

# Interval Forecasting for Airline Passenger Demand

An Application to Airline Network Development

C.E. Schot

Master of Science Thesis





# **Interval Forecasting for Airline Passenger Demand**

**An Application to Airline Network Development**

MASTER OF SCIENCE THESIS

For the degree of Master of Science in Aerospace Engineering at Delft  
University of Technology

C.E. Schot

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# Preface

Almost a year ago, I started this project for the graduation of my Master of Science degree. It has been a year of travelling back and forth between Delft, the Netherlands, and Nairobi, Kenya, in order to keep both the scientific and practical relevance as high as possible. By working together with industry experts, this graduation project has been a great learning experience in both a personal and professional perspective. This report is the result of the project.

The topic of this project, passenger demand forecasting, is something that I have been interested in for a while now. What inspired me most during this study, is the lack of including uncertainty in forecasting, both in literature and in practice. As mentioned by Wells (2013), “*one certainty about economic forecasts is that, almost certainly, they will prove to be incorrect. The best forecasters can hope for, is not to make systematic errors [...] and to ensure that forecasting errors are relatively small*”. It therefore surprised me that research on passenger demand forecasting hardly ever included uncertainty in some way or another, and thereby motivated me to take on the task of doing exactly this.

I would like to thank my supervisors, Dr.ir. B.F. Lopes dos Santos and Dr. O.A. Sharpanskykh, for their patient guidance, encouragement, and advice that they have provided me throughout my project. I would also like to express my gratitude to Kenya Airways for supporting this project and providing expert knowledge, guidance and actual airline data. In particular, I would like to thank Stephen Ngamau, Thomas Omondi, John Kariuki and Marco van Vliet for the support they have given me.

Emil Schot  
October 21, 2015  
Delft, The Netherlands



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# Abstract

In the past forty years, the volume of air travel has increased tenfold. While demand growth for OECD markets has slowed down in recent years, there is still a potential for markets where air services are currently not provided. It is the goal of the airline network development process to locate these potentially profitable markets. One of the main tools to support this process is passenger demand forecasting. However, experience has taught us that forecasting is inherently uncertain.

The primary goal of this thesis is to present how interval forecasts of passenger demand can be created by using Monte Carlo simulations. The results show that, by combining a causal econometric prediction model with interval forecasts of time-dependent parameters, it reliable interval forecasts for demand can be produced.

The secondary goal is to demonstrate the effects of using these intervals in a simplified airline network development model. By using actual airline data, it was concluded that the robustness of this process increases. This is particularly relevant for airlines, as they require confidence when making decisions about the development of their network.

*Keywords:* Passenger Demand Forecasting, Forecasting Uncertainty, Gravity Model, Airline Network Development





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# List of Acronyms

Acronym	Meaning
AIDS	Almost Ideal Demand System
ANN	Artificial Neural Network
AR	Autoregressive models
ARIMA	Integrated Autoregressive Moving Average
B/J	Box-Jenkins models
CPI	Consumer Price Index
DOC	Direct Operating Costs
FC	Flight cycle
FH	Flight hours
GDS	Global Distribution Systems
GDP	Gross Domestic Product
IOC	Indirect Operating Costs
KQ	Kenya Airways
MA	Moving average models
NB	Negative Binomial regression
O-D	Origin-Destination pair
OLS	Ordinary Least Squares
PI	Prediction Interval
PPML	Poisson Pseudo Maximum Likelihood estimator
Q-Q plot	probability plot for comparing two probability distributions
QSI	Quality of Service Index
RD	Residual Deviance
STSM	structural time series model
VAR	Vector-Autoregressive



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# List of Symbols

## Regression model symbols

Symbol	Unit	Meaning
$\alpha$	[-]	Control variable for attraction factors
$\gamma$	[-]	Control variable for repulsion factors
$i$	[-]	Integer that indicates country 1
$j$	[-]	Integer that indicates country 2
$k$	[-]	Gravity model constant
$t$	[-]	Integer that indicates the year
$A_i, A_j$	[-]	Attraction factors of countries $i$ and $j$
$AIC$	[-]	Akaike Information Criterion
$BOR_{ij}$	[-]	Common border dummy
$BTA_{ij}$	[-]	Bilateral trade agreement dummy
$COL_{ij}$	[-]	Colonial link dummy
$CPI_{ij,t}$	[-]	Consumer price index of $i$ times $j$ at time $t$
$D_{ij}$	[km]	Geographical distance between countries $i$ and $j$
$DT_1$	[-]	Distance < 100 km penalty dummy
$DT_2$	[-]	Distance < 750 km penalty dummy
$EFF_{ij,t}$	[-]	Index of government effectiveness of $i$ times $j$ at time $t$
$GDP_{ij,t}$	[USD]	Gross domestic product per capita of $i$ times $j$ at time $t$
$LAN_{ij}$	[-]	Common language dummy
$LL_1$	[-]	Single country landlocked dummy
$LL_2$	[-]	Both countries landlocked dummy
$P[\chi^2]$	[-]	Chi-squared goodness of fit
$POL_{ij,t}$	[-]	Index of political stability of $i$ times $j$ at time $t$
$POP_{ij,t}$	[-]	Total population of $i$ times $j$ at time $t$
$R^2$	[-]	Parameter describing the fit of a regression model
$R^2_{adj}$	[-]	Parameter describing the fit of a regression model
$V_{ij}$	[-]	Passenger volume between $i$ and $j$

Network development model symbols

Symbol	Unit	Meaning
$\beta$	[-]	Constant in S-curve market share model
$ac$	[-]	Aircraft type
$c_{j,ac}$	$[\frac{kg}{h*N}]$	Specific fuel consumption of aircraft type $ac$
$d_{ij}$	[km]	Flight distance of route $ij$
$f_{ij,ac}$	[-]	Frequency of roundtrips of aircraft type $ac$ on route $ij$
$g$	$[\frac{m}{s^2}]$	Earth's gravitation
$n_{crew,ac}$	[-]	Number of flight crew members per aircraft
$p$	[-]	Mission phase
$r$	[km]	Mission range
$seats_{ac}$	[-]	Number of seats in aircraft type $ac$
$seats_{offered,ij,ac}$	[-]	Number of seats offered on route $ij$ by aircraft type $ac$
$v_{cr,ac}$	$[\frac{km}{h}]$	Cruise speed of aircraft type $ac$
$y_{al}$	[USD]	Average yield of airline $al$
$C_{crew,FH}$	[USD]	Crew costs per hour
$C_{crew,ij,ac}$	[USD]	Crew costs for route $ij$ for aircraft type $ac$
$C_{fuel,ij,ac}$	[USD]	Fuel costs for route $ij$ for aircraft type $ac$
$C_{JF,l}$	[USD]	Jet fuel costs per liter
$C_{maint,FC,ac}$	[USD]	Maintenance costs per flight cycle per aircraft
$C_{maint,FH,ac}$	[USD]	Maintenance costs per flight hour for aircraft type $ac$
$C_{maint,ij,ac}$	[USD]	Maintenance costs for route $ij$ for aircraft type $ac$
$C_{own,ij,ac}$	[USD]	Ownership costs for route $ij$ for aircraft type $ac$
$(\frac{C_L}{C_D})_{ac}$	[-]	Lift to drag ratio of aircraft type $ac$
$DOC_{RT,ij,ac}$	[USD]	Direct operating costs per roundtrip on route $ij$ for aircraft type $ac$
$FC$	[-]	Flight cycle
$FH_{ij,ac}$	[h]	Amount of flight hours on route $ij$ for aircraft type $ac$
$FS_A$	[-]	Frequency share of airline A
$JF_{used,ij,ac}$	[l]	Amount of fuel used on route $ij$ by aircraft type $ac$
$LF_{max,ac}$	[-]	Maximum load factor of aircraft type $ac$
$M_{ff,ij,ac}$	[-]	Mission used fuel fraction per route per aircraft type
$MS_A$	[-]	Market share of airline A
$MTOW_{ac}$	[kg]	Maximum take-off weight of aircraft type $ac$
$Prof_{ij,ac}$	[USD]	Profit on route $ij$ for aircraft type $ac$
$Rev_{ij,ac}$	[USD]	Revenue on route $ij$ for aircraft type $ac$
$RT$	[-]	Roundtrip
$V_{ij,t}$	[-]	Airline specific demand on route $ij$ at time $t$
$W_{p,ij,ac}$	[kg]	Weight at the end of mission phase $p$ on route $ij$ for aircraft type $ac$

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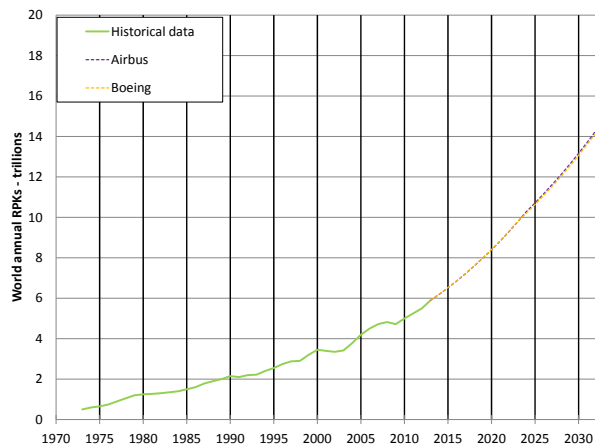
# Chapter 1

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## Introduction

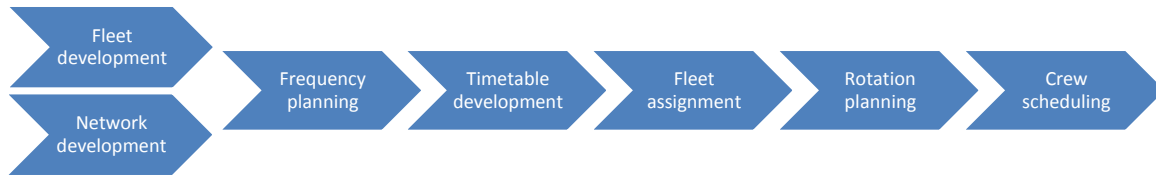
### 1-1 Research context

The global airline industry provides services to practically every country in the world. It has played an indispensable role in the creation of the global economy (Belobaba et al., 2009). For the past fifty years, the industry has been characterised by rapid and continued growth for its services. Inevitably, growth in the 1950s and 1960s (around 15% growth per year), when aviation was a new industry, was much larger than it is today, but growth rates are still impressive (around 5% per year) (Doganis, 2002). Figure 1-1 illustrates that the long-term demand for air transport is still increasing (Airbus, 2014; Boeing, 2014). Both Airbus and Boeing expect that demand for air traffic will double in the next fifteen years.



**Figure 1-1:** World annual traffic forecasts by Airbus (purple) and Boeing (orange) for the next twenty years. Adapted from Airbus (2014); Boeing (2014).

How airlines will meet this ever increasing demand, will continue to be a balance between efficiency, competition and passenger requirements. A fundamental element that enables dealing with this balance is the airline planning process. Figure 1-2 illustrates the airline planning process, based on Belobaba et al. (2009); Bazargan (2010); van Nunen (2014).



**Figure 1-2:** The airline planning process.

The airline planning process starts with both fleet planning and network development. Fleet planning is the strategic process of determining the type and number of aircraft that are required for the airline's operation in order to serve the anticipated market. Network development determines how the network should evolve, by looking at the specific routes to be flown. During frequency planning, it is calculated how often each of the routes should be operated. The times each of these flight should depart is then determined during the timetable development phase. The fleet assignment phase is used to assign aircraft to the available departure times. Rotation planning then assigns each individual aircraft (i.e. tail number) to flight legs. Crew scheduling finally identifies sequences of flight legs and assigns both cockpit and cabin crews to these sequences.

For each of the phases of the airline planning process, forecasts of the expected demand are required. For example, during the network development phase, an estimate of the expected amount of passengers and cargo should be known. Without these forecasts, it is not possible for an airline to determine if routes will have a positive or negative contribution to its network. However, it is important to realise that “one certainty about economic forecasts is that, almost certainly, they will prove to be incorrect. The best forecasters can hope for, is not to make systematic errors [...] and to ensure that forecasting errors are relatively small” (Wells, 2013).

## 1-2 Scope of this research

The primary aim of this project is to develop a modelling framework that can be used to generate interval forecasts for the total passenger demand for air travelling between two cities. The resulting demand model will be referred to as the market size model. The market size model will be developed by using traffic data from the inter-African market. Interval forecasts will be created by including uncertainty of different input parameters. This project is limited in the sense that other types of uncertainty have not been included.

The secondary aim of this study is to show how the resulting market size forecasts can increase the robustness of airline planning processes. In order to do this, the interval forecasts will be used in an illustrative example of the airline network development process. The decision-support tool combines the market size model with a market share model to generate airline specific demand forecasts, before maximising the profit of the network. A case study on a selection of city pairs that Kenya Airways operates at or is interested in opening soon will be used to test the network development decision-support tool.

Even though cargo can be the make-or-break difference in the business case for opening new routes, it is usually not the first trigger to start a route. It has therefore been decided not to include cargo in this study, and to focus on passenger demand only. Furthermore, this study only focuses on international traffic, and domestic traffic will not be part of the project. In accordance with industry practices, this study focuses on a forecasting horizon of three

years (Kariuki et al., 2015).

The main relevance is that this study provides a framework that can be used to forecast ranges of demand instead of point forecasts. By applying these forecasts in a network development model, it will be shown that the decision making process will become more robust. There is also practical relevance for the outcome of this project for Kenya Airways. They are currently studying yield forecasting for the medium-term, but they lack a medium-term demand forecasting model. With forecasts for both variables, it is expected that their decision-making process will become more robust.

## **1-3 Structure of this document**

The structure of this document is as follows. First, Chapter 2 gives a summary of the main findings from the literature review on relevant topics. Based on the findings from this, Chapter 3 outlines the research objective and the corresponding project plan for the current project. In Chapter 4, the modelling framework will be explained. The main focus of the project, the generation of interval forecasts for passenger demand will be elaborated on in Chapters 5 to 7. In Chapter 5, the prediction model form will be explained. Chapter 6 describes how the coefficients of this model were found. In Chapter 7 it will be explained how inserting randomly selected values from forecast intervals of the time-dependent parameters into the prediction model, will generate interval forecasts for the passenger demand. Chapter 8 then describes the modelling framework for the network development model. The input parameters and outcomes of applying the network development model to Kenya Airways will be given in Chapters 9 and 10. Finally, the conclusions and recommendations of this graduation project are given in Chapters 11 and 12.





# Literature Review

This literature review aims at briefly elaborating on available literature on forecasting the total market size for air-travelling in terms of passengers, market share modelling, forecasting uncertainty, and airline network development. The goal of this literature review is to identify both proven and novel techniques that others studies have been using for these topics. The available techniques and their limitations formed the starting point of this project.

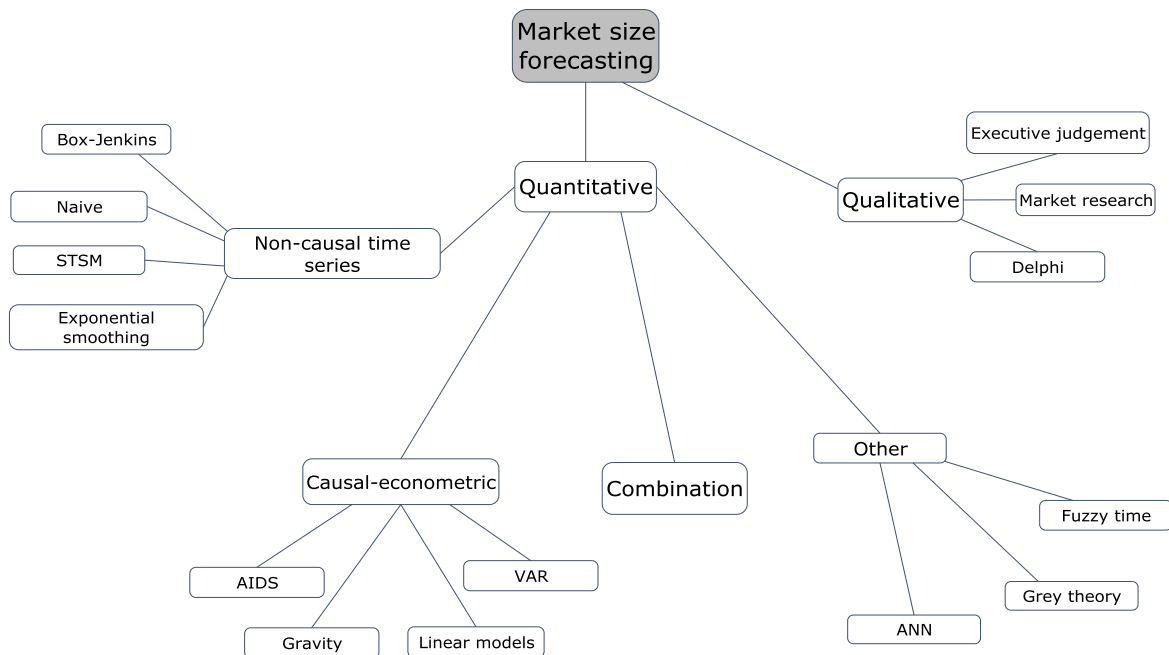
This chapter is structured as follows. First, Section 2-1 focuses on describing different market size forecasting techniques. Subsequently, in Section 2-2 it will be explained that uncertainty is inherent to forecasting, and it is explained how this uncertainty can be dealt with. Section then 2-3 focuses on describing available methods for airline network development. As will be explained, the network development model requires airline specific demand values, not the total demand for travelling via air. Therefore, Section 2-4 describes which three techniques can be used to forecast airline market shares. By combining market size forecasts with airline market share forecasts, the amount of passengers willing to travel between two cities with a given airline can be found. Finally, the conclusions from this literature review are given in Section 2-5.

### 2-1 Market size forecasting

The first step in creating airline specific demand forecasts, is to forecast the total demand for air travelling. Market size models are used to forecast the total demand for air travel. As reviews indicated, there are many different methods to forecast the market size for air travel (Witt and Witt, 1995; Song and Li, 2008; Shen et al., 2011). However, they also indicated that no single method consistently outperformed all others.

This section gives an extensive but not exhaustive overview of the methods most commonly used for air travel demand forecasting. From the overview, it is clear that different methods can be divided into two groups: qualitative and quantitative. Qualitative forecasting methods rely on the experience and judgement of experts. Unlike qualitative methods, quantitative forecasting methods use past information to describe phenomena according to mathematical rules, by using underlying patterns or relationships in the data (Frechtling, 2001). Quantitative methods can be further categorised into non-causal time-series, causal econometric, combination or other methods (Song and Li, 2008). Figure 2-1 shows a mind-

map of common methods.



**Figure 2-1:** Mind-map of the most common methods used to forecast air travel demand.

### Qualitative methods

Qualitative methods forecast demand based on judgements and the experience of experts, rather than on mathematical rules. Examples of qualitative methods are executive judgements, market research and Delphi techniques. Executive judgements are based on the insights of experts. Market research include attitudinal and behavioural surveys of passengers to derive an understanding of how demand varies. Delphi techniques are designed to produce a group consensus of the expected demand (Frechtling, 2001; Doganis, 2002). The main advantage of qualitative methods is their applicability. According to Frechtling (2001), they can be applied when there is insufficient historical data; the time series available is not reliable or invalid; the macro-environment is changing rapidly; major disturbances are expected; or when long-term forecasts are desired (more than three years). Disadvantages are the human tendency to confuse desires for the future with forecasts and the sensitivity of the expertise of individuals.

### Non-causal time-series methods

Non-causal time-series explore historic trends and patterns to predict the future (Kulendran and Witt, 2003; Hoshmand, 2010). As historic observations of one variable only are required, these methods are generally less costly in data collection and model estimation compared with other quantitative methods. The most frequently used methods include Box-Jenkins methods, exponential smoothing, Naïve methods and structural time series models (STSM) (Song and Li, 2008; Frechtling, 2001).

Box-Jenkins methods are a combination of autoregression and moving average methods in order to minimise errors in simulating the past. Exponential smoothing methods rely on the assumption that data are stationary with a slowly varying mean. Estimates are revised

continuously as more information becomes available. Naïve methods are useful for making quick forecasts due to their simplicity. The main limitation of these methods is that they only depend on the immediate past, and that they only work if the pattern of the data is stable (i.e. no big changes between periods) and if there is no significant randomness in the data (Hoshmand, 2010). Structural time series decompose a time series into its trend, seasonal, cycle and irregular components, and regards these components as stochastic. This method is particularly useful when modelling seasonal variation in demand (Song et al., 2011).

### **Causal econometric methods**

Where time series forecasting does not take into account how various socio-economic and other external conditions affect the development of demand (Profillidis, 2000), causal econometric methods assume that demand is affected by one or more economic, social, or supply factor (Doganis, 2002; Grosche et al., 2007; Sivrikaya and Tunç, 2013). Based on the causal relationships between demand and its influencing parameters, these methods can be used to study the impact of changing on the the variables on the demand. The most commonly used methods are gravity models, almost ideal demand systems (AIDS), linear models, and vector autoregressive models (VAR).

Gravity models are one of the first econometric models used for traffic forecasting. The models are based on the gravitational law, stating that demand can be positively or negatively influenced by its driving parameters (Grosche et al., 2007). They have been used to model demand for existing but also for new city pairs, for which historical demand data was not available (Sivrikaya and Tunç, 2013).

AIDS models are explicitly based on the microeconomics of consumer expenditure theory. In these models, *“demand is specified as a function of the consumer’s expenditure budget and the relative prices of the set of goods or services that the consumer can purchase”* (Han et al., 2006)[p. 2]. According to Frechtling (2001), consumer’s expenditure is very difficult to forecast.

Linear models assume that demand and its explanatory variables are linked through a simple linear relationship plus an error term (McKinney et al., 2011). According to Frechtling (2001) and Song and Li (2008), the possible occurrence of spurious regression (when explanatory variables may appear to be significant, but are not due to the autocorrelation of errors) is a major disadvantage.

VAR models are used to model relationships among multiple time series, and allow multiple evolving variables. An advantage of this approach is that it does not require the generation of forecasts for explanatory variables before forecasts of the dependent variable can be obtained (Song and Witt, 2006; Song and Li, 2008).

### **Combination methods**

Combination methods are a relatively new method of demand forecasting. These methods take advantage of the availability of multiple resources (Shen et al., 2011). For example, Andrawis et al. (2011) combined short-term and long-term tourism demand models to forecast inbound tourism demand of Egypt; and Shen et al. (2011) combined several econometric and time series models. Both studies concluded that by synthesising information from different methods, combination forecasting improved the forecasting accuracy.

### **Other methods**

Finally, there are several relatively new, mainly artificial intelligence methods. Examples are Grey theory, artificial neural networks (ANN), and fuzzy time series. Grey theory focuses on model uncertainty and information insufficiency. Hsu and Wen (2000, 2003) used a Grey

model to forecast annual country-pair or city-pair demand. These models incorporated effects on uncertain socio-economic variables, and thereby accounted for dynamic aspects of demand changes. ANN tries to imitate the learning process of a human brain. An extension to ANN are Back-Propagation Neural Networks (BPNN), which incorporate the back-propagation learning process to increase forecasting accuracy (Law, 2000). However, neural networks lack sufficient explanatory power, making it difficult to justify the results (Law, 2000). Finally, fuzzy time series can be used for analysing a short time series with limited past observations (Song and Li, 2008). Instead of being based on probabilistic functions, this method relies on possibility functions (Hsu and Wen, 2000). The main disadvantage of these recently developed methods is that to their structure, excessive training might be required to understand the methodologies.

## 2-2 Modelling with forecasting uncertainty

Because uncertainty is inherent to forecasting, it is important to clearly communicate the forecast risks to policy-makers. Measures of forecasting uncertainties can have numerous uses. First, it helps in getting a picture of the expected range of outcomes. Second, it can be used to evaluate forecasting models. Third, a distinction between poor forecasts (large numerical errors, but statistically accurate) and forecast failure (small numerical errors, but statistically lying outside of the range of anticipated uncertainty) can be made Ericsson (2001).

### Sources of uncertainty

Uncertainty can be categorised into model uncertainty and quantity uncertainty (Ericsson, 2001; Granger, 2007; Rasouli and Timmermans, 2012). Model uncertainty relates to whether the chosen model is correct or not. It is a type of uncertainty where “*we don’t know that we don’t know*” (Ericsson, 2001), making it very difficult to quantify. Granger (2007) argued that it is not appropriate to model this probabilistically.

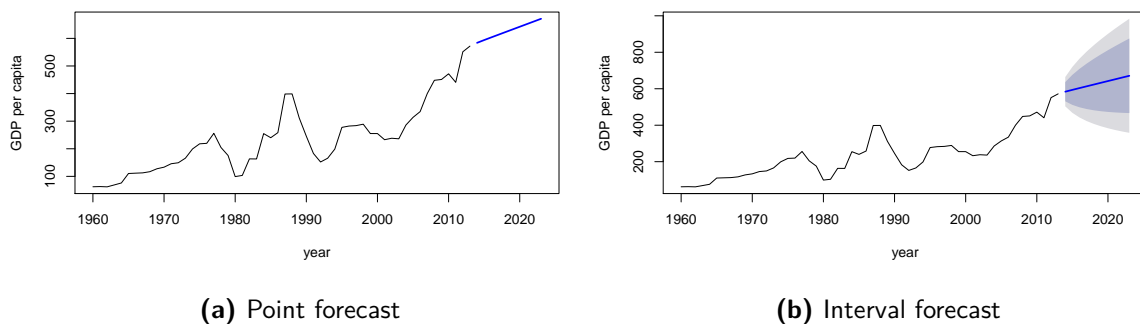
Uncertainty about empirical quantities are mainly related to input values. Several categories for this kind of uncertainty can be given:

- Approximations arise because models are simplified versions of reality;
- Disagreements relate to the differences in interpretations of the same available scientific evidence;
- Dynamics of the forecast uncertainty relates to the fact that uncertainty can be modelled statically or dynamically. Static models assume that model errors are independent over time, implying that the forecast uncertainty remains constant across different forecast horizons. Dynamic models often imply that forecast uncertainty increases with the forecast horizon;
- Error propagation occurs when in a successive series of submodels, outputs from one submodel are used as inputs for the next. Errors can then be amplified or reduced;
- Linguistic imprecision mainly arises due to ill-specified quantities;
- Random errors are caused by imperfections in measuring instruments and observation techniques;

- Systematic errors are defined as the difference between a quantity's true value and the value of the mean of the measurements to which it converges as more measurements are taken;
- Variability relates to the fact that quantities are often variable over time and space.

### Including uncertainty in the model

Despite the fact that uncertainty is an important element of demand forecasting, little attention has been paid to dealing with uncertainty. Before describing how previous studies modelled uncertainty, it is important to know the difference between point forecasts and interval forecasts. Point forecasts forecast the most likely value. On the other hand, interval forecasts indicate the likely uncertainty in point forecasts. Figure 2-2a illustrates what a point forecast looks like; Figure 2-2b shows what an interval forecast looks like.



**Figure 2-2:** Example of point and interval forecasts.

While some of the market size methods are able to deal with input uncertainties, none of the methods were able to calculate interval forecasts. Instead, they were only able to provide point forecasts. For example, Hsu and Wen (2000) used Grey forecasting to deal with input uncertainties, but their results are point values rather than intervals. To the best of the author's knowledge, no previous studies dealt with uncertainties in market share forecasting. However, an effective model should take risks with various input parameters into account, and should present that in the results. Previous studies used case-based modelling, Monte-Carlo simulations, and stochastic programming to do this.

Case-based modelling is frequently used to evaluate the base, worst and best case, based on the expected, worst and best possible values for the input parameters. It is the easiest method to use, and has been applied frequently (Raychaudhuri, 2008; Lammens, 2014).

Monte-Carlo simulations use statistical distributions as the source for each of the input parameters (Raychaudhuri, 2008). After creating a static model, distributions for the different input variables have to be determined. This can be done either from theories or from historical data. The core part of Monte Carlo simulations is the repetitive sampling of distributions and inserting these values in a model. The value of each output parameter is a particular outcome scenario in the simulation. According to Byrne (2013), "*since all possible runs is an infinite population, we must sample, and therefore we must tolerate some uncertainty about the true prediction made by the model*". Unfortunately, many studies suffered from not reporting information about the number of model runs that were used. The studies that did mention

this, often used an arbitrarily large number, and assumed that number is large enough for the issue to be addressed.

Another common approach is to run the model repeatedly until the mean converges. This might require a huge amount of runs, and is therefore only practical if model runs are very cheap. Byrne also described mathematical methods to determine the minimum required number of model runs. The mathematical formulations are beyond the scope of this project. For their formulation, the reader is referred to Byrne (2013).

Stochastic programming is an optimisation technique that is able to deal with uncertain input parameters. Different types of stochastic programming exist. For example, in two-stage stochastic programming, the first stage makes a decision for variables without uncertainty; the second stage determines the values of the variables with a stochastic nature (Yang, 2009).

## 2-3 Airline network development

The second purpose of this project is to illustrate how interval forecasts can be used to increase the robustness of the airline planning process. In order to do this, a network development decision-support tool will be created.

Network development is one of the first steps in the airline planning process. Given an airline's fleet with its corresponding characteristics, network development aims at determining the specific routes to be flown by adding or removing routes (Belobaba et al., 2009).

The main considerations for network development are forecasts of airline specific demand and profitability (Belobaba et al., 2009; Kariuki et al., 2015). Airline specific demand indicates the amount of passengers that are expected to be transported by an airline. It can be forecast by combining market size and market share forecasts. Expected profitability can be derived from combining yield and airline specific demand forecasts. Yield indicates the average fare per passenger per kilometer or mile. When forecasts for both demand and yield are available, airlines can estimate whether routes will add value to the network or not.

Unlike most phases of the airline planning process, very little research has focused on airline network development. Furthermore, the practical applicability of the limited amount of studies on this topic can be questioned. Most of the previous network development studies focused on hub location problems (Hsu and Wen, 2002; Yang, 2009, 2010). For example, Yang (2009, 2010) created a two-stage stochastic model for airline network design under uncertain demand. The first stage determined the number of hubs and their location; the second stage was used to construct the service network in an optimal fashion, based upon the hub location and realised uncertain scenarios. The objective of their model was to minimise the total hub set-up and transportation costs. According to the author, the two-stage process matched the decision procedure of airline companies in practice. However, according to industry experts, the number and location of hubs are hardly ever part of the actual decision making process.

According to Belobaba et al. (2009), "*the schedule planning and optimization processes at airlines produce plans that are rarely, if ever, executed*". Due to disruptions in the execution of the plans, recovery plans are needed to minimise the impacts these disruptions might cause. Several examples were given of how this robustness can be included into planning optimisation. However, these examples focused on short-term planning processes. No examples were mentioned for dealing with uncertainty in network development.

Due to the lack of mathematical models, airlines therefore often use qualitative analyses

to determine whether or not routes should be added or removed from the network.

## 2-4 Market share forecasting

To be able to use the demand interval forecasts for network development, they first have to be converted into airline specific demand. As mentioned above, this can be done by combining market size forecasts with the airline market share forecasts. The market share of an airline A is defined as the “proportion of the total market demand that is captured by airline A (Belobaba et al., 2009). Multiplying the total demand for air travel with this market share forecast therefore gives a forecast for the airline specific demand. Previous research identified three methods for forecasting market share: S-curve, Quality of Service Index (QSI) and discrete choice models.

### S-curve models

The easiest method to calculate an airline's market share is by assuming a disproportional, S-curve relationship between airline market share and frequency share. This method is based on the assumption that only the airline frequency is variable. All other variables (e.g. ticket prices and service quality) remain equal for all airlines. The mathematical model is given by Equation 2-1 (Belobaba et al., 2009).

$$MS_A = \frac{FS_A^\beta}{FS_A^\beta + FS_B^\beta + FS_C^\beta + \dots} \quad (2-1)$$

In this equation,  $MS_{al}$  is the market share of an airline  $al$ ,  $FS_{al}$  is the frequency share of an airline  $al$ , and  $\beta$  is an exponent greater than 1.0, and generally between 1.3 and 1.7. The larger  $\beta$  is, the more important frequency share is for an airline's market share.

### QSI models

QSI models are based on giving each of the services on a given itinerary a QSI score, which relates to the quality of the itinerary. Quality is defined as “a function of various itinerary service attributes and their corresponding preference weights” (Barnhart and Smith, 2012, p. 42). These preference weights are determined either by statistical techniques or analyst intuition. The QSI score for a given itinerary is expressed as a linear (Equation 2-2a) or multiplicative function (Equation 2-2b) of the characteristics and its preference weights. In these equations,  $QSI_i$  is the QSI score of airline  $i$ ,  $\beta$  is the preference weight for factor 1 :  $n$ , and  $X$  is the factor score.

$$QSI_i = \beta_1 * X_1 + \beta_2 * X_2 + \dots + \beta_n * X_n \quad (2-2a)$$

$$QSI_i = (\beta_1 * X_1)(\beta_2 * X_2)(\dots)(\beta_n * X_n) \quad (2-2b)$$

The market share a single itinerary is calculated by dividing the airline's total QSI score for a given itinerary by the total QSI score of all airlines for that route. The mathematical formulation of this is given by Equation 2-3.

$$S_i = \frac{QSI_i}{\sum_{j \in J} QSI_j} \quad (2-3)$$

In this equation,  $S_i$  is the passenger share of itinerary  $i$ ,  $QSI_i$  is the quality of service index for itinerary  $i$ , and  $\sum_{j \in J} QSI_j$  is the summation over all itineraries in the airport pair. After the itinerary shares have been calculated, an airlines total market share on a city-pair or in a region can be calculated by adding all the itinerary shares. Note that QSI models are similar to S-curve models, but it includes additional factors. It is therefore expected that QSI gives a more accurate representation of reality.

### Discrete choice models

Discrete choice models are used to model customer behaviour, and to “*predict the probability that a decision-maker will choose one alternative among a finite set of mutually exclusive and collectively exhaustive alternatives*” Barnhart and Smith (2012, p. 14). Discrete choice models can be characterised by four elements (Barnhart and Smith, 2012): a decision maker, a set of available alternatives, attributes of the alternatives, and a value for each alternative.

First, a decision maker is the one (e.g individual, group of individuals, organisation) that makes the decision to select one of the available alternatives. The available alternatives are the finite set of mutually exclusive and collectively exhaustive alternatives. Attributes are the characteristics of the alternatives that the decision-makers consider during the choice process. Finally, utility represents the value that the decision-maker places on different attributes, and captures how the decision-maker make trade-offs among different alternatives.

Different types of discrete choice models have been used in the literature. Coldren et al. (2003) used an aggregate multinomial logit function to forecast itinerary shares. MNL models describe how individuals choose among multiple discrete alternatives (Barnhart and Smith, 2012). Wei and Hansen (2005) used a (two-level) nested logit model to analyse the air traveller’s choice. According to Barnhart and Smith (2012), nested logit models group alternatives into nests. Alternatives belong to one and only one nest. Other discrete choice models used in literature are binary logit, generalised nested logit and multinomial probit (Barnhart and Smith, 2012).

## 2-5 Conclusions of the literature review

This literature gave an overview of existing literature in the fields of passenger demand forecasting, airline market share modelling, and airline network development modelling. Below, the conclusions of the literature review for each of these topics are given.

### Market size forecasting

Many different methodologies have been developed for forecasting the market size for air travelling. However, no single method that consistently outperforms all others has been found (Witt and Witt, 1995; Song and Li, 2008). Unfortunately, there are no specific guidelines to match a forecasting technique with a given economic or business situation. Hoshmand (2010) mentioned that the selection of a forecasting methodology depends on the nature of the problem, the time horizon, the cost associated with the forecast, and the level of sophistication.

Even though demand forecasting has been studied for many years, there are several gaps in the literature. For example, very little attention has been paid to dealing with uncertainty. Another limitation of previous studies is that almost all of them focused on forecasting demand for developed countries. However, as indicated by Naudé and Saayman (2005); Valdes (2015), demand for underdeveloped countries might be derived from other drivers.



**Modelling with forecasting uncertainty**

In past research, researchers included forecasting uncertainty by using a base, best and worst case scenario for the input variables to evaluate the risks. This is the simplest method to deal with. However, this approach has several disadvantages. To overcome these disadvantages issue, one could use Monte-Carlo simulations. This technique uses statistical distributions as the source for each of the input parameters of the static model. The core part of Monte Carlo simulations is the repetitive sampling of distributions and inserting these values in a model. Rather than generating only three outputs, this technique can create as many outputs as one is interested in. A third possibility is to use stochastic programming. Stochastic programming is an optimisation technique that is able to deal with uncertain input parameters.

**Airline network development**

Unlike most phases of the airline planning process, very little research has focused on airline network development. Furthermore, the practical applicability of the limited amount of studies on this topic can be questioned. Due to the lack of mathematical models, airlines often use qualitative analyses to determine whether or not routes should be added or removed from the network. Based on the main considerations for network development, which are forecasts for airline specific demand and profitability, airlines perform their network development (Belobaba et al., 2009; Kariuki et al., 2015).

**Market share models**

In past research, three different methods have been used to model an airline's market share: S-curve models, QSI models and discrete choice models. The easiest method is by assuming a disproportional, S-curve relationship between airline market share and frequency share. QSI is an extended version of an S-curve model, where additional factors are taken into account. The third type of models are discrete choice models. These do not suffer from the various modelling disadvantages that S-curve and QSI models have, but they are more difficult to understand and to model.



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## Chapter 3

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# Project Plan

This chapter focuses on describing the project plan. The goal of this is to guide the control and execution of the project. Typically, a project starts with writing such a plan. However, as one progresses, the project plan might also change. This chapter presents the final version of the project plan that has been used during this project.

This chapter is structured as follows. It starts with stating the research objective and questions in Section 3-1. It continues by giving the experimental set-up in Section 3-2. Finally, in Section 3-3, the expected outcomes will be described.

### 3-1 Research objectives and questions

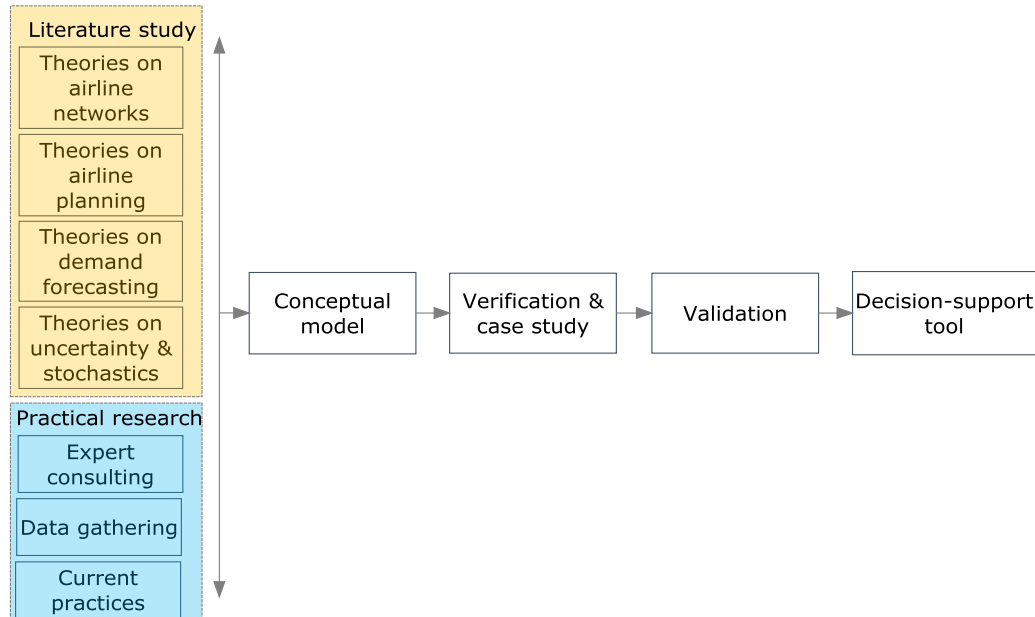
The literature review has indicated a research opportunity that can be described in terms of the following research objective:

*To develop a modelling framework for generating interval forecasts for airline passenger demand, and to show how this can increase the robustness of the airline's strategic planning process, by applying the results to a network development case study.*

This objective can be split into several smaller objectives. These sub-objectives are mentioned below, in the order by which they should be fulfilled.

- Develop a prediction model for the total passenger demand for air travelling between two cities;
- Combine the prediction model with interval forecasts of time-dependent parameters to create interval forecasts of the demand;
- Apply the resulting interval forecasts to a network development decision support tool;
- Perform a case study at Kenya Airways.

The next step is to determine how these objectives can be achieved. Figure 3-1 shows the research framework that has been used throughout project. This can be formulated as a study of passenger demand forecasting for airline network development, based on relevant scientific literature and on talks with experts, by means of which a conceptual model will be created. The conceptual model includes a forecasting model for the total market size and the expected airline market share for the inter-African market, and an optimisation model to come up with a decision-support tool for network development.



**Figure 3-1:** Research framework.

From this research framework, it is possible to come up with a set of research questions. These questions should be mutually exclusive and collectively exhaustive: each question adds to reaching the research objective, but the different questions should not solve the same problems. The resulting set of research questions can be further divided into sets of sub-questions, which again should be mutually exclusive and collectively exhaustive. The aim of formulating sub-questions is that the combined answers will roughly provide the answers to the central questions they belong to. Once all sub- and central questions have been answered, the research objective should be reached.

1. **What regression technique creates the most accurate predictions for the total passenger demand for air travelling between two cities?**
  - (a) What is the mathematical formulation of the model?
  - (b) What is the best technique to calibrate the coefficients of the prediction model?
  - (c) What is the accuracy of the results?
2. **What is the effect of combining the prediction model with interval forecasts of time-dependent parameters?**
  - (a) What are the time-dependent parameters?

- (b) What kind of model is most suitable to generate interval forecasts for time-dependent parameters?
  - (c) What happens to the outcomes of the prediction model after repetitively inserting randomly selected values from these distributions?
  - (d) What is the validity of the outcomes?
3. **What are the implications of applying interval forecasts of demand to a network development case study for Kenya Airways?**
- (a) What should a network development decision-support tool look like?
  - (b) What are the input parameters and what assumptions have to be made?
  - (c) What is the added value of this decision-support tool to the airline network development compared to the current practices?
  - (d) How can the decision-support tool be implemented in practice?
  - (e) What recommendations can be made for future research?

## 3-2 Experimental set-up

The main part of the project will be performed at the faculty of Aerospace Engineering of Delft University of Technology. The university's knowledge on airline planning, uncertainty modelling and project planning have been used throughout this project. Part of the research has been conducted at Kenya Airways. Expert knowledge was used to define and come up with a model. To make sure that Kenya Airways will be able to implement the model that has been developed, open-source software had to be used. It was decided to develop the entire project in R. This is because R is a commonly used language and environment for data analysis and statistical computing. It provides a wide variety of statistical and graphical techniques, and is highly extensible. The remainder of this section describes how each of the research questions will be answered.

## 3-3 Results, outcome and relevance

The result of this study will be a network development decision support tool that uses demand forecasts for air travel between city pairs. The demand forecasts will give the total demand between city pairs. The directionality of traffic will not be taken into account. Instead of providing point-forecasts as previous studies did, the forecasting model will give a range of outcomes and their corresponding distribution.

In order to get to the desired outcome, multiple sub-models will be used. The first sub-model forecasts the annual market size for country pairs within Africa, three years ahead. By including uncertainties in input parameters as inputs in a Monte-Carlo simulation, interval forecasts rather than point forecasts were created. Each of the individual outcomes of the simulation provided a specific scenario. After converting the demand to a city-pair basis, the second sub-model, a market share model, was used to forecast the airline specific demand, for each of the scenarios of the Monte-Carlo simulation. Finally, the network development optimisation gave recommendations regarding what cities to fly and the corresponding frequency, based on the airline specific demand.

The main relevance is that this study provides a framework that can be used to forecast ranges of demand instead of point forecasts. By applying these forecasts in a network development model, it is expected that the decision making process will become more robust. There is also practical relevance for the outcome of this project for Kenya Airways. They are currently studying yield forecasting for the medium-term, but they lack a medium-term demand forecasting model. With forecasts for both variables, it is expected that their decision-making process will become more robust.

# Modelling Framework

In order to reach the project purpose, four separate models will be developed and combined: a market size prediction model, a time-dependent parameter forecasting model, an airline market share forecasting model, and a profit maximisation model. In this chapter, each of these models will briefly be described. It will also be explained how these individual model will be combined to form an airline network development decision-support tool.

This chapter is structured as follows. Section 4-1 describes that a market size forecasting model and a market share model combined will give the airline specific demand. How these models, together with a will be combined in a network development model is the topic of Section 4-2.

### 4-1 Demand forecasting components

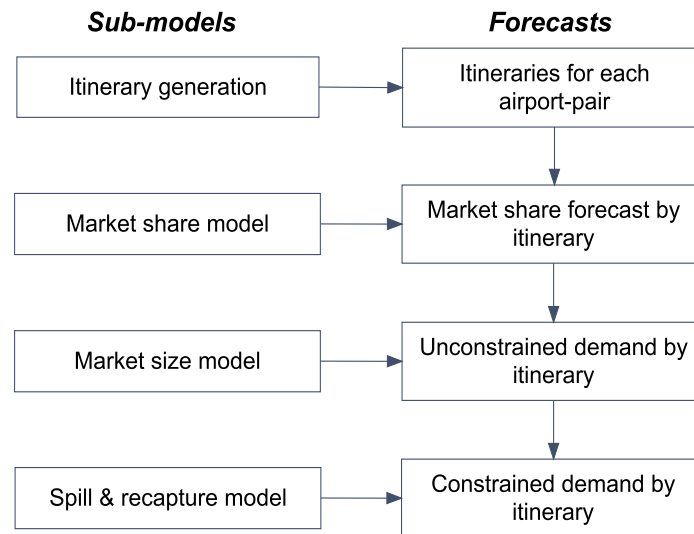
The main focus of the project is to come up with an airline specific demand forecasting model, that generates interval forecasts rather than point forecasts. Budhiraja (2007) and Barnhart and Smith (2012) showed that airline specific demand forecasting usually consists of four separate components. Figure 4-1 shows the sub-models, their forecasts and the results after combining the sub-models.

First, itinerary generation creates itineraries between airport pairs, using leg-based carrier schedule data. Itineraries are defined as (flight)legs or sequences of legs that connect a given airport-pair. They can be non-stop, direct (connecting itinerary without aircraft changes) or indirect (one or more changes of aircraft). It is the combination of flight legs that passengers choose to complete their journey in an O-D market.

Subsequently, combining a market share model with the resulting itineraries forecasts the market share per itinerary. In this case, market share refers to the proportion of the total market demand that is captured by a specific itinerary.

The third sub-model is a market size model, which forecasts the total demand (i.e. for all airlines) per airport pair. Multiplying this with the market share gives the unconstrained demand per itinerary, which is defined as “*the number of people who would like to travel by an itinerary when the capacity constraints are not taken into account*” (Budhiraja, 2007).

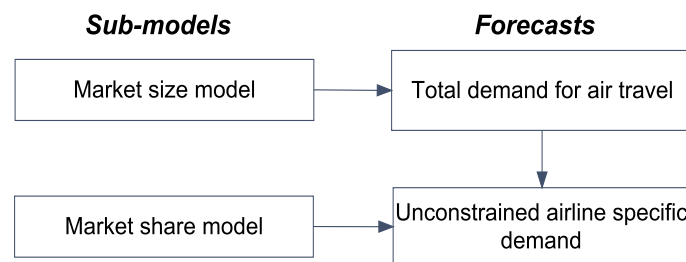
The final step is to include spill and recapture models, in order to take capacity constraints into account. Spill occurs when the “*total passenger demand exceeds capacity*; re-



**Figure 4-1:** Components for short-term air travel demand forecasting (Barnhart and Smith, 2012).

capture is defined as “the probability that a customer who is spilled from one flight leg books on another of the same airline” (Barnhart and Smith, 2012). The resulting forecast after including spill and recapture is defined as constrained demand.

Unfortunately, this approach can only be applied to short-term forecasting. The reason for this is that it requires itineraries as input, which are the result of schedule planning. This indicates the coupling between network planning and scheduling. However, it is not feasible to create schedules for multiple years ahead, due to the large amount of uncertainties involved. Instead, this study focuses on creating a non-itinerary-based market share model that forecasts market share at an O-D level, and that can be combined with the total O-D demand to forecast airline specific demand. Figure 4-2 shows the components that this study is based upon.



**Figure 4-2:** Components for long-term air travel demand forecasting.

## 4-2 Network development modelling components

From the literature review, it is clear that many methods are available for market size forecasting. Unfortunately, very little attention has been paid to include uncertainty in passenger

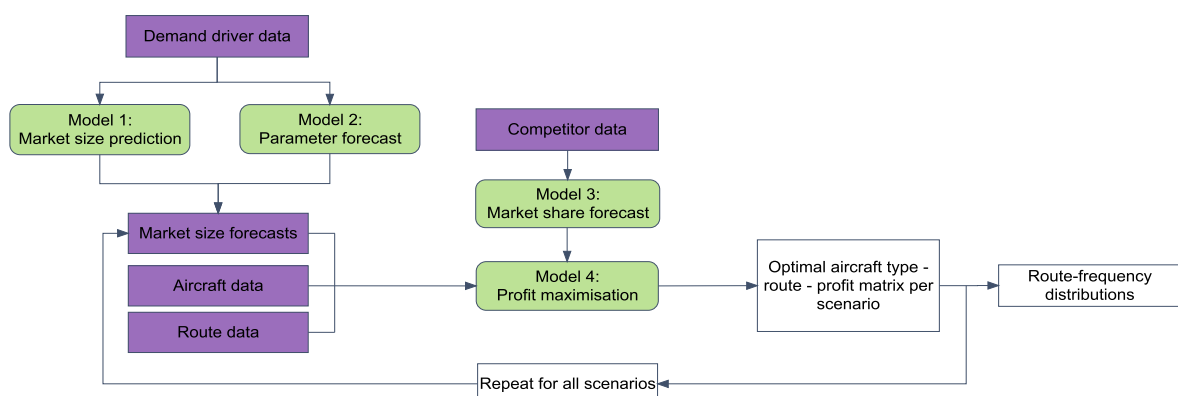


volume forecasting. Furthermore, the limited amount of models that were able to evaluate uncertainties can only create point forecasts, or were very complex. Rather than developing a novel forecasting methodology that can calculate interval forecasts, this project combines existing techniques. The technique that will be used is Monte Carlo (MC) simulation. MC simulations use statistical distributions as the source for each of the input parameters (Raychaudhuri, 2008). This has several advantages over case-based modelling, another frequently used method for dealing with input uncertainty. For example, it might be difficult to evaluate best and worst case scenarios for all input variables. Furthermore, all input variables may not be at the best or worst levels at the same time.

MC simulations typically follow a stepwise approach (Raychaudhuri, 2008). First, a deterministic model that closely resembles reality should be created. Second, the underlying distributions of the uncertain input parameters should be identified. Third, random samples from these distributions are generated. Each set, consisting of one value for each uncertain input parameter, will be used in the deterministic model, to calculate one set of output parameters. The core part of Monte Carlo simulations is the repetition of this process: generating many sets of random samples, and collecting the different sets of outcome values. Finally, statistical analysis on the output values will provide statistical confidence for decision making.

Raychaudhuri's approach is suitable for creating prediction models. However, there is a crucial difference between predictions and forecasts. Predicted values are calculated for observations in the sample used to estimate the regression, i.e. it pertains to in-sample observations. On the other hand, forecasts are made for dates beyond the data used to estimate the regression. Hence, their values are not in the sample used to estimate the regression: forecasts are made for dates beyond the data used to estimate the regression (Stock and Watson, 2011). However, in order to use MC simulations for forecasting, time-series forecasting these variables is required after determining the prediction model.

A high-level flow chart of the network development decision-support tool is given in Figure 4-3. Indicated in green are the different submodels; in purple are the different input data. The figure shows how each of the submodels and input parameters are connected to each other.



**Figure 4-3:** Components for network development decision-support tool.

#### **4-2-1 Model 1: market size prediction**

As is clear from the literature review, many different methods have been used to model passenger volumes. As the goal of this project is to come up with a demand forecasting model that shows the forecast uncertainties resulting from different uncertain input parameters, one of the causal econometric methods should be selected.

#### **4-2-2 Model 2: time-dependent parameter forecasts**

In order to use Monte-Carlo simulations for forecasting and not just for prediction, out-of-sample values need to be calculated. This is done by time-series forecasting the time-dependent variables. In order to use MC simulation, not only the most likely value of the forecast is required: the distribution of possible values should be known. Different techniques can be used to do this. The results are normal distributions around the expected values.

With the prediction intervals for the time-dependent parameters known, the next step is to randomly select one of the values from these distributions, for each of the parameters. These random variables are used as input parameters in the market size prediction model. By calculating the output for multiple randomly selected input parameters, a range of demand forecasts will be the result.

#### **4-2-3 Model 3: market share forecasts**

In the literature review, three different techniques to calculate airline market shares were described: S-curve, Quality of Service Index (QSI) and discrete choice models. Due to their simplicity, airlines frequently use S-curve and QSI models. However, due to the lack of statistical background of these models, researches often prefer discrete choice models.

Despite the lack of statistical background, this project uses S-curve models to model market shares. This choice is motivated by the following. QSI and discrete choice models are very data intensive. At the early stage of network development, this data might not be available yet. On the other hand, S-curve models only require data on flight frequencies, which, according to (Belobaba et al., 2009), is the most important factor. Furthermore, both QSI and discrete choice models are designed to calculate itinerary shares, which requires schedules as input. As mentioned in the previous section, itinerary shares can therefore only be applied to short-term forecasting.

#### **4-2-4 Model 4: profit maximisation**

With the models for the market size and airline market shares finished, the final step is to combine them into an airline network development decision-support tool. The goal of the network development model is to find the routes and the corresponding aircraft type and frequency that leads to the largest profit. Due to limited available project time, it was not feasible to develop a novel model. Instead, the network development model is based on the model from Lammens (2014). He created a simple model that is suitable for calculating the ideal airline fleet composition for profit under demand uncertainty. By making some adjustments to his model, it is possible to apply it to network development under demand uncertainty.

# Formulating the Market Size Prediction Model

The market size model is one of the most important inputs of the conceptual model and thus a big part of the graduation project. Based on the available data and objective of the model, the correct prediction model will be selected. This chapter focuses on describing the mathematical form of the prediction model, and will thereby provide an answer to research question 1(a). The resulting model can be used to predict the total demand for passengers travelling via air, between countries.

This chapter is structured as follows. First, the method selection will be described in Section 5-1. In Section 5-2, the mathematical formulation of the model will be given. In Sections 5-3 and 5-4, it is explained which parameters have been included in the model, and which ones have not. In Section 5-5, the format of the regression model will be explained.

### 5-1 Method selection

From the literature review, it is clear that many methods are available for forecasting the demand for air travel. Unfortunately, there are no specific guidelines to match a forecasting technique with a given economic or business situation. According to Frechtling (2001) and Hoshmand (2010), the selection of a forecasting methodology mainly depends on the objective, data availability, and the level of sophistication. In the previous chapter it was explained that the market size prediction model should be causal econometric.

The four causal econometric models identified during the literature review are: gravity models, AIDS, linear models, and VAR. Gravity models have been widely applied to analyse various cross-border flows and economic activities between cities or countries. In the field of transportation, gravity models have been used to model the interchange of passengers or cargo between two zones (Grosche et al., 2007; Chang and Lin, 2010; Shepherd, 2013; Sivrikaya and Tung, 2013; van Nunen, 2014). AIDS models are explicitly based on the microeconomics of consumer expenditure theory. However, according to Frechtling (2001), consumer's expenditure is very difficult to forecast. Linear models assume that demand and its explanatory variables are linked through a simple linear relationship plus an error term (McKinney et al., 2011). According to Frechtling (2001) and Song and Li (2008), the possible occurrence of spurious

regression is a major disadvantage. Finally, vector autoregressive (VAR) models are used to model relationships among multiple time series, and allow multiple evolving variables (McKinney et al., 2011).

It has been decided that gravity models are the correct form for modelling demand for the current project. This choice can be motivated by the following. First, according to the published studies, gravity models are capable of producing accurate medium- to long-term demand forecasts for both existing and new routes. Second, gravity models do not suffer from the disadvantages as the other methods: the complexity of AIDS requires extensive training, which is not feasible for this project, given the limited project time; linear models might suffer from spurious regression; and VAR did not perform well compared with other methods (Song and Li, 2008).

## 5-2 Mathematical formulation

Gravity models have frequently been used in trade analyses, as it is well documented and easy to grasp. It states that the gravity between two objects is directly proportional to their masses, and inversely proportional to their squared distance (Grosche et al., 2007). In its most elementary form, the gravity model can be expressed as Equation 5-1.

$$V_{ij} = k * \frac{(A_i A_j)^\alpha}{D_{ij}^\gamma} \quad (5-1)$$

Where:  $i$  and  $j$  are the origin and destination;  $V_{ij}$  is the passenger volume between  $i$  and  $j$ ;  $A_i$  and  $A_j$  are attraction factors of  $i$  and  $j$ ;  $D_{ij}$  is the distance between  $i$  and  $j$ ;  $k$  is the regression constant;  $\alpha$  controls the influence of the attraction factors;  $\gamma$  controls the influence of the repulsion factors.

This basic model can be extended to include multiple parameters such as GDP and population size for  $i$  and  $j$ . In the earliest models, the attraction factor that was used was the economic mass, measured in GDP. The equation meets the expectation that countries with a large GDP trade more, but countries that are further apart are expected to trade less (van Nunen, 2014).

The gravity model will be used to forecast demand on country-pair levels. The reason for forecasting demand on a country-basis rather than a city-pair basis is because of data issues. Even though it might be possible to collect data on a city-basis from official country databases, this would be too time-consuming to finish the project within the given time period. For this project, the gravity model is given by Equation 5-2. The next section will focus on describing the factors that are included in the model.

$$V_{ij,t} = k * (CPI_{ij,t}^{\alpha_1} * EFF_{ij,t}^{\alpha_2} * GDP_{ij,t}^{\alpha_3} * POL_{ij,t}^{\alpha_4} * POP_{ij,t}^{\alpha_5}) * (D_{ij}^{\alpha_6}) * (e^{BOR_{ij}^{\alpha_7} + BTA_{ij}^{\alpha_8} + COL_{ij}^{\alpha_9} + DT_{ij,1}^{\alpha_{10}} + DT_{ij,2}^{\alpha_{11}} + LAN_{ij}^{\alpha_{12}} + LL_{ij,1}^{\alpha_{13}} + LL_{ij,2}^{\alpha_{14}}}) \quad (5-2)$$

Note that variables have been categorised into three groups: time-dependent variables ( $CPI_{ij,t}$ ,  $EFF_{ij,t}$ ,  $GDP_{ij,t}$ ,  $POL_{ij,t}$ ,  $POP_{ij,t}$ ), a constant variable ( $D_{ij}$ ), and dummy variables ( $BOR_{ij}$ ,  $BTA_{ij}$ ,  $COL_{ij}$ ,  $DT_{ij,1}$ ,  $DT_{ij,2}$ ,  $LAN_{ij}$ ,  $LL_{ij,1}$ ,  $LL_{ij,2}$ ). Previous studies often neglected the time-dependency of variables (Grosche et al., 2007; Sivrikaya and Tunç, 2013; van Nunen, 2014). Instead, they assumed that the values of these variables remains constant over time.

However, ignoring the time-dependency of variables, and assuming that their values will remain constant, actually gives a prediction model, and not a forecasting model. Also note how dummy variables are included differently as the other variables. This is similar to what Sivrikaya and Tunç (2013) did.

Initially, the directionality of demand was taken into account. Taking directionality into account implies that the gravity model includes parameter values for the origin and destination separately. Hence, separate  $\alpha$ s will be found. However, the fact that origin and destination values were almost exactly the same for all parameters, indicated the traffic between two country pairs was equal in both directions. This model therefore assumes that there is no effect of directionality.

### 5-3 Parameters included in the gravity model

The parameters that are included in the gravity model are described below.

- $\alpha$  controls the influence of each of the attraction factors;
- $i$  and  $j$  are integers that indicate the two countries between which traffic flows;
- $t$  indicates the year in which the observation is made;
- $k$  is the regression intercept. It represents the prediction of the dependent variable if all the independent variables would be simultaneously set to zero. Regardless of the statistical significance, one should normally include the constant in the regression model. Only when one is particularly interested in what would happen if all independent variables were set to zero (this may not be physically meaningful), one might choose to neglect this constant;
- $V_{ij,t}$  is the dependent variable. It represents the annual amount of passengers travelling between countries  $i$  and  $j$ ;
- $CPI_{ij,t}$  is the annual average Consumer Price Index (2010 = 100) of country  $i$  times  $j$  at time  $t$ ;
- $EFF_{ij,t}$  is the index of government effectiveness of country  $i$  times  $j$  at time  $t$ . It reflects the annual average perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures. The values range from -3 (very weak) to +3 (very strong) governance performance;
- $GDP_{ij,t}$  is the GDP per capita of country  $i$  times  $j$  at time  $t$ . It is the annual average gross domestic product in current US dollars divided by the midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products;
- $POL_{ij,t}$  is the index of political stability of country  $i$  times  $j$  at time  $t$ . It reflects the annual average perceptions of the likelihood that the government will be destabilised or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. Values range from -3 (very unstable) to +3 (very stable);

- $POP_{ij,t}$  is the mid-year estimate of the population, counting all residents regardless of legal status or citizenship - except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin;
- $D_{ij}$  is the geodesic distance between the largest cities for each country, based on the great circle formula and the latitudes and longitudes of the cities. Values are given in km;
- $BTA_{ij}$  is a dummy variable that indicates whether countries have a bilateral trade agreement or not;
- $BOR_{ij}$  is a dummy variable that indicates if countries share a common border;
- $COL_{ij}$  is a dummy variable that indicates if countries have had the same colonisers;
- $DT_{ij,1}$  and  $DT_{ij,2}$  are dummy variables that give a penalty if the distance between the countries is less than 100km and 750km respectively;
- $LAN_{ij}$  is a dummy variable that indicates whether countries have a similar official language;
- $LL_{ij,1}$  is a dummy variable that indicates if only one of the two countries is landlocked;
- $LL_{ij,2}$  is a dummy variable that indicates if both countries are landlocked.

## 5-4 Parameters not included in the gravity model

Initially, more factors were included in the analysis. However, after solving the model indicated that their effect was insignificant, they were excluded from the analysis. The factors that were excluded because they were not significant are the following:

- *Exchange rate* is the annual average official exchange rate between the local currency relative to the U.S. dollar.
- *Relative price* are midyear estimates of the effective prices of goods and services for each destination country relative to the prices in the origin country. The impacts of inflation and exchange rate movements are included in this single variable (Lim, 1997; Naudé and Saayman, 2005; Song et al., 2011). It is given by  $\frac{CPI_j/EXR_j}{CPI_i/EXR_i}$ . Similar to what previous studies concluded, it did not have a significant effect on the demand.

During a brainstorming session with industry experts (Kariuki et al., 2015), additional factors were identified that might have a significant effect on the passenger volumes. However, they could not be included due to different reasons. Below, the additional factors are elaborated on.

- *Average fare* is one of the parameters that is expected to negatively affect passenger volumes. Unfortunately, due to a lack of data, this factor has not been included. Also, according to (Kariuki et al., 2015), it is too difficult to forecast this value, because average fares are inherently connected with demand itself. Hence, even though it might be used in the prediction model, it is too difficult to use simple time series forecasting

to include the factor in a forecasting model. As will be explained in Section 7-1, the other time-dependent parameters will be forecast this way.

- Whether or not a country is a *holiday destination* presumably has a significant effect on passenger volumes. Different variables have been used in the past: Jorge-Calderón (1997) used the ratio of hotel guests to inhabitants, but did not find a significant effect; Kulendran and Witt (2003) found a significant effect by using the amount of tourists arrivals. Unfortunately, data for neither of them is readily available, and hence, this factor could not be included.
- *Jet fuel price* is expected to negatively affect demand. Using past demand, it might be possible to test this. However, one would need to collect data on jet fuel prices in each country. On the other hand, assuming that all countries pay the same price, this factor might be included when a panel data is used. This way, the dynamic effect of changing fuel price over time could be included. However, as will be explained in the next section, this project does not include panel data sets. Finally, Valdes (2015) indicated that jet fuel prices are not a significant factor for passenger volumes in low and middle income countries.
- *Substitutes* for air travel might be another driving parameter. However, due to a lack of data, this parameter was not included.

## 5-5 Format of the regression model

Before being able to solve the gravity model, it is important to determine the format of the regression model, as this determines the solving techniques to be used. Three different formats are possible: time-series data, cross-sectional data, and panel data. Table 5-1 illustrates each of the three formats. Time-series data provide observations for a single individual (country-pairs in this case) over time. Cross-sectional data include observations for multiple individuals, but lack the time dimension. Finally, panel data sets follow a set of individuals over time, and thus provide multiple observations on each individual (Hsiao, 2014). For an overview of advantages of panel data sets compared to cross-sectional or time-series data sets, the reader is referred to Hsiao (2014).

**Table 5-1:** Fictitious examples of cross-sectional, time-series and panel data sets.

Country pair	Year	Demand [pax]		
		Cross-sectional	Time-series	Panel data
A-B	2013	400	400	400
	2014		420	420
	2015		435	435
A-C	2013	150		150
	2014			160
	2015			175
B-C	2013	12,300		12,300
	2014			12,780
	2015			13,100

Whether or not panel data sets can be used, depends on data availability. The most important factor is that data set should have a balance between being short and long. Short sets follow many samples but have few time periods, resulting in high Type I errors (detecting an effect that is not present); long sets have many time periods for only a small number of samples, leading to Type II errors (failing to detect an effect that is present) (Park, 2011).

Data for the dependent variable is given in monthly values, for a period of 2.5 years. Data for the independent variables are given in annual values, for a period of 10 to 50 years, depending on the variable. This data availability gives two possibilities. The first option is to use cross-sectional data. However, the lack of monthly data for the independent variables, and the fact that market size data is only available for 2.5 years gives a set that is too short to use a panel data set format with an annual interval.

The second option is to use a panel data set with a monthly interval. Because of the monthly interval, the set becomes longer and more balanced. However, as the data for the independent variables is given annually, one would have to make assumptions to get monthly values for them. It is the author's opinion that making assumptions to get monthly data for the independent variables is not feasible. For a cross-sectional set format, such assumptions do not have to be made. Therefore, this project uses a cross-sectional format for the regression model.



# Calibrating the Market Size Prediction Model

With the mathematical form of the prediction model known, the next step is to find the unknown coefficients of the model. The focus of this chapter is on describing the calibration of the coefficients of the prediction model. Thereby, the results in this chapter will answer research questions 1(b) and 1(c).

The structure of this chapter is the following. Additional background information on missing data will be given in Section 6-1. It is necessary to understand this information before moving on to the validation of the data, which is the topic of Section 6-2. In Section 6-3, the results of a comparison of regressions methods will be given, and a selection will be made. In Section 6-4, it is explained why clustering the data will increase the performance of the model.

### 6-1 Dealing with incomplete datasets

Before validating the data, the occurrence of incomplete data should be explained. A common occurrence in datasets is that it is incomplete. Missing data can have a significant detrimental effect on the conclusions that can be drawn from the data. In order to make valid and efficient inferences from the given data, it is therefore necessary that procedures for dealing with missing data will be applied. This section gives an overview of the types of missing data, how missing data could be identified, and how one could deal with it.

#### 6-1-1 Definitions of missing data

Several patterns of data missingness have been identified (Schafer and Graham, 2002).

- *Unit nonresponse*: when no information about a sampled unit is available. Country A in table 6-1 is an example of this case.
- *Item nonresponse*: when only partial data is available. Country B in table 6-1 is an example of this case.

- *Wave nonresponse*: when in longitudinal studies, data is available for some points in time, but not for others.

**Table 6-1:** Fictitious examples of unit (country A) and item (country B) nonresponse.

Country	CPI	Exchange rate	GDP per capita	Population	Demand
A	N.A.	N.A.	N.A.	N.A.	N.A.
B	101.5	0.7	N.A.	15,000,000	13,000
C	102	1.1	1020	8,230,000	2,500

Besides the pattern of missing data, the distribution of missingness is also an important aspect. Previous studies have identified three different distributions (Schafer and Graham, 2002; Gelman and Hill, 2007):

- *Missing at random (MAR)*: the probability a variable is missing depends only on available information.
- *Missing completely at random (MCAR)*: the probability a variable is missing is the same for all units. If data are MCAR, discarding cases with missing data does not bias the results.
- *Missing not at random (MNAR)*: the probability a variable is missing depends on more than just the available information.

These distribution can be mathematically denoted as follows (Schafer and Graham, 2002). The complete dataset is denoted as  $Y_{com}$ , which is partitioned as  $Y_{com} = (Y_{obs}, Y_{mis})$ , where  $Y_{obs}$  and  $Y_{mis}$  are the observed and missing parts. MAR can then be defined as 6-1.

$$P(R|Y_{com}) = P(R|Y_{obs}) \quad (6-1)$$

In other words, in MAR, probabilities of missingness depend on observed data but not on missing data. When Equation 6-1 is violated, the distribution is MNAR. When data also does not depend on the observed data, it is MCAR. MCAR can be denoted as 6-2.

$$P(R|Y_{com}) = P(R) \quad (6-2)$$

With complete datasets, statistical methods are based on the assumption that data is randomly sampled from a distribution. When data is missing, it is not automatically true that the sampling distribution is the correct one (Schafer and Graham, 2002). Different techniques are available for dealing with the different kinds of distributions. Many methods simplify the problem by discarding data. However, this only works if the distribution of missingness is MCAR. Otherwise, the approaches might lead to biased estimates and larger standard errors due to reduced sample sizes (Gelman and Hill, 2007).

On the other hand, attempts to recover missing data might distort estimated variances and correlations (Schafer and Graham, 2002). If a missing data problem can be solved by deleting only small parts of the data, the method can be quite effective. One should always be sure that the discarded cases are not unduly influential. Unfortunately, one can generally not be sure whether data is randomly missing or not, and there is no way to test whether

MAR holds for a given dataset, except by obtaining follow-up data. In practice, missingness is often beyond the control of the researcher and the distribution is unknown. This project therefore assumes that the MAR assumption holds.

### 6-1-2 Identifying missing data

In the ideal case, missing data is easy to spot. However, when multiple data sources have been combined, it might be possible that data from one set is missing, but from the other one it is given. If only the combination of the data is given, it is not clear whether or not data is complete or not. Hence, some additional techniques should be used to identify whether data should be treated as missing or not. Below, an overview of possible methods is given.

- Using standard deviations and the mean. This method would treat everything lying outside  $\mu \pm n * \sigma$  as outliers, where  $\mu$  is the mean of a specific route,  $n$  determines the boundaries and  $\sigma$  is the standard deviation of that route.
- Detecting anomalies using time series modelling. This method can detect patterns that are unexpected and not explained by a time series model. Level shifts, transitory changes, spikes at a particular point, and seasonal outliers can be identified. These models are good to capture the dynamics of quarterly, monthly or other data of moderate periodicity.
- More advanced methods for detecting outliers when the missingness follows a wave pattern. An overview of different techniques to deal with this pattern is given in (Gupta et al., 2014).
- Using thresholds to determine which values should be treated as missing.

As will be explained in 6-2-1, the demand data is subjected to missingness. However, it is not clear when exactly data is missing. It will be explained that thresholds will be used to identify missing data. As the dependent variables are taken from an individual source, missingness is easier to spot for these variables. Hence, no identification method is required.

### 6-1-3 Dealing with missing data

When it is clear for when data is missing, it must be determined how this should be dealt with. Below, the main methods are briefly described (Schafer and Graham, 2002; Gelman and Hill, 2007).

- *Complete-case analysis*: all units for which any dependent or independent variable is missing, will be excluded. Two problems arise from this: as mentioned before, when data is not MCAR, this might lead to biased results. Furthermore, if many variables are included in the model, very few complete cases might be available, and hence most of the data will be discarded.
- *Available-case analysis*: different aspects of a problem are studied with different subsets of available data. Again, only the available information will be used, and incomplete data will be discarded.
- *Single imputation*: single imputation is the process of replacing missing values by a single value, and proceed with the analysis rather than discarding the unit. By not discarding

any units, it is potentially more efficient than the methods explained above. Several methods of single imputation have been described. For instance, mean imputation replaces the missing value with the mean of the observed variables. Last value carried forward replaces the missing value by the previous one. Using information from related observations looks at the entire dataset and uses information from similar cases. There are also methods that replace the missing values randomly.

- *More advanced methods* such as maximum likelihood estimation, model-based imputation, and multiple imputation (which replaces the missing value by a distribution rather than a single value) have also been mentioned. These methods are more efficient, but are also more difficult to model.

For the demand data, a combination of single imputation and complete case analysis will be used. When data for dependent variables is missing, single imputation will be used. How this will be done will be explained in the next section.

## 6-2 Validation of data

The validation of the dependent and independent parameters is described in this section. It is also described how missingness will be dealt with for each of them.

### 6-2-1 Dependent variable

The dependent variable to be used for the regression analysis is the annual passenger volume between two countries. Data is taken from the MIDAS (2015) database. This dataset gives the total market sizes in terms of passengers, for all airlines operating on specific city pairs. Traffic is given for both directions for each city pair. Airlines can retrieve data for markets where at least one segment was operated or marketed by the airline. This allows airlines to collect O-D data with all possible routings, even operated and marketed by other airlines, but only when at least one segment was operated by the airline. Before using this data for the regression, the limitations of this data should be described.

MIDAS includes reservations made by travel agencies connected to the major Global Distribution Systems (GDS). Kenya Airways has subscriptions to the Abacus, Amadeus and TravelSky GDSs. Reservations through airline's own websites and offices are not included in the database. Especially for developing countries, where reservations are still frequently made via offices, MIDAS data is missing significant booking volumes (Kariuki et al., 2015).

The database only gives the combined dataset of all the GDSs an airline is subscribed to, and it is not possible to retrieve data from GDSs individually. It is possible that data from one of the GDSs is incomplete, but this can not be observed from the data. If for example in a given month an airline does not operate or market flights on an O-D pair from a given GDS, no data from this GDS can be accessed for this month. According to Kariuki et al. (2015), it is a common problem for airlines that data from MIDAS (2015) is incomplete. To be able to work with this data, airlines therefore often filter the data.

### Identifying missing data

The procedure for missing data in the demand data is based on thresholds of the maximum monthly demand per route in a given year. It is assumed that for each O-D city-pair, the maximum monthly demand has the correct order of magnitude. The input for the outlier

detection is a vector  $V$  with the monthly passenger demand on an O-D pair, for the period of one year. The monthly values will be compared with the maximum values for that O-D pair for that year. Due to effects such as seasonality, demand is expected to fluctuate. However, it is assumed that there is a limit on the feasibility of these fluctuations. The feasibility limit for this project has been set at 5%. Whenever the monthly demand for a given route is lower than this limit, the demand for this month is treated as missing. The outlier detection test is illustrated in Figure 6-1. In this figure,  $V$  is a vector with monthly demand for a single O-D pair for one year;  $i = 1, 2, 3, \dots, 12$  is the month index.

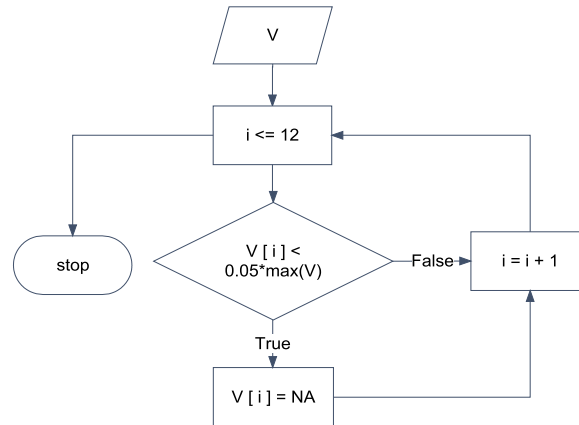


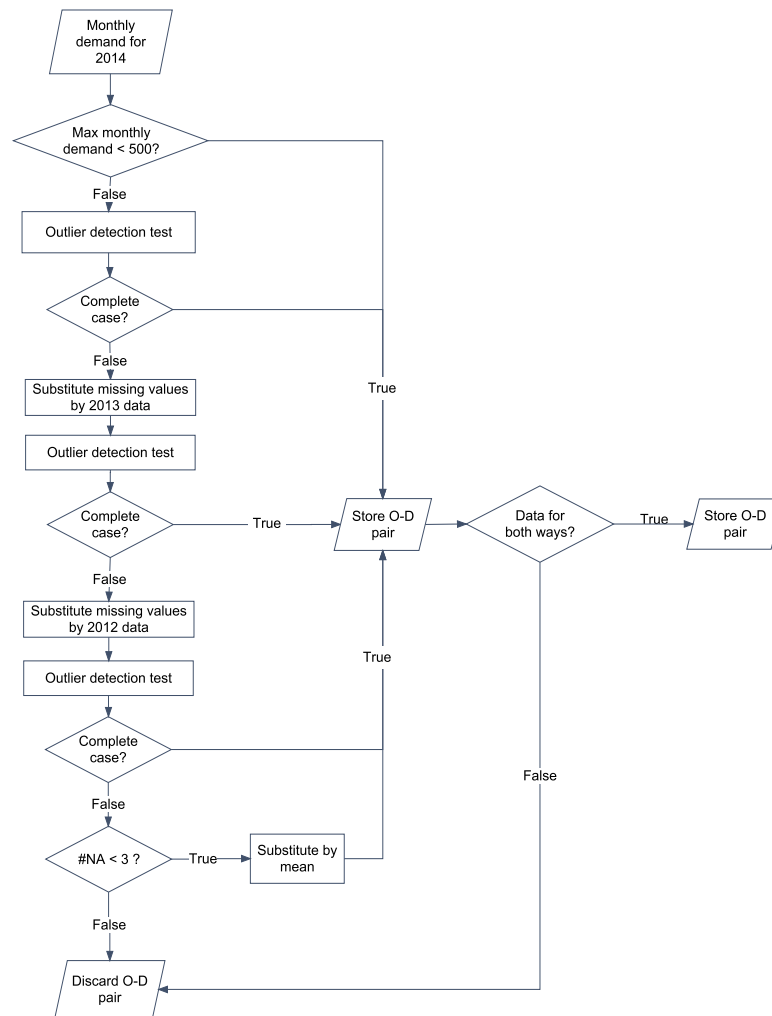
Figure 6-1: Outlier detection test.

### Dealing with missing data

The procedure for dealing with missing data is based on the assumptions that there is no error in the data, and that all data points are valid. The goal of the data filtering process is to create two datasets: one with all O-D pairs that should be kept, and one with all O-D pairs that should be discarded. In order to make the MAR assumption feasible, one should not discard too many O-D pairs. The technique for filtering is a combination complete-case analysis and single imputation. This way, few O-D pairs will be discarded. Using seven steps, it is determined whether O-D pairs should be kept or discarded. Below, it will be explained how this data was filtered in order to be usable in the gravity model. A graphical representation in the form of a flowchart is given in Figure 6-2.

1. Data for three airports are excluded (FIS, RYL and ZLX), as they are unknown. Furthermore, the gravity model requires country specific data, and since Réunion is a French island, this data is not available. Hence, all city pairs with airports in Réunion are thus removed from the dataset.
2. According to the author, large fluctuations can be expected for O-D pairs with a low demand, but not for pairs with a high demand. A 98% drop from 100 to 2 passengers seems more likely than one from 10,000 to 200. A threshold for accepting all city pairs with a monthly demand less than 500 has therefore been set.
3. When the maximum demand exceeds 500, outliers are detected using the outlier detection procedure from Figure 6-1. All the complete O-D pairs will be stored in the “store O-D pair” set. Any missing values are substituted by values for that same route and month from the previous year (2013).

4. The substituted data will be tested for outliers a second time. All complete routes will be temporarily stored in the “store O-D pair” set. Any missing values will be substituted by demand for that same route and month in 2012.
5. Data that is not stored after the second outlier test will be tested for outliers a third time. Once again, all complete O-D pairs will be stored.
6. For the data that is not stored yet, any O-D pair for which more than three data points are missing will be discarded. When data for three months or less is missing, the mean of that O-D pair will substitute the missing data.
7. Finally, for all O-D pairs that are complete, it will be tested whether data for both directions is available. If this is not the case, it is not possible to determine the total demand between the city pairs, and hence, the route will be discarded.

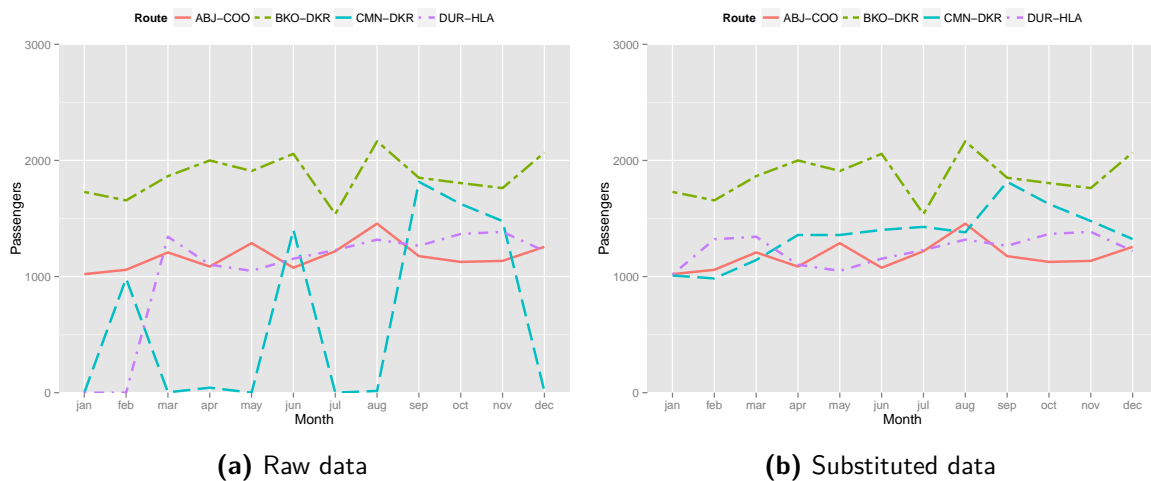


**Figure 6-2:** Flowchart for filtering demand data for a single O-D city pair.

As mentioned by Kariuki et al. (2015), it is common for airlines to use a similar approach. Airlines also frequently add an adjustment factor for the fact that MIDAS does not give

bookings made through airline's own websites or booking offices. Due to lack of data and knowledge, this adjustment factor can not be included in this project. This means that, in reality, the demand is larger than what has been used in this project.

Figure 6-3 shows the results after filtering the data for four O-D pairs. Figure 6-3a shows the raw data. From this figure it should be clear that demand on CMN-DKM and DUR-HLA is incomplete: the fluctuations do not seem feasible. After applying the data filtering technique from Figure 6-2, demand will be as illustrated in Figure 6-3b. Even though fluctuations remain, they seem more feasible than before.



**Figure 6-3:** Raw and adjusted market size data. In this figure, ABJ = Abidjan, COO = Cotonou, BKO = Bamako, DKR = Dakar, CMN = Casablanca, DUR = Durban, HLA = Lanseria.

Table 6-2 gives the amount of O-D pairs after each test. Note that these tests are applied to the data from MIDAS. Hence, the values represent the one-way traffic. As the results in this table show, only slightly more than 1% of the data was discarded.

**Table 6-2:** Amount of city pairs to keep and discard after each test phase.

Phase	O-D pairs to keep	O-D pairs to discard
Original dataset	12,747	0
After ignoring cities and countries	12,520	227
After maximum threshold of 500	12,202	545
After outlier test #1	12,412	335
After outlier test #2	12,454	293
After outlier test #3	12,456	291
After testing # of missing points	12,496	251
After entire filtering procedure	11,206	1,541

After combining data for the same city pairs, data for 5,603 unique city pairs remains. Next, because the gravity model requires the data to be on a country-pair basis, the city pair data will be converted to country pair data. Converting the demand data gives a dataset with 1,296 unique country pairs. As this project only focuses on international demand, all domestic data

will be ignored. After this, 1,270 country pairs remain. Finally, all country pairs with zero passenger flows will be discarded.

Most literature on trade flow models discard this data in order to be able to log-linearise the gravity model. Log-linearisation of data will be explained in the next section. Even though this has frequently been criticised in literature (Santos Silva and Tenreyro, 2006; Burger et al., 2009), the assumption to discard these pairs from the data is justified by the fact that one is unable to be certain that the passenger flow is truly zero, or whether data is incomplete. As mentioned by van Nunen (2014)[p. 52], “*assuming a zero flow between two countries is therefore as much an assumption as removing all the countries [for which] no data is known*”. Removing all domestic country pairs from the dataset results in 1,209 unique country pairs that will be used for the prediction model. A summary of the demand data is given in Table 6-3.

**Table 6-3:** Summary of dependent variable data.

Variable	Min	Max	Mean	Variance
$V_{ij,t}$	1	$2.07 \times 10^5$	$3.91 \times 10^3$	$2.60 \times 10^8$

### 6-2-2 Independent variables

After describing the validation of the dependent variable, this subsection focuses on validating the different independent variables. Data for the independent parameters is taken from four different sources.  $CPI_{ij,t}$ ,  $GDP_{ij,t}$  and  $POP_{ij,t}$  are taken from The World Bank (2015);  $EFF_{ij,t}$  and  $POL_{ij,t}$  are taken from Kaufmann et al. (2013);  $D_{ij}$ ,  $BOR_{ij}$ ,  $COL_{ij}$ ,  $DT_{ij,1}$ ,  $DT_{ij,2}$ ,  $LAN_{ij}$ ,  $LL_{ij,1}$  and  $LL_{ij,2}$  are taken from Mayer and Zignago (2011); and  $BTA_{ij}$  is taken from Dür et al. (2014).

The data from The World Bank (2015) is given in annual averages per country. Many researchers have used these indicators for modelling demand for air travelling between two countries (Grosche et al., 2007; Belobaba et al., 2009; Chen et al., 2012). For most of the data, values are available from 1960 to 2014. However, wave nonresponse sometimes occurs. When wave nonresponse occurs, data for missing years will be substituted by the expected value from the Box-Jenkins forecast (i.e. single imputation). A detailed explanation of the selected Box-Jenkins method will be given in the next chapter.

The data from Kaufmann et al. (2013) are based on several hundred individual underlying variables. Unlike the parameters mentioned above, these variables are more difficult to quantify. The data reflect the views on governance of survey respondents and public, private, and NGO sector experts worldwide. It also explicitly reports margins of error accompanying each estimate for each country. Details on the underlying data sources, the aggregation method, and the interpretation of the indicators can be found in Kaufmann et al. (2010). Unfortunately, data is only provided until 2013. The value for 2014 will be imputed by Box-Jenkins forecasts. As the gravity model can only deal with positive data, the data for  $EFF_{ij,t}$  and  $POL_{ij,t}$  were normalised by Equation 6-3.

$$Value_{new} = \frac{Value_{old} + 3}{3} \quad (6-3)$$

Mayer and Zignago (2011) provides an exhaustive set of gravity variables to analyse market access in global and regional trade flows. It gives both country-specific geographical variables



for 225 countries worldwide, as well as data for valid pairs of countries. A summary of the data of the independent parameters is given in Table 6-4.

**Table 6-4:** Summary of independent variable data.

Variable	Min	Max	Mean	Variance
$CPI_{ij,t}$	$7.23 \times 10^3$	$6.17 \times 10^4$	$1.71 \times 10^4$	$3.71 \times 10^7$
$EFF_{ij,t}$	0.12	1.48	0.56	0.05
$GDP_{ij,t}$	$3.36 \times 10^4$	$2.82 \times 10^8$	$7.49 \times 10^6$	$3.34 \times 10^{14}$
$POL_{ij,t}$	0.02	1.77	0.66	0.12
$D_{ij}$	10.5	$9.68 \times 10^3$	$3.69 \times 10^3$	$3.79 \times 10^6$
$BOR_{ij}$	0	1	$7.78 \times 10^{-2}$	$7.18 \times 10^{-2}$
$BTA_{ij}$	0	1	0.78	0.17
$COL_{ij}$	0	1	0.27	0.20
$DT_1$	0	1	$8.3 \times 10^{-4}$	$8.3 \times 10^{-4}$
$DT_2$	0	1	$4.05 \times 10^{-2}$	$3.89 \times 10^{-2}$
$LAN_{ij}$	0	1	0.45	0.25
$LL_1$	0	1	0.43	0.24
$LL_2$	0	1	$8.35 \times 10^{-2}$	$7.66 \times 10^{-2}$

## 6-3 Techniques to find the gravity model coefficients

After collecting and validating the data, the coefficients of the gravity model can be calculated. Before describing the different techniques that could be used to do this, it is important to clarify that the following assumptions have been made. Despite the fact that there are errors in the data, it has been assumed that the measurement errors are zero. Second, it has been assumed that all relevant drivers are included, and that all irrelevant drivers are excluded. Below, it will be explained how driver significance has been determined. After this, a comparison of solving techniques will be given.

### 6-3-1 Estimation of the regression coefficients

It is possible that parameters that have been included in the model were insignificant. Field (2009) described different ways how parameters can be included in a multiple regression model: forced entry, hierarchical and stepwise methods. In forced entry, all parameters are forced into the model simultaneously. Subsequently, all insignificant parameters are removed from the model. In hierarchical methods, known predictors (from previous research) are entered first. New predictors are then added, either all in one go, in a stepwise manner, or hierarchically. In stepwise methods, parameters are added one by one. The order in which parameters are added is based on mathematical criterion (Field, 2009).

This project used forced entry, due to its simplicity. A significance level of 0.10 was used. Hence, all parameters with a significance larger than 0.10 were discarded. When parameters are significant, the next step is to look at the effect they have on the dependent variable. When coefficients are positive, factors have a positive effect on demand; when they are negative, factors have a negative effect on demand.

### 6-3-2 Regression techniques

Different regression techniques can be used to find the coefficients of the gravity model. These techniques can roughly be divided into two groups. The first group requires an additive and linear model. In order to comply with this, log-linearisation is required. The second group does not require log-linear transformation. Examples of such techniques are poisson regression and negative binomial regression.

If the original model is given by Equation 6-4, the log-linear model is given by Equation 6-5, where  $\epsilon_{ij}$  is assumed to be independent and identically distributed. Subsequently, the coefficients of the log-linearised gravity equation can be solved using different techniques, of which ordinary least squares is the most frequently used.

$$V_{ij,t} = k * CPI_{ij,t}^{\alpha_1} * EFF_{ij,t}^{\alpha_2} * GDP_{ij,t}^{\alpha_3} * POL_{ij,t}^{\alpha_4} * POP_{ij,t}^{\alpha_5} * D_{ij}^{\alpha_6} * e^{BOR_{ij}^{\alpha_7} + BTA_{ij}^{\alpha_8} + COL_{ij}^{\alpha_9} + DT_{ij,1}^{\alpha_{10}} + DT_{ij,2}^{\alpha_{11}} + LAN_{ij}^{\alpha_{12}} + LL_{ij,1}^{\alpha_{13}} + LL_{ij,2}^{\alpha_{14}}} \quad (6-4)$$

$$\ln(V_{ij,t}) = \ln(k) + \alpha_1 * \ln(CPI_{ij,t}) + \alpha_2 * \ln(EFF_{ij,t}) + \alpha_3 * \ln(GDP_{ij,t}) + \alpha_4 * \ln(POL_{ij,t}) + \alpha_5 * \ln(POP_{ij,t}) + \alpha_6 * \ln(D_{ij}) + \alpha_7 * BOR_{ij} + \alpha_8 * BTA_{ij} + \alpha_9 * COL_{ij} + \alpha_{10} * DT_{ij,1} + \alpha_{11} * DT_{ij,2} + \alpha_{12} * LAN_{ij} + \alpha_{13} * LL_{ij,1} + \alpha_{14} * LL_{ij,2} + \epsilon_{ij} \quad (6-5)$$

#### Ordinary Least Squares

As indicated by Santos Silva and Tenreyro (2006) and Arvis and Shepherd (2011), coefficient values of gravity models have traditionally been estimated by log linearizing the model. Ordinary least squares (OLS) is then used to find the coefficients. This technique minimises the sum of squared errors. The validity of OLS critically depends on the homoskedasticity assumption. This assumption implies that the errors  $\epsilon_{ij}$  must be independently drawn from a normal distribution with fixed variance, i.e. the error terms are statistically independent of the regressors.

There are a number of disadvantages of log-linearising the model. First, as the log-normal model generates estimates of  $\ln(V_{ij,t})$  but not of  $V_{ij,t}$ , large passenger volumes tend to be underestimated. This is known as Jensen's inequality. A second disadvantage is the incompatibility with the existence of zeros in the data. The most common approaches are to delete the zero-valued observation, or to add small positive values to all observations. However, deleting all zero-valued flows can lead to biased results (Santos Silva and Tenreyro, 2006; Burger et al., 2009). Another disadvantage is that log-linear models are based on the homoskedasticity assumption. However, Santos Silva and Tenreyro (2006) showed that error terms in gravity equations are heteroskedastic, which violates this assumption. Hence, inconsistent estimates will be found.

#### Poisson Pseudo Maximum Likelihood

To overcome the problems faced with OLS, researchers started focusing on using Poisson Pseudo-Maximum Likelihood Estimator (PPML), as this has several advantages over log-linear estimators. PPML is an estimator that assumes that the dependent variable follows a Poisson distribution. It has frequently been used to model count data. Count data is the type of data in which the observations can only have non-negative integer values 0, 1, 2, ..., n. Recently, researchers started using this estimator to model gravity models (Shepherd, 2013).

One of the advantages of PPML is that it works well with heteroskedasticity. Furthermore, it can deal with dependent variables equal to zero. Another advantage is that it generates estimates of  $V_{ij,t}$  instead of  $\ln(V_{ij,t})$ , thereby avoiding underpredictions of large passenger volumes (Santos Silva and Tenreyro, 2006; Cameron and Trivedi, 2013; Shepherd, 2013). Unfortunately, PPML does not work when the data is overdispersed. Overdispersion is defined as the situation in which the variance of a variable is larger than its mean (Barron, 1992). When looking at the data in Tables 6-3 and 6-4, it can be seen that data is overdispersed.

### Negative Binomial Regression

Negative binomial regression (NB) has also been used to model count data and for gravity models. It is specifically useful when data is overdispersed, i.e. when the conditional variance exceeds the mean. It has a similar structure as Poisson regression, but has an additional parameter to model overdispersion (Barron, 1992; UCLA: Statistical Consulting Group, 2015). As NB is specifically useful for overdispersed data, it is expected that this method will be the best method to model the passenger demand.

### Other regression techniques

As an alternative to PPML and NB, Figueiredo et al. (2014) developed a robust quantile regression method. Despite the fact that this method also requires log-linearisation, it was proven that this method works well with zero trade flows, and is robust to heteroskedasticity. However, due to its complexity, this is beyond the scope of the project.

## 6-3-3 Comparison of regression techniques

Earlier in this section, it was explained that it is expected that NB would be the best option to model the passenger demand. Below, the results of the comparisons between the applications of the methods is described. For reproducibility purposes, Table B-1 in Appendix B gives the significance and effects of all parameters for each of the three methods.

### Fit of the regression models

One of the ways of comparing the different techniques is to look at the fit of the model. Different techniques have different values to look at. For OLS,  $R^2$  and  $R^2_{adj}$  describe the fit of the model. The closer these values are to 1, the better the fit is.

The goodness of fit of PPML and NB is tested by the Residual Deviances (RD) and the Chi-squared goodness of fit test (Cameron and Trivedi, 2013; UCLA: Statistical Consulting Group, 2015). If the residual deviance is small enough, the Chi-squared goodness of fit will be insignificant (i.e. larger than 5%), indicating that the model fits the data well. If the Chi-squared value is significant, the model does not fit the data well. In order to compare NB and PPML, authors have proposed model selection criteria based on the fitted log-likelihood function. The proposed diagnostic is the Akaike Information Criterion (AIC), where the model with the lowest value is preferred. Table 6-5 gives the fit of the different methods.

**Table 6-5:** Fit of OLS, NB and PPML regression.

OLS	NB	PPML
$R^2 = 0.65$	$RD = 1.45 \times 10^3$	$RD = 6.18 \times 10^6$
$R^2_{adj} = 0.65$	$P[\chi^2] = 8.74 \times 10^{-7}$	$P[\chi^2] = 0$
	$AIC = 1.78 \times 10^4$	$AIC = 6.19 \times 10^6$

OLS shows a reasonable fit, as  $R^2$  and  $R^2_{adj}$  are relatively close to 1. Unfortunately, this can not be compared to the other methods, as they use different diagnostics for describing the fit. NB can be compared with PPML, as they use the same diagnostics. When looking at the residual deviance and AIC, it should be clear that NB provides a better fit than the PPML.

### Prediction accuracy

Another way of comparing the different techniques is to look at the plot that compares the actual demand with the predicted value of the demand (predicted vs. actual plot) and the Q-Q plots. Predicted vs. actual plots graphically show how well the model can predict demand values. Ideally, the predicted and actual demand should be similar. The actual plots are given in Appendix A. Figures A-1a, A-1c and A-1e show the predicted vs. actual plots for the three methods. The main observation that can be made from these plots is that OLS indeed underestimates demand. For NB and PPML this is less the case.

Q-Q plots are a graphical way of testing the validity of a distributional assumption for a given data set. If data follow the assumed distribution, the points on a Q-Q plot fall on a straight line. Q-Q plots are especially useful for testing the distribution of the residuals: well-behaved residuals should be normally and independently distributed random variables with a mean around 0 (NIST/SEMATECH, 2012). Plotting the Q-Q plots of the residuals against a normal distribution shows how well the residuals are normally distributed: the more closely the plot follows the line  $y = x$ , the more normally distributed the residual are.

Figures A-1b, A-1d and A-1f show the residual normal Q-Q plots for the three regression techniques. Where the Q-Q plots of the OLS and NB regression follow the  $y = x$  line reasonably well, the residuals of PPML do not. Special attention should be paid to the very large scaling on the y-axis for PPML. The Q-Q plots indicate that OLS and NB regression follow the normality assumption reasonably well; PPML does not.

### Conclusions of comparing the regression techniques

Based on the model fit and the prediction accuracy of the different techniques, it has been decided to continue with the NB regression method. In the next section it will be explained how the fit and prediction accuracy can be increased.

## 6-4 Improving the regression model by clustering

Even though the fit and the prediction accuracy of the negative binomial regression seem feasible, it should be tested whether it is possible to increase them. As Grosche et al. (2007) showed, this could be done by clustering the regression. The main reason for clustering is to discover a structure in the data which we did not know about before. Furthermore, clustering the regression can also be used to test the structural stability of the model. For the current project, data was clustered in five ways: actual demand levels, distance, government effectiveness, income level of countries (high, middle or low, as defined by The World Bank (2015)), and political stability.

### Fit of the models

The fit of the clustered prediction models are given in Table 6-6. It gives the number of observations per cluster (OBS), RD, AIC, and  $P[\chi^2]$ . Unfortunately, not all of the clusters converged. According to Luxburg and Ben-David (2005), when clusters do not converge, the results will be unpredictable and unreliable. Hence, these clusters should not be used. Table 6-6 gives the model fit for the clusters that did converge. The clusters for which no solution

was found, are indicated by “x”.

The results in Table 6-6 indicate that clustering indeed increases the prediction accuracy of the model, as the residual deviance and AIC decreases. For some clusters,  $P[\chi^2]$  even becomes nonsignificant. Clustering with respect to the actual demand results in the largest improvement.

**Table 6-6:** Fit of the prediction models after clustering

Selection Criteria	Level	OBS	RD	AIC	$P[\chi^2]$
Basic model		1,209	$1.45 \times 10^3$	$1.78 \times 10^4$	$8.74 \times 10^{-7}$
Demand	< 50	314	339	$2.36 \times 10^3$	0.10
	50 - 750	492	524	$6.29 \times 10^3$	0.86
	750 - 10,000	312	333	$5.47 \times 10^3$	0.13
	> 10,000	91	96	$2.05 \times 10^3$	0.15
Distance	< 3,700 km	649	789	$1.04 \times 10^4$	$3.49 \times 10^{-5}$
	3,700 - 5,000 km	254	x	x	x
	> 5,000 km	306	354	$3.76 \times 10^3$	0.01
Effectiveness	Low - low	939	$1.12 \times 10^3$	$1.39 \times 10^4$	$8.29 \times 10^{-5}$
	Low - high	255	295	$3.58 \times 10^3$	0.02
	High - high	15	x	x	x
Income level	Low - low	282	316	$3.96 \times 10^3$	0.03
	Low - mid	592	701	$8.59 \times 10^3$	$3.94 \times 10^{-4}$
	Low - high	20	x	x	x
	Mid - mid	294	x	x	x
	Mid - high	21	x	x	x
	High - high	0	x	x	x
Stability	Low - low	611	729	$9.37 \times 10^3$	$1.76 \times 10^{-4}$
	Low - high	502	602	$7.17 \times 10^3$	$5.12 \times 10^{-4}$
	High - high	96	105	$1.21 \times 10^3$	$4.93 \times 10^{-2}$

### Prediction accuracy

Besides looking at the residual deviance, AIC and Chi-squared probability, it is also important to look at the prediction accuracy of the different clusters. Plots are only given when solutions were found for all levels of a cluster. Hence, the distance, effectiveness and income level clusters are not shown. The predicted vs. actual demand plots and the Q-Q plots are given in Appendix C.

Several observations can be made from these plots. The predicted vs. actual plots of clustering the data with respect to political stability (Figures C-1c, C-1e and C-1g show similar results as the basic model (Figure C-1a), but with less outliers. The predicted vs. actual plots for the demand clusters (Figures C-2a, C-2c, C-2e and C-2g) show very different results, and it is difficult to compare them to the basic model.

The Q-Q plots of both the models clustered with respect to the political stability levels (Figures C-1d, C-1f and C-1h) show similar results as with the Q-Q plot for the complete dataset (Figure C-1b). Clustering the data with respect to demand levels shows small improvements in terms of the Q-Q plots, as they show more equality to the line  $y = x$ . This

indicates that residuals are more normally distributed.

### Estimation of the coefficients

The signs of the coefficients indicate the effect of the variable on demand: positive factors have a positive influence; negative factors have a negative influence on demand. The coefficient values for the significant parameters are given in Table 6-7. Below, the results will be discussed. Also, it will be described whether or not the results are according to the expectations.

**Table 6-7:** Regression results for complete clusters.

Selection	Level	Coefficients						
criteria		Constant	$CPI_{ij,t}$	$EFF_{ij,t}$	$GDP_{ij,t}$	$POL_{ij,t}$	$POP_{ij,t}$	$D_{ij}$
Basic model Demand	< 50	-8.90 ***	-	1.92 ***	0.34 ***	-	0.75 ***	-1.59 ***
	50 - 750	-2.42 *	-	0.44 *	-	0.31 **	0.23 ***	-0.18 *
	750 - 10,000	0.74 -	-	0.48 ***	0.09 ***	-	0.24 ***	-0.50 ***
	> 10,000	5.65 ***	-	0.54 ***	-	-	0.18 ***	-0.44 ***
Stability	Low - low	-1.26 -	-	0.67 **	0.32 ***	-	0.30 ***	-0.45 ***
	Low - high	-12.01 ***	-	1.52 ***	0.26 ***	0.32 **	0.86 ***	-1.50 ***
	High - high	-8.24 ***	-	1.94 ***	0.38 ***	-	0.72 ***	-1.66 ***
		15.47 *	-1.88 **	2.71 ***	0.32 ***	-2.17 .	0.62 ***	-1.88 ***

Selection	Level	Coefficients							
criteria		$BOR_{ij}$	$BTA_{ij}$	$COL_{ij}$	$DT_{ij,1}$	$DT_{ij,2}$	$LAN_{ij}$	$LL_1$	$LL_2$
Basic model Demand	< 50	0.64 ***	-	0.38 ***	-10.80 ***	-0.92 ***	1.09 ***	-0.76 ***	-1.28 ***
	50 - 750	-1.00	-	0.43 **	-	-	-	-	-
	750 - 10,000	-0.49 *	-	-	-3.07 ***	-0.46 .	0.40 ***	-0.21 **	-0.37 **
	> 10,000	-	-	0.37 ***	-	-	-	-0.27 ***	-0.25 .
Stability	Low - low	0.41 *	-	-	-	-	0.53 ***	-	-0.80 *
	Low - high	0.73 ***	-	0.59 ***	-10.24 ***	-0.96 **	0.83 ***	-0.71 ***	-1.07 ***
	High - high	0.75 **	-	-	-	-0.88 **	1.42 ***	-0.76 ***	-1.77 ***
		-	0.61 .	0.93 ***	-	-2.25 ***	1.01 ***	-0.59 **	-2.25 ***

Significance codes: “\*\*\*” < 0.001; “\*\*” < 0.01; “\*” < 0.05; “.” < 0.1; “-” non significant

- *Intercept* can be positive and negative. Note that as was explained in the previous chapter, the intercept should generally not be removed from the model, not even when its effect is insignificant.
- *CPI* has a positive effect for almost all cases. This is according to the expectations.
- *Index of government effectiveness* consistently has a strong positive effect. This is according to the expectations, as it can be expected that the more positive effect governments have, the more people will travel.
- *GDP per capita* has a positive effect for all cases, which is according to the expectation that the more people have to spend, the more they will travel.
- *Index of political stability* has a positive effect for most clusters. This is expected, because the more stable a country is, the more people will travel (Naudé and Saayman, 2005).
- *Population* also has a positive effect. Again, this complies with the expectation that the more people a country has, the more people will travel (Grosche et al., 2007).
- *Distance* has a negative effect. This is in line with most trade models, which state that the larger the distance is, the less countries will trade with each other (Kariuki et al., 2015).

- *Common borders* are expected to have a positive effect on demand (van Nunen, 2014). For most clusters, this is true. However, for some, this dummy variable has a large negative effect.
- *Bilateral trade agreements* only have a small effect for some of the clusters. It is expected that this effect is positive (van Nunen, 2014). However, the results for the current study are not stable.
- *Colonial links* have a positive effect on demand. Again, this is according to the expectation that when countries share a border, the demand for air travelling increases (van Nunen, 2014).
- $DT_{ij,1}$  and  $DT_{ij,2}$  both have a large negative effect on demand. As these parameters aim at penalising the demand for countries with a small distance between them, the negative effect is according to expectations.
- *Common language* is another factor that is expected to be positive. As the results show, this is indeed the case.
- *Landlocked* countries have a negative effect on demand (Kariuki et al., 2015). As landlocked countries often offer the alternative of travelling via road or rail, which usually is less expensive than travelling via air, it is expected that this effect is negative.

### Conclusions of clustering the model

In this section, it was shown that clustering data before the regression, the fit of the models and the prediction accuracy can be improved. Despite the fact that clustering the data with respect to demand lead to the largest accuracy improvement, it has been decided to continue with clustering the data with respect to political stability. The reason for this is the following. The goal of this prediction model is to use it as a part of forecasting model for a network development tool. When data is clustered with respect to demand, only country pairs from the existing database could be used. When one is interested in forecasting demand for new country pairs, one would have to make an initial guess about the demand level. By clustering with respect to the political stability, this is not the case.

## 6-5 Conclusions of the market size prediction model

The preceding and the current chapters focused on one of the most important aspects of the graduation project: developing a model that can be used to predict the passenger demand between countries. The research described in these chapters showed the potential of using gravity models to do this.

These chapters were used to provide answers to the subquestions of research question 1. In the previous chapter it was explained that the mathematical formulation of the prediction model was a gravity model. This was mainly based on published studies that concluded that gravity models are capable of producing accurate medium- to long-term demand forecasts for both existing and new routes. Due to lack of data, the gravity model will be used to predict demand on a country-pair level rather than on a city-pair level.

This chapter focused on describing the calibration of the prediction model coefficient. Research questions 1(b) was answered by comparing the performances of three regression

techniques: ordinary least squares, poisson pseudo maximum likelihood, and negative binomial regression. The comparisons showed that the latter provides the most accurate results. In order to increase the performance of the prediction model, datasets were clustered with respect to political stability before calibrating the regression model. The three groups inside this cluster were: both the origin and destinations were politically stable; only one of them was stable; neither were stable. For each of the three clusters, a separate prediction model was found, each of which had a higher accuracy than without using clusters.

The accuracy of the model outcomes was given in terms of the residual deviance, Akaike Information Criterion, and the  $P[\chi^2]$  values. According to the author, the accuracy was high enough to assume that from here on, the models that have been found are the correct models. The consequence of assuming that these models are correct, is that prediction errors will propagate.

## 6-6 Recommendations for the market size prediction model

In terms of directions for future research, further work could focus on increasing the model's accuracy. Accuracy improvement is mainly expected to come from improving the quality of the input of the data. Especially improving the data from MIDAS could potentially result in more accurate predictions.

Due to time constraints, it was not possible to analyse outliers from the market size predictions. By not removing outliers, errors propagate to the forecasting and network development model. Future research should focus on increasing the model accuracy by looking at additional predictor variables, and to use interactions between predictor variables. Additional parameters might be able to identify why certain points are outliers. Adding additional parameters might reduce the number of outliers, and increase the model fit. Also, *"including interactions is a way to allow a model to be fit differently to different subsets of data"* (Gelman and Hill, 2007)[p. 36]. The exact consequences are difficult to predict, but it might have a significant effect on the accuracy of the results.

Rather than using forced entry methods, other methods of introducing predictor variables could be used, such as hierarchical and stepwise methods. In hierarchical methods, after known predictors have been entered, new predictors are added, either all in one go, in a stepwise manner, or hierarchically. In stepwise regressions, *"decisions about the order in which the predictors are entered into the model are based on a purely mathematical criterion"* (Field, 2009). The exact consequences of this are difficult to predict, but as it might have a significant effect on the accuracy, it would be interesting to test this.

One could also use different clustering techniques, such as DBSCAN or other automatic clustering techniques, to increase the accuracy. This project already showed how clustering data with respect to political stability and historical demand levels results in a better model performance compared to the basic model. However, it is expected that using automatic clustering techniques will further enhance the performance.

Finally, future research could focus on using other types of model formulations such as extended versions of VAR. Also, one could try to use panel data sets with monthly intervals. It is important that assumptions have to be made on the monthly values for the independent variables, as they are only available in annual values.



# Using the Prediction Model for Forecasting

In the two preceding chapters, it was explained how the prediction model was developed. As should be clear by now, predictions pertain to in-sample observations. On the other hand, forecasts are for data beyond what is available. Hence, forecasts are made for dates beyond the data used to estimate the prediction model. By forecasting the time-dependent parameters, and implementing their interval forecasts in the prediction model, interval forecasts for the market size can be generated. How this has been done is the topic of this chapter. Hence, the contents in this chapter will provide an answer to research question 2.

This chapter is structured as follows. In Section 7-1, the time-series forecasting of the time-dependent parameters will be explained. How the interval forecasts have been used in the prediction model will be explained in Section 7-2. In Section 7-3, the validation of the outcomes will be described. The conclusions and recommendations of using the prediction model for forecasting are given in Sections 7-4 and 7-5 respectively.

### 7-1 Time-series forecasting of time-dependent parameters

In order to use Monte-Carlo simulations for forecasting, one needs to know the future values of the time-dependent variables. For the current project, the time-dependent parameters are  $CPI_{ij,t}$ ,  $EFF_{ij,t}$ ,  $GDP_{ij,t}$ ,  $POL_{ij,t}$  and  $POP_{ij,t}$ . The literature review indicated that there are several methods available for time-series forecasting: Naïve methods, Stochastic Time Series Modelling (STSM) and Box-Jenkins (B/J) methods.

#### 7-1-1 Method selection for time-series forecasting

Naïve methods are a relatively simple method for making time-series forecasts. However, they are limited in the sense that they only depend on the immediate past, and they only work if the pattern of the data is stable. Due to these limitations, this method is not feasible for the current project.

STSM decomposes a time-series into its trend, seasonal, cycle, and irregular components, and regards these components as stochastic. Due to the added complexity and the increased data requirements, this method is also not feasible.

The B/J approach has become one of the most frequently used methods due to its ability to handle any time series, its strong theoretical foundations, and its operational success (Frechtling, 2001). It can handle complex data patterns, and test the reliability of forecasts by using well-specified rules and statistical measurement. Furthermore, it can produce forecasts based on a synthesis of historical patterns without initially assuming a fixed pattern. Other time-series methods require an assumption of a pattern before proceeding with subsequent steps (Hoshmand, 2010).

Based on the preceding, it has been decided to forecast the time-dependent parameters by using the B/J methodology. A limitation of this approach is its complex nature. Fortunately, most statistics software programs (Minitab, R, SAS, SPSS) are able to automatically calculate the coefficients of the B/J such that the most likely models are found.

### 7-1-2 Characteristics of Box-Jenkins models

Below, a brief introduction to B/J models is given. For more detailed information and the mathematical formulations, the reader is referred to Hoshmand (2010) and Hyndman and Athanasopoulos (2013). B/J models are based on the assumption that “*a time series is a linear function of past actual values, and random shocks or error terms. The expectation is that the error terms are distributed as white noise*” (Hoshmand, 2010)[p. 272], where white noise is defined as normally and independently distributed, without any patterns, a mean of zero, and an error variance that is smaller than the variance of the time series.

Models are classified as autoregressive models (AR), moving average models (MA), or a combination of the two, called autoregressive integrated moving average models (ARIMA). All models follow a standard way of notation that identifies the orders of autoregression by  $p$ , integration or differencing by  $d$ , and moving average by  $q$ . The standard notation is  $ARIMA(p, d, q)$ .

AR models use previous values and an error term to calculate new values. MA models link the new value to random errors that have occurred in the past. In MA models, it is assumed that the new value is a direct and predictable result of past random errors. ARIMA models use a combination of past values and past errors to come up with the new value.

### 7-1-3 Finding appropriate Box-Jenkins models

Based on historical data, it is possible to select an appropriate B/J model. For this, one needs to follow a number of steps. First, one should plot data in order to identify unusual observations and to understand patterns. When there are no unusual observations in the data, the next step is to test whether the data is stationary. According to Hoshmand (2010), the basic assumption of B/J models is that the data is stationary. This means that data should be free of trends and seasonality.

In case data is not stationary, one should difference the data until it appears stationary. Differencing implies taking the difference between one period and the next. One should continue differencing the data until it becomes stationary. An example of a first-order difference is given in Table 7-1. The data in this table is clearly not stationary. However, after taking the first-order difference, the data is stationary.

The next step is to calculate the autocorrelation (ACF) and the partial autocorrelation (PACF) statistics of the time series. Based on these values, a selection of the most suitable ARIMA model can be made. In Appendix D, some examples are given that show how the ACF and PACF can be used to determine the orders of the ARIMA model.

**Table 7-1:** Example of first-order differencing (Hoshmand, 2010).

Original data	First difference	New series
10	$12 - 10 = 2$	2
12	$14 - 12 = 2$	2
14	$16 - 14 = 2$	2
16	$18 - 16 = 2$	2
18		

After selecting the orders of the model, the final step is to calculate the AIC statistic. This value should be compared with the AIC value of similar B/J models. The one with the lowest AIC value should be selected as the appropriate model.

The process of finding the most suitable B/J model is very time-consuming. With five parameters for 52 countries that have to be forecast, it is not feasible to perform this task manually. Fortunately, most statistics software packages are able to automatically calculate the most suitable B/J model. The algorithm for automatic detection of the B/J coefficients in R follows similar steps as what has been explained above. For the exact method how R automatically finds coefficients of B/J models, the reader is referred to Hyndman and Khandakar (2008) and Hyndman and Athanasopoulos (2013).

#### 7-1-4 Calculating interval forecasts of Box-Jenkins models

Now that the B/J models have been found, the next step in the Monte Carlo simulation is to determine their probability distributions. Raychaudhuri (2008) described several methods to determine the probability distribution for historical data. However, he did not describe how distributions of future parameters can be found.

The probability distributions are found by looking at the forecasting accuracy. Forecasting accuracy is usually expressed in two ways: confidence intervals (C.I.) and prediction intervals (P.I.). C.I.s are applied to estimates of fixed but unknown parameters. They describe how well the mean has been determined in a given dataset. The key point is that these intervals describe the likely location of a parameter.

On the other hand, P.I.s tell where one can expect to see the next data point to be sampled. It gives the distribution of values, not the uncertainty in determining the population mean. P.I.s are estimates of unknown future values that can be regarded as a random variable at the time the forecast is made. They account for both the uncertainty in knowing the value of the population mean, and data scatter. Therefore, P.I.s are always wider than C.I.s (Chatfield, 1993; GraphPad, 2009).

For the Monte Carlo simulation, it is important to know the distribution of the possible future values, not the distribution of their mean. Therefore, P.I.'s have been used to model future uncertainty in the Monte Carlo simulation.

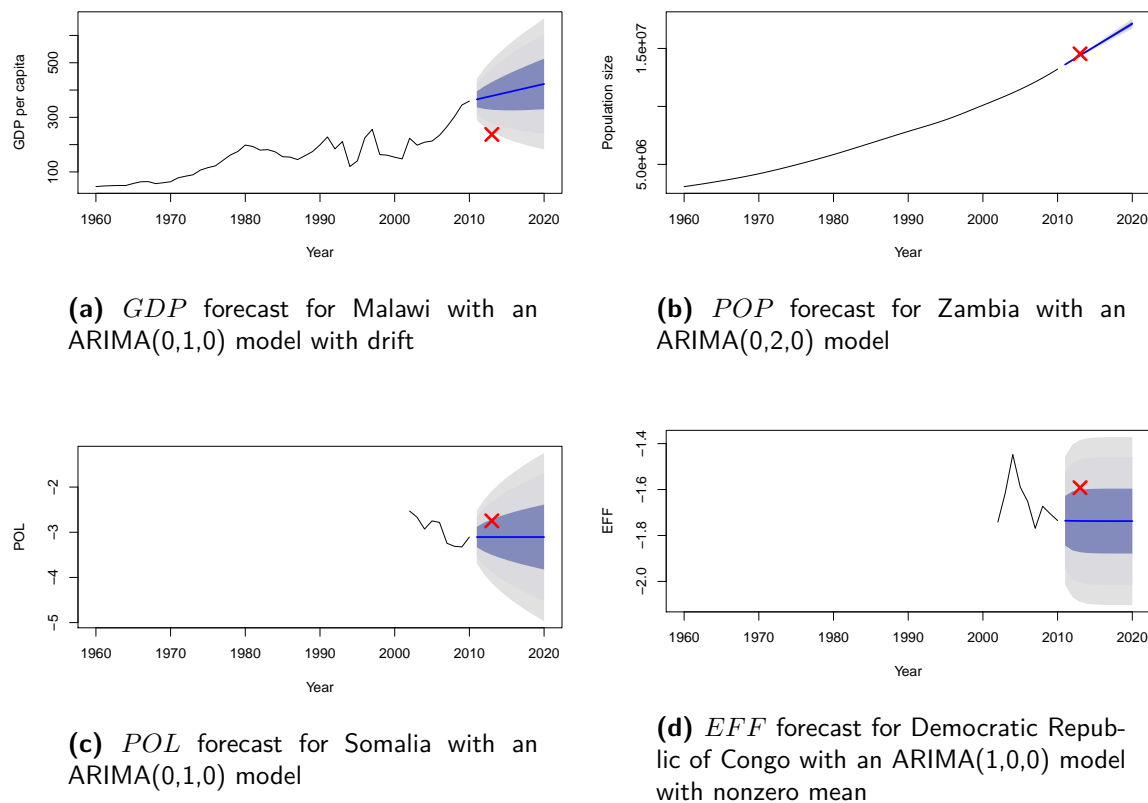
Calculating B/J forecast values is a complicated mathematical process, and the details of this are beyond the scope of this project. Instead, this project used a built-in function of R to calculate the interval forecasts. The way R calculates them is based on Brockwell and Davis (1991) and Hyndman and Athanasopoulos (2013). In Hyndman and Athanasopoulos (2013)[section 8.8] it is explained how point forecasts for B/J models can be calculated. Also, some examples of how interval forecasts can be found, are given. More general results and

special cases of calculating forecast intervals for B/J models, are given in more advanced textbooks such as Brockwell and Davis (1991)[section 9.5].

The calculations in R are based on three major assumptions. The first two assumptions state that residuals are uncorrelated and normally distributed. By plotting the ACF and histogram of the residuals, it can be checked whether these assumptions hold. However, with five parameters for 52 countries, it would be a very time consuming task to check all these plots. Instead, it has been assumed that the calculated interval forecasts are the correct ones. The third assumption is that the calculations assume that the historical patterns that have been modelled will continue into the forecast period. If any of these assumptions do not hold, the forecast intervals may be incorrect.

### 7-1-5 Validation of parameter forecasts

Now that it is clear how interval forecasts for B/J models have been calculated, the next step is to describe how the outcomes have been validated. For each of the five time-dependent parameters, 2010 was taken as the base year, and their values are forecast three years ahead. The outcomes are compared with the actual data from 2013. Figure 7-1 shows examples of the time-dependent parameter forecasts.



**Figure 7-1:** Validation of time-series forecasts of time-dependent variables. The actual values are indicated with a red cross.

Several observations can be made from these plots. It shows the prediction interval and the

expected values. The intervals are indicated by a fan chart, with the ranges set at 68%, 95% and 99% (one, two and three standard deviations respectively). The figures clearly show how uncertainty increases over time, and how past data affects the prediction intervals. When past data was smooth (Figure 7-1b), the prediction interval was smaller than when past data was not (Figure 7-1a). Furthermore, Figure 7-1c shows that the B/J forecasts do not take into account that *POL* should lie between  $-3$  and  $+3$  by definition. However, it is important to constrain *POL* and *EFF* the forecasts to lie within this interval. Finally, the plots also indicate how the actual data (indicated with a red cross) often lies within the interval forecast, as mentioned before.

Table 7-2 shows how often the forecasts were within the 68%, 95% and 99% coverages (1, 2 and 3 standard deviations respectively). The results in this table show that the actual value often lies within the forecast interval. However, for some factors the accuracy is better than for others. For example, the factors *POL* and *POP* lie well within the interval; *CPI* on the other hand is outside of the range, indicating that this factor is more difficult to forecast.

**Table 7-2:** Validation of B/J forecasting of time-dependent parameters.

Parameter	Within 68% interval	Within 95% interval	Within 99% interval
<i>CPI</i>	62%	73%	73%
<i>EFF</i>	69%	87%	90%
<i>GDP</i>	46%	83%	88%
<i>POL</i>	69%	92%	94%
<i>POP</i>	81%	90%	90%
Total	65%	85%	87%

## 7-2 Random variable generation and output analysis

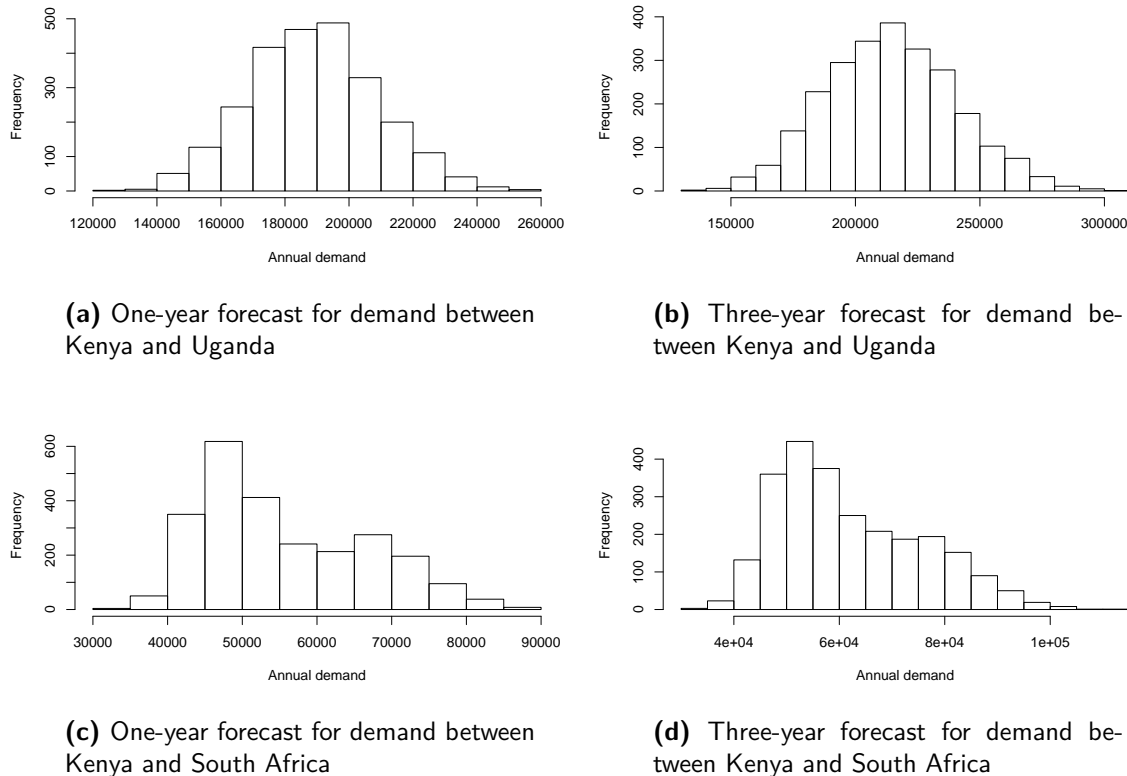
With the prediction intervals for the different parameters known and validated, the next step is to randomly select one of the values from the distribution, for each of the parameters. Rather than using a true random number generator, a pseudo-random number generator (PRNG) will be used. “*PRNGs are algorithms that use mathematical formulae or simply precalculated tables to produce sequences of numbers that appear random*” (Haahr, 2015). The main benefit of using PRNGs is that the results are reproducible. In R, the coefficient *seed* allows for reproducibility of PRNG results. The resulting random variables are used as input parameters in the market size prediction model.

The core part of Monte Carlo simulation is the repetition of randomly selecting and implementing values into the prediction model. It is important to determine the number of repetitions. It should be taken into account that each country pair is in fact a single model with its own characteristics. Ideally, one would therefore select the number of runs for each country pair separately.

However, due to the large number of country-pairs in this project, determining the minimum required number of iterations for each one of them is not feasible to do within the given time-frame for the project. Instead, this project uses a common approach: to select an arbitrarily large number, and assume that this is large enough. The exact consequences of this assumption on the reliability of the model are difficult to predict. However, it is not

unlikely that for some country-pairs, the selected number was too low.

The demand forecasts were calculated by the MC simulation with 2,500 runs and *seed* = 0, in which the base year was 2014. As the previous chapter already showed, the intervals for the time-dependent variables increased over time. It can therefore be expected that the demand forecasting interval also increases over time. Figure 7-2 shows that this is indeed the case.



**Figure 7-2:** Results of Monte-Carlo forecasting. These figures show how the forecast interval increases over time.

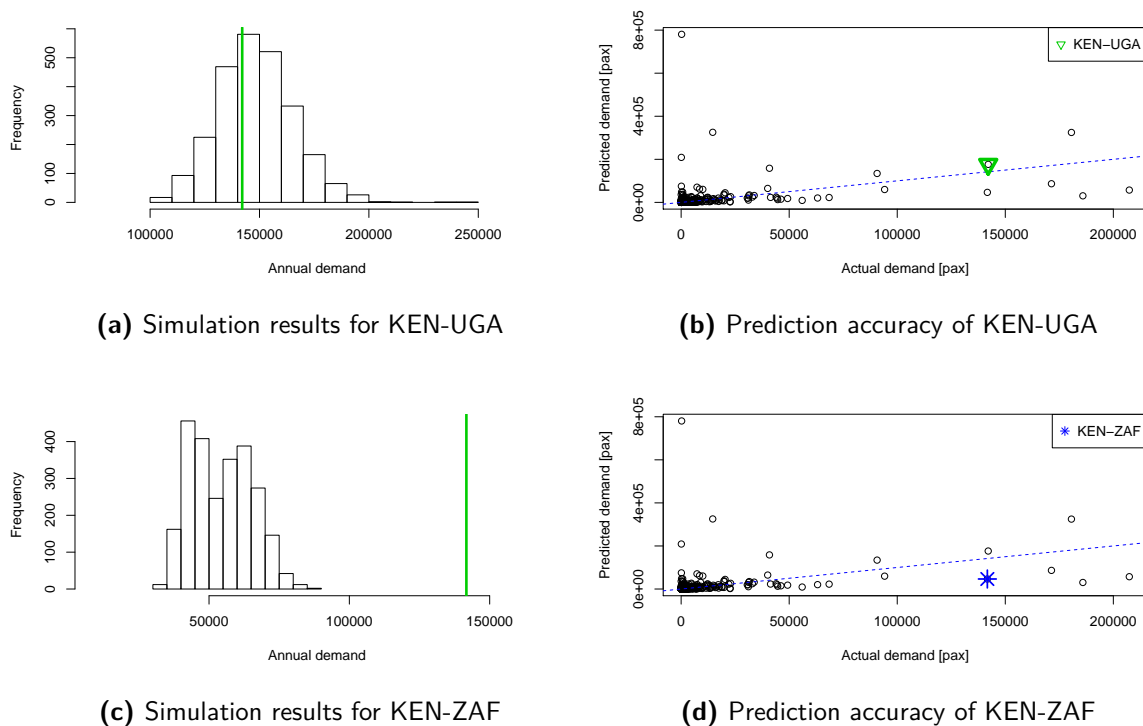
The figures show histograms, with on the horizontal axes the annual demand between a country-pair; the vertical axes indicate how often a demand value occurred after running 2,500 simulations. The figures on the left show the interval forecasts for one year ahead (2015). The figures on the right show the interval for three years ahead (2017). By comparing the figures on the left and right, it is clear that the interval indeed increases over time.

### 7-3 Validation of the forecasting model

After describing the methodology for time-series forecasting and how the prediction interval can be calculated, the outcomes should be validated. The validation of the complete forecasting model is done as follows. First, 2011 is taken as the base year. It is assumed that the prediction model from the previous two chapters is always valid, so it is also the correct model for 2011. The values of the time-dependent variables for the year 2011 are inserted into

this model. By using B/J to forecast them with the three years ahead, one gets the interval forecasts for these parameters for 2014. These intervals are then used in the Monte-Carlo simulation, to “forecast” the demand for 2014. The predicted demand was calculated by the MC simulation with 2,500 runs. These values are then compared to the actual data from 2014.

Figure 7-3 shows the forecast validation for Kenya-Uganda and for Kenya-South-Africa. The figures on the left compare the actual demand with the predicted demand. The figures show histograms, with on the horizontal axes the annual demand between a country-pair; the vertical axes indicate how often a demand value occurred after running 2,500 simulations. The green vertical line in the figures indicate the actual demand from 2014.



**Figure 7-3:** Validation of Monte-Carlo forecasting. The actual values are indicated with a green line.

Ideally, the actual demand would lie somewhere in the forecast interval. For Figure 7-3a this is true; for Figure 7-3c this is not true. The fact that the actual demand does not lie within the forecast range can be explained by looking at the prediction accuracy plots for the corresponding country-pair, shown on the right. Highlighted are the country-pairs. In Figure 7-3b, the predicted demand is almost exactly the same as the actual demand. Therefore, for this country-pair, it is expected that the actual demand should be close to the demand forecast. However, in Figure 7-3d, the difference between the predicted and actual demand is much larger. Hence, it can be expected that the actual demand does not lie within the forecast interval. For 69% of the cases, the actual demand was within the forecast interval; in 21%, the forecasting model overestimated the demand; for the remaining 10%, the actual demand was higher than the forecast.

## 7-4 Conclusions of using the prediction model for forecasting

After the two previous chapters focused on formulating and calibrating the prediction model, this chapter focused on describing how forecasts of the time-dependent parameters could be inserted into the prediction model in order to create interval forecasts for passenger demand. This chapter provided answers to research question 2.

Research question 2(a) should have already been answered in the previous chapters. It was mentioned that the time-dependent parameters for this project are  $CPI_{ij,t}$ ,  $EFF_{ij,t}$ ,  $GDP_{ij,t}$ ,  $POL_{ij,t}$  and  $POP_{ij,t}$ .

Subsequently, it was explained that Box-Jenkins models are the most suitable models for generating time-series forecasts for each of the time-dependent parameters. This was because of their strong theoretical foundations. This provided the answer to research question 2(b).

With prediction intervals for the time-dependent parameters, the next step was to repetitively select random variables from these distribution, and insert them into the prediction model. This gave intervals of the future demand. By comparing the three-year ahead forecast with base year 2011, with the actual data from 2014, it was shown that for 69% of the country pairs, the actual data was within the forecast interval. The most likely explanation for the actual demand sometimes being outside the interval forecast, was because the prediction model does not have a perfect fit. This answered research questions 2(c) and 2(d).

## 7-5 Recommendations for using the prediction model for forecasting

The results in this chapter showed that combining a market size prediction model with forecasts of the time-dependent parameters of a prediction model can be used to create interval forecasts of demand. There are a number of opportunities how future research could further develop the model.

The validity of the model could be improved by validating the assumptions that have been made. One of the major assumptions was that 2,500 iterations in the Monte Carlo simulation is sufficient for all country-pairs. However, to be sure, one should calculate the required number of iterations for each country-pair individually. Due to time constraints, it was not confirmed whether this is sufficient. The consequence of not specifically calculating the required number of iterations, is that it is currently not possible to state anything about the probability that the results are correct.

A second assumption that this project has used, is that the automatic forecasting function in R can find the correct B/J models and their corresponding interval forecasts. Due to the large amount of variables that had to be forecast, the assumptions behind the calculations have not been checked. It is therefore possible that some of the models are misspecified.

One could include additional types of uncertainty. This project only included uncertainty of the forecasts of time-dependent variables. Other types of uncertainty, such as error propagation, were outside the scope of this project. The consequence of limiting the project to this type of uncertainty, is that in reality, uncertainty will likely be larger.

Finally, it would be interesting to repeat the calculations presented in this chapter for multiple periods in the future. By doing this, one can generate trendlines with fan-charts indicating how forecasting uncertainty is expected to evolve.



# Network Development Decision-Support Tool

After the previous chapters focused on the generation of interval forecasts for the passenger demand between countries, the following chapters will focus on the secondary goal: to show how these interval forecasts can increase the robustness of the airline planning process. This will be done by showing the example of airline network development.

It should be taken into account that the outputs from the forecasting model can not be implemented into a network development model yet. The outcomes from the forecasting model are the annual, total passenger demand forecasts on a country-pair basis. However, for network development, the demand between city-pairs should be known. Therefore, demand should first be converted to a city-pair basis. The second additional step is that market size forecasts should be converted into airline specific demand forecasts. A network development model is useless to an airline unless it has data on how much traffic they are expected to attract.

This chapter is structured as follows. In Section 8-1, the conversion from country- to city-pair based demand is described. The method describing the conversion from total market size to airline specific demand will be explained in Section 8-2. The modelling framework for the network development model will be explained in Sections 8-3 and 8-4. Finally, recommendations for the network development model will be given in Section 8-5.

### 8-1 From country- to city-pair based demand

With the market size model at a country-pair basis, demand forecasts between any two countries can be made. However, to be able to use the demand forecasts from the forecasting model in a network development tool, the forecasts have to be converted from a country-pair basis to a city-pair basis.

The conversion towards city-pair based demand is done as follows. From the historical demand data from MIDAS, one can calculate the share of the demand for each city-pair in a country-pair. It is assumed that this share remains constant. For example, assume that in historical data, 75% of the demand between Kenya and South Africa was between Nairobi and Johannesburg. After creating a forecast of the traffic between Kenya and South Africa,

75% of this demand is between Nairobi and Johannesburg.

In Section 6-2 it was explained that after filtering the passenger traffic data, demand for 1,209 country pairs remained. The prediction model used this data to forecast the market size for each pair. Based on historical data from MIDAS, these forecasts were converted to demand forecasts for 5,273 individual city-pairs.

In areas with emerging economies, new opportunities constantly arise for airlines to expand their network. This is especially true for Africa, where large agricultural potential, banking, and the discoveries of natural resources such as gas and oil deposits create so-called boomtowns. For these emerging markets, historical data might not be available, and either the model will have to be expanded, or assumptions will have to be made about the division of passenger flows. Instead, in this project it is assumed that the demand data from MIDAS includes data for all relevant city pairs, and modelling emerging markets is outside the scope of this project. A consequence of this assumption is that profitable destinations might be overlooked.

## 8-2 Market share model

After the market size forecasts have been converted to a city-pair basis, the next step is to forecast airline market shares. The market share of an airline A is defined as the “*proportion of the total market demand that is captured by airline A*” (Belobaba et al., 2009). Multiplying the total demand for air travel with the market share forecast therefore gives a forecast for the airline specific demand. This airline specific demand is the expected amount of passengers that would be willing to travel between two cities with a specific airline.

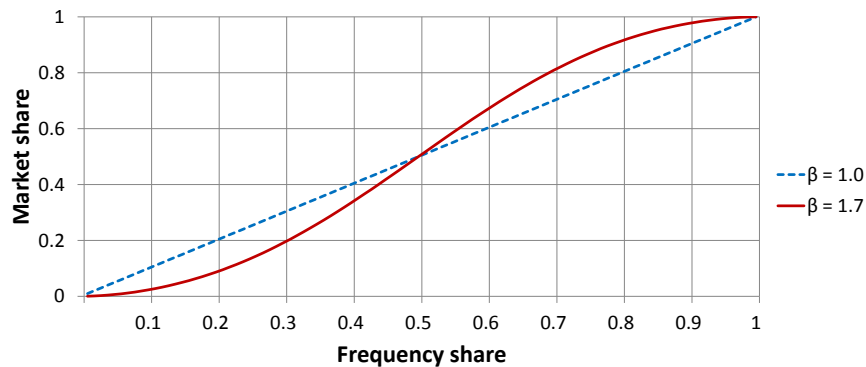
The literature review had identified three methods for forecasting airline market shares: S-curve, Quality of Service Index (QSI) and discrete choice models. This project uses S-curve models to forecast airline market shares. The motivation for is the following. QSI and discrete choice models are very data intensive. At the early stage of network development, this data might not be available yet. On the other hand, S-curve models only require data on flight frequencies. Furthermore, both QSI and discrete choice models are designed to calculate itinerary shares, which requires schedules as input. However, itinerary shares can only be applied to short-term forecasting.

S-curve models calculate an airline’s market share by assuming a disproportional, S-curve relationship between airline market share and frequency share. This method is based on the assumption that only the airline frequency is variable. All other variables (e.g. ticket prices and service quality) remain equal for all airlines. The mathematical model is given by Equation 8-1 (Belobaba et al., 2009).

$$MS_A = \frac{FS_A^\beta}{FS_A^\beta + FS_B^\beta + FS_C^\beta + \dots} \quad (8-1)$$

Where:  $MS_A$  is the market share of airline A;  $FS_A$  is defined as the non-stop frequency share of airline A;  $\beta$  is an exponent greater than 1.0, and generally between 1.3 and 1.7. In this equation, the  $\beta$  depends on the importance of frequency in a particular market. The larger  $\beta$  is, the more important frequency share is for an airline’s market share. Higher values are more likely to be associated with short-haul markets in which frequency of departures is important, and lower values are associated with longer-haul and/or leisure dominated markets (Belobaba et al., 2009). The S-curve relationship for a market with two airlines is given in Figure 8-1.

It shows that the larger  $\beta$  is, the more curved the relationship will be.



**Figure 8-1:** S-curve relationship between an airlines frequency share and market share.

Ideally, one would determine the specific value of  $\beta$  for each market. However, due to a lack of available market share data, this project assumes that  $\beta$  is a linear function of the route distance, where the shortest route has  $\beta = 1.7$ , and the longest has  $\beta = 1.3$ . This assumption was also used by Lammens (2014).

The example in Table 8-1 shows the effect of  $\beta$  on an airlines market share: on the shortest route, route A, Airline 1 has a market share of 76%. However, as distance increases, the market share of airline decreases to 71%.

**Table 8-1:** Example of market share calculations with S-curve model.

Route	Distance [km]	$\beta$ [-]	Frequency [-]		Market share [-]	
			Airline 1	Airline 2	Airline 1	Airline 2
A	100	1.7	12	6	0.76	0.24
B	500	1.5	12	6	0.74	0.26
C	900	1.3	12	6	0.71	0.29

### 8-3 Network development modelling framework

With a model to calculate the airline specific demand, it is now possible to develop a network development model. In this section, it will be explained how a route profitability analysis will determine the network lay-out, the number of frequencies per route, and the aircraft type per route for a single scenario. The entire process described below will be performed for every scenario in the analysis.

According to Belobaba et al. (2009), there are two approaches to calculate the profitability of an airline's network. The first is to calculate the profitability of each route individually and add them all up to get the total profitability. The second is to calculate the profitability of the entire network and then analyse the contribution of each individual route. For airlines with hub-and-spoke networks, changes to one route will likely impact others. Traffic flows from connecting flights can be critical for route profitability, especially for large hub networks. This is known as the airline network effect (Barnhart and Smith, 2012).

To facilitate the interpretation of the results and for the sake of modelling simplicity, it has been decided not to include network effects in the model. The consequence of this is that it is likely that the results from the model will not be the optimal network in terms of profitability. This choice is justified by the fact that the goal of the network development decisions-support tool is to illustrate how interval forecasts of demand could be used. It is not the goal to be very detailed about the network development modelling. For more specific works on modelling network effects, the reader is referred to Barnhart and Smith (2012).

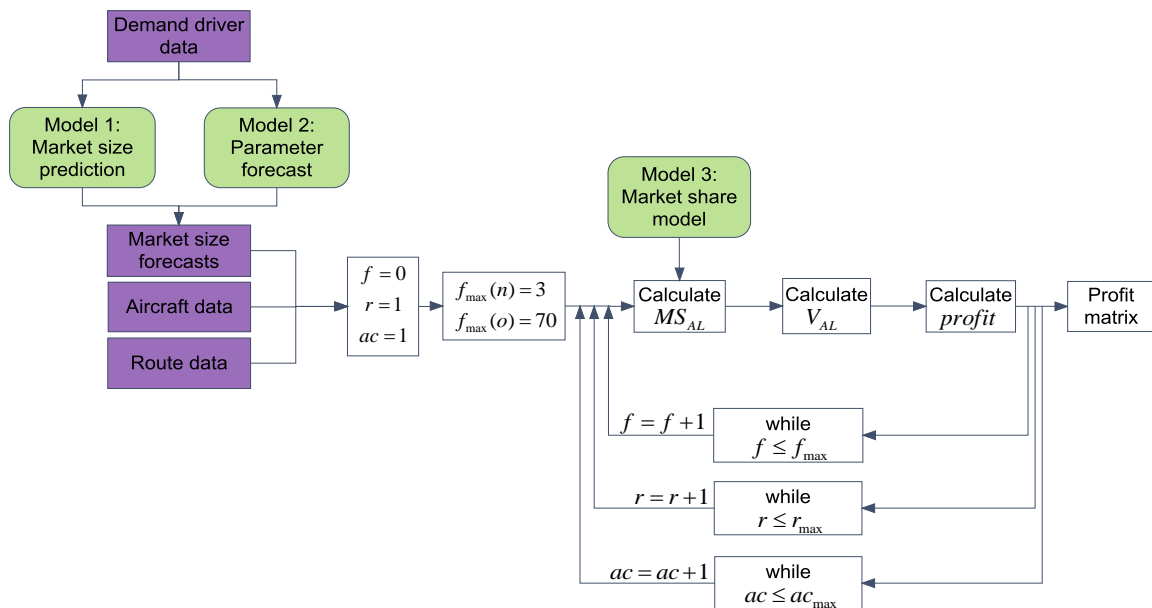
The modelling framework is based on the fleet development of Lammens (2014). His model works as follows. First, the costs per flight for each route - aircraft type combination are calculated. It is assumed that this remains constant. Next, the model iteratively calculated the profit for each aircraft - route - frequency combination, by constantly adding a frequency. As long as profit was increasing, a frequency was added. As soon as profit stopped increasing, the maximum profitability was found. These calculations continued until no profitable combinations remained. The final step of his model was to use the outputs of the model to determine the minimum required utilisation per aircraft type.

The current project split the network development process into two parts: the generation of profit matrices, and the profit maximisation. By following Lammens' approach (i.e. continuously updating the calculations), the case study ran into memory errors. Rather than continuously updating the profitability after a route - aircraft - frequency has been selected, this approach only requires profitability to be calculated once. As network effects have not been taken into account, it is allowed to do this.

The remainder of this section focuses on explaining these two steps. Details about the cost, revenue and profit calculations will be given in the next section.

### 8-3-1 Generation of profit matrices

Figure 8-2 illustrates the generation of the profit matrices in a flowchart. Below, the steps in this flowchart will be elaborated upon.



**Figure 8-2:** Network development model - generation of profit matrices.

The first steps are to load the different input parameters into the model, and to set the initial parameters. In the flowchart, the input parameters are highlighted in purple. Note that the market size forecasts are the ones generated by the forecasting model. The initial parameters for the number of frequencies ( $f = 0$ ), route number ( $r = 1$ ), and aircraft type ( $ac = 1$ ) are set. Also, the maximum number of frequencies per route will be set. The reason for constraining this will be explained in Section 9-2.

The input data and initial parameters will be combined with the market share model to calculate the market share of an airline  $AL$ . By multiplying this with the market size forecast, the airline specific demand of an airline  $AL$ ,  $V_{AL}$ , can be calculated.

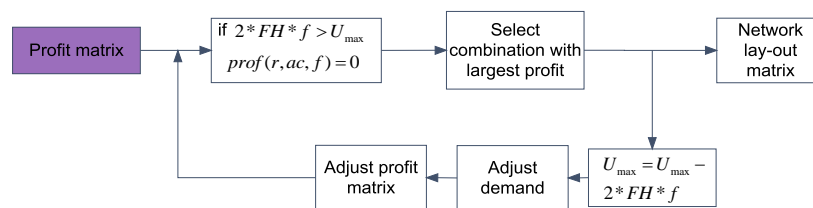
Finally, the profit per route-aircraft-frequency combination will be calculated. The calculations will be performed for all allowable frequencies, for all routes, and for all aircraft types. The results will be stored in the *Profit matrix*. An example of such a matrix is given in Table 8-2.

**Table 8-2:** Example of profit matrix for network development decision-support tool.

Route	Aircraft type	Frequency	$U_{used}$	$U_{left}$	Profit [USD]
A-B	E190	1	2	8	10,000
		2	4	6	25,000
		3	6	4	22,000
B-C	E190	1	3	7	17,500
		2	6	4	20,000
		3	9	1	22,000

### 8-3-2 Profit maximisation

With the completed profit matrix, the second part of the network development decision-support tool is the profit maximisation. This project uses a very simple approach to do this. Figure 8-3 illustrates the profit maximisation in a flow-chart.



**Figure 8-3:** Network development model - profit maximisation.

The process works as follows. For each combination in the profit matrix (i.e. for each row), it is checked if the combination is possible. If the required flight hours per combination are larger than the available utilisation, it means that the combination is not possible, and profit is set to zero. After setting the profit of all impossible combinations to zero, the combination with the largest profit is selected. The selected combination will be stored in the network lay-out matrix.

Subsequently, the maximum available utilisation of the selected aircraft type will be adjusted by subtracting the required number of flight hours from the available utilisation.

Also, the profit matrix will be adjusted: all combinations including the selected route, and all combinations with a profitability of zero or less, will be discarded from the matrix. Thirdly, the available demand will be adjusted. However, as this project does not include recapture models, these values will only be used to check whether demand is still available or not. The maximisation continues until there are either no profitable routes left, or until there is no aircraft utilisation left.

An example of this profit maximisation procedure is provided in Table 8-3. Table 8-3a shows the initial profit matrix. From this matrix, the most profitable combination is route A-B, with the aircraft type E190, and a weekly frequency of two. Table 8-3b shows the updated matrix after the first combination has been selected. There is sufficient utilisation left to also select the combination of route B-C, with the E190, and with a weekly frequency of two. The total weekly operational profit in this case is 45,000 USD.

Route	Aircraft type	Frequency	$U_{used}$	$U_{left}$	Profit [USD]
A-B	E190	1	2	8	10,000
		2	4	6	25,000
		3	6	4	22,000
B-C	E190	1	3	7	17,500
		2	6	4	20,000
		3	9	1	22,000

(a) First run

Route	Aircraft type	Frequency	$U_{used}$	$U_{left}$	Profit [USD]
B-C	E190	1	3	3	17,500
		2	6	0	20,000
		3	9	-2	0

(b) Second run

Routes	Aircraft type	Frequency	$U_{used}$	$U_{left}$	Profit [USD]
A-B	E190	2	4	6	25,000
B-C	E190	2	6	0	20,000

(c) Network lay-out matrix

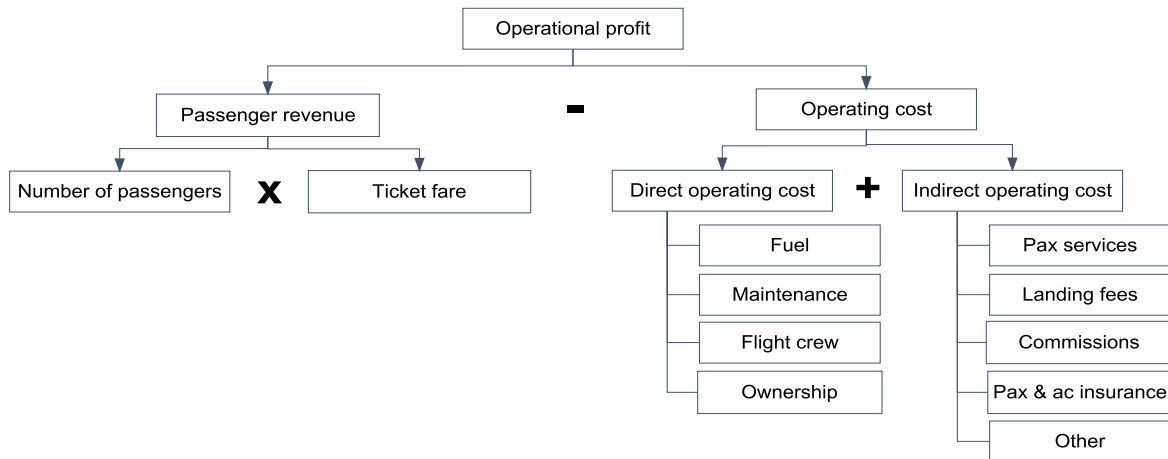
**Table 8-3:** Example of approach for profit maximisation and the resulting network lay-out matrix.

Due to its simplicity, there are a number of disadvantages of using the proposed approach. For example, it is unlikely that using this maximisation method will be able to show the overall optimum network. This is illustrated by the following. Consider the example presented above. In the initial profit matrix, assume that the weekly profit of the B-C - E190 - 3 combination gives a is 30,000 USD. In this case, this will be the initial selection. However, after adjusting the available utilisation of the E190, there is no utilisation left to also operate on the A-B route. Hence, in this case, the total profitability will be 30,000 USD, much lower than the overall optimum of 45,000 USD.

Another disadvantage is that this model did not include recapturing of passengers. It is possible that after the model selected one type of aircraft to operate on a specific route, a second type could serve the remaining demand and increase the airline's profitability.

## 8-4 Calculating route profitability

After describing the modelling framework in the previous section, this section focuses on describing the cost and profit calculations of the model in more detail. Figure 8-4 shows the ICAO standard breakdown of operational profitability. Note that we are interested in operational profitability of a route, not the total airline profitability. Operational profitability is given as revenue minus costs, where only passenger revenues are taken into account.



**Figure 8-4:** Simplified method of calculating route profitability (Doganis, 2002; Belobaba et al., 2009; van Nunen, 2014).

Passenger revenues are calculated by multiplying the number of passengers with the ticket fares. The costs of a route can be split into direct (DOC) and indirect operating costs (IOC). DOC include all expenses associated with operating aircraft, and are aircraft-dependent. They can also be referred to as the *flight operations costs*. An example of the aircraft-dependency is the fact that each aircraft has its own specific fuel consumption. This results in different fuel costs for each aircraft, even when all else is equal.

IOC include all those expenses that remain unaffected by a change of aircraft type because they are not directly dependent on aircraft operations. Because of this, the costs of operating a schedule mainly depends on the DOC. Therefore, the network development model will only include DOC to determine the network lay-out, aircraft type and number of weekly flights.

For the calculations of the DOC, the ICAO standard breakdown mentioned above will be used. However, note that this categorisation is not the same for all airlines. Sometimes, airlines assign passenger services and landing fees to the DOC.

### 8-4-1 Revenue per route - aircraft combination

As was mentioned above, the network development model calculates the operational profitability of the network based on passenger revenues and the DOC. Below, it will be explained how revenues are calculated.

The calculation of the revenue per route and per aircraft for  $f$  frequencies is given by Equation 8-2.

$$Rev_{ij,ac,f} = flow_{ij,ac,f} * 2 * y_{al} * d_{ij} \quad (8-2)$$

Where:  $Rev_{ij,ac,f}$  is the revenue on route  $ij$ , for aircraft  $ac$  and for  $f$  frequencies;  $flow_{ij,ac,f}$  is the flow of passengers on route  $ij$  with aircraft type  $ac$  and for  $f$  frequencies;  $y_{al}$  is the average yield of airline  $al$  in USD; and  $d_{ij}$  is the flight distance of route  $ij$  in km. Note that for the yield values, no distinction between economy and business class passengers is made.

The flow of passengers is determined by the available demand and the number of seats offered. The number of seats offered is given by Equation 8-3.

$$seats_{offered,ij,ac} = f_{ij,ac} * seats_{ac} * LF_{max,ac} \quad (8-3)$$

Where:  $f_{ij,ac}$  is the frequency of roundtrips of aircraft type  $ac$  on route  $ij$ ;  $seats_{ac}$  is the number of seats in aircraft type  $ac$ ; and  $LF_{max,ac}$  is the maximum expected passenger load factor of aircraft type  $ac$ . The expected passenger load factor is the proportion of available seats that is expected to be sold.

If the number of seats offered is larger than the airline specific demand, the flow will be equal to the airline specific demand. Otherwise, the flow will be equal to the number of seats offered.

#### 8-4-2 Cost per route - aircraft combination

For the calculations of the cost, it has been assumed that the costs per roundtrip for each route - aircraft combination are constant. The total DOC of a route - aircraft - frequency combination can be calculated by multiplying the costs with the number of round trips. This subsection only describes the cost calculations. The values that have been used for this project will be provided in the next chapter.

The calculation for the costs per roundtrip is given by Equation 8-4.

$$DOC_{RT,ij,ac} = 2 * (C_{fuel,ij,ac} + C_{maint,ij,ac} + C_{crew,ij,ac} + C_{own,ij,ac}) \quad (8-4)$$

Where:  $DOC_{RT,ij,ac}$  is the the DOC per roundtrip on route  $ij$  for aircraft type  $ac$ ;  $C_{fuel,ij,ac}$  are the fuel costs for route  $ij$  for aircraft type  $ac$ ;  $C_{maint,ij,ac}$  are the maintenance costs for route  $ij$  for aircraft type  $ac$ ;  $C_{crew,ij,ac}$  is defined as the crew costs for route  $ij$  for aircraft type  $ac$ ; and  $C_{own,ij,ac}$  are the ownership costs for route  $ij$  for aircraft type  $ac$ . In the following paragraphs, each of these cost components will be elaborated upon.

##### Fuel costs

Fuel costs typically define the largest part of the DOC of an airline. The fuel costs per route per aircraft can be calculated with Equation 8-5.

$$C_{fuel,ij,ac} = JF_{used,ij,ac} * C_{JF,l} \quad (8-5)$$

Where:  $JF_{used,ij,ac}$  is the amount of jet fuel used on route  $ij$  by aircraft type  $ac$ , in liters; and  $C_{JF,l}$  is the jet fuel cost per liter in USD.

In order to determine the fuel costs per aircraft per route, one needs to calculate the amount of fuel used per aircraft per route. In order to this, the method of fuel fractions will be used (Roskam and Lan, 1997). This is given by Equation 8-6.

$$JF_{used,ij,ac} = (1 - M_{ff,ij,ac}) * MTOW_{ac} \quad (8-6)$$



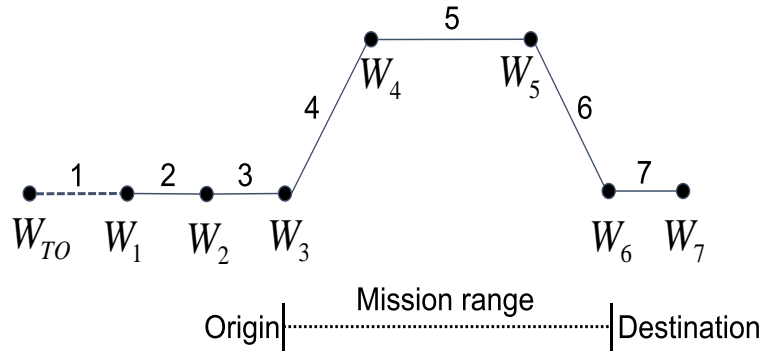
Where:  $M_{ff,ij,ac}$  is the mission used fuel fraction per route per aircraft type, and  $MTOW_{ac}$  is the maximum take-off weight of aircraft type  $ac$  in kilograms. The mission fuel fraction is calculated with Equation 8-7.

$$M_{ff,ij,ac} = \frac{W_{1,ij,ac}}{W_{TO,ij,ac}} \prod_{p=1}^{p=n} \frac{W_{(p+1),ij,ac}}{W_{p,ij,ac}} \quad (8-7)$$

Where:  $W_{p,ij,ac}$  is the airplane weight at the end of mission phase  $p$  on route  $ij$  for aircraft type  $ac$ .

A typical mission profile for commercial airlines is illustrated in Figure 8-5. It shows a typical flight profile from an origin (the point most on the left) to a destination airport (the one most on the right). The numbers above the lines are the different phases of the mission, and represent the following phases:

- |                             |                               |
|-----------------------------|-------------------------------|
| 1) Engine start and warm-up | 5) Cruise                     |
| 2) Taxi                     | 6) Descent                    |
| 3) Take-off                 | 7) Landing, taxi and shutdown |
| 4) Climb                    |                               |



**Figure 8-5:** Typical mission profile for commercial airlines.

Apart from  $W_{TO}$ , which is the take-off weight of the aircraft, the  $W$ 's below the lines are the weights after each phase. For phases that are not so fuel intensive, standard fuel fractions from Roskam and Lan (1997) have been used. These values are given in Table 8-4. The fuel fractions for the cruise phase are route dependent, and have to be calculated with the Breguet range equation, given by Equation 8-8 (Greatrix, 2012). By rewriting this as Equation 8-9, the fuel fractions for cruise can be calculated.

$$R = \frac{v_{cr,ac}}{g} \frac{1}{c_{j,ac}} \left( \frac{C_L}{C_D} \right)_{ac} \ln \frac{W_{cr}}{W_{cr+1}} \quad (8-8)$$

$$\frac{W_{5,ij,ac}}{W_{4,ij,ac}} = \frac{1}{\frac{R * c_{j,ac} * g}{e^{v_{cr,ac} * (\frac{C_L}{C_D})_{ac}}}} \quad (8-9)$$

Where:  $R$  is the range of the mission in kilometers;  $v_{cr,ac}$  is the cruise speed of aircraft type  $ac$  in kilometers per hour;  $g$  is the Earth's gravitation in  $m/s^2$ ;  $c_{j,ac}$  is the specific fuel consumption of aircraft type  $ac$  in  $kg/(h*N)$ ; and  $(\frac{C_L}{C_D})_{ac}$  is the lift to drag ratio of aircraft type

**Table 8-4:** Suggested fuel fractions for fuel un-intensive mission phases for transport jets (Roskam and Lan, 1997).

Phase	Fuel fraction
Engine start and warm-up	0.990
Taxi	0.990
Take-off	0.995
Brief climb	0.990
Brief descent	0.980
Landing, taxi and shutdown	0.992

*ac.* According to Roskam and Lan (1997),  $c_{j,ac}$  should lie between 0.051 and 0.082 kg/(h\*N) (i.e. between 0.5 and 0.8 lb/(h\*lb)) for transport jets.

### Maintenance costs

Maintenance is another large cost driver for an airline. According to (Lammens, 2014), maintenance costs can be split up into costs per flight cycle (FC) and costs per flight hour (FH). FC related costs are incurred after each flight cycle, regardless of FH. A typical mission profile was given in Figure 8-5. Examples of FC related costs are maintenance costs due to landings, or due to fuselage compression. FH related costs depend on the amount of FH. An example is engine maintenance costs due to flight time. The total maintenance costs per flight cycle is given in Equation 8-10.

$$C_{maint,ij,ac} = C_{maint,FC,ac} + C_{maint,FH,ac} * FH_{ij,ac} \quad (8-10)$$

Where:  $C_{maint,FC,ac}$  are the maintenance costs per flight cycle per aircraft;  $C_{maint,FH,ac}$  are the maintenance costs per flight hour for aircraft type *ac*; and  $FH_{ij,ac}$  are the amount of flight hours on route *ij* for aircraft type *ac*.

IATA compiled maintenance cost data of 48 airlines, in order to come up with industry averages (IATA, 2014). The value are given in Table 8-5. Noteworthy is the rightmost column, which indicates the ratio between flight costs per cycle and per flight hour. The lower this value is, the more suitable this aircraft is for short distances. The opposite is true for long distance flights.

**Table 8-5:** Industry averages of maintenance cost per aircraft category (IATA, 2014).

Aircraft category	Example aircraft type	USD/FH	USD/FC	FC / FH
Narrow body	B737, A320	713	1,387	1.95
Regional jet	E170, E190	865	1,222	1.41
Turboprop	Q400	779	733	0.94
Wide body with 2 engines	B777, A330	1,450	6304	4.35
Wide body with 3+ engines	B747, A380	1,650	9336	5.66

### Flight crew costs

The total costs for the flight crew on a route depends on the type of aircraft and on the stage length. It is given by Equation 8-11.

$$C_{crew,ij,ac} = n_{crew,ac} * FH_{ij,ac} * C_{crew,FH} \quad (8-11)$$

Where:  $n_{crew,ac}$  is the number of flight crew members per aircraft type;  $FH_{ij,ac}$  is the amount of flight hours on route  $ij$  of aircraft type  $ac$ ; and  $C_{crew,FH}$  are the crew costs per hour. The amount of flight hours per aircraft per route is given by Equation 8-12.

$$FH_{ij,ac} = v_{cr,ac} * d_{ij} \quad (8-12)$$

Where:  $FH_{ij,ac}$  are the flight hours per aircraft type per route  $ij$  for aircraft  $ac$ ;  $v_{cr,ac}$  is the cruise speed for aircraft type  $ac$  in km/h, and  $d_{ij}$  the flight distance of route  $ij$  in km.

Note that these calculations only take the flight crew costs incurred by the flight itself have been taken into account. Due to a lack of data, crew working times before and after the flight have not been taken into account. Hence, in reality, the crew costs will likely be higher than what is calculated with this equation.

### Ownership costs

Another large contribution to an airline's DOCs are the fleet ownership costs. Lammens (2014) explained that, from an ownership point of view, an airline's fleet can be split into two categories: owned and leased aircraft. Ownership costs are a combination of depreciation costs and financing costs. The depreciation cost is a metric that defines the decrease in value for an owned good for accounting purposes. Financing costs are the costs for paying for the capital that is used to finance the aircraft. The costs for leased aircraft depends to a large extent on the leasing contract, and it is usually a monthly cost for an airline. Example variables that drive the size of the leasing costs are the amount of aircraft to be leased or the duration of the contract.

Lammens (2014) explained that, from an airline's cost perspective, the costs of owning an aircraft and leasing one, are approximately the same. Therefore, as we are only interested in finding the total costs, no distinction between the costs for leasing and owning aircraft has to be made. The cost of ownership is modelled as a cost per block hour in the model. This cost is found by dividing the total monthly ownership costs by the amount of operational flight hours per month.

### 8-4-3 Profit per route - aircraft combination

With values for both the direct operating costs and the passenger revenues, profit can be calculated with Equation 8-13.

$$Prof_{ij,ac} = Rev_{ij,ac,f} - DOC_{RT,ij,ac} * f_{ij,ac} \quad (8-13)$$

Where:  $Prof_{ij,ac}$  is the profit on route  $ij$  for aircraft type  $ac$ ;  $Rev_{ij,ac,f}$  is the revenue on route  $ij$  for aircraft type  $ac$ ;  $DOC_{RT,ij,ac}$  are the direct operating costs per roundtrip for each aircraft-route combination; and  $f_{ij,ac}$  are the number of roundtrips of aircraft type  $ac$  on route  $ij$ .

## 8-5 Recommendations for the network development model

This chapter was used to describe the modelling framework for the network development decision-support tool. To improve the applicability and reliability of this model, it is recommended that future research should focus on the following areas.

In this model, it was assumed that airline market shares can be calculated with a relatively simple S-curved model. However, future research should focus on further developing this model. This could be done by adding factors such as whether flights are operated directly or indirectly, and whether airlines are flag carriers or low cost carriers. This gives a more realistic estimation of the airline market share and will allow for a more accurate network development model

Further research could also extend the model by including network effects. When one wants to include network effects in the model, the market share model and the profit maximisation will have to be adjusted. By including network effects in the model, a more realistic representation of reality will be the result. This is especially true for Kenya Airways, where nearly 55 percent of its passengers are transfer passengers. It is expected that by including network effects, more city-pairs will become profitable, and the resulting network will become larger.

Another possible extension would be to include a passenger recapture model. The model presented in this study can only assign one aircraft type to routes. However, it might be possible that after assigning one aircraft, there is still sufficient demand left to operate a second aircraft type. In the market share calculations, the number of frequencies of the first aircraft type should be added to the number of frequencies of the second aircraft type. Especially for airlines with a mixed fleet, it is expected that this could improve the overall profit.

A fourth possibility for future research is to extend the model by including more detailed cost calculations. Rather than assuming fixed costs per aircraft-route combination, one could calculate these per frequency. It is expected that by including more accurate cost calculations, additional possibilities for profitable routes might occur.

# Kenya Airways Case Study: Assumptions and Inputs

Now that the theoretical network development model has been developed, it is time to test it with a case study. For this case study, real data from Kenya Airways will be used. The goal of the case study is to show how the model works, and to show the benefits of using interval forecasts for demand rather than point forecasts. In order to do that, a comparison will be made between using point forecasts and interval forecasts in the network development model.

This chapter focuses on two topics. First, in Section 9-1, background information of Kenya Airways will be given. Second, the modelling assumptions and inputs for the model will be given in Section 9-2.

### 9-1 Background information of Kenya Airways

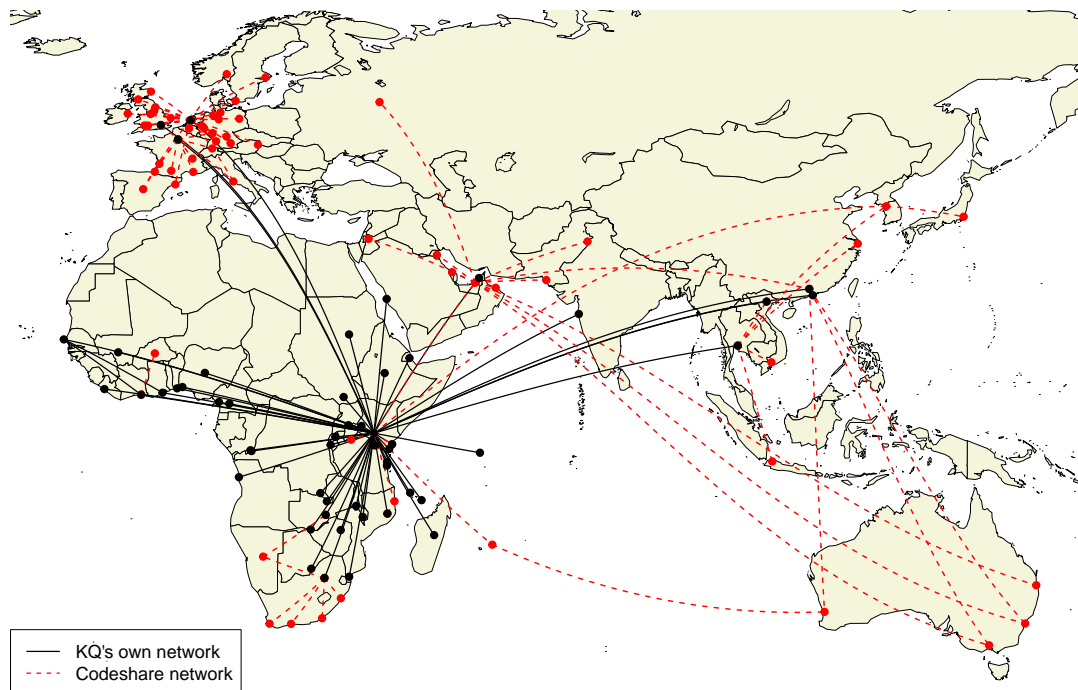
Kenya Airways (KQ) is the flag carrier of Kenya. In terms of the amount of passengers transported, it is the seventh largest airline in Africa. The main hub of the airline is Jomo Kenyatta International Airport in Nairobi.

#### 9-1-1 Network

KQ operates both domestically and internationally. Its international network consists of 56 destinations in Africa, the Middle East, Asia and Europe. Figure 9-1 illustrates the current network. The majority of KQ's passengers, around 55%, transfer at the hub (Kariuki et al., 2015).

#### 9-1-2 Fleet

Since a couple of years, KQ has actively been renewing its fleet. Its fleet renewal plan includes getting rid of old aircraft (Boeing 767-300 is supposed to be exited from operations soon) and replacing them with the Boeing 787-800, 777-300ER and 737-800NG. Table 9-1 gives the development of its fleet for the last three years.



**Figure 9-1:** Kenya Airways' current network (Kariuki et al., 2015).

**Table 9-1:** Development of KQs fleet.

Aircraft type	2013	2014	2015
Wide body			
Boeing 787-800	0	1	6
Boeing 777-300	0	1	3
Boeing 777-200	4	4	4
Boeing 767-300	6	6	5
Narrow body			
Boeing 737-800	5	5	6
Boeing 737-700	4	4	4
Boeing 737-300	5	4	4
Embraer 190	12	15	15
Embraer 170	5	5	3
Freighters			
Boeing 737-300	1	2	2
Boeing 747-400	1		

### 9-1-3 Key performance indicators

The investments for the fleet renewal plan unfortunately coincide with the difficult business environment that KQ is currently in. Driven by the incidences of terrorism in the region, together with adverse external factors such as the West African Ebola crisis and increased competition in their key markets resulted in negative effects on the Kenyan tourism and aviation sector. As a result, both the operational and financial performance of the airline were adversely impacted.

The key performance indicators of the airline are given in Table 9-2; the key financial indicators are given in Table 9-3. From these tables it is clear that, despite the difficult environment the airline is currently in, they still managed to get an transport more passengers. This boost mainly came from the extended services to Asia. Furthermore, it can also be seen that, despite this increment in passenger numbers, revenues hardly increased. However, as costs inflated, the operational performance of the airline deteriorated compared to the previous year.

**Table 9-2:** Key performance indicators of KQ (Kenya Airways, 2015).

	2014	2015
Passengers	3,719,590	4,179,046
RPK [millions]	9,309	9,793
ASK [millions]	14,188	15,406
Average load factor	65.6	63.6
Cargo tonnes	71,340	73,693
Pax yield [KSh]	10.47	9.55

**Table 9-3:** Key financial indicators of KQ (Kenya Airways, 2015).

	2014		2015	
	KShs' Million	USD Million	KShs' Million	USD Million
Revenue	106,009	1,234	110,161	1,237
Direct costs	−75,268	−876	−76,059	−854.1
Fleet ownership costs	−12,490	−145.4	−25,932	−291.2
Overheads	−20,972	−244.1	−24,503	−275.2
Operating profit	−2,721	−31.7	−16,333	−183.4
Operating margin	−2.60%		−14.80%	

## 9-2 Case study assumptions and inputs

Due to the lack of data availability and available project time, the scope of the case study had to be limited, and a number of assumptions had to be made. In this section, the modelling assumptions and inputs for the network development case study will be explained. Some of these assumptions have already been explained throughout the earlier parts of this report, but for the ease of understanding the case study, they will be mentioned again here.

### 9-2-1 Network inputs

One of the main inputs for the network development model are the O-D markets that are taken into account. Ideally, one would like to include as many markets as possible, to make sure that no potential markets will be overlooked. However, this is not feasible, as this requires an infinite number of markets to be included. To make the network development feasible, the following assumptions on the network inputs have therefore been made.

1. Only O-D pairs that have been taken into account in the demand forecasting model are included;
2. When airlines are looking for opportunities to expand their network, they only add connections from or towards their base station. This implies that for the KQ case study, only city-pairs with the origin or destination in Nairobi are included in the model. From the 5,273 city pairs for which demand forecasts were created, 184 have a direct connection with Nairobi. However, due to lack of competitor data, only 39 routes have been included. Table E-1 in Appendix E shows the destinations that have been included;
3. The number of weekly flights for new routes is limited to a maximum of three. According to Kariuki et al. (2015), airlines often limit their exposure to three weekly frequencies in order to explore the market;
4. The number of weekly flights for existing routes is limited to a maximum of seventy. This constraint also holds for competitor frequencies;
5. There are no limitations on the number of weekly flights imposed by regulations, bilateral agreements, and available airport slots.

The consequence of the first three assumptions is that profitable network expansions might be overlooked. The fourth assumption was made to prevent the model from assigning all its utility to a single route. According to the author, it is not feasible for KQ to assign more than seventy weekly return flights on a single route. The consequence of the final assumption is that model outcomes might not be realistic. However, the results could for example be used to negotiate new bilateral agreements.

### 9-2-2 Competitor inputs

The environment airlines are operating in, is highly dynamic and competitive. Based on available data, KQ currently faces competition from at least 19 airlines. For the sake of modelling simplicity and due to lack of data, the following assumptions with respect to the market environment have been made.

1. The amount of competitors remains constant, i.e. airlines will not emerge or go bankrupt;
2. No competitors open new or cancel existing routes;
3. Competitor frequencies grow linearly with demand growth. That is, if demand on a given route increases with 10%, competitors increase their frequencies with 10%;
4. When there are currently no competitors on a market, KQ's expected market share is assumed to be 100%. KQ also follows this assumption (Kariuki et al., 2015).

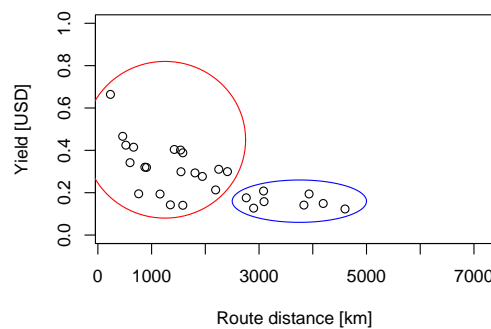


These assumptions might have a significant impact on the reliability of the network development model results. For example, when the demand forecasting model shows that the expected demand on a given city-pair will quadruple, but when there are currently no competitors on this route, it is highly unlikely that KQ will get a market share of 100%. Competitors will also try to gain market shares on these routes. However, due to the added complexity and lack of available data, it is not feasible to model competitor behaviour three years ahead.

### 9-2-3 Ticket price inputs

One of the main parameters in the model is the ticket price. Unfortunately, it was not possible to collect route-specific yield or fare data. Instead, current fares were collected from KQ's website. The departure date was arbitrarily set at 9 February 2016  $\pm$  three days, the return flight was on 16 February 2016  $\pm$  three days. The lowest economy fares for these dates were selected. No distinction between different classes was made (i.e. business and economy). When fare data was not available, fares were assumed to vary with yield times distance.

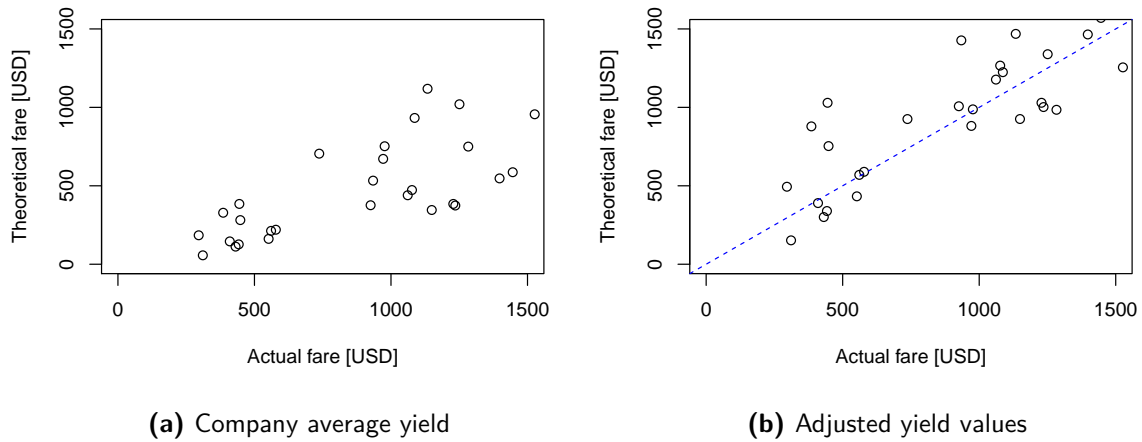
Rather than using the airline's average yield, this project used the available fare data to calculate the average yield. The reason for this is that this project only looks at the inter-African market, and intercontinental routes have not been taken into account. It is expected that the average yield for the inter-African market is larger than the overall airline yield. Figure 9-2 shows the distribution of yield for the routes for which data is available.



**Figure 9-2:** Yield versus distance plot.

In this figure, the vertical axis indicates the route distance, and the horizontal axis indicates the yield value. This figure shows how yield tends to decrease as route distance increases. This plot also shows how yield values fluctuate heavily for distances less than 2,500km. When distance exceeds 2,500km, yield is more stable. It is not clear why yield values fluctuate this much. It is expected that this is because KQ has a monopoly position on some of the short-haul markets, and is therefore able to use high yield values. For example, for FBM-NBO ( $MS = 99.3\%$ ,  $yield = 0.40$ ) and LLW-NBO ( $MS = 95.7\%$ ,  $yield = 0.40$ ), this might be true. However, the values for JRO-NBO ( $MS = 48.0\%$ ,  $yield = 0.66$ ) and MWZ-NBO ( $MS = 9.1\%$ ,  $yield = 0.47$ ) indicate that this is not always valid.

Based on the available data, the average yield values for distances less than or equal to 2,500km ( $yield = 0.3255USD$ ), and with distances of more than 2,500km ( $yield = 0.1596USD$ ) were used. Figure 9-3 shows the comparison between the actual and predicted fares, for the company average yield, and the adjusted yield values. Figure 9-3a confirms that using KQ's overall average yield underestimates fares. Figure 9-3b shows that using the adjusted yield values gives more accurate fare estimates.



**Figure 9-3:** Comparison between actual and theoretical fares.

The distances,  $\beta$ , competitor frequencies, and fares for each route included in the network development model are given in Table E-2 of Appendix E. In this table,  $C_1$ ,  $C_2$ ,  $C_3$  and  $C_4$  represent the competitor frequencies of competitor 1,2,3 and 4 respectively. Because data competitor frequency data for 2014 was not available, values for 2013 were used. Unless stated otherwise, the fares shown are the actual fares for an arbitrary date five months from now.

#### 9-2-4 Demand inputs

Demand inputs are route and scenario specific. For each route and scenario, the forecasting model created demand forecasts. These forecasts are three-years ahead, with 2014 as the base year. The resulting forecasts were given in annual values. In order to make the results of the network development easier to interpret, weekly values were used instead. This was done by dividing the annual forecasts by 52. It is assumed that these weekly forecasts are representative for the entire year. No seasonality effects were taken into account.

Furthermore, it is assumed that the interval forecasts from the demand forecasting model are correct, and outliers have not been removed from the prediction model. The consequence of this assumption is that demand values might be improbably high or low, leading to skewed outcomes from the network development model.

#### 9-2-5 Fleet inputs

The designed model is able to include any type and amount of aircraft, without the need of being adapted. However, KQ does not only operate at the African market, meaning that part of the fleet will be assigned to the other markets. The amount and type of aircraft are based on recommendations from Kariuki et al. (2015).

In this case study, three aircraft types will be included: Boeing 787-8 (B787), Boeing 737-800 (B737), and Embraer 190AR (E190). These are the aircraft that KQ mainly uses for their African network. The characteristics of these aircraft are provided in Table 9-4. Unless stated otherwise, these values are taken from Lammens (2014).

**Table 9-4:** Aircraft characteristics for Kenya Airways case study.

	Unit	B787	B737	E190
Amount	[—]	1	6	15
$\frac{C_L}{C_D}$	[—]	20.5	17.26	16
Cruise altitude	[m]	11,000	11,000	11,000
Range	[m]	14,500,000	5,665,000	2,935,000
MTOW	[kg]	227,930	79,010	51,800
Cruise speed	[Mach]	0.85	0.79	0.82
Seats available	[—]	234	145	96
Flight crew members	[—]	2	2	2
$C_{maint,FC,ac}$ IATA (2014)	[USD]	6,304	1,387	1,222
$C_{maint,FH,ac}$ IATA (2014)	[USD]	1,450	713	865
SFC	$[\frac{kg}{h*N}]$	0.0715	0.0715 <sup>[1]</sup>	0.0524 <sup>[2]</sup>
Lease cost per month	[USD]	950,000	300,000	250,000

[1] Air Berlin (2015); [2] Finnair (2015)

Besides the input characteristics for each aircraft, three additional assumptions with respect to the airline's fleet have been made. These assumptions are given below.

1. Aircraft will always take-off their maximum take-off weight (MTOW);
2. Based on Mack et al. (2013), the maximum weekly utilisation of wide body aircraft (i.e. B787) is 80.5 hours, the maximum weekly utilisation of the single aisle aircraft (i.e. B738 and E190) is 59.5 hours;
3. The maximum load factor for all aircraft types is 75%.

### 9-2-6 Operational inputs

In the previous chapter, it was explained what an average mission looks like for commercial airlines. However, for this project, a slightly different mission has been assumed. Due to lack of data, it was not possible to calculate the distance covered during climb and take-off. Therefore, the standard fuel fractions for these phases will be used. Also, it will be assumed that the cruise phase covers the entire distance between the origin and destination. As the cruise phase usually is the most fuel-intensive phase, it is expected that this assumption overestimates the amount of fuel used, and hence, overestimates the amount of fuel costs. The remaining operational inputs are given below.

1. Based on Lammens (2014), an average jet fuel price of 0.97 USD per liter was used. The average density of jet fuel was set at 0.81 kg/l.
2. The average costs per flight crew member are taken from Lammens (2014). Based on KQ data, he used an average of 20.01 USD per flight hour.



# Kenya Airways Case Study: Results and Analysis

This chapter focuses on describing the results of using the input values from the previous chapter in the network development model from Chapter 8. The structure of this chapter is the following. Section 10-1 describes the validation of the network development model by comparing the model outputs with actual data from June 2013. Section 10-2 gives the results of a sensitivity analysis on some of the assumptions that have been made. After validating the model, the outcomes of the case study are described in Section 10-3. The conclusions and recommendations for the network development model are given in Sections 10-4 and 10-5.

### 10-1 Validation of the network development model

Before using the network development model for forecasting, the outcomes of the model have to be validated. This was done by comparing the model outputs with actual data from 2013. For the validation, input data was mostly similar to what was described in Chapter 9. However, rather than using demand forecasts, actual demand values from June 2013 were used. Also, actual competitor frequencies were used, rather than forecasts. Due to a lack of available competitor frequency data, it was not possible to use a more recent date.

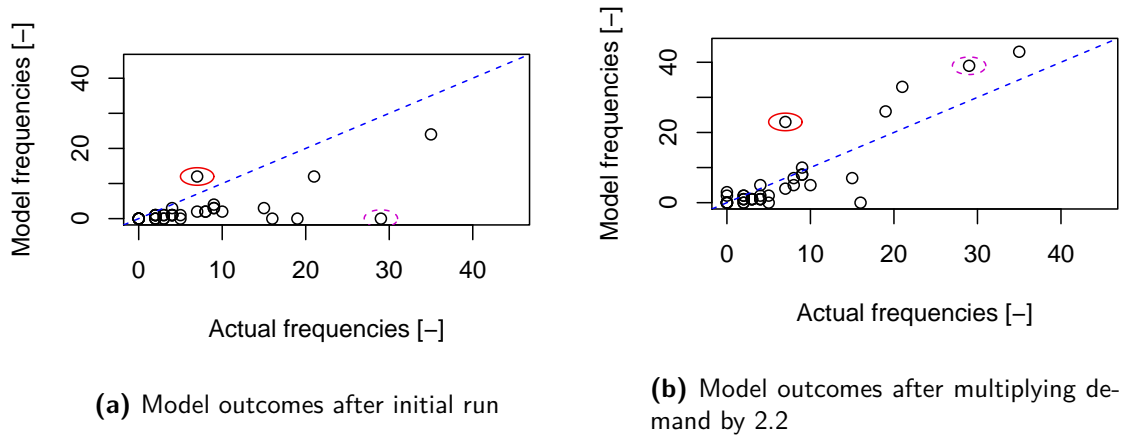
#### 10-1-1 Fit of the model

Before describing the outcomes of the model, this subsection is used to describe the fit of the model to actual data. The comparison between the model frequencies and actual frequencies is shown in Figure 10-1a. In this figure, the horizontal axis indicate the actual frequencies; the vertical axis represents the outcomes of the model. This figure shows that the outcomes of the model are consistently lower than what KQ actually flew. The fact that  $R^2$  is 0.52, also indicates that the model does not fit the data very well (remember that this value should be close to one, as was mentioned in Subsection 6-3-3).

A likely explanation is that demand estimates are too low: as was mentioned in Section 9-1, 55% of KQ's passengers are transfer passengers. This means that for every 45 direct passengers, there are 55 additional transfer passengers. However, the model has included direct demand only. Hence, the demand values should actually be larger. It can therefore

be expected that the network development will recommend fewer frequencies than what was actually flown.

To overcome this issue, it was tested what the effect was of increasing demand with a fixed factor. Taking into account that 55% of KQ's traffic flies indirectly, all demand values were multiplied with factor of 2.2 ( $1 + 55/45 = 2.2$ ). After running the model with adjusted demand values,  $R^2$  increased to 0.83. The results of the second model run are illustrated in Figure 10-1b.



**Figure 10-1:** Comparison between actual and model outcomes.

Comparing these outcomes with the previous ones, it can be observed that the model fits the data better. It shows that some of the markets that were not included at first, are now included. This suggests that on these markets, there are indeed a lot of indirect passengers. An example of this is DAR-NBO, indicated by the dashed, magenta ellipse. Another observation that can be made, is that adjusting the demand can also lead to overestimations of frequencies. An example is ADD-NBO, indicated by the red ellipse.

Over- and underestimations of the number of frequencies can have several causes. The first one is that it has been assumed that all markets have a ratio of 45% to 55% of direct and indirect traffic. However, each route has its own ratio. A different ratio will result in different estimates of the demand. Unfortunately, market-specific data on the ratio between direct and indirect traffic was not available. Second, inaccurate estimates of the number of frequencies per market can be the results of erroneous market share values, causing erroneous values of airline specific demand. Finally, they also be caused by the fact that the model selected a smaller or larger aircraft than what KQ actually used. Assigning smaller aircraft will result in overestimations of the number of frequencies, and vice versa.

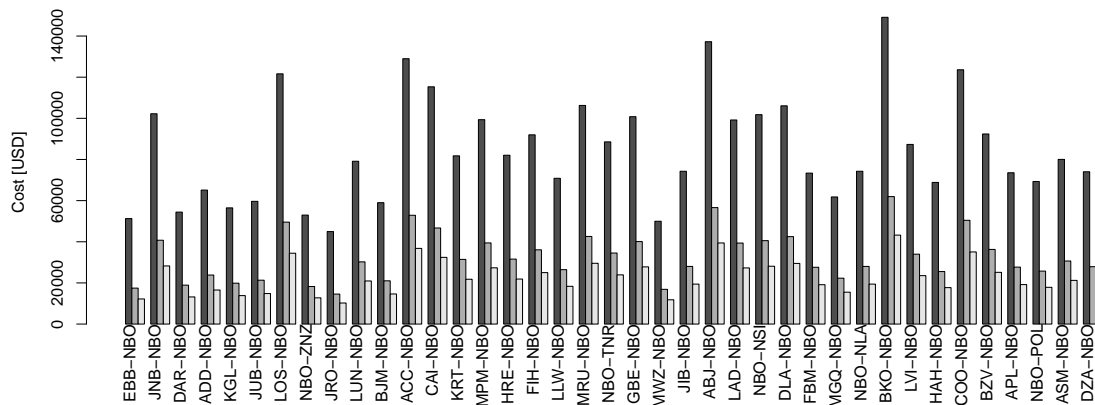
### 10-1-2 Results of the network development model

In this subsection, the remaining outcomes of the model are described. The results are described for the model with the adjusted demand, as was explained above.

#### Costs per route per aircraft

Before describing the network and frequency outcomes of the model, this paragraph is used to show the costs per route per aircraft. It will be assumed that the costs per route will stay constant for the forecasting case study. The results are given in Figure 10-2. As the results

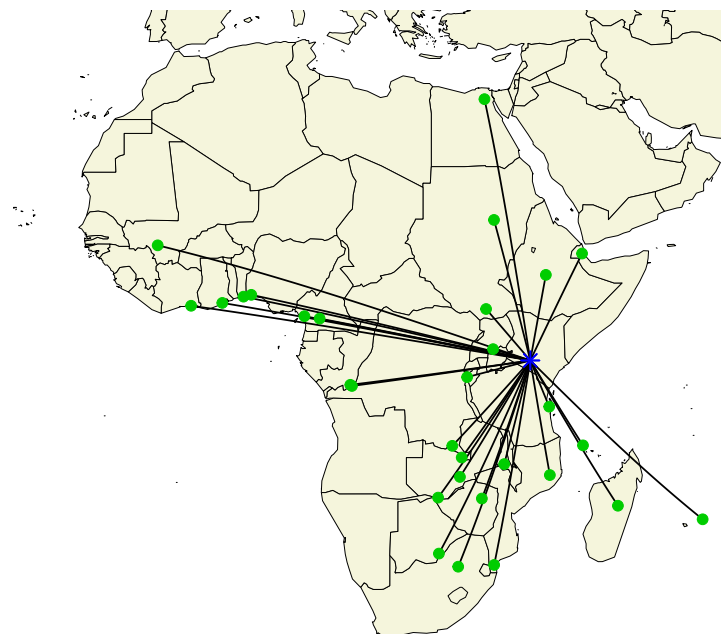
in this figure show, costs for the B787 are much higher than the costs for the B738 and the E190. The cost difference between the B738 and the E190 is much smaller.



**Figure 10-2:** Costs per route per flight for each aircraft type. B787 is indicated in black; B738 in grey; E190 in white.

### Network lay-out

One of the most important results of the network development model, is whether it recommends to operate specific routes. A geographical representation of all the routes recommended by the model is given in Figure 10-3.



**Figure 10-3:** Geographical lay-out of network.

### Model outcomes per route

Besides determining the routes that might be profitable, the network development model also gave the number of frequencies per route. The overall results in terms of frequencies, load factor, market share and operating profit are presented in Table 10-1.

**Table 10-1:** Summary of results of applying the network development model to actual data from 2013.

Route	Frequencies		LF [-]	MS [-]	Operating profit [USD]
	Model	Reality	Difference		
<b>Total</b>	<b>246</b>	<b>258</b>	<b>-12</b>	<b>0.68</b>	<b>0.90</b>
					<b>6,691,994</b>

As these overall results indicate, the difference between the total number of frequencies between the model outcomes and reality is small. Furthermore, the average load factor of 0.68 is similar to KQ's average load factor in 2013, which was 0.687. Finally, the average market share of 0.90 indicates that there is not much competition on the analysed routes.

The following paragraphs will discuss the weekly results from the model. The results will be split into results for the B738, results for the E190, and routes that were not included by the model. Each of these results will be presented in tables, in which the first column indicates the route; the second column the aircraft type; the third to the fifth indicate the frequencies recommended by the model, flown in reality, and the difference between them; column six and seven indicate the resulting load factor and market share; the final column gives the operating profit per route in USD. Unfortunately, actual data on load factors and market shares per route was not available.

### Model outcomes for the B738

The results for routes recommended for the B738 are given in Table 10-2.

**Table 10-2:** Routes recommended to be operated by the B738.

Route	Aircraft	Frequencies			LF [-]	MS [-]	Operating profit [USD]
		Model	Reality	Difference			
ACC-NBO	B738	8	9	-1	0.72	1.00	621,332
LOS-NBO	B738	8	9	-1	0.70	1.00	480,455
NBO-TNR	B738	2	2	0	0.64	1.00	190,909
GBE-NBO	B738	2	5	-3	0.63	1.00	85,655
DLA-NBO	B738	1	4	-3	0.64	1.00	76,816
ABJ-NBO	B738	1	3	-2	0.74	1.00	65,851
BKO-NBO	B738	1	3	-2	0.53	1.00	65,606
COO-NBO	B738	1	2	-1	0.44	1.00	48,001
NBO-NSI	B738	1	4	-3	0.66	1.00	47,662
CAI-NBO	B738	3	0	3	0.75	0.23	44,691
MRU-NBO	B738	2	0	2	0.75	0.50	34,971
JIB-NBO	B738	2	2	0	0.64	1.00	26,007

As the results in this table indicate, the model outcomes in terms of frequency are similar to the actual frequencies. However, the model tends to underestimate the actual frequencies. As KQ's market share is 100% for almost all of the routes, this could imply that the actual demand was larger because these routes had more transfer passengers than what has been assumed. Another possibility is that KQ used E190s instead. With smaller aircraft assigned



to these routes, more frequencies would be flown. A third possibility is that the actual load factors were lower. With lower load factors, the number of frequencies will increase. However, due to insufficient data, neither of these possibilities could be checked.

Another observation to be made is that the model recommended two routes to be operated that were not operated in reality: CAI-NBO and MRU-NBO.

- **Cairo (CAI), Egypt:** KQ used to fly to Cairo, but cancelled this. Reasons for cancellation include the fact that it is an expensive destination (crew has to stay overnight), there is sufficient supply (from Egyptair and Ethiopian), and most traffic to and from Cairo is from north of Egypt (Kariuki et al., 2015);
- **Mauritius (MRU):** this is a route that KQ is currently planning to open in the future (Kariuki et al., 2015).

### Model outcomes for the E190

The model recommended using the E190 for eighteen of the 39 routes. These routes are presented in Table 10-3.

**Table 10-3:** Routes recommended to be operated by the E190.

Route	Aircraft	Frequencies			LF [-]	MS [-]	Operating profit [USD]
		Model	Reality	Difference			
JNB-NBO	E190	33	21	12	0.75	0.85	811,492
EBB-NBO	E190	43	35	8	0.75	0.73	613,090
LUN-NBO	E190	10	9	1	0.71	1.00	515,880
KRT-NBO	E190	7	8	-1	0.74	1.00	471,738
ADD-NBO	E190	23	7	16	0.75	0.69	359,926
DAR-NBO	E190	39	29	10	0.65	0.63	332,415
LLW-NBO	E190	5	8	-3	0.72	1.00	306,514
FIH-NBO	E190	4	7	-3	0.73	1.00	304,086
HRE-NBO	E190	5	10	-5	0.75	1.00	278,284
MPM-NBO	E190	5	4	1	0.75	0.80	208,592
BJM-NBO	E190	7	15	-8	0.75	0.96	180,297
JUB-NBO	E190	26	19	7	0.67	0.57	172,172
FBM-NBO	E190	2	4	-2	0.65	1.00	114,934
NBO-NLA	E190	1	4	-3	0.70	1.00	62,868
BZV-NBO	E190	1	3	-2	0.52	1.00	54,029
HAH-NBO	E190	1	2	-1	0.75	1.00	44,585
LVI-NBO	E190	1	2	-1	0.75	1.00	43,745
APL-NBO	E190	1	3	-2	0.55	1.00	29,392

The two most noteworthy observations from this part of the table are the following. First, for many of the routes, the number of frequencies are lower than the actual operations. The fact that many of these routes had no competitors (i.e.  $MS = 1.00$ ) and the fact that no demand was left after running the model (see Figure 10-4 below) implies that either demand was larger, or KQ had lower load factors.

Second, with the exception of BJM-NBO, the frequencies for all the routes with competitors (i.e. when  $MS \neq 1.00$ ) are overestimated by the model. This could imply that the market share model is inaccurate. However, it could also mean that KQ used larger aircraft on these routes, thereby using less frequencies.

### Routes not recommended by the model

From the 39 routes in the analysis, nine were not recommended by the model. These routes are presented in Table 10-4.

**Table 10-4:** Routes not recommended by the model.

Route	Frequencies		
	Model	Reality	Difference
DZA-NBO	0	2	-2
JRO-NBO	0	5	-5
KGL-NBO	0	16	-16
LAD-NBO	0	2	-2
ASM-NBO	0	0	0
MGQ-NBO	0	0	0
MWZ-NBO	0	0	0
NBO-POL	0	0	0
NBO-ZNZ	0	0	0

It is interesting to see that, where the model did not recommend any of these routes, KQ actually operated four of them. These routes are the following:

- **Dzaoudzi (DZA), Mayotte:** KQ did not offer direct operations, but flew indirectly with the triangular route NBO-HAH-DZA-NBO. By flying in a triangular route, it is possible to attract additional passengers, and thereby make additional profit;
- **Kilimanjaro (JRO), Tanzania:** competitors offered 25 weekly flights already. As this is the shortest route in the analysis (i.e.  $\beta = 1.7$ ), the market share model will likely underestimate KQ's actual market share. However, as route-specific market share data is not available, this could not be checked;
- **Kigali (KGL), Rwanda:** there is a reasonable amount of demand, but RwandAir already offered 18 weekly flights. It is possible that the market share model underestimates KQ's market share, as KGL also belongs to one of the shortest routes ( $\beta = 1.66$ );
- **Luanda (LAD), Angola:** this is a small market, on which Angola Airlines offered services twice a week. Demand is not sufficiently large enough for KQ to operate this profitably.

### Remaining demand per route

Another important outcome of the model is the remaining demand per route. Figure 10-4 shows the initial and remaining demand per route. To improve the readability, two plots are shown, each with different scales on the y-axis. These figures show that after running the network development model, there is little demand left.

Going back to the previous paragraphs where it was shown that the model often underestimated the number of frequencies, these figures suggest that either demand estimates are too low, or KQ operated with lower load factors.

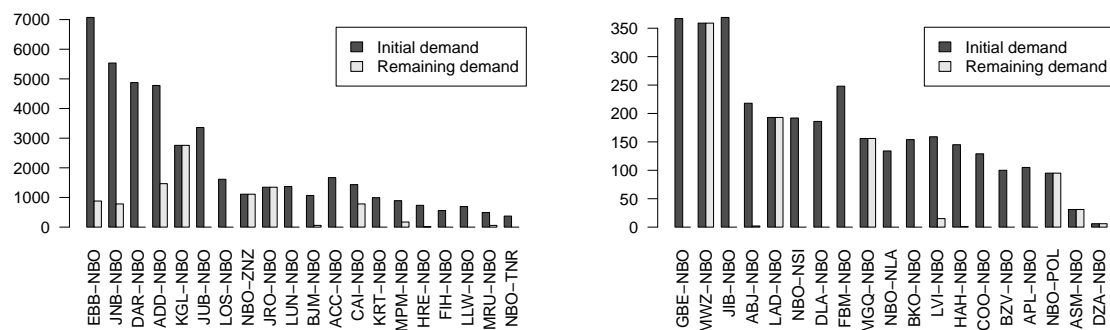


Figure 10-4: Initial and remaining demand per route.

### Remaining aircraft utilisation

The final outcome that is analysed is the remaining utilisation per aircraft type. The remaining utilisation per aircraft type is given in Table 10-5.

Table 10-5: Utilisation per aircraft type.

Aircraft type [-]	Utilisation [hr]	
	Available	Remaining
B787	80.5	80.5
B738	357	121.4
E190	892.5	326.4

From this table, it is clear that there is sufficient utilisation left of each aircraft type to increase the number of frequencies. This could imply that the daily utilisation per aircraft type is too large. Note that this project has used industry averages as to determine the maximum daily utilisation. However, a more likely implication is that, as was already suggested from the discussion above, the demand estimates are too low. This leads to less required frequencies, and therefore more available utilisation.

As has already been mentioned earlier, the results in this table also show that the model did not use the B787. Note that this does not mean that operating the B787 can not be profitable. However, as the costs for operating the B787 are so much higher, operating one of the other aircraft types is much more profitable.

## 10-2 Sensitivity analysis of assumptions

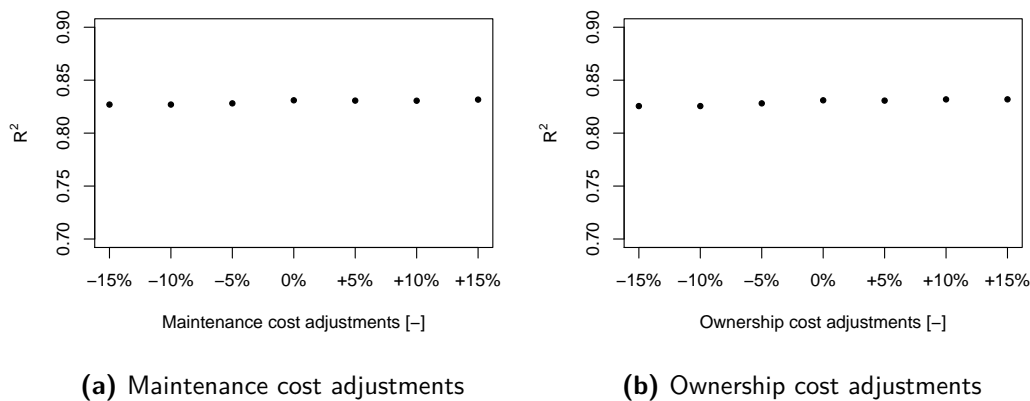
The accuracy of the assumptions and input parameters has a large impact on the output of the model. Sensitivity analysis is a technique used to determine how different values of input parameters affect the dependent variable. In order to do this, one independent parameter is adjusted, while the others remain constant. The sensitivity of the model has been tested to adjustments in the following parameters: maintenance costs, ownership costs, and the maximum load factor. It was expected that these parameters have a significant impact on the outcomes of the model. The sensitivity analysis generated a large set of plots. Therefore,

it was chosen to present only plots of the model fit (i.e.  $R^2$ ) for the different values assumed for the parameters

### 10-2-1 Cost inputs

In Subsection 8-4-2, it was mentioned that the ratio between the maintenance costs per flight cycle and per flight hour is an indicator for the preference of an aircraft for a specific range. When this value is low, an aircraft type is specifically useful for short-distance flights. On the other hand, when this value is large, this aircraft type is more suitable for long-distance flights. These ratios therefore play an important role in the selection of an aircraft type. It is expected that the aircraft type selection is very important for the fit of the model. It was therefore tested what the effect was of changing the ratio, by varying the costs per cycle. The costs for the B738 and B787 were adjusted from -10% to +10%, while at the same time, the costs for the E190 were adjusted from +10% to -10%, all of them in steps of 5%.

Another parameter that was expected to influence the selection of an aircraft type, is the ownership cost. In a similar way as was done for the maintenance costs, ownership costs were adjusted from -10% to +10% for the B738 and B787, and from +10% to -10% for the E190. The results of these adjustments are displayed in Figure 10-5.

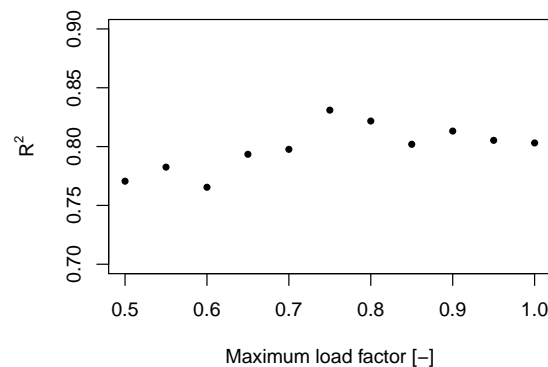


**Figure 10-5:** Impact on model fit after varying the maintenance costs and ownership costs.

The results in these figures indicate that neither adjusting the maintenance costs nor the ownership costs has a significant effect on the fit of the model.

### 10-2-2 Maximum load factor

Another important assumption used in the analysis, is the maximum allowed load factor. Usually, airlines aim for a load factor of around 80% (Doganis, 2002). However, Kenya Airways has not been able to achieve this for a couple of years. As was shown in Table 9-2, the average load factor for 2015 is just over 60%. The model was tested for maximum load factors varying from 50% to 100%, with an interval of 5%. The results are displayed in Figure 10-6. The results in this indicate that the fit of the model fluctuates as the maximum load factor changes. The best model fit is found for a maximum load factor of 0.75.



**Figure 10-6:** Impact on model fit after varying the maximum load factor.

### 10-3 Results of case study

Now that the network development model has been validated, the model can be used for forecasting. This section describes the results of including interval forecasts for the demand for 39 city pairs for which market share data is currently available. Due to a lack of recent competitor frequency data (up to and including 2013) and data for the time-dependent parameters of the gravity model (up to and including 2014), this case study uses 2013 as the base year, and performs the network development for 2016. The details of the model are given in Table 10-6.

**Table 10-6:** Details of model for case study in R.

Number of routes included [-]	39
Number of simulation runs [-]	2,500
Model run-time [s]	1,743

#### Demand forecasts

Before describing the results from the network development model, it should be known what the demand forecasts are. The distribution of the demand forecasts are presented in Table 10-7. This table presents the average weekly demand in 2013, and the minimum, mean and maximum demand from the forecasting model. In this table, colours have been used to indicate what happens compared to 2013: red indicates a decrease in demand; green indicates an increase. The brighter the colour, the larger the difference.

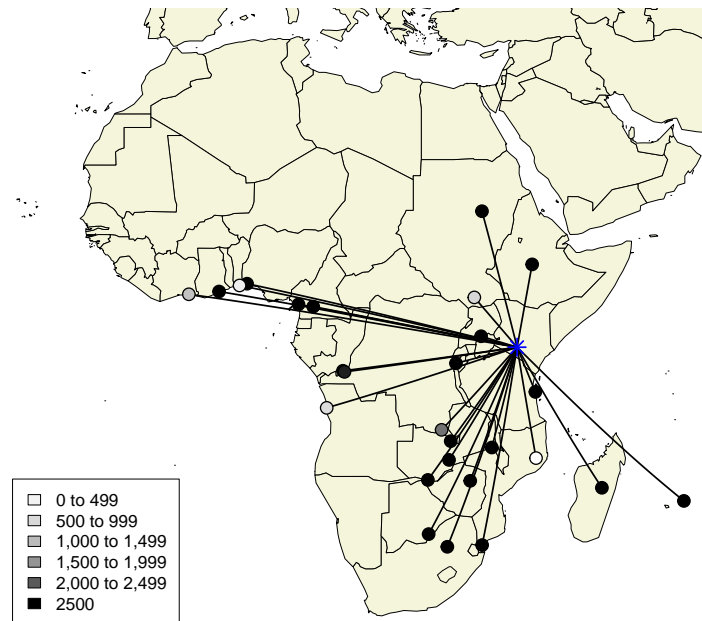
Noteworthy from this table is the fact that on some routes, the increase in demand does not seem feasible. For example for ADD-NBO, it does not seem feasible that the weekly demand increases from 857 to 10,057 in just three years. It is expected that this is the result of not removing outliers from the forecasting model. However, due to a lack of available project time, this has not been tested. The remainder of this section is used to describe the results from the network development case study.

**Table 10-7:** Passenger demand forecasts per route for case study, in weekly numbers.

Route	$V_{2013}$	$V_{min}$	$V_{mean}$	$V_{max}$	Route	$V_{2013}$	$V_{min}$	$V_{mean}$	$V_{max}$
ABJ-NBO	50	10	97	211	JNB-NBO	1121	1,043	1,885	3,168
ACC-NBO	208	560	1,004	1577	JRO-NBO	245	773	2188	4,075
ADD-NBO	857	2,487	5,945	10,057	JUB-NBO	572	150	783	1,729
APL-NBO	21	12	23	48	KGL-NBO	560	686	2,163	5,014
ASM-NBO	5	21	50	83	KRT-NBO	150	53	273	602
BJM-NBO	208	25	161	288	LAD-NBO	40	109	269	483
BKO-NBO	30	1	21	45	LLW-NBO	129	206	568	952
BZV-NBO	26	38	62	85	LOS-NBO	319	177	2398	4,077
CAI-NBO	215	130	509	1155	LUN-NBO	215	318	581	1,033
COO-NBO	26	36	57	106	LVI-NBO	27	63	114	203
DAR-NBO	930	2913	8247	15361	MGQ-NBO	30	8	174	628
DLA-NBO	35	173	253	349	MPM-NBO	169	72	139	294
DZA-NBO	3	1	2	5	MRU-NBO	108	332	473	659
EBB-NBO	1274	5169	7963	10909	MWZ-NBO	72	172	486	904
FBM-NBO	41	7	39	70	NBO-NLA	31	43	78	139
FIH-NBO	120	23	138	250	NBO-NSI	42	211	309	425
GBE-NBO	73	145	223	325	NBO-POL	15	9	17	36
HAH-NBO	23	4	17	40	NBO-TNR	78	26	185	352
HRE-NBO	147	129	415	864	NBO-ZNZ	282	950	2,688	5,006
JIB-NBO	63	19	34	60					

### Network lay-out

The resulting network is illustrated in Figure 10-7. This figure shows the geographical lay-out of the network. The colours indicate in how many simulation runs the model recommended to operate a specific route.

**Figure 10-7:** Geographical lay-out of network, with shades indicating in how many simulation runs a destination was recommended.

There are also a number of destinations that were not included by the model:

- **Bamako (BKO), Mali:** as can be seen from the demand forecasts, demand is not expected to increase significantly. The fact that KQ currently flies to this destination is explained by the fact that they operate it in the triangular route NBO-DKR-BKO-NBO. This way they can attract additional passengers;
- **Dzaoudzi (DZA), Mayotte:** the demand on this route is also not expected to increase significantly. Also for this destination, KQ currently flies in a triangular route: NBO-HAH-DZA-NBO;
- **Moroni (HAH), Comoros:** see DZA;
- **Ambouli (JIB), Djibouti:** in all scenarios, the forecasting model shows that demand is expected to decrease. Apparently, it decreases so much that operating this route will not be profitable anymore;
- **Kilimanjaro (JRO), Tanzania:** in Subsection 10-1-2 it was already explained that there is a lot of competition on this route. As demand grows, competitors will even add more frequencies. As this is one of the shortest routes, KQ should add an infeasible amount of frequencies to gain market share;
- **Kigali (KGL), Rwanda:** see JRO.

### Frequency per route

The frequencies per route are provided in Table 10-8. Two types of information are provided in this table. First, for each route, it shows the amount of scenarios for which the network development model recommended operating it. Values are given in the column *N*. These values can be used as an indication of the stability of the route. The larger this value is, the more often the model recommended operating on this route (with a maximum of 2,500). Most of the routes are included in every scenario of the simulation.

Second, the table shows the frequency per route. It gives the actual number of weekly frequencies for 2013, as well as the minimum, mean, and maximum of the model results. The colours in the table indicate what happens compared to 2013: red indicates a decrease in frequency, green indicates an increase, and blue indicates opening a new route. The intensity of the colour indicates the magnitude of the change. The results in this table clearly show the effect of demand uncertainty. For example, for DAR-NBO, the difference between 2013 and the model outcomes varies between  $-5$  and  $+41$  (note that the maximum number of frequencies is limited to 70, as was explained in Subsection 9-2-1).

### Operational profit per route

The operational profit per route is given in Table 10-9. Note that this table only gives the minimum values, provided that a route is operated. It does not take into account that profitability is zero when a route is not operated (see column *N* in Table 10-8 to see how often routes are operated in the model). The results in this table clearly show the effect of uncertainty in the input parameters: there is a lot of fluctuation in the values. It can also be observed that uncertainty is larger for some routes than for others. For example, LOS-NBO might have the largest maximum profit, but it only has the twelfth largest minimum profit. This indicates that profitability on this route is very uncertain. This could have been

**Table 10-8:** Distribution of frequencies per route. Colours are used to indicate the change compared to the actual frequencies: red indicates a decrease in frequencies, green indicates an increase in frequencies, and blue indicates a new route. The shade indicates the magnitude of the change: the darker the colour, the larger the change.

Route	N	$F_{2013}$	$F_{min}$	$F_{mean}$	$F_{max}$	Route	N	$F_{2013}$	$F_{min}$	$F_{mean}$	$F_{max}$
ACC-NBO	2,500	9	3	5	7	LOS-NBO	2,500	9	1	11	19
ADD-NBO	2,500	7	13	31	53	LUN-NBO	2,500	9	2	4	7
BJM-NBO	2,489	15	1	1	2	LVI-NBO	2,500	2	1	1	1
BZV-NBO	2,500	3	1	1	1	MPM-NBO	2,500	4	1	1	2
DAR-NBO	2,500	29	24	63	70	MRU-NBO	2,500	0	1	2	3
DLA-NBO	2,500	4	1	1	2	NBO-NLA	2,500	4	1	1	1
EBB-NBO	2,500	35	34	53	70	NBO-NSI	2,500	4	1	2	2
FBM-NBO	2,072	4	1	1	1	NBO-TNR	2,499	2	1	1	2
FIH-NBO	2,486	7	1	1	2	ABJ-NBO	1,124	3	1	1	1
GBE-NBO	2,500	5	1	1	2	COO-NBO	317	2	1	1	1
HRE-NBO	2,500	10	1	2	5	LAD-NBO	682	2	1	1	3
JNB-NBO	2,500	21	6	11	18	JUB-NBO	784	19	2	6	13
KRT-NBO	2,500	8	1	2	4	APL-NBO	10	3	1	1	1
LLW-NBO	2,500	8	1	3	7						

expected, as the results in Table 10-8 already showed that the number of frequencies on this route is very unstable.

**Table 10-9:** Distribution of operational profitability per route. The shade indicates the magnitude: the darker the cell, the larger the operational profitability is.

Route	$Prof_{min}$	$Prof_{mean}$	$Prof_{max}$	Route	$Prof_{min}$	$Prof_{mean}$	$Prof_{max}$
ACC-NBO	191569	366316	575403	LOS-NBO	46610	738396	1273509
ADD-NBO	122196	305310	525354	LUN-NBO	110924	219102	397004
BJM-NBO	798	26858	51513	LVI-NBO	5900	29416	60881
BZV-NBO	4943	24056	42153	MPM-NBO	7625	28843	50703
DAR-NBO	163279	443036	1054290	MRU-NBO	3322	29848	58903
DLA-NBO	68476	96689	138877	NBO-NLA	6985	28736	65939
EBB-NBO	347769	553292	752310	NBO-NSI	56391	75158	114160
FBM-NBO	13	6395	24107	NBO-TNR	6126	94740	176933
FIH-NBO	1740	71478	130716	ABJ-NBO	86	13141	63017
GBE-NBO	37275	55474	74550	COO-NBO	686	5267	30449
HRE-NBO	47580	154701	338920	LAD-NBO	382	2551	8327
JNB-NBO	145634	253801	428793	JUB-NBO	27	2847	9001
KRT-NBO	11534	125142	284124	APL-NBO	242	843	3018
LLW-NBO	91932	250495	418661				

### Market share per route

The market shares per route are given in Table 10-10. Note that this table only gives the minimum values, provided that a route is operated. Furthermore, this table only presents results for routes on which competitors were operating in 2013. For all other routes, KQ has an expected market share of 100%.

### Load factor per route

The load factors per route are given in Table 10-11. Note that similar as with the operational profitability, this table only gives the minimum values, provided that a route is operated. The



**Table 10-10:** Distribution of market share per route. Results only include routes with competitors. The shade indicates the magnitude: the darker the cell, the larger the market share is.

Route	$MS_{min}$	$MS_{mean}$	$MS_{max}$
ADD-NBO	0.6	0.62	0.64
DAR-NBO	0.47	0.57	0.61
EBB-NBO	0.66	0.67	0.68
JNB-NBO	0.75	0.81	0.88
MPM-NBO	0.5	0.9	1
MRU-NBO	0.25	0.5	0.5
LAD-NBO	0.26	0.34	0.5
JUB-NBO	0.33	0.4	0.59

most noteworthy observations from these results are the relatively high load factors. The fact that the load factors are high, is a possible explanation for the decrease in model frequencies: with high load factors, less frequencies are necessary. Unfortunately, route-specific data on load factors was not available, so it was not possible to compare whether load factors increased or decreased.

**Table 10-11:** Distribution of load factors per route. The shade indicates the magnitude: the darker the cell, the larger the load factor is.

Route	$LF_{min}$	$LF_{mean}$	$LF_{max}$	Route	$LF_{min}$	$LF_{mean}$	$LF_{max}$
ACC-NBO	0.63	0.72	0.75	LOS-NBO	0.59	0.73	0.75
ADD-NBO	0.75	0.75	0.75	LUN-NBO	0.59	0.71	0.75
BJM-NBO	0.29	0.67	0.75	LVI-NBO	0.33	0.59	0.75
BZV-NBO	0.2	0.32	0.44	MPM-NBO	0.38	0.64	0.75
DAR-NBO	0.6	0.66	0.75	MRU-NBO	0.64	0.74	0.75
DLA-NBO	0.49	0.71	0.74	NBO-NLA	0.22	0.41	0.72
EBB-NBO	0.75	0.75	0.75	NBO-NSI	0.59	0.72	0.75
FBM-NBO	0.16	0.22	0.36	NBO-TNR	0.22	0.67	0.75
FIH-NBO	0.19	0.64	0.75	ABJ-NBO	0.34	0.42	0.73
GBE-NBO	0.59	0.72	0.75	COO-NBO	0.23	0.25	0.37
HRE-NBO	0.56	0.69	0.75	LAD-NBO	0.68	0.74	0.75
JNB-NBO	0.75	0.75	0.75	JUB-NBO	0.51	0.68	0.75
KRT-NBO	0.28	0.68	0.75	APL-NBO	0.22	0.23	0.25
LLW-NBO	0.55	0.7	0.75				

### Remaining utilisation per aircraft type

Apart from the route-specific model outcomes mentioned above, there are also aircraft-specific results: the remaining utilisation per aircraft type. These values are given in Table 10-12. From these results, it is clear that the B787 is never being used by the model. As was already explained in the previous section, this can likely be explained by the fact that operating costs are significantly larger for this type than for the other two.

It also indicates that in all scenarios, all aircraft have utilisation left to open new routes or to increase the number of frequencies. Especially for the E190, the available utilisation is specifically large.

**Table 10-12:** Remaining utilisation in hours per aircraft type.

	$Util_{min}$	$Util_{mean}$	$Util_{max}$
B787	81	81	81
B738	49	173	275
E190	441	555	671

## 10-4 Conclusions of the network development case study

The purpose of the two preceding and the current chapters was to illustrate how the robustness of the airline planning process can be increased. By combining interval forecasts for the market size with a network development model, it was shown how airline profitability could become robust under uncertain demand.

Before being able to use the demand forecasts, they have to be converted from a country-pair basis to a city-pair basis. Subsequently, these forecasts have to be combined with a market share model to calculate the airline specific demand. The airline specific demand was used in a profit maximisation model to determine the route - aircraft - frequency combination. The developed model was based on the fleet development model from Lammens (2014), but with some adjustments applied to it.

The model gives several outcomes. First of all, it gives a map with all routes that turn out to be profitable, and all city-pairs that are not profitable. For each profitable route, the type of aircraft and the corresponding frequency of operations are given in a tabular format. In order to assess the overall network, histograms of the overall profitability and the number of routes in the network will be provided. The resulting network development decision-support tool is flexible enough that it can cope with any amount of routes, aircraft types, and scenes, without the need of any adjustments other than the input data.

The results from this case study can be used to assist the network development phase of airlines in different ways. One of the primary goal of airlines is to make a profit. Therefore, profitability of (new) routes is one of the first things to look at. The results of this case study indicate that the expected profitability can be very unstable. Hence, for network developers, it might not be a good choice to select such a route.

Another way how the current study assists with the airline network development, is that it shows what the probability is that a route is potentially profitable to the network. Especially for new routes, this is an important parameter to look at. The model might show very large expected profits for a new route, but if this route is only added for a small number of scenarios, it does not make sense to open up this route.

## 10-5 Recommendations for the network development case study

This illustrative case study has indicated that including demand uncertainty in airline network development can increase the robustness of this process. Due to lack of available data and available project time, the scope of the case study had to be limited, and a number of assumptions had to be made. Before implementing the developed model into practice, it is therefore recommended to increase the reliability and applicability of both the model and the input data.

First, lack of available data limited the applicability of the results. The model was limited to using 2013 as a base year, rather than 2015. With more recent data on the frequencies of competitors and on the time-dependent parameters of the gravity model, the applicability will increase. Furthermore, route-specific yield or fare data, and data on the ratio between direct and indirect traffic will increase both the reliability and applicability of the results.

Second, it is recommended that before using the interval forecasts, they should be checked for outliers. As had already been mentioned before, outliers have not been removed from the forecasting model. A consequence of this is that unlikely high demand values were found. This in turn led to improbable route - frequency combinations. To prevent the model from assigning all the available aircraft utilisation to these routes, it was assumed that the maximum available number of weekly flights is 70.

Third, the applicability of the results could be increased by adding more routes to the analysis. This project was limited by only including 39 routes. The aim was to perform second a case study with all 184 routes from the demand forecasting model included. However, due to a lack of available time, this has not been done. Adding more routes to the analysis might identify additional potentially profitable routes.

Finally, due to time constraints it was not possible to generate forecasts for the most likely scenario. It would be interesting to show how the results from this scenario compare to the outcomes in which demand uncertainty has been taken into account.



# Conclusions

The purpose of the current study was to develop a modelling framework for generating interval forecasts for airline passenger demand, and to illustrate how this can increase the robustness of the airline's strategic planning process, by applying the results to a network development case study. The primary aim of this project was to develop a model that creates interval forecasts for the total demand for air travelling between two cities. The secondary aim of this study was to use the resulting market size forecasts in a network development decision support tool. In order to reach the purpose of this study, three research questions had to be answered:

1. What regression technique creates the most accurate predictions for the total passenger demand for air travelling between two cities?
2. What is the effect of combining the prediction model with interval forecasts of time-dependent parameters?
3. What are the implications of applying interval forecasts of demand to a network development case study for Kenya Airways?

Throughout the report, answers to these questions have been provided. Below, a recap of them will be given.

### 11-1 Market size prediction

The first research question was answered by generating a market size prediction model. Based on the recommendations from previous studies, this model was expressed as a gravity model. Due to data collection issues, this gravity model was used to predict the demand on a country-pair level rather than on a city-pair level. The parameters that were included in this model were socio-economic factors such as GDP and CPI, and parameters such as the distance between the capitals of two countries. The market size model was developed by using passenger data from the inter-African market.

Before using the data, it had to be validated. Especially the dependent variable (annual market size) was subjected to several limitations. By using a methodology similar to

what other airlines use, this missingness could be dealt with. Industry experts validated the methodology.

After validating the data, the performance of three solving techniques were compared: ordinary least squares (OLS), poisson pseudo maximum likelihood (PPML) and negative binomial regression (NB). The comparison confirmed the hypothesis that NB is the best technique to model the demand with the given data. This is because NB is specifically useful for overdispersed gravity models.

In order to further increase the performance of the prediction model, the datasets were clustered before solving the regression model. Data was clustered with respect to income levels, political stability, government effectiveness, distance between countries, and the actual demand. Both the political stability and demand clusters showed an increased performance; the other clusters did not converge. Despite the fact that clustering the data with respect to demand lead to the largest improvement, it had been decided to continue with clustering the data with respect to political stability. This was explained as follows. The goal of the prediction model is to eventually create demand forecasts that will be used in a network development tool. When data was clustered with respect to demand, only country pairs from the existing database could be used. When one is interested in forecasting demand for new country pairs, one would have to make an initial guess about the demand level. By clustering with respect to the political stability, this is not the case.

It was concluded that all the coefficients of the significant predictor variables had the expected sign. The sign of a predictor coefficient indicate the kind of effect a predictor variable has on the demand: positive coefficients (e.g. population size) have a positive effect on demand; negative coefficients (e.g. distance) have a negative effect on demand.

## 11-2 Market size forecasting

The second research question was answered by creating interval forecasts of the time-dependent parameters of the gravity model, and using these distributions in a Monte Carlo simulation. The time dependent parameters were the Consumer Price Index, index of government effectiveness, Gross Domestic Product, index of political stability, and population size.

Box-Jenkins models were the most suitable models for generating time-series forecasts of the time-dependent parameters because of their strong theoretical foundations. However, finding such models is a very time-consuming process. Fortunately, most statistics software packages are able to do this automatically. These packages are also able to provide prediction intervals for the models. Prediction intervals are normally distributed estimates of unknown future values that can be regarded as a random variable at the time the forecast is made. By comparing the actual data from 2013 with the a three-year ahead forecast with base year 2010, it was shown that for most of the parameters, the actual values were within the forecast interval.

With the prediction intervals known, the next step was to randomly pick values and insert them into the prediction model. This gave intervals of expected future demand. By comparing the three-year ahead forecast with base year 2011, with the actual data from 2014, it was shown that for 69% of the country pairs, the actual data was within the forecast interval. The main reason why the actual demand was not within the interval forecast was because of the prediction accuracy of the prediction model. As the prediction model does not have a perfect fit, it can be expected that the forecasting will not have a perfect fit for all

country pairs.

### 11-3 Network development

The third research question was answered in two parts. First, a network development model was created. By combining the interval forecasts for the market size with a network development model, airline profitability could become more robust under uncertain demand.

Before being able to use the demand forecasts, these forecasts had to be converted from a country-pair basis to a city-pair basis. Subsequently, a market share model was developed to calculate the airline specific demand. It was decided to use S-curve models to model airline market shares. The main reason for this was because it is the least data intensive.

With expected values of the airline specific demand, a network development model was developed. The developed model was based on the fleet development model from Lammens (2014). By making some adjustments to his model, it was possible to use this model as a network development decision-support tool.

The outcomes of this model were overviews of routes, the type of aircraft for each route, and the corresponding frequency of operations, that would lead to the largest profit. The resulting network development decision-support tool is flexible enough that it can cope with any amount of routes, aircraft types, and scenes, without the need of any adjustments other than the input data.

### 11-4 Kenya Airways case study

The implications of the network development model to Kenya Airways' operations were explored by performing a case study on a selection of city pairs that Kenya Airways operates at or is interested in opening soon. The results of this study indicated that by combining interval forecasts for the market size with a network development model, airline network developers could plan for a more robust network. The results of this case study indicate that the expected profitability can be very unstable. Hence, for network developers, it might not be a good choice to select such a route.

Another way how the current study assists with the airline network development, is that it shows what the probability is that a route is potentially profitable to the network. Especially for new routes, this is an important parameter to look at. The model might show very large expected profits for a new route, but if this route is only added for a small number of scenarios, it does not make sense to open up this route.





# Recommendations

The purpose of this graduation project was to show how interval forecasts for the demand for air travelling could be created, and to illustrate how these intervals can increase the robustness of airline network development. This chapter gives an overview for each of the parts of this project that were used to reach the project's purpose.

### 12-1 Market size prediction

In terms of directions for future research, further work could focus on increasing the model's accuracy. Accuracy improvement is mainly expected to come from improving the quality of the input of the data. Especially improving the data from MIDAS could potentially result in more accurate predictions.

Due to time constraints, it was not possible to analyse outliers from the market size predictions. By not removing outliers, errors propagate to the forecasting and network development model. Future research should focus on increasing the model accuracy by looking at additional predictor variables, and to use interactions between predictor variables. Additional parameters might be able to identify why certain points are outliers. Adding additional parameters might reduce the number of outliers, and increase the model fit. Also, *"including interactions is a way to allow a model to be fit differently to different subsets of data"* (Gelman and Hill, 2007)[p. 36]. The exact consequences are difficult to predict, but it might have a significant effect on the accuracy of the results.

Rather than using forced entry methods, other methods of introducing predictor variables could be used, such as hierarchical and stepwise methods. In hierarchical methods, after known predictors have been entered, new predictors are added, either all in one go, in a stepwise manner, or hierarchically. In stepwise regressions, *"decisions about the order in which the predictors are entered into the model are based on a purely mathematical criterion"* (Field, 2009). The exact consequences of this are difficult to predict, but as it might have a significant effect on the accuracy, it would be interesting to test this.

One could also use different clustering techniques, such as DBSCAN or other automatic clustering techniques, to increase the accuracy. This project already showed how clustering data with respect to political stability and historical demand levels results in a better model performance compared to the basic model. However, it is expected that using automatic

clustering techniques will further enhance the performance.

Finally, future research could focus on using other types of model formulations such as extended versions of VAR. Also, one could try to use panel data sets with monthly intervals. It is important that assumptions have to be made on the monthly values for the independent variables, as they are only available in annual values.

## 12-2 Market size forecasting

The results of the market size forecasting showed that combining a market size prediction model with forecasts of time-dependent parameters of a prediction model can be used to create interval forecasts of demand. There are a number of opportunities how future research could further develop the model.

The validity of the model could be improved by validating the assumptions that have been made. One of the major assumptions was that 2,500 iterations in the Monte Carlo simulation is sufficient for all country-pairs. However, to be sure, one should calculate the required number of iterations for each country-pair individually. Due to time constraints, it was not confirmed whether this is sufficient. The consequence of not specifically calculating the required number of iterations, is that it is currently not possible to state anything about the probability that the results are correct.

A second assumption that this project has used, is that the automatic forecasting function in R can find the correct B/J models and their corresponding interval forecasts. Due to the large amount of variables that had to be forecast, the assumptions behind the calculations have not been checked. It is therefore possible that some of the models are misspecified.

One could include additional types of uncertainty. This project only included uncertainty of the forecasts of time-dependent variables. Other types of uncertainty such as error propagation, were outside the scope of this project. The consequence of limiting the project to this type of uncertainty, is that in reality, uncertainty will likely be larger.

Finally, it would be interesting to repeat the calculations presented in this chapter for multiple periods in the future. By doing this, one can generate trendlines with fan-charts indicating how forecasting uncertainty is expected to evolve.

## 12-3 Network development

The second purpose of this project was to illustrate how interval forecasts of demand can be used to increase the robustness of the airline network development process. As this was only an illustrative example, it was not the goal to perform this process very detailed. Therefore, a number of simplifications were made. Future research could focus on the following.

In the proposed model, it was assumed that airline market shares can be calculated with a relatively simple S-curved model. However, future research should focus on further developing this model. This could be done by adding factors such as whether flights are operated directly or indirectly, and whether airlines are flag carriers or low cost carriers. This gives a more realistic estimation of the airline market share and will allow for a more accurate network development model.

Further research could also extend the model by including network effects. When one wants to include network effects in the model, the market share model and the profit maximisation will have to be adjusted. By including network effects in the model, a more

realistic representation of reality will be the result. This is especially true for Kenya Airways, where nearly 55 percent of its passengers are transfer passengers. It is expected that by including network effects, more city-pairs will become profitable, and the resulting network will become larger.

Another possible extension would be to include a passenger recapture model. The model presented in this study can only assign one aircraft type to routes. However, it might be possible that after assigning one aircraft, there is still sufficient demand left to operate a second aircraft type. In the market share calculations, the number of frequencies of the first aircraft type should be added to the number of frequencies of the second aircraft type. Especially for airlines with a mixed fleet, it is expected that this could improve the overall profit.

A fourth possibility for future research is to extend the model by including more detailed cost calculations. Rather than assuming fixed costs per aircraft-route combination, one could calculate these per frequency. It is expected that by including more accurate cost calculations, additional possibilities for profitable routes might occur.

## 12-4 Kenya Airways case study

Finally, the illustrative case study has indicated that including demand uncertainty in airline network development can increase the robustness of this process. Due to lack of available data and available project time, the scope of the case study had to be limited, and a number of assumptions had to be made. There are several possibilities how the the reliability and applicability of this case study can be increased.

First, lack of available data limited the applicability of the results. The model was limited to using 2013 as a base year, rather than 2015. With more recent data on the frequencies of competitors and on the time-dependent parameters of the gravity model, the applicability will increase. Furthermore, route-specific yield or fare data, and data on the ratio between direct and indirect traffic will increase both the reliability and applicability of the results.

Second, it is recommended that before using the interval forecasts, they should be checked for outliers. As already has been mentioned before, outliers have not been removed from the forecasting model. A consequence of this is that unlikely high demand values were found. This in turn led to improbable route - frequency combinations. To prevent the model from assigning all the available aircraft utilisation to these routes, it was assumed that the maximum available number of weekly flights is 70.

Third, the applicability of the results could be increased by adding more routes to the analysis. This project was limited by only including 39 routes. The aim was to perform second a case study with all 184 routes from the demand forecasting model included. However, due to a lack of available time, this has not been done. Adding more routes to the analysis might identify additional potentially profitable routes.

Finally, due to time constraints it was not possible to generate forecasts for the most likely scenario. It would be interesting to show how the results from this scenario compare to the outcomes in which demand uncertainty has been taken into account.

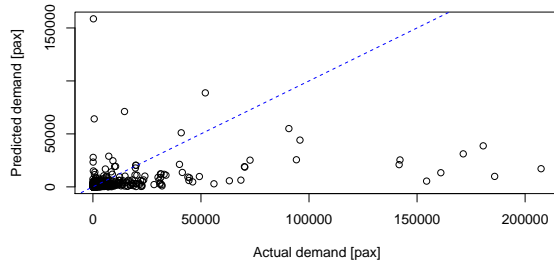


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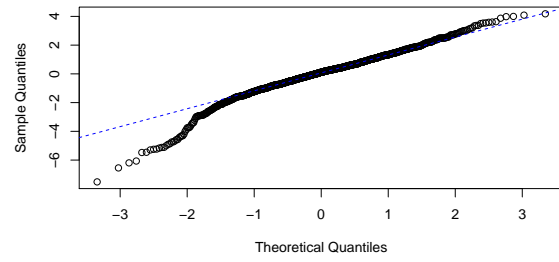
## Appendix A

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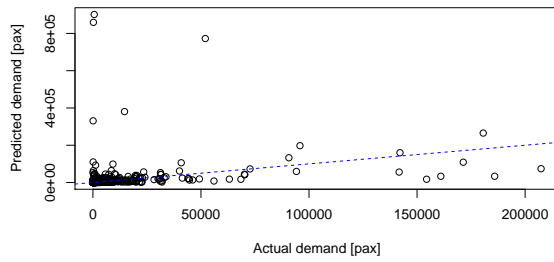
# **Prediction Accuracy Plots for Different Regression Techniques**



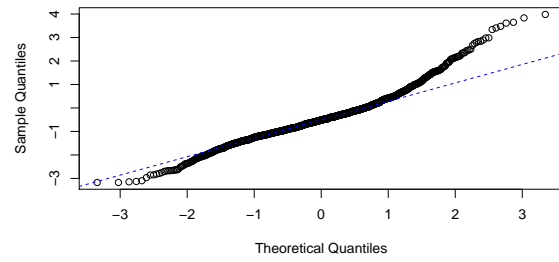
(a) Predicted vs. actual - OLS



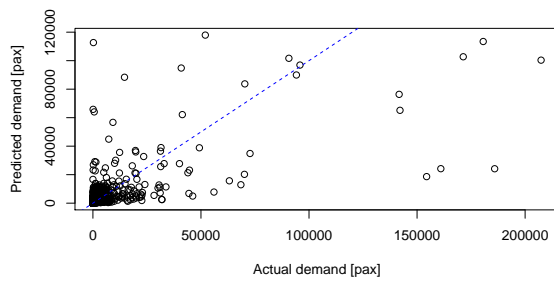
(b) QQ plot - OLS



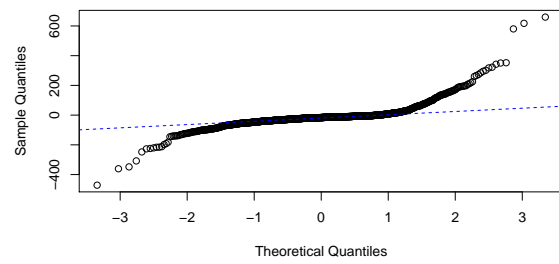
(c) Predicted vs. actual - NB



(d) QQ plot - NB



(e) Predicted vs. actual - PPML



(f) QQ plot - PPML

**Figure A-1:** Comparison of regression techniques.

## Appendix B

# Significance of Parameters for OLS, NB and PPML Regression

**Table B-1:** Significance of parameters for OLS, NB and PPML regression.

	OLS	NB	PPML
(Intercept)	−12.96 ***	−8.89 ***	−16.21 ***
$\log(CPI_{ij,t})$	0.40*	-	.98 ***
$\log(EFF_{ij,t})$	2.10 ***	1.92 ***	1.83 ***
$\log(GDPC_{ij,t})$	0.17 ***	0.34 ***	0.16 ***
$\log(POL_{ij,t})$	0.21 *	-	0.21 ***
$\log(POP_{ij,t})$	0.76 ***	0.75 ***	0.57 ***
$\log(D_{ij})$	−1.38 ***	−1.59 ***	−0.73 ***
$BOR_{ij}$	-	0.64 *	0.83 ***
$BTA_{ij}$	-	-	−0.49 ***
$COL_{ij}$	0.45 ***	0.38 ***	0.05 ***
$DT_{ij,1}$	−7.43***	−10.80 ***	−7.21 ***
$DT_{ij,2}$	−1.71***	−0.92 **	−0.36 ***
$LAN_{ij}$	0.98 ***	1.09 ***	1.24 ***
$LL_{ij,1}$	−0.62 ***	−0.76 ***	−0.60 ***
$LL_{ij,2}$	−0.97 ***	−1.28 ***	−1.26 ***

Significance codes: “\*\*\*” < 0.001; “\*\*” < 0.01; “\*” < 0.05; “.” < 0.1; “-” non significant

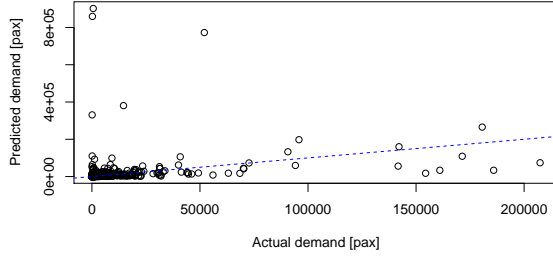




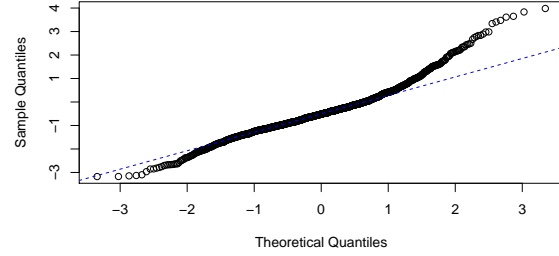
# Prediction Accuracy Plots for Data Clustered with Respect to Demand

**Table C-1:** Abbreviations used in figures C-1 and C-2.

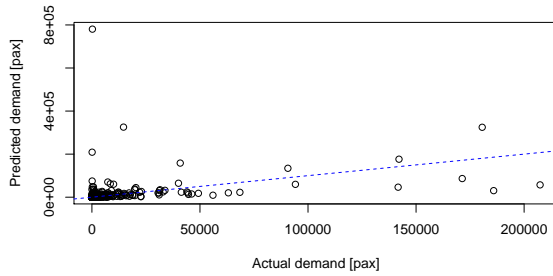
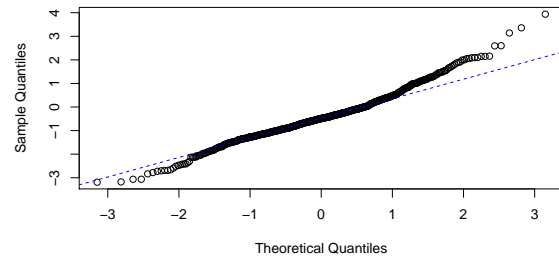
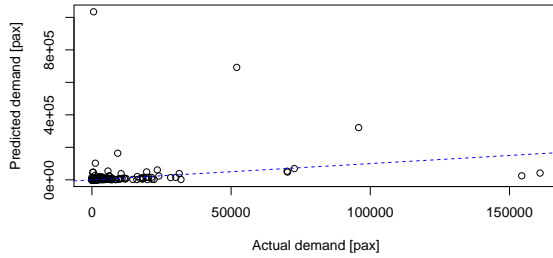
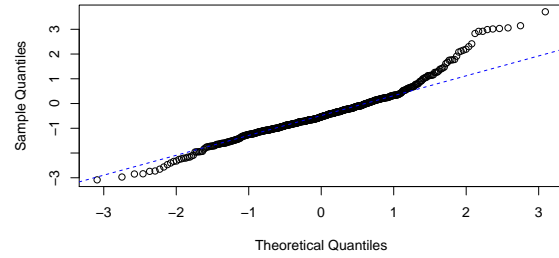
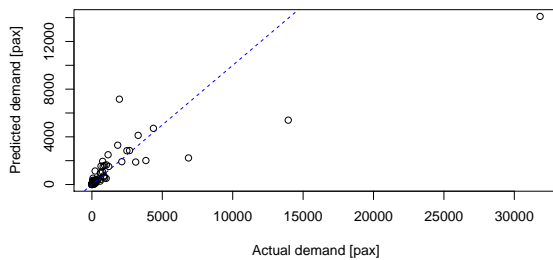
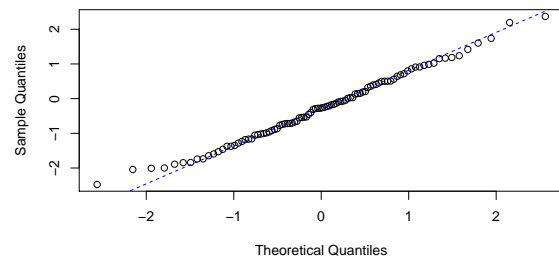
BM	Basic model
$Dem_1$	Demand $< 50$
$Dem_2$	$50 \geq \text{Demand} < 750$
$Dem_3$	$750 \geq \text{Demand} < 10,000$
$Dem_4$	$10,000 \geq \text{Demand}$
$P_1$	Both countries politically unstable
$P_2$	One country stable, one unstable
$P_3$	Both countries politically stable

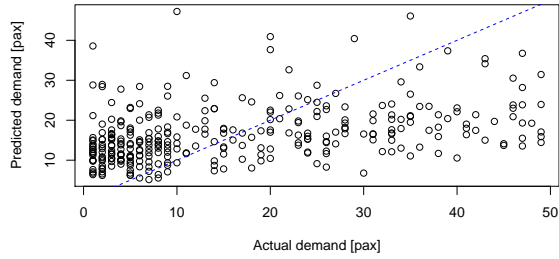
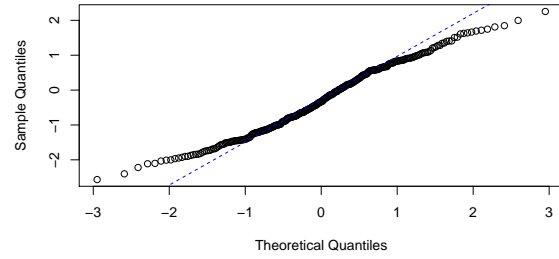
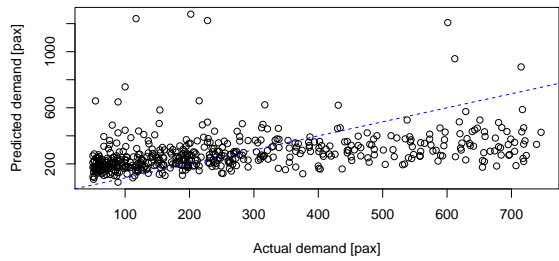
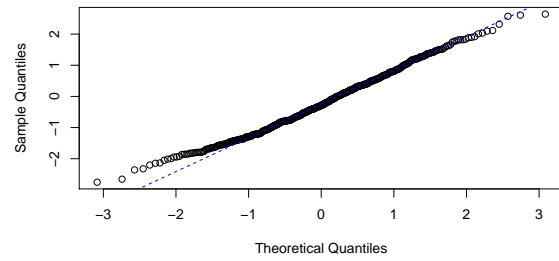
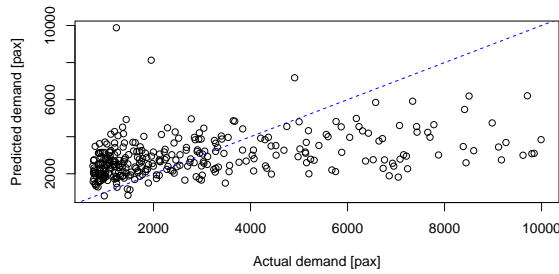
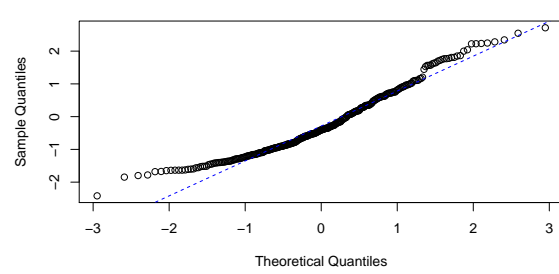
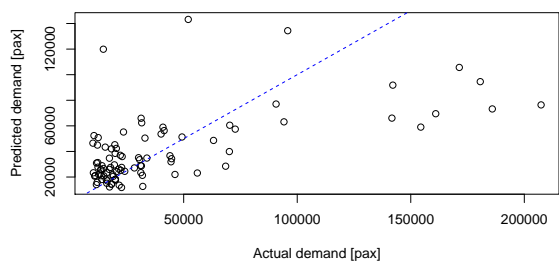
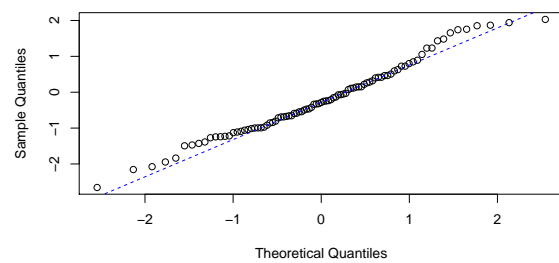


(a) Predicted vs. actual - BM



(b) QQ plot - BM

(c) Predicted vs. actual -  $P_1$ (d) QQ plot -  $P_1$ (e) Predicted vs. actual -  $P_2$ (f) QQ plot -  $P_2$ (g) Predicted vs. actual -  $P_3$ (h) QQ plot -  $P_3$ **Figure C-1:** Prediction accuracy for basic model and political stability clusters.

(a) Predicted vs. actual -  $Dem_1$ (b) QQ plot -  $Dem_1$ (c) Predicted vs. actual -  $Dem_2$ (d) QQ plot -  $Dem_2$ (e) Predicted vs. actual -  $Dem_3$ (f) QQ plot -  $Dem_3$ (g) Predicted vs. actual -  $Dem_4$ (h) QQ plot -  $Dem_4$ **Figure C-2:** Prediction accuracy for demand clusters.



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## Appendix D

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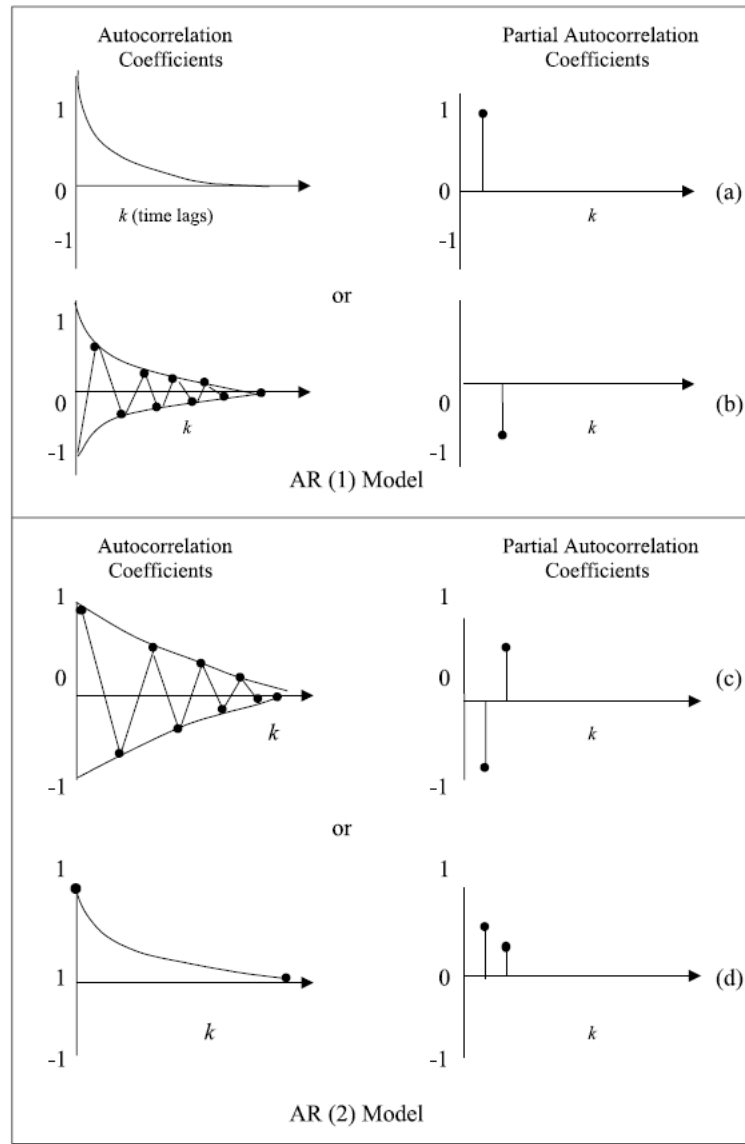
# Autocorrelation and Partial Autocorrelation Coefficients for ARIMA Models

This appendix shows how the Autocorrelation and Partial Autocorrelation Coefficients can be used to identify which AR or MA model fit the data. Table D-1 gives rough guidelines that can help in selecting a model based on the ACF and PACF statistics.

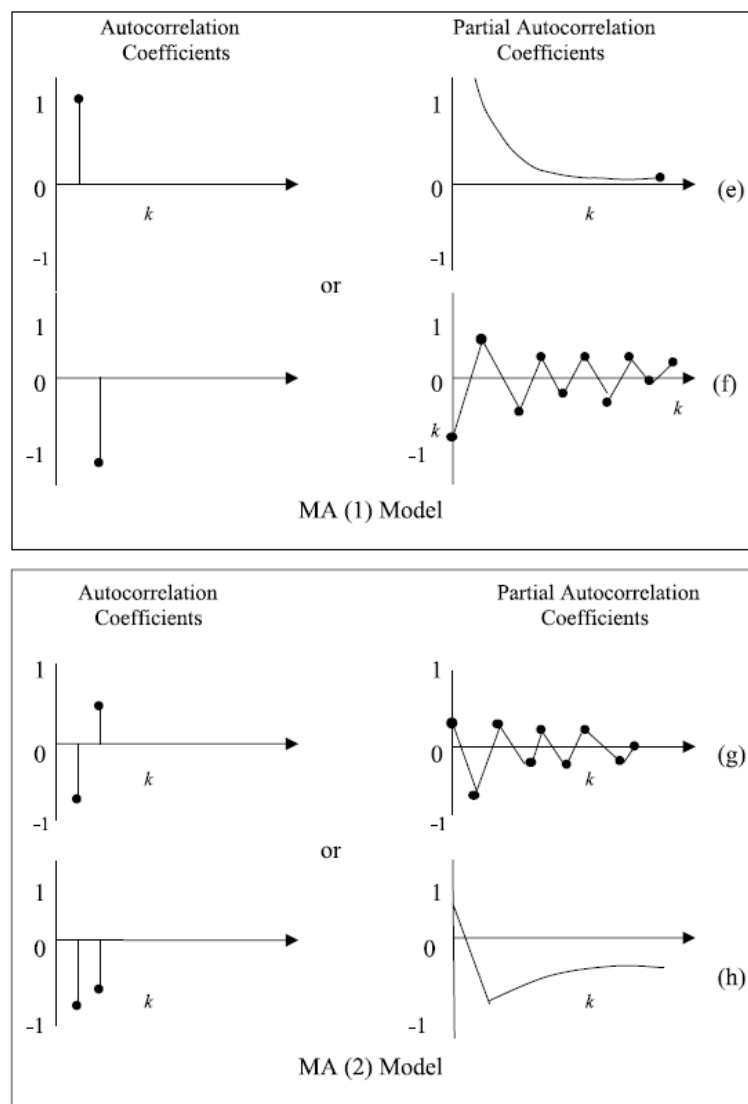
**Table D-1:** Guidelines for identifying Box-Jenkins model coefficients.

Combined ACF and PACF pattern		Possible model
Sample's ACF	Sample's PACF	
Tapering or sinusoidal pattern that converges to 0. Might alternate between positive and negative signs.	Significant values at first $p$ lags, then non-significant.	AR of order $p$ .
Significant values at first $q$ lags, then non-significant.	Tapering or sinusoidal pattern that converges to 0. Might alternate between positive and negative signs.	MA of order $q$ .
Tapering or sinusoidal pattern that converges to 0. Might alternate between positive and negative signs.	Tapering or sinusoidal pattern that converges to 0. Might alternate between positive and negative signs.	ARIMA model with both AR and MA components. Identifying involves some guessing.

Figure D-2 shows theoretical ACF and PACF distributions for AR(1), AR(2), MA(1) and MA(2). These theoretical distributions show how one can identify the type of model by looking at the ACF and PACF, based on the guidelines from Table D-1. When the ACF gradually drops to zero and the PACF drops to zero after only one or two time lags, the data should be modelled with an AR(1) or AR(2) model respectively. On the other hand, when the PACF gradually drops to zero and the ACF drops to zero after one or two time lags, data should be modelled with a MA(1) or MA(2) model.



**Figure D-1:** Autocorrelation and Partial Autocorrelation Coefficients for AR(1) and AR(2) models (Hoshmand, 2010).



**Figure D-2:** Autocorrelation and Partial Autocorrelation Coefficients for MA(1) and MA(2) models (Hoshmand, 2010).





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## Appendix E

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# Route Specific Inputs for Kenya Airways Case Study

This appendix gives the route specific inputs that have been used for the Kenya Airways network development case study. Table E-1 gives the IATA airport codes, city names, and country names for all airports that have been included in the case study. Table E-2 gives an overview of routes, together with market-specific data on distances,  $\beta$  for the market share calculation, competitor information, and return fares.

**Table E-1:** IATA airport codes, city names and country names for all airports included in the network development case study.

IATA code	City	Country	IATA code	City	Country
ABJ	Abidjan	Ivory Coast	JNB	Johannesburg	South Africa
ACC	Accra	Ghana	JRO	Kilimanjaro	Tanzania
ADD	Addis Ababa	Ethiopia	JUB	Juba	Sudan
APL	Nampula	Mozambique	KGL	Kigali	Rwanda
ASM	Asmara	Ethiopia	KRT	Khartoum	Sudan
BJM	Bujumbura	Burundi	LAD	Luanda	Angola
BKO	Bamako	Mali	LLW	Lilongwe	Malawi
BZV	Brazzaville	Congo	LOS	Lagos	Nigeria
CAI	Cairo	Egypt	LUN	Lusaka	Zambia
COO	Cotonou	Benin	LVI	Liningstone	Zambia
DAR	Dar Es Salaam	Tanzania	MGQ	Mogadishu	Somalia
DLA	Douala	Cameroon	MPM	Maputo	Mozambique
DZA	Dzaoudzi	Comoros	MRU	Mauritius	Mauritius
EBB	Entebbe	Uganda	MWZ	Mwanza	Tanzania
FBM	Lubumbashi	D.R. Congo	NBO	Nairobi	Kenya
FIH	Kinshasa	D.R. Congo	NLA	Ndola	Zambia
GBE	Gaborone	Botswana	NSI	Yaounde	Cameroon
HAH	Moroni	Comoros	POL	Pemba	Mozambique
HRE	Harare	Zimbabwe	TNR	Antananarivo	Madagascar
JIB	Djibouti	Djibouti			

**Table E-2:** Network, competitor and ticket price inputs per market for Kenya Airways case study.

Market	Distance [ <i>km</i> ]	$\beta$	$C_1$	$C_2$	$C_3$	$C_4$	Fare [USD]
JRO-NBO	233	1.700	4	21	0	0	277.58
MWZ-NBO	462	1.682	7	0	0	0	384.66
EBB-NBO	521	1.677	14	17	3	0	395.00
NBO-ZNZ	599	1.671	3	14	0	0	365.74
DAR-NBO	665	1.665	27	6	1	0	492.74
KGL-NBO	758	1.658	1	18	0	0	264.08
BJM-NBO	875	1.648	1	0	0	0	500.78
JUB-NBO	906	1.646	14	14	2	1	516.34
MGQ-NBO	1,002	1.638	3	2	1	5	243.87 *
ADD-NBO	1,157	1.625	14	0	0	0	400.22
HAH-NBO	1,329	1.612	0	0	0	0	323.13 *
NBO-POL	1,350	1.610	2	0	0	0	344.12
LLW-NBO	1,422	1.604	0	0	0	0	1026.19
FBM-NBO	1,538	1.595	0	0	0	0	1103.18
APL-NBO	1,546	1.594	0	0	0	0	826.25
DZA-NBO	1,569	1.592	0	0	0	0	381.49 *
JIB-NBO	1,580	1.591	0	0	0	0	396.98
NBO-NLA	1,580	1.591	0	0	0	0	1096.62
LUN-NBO	1,807	1.573	0	0	0	0	947.62
ASM-NBO	1,850	1.569	1	0	0	0	449.81 *
KRT-NBO	1,931	1.563	0	0	0	0	469.51 *
HRE-NBO	1,945	1.562	0	0	0	0	961.47
LVI-NBO	2,191	1.542	0	0	0	0	834.33
NBO-TNR	2,249	1.537	0	0	0	0	1247.90
FIH-NBO	2,412	1.524	0	0	0	0	1290.95
BZV-NBO	2,431	1.523	0	0	0	0	591.32 *
LAD-NBO	2,755	1.496	2	0	0	0	669.85 *
MPM-NBO	2,761	1.496	2	0	0	0	867.25
GBE-NBO	2,830	1.490	0	0	0	0	688.33 *
NBO-NSI	2,877	1.487	0	0	0	0	699.76
JNB-NBO	2,898	1.485	10	0	0	0	658.21
DLA-NBO	3,083	1.470	0	0	0	0	1145.54
MRU-NBO	3,092	1.469	2	0	0	0	872.15
CAI-NBO	3,528	1.434	7	0	0	0	858.04 *
LOS-NBO	3,834	1.409	0	0	0	0	970.17
COO-NBO	3,931	1.402	0	0	0	0	1362.77
ACC-NBO	4,193	1.380	0	0	0	0	1116.73
ABJ-NBO	4,600	1.348	0	0	0	0	1012.40
BKO-NBO	5,189	1.300	0	0	0	0	1261.66 *

\* Values estimated by  $Fare = 2 * yield * distance$

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