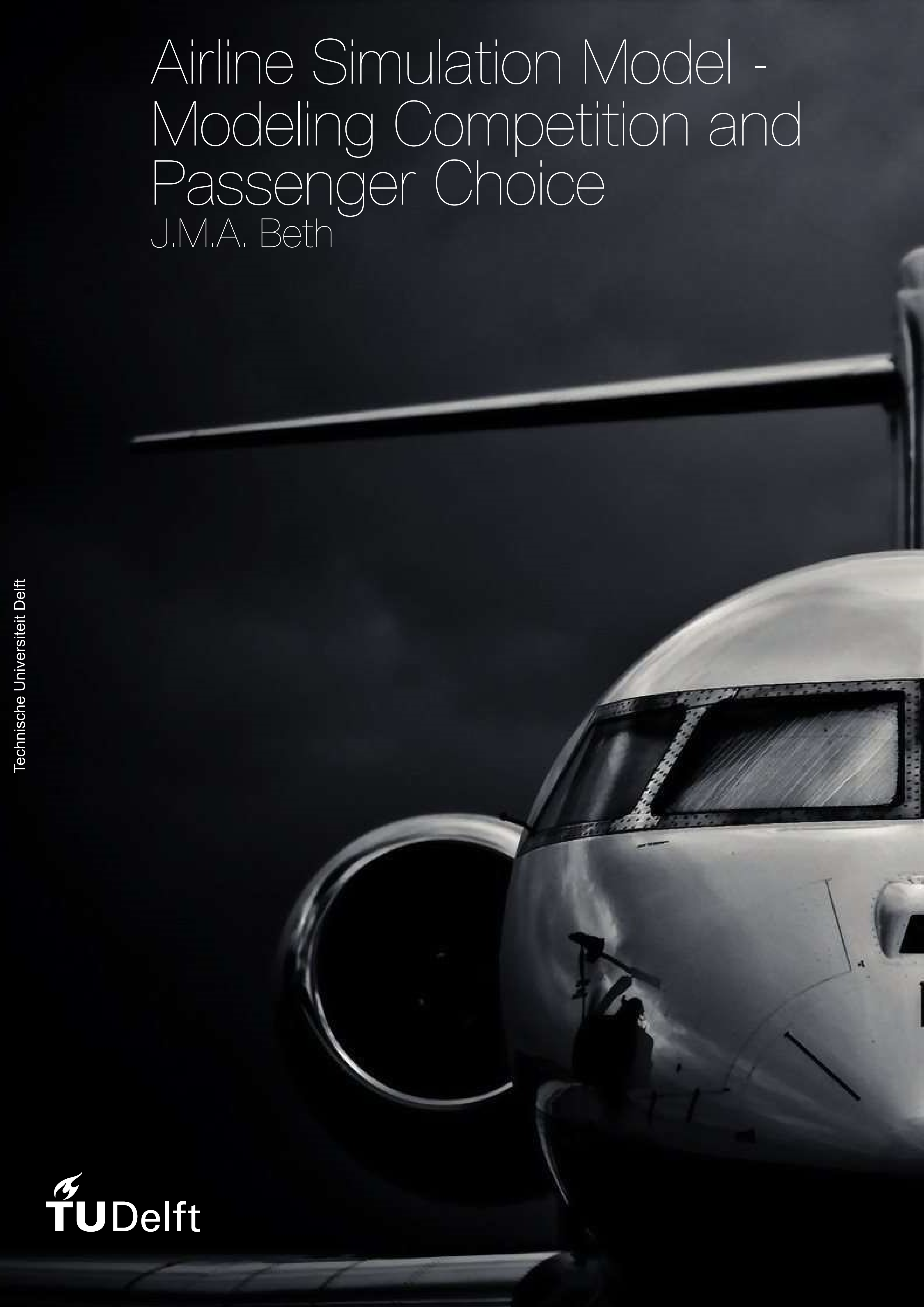
Airline Simulation Model - Modeling Competition and Passenger Choice

J.M.A. Beth



Technische Universiteit Delft

TU Delft

Airline Simulation Model - Modeling Competition and Passenger Choice

by

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to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on Monday August 28, 2017 at 14:00.

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Date:	August, 2017	
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Preface

The choice of research topic for a masters degree relies on a number of factors. Similar to the aviation market, supply and demand of research topics do not always align. Thankfully though, during my search for a subject I was presented with two interesting topics on which a master thesis research could be built. Through extensive discussions with my supervisor, I obtained my interest in the possibilities of building aviation simulation models. Sparked by a sense of curiosity and enthusiasm, I decided that the development of a simulation framework for the aviation market would be an ideal topic to graduate on. I am glad to say, that after a hard year of work, a simulation model has now been designed for which I am proud. My research may now have come to an end, but I have truly realized that research can never be considered finished. I am convinced that my research can contribute to that of others and hopefully will be continued in the future.

I would like to thank my two supervisors, Bruno Santos and Nicola Volta, for their continuous support during the thesis process. Without their constant encouragement, critical feedback and push, I would not have been able to produce the work I have done. I have learned an incredible amount from both and for that I am ever grateful.

To my friends and family, a big thanks for rooting for me. A year of research can sometimes weigh heavy on the shoulders, but with your support I have managed to pull through. A special thanks to Hugo, for taking the time to reflect on my work and to my sister for believing in me.

To the boys in room 3.15, it has been a blast sharing the thesis times with you and you all have been an inspiration to my work.

To the Breda GlobeCorporates, seeing our NAC achieve promotion has been one of the highlights of my year. Thank you for being the friends that you are.

To my support team in Bahrain, Johan and Myrra, thank you for the encouragement and giving me confidence during the entire process.

To my dearest Micky, thank you for putting up with me during these busy times and for your endless support during the past year. It is a joy to have you by my side.

Last but not least, I would like to thank my thesis team in Bavel. Angeline and J.J., thank you for getting me through the roughest of times, supporting me on my thesis and providing a wonderful home to fall back on whenever I needed it.

Jiwan Beth
Delft, August 2017

Abstract

Problem Statement
This thesis will discuss the development of an airline simulation model, that will be able to realistically reproduce the aviation market with respect to passenger choice and market competition. There are various reasons which stress the need for such a model.

From a scientific perspective: the current airline development models often assume competition to be static and acting irrespectively of airline strategy. In reality, competition strategies change constantly, taking market characteristics and choices of competition into account. Additionally, in airline operations research, an opportunity exists to combine different models describing specific traits of the aviation market to be able to develop a model which captures the main effects of the total aviation market.

From an industry perspective: to be able to understand the market dynamics of the aviation market as a whole, with all its underlying specifics is complicated but is desirable for educational and airline prediction purposes.

Research Objective & Scope
The research objective is to contribute to the development of an integrated simulation framework, which has the capability of realistically simulating the aviation market by being able to reproduce the competition and passenger choice for an airline in the aviation market by combining a demand generation, passenger choice and market competition model. Additionally, exogenous players should be able to be incorporated in the simulation framework, providing a platform for simulation game play. The integrated simulation framework will not be developed with the goal of optimizing airline behaviors or strategies, but rather to model realistic aviation market dynamics with respect to competition and passenger choice. The scope of this simulation framework is the internal European market.

Methodology
To achieve the above, while also ensuring a stand-alone model, three different sub-models have been designed: a demand generation model, a demand allocation model and a competitor reaction model. The simulation of market competition spans both the demand allocation model and the competitor reaction model. The competition for passengers between airlines is simulated in the demand allocation model, while the competitor reaction model is centered around the active reaction of the computer player with respect to the different competitors in the simulation game. The simulation framework has been coded in Python, an open source programming language.

The demand generation model used in this thesis is based on a gravity model with decision variables on the total passenger flow at both airports, the distance between the two airports and dummy variables to split demand into the specified classes. Additionally, the model includes the effects of seasonality for the different quarters in a year for each route included in the simulation framework. The function of the demand generation model is to generate demands for the specified number of classes of each origin and destination pair and for every simulation quarter found in the simulation framework. Logarithmic techniques have been used to facilitate a linear regression for calibration purposes. The calibration has been done in the statistical software package SPSS.

The demand allocation model included in this thesis consists of a multinomial logit model. The decision variables are based on the flight frequency, yield, extra-distance and dummy variables per cabin class. The demand allocation model is capable of determining market shares for the different flight options found in a route per quarter. In the simulation framework, the demand allocation model is applied separately per class to determine the market shares of the different flight options. As with the demand generation model, calibration has been done using a linear regression in SPSS.

The competitor reaction model found in the simulation framework is based on a non-linear profit optimization of a single computer player. This computer player is present in every market with flight options in all classes for the routes specified in the model. The optimization decision variables include the yield of each class and the flight frequency in each route. The optimization takes the strategies of other competitors into account as well as the demands for each class in each route when optimizing and reacts accordingly. The optimization is constrained using capacity constraints, as well as bounds on the yields per class.

Simulation Model Calibration
The gravity model used for the demand generation purposes was found to achieve an R^2 of 0.766, which is considered a reasonable total overall model performance. The predicted demands for each class in the different calibration routes were, in comparison to the actual demand data, found to be representative in terms of the total demand. With respect to the demand splits over the different classes, the model is capable of making the split. However, the realistic performance of the gravity model differs per route. The discount economy class was found to have the best prediction performance.

The demand allocation model achieved an overall performance represented by an R^2 level of 0.711, which is also considered reasonable. When comparing the models passenger choice predictions to that found in the actual data, the multinomial logit model can be considered representative of the actual data. The trends and market shares predicted agree well with those seen in reality.

Simulation Games & Results
Multiple simulation games were played to test the simulation framework as a whole and observe the behaviour of the competitor reaction model. In general, it can be noted that the simulation games proved that the integrated sub-models worked together in the expected manner.

With respect to the computers' optimization behaviour, it was observed that the goal to optimizing profit of the computer works well. The tendency of the computers optimization was to optimize its profit by achieving a maximal load factor. The computer does this by flying the lowest possible frequency to cater for all demand while having the highest possible yield levels. From a profit optimization perspective, this is an understandable outcome.

When testing the computers reaction in a multi-route environment of three routes, with two routes under stiff competition, no shift was found in focus to the third route.

Validation & Verification
The verification process of the set requirements saw all simulation framework and sub-model requirements to be fulfilled.

Concerning the generalizability of the demand generation model, the demands generated for the discount economy class and premium economy class were sufficiently accurate to be used for the simulation frameworks purposes. However, the other classes displayed deficiencies which cannot be considered to accurately reflect reality. The gravity model in this form is considered not to be confidently generalizable for routes with similar characteristics.

For the demand allocation model, the results between the calibration and validation routes proved to be similar and thus it can be concluded that with the same level of confidence as for the calibration routes, the model used can be generalized to routes with similar characteristics.

Conclusions & Limitations
In this thesis, a contribution has been made to the development of a simulation framework which is capable of realistically simulating market dynamics with respect to competition and passenger choice in the European aviation market. In total, 22 routes have been included into the simulation framework, with airports including those in Amsterdam, Copenhagen, Frankfurt, London and Madrid. To achieve this, a demand generation model, demand allocation model and market competition model have been combined. Additionally, the simulation framework is compatible with exogenous competitor inputs to create a game environment while hosting dynamic competition by the computer player. The demand generation model has proved to be sufficiently accurate to be used for the purpose of this simulation framework. The model in its current form is however not sufficiently accurate to be generalizable for routes with similar characteristics. The demand allocation model is considered capable of simulating

passenger choice between flight options representable to what happens in reality, while being generalizable for routes with similar characteristics. The competitor reaction model with the profit optimization strategy works as expected.

The main two limitations of the simulation framework include the absence of capacity constraints per OD-Route and inherent incapability of simulating indirect flights. With respect to the capacity constraints, there is no constrain which ensures that the number of flights between an origin and destination pair are equal to the number of flights returning. Therefore, capacity deficiencies which might occur in reality are not accounted for in the current setup. With respect to the indirect flights inclusion, the simulation framework can only handle indirect flights when inputted manually by exogenous players. Currently, no controls on determining the possible connections and seat availability for indirect passengers is implemented in the simulation framework. However, the demand allocation model can cope with the indirect flight market share predictions.

Contents

List of Figures

List of Tables

Acronyms

Abbreviation	Description
CASK	Costs Available Seat Kilometer
DCM	Discrete Choice Model
GEV	Generalized Extreme Value
IIA	Independence from Irrelevant Alternatives
LC	Latent Class
LCC	Low Cost Carrier
LF	Load Factor
ML	Mixed Logit
MNL	Multinomial Logit
NL	Nested Logit
NWN	Nested Weighted Nested
OD	Origin and Destination
PIM	Passenger Itinerary Model
PM	Probit Model
RASK	Revenue Available Seat Kilometer
RP	Revealed Preference
RUT	Random Utility Theory
SP	Stated Preference
Y#OP	Optimization Year #

List of Symbols

Symbol	Unit	Description
α	[-]	Control variable in gravity model for $A_i A_j$
β_n	[-]	Independent variable coefficient utility function
γ	[-]	Control variable in gravity model for distance
λ	[°]	Longitude
ϕ	[°]	Latitude
A_i	[# Pax]	Total amount of yearly passengers at airports i
A_j	[# Pax]	Total amount of yearly passengers at airports j
Bus	[-]	Dummy variable which represents the business class
d	[km]	Greater-circle distance between two airports
D_{ij}	[km]	Shortest distance between the two airports i and j
$ExtDist_i$	[km]	Extra distance flown when using an indirect flight option for flight option i
$First$	[-]	Dummy variable which represents the first class
$FullY$	[-]	Dummy variable which represents the full economy class
K	[-]	Gravity model constant
MS_i	[-]	Market share for flight option i
P_c	[-]	Constant for distribution of passenger demand per class c in gravity model
$PremE$	[-]	Dummy variable which represents the premium economy class
R	[km]	Earths radius
R^2	[-]	Coefficient of multiple determination
T_{ijc}	[# Pax]	Passenger demand between airports i and j for each different class c
V_i	[-]	Utility values for flight option i

1 Introduction

The airline industry is one of the most exciting and harshest business environments that exist. With a vast number of competitors, each differentiating themselves to convince passengers to choose to travel with their respective companies, it can become overwhelming for an airline to decide what strategy would be most suitable. Airline seats can be considered the most perishable commodity in the world as, as soon as the aircraft leaves the ground, the seats can no longer be sold (Park et al., 2009). This makes defining the correct strategy, including decisions on frequency and fare, ever so critical. Especially if you consider that your competitors are facing a similar challenge. What strategies can you choose, to convince passengers they should fly your colors?

In order to make educated decisions on airline strategy, one needs to be able to first understand the market dynamics which are present in the aviation markets. These market dynamics are increasingly difficult to understand, as so many different elements affect the market in one manner or another. Before addressing the challenges found in aviation markets, it is essential to get a better understanding on these dynamics.

There are a multitude of different aspects to be taken into account in order to simulate aviation market dynamics. In basis, there are passengers and goods which need to be transported between different city pairs. To transport these passengers and goods, aircrafts are needed. However, in deregulated markets like Europe and the US, the airlines flying these aircrafts need to ensure that their businesses are commercially viable. To do this, airlines optimize their flight frequency, cabin configuration and fares to ensure that passengers want to travel with them allowing the airlines to make profit and achieve their (financial) objectives. Additionally, long-term decisions need to be made on the size of an airline's fleet, as well as the type of aircraft that should be used. These aircrafts need to undergo maintenance and inspection from time to time, to ensure safety and that they adhere to legal constraints. The above are just a few of the major forces which effect aviation markets globally, but it demonstrates perspective on how incredibly complex the aviation market is.

Building a simulation framework which addresses all characteristics of the aviation market is very complex, given the large number of external parameters which all influence the markets. However, research should be done to determine the modeling possibilities and discover what is possible when trying to simulate the aviation market as a whole. There are an exorbitant number of researches which strive to model specific aspects of the aviation market, with variable success. Combining different sets of specific models could be an opportunity to further refine a model for the aviation market, which would be considered beneficial from many perspectives.

To address this opportunity and challenge, the TU Delft and Cranfield University have undertaken the development of an airline simulation framework which will be able to realistically reproduce the aviation market with respect to passenger choice and market competition in order to assist in understanding aviation market dynamics. The simulation framework will strive to include multiple sub-models, each providing the simulation framework with specific characteristics of the aviation market. The sub-models included in this study describe the demand generation, demand allocation and market competition processes as can be found in the aviation market. In this master thesis, the first contributions have been made to the development of this simulation framework.

This master thesis will commence with a discussion on the state-of-the-art currently found in literature, described in the literature review found in Chapter 2. Chapter 3 will define the research proposal, which contains the research objective and scope. In Chapter 4, details the methodology applicable to the total simulation framework and its sub-models. This is followed by the presentation of the calibration results of the demand generation and demand allocation models in Chapter 5. In Chapter 6, the results of several simulation games will be portrayed, with which observations of the simulation frameworks model behaviour will be observed. Chapter 7 presents the verification and validation results of the simulation framework and its sub-models. In the conclusions and recommendations chapter found in Chapter 8, the final findings of the simulation framework will be described, together with the frameworks limitations and recommendations for future research. The Appendices contain supporting data and figures on the results found throughout this thesis.

2 Literature Review

The literature review described in this chapter is the first step to facilitate the MSC thesis with knowledge created and tested in the past on the different modeling techniques. Relevant knowledge that is deemed applicable and relevant to assist in the development of the simulation framework described previously will be collected and analyzed to determine the state-of-the-art in modeling characteristics of the aviation market.

The literature review will be structured as follows. First, the literature relevant to the demand generation models will be portrayed. This will be followed by a section on passenger itinerary models. This will include sections on passenger segmentation, pricing, service-levels, path quality and passenger itinerary modeling techniques. The following chapter will incorporate the literature relevant to market competition models. Here sections on competitors and modeling competition reaction will be discussed. After each section of the literature review, a conclusion of the findings will be given.

2.1. Sub-Model: Demand Generation

In designing a simulation model for the aviation market, an accurate demand generation model is needed to provide expected demands on the routes that are in scope. The difficulty with generating these expected demands is described by the dichotomy of the demand and supply in the air travel market. As described by Belobaba et al. (2009), this dichotomy is characterized by the fact that there is an inherent inability to compare the demand and supply within air travel of an origin and destination (OD)-pair. To clarify, demand is focused around the origin and destinations of passengers, while the supply is focused on the amount of flights and flight structures between the OD-pairs. This leads to the quick conclusion, that directly comparing supply and demand in air travel is not possible. A flight leg between a city-pair does not necessarily only carry OD passengers for that city-pair, but may also carry passengers traveling between other OD-pairs using the flight leg only as a connection.

Yet despite the dichotomy of demand and supply, airlines need to be able to forecast and predict demand to ensure that they know what demands to expect on different routes and at different times. To do this, different demand generation models have been researched to achieve different goals. For example, airlines can be interested in forecasting future traffic growth, or the response of passenger demand due to a change in flight frequency. Another reason could be that airlines need to forecast demand on new routes or between new city-pairs (Doganis, 2002). Last, airlines could be interested in how demand differs between passenger segments which have different characteristics, as this could potentially generate more accurate forecasts (Doganis, 2002).

In the following section an overview will be given on the different types of demand generation models that exist. Furthermore, the most used variables in demand generation will be described, as well as a section on the methods of calibration.

2.1.1. Demand Generation Model Types

In the following section, the different methods used for demand generation are discussed. The type of demand generation model airlines use depends on the goal that they need to achieve. The section has been divided into subsections which each describe a separate set of models. In Figure 2.1, an overview of the main demand models is given.

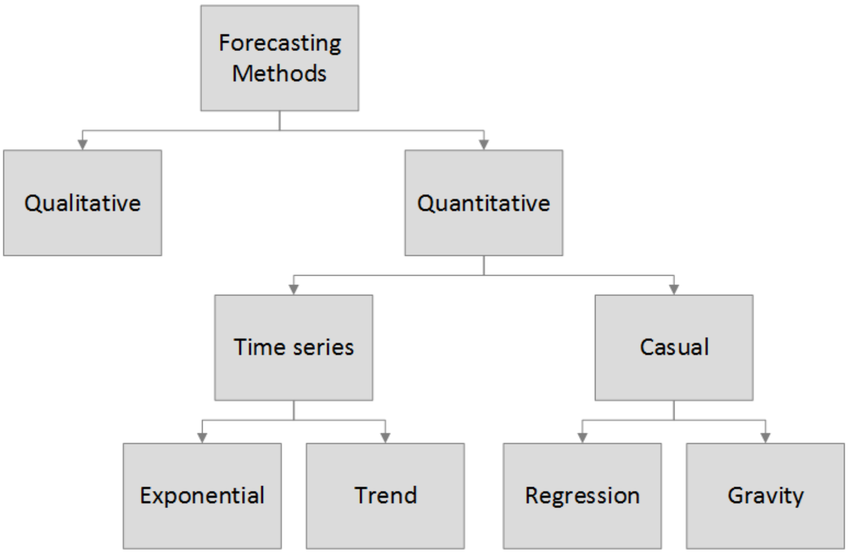


Figure 2.1: Demand Models as described by Doganis (2002)

Qualitative methods

Qualitative demand generation is based around rough estimations by experts as well as analysis of expected trends. This method includes techniques such as executive judgment, market research and Delphi techniques (Grosche, 2009). Each technique is described below.

Executive Judgment Executive judgment is a technique where a person with expertise on a certain area or route forecasts demand based on his/her insights and assessments. It is a quick manner of forecasting demand and has as an advantage that the forecaster may be aware of aspects not always captured in mathematical models. However, long term forecasts will not be very accurate. This forecasting technique is often used to verify or specify demands forecasted by mathematical models (Doganis, 2002).

Market Research Market research is based on techniques where the main activity consists of collecting data on different market characteristics. Examples of data collected are passenger preferences through passenger surveys, tourism statistics, trade flows and information on business interactions. With this data, demand between OD-pairs can be developed. This method is especially interesting when no past traffic data is available between city-pairs, however the method can be time consuming (Doganis, 2002).

Delphi Techniques The Delphi technique is similar to that of executive judgment, except that multiple specialists are being consulted. With this method, multiple individuals are asked to forecast demands. These forecasts are then combined, after which the experts again share their opinion. Multiple iterations of this process are possible. It has been found that this method is most suitable for forecasts for regions or markets instead of specific routes (Doganis, 2002).

Time-Series Projections

Time-series projections are mathematical models which are based on one essential independent variables, namely time. In these models, it is assumed that current factors that influence demand are relatively stable through time. As described by Grosche (2009), this assumption does not always hold in the fast-moving aviation market. Furthermore, Grosche (2009) describes that for time-series projections to be accurate, sufficient accurate data is needed to calibrate these types of models. Time-series models include exponential forecasts and liner trend projections.

Exponential Forecasts Exponential forecasts are forecasts where the traffic demand is influenced by a constant percentage per unit of time. This has as an effect that the change in total demand in absolute terms is greater with each year but the yearly percentual change is close to constant. Exponential forecast can be done using the average rate of growth or by exponential smoothing (Doganis, 2002).

Linear Trend Projections Linear trend projections are characterized by the fact that with each unit of time, the absolute change is constant. This means that over the course of time, the percentual change per unit time decreases. Linear trend projections can be done as a simple trend or as a moving average trend (Doganis, 2002).

Casual Methods

Demand generation based on casual methods are characterized by the variables taken into account. With casual methods, air travel demand is being related to economic, social or supply variables such as the level of business or tourism activities in a city. The unique principle of using casual methods is that the individual effect of these variables on air travel demand can be predicted. Therefore, when the value of such a variable changes, a new air travel demand between city-pairs can be predicted. This is in contrast to the previously discussed methods, where the influence of individual independent variables on the demand can not be tested. The advantage of using such a model is that, for example, evaluation of different airline strategies or changes in economic situation and its effect on the demand can be analyzed. Common casual methods include the regression model, and one of its variations namely the gravity model (Grosche, 2009).

Regression Models Regression models tend to be a function of multiple independent variables. Commonly used variables are the air fare and a variable describing the level of income of a region. Regression models can both be used for specific routes or for entire regions (Doganis, 2002).

Gravity Models Gravity models are based on the principle that two cities are attracted to each other due to certain variables and lose attraction due to others. A simple gravity model for example will incorporate the relationship of the distance between two cities and their populations (Doganis, 2002). In more extensive gravity models, multiple attracting and deterring variables between city-pairs are included. Furthermore, gravity models are especially know for generating demand for routes where little or no traffic data is available, the model is very often applicable for new routes (Doganis, 2002). A simple example of a gravity model developed in the research by Doganis (1966) can be found in Equation 2.1, here the main variables included were the total air traffic at the origin and destination airports ($A_i A_j$) as well as the distance between the two airports (D_{ij}).

$$T_{ij} = K \frac{A_i A_j}{D_{ij}^P} \tag{2.1}$$

Demand Generation Method Choice

As can be seen in Section 2.1.1, there are multiple types of demand generation models which can be used for different purposes and in different situations. In the following section, the choice for demand generation models will be discussed. In Table 2.1, the main demand models discussed can be found along with data on their performance with respect to different criteria.

In reality, an airline often does often use multiple demand generation models at the same time, based on its forecasting needs. The reason for this is that no single existing model can guarantee being completely accurate (Doganis, 2002). However, when choosing demand generation models, distinct choices are made based on the needs of an airline. The objective of the forecast, the speed of a forecast, the cost of setting up the model and data availability are all important factors which need to be taken into account.

Preliminary requirements for a demand generation model have been determined to guide the selection of the appropriate demand model to be further researched. These requirements include that the relationship between air travel demand and market characteristics should be captured. Furthermore, the possibility of new routes should not be excluded. The demand model should be simple yet meaningful enough to ensure that the collecting efforts of market characteristics is kept feasible. The model should furthermore be accurate in the short and long term. These characteristics were all found to best apply to gravity models and therefore it was decided to concentrate on this type of demand generation model. Additionally, according to Grosche et al. (2007), this is one of the most widely used forecasting methods for airlines which means it is well known to literature. The following sections will thus concentrate on gravity models.

Table 2.1: Trade-off Diagram (Doganis, 2002)

		Qualitative methods		**Time-series projections**			**Causal methods**	
		Executive judgment	*Market research*	*Annual average growth*	*Linear trend*	*Linear w/ moving averages*	*Regression analysis*	*Gravity model*
Accuracy	*Short-term (0-6 mo.)*	Good	Good	Fair/ good	Fair/ good	Good	Good	Good
	Long-term (> 6 yrs)	Poor	Poor/ fair	Poor	Poor	Poor/ fair	Fair	Fair
Suitability for forecasting	*Growth*	Good	Good	Good	Good	Good	Good	Good
	Reaction	Fair	Good	n.a.	n.a.	n.a.	Good	Poor
	New routes	Poor	Fair	n.a.	n.a.	n.a.	Fair	Good
Ability to identify turning point		Poor/ fair	Fair	Poor	Poor	Poor/ fair	Good	Poor
Days required to produce forecast		1 - 2	90+	1 - 2	1 - 2	1 - 2	30 - 90	20 - 60
Cost of implementation		Very low	Very high	Low	Low	Low	High	Moderate

2.1.2. Demand Generation Variables

Within literature, demand is generally defined to be dependent on two main driver groups. Namely, geo-economic factors and service-related factors (Rengaraju and Thamizh Arasan, 1992)(Jorge-Calderón, 1997). Geo-economic factors are described by the economic activity and geographical aspects of the region in which the the origin and destination of a trip are located. Service-related factors are focused on the product with which a trip is made and thus is dependent on the service-level a transportation company provides.

- **Economic Factors** The main characteristics used in relevant literature linked to economic activity are centered around factors such as a regions population and it's level of income (Anderson and Kraus, 1981)(Brueckner, 1985)(Rengaraju and Thamizh Arasan, 1992)(Jorge-Calderón, 1997). Other variables that have been used which were more specific included the ratio of university degree-holders(Rengaraju and Thamizh Arasan, 1992), the ratio of employment (Rengaraju and Thamizh Arasan, 1992), the regions type of production sector (Fleming and Ghobrial, 1994) and the level of interaction between two cities in terms of economy, politics and social aspects (Russon and Riley, 1993). Doganis (1966) used another interesting factor, namely the total traffic at both airports. It was found that this was a good measure of the economic activity and level of income of the airports region and catchments area. Thus, by using airport traffic data it is not needed to incorporate more specific economic variables.
- **Geographic Factors** With respect to the locational factors between two regions, the main variable

with which is modeled is the distance between the origin and destination of the route. The distance between two regions or cities has two aspects in which the demand to travel between the two is affected. The social and commercial interaction between two cities or regions decreases with increasing distance, negatively effecting demand. On the other hand, with increasing distance the demand for air travel increases with respect to other transportation modes due to air travels competitive advantage with respect to travel time (Jorge-Calderón, 1997).

Another locational factor often taken into account is the closeness of airports in a region or city. In regions with multiple airports, different airport characteristics such as the services provided, the airlines flying through the airports and the ease of access effect the demand an airport generates (Brueckner, 1985)(Rengaraju and Thamizh Arasan, 1992)(Russon and Riley, 1993).

- **Service-Related Factors** The service-related variables most commonly discussed in literature are characteristics to do with the quality and the price of the service provided (Jorge-Calderón, 1997). With respect to service-quality variables used in literature, often occurring aspects include flight frequency, load factor, aircraft type and airline branding (Jorge-Calderón, 1997)(Grosche et al., 2007). With respect to pricing, all relevant literature on demand generation agree that the fare of the service significantly impacts the demand of the product. According to both the studies done by Jorge-Calderón (1997) and Grosche et al. (2007), pricing in the airline industry is often considered to be exogenous as airlines have limited control over pricing due to competition and other market elements such as the fuel price.

According to Grosche et al. (2007), the benefit of excluding service-related variables lies in the fact that the output of these type of models, namely the amount of passengers willing to travel, give a basis for airline-specific scheduling. The reason being that airlines can then predict the total potential travel demand between city pairs and not only the current demand which is affected by the current level of service.

2.1.3. Calibration Methods

As the focus in this chapter has been on gravity models, this section will focus on the calibration/parameter estimation methods for these types of models are discussed. To ensure a demand generation model can achieve good model fit with respect to real life situations, the model parameters are calibrated using real world data. The calibration method itself usually considers using logarithm techniques together with linear regressions (Grosche, 2009).

Calibration furthermore often happens in one of two manners (Grosche, 2009).

- The first method is by time-series calibration, here the demand model is calibrated for a specific city-pair using demand data for different time periods.
- The second calibration method used is cross-sectional calibration. Here a demand generation model is calibrated for multiple city-pairs and is thus calibrated using data from the different city-pairs at a single period in time.

Another possibility is a combination of the above two methods, namely panel data calibration. Here the calibration is done for data on multiple city-pairs over different time periods. The type of calibration used is based on the objective of a specific research. If sufficient data is available, calibration can also be done for specific subsets of demand such as for different fare classes or different sets of passengers.

After calibration has been done, it is important to check for the reliability of the models. This is most often done using the coefficient of multiple determination (R^2), which is a measure of the fit of the model to actual data. To ensure independent variables in a regression model are statistically related to demand, partial correlation measurements are used (Doganis, 2002).

2.1.4. Conclusions on Demand Generation

In the previous section, the different demand generation models have been discussed. First, an overview was given on the different types of models that exist and what characteristics they have. Next, the choice process of demand models was portrayed after which the focus was decided to be put on gravity models.

Variables used in demand generation models were next to be discussed, followed by an overview of the calibration techniques specified to gravity models.

It was found that there are two main subsets of demand generation models namely, qualitative models and quantitative models. The first subset is mainly based on expert opinions and market research. The second subset is based on mathematical models including time-series models and casual models. For reason discussed previously, it was decided to focus on the casual models and specifically gravity models.

Variables used in the gravity models were centered around two subsets namely, geo-economic factors and service-related factors. The choice of variable used in the models was very much dependent on the goal of the researchers and the data available to them. Additionally, the type of demand that needed to be generated was heavily affected by the choice of variable. By combining service-related and geo-economic variables into a model, constrained demand models with respect to supply which capture the effect of the level of service and price between the two airports is generated. Unconstrained demand on the other hand, which only uses geo-economic factors, has as an advantage that one can develop models where different transportation modes can be modeled as these models are not specified towards air travel. However, finding data to develop these models is often difficult and time-consuming, therefore constrained demand models are easier to develop.

The extensiveness of models is also a differentiator between demand generation models. More extensive models, are most interesting if the goal of the research is to enhance accuracy and to determine the effect of different variables on demand. However, the downside to modeling with large amounts of variables is the availability, time needed to find and accessibility of data, as described by Grosche et al. (2007). The exact definition of the demand generation model used in the thesis research can be found in Section 4.2.

2.2. Sub-Model: Demand Allocation

In the previous section, methods were discussed on how to generate demand between different city pairs. With these demands, we can now look at how to specify what share of the total demand between two city-pairs will be split among the different travel options. However, to be able to allocate the demand accurately over the different travel alternatives, it is key to understand consumer preference which enables to better predict travel demand. Additionally, a model which can accurately simulate passenger choice, is essential in testing the development strategy of an airliner.

This section will be structured as follows. First the different types of passenger itinerary choice models will be discussed, followed by a section on the different available data types used for these models. Next, an explanation will be given on discrete choice models, the basis of modeling passenger itinerary choice. Following, a review will be given on the different passenger choice variables used in passenger choice modeling.

2.2.1. Types of Passenger Itinerary Models

Throughout the years, many studies have been done on how to distribute passenger demand at different levels of aggregation. As described by Coldren and Koppelman (2005), the main distinction can be made between three types of passenger itinerary models: models with a very high level of aggregation, models with only limited scope and models using stated preference data.

During this literature study, multiple studies were found modeling passenger demand at different levels of aggregation. The first set of studies were based on the total amount of passenger travel between for example airport-pairs (Ippolito, 1981) (Anderson and Kraus, 1981) (Abrahams, 1983) (Baena Moreno, 2006) (Hsiao and Hansen, 2011) and domestic competition with other modes of transportation (Jung and Yoo, 2014). Other studies however focused on the allocation of passenger demands to airlines at different levels of aggregation. With these studies, airline service-attributes and their effect on demand were modeled. The levels of aggregation used here were for example at the level of airport-pairs (Proussaloglou and Koppelman, 1995) (Carrier, 2008), flight shares on point-to-point networks (Proussaloglou and Koppelman, 1999) and itinerary shares for airport pairs Coldren et al. (2003) (Coldren and Koppelman, 2005) (Koppelman et al., 2008).

These last set of researches, where specific itineraries are modeled, are especially of interest to the current literature review. Here, passenger demands are distributed between different itineraries based on the preferences of passengers and the characteristics of the itineraries. The potential for these types of models are that they allow airlines to more accurately plan their services up to itinerary level in comparison to designing their services based on a total demand between an airport-pair.

2.2.2. Data Types

Within passenger itinerary models, there are two main types of data input: stated preference (SP) data and revealed preference (RP) data. The type of data available to a research strongly affects the factors that can be researched and tested, and thus it is important when determining what should be achieved with the research.

Stated Preference SP data has been used for the majority of the researches which strive to model passenger choice (Carrier, 2008). SP data is generally collected using passenger surveys, which has as an advantage that the researchers can be as specific as they want to be. Often collected data includes information on the socio-economic characteristics of the travelers, the characteristics of their current and future travel and travel history (Carrier, 2008). The surveys are designed to simulate the choice environment passengers experience when determining what choice they will want to make. This is however done in a simplified manner, as simulating the complete choice scope would be very difficult, especially with the amount of ways one can buy air tickets online. Another disadvantage of SP data is based on two sorts of bias. The first is based on non-response bias, where the data acquired might not represent the broader passenger scope. The second form of bias, response bias, is based on the notion that the responses collected by the survey do not actually represent what the responder would do in real life (Carrier, 2008).

Revealed Preference RP data is based on historical booking data. Here the choices made by passengers are extracted from the actual bookings they have made, which has as an advantage that the data reflects actual passenger choice. The disadvantage of RP data is on the other hand that the booking data does not portray the choice scope the booking was made in, which makes it difficult to determine what type of choice trade-off was made (Carrier, 2008). Additionally, with booking data, the researcher is dependent on the available data types in contrast to SP data where specific data on points of interest can be collected.

2.2.3. Discrete Choice Models

In the modeling of passenger choice, researchers have typically made use of the concept of discrete choice modeling (DCM) based on random utility theory (RUT) (Carrier, 2008) (Wen and Lai, 2010). This modeling technique has proven to be capable of modeling the effect of different factors on the demand of air travel and thus provide a manner in which passenger choice and preference can be understood (Proussaloglou and Koppelman, 1999). In the following section, the RUT and the different DCM models that are found in literature will be discussed.

Random Utility Theory RUT was first discussed in the psychology research done by Thurstone (1927) and was extended on by Marschak (1960). RUT is based on the assumption that the utility value of each choice option is known to the choice-maker. However, this perception of utility is not fully known to the researcher so uncertainty needs to be taken into account. This is done by modeling utility with two parts, one determined by the research and one random component to account for the uncertainty (Carrier, 2008). In the research by Manski (1977), the four main types of uncertainty were described:

- Unobserved attributes - *Information on attributes is incomplete*
- Unobserved taste variations - *Unobserved variations found from person to person*
- Measurement errors and imperfect information - *Imperfect measurement data*
- Instrumental variables - *Some characteristics of variables are not fully observable*

Additionally, the assumptions is made that the choice-maker always chooses the alternative with the highest level of utility (Ben-Akiva and Lerman, 1985).

Discrete Choice Models DCMs is a collective name for models that are used to simulate choices between multiple discrete choice alternatives. The alternatives among which has to be chosen with DCMs need to cohere to a number of conditions: the alternatives have to be collectively exhaustive, mutually exclusive and there has to be a finite amount of choices that can be made (Carrier, 2008). The condition that all alternatives need to be collectively exhaustive refers to the fact that all possible choices that can be made, should be represented in the model. Mutually exclusiveness refers to the fact that each alternative is unique, thus choosing one means not choosing any of the others. The fact that there should be a finite amount of alternatives ensures that a choice can always be made. The choices made in a DCM are, apart from the alternatives themselves, based on the characteristics of the choice maker. This is based on the fact that choice makers with different traits an characteristics make different choices. For DCM modeling, both RP and SP data can be used depending on the goal of the researcher and the available data. Below, the main DCMs used are described.

Probit Model The earliest usage of DCMs can be found in the use of so called Probit Models (PM) (Carrier, 2008). PMs assume that the uncertainties found in DCMs are captured by a multivariate normal distribution. The advantage of a PM is that it is very flexible in its usage as it is able to achieve an unrestricted covariance matrix of the uncertainties. However, computationally there are difficulties, as the choice probabilities produce by PMs do not take a closed form solution (Carrier, 2008).

Multinomial Logit Model The multinomial logit model (MNL) is known to be the most popular DCM used for passenger choice modeling (Wen and Lai, 2010). The reason for this is that this type of DCMs are computationally simpler and that the output estimates of these models are of closed form. This eases interpretation, making the MNL models more preferable to use with respect to the PM (Carrier, 2008). The MNL model assumes that the uncertainties found in DCMs are captured by a an extreme value distribution, while being independently and identically distributed (Carrier, 2008). This has as a consequence, as described by Wen and Lai (2010), that the MNL model has as a disadvantage that when options in the choice subset are perceived to be similar, the model is known to generate unreliable results. This characteristic is described by the property known as the independence from irrelevant alternatives (IIA) (Carrier, 2008).

An example of a MNL model used in the research by Coldren et al. (2003) can be found in Equation 2.2. Here the probability function can be found that was used to determine the share of passengers per itinerary, which thus reflects the number of choices people make for a certain option.

$$Si = \frac{exp(V_i)}{\sum_J exp(V_j)} \tag{2.2}$$

Here, Si was deemed the passenger share on itinerary i, Vi the value of itinerary i and the summation was over all values of itineraries of a specific city-pair on a specific day (Coldren et al., 2003).
The utility values of each itinerary were computed using a linear relationship. This was done by summing the weighted independent explanatory variables for each individual itinerary. In Equation 2.3, the explanatory variables are denoted by X and the weights of each parameter are denoted by β.

$$V_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_n X_{ni} \tag{2.3}$$

Generalized Extreme Value Models Generalized extreme value (GEV) models have been known to overcome the disadvantage of IIA found in MNL models by being able to represent different substitution patterns among the different alternatives found in the choice set (Carrier, 2008). GEV models assumes that the uncertainties found in DCMs are captured by a joint extreme value distribution (Carrier, 2008). The most used GEV model was designed by Ben-Akiva (1974) and consists of a nested logit (NL) model and is known for the simple manner in which it is constructed. The nesting in NL models has to do with how a model segments its choices into different groups. For example nesting can be done with respect to time periods, city-pairs or air carriers. This has as an advantage that sub-choice sets can be made with itineraries which are perceived as similar within the total choice set. Therefore, the need to model choices between options which are not related diminishes.

An example of such a nesting structure can be found in Figure 2.2. Here the nesting structure is depicted which was used in the research by Hsiao and Hansen (2011). The first level contains the split between travel mode. In the air travel nest, this is then followed by the origin-destination pair nests which is further segmented into route connection types. To clarify, $O - D$ stands for origin and destination, while H stands for a hub.

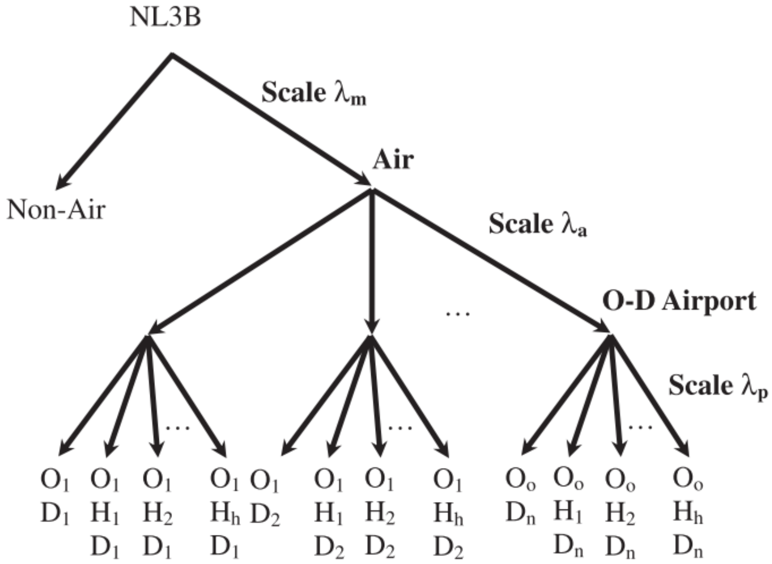


Figure 2.2: Example of a Three-level Nested Logit Model (Hsiao and Hansen, 2011)

Mixed Logit Model Mixed logit (ML) models are a form of DCM models which in the past was computationally unfeasible but have now started to be used more and more due to the increase in computational power (Carrier, 2008). The ML models are considered to be highly flexible and are able to account for preference heterogeneity as well as flexible substitution patterns among alternatives. However, the computational complexity of these models can still be considered to be unaffordable (Hsiao and Hansen, 2011). Furthermore, according to Garrow (2016), there are currently no ML models being used to model passenger itinerary choice using RP data.

2.2.4. Passenger Choice Variables

All the different types of DCMs discussed above, combined with different choice variables, produce the passenger itinerary models that are being researched in this literature study. The following section provides a concise overview of the different techniques and variables used in literature effecting passenger choice.

The structure of the following section will be as follows. The section will begin with the different manners in which passengers are segmented. Next, the effect of pricing and service-levels on passenger choice are discussed. The section will end with a discussion on the passenger preference for different levels of path quality.

Passenger Segmentation

Before looking at the different elements which have an effect on passenger choice, it is important to define what different types of passengers exist and what general elements affect the choices they make. Already in 1956, it was recognized that a market population can be segmented into different groups who share certain traits or needs (Smith, 1956). This segmentation has also been widely applied to the aviation sector.

Passenger Types Segmentation based on passenger types is the technique of creating sub-groups which describe a specific group of passengers which have similar traits (Haaijer et al., 1998). The main methods used for passenger segmentation can be split into two types: *a priori* approaches and *post-hoc* approaches (Teichert et al., 2008).

A priori approaches are based on predefining segments using known characteristics such as socio-demographic traits. A common segmentation between passenger types is found to be between business and leisure passengers (Proussaloglou and Koppelman, 1999)(Adler, 2005) as these two groups have very different needs and traits with respect to their travel preferences. For example, Carrier (2008) noted that passengers with high frequent flyer levels could indicate business travel, as business travelers will most likely fly more often than leisure travelers, accumulating frequent flyer miles more quickly.

Post-hoc approaches are used to create segments by using clustering techniques. These clustering techniques cluster similarities found in one or a combination of multiple selected descriptive variables (Teichert et al., 2008). Researches which have used clustering techniques are for example those by Mason and Gray (1995), Chiang et al. (2003) and Wen et al. (2008). The disadvantage of using clustering is that there is a tendency to generate a large amount of segments when dealing with a lot of descriptive variables; this makes the segmentation technique inefficient to work with (Wen and Lai, 2010). To overcome this disadvantage, research has been put into another post-hoc technique, the latent class (LC) model. The LC model has as an advantage that the researcher can predefine the amount of segments to be made. For each segment, the model will then determine the size and the profiles of the choice makers (Wen and Lai, 2010). It has been found, that LC models generally improve the fit of passenger segmentation models in comparison to the other described models (Carrier, 2008). In the research done by Carrier (2008), the LC model furthermore lead to a intuitively better passenger segmentation in cases where the market was split between time-sensitive business travelers and price-conscious travelers instead of only the passengers trip purpose as in the study by Proussaloglou and Koppelman (1999).

The features and data used for passenger segmentation relies on the purpose and the data available to the researcher. Often, segmentation is done using SP data collected through surveys, as was done in the studies done by O'Connell and Williams (2005), Teichert et al. (2008) and Wen and Lai (2010). As discussed previously, as SP data is based on the questions asked in the surveys, a multitude of factors can be taken into account. The focus of most studies has been on trip purpose, while others also included factors based on fare, catering and frequent flyer programs (Carrier, 2008). RP, on the other hand, is limited to the booking data available to the researchers. This data does not provide the flexibility in asking the questions the researcher needs answered. The data also does not clearly contain information on the interviewed persons' trip purpose or travelers traits. Yet, there are a few ways in which trip purpose and passenger traits can be deduced from RP data. The travelers profile can for example be deduced using the frequent flyer status, which provides information on how often the passenger flies. Furthermore, information on gender is generally easily available from booking data (Carrier, 2008). Trip purpose can in some cases be deduced using the characteristics of the in and outbound flights. For example, round trips which are completed within the week are strongly related to business travel (Carrier, 2008). Distribution channels through which bookings were made can also indicate the purpose of travel, as non-business travelers have been found to have booked flights using the internet while business travelers more often make use of travel agents (Carrier, 2008).

With respect to the performance of the different manners in which to segment passengers, the study of Teichert et al. (2008) clearly makes a comparison between two a priori models and several latent class models with different numbers of predefined segments. The first a priori model segmented passengers into business and leisure and was found to achieve an R^2 of 0.29 and 0.25 respectively. The second a priori model which segmented between business class (BC) on business routes (BR), BC on leisure routes (LR), Economy (EC) on BR and EC on LR achieved R^2 levels of 0.3, 0.31, 0.27 and 0.13 respectively. The different LC models, which differed in amount of segments from two to five achieved R^2 levels between 0.31 and 0.33.

Passenger departing time preferences Besides trip purpose and passenger characteristics, passenger segmentation can also been done with respect to their preferences in departing time. This can for example be done for the preferred time of the day and for the preferred day of the week. The accustomed approach to segment the day, is by allocating multiple fixed time-slots which represent passenger preferences (Carrier, 2008). An example of this is found in the research by Coldren et al. (2003) where the day was segmented into slots of an hour, except for the segments of 22.00-00.00 and 00.00-05.00 which were defined as two larger segments due to the fact that demands in these periods are at a low. For each fixed time period, a dummy variable was included in the passenger utility function.

Another option is to group times of day with respect to the connection banks at an airport (Carrier, 2008). This has as an advantage that it takes network airliner's preferences into account as they group departures and arrivals together to ensure connection possibilities.

A more sophisticated model to segment time-of-day preferences is discussed by (Abou-Zeid et al., 2006). This model introduces the concept of segmenting the time-of-day preferences as a continuous function of time. To model the continuous time function for passenger time preference, weighted sin and cos curves were used. These curves were added to the utility function described in Equation 2.3 in the following form:

$$V_i = ... + \beta_1 \times sin(\frac{2\pi t_i}{1440}) + \beta_2 \times sin(\frac{4\pi t_i}{1440}) + \beta_3 \times sin(\frac{6\pi t_i}{1440}) + \beta_4 \times cos(\frac{2\pi t_i}{1440}) + \beta_5 \times cos(\frac{4\pi t_i}{1440}) + \beta_6 \times cos(\frac{6\pi t_i}{1440}) \quad (2.4)$$

In Equation 2.4, t_i represents the departure time of the modeled flight and 1440 accounts for the number of minutes per day.

In the research by Koppelman et al. (2008) it was found that the continuous time function was behaviorally superior to the discrete time-periods, it contained less parameters and was statistically more significant.

Besides the time-of-day preferences of passengers, it is also of importance to take the passenger preferences with respect to the day of the week into account. This was acknowledged by Baena Moreno (2006), who used the day of the week as one of their three criteria when modeling the effect of flight frequency on an airlines' level of service. It is essential to realize that trip characteristics will have an effect on what day of the week people prefer to fly. For example, travel which is completed within weekdays can be expected to be generated by business passengers, especially when looking at short-haul markets (Carrier, 2008). Leisure passengers on the other hand might center their travels around the week-end. Yet, in the research done by Coldren et al. (2003), it was realized that time-of-day preferences and day of the week preferences were dependent on each other. Thus in their model, itineraries were generated for specifically for each day of the week. As with the time-periods, the preference for day of the week was accounted for using dummy variables, or by estimating the models parameters for each specific day.

Pricing

In this section, the focus will be on the literature relevant to passenger choice models and pricing. Here a differentiation will be made between the fare and fare rules and how they affect passenger choice. In the following section, fare is defined as the price passengers pay for their flight tickets and fare rules are defined as the non-monetary implications of a ticket such as the option to change or cancel a ticket or the minimum stay that is needed (Carrier, 2008). In general, the influence of an increase in airfare is found to lead to a decrease in the demand for an airline ticket (Wen and Lai, 2010).

Fares The pricing of airline tickets is in almost all literature (focusing on passenger choice) one of the leading factors which affect the demand shares of airliners. It is a monetary variable which is most directly observed and felt by any customer and thus provokes one of the largest incentives to buy or not buy a certain ticket. This is confirmed by Wen and Lai (2010) who observed. In their studies based around passenger SP, that passengers are more responsive to changes in the pricing of tickets than any other aspect. This same result is also established in an more recent study, where fare along with access time and journey time are seen to be of essence in passenger choice (Jung and Yoo, 2014). In this same study, it was also found that business travelers have a higher willingness to pay more to reduce the overall journey time in comparison to economy passengers (Jung and Yoo, 2014). This conclusion stands to reason that business travelers are willing to pay more for enhanced services, and should be kept in mind during the segmentation of passenger groups.

With respect to fare modeling, multiple manners have been researched and tested in the relevant literature. In general, fare is used as an independent variable, implemented in a form of a DCM. This can be done using the actual monetary variable (Proussaloglou and Koppelman, 1999) (Jung and Yoo, 2014), as a dummy variable (Jorge-Calderón, 1997) or as a fare ratio (Coldren and Koppelman, 2005) (Martín et al., 2008). The choice of how fare is modeled depends on the availability of fare data. Often studies based on RP data include actual monetary values or fare ratios. Studies based on SP data however, can comprises of the whole spectrum of fare variable types.

The fare variables are also often segmented into multiple segments for different groups of passengers. For example, Proussaloglou and Koppelman (1999) determined three fare classes for both business and leisure passengers, as did Jorge-Calderón (1997) and Martín et al. (2008). Coldren and Koppelman (2005) however lacked extensive fare data, thus resorted to using one fare ratio based on the average carrier fare between two airport-pairs divided by the average fair of the city pair for all computations. What was evident in all studies was that fare has a significant negative impact on passenger demand, whereas business passengers were slightly more insensitive to price change than leisure passengers.

Fare Rules As mentioned, fare rules are the non-monetary implications applicable to airline tickets. Commonly used fare rules by flag carriers included a minimum travel stay, a round-trip requirement, the ability to change or cancel a ticket or purchase requirements (Carrier, 2008). Fare rules are used to do two main things: to ensure that business passengers are discouraged to buy discounted air tickets and to channel low-fare passengers on to low demand flights and thus allowing seat-availability for high-pay passengers on the higher demand flights (Carrier, 2008). These measures therefore affect the manner in which passengers make choices on air travel, as they have to determine to which fare rules they are able and willing to adhere. Data on fare rules is key to being able to model the effects on passenger choice. With SP data the effects can be measured by questioning the respondents correctly, but in booking data this information is not always available and thus may be incorporated as a modeling uncertainty due to lack of information.

However, with the introduction of low cost carriers, the aviation market changed. Low cost carriers (LCC), in comparison to the established legacy airliners, focused on the relaxation of fare rules and with that disrupted the pricing market (Carrier, 2008). LCC's did this by selling lower priced one-way flights, obviating the conditions of a fixed trip duration or round-trip (Currie et al., 2008). In response, the large majority of legacy carriers were obliged to change their pricing methods to be able to compete with the LCCs. This is especially visible in the medium and short-haul markets where fare rules were relaxed and the pricing range was reduced (Carrier, 2008). Therefore, the effect of fare rules in medium and short-haul markets could be deemed negligible, which would make the lack of information on fare rules less harmful to passenger choice modeling activities.

Level of Service

Besides looking at the pricing of a flight ticket, passengers will also be influenced by what level of service they will be receiving for the agreed price. Service levels especially can be assumed to have a large effect on demand in markets where pricing competition has saturated and prices are relatively similar (Vaze and Barnhart, 2012). In this section, the PIM will be further extended with findings from literature on the effect of different service level aspects provided by airliners. This will be done by looking at pre-flight services, in-flight services and other relevant services which contribute to a passengers choice. For each segment, an outline of different aspects found in literature and their highlights will be enlightened on.

Pre-Flight Service Levels Pre-flight services include aspects such as the check-in-service (Wen and Lai, 2010) (Chang and Yeh, 2002), distribution channel (Carrier, 2008), frequent flyer memberships (Proussaloglou and Koppelman, 1995)(Borenstein and Rose, 2011) and marketing and promotion (Proussaloglou and Koppelman, 1995)(Coldren et al., 2003). In the study performed by Wen and Lai (2010), it was found that check-in services were seen as one of the aspects which passengers feel are most important with respect to service levels, as long delays at check-in are disliked and should be avoided. Another interesting highlight was the high impact of frequent-flyer programs on the choices of passengers on flights, especially those passengers who travel frequently (Proussaloglou and Koppelman, 1995).

In-Flight Service-Levels The in-flight service-levels provided by an airline can be divided into two main elements: the flight services and the fleet allocation. Flight services are based around services such as on-board comfort including food and beverages, entertainment, seat comfort (Wen and Lai, 2010) (Chang and Yeh, 2002) (Coldren et al., 2003) (Martín et al., 2008) and cabin staff services (Wen and Lai, 2010) (Chang and Yeh, 2002) (Coldren et al., 2003). Interestingly enough, it was found in the study done by Wen and Lai (2010) that food and beverages did not provide positive influence on passenger choice as the other mentioned attributes did. It was hypothesized that this was due to the fact that only short-hauled flights were investigated and that this parameter thus might not have the same effect as on a long-haul flight.

Fleet allocation concerns the airlines choice of aircraft type which will be used on the different flight legs. Aircraft types have been used to model passenger choice in the researches by Coldren et al. (2003) and Coldren and Koppelman (2005) as they found that passengers prefer larger aircraft based on the notion that these aircraft are safer and have a higher level of comfort. This is backed up by Belobaba (2014) who states that the aircraft type becomes more and more important as the distance of the flight increases.

Other Service-Levels Besides pre-flight and in-flight services, two more factors that affect passenger itinerary choice have been identified in the relevant literature. The first is the handling of abnormal conditions, which weighs in on passenger choice and includes factors such as the handling of flight delays, customer complaints and luggage loss or damage (Chang and Yeh, 2002). The second interesting aspect to look at is the reliability of service provided by the airline (Chang and Yeh, 2002). Aspects to do with reliability mentioned in different researches included: On-time performance (Wen and Lai, 2010) (Coldren et al., 2003) (Hsiao and Hansen, 2011) and safety standards (Coldren et al., 2003). In the research done by Hsiao and Hansen (2011) a useful manner to model on-time performance of an airline was discussed. Here, the average delay per flight at each airport in a flights itinerary was used as an indicator of the on-time performance of different flight options.

2.2.5. Path Quality

Another element that is essential to take into account is the effect airline path quality has on passenger itinerary choices. This is especially interesting when looking at indirect flights as new aspects such as extra travel time and connections arise. In this section, the effect of path quality on passenger itinerary choice will be considered, focusing on the type of routing, the value of time and the frequency of flights.

Routing There are multiple ways in which passengers can route flights between their choice of origin and destination pair as shown in Figure 2.3. As discussed in the research done by Alamdari and Black (1992), flights can be:

- Direct between city-pairs
- Indirect between city-pairs, with or without change of airline or airplane
- A combination of the indirect path described above, including alternatives in departure and arrival airports

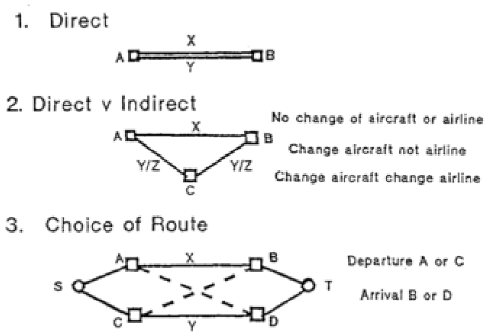


Figure 2.3: Route Models (Alamdari and Black, 1992)

The definition of an itinerary, which depicts the linking of a city-pair by one or more flight legs is widely used in aviation network theory (Coldren et al., 2003). A flight leg is thus a flight between two airports (Bertsimas and Patterson, 1998), which means that an itinerary can consist of multiple flight legs. Modeling all the different possibilities within an actual network can become very complex, which is why researchers often simplify the networks they model to a scope they find relevant and suitable for their research.

Path Preference When looking at the preferences of passengers, it is found that airline passengers greatly favor direct flights between their chosen city-pair (Hansen, 1990)(Alamdari and Black, 1992). Yet, a direct itinerary to a chosen destination is not always a possibility. Therefore, it is important to include how choices are made when it comes to indirect flights. An important variable to consider is the total travel time of different itineraries between the same OD-pairs (Coldren et al., 2003). According to Coldren et al. (2003) passengers prefer shorter travel times when choosing itineraries. Yet, total travel time is not the only parameter that effects passengers decisions on which itinerary to take, it has also been found that between itineraries with the same airport of connection, the itinerary with the shortest ground time is preferred (Coldren et al., 2003). The importance of connection time was also discussed by Dobson and Lederer (1993) who concluded that itineraries have a maximum time that passengers want to wait on a connection to ensure realistic modeling. Narangajavana et al. (2013) furthermore adds that, in general, business passengers are more sensitive to waiting times than to prices.

Monetary Value of Time To determine the effect of having a connecting flight and departing or arriving earlier or later than the desired time, it is of importance to determine the value that time has on a passengers choice. In a study done by Ramjerdi et al. (1997) on Norway, it was found that the value of time was equivalent to \$54.5 and \$73.2 per hour for leisure and business passengers respectively. Sadly, due to a lack of information the difference between waiting time and travel time value was not determined. However, the value of an hour of scheduled displacement was set to be equivalent to \$11.0 and \$43.6 per hour for leisure and business passengers respectively. In another study, the US values of travel time were determined. Here, travel time with business purposes was found to be \$57.20 and \$31.90 for leisure purposes (Institute, 2013). Values such as these can be applied to determining the cost experienced by the traveler.

Desired Arrival Time Another point of interest with respect to path quality, is the potential passengers preference with respect to arriving earlier or later than their desired arrival time. According to both Adler et al. (2006) and Lijesen (2006), passengers in general prefer arriving before rather than after their desired arrival time, especially for passengers with short stays at their destination.

Flight Frequency The frequency an airline provides is another important dimension on which passengers base their choice. The reason being that a higher flight frequency will lead to more choice and will better suit ones needs with regards to traveling moments between city-pairs (Brueckner, 2010). An increase in frequency on a particular route will thus create a higher demand for that particular airline (Vaze and Barnhart, 2012). The reason for this is, is the so called scheduled displacement of a passenger. The scheduled displacement of a passenger is the disutility of a flight leaving at a time earlier or later than ones preference. Therefore, the larger the scheduled displacement the less attractive a set of itineraries will be for a passenger. Increasing the frequency of flights, decreases the scheduled displacement and thus leads to a more attractive situation.

2.2.6. Conclusions Demand Allocation

In the previous section, the passenger itinerary choice model has been discussed. The chapter started with a discussion on the different types of passenger itinerary choice models, which was followed by a section on the different available data types used for these models. After this, an explanation was given on discrete choice models, the basis of modeling passenger itinerary choice. Lastly, the different variables which are affecting passenger choice and are used in modeling were considered.

We can conclude from the literature that a great deal of research has been done into different passenger choice models at different levels of aggregation. From simple demands between city-pairs to demand allocation to itineraries with specific times and days and everything in between. Furthermore, an extensive set of different types of variables has been used in the different studies. What variables to be used to determine passenger choice in each research, was heavily dependent on the type of data available to the researcher. With stated preference data, researchers were often able to develop their own data sets through questionnaires. Researchers working with revealed preference data were limited to what was being recorded.

With respect to modeling methods, it became clear that DCMs were the manner in which passenger choice was modeled. The most relevant DCM methods included the most often used multinomial logit models and nested logit models.

Passenger choice models have become increasingly more complex and detailed. Simple MNL models, using discrete time periods, were improved with the use of for example continuous time functions and penalties for scheduled displacement. The development of newer NL model was a direct consequence of the fact that MNL models did not realistically take inter-itinerary competition into account and generated unreliable results when alternatives were too similar. With NL models, the complexity of nesting structure was introduced to enable more accuracy in determining itinerary demand shares and inter-itinerary competition. In general, the level of complexity of the model lead to higher representations of reality.

Concluding form the literature study: what is especially important with respect to the research of this thesis, is to determine what type of passenger choice model will best fit into simulation framework as a whole. A trade-off between modeling accuracy, data availability and model complexity essential. The exact definition of the demand allocation model used in this thesis research can be found in Section 4.3.

2.3. Sub-Model: Market Competition - Competitor Reaction

When designing a simulation framework that can model the aviation market in a way that integrates demand generation, demand allocation and competition, it is important to review what has been described in literature on current competition modeling techniques. Since the airline deregulation act in 1978, the aviation market has changed dramatically with respect to competition. The act ensured that airliners were now able to compete in a free market, giving them control of their pricing, scheduling and routing. This also opened the door for airlines with new revenue models, such as LCCs who would challenge the legacy carriers in a manner not seen before (Carrier, 2008). In the following chapter, the literature relevant to market competition, including that of LCCs will be discussed.

The coming section will be structured as follows. The first section will contain a discussion on regularly seen airline business models, which will be followed by a section on how competitive reaction in the aviation market is modeled. The final section will summarize and conclude on the relevant literature for a market competition model.

2.3.1. Airline Business Models

In the aviation market, several types of can networks be observed. The basic segmentation can be based on the type of routes an airline flies: hub-and-spoke or point-to-point. An airline with a hub-and-spoke model has one or multiple hubs at specific location(s) and from there flies all its flights directly to one of its many destination or spokes. Connecting flights are possible but only through the hub (Hansen, 1990). A point-to-point airline only flies direct flights between two city pairs and does not support connecting flights (Hansen, 1990). Airlines however do not see their business models in such a black and white manner, thus it is possible to see airlines which combine business models if needed.

The two general competitors types in the aviation market are the full service carriers and the LCCs. The designation is self-evident: the full service carriers provide passengers with a product which includes multiple levels of service and comfort, differentiation in airfares and usually fly according to a hub-and-spoke model (O'Connell and Williams, 2005). The LCCs on the other hand operate in a much more simple and cost effective manner: one class operations, point-to-point services, online booking modes and electronic ticketless systems are all used to keep costs low and operations efficient (Ko, 2016). These differences in business models have an effect on the amount and type of passengers that will use the services of an airline. The manner of choice of passengers has been discussed in Section

2.2. For this section, it is interesting to see how the airlines with different business models compete. Inherently, due to the different business models, it can be expected that airlines react in different manners as their goals are different. In the following section, this will be researched.

2.3.2. Modeling Competitive Reaction

Previously, the airline business models have been described but there still lies a gap in how competitors react to one another. Research has proved that competitors in the aviation field are quite efficient in reacting to one another's price changes (Jones and Jr., 1995). However, the difficulty here is how this competitive reaction can be modeled.

In literature, a few different methods on modeling competitive reaction have been discovered. However, these methods are more focused on how competitors can maximize certain variables such as profit in a competitive environment instead of simulating real life situations or competition between different business models. Yet, these researches are thought to be relevant, as an airlines goal can for example be to maximize its profit or market share in a competitive environment. Linking different goals to different types of business models could be a way to simulate competition between different business models, but as this is not described in the found researches this is merely a suggestion. The main methods and principals of modeling competitive reaction are discussed below.

Non-cooperative Games
Non-cooperative describes the characteristic that players of the game only consider their own (profit) function when making choices (Hansen, 1990).

An example of this is found in the study done by Hansen (1990). Here, a non-cooperative game between a set of hub-and-spoke and point-to-point carriers seeking to maximize profit was designed and tested to model airline hub competition. Through the assumptions made in the research, the models pay-off function, which determines the profit an airline makes, limits itself to decision variables for each player based on its flight frequencies. Inputs for the pay-off function were derived using underlying models including a market share model, airline cost model and an average fare model.

The market share model is developed based on the logit form, similar to those discussed in the Section 2.2. The average fare model was based on the analysis of 250 markets in the US. It was found that the ideal model was only a function of distance. The model had the following form:

$$\frac{F}{D} = \alpha + \frac{\beta}{D} + \frac{\gamma}{D^2} \tag{2.5}$$

The airline cost model was designed as a function of the distance flown, the operating costs, the flight frequency and the number of seats per flight.

The final model then used numerical methods to optimize each airlines frequencies for profit maximization, which lead to quasi-equilibria within five to six rounds of iterations. After these optimization rounds, changes to the airline frequency sets lead to insignificant changes to the equilibrium states and was thus considered to be applicable to compare to actual data. Looking at the simulation model, the load-factors, proportion of trips using connecting services, the average on-plane length and activity levels at the largest hubs resembled those of the actual system. The main discrepancies were found in the levels of activity at airports in multi-region airports which were over predicted and airports situated in thin local markets which were under predicted. Explanations for these discrepancies were that the model assumed one city to be served by one local airport and the lack of competition advantages of airports in thin local market locations. The research suggested these discrepancies to be further researched, as well as incorporating airline pricing into the model. Furthermore the assumption that complete demand inelasticity should be replaced, as it was deemed to be unrealistic. According to the authors, the overall performance of the model proved potential in predicting of competitive outcomes.

One-shot Simultaneous Game
In the one-shot simultaneous game, both players make a choice on the available decision variables simultaneously while assuming that the competitor does the same and that their choice is then fixed. Both competitors know the options that the other can choose from, and what result that will have on their profit (Wei and Hansen, 2007).

An example of this is found in the research done by Wei and Hansen (2007) where the competition between two competitors was simulated. Here, both players choose the aircraft size and frequency simultaneously while assuming that the competitor does the same and that their choice is then fixed. Both competitors know the options that the other can choose from, and what result that will have on their profit. Therefore, the choice made by both competitors will be optimal for themselves, while the games total optimal is dependent on both competitors choice.

A variation of the one-shot simultaneous game was also researched by Wei and Hansen (2007). Here, a two-level one-shot simultaneous game was designed. This was setup up by dividing the choices on aircraft size and frequency into two sections. First both airlines simultaneously made a choice on the aircraft size they will provide. Next, both competitors as a reaction on the first choice simultaneously make a choice on the frequency that will be flown.

The research by Zito et al. (2011) also makes use of a one shot simulation game. In this research a duopoly market is modeled. The decision variables of the competitors in this research were focused on fare and frequency for a short-haul market. The model is based on a hierarchical bi-level optimization. Where the airline is trying to maximize its profit by optimizing its revenues through fares while keeping the cost due to the frequency of flights low. On the other hand, the demand from passengers will be affected by cost of the fare and flight frequency which they will want to keep low. The model was able to find Nash equilibriums between the two airlines on the basis of fare and frequency while being able to simulate the interaction between airline and passenger demand. A Nash equilibrium is defined as an equilibrium that is found in solutions of games of two or more players. A Nash equilibrium is found when no player can benefit from only changing their own strategy, but needs the others to change their strategies as well to find a new optimum (Ko, 2016).

Leader-and-follower Stackelberg Game
In the leader-and-follower Stackelberg game it is assumed that one of the competitors has the advantage to decide on its variables before the other competitors can. The other competitors will thus have to react. The first choice maker however does realize that the competitors will react, and takes this into account in the choice making (Wei and Hansen, 2007).

The third model designed in the study by Wei and Hansen (2007) was based on the leader-and-follower Stackelberg game. Here, it is assumed that one of the two competitors has the advantage to make choices on aircraft size and frequency before the other competitor. The second competitor will thus have to react to the strategy of the first competitor. As described above, the first competitor realizes that the second competitor will react, and takes this into account in the choice making. The solution process in this model will thus first determine the optimal choices of competitor two with respect to all choices of competitor one and from that the optimal choice will be made for competitor one.

In the research by Ko (2016) competition between three types of airlines was modeled using the principal of the leader-and-follower Stackelberg game. These airlines include a full service carrier (FSC), a low cost carrier (LCC) and a subsidiary LCC of the FSC. Each airline is a player in the model and makes decisions on variables including the fare, flight frequency and the number of aircrafts used on the route while maximizing its own profit. The demands of the airlines are a function of the flight fares and the flight frequency. The profit function of the airlines is built up out of four components: the sales revenue, the variable cost of passengers, the variable cost of operation and the fixed cost of aircraft. In the first game the FSC is seen as the first decision maker, after which the decisions of both LCCs follows.

In the second model, Ko (2016) developed a similar model to the one described above only now the FSC and subsidiary LCC work together. The FSC and subsidiary thus can be seen as one group, to which the rival LCC has to react.

Performance Comparison
In two of the researches described above, different models were compared to determine their respective performance in comparison to each other. Below, these results are discussed.

Wei and Hansen (2007) As Wei and Hansen (2007) compared multiple competitor reaction models in their research, a performance comparison could be done. To recap, the models tested were the one-shot simultaneous game, the two-level hierarchical game and the leader-and-follower Stackelberg game. With respect to the different models, the authors stated that with respect to reality, the two-level hierarchical game was found to be most accurate. The reason being that airlines usually fix decisions on aircraft size for the long-term and will vary with the flight frequency on a more short-term level. All models showed that competitors regularly chose for smaller aircrafts with a higher frequency. This matches reality, as increasing frequency has a higher effect on market share than increasing the size of an aircraft (Hansen and Liu, 2015).

Ko (2016) The models compared in the research by Ko (2016) included two leader-and-follower Stackelberg games. It was found in the research by Ko (2016) that the FSC can make the most profit when it is market leader and working together with its subsidiary LCC as done in the second model described. In this case, the subsidiary LCC caters to the mid-cost segment passengers while the FSC caters to the high-cost segment passengers. In general, the author concludes the research in suggesting that future work should not only focus on maximizing profit, but also on market shares or eliminating competition.

2.3.3. Conclusions Market Competition - Competitor Reaction

In the previous chapter, a discussion was given on the most common form of business models found in the aviation market. This was followed by a section on how competitive reaction is modeled in found researches.

It was found that there are two main business models which airlines adhere to, namely hub-and-spoke models and point-to-point models. However, the modeling of competition between the two types of business models or even within competitors of the same business model were not specifically described in the literature found. On the other hand, what is described in literature is how to model reaction between competitors based on a set goal. This goal was most often maximizing profit on the basis of different variables. However, as described by Ko (2016) future work should also focus on being able to model the goal of maximizing market share or eliminating competition. It might also be possible to set different goals for different competitors in the same model, simulating competition between different airlines with different business models. However, to the authors best knowledge this has not yet been done.

When looking at what has been modeled with respect to competition reaction, it is interesting to note that all studies model competition reaction on a very small scope. Most studies reviewed in this literature study modeled the reaction between two players on a route or small set of routes. In the study by Ko (2016) this was brought to three players, namely an FSC, LCC and a subsidiary LCC. How the modeling technique could be extended towards a realistic network size was not apparent.

Additionally, as is common in research: the longer research is done, the more complex the researches become. Where Hansen (1990) modeled competition reaction in a non-cooperative game in which only the airlines own strategy is taken into account, Wei and Hansen (2007) modeled competitor reaction using three different game-theory types which considered the choice set of the competition before making a choice on their own reaction strategy. This last method of also taking the competitors choices into account was continued in the research found in later time periods.

Another element that changed in time with research, is the amount of decision variables taken into account. Hansen (1990) focused on modeling competition reaction solely on the flight frequency, Wei and Hansen (2007) extended this to frequency and aircraft size while Zito et al. (2011) used frequency and fare. Ko (2016) was the most extensive research found: it included the decision variables of fare, flight frequency and the number of aircrafts on a route as input to its simulation.

It seems that the modeling of competition is not done in as an extensive fashion as for example passenger itinerary modeling. Despite this, methods have been developed to simulate possible reactions between competitors based on set goals. These modeling techniques might be applicable to implementing in a grand simulation model, for which simulation of competition between airlines would be relevant. However, it should be noted that, in reality the reaction of competitors to changes in strategy may not be focused on only one specific goal such as profit maximization. Different combinations of goals coming from complex strategies and business plans could lead to different reactions then to those modeled in the discussed papers. The exact definition of the computer reaction model used in this thesis can be found Section 4.4

3
Research Plan

In the following chapter, a description of the thesis research plan is given. It provides an insight on how the research was initiated, progressed and how it was fulfilled. This chapter consists of a discussion on the problem statement, past research, the project plan, the research scope, and finally the prospected research contributions. It is important to realize that the research plan is an evolving process, where different situations and findings during the research have steered the research and therefore the plan in a certain direction. The research plan described in this chapter thus reflects the final research plan which has been executed.

3.1. Problem Statement

In the coming section, the problem statement which inspired towards this thesis is described. The problem statement for this thesis is not necessarily a problem, but more of an opportunity. In any case, the problem statement will be described from two perspectives, namely from the scientific and from the industry perspective.

- **Scientific Perspective**
  - In the current airline development models, competition is often assumed to be static and acts irrespectively of airline strategy. Therefore, simulating an airline market is difficult as the modeled competition does not react to the strategies of the other competitors. In reality, competition strategies change constantly, taking market characteristics and choices of the competition into account.
  - In airline operations research, there are a multitude of different models which are designed to simulate, forecast and/or predict certain traits within the airline market. Each model on its own provides an understanding of the specified research scope. However, each model independently does not portray the dynamics of the aviation market as a whole.
- **Industry Perspective**
  - The aviation market is a complicated combination of different processes which occur simultaneously. Describing and understanding these separate market dynamics can be tough enough as it is, but being able to combine all these dynamics into one and being able to clearly understand what is happening can be even more difficult. This difficulty arises from both the complexity of the underlying processes, as well as the broad scope of different processes which come together in the total dynamics of the aviation market.

In summary, from a scientific perspective competition in airline development models are often assumed to be static, which is unrealistic. Furthermore, an opportunity exists to combine different specific models describing the aviation market, to be able to develop a model which captures the main effect of the total aviation market. From an industry perspective, being able to understand the market dynamics of the aviation market as a whole, with all its underlying specifics is complicated but is desirable for multiple purposes. The contributions that this thesis could make with respect to the problems described above are discussed in Section 3.5.

3.2. Past Research

The main basic components when considering the aviation market dynamics as a whole are, in general, based around two concepts: supply and demand. Supply within the aviation market can be seen as the flights and flight options which different competitors provide to a market. These different options compete with each other for passenger demand, a continuous process which is influenced by market forces, especially since aviation markets around the world have been deregulated. Demand in the aviation market is generally based around people wanting to travel between two locations for whatever purpose and how they make the choice to travel between different flight options.
As mentioned in Section 3.1, specific models which describe certain traits of the aviation markets are often well researched. So are models on demand generation, passenger choice and dynamic competition. However, the development of a simulation framework which can reproduce the competition and passenger choice for an airline while integrating models on demand generation, passenger choice and market competition is found to be unknown to literature. With respect to the authors best knowledge, such a framework has yet to be researched. In contrast, with respect to the underlying models, much research has been done and so these models have been reviewed in detail to discover how these models have been constructed. From these findings, it has been determined what possibilities there are to combine the different models to develop one integrated simulation framework.

Demand Generation Demand generation is a well-researched area in literature. Over the years, extensive models have been developed to forecast demands between cities and airports at multiple levels of aggregation. It was found that, with respect to modeling simplicity and model effectiveness, gravity models were considered the optimal way to generate demand. This decision was based on preliminary set goals, including that the demand generated should take the influence of market characteristics into account as well as being simple to compute but at the same time be meaningful.

Passenger Itinerary Models Passenger choice models have extensively been researched by a great number of academic studies. The use of discrete choice models often were at the basis of this type of modeling. It was found in the literature review, that the most used model type consisted of the multinomial logit models. However, the later developed, nested logit models have proven to model passenger choice in a more realistic fashion by being able to accurately model between choice options which are very similar and being able to account for increased inter-itinerary competition. Something the MNL model could not.

The combination of demand generation and passenger choice models is furthermore logical and often seen. This is due to the fact that the demand generated between city-pairs, by for example a gravity model, can be used as an input for demand allocation by a passenger choice model to different itinerary alternatives.

Market Competition Models Market competition modeling which simulate competitor reaction have been found to be the least developed modeling area of the three discussed in this literature review. Modeling of competitor reaction is currently done with respect to predefined goals, such as maximizing profit instead of simulating reality. This need not be a problem, as if goals per competitor are defined correctly, reality can be simulated. However, to the authors best knowledge market competition is currently simulated in a basic fashion at small scope and with up to three players and three decision variables. However, market competition models have included simple passenger itinerary models, thus the possibility to link these models to a passenger choice model is certainly plausible.

3.3. Project Plan

The development of a simulation framework which integrates demand generation, passenger choice and market competition has yet to be designed. Thus, the proposed research objective has been defined to be:

To contribute to the development of an integrated simulation framework, which has the capability of realistically simulating the aviation market by being able to reproduce the competition and passenger choice for an airline in the aviation market by combining a demand generation, passenger choice and market competition model.

The hypothesis of this research will be that the developed simulation framework is able to realistically reproduce the market dynamics found in the aviation market with respect to passenger behavior and competition among airlines. Additionally, exogenous players should be able to be incorporated in the simulation framework, providing a platform for simulation game play.

To ensure the research objective is properly defined on which to continue this thesis research, the implication of *'realistic simulation'* needs to be further defined. The different sub-models which are combined within the integrated simulation framework must all be represented in this simulation. Below, the thesis definition of realistic simulation is described per sub-model.

Demand Generation Realistic simulation of a demand generation model is defined as a model which is able to predict demand between a specific OD-pair where the values are similar to actual demand values and the demand split between classes follow the actual class distribution of demand. The model should furthermore be generalizable to routes with similar characteristics. The demand model itself should additionally host coefficients with the expected signs for the different independent variables.

Demand Allocation Realistic simulation with respect to demand allocation is defined as a model which is capable of simulating passenger choice between flight options in a similar manner to that found in the actual data, based on the included selection of parameters. The choice model should furthermore be generalizable to routes with similar characteristics which are not included in the model. Additionally, as with the demand generation model, the demand allocation model should host coefficients with the expected signs for the different independent variables.

Market Competition - Competitor Reaction Realistic simulation when focusing on competitor reaction is difficult to determine, as accurately defining the reaction of competitors is based on a great number of variables. Furthermore, the competitors' strategy is also hard to define as accurate airline strategies are confidential. Realistic simulation for the competitor reaction model is thus in this thesis defined as that the competitor reaction model behaves in the manner and following the strategy which is specified and for which it has been designed.

The model in its totality, is considered to realistically simulate the aviation market if each sub-models performs in the manner described above.

3.4. Research Scope

Besides the objective of the research, it is also of essence to limit the scope that this research will have. The scope is defined with respect to specific processes within the aviation market, hardware and software availability, locational interest as well as thesis time constraints. This leads to the following scope:

- The thesis will focus on combining a demand generation model, a passenger choice model and a competitor reaction model into a single integrated simulation framework. The integrated simulation framework will not be developed with the goal of optimizing airline behaviors or strategies, but rather to model realistic aviation market dynamics with respect to competition and passenger choice.
- The thesis is looking to bring a contribution towards an integrated simulation framework of the aviation market, with which in the future can be built upon and improved. Therefore the simulation framework should be designed in a software package which is available to the interested parties, namely the TU Delft and Cranfield University.
- The scope has been set on the development of a simulation framework for the internal European market. The European aviation market is known for its high level of competitiveness, many operators and broad selection of travel options between city-pairs. This creates the need to understand the European market, to be able to facilitate the analysis of the market and when making educated

decisions on for example airline strategies. Furthermore, data on the European aviation market is available through the University of Cranfield.

With the scope in mind, the specific goals of this research will include the following:

1. Determine an integrated model framework
2. Develop a demand generation model
3. Develop a passenger choice model
4. Develop a market competition - competitor reaction model
5. Combine the three models into a unique integrated simulation framework
6. Validate the model according to a European case study

The scope and goals can further be summarized in the below model framework (Figure 3.1), which depicts the general process in which the research project is designed. As the figure shows, the initial research bases itself on determining what is already available in literature with respect to the different sub-models, as has been described in Chapter 2. This is followed by the technical design of the simulation framework, where each sub-model is designed and integrated. Following, the sub-models and complete integrated simulation framework are tested, after which the results are analyzed. Then verification and validation procedures follow. The complete process of design and testing is iterative, with the resource constraints in mind. With an acceptable model in place, the integrated simulation framework is finalized and this thesis is concluded.

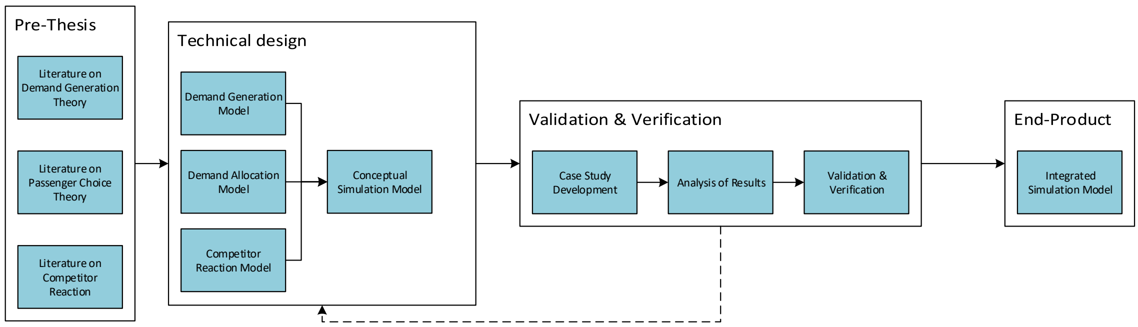


Figure 3.1: Research Framework

3.5. Research Contribution

The research will be, to the best knowledge of the author, the first integrated simulation framework which can reproduce both the competition and passenger choice in the aviation market, while also being able to determine general travel demand between city-pairs. The scientific and industry contributions are described specifically in the paragraphs below.

Scientific Contribution

- By combining different models which are specifically designed to simulate certain market traits, a generalized simulation framework can be built which is able to simulate basic aviation market dynamics. Of interest here is to determine the possibilities of combining different models, and to what level they are able to accurately capture these market characteristics.
- The model will be the foundation on which in the future can be extended with other models, such as for example a fleet scheduling and maintenance planning model. Additionally, the currently integrated models can be extended and improved on.

Industry Contribution

- The integrated simulation framework could be used to train (future) aviation professionals in the dynamics of the aviation market, by giving a look and feel on how different choices affect the levels of demand for a flight option and how a potential competitor would react.
- The final model could potentially be a cost-effective tool for airlines to predict the outcomes of future strategies, where different exogenous changes to the aviation market can be modeled and where market structures can be analyzed in a simplified manner.

4

Methodology

4.1. The Integrated Simulation Framework

In the following section, the design of the integrated simulation framework will be explained. Here the focus will be on both the simulation framework as well as all the sub-models present. First, a discussion on the simulation framework will put the model as a whole into perspective. With this in place, the sub-models and their build will be discussed as well as how they are connected.

4.1.1. The Integrated Simulation Framework

The simulation framework has been designed according to the requirements originated from the thesis assignment, the literature study and the project plan. The summarized process that occurred from requirements to simulation model can be found in Figure 4.1.

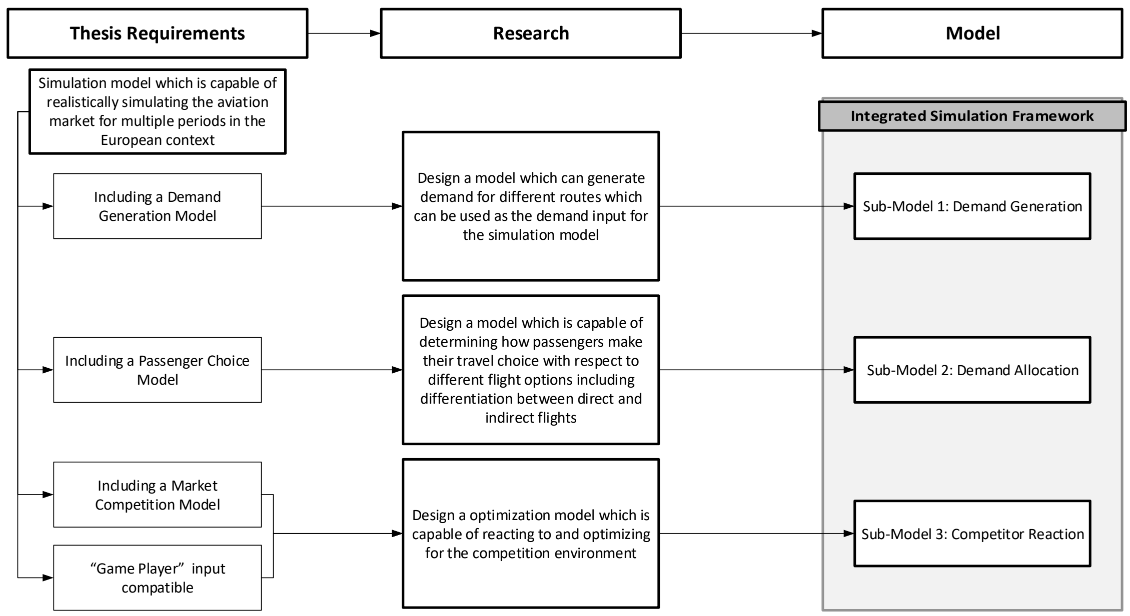


Figure 4.1: The Integrated Simulation Framework - from Requirements to Model

From Requirements to Model In general, the goal of the model is to be able to realistically simulate passenger choice and the competition between carriers for the passengers choice, in an 'as realistic as possible' method for the aviation market in the European context. Additionally, a requirement was to make the simulation model interactive, by being able to included exogenous players inputs into the model to create a game environment. To enable the above, while also ensuring a stand-alone model, three different sub-models had to be designed. These three sub-models included a demand generation model, a demand allocation model and a competition model. Each separate model will be discussed later on in this report. The integrated simulation model has been written in Python, an open source programming language.

Simulation Framework Setup Before the different sub-models are described in detail, it is key to described the total models setup as a whole. In summary, the setup of the integrated simulation framework can be found in Figure 4.2.

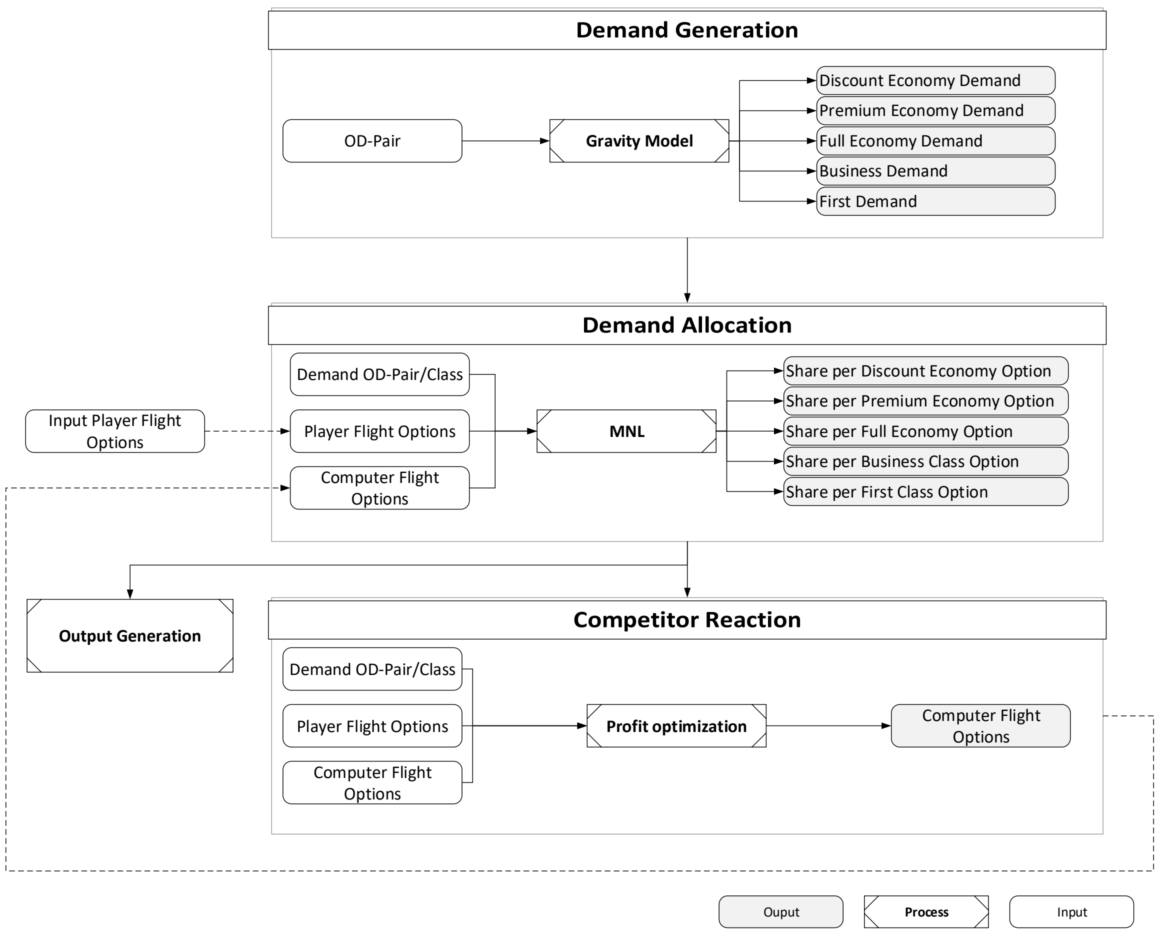


Figure 4.2: Integrated Simulation Framework

Simulation Framework Setup Description The integrated simulation framework will be described with respect to the general steps below, for an in-depth look with respect to the sub-models you are referred to Section 4.1.2. The general setup of the framework is as follows:

1. Demand Generation
   (a) In the first step of the model, the demand is generated for each OD-pair split per class for all four quarters of the year. This is used as an input for the models of the simulation framework.
2. Demand Allocation
   (a) In the second step, the demand generated is allocated over the different flight options which are available.

(b) The demand allocation process takes the static input coming from the demand generation model, as well as variable inputs of flight options coming from the players and the computer.

(c) The demand allocation process is repeated for every simulation round.

3. Competitor Reaction

(a) The third step, is the competitor reaction sub-model. Here the computer player optimizes its flight options over the different OD-pairs, in order to maximize its profit with respect to the flight options provided by the different players.

(b) The output of the optimization step is then used as the new strategy set of the computer player in the next simulation year.

4. Output Generation

(a) After every iteration of the demand allocation model, the simulation model produces output which describes different key performance indicators (KPI's) of the competitors included in the model.

It should be noted that the simulation of market competition spans both the demand allocation model and the competitor reaction model. The competition for passengers between airlines is simulated in the demand allocation model, while the competitor reaction model is centered around the active reaction of the computer player with respect to the different competitors in the simulation game.

4.1.2. The Sub-Models

In this subsection, the different sub-models included in the integrated simulation framework will be described in more detail. The inputs, outputs and the process within each sub-model will be described. Additionally, a description will be given on the simulation frameworks' total output generation process.

Sub-Model 1: Demand Generation
The function of the demand generation model is to generate the demands for the specified number of classes of each OD-pairs found in this model. The demands are generated for every quarter in the simulation year, and are then used as input for the two models which follow the demand generation model. In Figure 4.3, the diagram explaining the demand generation model can be found.

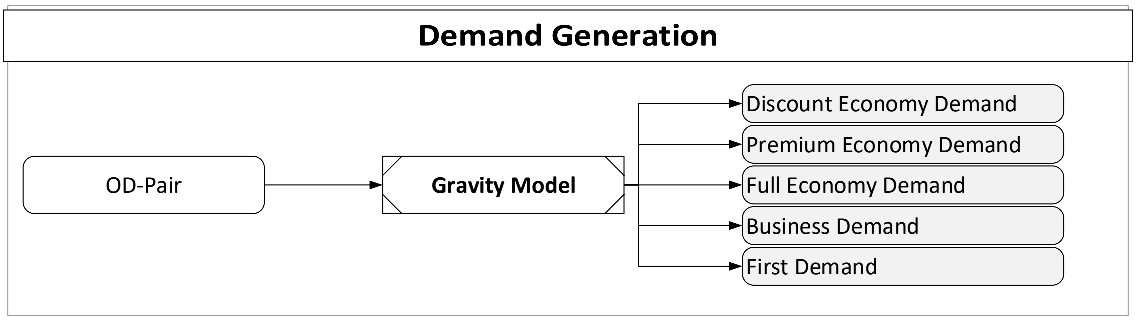


Figure 4.3: The Demand Generation Model with an Example for Five Seat Fare Classes

Below, the inputs, outputs and the demand generation process are explained:
Inputs

- The OD-pairs for which the demand should be generated. Which includes:
  - The total number of passenger movements at both airports.
  - The distance between the two airports, calculated as described in Section 4.2.4 using the data as found in Table 4.4.

– The seasonality effects of demand per quarter per route, as described in 4.2.5.

Process

- The demand generation process consists of a gravity model, which for the different specified routes computes the expected demand per cabin class. The specific setup of the gravity model can be found in Section 4.2 as well as the specifics for the calibrated gravity model in Section 5.2.

Outputs

- The outputs of the demand generation process are the demands per cabin class for the different specified routes in number of passengers per quarter including the effects of seasonality.

Sub-Model 2: Demand Allocation
The function of the Demand Allocation model is to determine with which flight options the different passengers will fly towards their destination. The flight options are differentiated by class, frequency, yield, whether the are direct or in direct and the OD-pair. Below, the different inputs, outputs and the demand allocation process will be described in detail. In Figure 4.4, the models explanatory diagram can be found.

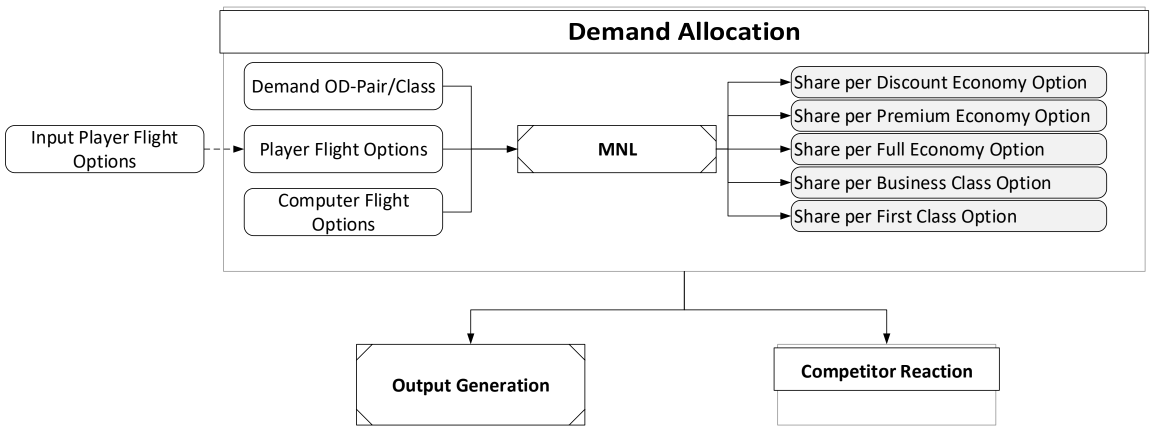


Figure 4.4: The Demand Allocation Model with an Example for Five Seat Fare Classes

Inputs

- Demand OD-Pair/Class - As described previously, the demands for the different classes per route coming from the demand generation model serve as an input for the demand allocation model.
- Player Flight Options - The player flight options include the different flight options which the simulation game players have decided on. This differs per simulation iteration based on the player decisions.
- Computer Flight Options - The computer flight options are set by the simulation model. The computer flight options differ per iteration, with the input coming from the Competitor Reaction model where the computers reaction is based on the players declared flight options. In Table 4.1, an example of the flight inputs can be found.

Process
The demand allocation process is centered around the multinomial logit model (MNL), the buildup of this model, as well as the calibrated model, can be found in Sections 4.3 and 5.3 respectively. Below the general process can be found.

- In the MNL model, the market share of each different flight option of both computer and players is computed based on its characteristics.
- As the demand inputs are split per class, the market shares are computed for every class separately. As a consequence, the market share per flight option, within the same class, is effectively calculated with respect to the three independent variables: yield, flight frequency and extra distance. Business class flight options will thus compete for market share among each other, while first class tickets will compete with the other first class tickets in the same OD-pair.

Outputs

- The outputs include the market shares for every flight option in the simulation model
- These market shares also directly lead to the computation of the passenger demand for each flight option, irrespective of the capacity of the flight option.

Table 4.1: Flight Option Input Example

Player	Flight Option	Flight	Origin	Destination	Gateway	Quarter	Distance	Extra Distance	Class	Fare	Frequency	Seat Share	Aircraft Seats	Yield
1	1	1	AMS	CPH	0	QTR3	633	0	Disc_EC	50	90	60	180	0.079
1	2	1	AMS	CPH	0	QTR3	633	0	Prem_EC	70	90	40	180	0.111
2	3	2	AMS	CPH	0	QTR3	633	0	Disc_EC	45	40	100	180	0.071
Computer	4	3	AMS	CPH	0	QTR3	633	0	First	300	800	10	180	0.474
Computer	5	3	AMS	CPH	0	QTR3	633	0	Business	250	800	10	180	0.395
Computer	6	3	AMS	CPH	0	QTR3	633	0	Full Y	200	800	20	180	0.316
Computer	7	3	AMS	CPH	0	QTR3	633	0	Prem_EC	150	800	20	180	0.237
Computer	8	3	AMS	CPH	0	QTR3	633	0	Disc_EC	100	800	40	180	0.158

As the table depicts, each flight option has its own cabin class, yield and seat share. Flight options are combined into flights, where each flight has a maximum number of seats and a flight frequency. For example, from Table 4.1, flight 1 has two flight options: discount economy and premium economy with a maximum of 180 seats for the total flight and a flight frequency of 90 flights. 60% of those flights are in the discount economy class, while the other 40% are found in premium economy.

Sub-Model 3: Competitor Reaction
The last sub-model in the integrated simulation framework consists of the competitor reaction model as depicted in Figure 4.5. This model is specifically designed for the computer player in the simulation model. The model consists of an optimization model which is described in detail in Section 4.4. Below, the general workings are explained.

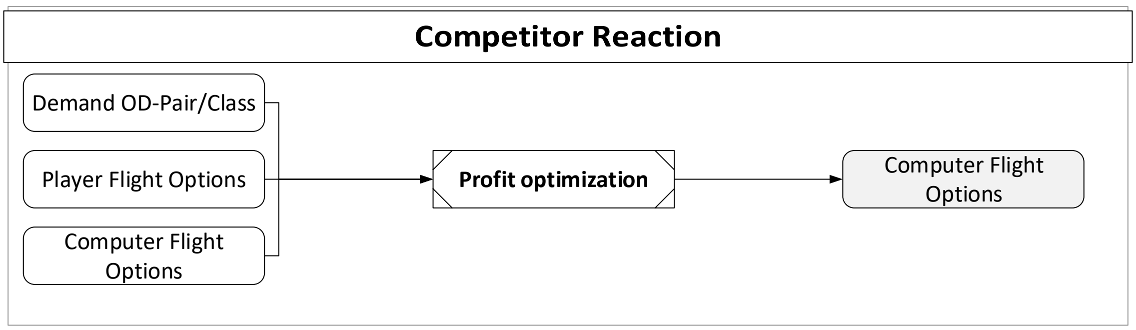


Figure 4.5: The Competitor Reaction Model

Inputs

- Demand OD-Pair/Class - The demands for every cabin class per OD-pair determine the potential for every flight option to generate revenue.
- Player Flight Options - The player flight options, along with the calculated utility values are used to determine the competition the computer is up against. These strategies will be taken into account in the optimization.

- Computer Flight Options - The computer flight options are the flight options which will be optimized for by the simulation framework with respect to flight frequency and yield. The computer has flight options in every route for every class in each quarter of the simulation.

Process

- Profit Optimization - The competitor reaction is based on a profit optimization of the computers strategy. This effectively means that the computer player plays to survive against the decisions the other competitors make. The exact method which is used to do this is explained in detail in Section 4.4, but the general method is described below:
  - The Computer flight options are optimized with respect to the flight frequency and yield, taking the effect of these choices on the market share, flight cost and profit into account. Additionally, the optimal seat share within the aircraft is determined to maximize profit.
  - Constraints in the optimization include the number of seats available on the aircraft and several capacity constraints for each simulation year.

Outputs

- Optimized Computer Flight Options - The output of the competitor reaction model consists of the flight options of the computer for the next simulation year.

Output Generation
The output generation process of the integrated simulation model, computes the different outputs from the simulated data. This can then be used to reflect on the simulation model and serve as input for the players to make choices for a possible new simulation round. The different outputs generated in this sub-model are the following:

- Demand related
  - The demand per flight option
  - The capacity per flight option
  - The spill per flight option and per route
  - The load factor of the different flight options and the players as a whole
- Operational KPI's
  - Available Seat Kilometer (ASK)
  - Revenue Passenger Kilometers (RPK)
  - Revenue Available Seat Kilometer (RASK)
  - Cost Available Seat Kilometer (CASK)
- Monetary values
  - The revenue per flight option
  - The cost per flight
  - The profit per flight
  - The profit per player

4.1.3. Data Availability

Supplement to the thesis models was the available data for the different sub-models within this simulation framework. In this subsection, the different data-sets available and used will be discussed. The exact manner in which the data was mined and cleaned to make it applicable to use for different purposes during this research will be explained in the appropriate sections.

OAG
OAG, the main data source for this thesis, was generously made available by the University of Cranfield. OAG is a global leader with respect to digital flight data, with data ranging from flight schedules, passenger booking data up until real time flight statuses. Below, a small description can be found of the exact data-sets provided for this thesis work.

OAG - Marketing Information Data Tapes
The OAG Marketing Information Data Tapes(MIDT) consists of data on passenger bookings including information on Origin and Destination (OD) pairs, average fare prices per cabin class for both direct and connecting flights. Effectively this data consists of OD pair MIDT data at a monthly level. OAG presents the raw data in the form as found in Table 4.2. The data available consists of monthly booking information for the years 2011-2015. The OAG MIDT data has been used specifically for its booking data, helping to calibrate the gravity model and MNL model for demand generation and demand allocation purposes respectively.

Table 4.2: Summarized Example data OAG - MIDT

Pub. Al. (Dominant)	Origin	Gateway 1	Destination	Cabin	Bookings	Fare	Timeseries
Lufthansa German Airlines	Madrid Barajas Apt	Frankfurt International Apt	Copenhagen Kastrup Apt	Premium Economy	9.45	104	201104
Lufthansa German Airlines	Madrid Barajas Apt	Frankfurt International Apt	Copenhagen Kastrup Apt	Discount Economy	89.08	0	201104
Air Berlin	Frankfurt International Apt	Palma de Mallorca	Madrid Barajas Apt	Discount Economy	98.5	0	201110
KLM-Royal Dutch Airlines	Copenhagen Kastrup Apt	Amsterdam	Madrid Barajas Apt	First	26.76	108	201107

OAG - Schedules
The OAG - Schedules database consists of data with information on airline schedules, capacity and airline movements. Effectively the data consists of flight schedules for the selected routes on the daily level , an example of this can be found in Table 4.3. The data was used to determine flight frequencies of the different flight options in the MIDT data-set.

Table 4.3: Example data OAG - Schedules

Published Carrier	Flight Number	Origin	Destination	Departure Time	Arrival Time	Elapsed Time	Distance (KM)	Equipment	Frequency	Seats	Time series
9U	864	CDG	FRA	1155	1315	1:20	449	320	8	1312	201111
AF	1000	CDG	MAD	715	920	2:05	1061	32S	5	750	201107
AF	1001	MAD	CDG	1015	1220	2:05	1061	32S	4	600	201105

Eurostat
Eurostat, the official statistics office of the European Union, strives to set data collection standards and distribute high-quality data and statistics on a multitude of sectors and subjects within the European Union. Sectors of which data is available include: the general economy, population and transport. This data source is free to use.

Eurostat - Air Transport Measurements - Passengers
For this thesis, the Eurostat air transport measurements - passengers was collected and used. This set of data provided information on the total traffic at the different airports specified for a selection of years.

OpenFlights Airports Database
For this thesis, the distances between airports had to be computed and to achieve this, the open source airport database provided by OpenFlights was used (OpenFlights, 2014). This database holds information on over 10,000 airports around the globe, including the needed locational data which could be used to determine the distance.

4.2. Sub-Model: Demand Generation

In the following section, the design methodology of the demand generation model will be described. The section will start off with a description of the method selection, followed by the models mathematical formulation. Next, the data used and in which manners it was manipulated to be used for calibration will be described. Additionally, the process of deseasonalization is described, which is the last step before the data is used for calibration. The final subsection describes the gravity model calibration itself, as well as the software with which it is done.

4.2.1. Method Selection

As described in Section 2.1.1, a distinction can be made between two main subsets of demand generation models which are used to predict demands between two airports: qualitative and quantitative models. For this thesis, the decision was made to specifically look at demand generation from a mathematical perspective, thus quantitative models have been considered to be most suitable to focus on. The demand generation model sought after had one generic requirement: it should be simple to develop and to implement, while staying meaningful. Furthermore, the model was intended to be used for a multitude of markets and thus be robust and flexible in demand prediction, adding new routes should only require minimal changes to the model. Additionally, a relationship between air travel demand and market characteristics should be captured, while being applicable in both the long and short term time frames. With the previously stated criteria in mind and the trade-off table between the different model types found in Table 2.1, the decision was made to develop a gravity model which could accurately predict demand between two airports.

4.2.2. Mathematical Formulation

The main concept of a gravity model is that there are attracting and deterring variables which affect the amount of attraction felt for example between two cities. The type of variables used to model these attracting and deterring effects can consist of a multitude of different types and is very much subjective to the available data. In the following subsection, the mathematical formulation and the accompanying parameters used in this thesis will be described.

Gravity Model Formulation
The demand generation gravity model used in this thesis is represented by Equation 4.1:

$$T_{ijc} = \frac{A_i A_j^{\alpha}}{D_{ij}^{\gamma}} * e^{c_1 * PremE + c_2 * FullY + c_3 * Bus + c_4 * First + K} \tag{4.1}$$

Here T_{ijc} describes the passenger demand between airports i and j for each different class $c.D_{ij}$ represents the shortest distance between the two airports, while A_i and A_j contain the total amount of yearly passengers at both airports. To account for the distribution of passenger demand per class, dummy variables for each class are included with accompanying coefficients c_c. K is an equation constant.

As can be seen in Equation 4.1, the demand generation formula will compute the passenger demand between two airports per class irrespectively of the supply. As described by Grosche et al. (2007), the advantage of predicting demand in this manner is that demand can be considered unconstrained by the levels of service between the two airports and thus consists of the total potential travel demand. This is ideal for simulating realistic air transport demand environments, while also being applicable to new routes between airports. However, as the gravity model designed uses the total traffic at both airports as one of its input variables, the demand is not fully unconstrained as it is assumed these passengers have already proved willingness to use air transport over other forms of transport. This is on the other hand an advantage for the same reason, namely these passengers are willing to fly. If demand were to be predicted completely unconstrained, geo-economic variables should be used which are not directly affected by air travel supply. The scaling of the travel proportions between air travel and non-air travel between city-pairs have not been researched as this was considered out of scope here.

Another observation can be made with respect to the fact that a split per class is made in the gravity model. The reason for this is that, for model simplicity purposes, the assumption is made that passengers of the different classes will only be interested in flying that specific class. It has thus been assumed that for example passengers who usually fly discount economy will not be willing to buy business class tickets.

Parameters Included
The parameters included in Equation 4.1 are individually described below:

- A_i **and** A_j - the passenger traffic at both ODs airports
  - The use of parameters which describe the passenger traffic at both ODs give a good measure of the economic activity and the level of income of the airports region and catchments area (Doganis, 1966). Therefore, separate data (often difficult to come by) can be replaced by using airport traffic data.
  - In this gravity model, the product of the passenger traffic is used as an independent variable. Therefore, the demand predicted can be considered unidirectional.
- D_{ij} - Shortest distance between the two airports i and j
- c_c- Coefficient for distribution of passenger demand per class c
- $PremE$- Dummy variable which represents the premium economy class
- $FullY$- Dummy variable which represents the full economy class
- Bus- Dummy variable which represents the business class
- $First$- Dummy variable which represents the first class
- K - Regression intercept
  - The regression intercept is a constant which describes the value for the regression if all independent variables were to be zero.

To clarify: the demand for a route in the economy class can be computed when all cabin class dummy variables described above are set to zero.

Gravity models can be extended with a multitude of different parameters. As described in Section 2.1.2, these parameters comprise of geo-economic or service related components. The choices of using the above described parameters was to ensure a simple yet meaningful model, while maximizing the use of the information coming from the data available. More on the data available for this model will be discussed in the following section.

4.2.3. Data

In the following section, the steps taken to construct data-sets which will be used for the calibration of the demand generation gravity model will be discussed. A general overview of the numbered steps can be found in Figure 4.6, this will also be the manner in which the data manipulation process will be described.

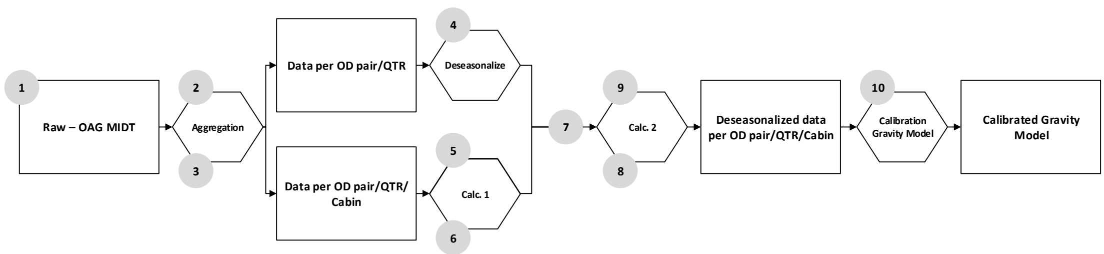


Figure 4.6: Data Use Demand Generation Model

The data manipulation steps are as follows:

1. Collection of MIDT data
2. Aggregation - The raw data-set is aggregated for demand for every route per quarter

3. Aggregation - The raw data-set is aggregated for demand for every route per cabin class and per quarter
4. Deseasonalization of demands data using the technique of moving averages. For more on this technique see Section 4.2.5
5. Calculation of the total number of passengers per route per quarter
6. Calculation of the percentage of passengers per cabin class over the total amount of passengers for that route per quarter.
7. Computation final dataset: Combining the aggregations, the outputs of the deseasonalization and calculation one
8. Total number of passengers per route per quarter is deseasonalized
9. Percentage of passengers per cabin class is multiplied with the deseasonalized total demand per route per quarter to obtain the deseaonalized passenger demand per cabin per route per quarter
10. The gravity model is calibrated with the final data-set

4.2.4. Airport Distance Calculations

For the demand generation model, as well as multiple other sub-models within the simulation framework, the distance between the different specified airports needs to be computed. This is done using a data-set which includes all the locations of airports in Europe. The data comes in the format found in Table 4.4. As can be seen, the locations are specified with respect to their latitudinal and longitudinal locations. To compute the distance between two locations using these parameters, the 'haversine' equations are used:

$$
\begin{aligned}
a = sin^2(\frac{\Delta\phi}{2}) + cos(\phi_1) * cos(\phi_2) * sin^2(\frac{\Delta\lambda}{2}) \\
c = 2 * asin(\sqrt{a}) \\
d = R * c
\end{aligned}
\tag{4.2}
$$

Here ϕ is the latitude, λ is the longitude, R is the earths radius (which is approximately 6,371km) and d is the greater-circle distance between the two airports.

Table 4.4: Airport Locations Example

Name	City	Country	IATA/FAA	ICAO	Latitude	Longitude	Altitude
Heathrow	London	United Kingdom	LHR	EGLL	51.4775	-0.46139	83
Schiphol	Amsterdam	Netherlands	AMS	EHAM	52.30861	4.763889	-11
Barajas	Madrid	Spain	MAD	LEMD	40.49356	-3.56676	2000
Charles De Gaulle	Paris	France	CDG	LFPG	49.01278	2.55	392

4.2.5. Deseasonalization of MIDT Data

The deseasonalization of data is used to remove the seasonal effects found in the data and make the data more stable for calibration. By doing this, the cyclic trend is removed and what remains is the underlying trend of the data. For an example of this process please refer to Figure 4.7.
In first instance, an attempt was done at deseasonalizing the data for every route, per quarter and per cabin classes. However, due to the lack of datapoints in some cabin classes, this was not a viable option. It was therefore decided to deseasonalize the data points per route per quarter, to ensure reliable results.

Deseasonalization was done through the method of moving averages, which is described step for step below:

1. Computation of the average quarterly values for every route
   (a) The average quarter one value would for example be equal to:
$$qa_n = (q_1, q_5, q_9, q_{13}, ...)/\#years \tag{4.3}$$
   (b) Where q_n are the demands for the specified quarter of each year and qa is the average demand for the specified quarter
2. Computation of the average value of demand of the entire data-set ($\bar{A}$)
3. Compute the deseasonalized demand value (dd)
   (a)
$$dd = q_n - (qa_n - \bar{A}) \tag{4.4}$$

With the data deseasonalized, the gravity model could then be calibrated. The cyclic effects of seasonality were however not discarded, but added back to the predicted data to reproduce seasonal effects. In the integrated simulation framework you will therefore provide demand with seasonality effects, similar to reality.

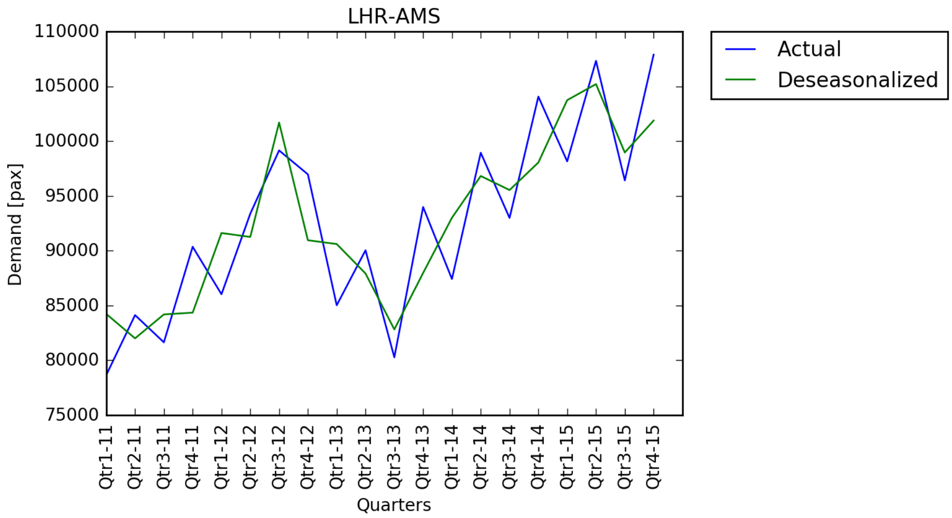


Figure 4.7: Example of Deseasonalized Demand for the London Amsterdam Route

4.2.6. Calibration Techniques and Software

There are multiple manners in which calibration can be done, 'ordinary least squares' being the most common (Grosche, 2009). Below, this technique is described as is the software package used and the performance checks which followed. In Section 5.2, the results of the calibration process done during this thesis will be described.

Calibration Technique - Ordinary Least Squares
The calibration of the gravity model as described in Equation 4.1 was done using the method of ordinary least squares (OLS), as is used to calibrate in the research by Grosche et al. (2007) and many others. Here, the Equation for the gravity model first had to be transformed using logarithmic techniques to develop a linear function which could be used for the linear regression technique. Equation 4.5 depicts the transformed Equation 4.1.

$$ln(T_{ijc}) = k + \alpha * ln(A_i A_j) - \gamma * ln(D_{ij}) + c_1 * PremE + c_2 * FullY + c_3 * Bus + c_4 * First \tag{4.5}$$

The OLS technique is based on the minimization of the sum of squares of the difference between the predicted values by the linear model and the actual values which are being predicted. This method however, as pointed out in Silva and Tenreyro (2006), estimates the values of $ln(T_{ijc})$ and not of T_{ijc} which can lead to discrepancies. This inequality is known as the Jensen's inequality and has as an effect that estimates may be unreliable, yet in many applications this has been neglected (Silva and Tenreyro, 2006).

Data Analysis Type

Calibration of the gravity model can, as explained in Section 2.1.3, be done using different types of data-sets. Time-series calibration for example consists of calibration for a specific city-pair using demand data for different time periods, while cross-sectional calibration uses data for multiple city-pairs at a single period in time. Panel data calibration on the other hand is done using data on multiple city-pairs over different time periods.

The manner in which the type of analysis is possible is highly dependent on the available data. In this thesis, the data-set used for calibration of the gravity model originated from the OAG-MIDT data-set. The data consisted of monthly records of the amount of passengers, per flight option, per time period. This has been aggregated to a data-set with quarterly demands, per route, per year. The final data-set thus includes all OD-pairs, with quarterly demand spread over the years between 2011 and 2015. Furthermore, with the goal of developing a demand generation model which could be generically used for all routes in the model, a preference for the thesis was to calibrate using panel data. With the availability of the data and the mentioned goal for the model, the choice for panel data calibration was evident.

Calibration Software - SPSS

The software package SPSS, a renowned statistical software package, was used to calibrate the parameters found in the demand generation gravity model. A built-in function for linear regression allowed the simultaneous entering of parameters into the model for which the different regression coefficients were found. After calibration, the gravity model calibration had to be tested to determine the models performance and if it was statistically sound. The methods used to do this are described below.

Parameter Control

The first check after calibration was to determine if the parameters had the correct significance levels and had the expected effect on the dependent variable. This was done using a t-test, which indicates if the independent variable is explanatory of the dependent variable or if the independent variable has little or no relation to the dependent variable. The higher the significance level is found by the t-test, the worse the relationship between the dependent and independent variables. For this thesis, a threshold of 0.05 was set for the significance of the parameters; if the parameter had a significance level under the stated threshold it had the accepted significance.

If the parameters were accepted, the next step was to determine if the parameters had the expected effect on the dependent variable, in this case the passenger demand. Positive coefficients for parameters indicated that, with an increase of the variable, a positive effect would be seen with respect to the dependent variable. Vice-versa, a negative effect on the dependent variable would be experienced in the case for parameters with a negative coefficient.

Following these checks, an additional significance test was done to ensure that the included parameters in the gravity model were not affected by multicollinearity. Multicollinearity is defined as the situation where seemingly independent variables are dependent of each other (Doganis, 2002). This can be checked through the correlations table of the independent variables, where multicollinearity can be identified by correlation values of over 0.86 (Doganis, 2002).

Calibration Performance Testing

After the parameter checks had been done, the total performance of the calibrated gravity model was checked with the use of four different methods.

The first method that was used to determine the performance of the gravity model was to determine its goodness-of-fit. The goodness-of-fit describes how well the predicted model fits the actual data. For OLS models, the goodness-of-fit can be derived from the coefficient of multiple determination (R^2). The closer R^2 is to 1, the better the fit of the the OLS model.

For the second method, the Analysis of Variance (ANOVA) table was used to determine the overall significance of the calibrated gravity model. In this table, the significance parameter should be below

0.05 to be accepted. With these two performance tests in place, a good view of the overall models performance can be given.

To determine the models workings per subset, a third method of performance testing was used. Here, the accuracy of the different predictions were tested using the method of the standard error of the estimate. The standard error of the estimate was computed using Equation 4.6 (Lane, 1999). In this equation, the square root is taken of the sum of the squared differences between the actual and predicted values divided by the amount of data entries compared. With this value in place for different data subsets, the accuracy of the calibrated gravity model can be tested for different specific cases.

$$[H]\sigma_{est} = \sqrt{\frac{\sum(ActualValue - PredictedValue)^2}{\#DataEntries}} \tag{4.6}$$

The fourth and final method used to determine the models performance compared the plots of the actual values vs. the predicted value plots of the gravity model. This visual check was used to determine how well the predicted data fitted the actual data.

4.3. Sub-Model: Demand Allocation

4.3.1. Method Selection

For the demand allocation process, there are multiple methods which can be implemented to simulate passenger choice with respect to different travel options. Of these options, the discrete choice models are most popular. In this thesis, the demand allocation model was chosen with respect to expected accuracy, the data available as well as the models complexity. The model was expected to deliver a reasonable accuracy with the available demand, while being feasible with respect to modeling complexity to fit within the time constraints of the thesis. Additionally, the demand allocation model needed to fit well within the simulation framework as a whole. The focus was therefore on the two main models used in literature to simulate passenger choice, namely: multinomial logit models and nested logit models. Within the total build-up of the model, the MNL model was found to be most compatible due to its simplicity and ease of design. The MNL model was furthermore the most popular model type used for passenger allocation (Wen and Lai, 2010), which leads to the assumption that, in general, the model produced acceptable results. The data available was found to be compatible as well. Therefore, the purpose of including a simple but effective demand allocation model, the multinomial model was considered optimal.

The model however does have a few drawbacks, as has been discussed in the literature review section of this report. The main drawbacks is that the model produces unreliable results when the different choices are perceived to be similar. For example, two flight options which in the model are identical with respect to characteristics will result in equal shares. However, in reality carrier preference may influence passengers choice for example. This has been considered a limitation of the model in use.

4.3.2. Mathematical Formulation

Multinomial Logit Model Formulation
The multinomial logit model which is used for demand allocation purposes consists of two main formulas, which can be found in Equations 4.7 and 4.8. Equation 4.7, describes the manner in which the market share of a certain itinerary is computed with respect to the other available itineraries. This is done by taking the exponential of the utility of the itinerary, and dividing it by the sum of the exponential values of all competing itineraries. By doing this for every separate itinerary, the shares of each different itinerary can be defined.

$$MS_i = \frac{exp(V_i)}{\sum_J exp(V_j)} \tag{4.7}$$

In the above equation MS_i is the market share for itinerary i, while V_i and V_j are the utility values for routes i and j.

In Equation 4.8, the utility values needed to compute the market shares with the formula above are determined. As can be seen in the equation, the utility function is a linear function which is based on multiple parameters which increase or decrease the utility of a flight option.

$$V_i = K + \beta_1 Frequency_i + \beta_2 Yield_i + \beta_3 ExtDist_i + \beta_4 First_i + \beta_5 Business_i + \beta_5 FullY_i + \beta_6 PremE_i \quad (4.8)$$

In the above equation V_i is the utility value for route i. β_n are the coefficients for the different variables included in the model and determine the magnitude and effect of the variable on the flight options utility.

Parameters Included
During the thesis process, different sets of independent variables were tested to determine an optimal set of variables to be included. Below, the different parameters included in the utility function are described.

- K - The regression intercept
- $Frequency_i$ - The flight frequency provided for the flight option per quarter
- $Yield_i$ - The yield of the flight option
- $ExtDist_i$ - The extra distance flown when using an indirect flight option
- $First_i$ - Dummy variable which represents the first class for which the value is 1 when calculating the utility of a first class flight option
- $Business_i$ - Dummy variable which represents the business class for which the value is 1 when calculating the utility of a business class flight option
- $FullY_i$ - Dummy variable which represents the full economy class for which the value is 1 when calculating the utility of a full economy class flight option
- $PremE_i$ - Dummy variable which represents the premium economy class for which the value is 1 when calculating the utility of a premium class flight option

Independent variables such as the flight frequency are expected in the utility function describing passenger choice. Some variables however need some further explaining.

During the calibration procedure it was found that the yield was the best manner in which to describe fare in the utility function. The big advantage of using yield is that it is comparable over flight options, irrespective of the route. Furthermore, yield also benefited within the total integrated simulation framework.

The variable for extra distance is included to be able to simulate the effect on demand when passengers take an indirect route. This parameter was chosen over a time parameter due to data availability. The extra distance of indirect routes is quite simply computed, while extra travel time is very much dependent on connection times between the different flights. Data on these times was unavailable so extra travel time was therefore not an option during this thesis research.

4.3.3. Data

A number of manipulation steps have been undertaken to ensure the data was ready for the calibration of the previously discussed MNL model. In this subsection, the different steps are discussed.

General Data Manipulation Process
The general data manipulation process can be found in Figure 4.8. The steps taken were the following:

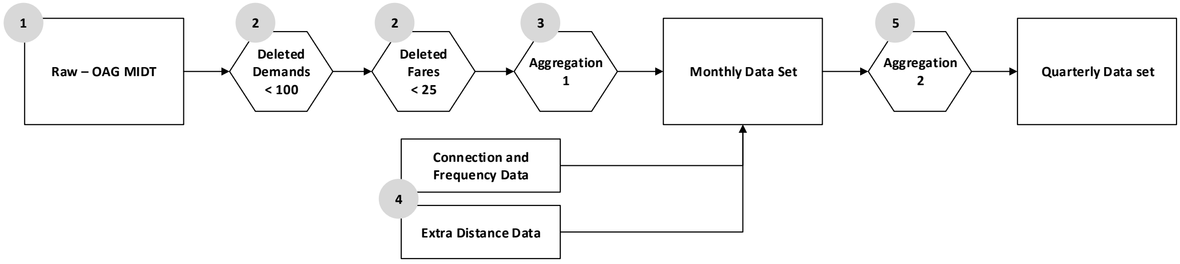


Figure 4.8: General Data Use Demand Allocation

1. OAD-MIDT raw data collection
2. As advised by an industry expert often using similar data, data entries of demands of under 100 passengers and fares of under 25 EUR were removed. According to the industry expert this data can be considered unreliable as it is incorrect. (Nicola Volta,personal communication, April 19, 2017).
3. The first aggregation ensured that the data was aggregated to contain one data entry per route per month per carrier per cabin.
   (a) Before aggregation, the stated fare was multiplied by the number of bookings to determine the revenue. This revenue was aggregated along with the data set. After aggregation the revenue was divided by the number of bookings to determine the average paid fare.
4. With the outputs coming from the connection frequency data, direct frequency data and the extra distance data outputs, the final monthly data-set was created. For each data entry, the accompanying frequency and extra distance were added. The blocks where the connection and frequency data and extra distance data are computed will be described separately.
5. The second aggregation round consolidated the data to a data-set which included the different data entries at a quarterly level.
   (a) The same procedure as described in step 3 was used with respect to the average fare
   (b) With the average fare in place, the average yield was computed by dividing the average fare by the OD-distance
   (c) Columns were added to the data-set to account for the dummy variables for the different classes
   (d) Market share calculations were done for every data entry
   (e) The final step included the splitting of the final data-set into one data set for calibration and one for validation

Direct and Connecting Flight Frequency Computation

The general process for the computation of the direct and connecting flight frequency process can be found in Figure 4.9. Specifically, the following steps were taken:

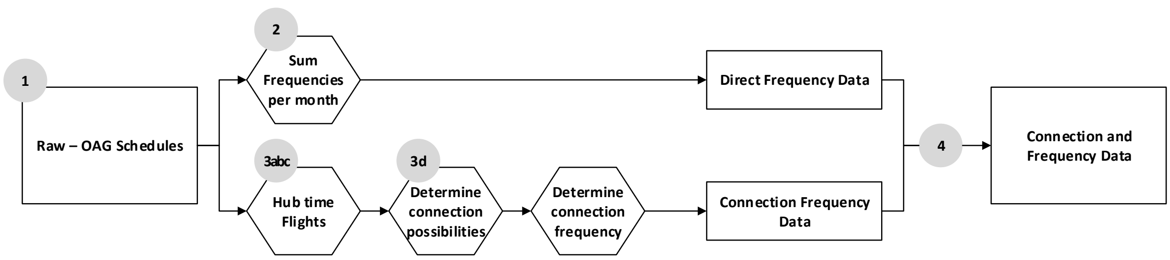


Figure 4.9: Flight Option Frequency Computation Process

1. OAG - Schedules data collected
2. Direct frequency computation
   (a) The data included had the format as described in Table 4.3. For every route, per carrier, per month the data was aggregated to determine the total frequency for that specific month. This was used as the direct frequency available.
3. Connecting frequency computation
   (a) The raw schedule data was aggregated to determine the flight frequency, per flight number, for each month, keeping the departure and arrival times intact.
   (b) The aggregated schedule data was duplicated and positioned under the original aggregated data-set.
   (c) A new column was included to determine the time at the hub. The arrival times of flight options in the original data-set were set as the hub time, as were the departure times of the flight options in the duplicated data. By doing this, a possibility arose to link the different flights to one another and determine possible connections. An example of what the new data-set looked like can be found in Table 4.5, the data entries depicted in bold are an example of possible connections.
   (d) The criteria which determined if a flight had a possible connection were the following:
      - The connecting flight had a minimal layover time of 45 minutes
      - The connecting flight had a maximal layover time of 180 minutes
      - The two flights were scheduled in the same year, month, location of hub and were flown by the same carrier
      - The final connection frequency was determined by the effective connection frequency experienced by the passenger. This meant that if there was only one flight to the hub, but three out of the hub to the destination, the passenger effectively had one connecting flight option towards the destination. Vice-versa the same was also true. Therefore the affected connection frequency was assumed to be limited by the minimum flight frequency of one of the two flight legs.
4. The direct and connecting frequency outcomes were then combined to be used in the general data use process as found in Figure 4.8.

Table 4.5: Determining Connection Possibilities

Origin	Hub	Destination	Published Carrier	Flight Number	Dep_time	Hub_time	Arr_time
CPH	**AMS**		**KL**	**1124**	**06:35**	**08:10**	
FRA	AMS		KL	1762	06:55	08:20	
	AMS	LHR	KL	1007		08:35	09:00
MAD	AMS		KL	1708	06:00	08:40	
	AMS	FRA	KL	1765		08:45	10:05
	AMS	CPH	KL	1125		08:50	10:15
LHR	AMS		KL	1000	06:35	09:05	
	AMS	**MAD**	**KL**	**1701**		**09:35**	**12:10**
	AMS	**LHR**	**KL**	**1009**		**10:25**	**10:50**

Extra Distance
To compute the extra distance flown by a connecting flight, simple formula was used. This can be found in Equation 4.9.

$$ExtDist_i = (DistLeg1_i + DistLeg2_i) - DistOD_i \tag{4.9}$$

Here the extra distance of flight option i is computed by the difference between the distance of the sum of the two flight legs, minus the distance that would have been flown if the flight were direct. The assumption here is that the distances are the shortest distances between the two airports.

Market Share
The last step in the manipulation of the data-set to ensure it is ready to be used for the calibration of the MNL model was to add a column describing the market shares of each flight option. The calculation of the different market shares can be described by Equation 4.10.

$$MS_i = \frac{\#Bookings_i}{\sum \#Bookings_j} \tag{4.10}$$

Here the market share was computed for flight option i by dividing the demand for flight option i by the sum of all bookings for flight options in the same OD-pair, in the same year and in the same quarter.

4.3.4. Calibration Technique and Software

With the steps described in Subsection 4.3.3 complete, the data was ready to calibrate the MNL Model. In particular, the coefficients of the independent variables in the utility function found in Equation 4.8 needed to be determined. This subsection will describe the manner in which this was done, as well as which software package was used to accomplish this.

Calibration Technique - Ordinary Least Squares
The calibration technique used to determine the coefficients of the independent variables in the utility function is based on the method used in the research done by Hsiao and Hansen (2011). The technique consists of a method of a number of steps after which the method of ordinary least squares can be used to determine the coefficients. The steps made and the accompanying assumptions are described below.

The market share of a flight option is describe with Equation 4.10. With this in mind, the difference of the market shares of two flight options in logarithmic form, can be described using Equation 4.11. Here, the natural logarithm of the market shares of route i and j are found to be equal to the differences between their utilities.

$$ln(MS_i) - ln(MS_j) = V_i - V_j \tag{4.11}$$

The above equation creates a possibility to a linear regression which implies that the coefficients of the variables can be computed. However, before this can be done, flight option pairs need to be determined allowing the regression. In the research by Hsiao and Hansen (2011), it is assumed that the pairs of alternatives will consist of a flight option and a non-air alternative. This non-air alternative is assumed to have a market share of zero, and a utility function of zero. The assumption implies that the option of not flying is not applicable to any passengers in the model. With respect to the total integrated simulation framework, this assumption is acceptable as has been described previously. Therefore, it is possible to simplify Equation 4.11 into Equation 4.12.

$$ln(MS_i) = V_i \tag{4.12}$$

Extending the above equation to its full form, leads to Equation 4.13 over which a linear regression is done to determine the β coefficients. The market share and independent variables are obtained from the calibration data set.

$$ln(MS_i) = K + \beta_1 Frequency_i + \beta_2 Yield_i + \beta_3 ExtDist_i + \beta_4 First_i + \beta_5 Business_i + \beta_5 FullY_i + \beta_6 PremE_i \tag{4.13}$$

Calibration Software - SPSS
As used in the calibration of the gravity model for the demand generation purposes of this thesis, the

calibration of the MNL model was done using SPSS. Additionally, the regression was also done using the built-in linear regression option of this software package. Below, the different techniques used to verify the estimated coefficients and to test the workings and accuracy of the model are described.

Parameter control
With the regression technique similar to that of the gravity model, the different methods used to check the calibrated MNL model are the same as with that of the gravity model. They will briefly be discussed below.

1. Coefficient significance check - Ensure that the significance of the calibrated coefficients is below the threshold of 0.05.
2. Coefficient expected effect on dependent variable - Ensure that the coefficients have the expected sign and thus effect on the dependent variable.
3. Multicollinearity check - Determine that the independent variables included in the calibration do not have correlations of above the set threshold of 0.86.

Calibration Performance Testing
As described above, due to the similarity of the calibration of the two sub-models, the performance tests for the calibrated MNL model are also equal to that for the gravity model. The techniques used are listed here.

1. Goodness-of-fit - To determine how well the predicted values from the calibrated model fit the actual data the coefficient of multiple determination (R^2) is used. The closer R^2 is to one, the better the fit.
2. Analysis of Variance (ANOVA) - To ensure the overall significance of the calibrated model, the ANOVA is used to determine if the significance of the model is below 0.05. If this is the case, the model is considered significant
3. Standard error of the estimate - To determine the accuracy of the demand allocation model for several different specific cases
4. Visual control - By comparing the plots of the actual and predicted data to observe performance of the demand allocation model and identify complications

Independent Variable Impact
The MNL model is built of several independent variables which describe the utility function of a flight option. These variables differ in magnitude and size and are thus difficult to compare to one another. It is therefore interesting to determine what impact each variable has on the market share, in a manner which allows comparing the different variables to each other. To do this, the following equation can be used:

$$Impact_v = \frac{abs(Range_v * \beta_j)}{\sum abs(Range_v * \beta_j) + abs(K)} \tag{4.14}$$

Here the numerator consists of the range of variable v multiplied by the coefficient of the variable v. This is then divided by the sum of the ranges multiplied, by their respective coefficients plus the regression intercept. With this computation done for every independent variable, conclusions can be made on the importance of the different variables on the market share.

4.4. Sub-Model: Competitor Reaction

The competitor reaction model consists of an optimization model which optimizes the strategy of the single computer player. This computer player represents an average competitor to be found on a specific route. For this model, the computers definition will be given in Section 5.1.2. This model is specifically based on a profit optimization of the computer player over the different routes for each quarter. This includes taking the other player strategies into account and reacting accordingly. In the following section, the build of the optimization model will be described. Furthermore, the software used to optimize with will be mentioned.

4.4.1. Mathematical Formulation

In the following section, the mathematical formulation of the competitor reaction model will be described. This subsection will be split into five parts: the model parameters, variables, intermediate formulas, constraints and the optimization itself.

Parameters
The parameters included in this optimization model are static for every run of the optimization sequence. However, values may differ from simulation run to simulation run. Below, the parameters required to run this model are listed, as well as a description whether they are static or not.

- The player flight option utility values (Excluding computer flight options).
  - With every new input of player flight options, the utilities of the flight options change. This parameter may thus change between different simulation runs.
- The computer flight options
  - The computer flight options are in principal an empty set of all flight options waiting to be filled in with the variables of yield and frequency. This empty set is thus static.
- The demands per class per route
  - Depending on the demand generation inputs, the values here can change form simulation run to simulation run.
- The flight durations between OD-pairs
  - Flight durations between OD-pairs are assumed to be static.
  - Flight durations are computed by assuming an average speed of 880km per hour for the aircrafts in the model and dividing the distance between the OD-pairs by the aircraft speed.
- The block hour restrictions
  - The block hour restrictions parameter-set differs per simulation year. The block hour restrictions determine the range in block hours per route between which the computer player should stay.
  - In the first simulation year, the block hours are constrained with respect to the pre-defined market averages. For this thesis, these averages have been defined in Section 5.1.2. After the first optimization run, the block hour restrictions are based on the following defined rules:
    - ◇ The maximum increase and decrease of the block hours per route per optimization year is 20%
    - ◇ If the block hours in a route are within the lowest 10% of the range after an optimization year, the following year will have a block hour lower bound which is 5% lower in that route.

Variables
In the optimization model, the variables to be optimized are found below. For every route and every flight option within the computer flight option set, the optimized values will need to be found. This implies that for every route five yields will be optimized for each class, as well as one flight frequency for the flight containing the different cabin classes.

- Yields per class per route
  - The yields are constrained by upper and lower bounds. The bounds used in this thesis are the following:
    - ◇ Upper bound: The average yield value of the class plus twice the standard deviation.

◇ Lower bound: The minimum value of zero or the average yield value of the class minus twice the standard deviation.

◇ Twice the standard deviation on top of or less than the average value of yield is used to set realistic bounds and remove unwanted outliers. By using twice the standard deviation, according to Chebyshev's inequality irrespective of the distribution of the data, 75% of the values will be within the 2 standard deviations of the mean (Taylor Courtney, 2016). This is assumed a reliable bound to work with.

◇ In the lower bound, the maximum value is determined between the two stated values to ensure the minimum yield does not return negative values.

- Flight frequency per flight
  - The flight frequency is bound by the block hour restrictions, which have been previously described. Conversion from block hours to frequency is done using the flight time between OD-pairs.
  - The flight frequency variable was specified to be an integer.

Pre-Computations
To ease computation and understandability of the optimization model, several preliminary computations were done. These can be found in the equations below, along with their separate descriptions.

In Equation 4.15, the market share calculation for the computer flight option per class c and per route n can be found. It was derived from the market share equation found in Equation 4.7. In Equation 4.15, the market share is computed with respect to the static utilities of the player flight options. This equation is later on used in the optimization process.

$$MS_{nc} = \frac{EXP(ComputerUtility_{nc})}{EXP(ComputerUtility_{nc}) + \sum_{nc} EXP(PlayerUtility_{nc})} \tag{4.15}$$

In Equation 4.16, the total flight block time per route n is computed which is later on used to build constraints on. It consists of the flight time between the OD-pair, multiplied by the flight frequency of the computer in that route.

$$TotalFlighTime_n = FligtTime_n * FlightFequency_n \tag{4.16}$$

In Equation 4.17, the revenue of all the different flight options are computed. This is done by summing the revenue of all classes c for every route n. As can be observed, the revenue is a function of the market shares. With the market share being a non-linear function based on a MNL model, this leads to the entire equation being non-linear.

$$Revenue = \sum_{nc} Distance_n * Yield_{nc} * MS_{nc} * Demand_{nc} \tag{4.17}$$

In Equation 4.18, the cost of the flight per route n are calculated. This is done using the flight frequency, distance and number of aircraft seats available. The formula for this cost model has been researched and designed by Swan and Adler (2006) to estimate cost for short-haul flights (≤5000km). Adler et al. (2010) improved the cost model to make it applicable to European short haul flights by multiplying the equation by 2.2 to be able to convert dollars into euros as well as account for general administrative overheads and commission costs.

$$Cost = FlightFrequency_n * (0.019 * (Distance_n + 722) * (AircraftSeats + 104) * 2.2) \tag{4.18}$$

In Equation 4.19, the profit of the computer player is determined. This equation is optimized to determine the computer players' reaction. As the revenue is a non-linear function, the profit optimization is found to be non-linear.

$$Profit = Revenue - Cost \tag{4.19}$$

Constraints
To ensure the optimization model stays within realistic bounds, constraints have been added to the model. The first set of constraints can be found in Equation 4.20 which describes the capacity constraint. This constraint ensure that for every route n in the model, the sum of passengers for all cabin class c does not exceed the total number of aircraft seats available on that route.

$$\sum_{c} Demand_{nc} * MS_{nc} \leq AircraftSeats \quad \forall n \in \mathbb{N} \tag{4.20}$$

The second set of constraints is used to ensure that a minimum number of block hours is achieved per route n. This is done to ensure that the computer player, which is supposed to simulate the average competitor found in a route, represents general competition in a market. The constraint can be found in Equation 4.21.

$$TotalFlightTime_{n} \geq BlockHoursMinimum_{n} \quad \forall n \in \mathbb{N} \tag{4.21}$$

The final constraint is found in Equation 4.22. In this constraint the total number of block hours available over all routes is defined. The total number of block hours is a maximum number of block hours which the computer player can fly over all routes. This ensures that the total amount of block hours, which would be limited by capacity constraints in reality, is limited in the model as well. The maximum total amount of block hours used in this thesis can be found in Section 5.1.2.

$$\sum_{n} TotalFlightTime_{n} \leq TotalBlockHours \tag{4.22}$$

Optimization
With the parameters, variables and preliminary computations defined, the optimization itself is simple to explain. For every quarter in the year that is optimized for, the optimization model optimizes the profit function as found in Equation 4.19. The decision variables include the flight frequency, the yields per separate class and the seat share per class per flight for the computer in every route. By combining the four optimized quarters of computer flight options, a new computer flight option strategy set is created with which the rest of the simulation can be run.

4.4.2. Optimization Software

As can be deduced from Section 4.4.1, the optimization is based on a non-linear formulation. To be able to cope with this non-linear optimization problem, a software package was sought which could handle this type of optimization and also be integrated within the Python environment (in which the integrated simulation framework was programmed). The software package capable of doing the optimization was found in the open source APMonitor optimization software (Hedengren et al., 2014). This software package is a combination of different large-scale optimization solvers used for linear, quadratic, nonlinear, and mixed integer programming and was thus capable of optimizing the problem found in this thesis.

4.5. Simulation Model Assumptions and Their Implications

With the general operation method of the integrated simulation framework defined, there are a number of assumptions which have been made in the different sub-models which apply to the entire model. These assumptions and their implications are described below.

- All demand generated is assumed to want to fly. Passengers will only not fly if and when capacity levels are too low to accommodate these passengers.
  - This assumption has as a consequence, that it is assumed that the passenger demand generated is irrespective of supply effects. Therefore pricing and frequency will not have an effect on the demand itself. In reality, this will not be the case but as an assumption it is reasonable if frequencies and fares are kept to an average experienced industry level.
- Demand generated is directly split over the different cabin classes.

  - This assumption has as a consequence that buy-ups of buy-downs do not occur in this model. Passengers will thus only fly in the class in which they have been split. In reality shifting between classes would be possible, however large shifts between different cabin levels are not expected. Passengers flying economy class are not expected to quickly divert to business class and vice versa. This simplification in the simulation model is expected to effect the reliability of the model, but not very severely.

- The non-air alternative has a market share of zero
  - As described in the demand allocation model, the market share and utility of the non-air alternative, which is used to calibrate, is assumed to be zero. This is in accordance to the first assumption stated, which assumes all passengers in the model are wanting to fly. Furthermore, the demand generation model is calibrated using the total passengers at both airports who are already showing their readiness to fly, thus it is a reasonable assumption that these passengers only want to fly.

5

Simulation Model Calibration

This chapter will describe the simulation model calibration process and results. The focus of this chapter will be on the general definition of the simulation framework, including descriptions on the airports used, the routes included and supply and demand characteristics. These sets of information will provide the simulation framework with a scope definition, the opportunity to calibrate two of the three underlying sub-models and provide the computer player with possible strategy sets.

The chapter will commence with the definition of the simulation frameworks scope. This will be followed by the calibration results of the demand generation model. In the final section of this chapter, the calibration results of the demand allocation model will be enlightened on.

5.1. Simulation Framework Scope

The integrated simulation model has been built with the European context in mind. Therefore, decisions have been made to determine what the scope would be within this European context, while ensuring the feasibility of the development within the time limit set for the thesis. Below, the decisions made with respect to the airports that would be included in the model have been explained. These airports define the scope for which the model will simulate and determines the data for which the different sub-models are calibrated. In Section 5.1.2 the route characteristics, which follow from the airport selection, are described.

5.1.1. Airport Selection

Airport Criteria
The simulation model has a focus on the internal European market. Besides, it was decided that the airports in this model would only include those which are the major airport of their country. The assumption behind this being that these airports fulfill a similar of transportation function and cater for a broad selection of passengers types. Additionally, major airports provide services from many different type of air carriers with different business models. The final intention with respect to selecting the airports to be included in the simulation model was based on ensuring a locational spread of airport location from north to south.

Selected Airports and Routes
With the criteria and intentions described above in mind a selection of airports was made. The airports all fall within Western European states including the north of Denmark's Copenhagen airport as well as Spain's largest airport (with respect to passengers) Madrid Barajas. In Table 5.1 the complete selection of included airports in the simulation model can be found.

With respect to the routes included in the model, not all possible OD-pairs from this selection are included in the model. The reason for this is the distance between the two cities. As described in the

Table 5.1: Airport Selection

Country	Airport	City Served	Passengers 2015	Passengers 2016
United Kingdom	Heathrow Airport	London	74,985,475	75,711,130
France	Charles de Gaulle Airport	Paris	65,766,986	65,933,145
Netherlands	Amsterdam Airport Schiphol	Amsterdam	58,284,848	63,625,664
Germany	Frankfurt Airport	Frankfurt	61,032,022	60,786,937
Spain	Adolfo Suárez Madrid–Barajas Airport	Madrid	46,824,838	50,420,583
Denmark	Copenhagen Airport	Copenhagen	26,610,332	29,043,287

research by Grosche et al. (2007), routes above 500km experience less competition from other modes of transportation. With this constraint, the assumption is made that the travel between the OD pair will consist out of air travel. Therefore, in this thesis only routes above 500km are in scope. An exception is made between the airports of London and Amsterdam, to the authors best knowledge, the travel time due to the sea and the route needed to be taken by rail transport give reason to exclude the route from this constraint. The route from Paris to London does not apply for this assumed exclusion, as the rail link between the cities is in comparison to that from Amsterdam much more effective. In comparison, Amsterdam-London by train will take around five hours, while a flight will take one hour. Paris-London on the other hand is approximately two hours by train, while the flight is around one hour.

Calibration and Validation Routes
During the process of calibration and validation of the different sub-models in the integrated simulation model, a split was made between routes that would be used for calibration and those that would be used for validation of the sub-models. This selection can be found in Table 5.2. The validation process was constructed to be cross panel, to be able to test if the simulation framework was generalizable to routes with similar characteristics. If this were found to be the case, the simulation framework could then be extended for routes with similar characteristics with minimal modifications. This would greatly ease scaling the simulation framework to a larger network.

Table 5.2: Model Routes

Calibration	Validation	Excluded Routes
AMS-LHR	CPH-FRA	AMS-CDG
LHR-AMS	FRA-CPH	CDG-AMS
LHR-MAD	CPH-LHR	CDG-FRA
MAD-LHR	LHR-CPH	FRA-CDG
AMS-MAD	FRA-MAD	AMS-FRA
MAD-AMS	MAD-FRA	FRA-AMS
AMS-CPH		CDG-LHR
CPH-AMS		LHR-CDG
CDG-CPH		
CPH-CDG		
CDG-MAD		
MAD-CDG		
FRA-LHR		
LHR-FRA		
MAD-CPH		
CPH-MAD		

5.1.2. Route Characteristics

In this subsection, the route characteristics which follow from the airport selection are discussed. In this part of the report, the focus will be on the characteristics which influence and are used in the integrated simulation framework as a whole, and some of which are used as inputs for the computer player. These characteristics include the total traffic at the airports for different years, block hour statistics and yield statistics.

Demand statistics are not described here, as they are used for calibration purposes only and not as inputs for the simulation model itself. Information on demand statistics are thus discussed in the appropriate sections of this thesis report.

Total Traffic Airports
In Table 5.3 the total traffic at each airport can be found. It can been seen that the largest airport in terms of traffic in this data-set is London Heathrow. The smallest airport in this data set is the Copenhagen airport, while the other three airports are quite similar in size. As described previously, these values are used in the demand generation process. The values have been collected for the data source Eurostat for the years 2011-2015, in accordance with the years available in the OAG MIDT data sets. Depending on the settings used in the integrated simulation framework, the corresponding values from Table 5.3 are used for the applicable simulation year.

Table 5.3: Total Traffic at the Airports

	MAD	AMS	LHR	CPH	FRA	CDG
2011	49574061	49838392	69475746	22707908	56561629	60871885
2012	45181569	51107756	70108071	23310622	57752093	61620823
2013	39708868	52626164	72402110	24041898	58158784	62027269
2014	41581093	55029358	73439386	25681268	59687019	63781392
2015	46335711	58315280	75017520	26625779	61139124	65764343

Block Times
In Table 5.4, the block time statistics of every route in the data set can be found. This table consists of values on the average, maximum and minimum block times flown in each route, as well as the average, maximum and minimum frequency flown in reach route. Additionally, the flight time is stated in index form. The block times found in this table are used in the competitor reaction model when optimizing the computer player, which acts as a typical competitor that is on average found in each route. The block times below are the values which represent the average of the competition in each route. The total maximum block time over all routes has been defined as the sum of all average block times over all routes found in the table below. This value is used to determine a maximum capacity over all routes for the computer player. The minimum values for each route, are used as minimum block time constraints in each route for the optimization model.

Table 5.4: Block Times Typical Competitor

Route	Avg. Block Time [h]	Max. Block Time [h]	Min. Block Time [h]	Avg. Freq. [Flights/QTR]	Max. Freq. [Flights/QTR]	Min. Freq. [Flights/QTR]	Flight Duration [h]
AMS-CPH	400	584	25	378	552	24	1.06
AMS-LHR	609	764	222	811	1018	296	0.75
AMS-MAD	580	1097	44	292	552	22	1.99
CDG-CPH	454	696	118	307	470	80	1.48
CDG-MAD	463	1093	37	301	710	24	1.54
CPH-AMS	409	584	27	387	552	26	1.06
CPH-CDG	469	696	133	317	470	90	1.48
CPH-FRA	359	513	125	322	460	112	1.12
CPH-LHR	627	760	189	434	526	131	1.44
CPH-MAD	172	796	27	64	297	10	2.68
FRA-CPH	377	513	134	338	460	120	1.12
FRA-LHR	852	1188	339	792	1105	315	1.08
FRA-MAD	506	898	109	260	462	56	1.94
LHR-AMS	613	764	224	817	1018	298	0.75
LHR-CPH	639	760	208	442	526	144	1.44
LHR-FRA	856	1188	329	796	1105	306	1.08
LHR-MAD	1546	2087	403	886	1196	231	1.74
MAD-AMS	565	1097	26	284	552	13	1.99
MAD-CDG	460	1093	37	299	710	24	1.54
MAD-CPH	182	750	29	68	280	11	2.68
MAD-FRA	513	897	115	264	461	59	1.94
MAD-LHR	895	1284	244	513	736	140	1.74

Yield
Table 5.5 describes the yield statistics found in the data set per class. As with the block times, the computer player acts as a typical competitor that is on average found in each route. The yields below are the values which represent the average, maximum and minimum of the competition in each route

per class. The yields found in this table are used as inputs in the optimization model. How this is implemented, has been explained in Section 4.4.1.

Table 5.5: Yields Computer

Cabin	Average Yield	Max. Yield	Min. Yield	Std. Dev. Yield
Business	0.757	5.510	0.054	0.386
Full Economy	0.571	1.139	0.172	0.178
Premium Economy	0.225	1.205	0.021	0.197
Discount Economy	0.124	0.414	0.019	0.082
First	0.085	0.549	0.013	0.080

Seasonality
Table 5.6 shows the seasonality data used to simulate seasons in the model for quarter 1. During the process of deseasonalization, the seasonal variability per quarter was computed. The demand generated with the gravity model, generates deseasonalized demand. Thus by adding the values found in the mentioned tables back to the demand generated, seasonality effects are returned to the generated demand. For the seasonality tables of the other quarters, please refer to Tables A.1, A.2 and A.3.

Table 5.6: Route Demand Seasonality Quarter 1

Route	Month	Moving Average	Seasonality Effects	Seasonality Percentage
AMS-MAD	Qtr1	31063	-6522	79.0%
CPH-MAD	Qtr1	4617	-1198	74.1%
MAD-AMS	Qtr1	33471	-5044	84.9%
MAD-CPH	Qtr1	3993	-1262	68.4%
CPH-CDG	Qtr1	26521	-6936	73.8%
AMS-CPH	Qtr1	27788	-4629	83.3%
CDG-CPH	Qtr1	26473	-7663	71.1%
LHR-MAD	Qtr1	40209	-3914	90.3%
FRA-LHR	Qtr1	87191	-5050	94.2%
LHR-FRA	Qtr1	90379	-4976	94.5%
MAD-CDG	Qtr1	30776	-7007	77.2%
CDG-MAD	Qtr1	29164	-8165	72.0%
CPH-AMS	Qtr1	28359	-3728	86.9%
MAD-LHR	Qtr1	40185	-4051	89.9%
AMS-LHR	Qtr1	81494	-4520	94.5%
LHR-AMS	Qtr1	87053	-5587	93.6%

5.2. Sub-Model Calibration: Demand Generation

This section discusses the results of the calibration of the demand generation model. This model is one of the sub-models within the simulation framework and to understand its standalone performance it is of essence to discuss its calibration results separately. The section will start off with a description on the data used for the model, followed by the results of the calibration on the overall performance and subset-specific performances. Last, significance checks for the model and its parameters will be done and the results of this displayed.

5.2.1. Data Input

In Table 5.7, the data descriptives of the data used for the calibration of the demand generation gravity model can be found. As can be seen from this table, there were in total 1194 inputs into the gravity model for calibration, originating from the OAG dataset for the years 2011-2015. The spread of the data entries per route, per cabin and per quarter were very much dependent on the availability in the data set. It was assumed that differences in data availability were caused by the fact that some flight options were not supplied on a route in a specific year and were therefore not available in the data-set. The spread of data entries for the different routes and classes can be found in Appendix C, Table C.22. With respect to the data itself, it can be seen that the ranges of the dependent variable (*Deseasonalized demand*) and the independent variables (*Distance* and *AiAj*) are large. This is due to the fact that the data entries are spread over 16 different routes over five cabin classes and five years.

Table 5.7: Total Data Set - Dependent and Independent Variable Descriptives

	Descriptive Statistics							
	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Distance	1194	1.698E+03	3.670E+02	2.065E+03	9.735E+02	1.337E+01	4.619E+02	2.133E+05
Deseasonalized Demand	1194	8.841E+04	8.115E+01	8.849E+04	1.255E+04	5.542E+02	1.915E+04	3.667E+08
AiAj	1194	3.632E+15	9.547E+14	4.587E+15	2.747E+15	3.194E+13	1.104E+15	1.218E+30

In Table 5.8, the demand averages per route and cabin can be found. As expected, the discount economy class is the class which caters for the most demand per route. The order in passenger volumes for the other classes differs per route. Interestingly enough, it does seem that the first class also caters for quite a number of passengers in the different routes. This could be explained by the fact that the routes included in the model are between cities which have business links, which would lead to business travel and thus passengers flying in classes with higher prices and higher levels of services than discount economy class.

Table 5.8: Demand Averages, Minimums and Maximums per Route and Cabin

Route	Cabin	Data Count	Min	Max	Average	Route	Cabin	Data Count	Min	Max	Average
AMS-CPH	Discount Economy	20	19415	42381	29634	FRA-LHR	Discount Economy	20	60248	74547	69709
AMS-CPH	First	18	731	5099	1855	FRA-LHR	Premium Economy	20	2785	24475	16036
AMS-CPH	Premium Economy	17	108	1865	738	FRA-LHR	Business	20	2384	6323	3920
AMS-CPH	Full Y	14	225	1377	659	FRA-LHR	Full Y	20	1222	4220	2293
AMS-CPH	Business	2	243	251	247	FRA-LHR	First	5	715	2261	1131
AMS-LHR	Discount Economy	20	53903	90684	68225	LHR-AMS	Discount Economy	20	59960	93389	75332
AMS-LHR	Full Y	20	3556	10097	7468	LHR-AMS	First	19	2129	9998	5131
AMS-LHR	First	19	1218	6360	3731	LHR-AMS	Full Y	20	2471	7551	4896
AMS-LHR	Premium Economy	20	576	7265	3475	LHR-AMS	Premium Economy	20	1539	6790	3966
AMS-LHR	Business	20	1854	4492	3302	LHR-AMS	Business	20	2229	4833	3571
AMS-MAD	Discount Economy	20	18651	34836	28532	LHR-FRA	Discount Economy	20	63367	79188	72356
AMS-MAD	First	20	3078	10983	6836	LHR-FRA	Premium Economy	20	2580	27893	16735
AMS-MAD	Premium Economy	18	255	5613	2040	LHR-FRA	Business	20	3098	6694	4218
AMS-MAD	Full Y	14	228	1069	545	LHR-FRA	Full Y	20	496	3822	1816
CDG-CPH	Discount Economy	20	18386	46956	30500	LHR-FRA	First	5	514	1685	922
CDG-CPH	First	19	354	8723	2800	LHR-MAD	Discount Economy	20	21890	52141	34026
CDG-CPH	Premium Economy	20	105	1965	874	LHR-MAD	Business	20	3007	7097	4139
CDG-CPH	Business	3	171	422	295	LHR-MAD	Premium Economy	20	576	9770	3043
CDG-CPH	Full Y	5	114	533	233	LHR-MAD	Full Y	20	942	5527	2649
CDG-MAD	Discount Economy	20	18163	35645	27300	LHR-MAD	First	3	779	2535	1770
CDG-MAD	First	20	1201	16351	6327	MAD-AMS	Discount Economy	20	19707	36221	28993
CDG-MAD	Premium Economy	20	585	9377	3158	MAD-AMS	First	20	3881	11732	6979
CDG-MAD	Business	10	102	2802	880	MAD-AMS	Premium Economy	19	105	5206	2357
CDG-MAD	Full Y	6	102	736	347	MAD-AMS	Full Y	14	111	1012	433
CPH-AMS	Discount Economy	20	22403	37810	28998	MAD-CDG	Discount Economy	20	18390	38850	28505
CPH-AMS	First	19	817	5488	2124	MAD-CDG	First	20	1379	18954	5832
CPH-AMS	Full Y	17	104	1011	641	MAD-CDG	Premium Economy	20	630	6341	3100
CPH-AMS	Premium Economy	16	108	1252	595	MAD-CDG	Business	9	172	1436	569
CPH-AMS	Business	6	100	272	169	MAD-CDG	Full Y	5	235	629	362
CPH-CDG	Discount Economy	20	19184	47877	30059	MAD-CPH	Discount Economy	20	1565	9811	4681
CPH-CDG	First	20	836	8022	2718	MAD-CPH	Premium Economy	13	230	1374	609
CPH-CDG	Premium Economy	19	178	1791	684	MAD-CPH	First	10	106	631	328
CPH-CDG	Business	1	245	245	245	MAD-CPH	Full Y	1	283	283	283
CPH-CDG	Full Y	2	163	194	178	MAD-LHR	Discount Economy	20	27870	43974	35970
CPH-MAD	Discount Economy	20	1554	9790	5243	MAD-LHR	Business	20	1539	6816	3427
CPH-MAD	Premium Economy	11	113	1911	648	MAD-LHR	Full Y	20	763	5383	2389
CPH-MAD	First	9	198	1152	480	MAD-LHR	Premium Economy	20	486	5890	2099

5.2.2. Calibration Results

With the data for the independent and dependent variables described in Section 5.2.1, as well as the dummy variables for the different classes, the model was calibrated using OLS. The results from this calibration can be found in the following section.

Calibration Coefficients
In Table 5.9, the coefficients of the regression intercept, independent variables and dummy variables can be found. As described in Section 4.2.6, the variable coefficients were first verified on their significance. The threshold to accept the coefficients was set at 0.05 and as can be seen below, all coefficients were accepted.
Following, the effect on the dependent variable was controlled. The findings for each parameter were the following:

- Regression Intercept (K) - The effect here was stated as negative. As it is a regression intercept, this value is accepted as a given.
- Distance - The coefficient for the distance is found to be negative, which is expected. The increase in distance is in general known to decrease the amount of social and commercial interaction of two cities (Jorge-Calderón, 1997).
- Dummy variables for class - All dummy variable coefficients for class in the table below are negative. This is because the classes are in comparison to the situation in the discount economy class. The discount economy class has much higher demand levels than the other classes and thus with respect to discount economy, all other classes will have a negative effect on the demand. This coefficient is thus as expected.
- The product of the total traffic at both airports ($AiAj$) - the coefficient of this variable is seen to be positive as expected. The more passengers both airports have traveling through them, the more passengers that will want to fly, implicitly increasing the demand.

Table 5.9: Gravity Model Parameter Coefficients

Coefficients			
Parameters	**Unstandardized Coefficients**		
	Coeff.	**Std. Error**	**Sig.**
K	-38.7572	2.183761	0.00***
Distance	-0.36013	0.050237	0.00***
Business	-3.21767	0.080193	0.00***
Premium Economy	-2.84439	0.06363	0.00***
Full Y	-3.46384	0.072082	0.00***
First	-2.37923	0.067905	0.00***
AiAj	1.456408	0.057051	0.00***
Significance level : '***'< 0.001; '**'<0.01; '*'<0.05, '-' insig.			

In literature, different forms of gravity models have been tested. Of the independent variables found above, it is possible to compare the coefficient value of the distance to other studies. The other variables and dummy variables included are not easily compared as the reviewed literature does not implement these in an identical manner. For the literature where a gravity model which only included geo-economic variables was used as in this thesis, the coefficient of distance is very similar. In the research done by Rengaraju and Thamizh Arasan (1992), the coefficient for distance was computed to be -0.355 while Jorge-Calderón (1997) found a coefficient of -0.31.

A curiosity is found with the coefficient of the dummy variable for first class. As can be seen in Table 5.9, the coefficient of first class is surprisingly lower than that of Full Y and Business. Contemplating the data set, this coefficient was confirmed. In Table 5.8, the first class demand is often found to be ranked second or third for the demand per route. Furthermore, over the complete data set, first class was observed to rank third in demand over the entire data set. First class flight options attracted almost twice the demands of Full Y and Business, while only being slightly less than premium economy. This explains why the coefficient for the first class is lower than expected, compared to the other classes.

Correlation Matrix

With the variable checks in place and with all coefficients for the different variables accepted, the independent variables were checked against multicollinearity to ensure that the independent variables are all sufficiently independent of each other. As stated previously, the threshold set by Doganis (2002) of 0.86 was used. As can be seen in Table 5.10, all independent variables are well below this threshold, thus no effect of multicollinearity has to be expected.

Table 5.10: Gravity Model Correlation Matrix

Coefficient Correlations						
	AiAj_LN	Premium Economy	Full Y	Business	Dist_LN	First
AiAj_LN	1.000	-0.039	-0.113	-0.197	0.417	0.051
Premium Economy	-0.039	1.000	0.429	0.390	0.009	0.446
Full Y	-0.113	0.429	1.000	0.376	0.064	0.393
Business	-0.197	0.390	0.376	1.000	0.061	0.350
Dist_LN	0.417	0.009	0.064	0.061	1.000	0.051
First	0.051	0.446	0.393	0.350	0.051	1.000

Performance Testing

Total Model Performance

With the coefficient checks in place, the total performance of the calibrated gravity model was tested. To do this, the gravity model calibration outcomes in Tables 5.11 and 5.12 were analyzed. In Table 5.11, the value for the coefficient of multiple determination (R^2) can be found. As described previously, this coefficient gives an indication of the overall goodness-of-fit of the model. With a value of 0.766, which is reasonably close to the maximum of 1.000, the calibrated gravity model seems to have a reasonable performance overall. Comparing this value to similar researches done by Doganis (1966), Rengaraju and Thamizh Arasan (1992) and Jorge-Calderón (1997) who achieved values of 0.74, 0.95 and 0.37 respectively, the gravity model in this thesis can be considered to perform adequately. The higher value found in the research by Rengaraju and Thamizh Arasan (1992), may be explained by the larger amount of independent variables taken into account. The model performance for different subsets of data will be discussed below.

Table 5.11: Gravity Model Goodness-of-fit

Model Summary			
R	R^2	Adjusted R^2	Std. Error of the Estimate
.875	0.766	0.765	0.786

The Analysis of Variance (ANOVA) table found in Table 5.12 is important as it determines whether the calibrated gravity model is significant as a whole. To determine this, it is important to review the significance parameter of the regression. As can be seen in the table, the significance value is 0, which indicates that the gravity model as a whole is significant and thus may be used with confidence.

Table 5.12: ANOVA Test Gravity Model

ANOVA					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Regression	2405.133	6	400.856	648.777	.000***
Residual	733.404	1187	0.618		
Total	3138.537	1193			

Significance level : '***'< 0.001; '**'<0.01; '*'<0.05, '-' insig.

Specific Performance

To accurately define the gravity models performance, an analysis on the model performance for different data subsets needs to be performed. This is done on to the different routes for which the gravity model has been calibrated, as well as the different classes for which this has been done. Below Tables 5.13 and 5.14 give a representation of the performance per cabin and per route respectively. The standard error of the estimate is used to determine the performance. This standard error provides a level of the accuracy of the prediction done by the gravity model. Additionally, the standard error has been presented as a percentage of the average value over the complete dataset of the particular subset input. This is done to make it possible to compare the standard errors between different subsets, as the magnitude of demand for different subsets often differs significantly. This percentage should however be used with caution for the performance comparisons of the routes and cabins separately, the reason being that within a cabin the demand varies strongly per route and within a route the demand varies strongly per cabin. The standard error percentage is very useful in the performance test per route per cabin as found in Table C.22.

Table 5.13: Gravity Model Performance per Cabin Class

Cabin	Std. Error of Estimate	Data Entries	Std. Err. Perc. of Average Demand
Discount Economy	12260	320	33%
Business	1576	151	51%
Full Y	2095	198	88%
First	3890	232	100%
Premium Economy	4965	293	123%

Table 5.13 describes the performance of the gravity model with respect to the different cabins. Here, the discount economy class has the best relative performance in the calibration of the gravity model, with an standard error of 33% over the average demand for that class. Given the fact that the most passengers fly within this cabin class in the data set with which was calibrated, this can be considered as desired. The other class which seems to perform well is the business class, with a standard error of 51%. Premium Economy, Full Y and First class are not performing too well, with relatively high standard errors of the estimate. Noticeable is that the number of data entries of the different classes differs. This, however, does not seem to have a direct effect on the performance of the model on the different classes. For a graphical representation of the above table, please refer to Appendix C.

Table 5.14: Gravity Model Performance per Route

Route	Std. Error of Estimate	Data Entries	Std. Err. Perc. of Average Demand
MAD-AMS	3616	73	21%
AMS-MAD	3605	72	17%
LHR-AMS	6635	99	30%
LHR-FRA	9310	85	91%
FRA-LHR	9523	85	88%
MAD-LHR	4784	86	52%
MAD-CDG	5599	74	68%
LHR-MAD	5862	83	31%
AMS-LHR	9942	99	101%
CDG-MAD	6132	76	58%
CPH-MAD	1995	40	20%
CPH-CDG	8730	62	85%
CDG-CPH	8755	67	83%
CPH-AMS	7245	78	69%
AMS-CPH	8050	71	337%
MAD-CPH	2389	44	82%

Table 5.14 describes the standard error of the estimate per route, which has been used to determine the gravity models performance in each route as was done previously per cabin. Here, the main finding is that especially OD-pairs which include Copenhagen have relatively high standard errors of the estimate. Taking to the plots of the CPH routes in Appendix C, it can be clearly observed that the discount economy class is being mis-predicted in a more significant manner than other routes. As the discount economy class caters for the largest amount of passengers in comparison to the other classes, this error leads to a noticeably larger error for the routes including Copenhagen as an origin or destination. For a graphical representation of the above table, please refer to Appendix C.

A more specific look at the standard error of the estimate per route and per cabin can be found in Appendix C in Table C.22. The main observations are described below:

- In general, it seems that the routes and cabin data entries with the highest entry counts are the most accurate. This is coherent with expectations, as these data subsets will have had the most effect on the gravity model calibration.
- The problems with the standard errors of the estimate described previously with respect to the Copenhagen airport are confirmed. The discount economy class performance of the routes including CPH have the lowest performance of the discount economy classes.
- The discount economy classes of the routes including CPH are generally underpredicted, with an exception for the routes between MAD-CPH which are overpredicted.
- In general the performance of the gravity model to predict the demand for discount economy is good. This is also the case when looking at the standard errors of the estimates per route per cabin.

The cause of the performance deficiencies found with the Copenhagen route are difficult to explain. However the hypothesis is that the reason for the deficiencies mainly lies in the characteristics of the airport. The Copenhagen airport caters for much less passengers than the other airports included in this thesis. However, in general, the demands are under-predicted by the gravity model which is counterintuitive. The reason for this may lie in the fact that travel from or to Copenhagen with non-air travel transport is much more troublesome, which increases the travel demand in comparison to the other routes. Further research on this observation should however be done to come to a definitive conclusion. Additionally, the over-prediction found in the routes linking Copenhagen and Madrid are expected to be due to the distance between the cities. In comparison to the other routes in the thesis, this route is much longer.

5.3. Sub-Model Calibration: Demand Allocation

In the following section, the calibration results for the MNL model used in the demand allocation process will be described. This will be done in similar fashion to that of the gravity model, starting with a description on the data with which the model was calibrated. This will be followed by the results of the calibration itself, including discussions on the calibrated coefficients, the models performance and the impact of each independent variable on the market share.

5.3.1. Data

In total, 2087 data entries were used to calibrate the coefficients of the independent variables. The non-dummy variable descriptives can be found in Table 5.15. As can be derived from the table, most flights in the data set concerned direct flights. This can be derived from the fact that the mean value for the extra-distance is found to be 0.61 km, which can be explained, as for direct flights the extra-distance was equal to zero. With respect to frequency, the data variance was large, ranging from carriers flying ten flights per quarter to carriers with more than a thousand flights. A more specific look on the yield and flight frequency is done below. When considering the data set regarding the different yields offered,

it is especially interesting to consider Table 5.16. Here the yields‘ descriptives for the different classes are listed. As can be derived from the data count in Table 5.16, the most frequent class found in the

Table 5.15: Independent Variable Descriptives

Descriptive Statistics							
Variable	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Extra Distance [km]	2087	829.43	0	829.43	0.61	18.47	340.97
Frequency [Flights/QTR]	2087	1186	10	1196	498.91	320.42	102670.26
Yield [EUR/km]	2087	5.497	0.013	5.510	0.285	0.301	0.091

data set are discount economy and premium economy. As expected, these two cabin classes have the low average yields. Also as expected, these classes are followed by full economy, and business class. Interesting however is that in the total data set, first class yields have the lowest average yield which is very counter intuitive. During discussions with an industry expert from the University of Cranfield, strongly acquainted with the data source, the reason for this occurrence is that most passengers in this class pay with miles (Nicola Volta,personal communication, April 19, 2017). Therefore distortion in the yield values occur. Another value that pops out of the table below, is the maximum value of the yield of business class. This value was found once within the data set and can be considered an outlier. On average, the yield values were around the value found in Table 5.16. In Table 5.17 and

Table 5.16: Yield Averages, Minimums and Maximums per Cabin

Cabin	Data Count	Min	Max	Average
Business	258	0.053723	5.509896	0.756678
Full Y	300	0.17182	1.139291	0.570792
Premium Economy	503	0.021308	1.204524	0.225201
Discount Economy	695	0.019278	0.414366	0.123919
First	331	0.013283	0.54942	0.085244

5.18 two descriptives of the data set with respect to the flight frequency are shown. Table 5.17, lists the flight frequencies descriptives over the data entries. Here, it can be deduced that different carriers have significantly different flight frequencies per route. Where some carriers have frequencies over a thousand flights, others supply only 20 flights per quarter. The frequency is of course heavily influenced by the size of the carrier, and the supply (i.e. size of the planes, number of aircraft) they are flying on a route.

Table 5.17: Frequency per Data Entry

Route	Data Count	Min	Max	Average
AMS-CPH	109	24	552	378
AMS-LHR	175	296	1018	811
AMS-MAD	154	22	552	292
CDG-CPH	101	80	470	307
CDG-MAD	127	24	710	301
CPH-AMS	111	26	552	387
CPH-CDG	96	90	470	317
CPH-MAD	74	10	297	64
FRA-LHR	161	315	1105	792
LHR-AMS	178	298	1018	817
LHR-FRA	161	306	1105	796
LHR-MAD	104	231	1196	886
MAD-AMS	161	13	552	284
MAD-CDG	127	24	710	299
MAD-CPH	86	11	280	68
MAD-LHR	162	140	736	513

When looking at Table 5.18, the total frequency statistics at quarterly level can be found. Along with being able to get a feel for the number of flights between an OD-pair per quarter, it is also useful to conclude that the data set seems logical: as can be seen in the table, the number of flights between each OD-pair and their opposite hold similar values in all three columns. The flights in one direction are thus also flying in approximately in the same numbers the other way, as expected.

Table 5.18: Total Frequency per Route per Quarter

Route	Min	Max	Average
MAD-CPH	175	402	297
CPH-MAD	182	403	309
CDG-CPH	397	793	616
CPH-CDG	426	789	619
CDG-MAD	429	906	639
MAD-CDG	474	897	647
CPH-AMS	517	971	821
AMS-CPH	509	1017	824
MAD-AMS	459	1168	883
AMS-MAD	571	1137	886
MAD-LHR	824	1189	1028
FRA-LHR	1307	1757	1586
LHR-FRA	1305	1757	1596
AMS-LHR	1286	1748	1603
LHR-MAD	891	1924	1607
LHR-AMS	1286	1748	1613

5.3.2. Calibration Results

Now that the data used for the calibration has been described in the previous subsection, the actual calibration results are highlighted. In the following subsection, the parameter coefficients, the parameter correlations, the models goodness-of-fit, the models overall significance, the models performance and the impacts of the different parameters will be addressed.

Calibration Coefficients

Table 5.19, shows the calibrated coefficients for the MNL model. As discussed previously, the first check done on the coefficients is to determine their significance. The threshold set for accepting or declining the significance of the coefficients was set at 0.05. As can be seen in the table below, all independent variable coefficients passed this test without any problems.

Second, the effects of the different independent variables on the dependent variable were evaluated. In general, the signs of the coefficients were as expected, the evaluations for each variable specifically were as follows:

- Regression Intercept K - The regression intercept is a negative constant, which is assumed as a given
- Extra Distance - As expected, if a route is indirect and thus incurs extra distance on top of that of the direct route, the demand and hence the market share will be negatively affected.
- Frequency - With increasing frequency, the market share will be positively influenced. This is as expected.
- Yield - The coefficient for yield is calibrated to a negative value. An increasing yield would thus have a negative effect on market share which is expected
- Dummy variables for class - As in the calibration for the gravity model, all dummy variable coefficients are negative. This is as expected, with the same reasoning as previously explained. In comparison to the discount economy class the other classes experience less demand.

Furthermore, the inclusion of the dummy variables into the multinomial logit model is hypothesized to combine different unobserved choice factors of the different classes into one variable coefficient. By doing this, the other variables such as the yield and the frequency are assumed to be more independent of the type of class flown by the passenger.

Comparing the coefficients of the MNL model to those found in literature, the coefficients are similar in sign. It is however not possible to compare the coefficients directly, as the different researches use different combinations of variables and different levels of aggregation lead to different magnitudes of the coefficients. The effect of the frequency, yield and extra-distance however are in line with what is found in literature.

Table 5.19: Multinomial Logit Model Parameter Coefficients

Parameters	Unstandardized Coefficients		
	Coeff.	**Std. Error**	**Sig.**
K	-1.567	0.042	0.000***
Extra Distance	-0.007	0.001	0.000***
Frequency	0.001	0.000	0.000***
Yield	-1.021	0.099	0.000***
Business	-2.428	0.086	0.000***
Premium Economy	-2.530	0.050	0.000***
Full Y	-2.683	0.072	0.000***
First	-1.908	0.056	0.000***

Significance level : '***'< 0.001; '**'<0.01; '*'<0.05, '-' insig.

Correlation Matrix

In Table 5.20, the correlation matrix following the calibration can be found. This table is used to ensure that no multicollinearity is experienced between the different independent variables. As discussed previously, the threshold for which multicollinearity is determined is set at above 0.86. Between all independent variables, this is not the case and thus the effect of multicollinearity is not applicable.

Table 5.20: Multinomial Logit Model Correlation Matrix

Coefficient Correlations							
	First	Extra Distance	Frequency	Full Y	Business	Premium Economy	Yield
First	1.000	0.031	0.020	0.209	0.160	0.348	0.061
Extra Distance	0.031	1.000	0.017	0.019	0.014	0.031	0.004
Frequency	0.020	0.017	1.000	-0.006	-0.007	0.040	-0.223
Full Y	0.209	0.019	-0.006	1.000	0.587	0.397	-0.584
Business	0.160	0.014	-0.007	0.587	1.000	0.372	-0.690
Premium Economy	0.348	0.031	0.040	0.397	0.372	1.000	-0.201
Yield	0.061	0.004	-0.223	-0.584	-0.690	-0.201	1.000

Performance Testing

With the calibration coefficient checks in place, the performance of the MNL models performance is tested. This is done with respect to the model as a whole, as well as per cabin class, per route and for both differentiations simultaneously. These performance checks will provide a good idea of how well the model will be able to allocate demand to the different flight options in the integrated simulation framework.

Total Model Performance

In Table 5.21, the coefficient of multiple determination R^2 can be found. The closer this coefficient is to 1.0, the better the global performance of the model. As can be seen in the table, the performance is reasonably good with an R^2 of 0.711. Comparison of this thesis' model to model performances found in the literature are not feasible, as the different MNL models are constructed with a multitude of different variable setups, data sets, levels of aggregation and scopes. These differences are unsurmountable to make a worthwhile comparison.

Table 5.21: Multinomial Logit Model Goodness-of-fit

Model Summary			
R	R^2	Adjusted R^2	Std. Error of the Estimate
0.843	0.711	0.711	0.829

With the R^2 determined, it is of essence to know if the model is also significant. As described previously, the significance of the total model can be derived with the ANOVA table. This table can be found in Table 5.22. Here it can be seen that the regression's significance is zero, and the calibrated model can thus be considered significant.

Table 5.22: ANOVA test Multinomial Logit Model

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	3524.000	7	503.429	732.378	0.000***
Residual	1429.082	2079	0.687		
Total	4953.081	2086			

Significance level : '***'< 0.001; '**'<0.01; '*'<0.05, '-' insig.

Specific Performance
The overall performance of the MNL model gives a good indication in general on what to expect from the model. However it is also of interest to determine how the model works for the different segments it is used for. In Table 5.23, the standard error of the estimate can be found which gives an indication of the accuracy of the model. As the model is calibrated with respect to market share, it is difficult to compare the different standard errors of the estimate due to difference in magnitude that the average market share has per class. To help with this, the last column in the table portrays the standard error of the estimate as a percentage of the average share of the cabin class. In this manner comparison of the models accuracy per cabin class can be made.
As can be seen in Table 5.23, the lowest error percentage is made with the discount economy class. The other classes have worse performances.

Table 5.23: Multinomial Logit Model Performance per Cabin Class

Cabin	Sum of Squared Residuals	Std. Error of Estimate perc	Data Count	Perc. Of Average Share
Discount Economy	8.57	0.11	695	29.4%
Business	0.10	0.02	258	71.5%
First	0.99	0.05	331	80.4%
Full Y	0.13	0.02	300	88.3%
Premium Economy	1.08	0.05	503	114.3%

In Table 5.24, the standard error of the estimate can be found for the calibrated MNL model per route. Apparent from the table is that the standard error of the estimate for the routes including the same airport pairs have very similar errors of the estimate. It also shows that the route with the furthest flight distance, namely between Madrid and Copenhagen, has the largest error of the estimate. The other routes have similar errors of the estimate, which could insinuate that the routes different slightly in their characteristics in comparison to the MAD-CPH routes.

Table 5.24: Multinomial Logit Model Performance per Route

Route	Sum of Squared Residuals	Std. Error of Estimate	Data Entries
MAD-LHR	0.13	0.03	162
LHR-AMS	0.24	0.04	178
AMS-LHR	0.30	0.04	175
LHR-MAD	0.27	0.05	104
CPH-CDG	0.20	0.05	96
CDG-CPH	0.29	0.05	101
AMS-CPH	0.31	0.05	109
CPH-AMS	0.36	0.06	111
AMS-MAD	0.54	0.06	154
MAD-AMS	0.67	0.06	161
FRA-LHR	0.69	0.07	161
LHR-FRA	0.76	0.07	161
CDG-MAD	0.93	0.09	127
MAD-CDG	0.99	0.09	127
MAD-CPH	1.92	0.15	86
CPH-MAD	2.27	0.18	74

In Table D.1, the standard errors of the estimate and the percentual error of the average market share per route and cabin are listed. Accompanying this table, are the plots of the actual data, the predicted data and the actual data points plotted against the predicted data points colored per cabin class. The following main findings were done with respect to the table and different plots:

- In general the multinomial logit model performs best when predicting the discount economy class shares.
- Confirming what was previously observed, the plots also show that the route MAD-CPH have more erroneous predictions.
- In general, premium economy and first class shares are under-predicted. This can be clearly be seen in for example Figure D.7
- The general performance, as seen from the different plots, is that the model estimates the market share in a reasonable fashion. The actual-vs-predicted value plots follow the same trend, just as that the market share plots are visually similar.

Variable Impacts
As mentioned previously, the coefficients found during calibration clearly show the effect each independent variable has on the dependent variable. However, as the magnitudes of the different variables differ, it is difficult to determine the impacts of each variable in a manner where the different impacts can be compared. As described in Section 4.3.4, a method has been devised to overcome this comparison problem. In Table 5.25, the relative percentual impacts of each independent variable can be found. As expected, the extra distance and yield have the largest impact on passenger choice. The extra distance is an indicator for an indirect flight, thus the more extra kilometers flown the less attractive it will become. Additionally, when making the choice between an indirect and a direct flight, it is expected that passengers will greatly favor direct flights, also adding to the fact that the high relative impact of this variable is explicable. With respect to the yield, as mentioned previously, the yield is related to the fare, which according to literature, is one of the main influencers of passenger choice. It could therefore be expected that this has a high impact. It should however be noted that the impact here may be larger than that experienced, as the range of yield used covers all classes. For the different classes in the simulation framework, the yield ranges differ and are smaller than the one used for this calculation. Percentualy, the yield effect may be slightly lower if this calculation were done for each class separately. The fact that the flight frequency has a relatively low impact with respect to the other variables does not necessarily mean it is unimportant. In the set of variables used it may be the one with the least impact, however, in models with different variables included this would be different, as frequency is also in the literature seen as an important choice factor of passenger choice. The impacts of the dummy variables are again

very much relative to the discount economy class, and how the general magnitude of the market share each class achieves.

Table 5.25: Independent Variable Impacts Multinomial Logit Model

Variable Impacts			
Variable	Coefficient	Range	Impact
Extra Distance	-0.007	829.43	24.74%
Frequency	0.001	119	5.95%
Yield	-1.021	5.497	23.25%
Business	-2.428	1	10.06%
Premium Economy	-2.530	1	10.48%
Full Y	-2.683	1	11.12%
First	-1.908	1	7.91%
Constant	-1.567	-	6.49%

6

Simulation Games & Results

With the general simulation framework scope defined and the sub-models needing calibration calibrated, the simulation framework can be tested as a whole to determine its behaviour. The behaviour of the simulation framework will be tested on the basis of several simulation games which have been designed to test different areas of the simulation framework.

This chapter begins with the definition of the different simulation games played, including descriptions on the different exogenous players included and the optimization strategy of the computer player. Following the game definitions, the results of these games will be described which will give an insight on the simulation models behaviour. The chapter will be concluded with the general findings from the played simulation games.

6.1. Simulation Games Definition

This section discusses the setup of the different simulation games used to test the simulation framework. In total, four different games have been designed to which the integrated simulation framework will be played and tested. The results of this testing can be found in Section 6.2. Before the four games are discussed, the general manner in which the games will be played need to be defined. The computer player is the player for which the simulation framework optimizes the strategy. Competition is included through exogenous players who can be static or dynamic. Additionally, the general simulation process can be found in Table 6.1. As shown, in year 0 the computer is on its own and the starting strategy is initialized based on the market averages for yield, frequency and pre-set seat share distributions. In year 1, the player strategies are added to the model, for which the general outputs are computed. Next, the first optimization of the computer player takes place. In year 1 optimized (Y1OP), the outputs are generated for the players with their year 1 strategies and the computer with its optimized strategy. In year 2, both exogenous players determine their plan for year two, after which outputs are computed again. The year 2 optimization is the same optimization as done after year 1. Year 3 and the optimization of year 3 are identical to the years described previously. After these years have been played, the game ends in this thesis. With the results from the different game years, conclusions on the working of the model will be taken. In essence, this game form can be considered to be a leader-and-follower Stackelberg game.

Table 6.1: Example Simulation Game Sequence with Two Exogenous Players

	Strategy						
Competitor	Year 0	Year 1	Year 1 Optimized	Year 2	Year 2 Optimized	Year 3	Year 3 Optimized
Computer	Strategy Y0	Strategy Y0	Strategy Y1	Strategy Y1	Strategy Y2	Strategy Y2	Strategy Y3
Player 1	-	Strategy Y1	Strategy Y1	Strategy Y2	Strategy Y2	Strategy Y3	Strategy Y3
Player 2	-	Strategy Y1	Strategy Y1	Strategy Y2	Strategy Y2	Strategy Y3	Strategy Y3

The simulation games will be played for one-route, which has been determined to be representative for routes within the data's scope. This is done to be able to specifically look at the behavior of the computer reaction in different situations and not be diluted by the size of the game. The model can be played with all routes included, but this would make an effective observation of the optimization models behavior difficult, due to the size of the simulation environment it is in. The chosen route for which the simulation games are played is the route AMS-MAD. As can be seen in Figure 6.1, the AMS-MAD route was observed to be an average route with respect to demand hence its choice.

An exception to the one route simulation game is found in game 4, where a multi-route game is played. This is specifically done to determine if the computer player will have migratory behaviour if it experiences increased competition in some of the routes it is playing. The routes included in game 4 include those from Amsterdam to Copenhagen, London and Madrid. More on how the game is setup can be found in Section 6.1.5.

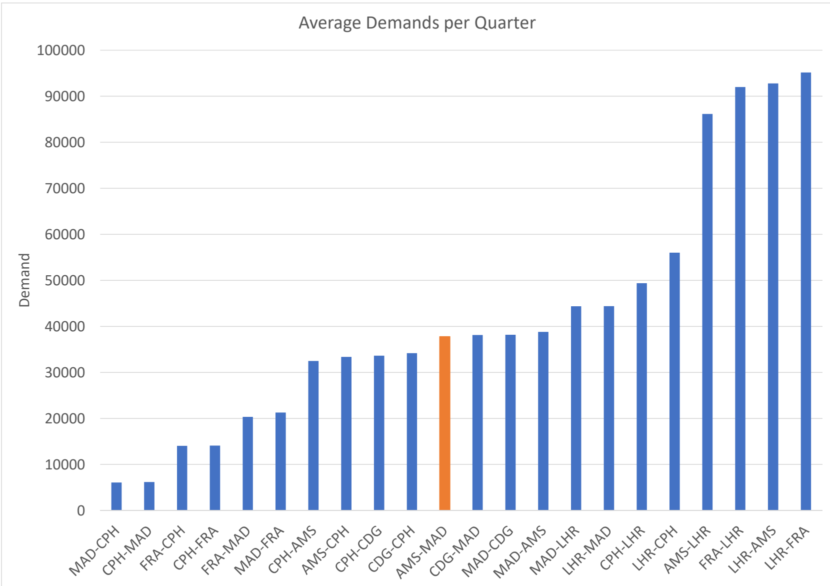


Figure 6.1: Average Route Demands per Quarter

6.1.1. Simulation Game 0

In the first simulation game, the computer player is tested on it's own in the AMS-MAD market. The game uses $AiAj$ data of the year 2015, and is set to be constant to ease comparison over the different game years.

With respect to the block hour constraints, game 0 uses the total summed frequency maximum, minimum and averages of a route found in Table E.1. This has an effect that the game 0 computer represents a combination of all players that one would find in a market and could be described as a 'super' player with respect to size. The reasoning behind this game is, to test the simulation model as a whole and observe what the optimization model does in such an extreme case.

6.1.2. Simulation Game 1

The second simulation game is similar to the first, only that now the block hours constraints are designed to force the computer into playing as an average competitor in the route with respect to frequency. The block hour constraint used in this game can be found in Table 5.4. The yield constraints are set as described in Table 5.5 and used as described in Section 4.4.1. As with simulation game 0, simulation game 1 is used to observe the optimization characteristics of the model.

6.1.3. Simulation Game 2

In simulation game 2, a competitor is added to the simulation framework. This competitor resembles a low cost carrier, in the manner that it only has one class. The competitor will be flying a constant two flights per day for each input year. Furthermore, the competitor will drop it's price for the discount economy class by EUR 20 each simulation year. The other characteristics are as stated with simulation game one.

6.1.4. Simulation Game 3

In simulation game 3, a different competitor type is added to the simulation framework. This competitor resembles a legacy carrier, in the manner that it has all five classes on board. As with game 2, the competitor flies two flights a day for each input year while dropping it's price for every class by EUR 20 over each simulation year. Other characteristics are identical to the other games.

6.1.5. Simulation Game 4

In simulation game 4, a multi-route simulation game is played. This simulation game is initiated to test the models working in a multi-route system, as well as determine the reaction behavior in the computer if multiple routes are involved. To create this game, three routes in total have been chosen to be simulated. The routes included are the flights from Amsterdam to Copenhagen, London and Madrid.
For each route, to be able to simulate competition in a similar manner to reality, actual data has been collected on the different competitors in each route. These different competitors are implemented into the simulation model as players, with characteristics which resembles those found in the actual data. The different flight options in each route for each competitor can be found in Table 6.2. The computer player in simulation game 4 replaces KLM, which has been excluded from the data. The computer player is restricted with respect to yields and frequency in a similar manner as found in the previous three games.

Table 6.2: Competitor Data Quarter 1 2015

Carrier	Code	Route	Cabin	Frequency	Fare [EUR]	Seats	Seat Share [%]
Air Europa	UX	AMS-MAD	Discount Economy	180	50	160	67
Air Europa	UX	AMS-MAD	First	180	37	160	28
Air Europa	UX	AMS-MAD	Premium Economy	180	63	150	5
Iberia	IB	AMS-MAD	Discount Economy	242	77	150	68
Iberia	IB	AMS-MAD	First	242	93	150	10
Iberia	IB	AMS-MAD	Premium Economy	242	117	150	22
Norwegian Air Shuttle	DY	AMS-CPH	Discount Economy	50	57	186	100
SAS Scandinavian Airlines	SK	AMS-CPH	Discount Economy	330	94	150	95
SAS Scandinavian Airlines	SK	AMS-CPH	Full Y	330	448	150	2
SAS Scandinavian Airlines	SK	AMS-CPH	Premium Economy	330	148	150	3
British Airways	BA	AMS-LHR	Business	709	465	166	7
British Airways	BA	AMS-LHR	Discount Economy	709	137	166	77
British Airways	BA	AMS-LHR	Full Y	709	365	166	12
British Airways	BA	AMS-LHR	Premium Economy	709	122	166	4

The game is first played by keeping all player strategies constant, by which a base reaction can be determined for the computer (Null Game). In the second iteration of the game, the strategies of two of the players in the game change. These strategies have been designed to increase competition in the market and thus challenge the computer player. The strategies and to which players these strategies belong can be found in Table 6.3. The strategy for DY resembles a competing LCC, which severely lowers its fare while increasing the number of flights on the route. The strategy of BA represents that of a competing legacy carrier, which increases its frequency steadily, while gradually also lowering its price.

Table 6.3: Game 4 Player Strategies

Route	Player	Y1 Freq.	Y1 Fare	Y2 Freq.	Y2 Fare	Y3 Freq.	Y3 Fare
AMS-CPH	DY	-	-	10%	-20%	10%	-20%
AMS-LHR	BA	-	-	15%	-10%	15%	-10%
AMS-MAD	-	-	-	-	-	-	-

As mentioned before, it will be interesting to see how the computer player reacts to the different market situations. A special focus will be on if the computer will start shifting its focus to the Madrid route when the other routes come under enhanced competition.

6.2. Simulation Framework Game Results

In the following section, the simulation game results of the different games tested will be described. The focus of this section is to determine the behavior of the computer player and the optimization process which effects it. The section will be discussed in sequence of each played game, according to the games described in Section 6.1. The results are explained with respect to the game results for the first quarter of each game. The reason being that differences to the quarter one simulations were not significant, and thus the results for quarter one are taken to be representative for the entire simulation.

6.2.1. Simulation Game 0

In this section, the results of game 0 will be described. As mentioned in Section 6.1.1, the route tested here is the AMS-MAD route with the computer in the form of a 'super' player. The focus of game 0 is to determine the general optimization behaviour of the computer over the different simulation game years. Furthermore, the effect of the size of the computer player will be observed. Game 0 will be described using results on the ASK and RPK development, the profit development, the game KPIs and the seat share development for the different simulation game years. The section on game 0 will conclude with the general findings of the game.

ASK & RPK Development

In Figure 6.2, the development of the game player with respect to its ASK's and RPK's is found. As mentioned before, the player starts off with a frequency which is based on the average frequency of all players combined in the market. From there on, it optimizes towards a value for which the profit has been optimized. As can be seen in the figure, in each optimization year (indicated by $Y\#OP$) the number of ASKs drop. This indicates that the computer player is decreasing its frequency with every optimization. With respect to the step size of the decrease in ASKs, year 0 (Y0) is an initiation year for the computer player. Between year 0 and year 1 optimization, the maximum change is bound by the predefined minimum and maximum values of frequency in the simulated route. This is why the decrease is large in comparison to the other optimization steps. The other optimization steps are bound by a maximum increase and decrease of 20%. Additionally, if the bound of the minimum frequency of the player is met, the next year will have a bound which is 5% lower. This decrease of the lower bound by 5% are the steps we see in optimization years Y2OP and Y3OP. As the game is not continued after optimization 3 (Y3OP) it cannot be stated that this process will continue, however as the RPKs are much lower than the ASKs it is expected that the model would continue to decrease its frequency and thus ASK. The RPK level is constant due to the fact that all passengers are being transported by the computer player, and no additional demand is available.

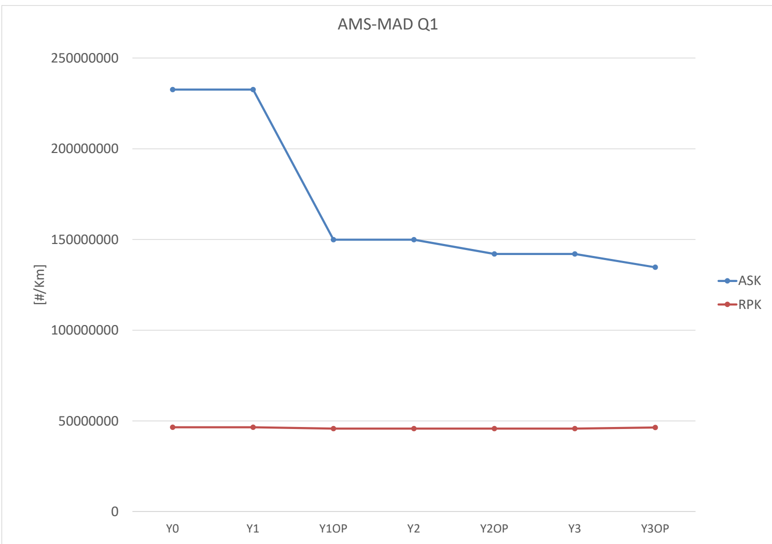


Figure 6.2: Game 0 ASK and RPK Development

Profit Development
In Figure 6.3 the revenue, cost and profit development for game 0 can be found. In line with the ASK's, a drop of cost is expected due to the decreasing frequency. New from this figure is the optimizers effect on the revenue. With a constant RPK, from the previous figure it can be deduced that to increase revenues, the computer will have increased its fares. Skipping ahead to Figure 6.4, you can indeed see this is the case as the yields have increased quite a bit. With the increase in revenue and the decrease in cost, Figure 6.3 does indeed show the computer player to change the losses into a profit.

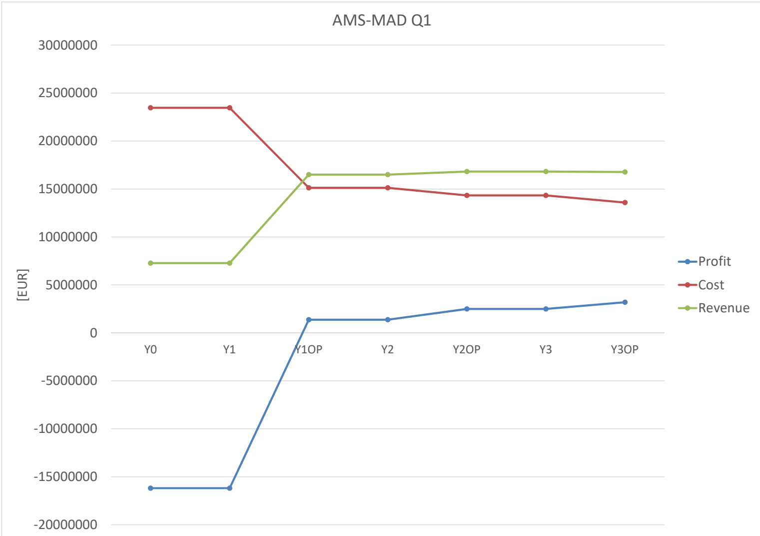


Figure 6.3: Game 0 Revenue, Cost and Profit Development

Game KPIs
In Figure 6.4, the KPIs with respect to RASK, CASK, yield and load factor can be found. These KPIs are in line with the previous two figures. With decreasing frequency and a constant amount of passengers, the load factor increase with each game year. The CASK is constant over the different years, which is due to the fact that the cost per flight is constant as well as the number of seats provided and thus with every flight decrease the decrease in cost and ASKs does not alter the CASK. The RASK shows a clear increase over the different game years. With decreasing ASKs as well as increasing revenues, this is as expected.

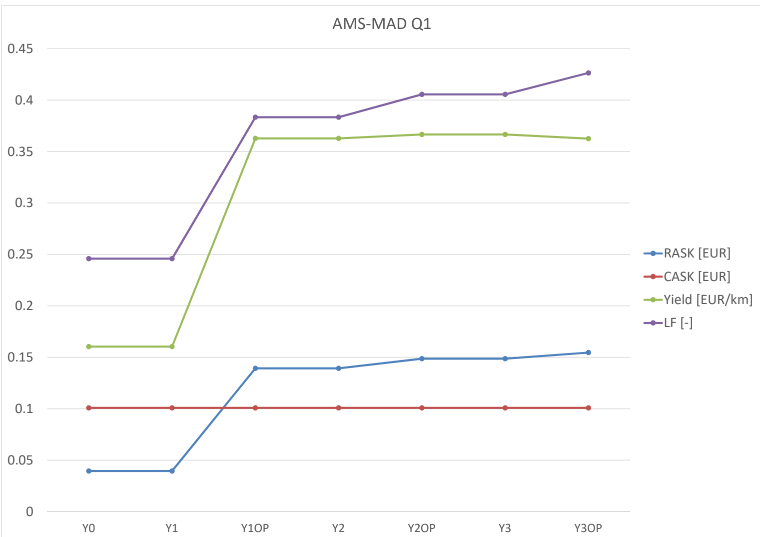


Figure 6.4: Game 0 RASK, CASK, Yield and Load Factor Development

Seat Share Development
In Table 6.4, the development of the seat share in the different cabin classes can be found. This table will only be described here, for the purpose of enlightening the manner in which the optimization model optimizes the seat share in the aircraft. In year 0, the seat share is initiated with assumed seat shares. With each optimization year, the model determines the minimum seat share needed to cater for passengers in each class. As can be seen, the configuration of the aircraft quite quickly settles around certain values. These values however do not add to 100%. The reason for this is that the model indicates the minimum seat share needed, limited of course by a total seat share of 100%. These seat shares thus give an indication for the minimum seats in each class needed to transport the right consistency of passengers.

Table 6.4: Game 0 Seat Share Computer Player Quarter 1

Class	Y0	Y1	Y1OP	Y2	Y2OP	Y3	Y3OP
Discount Economy	40%	40%	25%	25%	27%	27%	28%
Premium Economy	20%	20%	2%	2%	2%	2%	2%
Full Y	20%	20%	1%	1%	2%	2%	2%
First	10%	10%	3%	3%	3%	3%	3%
Business	10%	10%	2%	2%	2%	2%	2%

General Findings Game 0
The game described above, as well as the computer player optimized here has clearly showed the manners in which the optimization model works. It is clear from the game results above, that the computer optimization process improves the computer players profitability. In game 0 this profitability was achieved by decreasing the frequency while increasing the yield levels. However, using the computer player in this form would be unrealistic due to its size and characteristics. The computer player in this form would, in comparison to competitors in real life, be too large and monopolistic. With respect to the model itself, having a player which is the average of all competition combined would not be of use, as the market share calculations by the logit model would be distorted and unreliable. The reason being that due to the size of the computer player in terms of frequency, an unrealistic amount of share would be distributed to the computer player. This is irrespective of its choices to fare in comparison to a player of normal size. Therefore, realistic competition with a 'super' computer would not be possible. This game has thus has proved to test the optimization model in an extreme case, showing the capabilities of the optimization procedure, but from now on the games will be played with a computer player of realistic size.

6.2.2. Simulation Game 1

In game 1, the computer takes on the size of an average competitor in the AMS-MAD market. As in game 0, the demand over the years is kept constant to ensure ease of comparison. The focus of game 1 is similar to that in game 0. The optimization behaviour of the computer will be observed, as well as the effect of the sizing of the computer player. Additionally, this game will serve as a null game, to which games 2 and 3 can be compared. The results of game 1 will include discussions on the ASK and RPK development, the profit development, the game KPIs, a spill analysis and will conclude with the general findings of the game.

Ask & RPK Development
In Figure 6.5, the ASK and RPK development of the computer player can be found. As with game 0, the optimization model first sees it fit to decrease the frequency and thus ASKs. In game 1, a steady state with respect to ASKs is already reached in the optimization of year one, where this was not the case in game 0. This indicates that with respect to size the computer in game 1 is more realistic, as it achieves an ASK level which, with respect to size, is similar to the available RPKs. In game 0, the computer players ASKs after 3 optimization years is still almost three time as large as the RPKs available.

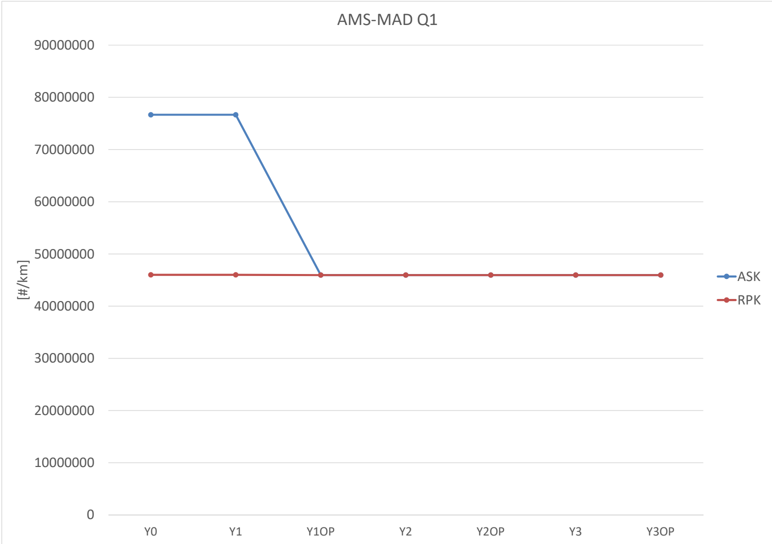


Figure 6.5: Game 1 ASK and RPK Development

Profit Development
In Figure 6.6, the revenue, cost and profit development of the computer in game 1 can be found. In accordance with the decrease of ASKs and thus frequency found previously, the costs of the computer player decrease to the 'optimum' level in the first optimization year. Revenue wise, the computer player sees a quick increase due to an increase in yield to its maximum levels constrained by the yield bounds. This can be deduced from the fact that the RPK levels from the previous figure stay constant, while the yield found in Figure 6.7 show a clear increase. The result of the decreasing cost and increasing revenue lead to a clear increase in profit.

Figure 6.6: Game 1 Revenue, Cost and Profit Development

Game KPIs
In Figure 6.7 the RASK, CASK, yield and load factor are shown. Correspondent to the previously described KPI's, the RASK increase due to optimization is evident. CASK is constant for the same reason as described in game 0. The load factors of the computer show a clear increase, analogous to the decrease in ASKs while having constant RPKs. It is observed that from the optimization of year 1, the computer will fly with a load factor of one.

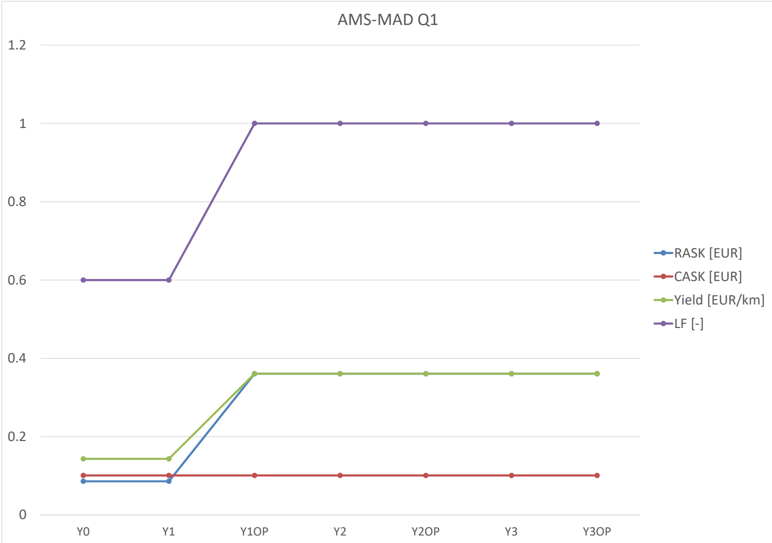


Figure 6.7: Game 1 RASK, CASK, Yield and Load Factor Development

Spill Analysis

In Figure 6.8, the seats available, per flight, per cabin class can be observed. The value of the seats available, per flight, per cabin class are computed using the seats available in the aircraft, per class, per flight, subtracted by the demand for that class, per individual flight. A negative value thus indicates that there is more demand than supply of that class per flight. For game 1, this is only the case for the discount economy class in Y0 and Y1. After the optimization in Y1OP, the computers strategy has been optimized, with as an effect that no spill of passengers is found for the rest of the simulation years.

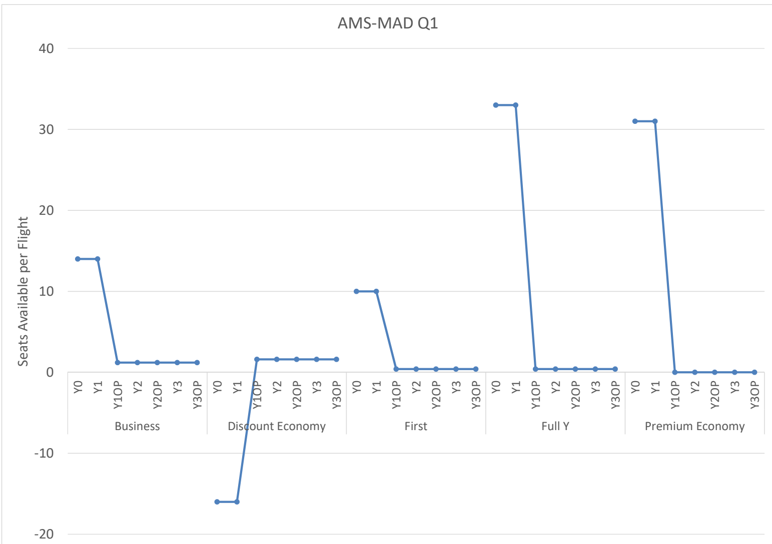


Figure 6.8: Game 1 Seat Availability per Flight Development

General Findings Game 1

As can be deduced from game 1, the computer player described here is a more realistic player type with respect to size in comparison to the computer player from game 0. Competition bias due to the limitations of the simulation framework leading to the outwaying of other competitors with an abnormal frequency is not expected to be the case with this player size. It is therefore recommended to use the computer player in this manner. The computer in this game however did not have any competition and thus was free to determine the price as it wanted. The maximum yields were thus quickly used by the optimization model. This as expected due to the fact that all passengers are expected to fly irrespective of the high pricing. The tendency for high prices can be shown in Table 6.5. It is found that from the first optimization year onwards, all the yield values are at the maximum allowed values.

Table 6.5: Game 1 Yield Development

	Y0	Y1	Y1OP	Y2	Y2OP	Y3	Y3OP
Computer							
Discount Economy	0.12	0.12	0.29	0.29	0.29	0.29	0.29
Premium Economy	0.23	0.23	0.62	0.62	0.62	0.62	0.62
Full Y	0.57	0.57	0.93	0.93	0.93	0.93	0.93
Business	0.76	0.76	1.53	1.53	1.53	1.53	1.53
First	0.09	0.09	0.24	0.24	0.24	0.24	0.24

Below, Figures 6.9 and 6.10 display the yield development per class and the frequency development of the computer player. These will be used as reference points in comparisons with the other games described.

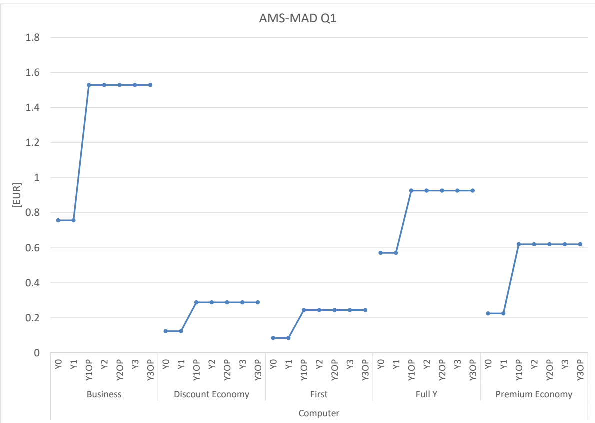


Figure 6.9: *Game 1 Yield Development*

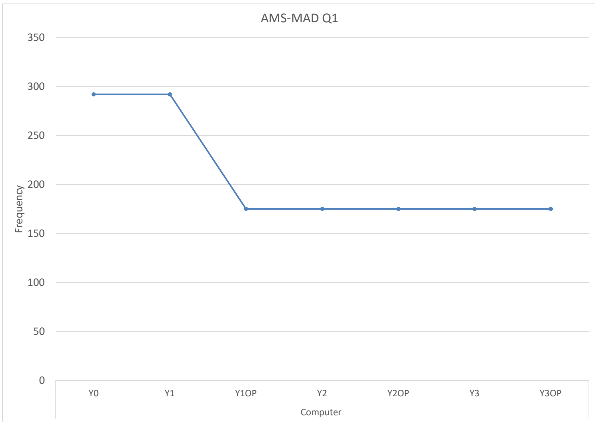


Figure 6.10: *Game 1 Frequency Development*

6.2.3. Simulation Game 2

With the general behaviour of the computer profit optimization observed in the previous two games, the focus will now be on how the computer and the optimization software react to the added competition in the AMS-MAD route. In game 2, the goal is to observe the reaction of the computer player with respect to a competitor resembling a LCC. In this game, the LCC competitor is assumed to fly the route AMS-MAD twice a day, while it decreases its fares by 20 EUR per year. The results of the computer reaction will be described using the observations found from the yield development, the frequency development and the market share development. The discussion on the results of simulation game 2 will be concluded with some additional general game findings.

Yield Development

In Figure 6.11, the yields of both the LCC and the computer player can be found. The decrease in fares per game year of the LCC can clearly be seen in the figure, however it shows that this does not effect the yields of the computer player. Contemplating Table 6.6, this observation is confirmed. The yields of each of the cabin classes are still at the maximum values allowed by the yield bounds.

Table 6.6: Game 2 Yield Development

	Y0	Y1	Y1OP	Y2	Y2OP	Y3	Y3OP
LCC							
Discount Economy		0.12	0.12	0.11	0.11	0.10	0.10
Computer							
Business	0.76	0.76	1.53	1.53	1.53	1.53	1.53
Discount Economy	0.12	0.12	0.29	0.29	0.29	0.29	0.29
First	0.09	0.09	0.24	0.24	0.24	0.24	0.24
Full Y	0.57	0.57	0.93	0.93	0.93	0.93	0.93
Premium Economy	0.23	0.23	0.62	0.62	0.62	0.62	0.62

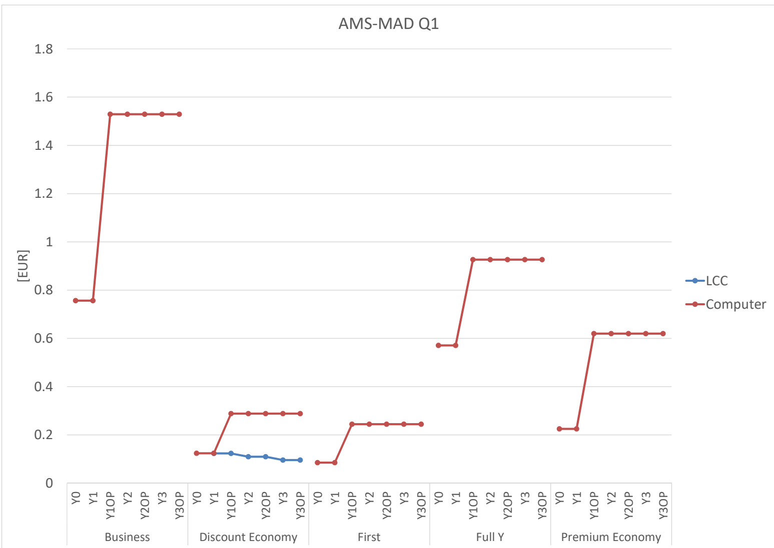


Figure 6.11: Game 2 Yield Comparison

Frequency Development

In comparison to the yield levels, when comparing the flight frequency of game 1 with game 2 a change can be observed. In Figure 6.12, the frequencies of both players in game 2 are shown. What is evident is that the frequency of the computer player has dropped with respect to game 1. Where the frequency of the computer player in game 1 was 175 flights per quarter in simulation run Y3OP, the computer in game 2 only hosts 94 flights in Y3OP per quarter. The computer has thus reacted to the LCC competitor by changing the flight frequency.

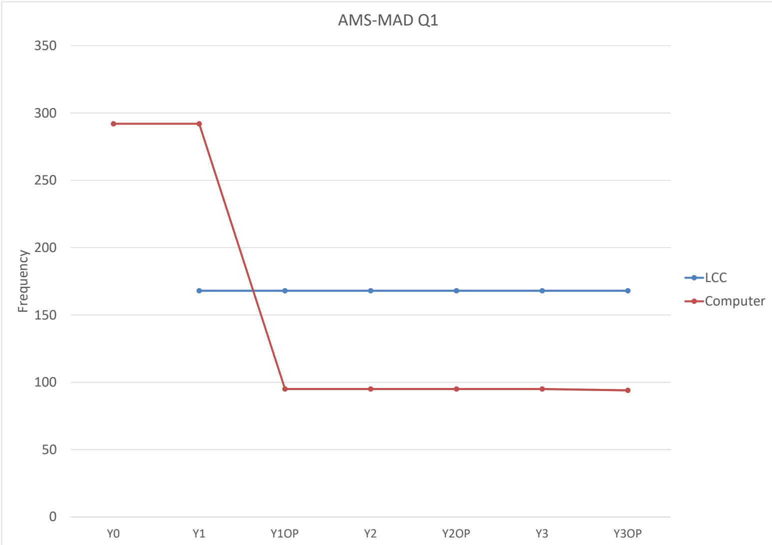


Figure 6.12: Game 2 Frequency Development

Market Share Development

In Figure 6.13, the market share development of the two players in game 2 can be observed. In all classes where the computer player is the sole competitor, the expected market share of one is found. For the cabin class in which competition is experienced from the LCC, the market share is observed to slowly decrease for the computer player. This is as expected when keeping the frequency and yield developments in this game into account. With a near constant frequency for both players after simulation year Y1OP and the decreasing fares of the LCC, while the computer keeps its yield steady, the discount economy passenger demand shifts to the LCC competitor as expected.

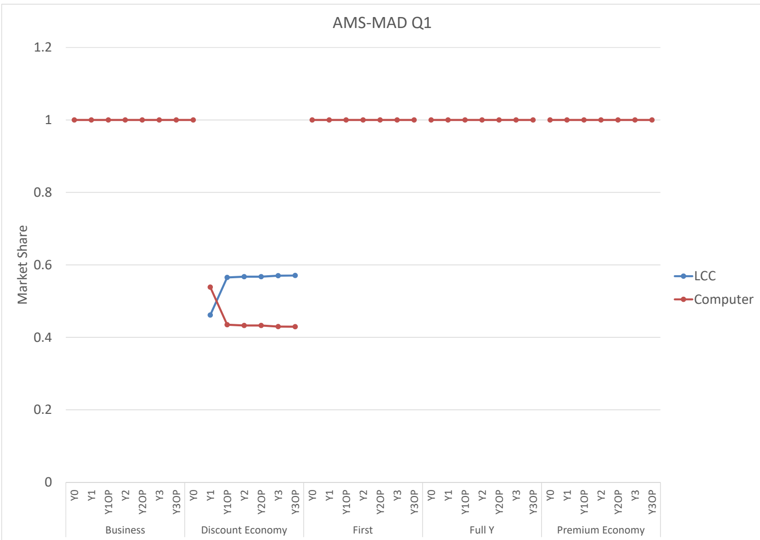


Figure 6.13: Game 2 Market Share Development

General Findings Game 2

In general, it can be concluded that the computer has clearly reacted to the addition of competition to the AMS-MAD market. A clear decrease in frequency was seen with respect to game 1, however no change in yield was found. This is due to the fact that flying less flights will lead to less ASKs to fill, and as this was within frequency limits, this reaction was possible. With the maximum yields in place,

it is observed that the aircraft are still filled and thus no additional reaction is needed to be made with respect to fare. This is confirmed in Figure E.2, where the load factor of the two players can be found. The computer player reaches load factors of approximately 100%, which is similar to the load factors found in game 1.
In Figures E.1, E.2, E.3 and E.4, the revenue, cost, profit, Game KPI's, ASK, RPK, and seat available developments can be found of game 2. For completeness reasons they have been added to the appendix, however the figures are not essential when observing the computer players reaction. It is interesting to note however that the profit maximizing behaviour of the simulation framework for the computer player is again clearly observed.

6.2.4. Simulation Game 3

Game 3 is similar to game 2, only now the competitor for the computer player resembles a legacy carrier offering flights including all cabin classes. Similar to that described in game 2, the focus of this section will be on how the computer reacts to the added competition during the optimization process. The game results will be described using sections on yield development, frequency development, market share development and spill analysis. The final discussion in this section will include additional findings and general conclusions on the game results.

Yield Development
In Figure 6.14, the yields over the different simulation years are compared for both competitors. With exception of the business class yields, all yields remain at their maximum bounded values, seemingly unaffected by the competitor. However, the business class yields have decreased with respect to games 1 and 2. In Table 6.7, it can be observed that the business yield has decreased from its maximum value of 1.53 in the games before, to 1.41. Furthermore, it is observed in Table 6.7 that in simulation Y2OP the yield of the business class is slightly increased. Key to understanding this, is observing that in that optimization year, the available seats per flight for the business class stay equal between the simulation years Y2, Y2OP and Y3 as can be seen in Table 6.17, but the flight frequency decreases with one flight in Y2OP. This decrease in frequency, but level seat availability effectively means their are less seats to fill, thus increasing the price slightly will decrease the demand in such a way that the seat availability per flight stays constant. In the year following, the Legacy carrier again lowers its fares. The computer reacts to this in Y3OP not by changing its frequency, but by decreasing the yield of the business class. These findings show that the simulation framework does react with respect to fare if needed.

Table 6.7: Game 3 Yield Development

	Y0	Y1	Y1OP	Y2	Y2OP	Y3	Y3OP
Legacy							
Business		0.75	0.75	0.74	0.74	0.73	0.73
Discount Economy		0.12	0.12	0.11	0.11	0.10	0.10
First		0.09	0.09	0.07	0.07	0.06	0.06
Full Y		0.57	0.57	0.56	0.56	0.54	0.54
Premium Economy		0.22	0.22	0.21	0.21	0.20	0.20
Computer							
Business	0.76	0.76	1.42	1.42	1.44	1.44	1.41
Discount Economy	0.12	0.12	0.29	0.29	0.29	0.29	0.29
First	0.09	0.09	0.24	0.24	0.24	0.24	0.24
Full Y	0.57	0.57	0.93	0.93	0.93	0.93	0.93
Premium Economy	0.23	0.23	0.62	0.62	0.62	0.62	0.62

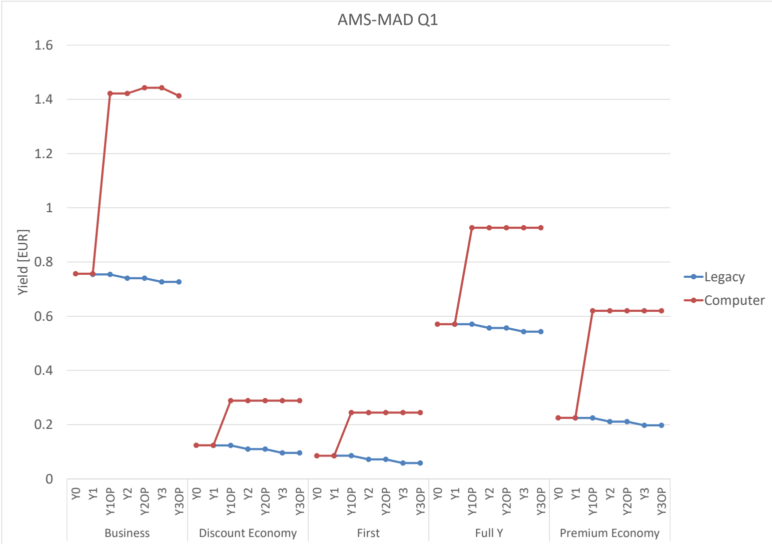


Figure 6.14: Game 3 Yield Comparison

Frequency Development
In Figure 6.15, the flight frequency development of game 3 can be observed. The frequency of the computer player after the first optimization year can be seen to be rather steady, with a minimal decrease of frequency of one flight in the second optimization year. When comparing the flight frequency of the computer in game year 3 to that of game year 1, a reaction by the computer player can be observed. Here the frequency has decreased from 175 flights per quarter for a route with no competitors, to 73 flights in game 3 with the legacy carrier. In comparison, in game 2 where an LCC was the competitor, the flight frequency was found to be 94 flights in Y3OP. It seems that the increased competition on the computer player has a severe effect on the number of flights it is optimized to provide.

Using Figure E.6, it can be further observed that as in games 1 and 2, the load factor of the computer player in game 3 remains at approximately 100%.

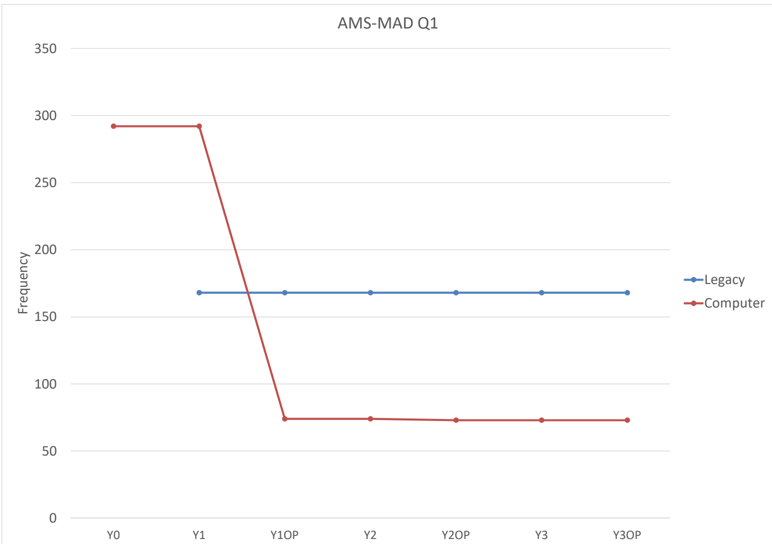


Figure 6.15: Game 3 Frequency Comparison

Market Share Development
Figure 6.16, displays the market share development in game 3. Clear is the difference between the market share developments of the business class in comparison to the other cabin classes. After the initial change in frequency found in Y1OP, no large changes are found in the computer's strategy for the

non-business classes. With the constant decrease of the legacy carriers prices over the different classes that follows, the slight increase in market share for the legacy carrier after each simulation year can be seen. For the business class, the market share development is slightly different. Here the change in frequency and the changes in yield display the battle for market share over the simulation years. Evident is the decrease in yield of the computer's business class in Y3OP, which increases the market share strongly.

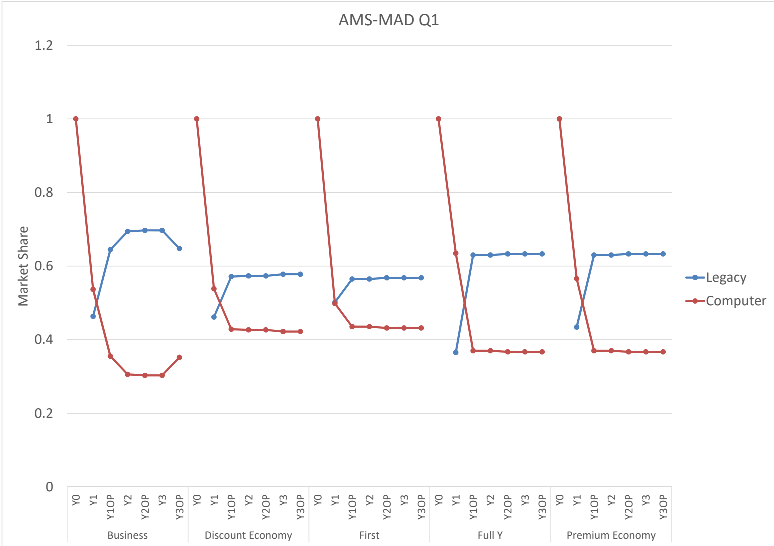


Figure 6.16: Game 3 Market Share Development

Spill Analysis

Figure 6.17 displays the seat availability per class, per flight and per competitor for the different simulation years. In this game, an interesting observation is made. As can be seen in the discount economy class, there is a negative value for the seat available per flight for the legacy carrier. This indicates that in this game, from Y1OP onwards, a demand spill is found for discount economy passengers. As the simulation framework does not consider a spill and recapture model and passengers are not allowed to switch to other cabin classes, these passengers are lost. It is interesting to see that the computer player in this situation does not capture this opportunity. This indicates that adding frequency and decreasing the fares would not lead to higher profits, thus the computer does not act on this.

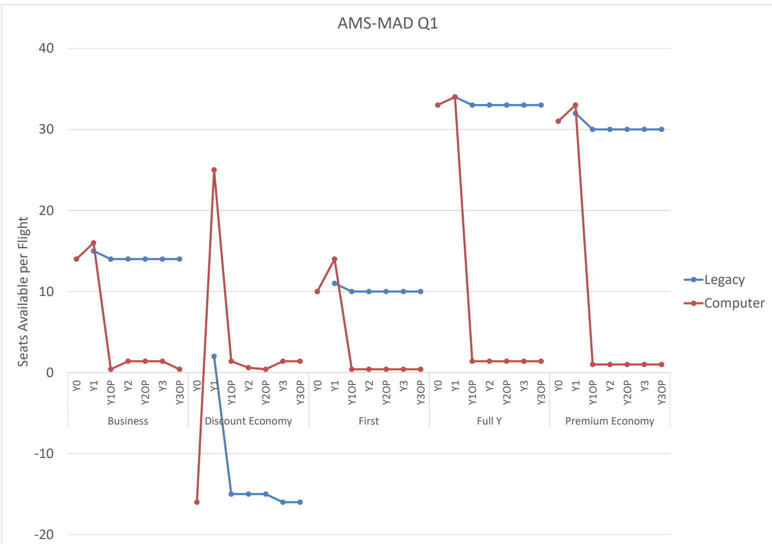


Figure 6.17: Game 3 Seat Availability per Flight Development

General Findings Game 3
Game 3 portrayed a number of extra behavioral aspects of the computers reaction to competition. The competition felt from the legacy carrier was found to be more substantial than that of the LCC, leading to a further decrease in flight frequency. Game 3 further showed that the optimization process also has an effect on the yield but it seems that this only occurs if frequency changes are no longer possible to increase profitability. Another interesting find was the fact that the computer player spills demand if that demand does not increase it's profitability.
In Section E, the ASK, RPK, game KPI's, revenue, cost and profit development can be found for of game 3. For completeness reasons they have been added to the appendix, however are not essential when observing the computer players reaction.

6.2.5. Simulation Game 4

In the final game, multiple routes have been simulated to determine the computer reaction when it has to optimize for different routes at the same time. Additionally, it is a chance to observe the workings of the integrated simulation framework as a whole, in a multi-route environment. As described in Section 6.1.5, the game has been played twice. First in a situation where all exogenous players keep there strategies constant, the so called null game, and second with changing strategies. The figures for the null game can be found in Appendix E, but will be referred to when appropriate. In the following section, the findings of game 4 will be discussed. This will be done according to the results on yield development, frequency development, market share development and profit development. The section will conclude with the general findings from simulation game 4.

Yield Development
In Figure 6.18, the yield development of game 4 for the route AMS-LHR can be found. As represented by the blue lines, it can be seen that the fares of British Airways are decreasing with each simulation year. The computer reaction to the competition can be observed from Y2OP onwards in the business class. The computer clearly decreases its yield with each optimization year as a reaction to the price decrease of BA. With respect to the other cabin classes, no reaction is found in the yield levels and thus they maintain the maximum values as constrained by the simulation model. These yield levels are identical to those found in the null game, as can be seen in Figure E.10. In the Copenhagen route, where enhanced competition was also experienced by the computer, no changes to the yield levels were found as can be seen in Figures E.8. The yield values for the AMS-CPH route were thus found to be equal to those in the null game found in Figure E.9. The Madrid route, with it's static competition, was also not affected in any way in terms of yield.

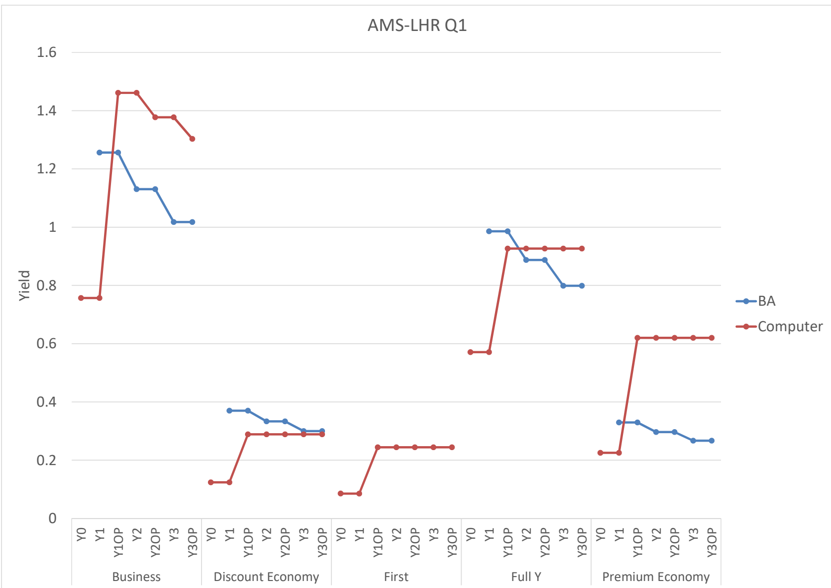


Figure 6.18: Game 4 Yield Development AMS-LHR

Frequency Development
In Figure 6.19, the frequency development of game 4 can be observed. A clear reaction can be found when comparing the AMS-LHR market between the shown game and the null game found in Figure E.13. With the increasing frequency of BA, the computer reacts by decreasing its flight frequency. This reaction is less profound in the AMS-CPH route, where the decrease in frequency between this game and the null game is only one flight in the final optimization year. In the route to Madrid, no difference in flight frequency can be observed.
Linking the observations made here to the figures showing the load factors of the different players found in Figure E.20, an interesting observation can be made. The reaction with respect to frequency, directly influences the load factors of the different players. It can be seen that the computer player reacts most strongly, the further it is removed from the maximum load factor of one. The decrease in frequency of the computer player in the AMS-LHR route after each optimization year, shows the computers behaviour in trying to achieve the highest load factor possible. The reaction in the CPH route is less profound, as the load factor over the different simulation years is always close to 100%, thus no large reaction is needed.

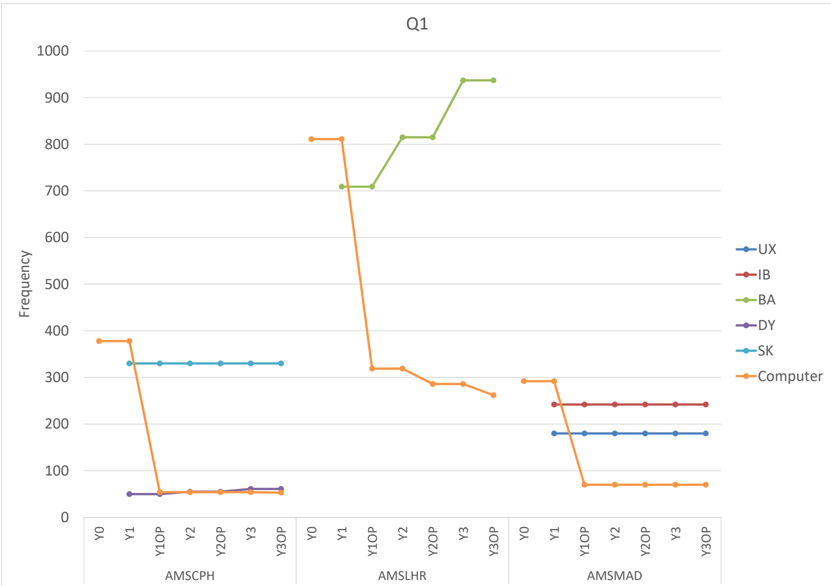


Figure 6.19: Game 4 Frequency Development

Market Share Development
In Figure 6.20, the market share development for the AMS-LHR can be found. Comparing this figure to the one describing the null game in Figure E.16, the improvement of market share of BA can be observed. This is as expected, as BA is constantly decrease its fares while increasing the frequency, making the BA flight options increasingly attractive for passengers. The computer on the other hand is decreasing its frequency while keeping the yields high, decreasing the attractiveness and thus negatively affecting the market share. In the first class, no competition can be found and thus the computers market share here is one. The market shares for the competitors in the CPH route, are found in Figure E.14. The competition in this market seems to have the strongest effect on the other exogenous competitor, as hardly any difference with respect to market share is found for the compute player. As in the previous results, no changes in the market share of the Madrid route have been observed.
The results described above, clearly show the underlying models workings with respect to allocating demand over the different flight options. However, it also shows that the computer player does not focus on maintaining or improving its market share.

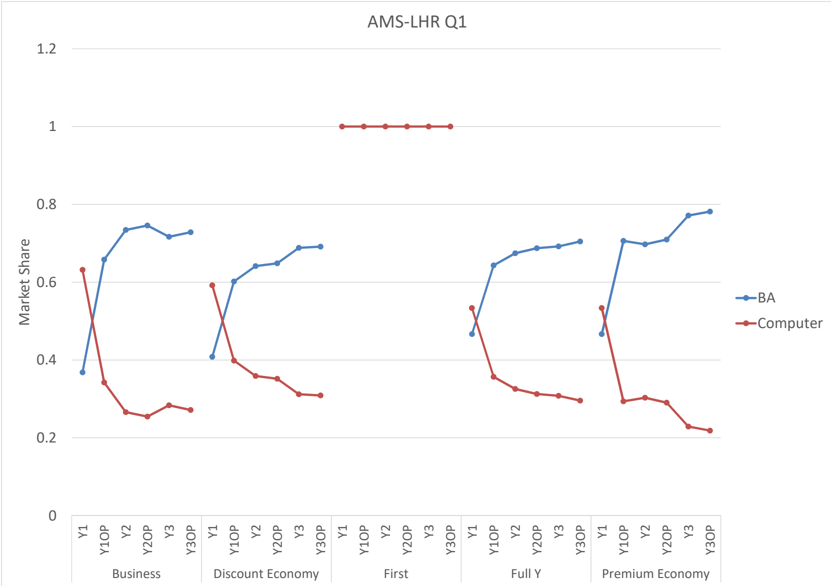


Figure 6.20: Game 4 Market Share Development AMS-LHR

Profit Development

Figure 6.21 portrays the profit development of game 4 in the first quarter for the different games. The profit optimization procedure is especially apparent in the AMS-LHR route, where after each optimization year, the simulation framework clearly improves the profitability of the computer player. In the CPH route, the profit optimization is less visible, as it is only slight. When comparing the game with competition to the null game in Figure E.19, it can further be observed that the change in profit is most apparent in the LHR route. Here the profit of the computer player has reduced most drastically, indicating that the competition is affecting the computer here strongly. As expected after the previous analyses, no changes were found in the AMS-MAD market.

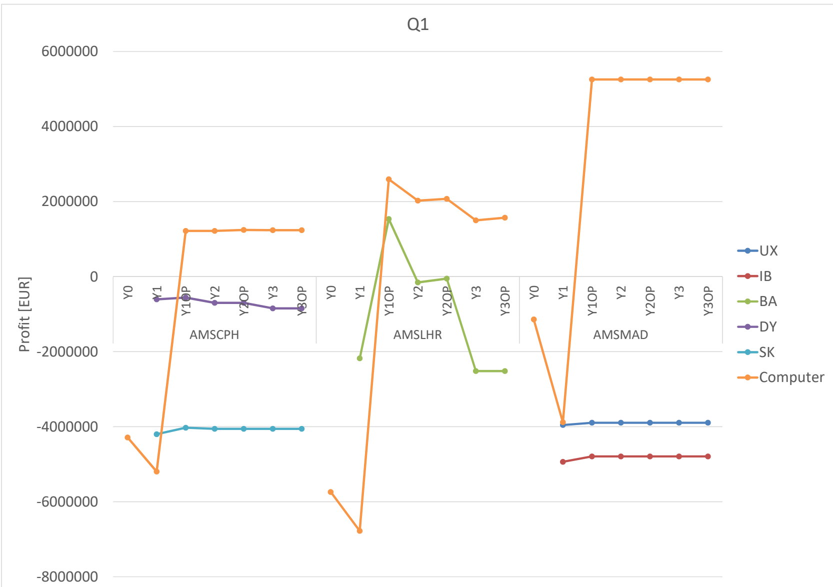


Figure 6.21: Game 4 Profit Development

General Findings Game 4

In game 4, a number of characteristics of the simulation framework have become clear. Even though the game was played in a network including three routes, including two of which experienced increased competition, no shifts were found to the third market which did not experience enhanced competition.

This was observed due to the fact that no difference could be found between the results in the Madrid route between the null game and the game with competition. Another observation was done that confirmed observations from previous games, namely that the computer's reaction is based on first changing the frequency and only if this is not possible, changing the yield level. The tendency relates to the computer trying to keep the load factors as high as possible, with the highest possible fares. Other than that, the simulation framework proved to generate and allocate demand in a multi-route environment as expected.
For completeness reasons the figures not discussed with respect to the null game and other routes have been added to the appendix. They are however not essential when observing the computer players reaction in this game.

6.2.6. Conclusions Simulation Framework Game Results

In Section 6.2, the results of different games played with the integrated simulation framework have been described. These games have been played to determine in what manner the computer player reacts to the market and competition it is placed in. In this section, the general conclusions of the different games will be described. Furthermore, a comparison to results gathered by previous research found in literature will be described.

Game Conclusions
In general, the following conclusions can be made from the different games which have been played:

- The simulation framework and its underlying models produce the expected results with respect to the inputs and constraints they are given.
- The process of profit optimization for the computer players works well, in all games played the computer player increases its profit when comparing the initiation year and the final year of simulation.
- The tendency of the computers reaction is to find a strategy, which has an as high as possible load factor, while supplying an as low as possible frequency with the highest yield levels possible. From a profit maximization reasoning, this manner of operation is understandable.
- In the presence of spill in a market, the computer player will only act if it could improve its profitability. If the passengers it could transport would not lead to higher profits, these passengers will not be catered for.
- From a multi-route perspective, stiff competition does not lead to a shift in focus by the computer player to other routes. This could be simulated by implementing an extra constraint, which implies a minimum frequency over all routes. This however should be further tested.

Comparison of Results to Literature
In the research done by Zito et al. (2011), the conclusion was made that in markets where a monopoly exists, the total amount of service frequency is lower, fares are higher and profits are higher than in a market with competition. In this thesis, similar results are found with respect to the profit and frequency. In comparison to game 1, where the computer was flying in a monopolistic market with 175 flights a quarter, games 2 and 3, which included competition, had a frequency of 262 and 241 per quarter respectively. The fares of the computer player were however more or less equal. This is an interesting find, as it seems that in the simulations done by Zito et al. (2011) the competitors were found to compete. In this thesis, the computer is in search of the highest possible profit for itself and is thus not necessarily competing with the other competitors. This may change if different bounds were set to the computer. This could for example be done by setting a minimum market share for the computer.

The research conducted by Wei and Hansen (2007) was slightly different from the competitor reaction model found in this thesis as its decision variables included the aircraft size and the frequency. However, their model resulted in a situation where competitors would fly smaller aircrafts at higher frequencies to attract more passengers. According to Hansen and Liu (2015), this is similar to what is found in reality. In this thesis, the computers reaction, is centered around the change in frequency to ensure high load factors. Therefore, increasing the frequency would need to lead to a similar load factor or it would not happen. To make the computers reaction more realistic, the results of Wei and Hansen (2007) should be taken into account in the future. It is hypothesized that a similar computer reaction could be found if the aircraft size would be added to the optimization model as a decision variable.

In the research by Ko (2016), it was mentioned that it would be desirable to change the objective function of the model to strive for different goals. With respect to the optimization strategy of the computer player in this thesis, it might be interesting to considered optimizing for other strategies than just profit such as market share. This could change the reaction of the computer player significantly, and might lead to more realistic or desirable reactions in a market.

7

Verification and Validation

In the following chapter, the verification and validation process will be described. Additionally a sensitivity analysis will be discussed for the demand allocation and competitor reaction models.

The verification process will describe if the simulation framework and its sub-models comply with the requirements set at the start of this thesis. For some of the requirements a validation process is possible, where the results from various sub-models will be tested against reality. Sensitivity analyses will be included to determine how different independent variables included in the different sub-models effect the applicable dependent variable.

The chapter will start-off with the verification of the simulation framework as a whole. This will be followed by a discussion on the sub-models of the simulation framework separately. The chapter will be concluded with the general findings done during the verification and validation process.

7.1. Simulation Framework

In the coming section, the general requirements set ot the simulation framework will be discussed. For these requirements, verification processes will be used to determine if the requirements have been met. The requirements to be verified here can be found below:

- **Verification** - Combining a demand generation, demand allocation and market competition model into a simulation framework
- **Verification** - The simulation framework should allow for exogenous players to compete in the different markets

Combining to Create Simulation Framework To achieve being able to simulate competition and passenger choice for an airline in the aviation market, it was determined that for this simulation framework a demand generation, demand allocation and market competition model were to be combined. In this thesis the combination of these different sub-models was successful and a simulation framework has been developed including the separate elements. The separate sub-models are combined in the manner described in Section 4.1.1, while each sub-model have the following key characteristics:

- The demand generation model is based on a gravity model, capable of generating demand between the specified city-pairs for the different classes implemented in the simulation framework. The output of this sub-model is an input for the demand allocation and competitor reaction models.
- The demand allocation model simulates passengers choice and consists of a multinomial logit model. Here, the different flight options provided in the simulation framework are assigned a computed market share, which their flight option will attract based on its characteristics.
- The market competition model is centralized around the competitor reaction model, which is based on a profit optimization of the computer player in the simulation model. This computer player reacts

to the competition in each route and optimizes its strategy with respect to profit maximization. Furthermore, the market competition between players is simulated by the demand allocation model, where the demand for different flight options are predicted.

Exogenous Players The inclusion of exogenous players in the simulation framework has been implemented as an option which can be used in each simulation game year. The exogenous players are able to determine their strategies and input this into the model. The strategies consists of choices on fare, frequency, aircraft size and seat shares per class. These inputs are then taken into account in the demand allocation process as well as the competitor reaction model. The simulation framework is thus applicable to be used by several players at once, according to which the simulation will then be run.

7.2. Sub-Model: Demand Generation

In the following section, the verification and validation process of the demand generation model will be discussed. The sections starts with a discussion on the verification process which is followed by the validation process. In the validation process, demand is generated for routes which have not been calibrated for, to determine the demand generations model performance.

Below, a short recap on the requirements which had to be met for the demand generation model are found as in which section the will be treated:

- **Verification** - The independent variable signs used in the gravity model are as expected.
- **Verification** - The magnitude of demand is similar to actual demand values, as is a similar distribution between classes with respect to actual demand splits
- **Validation** - The model is generalizable to routes with similar characteristics, for which have not been calibrated

7.2.1. Verification

In the verification of the demand generation model, it is of interest to determine if the demand generation model complies to the requirements set during the project proposal. As described above, the requirements to verify are on if the independent variable signs are as expected and if the magnitude and split are similar to those found in the actual aviation markets.

Independent Variable Signs Described in Section 5.2.2, all coefficients for the different independent variables used in the gravity model were found to be as expected.

Demand Magnitude & Splits In general it can be concluded from Section 5.2 that, as the majority of demand comprises of discount economy passengers and the sub-models performance of this class is best, the magnitude of the demand generated for each OD-pair is found to reflect reality. Specifying to the demand splits over the different classes, it can be said that the demand split is available however the accuracy differs per route.

7.2.2. Validation

As described previously, one of the requirements set in the research plan was to make the demand generation model generalizable with respect to routes with similar characteristics. To validate if this is possible, a number of routes were kept for validation purposes, as described in Section 5.1. The figures and table with descriptives of the performance of the demand generation model for these routes can be found in Appendix C. In this section, the main findings will be described with references to the appropriate table and figures when necessary. The section will conclude with the main conclusions with respect to the validation process.

Main Observations Gravity Model Performance Plots The gravity models performance with respect to the FRA-MAD route in both directions can be found in Figures C.22 and C.24. Here it can clearly be observed that the discount economy class is over predicted by the gravity model used in the demand generation model. The LHR-CPH routes in both directions however experience the exact opposite. As can be seen in Figures C.23 and C.26, the demand generation model is under estimating the demand of the discount economy class between the two routes. These over and underestimations are considered severe, as they are approximately twice or half of the actual values for the respective markets. The routes which have the best performance, with respect to performance of estimating the discount economy class include FRA-CPH and CPH-FRA. As can be seen in Figures C.25 and C.27, there is a slight over prediction of the discount economy class, but it is less severe than seen in the other routes. When contemplating Table C.34, the above observations are confirmed. The routes with the best performance with respect discount economy class are indeed those between the airports of Copenhagen and Frankfurt.

Figures C.32, C.30, C.31, C.29 and C.28 described the performance of the gravity model for the validation routes with respect to the different classes in the model. In general, it can be noted that the business class and premium economy class are under predicted. The first class is in general over predicted, while the discount economy and full economy cabin class do not have a general over or under prediction.

Main Observations Gravity Model Performance Validation Table In Table C.34, the performance of the gravity model used in the demand generation model for the validation routes can be found per cabin class. Apparent is the fact that the discount economy class and premium economy class have the best performance irrespective of the route in comparison to the other classes. This performance, as mentioned before, is derived from the value of the percentual value of the standard error with respect to the average demand. These values are lowest for the discount economy and premium economy classes. The worst performing class is the first class, which have large relative standard errors.

When comparing the validation routes to the calibration routes in Table C.22, a consideration can be made on the quality of the estimation of the validated routes. The estimates of the discount and premium economy class for the validated routes may, in general, be considered acceptable however, the other classes are in general unreliable. A threshold to determine from when an standard error is unacceptable is difficult to set. However, it is clear that when a standard error is more than 100% of the average demand value, the estimated demand no longer reflects reality.

General Conclusions In the previous section, the validation process of the demand generation model was discussed. As known by the reader, the validation is centered around the gravity models performance when used on routes it was not calibrated for. The general validation conclusions that can be made are the following:

- The discount and premium economy cabin classes of the validation routes are considered to be sufficiently accurate for the integrated simulation games purposes. The other classes can be used, but cannot be confidently considered as accurately reflecting reality.
- In general, the gravity model used for demand generation is not confidently generalizable for different routes with similar characteristics as those calibrated with. Recommendations on how this the calibration can be improved to make the model generalizable will be discussed in Section 8.4.

7.3. Sub-Model: Demand Allocation

For the demand allocation model, a description will be found on the process of verification and validation to determine if the model complies with the set requirements and to observe if the model reflects reality. Additionally, a sensitivity analysis of the model will describe the effect of changing the values of different independent variables and how this impacts the dependent variable, in this case the passenger choice.

For the verification and validation processes, the initially set requirements as well as in which section they are discussed can be found below:

- **Verification** - The independent variable signs used in the demand allocation model are as expected

- **Verification** - The choice distributions predicted by the demand allocation model are similar to those found with respect to actual data
- **Validation** - The demand allocation model is generalizable to routes with similar characteristics which have not been used to calibrated the model

7.3.1. Verification

For the verification of the demand allocation model, two requirements are tested to ensure they have been met in the design of the integrated simulation framework. The requirements to be verified include those describing the signs of the independent variables, as well as the similarity in choice distributions between the predicted and actual data. The verification process is described below.

Independent Variable Signs As thoroughly described in Section 5.3.2, all coefficients of the independent variables included in the demand generation model were of the expected sign and thus this requirement was easily verified.

Similar Choice Distributions For the verification of the choice distribution requirement, the analysis found in Section 5.3.2 is of use. Here it was found that on average the values predicted by the demand allocation model were similar to those found in the actual data. It was however noted that some under prediction was expected in the premium economy and first classes. Yet in general the predicted choice distributions of the demand allocation model can be found to be representative for the actual aviation market.

7.3.2. Validation

As with the validation of the demand generation model, the demand allocation model is validated with respect to the validation routes to determine if it is generalizable for routes with similar characteristics. In similar fashion to the demand generation validation, this section will hold a discussion on the main conclusions coming from the validation process with respect to the applicable plots and tables describing the models performance. The section will end with the main validation conclusions for the demand allocation model. The plots and tables used in this discussion can be found in Appendix D and will be referred to when necessary.

Main Observations MNL Performance Plots As seen in Section 5.3.2, the premium economy and first class flight options are underestimated. This can clearly be seen in Figures D.19 and D.20, which depict the demand allocation shares in the routes between Madrid and Frankfurt. As said previously, this behaviour was also observed in the calibration route set and is thus not surprising. In Figures D.21 and D.22, the demand allocation performance for the routes between Frankfurt and Copenhagen can be found. Of the validation routes tested, it is observed that these routes have the worst performance. This is especially visible from the actual-vs-predicted shares plot, where the discount economy shares follow a different trend than that of the actual-vs-actual data points. Examining Table D.3 this observation is confirmed, the routes between Frankfurt and Copenhagen are indeed the worst performing. In general however, it can be deduced from the performance plots that the demand allocation model resembles the actual demand splits represent the shares with respect to size and magnitude.

Main Observations Gravity Model Performance Validation Table In respect of the performance of the different cabin classes in the validation routes, it can be observed from Table D.2 that the discount economy class performs best. Comparing the results to the calibration routes found in Table 5.23, the errors are comparable to those found in the validation routes. The first class does perform worse, while the premium economy class performs slightly better than in the calibration routes.

Looking at the the performance results per route as described in Table D.3, the validation routes do not stand-out in comparison to those found in Table 5.24 which describe the calibration route performances. The errors are quite similar in both performances tests.

The final table to be contemplated describes the performance of the demand allocation model with respect to each validation route per class and can be found in Table D.4. Confirming previous observations, the discount economy class is observed to have the best performance. In general, when comparing the performance results to that of the calibration routes found in Table D.1, it can be concluded that the demand allocation model can be used with the same level of confidence as for the routes with which the model was calibrated. It should however be noted that the performance for flight options of data entries with low data counts show high signs of error, and can not deliver estimations which are representable for real life situations. In the validation performance results this is especially the case for a number of first class flight options.

General Conclusions Above, the performance of the demand allocation model has been discussed with respect to the validation routes. It can be concluded that the results found for the validation routes were similar to those found in the calibration routes. The demand allocation model can thus be considered to be generalizable for routes with similar characteristics with the same level of confidence as for the calibrated routes.

7.3.3. Sensitivity Analysis

In the sensitivity analysis done for the demand allocation model, the MNL models sensitivity has been tested to the different independent variables included. The sensitivity analysis consisted of developing a base situation, from which the change in market share due to the changed input of the independent variable was computed.
The base market share was based on the route AMS-MAD, which has been used in the development of multiple games played in this thesis. For the base market share calculations, the average frequency and average yields per class were used as inputs as well as an extra distance of zero.
To test the models sensitivity, the minimum and maximum values of each independent variable were used to calculate the percentual difference in market share. To stay in line with the rest of the thesis, the yield minimums and maximums were based on the average yield value, plus or minus twice the standard deviation. Furthermore, as the data set for the route AMS-MAD did not contain connecting flights, a maximum extra distance was included which was based on the extra distance that would have been flown if a stopover would be made in London. The inputs for the sensitivity analysis have been summarized in Table 7.1.

Table 7.1: Demand Allocation Model Sensitivity Analysis Inputs

Descriptive	Variable	Max.	Min.	Avg.
AMS-MAD	Frequency	1137	571	886
AMS-MAD	Extra distance	156	0	0
Discount Economy	Yield	0.29	0.00	0.12
Premium Economy	Yield	0.62	0.00	0.23
Full Y	Yield	0.93	0.22	0.57
Business	Yield	1.53	0.00	0.76
First	Yield	0.24	0.00	0.09

The results of the sensitivity analysis can be found in Table 7.2. The sensitivity analysis has been computed per cabin class thus the sensitivity for each separate class can be examined. In general, the effect on the market share of each independent variable has the expected sign. The easiest independent variables to compare are the frequency and extra distance as these vary in a constant manner for the different classes. The market share with respect to the frequency of a flight is found to be less sensitive in the discount economy class in comparison to the more expensive classes. This same observation is done when looking at the effect of the extra distance on the market share. It is hypothesized that this is due to the fact that in more expensive classes, passengers will increasingly consist of business passengers who become increasingly time-sensitive, as described in the research by Carrier (2008). Additionally, as expected from the variable impact results found in Section 5.3.2, the extra distances has a stronger effect on the market share of a flight option than the frequency does.

For the sensitivity of the market share for the yields on the market share, it can be observed that the percentual effect varies greatly over the different classes. This is due to the fact that the ranges for which the sensitivity analysis is done differs per class, as can be seen in Table 7.1. It is therefore difficult to directly compare the different cabin classes in the manner that was done for the other two independent variables. The signs are however portray typical effects.

Table 7.2: Demand Allocation Model Sensitivity Analysis

Sensitivity Analysis						
Variable	Setting	Change in MS Disc.	Change in MS Prem. E.	Change in MS Full Y	Change in MS Bus.	Change in MS First
Frequency	Min.	-23.2%	-30.9%	-31.1%	-31.2%	-30.0%
	Max.	20.6%	33.8%	34.3%	34.4%	31.9%
Yield	Min.	8.4%	24.6%	42.1%	110.5%	8.3%
	Max.	-10.6%	-32.3%	-29.9%	-53.9%	-14.0%
Extra Distance	Min.	0.0%	0.0%	0.0%	0.0%	0.0%
	Max.	-57.4%	-66.6%	-66.9%	-66.9%	-65.7%

7.4. Sub-Model: Competitor Reaction

In the coming section, the verification process of the competitor reaction model will be discussed. This model will not have a discussion on validation procedures as the model actual data with respect to competitor reaction is unavailable. This section will however contain a sensitivity analysis of the competitor reaction model, focused on changing the constraints for multiple independent variables included in the model.

In similar form as done for the previous models, below the requirements for the competitor reaction model are found. These requirements will all be verified in the upcoming thesis section.

- **Verification** - The behaviour of the computer player is as set in the defined strategy
- **Verification** - The computer is able to react to the changes made by other competitors in the market

7.4.1. Verification

The verification of requirements ensures that the requirements set for the model are met by the design of the model. For the competitor reaction model, these requirements include that the behaviour of the computer reflects the strategy that it was set as well as that the computer player is able to react to competition it experiences. The verification process of these two requirements is discussed below.

Computer Behaviour as Specified As explained in the methodology section of this thesis, which can be found in Section 4.4, the competitor reaction for the computer was based on the computer optimizing its profit over the different routes. As observed in the results of all the different simulation games played in this thesis, as found in Section 6.2, this optimization behaviour was clearly observed. The computer player's profit was found to improve after each optimization game year, with the exception if the computer had already found a steady-state and no further optimization was possible.

Computer Reaction Capabilities The requirement of the computer being able to react to competition changes, was inherently implemented within the competitor reaction model. The computer takes the strategies of the competitors into account when optimizing its own strategy for profit.

In the games played in Sections 6.1.3, 6.1.4 and 6.1.5 competitors challenged the computer in different manners. It was clear from these games that the computer changed its strategy as a reaction to these competitors. The main reaction was found to be with respect to the flight frequency. Yield reactions were also observed but these were implemented less frequently. The computers reactions observed, were all within the specific route it was playing in. A strategy of deferring to different routes if competition in one of the routes was increased was not found with the current set-up. It is hypothesized that with additional constraints this could be implemented. More on these additions can be found in the Section 8.4.

7.4.2. Sensitivity Analysis

The sensitivity analysis designed to test the competitor reaction model is based on the decision variables included in the model, with the focus on their upper and lower bounds. The upper and lower bounds are set to ensure the computer player optimizes its strategy within certain limits, leading to a strategy which represents realistic competition.

For the sensitivity analysis, game 2 is denoted as the null game to enable a basis for comparison. This game was set on the AMS-MAD route and consisted of the competition between a player representing a LCC and the computer player. In total, three different sensitivity analysis have been done. The results of the sensitivity analysis can be found in Table 7.3. The sensitivity analysis games have been defined below:

- Sensitivity Analysis Yield
  - The standard yield bounds are derived from Table 5.5, where the upper and lower bounds for each class were the average yield, plus or minus twice the standard deviation of the yield. For the sensitivity analysis, the standard deviations of the yield have been set to 5.0, which severely broadens the yield ranges. A minimum of 0.00 was always ensured for the different yields to guarantee that negative yields were not a strategy option. Frequency bounds were as normal.
- Sensitivity Analysis Frequency
  - The standard frequency bounds for the AMS-MAD route can be found in Table 5.4. For the sensitivity analysis, the minimum and maximum bounds were changed to a minimum of one flight and a maximum of 10.000 flights per month. Yield bounds were as normal.
- Sensitivity Analysis Yield and Frequency
  - In the final sensitivity analysis, both yield and frequency bounds were let go and the above mentioned changes were implemented. This sensitivity analysis gives the computer a large amount of freedom to determine its strategy in the optimization process.

Table 7.3: Sensitivity Analysis Comparisons

Sensitivity Game	Freq. [Month]	Yield Disc.	Yield PremE	Yield FullY	Yield Bus	Yield First	Profit [EUR]	Load Factor
Null	94	0.29	0.62	0.93	1.53	0.24	3.96E+07	0.99
Yield	62	1.29	10.23	10.57	10.76	10.09	4.82E+08	1
Frequency	94	0.29	0.62	0.93	1.53	0.24	3.96E+07	0.99
Both	62	1.29	10.23	10.57	10.76	10.09	4.82E+08	1

The results of the sensitivity analyses can be found in 7.3. The main findings are described below:

- Sensitivity Analysis Yield
  - The computer player is found to increase its yields to the highest possible values for the cabins in which it does not experience competition. A logical consequence as the passengers will fly irrespective of the unrealistically high yields.
  - The discount economy class also experiences a larger yield than in the null game, however this is much lower than the maximum value it could achieve. This is due to the fact that it has competition in this cabin class and thus must keep a yield level for which passengers will want to fly with the computers flight option while having a frequency of 62 flights.
- Sensitivity Analysis Frequency
  - Interestingly, the broadening of the frequency strategy space has not lead to a change in strategy with respect to the null game. The yield bounds thus have a significant effect on the optimization strategy and find the optimum frequency level to be the same as within the null game, while the yields are all at their maximum levels.
- Sensitivity Analysis Yield and Frequency

- Combining both yield and frequency range broadenings leads to an optimal strategy equal to that of the yield sensitivity analysis. Comparing this to the previous sensitivity analysis it is a logical step as now the yield restrictions are less restrictive and give opportunity to decrease the frequency and increase the yields.

In general it can be concluded that the competitor reaction model has a tendency to fly the minimum amount of flights necessary, with high load factors, at the highest prices possible. The yields however do take into account the competition and thus yield levels are affected by the competition. From a profit optimization goal, this finding is as expected, however it thus shows the importance of setting realistic bounds to the computer player reflecting the type of competitor one would like to simulate.

8

Conclusions and Recommendations

In this chapter, the conclusions concerning the simulation framework designed over the course of this study will be described. The discussion will focus on the general contributions of the research as well as the limitations of the simulation framework and the recommendations for future research.

8.1. Conclusions

In the following section, the conclusions describing the simulation framework will be discussed. This will be done according to a similar structure as found in the research proposal. The section will start with the conclusions regarding the research objective and scope. This will be followed by the contributions made to science and to the airline industry.

8.1.1. Research Objective and Scope

At the start of this thesis, a number of needs and opportunities have been identified. In general, it was found that being able to understand the dynamics of the aviation market as a whole, with its underlying specifics, is complicated but is desirable for multiple scientific and industry purposes. The main needs to such a framework, have been identified to be the inclusion of sub-models which describe the general traits of the aviation market while specifically including dynamic competitor reaction and the possibility to include exogenous players into the simulation to provide a platform for simulation game play. From this, the research objective was thus defined to be:

> *To contribute to the development of an integrated simulation framework, which has the capability of realistically simulating the aviation market by being able to reproduce the competition and passenger choice for an airline in the aviation market by combining a demand generation, passenger choice and market competition model.*

Below, the conclusions on the different sub-models, as well as a conclusion on the total simulation framework are discussed. The conclusions will also reflect on the requirements set in the research proposal with respect to realistic simulation.

Demand Generation
The demand generation model used in this thesis is based on a gravity model with decision variables on the total passenger flow at both airports, the distance between the two airports and dummy variables to split demand into the specified classes. Additionally, the model includes the effects of seasonality for the different quarters in a year for each route included in the simulation framework.

The independent variables included in the gravity model are found to have the expected signs, while all being significant. Furthermore, the effects of multicollinearity were not found between the different independent variables. The total model is found to achieve an R^2 of 0.766, which describes a reasonable total performance.

Comparing the predicted demands for each class in the different calibration routes to the actual demand data, it can be concluded that in terms of total demand the gravity model performs well. The reason for this is the fact that the models performance is best for the discount economy class, which caters for the largest group of passengers. An exception is found in routes including CPH as an origin or destination. It is expected this is due to unforeseen differences in airport characteristics in comparison to the other airports with which were calibrated. With respect to the demand splits over the different classes, the model is capable of making the split, however the realistic performance of the gravity model differs per route.

With respect to the generalizability of the demand generation model, it was found in the validation process that the demands generated for the discount economy class and premium economy class were sufficiently accurate to be used for the simulation frameworks purposes. However, the other classes display deficiencies which cannot be considered to accurately reflect reality. The gravity model in this form is therefore not considered to be confidently generalizable for routes with similar characteristics.

In general, the demand generation model has proven to be sufficiently accurate to be used for the purpose of this simulation framework. As the gravity model included is basic in its build, the performance can be considered to be good. With respect to calibration and data gathering, the gravity model in this form is efficient and thus can easily be extended. The model in its current form is however not sufficiently accurate to be generalizable for routes with similar characteristics for all classes.

Demand Allocation
The demand allocation model included in this thesis consists of a multinomial logit model. The decision variables are based on the flight frequency, yield, extra-distance and dummy variables per cabin class. The demand allocation model is capable of determining market shares for the different flight options found in a route per quarter. In the simulation framework, the demand allocation model is applied separately per class to determine the market shares of the different flight options.

The models' calibration delivered the expected signs for the different decision variables, at the correct levels of significance and excluding any effects of multicollinearity. The overall performance of the model was found to achieve an R^2 level of 0.711, which can be considered reasonable.

When comparing the models' passenger choice predictions to those found in the actual data, the MNL model can be considered to be representing the actual data. The trends and market shares predicted agree well with those seen in reality. For the purpose of the simulation framework, the models' performance has been as expected. Looking more specifically at the performance of the demand allocation model for the different cabin classes, it can be concluded that the performance is best for the discount economy class. The premium economy class and first class were however found to be under-predicted.

During the validation process, the generalizability of the demand allocation model was tested. The results between the calibration and validation routes proved to be similar and thus it can be concluded that with the same level of confidence as for the calibration routes, the model used can be generalized to routes with similar characteristics.

The demand allocation model is hence considered capable of simulating passenger choice between flight options representable to what happens in reality, while being generalizable for routes with similar characteristics. This is in line with the expectations set at the start of this thesis and the simulation framework can thus confidently be used for simulation purposes.

Market Competition - Competitor Reaction
The competitor reaction model found in the simulation framework is based on a non-linear profit optimization of a single computer player. This computer player is present in every market with flight options in all classes for the routes specified in the model. The optimization decision variables included the yield of each class and the flight frequency in each route. The optimization takes the strategies of other competitors into account, as well as the demands for each class in each route while optimizing and reacts accordingly. The optimization is constrained by capacity, as well as by the yields per class.

In the multiple simulation games played, the computers' optimization behavior has been determined. It has been found that the goal set to the computer of optimizing profit works well. In all optimization years for which a profit increase could be made, the computer player increases its profits. In general, the computer optimizes its profit by achieving an as high as possible load factor. The computer does this by flying the lowest possible frequency to cater for all demand while having the highest possible yield levels. From a profit optimization perspective, this is an understandable outcome. When testing the computers reaction in a multi-route environment of three routes, with two routes under stiff competition, no shift was found in focus to the third route. Extra constraints to the computer should be added to achieve this behaviour.

In general, the profit optimization strategy, of the computer reaction, works as expected. In the thesis objective, it was defined that the competitor reaction model would be considered realistic if it behaves in accordance with the strategy which is specified and for which it has been designed. From this point of view, a realistic model has been achieved. However, while the computer does react to the strategies of the different exogenous competitors when optimizing the profit, the model cannot be said to compete with the competitor. The strategy of optimizing profit will always try to improve on the simulation year previous to the optimization year. However, under stiff competition this could mean that in the long run, the computer will phase itself out of a market.

Total Simulation Framework
In this thesis, a contribution has been made to the development of a simulation framework which is capable of realistically simulating market dynamics with respect to competition and passenger choice in the European aviation market. In total, 22 routes have been included into the simulation framework, with airports including those in Amsterdam, Copenhagen, Frankfurt, London and Madrid. To achieve this, a demand generation model, demand allocation model and market competition model have been combined. Additionally, the simulation framework is compatible with exogenous competitor inputs to create a game environment while hosting dynamic competition by the computer player.

8.2. Research Contribution

In the following section, the research contributions of this thesis will be described. In general, to the authors best knowledge, this is the first simulation framework which can reproduce (dynamic) competition and passenger choice in the European aviation market via a serious-gaming -environment. The contributions with respect to science and industry are described separately below.

8.2.1. Scientific Contribution

- The simulation framework in this thesis can be seen as a proof-of-concept in such a way that there are large possibilities in combining different models which model specific traits of the aviation market. By combining these different models, simulation frameworks can be designed which hold the potential of accurately simulating larger scope aviation market dynamics.
- The designed simulation framework can act as a base framework, on which improvements and extensions can be built in the future. This solid foundation is an ideal basis on which new research can be started, for example related to improvements of the demand generation model or the extensions into fleet scheduling.
- The simulation framework includes dynamic competition, which is rare in simulation models. The dynamic competition is an improvement on static competition, as it is capable of reacting to changes in competitor strategies, as is found in reality. Depending on the strategy set to the computer player, different types of realistic competition can be simulated. This addition, increases the simulation frameworks resemblance of the market dynamics found in reality.

8.2.2. Industry Contribution

- For educational purposes, the simulation framework designed in this thesis could be of great value to (future) aviation professionals. The simulation framework has the capability of simulating market dynamics in a representative way with respect to reality. Additionally, being able to play as an exogenous competitor and change strategy with respect to the models' outputs, provide an environment where one can learn about aviation market dynamics by playing games with various roles and settings.

- The simulation framework has the potential to become a cost-effective tool to predict the outcomes of future strategies for airlines. The simulation framework could for example be used to determine the effect of exogenous market changes, or the opening of a new route.

8.3. Limitations

The following section will discuss the limitations of the simulation framework and its sub-models. The limitations will take a substantial amount of effort to be tackled , but at the same time may be input for continuing and interesting research projects. For every disclosed limitation, a possible solution has been described.

Simulation Framework

- **Capacity Constraints per OD-Route**
  - With respect to the capacity constraints, no constraints have currently been included which ensure that the number of flights between an OD-pair are equal to the number of flights returning. Therefore, capacity deficiencies which might occur in reality are not accounted for in the current setup.
  - Possible Solution: This limitation could be overcome by introducing a general model constraint which does not allow capacity differences in both directions for an OD-pair. This constraint should hold for both exogenous players as well as the computer player.
- **Aircraft Configurations**
  - As with the capacity constraints, no constraints exist which ensure that the aircrafts flying in one quarter in both directions of an OD-pair have the same seating configuration.
  - Possible Solution: This limitation could be overcome with the introduction of a general simulation framework constraint which ensures that the aircraft flying between an OD-pair have a fixed configuration per quarter.
- **Indirect Flights**
  - The simulation framework can only handle indirect flights when inputted manually by exogenous players. Currently, no controls on determining the possible connections and seat availability for indirect passengers are implemented in the simulation framework. However, the demand allocation model can cope with the indirect flight market share predictions.
  - Possible Solution: To overcome this limitation, a number of additions have to be made to the simulation framework. These additions include a script which determines the possible connections and connection frequency and, a constraint which ensures that the sum of the direct and indirect passengers on a flight stays within capacity limits.

Demand Generation

- **Dynamic Demand Generation**
  - In the current demand generation model, supply effects are not considered when determining demand. Therefore, the different players in the model have the opportunity to supply unrealistic flight frequencies or yield levels. Currently, this is restricted in the model by the users themselves and several constraints on the computer player. It might however be more realistic to have the demand change with respect to supply effects. Low frequencies and high yields may for example decrease demand, as passengers will decide not to travel anymore or look for other means of transportation.

- Possible solution: For a dynamic demand generation model, the gravity model currently used would need to undergo an overhaul. Decision variables based on supply would need to be added and research needs to be done on the criteria based on which potential travelers make decisions on how and whether or not they travel. Furthermore, the new decision variables should be coherent with the rest of the sub-models in the simulation framework.

Demand Allocation

- **Spill and Recapture Model**
  - In the current simulation framework setup, the demand allocation model splits the demand on the basis of the expected passenger choice but does not take the capacity of the flight option into account. Therefore, demand for a flight option which exceeds the capacity is spilled. This spill is in no way recaptured and can be considered lost forever.
  - Possible Solution: To overcome this limitation, a spill and recapture model should be designed. Opportunity here is to determine what number of passengers 'spilled' would be willing to fly an alternative flight option. Parameters that might be included in such models are for example buy ups and buy downs with respect to class, flying on a more expensive alternative and taking an indirect alternative. Additionally, a demand penalty could be issued for upcoming game years if demand was found to be lost. More research related to options and possibilities would have to be done in this area to overcome this limitation.

Market Competition - Competitor Reaction

- **Short-Term Strategies**
  - The optimization software which controls the computer reaction does not take long term strategies into account. In this setup the computer will try to improve its profit with respect to the previous game year, but not necessarily ensure its survival. As a consequence, the computer over a number of simulations may optimize itself until it is practically non-existent.
  - Possible Solution: This limitation is currently not a big problem, as the simulation currently only plays over three simulations years. If one would prolong the simulations game time, research should be done to determine if the above behaviour is acceptable or not.

8.4. Recommendations

In the upcoming section, recommendations for further and future research related to the simulation framework will be discussed. These recommendations capture leads on which future effort(s) could focus, which would most likely result in a more comprehensive simulation framework.

Simulation Framework

- **Passenger Segmentation**
  - Passenger segmentation in the model designed in this thesis is based on class preference, acquired from the actual data. It may be interesting to change the passenger segmentation to for example trip purpose and determine if this would more accurately represent reality. The segmentation by trip purpose may also provide insight on the behaviour of passengers when determining their second best choice. It is for example hypothesized that passengers with business purpose, in comparison to leisure travelers, would more quickly go for more expensive flight options if their first flight option preference is not available.
- **Non-Air Travel Modes**
  - The current simulation framework assumes that all passengers in the model are willing to fly. It would however be interesting to include the options of non-air travel to the simulation frame-

work, to better simulate the competition between air and non-air travel alternatives and the choice of whether or not to fly. With this implemented, it might even be possible to reintroduce the routes under 500km which have currently, in general, been excluded.

- **External Market Influences**
  - Currently, external market influences such as an increase in fuel prices or an economic downturn cannot easily be implemented. In case that there is a need or wish to simulate such a situation, it would be interesting to add parameters which could simulate these effects. With this in place, the correct reaction of an airline could be tested using the simulation framework. Research would need to be done to discover what exogenous market effects would be most interesting to include.
- **Cost Model**
  - The current cost model which determines the cost of flight operation is very basic and can be considered econometric. In the future it would be interesting to include a more extensive cost model, which for example also takes into account the costs of different airlines and landing fees at airports. Furthermore, cost differentiation for different types of players could be introduced, for example lower costs for cost sensitive low cost carriers.
- **Model Extensions**
  - The simulation framework in its current form is a basis which can be extended with additional sub-models. These opportunities should be explored, to increase the complexity and scope that it covers within the aviation market. An addition which comes to mind is a fleet allocation model, which determines the types and availability of aircraft over the different routes and for different carriers.

Demand Generation

- **Model Complexity**
  - The demand generation model is currently in an effective and meaningful yet simple form. In the future, the extension of this model could potentially increase its accuracy and generalizability to routes with similar characteristics. Further additions which could be made are for example the inclusion of the GDP, airport catchment area and variables on the social and commercial interaction between two cities.
- **Directional Demand**
  - A simple addition to the demand generation model, would be to split the current variable which comprises the product of the passenger flow at both airports into two separate variables. By doing this, directional demand could be generated between OD-pairs.
- **Calibration Clustering**
  - To increase the accuracy of the gravity model, multiple gravity models could be calibrated for different clusters of route characteristics. Examples of this clustering would be on the basis of distance between the OD-pairs, leisure and business markets, magnitude of demand on the routes, time period or airport sizes. In the current thesis, multiple clusters were experimented with, however with the available data set this was not possible.

Demand Allocation

- **Model Complexity**
  - By increasing the model complexity, the accuracy of prediction of passenger choice could be improved. Additions which could be interesting are the time-of-day preference of passengers to fly, the preference for the type of carrier and the preference for aircraft type and size. Also, the inclusion of the extra time of flying an indirect flight, instead of the extra distance, is expected to be beneficial. Literature showed that especially the extra time of flying an

indirect flight has significant effect on passenger choice. Including the above was currently not possible due to limitations of the available data.

- **Calibration Clustering**
  - As with the demand generation model, it may be interesting to develop multiple multinomial logit models to more accurately determine passenger choice for different groups of passengers. Clusters could include different passenger types, age groups and seasons of travel.

Market Competition - Competitor Reaction

- **Different Computer Strategies**
  - In this thesis, the competitor's (computer player) reaction was based on a profit optimization. It would be useful to determine what the behavior of the computer player would be if exposed to different predefined strategies. Examples could be the optimizations of market share, frequency and minimum passenger spillage.
- **Load Factor Constraint**
  - In the current competitor reaction model, the computer has the tendency to lower the flight frequency to ensure high load factors with high yields. This could lead to situations under hefty competition that the computer optimizes itself out of a market. It might be of interest to prevent this. A solution could be found in implementing constraints on, for example, maximum load factors and minimum market shares.
- **Minimum Total Frequency Constraint**
  - As found in Game 4, no shift in focus was found to a route where no competition was experienced by the computer player, while competition in other routes was increasingly more hefty. If an active behavior would be desired in this situation, it is hypothesized that a minimum total frequency over all routes for the computer player would suffice. This constraint would ensure that the computer player cannot layoff flights indefinitely, and would have to redistribute them over the simulated markets. With such a constraint, a shift to markets with less competition may be seen.

A

Seasonality Effects

Table A.1: Route Demand Seasonality Quarter 2

Route	Month	Moving Average	Seasonality Effects	Seasonality Percentage
AMS-MAD	Qtr2	41194	3609	108.8%
CPH-MAD	Qtr2	6611	795	112.0%
MAD-AMS	Qtr2	40347	1832	104.5%
MAD-CPH	Qtr2	6155	900	114.6%
CPH-CDG	Qtr2	41652	8196	119.7%
AMS-CPH	Qtr2	38474	6058	115.7%
CDG-CPH	Qtr2	42913	8776	120.5%
LHR-MAD	Qtr2	47042	2919	106.2%
FRA-LHR	Qtr2	94446	2205	102.3%
LHR-FRA	Qtr2	98915	3560	103.6%
MAD-CDG	Qtr2	46664	8881	119.0%
CDG-MAD	Qtr2	45766	8438	118.4%
CPH-AMS	Qtr2	36957	4870	113.2%
MAD-LHR	Qtr2	46334	2099	104.5%
AMS-LHR	Qtr2	87647	1633	101.9%
LHR-AMS	Qtr2	94761	2122	102.2%

Table A.2: Route Demand Seasonality Quarter 3

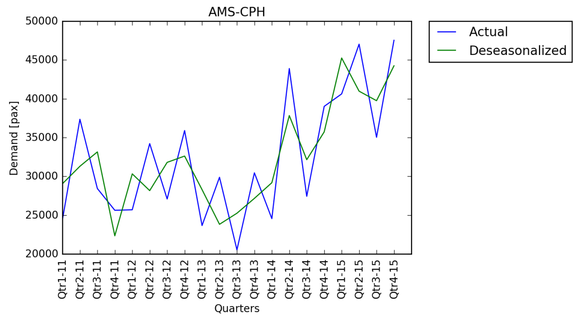
Route	Month	Moving Average	Seasonality Effects	Seasonality Percentage
AMS-MAD	Qtr3	37405	-181	99.5%
CPH-MAD	Qtr3	6590	775	111.8%
MAD-AMS	Qtr3	37728	-786	97.9%
MAD-CPH	Qtr3	5420	164	103.0%
CPH-CDG	Qtr3	34226	769	102.2%
AMS-CPH	Qtr3	27700	-4717	83.0%
CDG-CPH	Qtr3	33678	-459	98.6%
LHR-MAD	Qtr3	47186	3063	106.5%
FRA-LHR	Qtr3	91567	-674	99.3%
LHR-FRA	Qtr3	97934	2580	102.6%
MAD-CDG	Qtr3	38973	1190	103.1%
CDG-MAD	Qtr3	38908	1579	104.1%
CPH-AMS	Qtr3	29349	-2738	90.7%
MAD-LHR	Qtr3	45067	831	101.8%
AMS-LHR	Qtr3	82781	-3233	96.1%
LHR-AMS	Qtr3	90094	-2546	97.2%

Table A.3: Route Demand Seasonality Quarter 4

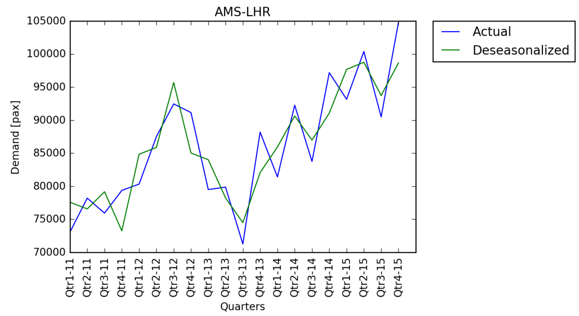
Route	Month	Moving Average	Seasonality Effects	Seasonality Percentage
AMS-MAD	Qtr4	40679	3094	107.6%
CPH-MAD	Qtr4	5443	-372	93.2%
MAD-AMS	Qtr4	42512	3998	109.4%
MAD-CPH	Qtr4	5453	198	103.6%
CPH-CDG	Qtr4	31427	-2029	93.5%
AMS-CPH	Qtr4	35705	3288	109.2%
CDG-CPH	Qtr4	33483	-654	98.0%
LHR-MAD	Qtr4	42054	-2069	95.1%
FRA-LHR	Qtr4	95760	3519	103.7%
LHR-FRA	Qtr4	94192	-1163	98.8%
MAD-CDG	Qtr4	34719	-3064	91.2%
CDG-MAD	Qtr4	35478	-1851	94.8%
CPH-AMS	Qtr4	33682	1595	104.7%
MAD-LHR	Qtr4	45357	1121	102.5%
AMS-LHR	Qtr4	92134	6120	106.6%
LHR-AMS	Qtr4	98651	6011	106.1%

B

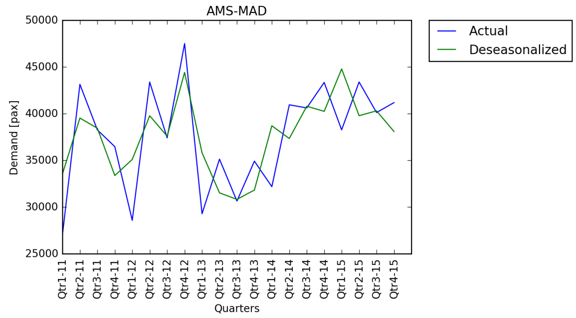
Gravity Model Deseasonalization Plots



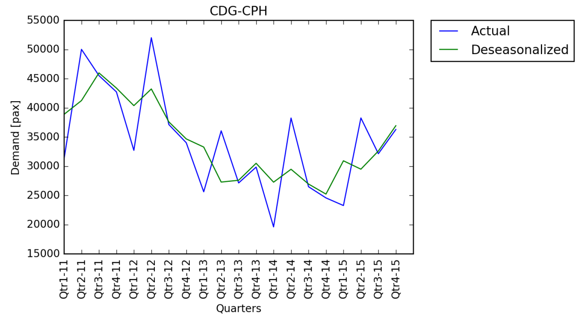
(a) Deseasonalizated demand AMS-CPH



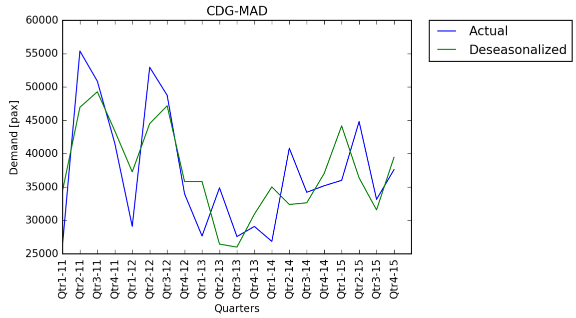
(b) Deseasonalizated demand AMS-LHR



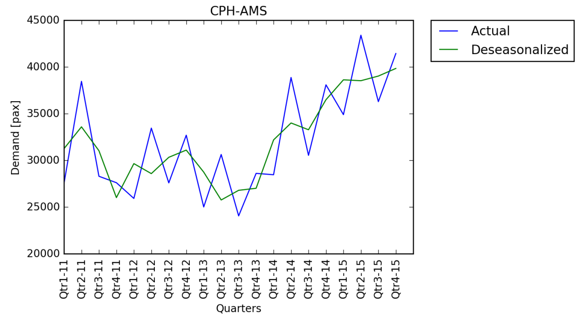
(c) Deseasonalizated demand AMS-MAD



(d) Deseasonalizated demand CDG-CPH

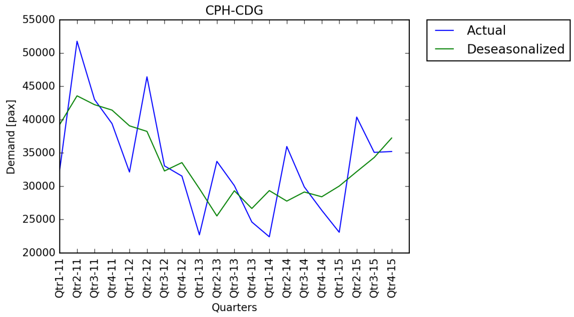


(e) Deseasonalizated demand CDG-MAD

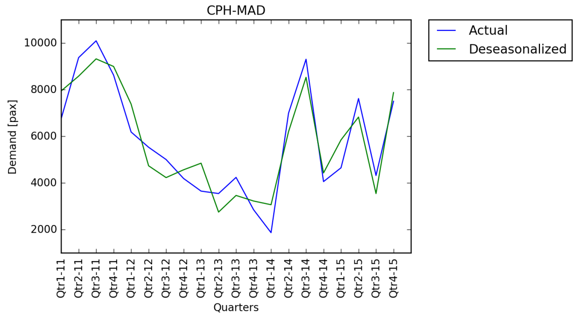


(f) Deseasonalizated demand CPH-AMS

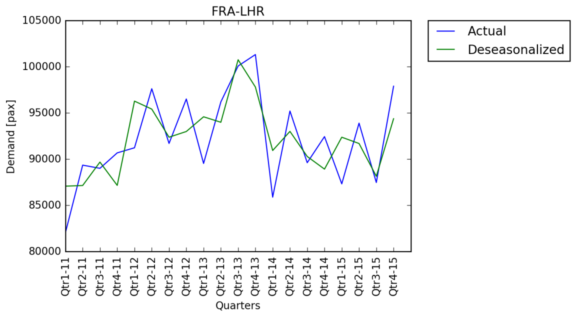
Figure B.1: Deseasonalizated demand set 1



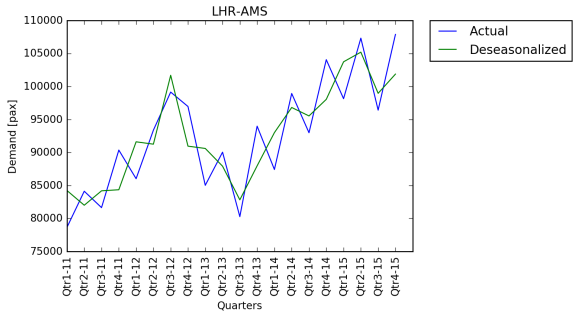
(a) Deseasonalizated demand CPH-CDG



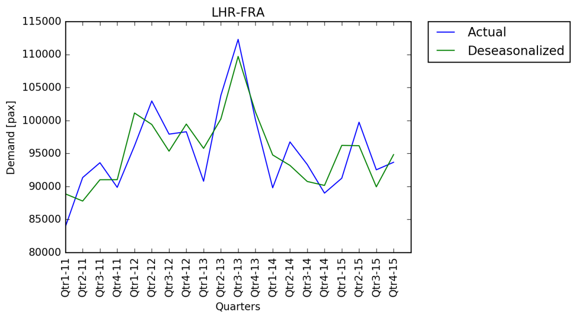
(b) Deseasonalizated demand CPH-MAD



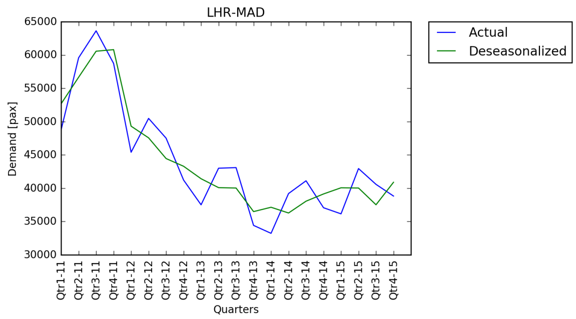
(c) Deseasonalizated demand FRA-LHR



(d) Deseasonalizated demand LHR-AMS

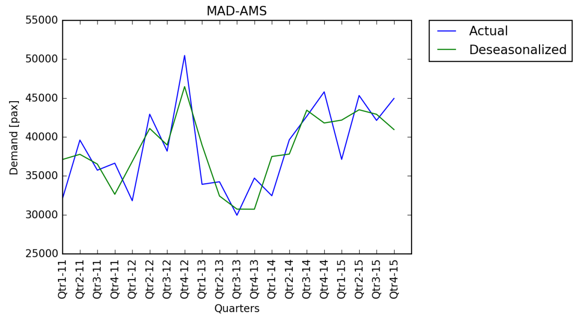


(e) Deseasonalizated demand LHR-FRA

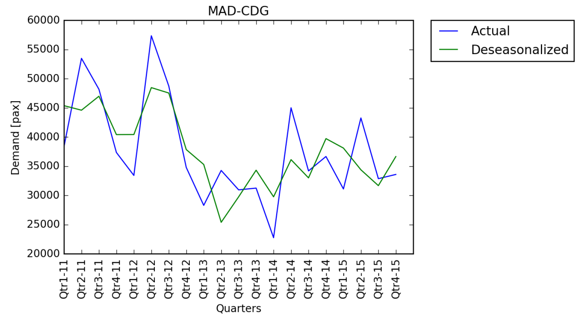


(f) Deseasonalizated demand LHR-MAD

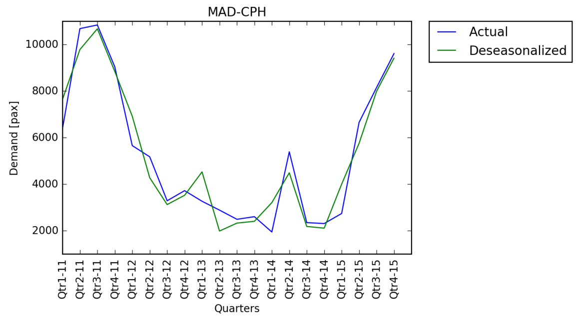
Figure B.2: Deseasonalizated demand set 2



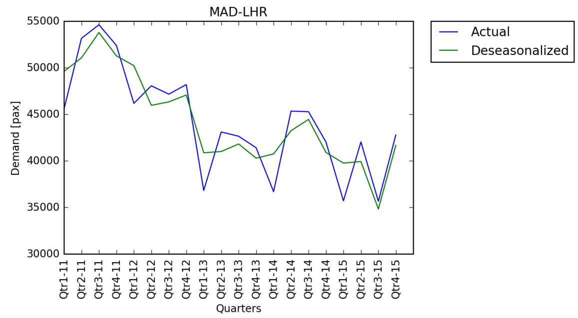
(a) Deseasonalizated demand MAD-AMS



(b) Deseasonalizated demand MAD-CDG



(c) Deseasonalizated demand MAD-CPH



(d) Deseasonalizated demand MAD-LHR

Figure B.3: Deseasonalizated demand set 3

C

Gravity Model Performance

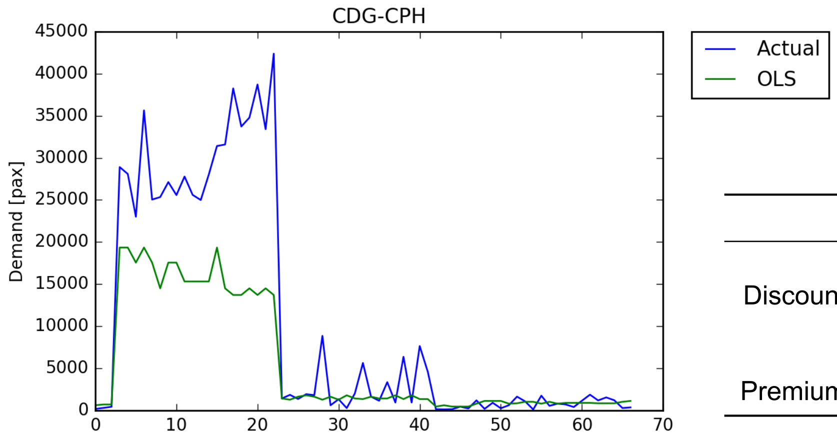


Figure C.1: Gravity Model Performance CDG-CPH OLS

Cabin	x-min	x-max
Business	0	2
Discount Economy	3	22
First	23	41
Full Y	42	46
Premium Economy	47	66

Table C.1: Cabin Ranges CDG-CPH OLS

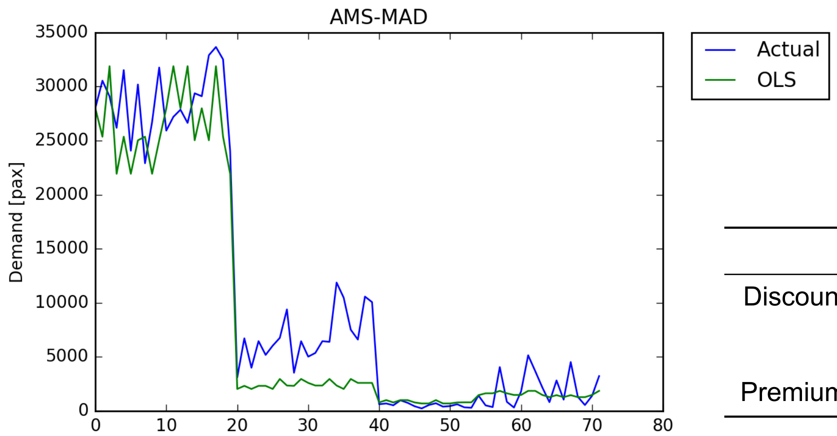


Figure C.2: Gravity Model Performance AMS-MAD OLS

Cabin	x-min	x-max
Discount Economy	0	19
First	20	39
Full Y	40	53
Premium Economy	54	71

Table C.2: Cabin Ranges AMS-MAD OLS

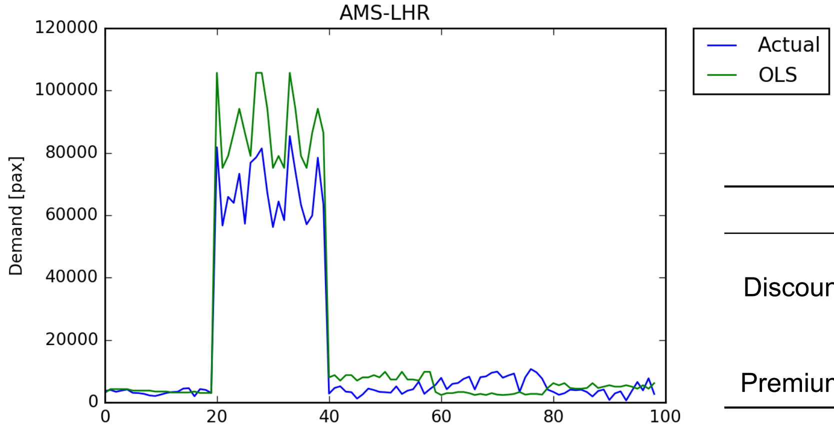


Figure C.3: Gravity Model Performance AMS-LHR OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	58
Full Y	59	78
Premium Economy	79	98

Table C.3: Cabin Ranges AMS-LHR OLS

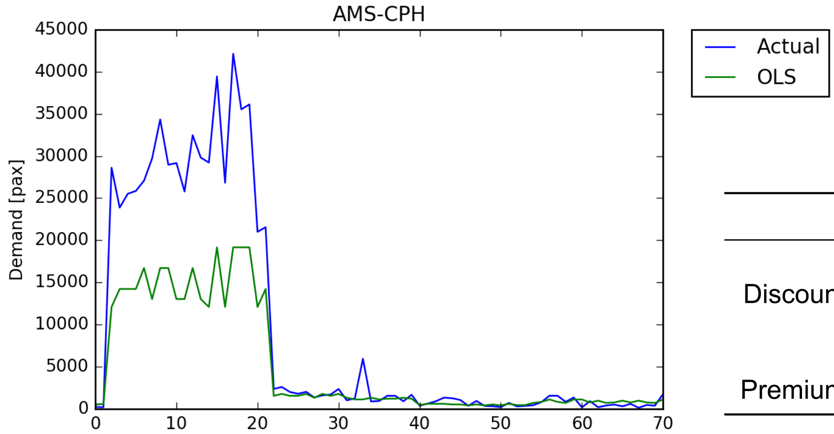


Figure C.4: Gravity Model Performance AMS-CPH OLS

Cabin	x-min	x-max
Business	0	1
Discount Economy	2	21
First	22	39
Full Y	40	53
Premium Economy	54	70

Table C.4: Cabin Ranges AMS-CPH OLS

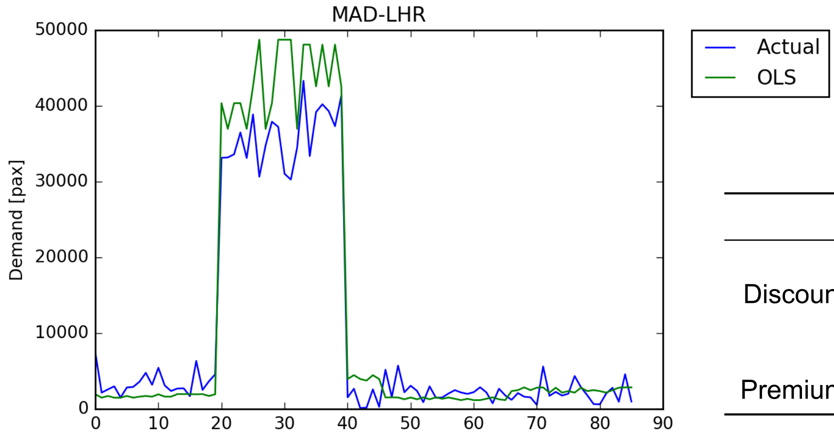


Figure C.5: Gravity Model Performance AMD-LHR OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	45
Full Y	46	65
Premium Economy	66	85

Table C.5: Cabin Ranges MAD-LHR OLS

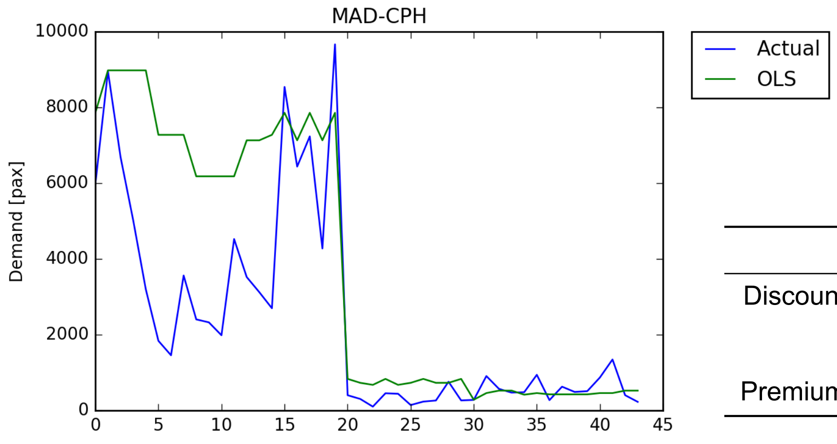


Figure C.6: Gravity Model Performance MAD-CPH OLS

Cabin	x-min	x-max
Discount Economy	0	19
First	20	29
Full Y	30	30
Premium Economy	31	43

Table C.6: Cabin Ranges MAD-CPH OLS

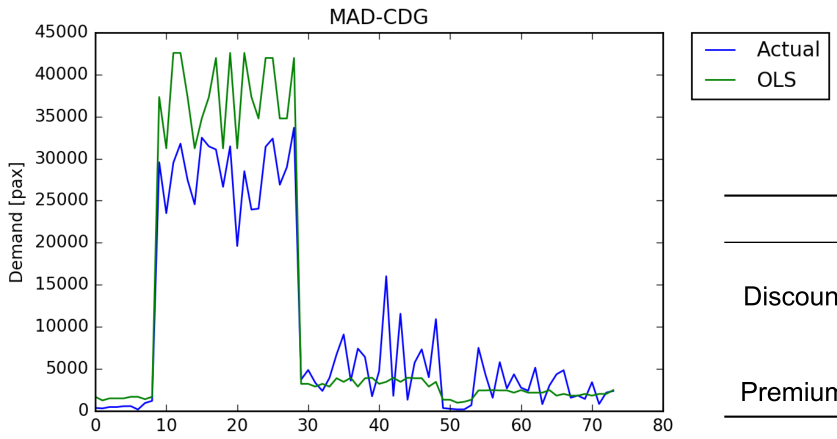


Figure C.7: Gravity Model Performance MAD-CDG OLS

Cabin	x-min	x-max
Business	0	8
Discount Economy	9	28
First	29	48
Full Y	49	53
Premium Economy	54	73

Table C.7: Cabin Ranges MAD-CDG OLS

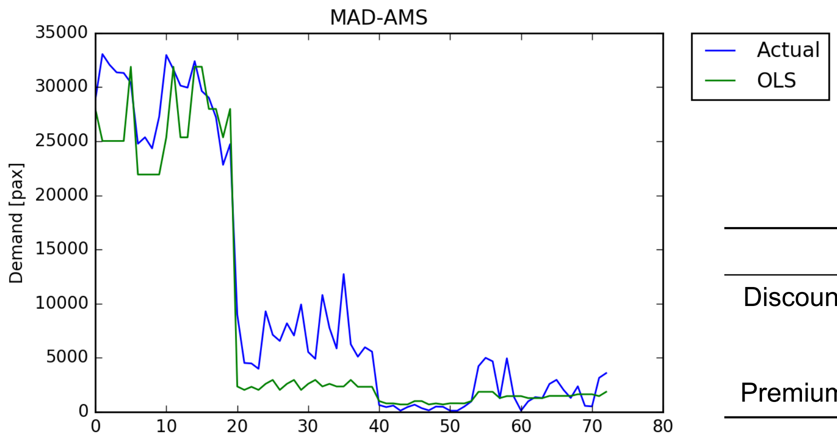


Figure C.8: Gravity Model Performance MAD-AMS OLS

Cabin	x-min	x-max
Discount Economy	0	19
First	20	39
Full Y	40	53
Premium Economy	54	72

Table C.8: Cabin Ranges MAD-AMS OLS

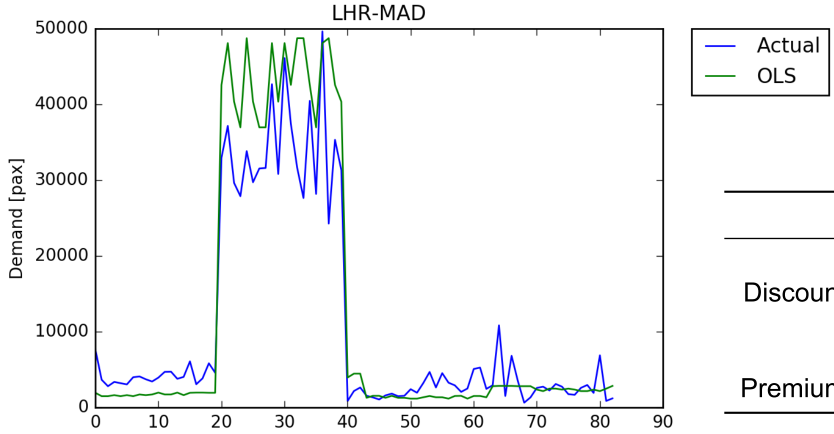


Figure C.9: Gravity Model Performance LHR-MAD OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	42
Full Y	43	62
Premium Economy	63	82

Table C.9: Cabin Ranges LHR-MAD OLS

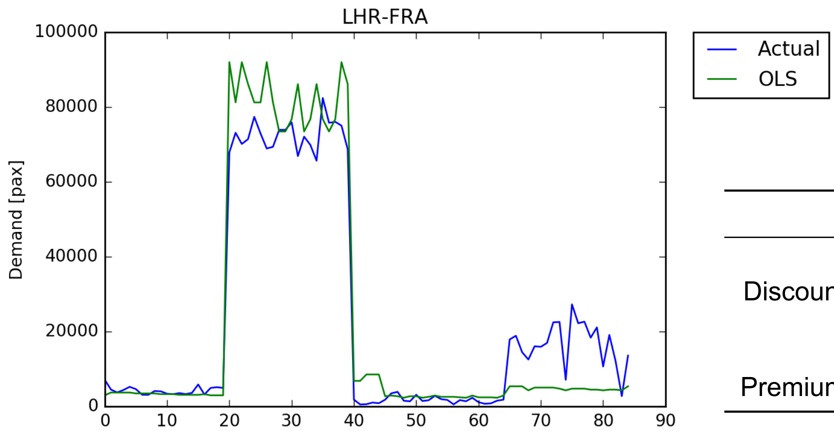


Figure C.10: Gravity Model Performance LHR-FRA OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	44
Full Y	45	64
Premium Economy	65	84

Table C.10: Cabin Ranges LHR-FRA OLS

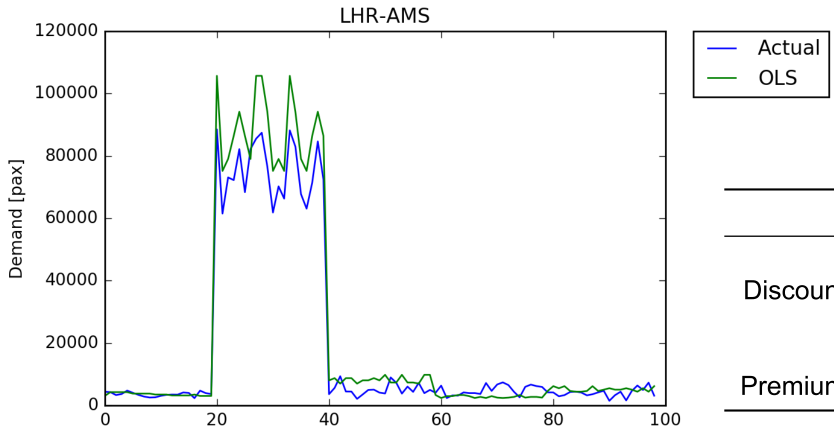


Figure C.11: Gravity Model Performance LHR-AMS OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	58
Full Y	59	78
Premium Economy	79	98

Table C.11: Cabin Ranges LHR-AMS OLS

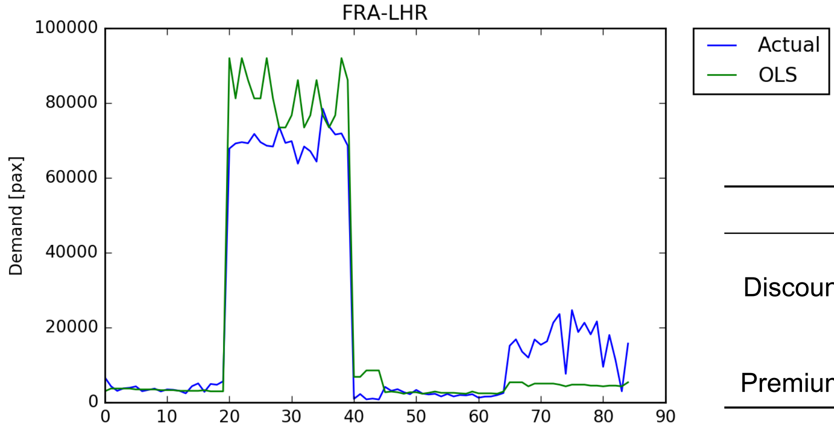


Figure C.12: Gravity Model Performance FRA-LHR OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	44
Full Y	45	64
Premium Economy	65	84

Table C.12: Cabin Ranges FRA-LHR OLS

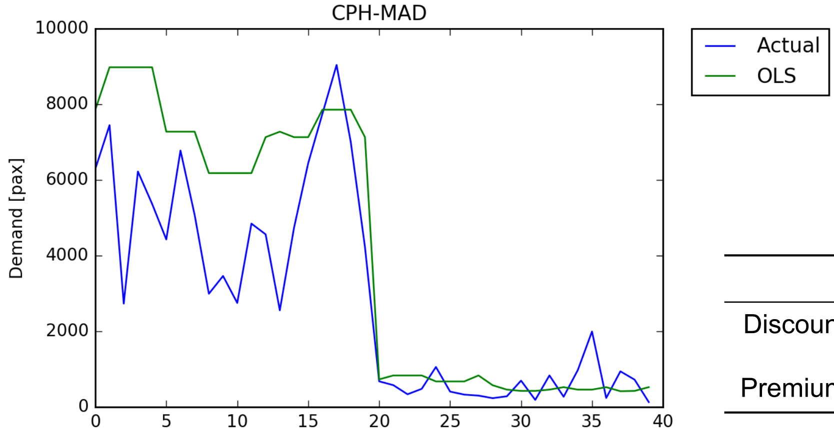


Figure C.13: Gravity Model Performance CPH-MAD OLS

Cabin	x-min	x-max
Discount Economy	0	19
First	20	28
Premium Economy	29	39

Table C.13: Cabin Ranges CPH-MAD OLS

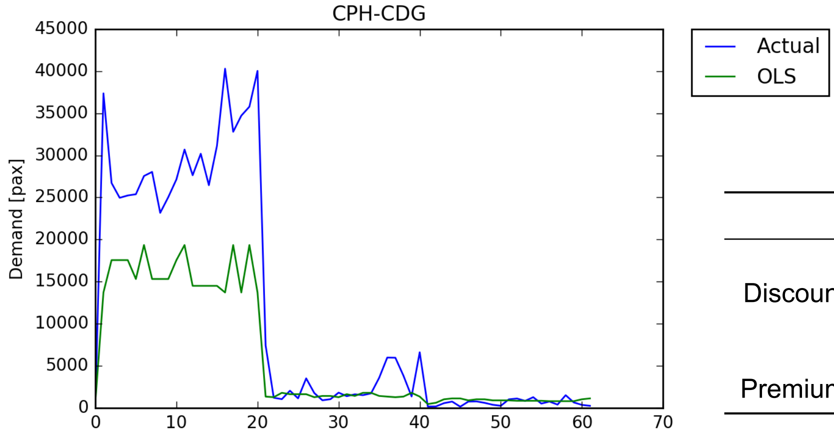


Figure C.14: Gravity Model Performance CPH-CDG OLS

Cabin	x-min	x-max
Business	0	0
Discount Economy	1	20
First	21	40
Full Y	41	42
Premium Economy	43	61

Table C.14: Cabin Ranges CPH-CDG OLS

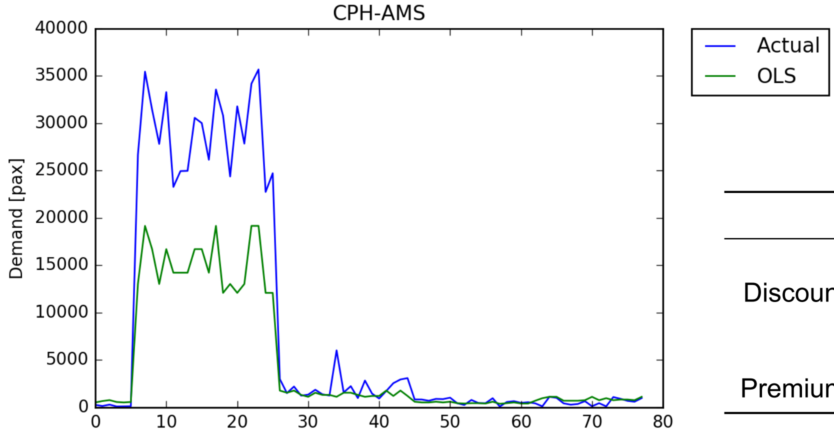


Figure C.15: Gravity Model Performance CPH-AMS OLS

Cabin	x-min	x-max
Business	0	5
Discount Economy	6	25
First	26	44
Full Y	45	61
Premium Economy	62	77

Table C.15: Cabin Ranges CPH-AMS OLS

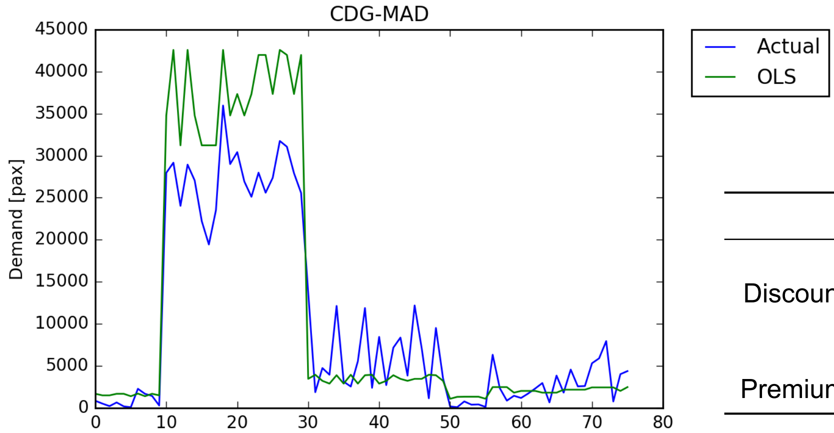


Figure C.16: Gravity Model Performance CDG-MAD OLS

Cabin	x-min	x-max
Business	0	9
Discount Economy	10	29
First	30	49
Full Y	50	55
Premium Economy	56	75

Table C.16: Cabin Ranges CDG-MAD OLS

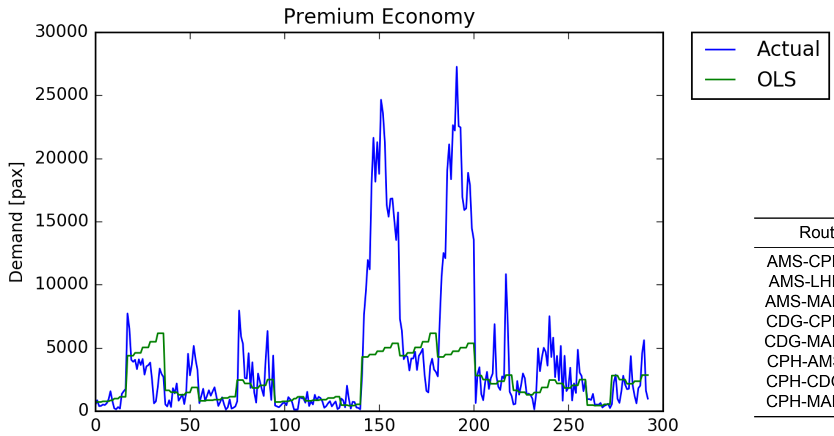


Figure C.17: Gravity Model Performance Premium Economy OLS

Route	x-min	x-max	Route	x-min	x-max
AMS-CPH	0	16	FRA-LHR	141	160
AMS-LHR	17	36	LHR-AMS	161	180
AMS-MAD	37	54	LHR-FRA	181	200
CDG-CPH	55	74	LHR-MAD	201	220
CDG-MAD	75	94	MAD-AMS	221	239
CPH-AMS	95	110	MAD-CDG	240	259
CPH-CDG	111	129	MAD-CPH	260	272
CPH-MAD	130	140	MAD-LHR	273	292

Table C.17: Route Ranges Premium Economy OLS

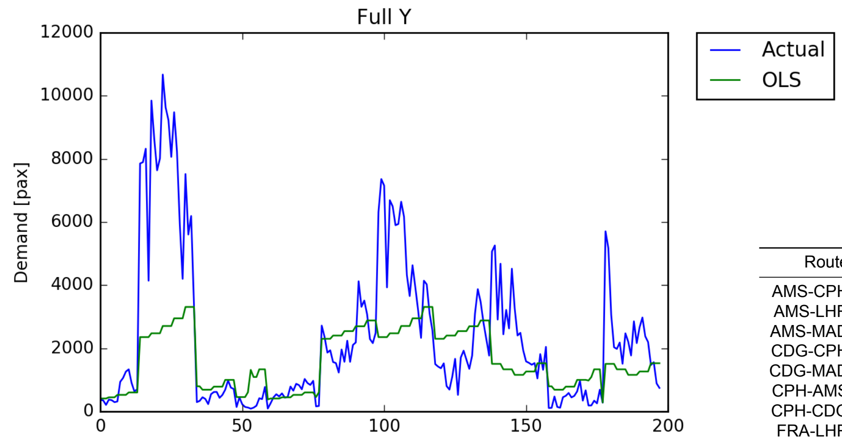


Figure C.18: Gravity Model Performance Full Y OLS

Route	x-min	x-max	Route	x-min	x-max
AMS-CPH	0	13	LHR-AMS	98	117
AMS-LHR	14	33	LHR-FRA	118	137
AMS-MAD	34	47	LHR-MAD	138	157
CDG-CPH	48	52	MAD-AMS	158	171
CDG-MAD	53	58	MAD-CDG	172	176
CPH-AMS	59	75	MAD-CPH	177	177
CPH-CDG	76	77	MAD-LHR	178	197
FRA-LHR	78	97			

Table C.18: Route Ranges Full Y

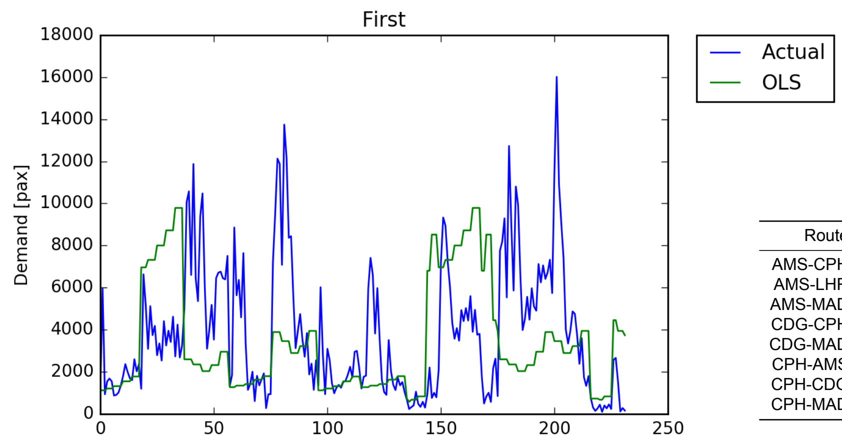


Figure C.19: Gravity Model Performance First OLS

Route	x-min	x-max	Route	x-min	x-max
AMS-CPH	0	17	FRA-LHR	144	148
AMS-LHR	18	36	LHR-AMS	149	167
AMS-MAD	37	56	LHR-FRA	168	172
CDG-CPH	57	75	LHR-MAD	173	175
CDG-MAD	76	95	MAD-AMS	176	195
CPH-AMS	96	114	MAD-CDG	196	215
CPH-CDG	115	134	MAD-CPH	216	225
CPH-MAD	135	143	MAD-LHR	226	231

Table C.19: Route Ranges First OLS

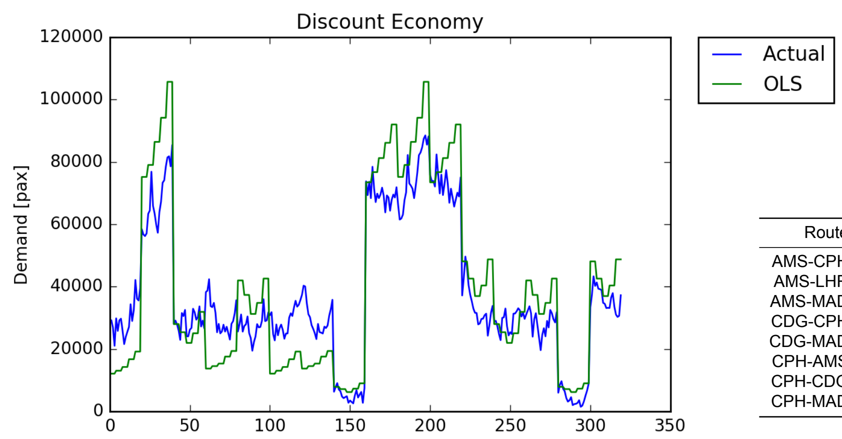


Figure C.20: Gravity Model Performance Discount Economy OLS

Route	x-min	x-max	Route	x-min	x-max
AMS-CPH	0	19	FRA-LHR	160	179
AMS-LHR	20	39	LHR-AMS	180	199
AMS-MAD	40	59	LHR-FRA	200	219
CDG-CPH	60	79	LHR-MAD	220	239
CDG-MAD	80	99	MAD-AMS	240	259
CPH-AMS	100	119	MAD-CDG	260	279
CPH-CDG	120	139	MAD-CPH	280	299
CPH-MAD	140	159	MAD-LHR	300	319

Table C.20: Route Ranges Discount Economy OLS

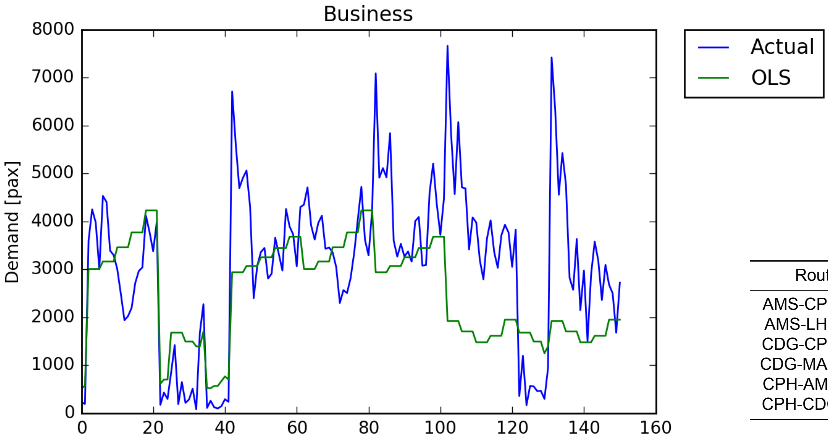


Figure C.21: Gravity Model Performance Business OLS

Route	x-min	x-max	Route	x-min	x-max
AMS-CPH	0	1	FRA-LHR	42	61
AMS-LHR	2	21	LHR-AMS	62	81
CDG-CPH	22	24	LHR-FRA	82	101
CDG-MAD	25	34	LHR-MAD	102	121
CPH-AMS	35	40	MAD-CDG	122	130
CPH-CDG	41	41	MAD-LHR	131	150

Table C.21: Route Ranges Business OLS

Table C.22: Gravity Model Performance per Route per Class

Route	Cabin	Std. Error of Estimate	Data Entries	Std. Err. Perc. of Average Demand
MAD-CPH	Full Y	4	1	1%
MAD-AMS	Discount Economy	4341	20	15%
AMS-MAD	Discount Economy	4421	20	16%
LHR-AMS	Discount Economy	13782	20	18%
LHR-FRA	Discount Economy	13358	20	18%
FRA-LHR	Discount Economy	14755	20	21%
LHR-AMS	Business	843	20	24%
MAD-LHR	Discount Economy	9292	20	26%
AMS-LHR	Business	938	20	28%
AMS-LHR	Discount Economy	20788	20	30%
FRA-LHR	Full Y	711	20	31%
LHR-MAD	Discount Economy	11199	20	33%
MAD-CDG	Discount Economy	9604	20	34%
FRA-LHR	Business	1349	20	34%
LHR-FRA	Business	1483	20	35%
CPH-AMS	Full Y	241	17	38%
CDG-MAD	Discount Economy	10719	20	39%
CPH-AMS	Discount Economy	14235	20	49%
CPH-CDG	Discount Economy	15159	20	51%
AMS-CPH	Discount Economy	15113	20	51%
CDG-CPH	Discount Economy	15757	20	52%
LHR-AMS	Premium Economy	2067	20	52%
CPH-MAD	Discount Economy	2779	20	53%
AMS-CPH	Full Y	355	14	55%
MAD-CPH	Premium Economy	348	13	56%
AMS-MAD	Full Y	308	14	57%
LHR-AMS	Full Y	2837	20	58%
LHR-FRA	Full Y	1067	20	59%
MAD-CDG	Premium Economy	1947	20	62%
LHR-MAD	Business	2662	20	64%
MAD-LHR	Business	2226	20	65%
AMS-CPH	First	1209	18	65%
CPH-AMS	First	1381	19	65%
MAD-LHR	Full Y	1575	20	66%
MAD-LHR	Premium Economy	1396	20	67%
CDG-MAD	Premium Economy	2148	20	68%
LHR-MAD	Full Y	1798	20	68%
AMS-CPH	Premium Economy	502	17	69%
AMS-LHR	Full Y	5216	20	69%
MAD-AMS	Premium Economy	1623	19	70%
CDG-CPH	Premium Economy	619	20	70%
CPH-CDG	Premium Economy	490	19	73%
AMS-MAD	First	5026	20	73%
MAD-AMS	First	5124	20	73%
AMS-MAD	Premium Economy	1460	18	73%
CPH-MAD	First	362	9	74%
AMS-LHR	Premium Economy	2603	20	75%
MAD-CDG	First	4393	20	75%
MAD-CPH	Discount Economy	3517	20	75%
CDG-MAD	First	4754	20	76%
CPH-AMS	Premium Economy	449	16	77%
FRA-LHR	Premium Economy	12399	20	77%
LHR-AMS	First	3963	19	78%
LHR-FRA	Premium Economy	13207	20	79%
LHR-MAD	Premium Economy	2444	20	81%
CPH-MAD	Premium Economy	572	11	87%
CPH-CDG	First	2496	20	90%
MAD-AMS	Full Y	436	14	102%
CDG-CPH	First	2910	19	103%
CDG-MAD	Business	1012	10	124%
CDG-CPH	Business	379	3	126%
AMS-LHR	First	4841	19	131%
LHR-MAD	First	2463	3	131%
MAD-CPH	First	463	10	138%
CDG-CPH	Full Y	311	5	145%
AMS-CPH	Business	337	2	160%
MAD-CDG	Business	1034	9	185%
CPH-CDG	Business	465	1	195%
CPH-CDG	Full Y	371	2	224%
MAD-LHR	First	2986	6	245%
CPH-AMS	Business	440	6	256%
MAD-CDG	Full Y	895	5	270%
CDG-MAD	Full Y	942	6	288%
FRA-LHR	First	6815	5	600%
LHR-FRA	First	6984	5	746%

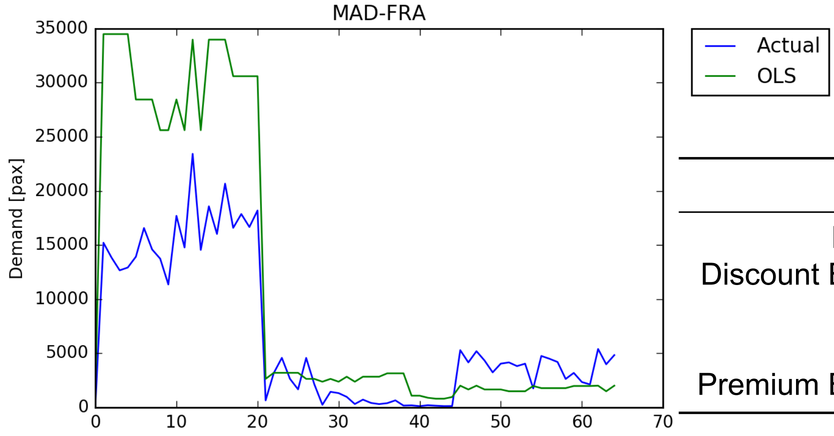


Figure C.22: Gravity Model Performance MAD-FRA OLS

Cabin	x-min	x-max
Business	0	0
Discount Economy	1	20
First	21	38
Full Y	39	44
Premium Economy	45	64

Table C.23: Cabin Ranges MAD-FRA OLS

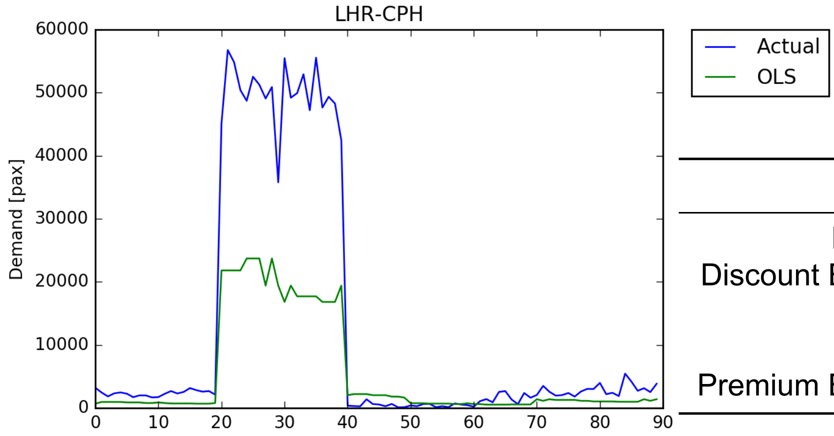


Figure C.23: Gravity Model Performance LHR-CPH OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	49
Full Y	50	69
Premium Economy	70	89

Table C.24: Cabin Ranges LHR-CPH OLS

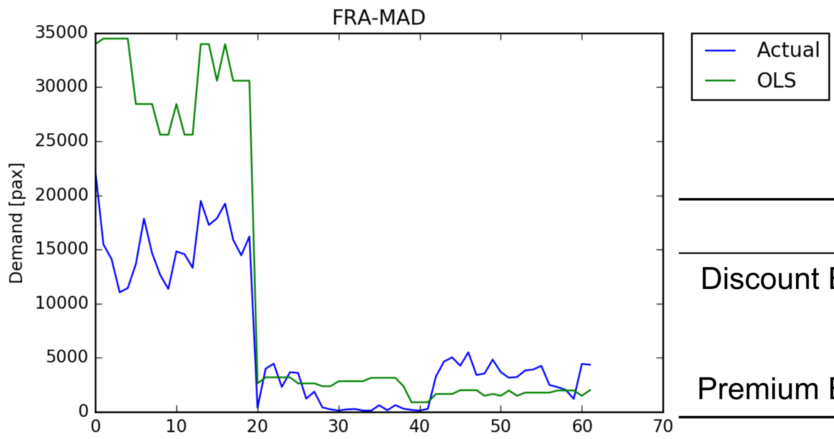


Figure C.24: Gravity Model Performance FRA-MAD OLS

Cabin	x-min	x-max
Discount Economy	0	19
First	20	38
Full Y	39	41
Premium Economy	42	61

Table C.25: Cabin Ranges FRA-MAD OLS

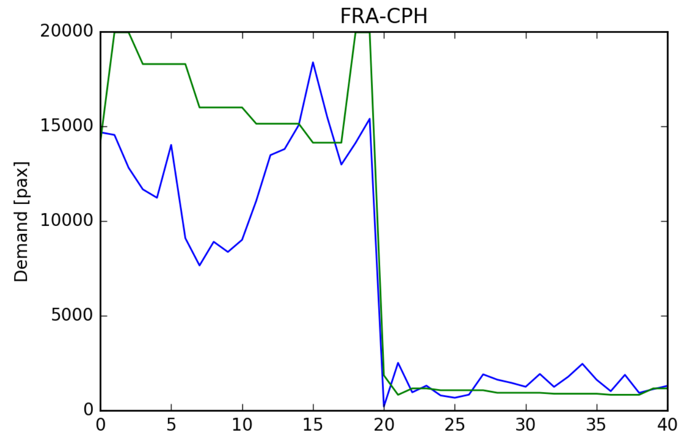


Figure C.25: Gravity Model Performance FRA-CPH OLS

Cabin	x-min	x-max
Discount Economy	0	19
First	20	20
Premium Economy	21	40

Table C.26: Cabin Ranges FRA-CPH OLS

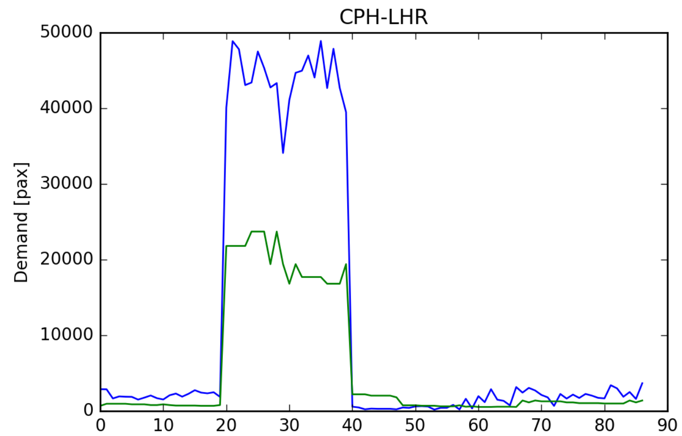


Figure C.26: Gravity Model Performance CPH-LHR OLS

Cabin	x-min	x-max
Business	0	19
Discount Economy	20	39
First	40	47
Full Y	48	66
Premium Economy	67	86

Table C.27: Cabin Ranges CPH-LHR OLS

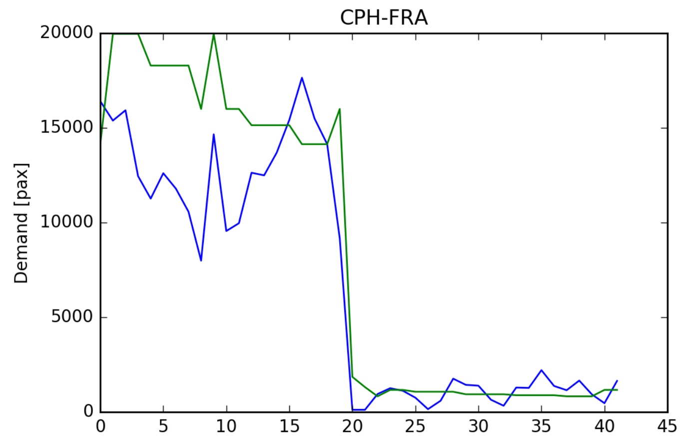


Figure C.27: Gravity Model Performance CPH-FRA OLS

Cabin	x-min	x-max
Discount Economy	0	19
First	20	21
Premium Economy	22	41

Table C.28: Cabin Ranges CPH-FRA OLS

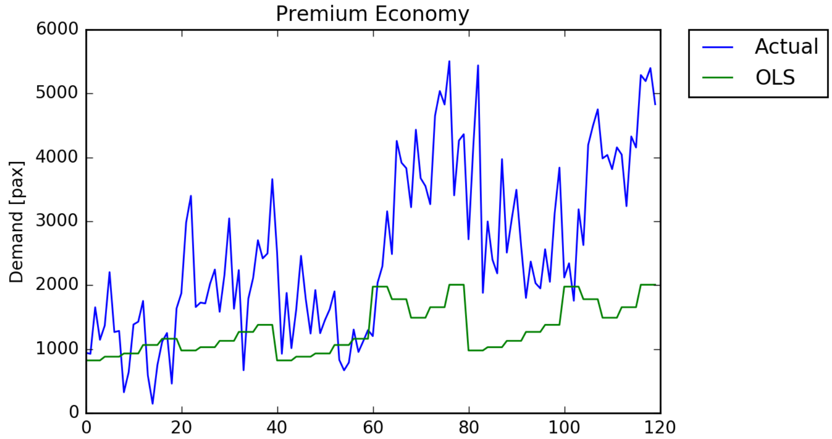


Figure C.28: Gravity Model Performance Premium Economy OLS Validation

Route	x-min	x-max
CPH-FRA	0	19
CPH-LHR	20	39
FRA-CPH	40	59
FRA-MAD	60	79
LHR-CPH	80	99
MAD-FRA	100	119

Table C.29: Route Ranges Premium Economy OLS

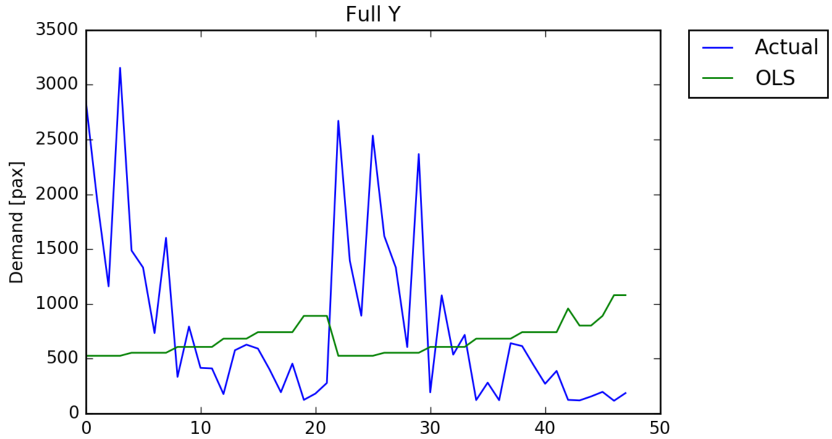


Figure C.29: Gravity Model Performance Full Y OLS Validation

Route	x-min	x-max
CPH-LHR	0	18
FRA-MAD	19	21
LHR-CPH	22	41
MAD-FRA	42	47

Table C.30: Route Ranges Full Y OLS Validation

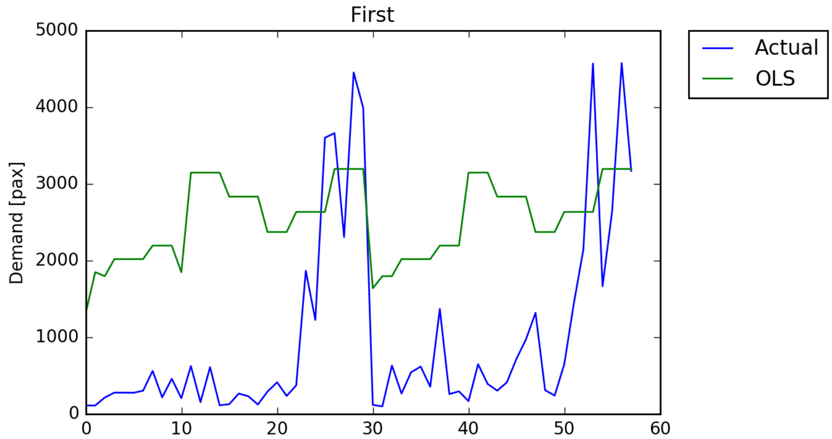


Figure C.30: Gravity Model Performance First OLS Validation

Route	x-min	x-max
CPH-FRA	0	1
CPH-LHR	2	9
FRA-CPH	10	10
FRA-MAD	11	29
LHR-CPH	30	39
MAD-FRA	40	57

Table C.31: Route Ranges First OLS Validation

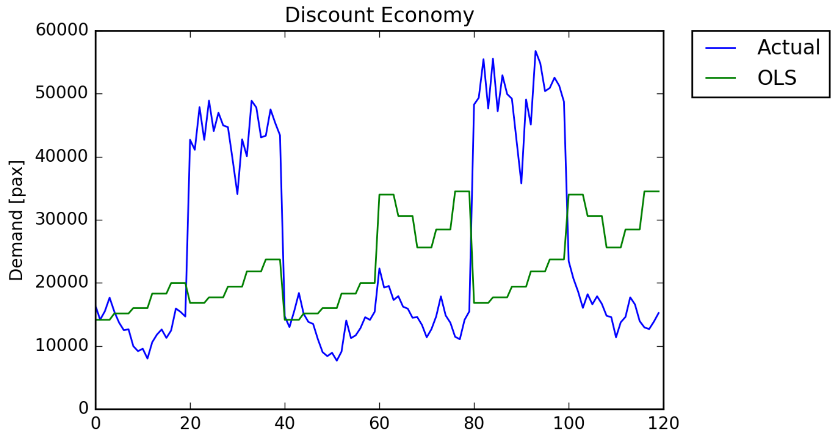


Figure C.31: Gravity Model Performance Discount Economy OLS Validation

Route	x-min	x-max
CPH-FRA	0	19
CPH-LHR	20	39
FRA-CPH	40	59
FRA-MAD	60	79
LHR-CPH	80	99
MAD-FRA	100	119

Table C.32: Route Ranges Discount Economy OLS Validation

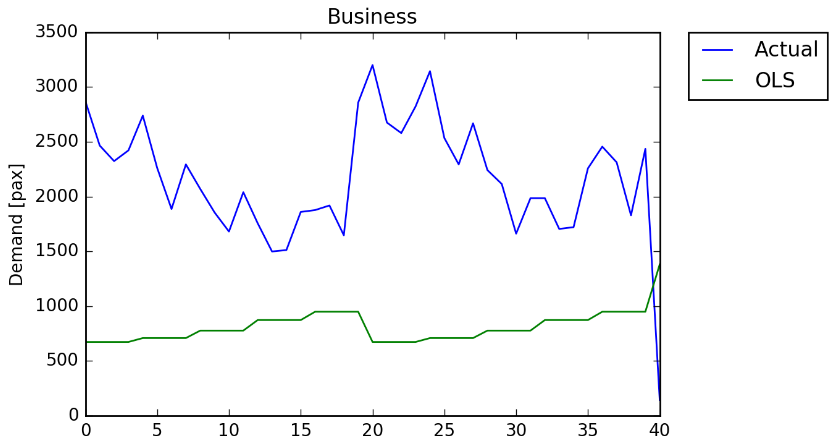


Figure C.32: Gravity Model Performance Business OLS Validation

Route	x-min	x-max
CPH-LHR	0	19
LHR-CPH	20	39
MAD-FRA	40	40

Table C.33: Route Ranges Business OLS Validation

Table C.34: Gravity Model Performance Validation per Route per Class

Route	Cabin	Sum of Squared Residuals	Std. Error of Estimate	Data Entries	Perc. Of Average Demand
CPH-FRA	Discount Economy	528910722	5143	20	0.40
FRA-CPH	Discount Economy	601320579	5483	20	0.44
CPH-FRA	Premium Economy	6401163	566	20	0.51
FRA-CPH	Premium Economy	10904454	738	20	0.52
CPH-LHR	Discount Economy	11963294485	24457	20	0.56
CPH-LHR	Premium Economy	31299439	1251	20	0.57
FRA-MAD	Premium Economy	96083380	2192	20	0.60
MAD-FRA	Premium Economy	111615315	2362	20	0.61
LHR-CPH	Discount Economy	18265579945	30221	20	0.61
CPH-LHR	Business	37999860	1378	20	0.66
LHR-CPH	Premium Economy	76456055	1955	20	0.68
LHR-CPH	Business	52156128	1615	20	0.69
MAD-FRA	Discount Economy	4537747112	15063	20	0.94
LHR-CPH	Full Y	16216987	900	20	0.96
CPH-LHR	Full Y	18419407	985	19	0.97
FRA-MAD	Discount Economy	4896341084	15647	20	1.02
MAD-FRA	First	66761639	1926	18	1.32
FRA-MAD	First	83603494	2098	19	1.62
LHR-CPH	First	24578895	1568	10	3.44
FRA-MAD	Full Y	1466595	699	3	3.60
MAD-FRA	Full Y	3789811	795	6	5.32
CPH-LHR	First	24155524	1738	8	5.38
FRA-CPH	First	2701809	1644	1	8.02
MAD-FRA	Business	1533390	1238	1	8.66
CPH-FRA	First	4458589	1493	2	13.51

D

Demand Allocation Performance

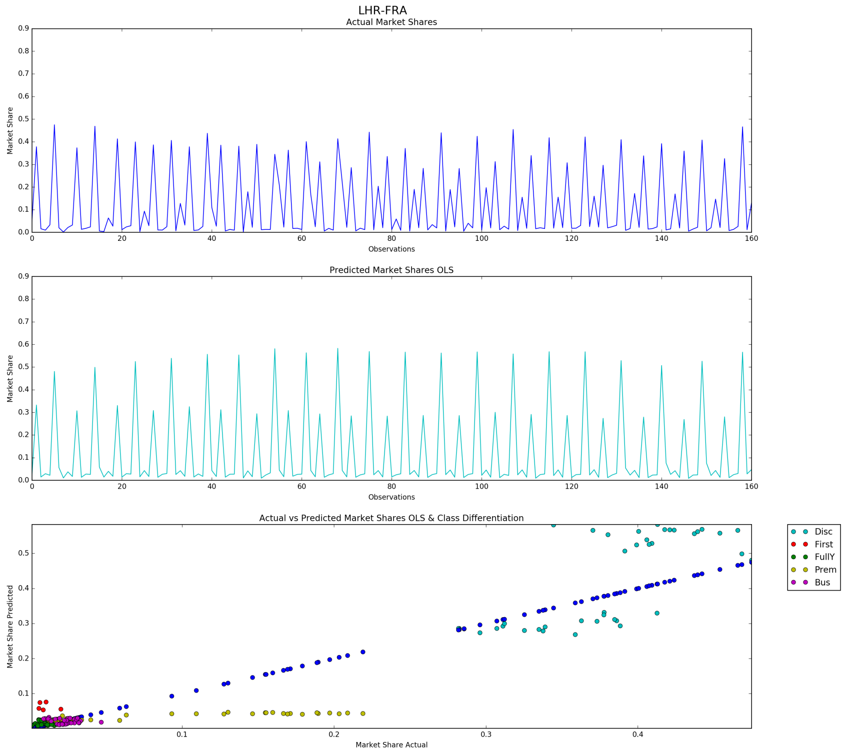


Figure D.1: Demand Allocation Performance LHR-FRA

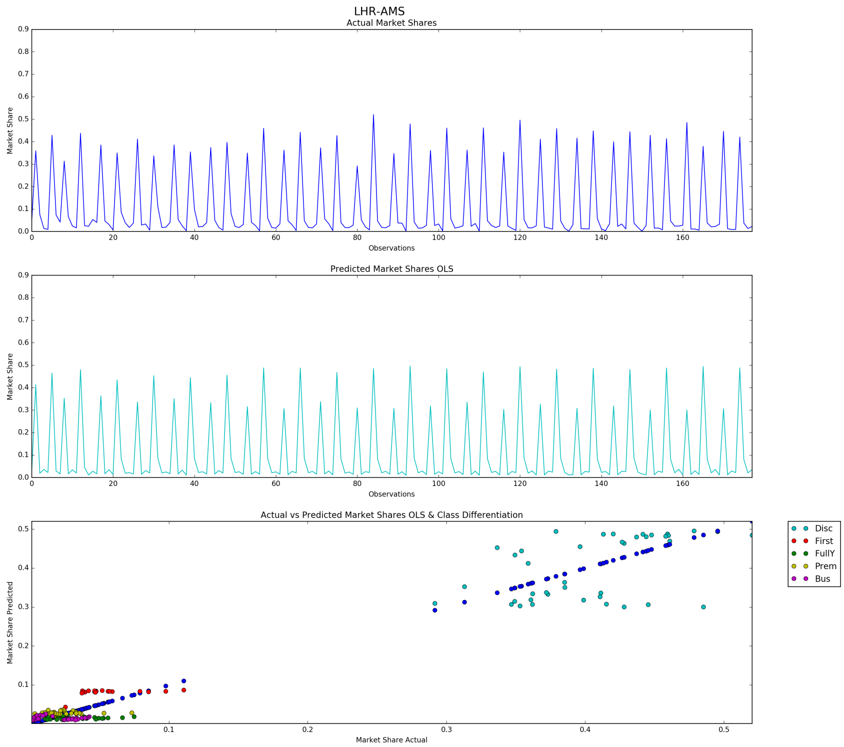


Figure D.2: Demand Allocation Performance LHR-AMS

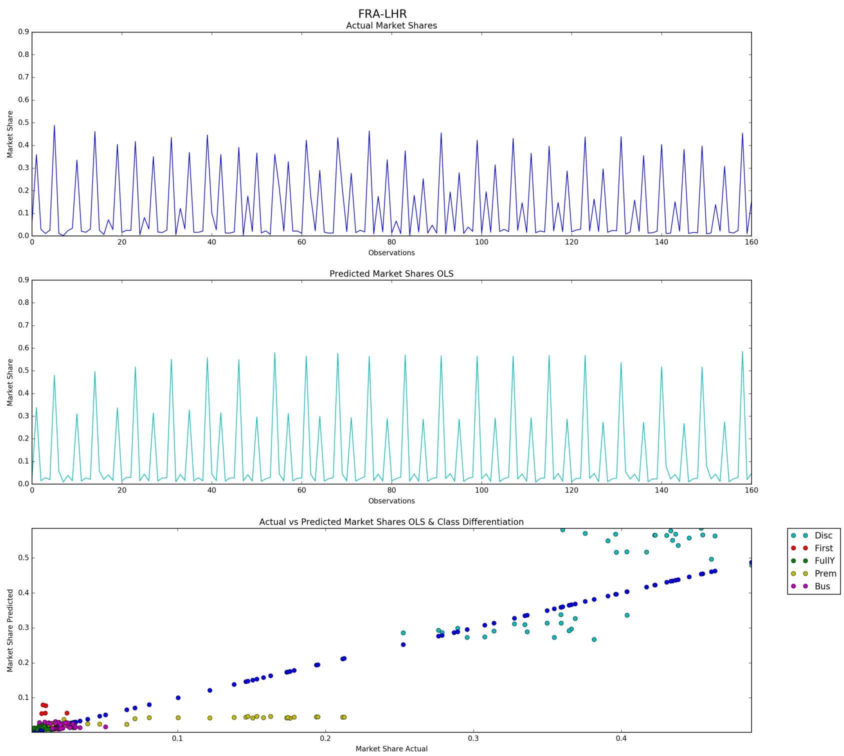


Figure D.3: Demand Allocation Performance FRA-LHR

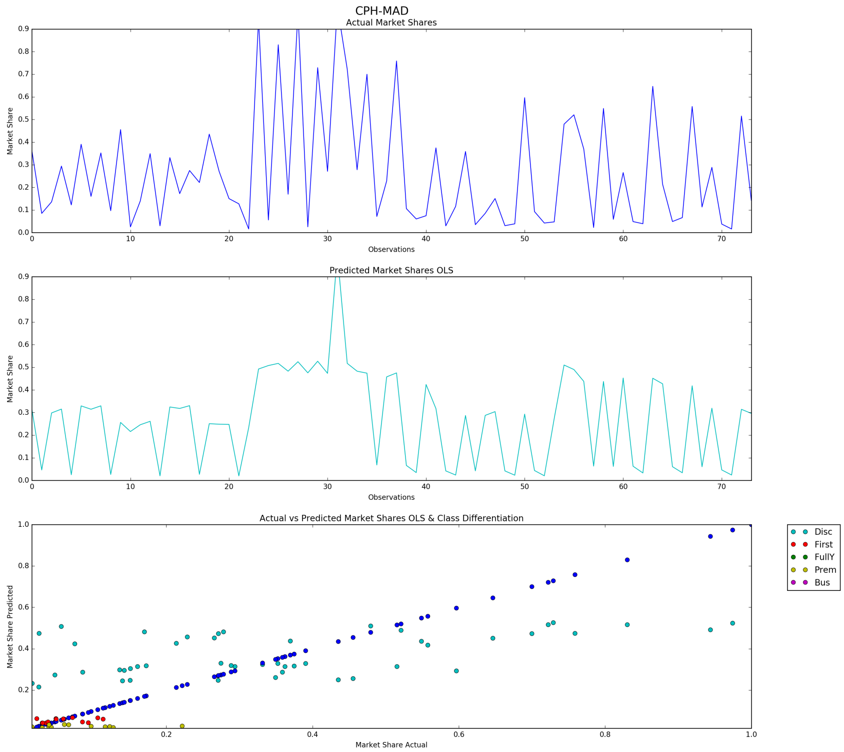


Figure D.4: Demand Allocation Performance CPH-MAD

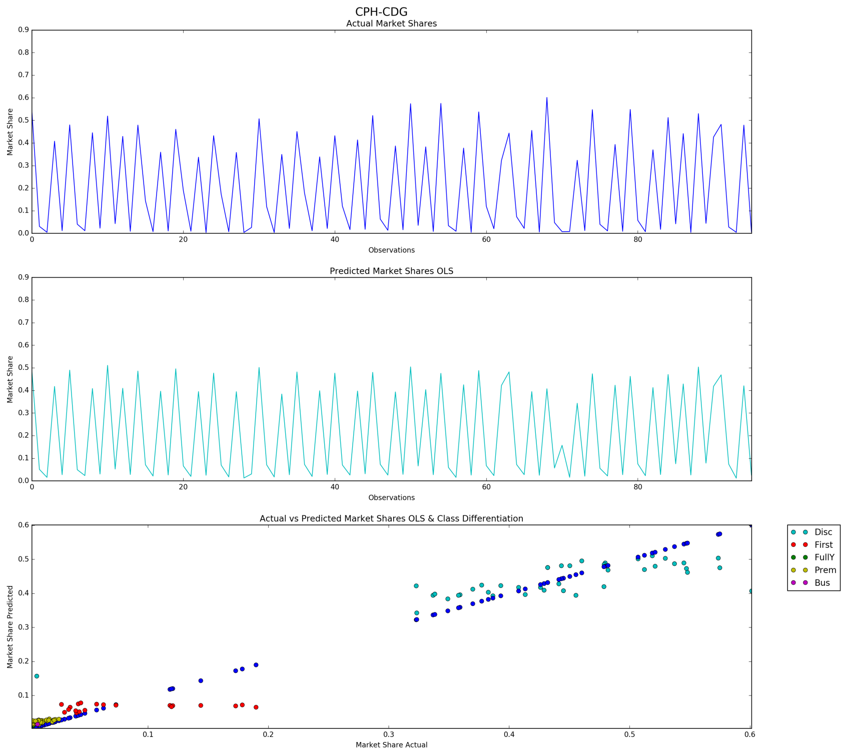


Figure D.5: Demand Allocation Performance CPH-CDG

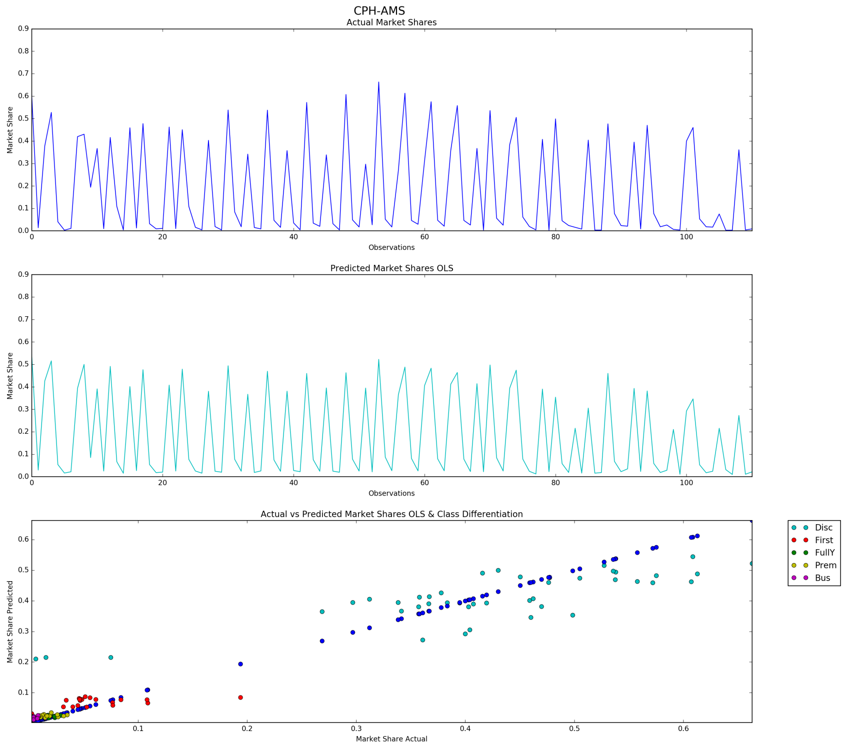


Figure D.6: Demand Allocation Performance CPH-AMS

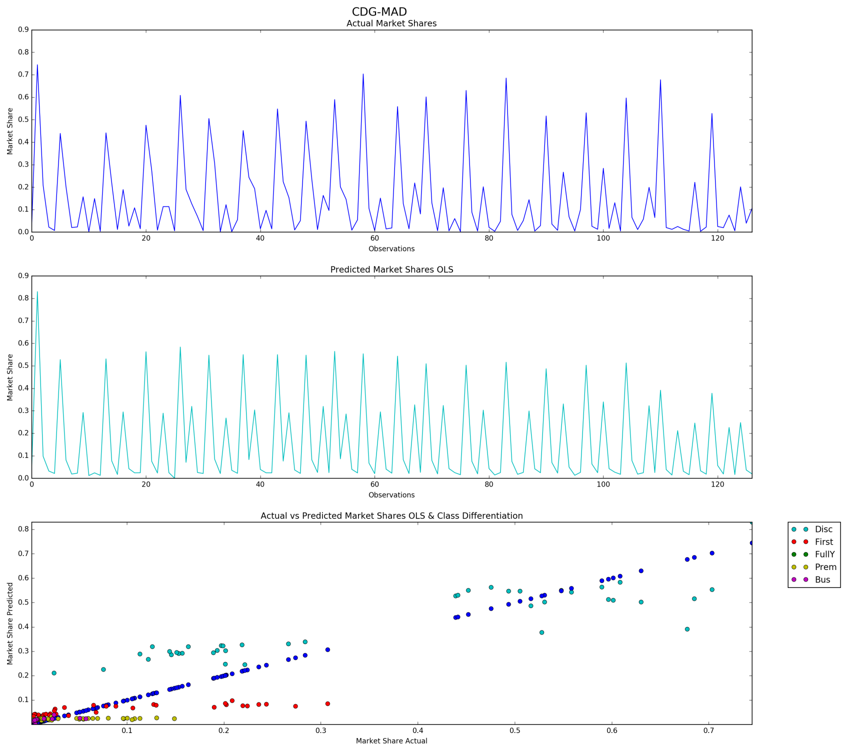


Figure D.7: Demand Allocation Performance CDG-MAD

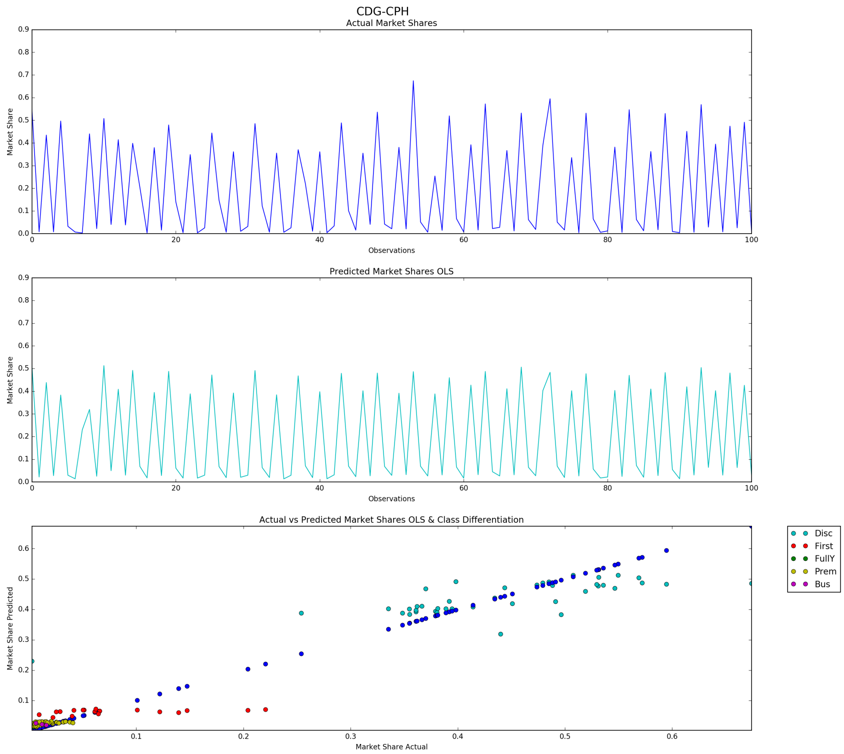


Figure D.8: Demand Allocation Performance CDG-CPH

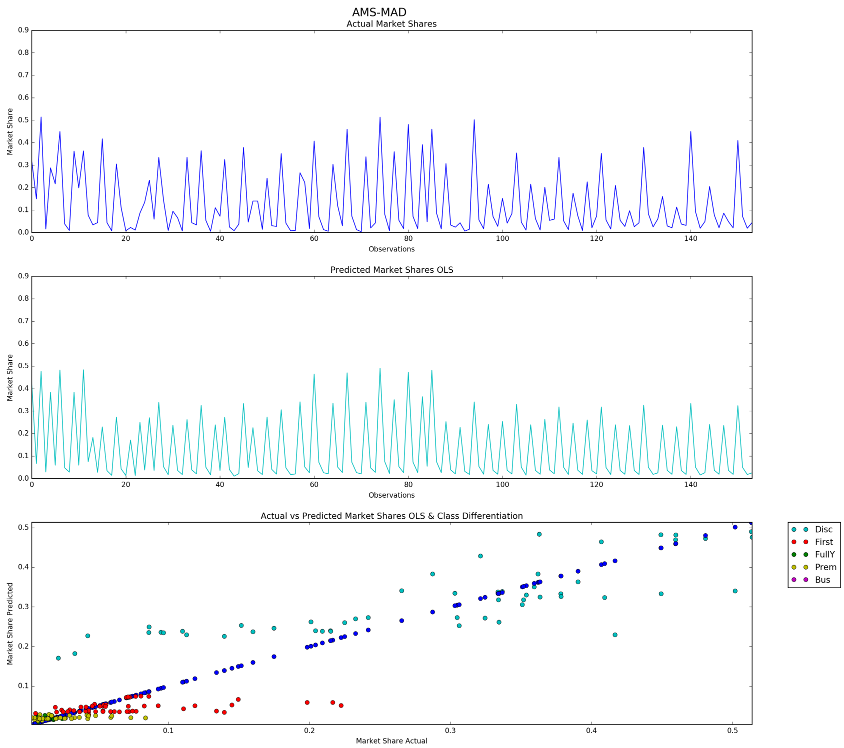


Figure D.9: Demand Allocation Performance AMS-MAD

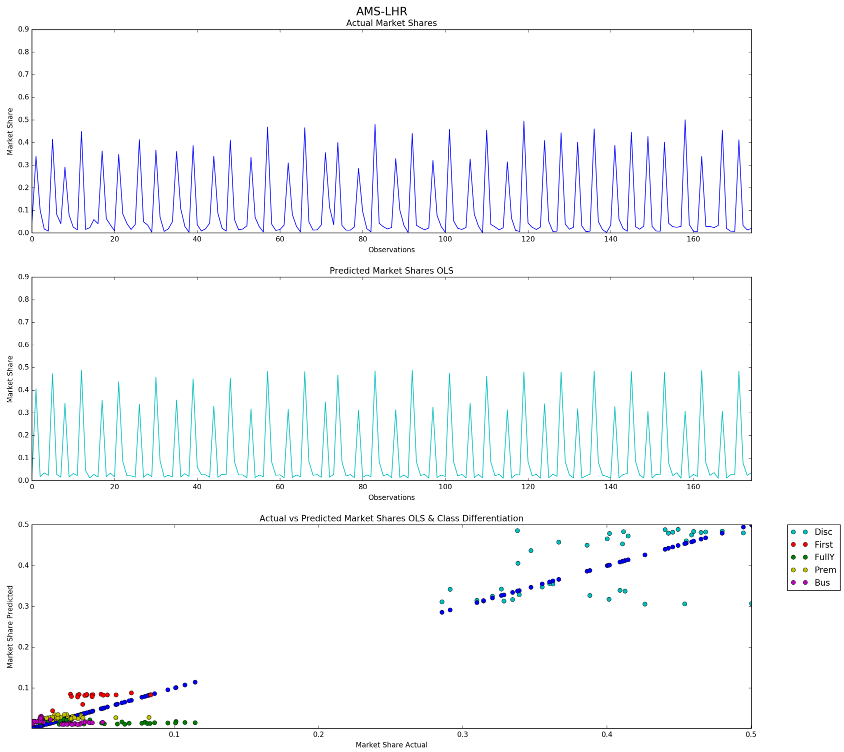


Figure D.10: Demand Allocation Performance AMS-LHR

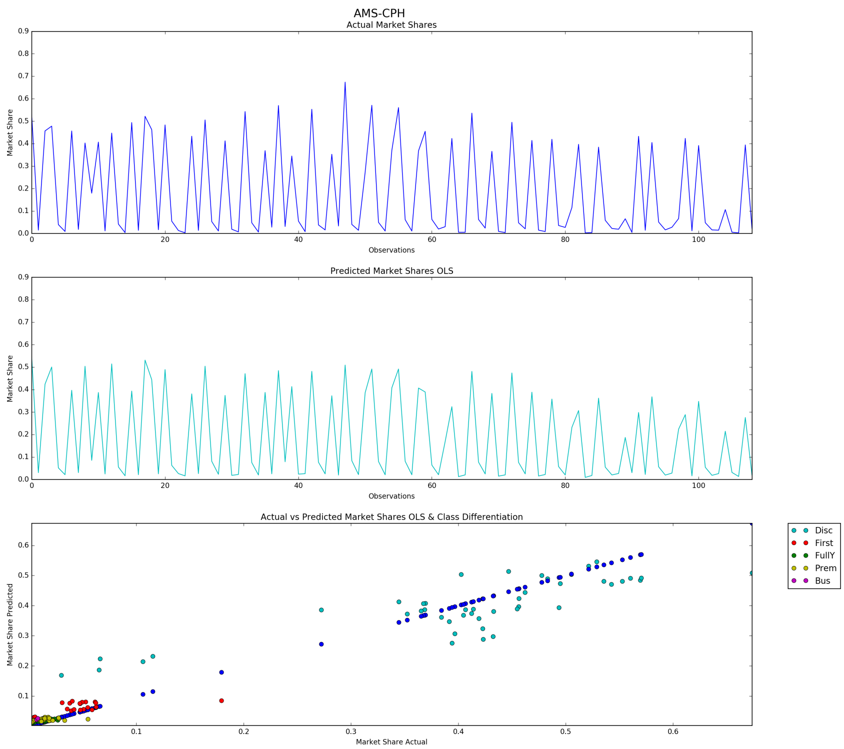


Figure D.11: Demand Allocation Performance AMS-CPH

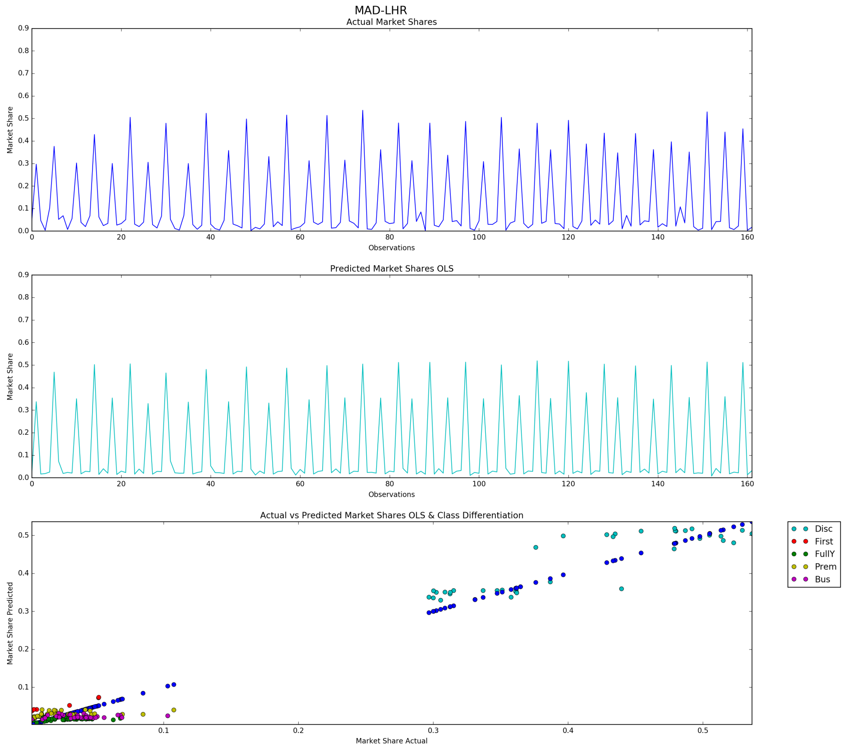


Figure D.12: Demand Allocation Performance MAD-LHR

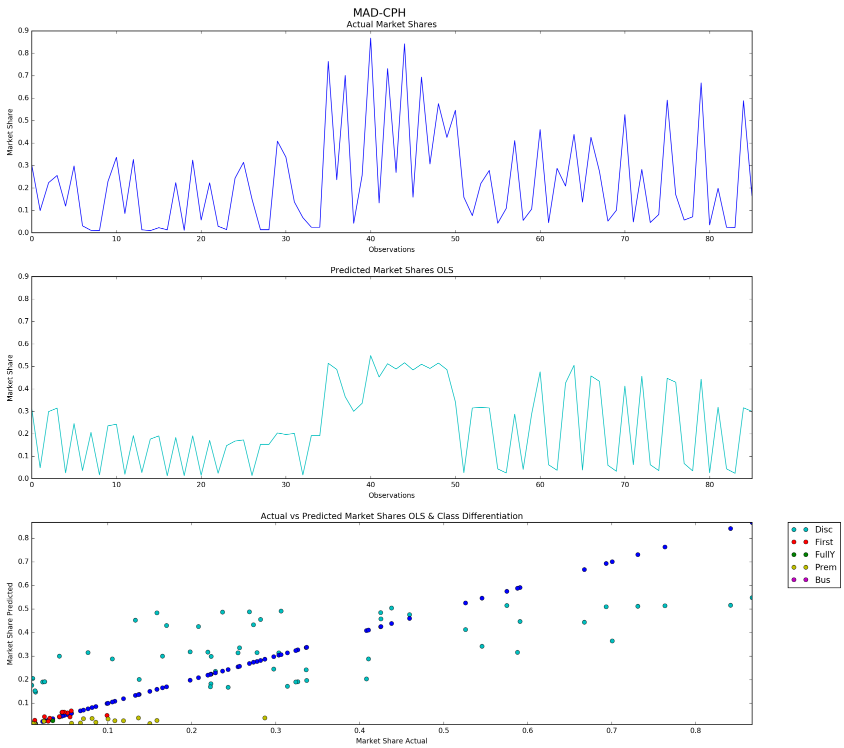


Figure D.13: Demand Allocation Performance MAD-CPH

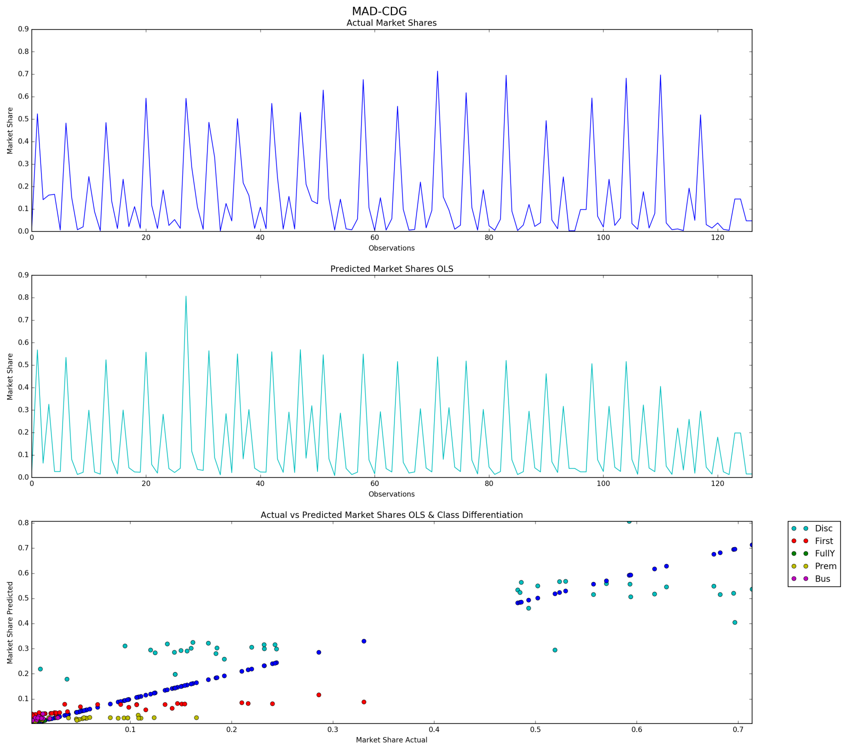


Figure D.14: Demand Allocation Performance MAD-CDG

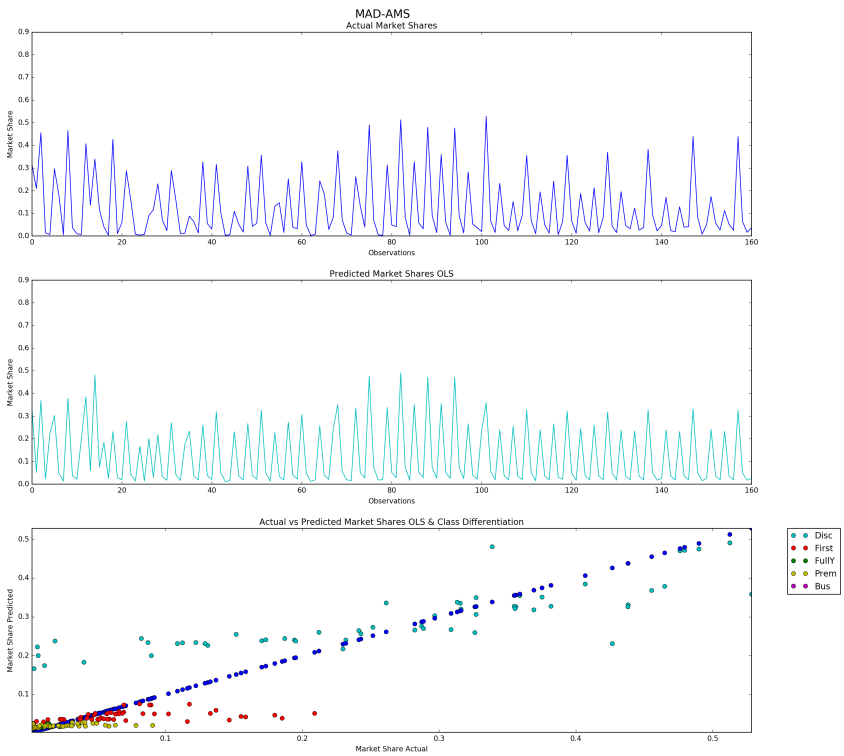


Figure D.15: Demand Allocation Performance MAD-AMS

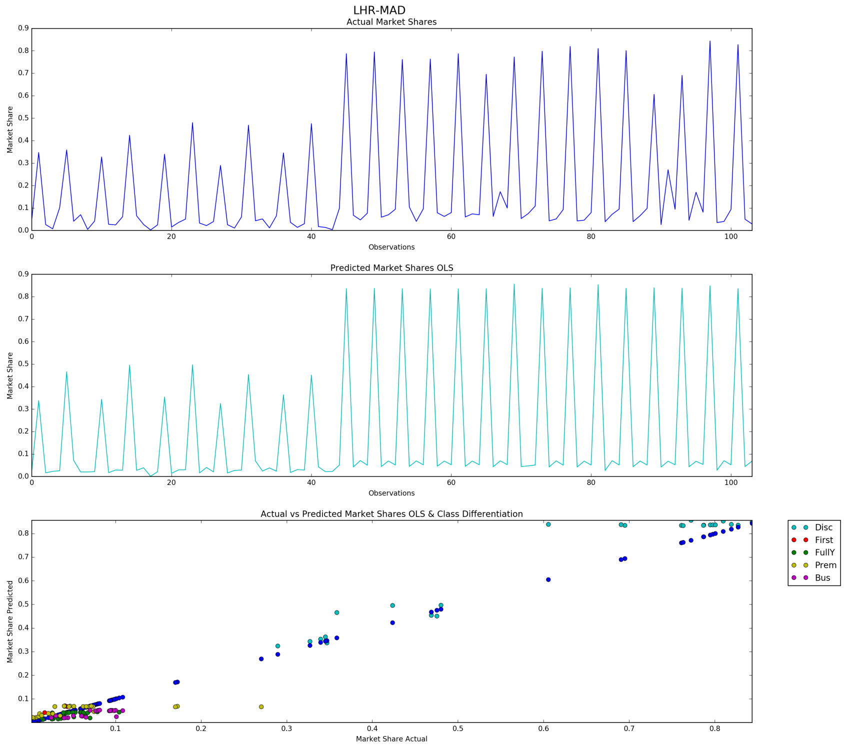


Figure D.16: Demand Allocation Performance LHR-MAD

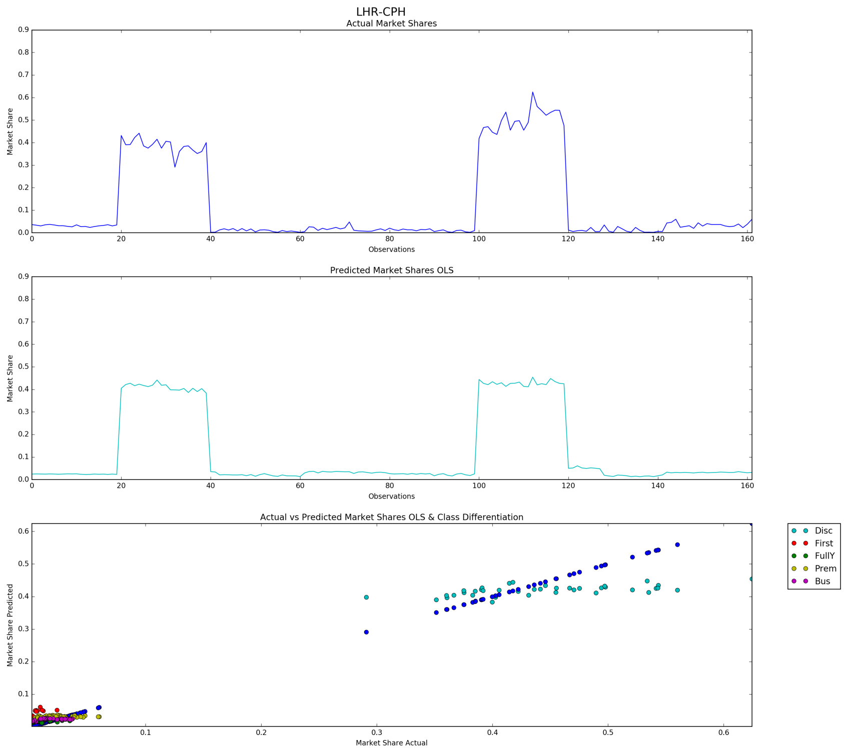


Figure D.17: Demand Allocation Performance LHR- CPH

Table D.1: Multinomial Logit Model Performance per Route per Class

Route	Cabin	Sum of Squared Residuals	Std. Error of Estimate	Data Count	Perc. Of Average Share
MAD-LHR	Discount Economy	0.07	0.04	40	10.1%
LHR-MAD	Discount Economy	0.15	0.07	26	12.6%
CPH-CDG	Discount Economy	0.14	0.06	41	13.4%
CDG-CPH	Discount Economy	0.22	0.07	41	16.7%
AMS-LHR	Discount Economy	0.17	0.07	40	16.7%
LHR-AMS	Discount Economy	0.19	0.07	40	17.0%
AMS-CPH	Discount Economy	0.28	0.08	45	19.4%
CPH-AMS	Discount Economy	0.33	0.09	43	20.9%
MAD-CPH	Full Y	0.00	0.01	1	26.1%
FRA-LHR	Discount Economy	0.40	0.10	40	26.4%
LHR-FRA	Discount Economy	0.44	0.11	40	27.7%
AMS-MAD	Discount Economy	0.39	0.09	53	29.9%
CDG-MAD	Discount Economy	0.60	0.12	41	33.2%
MAD-AMS	Discount Economy	0.51	0.09	57	35.7%
MAD-CDG	Discount Economy	0.72	0.13	42	36.3%
MAD-CPH	First	0.00	0.02	12	41.8%
CPH-AMS	Full Y	0.00	0.01	21	44.2%
CPH-MAD	First	0.01	0.03	13	47.6%
LHR-MAD	Full Y	0.01	0.02	25	47.8%
LHR-FRA	Business	0.01	0.01	40	50.3%
LHR-MAD	Business	0.04	0.04	25	50.6%
FRA-LHR	Full Y	0.00	0.01	36	52.6%
AMS-CPH	Full Y	0.00	0.01	18	53.3%
FRA-LHR	Business	0.01	0.01	40	55.7%
MAD-CPH	Discount Economy	1.78	0.18	57	56.1%
CPH-MAD	Discount Economy	2.18	0.21	49	56.7%
CPH-AMS	First	0.03	0.04	20	57.1%
AMS-MAD	Full Y	0.00	0.01	14	58.1%
LHR-AMS	First	0.02	0.03	19	59.4%
MAD-CDG	Full Y	0.00	0.01	5	59.5%
LHR-AMS	Premium Economy	0.01	0.01	40	63.0%
MAD-LHR	Business	0.02	0.02	40	63.6%
AMS-CPH	First	0.02	0.03	20	63.7%
MAD-LHR	Full Y	0.01	0.02	39	65.9%
CPH-CDG	First	0.06	0.05	20	66.0%
AMS-LHR	Premium Economy	0.01	0.02	38	69.7%
AMS-MAD	First	0.13	0.05	51	71.3%
MAD-AMS	First	0.14	0.05	50	72.1%
MAD-AMS	Full Y	0.00	0.01	14	73.6%
LHR-AMS	Full Y	0.02	0.02	39	74.4%
CDG-CPH	First	0.06	0.06	19	74.4%
MAD-AMS	Premium Economy	0.02	0.02	40	76.5%
AMS-MAD	Premium Economy	0.01	0.02	36	77.3%
AMS-CPH	Premium Economy	0.00	0.01	24	80.4%
LHR-MAD	First	0.00	0.03	3	80.8%
MAD-LHR	Premium Economy	0.02	0.02	37	82.2%
LHR-AMS	Business	0.01	0.02	40	82.5%
CDG-MAD	Full Y	0.00	0.01	6	84.4%
LHR-FRA	Full Y	0.00	0.01	36	86.7%
CDG-CPH	Premium Economy	0.01	0.01	33	86.9%
MAD-CDG	First	0.19	0.07	35	87.0%
CDG-MAD	Business	0.00	0.02	12	88.0%
CPH-AMS	Premium Economy	0.00	0.01	21	88.3%
CPH-CDG	Business	0.00	0.01	1	89.7%
AMS-LHR	First	0.03	0.04	19	90.0%
CDG-MAD	First	0.25	0.09	34	90.4%
AMS-LHR	Business	0.01	0.02	39	91.3%
LHR-MAD	Premium Economy	0.07	0.05	25	91.8%
FRA-LHR	Premium Economy	0.27	0.08	40	94.6%
CPH-MAD	Premium Economy	0.08	0.08	12	96.9%
MAD-CDG	Premium Economy	0.08	0.05	35	97.1%
LHR-FRA	Premium Economy	0.29	0.08	40	97.8%
AMS-LHR	Full Y	0.08	0.04	39	98.4%
MAD-CPH	Premium Economy	0.14	0.09	16	101.2%
CDG-MAD	Premium Economy	0.08	0.05	34	101.6%
CPH-CDG	Premium Economy	0.01	0.01	32	110.3%
CDG-CPH	Business	0.00	0.01	3	113.6%
MAD-CDG	Business	0.00	0.02	10	120.4%
MAD-LHR	First	0.01	0.03	6	123.3%
CPH-CDG	Full Y	0.00	0.01	2	176.3%
CDG-CPH	Full Y	0.00	0.01	5	184.1%
AMS-CPH	Business	0.00	0.02	2	216.3%
CPH-AMS	Business	0.00	0.01	6	271.9%
FRA-LHR	First	0.01	0.05	5	423.8%
LHR-FRA	First	0.02	0.05	5	538.2%

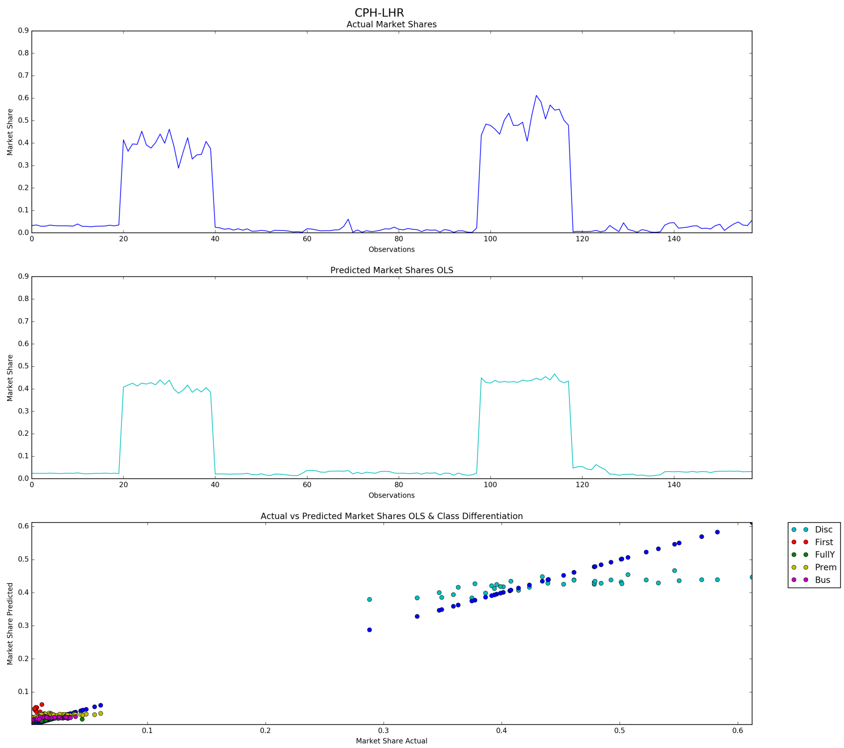


Figure D.18: Demand Allocation Performance CPH - LHR

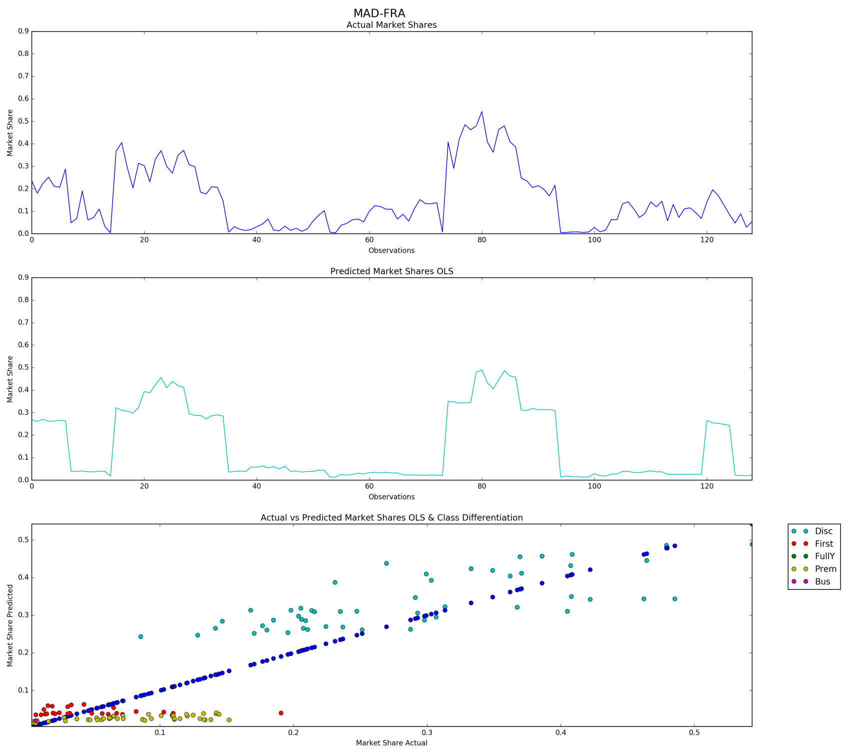


Figure D.19: Demand Allocation Performance MAD - FRA

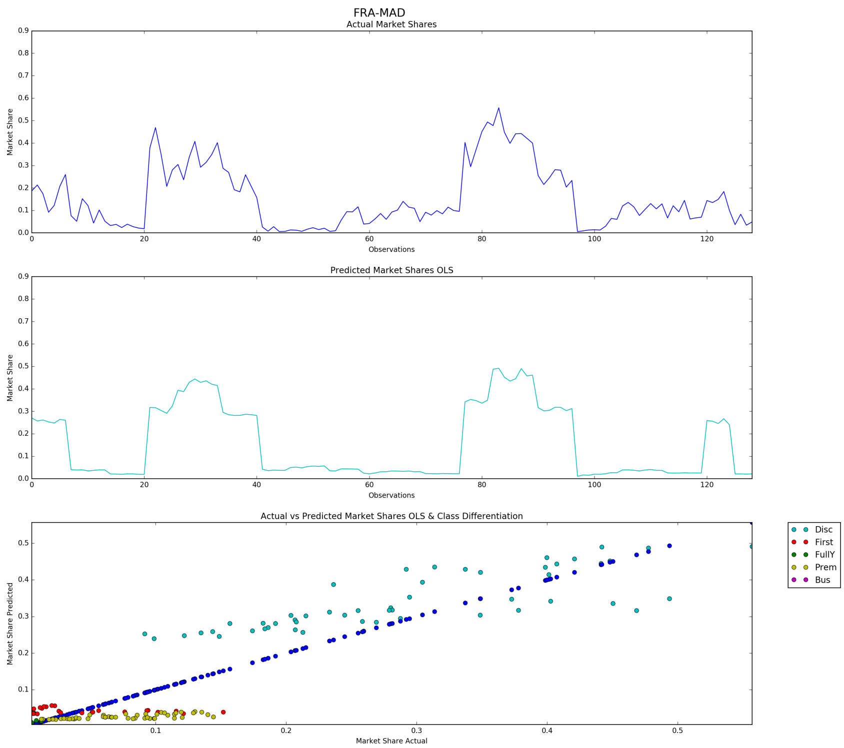


Figure D.20: Demand Allocation Performance FRA - MAD

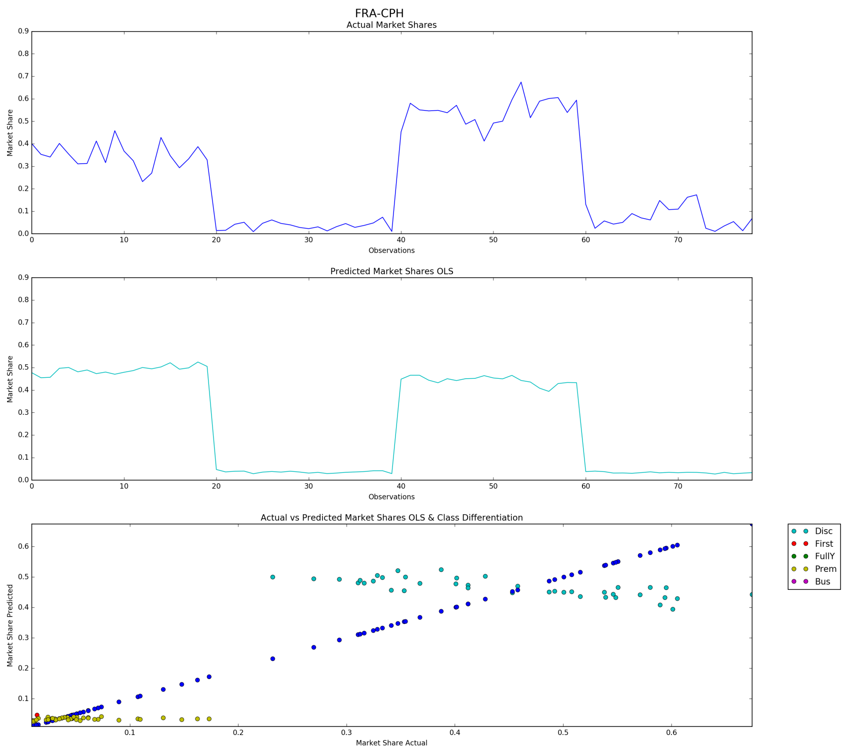


Figure D.21: Demand Allocation Performance FRA - CPH

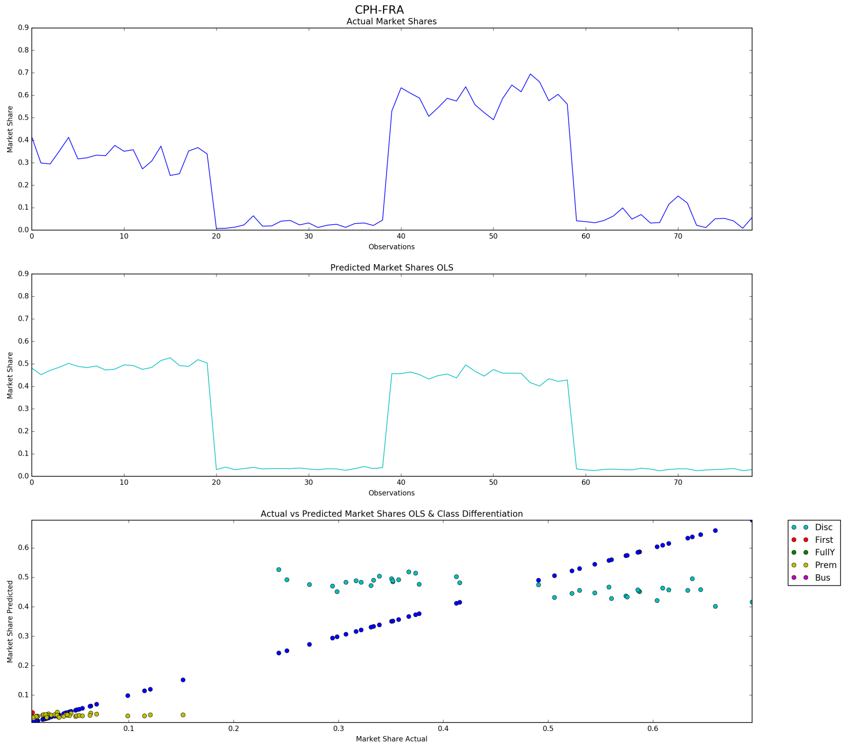


Figure D.22: Demand Allocation Performance CPH - FRA

Table D.2: Multinomial Logit Model Performance Validation per Cabin Class

Cabin	Sum of Squared Residuals	Std. Error of Estimate perc	Data Count	Perc. Of Average Share
Discount Economy	2.85	0.10	264	26.9%
Business	0.01	0.01	80	49.6%
Premium Economy	0.52	0.05	248	87.2%
Full Y	0.01	0.01	73	88.8%
First	0.13	0.04	71	121.7%

Table D.3: Multinomial Logit Model Performance Validation per Route

Route	Sum of Squared Residuals	Std. Error of Estimate	Data Entries	Perc. Of Average Share
CPH-LHR	0.19	0.03	158	14.0%
LHR-CPH	0.21	0.04	162	15.4%
MAD-FRA	0.64	0.07	129	28.4%
FRA-MAD	0.59	0.07	129	29.1%
FRA-CPH	0.85	0.10	79	40.9%
CPH-FRA	1.03	0.11	79	45.1%

Table D.4: Multinomial Logit Model Performance Validation per Route per Class

Route	Cabin	Sum of Squared Residuals	Std. Error of Estimate	Data Count	Perc. Of Average Demand
CPH-LHR	Discount Economy	0.16	0.06	40	14.1%
LHR-CPH	Discount Economy	0.18	0.07	40	15.0%
FRA-MAD	Discount Economy	0.37	0.08	52	29.0%
MAD-FRA	Discount Economy	0.39	0.09	52	29.8%
FRA-CPH	Discount Economy	0.77	0.14	40	31.0%
CPH-LHR	First	0.01	0.04	8	34.2%
CPH-FRA	Discount Economy	0.99	0.16	40	34.2%
CPH-LHR	Business	0.00	0.01	39	45.2%
LHR-CPH	Business	0.00	0.01	40	52.9%
LHR-CPH	Premium Economy	0.01	0.02	39	58.6%
FRA-MAD	Full Y	0.00	0.01	3	63.4%
CPH-LHR	Premium Economy	0.01	0.02	40	69.0%
CPH-LHR	Full Y	0.00	0.01	31	76.6%
CPH-FRA	Premium Economy	0.04	0.03	37	77.6%
FRA-MAD	Premium Economy	0.17	0.06	49	78.2%
MAD-FRA	Premium Economy	0.21	0.07	45	82.6%
FRA-CPH	Premium Economy	0.08	0.05	38	83.4%
MAD-FRA	First	0.05	0.04	25	89.9%
FRA-MAD	First	0.05	0.05	25	98.3%
LHR-CPH	Full Y	0.00	0.01	33	100.2%
MAD-FRA	Full Y	0.00	0.01	6	117.5%
MAD-FRA	Business	0.00	0.01	1	173.2%
FRA-CPH	First	0.00	0.03	1	227.7%
CPH-FRA	First	0.00	0.03	2	365.6%
LHR-CPH	First	0.02	0.04	10	506.9%

E

Simulation Game Results

Figure E.1: Game 2 Revenue, Cost and Profit Development

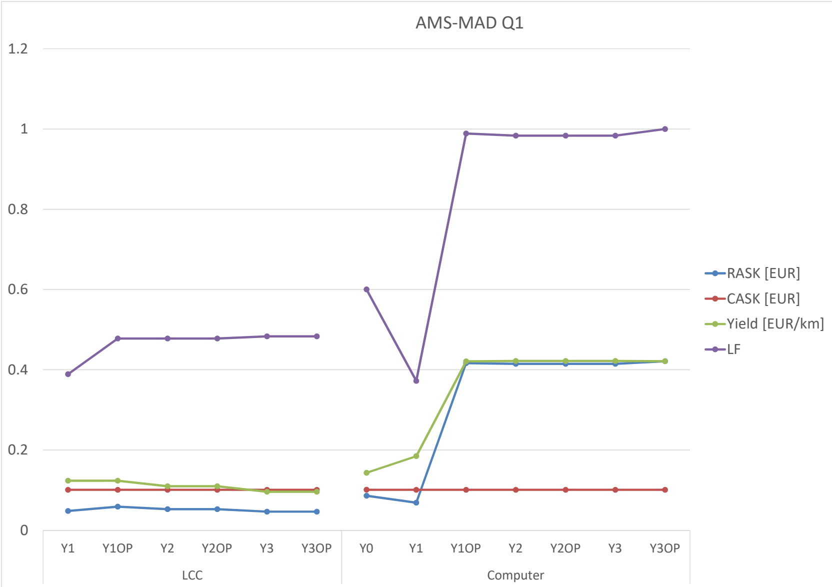


Figure E.2: Game 2 RASK, CASK, Yield and Load Factor Development

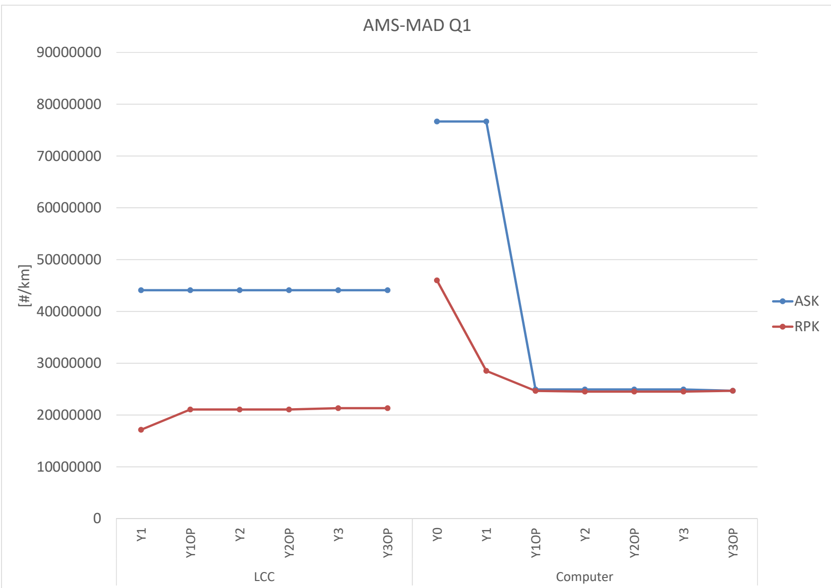


Figure E.3: Game 2 ASK and RPK Development

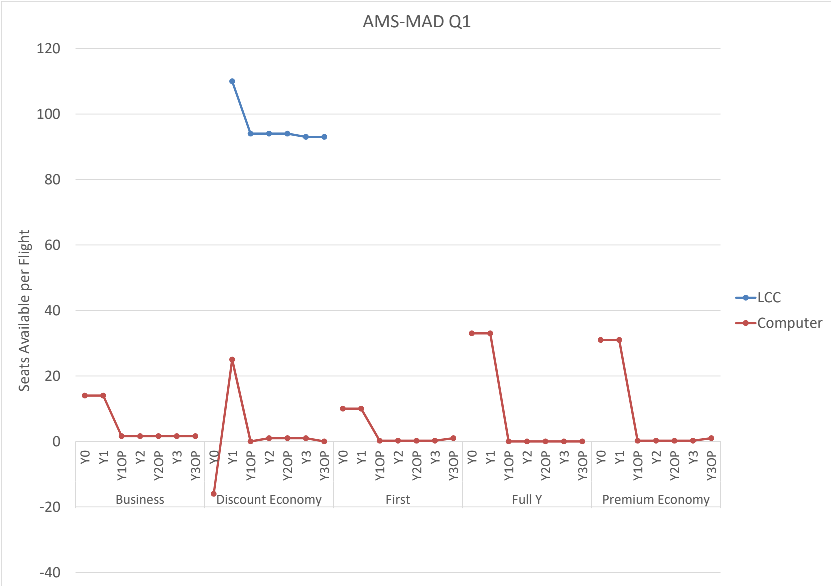


Figure E.4: Game 2 Seat Availability per Flight Development

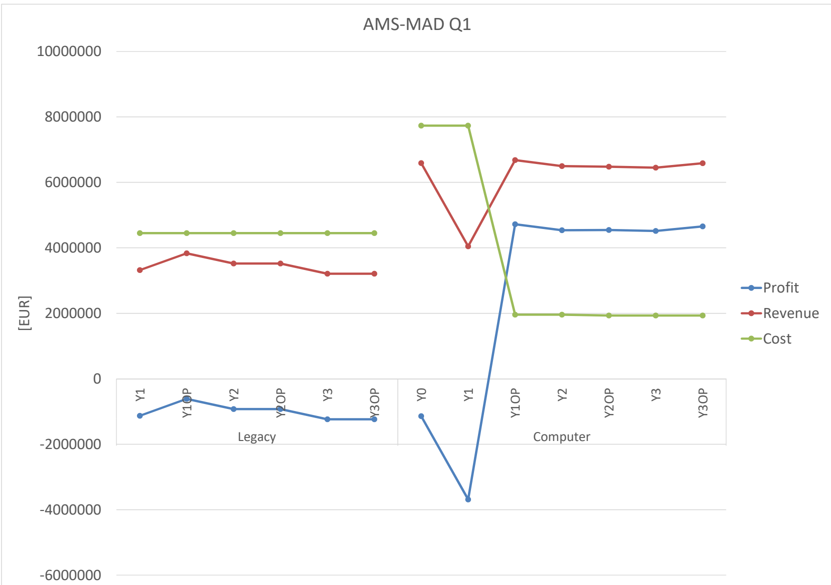


Figure E.5: Game 3 Revenue, Cost and Profit Development

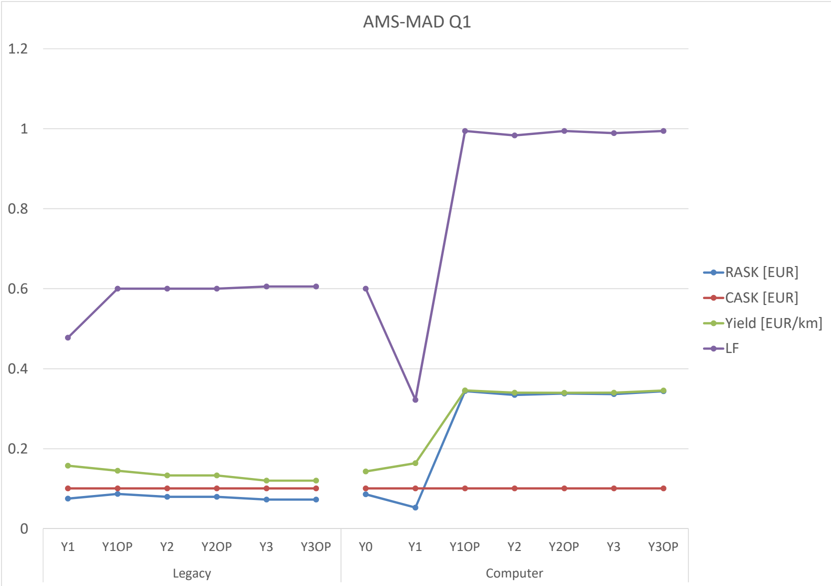


Figure E.6: Game 3 Revenue, Cost and Profit Development

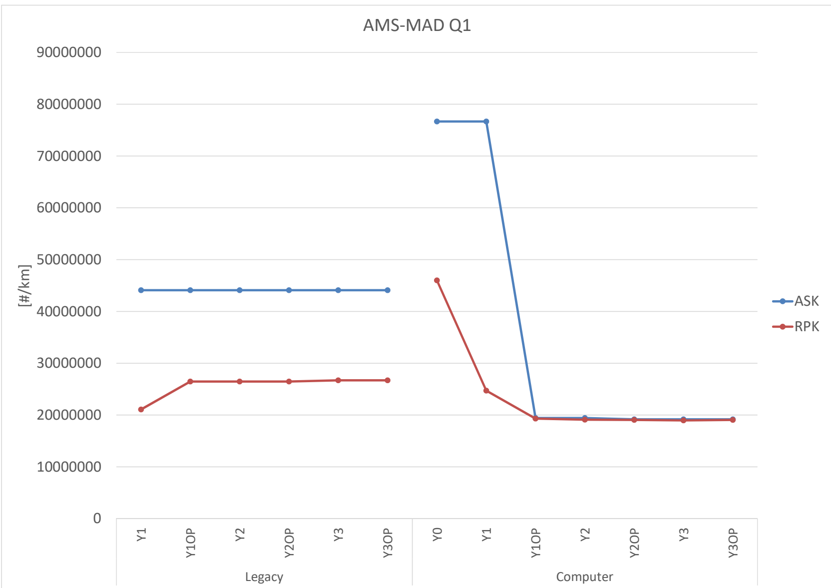


Figure E.7: Game 3 ASK and RPK Development

Table E.1: Block Times 'Super' Competitor

Route	Avg. Block Time	Max. Block Time	Min Block Time	Avg. Freq.	Max. Freq	Min. Freq	Flight time
AMS-CPH	871	1075	538	824	1017	509	1.057
AMS-LHR	1203	1312	965	1603	1748	1286	0.750
AMS-MAD	1761	2261	1135	886	1137	571	1.988
CDG-CPH	912	1174	587	616	793	397	1.480
CDG-MAD	983	1395	661	639	906	429	1.539
CPH-AMS	868	1027	547	821	971	517	1.057
CPH-CDG	916	1167	631	619	789	426	1.480
CPH-FRA	728	909	509	652	814	456	1.116
CPH-LHR	1254	1479	918	868	1024	635	1.445
CPH-MAD	827	1080	488	309	403	182	2.680
FRA-CPH	755	916	516	676	821	462	1.116
FRA-LHR	1706	1889	1406	1586	1757	1307	1.075
FRA-MAD	1780	2219	1264	915	1141	650	1.945
LHR-AMS	1210	1312	965	1613	1748	1286	0.750
LHR-CPH	1279	1472	1067	885	1019	739	1.445
LHR-FRA	1716	1889	1403	1596	1757	1305	1.075
LHR-MAD	2804	3357	1555	1607	1924	891	1.745
MAD-AMS	1756	2322	912	883	1168	459	1.988
MAD-CDG	995	1380	730	647	897	474	1.539
MAD-CPH	797	1076	468	297	402	175	2.680
MAD-FRA	1765	2315	1196	908	1190	615	1.945
MAD-LHR	1793	2075	1438	1028	1189	824	1.745

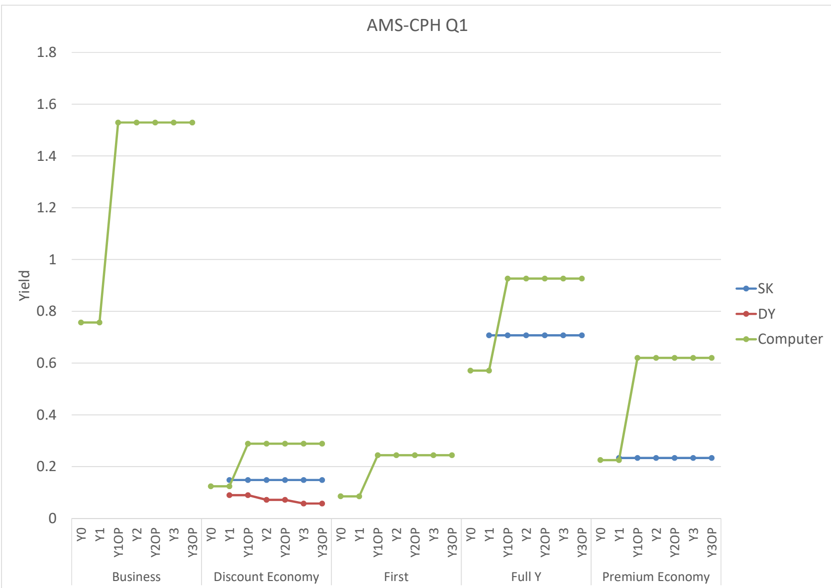


Figure E.8: Game 4 Yield Development AMS-CPH

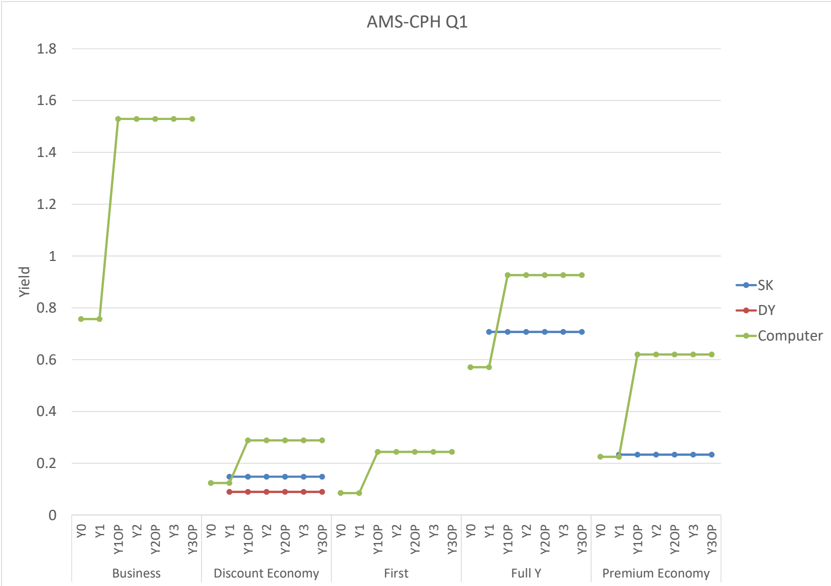


Figure E.9: Game 4 Null Yield Development AMS-CPH

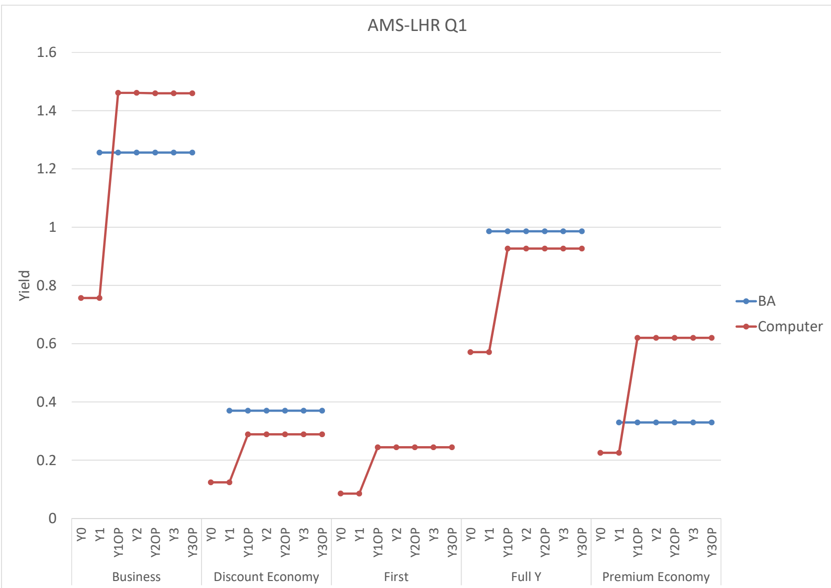


Figure E.10: Game 4 Null Yield Development AMS-LHR

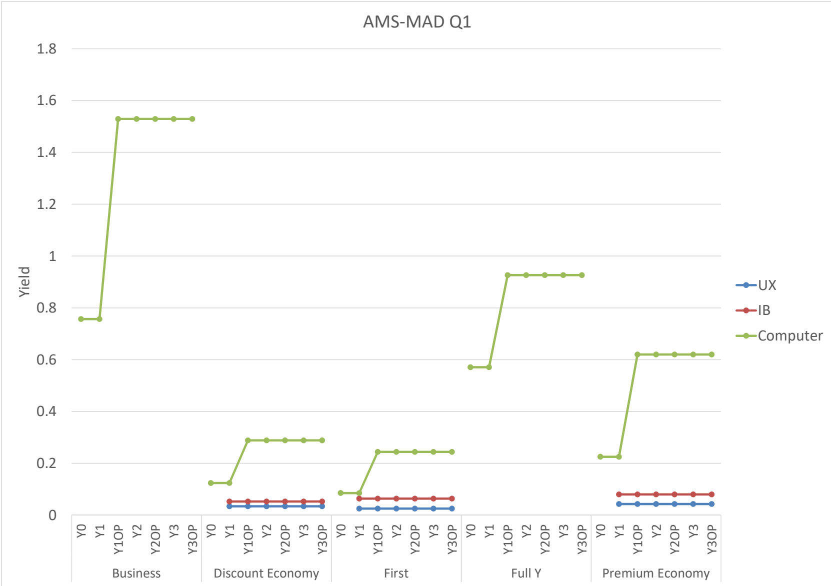


Figure E.11: Game 4 Yield Development AMS-MAD

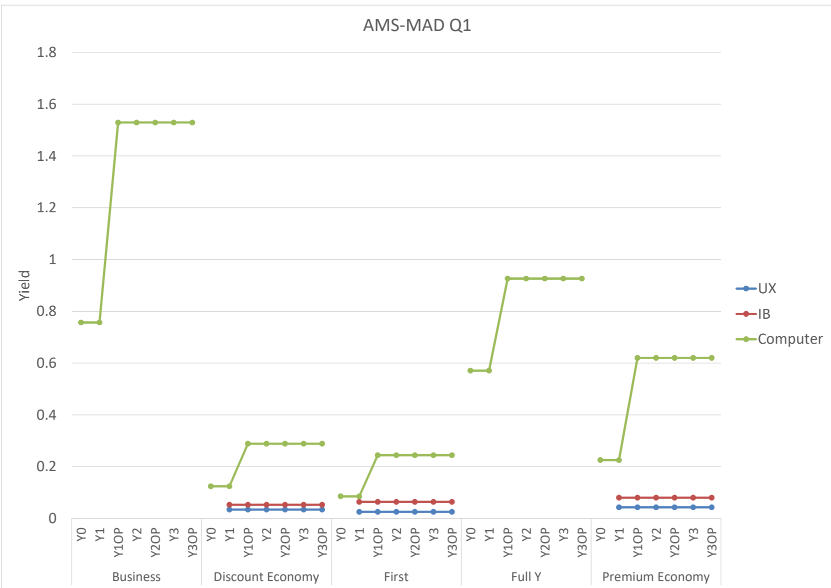


Figure E.12: Game 4 Null Yield Development AMS-MAD

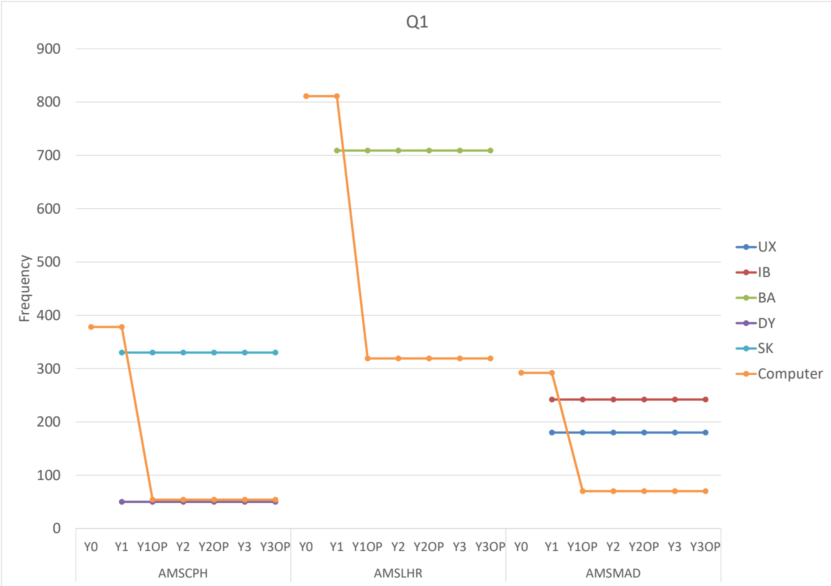


Figure E.13: Game 4 Null Frequency Development

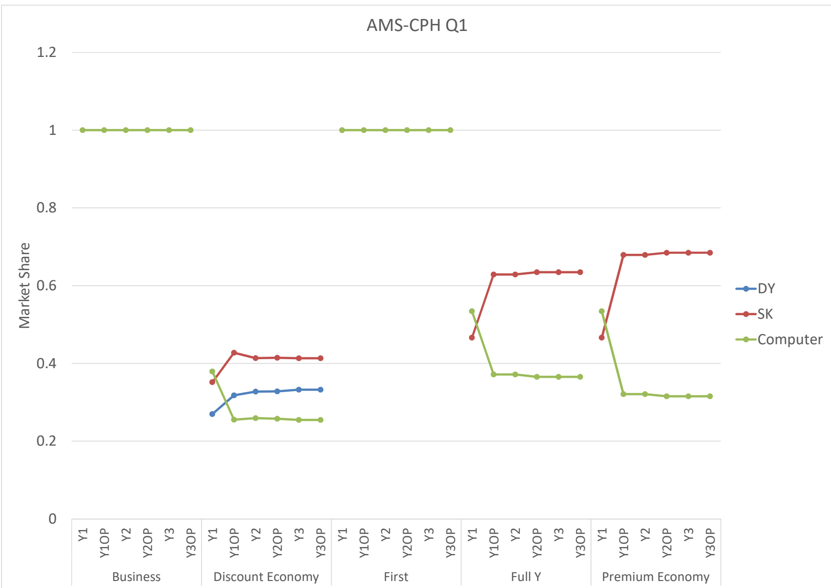


Figure E.14: Game 4 Market Share Development AMS-CPH

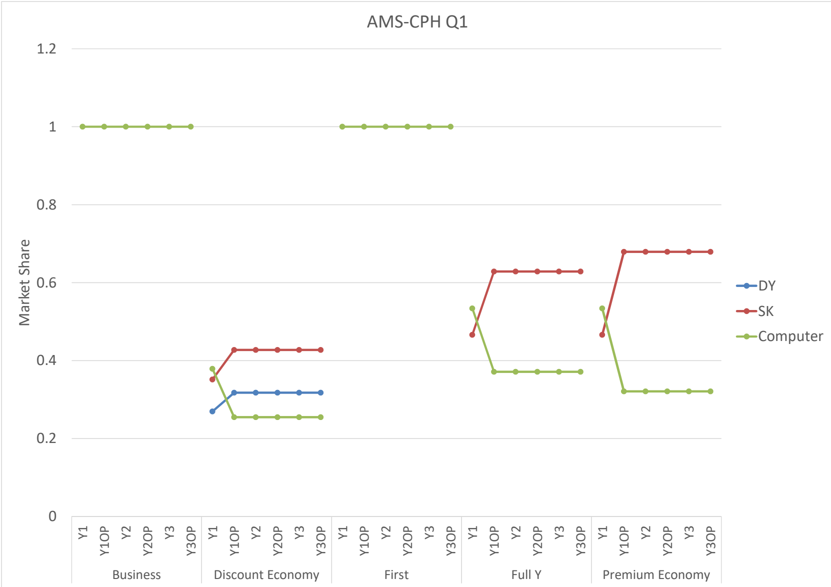


Figure E.15: Game 4 Null Market Share Development

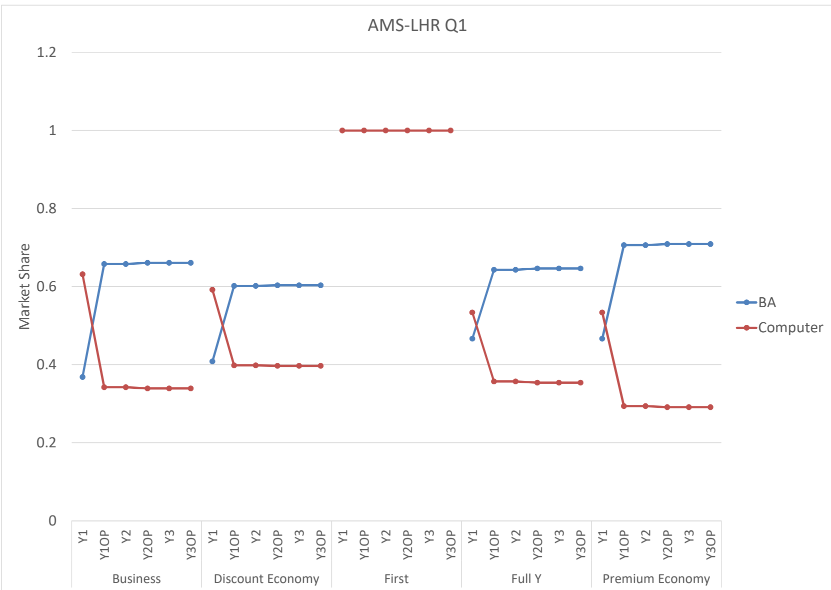


Figure E.16: Game 4 Null Market Share Development AMS-LHR

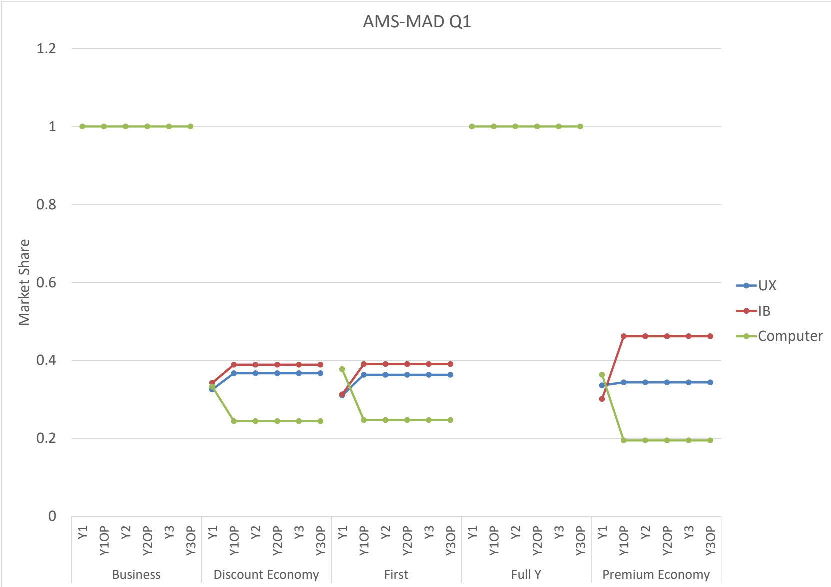


Figure E.17: Game 4 Null Market Share Development AMS-MAD

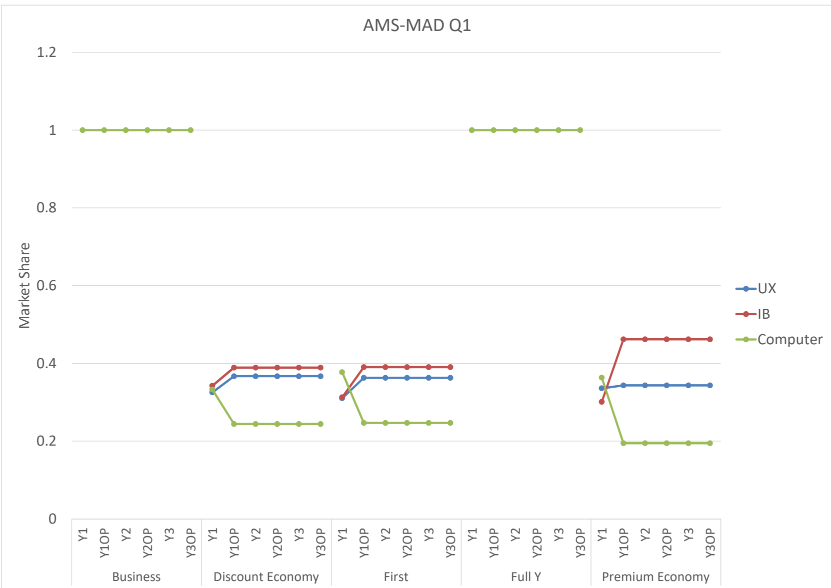


Figure E.18: Game 4 Market Share Development AMS-MAD

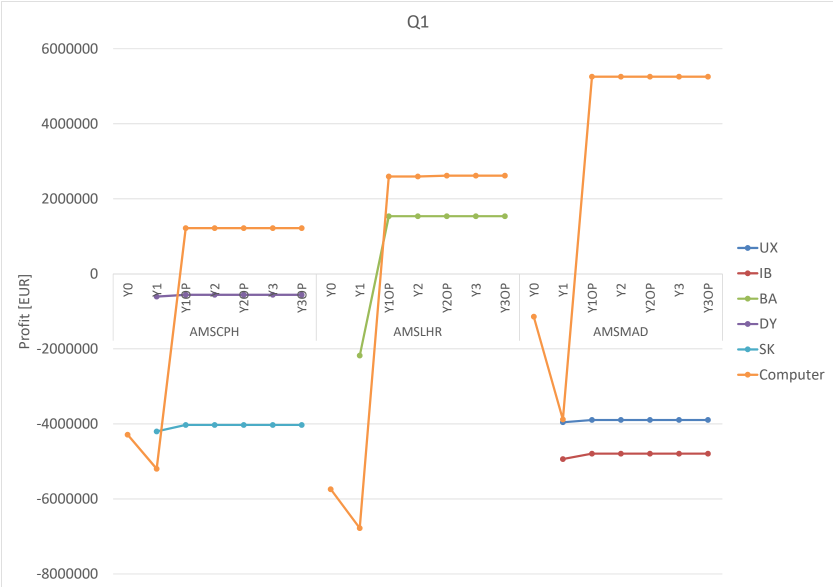


Figure E.19: Game 4 Profit Development

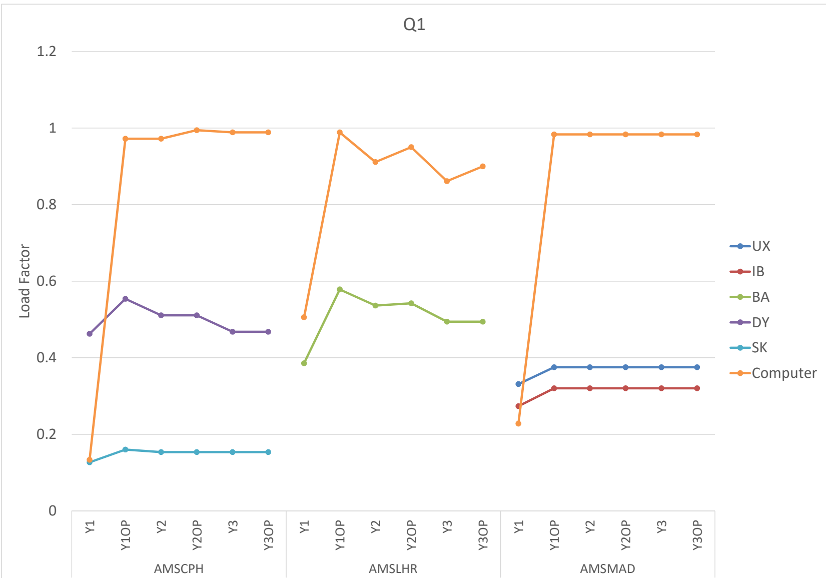


Figure E.20: Game 4 Load Factor Development

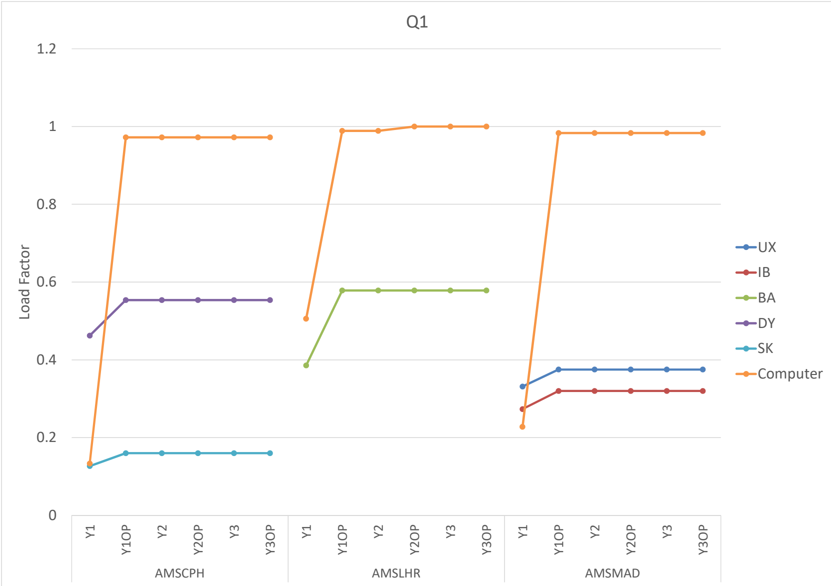


Figure E.21: Game 4 Null Load Factor Development

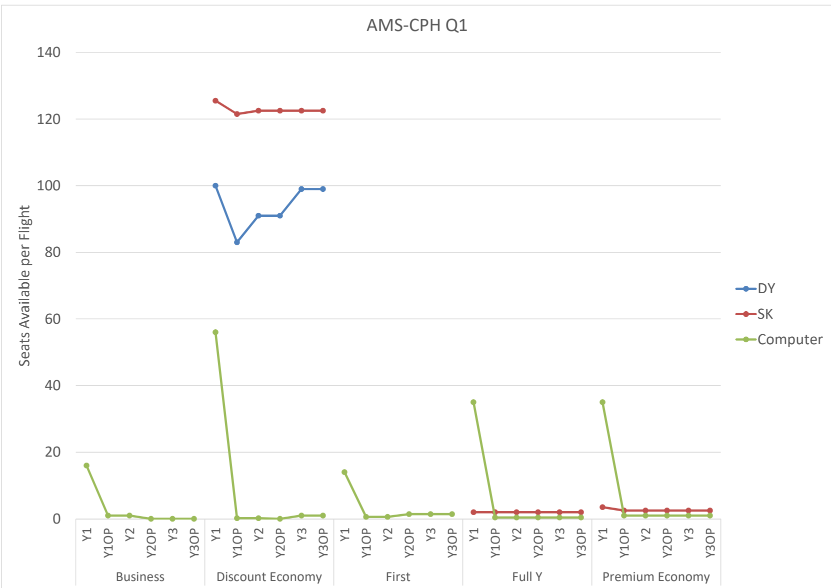


Figure E.22: Game 4 Seat Availability per Flight Development AMS-CPH

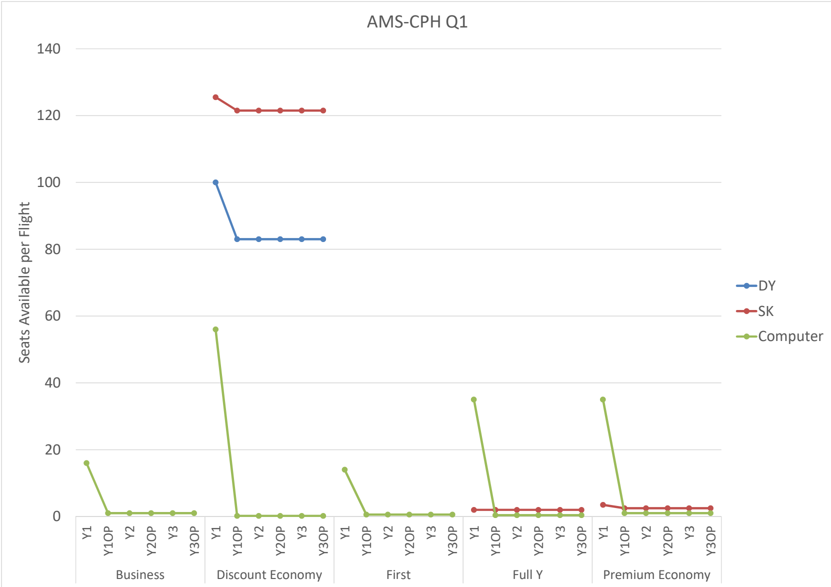


Figure E.23: Game 4 Null Seat Availability per Flight Development AMS-CPH

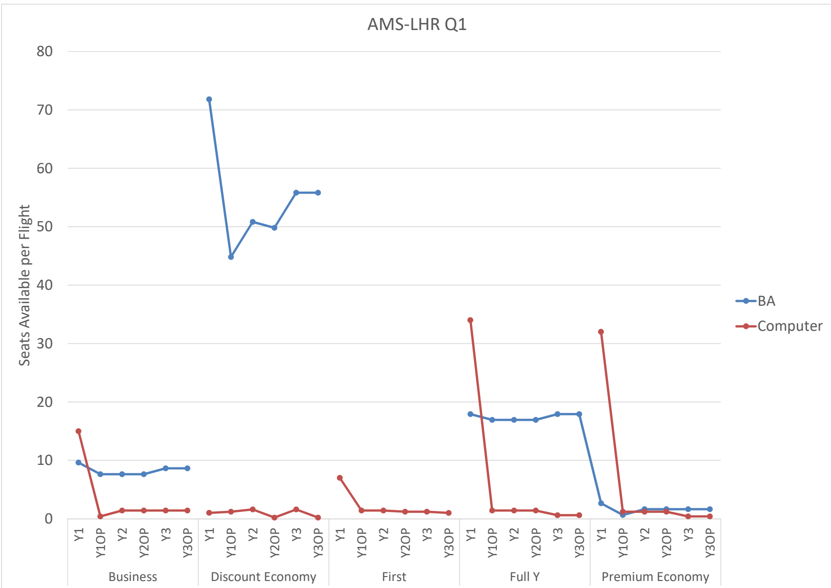


Figure E.24: Game 4 Seat Availability per Flight Development AMS-LHR

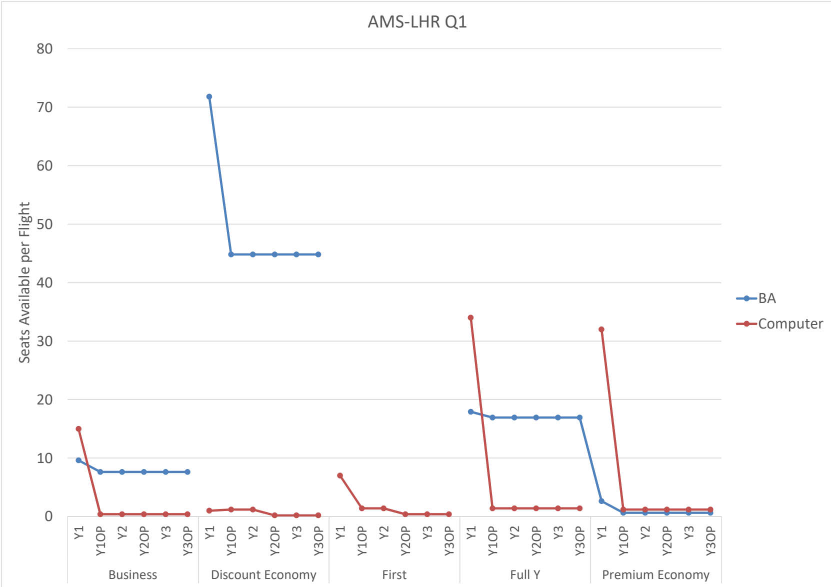


Figure E.25: Game 4 Null Seat Availability per Flight Development AMS-LHR

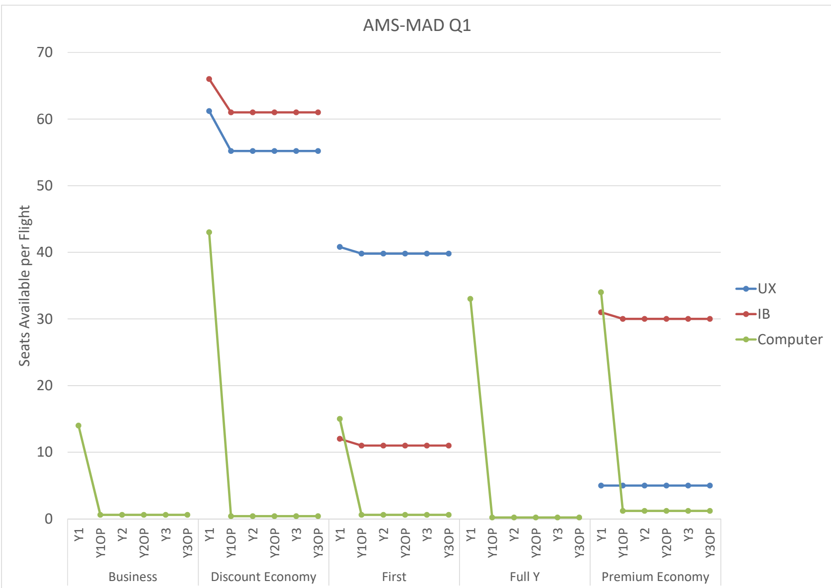


Figure E.26: Game 4 Seat Availability per Flight Development AMS-MAD

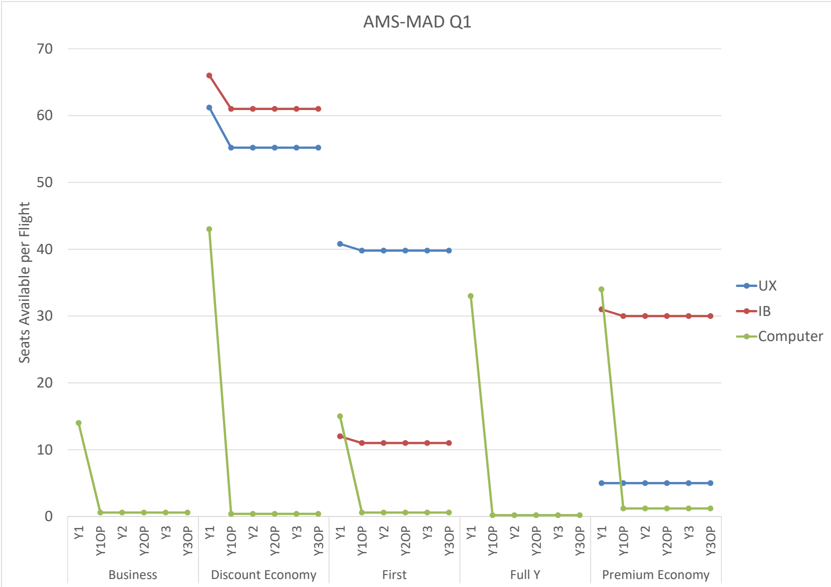


Figure E.27: Game 4 Null Seat Availability per Flight Development AMS-MAD

Bibliography

Maya Abou-Zeid, Thomas Rossi, and Brian Gardner. Modeling Time-of-Day Choice in Context of Tour- and Activity-Based Models. *Transportation Research Record*, 1981(1):42–49, 2006. ISSN 0361-1981. doi: 10.3141/1981-08.

Michael Abrahams. A service quality model of air travel demand: An empirical study. *Transportation Research Part A: General*, 17(5):385–393, 1983. ISSN 01912607. doi: 10.1016/0191-2607(83)90007-9.

Nicole Adler. Hub-Spoke Network Choice Under Competition with an Application to Western Europe. *Transportation Science*, 39(1):58–72, 2005. ISSN 0041-1655. doi: 10.1287/trsc.1030.0081. URL http://www.scopus.com/inward/record.url?eid=2-s2.0-16244404632{&}partnerID=tZOtx3y1.

Nicole Adler, Eric Pels, and Chris Nash. High-speed rail and air transport competition: Game engineering as tool for cost-benefit analysis. *Transportation Research Part B: Methodological*, 44(7):812–833, 2010. ISSN 01912615. doi: 10.1016/j.trb.2010.01.001. URL http://dx.doi.org/10.1016/j.trb.2010.01.001.

T. Adler, V. Warburg, and C. Bhat. Modeling demographic and unobserved heterogeneity in air passengers' sensitivity to service attributes in itinerary choice. *Transportation Research Record*, (1951): 7–16, 2006. ISSN 03611981. doi: 10.3141/1951-02.

Fariba E. Alamdari and Ian G. Black. Passengers' choice of airline under competition: the use of the logit model. *Transport Reviews*, 12(October 2014):153–170, 1992. ISSN 0144-1647. doi: 10.1080/01441649208716811.

James E. Anderson and Marvin Kraus. Quality of Service and the Demand for Air Travel. *The Review of Economics and Statistics*, 63(4):533–540, 1981.

M. Baena Moreno. Airline choice for domestic flights in São Paulo metropolitan area: an application of the conditional logit model. *Journal of Air Transportation*, 11(2):22–42, 2006. doi: 10.1002/cjce.20423.

Peter Belobaba. Modeling Passenger Choice of Flight Options. Technical Report March, 2014.

Peter Belobaba, Amedeo Odoni, and Cynthia Barnhart. *The Global Airline Industry*. 2009. ISBN 9780470740774. doi: 10.1002/9780470744734.

M. Ben-Akiva. Structure of passenger travel demand models, 1974. ISSN 0361-1981.

Moshe Ben-Akiva and Steven R Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand*, volume 6. 1985. ISBN 0262022176. doi: 10.2307/1391567. URL http://www.jstor.org/stable/1391567?origin=crossref.

Dimitris Bertsimas and Sarah Stock Patterson. The air traffic flow management problem with enroute capacities. *Operations research*, 46(3):406–422, 1998. ISSN 0030-364X. doi: 10.1287/opre.46.3.406. URL http://tinyurl.com/c9octaf.

Severin Borenstein and Nancy L Rose. Competition and Price Dispersion in the U . S . Airline Industry. *Journal of Political Economy*, 102(4):653–683, 2011. ISSN 0022-3808. doi: 10.1086/261950.

Jan K. Brueckner. Schedule competition revisited. *Journal of Transport Economics and Policy*, 44(3): 261–285, 2010. ISSN 00225258.

JK Brueckner. A note on the determinants of metropolitan airline traffic. *International Journal of Transport Economics/Rivista*, 1985. URL http://www.jstor.org/stable/42748169.

Emmanuel Carrier. Modeling the Choice of an Airline Itinerary and Fare Product Using Booking and Seat Availability Data. pages 1–47, 2008. URL http://agifors.org/award/submissions2008/Carrier{_}paper.pdf.

Yu-Hern Chang and Chung-Hsing Yeh. A survey analysis of service quality for domestic airlines. *European Journal of Operational Research*, 139(1):166–177, 2002. ISSN 03772217. doi: 10.1016/S0377-2217(01)00148-5.

Ian Wen-Yu Chiang, Gin-Shuh Liang, and Shmuel Yahalom. The fuzzy clustering method: Applications in the air transport market in Taiwan. *Journal of Database Marketing & Customer Strategy Management*, 11:149–158, 2003. ISSN 1741-2439. doi: 10.1057/palgrave.dbm.3240215. URL http://www.palgrave-journals.com/doifinder/10.1057/palgrave.dbm.3240215.

Gregory M. Coldren and Frank S. Koppelman. Modeling the competition among air-travel itinerary shares: GEV model development. *Transportation Research Part A: Policy and Practice*, 39(4 SPEC. ISSS.):345–365, 2005. ISSN 09658564. doi: 10.1016/j.tra.2004.12.001.

Gregory M. Coldren, Frank S. Koppelman, Krishnan Kasturirangan, and Amit Mukherjee. Modeling aggregate air-travel itinerary shares: Logit model development at a major US airline. *Journal of Air Transport Management*, 9(6):361–369, 2003. ISSN 09696997. doi: 10.1016/S0969-6997(03)00042-5.

C.S.M. Currie, R.C.H. Cheng, and H.K. Smith. Dynamic pricing of airline tickets with competition. *Journal of Operational Research Society*, 59(8):1026–1037, 2008. ISSN 0160-5682. doi: 10.1057/palgrave.jors.2602425. URL http://eprints.soton.ac.uk/64207/.

Gregory Dobson and Phillip J. Lederer. Airline scheduling and routing in a hub-and-spoke system. *Transportation Science*, 27(3):281–297, 1993. ISSN 0041-1655. doi: 10.1287/trsc.27.3.281. URL http://pubsonline.informs.org/doi/abs/10.1287/trsc.27.3.281.

R Doganis. *Flying off course: The economics of international airlines*. 2002. ISBN 0203995260. URL https://books.google.nl/books?hl=nl{&}lr={&}id=eR5unZWjOEUC{&}oi=fnd{&}pg=PR8{&}ots=tFdzv6IABx{&}sig=g5NCoeF1xBm2MzBx2Cp9iDc3BGI.

Rigas Doganis. Traffic forecasting and the gravity model. *Flight International*, (29):547–549, 1966.

K Fleming and A Ghobrial. An analysis of the determinants of regional air travel demand. *Transportation Planning and Technology*, 1994. URL http://www.tandfonline.com/doi/abs/10.1080/03081069408717531.

Laurie A Garrow. *Discrete choice modelling and air travel demand: theory and applications*. 2016. URL https://books.google.nl/books?hl=nl{&}lr={&}id=Tjo3DAAAQBAJ{&}oi=fnd{&}pg=PP1{&}dq=Discrete+choice+modelling+and+air+travel+demand{&}ots=nPihRgg83y{&}sig=tQ0xORQNUGpDKocSf{_}XfvW5hChE.

Tobias Grosche. Integrated airline scheduling. *Studies in Computational Intelligence*, 173:59–171, 2009. ISSN 1860949X. doi: 10.1007/978-3-540-89887-0_4.

Tobias Grosche, Franz Rothlauf, and Armin Heinzl. Gravity models for airline passenger volume estimation. *Journal of Air Transport Management*, 13(4):175–183, 2007. ISSN 09696997. doi: 10.1016/j.jairtraman.2007.02.001.

Rinus Haaijer, Michel Wedel, Marco Vriens, and Tom Wansbeek. Utility Covariances and Context Effects in Conjoint MNP Models. *Marketing Science*, 17(3):236–252, 1998. ISSN 0732-2399. doi: 10.1287/mksc.17.3.236. URL http://www.jstor.org/stable/193229.

Mark Hansen. Airline competition in a hub-dominated environment: An application of noncooperative game theory. *Transportation Research Part B*, 24(1):27–43, 1990. ISSN 01912615. doi: 10.1016/0191-2615(90)90030-3.

Mark Hansen and Yi Liu. Airline competition and market frequency: A comparison of the s-curve and schedule delay models. *Transportation Research Part B: Methodological*, 78:301–317, 2015. ISSN 01912615. doi: 10.1016/j.trb.2015.04.012. URL http://www.sciencedirect.com/science/article/pii/S0191261515000946.

John D Hedengren, Reza Asgharzadeh Shishavan, Kody M Powell, and Thomas F Edgar. Nonlinear modeling, estimation and predictive control in {APMonitor}. *Computers & Chemical Engineering*, 70:133–148, 2014. ISSN 0098-1354. doi: http://dx.doi.org/10.1016/j.compchemeng.2014.04.013. URL http://www.sciencedirect.com/science/article/pii/S0098135414001306.

Chieh Y. Hsiao and Mark Hansen. A passenger demand model for air transportation in a hub-and-spoke network. *Transportation Research Part E: Logistics and Transportation Review*, 47(6):1112–1125, 2011. ISSN 13665545. doi: 10.1016/j.tre.2011.05.012. URL http://dx.doi.org/10.1016/j.tre.2011.05.012.

Victoria Transport Policy Institute. Transportation Cost and Benefit Analysis II –Travel Time Costs. Technical report, 2013. URL http://www.vtpi.org/tca/tca0502.pdf.

Richard A. Ippolito. Estimating Airline Demand with quality of service variables. *Journal of Transport Economics and Policy*, 15(1):7–15, 1981.

Thomas O. Jones and W. Earl Sasser Jr. Why Satisfied Cutomers Defect. *Harvard Business Review*, 4 (November-December):88–99, 1995. ISSN 0742597X. doi: 10.1061/(ASCE)0742-597X(1996)12:6(11.2).

J.D. Jorge-Calderón. A demand model for scheduled airline services on international European routes. *Journal of Air Transport Management*, 3(1):23–35, 1997. ISSN 09696997. doi: 10.1016/S0969-6997(97)82789-5.

Se Yeon Jung and Kwang Eui Yoo. Passenger airline choice behavior for domestic short-haul travel in South Korea. *Journal of Air Transport Management*, 38:43–47, 2014. ISSN 09696997. doi: 10.1016/j.jairtraman.2013.12.017. URL http://dx.doi.org/10.1016/j.jairtraman.2013.12.017.

Young Dae Ko. An airline's management strategies in a competitive air transport market. *Journal of Air Transport Management*, 50:53–61, 2016. ISSN 09696997. doi: 10.1016/j.jairtraman.2015.10.005.

Frank S. Koppelman, Gregory M. Coldren, and Roger A. Parker. Schedule delay impacts on air-travel itinerary demand. *Transportation Research Part B: Methodological*, 42(3):263–273, 2008. ISSN 01912615. doi: 10.1016/j.trb.2007.10.006.

David M Lane. Online Statistics Education: A Multimedia Course of Study - Standard error of the estimate, 1999. URL http://onlinestatbook.com/2/regression/accuracy.html.

MG Lijesen. A mixed logit based valuation of frequency in civil aviation from SP-data. *Transportation Research Part E: Logistics and*, 2006. URL http://www.sciencedirect.com/science/article/pii/S1366554505000736.

Charles F. Manski. The structure of random utility models. *Theory and Decision*, 8(3):229–254, 1977. ISSN 00405833. doi: 10.1007/BF00133443.

J Marschak. Binary-choice constraints and random utility indicators. *Mathematical Methods in the Social Sciences*, (1960):312–329, 1960. ISSN 1938-808X. doi: 10.1007/978-94-010-9276-0_9. URL https://cowles.econ.yale.edu/P/cp/p01b/p0155.pdf.

Juan Carlos Martín, Concepción Román, and Raquel Espino. Willingness to Pay for Airline Service Quality. *Transport Reviews*, 28(2):199–217, 2008. ISSN 0144-1647. doi: 10.1080/01441640701577007. URL http://search.ebscohost.com/login.aspx?direct=true{&}db=bth{&}AN=29984023{&}site=ehost-live{%}5Cnhttp://www.tandfonline.com/doi/pdf/10.1080/01441640701577007.

Keith J. Mason and Richard Gray. Short haul business travel in the European Union: a segmentation profile. *Journal of Air Transport Management*, 2(3-4):197–205, 1995. ISSN 09696997. doi: 10.1016/0969-6997(96)00006-3.

Yeamduan Narangajavana, Fernando J. Garrigos-Simon, Javier Sanchez García, and Santiago Forgas-Coll. Prices, prices and prices: A study in the airline sector. *Tourism Management*, 41:28–42, 2013. ISSN 02615177. doi: 10.1016/j.tourman.2013.08.008.

John F. O'Connell and George Williams. Passengers' perceptions of low cost airlines and full service carriers: A case study involving Ryanair, Aer Lingus, Air Asia and Malaysia Airlines. *Journal of Air Transport Management*, 11(4):259–272, 2005. ISSN 09696997. doi: 10.1016/j.jairtraman.2005.01.007.

OpenFlights. OpenFlights: Airport and Airline Data, 2014. URL http://openflights.org/data.html.

J W Park, R Robertson, and C L Wu. Differences in air passengers' buying behaviour: findings from Korean and Australian international passengers. *Transportation Planning and Technology*, 32(5):441–460, 2009. ISSN 10290354. doi: 10.1080/03081060903017176.

Kimon Proussaloglou and Frank Koppelman. An analysis of market share determinants. *Transportation*, 22:371–388, 1995. ISSN 0049-4488. doi: 10.1007/BF01098165.

Kimon Proussaloglou and Frank S. Koppelman. The choice of air carrier, flight, and fare class. *Journal of Air Transport Management*, 5(4):193–201, 1999. ISSN 09696997. doi: 10.1016/S0969-6997(99)00013-7.

F Ramjerdi, L Rand, A-I. S'termo, and K. S'lensminde. *The Norwegian Value of Time Study Part I and Part II*. Number October 2016. 1997. ISBN 8248000354. URL https://www.researchgate.net/profile/Farideh{_}Ramjerdi/publication/265206352{_}The{_}Norwegian{_}Value{_}of{_}Time{_}Study{_}Part{_}I/links/54bbd5730cf253b50e2d1261.pdf.

V.R. Rengaraju and V. Thamizh Arasan. Modeling for air travel demand. *Journal of Transportation Engineering*, 118(3):371–380, 1992. ISSN 0733947X. URL http://www.scopus.com/inward/record.url?eid=2-s2.0-0026867734{&}partnerID=tZOtx3y1.

MG Russon and NF Riley. Airport substitution in a short haul model of air transportation. *International Journal of Transport Economics/Rivista*, 1993. URL http://www.jstor.org/stable/42747237.

J. M. C. Santos Silva and Silvana Tenreyro. The Log of Gravity. *Review of Economics and Statistics*, 88(4):641–658, 2006. ISSN 0034-6535. doi: 10.1162/rest.88.4.641. URL http://www.mitpressjournals.org/doi/10.1162/rest.88.4.641.

Wendell R. Smith. Product Differentiation and Market Segmentation as Alternative Marketing Strategies. *Journal of Marketing*, 21(1):3–8, 1956.

William M. Swan and Nicole Adler. Aircraft trip cost parameters: A function of stage length and seat capacity. *Transportation Research Part E: Logistics and Transportation Review*, 42(2):105–115, mar 2006. ISSN 13665545. doi: 10.1016/j.tre.2005.09.004. URL http://linkinghub.elsevier.com/retrieve/pii/S1366554505000761.

Taylor Courtney. What Is Chebyshev's Inequality in Probability, 2016. URL https://www.thoughtco.com/g00/chebyshevs-inequality-3126547?i10c.referrer=https{%}3A{%}2F{%}2Fwww.google.nl{%}2F.

Thorsten Teichert, Edlira Shehu, and Iwan von Wartburg. Customer segmentation revisited: The case of the airline industry. *Transportation Research Part A: Policy and Practice*, 42(1):227–242, 2008. ISSN 09658564. doi: 10.1016/j.tra.2007.08.003.

L. L. Thurstone. A law of comparative judgment. *Psychological Review*, 34(4):273–286, 1927. ISSN 0033-295X. doi: 10.1037/h0070288.

Vikrant Vaze and Cynthia Barnhart. Modeling Airline Frequency Competition for Airport Congestion Mitigation. *Transportation Science*, 46(4):512–535, 2012. ISSN 0041-1655. doi: 10.1287/trsc.1120.0412. URL http://pubsonline.informs.org/doi/abs/10.1287/trsc.1120.0412.

Wenbin Wei and Mark Hansen. Airlines' competition in aircraft size and service frequency in duopoly markets. *Transportation Research Part E: Logistics and Transportation Review*, 43(4):409–424, 2007. ISSN 13665545. doi: 10.1016/j.tre.2006.01.002.

Chieh Hua Wen and Shan Ching Lai. Latent class models of international air carrier choice. *Transportation Research Part E: Logistics and Transportation Review*, 46(2):211–221, 2010. ISSN 13665545. doi: 10.1016/j.tre.2009.08.004.

Chieh-Hua Wen, Shan-Ching Lai, and Wen-Ya Yeh. Segmentation and Positioning Analysis for International Air Travel Market: Taipei-to-Tokyo Route. *Transportation Research Record: Journal of the Transportation Research Board*, 2052(-1):46–53, 2008. ISSN 0361-1981. doi: 10.3141/2052-06.

Pietro Zito, Giuseppe Salvo, and Luigi La Franca. Modelling airlines competition on fares and frequencies of service by bi-level optimization. In *Procedia - Social and Behavioral Sciences*, volume 20, pages 1080–1089. Elsevier, 2011. doi: 10.1016/j.sbspro.2011.08.117.