which subsequently arises is to which extent these design changes may affect the market position of the aircraft. In order to model this uncertainty, a sensitivity analysis was conducted with regard to the design OEW of the PrandtlPlane. Changing the OEW of the aircraft has several consequences on aircraft performance. For example, keeping all other parameters constant, increasing the operating empty weight will increase fuel consumption and reduce the payload capacity for flights on the edges of the payload-range diagram. This well-known snowball effect can contribute to other aircraft becoming more competitive in terms of fuel consumption and may be favoured for specific flights. Furthermore, flights which were near the range limit of the aircraft may now not be possible anymore due to the requirement to carry extra fuel to offset increased fuel consumption.

Figure 12 shows how the global market share of the PrandtlPlane is affected by changes in design OEW with the current baseline design of the aircraft as a reference. For all three analysis networks, which are evaluated under the condition of €0 slot cost per flight, a minor OEW increase of 5% does not significantly impact the market share of the aircraft. However, when the PrandtlPlane programme suffers significant setbacks in terms of meeting its current design OEW, adverse effects are much more pronounced. Furthermore, the sensitivity of OEW changes to PrandtlPlane market share become smaller with increasing passenger demand, suggesting that competition under high passenger demand scenarios is less strong compared to lower passenger demand scenarios. Even though higher slot costs adversely affect PrandtlPlane market share, design sensitivity with respect to market share does not change significantly.

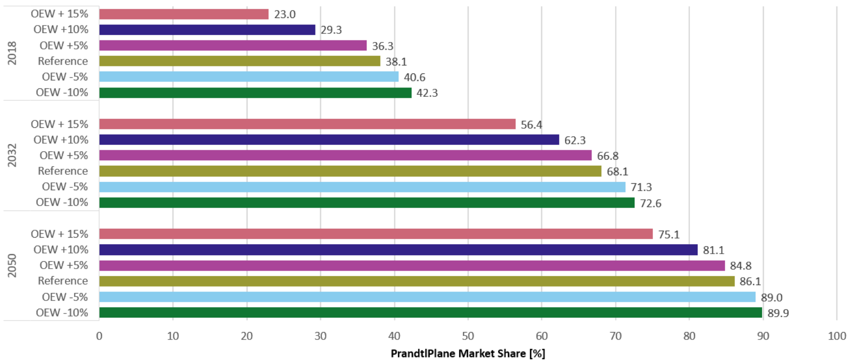

Fig. 12 Impact of design OEW changes on PrandtlPlane market share with €0 slot cost per flight

This case study has evaluated the market impact and potential of the PrandtlPlane on a global level. The analysis has shown that the PrandtlPlane can gain significant market share in different areas of the world. When slot costs remain low, the main strength of the aircraft lies in its ability to efficiency transport large passenger numbers over short distances on some of the busiest routes in the world, predominantly in Asia. In this case the PrandtlPlane takes significant market share from existing narrowbody jets such as the Airbus A321neo and the Embraer E195E2, with market share figures in the range of 70% to 85% for the years 2032 and 2050. When slot costs increase further, the Airbus A380 starts to dominate in this market segment and the PrandtlPlane shifts its optimal utilisation to medium-range, medium-density routes where a strong market presence can be established especially in the United States. Under the most extreme scenario of €50000 slot cost per flight, the market share of the aircraft will be approximately 30% in 2032 and drop to 10% in 2050. The sensitivty of market share to design OEW changes is moderate when it concerns small adverse changes, but when larger weight increases set back the programme these effects become significantly more pronounced.

B. Flights through Amsterdam (AMS) with Aircraft Flow

Whereas the previous case considered each route on the global network to be independent and did not take into account airport capacity constraints, the second case will enforce stricter network operational constraints to enhance model realism. However, as these operational requirements significantly increase the complexity of the problem, the trade-off had to be made to analyse a smaller network in the form of all flights in the dataset which either arrive or depart from Amsterdam Airport Schiphol (AMS) in the Netherlands. This airport was selected due to its hub function and severe capacity limitations which are challenging to resolve in the near future which result in a persistent limitation to the number of possible flight movements.

This section is structured similar to the other case discussed in section V.A. First of all, subsection V.B.1 will further describe the network operational constraints which apply to this specific case study and how these were established. Subsection V.B.2 will elaborate on the network differences which arise when the PrandtlPlane is made available for operation by looking at the number of flights, passenger demand satisfaction, market share and fuel efficiency. Subsection V.B.3 then zooms in on PrandtlPlane utilisation by analysing the airports and routes which suit the novel aircraft best, omitting the regional analysis conducted earlier due to the smaller and more concentrated network. Last but not least, subsection V.B.4 evaluates PrandtlPlane design weight sensitivity with respect to its network market share. This section will also feature an additional analysis into the aircraft type swaps which occur when these design weight changes materialise.

1. Network Operational Constraints

Specific to this case study, the network limitation constraints presented in equations 13 through 16 apply compared to the previous case study. In these constraints, three key parameters have been tuned specifically to match the characteristic of the airport under consideration. First of all, FH^f, the maximum number of allowed daily flight hours per aircraft type, has been set at 16 hours per day for all aircraft type. This limitation is in place to allow time for aircraft maintenance and other operations to be conducted. Second, the total number of aircraft movements per hour has been capped at 45, equal throughout the day and equal for 2018, 2032 and 2050. Even though this number is less than the actual hourly capacity the airport, which is roughly double that at peak capacity, the total number of conducted flights in the model at the baseline case of 2018 also equals approximately half of the actual number of flights performed that day according to Schiphol (July 2018). By keeping this ratio constant, the capacity constraint is modelled as accurate as possible for future demand increases. This constraint theoretically caps the total number of flights per day at 1080 and becomes the limiting factor especially in high-demand, low slot-cost scenarios. With increasing slot costs at the airport, less flights become financially attractive and the impact of this constraint reduces. Third and last, following similar reasoning, the total number aircraft which can be on the ground at the start of the day is set at 100 which is half the normal parking capacity of the airport. By enforcing these constraints at the set levels the operational limitations for the airport are incorporated as realistic as possible.

2. PrandtlPlane Network Impact

The total number of flights in the network at a slot cost of €0, shown in figure 13, does increase for the years 2032 and 2050, but significantly less than in the earlier discussed global case in section V.A. This can readily be explained by the capacity restraining constraints which do not allow for much additional flight movements compared to the 2018 base case. With increasing slot costs a similar trend can be seen as in the global case study: more flights become financially unattractive and the total number of flights decreases. However, due to network effects and the lower number of total flights the volatility in the figure has increased significantly. Even though the general trend that the introduction leads to a slight increase in airport movements does seem to be present for most cases some exceptions can definitely be observed. In any case, the change of total airport movements with the introduction of the PrandtlPlane is small.

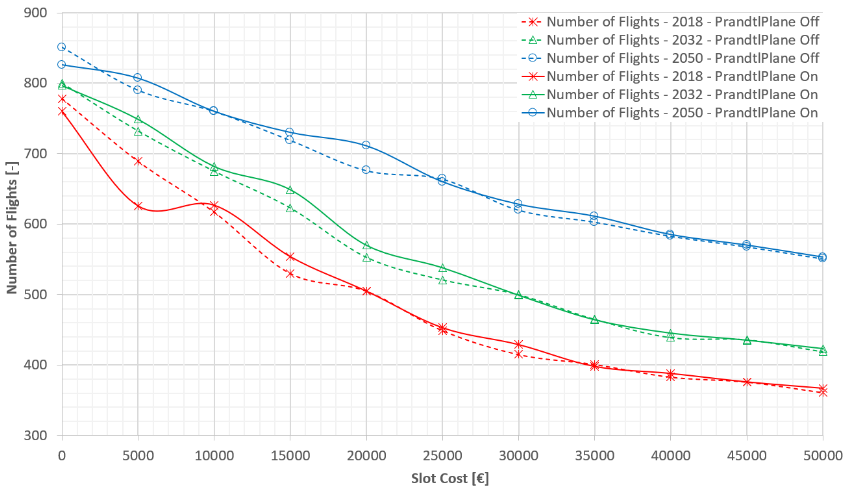

Fig. 13 Total number of flights in the network with and without the PrandtlPlane for various slot costs

When combining the information on the number of flights performed with passenger transport information, roughly the same trend can be observed compared to the global scenario. Figure 15, which shows the percentage of spilled passengers for all three analysis years and presence of the PrandtlPlane, shows that the percentage of spilled passengers increases with increasing slot costs. Furthermore, the percentage of spilled passengers eventually reaches lower levels for the years 2032 and 2050 compared to the baseline of 2018-level demand. When making a direct comparison to networks with and without the PrandtlPlane in service, the total percentage of spilled passengers does generally seem to decrease with the introduction of the PrandtlPlane but the trend is not as clear as before. The same holds for figure 15, which also shows a minor reduction to the percentage of spilled passenger kilometers in the situations with the PrandtlPlane available for service. Again, the most likely explanation for this behaviour is attributed to network effects which entails that a specific combination of aircraft which is most cost-efficient for a given slot cost can result in either deterioration of or improvements in the number of spilled passengers.

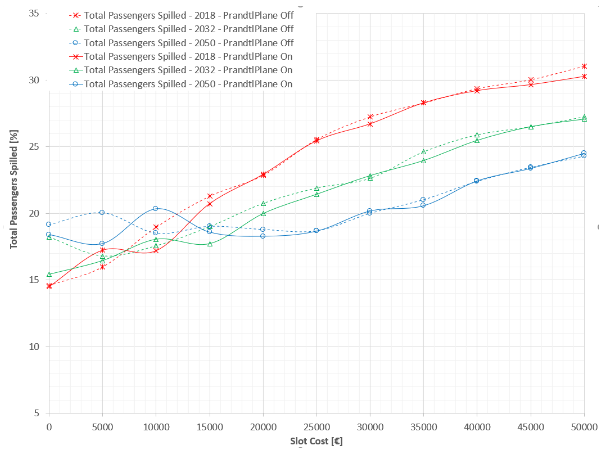

Fig. 14 Percentage of passengers spilled with and without the PrandtlPlane for various slot costs

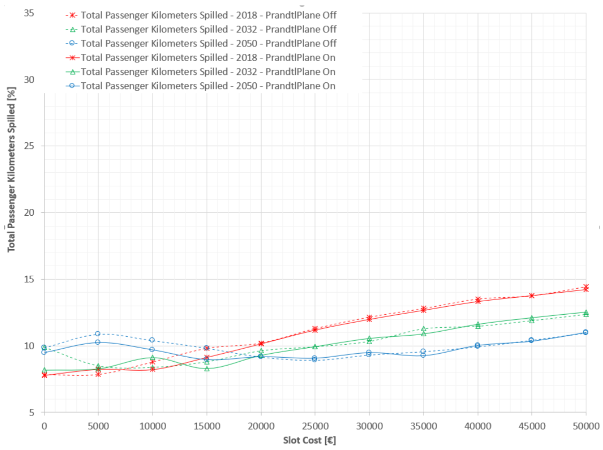

Fig. 15 Percentage of passenger kilometers spilled with and without the PrandtlPlane for various slot costs

Even though the effects of the PrandtlPlane introduction are not as clear when it comes to a reduction in flights or spilled passengers, figure 16 does provide a very clear overview of the expected market share of the new aircraft. For all slot costs, the market share of the aircraft first increases from 2018 to 2032 but subsequently decreases from 2032 to 2050. In 2050, PrandtlPlane market share eventually reaches a level below that of the 2018 reference demand. Contrary to the global analysis, shown earlier in figure 8, the market share curves do not cross over: In all situations the forecasted market share for 2050 is lower than the forecasted market share for 2018 which in turn is again lower than the forecasted market share for 2032. In the global case, market share in 2050 initially increased to levels above that in 2032, before decreasing to sub-2018 levels with increasing slot costs. Furthermore, the 2032 market demand forecast also dropped below the forecasted market demand in 2018 with increasing slot costs, something which is not observed in figure 16. Several reasons for this change may be possible. First of all, the network composition of flights connecting through AMS airport does not directly scale up to that of the global network. As most flights to or from AMS are intra-European flights, the passenger demand growth rates on these routes are significantly lower than that of emerging markets such as Asia and Africa. The lack of extremely high-density routes in this network has an adverse impact on PrandtlPlane market share, especially in the low slot cost area of the graph. This effect is strengthened by the flight movement constraints making the assignment of multiple PrandtlPlanes to a single flight less attractive which further drove high market share potential in the global scenario.

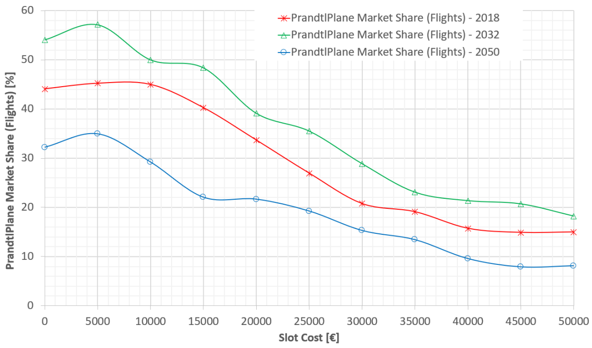

Fig. 16 PrandtlPlane market share as proportion of total conducted flights in network

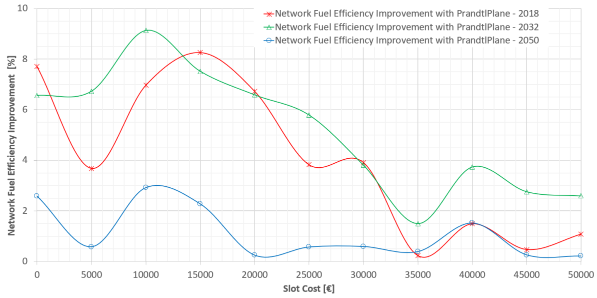

Fig. 17 Network Fuel Efficiency improvement with introduction of the PrandtlPlane

The curves depicting network fuel efficiency improvements caused by PrandtlPlane availability, depicted in figure 17, are significantly more volatile compared to those of the global network shown earlier in figure 9. For the years 2018 and 2032 a downward trend in fuel efficiency improvements with increasing slot costs can be identified. Decreasing fuel savings with increasing slot costs are consistent with the decreasing market share and hence impact of the PrandtlPlane on the network. However, when looking at the year 2050, the fuel savings with PrandtlPlane in service appear to be nearly constant and independent of PrandtlPlane market share at around 1.5%. The most probable explanation for this behaviour is that, when the PrandtlPlane becomes less attractive to operate and is substituted, this has collateral effects throughout the network on other connecting flights. For example, if a PrandtlPlane is removed from a flight and substituted with a larger aircraft, a subsequently departing flight can now also no longer make use of the PrandtlPlane. As demand for this connecting flight may actually be smaller than the capacity of the replacement aircraft, it may now be more cost efficient to use a smaller aircraft than to fly with significantly reduced load factors and use the larger inbound aircraft elsewhere. As a result, the increased fuel consumption by removal of a PrandtlPlane from one route may lead to fuel savings due to aircraft downsizing on other routes, resulting in a near constant rate of network fuel efficiency improvements. The fact that in the 2050-demand scenario the airport capacity constraints are a severely limiting factor with little room for additional flights entails that these ripple effects are felt throughout the network more severely compared to the 2018 and 2032 demand cases.

3. PrandtlPlane Utilisation Characteristics

Table 5 lists airports in the network with the most movements of the PrandtlPlane for the €0 slot cost scenario. As the network under consideration only involves flights from and to Amsterdam, this airport has been omitted from this overview. The routes flown by PrandtlPlanes are much more diverse compared to those in the global case which were all short-haul, high-density routes. For example, multiple short-range destinations from Amsterdam see high PrandtlPlane utilisation such as Barcelona (BCN) and Copenhagen (CPH). On the other hand routes such as Dubai (DXB) and New York (JFK), which stretch the range limits of the aircraft, are also flown often even at low slot cost levels. As the range from Amsterdam to Dubai exceeds the maximum available range with full seat capacity, only 279 out of 280 seats can be filled in order to reach this destination. The flight from Amsterdam to New York exceeds the maximum available range even further. On this route only 255 out of 280 seats can be sold which means that the load factor on this flight never exceeds 91%. Out of the 13 flights to and from New York in 2032, 11 operate on this maximum available load factor. This result provides evidence that the PrandtlPlane should also be considered to be a competitive option on the medium-range market and that a long-range version of the PrandtlPlane with increased fuel capacity and MTOW could make the aircraft even more competitive on the edge of its current design envelope.

Table 5 Airports with Most PrandtlPlane Movements - €0 Slot Cost

2018[1]				2032				2050[2]			
Airport	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**
BCN	Spain	10	1241 km	DXB	UAE	18	5169 km	DXB	UAE	25	5169 km
CPH	Denmark	10	633 km	BCN	Spain	17	1241 km	DUB	Ireland	13	750 km
LIS	Portugal	10	1846 km	LIS	Portugal	14	1846 km	BCN	Spain	8	1241 km
CDG	France	9	398 km	JFK	USA	13	5847 km	AYT	Turkey	7	2655 km
DXB	UAE	9	5169 km	CPH	Denmark	12	633 km	LHR	England	7	370 km

[1] Not complete: 1 other airport also has 9 daily PrandtlPlane flights
[2] Not complete: 3 other airports also have 7 daily PrandtlPlane flights

Moving to the case where slot costs approach €50000 euro per flight, a situation in which PrandtlPlane market share is significantly reduced, does not fundamentally change the earlier findings. These results are shown in table 6 and show a slight increase in the average flight distance on which the PrandtlPlane operates, but not by much. Routes to for example Tel Aviv (TLV) and Cairo (CAI) in the medium-range market segment pop up as interesting targets but the total number of flights remains small. Furthermore, the routes from Amsterdam to Dubai and New York are still present in this overview suggesting they could be considered more robust with respect to slot cost changes for the year 2018. When demand significantly grows however in the years 2032 and 2050, the PrandtlPlanes on these routes also get replaced by, most dominantly, Boeing 767-400s.

Table 6 Airports with Most PrandtlPlane Movements - €50000 Slot Cost

2018[1]				2032[2]				2050			
Airport	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**
JFK	USA	7	5847 km	LPA	Spain	3	3183 km	AES	Norway	2	1143 km
DXB	UAE	3	5169 km	TLV	Israel	3	3312 km	ATH	Greece	2	2182 km
IST	Turkey	3	2184 km	BOJ	Bulgaria	2	2012 km	BRI	Italy	2	1538 km
TLV	Israel	3	3312 km	CAI	Egypt	2	3287 km	DRS	Germany	2	633 km
ATH	Greece	2	2182 km	CHQ	Greece	2	2411 km	FAO	Portugal	2	1970 km

[1] Not complete: 9 other airports also have 2 daily PrandtlPlane flights
[2] Not complete: 15 other airports also have 2 daily PrandtlPlane flights
[3] Not complete: 5 other airports also have 2 daily PrandtlPlane flights

4. Sensitivity Analysis

As the smaller network with the flow constraint active provides a more accurate representation of a real world situation, the general sensitivity analysis of market share with respect to OEW was extended by investigating which competing aircraft replace the PrandtlPlane in the network when its design changes. As the PrandtlPlane was designed as a middle of the market aircraft it faces competition from both narrowbody and widebody aircraft. Table 7 shows the top three aircraft with largest changes in utilisation in both narrowbody and widebody categories for different changes in OEW in the year 2018 with a slot cost of €0. For example, when the OEW of the aircraft decreases with 10% and keeping all else equal, the total number of PrandtlPlane flights increases by 55. The total number of narrowbody aircraft flights reduces by 45, where the PrandtlPlane takes significant market share from the Airbus A321neo. Because the PrandtlPlane has a higher seat capacity of 280 seats compared to the 185 of the A321neo, smaller aircraft such as the Embraer E195E2 and the Airbus A220-300 are used more frequently to keep the total seats offered approximately equal. In the widebody segment, the weight reduction of the PrandtlPlane provides the aircraft with extra payload capacity which can be used to carry extra fuel to extend its range. The earlier discussed route from Amsterdam to New York can now be made without any empty seats. This results in the aircraft taking market share from the fleet of widebody aircraft as well, most notably from the Boeing 767-300 and -400 aircraft with 290 and 325 seats respectively.

When the OEW of the PrandtlPlane increases with 10% the total number of PrandtlPlane flights decreases with 58. Whereas an improved PrandtlPlane managed to take significant market share in the narrowbody market from the A321neo, weight increases on the PrandtlPlane do not see the A321neo become more competitive. The total number of narrowbody flights increases only slightly with the same trend that the A321neo is replaced by a combination of smaller aircraft still visible. This is because the short- to medium-range PrandtlPlane flights do not get replaced by A321neo aircraft but by the widebody Boeing 767 family aircraft. These aircraft are slightly bigger than the PrandtlPlane which entails that they can be paired with smaller aircraft such as the Embraer E195E2 to move the same number of passengers. On the longer range market the PrandtlPlane also loses market share to the Boeing 767 aircraft family and to a lesser extent to the Boeing 777-300. The weight increase on the PrandtlPlane causes the range of the aircraft to be significantly reduced due to its decreased fuel capacity. Routes such as Amsterdam to Dubai or New York, which with the reference PrandtlPlane design can only be operated with a few empty seats, now have to be operated with so many empty seats such that other aircraft become more price competitive.

Table 7 Top three flight number changes per aircraft under changing PrandtlPlane OEW - 2018, €0 Slot Cost

	Narrowbody Aircraft				PrandtlPlane	Widebody Aircraft			
Design Scenario	BCS3	E295	A21N	**All**		**All**	B764	B763	B773
OEW -10%	10	35	-74	-45	55	-11	-8	-1	0
OEW -5%	2	28	-49	-29	33	-3	-6	2	1
Reference	-	-	-	-	-	-	-	-	-
OEW +5%	4	7	-4	10	-43	39	20	12	7
OEW +10%	-2	13	-23	2	-58	53	28	14	5
OEW +15%	11	28	-19	29	-71	52	26	16	7

Comparing the situation for the base year 2018 with the forecast for 2032, which is shown in table 8, shows interesting results. When the weight of PrandtlPlane decreases, little market is share is to be gained amongst narrowbody aircraft. This is due to the fact that the narrowbody market is already dominated by the PrandtlPlane due to the larger passenger numbers in the network. In the widebody segment the trend that the lighter PrandtlPlane with slight increases in range makes more destinations within reach sees it replacing most dominantly the Boeing 767-400 in the network. Furthermore, the Airbus A380 starts to become more interesting to utilise next to the PrandtlPlane due to its smaller size compared to the Boeing 767-400 it replaces. When the PrandtlPlane increases in weight and becomes less attractive compared to its reference design the effects are different in 2032 compared to 2018. Whereas in 2018 the PrandtlPlane was replaced by Boeing 767 series aircraft and Embraer E1952E2 jets on short-range routes it is now replaced with the combination of Boeing 767 series aircraft and larger A321neo jets to fit the increased network demand. Tighter aircraft operational constraints limit the total number of additional flights, which results in reduced operation for smaller aircraft such as the Embraer E195E2 and Airbus A320 in favour of the A321neo. When investigating the widebody market, a significant increase can be seen in operation for the Airbus A380 which is now commonly paired together with the Boeing 767 series family on long-range routes where demand has strongly increased. A further interesting observation to note in this case is that in some cases the Airbus A321neo is also used as a long-range aircraft in conjunction with either the Boeing 767 series or the Airbus A380 dependent on the level of demand for specific routes, which contributes to the strong increase of the Airbus A321neo aircraft in this scenario. Together with potential widespread utilisation of the -LR and -XLR variants of the A321neo, which have not been included in the model but are specifically targeting the longer-range market segment, this poses a significant threat to the utilisation of the PrandtlPlane.

Table 8 Top three flight number changes per aircraft under changing PrandtlPlane OEW - 2032, €0 Slot Cost

	Narrowbody Aircraft				PrandtlPlane	Widebody Aircraft			
Design Scenario	A320	E295	A21N	**All**		**All**	B764	A388	B763
OEW -10%	-1	9	-8	7	23	-26	-27	6	-3
OEW -5%	-1	1	-2	3	13	-15	-11	2	-4
Reference	-	-	-	-	-	-	-	-	-
OEW +5%	-15	-6	28	-2	-45	44	14	18	2
OEW +10%	-10	-5	40	27	-88	62	37	16	4
OEW +15%	-13	-22	88	64	-110	14	13	22	7

The second case study analysed the utilisation characteristics and impact of the PrandtlPlane on the flow-preserved network with all flights arriving at or departing from Amsterdam Airport Schiphol (AMS). Due to network interaction effects determining the exact impact of the PrandtlPlane on general network characteristics such as flight movements or passengers spilled proved to be challenging although the differences, if present at all, are minor. With the introduction of network flow and operational constraints the network market share of the PrandtlPlane caps at 55% compared to the rather unrealistically high 85% in the unconstrained global scenario. In a network setting the PrandtlPlane does not only show good capabilities on short-range, high-demand routes but also on the edges of its current design range. A sensitivity analysis with respect to competing aircraft has shown that sufficient potential is present for a long-range version of the aircraft which could take market share of the current Boeing 767 fleet, further reinforcing its position as a "middle of the market" aircraft.

VI. Discussion and Recommendations

Even though the two scenarios presented in this paper provide give broad and complete indication of the operational role and market potential of the PrandtlPlane, several important remarks have to be kept in mind when interpreting these results. In order to make accurate trade-offs between different aircraft types on different routes it is required that these aircraft are modelled as accurate as possible. Even though the methodology provided in this paper provides a good starting point to do so with minimal input data, aircraft performance in the model is calibrated by making use of a single reference mission. The significant resources dedicated to making this information as accurate as possible such as cross-checking with multiple sources, cross-checking with other aircraft in the model and expert consultation does not fully eliminate the possibility that aircraft performance may be different in reality and dependent on the exact seat configuration of the aircraft. This is a direct result of the used methodology which only allowed basic aircraft performance data to be used but nonetheless something to keep in mind when interpreting these results. For example, the high utilisation rate of the Airbus A380 on short-range routes under high passenger demand scenarios is not considered to be a realistic outcome of the model compared to real world observations considering that multiple airlines have opted phase out this aircraft from their fleets due to falling passenger demand and corresponding relief of capacity-constrained airports. This would entail that the need for efficient large-scale, short-range passenger transport aircraft is larger than currently modelled which can result in further operational possibilities for the PrandtlPlane.

Similar reservations can be made with respect to the growth forecasts for passenger traffic. Considering the fact that the required analysis years of 2032 and 2050 lie multiple decades into the future compared to the reference traffic numbers there is a real risk that these forecasts end up being inaccurate. The recent developments regarding the SARS-CoV-2 virus outbreak have hammered the aviation industry and will inevitably have a significant on future air travel which will require the forecasts to be adjusted and the model to be updated accordingly when more data becomes available. A further limitation with respect to passenger behaviour is the fact that the passenger data does not take into account passenger itineraries but instead gives a total seat demand per route. This entails that it is not possible for the model to directly take into account transit passengers which could significantly enhance model realism especially in a network context. Combining passenger itinerary data with booking data such as ticket price could also make the decision of which passenger to spill more accurate rather than through the currently implemented range-dependent cost to spill.

Whereas the scenarios in this paper described a global case study without preservation of aircraft flow and a local case study with preservation of aircraft flow, the role of airlines in the network has been omitted from analysis. Considering that these airlines actually have to operate the aircraft and that their networks may vary from airline to airline, this is a further limitation of this research. A recommendation would hence be to evaluate the presented model with the (forecasted) network specific to one airline. This way a more accurate assessment can be made with respect to how aircraft fit in the operating schedule of an airline which is a significantly different point of view. This airline-specific case could be extended further by limiting the total number of available aircraft for the model to assign in line with the current available fleet of the airline. Further potential is present when pairing network demand forecasting with a modelling extension which could make it possible to acquire new aircraft or sell existing aircraft. This way the model can be adapted to a data-driven aircraft acquisition and disposal framework which indicates which aircraft the airline should buy or sell under developing passenger demand.

The final limitation to this research and a good area for future recommendation would be to implement additional constraints to improve the connection between the model and operational reality. Think about constraints which provide limits on hourly passenger flows at airports which may become problematic when air traffic demand increases significantly. Going back to the utilised aircraft in the model, a further constraint can be added to evaluate whether a certain aircraft type is actually allowed to operate at specific airport. Constraints on the available runway length for take-off and landing or compliance with the maximum wingspan classification of the airport could enhance operational accuracy. Last but not least, there is currently no constraint implemented which limits the number of aircraft per type which can be allocated to flights. Several aircraft used in the model have only recently entered production and for some types the number of aircraft used in the model are not available on the present market. This research had initially aimed to tackle this issue as well by implementing a fleet ratio constraint which first determines the current market share of a specific aircraft type and subsequently enforcing lower and upper bounds to this market share. A significant downside to this method was that for future years these market share ratios would have to be adjusted based aircraft sales and disposal figures which added significant noise to the model. For this reason this constraint was not included in the current modelling framework but for future research this is definitely something which could still be incorporated.

VII. Conclusion

This paper addressed and tackled the problem of determining the market potential and operational strengths and weaknesses of novel aircraft in the conceptual design phase with limited performance data. The research provides one of the first academic aircraft market assessment models for forecasting future demand for novel aircraft concepts under development. A modelling framework was constructed which allow novel aircraft designs to compete with currently operational aircraft on the market. The results provide information on the main areas of opportunity and most significant threats for the concept as demonstrated by two operational case studies.

The first case study, which considered the global air traffic network without taking into account network effects or airport operational constraints, demonstrated strong market demand for the aircraft especially on short-range, high-demand routes in Asia. On these routes the aircraft can take significant market share from other, recently developed A321neo and Embraer E195E2 aircraft which become too small for operation when passenger demand increases significantly. However, when fixed costs per flight start to increase as well, market share is lost to the even larger Airbus A380 aircraft. Under this scenario market potential for the PrandtlPlane shifts from Asia to the United States and Europe where a strong presence can be established on medium-range, medium-demand routes and market share is taken from widebody Boeing 767 family jets. Introduction of the aircraft in the network resulted in a lower number of spilled passengers with the same number of flights or vice versa and sensitivity of the current design with respect to adverse weight changes is moderate with most losses in the medium-range market segment to the Boeing 767 family aircraft.

The second, smaller case study on all flights connecting through Amsterdam Airport Schiphol with network and airport operational constraints in place showed that the introduction of the PrandtlPlane results in less spilled passengers at the cost of a slight increase in flights which is eventually bounded by airport capacity. For all fixed cost scenarios, PrandtlPlane market share is projected to increase from baseline 2018 network demand figures until the year 2032. This growth is primarily driven by market share taken from A321neo and E195E2 aircraft which become too small with increasing demand on short-range routes. However, with further increasing network demand up to 2050, PrandtlPlane market share drops to below 2018 levels due to Airbus A380 competition and the PrandtlPlane again shifts operation to medium-range, medium-demand routes. Network fuel efficiency increases up to 8% dependent on PrandtlPlane market share. The sensitivity analysis with respect to design weight has shown that operating weight decreases of the aircraft result in significant opportunities on the widebody market as multiple popular long-range routes such as Amsterdam to New York or Dubai can now be flown without empty seats to carry extra fuel. This provides strong evidence that a possible long-range version of the PrandtlPlane could be considered to further enhance long-range operational strengths in addition to the aircrafts already strong short-range operational strengths in light of increasing passenger demand for the foreseeable future.

Summarising, from a network perspective the PrandtlPlane has more than sufficient potential to be a successful aircraft and poses a significant threat to currently available aircraft types in both the narrowbody as well as the widebody segments. Potential caveats for the concept are potential issues with integrating the aircraft in airline fleets. In this field the lack of maintenance similarity with existing jets in service and the potential need for separate pilot training may adversely affect the jets operational potential. Future work in this field could be centered around model improvements with respect to inclusion of passenger itineraries or aircraft market availability. Alternatively, the model could also be rapidly adjusted as a fleet development decision framework when the optimum fleet composition is not independent for subsequent analysis years.

Appendix

Table 9 Global annual passenger demand growth rates per continent and sub-region IATA (2018)

Continent	Sub-Region	Growth Rate
Africa	North-Africa	4.60%
	Sub-Saharan Africa	4.60%
America	Latin America	2.40%
	North-America	2.40%
Asia	Central Asia	4.80%
	Eastern Asia	4.80%
	South-Eastern Asia	4.80%
	Southern Asia	4.80%
	Western Asia	4.80%
Europe	Eastern Europe	2.00%
	Northern Europe	2.00%
	Southern Europe	2.00%
	Western Europe	2.00%
Oceania	Australia & New Zealand	2.40%
	Malenesia	3.50%
	Micronesia	3.50%
	Polynesia	3.50%

Table 10 Included competitor aircraft by ICAO classification code

Modelled Reference Aircraft by ICAO code [1]								
E170	E175	E275	E190	E290	E195	E295	BCS1	BCS3
B736	B737	B738	B739	B37M	B38M	B39M	B3XM	A318
A319	A320	A321	A19N	A20N	A21N	B762	B762ER	B763
B763ER	B764	B788	B789	B78X	A332	A333	A338	A339
B772	B77L	B77ER	B773	B77W	B779	A359	A35K	A388

[1] B762ER, B763ER and B77ER are not official ICAO codes but included for differentiation

Table 11 Input performance data of selected aircraft in the model

	MTOW [kg x 10^3]	OEW [kg x 10^3]	Speed [km/h]	TPR [km]	Seats@TPR [-]	C [-]	Model Seats	Price [€ x 10^6]
E295	61.5	35.7	750	4800	120	23898	120	66.4
A21N	97.0	50.1	800	7400	206	27120	200	129.5
PrandtlPlane	117.9	65.5	850	4382	308	27282	280	175.0
B763	158.8	86.1	850	7200	261	24438	290	200.0
B764	204.1	103.9	850	10415	296	27503	325	240.0
A388	575.0	277.0	850	14800	575	29753	575	445.6

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II

Extensions to Thesis Paper

1

Elaboration on Methodology

This section aims to provide further background to the methodology of this thesis in addition to the information provided in the research paper included in this document. Three different fields will be briefly touched upon. First, section 1.1 will provide a flow chart of the full model which gives an overview of the different subsections of code and their integration into the full model used for the results generation. Next, section 1.2 will provide an example case which further explains the distinction been fixed and flexible passenger demand and how these demand figures were calculated for all routes in the network and analysis years. Last, section 1.3 will provide a complete overview of all aircraft parameters which were used as input data in order to improve the reproducibility of the model and results.

1.1. Model Flowchart

The constructed model for this thesis comprises of different modules of code and datasets which need to be integrated in order to obtain the required results for this research. Figure 1.1 provides a graphical overview of how all different parts of the model are intertwined. In this figure, circles indicate either input or output files and squares indicate Python programming modules.

Two key datasets serve as a starting point for the modelling framework: the dataset containing all relevant information on the network which is to be analysed and a dataset which contains the required input data to model all aircraft included in the model. These two datasets require prepossessing before they can be used. The network demand modelling module calculates future demand based on the information from the base dataset, which dates back to 2018, and also dissects the total passenger demand into fixed and flexible passenger demand based on the departure hour of the flight. This will be further elaborated on by and example in section 1.2. The relevant input data to model all aircraft in the model needs to be prepossessed as well. This module, the aircraft fleet modelling module, calculates the key aircraft performance parameter *C* and also contains all equations required to calculate the fuel quantity for all possible mission combinations and other cost parameters highlighted in the paper.

These two modules provide key information for the fleet allocation problem module which is forms the central module of this research. It first creates all variables and objective function of the ILP-problems to formulate an unconstrained problem and splits the network into different sub-networks if possible. Next, the constraint modelling module adds all required constraints to the model which can either be turned on or turned off with an easy toggle. Toggling the constraints allows for swift switching between the global, relaxed problem formulation and the Amsterdam-hub, flow-constrained problem formulation which improves model utilisation. After the problem including constraints has been formulated, this module outputs a CPLEX LP-file, which contains all problem information in a format compliant with the solver. These files are subsequently moved to the dual AMD EPYC 7551 server for solving.

With the problem file now present on the server the solver can be called to the problem. This is done by means of the LP-problem solving module. The module contains all information to solve the problem and reads the LP-problem file, subsequently sets all solver settings and in some cases loops to solve multiple problems in a subsequent manner. Key solver settings used are the ability to either limit or increase the total number of available threads which CPLEX can use to solve the problem or a limitation of the total runtime for the problem if an intermediate analysis after a set time is required. The ability of the module to complete subsequent optimisation runs without manual intervention allowed for overnight runs to take place which further reduced computational efforts. Output of this module are CPLEX solution files which contain all information on the values of the decision variables such as the number of passengers, acquired aircraft and flights.

The CPLEX solution files do not provide the solutions in a clear-cut manner but still require further postprocessing. This is solved by means of the postprocessing module which processes the solution file and outputs key performance indicators which are required for providing solutions to the research questions such as the number of aircraft of each type, total network fuel consumption, total passengers transported and more. Furthermore, this module also merges the results of all potential sub-networks into one master file to provide a complete network overview. The results, which are provided in a Microsoft Excel file format, are subsequently graphed or tabulated and last but not least, shown in the paper or this overarching document.

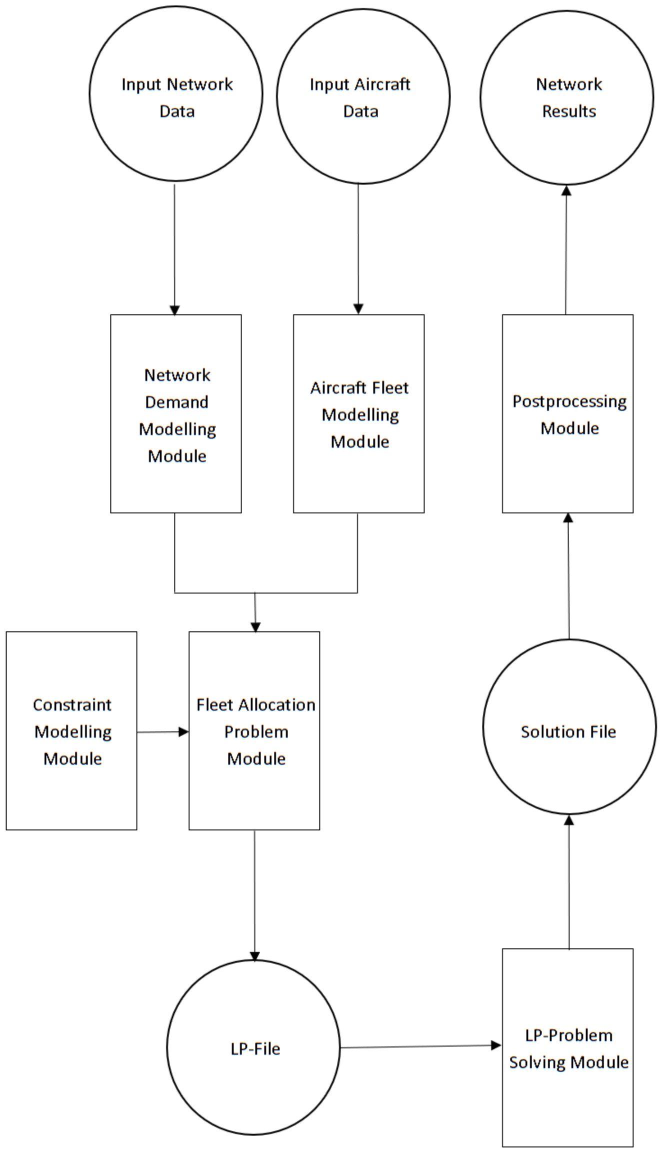

Figure 1.1: Model flow chart linking input/output datasets (circles) to Python modules (squares)

1.2. Passenger Demand Forecasting

The passenger demand forecasting module forms an essential part of the network as it established the total network demand to which the aircraft are subsequently allocated. This subsection aims to provide a brief example of the functioning of the demand forecasting module and the distinction between fixed and flexible passenger demand as explained in the paper. Table 1.1 does exactly that for all five flights between Amsterdam (AMS) and New York (JFK). For each flight, the total offered seats column of the OAG dataset serves as a starting point for passenger demand. For the analysis year 2018 no growth rates will be applied. For all subsequent analysis years the base passenger demand per flight will be multiplied with the average passenger demand growth rate value for the regions Europe and North America as provided by IATA (2018). After this has been completed, the distinction between fixed and flexible demand passengers is made. Based on the local departure time of each flight the percentages for fixed and flexible demand passengers are looked up. These rates are subsequently applied to the total passenger demand which results in a number of passengers who are only willing to travel on that specific flight plus a number of passengers who can be reallocated on other flights on the same day as well. In the case that the number of passenger is not an integer, the number is rounded to the nearest integer. For values ending with 0.5 passengers, the number is always rounded up. For all routes in the network, the total number of flexible demand passengers is summed over all flights on that route which results in a pool of flexible demand passengers.

Table 1.1: Passenger demand computations for the route AMS - JFK

Flight Number	Origin	Destination	Offered Seats	Departure Time	Fixed Demand %	Flexible Demand %	Fixed Demand Seats	Flexible Demand Seats
XX 02440	AMS	JFK	246	09:00	75	25	185	62
XX 02441	AMS	JFK	293	10:00	50	50	147	147
XX 02442	AMS	JFK	320	14:00	25	75	80	240
XX 02443	AMS	JFK	344	15:00	50	50	172	172
XX 02444	AMS	JFK	294	17:00	75	25	221	74
							Total Flexible Demand Seats	**695**

This pool of flexible demand passengers provides the model with a wide variety of options. For example, the model can decide to spill these flexible demand passengers if it is not economically efficient to do so. Alternatively, the model can easily allocate some flexible demand passengers onto a flight with excess seat capacity due to the total number of fixed demand passengers on that route being too small to achieve a 100% load factor for that flight. The model can also decide to utilise a larger aircraft than strictly required for the fixed demand passengers such that a significant number of flexible demand passengers can join as well. A last observed finding in the results is that, due to the sometimes unconstrained number of flights, dedicated flexible demand passenger flights are introduced. These flights almost always operate at a load factor of 100% which significantly increases network efficiency. All in all, the introduction of fixed and flexible demand passengers in the model allow for a variety of network effects to be taken into account which should enhance model accuracy.

1.3. Modelled Aircraft Input Data

As has been highlighted in the paper multiple times, the input data for all modelled aircraft are a key driver for aircraft competitiveness. For accurate modelling purposes it is hence required that these aircraft are represented as fair as possible with respect to their strengths and weaknesses. Table 1.2 provides a complete overview of all input parameters for all 46 aircraft which are modelled in the case studies, including the novel PrandtlPlane.

The values in this table have been gathered from a wide variety of sources. For some aircraft contradictory information was present which made the data gathering exercise even more difficult. Several strategies have been adopted in order to make this information as accurate as possible in which cross checking multiple sources and expert consultation are the most important ones. Furthermore, an independent analysis was conducted which aimed to model the optimal aircraft for specific combinations of passengers and flights to assess whether the input data result in an allocation of aircraft which is in line with operational reality. These results will be further discussed in section 3.2. Even though significant care has been taken to ensure that this information is as accurate as possible and that this issue is a direct result of the adopted methodology which allowed limited aircraft design data as input, it does not fully eliminate potential errors but significantly suppresses their impact on overall model performance.

Table 1.2: Input performance data of all aircraft types included in the model by ICAO code

Aircraft Type	MTOW [kg x 10^3]	OEW [kg x 10^3]	Speed [km/h]	TPR [km]	Seats@TPR [-]	C [-]	Model Seats	Price [€ x 10^6]
E170	38.6	21.1	750	3982	66	16234	66	41.0
E175	40.4	21.9	750	4074	76	17275	76	45.7
E275	44.8	27.0	750	3735	80	20553	80	51.5
E190	51.8	27.8	750	4537	96	18102	96	51.0
E290	56.4	33.0	750	5280	96	23480	96	59.0
E195	52.3	28.7	750	4260	100	18534	100	53.5
E295	61.5	35.7	750	4800	120	23898	120	66.4
BCS1	63.0	35.2	750	6300	116	25400	116	81.0
BCS3	69.9	37.1	750	6200	141	23931	141	91.5
B736	65.5	36.4	800	5991	110	22578	108	84.6
B737	70.1	37.6	800	5570	126	20618	128	89.1
B738	79.0	41.4	800	5436	162	21240	160	106.1
B739	85.1	44.7	800	5460	178	21780	177	112.6
B37M	80.3	35.0	800	7130	126	16233	140	99.7
B38M	83.2	45.1	800	6570	162	25551	160	121.6
B39M	88.3	44.4	800	6570	177	22233	177	128.9
B3XM	89.8	48.0	800	6110	187	24671	187	134.9
A318	68.0	39.5	800	5741	107	23284	107	77.4
A319	75.5	40.8	800	6945	124	23549	124	92.3
A320	79.0	45.1	800	4403	186	25972	165	110.6
A321	93.5	48.5	800	5926	185	21606	185	118.3
A19N	75.5	42.6	800	6950	140	28363	130	101.5
A20N	85.6	45.1	800	6500	165	23576	160	110.6
A21N	97.0	50.1	800	7400	206	27120	200	129.5
PrandtlPlane	117.9	65.5	850	4382	308	27282	280	175.0
B762	142.9	80.1	850	7200	214	24909	214	170.0
B762ER	179.2	82.4	850	12200	214	24755	214	190.0
B763	158.8	86.1	850	7200	261	24438	290	200.0
B763ER	186.9	90.0	850	11070	261	25953	261	200.0
B764	204.1	103.9	850	10415	296	27503	325	240.0
B788	227.9	120.0	850	13620	242	32564	242	248.3
B789	254.0	128.9	850	14140	290	32405	290	292.5
B78X	254.0	135.5	850	11910	330	32086	330	338.4
A332	242.0	120.6	850	13450	246	28931	246	238.5
A333	242.0	129.4	850	11750	300	31208	300	264.2
A338	251.0	132.0	850	15094	257	35245	257	259.9
A339	251.0	137.0	850	13334	287	35165	287	296.4
B772	247.2	135.9	850	9700	313	28137	313	306.6
B77L	347.4	145.2	850	15843	317	25455	317	346.9
B77ER	297.6	138.1	850	13080	313	25594	313	306.6
B773	299.4	160.5	850	11165	396	30873	396	335.5
B77W	351.5	167.8	850	13649	396	28345	396	375.5
B779	351.5	181.4	850	13940	414	33346	414	442.5
A359	280.0	142.4	850	15000	315	34147	315	317.7
A35K	316.0	155.0	850	16100	369	34764	369	366.5
A388	575.0	277.0	850	14800	575	29753	575	445.6

2
Elaboration on Results

This section provides further insight into the results of the two case studies which were discussed in brief in the academic paper. This section is subdivided into two different subsections. First, section 2.1 will provide additional results to the first case study presented in the paper which considered the global analysis framework. Next, section 2.2 will do the same but then for the smaller case study at Amsterdam airport with the aircraft flow constraint active.

2.1. Case 1: Global Analysis

The global analysis framework involved a lot of additional data which was omitted in the paper due to conciseness. This further section elaborates by discussing four different aspects of the model in further detail. First, subsection 2.1.1 will further visualise the decisions of the model with respect to spilling either fixed demand passengers of flexible demand passengers. Second, subsection 2.1.2 provides additional information on the network utilisation of the PrandtlPlane by extending the list of most operated routes and airports from the report. Third, subsection 2.1.3 provides additional insight into the market share of the PrandtlPlane and developments in market share of competing aircraft. Fourth and last, subsection 2.1.4 will aim to highlight the operational characteristics of the PrandtlPlane by comparing the passenger composition on board of this aircraft compared to that of the network average.

2.1.1. Passenger Information

Whereas the attached academic paper only provided information on the total number of passengers and passenger kilometers which were spilled similar information is also present on the distinction between fixed demand and flexible demand passengers. Figure 2.1 and figure 2.2 provide information on the number of fixed and flexible passenger kilometers spilled respectively. Looking at the total fixed passenger kilometers spilled, figure 2.1, a clear trend shows. With increasing slot costs and decreasing passenger demand, the percentage of spilled fixed demand passenger kilometers increases. Especially the latter statement seems to be an interesting conclusion, as relatively less fixed demand passenger kilometers are spilled in the larger 2050 network scenario compared to the baseline 2018 case. This can readily be attributed to the increasing market share of the Airbus A380 in these scenario's which scales up network seat availability significantly. In all cases the introduction of the PrandtlPlane to the network reduces the total number of spilled passenger kilometers and this effect becomes stronger with increased slot costs, although overall the effect is not that large.

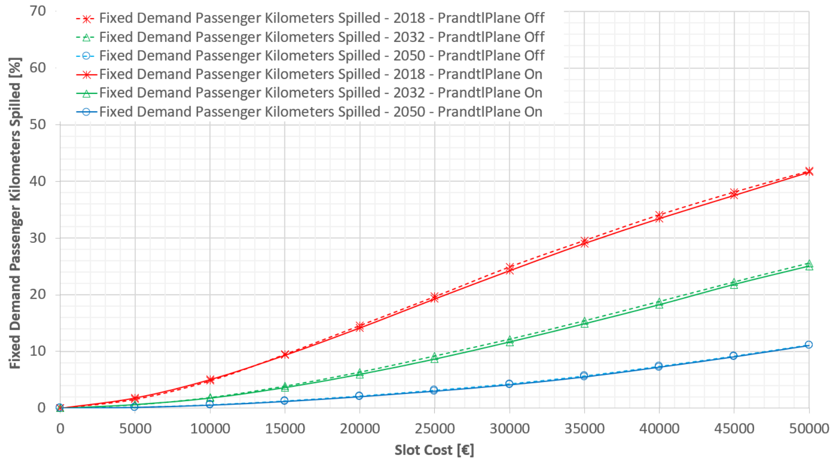

Figure 2.1: Fixed Demand Passenger Kilometers Spilled in the global scenario

The flexible passenger kilometer spillage curves presented in figure 2.2 show interesting patterns. First of all, the reduction of spilled flexible passenger kilometers by introduction of the Prandtlplane seems to be larger with lower slot costs. The exact opposite was found for fixed demand passenger kilometers in the previous paragraph. Furthermore, the percentage of spilled flexible demand passenger kilometers increases with a larger network which is also opposite to the behaviour of flexible passenger demand kilometers. This effect however decreases with increasing slot costs compared to an increased effect observed for spilled fixed passenger kilometers. This shows that the differences between fixed and flexible demand passengers in both spill cost and allocation flexibility is something the model actively makes use of.

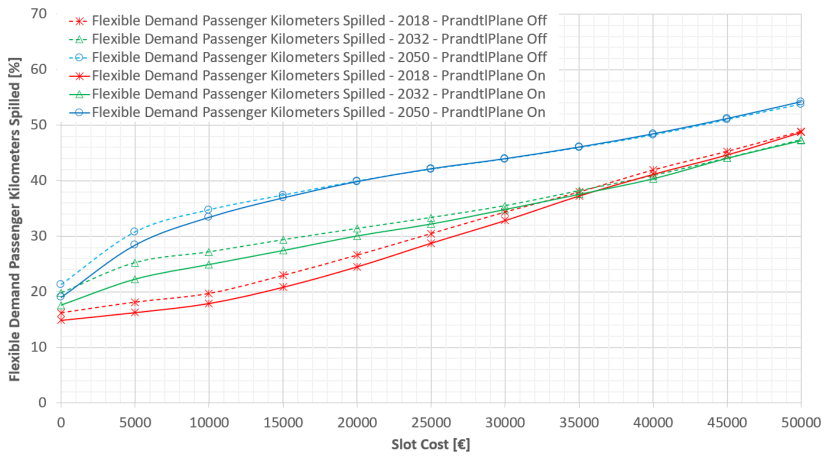

Figure 2.2: Flexible Demand Passenger Kilometers Spilled in the Global Scenario

2.1.2. Network Information

In addition to the limited utilisation characteristics presented in the technical paper, the following three tables 2.1, 2.2 and 2.3 provide an extensive overview of the routes in the network which see the most operations of the PrandtlPlane. These tables further highlight the conclusions from the research paper which entailed that increasing PrandtlPlane utilisation can be observed with higher levels of demand, but decreasing PrandtlPlane utilisation is observed with higher levels of slot cost. Increasing slot costs causes the average operational range of the PrandtlPlane to increase.

Table 2.1: Most popular daily PrandtlPlane routes - €0 Slot Cost

2018				2032				2050			
Route		Flights	Distance	Route		Flights	Distance	Route		Flights	Distance
GMP	CJU	146	451 km	GMP	CJU	282	451 km	GMP	CJU	656	451 km
CTS	HND	125	820 km	CTS	HND	140	820 km	CTS	HND	561	820 km
FUK	HND	95	881 km	FUK	HND	183	881 km	FUK	HND	430	881 km
BOM	DEL	84	1138 km	BOM	DEL	163	1138 km	BOM	DEL	381	1138 km
LAS	LAX	75	380 km	CGK	DPS	136	983 km	CGK	DPS	317	983 km
CGK	DPS	69	983 km	HND	ITM	106	405 km	HND	ITM	246	405 km
OKA	HND	59	1554 km	OKA	HND	105	1554 km	OKA	HND	235	1154 km
BOG	MDE	56	215 km	LAS	LAX	104	380 km	BLR	DEL	233	1703 km
HND	ITM	54	405 km	JNB	CPT	102	1271 km	JNB	CPT	230	1271 km
CUN	MEX	54	1286 km	BLR	DEL	100	1703 km	DAD	HAN	224	3806 km

Table 2.2: Most popular daily PrandtlPlane routes - €25000 Slot Cost

2018				2032				2050			
Route		Flights	Distance	Route		Flights	Distance	Route		Flights	Distance
BWI	DEN	23	2399 km	DFW	LGA	23	2235 km	BNA	LAX	20	2893 km
LAX	JFK	23	3983 km	BNA	LAX	23	2893 km	MSP	IAH	18	1664 km
MCO	MDW	22	1593 km	ORD	MIA	22	1926 km	MKE	MCO	18	1716 km
BKI	KUL	22	1630 km	PHX	PHL	22	3340 km	LAS	HOU	18	1988 km
ORD	PHX	22	2317 km	PHX	CLT	21	2854 km	EWR	LAX	18	3950 km
PHX	MDW	22	2324 km	BNA	DEN	20	1631 km	LAX	MSY	17	2688 km
MDW	DEN	21	1441 km	LAX	DFW	20	1987 km	MDW	LAX	17	2817 km
EWR	FLL	21	1713 km	EWR	DFW	20	2208 km	HOU	PHX	16	1641 km
ORD	LAX	21	2807 km	LAX	MSY	20	2688 km	IAH	LGA	16	2279 km
LAX	BOS	21	4202 km	HOU	PHX	19	1641 km	HOU	ATL	15	1120 km

Table 2.3: Most popular daily PrandtlPlane routes - €50000 Slot Cost

2018				2032				2050			
Route		Flights	Distance	Route		Flights	Distance	Route		Flights	Distance
ATL	LAX	16	3126 km	LAX	MDW	17	2812 km	BOS	PHX	14	3694 km
PHX	PHL	15	3333 km	BNA	LAX	15	2886 km	LAX	MDW	13	2812 km
LAX	EWR	15	3941 km	ATL	LAX	15	3126 km	BNA	LAX	13	2886 km
BOS	DEN	14	2816 km	PHX	PHL	15	3333 km	PHX	JFK	13	3458 km
BNA	LAX	14	2886 km	DFW	LGA	14	2231 km	LAX	FLL	13	3736 km
IAD	LAX	14	3682 km	LAX	MSY	13	2688 km	LAX	EWR	13	3950 km
LAX	JFK	14	3983 km	IAD	LAX	12	3682 km	IAH	LGA	12	2279 km
LAX	BOS	14	4202 km	LAX	PHL	12	3865 km	LAX	MSY	12	2688 km
BWI	PHX	13	3216 km	BOS	DFW	11	2513 km	LAX	BWI	12	3748 km
PHX	JFK	13	3465 km	ATL	LAS	11	2811 km	LAS	HOU	11	1988 km

Furthermore, tables 2.4, 2.5 and 2.6 show the airports in the global network with the most movements of the PrandtlPlane. In line with the report, higher passenger demand sees dominant PrandtlPlane utilisation in Asia, whereas increasing slot costs cause operation to shift to the United States. In the €50000 slot cost scenario, some of the well known middle-eastern hub airports such as DOH and DXB also start to become interesting which signals operational opportunities for the gulf carriers as well. These findings complement the role of the PrandtlPlane as a medium- to long range passenger transport aircraft as concluded in the report.

Table 2.4: Airports with most PrandtlPlane movements per day - €0 Slot Cost

2018			2032			2050		
Airport	Country	Movements	Airport	Country	Movements	Airport	Country	Movements
ATL	United States	1063	ATL	United States	1743	HND	Japan	3482
LAX	United States	905	HND	Japan	1476	DEL	India	3123
DEN	United States	848	LAX	United States	1403	ATL	United States	2931
PHX	United States	806	DEN	United States	1383	CGK	Indonesia	2827
HND	Japan	728	DEL	India	1312	PEK	China	2613
LAS	United States	710	PHX	United States	1285	BOM	India	2443
MCO	United States	668	CGK	Indonesia	1198	KUL	Malaysia	2408
DEL	India	609	LAS	United States	1106	DEN	United States	2309
CGK	Indonesia	588	MCO	United States	1090	LAX	United States	2251
ORD	United States	550	PEK	China	1067	BKK	Thailand	2235

Table 2.5: Airports with most PrandtlPlane movements per day - €25000 Slot Cost

2018			2032			2050		
Airport	**Country**	**Movements**	**Airport**	**Country**	**Movements**	**Airport**	**Country**	**Movements**
LAX	United States	501	LAX	United States	538	LAX	United States	430
DEN	United States	497	DFW	United States	515	DFW	United States	408
PHX	United States	455	DEN	United States	452	LAS	United States	367
MCO	United States	411	PHX	United States	449	IAH	United States	326
DFW	United States	390	MCO	United States	407	ATL	United States	317
ORD	United States	358	ORD	United States	384	MIA	United States	296
ATL	United States	339	ATL	United States	382	PHX	United States	283
LAS	United States	335	LAS	United States	363	BOS	United States	275
MSP	United States	289	FLL	United States	337	DEN	United States	266
FLL	United States	289	BOS	United States	331	MSP	United States	250

Table 2.6: Airports with Most PrandtlPlane Movements - €50000 Slot Cost

2018			2032			2050		
Airport	**Country**	**Movements**	**Airport**	**Country**	**Movements**	**Airport**	**Country**	**Movements**
LAX	United States	298	LAX	United States	306	LAX	United States	327
PHX	United States	170	PHX	United States	198	LAS	United States	210
JFK	United States	165	LAS	United States	156	PHX	United States	159
LAS	United States	133	JFK	United States	148	BOS	United States	135
DEN	United States	118	BOS	United States	142	MIA	United States	131
EWR	United States	117	DXB	UAE	141	ATL	United States	125
BOS	United States	116	ATL	United States	138	AMS	the Netherlands	112
ATL	United States	110	DFW	United States	136	EWR	United States	110
DOH	Qatar	110	EWR	United States	127	LIS	Portugal	104
BKK	Thailand	106	KUL	Malaysias	121	FLL	United States	101

2.1.3. Market Share Information

Other than the market share developments of the PrandtlPlane discussed in the paper, market share development curves of other aircraft in the model can also yield valuable information on the behaviour of the model. This section aims to describe such changes of market share for aircraft other than the PrandtlPlane and investigate the reasons for these changes. The first conclusion in the report was that on the short-haul market segment, the PrandtlPlane initially takes market share from the Airbus A321neo and the Embraer E195E2. Figure 2.3 shows the developments in network market share for this aircraft in the model. It can be swiftly observed that both an increase in slot costs as well as an increase in network size adversely impacts the market share of this aircraft. On smaller scale networks and small slot costs the PrandtlPlane takes most market share from this aircraft and, to a lesser extent, from the A321neo.

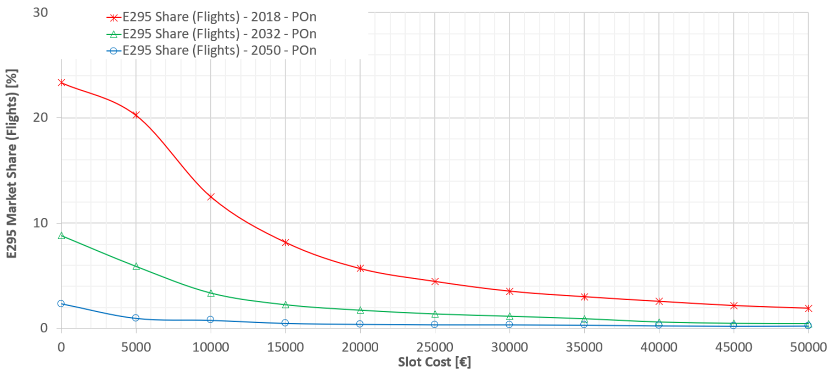

Figure 2.3: Market share developments of the Embraer E195E2 with PrandtlPlanes active

However, when network size significantly increases, the PrandtlPlane loses market share to the Airbus A380 also on short-haul routes. For this aircraft, the market share developments are shown in figure 2.4. The Airbus A380 only starts to be used in the model after a slot cost of €5000 euro, which is also the area where the PrandtlPlane starts to lose market share on the short-haul routes. As already discussed in the paper this behaviour is not necessarily very realistic, but it can very well be explained due to the extremely high passenger demand figures for the 2050 network scenario.

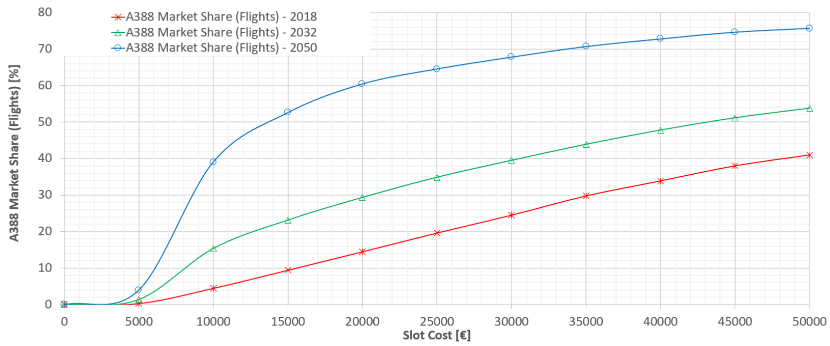

Figure 2.4: Market share developments of the Airbus A380 with PrandtlPlanes active

As the PrandtlPlane is a "middle of the market" aircraft, the aircraft also faces competition from widebody aircraft on medium- to long-haul routes. On this market segment, increasing slot costs cause the PrandtlPlane to lose market share to widebody aircraft such as the Boeing 767-400 and Boeing 777-300. For these two aircraft, the market share curves are shown in figures 2.5 and 2.6 respectively. Both figures show similar behaviour in that increasing model slot costs favourably affect market share percentages for both jets. As the Boeing 777-300 is a slightly larger aircraft, its point of maximum market share is achieved at a higher slot cost than for the smaller Boeing 767-400.

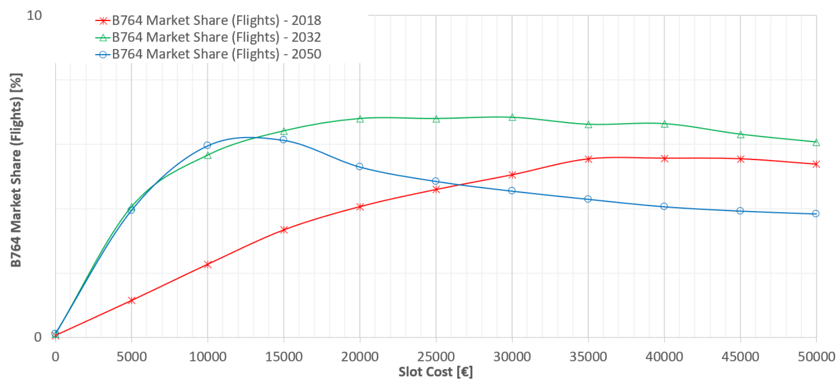

Figure 2.5: Market share developments of the Boeing 767-400 with PrandtlPlanes active

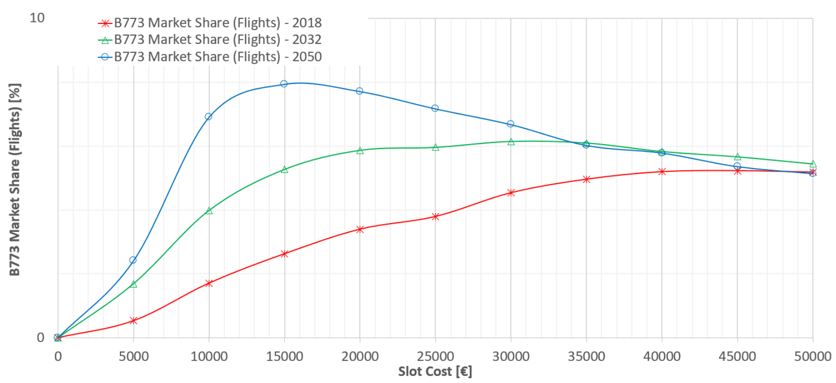

Figure 2.6: Market share developments of the Boeing 777-300 with PrandtlPlanes active

2.1.4. PrandtlPlane-Passenger Interaction

As the model assigns both fixed demand and flexible demand passengers to flights on the network, a further question which could be raised is whether there is a significant difference in the type of passenger on board of different aircraft. This has been analysed by taking the fixed demand passenger as a reference. First of all, the percentage of fixed passenger kilometers moved on all aircraft in the network has been calculated. Next, the same analysis has been done for fixed demand passenger kilometers transported only using PrandtlPlanes. Figure 2.7 subsequently shows the results of the comparison between the percentage of fixed demand passenger kilometers on PrandtlPlanes and the network average. For example, in 2018 and with €0 slot costs, the percentage of fixed demand passenger kilometers moved on PrandtlPlanes is 5.1% lower than the network average. This indicates that in this scenario, the PrandtlPlane is utilised for flexible demand passengers disproportionally. As can be observed, the proportion of flexible demand passengers on board of PrandtlPlanes eventually decreases to the point that the aircraft is dominantly used for fixed demand passengers in, for example, the 2050 scenario with a slot cost of €50000. This information could be interesting from an airline acquisition perspective. A legacy carrier may have a larger share of fixed demand ”business” passengers compared to flexible demand ”leisure” travellers and could hence prefer the PrandtlPlane under high demand, high slot cost scenarios. The exact opposite can be said or budget airlines, who may be more interested in the aircraft on lower density routes with lower slot costs. These conclusions however are preliminary and would require further investigation to be confirmed but do provide some additional insights into operational opportunities different types of airline.

	Difference in Share of Fixed Passenger Kilometers on PrandtlPlanes vs Network Average [%]		
Slot	2018	2032	2050
0	-5.1	-3.3	-2.7
5000	-5.5	-3.2	-2.6
10000	-6.1	-3.8	-1.9
15000	-5.2	-3.5	2.1
20000	-4.5	-3.0	3.3
25000	-3.4	-1.8	3.3
30000	-2.1	-0.5	4.1
35000	-0.4	0.7	4.7
40000	0.9	2.3	5.4
45000	2.3	4.0	6.2
50000	3.3	5.3	6.4

Figure 2.7: Fixed demand passenger kilometers transported on PrandtlPlanes compared to the network average

2.2. Case 2: Flights through Amsterdam Analysis

The second case in the report, which involved all flights in the dataset connecting through Amsterdam, also contains more information than could be presented in the report. This section is structured similarly to the first case study: First, subsection 2.2.1 provides additional passenger information, subsection 2.2.2 provides more operational info on the PrandtlPlane, subsection 2.2.3 looks at the market share of competing aircraft and interactions with the PrandtlPlane and last but not least, subsection 2.2.4 again investigates the passenger composition on board of the PrandtlPlane compared to the network average.

2.2.1. Passenger Information

In the report the conclusion was drawn that the total reduction in spilled passenger kilometers with the introduction of the PrandtlPlane to the market is small and more volatile compared to the global case study. This conclusion is reaffirmed by the fixed demand passenger kilometer spillage curves which are depicted in figure 2.8. Especially up to a point of approximately €15000 slot cost, the percentage of spilled fixed passenger kilometers remains constant until it starts to increase in line with the global observations afterwards. The most likely root cause for this behaviour is the spillage of short-range passengers in the network which have little impact on this parameter. After slot costs start to increase further, more and more medium- to long-range flights also start to be unattractive and the percentage of spilled fixed demand passenger kilometers starts to climb.

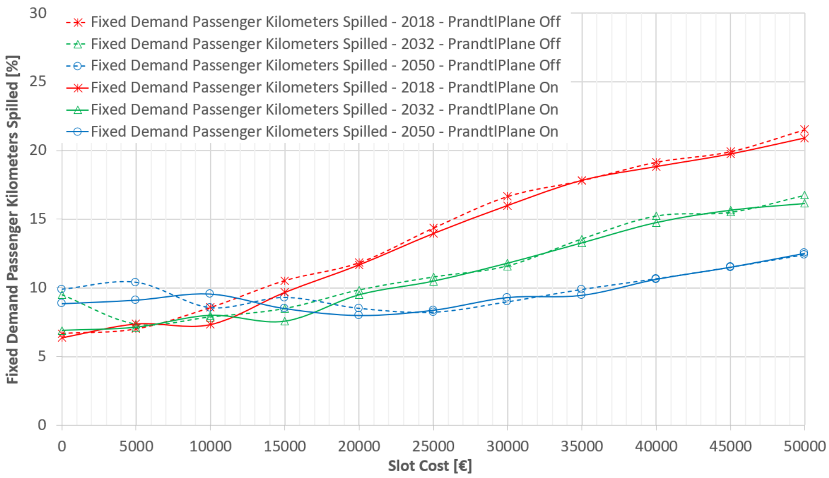

Figure 2.8: Fixed demand passenger kilometers spilled in the Amsterdam scenario

A second interesting observation on passenger behaviour in the Amsterdam scenario can be observed in figure 2.9. The figure shows that the percentage of spilled flexible demand passenger kilometers is nearly constant with slot costs, much on the contrary of the situation observed for the global analysis in figure 2.2. Even though the network flow effects make it challenging to point to an exact cause for this behaviour, a constant rate of spilled fixed demand passengers can most likely be attributed to recapture effects in the network. Increasing slot costs favour larger aircraft in the model. For example, a route which used to be operated with three medium-size aircraft with dominantly fixed demand passengers could now be more efficiently operated with two large-size aircraft in which the excess capacity is filled with flexible demand passengers.

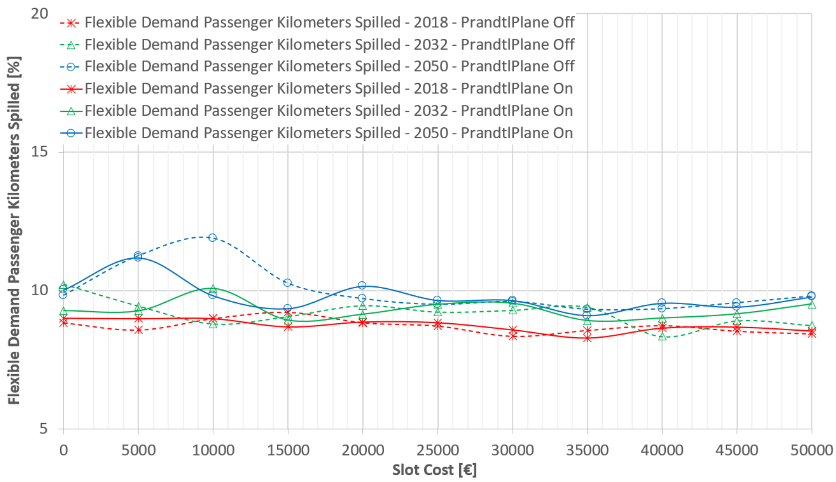

Figure 2.9: Flexible demand passenger kilometers spilled in the Amsterdam scenario

2.2.2. Network Information

Similar to the previously discussed case study, tables 2.7, 2.8 and 2.9 contain elaborate information on the routes the PrandtlPlane operates most often in the scenario with AMS airport as a hub. These tables provide additional routes of operation and reinforce the conclusions drawn earlier in this paper that with increasing slot costs and moderate demand growth, the main market focus of the PrandtlPlane should be in the medium-demand and medium- to long-range market segments. However, with very high passenger demand growth and in high slot cost scenarios, the market share of the PrandtlPlane decreases significantly and the total number of PrandtlPlane flights is reduced accordingly.

Table 2.7: Airports with Most PrandtlPlane Movements - €0 Slot Cost

2018				2032				2050			
Airport	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**
BCN	Spain	10	1241 km	DXB	UAE	18	5169 km	DXB	UAE	25	5169 km
CPH	Denmark	10	633 km	BCN	Spain	17	1241 km	DUB	Ireland	13	750 km
LIS	Portugal	10	1846 km	LIS	Portugal	14	1846 km	BCN	Spain	8	1241 km
CDG	France	9	398 km	JFK	USA	13	5847 km	AYT	Turkey	7	2655 km
DXB	UAE	9	5169 km	CPH	Denmark	12	633 km	LHR	England	7	370 km
FCO	Italy	9	1297 km	DUB	Ireland	10	753 km	IST	Turkey	7	2188 km
ARN	Sweden	8	1155 km	LHR	England	10	371 km	MXP	Italy	7	797 km
JFK	United States	8	5863 km	MUC	Germany	10	665 km	NCE	France	7	978 km
LHR	England	8	371 km	AGP	Spain	9	1883 km	ARN	Sweden	6	1155 km
MAD	Spain	8	1459 km	EDI	Scotland	9	668 km	BSL	Switzerland	6	561 km

Table 2.8: Airports with Most PrandtlPlane Movements - €25000 Slot Cost

2018				2032				2050			
Airport	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**	**Airport**	**Country**	**Flights**	**Distance**
LIS	Portugal	9	1847 km	DXB	UAE	12	5174 km	ALC	Spain	6	1613 km
BCN	Spain	7	1241 km	LIS	Portugal	10	1847 km	FCO	Italy	6	1297 km
JFK	United States	7	5863 km	AGP	Apain	9	1883 km	LIS	Portugal	6	1847 km
AGP	Spain	5	1883 km	BCN	Spain	7	1241 km	AGP	Spain	5	1883 km
IST	Turkey	5	2188 km	FCO	Italy	5	1297 km	BCN	Spain	5	1241 km
MAD	Spain	5	1459 km	AUH	UAE	4	5196 km	DXB	UAE	5	5174 km
ARN	Sweden	4	1155 km	BEG	Serbia	4	1413 km	MAD	Spain	5	1459 km
DXB	UAE	4	5174 km	FAO	Portugal	4	1970 km	ATH	Greece	4	2184 km
FAO	Portugal	4	1970 km	HER	Greece	4	2483 km	BJL	Gambia	4	4726 km
FCO	Italy	4	1297 km	MAD	Spain	4	1459 km	NCE	France	4	978 km

Table 2.9: Airports with Most PrandtlPlane Movements - €50000 Slot Cost

2018				2032				2050			
Airport	Country	Flights	Distance	Airport	Country	Flights	Distance	Airport	Country	Flights	Distance
JFK	USA	7	5847 km	LPA	Spain	3	3183 km	AES	Norway	2	1143 km
DXB	UAE	3	5169 km	TLV	Israel	3	3312 km	ATH	Greece	2	2182 km
IST	Turkey	3	2184 km	BOJ	Bulgaria	2	2012 km	BRI	Italy	2	1538 km
TLV	Israel	3	3312 km	CAI	Egypt	2	3287 km	DRS	Germany	2	633 km
ATH	Greece	2	2182 km	CHQ	Greece	2	2411 km	FAO	Portugal	2	1970 km
BOJ	Bulgaria	2	2016 km	FAO	Portugal	2	1970 km	LIS	Portugal	2	1847 km
DMM	Saudi-Arabia	2	4709 km	FNC	Portugal	2	2785 km	LOS	Nigeria	2	5072 km
EWR	United States	2	5884 km	HAJ	Germany	2	335 km	LUX	Luxemburg	2	315 km
FAO	Portugal	2	1970 km	HUY	England	2	372 km	MAD	Spain	2	1459 km
KRS	Norway	2	689 km	IBZ	Spain	2	1516 km	OLB	Italy	2	1319 km

2.2.3. Market Share Information

In conjunction with the results from the first case study, the market share of the PrandtlPlane initially slightly increases when slot costs increase simultaneously. The dominant driver for this increase in market share is the PrandtlPlane taking market share from the Airbus A321neo aircraft, for which the market share is depicted in figure 2.10. This effect is much stronger for the 2018 base case analysis as for increasing demand, the PrandtlPlane market share on the short-range market segment is already very strong. For increasing slot costs and increasing market demand, the market share of the A321neo decreases further.

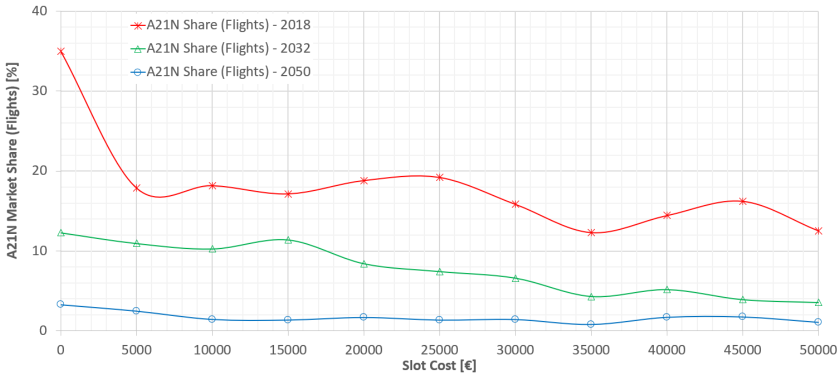

Figure 2.10: Market share developments of the Airbus A321neo with PrandtlPlanes active

Another observation from the network is that in the 2018, low slot cost scenarios the reduction of short-range market share for the A21N at the cost of more PrandtlPlanes also has a positive impact on the Embraer E195E2. This can be observed in figure 2.11 which shows that the market share of this aircraft peaks at slot costs between €5000 and €10000. Reason for this is that the combination of the larger PrandtlPlane and the smaller E195E2 are a more favourable pair for this level of demand and slot cost than utilising Airbus A321neo jets. However, when slot costs and market demand increase further, the utilisation of the Embraer E195E2 swiftly drops to near-zero levels.

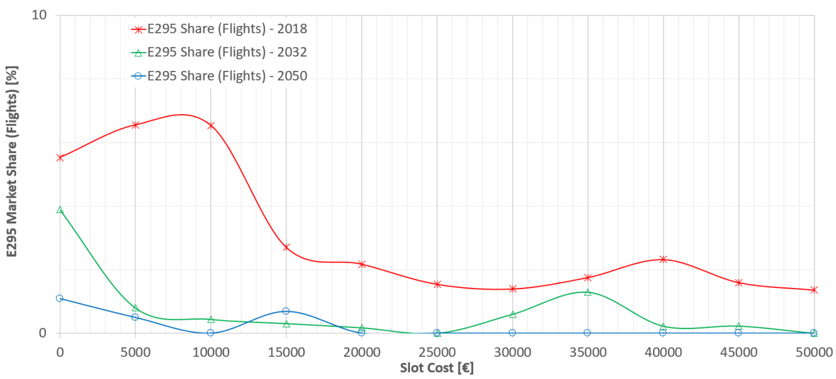

Figure 2.11: Market share developments of the Embraer E195E2 with PrandtlPlanes active

Just like in the worldwide analysis case, increasing slot costs and increasing market demand have a positive impact in the Airbus A380, for which the market share curves are depicted in figure 2.12 as mentioned the Airbus A380 becomes a strong contender to the PrandtlPlane on very high density, short range routes. Market share for this aircraft steadily increases along both axes of the figure. Next to becoming a threat in the short-range market, the A380 also sees increased utilisation on longer-range routes as well when network demand increases further.

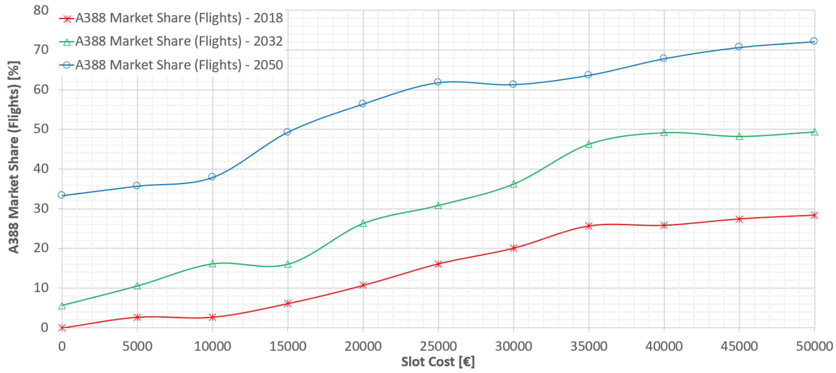

Figure 2.12: Market share developments of the Airbus A380 with PrandtlPlanes active

Another direct competitor to the PrandtlPlane is the Boeing 767-400. In low network demand scenarios with increased levels of slot cost, the larger Boeing 767-400 starts to increasingly threaten the market share of the PrandtlPlane in the long-range segment as can be observed in figure 2.13. However, when network demand starts to increase, the market share of the Boeing 767-400 decreases again as the jet is swapped with larger aircraft such as the Airbus A380 or the Boeing 777-300. For the latter aircraft, the market share is depicted in figure 2.14. In the long-range segment of the market the decrease in smaller Boeing 767-400 aircraft is most dominantly offset by increased utilisation of the Boeing 777-300 for higher market demand cases.

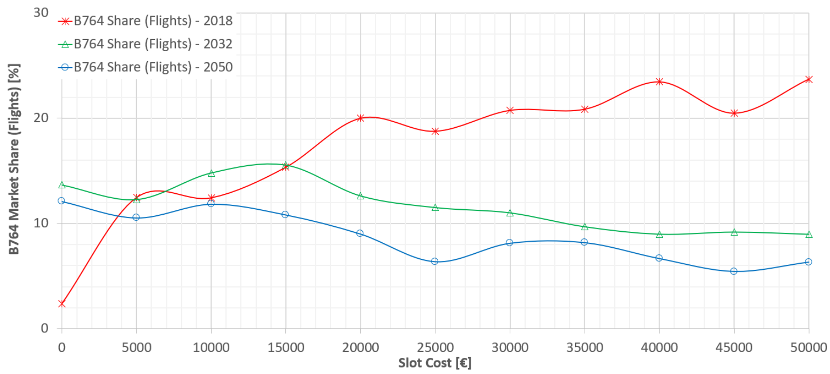

Figure 2.13: Market share developments of the Boeing 767-400 with PrandtlPlanes active

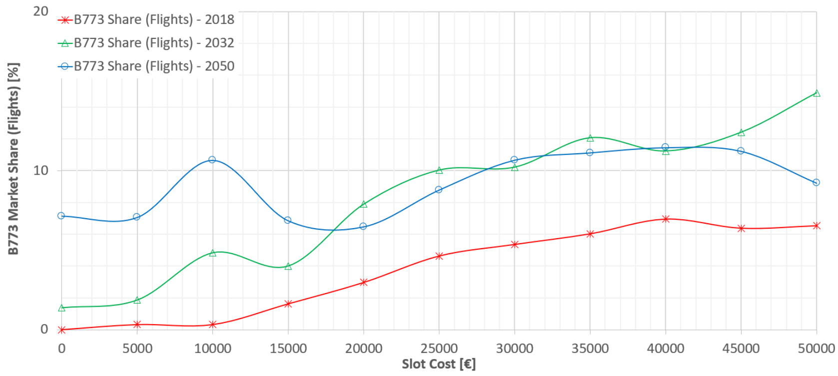

Figure 2.14: Market share developments of the Boeing 777-300 with PrandtlPlanes active

2.2.4. PrandtlPlane-Passenger Interaction

This section is concluded with an analysis into the type of passenger on the PrandtlPlane in a network context. The results in figure 2.15 show that for the low slot cost region of the graph, little is changed. Even in a network context the PrandtlPlane is utilised for flexible demand passengers disproportionately compared to all other aircraft in the network. However, when slot costs start to increase for all three scenario years, PrandtlPlane operations start to be centered around fixed demand passenger operations much more compared to the global case without network effects. In the most extreme scenario, the 2050 network with a slot cost of €50000, almost 75% of all passenger kilometers on the PrandtlPlane are fixed in demand compared to the network average of little over 44%. This large change can be attributed to the high prevalence of the Airbus A380 in the network on which flexible demand passengers are transported much more frequently. This provides some further indications that for legacy carriers the PrandtlPlane could be a feasible option for high-demand, high slot cost operations but, as indicated before, care is to be taken when interpreting these results and more research may be required to reach an adequate judgement.

	Difference in Share of Fixed Passenger Kilometers on PrandtlPlanes vs Network Average [%]		
Slot	2018	2032	2050
0	-4.6	-3.1	-1.0
5000	-4.5	-0.9	-1.7
10000	-4.2	0.6	0.1
15000	-2.0	1.2	8.3
20000	0.7	4.0	3.8
25000	3.4	9.2	19.3
30000	7.4	11.5	17.3
35000	7.8	13.0	24.9
40000	7.1	17.0	22.0
45000	11.4	12.3	19.3
50000	8.2	11.2	30.7

Figure 2.15: Fixed demand passenger kilometers transported on PrandtlPlanes compared to the network average

3
Verification and Validation

Throughout the development cycle of the model presented in this research, verification and validation exercises have played an essential role in order to ensure that the model works as expected and meets the desired requirements. This section aims to describe the need for these procedures and their outcomes in more detail starting with the verification steps in section 3.1 followed by the validation steps in section 3.2.

3.1. Model Verification

Model verification is centered around the key question whether the model in question is built in the right manner and does not contain any errors. Verification steps are hence taken in order to ensure that different segments of code as well as the implementation of these segments in the overarching framework does not lead to programming mistakes which may undermine integrity of the model.

The verification steps for this project follow the same reasoning, by first analysing all different segments of code individually for correctness and potential errors and subsequently verifying correct integration into the complete model. The two key input modules for this research, which are centered around future passenger demand forecasting and aircraft fuel calculations have been verified by performing manual computations independent of the *Python* framework in which the model was eventually coded. For the passenger forecast section, the model was rather straight-forward to verify as the model assumed a constant growth rate. Simple manual computations can hence be performed to check whether the model outputs the correct passenger numbers. Furthermore, the distinction between fixed and flexible passengers could be validated this way by also taking into account the departure time of the flight. With respect to the fuel calculations of all aircraft in the model, these equations have been verified as well by working out a number operational cases on paper and comparing outcomes with the results of the implemented code. After completion of the verification campaign for these two model sections no further anomalies have been found.

The second step involves the integration of these two domains into the larger fleet allocation problem framework. A first key step in the development of the model which highlights the prime importance of verification throughout this study is the clear labelling of all (decision) variables in the model. Even though it required some additional time to implement, the clear labelling of all variables in the model exponentially increased the efficiency of the complete verification campaign resulting in significant overall time saving. In the ILP-problem formulation the first step was to verify the successful creation of all decision variables in the model. This also included the inclusion or omission of the aircraft flow decision variables or omission of the PrandtlPlane decision variables when utilisation the aircraft is turned off. Both of these model flexibilities can be toggled with the press of a button. After this part of the model had been verified the creation of the constraints was started. All constraints have been added to the total modelling framework one-by-one after each individual constraint had been validated for correct functioning. It is in this field where the labelling of decision variables was key, as the LP-file created by the *CPLEX* optimiser allowed for easy manual verification of constraint functioning.

The final steps for verification of the complete model was performed by conducting multiple small-scale case studies. One of the easiest verification steps was named the so called ”baseline” test. It exploited one specific solution to the problem in which no aircraft are bought, no flights are operated and all passengers in the model are spilled. In this case, no aircraft acquisition costs or costs per flight would have to be paid and only the cost of spilling all passengers in the network have to be calculated. As it is rather straight-forward to calculate the total cost of spilling all passengers for the network under consideration this could easily be compared to the initial incumbent solution provided by the solver. If these two values match, it can at least be verified that a solution which is known to be valid in the modelling framework is also valid in the written computer code which contributes to increased confidence of a correct modelling implementation. The total package of all verification steps discussed in this section involving both individual model tests as well as complete model tests contribute to a strong confidence that the model does indeed function as intended in its formulation.

3.2. Model Validation

Model validation involves testing whether the developed model meets the desired outcomes of the project. As one of the key goals of this project is to construct a competitive environment in which all aircraft compete, modelling all aircraft such that their strengths and weaknesses are exposed is of prime importance. One aircraft which, for example, beats all other aircraft in every operation aspect will render the model useless for market assessment purposes. This section will hence highlight the key steps and checks which have been conducted to ensure that the aircraft modelling phase is accurate under the constraint that limited aircraft design data is used.

The first step to validate whether aircraft are modelled accurate is an analysis which determines the best aircraft for a combination of passengers and mission range. These results are shown in figure 3.1. This table hence provides an indication on the operational strengths and weaknesses of the modelled aircraft and shows some of the data on which the model bases its decision to pick an aircraft for a specific mission in the network. It is worth noting that the optimum aircraft for a mission in this table is chosen based on the constraints that only a single flight can be operated, no passengers can be spilled and that the slot cost per flight is €0. These constraints are not present in the model and may hence lead to differences in allocation. For example, the table shows that the optimum aircraft to transport 400 passengers over 4000 kilometer is the B779 whereas the model may actually prefer to operate two A21N aircraft as a cheaper alternative. Or, when 210 passengers have to be transported over the same distance, the table shows that the B762 is the selected aircraft of choice whereas the model may actually decide it is more efficient to use the A21N with 200 passengers and spill the remaining 10. Even though these modelling results are not necessarily incorrect it is definitely something to keep in mind.

As it is hard to exactly quantify the optimum aircraft allocation for a specific mission due to a lack of available data, the distribution of the optimum aircraft for a specific mission in the table has been visually inspected for any major issues with respect to unrealistically attractive aircraft. For example, if the optimum aircraft for a 2000 km mission with 180 passengers would be an A388, this would be a strong indication that the aircraft is not modelled accurately as it is obvious that in a real world situation a narrowbody aircraft would be more efficient. Specific aircraft have niche roles in the network and the landscape is not dominated by a small number of aircraft either which may further skew model reality from operational realism. In this table, the green cells indicate which segment of the market would be taken by the PrandtlPlane if the aircraft was introduced in the network. The acquired market segment is in line with the design expectations of the aircraft and indeed excels at medium- to short-range missions with passenger numbers larger than that of current narrowbody aircraft. When utilising the PrandtlPlane on longer range routes the aircraft slots between the A21N, which is better for smaller passenger numbers, and the B763, which performs better in cases with larger passenger numbers.

The validation steps performed in this section form a key check that the modelled competitive environment represents the operational reality as good as possible which is essential for model reliability. Even though it is difficult to exactly judge what the operational reality should look like and some deviations may be present, the results provide sufficient confidence that the model results can be considered valid especially considering the fact that these results were obtained with limited aircraft performance data.

	Mission Range (km)													
Passengers	500	1000	1500	2000	2500	3000	3500	4000	4500	5000	5500	6000	6500	7000
10	E175	E175	E170	E170	E170	E170	E170	E170	E175	E175	E175	E175	E175	E175
20	E175	E175	E175	E170	E170	E170	E170	E175	E175	E175	E175	E175	E175	E175
30	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E290
40	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E290	E290
50	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E290	E290	E290
60	E175	E175	E175	E175	E175	E175	E175	E175	E175	E175	E290	E290	E290	E290
70	E175	E175	E175	E175	E175	E175	E175	E175	E290	E290	E290	E290	E290	E295
80	E275	E275	E275	E275	E275	E275	E275	E290	E290	E290	E290	E290	E295	BCS1
90	E290	E290	E290	E290	E290	E290	E290	E290	E290	E290	E290	E295	BCS1	BCS1
100	E295	E295	E295	E295	E295	E295	E295	E295	E295	E295	E295	BCS1	BCS1	BCS1
110	E295	E295	E295	E295	E295	E295	E295	E295	E295	E295	BCS1	BCS1	BCS1	A19N
120	E295	E295	E295	E295	E295	E295	E295	E295	E295	A19N	A19N	A19N	A19N	A19N
130	BCS3	A19N	A19N	A19N	A19N	A19N	A19N	A19N	A19N	A19N	A19N	A19N	A19N	A19N
140	BCS3	BCS3	BCS3	BCS3	BCS3	BCS3	BCS3	BCS3	BCS3	BCS3	BCS3	BCS3	B38M	B38M
150	A320	A320	A320	A320	A320	A320	A320	A320	A320	A320	A320	B38M	B38M	B38M
160	A320	A320	A320	A320	A320	A320	A320	A320	A320	A320	B38M	B38M	B38M	A21N
170	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N
180	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N
190	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N
200	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N	A21N
210	B762	B762	B762	B762	B762	B762	B762	B762	B762	B762	B762	B762	B762	B762
220	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763
230	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763
240	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763
250	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763
260	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763
270	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763
280	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B764
290	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B763	B764
300	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764
310	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764
320	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764	B764
330	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X
340	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K
350	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K
360	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K
370	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773
380	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773
390	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773	B773
400	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779
410	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779
420	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
430	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
440	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
450	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
460	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
470	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
480	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
490	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
500	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
510	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
520	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
530	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
540	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
550	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
560	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
570	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
580	X	X	X	X	X	X	X	X	X	X	X	X	X	X

	Mission Range (km)														
Passengers	7500	8000	8500	9000	9500	10000	10500	11000	11500	12000	12500	13000	13500	14000	14500
10	E175	E175	E290	E290	E290	E290	E295	BCS1	BCS1	BCS1	BCS1	A19N	A19N	A19N	A21N
20	E175	E290	E290	E290	E290	E295	BCS1	BCS1	BCS1	A19N	A19N	A19N	A21N	A21N	A21N
30	E290	E290	E290	E290	E295	BCS1	BCS1	BCS1	A19N	A19N	A19N	A21N	A21N	A21N	A21N
40	E290	E290	E295	E295	BCS1	BCS1	BCS1	A19N	A19N	A19N	A21N	A21N	A21N	A21N	B762ER
50	E290	E295	BCS1	BCS1	BCS1	BCS1	A19N	A19N	A19N	A21N	A21N	A21N	A21N	B762ER	B762ER
60	E295	BCS1	BCS1	BCS1	A19N	A19N	A19N	A19N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER
70	BCS1	BCS1	BCS1	A19N	A19N	A19N	A19N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER
80	BCS1	BCS1	A19N	A19N	A19N	A19N	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER
90	BCS1	A19N	A19N	A19N	B38M	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER
100	A19N	A19N	A19N	B38M	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER
110	A19N	A19N	B38M	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER
120	A19N	B38M	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788
130	B38M	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788
140	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788
150	A21N	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788
160	A21N	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788	B788
170	A21N	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788	B788
180	A21N	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788	B788	B788
190	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788	B788	B788
200	A21N	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788	B788	B788
210	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B762ER	B788	B788	B788	B788	A338
220	B763	B763	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B788	B788	B788	B788	B788	A338
230	B763	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B788	B788	B788	B788	A338	A338
240	B763	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B788	B788	B788	B788	A338	A338
250	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	A338	A338	A338	A338	A338	A338	A338
260	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	B763ER	A339	A339	A339	A339	A339	B789	B789
270	B764	B764	B764	B764	B764	B764	B764	A339	A339	A339	A339	A339	A339	B789	B789
280	B764	B764	B764	B764	B764	B764	B764	A339	A339	A339	A339	A339	B789	B789	A359
290	B764	B764	B764	B764	B764	B764	B764	A333	A333	B789	B789	B789	B789	B789	A359
300	B764	B764	B764	B764	B764	B764	A333	A333	A333	A359	A359	A359	A359	A359	A359
310	B764	B764	B764	B764	B764	B764	A359	A359	A359	A359	A359	A359	A359	A359	A359
320	B764	B764	B764	B764	B764	B78X	B78X	B78X	B78X	B78X	A35K	A35K	A35K	A35K	A35K
330	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	B78X	A35K	A35K	A35K	A35K	A35K	A35K
340	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K
350	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K
360	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K	A35K
370	B773	B773	B773	B773	B773	B773	B773	B773	B773	B779	B779	B779	B779	B779	B779
380	B773	B773	B773	B773	B773	B773	B773	B773	B779	B779	B779	B779	B779	B779	A388
390	B773	B773	B773	B773	B773	B773	B773	B773	B779	B779	B779	B779	B779	B779	A388
400	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	A388
410	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	B779	A388	A388
420	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
430	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
440	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
450	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
460	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
470	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
480	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
490	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
500	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
510	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
520	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
530	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
540	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
550	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
560	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
570	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388	A388
580	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

	Mission Range (km)										
Passengers	15000	15500	16000	16500	17000	17500	18000	18500	19000	19500	20000
10	A21N	A21N	B762ER	B762ER	B762ER	B788	B788	B788	B788	A338	A338
20	A21N	B762ER	B762ER	B762ER	B762ER	B788	B788	B788	A338	A338	A338
30	B762ER	B762ER	B762ER	B762ER	B788	B788	B788	B788	A338	A338	A338
40	B762ER	B762ER	B762ER	B762ER	B788	B788	B788	A338	A338	A338	A338
50	B762ER	B762ER	B762ER	B788	B788	B788	B788	A338	A338	A338	A359
60	B762ER	B762ER	B762ER	B788	B788	B788	A338	A338	A338	A338	A359
70	B762ER	B762ER	B788	B788	B788	B788	A338	A338	A338	A359	A35K
80	B762ER	B788	B788	B788	B788	A338	A338	A338	A338	A359	A35K
90	B762ER	B788	B788	B788	B788	A338	A338	A338	A359	A359	A35K
100	B788	B788	B788	B788	A338	A338	A338	A338	A359	A35K	A35K
110	B788	B788	B788	B788	A338	A338	A338	A359	A359	A35K	A35K
120	B788	B788	B788	A338	A338	A338	A338	A359	A35K	A35K	A35K
130	B788	B788	B788	A338	A338	A338	A359	A359	A35K	A35K	A35K
140	B788	B788	A338	A338	A338	A338	A359	A35K	A35K	A35K	A35K
150	B788	B788	A338	A338	A338	A359	A359	A35K	A35K	A35K	A35K
160	B788	A338	A338	A338	A338	A359	A359	A35K	A35K	A35K	X
170	B788	A338	A338	A338	A338	A359	A35K	A35K	A35K	A35K	X
180	A338	A338	A338	A338	A359	A359	A35K	A35K	A35K	A35K	X
190	A338	A338	A338	A338	A359	A35K	A35K	A35K	A35K	X	X
200	A338	A338	A338	A359	A359	A35K	A35K	A35K	A35K	X	X
210	A338	A338	A338	A359	A359	A35K	A35K	A35K	X	X	X
220	A338	A338	A359	A359	A35K	A35K	A35K	A35K	X	X	X
230	A338	A338	A359	A359	A35K	A35K	A35K	A35K	X	X	X
240	A338	A359	A359	A35K	A35K	A35K	A35K	X	X	X	X
250	A338	A359	A359	A35K	A35K	A35K	A35K	X	X	X	X
260	A359	A359	A359	A35K	A35K	A35K	A35K	X	X	X	X
270	A359	A359	A35K	A35K	A35K	A35K	X	X	X	X	X
280	A359	A359	A35K	A35K	A35K	A35K	X	X	X	X	X
290	A359	A35K	A35K	A35K	A35K	A35K	X	X	X	X	X
300	A359	A35K	A35K	A35K	A35K	X	X	X	X	X	X
310	A359	A35K	A35K	A35K	A35K	X	X	X	X	X	X
320	A35K	A35K	A35K	A35K	A388	X	X	X	X	X	X
330	A35K	A35K	A35K	A35K	X	X	X	X	X	X	X
340	A35K	A35K	A35K	A35K	X	X	X	X	X	X	X
350	A35K	A35K	A35K	A388	X	X	X	X	X	X	X
360	A35K	A35K	A35K	A388	X	X	X	X	X	X	X
370	A388	A388	A388	A388	X	X	X	X	X	X	X
380	A388	A388	A388	A388	X	X	X	X	X	X	X
390	A388	A388	A388	X	X	X	X	X	X	X	X
400	A388	A388	A388	X	X	X	X	X	X	X	X
410	A388	A388	A388	X	X	X	X	X	X	X	X
420	A388	A388	A388	X	X	X	X	X	X	X	X
430	A388	A388	A388	X	X	X	X	X	X	X	X
440	A388	A388	X	X	X	X	X	X	X	X	X
450	A388	A388	X	X	X	X	X	X	X	X	X
460	A388	A388	X	X	X	X	X	X	X	X	X
470	A388	A388	X	X	X	X	X	X	X	X	X
480	A388	A388	X	X	X	X	X	X	X	X	X
490	A388	A388	X	X	X	X	X	X	X	X	X
500	A388	X	X	X	X	X	X	X	X	X	X
510	A388	X	X	X	X	X	X	X	X	X	X
520	A388	X	X	X	X	X	X	X	X	X	X
530	A388	X	X	X	X	X	X	X	X	X	X
540	A388	X	X	X	X	X	X	X	X	X	X
550	A388	X	X	X	X	X	X	X	X	X	X
560	X	X	X	X	X	X	X	X	X	X	X
570	X	X	X	X	X	X	X	X	X	X	X
580	X	X	X	X	X	X	X	X	X	X	X

Figure 3.1: Optimum aircraft allocation per combination of passenger demand and mission range. PrandtlPlane market share in green, infeasible missions in yellow

III
Literature Study (AE4020)

1
Introduction

In the airline industry, new aircraft types are continuously under development. Due to advances in technology new aircraft can be larger, more efficient and cause less noise pollution compared to existing types. Even though a novel aircraft design can be very interesting from a technical point of view, it can be challenging to assess the exact role of such an aircraft with respect to its competitors. This project aims to bridge this gap between the technological design of new airliners and the market position of such an aircraft. This is done by analysing optimal novel aircraft utilisation strategies whilst taking into account their performance characteristics and time-of-day sensitive passenger demand. This will be achieved by merging several theoretical concepts. First of all, a market demand model will be constructed in order to analyse future passenger demand on routes between airports, taking into account time-of-day sensitivity. Next, by solving a fleet allocation problem on a per-route basis using parameters of the new aircraft design as input, an optimal operational strategy can be established which can be used to draw conclusions on the market impact of the new aircraft. The *ParsifalProject*, a research initiative which aims to develop the concept of a Prandtl-wing aircraft, provides an interesting test-case to assess the quality of such a model.

Before immediately starting with conducting the research, it is important for any researcher to get acquainted with the current state of the art in his or her research field. To achieve this, a lot of systematic reading and synthesis of key academic literature is required. Next, after this knowledge has been acquired, it is important to realise how these findings affect the research which the researcher aims to conduct and assess its role in the academic landscape. This literature review aims to document the search for answers to these two questions, which are key for a successful completion of the master thesis project later on.

This document is structured as follows. Chapter 2 will elaborate on the project context and explain the reasoning and rationale behind the research under consideration. After this introduction the literature review will go in depth on three different research fields which have been identified. First of all, chapter 3 will elaborate on the field of demand modelling. It will discuss the different means through which future airline demand can be forecasted as well as the advantages and disadvantages of these methods. Second, in chapter 4, the fleet allocation model will be discussed. This chapter will provide an elaborate basis on the historical foundation of the fleet allocation problem, the major academic advances in is formulation, the large impact it has on the airline industry as well as a wide variety of extensions which have been formulated to tailor the model to fit a range of cases. Third, chapter 5 will elaborate on the integration of aircraft design and performance characteristics in the fleet allocation model. A derivation of the methodology used to calculate the aircraft fuel consumption based on payload-range diagrams and other basic performance characteristics will be provided. After these three modules have been discussed thoroughly, chapter 6 will bridge the gap between the academic landscape and the research under consideration for this master thesis. First, it will briefly restate the project objectives in order to ensure that these are clearly defined. Next, the major learnings and preliminary research design decisions based on the literature review learnings will be sated and explained. Last but not least, chapter 7 will draw up the most important conclusions of this literature review and discuss the implications for the next stage of this master thesis.

2 Project Context

Under the strong and continued growth of air traffic demand, more and more airports are facing capacity constraints. Estimates from IATA (2015) show that 45 out of the 100 busiest airports are already heavily congested and this problem is only expected to get worse in the following decades. New aircraft designs provide an interesting opportunity to decongest these airports and assist them in coping with continued passenger growth because of their capabilities to carry higher passenger numbers at increased efficiency. Think about for example the blended wing-body configuration which seeks to seamlessly integrate the wings and fuselage into one large flying wing. This proposal has been worked out by Boeing as aircraft which seat anywhere between 200 to 800 passengers combined with decreased fuel burn of up to 27% per seat (Liebeck, 2004). Another alternative is the closed Prandtl-wing layout which, according to Frediani (2005), yields similar significant boosts in fuel efficiency and increased lifting capacity at the same wingspan which entails that more passengers can be taken on board of such an aircraft under the same conditions.

Even though such concepts sound extremely promising from both a practical as well as an engineering point of view, these new visions still remain theoretical concepts and are far from being implemented on a medium to large scale airliner. In light of a lack of concrete development on a larger scale for these concepts, the *ParsifalProject* was started. *ParsifalProject* aims to further develop the concept of a Prandtl-wing aircraft, the Prandtlplane, by tackling the most common engineering and scientific issues with the concept (Parsifal, 2019). The project is a joint effort of multiple research institutes such as DLR, University of Pisa and Delft University of Technology. The newly developed airliner has the wingspan and fuel consumption equal to a Boeing 737 or Airbus A320 and a payload capacity equal to that of a Boeing 767 or Airbus A330 and is specifically targeted at providing efficient decongestion at slot-constrained airports.

The aim of this project is to construct a market assessment framework for novel aircraft designs by analysing their top-level design parameters and solving a fleet allocation problem to determine the most efficient aircraft type per route considering future, time-of-day sensitive passenger demand. In this model, novel aircraft concepts will compete with currently existing aircraft types in terms of efficiency and operational opportunities in such a way that conclusions can be drawn on the current cost-competitiveness of the novel design as well as the potential market impact and demand for such a new airliner. The developed model will subsequently used in a case study to determine the market opportunities of a novel Prandtl-wing aircraft in the context of the *ParsifalProject*. The model however could easily be generalised to applications beyond this project such as assessing the impact of engine retrofitting or development of a smaller or larger aircraft in an already existing aircraft family.

This research and developed model are interesting from both a practical as well as from an academic point of view. It will allow aircraft designers to comprehensively assess the market impact of novel aircraft designs and variations of existing aircraft designs. Furthermore, it adds to a broad body of existing academic literature on demand modelling, aircraft performance and the fleet allocation linear programming problem which are the three project modules under investigation in this literature review.

3

Literature on Demand Modelling

In any business, modelling the future demand for your product, service or commodity is essential in order make successful business decisions. The airline industry is no exception. Large aircraft manufacturers often release annual market forecasts to inform their investors about what they expect future aircraft sales to be. These meetings are often considered of high importance as expectations about the future sales affect the current value of the firm. Airbus for example state in their Global Market Forecast (GMF) of 2019 that they expect over 38.500 new aircraft will be delivered between 2019 and 2038, with world annual traffic growth (in revenue passenger kilometers) increasing by 4.3% per year (Lange, 2019). The exact methods by which these calculations are conducted however are well kept industry secrets.

Fortunately, there does exist a large portion of literature on the means by which demand for services or commodities can be modelled and this section will summarise the most common and adequate means by which such analysis can be performed. Two different parts of the demand modelling process will be discussed. First, in section 3.1, the problem of demand unconstraining will be discussed. Next, in section 3.2 several techniques which can be used to forecast future demand will be highlighted.

3.1. Demand Unconstraining

One key question in the field of demand modelling is related to how demand can be quantified. More often than not, historical booking data is used to make an assessment of the total demand. There are, however, some obvious limitations to using booking data as a proxy for the total demand. Imagine a scenario in which 80 seats of a 100 seat aircraft are sold on a single flight between Amsterdam Schiphol Airport and London Heathrow. In this case it would be a fairly good estimation to state that the demand for this flight is equal to 80 seats. But now imagine the same flight operating at a maximum capacity of 100 seats. Now the statement that the demand is equal to 100 seats is inaccurate because there could be, in theory, demand for a total of 300 seats of which only 100 could be fulfilled considering the capacity constraint of the aircraft. This is an example of constrained or (in this case right-)censored data. Furthermore, imagine that data regarding the aircraft type is available for this trip and only the number of seats, again 100 in this example, can be determined. It could very well be that the aircraft is only carrying 50 passengers and that demand is lower than the 100 seats, or the aircraft is operating at full capacity even though the demand is significantly higher. In both these cases, the constrained data provides a limited overview of the underlying fundamentals

Several methodologies exist which can correct for constrained data, which are commonly denoted as data unconstraining methods in literature. This problem is not unique to the airline demand forecasting case under consideration here but also has many other applications in for example aircraft part-life predictions (see for example Wang and Zhang (2005)). Reaching back to airline demand data, Weatherford and Pölt (2002) provide an excellent overview of demand unconstraining methodologies in the context of improving airline revenue management systems in which the booking data plays an important role. The authors provide the following six methodologies to tackle the problem of constrained booking data, which will be briefly summarised below.

1. **Replace constrained measures with mean of all measures (Naive1)**

   The first option provided by Weatherford and Pölt (2002) is to replace all constrained measures with the mean of all the measures in the dataset, including the constrained ones.

2. **Replace constrained measures with mean of all open measures (Naive2)**

   The second strategy is to correct all the constrained measures in the dataset with the mean of all open measures in the dataset, expelling the measures which are constrained in calculating this mean.

3. **Replace constrained measures with mean of all closed or all open measures (Naive3)**

   Third, a proposal is made to replace the constrained measures with the larger value of the mean of all constrained (closed) measures or the mean of all unconstrained (open) measures.

4. **Booking Profile method (BkgProfile)**

   The fourth method aims to correct the constrained measures using historical trends of demand growth. On a set number of occasions the current demand for the product is measured. These points in time are called data collection points. For the first data collection point (DCP), all at that point constrained measures are replaced with the mean of all unconstrained observations in the same point. This subsequently unconstraints these measures. For all subsequent data collection points, the replacements for the constrained values are calculated by summing the the revised, now unconstrained observations of the previous data collection points and multiplying them with a large factor according to equation 3.1 below. In equation 3.1, μ_t is used to indicate the mean of all revised open data values DCP_t during time *t*. This equation is subsequently used to replace, per time period *t*, all constrained values occurring in DCP_t until no constrained values remain. In brief, this process adjusts the constrained values in the time period under consideration by analysing the historical trends on how the demand has changed over the past time periods.

$$\text{DCP}_{t+1} = \left(\sum_{t=1}^{t} \text{DCP}_t\right)\left(\frac{\sum_{t=1}^{t+1} \mu_t}{\sum_{t=1}^{t} \mu_t} - 1\right) \tag{3.1}$$

5. **Projection Detruncation method (ProjDetrun)**

   The fifth method is called the projection detruncation method. It is a two-step iterative process which first uses heuristics to replace the constrained parameters. This is achieved by calculating the mean and standard deviation of all data in the sample such that a normal distribution can be constructed. Next, using the probability distribution, the method seeks to balance the area marked by the constrained value and the new projected value with the area marked by the projected value and the right tail. This ratio can be tuned with the parameter τ, where a higher value of this parameter indicates a more conservative estimation. This process is graphically illustrated in figure 3.1

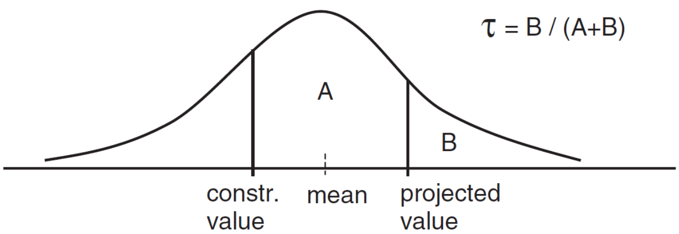

Figure 3.1: A graphical illustration of the projected value estimation under the projection detruncation method (Weatherford and Pölt, 2002)

After the estimation of the values which have to be replaced has been completed, the process is repeated with updated values of the mean and standard distribution obtained from the sample with the replaced values. This method should eventually converge to yield the final values which can be used for subsequent analysis.

6. **Expectation Maximisation method (EM)**

   Last but not least, the sixth method is called expectation maximisation. As a matter of fact, this strategy shares a lot of characteristics with the projection detruncation method discussed earlier. Instead of balancing two areas under the probability distribution, the expectation maximisation method calculates the expected value resulting from the distribution under the condition that this estimate must at least be larger than or equal to the constrained value. This new estimate shifts the original distribution which entails that the estimation can be redone until the problem converges to a final solution.

The authors performed an analysis to compare the performance of these methodologies. Several scenarios were generated by first estimating the ”true” demand which is known to have a mean equal to 20.0 and subsequently applying a data constraining algorithm to simulate the booking data. The unconstraining algorithms can subsequently be applied to the constrained data and the results compared to the reference ”true” data to judge the algorithm performance. The results are indicated in figure 3.2.

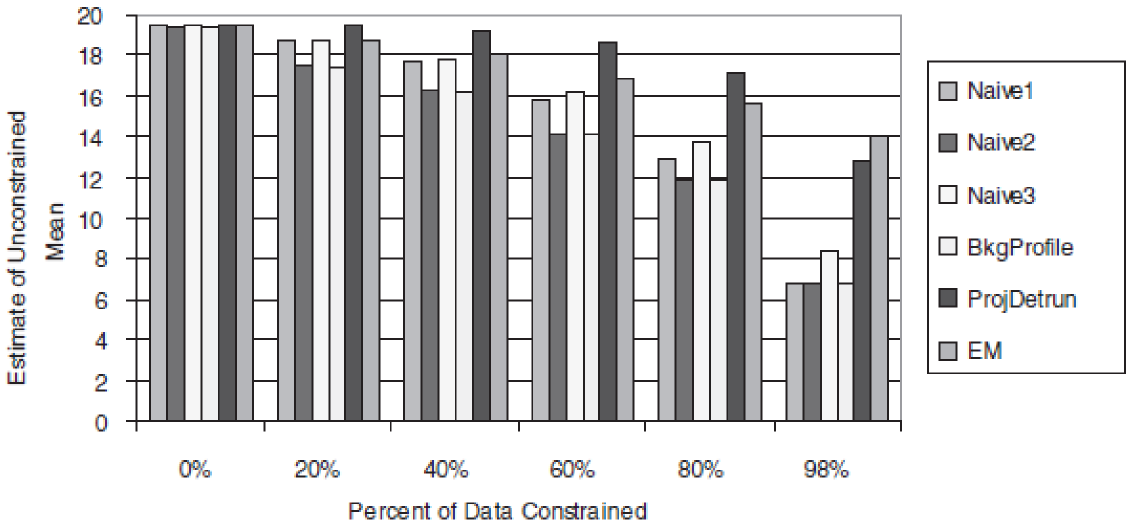

Figure 3.2: A performance overview of the demand unconstraining methodologies discussed in this section (Weatherford and Pölt, 2002)

The results in figure 3.2 show interesting patterns. Note that the reference ”true” mean which is to be approached is equal to 20.0. It can be observed that for all the unconstraining methodologies the expected mean is lower than the true mean, hence indicating a constant negative bias in underestimation. With little constrained data in the sample, all methodologies are approximately similar in performance and come rather close to the value true value of 20.0. However, with significantly higher percentages of constrained data some clear differences can be observed. In terms of highly constrained data, the naive models show clear underperformance compared to the projection detruncation and expectation maximisation methods in the fact that they underestimate the demand by more than a factor of two in the most extreme case. Even though in this case all models fail to get realistically close to the to be approached value, the difference in performance is extremely significant and advocates for the use of either the projection truncation method or the expectation maximisation method when dealing with heavily constrained data in the sample. Especially considering the fact that, when using this data to make forecasts, these errors compound over time and can lead to very inaccurate values for future demand.

In this section we have discussed the problem of censored data in the context of demand modelling. We have shown that it is required to be aware of the fundamental problems which are faced when dealing with constrained data and that the quality of multiple methods to deal with these issues vary greatly. Especially in the forecasting context, minor inaccuracies in the data which forms the foundation of the forecast can compound to very large errors over multiple periods of time and significantly compromise the quality of the forecast. With this issue discussed, the following sections will elaborate further on some key demand forecasting methods which are described in literature.

3.2. Demand Forecasting

Making well-educated predictions about the future is an essential part of the decision making process at many firms and the airline industry is no exception. For example, aircraft delivery times can easily extend to multiple years and it it hence essential to know what the situation of the airline will be in the future to decide whether acquiring this new aircraft will be worth it for a prolonged period of time. A variety of methods to forecast demand are available in literature, which will be summarised in this section and have their advantages and disadvantages discussed.

This section will be centered around the two main ways of demand forecasting. In subsection 3.2.1, deterministic forecasting techniques will be discussed. Subsection 3.2.2 will deal with the advantages and disadvantages of stochastic forecasting techniques.

3.2.1. Deterministic Forecasting

Deterministic forecasting techniques are characterised by the fact that they do not incorporate any randomness; The outcome of the model is therefore fully governed by the initial inputs and will result in the same answer every time the same input parameters are used. In the aerospace engineering context, a non-exhaustive summary of deterministic demand forecasting methods is provided by Doganis (2019). Doganis (2019) distinguished three different categories of forecasting techniques: The use of qualitative models, time-series projections and causal models. Figure 3.3 below provides a graphical top-down overview of deterministic demand forecasting models.

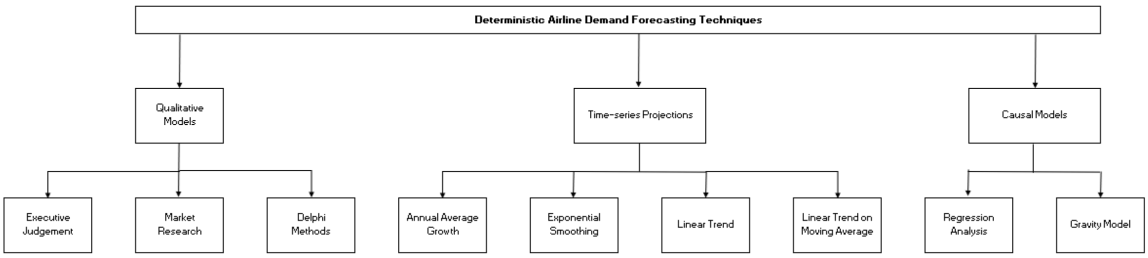

Figure 3.3: An overview of deterministic airline demand forecasting techniques. Adapted from Doganis (2019)

3.2.1.1. Qualitative Models

Use of qualitative modelling techniques is uncommon in academics due to a lack of inherent transparency and tangibility. Executive judgement for example revolves around having executives of the firm making educated guesses about what they think will happen to their business. In general, it is only feasible for short-term forecasts and is heavily founded on inside knowledge and personal vision. This analysis can either be performed by a single executive or together with a team of executives and advisers. The latter has the advantage that, in the group composition, the members can challenge each others input and that it may remove very strong individual biases increasing reliability of the method. The main advantage of this method however is that it can be performed at the back of an envelope, at any point at any time. Furthermore, it could be used to check the results of other forecasting methodologies for sanity, which is something that should always be conducted. Little to no academic literature is available on forecasting results using the executive judgement strategy, presumably due to the fact that these forecasts are for internal use only and may face constraints regarding declassification as they are specific regarding to the airline and give an indication on how the airline makes its strategic decisions.

The second qualitative model proposed by Doganis (2019) is to conduct market research. This can either be outsourced to specialised (consultancy) organisations or performed in-house using own data. Passenger surveys are commmonly used as a source of data especially with respect to behavioural aspects such as decision making rationale. A market analysis does not only have to be restricted to qualitative aspects but can also be expanded with quantitative data sources to achieve a more in-depth overview of the problem under consideration. Good market analyses can be a very powerful tool in predicting future passenger demand. This, however, comes at a cost. Market analyses are often very expensive to conduct, especially when external consultants are hired to conduct or assist with the analysis. Furthermore, an elaborate market research can take a very long time which may not always be available. In addition, the often expensive and detailed market analyses are frequently kept classified and results are rarely discussed in literature.

Last but not least under the qualitative models, Delphi methods involve consulting multiple experts in a panel formation with the aim to reach a consensus solution. Initially, each expert is asked for his or her own opinion, which is subsequently fed back anonymously to the panel and discussed. Discussions surrounding the views of other panel members can lead to individual experts adjusting their own views in multiple directions, leading to a new status quo which in turn sparks further debate. After multiple rounds of discussions, adjustment and further discussion the aim is to form a consensus on the problem under consideration. Examples of uses of Delphi methods in academic literature are significantly more common than the initial two methods discussed. Back in 1976, English and Kernan (1976) performed a large Delphi method study to forecast the future of air travel and corresponding aircraft technological advancements by the year 2000. Questions regarding the expected developments of supersonic flights, subsonic flights and route development were asked to panels comprising anywhere between 11 and 16 experts over two rounds. In a more recent study, Chang et al. (2008) discuss an interesting application of the Delphi method in the context of route development for low-cost carriers operating between Taiwan and China. The Delphi panel members were asked to judge a wide variety of routes for attractiveness based on their characteristics such as airport charges, traffic demand and airport runway classifications. Their answers were subsequently checked for convergence using statistics and the results drawn up.

3.2.1.2. Time-series Projections

Time-series projections are already a step up from qualitative models in the sense that the results of the forecasts are quantified. However, they are still considered to be rather straight forward considering the fact that they only take into account growth rates and time and ignore other external variables which may be of interest. The annual average growth methodology as described by Doganis (2019) for example takes the form of a simple exponential growth equation as shown in equation 3.2.

$$y = c \cdot (1 + g)^t \tag{3.2}$$

In which *y* is the forecasted traffic number, *c* the base number of traffic at the initialisation of the forecast, *g* the average annual growth rate and *t* the number of time-steps. The average annual growth rate *g* can be determined through several mechanisms. One methodology is to average all the historical annual growth rates which are available and use this single number for the future projection, assuming that the historical growth will continue indefinitely with approximately the same rate. A further proposed methodology is to determine the expected growth rate for each individual year by calculating a rolling moving average of growth rates. For example, the growth rate corresponding to time period *t* is equal to the weighed average of the growth rates of the past *n* time periods. This methodology is better at taking into account the inherent variability of the growth rate and can better detect changes in trends. A low value of *n* will mean that the average growth rate is highly sensitive whereas a higher value of *n* will mean that the average growth rate responds slower to changes in trends. Average annual growth rate computations are, presumably due to their simplicity, rarely used in academic literature as a stand-alone method to forecast demand. They are however often used as a base metric to compare more sophisticated methods, which is indicated by for example Weatherford et al. (2003) who use the method as a baseline to compare the effectiveness of a novel neural network forecasting tool for airline booking data.

The next time-series strategy under consideration is the exponential smoothing method. This method is similar to the rolling moving average strategy discussed in the previous section, but instead of treating all historical observations equally it assigns different weights to each historical observations. The idea behind this reasoning is the fact that more recent historical observations tell more about the future than historical observations taken a long time ago. Hence, by assigning a larger weight to the more recent observations, a more accurate indication of the expected future growth can be obtained. A basic formulation of the exponential smoothing methodology taking into account only one time period lag is shown in equation 3.3.

$$y_{t+1} = \alpha y_t + (1 - \alpha) y_{t-1} \tag{3.3}$$

In which y_{t+1} is the expected future value, y_t the current value and y_{t-1} the past value. The parameter α can be tuned anywhere between 0 and 1, where at the limits of this value the forecast will turn into a naive forecast taking only into account present or past values as estimate for the future value. Equation 3.3 is an example of a simple exponential smoothing equation with only one time period lag, but many more sophisticated exponential smoothing formulations also exist. For example, the Holt-Winters exponential smoothing method is a very well known and powerful method which and takes into account three key time-series parameters: value, trend and seasonality. Especially due to its ability to also forecast seasonality trends, it is often used for airline industry forecasting due to the large seasonal trends in passenger demand. In academic literature, Bermúdez et al. (2007) and Grubb and Mason (2001) both make use of Holt-Winter methods to forecast passenger numbers for airports in the United Kingdom. Samagaio and Wolters (2010) use a variety of methods including Holt-Winters smoothing to test the forecasts made by the government of Portugal regarding air passenger growth at Lisbon airport. Last but not least, Dantas et al. (2017) propose an adaptation of the classical Holt-Winters model which includes machine learning techniques to predict air passenger demand for 14 airports worldwide of which 11 are located in in Europe.

The third time-series method which is proposed by Doganis (2019) is the straightforward linear regression analysis. This method draws a straight line through the available data which can subsequently be extrapolated to yield information about the future. It takes the form of equation 3.4 below:

$$y = ax + b \tag{3.4}$$

In which *a* is the slope of the regression equation and *b* the intercept with the y-axis of the graph. The method has low depth and fails to take into account changing trends or compound growth but is, as a consequence, very easy to use. The final time-series forecasting tool mentioned by Doganis (2019) is a variant of this method which is called linear trend on moving average. Instead of linearly regressing on the exact passenger data, it first calculates a rolling moving average for each individual time period and subsequently performs the linear regression on those values. This has the main advantage that large fluctuations of year-to-year values are damped which may result in a more accurate trend and narrower fit of the trend to the existing data. These two linear regression methods however are not often used in academics as a standalone forecasting tool but often used as a baseline reference for testing more complex models. This is indicated by, for example, Önder and Kuzu (2014) who use the linear moving average model as a comparison to various more complex exponential smoothing methods for air passenger demand as well as air freight traffic demand in Turkey. In the larger research by Weatherford et al. (2003), who compare multiple forecasting tools for their performance in predicting passenger numbers, the simple linear regressions model is one of the least accurate forecasting tools used in their methodology set. This however trades off against very straightforward implementation compared to some of the other methodologies. Users should hence reflect on the required level of accuracy of the forecast versus the desired model complexity before deciding whether simple linear regression methods are suitable for their application.

3.2.1.3. Causal Models

Causal models, which are also denoted as econometric models, are characterised by the fact that they incorporate multiple variables to analyse trends in data. Because of their ability to analyse the causal relationship between variables other than just time trends, their use in academic literature has become widespread. The first causal model proposed by Doganis (2019) is the regression analysis, which seeks to relate the dependent variable to multiple independent variables. The mathematical formulation of the causal regression analysis methodology for two independent variables is shown in equation 3.5 but can easily be extended to incorporate multiple variables.

$$y = a_0 + a_1 x_1 + a_2 x_2 + u \tag{3.5}$$

In which y is the dependent variable, a_0 the intercept with the y-axis, a_1 the coefficient belonging to independent variable x_1, a_2 the coefficient belonging to independent variable x_2 and u an error term. In the field of airline passenger demand, causal regression analysis has been conducted a vast amount, mainly to figure out the exact drivers of passenger growth. Chevallier et al. (2011) for example uses causal regression to forecast world air travel demand for the period 2011 to 2025. The authors find, for example, a strong and positive relationship between growth in air travel demand and gross domestic product (GDP) growth. Furthermore, air travel demand seems to be negatively correlated with jet fuel prices and also decreases when air travel markets are maturing which is especially the case for Europe and North America. Dobruszkes et al. (2011) conducted similar research and also found that, amongst others, GDP, the economic decision power and the presence of tourism are strong drivers for growth in airline demand. In Sweden Kopsch (2012) also shows that air travel demand is strongly positively correlated with GDP and negatively correlated with increasing ticket prices, where the sensitivity for business travellers to price changes is lower than for leisure travellers. Especially the strong correlation of GDP with air travel demand has received special interest. For example, Hu et al. (2015) raise the important question in which way this relationship runs. Does GDP growth drive airline passenger transport or does increasing airline passenger transport contribute to further GDP growth? In order to test this trend they collected economic and domestic passenger data from all 29 provinces in China and perform a Granger causality analysis. A Granger causality analysis tests whether or not a time series trend for variable *A* is a good predictor for the time series trend of variable *B*. They find that in the short-term, increasing airline passenger transport Granger-causes GDP growth but not vice versa. This entails that in the short-term, airline passenger transport growth is a good predictor for GDP growth but that GDP growth can not be used as a reliable forecasting metric for airline passenger transport. In the long-term however, Hu et al. (2015) conclude that this relationship runs both ways, entailing that GDP growth can be used as a reliable forecasting metric for airline passenger transport. For every 1% increase in GDP growth, the authors estimate a corresponding increase of 1.06% of domestic air travel demand.

The second and last causal model mentioned by Doganis (2019) is the gravity model. Gravity models are common forecasting tools in multiple disciplines such as economic trade analysis, migration analysis and passenger forecasting for the airline industry. Their name originates from their analogy with Newtons law of gravitation, which states that the force with which two bodies are attracted to one another increases if their are larger in size and decreases proportional to the distance between those two bodies. When comparing astronomical bodies with with towns of different populations, this relationship can be mathematically formulated as equation 3.6.

$$V_{ij} = K\frac{P_i P_j}{D_{ij}} \tag{3.6}$$

In which V_{ij} is the resulting air transport demand between the two towns, P_i and P_j the population of towns *i* and *j* respectively, D_{ij} the distance between these two towns and K a constant calibration factor. This simple formulation of the gravity model however fails to incorporate other important factors which have been discussed in this section. Fortunately, work has been done to extend gravity models from this basic formulation to include a wide variety of (socio)economic parameters which greatly increases its usability and forecasting accuracy. In the context of forecasting air passenger demand, the following elaborate formulation is provided by Grosche et al. (2007) and shown in equation 3.7.

$$V_{ij} = e^{\epsilon} P_{ij}^{\pi} C_{ij}^{\gamma} B_{ij}^{\beta} G_{ij}^{\gamma} D_{ij}^{\delta} T_{ij}^{\tau} \tag{3.7}$$

In which V_{ij} is still the resulting air transport demand between the two towns, e a constant, P_{ij} a metric indicating the population of the two towns, C_{ij} indicates the total catchment areas of the airports, B_{ij} a metric for the total buying power of the two towns, G_{ij} includes the total GDP of the two towns, D_{ij} is the geographical distance between the two towns and T_{ij} the average travel time between the two towns. The superscripts $\epsilon, \pi, \gamma, \beta, \gamma, \delta$ and τ are parameters which are used to calibrate the model, which is often performed by means of a simple regression analysis. Other variables than the ones mentioned here can easily be added, entailing that the gravity model is flexible in terms of application and hence interesting for research. Wadud (2011), Sivrikaya (2013), Nommik and Kukemelk (2016), Hazledine (2017) and Perez and Jansen (2017) are amongst the many to use gravity models or minor variations of gravity models for forecasting passenger numbers in the context of the airline industry.

3.2.1.4. Other Models

Last but not least, plenty of methods are available which do not find their way into figure 3.3. For example, Alekseev and Seixas (2009) make use of a multivariate neural network in order to assess future air travel demand in Brazil. Furthermore, Benitez et al. (2013) adapt the standard Grey Model, which is commonly used to model nonlinearities in forecasts. They include a dampening factor which improves the undamped Grey Model to produce more accurate forecasts for passenger numbers travelling on domestic flights in the United States. Such models however serve a niche role in the deterministic forecasting domain and are mentioned for completeness but will not be elaborated upon further.

3.2.2. Stochastic Forecasting

Stochastic forecasting techniques were created in order to incorporate inherent ”randomness” in the model. When translating to an industry perspective, the use of stochastic forecasting is interesting from a robustness point of view. One can easily optimise for a certain future demand scenario with a fixed number of passengers, but the probability that exactly this amount of passengers will travel in the future is rather close to zero. It is then the aim to optimise for a range of demand scenario's, such that not all eggs are put in one basked and that the chosen strategy remains optimal under uncertainty. As an initial example from literature, Jansen and Perez (2013) use a simple discrete time simulation to incorporate randomness in their demand forecast for a multidisciplinary design optimization task in the airline industry. The authors however do not exactly forecast their demand, but simply allow their demand to vary randomly around a set level to simulate the stochastic component. This section will elaborate on the most commonly used stochastic forecasting techniques and will be focused on stochastic time-series analysis methods. First, two basic modelling techniques will be discussed in the form of autoregressive and moving average models. These two models form the basis of a more complex method which is currently the most used method time-series forecasting: (S)ARIMA. The last subsection will briefly discuss the current state of art in stochastic forecasting in terms of network forecasting.

3.2.2.1. Autoregressive Models

Autoregressive (AR) models make use of a linear combination of past time-series values and a random error term to introduce uncertainty in the model. Autoregressive models are denoted as AR(p) models, in which the parameter p indicated the number of lagged terms. The basic formulation of the autoregressive model with only one lagged term, AR(1), is shown in equation 3.8 below.

$$y_t = a_0 + a_1 y_{t-1} + \epsilon_t \tag{3.8}$$

In which a_0 is the intercept with the y-axis, a_1 the slope coefficient belonging to the first lagged variable y_{t-1} and ϵ_t a the white noise error term which follows a normal distribution with zero mean and variance σ^2. Even though formulation as provided in equation 3.8 is rarely used due to its simplicity, autoregressive models are often applied in a more complex vector framework with multiple lag periods. In this framework multiple variables are forecasted simultaneously which may also be interconnected with each other. By incorporating these interaction effects in the forecast, a more accurate estimate of future demand can be established. Fildes et al. (2011) for example use such a vector autoregressive framework to forecast the demand for air travel using growth of income, trade and price as variables. This model is subsequently compared with other methods to assess the performance of these tools on flights departing in United Kingdom with destinations in Europe and North America. Similar research conducted by Song and Witt (2006) focuses on forecasting the flow of international tourists to Macau using vector autoregressive modelling.

3.2.2.2. Moving Average Models

Moving average (MA) models make use of historical forecasting errors in order to steer the forecast instead of relying on past values as shown in the autoregressive model. Similar to the autoregressive model, multiple lagged errors can be used which generalises to MA(q) models in which q indicates the number of lagged errors. The simplest form of the moving average model, MA(1), is shown below in equation 3.9.

$$y_t = \mu + \epsilon_t + a_1\epsilon_{t-1} \tag{3.9}$$

In which μ is the starting value of the analysis, ϵ_t the error in the current time period, ϵ_{t-1} the error of the previous time period and a_1 the coefficient belonging to this term. As a result, this equation will adjust its best forecast estimate y_t based on how wrong the forecast of the previous time period was. It is not often used for forecasting time series with a growth trend, which we often deal with in the context of airline passenger numbers, due to the fact that the model will continuously oscillate around the predetermined value of μ. Even though this behaviour is annoying from a time series with trend forecasting point of view, it however is does see a very nice application when it is combined with the autoregressive model and integrating techniques, as we will see in the next section.

3.2.2.3. Autoregressive Integrated Moving Average Models

Autoregressive Integrated Moving Average Models (ARIMA) are by far the most common types of models to stochastically forecast demand. The model combines characteristics of the autoregressive model (AR) and the moving average model (MA) with the mathematical manipulation technique of integration (I). Integrating the time series deals with taking the first, second or multiple differences of the observations to form a new time series. For example, a first order integration or difference equation is shown in equation 3.10

$$y_t^{'} = y_{t+1} - y_t \tag{3.10}$$

As a result of this trick, the time trend can be removed from the original time series, resulting in new and stationary time series which can very well be modelled using both the autoregressive model and the moving average model. ARIMA models are often denoted as ARIMA(p,d,q) models in which p denotes the number of autoregressive terms, d the degree of difference which was taken and q which denotes the number of moving average terms. An ARIMA(1,1,1) model is shown in equation 3.11 below.

$$y_t^{'} = a_0 + b_1 y_{t-1}^{'} + c_1\epsilon_{t-1} + \epsilon_t \tag{3.11}$$

In which $y_t^{'}$ is the integrated series forecast, a_0 is the mean of the integrated series, b_1 the coefficient belonging to the first integrated autoregressive lag $y_{t-1}^{'}$. The coefficient belonging to the first moving average lagged error ϵ_{t-1} is c_1 and ϵ_t is the error term of the current time period. The transition back to the series with trend can easily be made by reversing the integration equation 3.10 and substituting back the terms to obtain y_{t+1}. This strategy results in a forecast which is able to account for past values, previously made errors and time trends which makes it a very powerful method with wide applications.

There is however one more issue. In the context of airline passenger forecasting, demand is often highly seasonal. In order to take into account these recurring trends, the conventional ARIMA model needs to be adjusted. This is done by means of adding an additional (P,D,Q) series for seasonality, which for notation purposes are now capitalised to distinguish them from their non-seasonal counterparts. This additional (P,D,Q) series focuses on modelling the seasonal trend using the same AR, I and MA techniques by running over only a small sub-sample of the available data. For example, if the data is quarterly and shows clear seasonality, the (P,D,Q) series will operate to absorb the quarterly variations such that the original (p,d,q) series can work on the deseasonalised subset which greatly increases modelling accuracy. Due to the fact that seasonal ARIMA (or SARIMA for short) models can take into account a vast majority of the factors which are important in airline time series and can be implemented relatively easily with existing mathematical software packages they have received a vast amount of attention in literature. Bougas (2013) for example discusses the use of SARIMA models for forecasting passenger traffic flows in Canada and shows that SARIMA models clearly outperform simpler exponential smoothing methods. Tsui et al. (2014) perform a similar analysis at Hong Kong International Airport and Janiszewski and Wojtowicz (2014) at the airport of Oslo. Li et al. (2017) use SARIMA models to forecast the passenger throughput at the airport of Kunming Changshui located in China and conclude that their SARIMA models lead to forecasting errors which were as small as 1% to as much as 3% compared to the reference values.

3.2.2.4. Other Models

Even though the last three sections described the most common stochastic modelling techniques which are used in academic literature, the current state of the art in stochastic forecasting techniques is centered around machine learning strategies. Vu et al. (2018) for example mention the use of a least-squares support vector machine (LSSVM) approach to forecast passenger numbers at Changi airport in China and show that this method outperforms the SARIMA model which has been discussed in the previous section in terms of accuracy. The LSSVM approach is also demonstrated by Xie et al. (2014) who also show that this approach is superior to many other time series forecasting techniques. Alekseev and Seixas (2009) make use of multivariate artificial neural networks (ANN) to forecast air passenger demand in Brazil. Similar research by Srisaeng et al. (2015) shows the applicability of ANN forecasting techniques by forecasting the passenger demand for low-cost airlines in Australia. These machine learning strategies show increased accuracy compared to the more traditional forecasting techniques, but come at significant additional mathematical and modelling complexity.

3.3. Conclusions

This chapter has elaborated on the different methods through which demand for air travel can be forecasted. First of all, the problem of demand unconstraining has been discussed which deals with the problem of censored data in the context of the airline industry. It has been shown that it is important to be aware of this problem as it could result in significant modelling errors if not addressed appropriately. Following the discussion on data censoring, the first class of forecasting techniques were discussed in the form of deterministic methods. Multiple deterministic forecasting tools have been elaborated on with both their advantages, disadvantages and relevant occurrences in academic literature. The next section dealt with the analysis of stochastic forecasting techniques, which aim to address the problem of forecasting uncertainty into the modelling framework. After discussing the basic autoregressive and moving average models, properties of these models have been combined which leads to discussion on the seasonal autoregressive integrated moving average model (SARIMA) which currently is the most commonly applied forecasting framework in the context of airline demand forecasting. The chapter is concluded with a discussion on current, state-of-the-art, machine learning forecasting techniques such as an artificial neural network (ANN) or least-squares support vector machine (LSSVM).

It is important to note that one forecasting technique is not necessarily better than the other. In terms of forecasting accuracy, it can generally be concluded that the more complex method is better suited for the job. The widespread application of the SARIMA model for forecasting airline demand has shown that it is a complete model which can be applied with relative ease compared to more complex machine learning frameworks which, even though they are superior in accuracy, are significantly harder to implement in practice. The key takeaway of this chapter is that there is a continuous trade-off to be made between more accurate forecasting techniques and increasing modelling complexity. It is therefore up to the user of these methods to balance the need for forecasting accuracy with the ease of implementation and select the method which is most suitable for the case under consideration.

4

Literature on Fleet Allocation

The classical fleet allocation model (FAM), which also commonly denoted as the fleet *assignment* model in literature, aims to optimally assign different types of available aircraft to the different flights which are in the schedule of the airline. The linear-programming (LP) model hence provides an optimal match between the available demand on a certain route and performance and cost characteristics of the aircraft under consideration. An exact definition of the problem statement of the fleet allocation problem is provided by Mancel and Mora-Camino (2006) and is as follows:

> *"Given a flight schedule with fixed departure times and costs (fleet and flights specific operating costs and spill costs), find the minimum cost assignment of aircraft types to flights, such that each flight is covered exactly once by an aircraft, flow balance of aircraft by type is conserved at each airport and only the available number of aircraft of each type are used." (Mancel and Mora-Camino, 2006)*

This section will further elaborate on previous research which has been conducted in this field. First of all, section 4.1 will elaborate on the earliest occurrences of the problem described above in academic literature. Next, section 4.2 will continue with these findings and discuss a highly influential paper which demonstrates the operational opportunities of applying this modelling framework in an industrial context. Section 4.3 will deal with an alternative formulation of the problem which tackles several efficiency-related issues and section 4.4 generalises these results to present a "basic" formulation of this problem which serves as a basis for most future work in this field. When the "basic" formulation has been established, section 4.5 will discuss variants of this formulation which are tailored to incorporate different aspects of the airline business. Last but not least, section 4.6 will briefly summarise utilisation of the fleet allocation model in other industries and section 4.7 concludes this overview.

4.1. An Initial Formulation

The initial formulation of this problem in literature can be traced back as far as Ferguson and Dantzig (1954) who provided an LP-formulation to develop an optimal routing for transporting a fixed amount passengers between five origin-destination (OD) pairs using four aircraft types. In total, the problem proposed counted a fleet of 69 aircraft and the total network demand equated to 124.000 passengers per month. Solving the problem is done by hand, taking several intermediate solutions before a final, optimal solution of the problem can be validated. Two years later the same authors published another influential paper, extending the model they designed earlier to incorporate demand uncertainty (Ferguson and Dantzig, 1956). This was achieved by assigning fixed but unique probabilities to different demand realisations on the same network as in the previous paper, which also makes this paper one of the earliest to discuss linear programming under uncertainty. An iterative, heuristic solution procedure is presented to solve this problem, which can still be done by hand at the cost of only a slight increase of mathematical effort.

4.2. First, Large Scale Application

Since the initial formulation of the problem in the 1950's, a wide variety of academic literature is available which seeks to improve, alter or extend the FAM. Whereas the initial problems as proposed by Ferguson and Dantzig (1954) and Ferguson and Dantzig (1956) could be solved by hand if the person is experienced enough and were limited to small theoretical cases, swift advances in computational performance ensured that larger problems were no longer out of feasibility to be solved. This is very well demonstrated by Abara (1989), who built a fleet allocation model which is applied at various departments in American Airlines. The model has different objective functions which enables the model to either maximise profit, minimise cost or maximise aircraft type utilisation when assigning aircraft types to different flights. In a profit maximising framework, results have shown that operating costs can be decreased with up to 0.4% whilst simultaneously increasing the operating margin of the airline with up to 1.4%. When optimising for aircraft utilisation, the flight time of the airlines' MD80's was increased with more than one hour per day. This study is generally regarded as one of the first to propose a so called time-space network as a solution methodology for the problem. Decision variables are indicated as flight turns, which are all possible connections between inbound and outbound flights, for all different aircraft types available. Furthermore, this formulation of the problem also requires to take into account multiple decision variables to ensure network balance and decision variables for extra aircraft which have to be utilised compared to the default if the network is too large to be flown by the existing fleet. The disadvantage of this formulation is that the problem size is rather large. Abara (1989) states that for a schedule with 400 flights between 60 airports while utilising 3 different aircraft types, the LP-problem has 6.300 columns and 1.800 rows with solution times ranging anywhere between 2 and 60 minutes.

4.3. Towards an Arc-Based Formulation

Berge and Hopperstad (1993) recognised this issue with computational times and proposed an alternative formulation of the FAM. The problem stated by Abara (1989) could be regarded as a formulation based on connections as the decision variables were based on the connecting flights an aircraft makes through an airport. The problem modified by Berge and Hopperstad (1993) however could be regarded as a formulation based on arcs as the decision variables are now based on whether an aircraft performs a flight (along a flight arc) and the number of aircraft of the same type which remain on the ground (along a ground or null arc). Different types of arcs are connected by each other with nodes, which are the points in time at which a scheduled flight is departing or arriving at the airport. This interconnection of arcs and notes yields the so called time-space network and is graphically shown in figure 4.1.

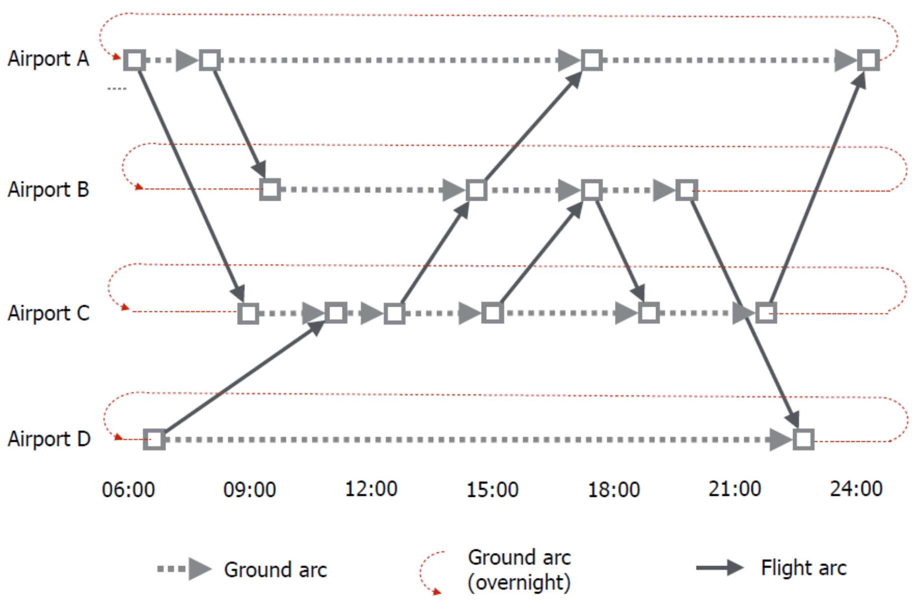

Figure 4.1: An intuitive overview of an arc-based time-space network (Santos, 2018)

Berge and Hopperstad (1993) furthermore propose two heuristic algorithms to improve the solution speed by exploiting characteristics of the LP-matrix resulting from the problem formulation. The algorithms were able to solve even very large problems which were not able to be solved by simple LP-operations in a matter of minutes, whilst still reaching upwards of 99.9% of the optimal solution. For reference, the largest case study in their paper consisted of an LP-matrix with more than 100.000 rows and 50.000 columns and was solved in either 3 or 4 minutes depending on the algorithm selection whereas a solution with regular LP-operations could not be established due to the excessive runtime. The model is used in a Demand Driven Dispatch (DDD) framework in which the fleet allocation problem is solved multiple times ahead of the time of operation when new airline information on passenger numbers and aircraft availability becomes available. This allows the airline to continuously analyse the optimal allocation of their fleet in quick and clean fashion.

The formulation by Berge and Hopperstad (1993) and the large associating advantages sparked a lot of interest, also with airlines. This is illustrated by for example Subramanian et al. (1994), who used the arc-based formulation of the FAM to improve efficiency at Delta airlines. The model, named *Coldstart*, supports multiple optimisation objectives such as cost minimisation and profit maximisation and also supports recapturing spilled passengers due to a lack of capacity on one flight onto another flight. Furthermore, the tool can be used as a route development tool when the constraint that each leg is to be flown is relaxed, providing the airline with an optimal operational network. Computational speed is greatly improved by the use of interior-point solution algorithms, reducing said times well beyond a factor of 25 compared to conventional solution methods. The power and versatility of the *Coldstart* model will result in the airline expecting to save up to 100 million USD per year for the next three years after the paper was released, showing the great improvements that FAM tools can make with respect to airline operational efficiency.

4.4. A Basic Formulation

Whereas earlier papers considered research which was mostly tailored to case studies at airlines, a good, high-level description from an academic point of view of the FAM using an arc-based formulation is provided by Hane et al. (1995). Their self-proclaimed "basic" FAM involves a cost minimisation objective function with four operational constraints and two mathematical constraints. The model is formulated as follows:

Sets

C = Set of cities
F = Set of available fleets
H = Set of required throughs
L = Set of flights in schedule
N = Set of network nodes
O(f) = Set of flight arcs containing 3 pm (for all f ∈ F)
X = Set of flight arcs
Y = Set of ground arcs

Subscripts

o = Origin
d = Destination
t = Time
i = Shorthand for *odt* combination or a flight arc
j = Similar to *i*, but *j* is the reverse *od* combination of *i*
f = Fleet type
t^- = Time preceding *t*
t^+ = Time following *t*
t_n = Time of last network node (before 3 pm)
t_1 = Time of first network node (after 3 pm)

Other

c_{fi} = Total cost associated with operating fleet *f* on flight *i*
S(f) = Number of aircraft in fleet f (for all f ∈ F)
X_{fodt} = X_{fi} = Decision variable equal to 1 if fleet *f* flies leg *i* and 0 otherwise
Y_{fott^+} = Ground arc for fleet *f* at airport *o* between time *t* and t^+

Objective Function

$$\min \sum_{i \in L} \sum_{f \in F} c_{fi} X_{fi} \tag{4.1}$$

Operational Constraints

$$\sum_{f \in F} X_{fi} = 1 \qquad \text{for all} \quad i \in L \tag{4.2}$$

$$\sum_{d} X_{fdot} + Y_{fot^-t} - \sum_{d} X_{fodt} - Y_{fott^+} = 0 \qquad \text{for all} \quad \{fot\} \in N \tag{4.3}$$

$$X_{fi} - X_{fj} = 0 \qquad \text{for all} \quad (i,j) \in H \tag{4.4}$$

$$\sum_{i \in O(f)} X_{fi} + \sum_{o \in C} Y_{fot_n t_1} \leq S(f) \qquad \text{for all} \quad f \in F \tag{4.5}$$

Mathematical Constraints

$$Y_{fott^+} \geq 0 \qquad \text{for all} \quad \{fott^+\} \in N \tag{4.6}$$

$$X_{fi} \in \{0, 1\} \qquad \text{for all} \quad i \in L \quad \text{and} \quad f \in F \tag{4.7}$$

Equation 4.1 depicts the objective function of the model. The objective function is a simple cost minimisation problem, which aims to minimise the total cost of the total network allocation problem by multiplying the total cost associated with operating fleet *f* on flight arc *i* (c_{fi}) with the decision variable which indicates whether the flight is actually flown (X_{fi}). The total cost coefficient can be built up using various different components such as fuel costs, crew costs, landing rights, air traffic control charges, spill costs and much more. As a consequence, this cost coefficient can vary per different aircraft type operating the same flight, which creates valuable dynamics in the model.

Next, we take a look at the constraints. The first operational constraint is shown in equation 4.2. This rather basic constraint ensures that all flight legs in the model are flown by at least one of the different aircraft types which are available to the airline. As a result, it is not possible for the model to remove flights which are not profitable, ensuring full network coverage as a requirement.

The second operational constraint in equation 4.3 is more complicated and ensures aircraft continuity at the nodes. The first two terms are all inbound terms, with the first term equating to all arriving flights at the *o* airport and the second term all aircraft travelling on the ground arc inbound to that node. The second two terms are all outbound terms, with the third term being all departing aircraft from airport *o* and the fourth and last term all aircraft travelling on the ground arc outbound of that node. When this constraint is satisfied for all nodes on all airports during the time of operation it can be ensured that aircraft do not ”appear out of nowhere” to complete a flight when they were not at that physical location and ready to complete the flight.

Third, the constraint in 4.4 is present to account for possible flights which have to be flown by the same aircraft type, also called required throughs. This constraint has been added to take into account flights who have to make a stop to, for example, refuel because the initial trip length is too long. By ensuring that the inbound and outbound flight have to be flown by the same aircraft type, this means that it is not possible for the airline to schedule two different aircraft types on the different legs in this flight. In practice, this could be interpreted as a constraint which prevents passengers from having to switch aircraft when on a connecting flight.

Constraint number four in equation 4.5 ensures that the number of aircraft of each type which are operated in the optimal solution of the problem does not exceed the predetermined number of aircraft which are available to the airline. This is done by ”cutting” the time space network at a random point in time; In this case 3 pm has been selected. The first term in the constraint counts all flights which are being operated at that exact point in time, whereas the second term in this constraint counts all the aircraft of different types which are on ground arcs between nodes ahead of the 3 pm time slot and nodes after the 3 pm time slot. This check can be performed at any random point in time and will ensure that the number of aircraft flying around will not exceed the number of available aircraft for the entire window of operation.

In addition to four operational constraints, two mathematical constraints to provide the basic conditions for the model to work in a feasible manner. First of all, in equation 4.6 a constraint is added which ensures that the number of aircraft travelling on ground arcs is always positive. This ensures that aircraft cannot travel back in time to perform a flight which departs earlier than the arrival time of a previously flown flight. Last but not least, constraint 4.7 ensures that the value of the decision variables, which are either flights that are operated by a certain aircraft type or flights that are not operated by a certain aircraft type are always take the boolean values of 0 (for false) or 1 (for true). This provides the last necessary conditions that it is not possible for multiple similar aircraft to perform the same flight and that ”negative flights”, are disallowed. Negative flights are both impossible from a practical point of view and would also interfere with the objective function defined in equation 4.1.

The ”basic” formulation of the FAM provided by Hane et al. (1995) is considered to be the starting point for many literature researching a wide variety of different alterations of this problem. Even though the problem formulation by Hane et al. (1995) could easily be made more ”basic”, by for example relaxing the first constraint which requires all flights to be flown or by removing the third constraint regarding the operation of subsequent flights with the same aircraft type, the prominent role of the formulation proposed by Hane et al. (1995) in further literature provides sufficient reasons to indeed name this formulation as the ”basic” formulation of the FAM. Hence, when referencing to the ”basic” fleet allocation model in this paper, we mean the formulation as proposed by Hane et al. (1995).

4.5. Alterations to the Basic FAM

The following subsections will discuss different variants of the model proposed by Hane et al. (1995) in the previous section and is tailored to discussing alterations which could be of interest for the model under consideration for this research. For example, section 4.5.1 will elaborate on research which has been conducted regarding the flexibility of passenger demand. Next, section 4.5.2 will discuss the integration of stochastic demand forecasting, which has been separately discussed in section 3.2.2. In section 4.5.3, opportunities to incorporate flexible flight scheduling will be highlighted. Last but not least, the section concludes with section 4.5.4 aimed to briefly describe other influential alterations which have been proposed in literature.

4.5.1. Passenger Demand Flexibility

One of the requirements of the FAM under development for this thesis is that is is able to take into account flexibility of passenger demand. This can broadly be generalised to two different types of flexibility. Fist of all, there is inherent flexibility in passenger demand per period of the day. For example, the demand for a flight between Amsterdam and London is likely to be in higher demand in the morning and late afternoon due to the fact that this route is popular from a business perspective. This can be be incorporated on the input side of the fleet allocation model by allocating the demand which exists on a certain time to flight arcs which leave the airport in the same time period.

A second, more complex form of passenger demand flexibility to take into account is the interchangeability of passenger demand between different times of the day. Consider, for example, time-fixed demand of passengers who are only willing to travel on certain times (such as business travellers) and time-flexible demand of passengers who are less interested in their departure time and more interested in cost incentives (such as leisure travellers). For overall efficiency reasons it could significantly pay off to shift some of the flexible demand to other times of the day such that possible empty seats could be filled or that a more efficient combination of aircraft types could be utilised.

Some efforts have been made to adapt the standard fleet allocation model to support this demand flexibility. Although not entirely similar, recapturing spilled passengers from one flight at maximum capacity to another flight where seats are still available has been discovered extensively in literature and can be seen as a good starting point for the discussion on demand flexibility. The largest contribution in passenger recapturing is made by Barnhart et al. (2002). Barnhart et al. (2002) formulated a fleet allocation problem which is based on passenger itineraries instead of flight legs. This is achieved by combining aspects of the standard fleet allocation model as described above with aspects of the *Passenger Mix Model (PMM)*, which seeks to optimally assign passenger itineraries to existing aircraft-route combinations on the network of the airline.

This novel formulation results in several large advantages. For example,the fleet allocation model provided by Hane et al. (1995) only takes into account deterred revenue from spilled passengers as costs, but it does not actively reassign these spilled passengers to different flights. The formulation by Barnhart et al. (2002) has the big advantage that it does actively reassign spilled passengers to different itineraries by making the number of passengers who switch itineraries part of the solution space. This is done by means of the recapture rate, which indicates which proportion of the passengers spilled in one itinerary can be recaptured to a different itinerary, possibly at a lower cost level. This is further strengthened by the fact that this is incorporated through the entire network. Imagine, for example, a small, hypothetical network in which one flight feeds the hub airport which subsequently connects to two other destinations. If the flight feeding the hub airport is significantly constrained, the novel formulation will prefer connecting passengers to the more expensive destination on the inbound leg as they bring in more revenue at a later stage, which is something which was impossible under the old formulation.

Even though the model framework outlined by Barnhart et al. (2002) is close to solving the problem regarding demand flexibility, it does solve the issue which is under consideration here. The fundamental difference is that it only deals with the reallocation of spilled passengers to different itineraries instead of a fixed amount of passengers who are flexible in their demand irrespective of the fact whether or not they are spilled or not. To the best knowledge of the author, no previous literature on adaptations of the standard fleet allocation model exists which explicitly takes into account passenger demand flexibility which would entail that this research makes a further contribution to the broad variety of literature which exists in this field.

4.5.2. Incorporating Stochasticity

The solution of the fleet allocation model is heavily determined by the demand which exists for certain flights. As the problem is inherently used to determine which aircraft types are to be operated on future flights, this also means that it is required to forecast the demand in a way which is as accurate as possible. As has already been discussed in chapter 3 and section 3.2.2 specifically, the uncertainty accompanied with the demand forecasting may subsequently result in different solutions to the fleet allocation problem when demand data is updated. This could theoretically result in issues for the airline such as late aircraft swaps and associated problems such as crew availability. It was hence a logical step to integrate these forecasting techniques in the fleet allocation model which then aims to find a robust fleet allocation solution for multiple demand scenarios. Ferguson and Dantzig (1954), who proposed the initial formulation of the problem which has been discussed in section 4.1, already recognised this issue and proposed the first basic stochastic formulation of the problem two years later using fixed probabilities to take into account a small number of demand realisations (Ferguson and Dantzig, 1956).

In a more modern context, Sherali and Zhu (2008) published an influential paper into the incorporation of stochastic demand in the fleet allocation problem. Even though the model formulation has significantly changed from that proposed by Ferguson and Dantzig (1956) and is much more in line with the itinerary-based formulation proposed by Barnhart et al. (2002), the general working principle remains largely the same. The objective is to find the one airline fleet allocation which maximises the total expected profit under the multiple, uncertain, demand scenarios. Multiple unique demand scenarios are generated by sampling the demand, which follows a normal distribution, for all individual itineraries in the model and collecting them to generate the total network demand. The authors propose two different solution methodologies which both rely on the Benders Decomposition solution strategy. This strategy first solves a relaxed version of the full problem, which can be solved more easily, after which these results are tested for feasibility in smaller subproblems. If it is determined that the initial solution is unfeasible, a different problem is solved to determine where to cut the solution space of the full problem and the process is repeated until a total feasible solution is found. It is subsequently shown that the stochastic methodology of Sherali and Zhu (2008) outperforms the deterministic, mean-based formulation by Barnhart et al. (2002) by increasing the average profit by approximately 3.5%.

4.5.3. Flexible Flight Scheduling

Last but not least, it should be able to allow flight departure and arrival times to vary such that the varying demand over the day, including passenger flexibility, can be allocated as efficiently as possible. The first paper to mention varying departure and arrival times is Levin (1971), who proposes a constraint on multiple similar flights in terms of route, capacity and departure times, ensuring that only one of these is selected. The application of this model however is limited, as it only considers one aircraft type and does not follow the arc-based formulation, making it challenging to solve for larger problems. In the context of the arc-based formulation of the fleet allocation model however, Rexing et al. (2000) is the first to propose a similar approach to varying departure times as Levin (1971) by imposing a constraint on multiple similar flight arcs such that only one is selected. In other words, it modifies equation 4.2, which is repeated below as equation 4.8 for convenience:

$$\sum_{f \in F} X_{fi} = 1 \qquad \text{for all} \quad i \in L \tag{4.8}$$

Into a form which supports multiple copies of the same flight arc. This is achieved by summing equation 4.8, over all individual copies of the same flight arc *n* which are available in the total set of copied flight arcs *N*. In the notation below, X_{nfi} then is the decision variable whether the n^{th} copy of regular flight X_{fi} is operated.

$$\sum_{n \in N} \sum_{f \in F} X_{nfi} = 1 \qquad \text{for all} \quad i \in L \tag{4.9}$$

Furthermore, Rexing et al. (2000) propose a novel, two-stage solution strategy to deal with the increasing number of decision variables this problem now faces. First of all, three prepossessing steps are performed aimed at simplifying the network. The first step targets to reduce the problem size by reducing the number of flight arcs. This is achieved by analysing the properties (such as cost and possible connections) of each flight arc and deleting later copies of the same flight arc who partly share the same characteristics but are inherently worse. For example, if two flight legs are both as expensive, but the first flight leg enables two connections instead of one, the second flight leg is inherently worse than the first, will never be chosen and can hence be deleted. This also as the large advantage that an accompanying ground arc can be removed from the problem as well, further reducing computational effort required. The second step is to perform a so-called node consolidation exercise which aims at merging nodes without loss of generality. Nodes can then represent time windows instead of exact instances in time, reducing the number of rows in the LP-matrix by one for each removed node and the number of columns by one for each removed ground arc. The third and final prepossessing step deals with the formation of islands. This means that, on airports with low demand, the number of aircraft present on a ground arc can be derived from the problem without having to solve for this variable. For example, if there are *z* aircraft on the ground early in the morning and there is only one, mandatory flight to depart, the number of aircraft on the ground arc after that departure is equal to *z-1* and hence does not have to be part of the solution space.

The second stage of the solution framework involves an iterative solution technique. First of all, the problem is initialised without the multiple copies of the same arc and attempted to be solved. If found to be unfeasible, more and more parallel arcs would be added until the solution reaches and optimal state for all fleets in the model. This prevents all parallel arcs being dumped into the model at once and further reduces the computational effort required. In test problems when using data from a large airline in the United States, Rexing et al. (2000) found that, when enabling flexible flight scheduling, daily revenues could be improved with over 65.000 USD per day which demonstrates the added value of time-flexible planning in this field.

4.5.4. Other Alterations

A variety of other alterations of the classical fleet allocation problem have been proposed as well, of which the most important contributions will be briefly mentioned in this section. In the itinerary-based formulation by Barnhart et al. (2002), which has been discussed earlier in this section, the recapture rates of spilled passengers has been modelled using the Qualitative Share Index (QSI). Even though this model is commonly used in airline planning literature, Wang et al. (2014) criticise this approach due to the lack of flexibility of this metric. For example, the recapture rate between several itineraries remains constant independent of the pool of available itineraries to choose from hence ignoring passenger preference and market effects. Wang et al. (2014) aim to mitigate these limitations by construction of a novel framework for computing these recapture rates by explicitly taking into account the differences in attractiveness between itineraries and market competition of other airlines in a computationally attractive manner. Similar research by Atasoy et al. (2014) also shows a more elaborate itinerary choice model in an even broader framework by taking into account itinerary price, airline class and whether the itinerary is a direct flight or involves multiple legs. Wang et al. (2014) show that a more accurate representation of these recapture rates can result in increased profitability of more than 1% compared to the traditional itinerary-based formulation.

The classical formulation of the fleet allocation problem as proposed by Hane et al. (1995) has a further limitation in the form that the model does not take into account possible constraints which may be faced when looking at the incorporation of airline crew planning and airline maintenance planning into the problem. Elaborate research by Clarke et al. (1996) aims to address these limitations. The authors propose to add a constraint to the model which requires that a fixed proportion of the different fleet types in the model stay at overnight arcs on airports where the maintenance can be performed. This solution however faces some obvious limitations as it means that maintenance can only take place during nighttime which does not always lead to an optimum regime. Clarke et al. (1996) propose a further solution in the formation of maintenance arcs. These can be seen as flight arcs which arrive and depart at the same maintenance station, effectively freeing up time for maintenance to be completed. A constraint is then added to the basic formulation of the problem which requires each aircraft type to complete one of several available maintenance arcs. This ensures that maintenance is explicitly part of the allocation process, but still faces, albeit significantly smaller limitations. Larger maintenance checks such as B, C and D-checks for example can take multiple consecutive days during which the aircraft is unavailable and adds significant modelling complexity. Anyhow, the formulation by Clarke et al. (1996) provides a good starting point for the integration of maintenance considerations in the fleet allocation model. As a further discussion of the integration of maintenance is beyond the scope of this literature review, the reader is referred to Subramanian et al. (1994) and Barnhart et al. (1998) for additional reading.

Next to considerations regarding aircraft maintenance, Clarke et al. (1996) also consider the problem faced by integrating flight crew planning into the fleet allocation model. The authors aim to limit the number of *lonely overnights*, which take place when crew have to take the overnight arc on an airport away from their home base due to the fact that no aircraft is present for them to fly back. This is achieved through several mechanisms such as the addition of so-called legal rest arcs which crews can take in a similar fashion to maintenance arc to be temporarily extracted from operation in the model.

A further elaborate discussion of the integration of crew considerations in the fleet allocation process including mathematical formulation is provided by Cordeau et al. (2001).

4.6. FAM in Other Disciplines

Whereas the preceding sections have discussed applications and formulations of the fleet allocation model in the context of airlines, other industrial fields exist in which similar problems exist. Think about for example the question which cars, trucks or busses to allocate on the route network. Beaujon and Turnquist (1991) for example provide a dynamic, integrated fleet sizing and allocation model suitable for application in multiple fields amongst which cars and trucks are explicitly mentioned. Furthermore, Vasco and Morabito (2016) solve the dynamic vehicle allocation problem in the context of freight trucks. Their model aims to optimally assign different model types of trucks which can be either be carrying cargo or drive empty legs to repositioning in the context of Brazilian truck logistics firms.

Teichmann et al. (2015) perform fleet allocation in the context of rail transport. The goal of their research is to develop a model which optimally assigns certain locomotives to trains on the rail network of the Czech Republic and part of Slovakia. Several constraints have to be taken into account such as the fact that several routes require specific locomotives to be operated. Furthermore, the model also supports the hiring of external locomotives at an additional cost when the fleet of existing locomotives is either too small to operate all required trains or simply less efficient.

Fleet allocation problems are also common in the maritime sector. Powell and Perkins (1997) for example describe the allocation of vessels to shipping routes for *Flota Mercante Grancolombiana*, which is a subsidiary firm owned by the Colombian Coffee Federation and operates vessels for the export of homegrown coffee beans. Similar research performed by Fagerholt and Lindstad (2000) discusses fleet composition, route scheduling and subsequent fleet allocation for vessels owned by *Statoil* in the context of servicing offshore oil installations. Results from the model have identified that there is room for cost savings worth up to 7 million USD and the tool has been implemented by the firm in an attempt to capture these benefits.

This section is concluded by mentioning an interesting contribution in the field of helicopter transport. Menezes et al. (2010) establish an helicopter fleet allocation model for the purpose of optimising transport of oil rig crews for the Brazilian oil company *Petrobras*. The network consists of 80 offshore oil rigs and four mainland crew bases with all helicopters combined transporting approximately 1900 passengers every day. Menezes et al. (2010) make use of a column generation algorithm to reduce the computational time to less than one hour for the entire network and the following results are very positive. *Petrobras* was able to reduce their total flying time with up to 8% and cut their total operating costs with up to 14%, resulting in estimated savings of over 20 million USD per year.

4.7. Conclusions

This chapter has discussed intensively the available literature which exists on the fleet allocation problem. The first sections have elaborated on the initial formulation of the problem and its first appearance in academic literature (Ferguson and Dantzig, 1954) and first major application in industry (Abara, 1989). After that the large improvement in solving this problem by making use of the arc-based formulation as proposed by Berge and Hopperstad (1993) has been discussed extensively. This model was later generalised by Hane et al. (1995) to establish the basic fleet allocation model which serves as a broad basis for further research on this model. With this basic model in mind several alterations to the basic fleet allocation formulation which could be of interest for this project have been discussed in the fields of passenger demand flexibility, compatibility with stochasticity and flexible flight scheduling. Other alterations such such as improvements on the input-side of the model in terms of passenger recapturing, compatibility with aircraft maintenance and considerations with respect to aircraft crew have also been discussed to broaden the scope. The section has been concluded by elaborating on other applications of the fleet allocation model by looking beyond the airline industry and featured examples from road, rail, maritime and helicopter transport.

From the discussions it is clear that the field of fleet allocation problems is widely discussed in academic literature. The fact that the fleet allocation model can be tailored to specific cases by adjusting terms in the objective functions or by adding more or replacing existing constraints also helps with the attractiveness of this tool in industry and research. Furthermore, it has also been demonstrated that implementation of these modelling techniques in the day-to-day operation can result in large cost savings. There are however also some limitations. In most of the cases it is really hard to isolate the fleet allocation problem from the total operational context. For example, fleet allocation may be heavily linked to schedule design and fleet composition or heavily constrained by crew and maintenance considerations. Efforts to integrate or adapt the fleet allocation model to work in a broader framework have been made but often come at the cost of significant increases in computational time. The challenge to obtain higher model complexity without exploding computational times is subject to continuous research which makes this field highly dynamic and provides sufficient motivation for additional research in the form of this master thesis.

5
Literature on Aircraft Design Integration

In order to successfully optimise the fleet allocation model with multiple fleets, it is required that each fleet is utilised in an optimum manner other than simply being suited for the amount of passengers. For example, aircraft can be designed for different optimal mission ranges and strong deviations from this optimum may cause large inefficiencies in terms of fuel consumption. Furthermore, limitations may be in place in terms of available and required runway length at airports or available and required gate capacity. This are only a few examples of the variety of factors which should be taken into account before making informed decisions on allocating aircraft types to different routes in the network, especially when aiming to do so in an optimum manner.

This section aims to elaborate on how certain aircraft design parameters and design decisions are integrated into the fleet allocation model which is to be solved for the market demand analysis. Three different aspects of aircraft design or utilisation parameters will be discussed. First of all, section 5.1 will elaborate on how the aircraft design parameters work through in the objective function of the model whereas section 5.2 will state how aircraft design can provide limitations to the feasible solution space in the form of adding additional constraints. Section 5.3 will elaborate on comparable research which seeks combine aircraft design with fleet allocation or other related optimisation problems. Last but not least, section 5.4 summarises the findings of this chapter.

5.1. Integration in the Objective Function

The objective function of the optimisation model is the first section of the model in which aircraft performance parameters play an important role. According to Rexing et al. (2000) and Hane et al. (1995), determining accurate cost coefficients for the model is a very challenging and important part in obtaining an accurate solution to the fleet allocation problem. The objective function of the classical fleet allocation model has already been shown as equation 4.1 in chapter 4, but will be restated below as equation 5.1 for convenience.

$$\min \sum_{i \in L} \sum_{f \in F} c_{fi} X_{fi} \tag{5.1}$$

This objective forms a cost minimisation framework in which c_{fi} is the cost of assigning fleet f to flight leg i and X_{fi} a boolean decision variable which takes the value 1 if flight i is covered by fleet f and 0 otherwise. This way, the cost is only taken into account for the objective function if the flight is actually performed. The cost parameter c_{fi} can incorporate many different factors. Belobaba et al. (2016) for example presents the following formulation for determining the cost coefficients the objective function, as shown in equation 5.2.

$$c_{fi} = OpCost_{if} - Fare_i \cdot min(Dem_i, Cap_f) \tag{5.2}$$

In which $OpCost_{if}$ is the total cost of operating flight i with fleet f, $Fare_i$ the revenue per ticket sold on flight i which is multiplied with the minimum of either Dem_i, the total passenger demand for flight i, or Cap_f, the maximum passenger capacity of fleet type f. This formulation takes the total cost of operation and subtracts the revenues from ticket sales in order to determine the net cost of operating the flight. If the revenues from ticket sales are larger than the costs associated with operating the flight, which is a required condition for firm profitability, this coefficient will be negative and in a minimisation framework will be equal to a profit maximisation exercise. The $OpCost_{if}$ variable, which indicates the total operating cost, takes into account a further variety of performance-related factors associated with operating an aircraft. To adequately assess the most important of these underlying fundamentals, this section is separated into two different subsections. Subsection 5.1.1 will elaborate on the methodology which is used to calculate the fuel consumption and efficiency of different aircraft for a variety of combinations of mission range and mission payload, which is a prime performance objective to incorporate in this master thesis. Next, subsection 5.1.2 will discuss all other important parameters which play a role in determining this cost coefficient making notes on possible aircraft design decisions to reduce this cost along the way. When combining these sections, all relevant factors to take into account when considering the objective function for the optimisation model will then be covered.

5.1.1. Passenger Dependent Fuel Consumption

This section elaborates on the methodology which is used to calculate the fuel consumption of aircraft based on the combination of mission range and number of passengers, using basic aircraft design parameters and simple payload-range diagrams as input. Such a typical payload-range diagram, which depicts the possible feasible combinations of fuel, payload and range, is shown below in figure 5.1.

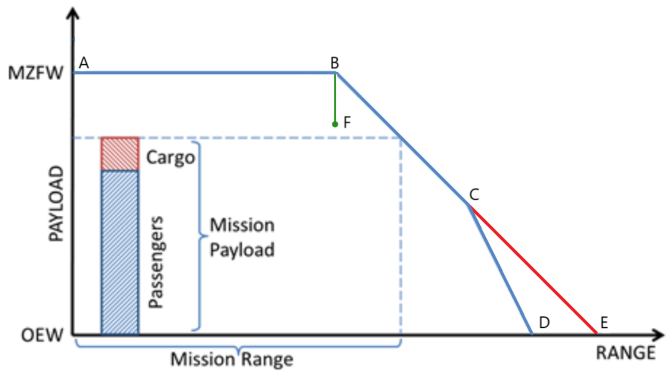

Figure 5.1: A typical aircraft payload-range diagram. Adapted from Baxter et al. (2018)

In figure 5.1, the mission range is on the x-axis and the total payload on the y-axis. This total payload comprises of a combination of passengers with their luggage and possible cargo. At the bottom of the y-axis is the aircraft operating empty weight (OEW), which is the weight of the aircraft without any fuel or payload, but taking into account aircraft structure and items required for operation such as seats, galleys and toilets. When looking at point A, which is at a fictitious zero range, maximum payload can be added to the OEW until the maximum allowed weight with zero fuel (MZFW) from this point on, fuel can continuously be added to increase the aircraft range without having to sacrifice on the maximum payload capacity. This is possible until point B in the graph is reached, at which the maximum payload weight and fuel weight combined reaches the maximum take-off weight (MTOW). As the MTOW can not be exceeded, from point B to point C in the graph payload has to be traded for additional fuel to make additional range possible. This can theoretically be continued until no payload remains, after which point E in the graph is reached, shown in red. If there is a technical limit to the maximum amount of fuel an aircraft can carry, the segment from point C to point D in blue represents the area where the maximum amount of fuel is reached and the only option is to further remove payload without adding extra fuel in return. It is worth noting that these lines present the operating limits, and that any combination of fuel, payload and range in the area enclosed by these lines is also feasible.

From a mathematical point of view this relationship between payload weight, fuel weight and range can be modelled using the Breguet range equation. The Breguet range equation is derived by integrating the change in aircraft weight over time using a constant speed and fuel flow rate and is shown in equation 5.3 below.

$$R = \frac{VC_L}{C_D C_T} \ln\left(\frac{W_{start}}{W_{end}}\right) \tag{5.3}$$

In which R is the aircraft range, V the cruise speed, C_L the lift coefficient, C_D the drag coefficient, C_T the thrust coefficient and two aircraft weights W_{start} at the start of the flight including fuel and payload as well as W_{end} the weight at the end of the flight, when all fuel has been burned. Alternatively, equation 5.3 can be rewritten in terms of the different weight components W_0, which is the operating empty weight, W_p, which is the payload weight and W_f the total fuel weight as in equation 5.4.

$$R = \frac{VC_L}{C_D C_T} \ln\left(\frac{W_0 + W_p + W_f}{W_0 + W_p}\right) \tag{5.4}$$

Under the condition that the aircraft is operating at MTOW, W_{MTOW}, we can rewrite equation 5.4 as equation 5.5

$$R = \frac{VC_L}{C_D C_T} \ln\left(\frac{W_{MTOW}}{W_{MTOW} - W_{f_{MTOW}}}\right) \tag{5.5}$$

Equation 5.5 can subsequently be solved for the fuel weight at maximum take off weight $W_{f_{MTOW}}$ for a variety of theoretical ranges R. The result is shown in equation 5.6.

$$W_{f_{MTOW}} = W_{MTOW}\left(1 - \frac{1}{e^{\frac{RC_D C_T}{VC_L}}}\right) = W_{MTOW}\left(1 - e^{-\frac{RC_D C_T}{VC_L}}\right) \tag{5.6}$$

As the maximum possible aircraft weight will always be constrained by the MTOW, it is now possible to assess the total theoretical payload capacity for a variety of ranges under the condition that the aircraft is operating at MTOW. This can be achieved by subtracting the OEW and fuel weight at maximum take-off weight for a given range from the design maximum take-off weight of the aircraft as shown in equation 5.7

$$W_p = W_{MTOW} - W_0 - W_{f_{MTOW}} \tag{5.7}$$

This equation can be used to determine the total possible payload capacity. Two different scenarios are now possible. If the total remaining payload capacity is larger than the total weight of the possible payload on an aircraft, which is set equal to the number of seats in the aircraft multiplied by the weight per passenger, then it is possible for the aircraft to carry the maximum number of passengers. The point of operation is equal to anywhere between points A and B on the payload range diagram as shown in figure 5.1. As the total weight of all passengers is now smaller than the total possible payload capacity, this also entails that not all fuel is required to be taken on board of the aircraft. In other words, as the aircraft is not flying at maximum take-off weight for that range, amount of fuel required is now smaller than the previously calculated fuel weight at maximum take-off weight. The actual required amount of fuel can now be calculated by solving equation 5.4 for the fuel weight W_f as shown in equation 5.8 using the maximum payload capacity of the aircraft for W_p.

$$W_f = \left(W_0 + W_p\right)\left(e^{\frac{RC_D C_T}{VC_L}} - 1\right) \tag{5.8}$$

On the other hand, if the total payload capacity is smaller than the maximum possible payload weight of the aircraft, this entails that payload has to be sacrificed for additional fuel. This corresponds to segment B to C and segment C to E on the payload range diagram in figure 5.1. As the aircraft will now for sure operate at MTOW, the total amount of fuel required for the given range is subsequently provided by equation 5.6. The total amount of passengers which are able to be taken on this range can last but not least be calculated by dividing the total remaining payload capacity from equation 5.7 by the weight per passenger.

Using this methodology it is possible to calculate the required fuel weight and maximum number of passengers for any point on the edges of the payload range diagram. There are, however, also a lot of possible combinations of payload and range which are not located at the edges of the payload range diagram but anywhere on the area enclosed by these edges. All points which lie on the interior of these edges are essentially points at which less payload is taken compared to the most limiting cases. This is indicated by point F in figure 5.1. The reduction in associated payload of point F compared to point B also results in the fact that less fuel is required to transport the mission cargo over the same mission range. The relationship between reduction in payload weight and subsequent reduction in required mission fuel can be mathematically formulated by taking the partial derivative of equation 5.8 with respect to the payload weight, which is shown in equation 5.9 below.

$$\frac{\partial W_f}{\partial W_p} = \left(\left(\frac{W_0 + W_p + W_f}{W_0 + W_p} \right) - 1 \right) = \left(e^{\frac{RC_D C_T}{VC_L}} - 1 \right) \tag{5.9}$$

The partial derivative in equation 5.9 indicates how much fuel needs to be added or removed with a corresponding change in payload weight and shows that this value is constant for a given mission range. This characteristic can be exploited such that for all points on the interior of the payload-range diagram the required fuel weight can be determined by first calculating the required fuel weight for the most limiting case for that particular range and subsequently subtracting the multiplication of this partial derivative with the reduction in payload. From a mathematical perspective, this can be formulated as equation 5.10

$$W_{f_{red}} = W_f - W_{p_{red}} \frac{\partial W_f}{\partial W_p} \tag{5.10}$$

In which $W_{f_{red}}$ and $W_{p_{red}}$ are the reduced fuel weight and the reduced payload weight compared to the limiting case on the edge of the payload range diagram. By adopting this strategy it is possible to now calculate the required fuel consumption for multiple aircraft based on their basic performance parameters, weights and mission characteristics. This is an important part which enables the model to assign the most efficient aircraft to combinations of routes and passengers such that an assessment of potential market impact of a novel aircraft can be made.

5.1.2. Other Cost Parameters

Next to the cost of fuel, which is required to transport passengers from their origin to their destination, they are plenty of other costs associated with operating an airline. Exact quantification of the exact values of these costs however may be difficult. More often than not they are a hard-kept secret by airlines due to the fact that it provides essential information on airline efficiency, which could also be of interest to competing airlines. Some information on these costs however are available, and in an economic development seminar organised by IATA (2017), details are shared on the most important cost categories for airlines operating in the United States. These categories and their relative impact will be briefly discussed below.

1. **Aircraft Operating Costs**
   Aircraft operating costs are all costs which can be directly related to operating an aircraft. According to IATA (2017), these costs are equal to approximately 44% of the total costs of the airline. Managing operating costs is therefore considered to be an essential requirement for an airline to be successful and can be heavily influenced by the choice of aircraft in the fleet. When looking further into this category, a distinction can be made to the following subgroups.

   I **Fuel Costs**
   Fuel costs are costs associated with the acquisition of jet fuel required for the aircraft to fly. This category and the impact of aircraft design decisions on the fuel consumption of aircraft has been discussed elaborately in section 5.1.1.

   II **Crew Costs**
   Crew costs are costs associated with the wage payment of crew on board of the aircraft. This category only involves cockpit crew, as cabin crew are considered to be costs related to passenger servicing (Belobaba et al., 2016). According to IATA (2015), the total cost of the cockpit crew members per block hour for a Boeing 757-200 aircraft ranges anywhere between 388 and 927 USD per block hour. This large range can be attributed to a wide number of factors such as whether the airline is low-cost or not, level of seniority, pilot age and quality of the collective labour agreement. On most modern aircraft, which do not require

an additional flight engineer to be present, there are two cockpit crew members which is also the minimum number of cockpit crew required by the Federal Aviation Regulation (FAR) (FAA, 2019). This limited flexibility entails that cockpit crew costs are considered rigid with respect to aircraft design considerations.

III **Maintenance Costs**
Conducting aircraft maintenance is essential to maintain the airworthiness of the aircraft and safely transporting passengers. Even though an extremely detailed analysis of all factors which play a role in aircraft maintenance is beyond the scope of this report, Urdu (2015) provides several interesting insights in the connection between aircraft design and consequences for maintenance. The author develops a new model which shows that maintenance cost increases proportional to aircraft weight and seating capacity which entails that smaller aircraft are cheaper to maintain than large aircraft; A perhaps somewhat intuitive conclusion.

IV **Cost of Ownership**
Cost of ownership costs are all costs which are associated with owning an aircraft. If the aircraft is leased, these costs are called leasing costs and are paid to the lessor. If the aircraft is purchased by the airline these costs are depreciation and amortisation of the aircraft plus a possible interest rate premium if the aircraft is purchased with loan-bearing external funds. The hourly depreciation rate of an aircraft can readily be computed by calculating the difference between the list price and the residual value after a set period of time divided by the total number of flight hours of the aircraft in that same time period. This entails that cheaper aircraft in terms of purchase price are also cheaper to operate and more effective utilisation results in lower costs. These depreciation rates are in the magnitude of 726 USD per hour for an Airbus A320-200 aircraft (Belobaba et al., 2016) and 923 USD per hour for a Boeing 757-200 (IATA, 2017).

2. **Ground Operating Costs**
Ground operating costs are all costs which are associated with the ground and service operations at the airport or on board of the aircraft. These costs are equal to approximately 29% of the total operating costs of an aircraft and involve aircraft servicing charges, traffic servicing charges and passenger servicing charges.

I **Aircraft Servicing**
Aircraft servicing costs are costs related to preparations which are needed to make the aircraft ready to fly. These costs involve, amongst others, aircraft cleaning costs, handling costs and landing fees. The latter two costs are often dependent on aircraft characteristics. For example, at Amsterdam Schiphol Airport landing and take-off fees are dependent on the maximum take-off weight of the aircraft, noise classification and whether the aircraft is serviced at a connected or remote stand Schiphol (2019). From a design and cost-competitiveness perspective it is hence important to limit the weight and noise classification of aircraft.

II **Traffic Servicing**
Traffic servicing charges are involve the charges which are applied to offset, for example, expenses made when passengers using the airport such as airport cleaning, security and luggage handling. They are often calculated on a per passenger basis and can be considered rigid with respect to aircraft characteristics other than the number of passengers travelling on the aircraft.

III **Passenger Servicing**
Passenger servicing costs are all costs related to the servicing of passengers such as meals and cabin crew wages. According to FWO (2019) cabin crew wages range anywhere between 15 to 45 USD per flight hour excluding benefits. In terms of aircraft design, flexibility exists in the number of cabin crew which are required on board of the aircraft. The number of cabin crew which are required to be on board of an aircraft is also defined by the Federal Aviation Regulations (FAR) and scales with the amount of passengers the aircraft can carry. As most commercial aircraft have a maximum payload capacity of more than 7500 pounds, it requires one cabin crew member for aircraft with a seating capacity between 9 and 51 passengers and two cabin crew members for aircraft with a seating capacity between 50 and

100. For aircraft with more than 100 seats, it is required to have two cabin crew members plus one extra for each 50 passengers above the 100 seats threshold (FAA, 2019). In terms of aircraft design it can hence pay off to take into account these regulations when determining the seating capacity of new aircraft such that the cabin crew utilisation is as efficient as possible.

3. **System Operating Costs**
   The last category mentioned by are the system operating costs. System operating costs are all costs which are not related to operation of aircraft such as costs associated with arranging reservations and sales as well as other overhead costs. Together, these two categories account for 27% of the total operating costs of the airline IATA (2017). Both categories are considered to be unaffected by aircraft performance characteristics but are mentioned for completeness.

   I **Reservations and Sales**
   Reservations and sales costs are all costs which are directly related to the operation and development of ticketing systems and revenue management frameworks. These costs are often calculated as a percentage of the total revenues generated by the airline (Belobaba et al., 2016).

   II **Overhead**
   Overhead is the general term for all costs associated with the organisational structure of the firm. Think about office personnel such as planning staff, finance departments, strategy departments and much more. Costs associated with these necessary activities have to be offset by ticket sales and are hence included in the total cost for flight operation.

5.2. Integration in Model Constraints

Aircraft performance characteristics do not only find their way into the objective function of the linear programming framework but may also induce additional constraints to the feasible solution space. This section aims to elaborate on some of these constraints such as limitations on available aircraft range, available runway length and fly-over noise. These constraints will check whether certain requirements for successful operation are met and force the decision variable to zero if these requirements are violated.

The first aircraft performance related constraint which is often used in linear programming models is related to the available range of the aircraft. This is closely related to the discussion regarding passenger-dependent fuel consumption which has been elaborated on in section 5.1.1. An aircraft is only able to perform a flight if the combination of payload and fuel results in sufficient available range to reach the intended destination. If this is not the case, the decision variable of this combination should be set to zero to indicate that this flight cannot physically be performed.

Another constraint is related to the available runway length. Both on departure as well as on arrival sufficient runway length should be available to either take off or land with all required mission fuel and payload. Design decisions which can be made to improve runway performance can be found in, for example, increasing available engine thrust, improved high-lift devices such as flaps and slats or improved braking systems. The first part of the ICAO Aerodrome Reference Code identifier categorises airports dependent on their available reference field length. This classification scheme is shown in figure 5.2. If an aircraft has a required landing or take-off field length which exceeds the available runway length on the airport it is not possible to operate on that airport. However, as most commercial airliners and commercial airports all comply with class 4 in this field, this constraint is not identified as being of prime importance. A notable exception to take into account however is London City Airport, well known for its business travel, which has a runway length of only 1500 meters (NATS, 2017).

Code element 1	
Code number	Aeroplane reference field length
1	Less than 800 m
2	800 m up to but not including 1 200 m
3	1 200 m up to but not including 1 800 m
4	1 800 m and over

Figure 5.2: The first part of the ICAO Aerodrome Reference Code classification (Airbus, 2019)

A similar constraint is related to the aircraft wingspan. Some airports may pose additional constraints on aircraft wingspan due to limited width and proximity of certain taxiways or the placement and layout of gates on the airport. The second part of the ICAO Aerodrome Reference code categorises these airports based on the aircraft wingspan the airport can accept. If an aircraft wants to operate on such an airport, it needs to comply with the wingspan requirements as outlined in figure 5.3. One of the prime objectives of the proposed PrandtlPlane for the *ParsifalProject*, which serves as a test case for the proposed model, is that the aircraft is compatible with class C airports who accept aircraft with a wingspan up to only 36 meters.

Code element 2	
Code letter	Wingspan
A	Up to but not including 15 m
B	15 m up to but not including 24 m
C	24 m up to but not including 36 m
D	36 m up to but not including 52 m
E	52 m up to but not including 65 m
F	65 m up to but not including 80 m

Figure 5.3: The second part of the ICAO Aerodrome Reference Code classification (Airbus, 2019)

Last but not least, gate capacity at the arrival and destination airports is another limitation to aircraft operation. Due to airport layout it may not be possible for a certain aircraft to dock at a particular gate, for example when the aircraft is too long or has a very large wingspan. At Amsterdam Airport Schiphol, 10 different categories of gates are available which each have a different limit on aircraft length and wingspan (Schiphol, 2019). Furthermore, additional constraints may be present if specific aircraft are located at neighbouring gates. Implementation of some of the aforementioned constraints in the model which is to be developed may be of prime importance to ensure that the final results are accurate from a technical point of view and contributes to enhancing realism of the developed solutions.

5.3. Research on Integration with Fleet Allocation

This section aims to elaborate on similar research which has been conducted in the field of combined aircraft performance integration in the fleet allocation model. Research on the integration of aircraft performance into the fleet allocation model can be distinguished into two different categories. The first category of research takes existing aircraft performance parameters as input and uses these to determine the cost of operating this aircraft on a certain route. As elaborated on in section 5.1 a variety of costs can be taken into account to resemble the difference in operating efficiency of different aircraft types. These costs are subsequently used as coefficients for the objective function of the fleet allocation model by means of which the trade-off between different aircraft types can be established. Even though researchers such as Rexing et al. (2000) and Hane et al. (1995) seem to widely agree on the notion that determining accurate cost coefficients for the objective function is key to obtaining realistic model solutions, the approach by means of which these cost coefficients are determined are not often disclosed.

The second category of research involves the concurrent optimisation of aircraft design and solving the fleet allocation problem. As an aircraft design with characteristics tailored to the network under consideration could result in significant increases in efficiency and hence cost-savings, this field of research has gained significant traction over the last decade. Davendralingam and Crossley (2009) are one of the first to provide a solution framework to this problem. Their model allows the aircraft to change in terms of take-off weight, aspect ratio, thrust-to-weight ratio and wing loading under the condition that requirements on take-off and landing distances are satisfied. Mane and Crossley (2012) provide a further elaboration on this framework by incorporating uncertainty in flight demand into the equation. Their results show that, for a single aircraft type fleet allocation problem, the alterations in design freedom allows for operating cost reductions up to 3.6%. Jansen and Perez (2013) solve the simultaneous aircraft design and fleet allocation problem by using much more design parameters than Davendralingam and Crossley (2009) and Mane and Crossley (2012). Their design variables include, amongst many others, seating capacity, wingspan, wing sweep angle, horizontal and vertical tail sizing, cruise speed and engine sizing. The problem is subsequently solved in an energy intensity framework, which seeks to minimise the total amount of energy required to satisfy a given minimum network coverage in terms of flight frequency. For a test case which allowed the model to resize only the engines of existing jets, the required network energy was reduced by over 16% and operating costs reduced with more than 4%. All these papers show that coupled optimisation of aircraft design and network allocation can yield significant improvements in fuel efficiency and lead to strong reductions in operating costs.

The novel proposed research which is under consideration in this literature review however is mainly targeted at correctly implementing existing and novel aircraft in the classical fleet allocation framework using basic aircraft design parameters such as operating empty weights and maximum take-off weights. The research is less focused at the coupled optimisation of aircraft design and network allocation even though it would still be in the scope of this research to conduct a sensitivity analysis based on the input parameters of the model. This way it would still be possible to provide guidance to aircraft designers which improvements in weights and basic performance parameters would result in improvements in efficiency and cost competitiveness whilst limiting the problem size and scope of this research.

5.4. Conclusions

This chapter has focused on discussing the importance to take into account aircraft performance characteristics in the fleet allocation model and the means by which this can be achieved. First, it has been shown how aircraft design parameters work through in the cost coefficients in the objective function. Special attention has been centered around the fuel consumption of aircraft and how this can be determined for various missions using payload-range diagrams and other basic performance parameters as input. Next, other cost parameters such as the cost of ownership, crew, maintenance and servicing as well as how they can vary between different aircraft types have been discussed. Modelling constraints related to capabilities and limitations of aircraft which should be taken into account when developing the model have also been stated and the chapter has concluded with an elaboration on existing research which seeks to integrate aircraft design into the fleet allocation model through multiple levels of complexity.

The learnings from this chapter will be key to ensure that the model which is to be developed can make accurate and realistic trade-offs between different existing aircraft as well as aircraft which are still under development. This is a necessary condition in order to be able to adequately assess the potential market impact of novel aircraft, which is the penultimate goal of this research. These methodologies can hence be seen as essential aspects for a successful completion of the project, warranting the separate discussion as provided in this section.

6 Research Framework

This chapter will provide an updated research framework of the work which is to be conducted in the context of this master thesis using the learnings from this literature review. It will also elaborate on some of the preliminary decisions which have been taken with respect to the wide variety of possible research strategies discussed in this document. First of all, in section 6.1, the research problem will be briefly restated. Next, in section 6.2, the objective of the research will be set out. Section 6.3 will deal with the formulation of some key research questions which are to be answered and section 6.4 will elaborate on some of the methodologies which have been selected for the three different modules which have been discussed in this document. Last but not least, section 6.5 will briefly summarise the findings of this chapter.

6.1. Research Problem

Due to strong demand for air travel, some major airports are already constrained in capacity. Taking into account the expected growth of air travel demand in the coming decades, this issue is only expected to get worse. New aircraft or radically different aircraft concepts could help to alleviate some of these capacity constraints. The purpose of this research is to construct a market demand model which uses basic aircraft design parameters and expected air travel demand growth scenarios as input to subsequently solve a fleet allocation problem under flexible passenger demand. This solution can then be used to determine the market attractiveness of the new aircraft and possible increases in operational efficiency which can be achieved. The model will subsequently be used to as a tool to assess these opportunities for a novel aircraft concept in the context of the *ParsifalProject*, which aims to further develop a Prandtlplane aircraft designed with the purpose of alleviating constrained airports.

6.2. Research Objectives

The research objective sets out two important facts. First of all, it outlines what can be expected from the results of the research. In addition, it should provide a general idea of the activities conducted as part of the research. After thorough consideration, the research objective has been concisely formulated as follows:

> *To evaluate the market demand and operational opportunities of novel aircraft designs by constructing a future air travel demand model and subsequently using aircraft performance data, air travel growth scenarios and the fleet allocation problem to assess the role of this new aircraft for airlines and the airline industry.*

6.3. Research Questions

After establishing the research objective, the research questions will elaborate further on the means by which the research objective will be achieved and provide a more detailed outline of the steps required to successfully complete the project within feasibility and time constraints. The main research question is defined as follows:

> *How much demand is there in the airline industry for the newly proposed Prandtlplane aircraft concept when in the years 2032 and 2050?*

In addition to the main research question above, which is to be answered by means of a case study using the complete model, the following sub-questions and sub-sub-questions have been defined. First of all, two main research questions are related to the model-building part of the research:

1. What is the best way to construct a market model to predict future airline seat demand between airports the future up to 2050?
   - I What are the requirements for the market model to be used for subsequent fleet allocation analysis?
   - II What is the most effective and accurate way to achieve these requirements in light of the above application?
2. What is the best way to construct a fleet allocation model to identify on which routes the new aircraft design is most attractive for operation?
   - I What are the requirements for the fleet allocation model to be used for subsequent analysis?
   - II What is the most effective and accurate way to achieve these requirements in light of the above?
3. What is the best way to take into account aircraft design parameters to accurately assess the varying performance of different aircraft on specific routes?
   - I What are the requirements these performance parameters to be compatible with the fleet allocation model?
   - II What is the most effective and accurate way to achieve these requirements in light of the above?

Next, the following subquestions are constructed regarding utilisation of the model and are tailored to the Prandtlplane case study:

1. What are the most constrained airports in terms of slot limitations by 2032 and 2050 where operating the Prandtlplane will have the most benefits?
   - I On which city-pair and airline combination could the Prandtlplane add most value?
   - II On an airport level, what would be the impact of the Prandtlplane usage on their capacity issue?
2. Which other, currently non-constrained airports provide strong market opportunities for the Prandtlplane in 2032 and 2050?
   - I On which city-pair and airline combination could the Prandtlplane add most value?
   - II On an airport level, what would be the benefits of the Prandtlplane operating on their airfield?
3. Are there alternative market concepts, such as cabin sharing, which provide further utilisation opportunities for the Prandtlplane in 2032 and 2050?
   - I What are the operational opportunities and challenges when multiple airlines share one cabin on the same Prandtlplane flight?
   - II Can the time-flexibility of airline demand be utilised in such a way that it further enhances operational performance?

4. What are, considering the results from the model, other implications of the introduction of the Prandtlplane for the airline industry as a whole?

Last but not least, the research framework is presented in figure 6.1. The research framework provides a schematic overview of how the different parts of the research are interconnected.

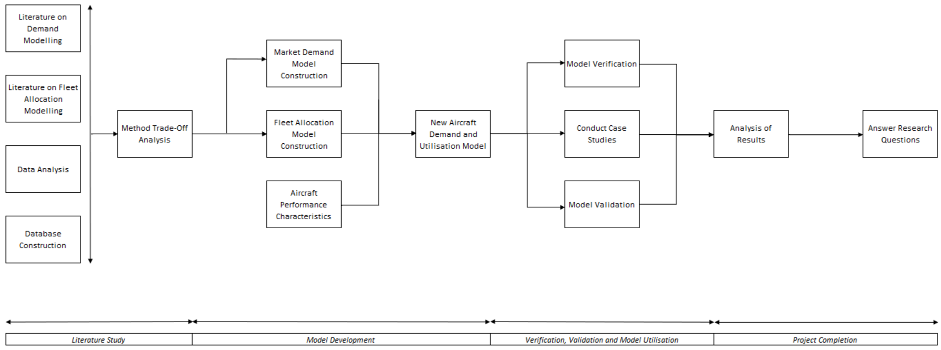

Figure 6.1: The research framework

6.4. Research Methodologies

The literature study described in this document has extensively covered academic literature which is in some way or another closely related to the research which is to be performed in the context of this master thesis. This section will elaborate on some of the preliminary research design conclusions which have been made using the learnings from the literature study conducted in this document. These conclusions will be discussed separately for each of the three research modules. Subsection 6.4.1 will discuss demand modelling choices, subsection 6.4.2 on the formulation of the fleet allocation problem and subsection 6.4.3 on the integration of aircraft design and performance characteristics.

6.4.1. Demand Modelling

The demand modelling sections has elaborated on two different possibilities of forecasting future air travel demand. First of all there are deterministic forecasting techniques, which do not incorporate any randomness and provide a set output for given input parameters. Next there are stochastic forecasting techniques which are commonly used to model the inherent uncertainty when creating forecasts. These techniques yield a variety of possible output scenario's and corresponding probabilities of these scenarios occurring. Furthermore, the problem of censored data and methods to deal with this phenomenon have been discussed.

In order to model demand and forecast future demand it is first required to obtain an accurate estimate of passenger numbers in present time. In order to achieve this the choice has been made to make use of data provided by OAG, which is a large travel data analyst located in the United Kingdom OAG (2020). The dataset contains elaborated timetable information on airline flight frequencies, arrival and departure times, aircraft type, the number of available seats on those flights and much more. This data can subsequently be analysed in order to determine the demand per hour for a given origin-destination pair. As has been discussed in section 3.1, it is important to be aware of the fact that we are dealing with censored data. It is not known how many people are actually on board of this aircraft with a set number of seats, nor are we aware of the amount of people who would have like to travel on that flight but were unable to because the aircraft is already fully booked. In order to resolve this issue, several methodologies have been discussed. There is however one issue in the fact that the data is a snapshot of the year 2018 and is provided by an external party, which makes it impossible to draw conclusions on historical trends. This makes it challenging to apply any of the more sophisticated demand unconstraining techniques which have been mentioned in section 3.1 as they rely on these historical trends. Furthermore, because of the fact that in the dataset there is no indication of whether the flight is operating at maximum capacity nor whether there is overcapacity, it is not possible to judge in which way the data is censored. Summarising, it is not possible to conduct measures which may tackle the issue of constrained data and the only option that remains is to continue with this data as if the seat data were representative for airline demand.

The data from OAG will subsequently be used to make forecasts for the years 2032 and 2050, which have been selected as milestones for evaluation as aligned with the objectives defined in the *ParsifalProject*. It has been decided to remain in the domain of deterministic forecasting techniques instead of stochastic forecasting techniques because of the following reasons. First of all, it enhances simplicity of the project; Especially the more elaborate stochastic forecasting techniques would require significantly more time for successful implementation. Furthermore, because of the long time horizon under consideration for this project, it could lead to a very broad range of possible forecasts which one one hand would be an improvement because of increased reliability, but adds further complexity with respect to the added noise in the model. As a result of these factors, a simple annual average growth time series projection with a fixed rate of growth has been chosen to forecast the passenger numbers. For reference, the chosen methodology has been elaborated on in section 3.2.1.2.

Due to the resulting inherent sensitivity of the forecast with respect to the selected growth rate, several measures have been taken in order to assure that the forecasts are as accurate as possible. First of all, the growth rates have been derived using data from the IATA (2018) 20-year air passenger growth forecast analysis report. The International Air Transport Association is independent organisation which overarches a large amount of the most prominent airlines in the industry with the purpose of serving their collective needs. IATA has built a strong reputation in industry and the fact that they are in direct contact with the airlines leads to their forecasts being more reliable than from other external sources. Due to the large uncertainty with respect to growth scenarios beyond the 20-year time window used in the IATA report, these growth percentages will be assumed to be valid in a perpetual framework which means that these growth rates will be used for forecast years beyond this 20-year time window as well. Even though the full report is not publicly disclosed, the press release states the most important expected growth percentages for various regions across the globe as well as global estimate. These figures are implemented in table 6.1

Table 6.1: Current estimation of long-term air travel growth forecasts. Adapted from IATA (2018)

Region	**Sub-region**	**Growth Rate**
Global		3.5%
Africa	North	4.6%
	Sub-Sahara	4.6%
America	North	2.4%
	Latin	3.6%
Asia	Central	4.8%
	Eastern	4.8%
	South-Eastern	4.8%
	Southern	4.8%
	Western	4.4%

Region	**Sub-region**	**Growth Rate**
Europe	North	2.0%
	East	2.0%
	South	2.0%
	West	2.0%
Oceania	Australia & New Zealand	2.4%
	Melanesia	3.5%
	Micronesia	3.5%
	Polynesia	3.5%

To allow the model to further distinguish differences in local growth rates, the five major continents have been subdivided into multiple sub-regions. Where detailed data from IATA (2018) was unavailable, the growth rate for the entire region has been used for all different sub-regions as can be observed in for example Europe. For the continent of Oceania no data was available, so the growth rates for these sub-regions has been set equal to the global average of 3.5% with the exception of the sub-region enclosing Australia and New Zealand. As these countries can be considered to be significantly more western with respect to the other sub-regions in the continent, the growth rate for these two countries has been set equal to that of North-America. This framework allows for sufficient detail to be present in the forecast and simultaneously ensures that regional effects are incorporated. Furthermore, the fact that these growth percentages can be readily adjusted when new figures are released means that sufficient modelling flexibility is present.

When forecasting future demand for rather straight-forward routes, which take place within one sub-region, the growth percentage of that sub-region will be used as the perpetual growth rate. However, for flights taking place between two cities which are located in different sub-regions of the world, a decision is needed on which growth rate to choose. For these routes has been chosen to make use of the average growth rate of the two sub-regions where the flight takes place. For example, this means that for a flight between Central Asia and North America, a perpetual growth rate of 3.6% will be used.

Last but not least, one of the objectives is to incorporate time-of-day flexibility with respect to airline demand. The data, as provided by OAG, does not allow for distinguishing between seat demand which is fixed in time or demand which may be shifted over multiple similar flights departing the same day. In order to solve this issue, it is assumed that a certain percentage of the total seats of a certain time are considered to be fixed, whereas the remaining seats are considered to be flexible. The preliminary percentages of fixed and flexible demand per hour of the day are shown in table 6.2.

Table 6.2: Current estimation of the ratio between fixed and flexible airline demand

Hour	Percentage Fixed	Percentage Flex
00:00	25%	75%
01:00	25%	75%
02:00	25%	75%
03:00	25%	75%
04:00	25%	75%
05:00	25%	75%
06:00	50%	50%
07:00	75%	25%
08:00	75%	25%
09:00	75%	25%
10:00	50%	50%
11:00	25%	75%

Hour	Percentage Fixed	Percentage Flex
12:00	25%	75%
13:00	25%	75%
14:00	25%	75%
15:00	50%	50%
16:00	75%	25%
17:00	75%	25%
18:00	75%	25%
19:00	50%	50%
20:00	25%	75%
21:00	25%	75%
22:00	25%	75%
23:00	25%	75%

From table 6.2 can be observed that during rush hour traffic, which is assumed to be between 7:00 and 9:00 in the morning as well as 16:00 and 18:00 in the afternoon, demand is considered to be more rigid compared to the other hours of the day. This is due to the fact that during these hours the share of business travellers, who are considered to be inflexible with respect to time, is assumed to be significantly higher compared to leisure travellers who are more driven by ticket prices instead of departure times. As a result, during rush hour traffic the demand ratio is assumed to be 75% fixed and 25% flexible whereas on the hours early in the morning and late hours in the evening the share is assumed to be exactly the other way around with 75% flexible and 25% fixed demand. In order to ensure a smooth transition, the hour leading up to and the hour just after the morning and afternoon rush hour windows are assumed to consist of a balanced mix of 50% fixed and 50% flexible demand. These percentages can readily be adjusted if further refinement is required but for now provide adequate accuracy for the modelling purposes under consideration.

6.4.2. Fleet Allocation

This section elaborates on the formulation of the fleet allocation problem which has been developed specifically for this project. In chapter 4, the current state of the art and most important contributions in the field of the fleet allocation problem have been discussed. Several challenges had to be tackled in order to meet the objectives of the project such as the possibility to incorporate flexible flight scheduling as well as the ability to deal with flexibility of airline passenger demand. In the formulation for this problem, the following notation will be used.

Sets

F = Set of available fleets
L = Set of flights in schedule as (i,j) combinations
N = Set of network nodes
T = Set of times
X = Set of flight arcs
Y = Set of ground arcs

A(n,f) = Set of flight arcs arriving at node *n* for fleet *f*
D(n,f) = Set of flight arcs departing at node *n* for fleet *f*
FA(f) = Set of flight arcs containing the 3 pm count time for fleet *f*
GA(f) = Set of ground arcs containing the 3 pm count time for fleet *f*

Subscripts

i = Origin
j = Destination
f = Fleet type

t = Time
t^{-} = Time preceding *t*
t^{+} = Time following *t*
t_n = Time of last network node (before 3 pm)
t_1 = Time of first network node (after 3 pm)

Other

c_{ijt}^{f} = Total cost associated with operating fleet *f* on a flight from *i* to *j* at time *t*
$cflex_{ij}$ = Total penalty cost associated with not bringing a flexible passenger from *i* to *j*
$cfix_{ijt}$ = Total penalty cost associated with not bringing a fixed passenger from *i* to *j* at time *t*

$FlexDem_{ij}$ = Total daily flexible demand for route *i* to *j*
$FixDem_{ijt}$ = Total fixed demand for route *i* to *j* at time *t*

X_{ijt}^{f} = DV equal to 1 if fleet *f* operates route *i* to *j* at time *t* and 0 otherwise

$PFlex_{ijt}^{f}$ = DV for number of flexible demand passengers travelling from *i* to *j* at time *t* on fleet *f*
$PFix_{ijt}^{f}$ = DV for number of fixed demand passengers travelling from *i* to *j* at time *t* on fleet *f*

$RFlex_{ij}$ = DV for number of not transported flexible passengers travelling from *i* to *j*
$RFix_{ijt}$ = DV for number of not transported fixed passengers travelling from *i* to *j* at time *t*

$Y_{nt^{-}t}^{f}$ = DV for number of aircraft of fleet *f* on ground arc inbound of node *n*
$Y_{ntt^{+}}^{f}$ = DV for number of aircraft of fleet *f* on ground arc outbond of node *n*
$Y_{at_nt_1}^{f}$ = DV for number of aircraft of fleet *f* on ground arc *a* which includes the count time

S^f = Number of seats on aircraft type of fleet f (for all $f \in$ F)
AC^f = Number of aircraft available in fleet f (for all $f \in$ F)

Objective Function

The objective function of the model follows a cost minimisation framework, similar to the formulation by Hane et al. (1995), and is shown in equation 6.1.

$$\min \quad Z = \sum_{(i,j)\in L} \sum_{f\in F} \sum_{t\in T} c_{ijt}^{f} \cdot X_{ijt}^{f} + \sum_{(i,j)\in L} cflex_{ij} \cdot RFlex_{ij} + \sum_{(i,j)\in L} \sum_{t\in T} cfix_{ijt} \cdot RFix_{ijt} \quad (6.1)$$

The objective function consists of three key parts. The first part of the objective function calculates the total operating costs as the result of assigning different aircraft types to different routes in the network. This summation is completed for all different departure times, all different aircraft types and also for each different route. The second part of the objective function is the total cost associated with not bringing a passenger who was flexible in demand in the network. As the flexible demand passengers can be considered a 'pool' of passengers on a route and are not constrained to any departure time, this summation only runs over the different routes in the network. Following similar reasoning, the third term in the model calculates the total cost for not bringing a passenger who is considered to be fixed in demand to his or her destination. As for fixed passengers the departure time is key, the total number of spilled fixed passengers must be calculated by summing over all the departure times for a given destination too.

Operational Constraints - Aircraft Routing

Several key operational constraints with respect to the routing of aircraft have also been adapted from the formulation by Hane et al. (1995) in order to be compatible with this research objective. The following three operational constraints will be added to the model:

$$\sum_{f\in F} X_{ijt}^{f} = 1 \quad \text{for all} \quad (i,j) \in L \quad \text{and} \quad t \in T \quad \text{or} \quad \sum_{f\in F} \sum_{t\in T} X_{ijt}^{f} = 1 \quad \text{for all} \quad (i,j) \in L \quad (6.2)$$

$$\sum_{(i,j)\in A(n,f)} X_{ijt}^{f} + Y_{nt^{-}t}^{f} - \sum_{(i,j)\in D(n,f)} X_{ijt}^{f} - Y_{ntt^{+}}^{f} = 0 \quad \text{for all} \quad n \in N \quad \text{and} \quad f \in F \quad (6.3)$$

$$\sum_{(i,j)\in FA(f)} X_{ij}^{f} + \sum_{n\in GA(f)} Y_{at_n t_1}^{f} \leq A^f \quad \text{for all} \quad f \in F \quad (6.4)$$

First of all, the constraint in equation 6.2 will be implemented in a flexible manner due to the multiple possibilities which have been identified. On the left hand side of equation 6.2 for example is the classical flight coverage constraint, which ensures that each flight in the model is operated by exactly one aircraft type. The second possibility on the right hand side of equation 6.2 is related to the fact that not each flight leg has to be covered, but that each and every route in the network needs to be served exactly once by one of the different aircraft types which are used. Furthermore, the requirement that each flight leg or route needs to be covered exactly once can also be dropped, leaving the model free to decide which flights to operate. Such a modification essentially changes the current ”equal to one” constraint into a ”greater or equal than 0” constraint which provides a further element of depth to the model. Which formulation of this constraint to choose will be part of the user interface of the model so the user can decide what to implement.

Next, equation 6.3 is a node balancing constraint similar to the formulation provided by Hane et al. (1995) which ensures that aircraft do not come out of nowhere and ensuring that aircraft flow is conserved. As a matter of fact it could also be interesting to test the model with this constraint turned off, which should result in the most optimal allocation possible of fleet possible. Therefore an additional toggle option will be implemented in the user interface to turn this constraint on or off.

Last but not least, equation 6.4 is adopted to ensure that the total amount of available aircraft in the model is not exceeded. This formulation is similar to that provided by Hane et al. (1995) in their basic formulation of the problem.

Operational Constraints - Passenger Allocation

Three further operational constraints have been added in order to ensure that the allocation of passengers to the flights which are or are not being operated works successfully. They are mathematically formulated as follows:

$$S^f \cdot X^f_{ijt} - PFix^f_{ijt} - PFlex^f_{ijt} \geq 0 \qquad \text{for all} \quad f \in F, \quad (i,j) \in L \quad \text{and} \quad t \in T \tag{6.5}$$

$$\sum_{f \in F} PFix^f_{ijt} - FixDem_{ijt} + RFix_{ijt} = 0 \qquad \text{for all} \quad (i,j) \in L \quad \text{and} \quad t \in T \tag{6.6}$$

$$\sum_{t \in T} \sum_{f \in F} PFlex^f_{ijt} - FlexDem_{ij} + RFlex_{ij} = 0 \qquad \text{for all} \quad \text{and} \quad (i,j) \in L \tag{6.7}$$

The constraint in equation 6.5 is present to ensure that the total number of available seats on a flight is not exceeded. This is done by ensuring that the total available seats on the flight, which is equal to the left hand side term is larger than zero after subtraction of the total amount of fixed demand passengers and flexible demand passengers on the same flight. This constraint needs to be evaluated for every combination of fleet, route and departure time.

Next, equation 6.6 ensures that the total amount of fixed demand passengers allocated to flights does not exceed the total demand for the route at that point in time. The constraint sums all fixed demand passengers departing at a set time to a set destination over the different fleets which may operate the flights. This gives the total amount of departing passengers, from which subsequently the total market demand for this specific combination of route and time is subtracted. When all passengers are taken, the residual of the fixed demand passengers is equal to zero. However, if the model does not transport all the passengers to their destination, the value of the fixed demand residual will be positive and used in the objective function to assign penalty costs for leaving these passengers behind. Following a similar reasoning, equation 6.7 performs the same analysis for the flexible demand passengers. However, as for the flexible demand passengers the residuals need to be considered on a route basis only (their departure time does not matter, as long as they are transported), the summation sign for this constraint also runs over their different departure times and the constraint is applied on a route-basis only.

Mathematical Constraints

Last but not least, a number of mathematical constraints need to be added to the model in order to ensure that the solution to the model makes sense. For example, the constraints in equations 6.8 and 6.9 ensure that there is always a positive amount of aircraft on a ground arc. Allowing negative aircraft on a ground arc does not make any sense from a practical point of view and from a modelling point of view allows aircraft to travel back in time, which is to be avoided. Constraint 6.10 currently ensures that each flight to a specific route at a specific time with a specific fleet can only be conducted at maximum once. As discussed earlier in this section, such a constraint could also be relaxed to allow for multiple similar flights to be conducted as long as the lower bound of 0 is preserved. Last but not least, constraints 6.11 through 6.13 ensure that the total amount of passengers transported and the total amount of passengers who are left behind is at least greater than zero, because negative passengers do not make any sense and should be avoided.

$$Y^f_{nt^-t}, \quad Y^f_{ntt^+} \geq 0 \qquad \text{for all} \quad n \in N \quad \text{and} \quad f \in F \tag{6.8}$$

$$Y^f_{at_nt_1} \geq 0 \qquad \text{for all} \quad a \in GA(f) \quad \text{and} \quad f \in F \tag{6.9}$$

$$X^f_{ijt} \in \{0, 1\} \qquad \text{for all} \quad f \in F, \quad (i,j) \in L \quad \text{and} \quad t \in T \tag{6.10}$$

$$PFlex^f_{ijt}, \quad PFix^f_{ijt} \geq 0 \qquad \text{for all} \quad f \in F, \quad (i,j) \in L \quad \text{and} \quad t \in T \tag{6.11}$$

$$RFix_{ijt} \geq 0 \qquad \text{for all} \quad (i,j) \in L \quad \text{and} \quad t \in T \tag{6.12}$$

$$RFlex_{ij} \geq 0 \qquad \text{for all} \quad (i,j) \in L \tag{6.13}$$

6.4.3. Aircraft Design

Chapter 5 has centered around the discussion on how to adequately model aircraft performance parameters and the means by which these can be integrated into the fleet allocation framework. The chapter has discussed elaborately all aspects of the fleet allocation model which, in one way or another, are affected by aircraft design or aircraft performance characteristics. In this section, the relevant learnings and implementation of these findings will be discussed.

The objective function of the fleet allocation model which will be developed for the research under consideration has been discussed in section 6.4.2. It requires determining the operating cost of an aircraft for a specific route in the network. One of the most important factors which contribute to the operating cost of such an aircraft is the fuel consumption. Section 5.1.1 has discussed the methodology by which it is possible to calculate the fuel consumption of an aircraft based payload-range diagrams and other general design characteristics for any combination of distance and number of passengers. This methodology has been implemented in a Microsoft Excel sheet which automatically calculates the coefficient values required for use in the fleet allocation model. The resulting coefficients can easily be imported in the model which subsequently reduces the need to recompute these values for recurring runs, saving computational time. Furthermore, the other cost parameters discussed in this chapter are also included in such a manner that they can be readily adjusted based on new insights on the exact magnitude of these contributions. This enhances the flexibility of the model and allows for sensitivity analyses to be conducted with respect to these parameters and their impact on the overall operating efficiency of the aircraft.

Constraints on aircraft performance which may hamper the usability of aircraft on certain routes, such as those caused by insufficient available range or constraints in terms of take-off or landing distance, are also supported in the model in line with the discussion of the previous chapter. Last but not least, the possibility of simultaneous optimisation of aircraft design together with the fleet allocation problem has been discussed using examples from literature. With regard to this field, the decision has been made to only optimise the fleet and passenger allocation based on an existing or forecasted network and to not simultaneously optimise the aircraft design. This would provide a further layer of complexity and could result into time constraints given the limiting time available time for this research. It can readily be identified that such an extension could provide an interesting starting point for future research in the same field.

6.4.4. Modelling Strategy

There are a lot of possible strategies which can be selected with respect to the model development. Think about different data types, coding language, optimisation algorithms and much more. This subsection aims to briefly motivate the choices made with respect to these factors, which will play an important role in the following phase after the conclusion of this literature review.

The airline demand dataset, which is provided by OAG, is delivered in a Microsoft Access (*.mdb* extension) format. Even though Microsoft Access is a powerful tool for database management, it does not have the capabilities required for large-scale model construction which is under consideration for this project. Hence, the decision has been made to construct the model using the *Python* programming language due to user familiarity and high flexibility. Microsoft Access databases can be seamlessly integrated using specified *Python* modules such that a clean connection between these two programs can be assured without any major issues.

As has been explained earlier in this section, the cost coefficients for the objective function of the model have been calculated using a Microsoft Excel sheet. It is hence required to connect these coefficients to the model in order to assure that it can be solved adequately. Fortunately, *Python* supports the integration of these sheets seamlessly which also entails that no major issues are expected with this regard.

Last but not least, also in the context of the fleet allocation problem, the *Python* processing language also facilitates the use of the *IBM CPLEX Optimizer* engine. This engine is one of the most well-known optimiser engines in the field of (linear) optimisation problems and is characterised by high efficiency and a lot of optimisation features. From this brief analysis it is evident that the *Python* processing language has a natural fit in the context of this project due to its large flexibility, ability to incorporate multiple other data types and the fact that the researcher is already familiar with this programming language.

6.5. Conclusions

This section has discussed the most important learnings of the literature study and the preliminary research design decisions which have been taken as a result of these learnings. For each of the three research modules of demand forecasting, fleet allocation and aircraft performance integration, the rationale behind these choices and the implications of these decisions has been elaborated on. The combined strategy of literature study and subsequent implementation strategy development ensures that, when the actual development of the model is about to start, it is clear what the end goal of the research is and what the major roadblocks have been or will be on the way to achieving such a model. Furthermore, it has been shown that the preliminary modelling decisions elaborated on in this chapter together form a package which is both feasible from a technical, as well as from a time-constrained point of view.

It is worth noting that these design decisions are preliminary decisions and may be subject to change if the research requires to do so. There can always be unexpected roadblocks which may require an imminent solution or changes in the model which result in enhanced performance at a minimum loss of detail. However, with the elaborate knowledge gained by conducting this literature review, the probability of finding an adequate solution to these issues has significantly increased.

7 Conclusions

The development of a market demand assessment framework for novel aircraft using fleet allocation which also incorporates the flexibility of passenger demand seemed to be a very overwhelming, challenging but simultaneously exiting task at first. Plenty of thoughts and ideas have been put forward when first discussing this topic, but evaluating these thoughts without a proper structure has proven to be challenging. A literature review, like the one conducted in this document, helps to structure these thoughts and provides the necessary boundaries to the research. These boundaries can be seen as constraints with respect to technical feasibility as well as in terms of feasibility with respect to the available time which has been allocated for this project.

Two major questions have been identified to which this literature review seeks answers. The first purpose of this literature review has been to gather a complete overview of the current academic state of the art in fields which are relevant for this master thesis project. Three different academic fields of interest have been discussed. The field which deals with demand forecasting methodologies, the field related to the linear-programming fleet allocation model as well as a third field centered around the theory of aircraft performance and the way this is integrated into the fleet allocation model. Discussion for these fields has focused on providing a historical introduction, an elaborate overview of all the possible methodologies including their individual advantages and disadvantages as well as the use of some of these methodologies in renowned academic literature.

Second, after the key academic state of the art had been identified, there has been a thorough discussion on the implications of these findings in comparable literature for the research which will be conducted by the author. The most adequate method for demand forecasting has been determined which finds a good middle ground between speed, accuracy as well as user friendliness. Furthermore, the literature study has resulted in the novel formulation of a fleet allocation with variable passenger numbers which also supports the distinction between passengers who are considered to be fixed with respect to departure times and passengers who are considered to be flexible. Last but not least, the theoretical framework on aircraft fuel consumption has been worked out in further detail and subsequently implemented in such a manner that it seamlessly provides the coefficients for the objective function of the fleet allocation model which will be solved.

Systematic completion of this literature review has helped with identifying the novel contributions of this research and possible obstacles. It has been shown that the strategies which have been chosen for further work meet the constraints in terms of available time and technical feasibility ensure that the probability of a successful project completion is maximised. It hence provides an excellent basis for the actual project execution stages of the master thesis, which will have already started but will be accelerated with the formal completion of this literature review.

The author would like to conclude on the note that the completion of this literature review has contributed to a significant improvement in understanding of the context of this research and that he is eager to take the following steps required towards a successful project execution.

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