Airport Market Share Forecasting in Multi Airport Regions

M.B. Vintges

Delft University of Technology

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by

M.B. Vintges

in partial fulfilment of the requirements for the degree of

Master of Science
in Aerospace Engineering

at the Delft University of Technology,
Control and Operations - Air Transport Operations

Student Number:	4471547
Date of publishment:	April 13, 2022
Thesis supervisors:	Prof. dr. ir. J.M. Hoekstra (TU Delft)
	Dr. ir. B.F. Lopes Dos Santos (TU Delft)
	Ir. A. Ruiz Martin (NACO)
	Ir. K. Brinkman (NACO)

TU Delft Delft University of Technology

Preface

I did my thesis at NACO (part of Royal HaskoningDHV) in the period between May 2021 and May 2022 to obtain my MSc Aerospace Engineering title at Delft University of Technology.

I genuinely enjoyed this last part of my academic journey to put all my learnings into practice. Interactions with the NACO team as well as the Delft University of Technology team gave me more insight and guidance in this research topic. I would like to thank the following persons more specifically:

- Dr.ir. B.F. (Bruno) Lopes Dos Santos and Prof.dr.ir. J.M. (Jacco) Hoekstra from Delft University of Technology helping me find solutions to detailed modelling concepts. Without their help, it would be difficult to find the right solution to the created and designed market share results in the Greater London multi-airport region;
- Ir. Albert Ruiz Martin, Ir. Koen Brinkman and Ir. Tessel Severs from NACO who despite their busy schedules took time to help me with the project, more specific about the technical aspects of it;
- Drs. Mario van Wingerde who helped me as external coach through all aspects of this research. His guidance was immensely helpful in balancing the importance of sub-tasks, structuring the research and clarifying the style of reporting and presenting (intermediate) results.

M.B. Vintges
Delft, April 2022

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Abstract

Urbanization is a worldwide trend that drives an immense increase in air traffic demand. The worldwide aviation network makes global business possible which generates economic growth, creates jobs and facilitates international tourism and trade. Many of the world's transport hubs like The Greater London Area have allocated this demand over various airports, which forms a multi-airport region (MAR). Airport expansion plans and infrastructural investments in multi-airport regions, therefore, depend not only on the total level of air traffic growth but on its allocation. Therefore, the goal of this research is to develop an analysis framework for the market dynamics driving airport activity levels, focusing on multi-airport regions, and analyse how this provides a base for strategic decisions in the region. This goal was split into two sub-goals. First, understand the evolution of airport's market shares based on the allocation of air traffic passengers amongst airports in a chosen MAR. Second, understand the market dynamics of passenger integrated transport systems in a MAR. Forecasting its underlying determinants can provide estimates for the future transport system in a MAR, which accommodate and facilitate smooth future operations of used logistical components. Greater London was chosen as a multi-airport region.

Part one consists of a quantitative model that can compute annual air traffic demand for a multi-airport region, and the allocation of this demand over airports within, for the period 2010 - 2050. Aggregate air traffic demand is based on UK's GDP projections and the allocation model was based on the relative performance of airports in terms of their accessibility, airfares and connectivity. A multivariate regression model was applied correlating historical (2010 - 2019) airport performance to their respective market shares. The results show regional air traffic demand is likely to grow 82% over the next 30 years. Based on 60 observations, the model can predict its market shares with an R-squared of 0,952.

Part two progresses the quantitative model to generate a forecasting framework for the next 30 years for various important aviation-related variables in the region. This concludes that for London Gatwick, City and Stansted airport the projected growth in air traffic demand will not form any capacity problems, but for London Heathrow, Luton and Southend airport, it will. A major factor influencing this is the rising environmental awareness and increasing costs for carbon emission abatement. London Heathrow Airport, being UK's most important airport, together with the UK government has identified several developments to facilitate the expected growth in air traffic demand.

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1 Introduction

1.1. Background

Worldwide population has increased by 30% since 2000 and is expected to further increase by 23% to 9.7 billion inhabitants in 2050 [106]. Due to this global population growth and increased migration, the majority of this increased population will live in urban regions [97]. This so-called urbanization is one of the major worldwide trends being observed. It drives an immense increase in human transport demand, resulting in increased traffic movements, especially in urban regions. People use transport modes like private vehicles or public transport for relatively short travel distances and aircraft for relatively longer distances. To accommodate the increased demand for global travel mobility, infrastructural developments have to take place.

The worldwide aviation network makes global business possible which generates economic growth, creates jobs and facilitates international trade and tourism. The total value of goods transported by air is $6.5 trillion, representing 35% of all international trade. 45% of international tourists travel by air and the global aviation industry contributes 4.5% to the global GDP and facilitates 88 million jobs [14] [78]. Accompanying the increased travel demand has resulted in a comparable increase in available seat kilometres in the sky. However, there has been a lack of airport and terminal capacity, especially in urban regions, to allocate both the increased air traffic passenger demand and seat kilometres.

As a result, many of the world's transport hubs like Greater London, New York Metropolitan Area, Greater Los Angeles Area and Washington, have naturally allocated air traffic demand amongst multiple airports, accessible through the region's infrastructure. These regions are referred to as *Multi Airport Regions* or *MARs*. Human/passenger transport within and amongst these MARs is a result of a dynamic behaviour between the following three topics.

1. Air traffic passengers' preference amongst airports;
2. Infrastructure within the MAR;
3. Airline and airport strategy.

Comprehending and quantifying expected traffic flows in these MARs is crucial to plan infrastructural changes and airport constructions and/or expansions, and to substantiate strategic and political decisions herein. These and their investments are all based on the projected levels of utilizing passengers. It is therefore important to comprehend the evolution of the three factors driving passenger transport within a MAR and the dynamic behaviour amongst them.

Planning airport expansions are complicated, especially in multi-airport regions, where airports are part of a network serving the region. Airport capacity expansions in such regions depend not only on the total level of air traffic growth but also on its allocation amongst the alternative airports serving the region. So, as the world's population and thus demand for transport and air travel will in all likelihood continue to increase, comprehending this allocation of air traffic passengers is crucial for airport expansion plans as well as accommodating infrastructural, strategic and political adaptations in the region. This allocation also provides insight into the market shares evolution of airports serving the MAR [22, 37].

In Figure 1.1, the context of this research is visualised.

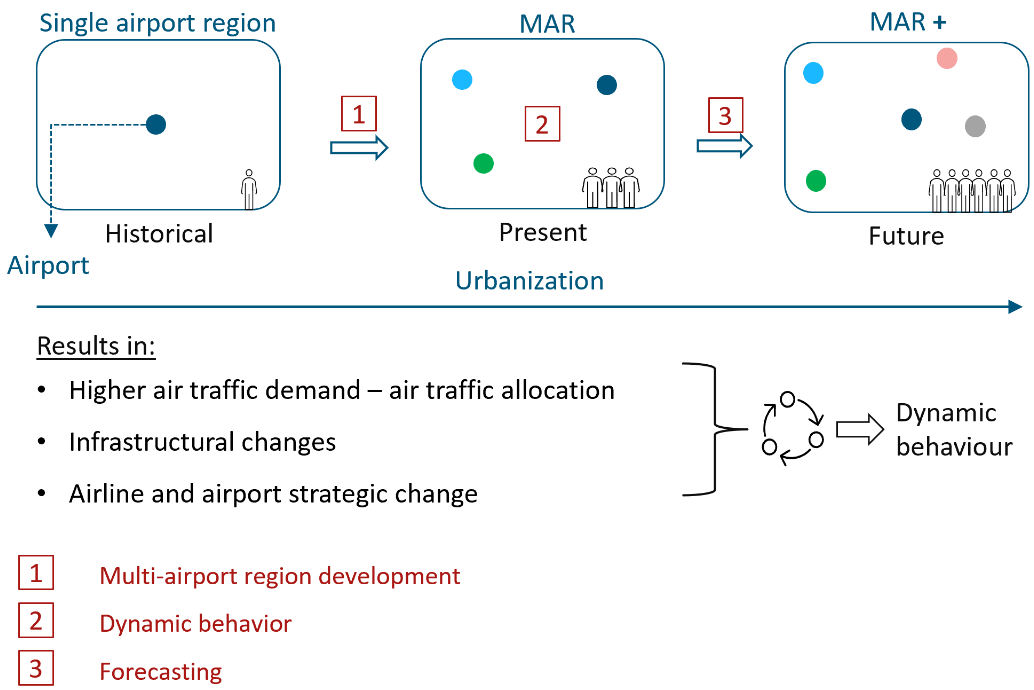

Figure 1.1: Project Context

1.2. Research Goals

The goal of this research is formulated as follows: *"Develop an analysis framework for the market dynamics driving airport activity levels, focusing on multi-airport regions, and analyse how this provides a base for strategic decisions in the region."* To achieve this, two sub-goals have been set up:

I Understand the evolution of airport market shares based on the allocation of air traffic passengers amongst airports in a chosen MAR;

II Understand market dynamics of passenger integrated transport system in a MAR. Forecasting its underlying determinants can provide estimates for the future transport system in a MAR, which accommodate and facilitate smooth future operations of used logistical components.

1.3. Report Structure

The research that has been performed to achieve these goals is explained in this report. First, a brief literature review on relevant topics is shared in chapter 2. The modelling methodology is explained in chapter 3, after which relevant aspects of the case study and illustrations of the methodology are shared in chapter 4. Its results are presented in chapter 5.

These results are used as a baseline for the forecasting framework, which is analysed in chapter 6, after which the research is discussed and concluded in chapter 7. Finally, some recommendations to potentially further enhance this research are suggested in chapter 8.

2

Literature Review

The research field of air traffic modelling is extensive and has been in place for quite some years. As urbanisation leads to increased air traffic and pressure on urban infrastructure, modelling air traffic demand has become more complex, which is the result of many airport operational and urban infrastructural operations. Many pieces of research focus on specific details of air traffic modelling. This only captures part of the equation and therefore, this research has combined and progressed several of these detailed studies to form an integrated approach to modelling air traffic demand.

In this chapter, the literature study is presented regarding air traffic modelling, relevant to achieving the goal of this research. Four major research blocks have been identified, in which this chapter is structured.

2.1. Multi Airport Region

2.1.1. Definitions

Origin and destinations are not restricted to single airports but represent urban agglomerations closely bound to an attractive centre by commerce, business or tourism. These regions are referred to as *metropolitan areas* [20]. Travelling amongst such metropolitan regions around the globe is done mainly through air travel, facilitated by airports and airlines. A multi-airport region (*MAR*) is defined as

"A set of two or more significant airports that serve commercial traffic within a metropolitan region."[24].

The size of such a metropolitan region is mainly defined using two methods. First, its population is defined as the number of people living within a fixed radius of x km from the regions' centre [20]. Second, through the geographical area that covers a combined 60-minute road access time from the airports serving the metropolitan area [148].

To provide an overview of the worldwide Multi-Airport Regions, Table 2.1 presents 12 of the world's largest, served by a minimum of four airports. Airports that are located outside the former city's boundaries are included, as they also serve the region. Military airbases without commercial traffic, heliports, and airports that only serve cargo services are excluded in this overview.

By analysing homogeneous urban and airline data, a link was found between activity in metropolitan areas (MARs) and their air traffic levels. It was found that GDP, the level of economic decision power, touristic attractions, and the distance from major air markets are more than two-thirds based on the variation in air service [49]. This seems to indicate air service and aviation activity remains profoundly rooted in metropolitan characteristics of urban regions (notably size and wealth). The same holds to a lesser extent for low-cost carriers as they are partly focused on niche markets and less expensive regional airports [49].

Therefore, it is important to comprehend the activity in these MARs to be able to describe changes in air traffic levels. This ultimately leads to a good understanding of the behaviour of passengers concerning

Multi-Airport Region	Number of Airports
United Kingdom, England, Greater London, London	6
United States, New York, New York metropolitan area, New York City	6
United States, California, Greater Los Angeles Area, Los Angeles	5
United States, Washington, Seattle	4
United States, California, San Francisco Bay Area	4
United States, Florida, Miami	4
United States, Massachusetts, Boston	4
Australia, Victoria, Melbourne	4
France, Île-de-France, Paris	4
Russia, Moscow	4
Japan, Tokyo Metropolis, Special wards of Tokyo	4
Sweden, Stockholm County, Stockholm	4

Table 2.1: Overview of Multi-Airport Regions

their mobility. Airports can be accessed using the MARs ground transportation systems. Corresponding transport modes consist of public transport, private motorised (cars), and individual active (cycling or walking). Travelling amongst these MARs is dominantly done using trains or aircraft [28, 72]. Long haul trips (1000+km), are dominantly travelled through aircraft. However, for shorter distances, faster-driving trains provide a good sustainable alternative. As many countries try to minimize their carbon emissions according to the Paris Agreement, pressure on more sustainable transport increases. This is likely to influence the aviation sector as demand could switch to more sustainable transport options like trains [129, 48].

2.1.2. Catchment Area

A relevant term in the air traffic modelling in MARs is an airport's *catchment area*, which is defined as

'The geographical area from which a facility (airport) attracts (the bulk of) its costumers' [149].

In many MARs, catchment areas overlap and thus create a region where potential air traffic passengers, based on the definition of the catchment area size, are not bound to one specific airport but have a choice [18]. Usually, airport's catchment areas are depicted by drawing concentric circles around the airports. The radii of these circles are based on an assumption of a maximum ground access time of 2 hours. This approach is easy to apply and interpret, but it results in a static visualisation of an airport's catchment area as it ignores the driving factors behind passenger airport choice: airport access times, flight frequencies and airfares. This means that it ignores the highly influential fact that airport market shares tend to decrease when one moves further away from the airport. The methodology presented in the research by Marcucci and Gatta does take the driving factors behind airport choice into account when measuring the size of airport catchment areas and the airport's market shares therein. It allows one to show how these differ by travel motive and destination and how they evolve. In addition, the methodology allows one to estimate the effects on an airport's catchment area of infrastructure improvements or improvements in an airport's service offering [95].

The research makes several relevant conclusions. First, market shares in regions further away quickly diminish. Second, as an airport offers higher service levels relative to surrounding airports, the catchment area increases. So, if airports facilitate more destinations, the catchment area increases as well [95].

A catchment area analysis like this allows airports to evaluate the spatial nature of their catchment area to understand passenger airport choice and the competitive forces in their respective hinterland regions. It identifies the regions where market share is relatively low and the reasons behind it. Airports may also use the catchment area information in their marketing efforts towards airlines. Furthermore, the methodology may be of use to policymakers as it not only provides them with information on the competitive position of airports in the OD-markets served but to assess the effects of infrastructure investments, ex-ante as well as ex-post [89, 95].

Precise analyses of airport catchment areas have been largely ignored in literature due to the lack of consistent data [149]. Many pieces of research are based on passenger surveys, which have relatively small sample sizes compared with the complete population scope of that region. So, catchment area studies have mostly been based on revealed [55, 116] but also, somewhat less often, on stated behaviour [90].

2.1.3. Transport Modes

Air traffic passengers use various transport modes to reach their desired airports. As mentioned before, these so-called ground surface access modes can be grouped into three categories; [28, 72].

I Private motorised consists of mechanised forms of non-scheduled transport that are not available for public use. Some examples of these are private cars and motorcycles, private taxis or minicabs, airline or corporate chauffeur-driven services and minibuses;

II Public transport consists of shared surface transport modes that operate to a set timetable on fixed routes and which are available for public use (like coach services, bus and rail services, and water ferries);

III Individual active consists of modes requiring physical effort/activity by an individual like walking and cycling.

The car and rail remain the most important access mode at nearly all European airports [6]. Rail consists of trains, trams and metro services and offers several benefits over cars. It is not prone to traffic jams which occur frequently in large metropolitan areas. Also, rail offers relatively high passenger capacity, frequency of rides and fast access times. Rail thereby increases the catchment areas of airports, which is beneficial for both railway and airport operators. Finally, rail offers a much more sustainable form of transport compared to cars [68].

Airport access by suburban trains is predominant in Europe (22/30 airports). Only a limited number of airports are connected to the long-distance train network. Out of these 30 airports, 9 are connected directly to the European high-speed rail network with cross-border services to neighbouring countries; Amsterdam, Dusseldorf, Frankfurt, and Paris-Charles de Gaulle [65]. These convenient rail connections allow passengers to travel faster and cheaper compared to conventional rail networks and could result in a modal shift from aircraft to trains for short-haul routes [131, 133].

Besides rail, coaches and busses are frequently used as airport access modes. Long-distance coach services are usually seen in countries where there is no rail solution. Short distance access by public transport is usually realised by buses. Additional advantages are multi-stop possibilities during the ride to the airport and general comfort. A disadvantage is often that they are subject to traffic jams in congested areas [93].

Car parking facilities at airports are an influential factor for in airports' operations. Parking fees account for a huge share of non-aeronautical revenues of airport operators. An alternative method to car parking is the ”kiss-and-ride” drop off facility. Taxis and rental companies pay fees to offer services at airports and thereby also contribute to their non-aeronautical revenues [115]. The attractiveness of infrastructural access depends not only on factors like frequency, comfort and speed but also on the availability of attractive ticketing options for travellers [41].

Airport accessibility can be understood as a measure to describe how difficult it is for potential air passengers to reach a particular airport [6], and is based on the transport modes discussed [134]. Passengers rate travel alternatives according to their subject preference which may vary according to the trip purpose (business vs leisure) and destination type (domestic, regional international (short-haul), intercontinental).

2.2. Dynamical Behavior

This section focuses on the dynamic behaviour driving passenger transport in MARs. First, literature substantiating the emergence and evolution of MARs due to their market dynamics is provided. This is done through relative case study analyses. Second, the dynamic infrastructure in a MAR is analysed. Third and final, strategic implementations in MARs are discussed, which forms a base for the strategic decisions that can be made with the modelling framework presented later in this report. An example of a strategic implementation could be integrating rail network schemes with inbound and outbound flights to support peak demand.

To emphasize its importance, passenger transport within and amongst MARs is a result of a dynamic behaviour between the following three topics:

1. Air traffic passengers' preference amongst airports;
2. Infrastructure within the MAR;
3. Airline and airport strategy.

The dynamics between these topics vary over time. Due to urbanisation, urban regions have become more densely built which restricts existing airports and infrastructural elements within to expand. Therefore, they have enhanced their operational efficiency to facilitate rising air traffic demand. Given the capacity constraints on existing major airports, the development of Multi-Airport Systems is going to be a key mechanism by which air transport operators around the world will be able to meet future demand [25, 39].

2.2.1. Air traffic passenger's preference amongst airports

To better understand how such systems and dynamics will evolve, a case study was performed on 59 airport systems worldwide [25]. This case study looked at the evolution and development of multi-airport regions, covering the development of airports, dynamics amongst airports and surrounding infrastructures. The analysis showed significant differences in the evolution of multi-airport systems across world regions:

- Europe & USA: Recent development In the United States and Europe primarily involves the emergence of secondary airports to allocate certain flights from low-cost carriers to other major hub airports. Low-cost carriers are using the existing airport infrastructure to optimize their cost structure. In the United States and Europe, protecting existing under-utilized airports will be key to meeting future demand [25].
- APAC: In Asia, MARs have generally evolved through the construction of new high capacity greenfield airports. Due to the lack of suitable airports, strong growth of traffic is perceived. In Asia, where existing under-utilized airport infrastructure is weak, and where projections of future air traffic demand are high, there is a need to develop and apply a dynamic approach to develop infrastructure for multi-airport systems [25].
- Off-shore airports offer sometimes a solution in highly populated areas with many buildings and/or caused by massive protests (like Hong Kong and Japan).

2.2.2. Infrastructure within the MAR

The development of multi-airport systems is the expression of the adaptation of the national air transportation system to capacity constraints and emergent market opportunities. As major hub airports around the world reach their capacity limits and become congested and thus over utilised, new airports merge in the region either through the construction of new high capacity airports or through the emergence of secondary airports from available and non-utilized airports. The development of multi-airport systems will be key by which air transportation systems around the world will be able to meet future demand. Not just extra airport capacity has to be created to relieve congested hub airports, but also the infrastructure around these newly used airports and their accessibility are just as important. If public transport systems and private vehicle access facilities do not match the provided extra demand of such a newly used airport, the airport will be underutilised. Another crucial thought is that urbanization will continue, so these airports and surrounding infrastructure need to be built and planned to accommodate this expected increased demand [73, 25].

Airlines generally have a considerable choice about which airports they serve, and choose according to their commercial advantage. In some scenarios, due to technical reasons, a second airport in the region will be used. This can occur when the airport's runway characteristics constrain the use of certain aircraft. A second airport is commercially attractive to airlines if it provides a good market. Airlines allocate flights to routes, utilizing large-scale optimisation programs. These are based on air traffic demand forecasts, allocation forecasts, metropolitan business levels, tourism activity and ground infrastructural supply [110].

It has been observed that the market share achieved by an airline is disproportionate to its frequency share; the fraction of the total flights it offers in a market [60, 39, 43]. An airline offering 60% of the flights in a market may, for example, get 75% of the passengers. Airlines that dominate a market will achieve higher yields and greater profits. Airlines thus try to focus their fleet on dominant markets or at least prevent competitive airlines from doing so. This is one example of the competitive dynamic that leads airlines to match flights on specific routes.

Because of this multiplier effect, the profitability of allocating any flight to a route is not determined solely by its loads. An additional flight in a major market reinforces the value of the other flights in that market. When airlines consider the possibility of allocating flights to secondary airports, they thus have to consider not only whether they can achieve competitive load factors in the secondary market, but whether there is sufficient additional traffic that will compensate for the loss in the airline's market share in the major market. This is a subtlety that analysts all too often ignore. This competitive dynamic leading airlines to match flights on routes also leads airlines to allocate flights to primary airports rather than provide service to the second airport. This is a stable result of the competitive interaction between airlines [60]. When airlines face a decision, they tend to allocate flights to secondary airports either when their primary airport is heavily congested or when metropolitan traffic is substantial enough [110].

Governments should improve surface access to new airports to attract and be able to facilitate suitable traffic to those airports. [9]. In Asia, air traffic levels are expected to experience the world's highest growth beyond 2021 [37]. However, aviation infrastructure is not keeping pace with this growth. Many Asian hubs are already operating above their planned capacity, resulting in a rapid escalation of delays since 2010. The passenger capacity of Asian hubs can be observed in Figure 2.1.

Current plans for the construction of mega-hub airports are not effective from a cost perspective and will fail to keep up with demand. Instead, many small pieces of research, from which the methodologies are confidential, have shown the government should plan more medium-sized airports to keep costs low, gain maximum operational efficiency, and build a wider aviation network, increasing the total capacity the region can allocate. This allows Asian commercial aviation to continue in its role as a key enabler of economic growth [37].

Despite these insights, airport operators and governments in Asia are competing to build the world's biggest airport, capable of allocating well over 100 million passengers annually. However, experience has shown that such size and growth lead to increased complexity, and airports suffer from significant dis-economies of scale above ±50 million passengers annually. This holds both for airport operators (CAPEX and OPEX wise) and for the airlines and passengers using them, as transport time within the airport significantly increases and becomes more complex. Simultaneously, the network advantages of such mega airports do not increase at an equal pace as their size. Therefore, Asian airport planners and operators will need to acquire capabilities in multi-airport systems or radically change how airports operate to overcome the inherent scale of mega-hubs. Not only do airport operators need to optimize all work-streams and operations at the airport, but the entire infrastructure allowing air traffic passengers to access the airport also needs to adapt. This entails scaling up train, metro and bus transport to and from the city's centre and major tourist locations. Also, public roads need to be scaled up to accommodate the increased amount of cars [37].

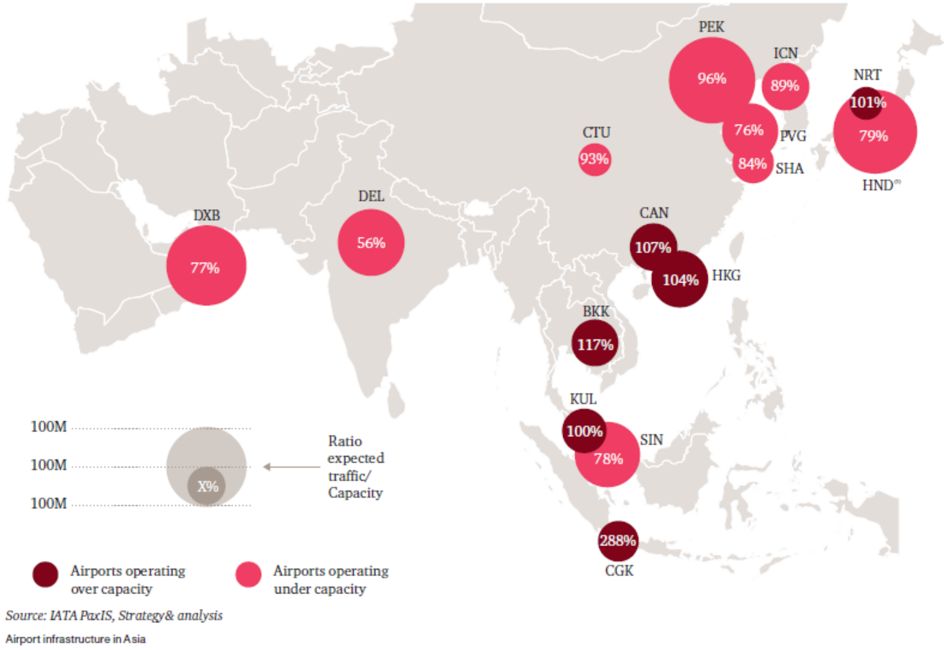

Figure 2.1: Asian Hubs in 2012

Research on the Asian aviation market suggests that government policymakers and planners in Asia consider moving beyond simply considering the provision of capacity to meet demand, and instead think through the options for providing a cost-effective travel experience for passengers [37]. Such options should take into account the following aspects:

I Surface travel distance to the airport;

II Time spent navigating the airport;

III Operating efficiencies that airlines gain with shorter taxi distances from runway to the gate as well as slots that are available to suit passenger and airline schedules.

It is expected that airports with terminal capacities from 20 to 25 million passengers and runway capacity of around 50 million passengers, namely twin independent parallel runways, will give the optimal combination of scale economy whilst allowing the majority of passengers to travel on point-to-point flights. So, air traffic demand allocation models have shown, considering the Asian region, airports with capacities of 20-50 million passengers annually will result in the most optimal operations, instead of mega-hubs with a capacity of 100+ passengers annually. This will thus stand a better chance of meeting Asia's growing demand in a way that enhances air connectivity and improves the quality of travel [37].

Sustainable surface transport modes
Simultaneously increasing the proportion of airport access journeys made by public transport and enhancing its environmental impact while accommodating growing consumer demand is a key goal for the UK to reach net-zero in 2050 [28]. Compared with earlier mentioned transport modes, public transport offers the greatest potential to reduce emissions and lessen congestion. However, there are several significant challenges associated with producing, planning, promoting and sustaining public transport services to airports. Besides needing to accommodate increasing demand, it needs to meet changing consumer needs and preferences concerning quality, speed and affordability, in an environmentally friendly yet cost-effective manner.

As mentioned before, surface access is a vitally important element of any airport's infrastructure. It materially affects investment in the local transport network, may generate congestion, almost inevitably degrades the local air quality and creates visual pollution. Surface access also directly impacts an

Airport	Long distance coach	Local bus	Busway	Mainline rail	Local rail	Light rail	Underground
Heathrow	✓	✓		✓	✓		✓
Gatwick	✓	✓		✓	✓		
Stansted	✓	✓		✓	✓		
Luton	✓	✓	✓	✓	✓		
City		✓				✓	
Southend		✓		✓	✓		

Table 2.2: Public transport modes to London Airports in 2015 [28]

airport's operational efficiency and commercial performance as airside activities rely on a continuous, unimpeded and timely flow of passengers, staff and goods accessing and egressing the site [29]. To provide a real-life example, if employees arrive late for a shift due to congestion on the approaching road or rail network, flights might be delayed or cancelled, passengers inconvenienced and the reputation of the airline and airport can be damaged [77]. Delay with the same cause can happen to passengers, who might miss their flights because of it. Therefore, airports must be able to offer a reliable, robust, safe, secure, affordable, integrated and attractive portfolio of surface access options to grow their business on the one hand while simultaneously minimising their environmental footprint on the other [29, 28]. This correlation is another example showing airports and airlines depend on a region's infrastructure through which air traffic passengers and staff can access airports.

To illustrate the available public transport services, Table 2.2 shows the situation in the London Area, one of the largest MARs in Europe.

2.2.3. Airline and airport strategy

According to a study from MIT, Air traffic passengers need to be distinguished between originating and transfer traffic [110]. Originating traffic consists of the passengers who either live in the metropolitan area or who have been there for some time. Transfer traffic on the other hand consists of the passengers who arrive at the airport by aircraft to change to another aircraft to continue their journey. Data has shown passengers routinely bypass close airports to use more distant airports that provide better service to passengers. Airlines recognize this and respond accordingly. So, airlines adapt their strategy to air traffic passengers' preferences, which in turn, are reflected in the strategy of airports. The same holds for public transport operators and other infrastructural organizations, who control public road expansions and improvements.

The six London airports' Surface Access Strategies commit them to reducing private vehicle journeys among passengers and staff and support mode shift towards the more sustainable public transport. Several policy changes have been identified in the UK and internationally to try and accomplish this. These can be split into strategic and operational policies. Strategic policies refer to long-term goals that help to implement a particular vision into specific plans and projects. These set a benchmark for monitoring progress and are designed to be measurable for performance monitoring and to help guide decision-making. Operational or tactical level policies generally operate short-term and are how broader policies are met. Operational policies are also designed to be measurable [28].

Three key strategic surface access policies and their associated operational objectives were identified from London and presented in Table 2.3. The policy's effect on the operational objective was graded with a five-grade-scale ranging from strongly positive (++) to strong negative effect (−−).

Operational	Strategic		
	Increasing service provision and attractiveness of public transport relative to private car use	Improving accessibility and information provision to travellers	Optimising existing assets and infrastructure
Marketing and promotions/incentives	+ +	±	+
Smart/integrated ticketing	+ +	+	+
Simplified fare and ticketing regimes	+ +	+	+
New technologies and alternative fuels	±	±	+ +
Upgrade infrastructure and increase capacity	+	++	− −
Improve frequency of services	+ +	++	+ +
24 h operations	+ +	+ +	++
Public transport hubs	+	+ +	+
Security and visibility of staff	+	±	±
Female only service provision	+	±	−
Discourage private cars	+ +	−	+
HOV lanes	+	±	− −
Real time information	+	+ +	±
Direct services	+ +	±	±
Dedicated services	+ +	+	±
Shared-ride vans	+	−	+ +
Wi-Fi and mobile broadband	+ +	±	±
Free travel zones	+	++	+ +
Free hotel shuttles	+	±	+ +
+ + strong positive effect, + positive effect, ± neutral, − negative effect, − − strong negative effect.			

Table 2.3: Strategic and operational Surface Access Policies for encouraging public transport use [28]

Through the use of such policies, transition to more sustainable transport modes is encouraged. However, there are numerous challenges and complexities associated with environmentally sustainable surface access provisions. These include, but are not limited to, financial and economic constraints, geographical hurdles, the seasonal nature of demand, the difficulty of getting users to accept alternatives to the private car, and prevailing regulatory and governance issues. It comes down to reducing attractiveness in comfort and price to enhance environmental impact. The challenges faced by decision-makers in this regard are perhaps exemplified no better than in the UK [28].

The growth in aviation is set to continue for the foreseeable future and as such, airport surface access will form an increasingly important consideration for airport operators, airport users and local and national authorities. This in turn has an impact on how airlines and airports must react with their strategy. Public transport has a major issue to play both in minimising the environmental impacts of surface access journeys while addressing the challenges inherent in increasingly congested road networks.

2.3. Macro Air Traffic Demand Forecasting

Air traffic demand forecasting and modelling entail computing the expected air traffic demand. This can be done in terms of air traffic passengers, air traffic movements (ATMs), or weight of cargo transported. These models can be applied at the national, regional and airport levels. This research focuses on modelling air traffic passenger demand. This section covers literature on air traffic demand modelling at macro (multi-airport regional) level, while the next section analysis literature on how this macro, or regional, demand can be allocated over airports in the region.

The air transport industry has experienced rapid growth with an average annual growth rate of almost 10% over the past 55 years. To put this into perspective economically, this equals three times the GDP growth in real terms, which is the broadest measure of world economic activity [113]. Reliable forecasts of civil aviation activity play a crucial role not just for MARs and airports, but also for airlines, engine and airframe manufacturers, suppliers, air navigation services, municipalities and other relevant organisations. To then make efficient use of forecasts developed by quantitative methods, the results must be easily understood by, and acceptable to, the decision-maker or the end-user.

Air traffic demand forecasting is important for airline management, air traffic planning and Intelligent Transport Systems (ITS) [84]. Short-term air traffic demand can be used and embedded as a Decision Support System (DSS), a valuable module in ITS. A wide range of methodologies and techniques were developed for short-term air traffic demand forecasting, depending upon the type of acquired data and the potential use of forecasting [118]. An example of short-term air traffic demand forecasting can be the forecasting for the next few months, given a time series of the previous month's air traffic demand. Here, historical data are collected and analysed to utilize a forecasting model. Then, this model is extrapolated for insight into future values of air traffic demand [159].

Different computational techniques are used for different forecasting horizons; short-term, medium-term or long-term, which depend on their intended use [113]. Short-term forecasts are up to 1 year, and medium-term forecasts are forecast for the coming 1 to 5 years. Long-term forecasts are for more than 5 years. Short-term forecasts generally involve some form for scheduling, which may include for example the seasons of the year, of planning purposes. Medium-term forecasts are generally prepared for planning, scheduling, budgeting and resource requirement purposes. Long-term forecasts are used mostly in connection with strategic planning to determine the level and direction of capital expenditures and to decide on ways in which goals can be accomplished [113]. In general, forecasting methods can be grouped into four categories:

1. Quantitative or mathematical;
2. Qualitative or judgemental;
3. Decision analysis (combination of quantitative and qualitative);
4. Artificial Intelligence.

In general, forecasting techniques that start with historical data and develop a forecast based on a set of rules fall into *quantitative methods*. Situations in which such data are not readily available or applicable and in which experience and judgement must be used are best suited for *qualitative methods*. *Artificial Intelligence* techniques are given their section despite their partial overlap with quantitative (causal) methods because their application can vary from that of quantitative methods. To provide structure to this section, Figure 2.2 shows an overview of air traffic demand forecasting methods.

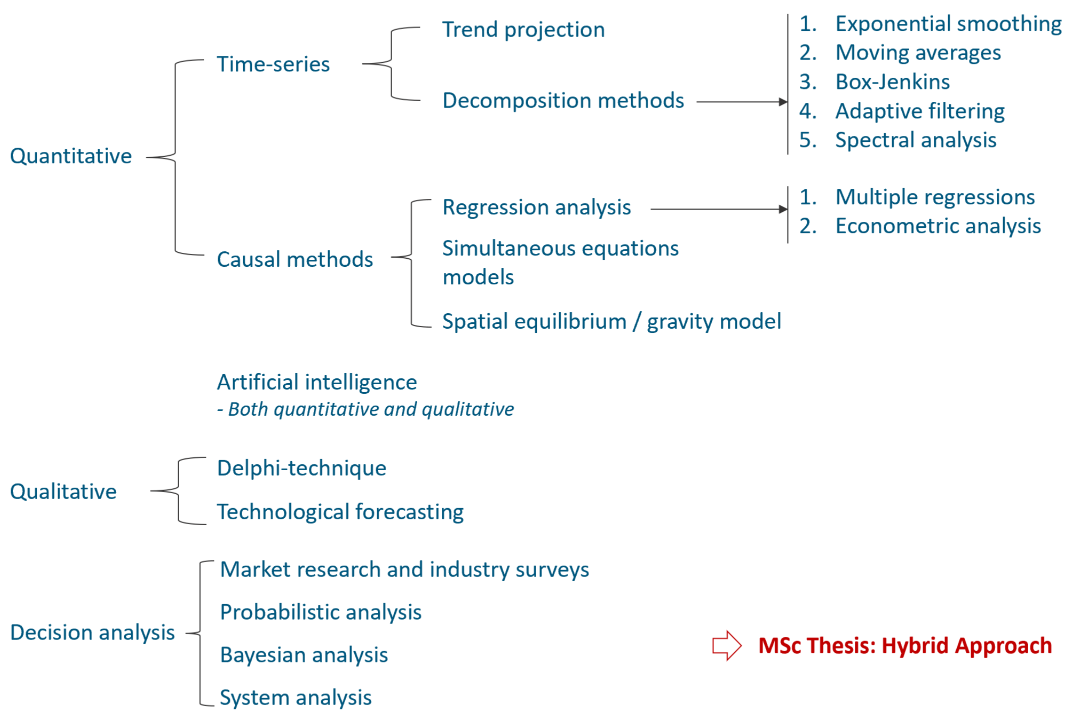

Figure 2.2: Air traffic demand forecasting techniques

2.3.1. Quantitative Forecasting Methods

For quantitative forecasting methods, there are two subcategories; time-series analysis and causal methods [113]. Time series analysis is where forecasts are made based on data comprising one or more time series. A *time series* is a collection of observations made sequentially through time [32]. Causal methods infer a cause-and-effect relationship [113].

Time Series Analysis

Two methods fall under time series analysis as can be seen below [113, 46, 47, 102].

1. Trend Projection:
   Here, historical trends in traffic developments are extrapolated to derive forecasts. It is assumed factors that determined historical traffic developments will continue in the future as well.

2. Decomposition methods:
   This involves dissecting the time series in components to account for seasonality, trend and cyclical patterns in historical data.

Causal Methods

Trend projecting and decomposition methods have been proven to be reliably for short-term air traffic forecasting. However, this type of forecasting is likely to be unreliable and theoretically difficult to substantiate for long-term forecasts. Consequently, forecasts derived by taking into account how economic, social and operational conditions affect the development of traffic offer an alternative to time-series analysis. Causal methods can predict the ups and downs of the market via their analysis of cause and effect relationships. It evaluates whether the relationship of the dependent variable to the independent (explanatory) variables is significantly related to the movements of these variables. These methods fall under this category:

1. Regression Analysis: [142]
   This is the most popular method of forecasting civil aviation demand and can take into account multiple explanatory variables. Multiple regression analysis with a price-income structure is generally referred to as econometric modelling. The starting point of such econometric analysis is a regression equation model that postulates a causal relationship between a dependent variable and one or more explanatory variables. The dependent variable is generally historical air traffic and its relationship with the explanatory variables is expressed as its elasticity [142, 113].

2. Simultaneous equations models: [91]
   These involve multiple equations where their variables simultaneously satisfy all of them. For example, suppose demand (D_0) for air traffic can be expressed as a function of price, income and level of service offered (LOS). The level of service itself can be expressed as a function of lagged demand, airline competitiveness and network effects. On the other hand, supply can be expressed as a function of lagged demand, price and operating costs. To represent and model this simultaneous causality, econometricians have developed simultaneous equations models.

3. Gravity models (spatial equilibrium):
   Demand between two cities is directly proportional to the population of the two and inversely proportional to the square of the distance between them [113]. The population is a measure of attractiveness, and the distance is a measure of impedance (resistance) [27]. These models have been refined using airfare, time and other factors to allow for the impedance effect and using a truncated population above a predetermined income level to represent those who would be potential candidates for air travel. Another name for such methods is 'air traffic distribution models'.

   Interesting adaptations to gravity models try to estimate a relationship between air traffic demand and relative shares of other transport modes when accessibility of service by different modes is available for the route concerned [35, 113]. For air transport demand, variables such as distance, travel time, level of service, and accessibility of service by other modes of transportation have been used. Another procedure to develop route group or city-pair forecasts is to express the traffic flow concerned as a share of the total market and to use the market share and historical growth patterns to ensure consistency between the city pair and the total market forecast. The underlying assumption of this procedure is that each city pair's share of the total approaches its eventual share of the market asymptotically, taking into account the concept of market maturity, where applicable.

4. Other variations of causal methods:

   (a) Lagged variables and distributed lags:
   A casual relationship where the influence of a change in an explanatory variable is expected to spread over a longer time is called the *'the distributed lag effect'*.

   (b) Stepwise regression:
   This procedure has been developed to enable the analyst to search through a list of possible explanatory variables to select those which provide the best regression model.

   (c) Air traffic distribution models:
   These models are used to forecast air traffic demand between designated airport pairs, city pairs and/or country pairs. Socio-economic factors, demographics and other relevant factors including economic characteristics of the cities themselves for the market concerned should be taken into consideration. Also, supply-side factors such as the level of service available between origin and destination can come into play.

2.3.2. Qualitative Forecasting Methods

All forecasting techniques discussed so far have assumed that historical observations are available, and they present an underlying pattern. Qualitative forecasting methods are used when such data is sparse or not available at all, and can be split up into two main forecasting techniques, namely the *Delphi technique* and *Technological Forecasting*.

The Delphi Technique is a spatial procedure for forecasting by the consolidation of opinions in the future. This entails bringing together information from many experts and moving towards a consensus among them. The Delphi Technique is defined as *"a way of obtaining a collective view from individuals about issues where there is no or little definite evidence and where opinion is important. The process can engender group ownership and enable cohesion among individuals with diverse views. It is an iterative questionnaire exercise with controlled feedback from a group of anonymous panellists. The design avoids the often counterproductive group dynamics that can occur where individuals are swayed or intimidated by others but allows panellists to reappraise their views in the light of the responses of the group as a whole."* [150].

Technological forecasting attempts to generate new information about future systems and performance. This method can be categorised into two categories; explorative and normative. Explorative technological forecasting uses the current basis of knowledge to broadly assess future conditions. Normative technological forecasting techniques start with assessing future goals and objectives and work backwards to determine the necessary developments to achieve the desired goals [113]. Technological forecasting, in general, applies to all purpose-full and systematic attempts to anticipate and understand the potential direction, rate, characteristics, and effects of technological change, especially invention, innovation, adoption, and use. Any individual, organization, or nation that can be affected by technological change inevitably engages in forecasting technology with every decision that allocates resources to particular purposes [53].

2.3.3. Decisions Analysis Methods

Decision analysis should be considered as a combination of both quantitative and qualitative analysis methods. Here, the analyst's judgement is used in preparing forecasts for a particular area of expertise in combination with some statistical or mathematical techniques including subjective inputs or probabilities. Decision analysis methods can be divided into four techniques as shown below.

1. Market Research and Industry Survey:
   Traffic forecasting through market research survey aims at analysing the characteristics of the

air transport market to examine empirically how the use of air transport varies between different sectors of the population and different industries [126, 62]. These results in combination with forecasts of socio-economic changes may indicate the likely future development of air transport [113].

2. Probabilistic Analysis:
   Having a distribution of possible outcomes for a variable can provide a more realistic outcome, and the range of the forecast can be assessed based on subjective probabilities. A simulation technique often used here is called Monte Carlo simulation [45, 99, 161, 40, 155]. Monte Carlo methods are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. Monte Carlo simulation differs from traditional simulation in that the model parameters are treated as stochastic or random variables, rather than as fixed values. So, the underlying concept is to use randomness to solve problems that might be deterministic [23]. This technique can also be applied to the performance of transport modes in metropolitan regions [7].

3. Bayesian Analysis:
   Forecasts based on subjective input and probability estimates require the use of an analytical model that is generally referred to as Bayesian analysis. It can improve a prior estimate using new data or using conditional regression, which is a method for using objective data to refine prior estimates of the regression coefficients. In this method, coefficients of one of the explanatory variables can be assigned based on an a priori basis and the coefficients of the other variables can then be re-estimated. This iteration can be repeated until all relationships have been estimated [36, 71, 70].

4. System Dynamics:
   This is used on large-scale computer models where there are many integrated mathematical algorithms. Such a method can be used to simulate the behaviour of the system concerned in response to certain variables. For example, an increase in demand increases the load factor when supply (capacity) remains stable and, in turn, increases airline revenue. This increase in demand reduces unit cost, which is a condition to reduce average fares and further stimulate demand, which in turn will increase the supply offered [147].

   System dynamics frameworks can be used to model, analyse and generate scenarios to increase the system's performance because of their capability of representing physical and information flows, based on information feedback control that is continuously converted into decisions and actions. It is found that airfare, level of service, GDP, population, number of flights per day and dwell time play an important role in determining the air passenger volume, runway utilization and total additional area needed for passenger terminal capacity expansion [143].

   A study regarding system dynamics for market forecasting and structural analysis in the aviation industry has led to some interesting conclusions. First, system dynamics models can provide more reliable forecasts of short- to mid-term trends than statistical models, and thus lead to better decisions. Second, system dynamics models provide a means of understanding the causes of industry behaviour, and thereby allow early detection of changes in industry structure and the determination of factors to which forecast behaviour is significantly sensitive. Third and final, system dynamics models allow the determination of reasonable scenarios as inputs to decisions and policies [92].

2.3.4. Artificial Intelligence

Definition

The literature describes also the use of artificial intelligence techniques in air traffic modelling. It overlaps with the previously discussed methods like regression and is increasingly used for complex forecasting models. Neural networks reflect the behaviour of the human brain, allowing computer programs to recognize patterns and solve problems in the field of AI, machine learning and deep learning. Neural networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs), are a subset of machine learning and are at the heart of deep learning algorithms.

Their name and structure are inspired by the human brain, mimicking the way that biological neurons signal to one another [51].

Artificial neural networks (ANNs) are comprised of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network. Neural networks rely on training data to learn and improve their accuracy over time. However, once these learning algorithms are fine-tuned for accuracy, they are powerful tools in computer science and artificial intelligence, allowing us to classify and cluster data at a high velocity. Tasks in speech recognition or image recognition can take minutes versus hours when compared to manual identification by human experts. One of the most well-known neural networks is Google's search algorithm. [51].

Deep learning and neural networks tend to be used interchangeably in conversations, which can be confusing. The "deep" of deep learning is just referring to the depth of layers in a neural network. A neural network that consists of more than three layers, including input and output, can be considered a deep learning algorithm. A neural network with two or three layers is considered a basic neural network [51].

Artificial neural networks for air traffic modelling
In recent years, air traffic demand forecasting literature has seen remarkable growth in research papers using Artificial Neural Networks, from now on referred to as ANNs. ANNs are primarily used when non-linearities occur in the data and have been used more often for complex phenomena in forecasting modelling. It is a common belief that ANN methodology provides a robust potential for modelling, analysing and forecasting, compared to traditional time series and econometric models [83, 156].

To provide confidence in the effectiveness of ANNs in real-time modelling and forecasting in air traffic demand, three questions are relevant:

1. Is ANN able to model and yield competent forecasting performance for monthly air traffic demand?
2. Is the empirical forecasting approach a simplified and efficient methodology?
3. Can this methodology be incorporated as a DSS (decision support system) in an ITS (Intelligent Transportation Systems) for one-step-ahead real-time forecasting?

The following literature examples are described:

- Pamula investigated if short term forecasting could be used in traffic control systems when incorporated into modules of ITS. The study aimed to examine the impact of time window length (20, 30 and 40 min) and days of the week on the quality of forecasting and to find the best model for short term forecast of traffic flow [118].
- Zhang and Qu state that ANNs are not able to compute seasonally or trend variations effectively with "un pre-processed" raw data and either de-trending or de-seasonalisation can dramatically reduce foresting errors [159]. A study that identified differences and similarities between ANNs and statistical methods concluded that complex nonlinear tools have both advantages and limitations, and frequently simpler models can give as good results as complex ones, depending on the data [82].
- Raeesi et al. used feedforward neural networks for traffic time series forecasting. The input of the neural network is the time delay data, exported from the road traffic data system of Monroe City and the performance of the ANN is validated, using the real observation data of the 301st data, from the past 300 days of traffic data [130].
- Spisaeng et al. focused on forecasting Australia's low-cost carrier passenger demand and RPK (revenue passenger kilometres) using traditional econometric and ANNs methodologies. It concluded that when comparing the forecasting ability of the two techniques, ANN responded the better performance than the multiple linear regression approach [141].

- Profillidis et al. analysed how modelling and forecast of future air transport demand can be conducted with the application of AI and particularly of the method of ANN. The method of ANN is used in the paper to model and forecast future air transport demand concerning the evolution of gross domestic product (GDP) and other driving forces of the problem, for mature and developing air transport markets [127].

- Research by Kolidakis aimed to test the robustness of an empirical computational intelligence model in one month ahead air traffic demand forecasting for the airport of Sydney (Australia). Results reveal the method achieves an impressive and remarkable low difference (2,20%) between measured and forecasted accumulative traffic demand for the period January 2018 to August 2018 [84]. The proposed methodology is characterized by high flexibility, comprehensive operation and low requirements for computational resources. Therefore, it can be used by modern utilities and transportation operators while it can be embedded in Intelligent Transport Systems, enabling proactive decisions to mitigate the economic and environmental impacts of extended transport systems congestion.

Air traffic demand series are volatile and can be influenced by a diverse group of variables. The results are essential for regulatory authorities, decision-makers, local and national authorities, and transportation system engineers. Accurate results for air traffic demand forecasts are crucial for decision-making strategy in the short-term horizon, as well as for long-term planning towards supporting decision-makers for transport systems planning and maintenance.

According to the literature, Artificial Neural Networks is a method providing applications in various scientific areas. It can take into account great amounts of data and simulate non-linearities and complex situations. Also, ANNs provide real-time results, have a high degree of flexibility, adaptability and generalization, and operate empirically. All of these features of ANN impress and attract many scientists in the forecasting field.

2.3.5. Forecasting for aviation planning

This subsection presents (forecasting) methods specifically for aviation, air navigation, airport and airline planning purposes.

Air Navigation Systems Planning

For air navigation systems and organisations, traffic forecasts and peak-period parameters are important in anticipating where and when congestion occurs. This section provides an overview of the methodology developed by ICAO and its regional traffic forecasting groups in the generation of these forecasts.

Crucial information for air navigation planners is estimates of expected aircraft movements. Estimates of aircraft movements may be obtained by simple trend projection techniques, using historical aircraft moving data and prolonging this trend into the future. However such forecasts are valid only for a very short term. Therefore, projected air traffic passengers are converted into aircraft movements taking into account the fleet mix and load factors [113].

Seasonality results in volatile traffic demand throughout the year. Also, daily traffic distributions vary significantly by the hour of the day. In markets with high seasonality patterns, peak-period patterns provide key information to determine areas of congestion that might occur in the airspace as well as in airports, which help with accurate future planning [113].

Modelling this seasonality and peak-period patterns is something that has not been researched thoroughly in literature due to a lack of consistent data. This can be overcome through modelling spatio-temporal dynamics in airports' catchment areas [148]. Air traffic demand varies by time of day, day of the week and seasonally, which results in varying airport access times accordingly [148]. Airport accessibility is a key decision variable for airport choice by air traffic passengers [73, 81]. An analytical framework was setup that explores the spatio-temporal variability in catchment areas of MARs, which is done through three steps:

I Analyse the geographies of access time by road to the different MAS airports;

II Parameterize MAR airport utility based on pricing, connectivity characteristics, and on-time performance and use this information as input to;

III A Huff model to calculate different airports' attractiveness and associated catchment areas at the level of census block groups [148].

This resulted in the importance of complex patterns of traffic congestion as well as seasonal variations in airport fare structures.

Airport Planning
Traffic forecasts provide criteria both for airport facility and financial planning. They are necessary to determine future airport capacity requirements. Peak demand must be determined to evaluate facility requirements since airport capacity becomes most critical during daily and hourly traffic peaks. The expected number of aircraft movements is a crucial determinant for runway, taxiway and apron requirements. The following planning parameters are commonly required:

1. Annual airport passengers categorized as international (scheduled or non-scheduled) or domestic, originating or terminating, and transiting or transferring;
2. Annual aircraft movements by type of operations (international commercial, domestic commercial, general aviation, military);
3. Peak-hour passengers by various categories;
4. Peak-hour aircraft movements by size/type;
5. Number of airlines serving the airport;
6. Number and type of aircraft requiring maintenance and overhaul services at the airport;
7. Number of visitors to the airport;
8. Number of employees at the airport;
9. Freight and mail traffic.

Terminal planning is assisted by breaking down passenger forecasts into passengers using the arrival and departure facilities and passengers using transfer or transit facilities. Driving factors for the number of originating/terminating passengers at an airport differs for direct transit and transfer passengers. Therefore it is important to analyse and forecast these traffic categories separately.

Aircraft movements are generally grouped into commercial air transport (for carriage of passenger and freight traffic), general aviation (flying training, private and business flying, aerial work), and military movements. Although it is wise to take historic trends in movements into account, a proven-to-be more accurate approach is to compute aircraft movements forecasts from passenger traffic forecasts and assumptions about the future load factors and aircraft sizes. There are no universally accepted definitions for modelling peak period traffic. Generally, ratios are applied of busy period traffic to annual traffic [113].

Airline planning
The airline planning process is influenced by the results of planning in other civil aviation sectors, particularly as reflected in the capacity of the aviation infrastructure, the products of the equipment manufacturers, and government policy. The airline's share in a given market depends on several factors. Traffic rights granted by governments in so-called bilateral agreements provide the basis for the operation of an airline's scheduled route system, the expansion of operations and the serving of new routes. The demand for air travel on particular routes is largely a function of traffic generating factors like population and economic conditions, price, and service levels [113]. Another factor driving demand is the relative attractiveness of competing destinations and other transport modes.

Fleet planning is described as the act of determining future fleet requirements and the timing of aircraft acquisition. Fleet planning considers the following;

1. Airline goals and objectives;
2. Passenger and cargo traffic demand;
3. Service pattern impact on market share;
4. Aeroplane performance;
5. Operating economics;
6. Operational and other system requirements.

This planning process can be complex because of a few main reasons. First, passenger and cargo traffic continue to increase as a result of urbanization, as mentioned in Chapter 1. Second, aircraft types and configurations that become available are changing and improving rapidly. Third, routes structures, traffic rights and airline competition changes and finally, financial results remain the driving factor for airlines and can frequently push the airline planning to adapt.

There are many methods to compute the market share of an airline. IATA has developed a computational method to estimate the market share, knowing the total market, as can be seen in Equation 2.1.

$$(M.S.)_x = \frac{F_x}{F_t} \tag{2.1}$$

where:

$(M.S.)_x$ = Market share of airline x
F_x = Frequency offered by airline x
F_t = Total frequency offered by all airlines serving the market

Another computation taking into account more variables is shown in Equation 2.2.

$$(M.S.)_x = \frac{F_x \cdot C_x \cdot S_x \cdot P_x \cdot A_x}{\sum F_t \cdot C_t \cdot S_t \cdot P_t \cdot A_t} \tag{2.2}$$

where:

$(M.S.)_x$ = Market share of airline x
F = Frequency offered by airline x
C = Total frequency offered by all airlines serving the market
S = Stop factor
P = Average price
A = Airline's market appeal
x = Airline x
t = Airline servicing the market; t takes values 1, ..., n

As trip distance increases, the importance of non-stop flights and flight frequency decreases. Airline related factors include the airline's position in the market, consumer preferences for the airline due to frequent flyer programs and passenger service on its own. These are all factors that also come into play for long-range markets.

2.4. Air Traffic Demand Allocation

Many factors drive people to choose a certain airport, from which an allocation and relative market shares of the airports in the region can be modelled. In modelling air traffic passengers' preferences, a distinction has to be made regarding the type of passenger and their trip purpose. For example, business travellers assign more weight to access time and flight schedule than they do to airfare in comparison with leisure travellers [117]. Also, passengers living in the airport's region have more knowledge of accessible infrastructure than cross-border passengers or foreign travellers.

Passengers choose airports that are more attractive to them [42]. This airport attractiveness is characterised by attributes that aim to represent both its accessibility and utility. An airport's accessibility is based on the infrastructure and transport systems through which passengers can access the airport from their original location in the MAR. The airport's utility is based on the service and utility passengers can experience by using that airport. This includes aspects like pricing, connectivity characteristics, and on-time performance [148].

According to classical transport literature, each region has the potential for generating passenger trips that are allocated among available destinations in proportion to their respective attractiveness. The drawback of this approach is that it overlooks potential substitution between markets and can lead to over and underestimation of trip-end totals [20]. If there are similarities in destination and travel purpose, passenger demand will switch. If nests of comparable alternatives are present, demand switching does not happen equally over all alternatives. For example, if transport modes metro, train and car are the available alternatives, the metro and train are in the same nest of alternatives, namely public transport. and the car is not. An increase in metro ticket prices will predominantly result in passengers switching from metro to train, rather than from metro to the car, because train and metro are comparable modes. Taking into account these nests of alternatives can be done via mixed logit modelling [19].

G. Harvey was one of the first researchers who started analysing the behaviour of air traffic passengers in choosing among departure airports in a multi-airport region [73]. Data from a 1980 survey of passengers in the San Francisco Bay Area were used to study the characteristics of airport choice for residents. To model the choices of air traffic passengers, a multinomial logit (MNL) model was used. Ground access time and frequency of direct air service to the chosen destination can account for a large portion of the variation in airport usage patterns. The model is based on a hierarchy of choices that are made during the planning process. In Figure 2.3, this can be observed.

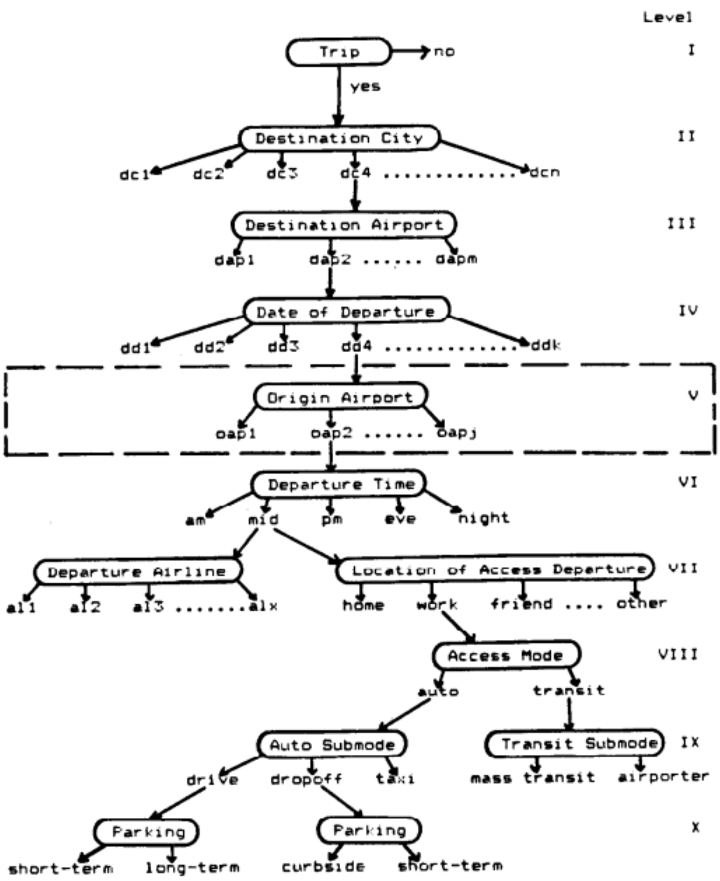

Figure 2.3: G. Harvey choice hierarchy [73]

The distinction is made between the origin of passengers, either being residents or non-residents, and between travel purposes, either being business or leisure travellers. These two distinctions are necessary for choice patterns to be detected. The MNL model computes elasticities in regards to decision variables; access time (min), frequency of flights (per week) and airfare (dollars). The results are shown in Table 2.4.

	Coefficients of:		
Traveller types	Time	Frequency	Fare
Business	-0.1	0.003	-0.4
Leisure	-0.1	0.02	-0.08

Table 2.4: Results Harvey's choice model [73]

The negative sign means an increase in such variable results in a decrease in air traffic demand. Both literature prior to and results of this research conclude that access time and schedule convenience are strong determinants for airport choice. They, therefore, suggest modelling airport choice on such decision variables. The results also conclude the importance of ground access in planning for multiple airport systems and the difficulty of predicting airport attractiveness use without information about market-specific airline schedules [73].

To date, the categorisation of residents vs non-residents and leisure vs business travellers has been used, with the latter categorisation usually being extended with VFR (visiting friends and relatives). Besides, all the choice dimensions as shown in Figure 2.3 are still used in modern pieces of research concerning air traffic modelling, but not in form of a choice hierarchy. Stated and revealed choices are used as input and their impact/importance on the explanatory variable is computed, resulting in weights instead of a hierarchy where a certain choice is made before the other. The same can be applied to the research following this literature review; not using a hierarchy but computing airport attractiveness levels based on the influence level of a choice dimension. Besides, the structure of this choice hierarchy will be used to define boundary conditions of the airport attractiveness model. If passengers aim to travel to destination x on date y, and certain airports do not provide options to fly to x on date y, this choice option will be removed from the choice set.

Air traffic demand is to be generated and allocated [20]. Demand generation refers to the estimation of total air traffic flows and demand allocation involves the study of underpinning the distribution of passengers over available travel itineraries within a specific market. Air demand generation is typically modelled via a gravity formulation approach in which travel demand between city pairs is assumed to be positively proportional to the mutual attraction factors of the respective cities and inversely proportional to the generalized cost of travel between them.

In the study by Birolini et al., a distinction is made between pull factors that attract passengers and push factors that supply passengers. Attractor factors depend on regional, geographical and socio-economical characteristics (demand-side characteristics) such as income and population. Supply factors are used to model the ease or difficulty of travelling between regions. Their study analysed how modifications to itinerary attributes can impact air trip generation and demand stimulation, and the substitutability between destinations at different travel lengths [20].

Passengers have a choice between airports within a MAR [44]. Interesting research for the New York Bay Area airports covers the spatio-dynamics in the airport's catchment area. The choice of an airport in a MAR is rooted in understanding the airport's catchment area [148]. Travel time by car is the key decision factor that results in an airport decision [81, 73]. Passengers envisage longer travel times to the airport as an increasing risk to miss their flight. Therefore, the travel time to the airports, which partly determines the accessibility, is a dominant decision variable in most airport choice models [121, 134, 76]. Koster et al. developed a mixed logit model to measure the effect of airport access travel time variability on access travel cost [85]. Both business and leisure passengers are sensitive to higher travel time costs when accessing an airport.

As mentioned before, there are two sets of considerations that make an airport more attractive than others [121, 42];

1. Its Accessibility;
2. Its Utility.

From this, a huff model can be made that calculates gravity-based probabilities of costumers at each origin location choosing a facility, a particular MAR airport, from all potential facilities (all MAR airports). Accordingly, catchment areas are geographical areas from which a facility attracts the bulk of its customers. Many research examines airport choices based on surveys. This method has three major drawbacks that need to be mentioned. Firstly, they are costly, proprietary or unavailable for analysts doing the research. Secondly, surveys reflect the interest of airports and airport planners instead of the interests of researchers. Thirdly, MAR is context-dependent, and without generalising, makes comparing difficult. Because of the latter drawback, generalising an airport demand forecast is extremely difficult as the majority of the input parameters are geographically specific and therefore not able to be applied over different regions [148].

Loo found that access time was statistically significant in modelling airport choice in a MAR, whereas the number of access modes, access costs, and queue time at check-in counters was not [90]. Surveys have shown airfares are often more important than service. Because of this reason, rising low-cost carriers have become increasingly popular as they serve popular routes for relative low fares. Especially leisure travellers who go on vacation prefer to travel with these airline companies. For business travellers, airfares are not as important as for leisure travellers because they usually do not pay for their trips themselves and leisure travellers do [21, 125, 56]. To quantify this preference gap, it has been found that 60% of leisure passengers and 45% of business passengers rate ticket fare as the most important factor when choosing a flight [160].

Passengers are willing to travel further for better fares [50, 145, 66]. Another interesting trend being observed is the rate of passengers switching to a new airline or airport is considerably higher for those with recurring delay or cancellation experiences [144]. Airport and/or airline choices are linked to each other, as airlines and airports use each other's services to operate and create revenue [80]. Therefore, passenger airport choice is a joint airport-airline decision, considering all other relevant variables to be equal. Besides, it has been observed airline brand loyalty plays a significant role in airport choice as well [80]. Taken together, neither operationalization of accessibility (access time by road) nor the choice sets and variables therein (fare, connectivity, on-time performance, etc) used in the so-called Huff model paint an exhaustive picture of MAR airport choice, with above all individual travel characteristics possibly playing a supplementary role. Therefore, the thesis research following this literature review aims to analyse passenger transport, focusing on air traffic passengers and their choices in a MAR through the use of dynamic behaviour of such linked decisions. Literature regarding this dynamic behaviour in a MAR can be observed in Chapter 3.

As mentioned in Chapter 2, according to Derudder and Teixera, a MAR is a set of two or more airports that commercially serve a regional market. Identifying MARs by their IATA code (International Air Transport Association) cannot be used systematically because some clear examples do not have one (for example in San Francisco). For each airport, the market area is defined as the destinations that are reachable within a maximum of two legs [44]. For each modelling step, min-max normalisations were applied so that the lowest utility equals 0 and the highest equals 1. This is done for ease of interpretation, the possibility of straightforwardly combining different variables, and reasons for comparability across time windows. The airport's utility's choice set is based on four variables; the number of markets served, the number of departures, the number of most directly served markets and the number of unique markets. The on-time choice set combines on-time, delayed and cancelled flights. Here, the researchers adopt the approach and data of the US Department of Transportation (DOT), which considers a flight to be on time if arriving or departing within 15 minutes of the scheduled time. There have been a few studies that have partially looked at this scenario and context, but not including the cancelled flights [146, 121].

The research computes total scores for each census block in the airport's catchment area representing the attractiveness of the airport to them. This total score is a function of the separate utilities for fare, connectivity and on-time performance. This produces, for each census block (j), the attractiveness

p_{ij} for a passenger departing from his census block to choose from the different airports (i) that are within a 60-minute radius [148]. These results vary in times, days, and seasons and it captures this changing behaviour. An important aspect in modelling airport choice is capturing the subjectivity of the choice-maker. If air travellers have positive experiences with their airports, this will influence their future choice of this passenger. So, a positive prior experience of an air traffic passenger influences airport choice in the future. This positive experience is a function of factors that, for a large portion, are still present and would thus result in the same airport choice for that individual, has he/she not travelled using that airport already [17, 134, 55, 95].

Many of the researches analysed in this literature review focus on a region of a single country. There is little research regarding airport choice for multi-airport regions covering multiple countries. The little that does exist is limited to large metropolitan areas in politically and economically stable western European countries [89, 122, 90]. The research of Paliskaet al. focuses on how country-specific individuals' characteristics may influence passengers' airport choice. This is done through the use of a double multinomial logit model. The base model for estimating the airport catchment area size and market shares therein, and the airport choice final model. This methodology extends the research work of Lian and Ronnevik [88] by using MNL (multinomial logit) airport choice model framework instead of logistic regression.

During the research, the presence of heterogeneity among categorised airport choices was observed, while the standard multinomial logit model assumes preference homogeneity. It was concluded this heterogeneity originates from the multi-national characteristics of these choices, and the influence of variables affecting passengers' airport choice varies across countries. This heterogeneity can be analysed and adapted using a so-called *integrated treatment* which can result in significant improvement in model accuracy and explanatory power [134, 95, 98].

Standard multinomial logit (MNL) models assume preference homogeneity. It is assumed that the influence of variables affecting passengers' airport choices may vary across individuals and countries. To measure the quality of the data and fit of the model, the likelihood is observed through the likelihood function. Using the mixed logit model formulation to account for taste heterogeneity used a modified Newton-Raphson algorithm with adaptive quadrature to evaluate the likelihood function, and numerical derivates are used to maximize this [117, 140].

The research by Paliska et al. concludes a few interesting points. First, leisure travellers are more willing to use public transport services than business travellers do because the price is lower. Despite a lower price, the travel time is higher, but the weight or importance of travel time is less than that of the total airport access price. Second, the highly expressed preference choice for the *'home airport'* is more common among business travellers and frequent flyers. For both of these types of travellers, minimizing total travel time has relative high importance compared to other parameters influencing airport choice. Third, leisure passengers consider on average more alternatives than business travellers. Fourth, in general, access time is the dominant variable. The decision amongst these alternatives is based on the airport characteristics that can be observed below.

1. Distance;
2. Ticket price (airfare);
3. Frequency of flights;
4. Convenience of flight times;
5. Other airport-related costs like parking and airport consumption.

Cross border passengers do not value airport distance as important in comparison to non-cross-border passengers. Ticket price, frequency of flights and other airport services proved more important for cross-border passengers in comparison to no-cross-border passengers. As mentioned, the analysis of the airport's catchment area and market share evolution based on airport choice preference was done so using a double logit model to fit the survey data. Variables included are categorised into socio-demographic and airport quality of service. Socio-demographic variables describe the demand for and supply of airports. Quality of service variables belongs to the allocation of this demand.

1. Socio-demographic:
   (a) Gender;
   (b) Age;
   (c) Type (student, worker, retired);
   (d) access mode (train, bus, car);
   (e) Country of origin.
2. Quality of service (QOS):
   (a) Airport ground access time (proxy driving time);
   (b) Number of direct destinations from an airport (a proxy for airport size);
   (c) Airports' share of passengers flying LCC > 10%;
   (d) Airports' share of passengers flying LCC > 30%.

Another interesting conclusion from the research from Paliska is the importance of local context in studying airport choice [117]. This has also been pointed out in earlier studies [154, 90]. Many interesting methods have been developed to measure airports accessibility. As mentioned in Chapter 2, Marucci and Gatta use a radius around the facilities (airports). Zhoe works with Thiessen polygons and derives distances between these polygons and airports. This method can take into account the population density in discrete city blocks [162]. Another measuring method done by Fuellhart takes a certain driving distance from the airports to define the accessibility [55].

Airport utility is more complex than measurements of airport accessibility because they involve a broad range of interlocking variables [148]. The following aspects influence passenger choice:

1. Inter alia flight frequency;
2. Number of direct connections to reach the destination;
3. Number of stops to reach the destination;
4. Aircraft type;
5. Travel purpose (business, leisure);
6. Socio-economic considerations;
7. Loyalty programs offered by the airlines at an airport;
8. Number of passengers travelling together;
9. Previous consumer experience.

These influence the level of service or utility an airport provides either directly itself or via its airlines that serve via that airport. These all influence passengers' choice of airport.

2.4.1. Decision Variables

In this subsection, an overview and analysis are made regarding the usage of decision variables by previous authors in air traffic and airport modelling. Which variables should be considered, which variables have proven to be relevant in literature, which can be easily determined and which variables do authors opt not to use and why are sub-questions that will be discussed here. The results of these questions lie in the availability, applicability and consistency of data.

Airport choice specifically in a multi-airport region has already been deeply analysed by many researchers and authors [96, 120, 57, 10]. From these researches, access time and frequency of flights have been shown to be dominant factors in airport choice. As mentioned before, business travellers assign more weight to access time and flight schedules than they do to airfare [117]. The exact opposite is true for leisure travellers [134, 121, 120, 90, 80]. In general, actors that influence airport choices also cause the spatial and temporal variations in the airport's catchment area and market shares [89]. The most common reported utility factors determining airport choice, according to literature are fare levels, frequency of service, direct vs indirect service, ground access, and length of hauls [89, 145, 160, 55, 90, 79, 119, 88]. Airports offering better service levels (more direct flights at a reasonable price) to various destinations can attract passengers from more distant regions [89]. Gjedakar reported that, in addition to differences in fares, improved road infrastructure around and towards the airport has significantly contributed to catchment area heterogeneity and higher levels of traffic leakage to the main airports in the case of Norway [61].

A common problem in air traffic demand modelling in general and also through regression analysis is the lack of availability of consistent fare data [113]. This is because fare data is volatile and not publicly available from airlines. Therefore, a single measure of price can be calculated as an average of the various fares, weighted by the number of passengers using each fare. In general, passenger yield, i.e. passenger revenue per passenger kilometre, can be used as a measure of price. Ideally, the average weighted fare for a particular route group or region concerned is more appropriate.

2.5. Conclusion Literature Review

Multi-Airport Region

This research is focused on Multi-Airport Regions, defined as a set of two or more significant airports that serve commercial traffic within a metropolitan region. Its scope is commonly defined by a radius from the airport, either defined by an x-minute drive time or by a straight line. Socio-economic characteristics and activity in MARs are linked to their air traffic activity, and can therefore be used to model and forecast. Analysing the airport's access network and comprehending passenger transport dynamics is crucial for logistical and airport developments to accommodate rising air traffic demand.

Research on multi-airport regions can be extended, as the following relevant gaps have been identified in the literature:

1. A more accurate catchment area definition can be obtained by comprising dynamic traffic data to develop detailed airport access time information. Continuously dynamic traffic levels will result in varying airport access times, thus a more realistic catchment area analysis.

2. Research on overlapping catchment areas is limited. The strength of this overlap influences the weights of decision variables concerning passenger mobility decisions. As the definition of catchment areas forms the basis of air traffic passenger allocation amongst airports, further insight regarding this matter can provide more realistic and significant modelling results.

3. Discretising MARs allows for socio-economic information and airport access time to be split amongst geographical blocks. This is likely to more realistically capture the information in a MAR, which can be used for modelling and forecasting purposes.

Taking into account these literature gaps, several technical considerations are taken into account for the research following this literature review.

I Dynamically model airport catchment areas more accurately based on live traffic data. Airport access times can be computed automatically using maps software packages like Google's routing API, which take into account live traffic situations. The routing network hereby forms a varying input, thus resulting in a dynamic definition and computation for airports catchment areas and their accessibility.

II Accurate and current access time computations can be combined with socio-economical information of population blocks from the surrounding region to develop a complete accessibility score for the various airports in the MAR. These blocks can be based on zip codes, and socio-economical information like household income, purchasing power and tourism supply can be used for such computations.

III The influence of improved rail within MARs and increased high-speed railways between MARs. Improved rail increases the potential supply of air traffic passengers for airports by increasing their catchment areas. Some airports might benefit from this more than others, which needs to be taken into account when accessing them, Besides, many big European cities are connected through this increasingly expanding high-speed rail network, which provides an alternative and extension to (short-haul) flights. Because of these reasons, the increasingly improving rail connections are relevant when analysing passenger mobility in the long term.

Dynamic model

Urbanization is driving an immense increase in passenger transport demand resulting in increased traffic movements, especially in urban regions. Private vehicles and public transport modes are used for short travel distances and aircraft are used for longer travel distances. As air traffic demand rises, more people have to be allocated to and from airports. This means (airport access) transport modes and systems need to be scaled up and optimised to accommodate this increased demand effectively and efficiently. Optimising passenger transport in a MAR can be done by focusing on its three driving topics; air traffic passenger preference amongst airports, infrastructure within the MAR, and airline/airport strategy. Based on the ”mega-hub” research in Asia, accommodating increased travel demand can be done most effectively by allocating air traffic passengers over multiple airports in the region, rather than converging all traffic to one mega-hub airport. So far, literature has only analysed the unidirectional links of strategic implementations on the performance of infrastructure operations.

Literature on this subject can be extended by focusing on the following two topics:

1. The dynamic behaviour amongst the topics driving human transport/mobility in a MAR can be analysed integrally. So far, previous pieces of research have only looked at partial drivers explaining such passenger movements and analysed the unidirectional dynamic between two factors.
2. The presence of generic models that can be applied to a larger variety of contexts.

State-of-the-art literature on the dynamics driving passenger transport and its gaps have resulted in the following considerations for the follow-up MSc research:

I Approach passenger transport and mobility integrally by analysing the dynamic behaviour of its three driving factors. The evolution of these dynamics can provide the basics for estimating how multi-airport regions will form. This insight is crucial for planning logistical implementations in a MAR and mega-cities to accommodate expected air traffic demand, as a result of urbanisation.

II Make a generic block in the dynamic model that can be used to model the dynamic behaviour for larger and various contexts. As infrastructure improves, passenger mobility in a MAR improves and the airport can be accessed faster and more convenient. This hypothesis is to be examined in the follow-up research.

III Model the environmental performance of airport surface access, including the sustainable gain of high-speed trains compared to short-haul flights. Besides, the potential modal shift from short-haul flights to trains as a result of increased environmental awareness and sustainable pressure from governments will be analysed. It can be relevant to analyse the ratio of the added value of good surface access on an airports’ operational efficiency to its environmental impact.

IV Quantify the benefit of strategic infrastructural implementations on passenger transport and mobility. This can be done based on previous infrastructural changes and their resulting gain in airport access. This could eventually lead to a change in the market share evolution of airports.

Passenger transport in multi-airport region

Air traffic demand forecasting methods can be divided into four categories; quantitative, qualitative, artificial intelligence and decision analysis. The first category can be split into two sub-categories, namely time-series and causal, of which the latter option has proven to be most accurate in air traffic

forecasting. The commonly used regression analysis and spatial equilibrium method fall under this sub-category. Both models try and link historical socio-economic and socio-demographic data to historical air traffic data and compute elasticities for these variables.
Tower control maintains smooth operations from expected peak-hour air traffic passengers and aircraft movements. Artificial Neural Networks (ANNs) provide a robust potential for modelling, analysing and forecasting compared to traditional time series and econometric models. ANNs' additional value to air traffic modelling is its ability to account for great amounts of data, simulate non-linearities in complex situations, provide real-time results, have a high degree of flexibility, adaptability and generalization, and operate empirically.
Allocating the total air traffic demand over airports is computed based on airport attractiveness levels, which is based on its accessibility and utility. Multinominal logit (MNL) models have proven to be effective in modelling this allocation and computing elasticities for explanatory variables based on stated and revealed passenger preferences. Access time, airfare and frequency of service are the most dominant explanatory variables for airport preference. Based on these results, the market shares of airports can be determined. Important to take into account is the categorisation of air traffic passengers' travel purpose (leisure/business/VFR) and type (resident vs non-resident).

Several relevant subjects in air traffic demand modelling literature are still to be researched:

1. Just as in the 'Dynamic model' section, there are no generic models that can model air traffic demand or its allocation amongst airports for multiple contexts or regions. This is because context-specific variables have proven to have a significant impact on the model result.
2. The majority of airport allocation models use static passenger preference as input. However, passenger preferences adapt and the decision variables that all together form passenger preference can vary. This has not been analysed yet in literature.

Based on these gaps and literature, the following technical concepts for the follow-up MSc research have been identified.

I Using discretized dynamic MAR data for airport allocation modelling. Dynamic passenger preference input in combination with discretised dynamic MAR data is likely to provide accurate allocation predictions. This challenging concept is to be analysed in follow-up research.

II Adapt such models to be generic and applicable to a larger scope of contexts and regions. This can be done by creating a modelling block that accounts for context-specifics and another generic block that can be applied to other regions as well.

III Allow strategic implementations as input for airport market share evolution computations. This could result in a changing market share evolution of the respective airports in a MAR if certain strategic implementation in MARs' infrastructure occurs.

3 Modelling Methodology

The goal of this research is to develop an analysis framework for the market dynamics driving airport activity levels, focusing on multi-airport regions, and analyse how this provides a base for strategic decisions in the region. This is achieved through a quantitative model, of which its results are progressed in a forecasting framework. The analysis framework can be performed on any multi-airport region if the minimum data requirements are satisfied. The methodology of the quantitative model is presented generically in this chapter. First, the general setup is presented, after which each modelling block will be analysed in detail.

3.1. Modelling Setup

The quantitative model considers the first sub-goal of this research which is to understand the evolution of airport market shares based on the allocation of air traffic passengers amongst airports in a chosen MAR. To achieve this, three necessary modelling blocks have been identified:

1. Regional Air Traffic Demand Forecast
2. Airport Performance
3. Airport Allocation and Market Shares

In this section, these blocks will be introduced briefly, after which a detailed analysis and substantiation for these steps/methods are provided.

First, to understand the evolution of the airport's market shares, the total market has to be defined and computed. This is done in the Regional Air Traffic Demand Forecast, which computes the aggregate air traffic demand in terms of passengers landing and departing at airports serving the MAR. The analysable period is split into historical, from 2010 to 2019, and projected, from 2020 to 2050. Air traffic passenger numbers dropped in late 2019 due to the COVID-19 pandemic, which disturbed its time series. To ensure the air traffic demand time series can be mathematically described without taking into account such extreme events, the historical period ends after 2019, after which the demand drop forms the start of the projected period. The projected period ends in 2050 since data that drive air traffic demand are projected up to 2050 as well.

Second, the performance of airports is computed relative to other airports serving the MAR. Their relative performance is based on three key performance indicators that have been proven to represent the attractiveness of airports, and thereby their utilisation levels and market shares:

1. Accessibility
2. Airfare
3. Connectivity

Insight into the relative performance of airports forms the basis for why and how air traffic passengers choose airports, and thus how many air traffic passengers use each airport. It is proven air traffic passengers prefer airports with convenient flight schedules according to their desired destination, which are affordable and easily accessible. These relative airport performance scores are analysed through the years 2010 - 2019 and can be projected up to 2050.

Third, based on the total performance or relative attractiveness of airports, regional air traffic passenger demand is allocated over the airports serving the multi-airport region. An airport's total performance is measured through the relative performance concerning its accessibility, airfares, and connectivity combined. However, not all key performance indicators contribute equally to total performance. Therefore, to analyse their contribution or weight to total performance, a multivariate regression analysis has been performed. Here, independent (explanatory) variables are presented by historical airport key performance indicator scores and the dependent (response) variable is presented by the historical market shares of airports.

A visualisation of the set-up of the quantitative model can be observed in Figure 3.1.

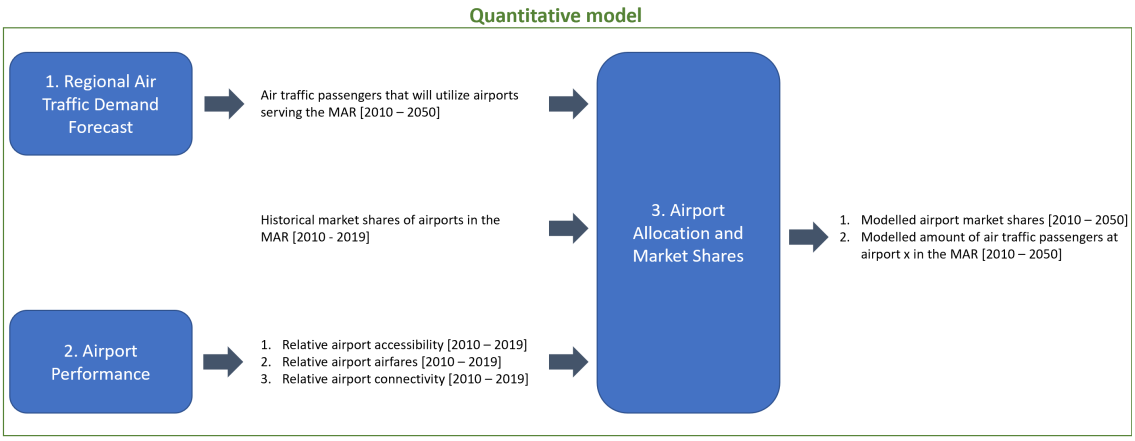

Figure 3.1: Set-up quantitative model

3.2. Regional Air Traffic Demand Forecast

Air travel is a derived demand. Demand for air transportation between origin and destination markets is derived from the socio-economic interactions between these markets, shaped by carriers' networks and available airlift capacity.

In general, history has shown that air traffic activity levels are driven by the economic and demographic performance of the key source markets of demand that an airport serves, defined by variables such as economic activity and personal income [1, 128]. In other words, there is a proven close relationship between economic activity and annual traffic growth. While this is generally true, each airport is different in terms of the traffic and air carriers it serves and the socio-economic environment in which it operates. Dependable forecasting, therefore, requires an in-depth awareness and understanding of the specific factors that will drive traffic development.

Multi-airport regions are served by multiple airports which have overlapping catchment areas. As such, originating travellers from the region and arriving passengers to the region have the option to choose between several airports for their needs. Therefore, predicting future traffic levels for one airport can not be done in isolation and should consider the trends and dynamics occurring at other airports.

To develop medium- to long-term projections of future activity, a macro-econometric approach has been adopted, relating demand for air travel to the developments of the underlying macro-econometric conditions in the market. This approach is generally referred to as multivariate regression analysis and belongs to causal forecasting methods as described in subsection 2.3.1. This method is chosen because it has proven to be the most accurate and efficient in forecasting aviation demand compared to other methods and can take into account multiple explanatory variables [142, 113]. This first part of the quantitative model entails modelling and forecasting air traffic passengers that will use the combined airports in the MAR from 2010 to 2050, based on data from 2010 to 2019.

Within this approach, historical traffic developments in the MAR are studied and related to various socio-economic indicators, for instance, national economic developments, population developments in the region, oil prices, and regional income per capita. According to data availability, multiple regressions were executed to estimate the strength of the relationship between variables across different models.

It has been found that the growth of income, often proxied by GDP, is a fundamental driver of the demand for air travel [34, 124]. During the past twenty years, global passenger traffic has expanded at an average annual growth rate of 5.1% while global GDP grew by an average annual rate of 3.7% over the same period. This implied an average elasticity of 1.4 and economic growth explaining most of the expansion in air travel seen in the past twenty years. Another proven driver of air traffic demand is oil prices [33]. Oil prices influence the pricing of aviation, and therefore indirectly the attractiveness and demand. Therefore, the correlation of GDP and oil prices with air traffic demand will be analysed, and if an adequate correlation is found, will be used in the quantitative model.

In addition, economic growth is now increasingly being driven by developing economies, where income elasticities are higher. Therefore, the underlying drivers for overall air travel growth are likely to remain strong for the foreseeable future [113].

The socio-economic variables that are correlated with air traffic demand depend on the region and country. Therefore, the correlation of various socio-economic variables with air traffic demand should be analysed. Data for projections of such data is usually only available at a national level. Therefore, the correlation between such a socio-economic variable and national air traffic demand is analysed first, after which the correlation between national and MAR air traffic demand is used to then analyse the correlation between (national) socio-economic variables and MAR air traffic demand. Once an adequate correlation is found, projections of the socio-economic(al) variable(s) can be used to project air traffic demand. An illustration of this modelling block can be observed in section 4.4. Besides, Figure 3.2 zooms in on modelling block 1 of the quantitative model.

Figure 3.2: Modeling block 1: Regional air traffic demand forecast

3.3. Airport Performance

Once aggregate air traffic levels to and from the MAR can be modelled using the Regional Air Traffic Demand Forecast, air traffic needs to be allocated over airports serving the multi-airport region. This is done by computing the relative performance of the airports amongst each other. Airport performance is characterised by their relative attractiveness to air traffic passengers. The performance of airports is determined through variables that represent their accessibility and utility [121, 42].

Literature has shown airport performance can be best measured based on three key performance indicators. First, airport accessibility was analysed since it has been shown to be a dominant decision variable for airport choice and thus its performance [121, 134, 76]. Airport accessibility considers the ease at which an airport can be accessed from the MAR, and vice versa, taking into account characteristics of the potential air traffic passengers. Second, airport airfares represent airport performance [89, 145, 160, 55, 90, 79, 119, 88], which is a function of the fares that airlines implement. Third and final, an airport's connectivity has shown to be relevant in measuring an airport's performance/attractiveness [42], which considers the number of reachable destinations on Earth and the quality of these routes. Airport connectivity implicitly captures the first criteria of an air traffic passenger in airport choice, which is his/her desired destination. Airport airfare and connectivity both belong to an airport's utility.

To bring structure to this section, visualisation of this second modelling block is shown below in Figure 3.3.

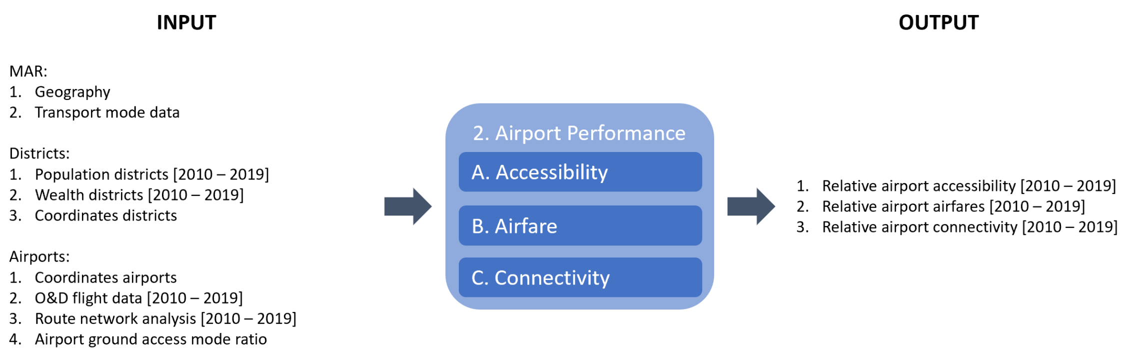

Figure 3.3: Modeling block 2: Airport performance

3.3.1. Accessibility

The accessibility of an airport has significant relevance to indexes such as passenger scale and the number of airlines. The higher the level of accessibility, the stronger the competitiveness of the airport will be, thus resulting in a higher market share of air traffic passengers in the region [16]. The accessibility typically measures "the ease and convenience of access to spatially distributed opportunities with a choice of travel".

This research implements a gravity-based accessibility measure, which is generically explained in subsection 2.3.1 [113, 27], as it has been proven to be more accurate and valuable in comparing airports than solely travel time indicators [8]. Gravity models were the earliest causal models developed for traffic forecasting. The gravitational law states the gravity between two objects is directly proportional to their masses and inversely proportional to their squared distance, as can be seen by equation Equation 3.1.

$$F_{12} = F_{21} = G \cdot \frac{m_1 \cdot m_2}{r^2} \tag{3.1}$$

Where:

F_{12} = Force from object 1 to object 2
F_{12} = Force from object 2 to object 1
G = Gravitational constant
m = Mass
r = Distance between objects

A simplified formulation of a general gravity model for human spatial interaction used for the prediction of travel demand between two places i and j can be seen in Equation 3.2. The concept of this formula is used to compute airport accessibility.

$$V_{\text{ij}} = k \cdot \frac{(a_i \cdot a_j)^{\alpha}}{d_{ij}^{\gamma}} \tag{3.2}$$

Where:

V_{ij} = Passenger volume between i and j
k = Constant
α = Attraction factor from location i or j
d_{ij} = Distance between i and j
γ = Parameter that controls the influence of the distance on travel demand

The attraction and/or 'repulsion' is expressed not only by a single variable but by a combination of various factors. This undirected gravity model can be extended to a directed model if V_{ij} which measures directed passenger flows from i to j.

The proposed model considers a gravity approach with the following three driving factors for airport accessibility.

1. Travel times. An air traffic passenger is more likely to choose an airport that is closest to his/her origin or desired final destination
2. Population. Regions with more inhabitants are more likely to supply air traffic passengers than regions with fewer inhabitants.
3. Income. Regions with wealthier inhabitants are more likely to supply air traffic passengers than regions with less wealthy inhabitants.

Travel Times
Multi-airport regions are divided into 'census' blocks, which are sub-regions that contain socio-economical and demographic data such as the number of inhabitants, age, gender, wealth and coordinates. These sub-regions will from now on be referred to as districts. Air traffic passengers are supplied to airports in the MAR from these districts. According to the classic gravity formulation as mentioned above, the distance between these so-called supply nodes and the airports is inversely proportional to the passenger volume. Therefore, an initial analysis considers computing the distance in kilometres between all airport-district combinations. This was computed in the form of straight-line distance, based on the coordinates of the district's centre-point and the airports, taking into account the spherical shape of the Earth, using the so-called *Haversine formulation*:

$$d = 2 \cdot R \cdot \sin^{-1}(\sqrt{\sin^2(\frac{\phi_2 - \phi_1}{2}) + \cos(\phi_1)\cos(\phi_2)\sin^2(\frac{\lambda_2 - \lambda_1}{2})}) \tag{3.3}$$

Where:

d = Straight-line distance
R = Radius of the Earth = 6371 km
ϕ = Latitude
λ = Longitude

Urban regions usually consist of a densely built region, with traffic congestion often disturbing airport access. Therefore, it was analysed how airport travel access times correlate to the recently computed straight-line distances. Another research examined a comparable correlation for hospital access in upstate New York, which is also a multi-airport region [123]. It concluded the correlation between travel distance and time was 0.987 for all observations and 0.825 for distances less than 15 miles (24.14 km). These very high correlations indicate that straight line distance is a reasonable proxy for travel time in most hospital demand or choice models, especially those with large numbers of hospitals [123]. This research was performed on driving distance and not straight-line distance, meaning the correlations with straight-line distance will be lower.

Therefore, it is analysed how long it takes people to access airports from the districts in the MAR. Transport modes in MARs consist of public road users (private cars and taxi) and railway users (trains and metros) [86]. Uncongested trips were analysed to eliminate the uneven influence of potential road constructions or emergency service obstructions on airports. This means car trips were analysed at

2:00 a.m. on a Wednesday and public transport trips were analysed at 2:00 p.m. on a Wednesday as well. The ratio of passengers accessing airports using cars and public transport differs per airport in the region. Therefore, this ratio is used as variable input to model travel times in Equation 3.4.

$$TT_{ij,k} = PTT_{ij,k} \cdot R_{public\ transport} + CTT_{ij,k} \cdot R_{private\ vehicle} \tag{3.4}$$

Where:

$TT_{ij,k}$ = Travel time from district j to airport i in year k
$PTT_{ij,k}$ = Public transport time from district j to airport i in year k
$R_{public\ transport}$ = Public transport access ratio
$CTT_{ij,k}$ = Car transport time from district j to airport i in year k
$R_{private\ vehicle}$ = Private vehicle access ratio

Now, for each airport-district combination, the travel times and straight-line distances are computed. For each combination, the mean value for each airport was computed to compare these methods. The hypothesis states that travel times should show a smaller disparity between airports than straight-line distances since longer straight-line distances can be bridged by higher transport velocities, resulting in shorter relative travel times. For example, many major hub airports are located further away from the city than smaller business-oriented airports. However, these hub airports are extremely well connected to the city and MAR districts through an extensive railway and highway infrastructure. This allows for efficient and fast travel over longer distances, compared to less popular locations where this extensive infrastructure is not available. The same distance can thus be bridged by higher velocities, resulting in relative shorter travel times.

Actual travel distance over a road network has shown to be a superior alternative compared to straight-line distance when calculating accessibility [26]. Besides, the research regarding hospital access has shown using travel times is more accurate than travel distance [123]. Despite these pieces of research being applied to different regions, both regions are urban areas served by multiple airports. Therefore, this methodology continues with the computational method concerning travel times, as described in Equation 3.4, over straight-line distances. Besides airport access travel times, airport accessibility also depends on the income and wealth of the districts in the surrounding MAR.

Population

As described in the introduction, urbanisation is a major worldwide trend where urban regions become more and more populated, resulting in an increased demand for air travel around the world. Therefore, increased population drives air traffic demand up. It is assumed the same holds for multi-airport regions and the districts herein, meaning there is a positive correlation between the population level in districts and the air traffic passengers supplied therefrom. This correlation specifically could not be determined or substantiated in this research because of the lack of availability of data. Therefore, it was assumed that districts with x% more inhabitants have the potential to supply x% more air traffic passengers to airports in the region.

Income

Just as described in the literature review and Regional Air Traffic Demand Forecast, it has been proven wealthy economies fly more. As such, there is a good correlation between GDP and air traffic levels for countries. Several pieces of research substantiate the positive relationship between wealth and air traffic demand. First, research indicates the World's richest 1%, people who earn more than 109,000 USD (£79,000), are responsible for 50% of flying emissions [87]. Second, a review revealed that 76% of overseas trips were taken by 29% of middle and high-income households in 17 Asia-Pacific countries, including Australia, China and Singapore [87]. Third and final, it is shown that there is high consistency in the Granger-causality relationship between wealth and transportation, and income and transportation. The study has three important contributions: First, the relationship between wealth and transportation is shown both theoretically and empirically. Second, transportation is shown to have a dual role in an economy. Third and final, it is shown that the wealth-transportation relationship and the transport-income relationship are equally robust and consistent [157].

It is therefore assumed wealth is positively correlated to air traffic demand in multi-airport regions. Wealth is taken into account for the accessibility measure by first gathering the average annual gross earnings per MAR district for 2010 to 2019. The currency depends on the multi-airport region. This research assumes income and population equally contribute to the performance of an airport's accessibility.

Scoring

To recap, one of the three key performance indicators for airports is accessibility, which comprises travel times, the district's population, and income data. Higher travel times result in a low performance whereas a higher population and income result in higher performance. To take this into account, a reversing method has been implemented through the accessibility computation equations. This is done so higher population, higher income and lower access times result in higher total accessibility. A scoring method is applied so airports' accessibility is measured relative to other airports in the MAR, so they can be compared. The list below provides a recap of the input data for accessibility.

1. Geographical data of airports within the MAR. Coordinates of MAR airports to account for their relative location within the MAR, used for travel time computations.
2. Population data of MAR districts. The number of inhabitants for all MAR districts over the years 2010 - 2019 is selected as weighting for the accessibility measure.
3. Income data of MAR districts. Average gross earnings data was selected for all MAR districts over the years 2010 - 2019 as weighting for the accessibility measure.
4. Geographical data MAR districts. Coordinates of centre-points for MAR districts to account for their relative position in the MAR, used for travel time computations.

The accessibility score for airports can now be computed through four steps. First, income values are reversed and transformed into points ($IP_{j,k}$), after which they are converted into a score ($IS_{j,k}$) ranging from 1 to 10, as is done in Equation 3.5 and Equation 3.6. Using this method, high income values result in a low income score.

$$IP_{j,k} = max(I_{j,k}) + min(I_{j,k}) - I_{j,k} \tag{3.5}$$

$$IS_{j,k} = \frac{IP_{j,k}}{max(IP_{j,k})} \cdot 9 + 1 \tag{3.6}$$

Where:

$I_{j,k}$ = Income of district j in year k
$IP_{j,k}$ = Income points of district j in year k
$IS_{j,k}$ = Income score of district j in year k

Second, the same method is applied to population data, as can be observed in Equation 3.7 and Equation 3.8. Again, high population values result in a low population score.

$$PP_j = max(P_{j,k}) + min(P_{j,k}) - P_{j,k} \tag{3.7}$$

$$PS_{j,k} = \frac{PP_{j,k}}{max(PP_{j,k})} \cdot 9 + 1 \tag{3.8}$$

Where:

$P_{j,k}$ = Population of district j in year k
$PP_{j,k}$ = Population points of district j in year k
$PS_{j,k}$ = Population score of district j in year k

Third, the accessibility of each airport is computed. This is done in three steps. First, for each airport-district combination, the travel times ($TT_{ij,k}$) are multiplied by the reversed income score ($IS_{j,k}$) and the reversed population score ($PS_{j,k}$). The average of each airport is computed by dividing by the number of districts (n), which is computed in Equation 3.9 and results in an accessibility index for each airport ($AI_{i,k}$). A low $AI_{i,k}$ means good accessibility. Second, to make sure high values translate to good accessibility, the accessibility index is reversed using Equation 3.10, resulting in the accessibility points ($AP_{i,k}$). The third and final step consists of a scoring computation, which converts accessibility points ($AP_{i,k}$) into an airport accessibility score ($A_{i,k}$) in Equation 3.11.

$$AI_{i,k} = \frac{\sum_{j=1}^{n} TT_{ij,k} \cdot IS_{j,k} \cdot PS_{j,k}}{n} \tag{3.9}$$

$$AP_{i,k} = max(AI_{i,k}) + min(AI_{i,k}) - AI_{i,k} \tag{3.10}$$

$$A_{i,k} = \frac{AP_{i,k}}{max(AP_{i,k})} \cdot 9 + 1 \tag{3.11}$$

Where:

n = Number of districts
$TT_{ij,k}$ = Travel time from district j to airport i in year k
$AS_{i,k}$ = Accessibility score for airport i in year k
$AP_{i,k}$ = Accessibility points for airport i in year k
$A_{i,k}$ = Accessibility for airport i in year k

3.3.2. Airfare

Airfare is defined as the price to be paid by an aircraft passenger for a particular journey [114]. Research in MAR Aburrá Valley, Colombia analysed relevant airport choice variables for air traffic passengers [101]. A Multinomial Logit Model (MNL) was used, which is based on the theory of maximizing utility, and data was obtained on revealed and stated preference surveys of users who reside in the metropolitan area of Aburrá Valley, Colombia. It was revealed the most common variables that affect passenger airport choice are airport access cost and time, and airfares [101]. Various other pieces of research have proven the accuracy of using MNL models in modelling airport choice [88, 73]. As discussed in the literature review, various other pieces of research have identified airfare as one of the leading variables affecting airport choice, thereby being a logical choice as a performance indicator when comparing airports in a MAR. Therefore, airfare is chosen as the third key performance indicator.

Airfares are implemented by airlines. The major expenses that affect companies in the airline industry are labour and fuel costs. Labour costs are largely fixed in the short term, while fuel costs can swing wildly based on the price of oil. For this reason, analysts pay more attention to fuel costs in the near term. Two-thirds of the costs of flying an aircraft are fixed, so changes in fuel costs can swing a flight from profit to loss depending on how many people are on the flight. Historically, the airline industry continues to be brutally competitive, even though the business of flying people all over the world and country has become an integral part of human life. The cost of flying continues to trend lower. The internet has also created greater price transparency, reducing margins.

Airlines pay airport fees/charges to make use of their facilities, like landings and take-offs. These charges depend on the type of aircraft, their weight en the number of passengers. Heavier larger aircraft pay more fees, mainly because they emit more noise and emissions to cover a certain distance. Long-haul trips require larger aircraft, more fuel, and more airline employees compared to short (domestic) flights. Therefore, airfares for longer trips are generally higher, but also have different fare structures, that make up the total price a passenger has to pay. Because of this, airfares are analysed according to their trip length. Besides, to compare airfares across airports, the length of each route has to be taken into account. If airport x serves, on average, flights of longer distances than airport y, given these flights are in the same trip level, the fare of airport x is likely to be higher than airport y because longer trips are generally more expensive. To remove this aspect, airfares are analysed per distance metric (km).

Data was gathered using subscription-based Sabre aviation data. The database contains data on all outbound and inbound flights for almost all airports worldwide. To model airport airfares, the model requires the following types of data:

- Origin data
  - Airport (name)
  - City
  - Country
  - Region
- Destination data
  - Airport (name)
  - City
  - Country
  - Region
- Year
- PPDEW (passengers per day each way)
- Average base fare (USD)
- Base revenue (USD)
- Average total fare (USD)
- Total revenue (USD)
- Distance (km)

Having this data, the model computes airfare scores using the following steps and equations:

1. Airline passenger yield is defined as the revenue per revenue passenger per kilometre flown [137, 138]. Since airfare data is hard to obtain due to fluctuating data, the yield is computed to represent the average airfare per passenger per flight distance in kilometres. Therefore, the airfare index is computed using Equation 3.12, which results in USD/passenger/km.

$$AI_{i,m} = \frac{\left(\frac{Total\ revenue_{i,m}\ (USD)}{Passengers_{i,m}}\right)}{Flight\ distance_{i,m}\ (km)} \tag{3.12}$$

   Where:

   $AI_{i,m}$ = Airfare index concerning flights to and from airport i on route m

2. Continents are added to the dataframe by linking regions to their corresponding continent. The regions' formulation according to the database can be observed in the list below, and belong to the continent that is written in between the brackets. Grouping these regions is done for departing and arriving routes.

   - Eastern Europe (Europe)
   - Western Europe (Europe)
   - Central Africa (Africa)
   - East Africa (Africa)
   - North Africa (Africa)
   - Southern Africa (Africa)
   - West Africa (Africa)
   - Caribbean (North America)
   - Central America (North America)
   - Gulf (North America)
   - North America (North America)
   - South America (South America)
   - Asia sub continent (Asia)
   - Central Asia (Asia)
   - Far East Asia (Asia)
   - Middle East (Asia)
   - Southeast Asia (Asia)
   - Australia (Australia)
   - Pacific (Australia)

3. Routes are classified in five trip levels (t = 1, 2, 3, 4, 5);

   I Domestic. Flights that depart and land in the same country.

   II Regional. Flights that depart and land in the same region, but not in the same country.

   III Continental. Flights that depart and land on the same continent, but not in the same region.

   IV Intercontinental. Flights that depart and land on different continents.

   V Total. Containing all flights together.

4. Airfare indices are grouped in their corresponding trip level, and relatively reverse ranked within, on a scale from 0 to 1. This means that, within a trip level, the route with the highest airfare index receives the lowest rank, being zero, and vice versa. This allows for low fares to result in high airfare performance.

5. For each airport for each trip level, the mean value of these ranks is computed. This value is represented by:

$$\overline{AI}_{i,t}(RR) = \frac{\sum_{i=1}^{n} AI_{i,m,t}(RR)}{n} \tag{3.13}$$

   Where:

   $\overline{AI}_{i,t}(RR)$ = Mean value of reverse ranked airfare indices for airport i on level t
   $AI_{i,m,t}(RR)$ = Reverse ranked airfare index of airport i, route m, and trip level t
   n = Number of routes
   i = Increment size

6. Airfare score for airport i in year k, being $F_{i,k}$, is computed for each trip level on a scale from 1 to 10 using the same concept as is done for accessibility, based on the mean value of ranks from step 5. This is done using Equation 3.14. The scores on total trip level (t = 5) are used in the quantitative model to compute the allocation of air traffic passengers over airports in the MAR. Airfare scores from other trip levels (t = 1, 2, 3, or 4) are relevant when evaluating an airport's performance on domestic or international, that is regional, continental or intercontinental level.

$$F_{i,k} = \frac{\overline{AI}_{i,m,t=5}(RR)}{max(\overline{AI}_{i,m,t=5}(RR))} \cdot 9 + 1 \tag{3.14}$$

   Where:

   $F_{i,k}$ = Airfare score for airport i in year k
   $\overline{AI}_{i,m,t=5}(RR)$ = Mean of reversed ranked airfare indices for airport i, in year k, for trip level 5 (total)

3.3.3. Connectivity

Definition and Importance

The third and final airport key performance indicator is its connectivity. Air connectivity reflects how well a country, city, or airport is connected to cities around the world. Access to greater air connectivity is fundamental for the ability of a given country or city to develop economic linkages with the rest of the world. Air connectivity provides the foundation for the international mobility of people and goods and is, therefore, a vital engine of economic growth worldwide. The connectivity of MAR airports combined make up the connectivity of that MAR, and thereby part of its country's connectivity worldwide.

In 2019, Australia's national carrier Qantas was testing a new non-stop commercial flight from Sydney to London. This flight takes 19.5 hours to complete and, if launched, means the world of air travel has reached ultra-long-haul travel. A century ago, it took 28 days to reach Australia from the UK by air with multiple stops on the way and no passengers on board [78]. In the late 1940s, the length of this trip was shortened considerably and yet it would take four days for passengers to reach Sydney from London with stops in Rome, Tripoli, Cairo, Karachi, Calcutta, Singapore and Darwin. The introduction of jet engines and other new aircraft technologies have made it possible to operate direct flights on long-haul and ultra-long-haul distances, allowing airlines to add and develop air connectivity regionally and globally. Consequently, it is now possible to reach London the same day one departs from Sydney.

Improved air connectivity benefits users of air transport networks (passengers and shippers). Perhaps the most important economic benefit of air transport is the value that passengers and shippers derive from the ability to access destinations and markets around the world [78].

Over the course of the past decades, air travel has offered consumers and producers more choice in routings and faster linkages to the rest of the world, at an ever-decreasing cost in real terms. In 2019, the air transport industry connected a record number of cities worldwide, reaching and exceeding 23,000 unique city-pair connections for the first time. Moreover, the cost of air travel and air freight transportation has been decreasing in real terms as savings from new technology adoption and greater efficiencies are being passed on to the consumer in the form of a lower price in real terms [78].

Improved air connectivity brings about wider economic benefits, beyond air traffic passengers. It serves as an important catalyst for economic growth and prosperity because it can boost the supply side of the economy and build additional productive capacity to enable economic growth without inflationary pressures [78].

A 10% increase in direct air connectivity comes with a 0,5% additional increase in GDP per capita [2]. Therefore, citizens' access to air connectivity is a fundamental part of the equation for economic and social cohesion. Using the connectivity models presented here, this analysis provides indices that matter most in citizens' access to direct and indirect connectivity, based on both quantitative and qualitative metrics. This means this is not simply a measure of how many city pairs there are, or how many direct services there are. Connectivity used in this research is a composite measure of the number of destinations, the frequency of services and the quality of the connections (in the case of hubbing or indirect services).

Methods

Regions with low connectivity can enhance their competitiveness by improving the connectivity of their airports [136]. Therefore there is no surprise that academics and practitioners in transport science have made efforts to develop indices for measuring the connectivity of airports [31]. Complex network science can be used to measure the connectivity of air transport networks and thus airports. A two-dimensional classification is considered for connectivity measures based on transport networks [136]:

1. Local versus global connectivity: The first connectivity airport measures that come to mind are the number of direct connections, passenger transported, and so on. These are measures of local or direct connectivity. However, the development of hub-and-spoke operations has enhanced the value of global or indirect connectivity or hubbing, that is, the availability of indirect connections of an airport.

2. Weighted versus unweighted measures: Direct connections can be considered unweighted or weighted. We consider that an unweighted direct connection between two airports exists if there is at least one direct connection between these airports in a time window. In weighted networks, we associate with each connection a measure of its intensity. The most common are the number of flights scheduled, available seats or available seats per kilometre.

One of the most popular methods derived from complex network analysis measuring airport connectivity is the SEO NetScan Connectivity Model, which is used by ACI. This method considers a global weighted measure of connectivity. Since 1997, NetScan has been applied in many consultancy studies for different stakeholders and has been widely published in international peer-reviewed academic journals [139]. Another reason for using the method is that it not only computes airport connectivity indices but also analyses the connectivity of multi-airport regions and their countries. This is useful when analysing developing countries and identifying the potential of new airports in terms of additional economic benefit as a result of this additional connectivity.

Besides ACI's NetScan model, another frequently used model is developed by the International Association of Air Transport (IATA) [78]. Just as the NetScan method, it considers a global weighted measure of connectivity. Both methods will be analysed and compared with each other to make sure the more relevant method is used in this research.

The connectivity of airports in a MAR is made up of four types of connectivity definitions, which all have their own computational method. Combined, they form the total connectivity of an airport [2]:

- Direct Connectivity. These are the direct air services available from the airport, measured not just in terms of destinations, but also factoring in the frequency of flights to the same destination (so for example, an airport with 5 daily flights to another airport, will register a higher score than one with only 4).
- Indirect Connectivity. This measures the number of places people can fly to, through a connecting flight at hub airports from a particular airport. For example, if you fly from Cork to a hub airport such as Amsterdam Schiphol, that's a direct flight from A to B. But with the vast choice of onward destinations you can fly to from there, the large number of available onward connections from these airports expands the range of destinations available from the airport of origin. Indirect connections are weighted according to their quality, based on connecting time and detour involved with the indirect routing. For example, a flight from Manchester to Johannesburg via Paris-Charles de Gaulle will register a higher score than an alternative routing via Doha.
- Airport Connectivity. This is the most comprehensive metric for airport connectivity, taking into account both direct and indirect connectivity from the airport in question. Airport connectivity is defined as the sum of direct and indirect connectivity – thus measuring the overall level to which an airport is connected to the rest of the World, either by direct flights or indirect connections via other airports.
- Hub Connectivity. Hub connectivity is the key metric hub airports. Essentially, it measures the number of connecting flights that can be facilitated by the hub airport in question, taking into account a minimum and maximum connecting time, and weighing the quality of the connections by the detour involved and connecting times. This measure is not taken into account in this research because transfer flights do not supply or attract passengers from the Greater London region.

SEO's NetScan method is presented first, after which IATA's connectivity model is analysed. Finally, both models are compared and a conclusion is made which model will be used and why.

SEO Netscan [2]
The NetScan model first identifies all direct and indirect (one-stop) connections available on an airport pair. The model uses OAG passenger flight schedule data on direct flights as input. Here, the flight schedule for the third week of June was used for the years 2010 - 2019. Indirect connections are created within the model by connecting two direct flights taking into account minimum and maximum connecting times. Indirect connections are possible at any given airport either between flights of the same airline or between flights of airlines working together in an alliance or through a codeshare agreement. Indirect connections are less attractive to passengers than direct connections, due to the transfer and circuity time involved. Therefore, each connection is weighted for its quality and ranges between zero and one.

A direct, non-stop flight operated by a jet aircraft is given the maximum quality of one. The quality of an indirect connection will always be lower than one since travel time is added due to transfer time and circuity time. The same holds for a direct multi-stop connection for a direct connection operated by a turboprop: passengers face a lower network quality because of a longer travel time. Connections with a too-long travel time relative to the theoretical direct flight time will be assigned a quality of 0. As such, these connections are considered to be unrealistic travel options for the passenger.

First, the maximum allowable perceived travel time (MAPTT) is calculated. the MAPTT $t_{x(h)y}^{perceived,\,max}$ between airport X and Y depends upon the non-stop flight time (NSFT) between both airports $t_{xy}^{flight,\,non-stop}$ and a factor that decreases with distance. The NSFT is determined by the geographical coordinates of origin and destination airport and the flight speed of an average jet aircraft taking into account the time needed for take-off and landing. Over longer distances, passengers are willing to accept longer transfer- and circuity times. Therefore, the MAPTT also depends on a factor that decreases with distance: the further apart two airports are, the longer the MAPTT will be. This is captured in Equation 3.15.

$$t_{xy}^{perceived,max} = t_{xy}^{flight,non-stop} + 5 \cdot log(t_{xy}^{flight,non-stop} + 0,5) \tag{3.15}$$

Second, the actual perceived travel time (APTT) is determined. For direct connections, the APTT between airport X and Y $t_{x(h)y}^{perceived,actual}$ equals the actual flight time (AFT) $t_{xy}^{flight,actual}$. For indirect flights the APTT equals the flight times on both flight legs plus the transfer time at hub h $t_{h}^{transfer}$. As transfer time is considered more uncomfortable than flight time, the transfer time is penalized by a factor that decreases with distance P_{xy}.

$$t_{x(h)y}^{perceived,actual} = \begin{cases} t_{xy}^{flight,actual}, & \text{for direct flights} \\ (t_{xh}^{flight,actual} + t_{hy}^{flight,actual}) + P_{xy} \cdot t_{h}^{transfer}, & \text{for indirect flights} \end{cases} \tag{3.16}$$

If the AFT is smaller than or equal to the average NSFT, then the weight of the connection $q_{x(h)ya}$ equals 1. In practice, this is only the case on direct flights operated by aircraft that are at least equally fast as the average jet aircraft on which the non-stop flight time is based. When the APTT becomes larger than the MAPTT, the weight of the connection is zero and the connection will be considered enviable. In any other case, the APTT lies between the NSFT and the MAPTT. In these cases, the weight of the connection depends on the relative difference between the perceived and maximum allowable travel time.

$$q_{x(h)ya} = \begin{cases} 1, & if\ t_{x(h)y}^{perceived,actual} \leq t_{xy}^{flight,non-stop} \\ 1 - \frac{t_{x(h)y}^{perceived,actual} - t_{xy}^{flight,non-stop}}{t_{xy}^{perceived,max} - t_{xy}^{flight,non-stop}}, & if\ t_{xy}^{flight,non-stop} < t_{x(h)y}^{perceived,actual} < t_{xy}^{perceived,max} \\ 0, & if\ t_{x(h)y}^{perceived,actual} \geq t_{xy}^{perceived,max} \end{cases} \tag{3.17}$$

When the APTT is relatively small compared to the MATT, the weight of the connection is high and vice versa. The connectivity $CNU_{x(h)ya}$ of an individual direct or indirect connection equals its quality $q_{x(h)ya}$.

$$CNU_{x(h)ya} = q_{x(h)ya} \tag{3.18}$$

The CNU is calculated for each individual direct and indirect connection. This means that when a flight is offered with a daily frequency, the CNUs for each of these seven flights as well as for each possible connection have been calculated. The reason for distinguishing between individual flights is twofold. First, the flights might be carried out by different aircraft types during the week leading to different flight times and therefore differing CNUs. Second, the same flight might connect to different flights on for example Monday than on a Friday.

Summing the quality-adjusted connectivity values offered by an airport on a certain route provides the total connectivity on the route. Summing direct and indirect connectivity offered from airport i in year k yields the airport connectivity index $CI_{I,k}$, which measured the connectivity available to air traffic passengers using that airport.

IATA [78]
IATA has developed a connectivity indicator to measure the degree of integration of a country into the global air transport network. It is a composite measure reflecting the number and economic importance of the destinations served from country's major airports and the number of onward connections available from each destination. Geographically, IATA's air connectivity index enables the reporting of connectivity scores at different levels of aggregation: city, country and region. The index has global coverage and encompasses virtually all countries around the world. It covers more than 3,000 cities globally. The countries covered are grouped into different regions as follows:

1. Africa
2. Asia
3. Europe
4. Latin America
5. The Middle East
6. North America

The connectivity indicator is based on the number of available annual seats to each destination between 2014 and 2019. The source of available seat capacity is SRS Analyser, a comprehensive database containing passenger and cargo schedules for more than 900 airlines worldwide. The number of available seats to each destination is then weighted by the size of the destination airport (in terms of the number of passengers handled at that airport each year). The weighting for each destination indicates the economic importance of the destination airport and the number of onward connections it can provide.

For example, Beijing airport, the world's largest airport, is given a weighting of 1 while Austin airport, which handles 15% of the number of passengers handled by Beijing, is given a weighting of 0.15. Therefore, if an airport has 1,000 seats available in Beijing it is given a weighted total of 1,000. But it also has 1,000 seats available to Austin, these are given a weighted total of 150. The weighted totals are then summed for all destinations served out of a given airport to determine the connectivity indicator.

Another way to illustrate the impact of destination airport weights is to think of a single flight from Geneva to Beijing or Austin. Other things being equal, a flight from Geneva airport to Beijing would receive a higher connectivity score compared to a flight from Geneva to Austin airport (Figure 5). The difference in destination weights reflects the extent to which destination airports are connected to the rest of the global air transport network.
Therefore, the connectivity indicator for a given airport can be represented as the sum of destination weighted available seats from the airport to all destination airports:

$$ACI = \sum_{k=1}^{all\ destination} (Annual\ Outbound\ Seats_k \cdot Destination\ Airport\ Weight_k \tag{3.19}$$

Where:

ACI = Air connectivity index
k = Destination

Another mathematically equivalent way to write this formula, according to IATA, shows that the frequency of service from the origin airport to other destinations is taken into consideration:

$$ACI = \sum_{k=1}^{all\ destination} (Flight\ Frequency_k \cdot Average\ Available\ Seats\ per\ Flight_k \tag{3.20}$$

As evident from the second formulation, air connectivity increases as the range of destinations increases, the frequency of service increases or larger "hub" airport destinations are served.

Conclusion
Complex network science forms the basis for airport connectivity models by analysing the network of nodes, which represent airports. Due to increasing hub-and-spoke networks, this science has become more interesting and detailed over the years. Two connectivity models were identified to compute the connectivity of airports in a MAR; ACI's SEO NetScan Connectivity Model and IATA's Connectivity Model. There are three main differences among these methods that have resulted in the decision for ACI's NetScan Connectivity Model:

- The ACI method is primarily focused on European airports and includes the major airports outside. IATA's method has a broader scope concerning worldwide airports. However, the results, as will be shown below this list, shows that taking into account smaller airports located far away from the airport in question does not affect the connectivity index significantly.
- The main application of ACI's NetScan air connectivity model is for competitive analysis of continents, countries, cities, airlines and airports. By contrast, the IATA air connectivity index is focused on country and regional levels, and is not airport specific. When comparing airports, this is crucial.
- ACI's measure emphasizes the quality of indirect connections, whereas IATA's measure implicitly captures indirect connectivity by measuring the quality of the destination in terms of its connectivity to the rest of the air transport network, which is less accurate.

In terms of results on a country level, ACI's connectivity index closely correlates with the method from IATA, as can be seen in Figure 3.4.

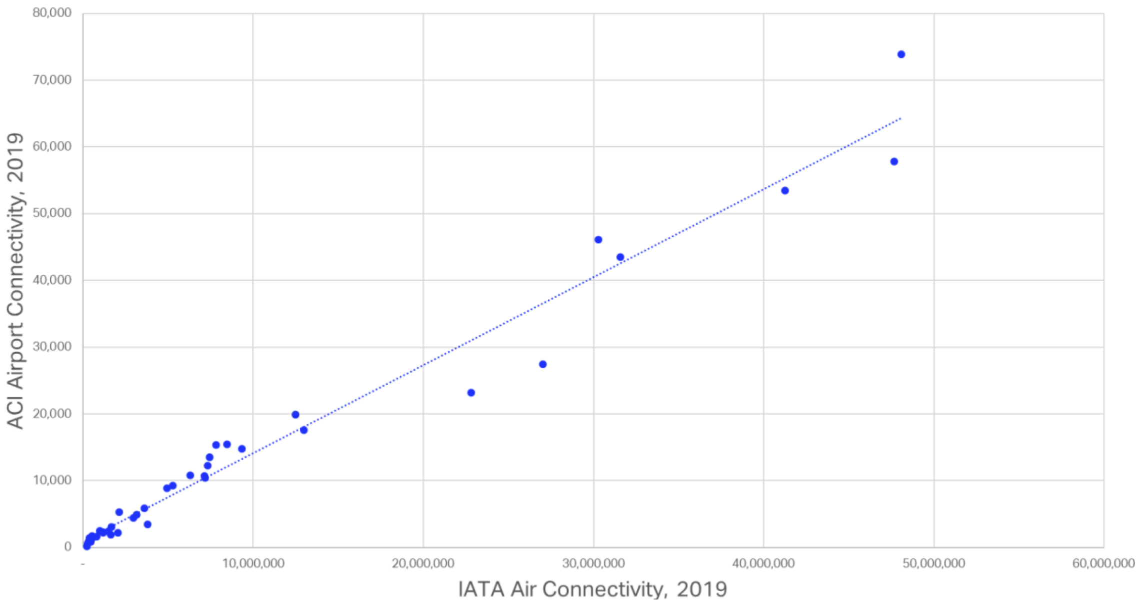

Figure 3.4: ACI and IATA air connectivity score by country 2019 (R-squared = 0.98)

So, NetScan connectivity indices for MAR airports are compared amongst each other and converted into a connectivity score ranging from 1 to 10 using Equation 3.21, which uses the same concept as is done for accessibility and airfare. This ensures cross comparing airports according to their key performance indicators is possible.

$$C_{i,k} = \frac{CI_{i,k}}{max(CI_{i,k})} \cdot 9 + 1 \tag{3.21}$$

Where:

$C_{i,k}$ = Connectivity score for airport i in year k
$CI_{i,k}$ = Connectivity index for airport i in year k, obtained from the NetScan model (Equation 3.18)

3.4. Airport Allocation and Market Shares

In the first modelling block regarding the regional air traffic demand forecast, the amount of air traffic passengers that use MAR airports is modelled. The allocation of this regional demand over the airports in the MAR is based on the relative performance of airports, regarding their accessibility, airfares, and connectivity, which is computed in the second modelling block of the quantitative model. This is done using Equation 3.11, Equation 3.14, and Equation 3.21, which results in a score for each KPI from 1 to 10, for all MAR airports, for 2010 - 2019. These scores combined should represent the relative performance of airports.

The goal of the quantitative model is to understand the evolution of airport market shares based on the allocation of air traffic passengers amongst airports in the MAR. The evolution of airport market shares in the MAR is split into a historical period, ranging from 2010 to 2019 and a projected period, ranging from 2020 to 2050. To accomplish this goal, the methodological steps of the third and final modelling block of the quantitative model are presented in this section. In Figure 3.5, visualisation of this third modelling block is presented.

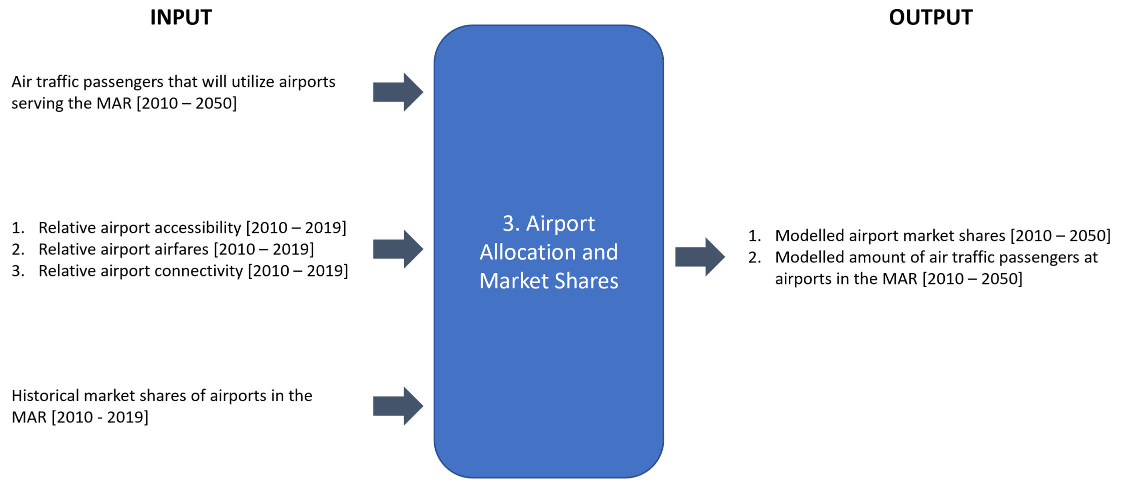

Figure 3.5: Modelling block 3: Airport allocation and market shares

First, the research aims to accurately model historical market shares based on the recently computed scores for airport key performance indicators. This is done through a multivariate regression analysis, where historical airport market shares in MAR are mathematically dependent and explained by the airport's key performance indicators. Here, historical market shares form the dependent variable and the KPI scores form the independent (explanatory) variables.

Second, the projected market shares of airports in the MAR are computed based on:

1. Projections of the accessibility of airports in the MAR;
2. Projections of the airfares of airports in the MAR;
3. Projections of the connectivity of airports in the MAR;
4. Results of the regression analysis. These provide the correlation between airport performance, based on accessibility, airfare, and connectivity, and their market shares.

For example, an airport expands by building a new runway which allows more operations by existing or new airlines at the airport. If new routes are flown that has not yet been flown before from that airport, the connectivity increases, thus increasing its relative connectivity score. In combination with the results from the regression analysis, the adapted market shares projections can be computed. This will in all likelihood result in an increased market share for the expanded airport and a decrease in all other airports serving the MAR.

The regression analysis allows the model to calculate market shares of airports serving the MAR, based on their relative performance on accessibility, airfares, and connectivity. The mathematical explanation can be observed below.

$$Y_{i,k} = \beta + \alpha \cdot A_{i,k} + \tau \cdot F_{i,k} + \sigma \cdot C_{i,k} \tag{3.22}$$

Where:

$Y_{i,k}$ = Market share of airport i in year k
β = Interception point
α = Coefficient for accessibility
$A_{i,k}$ = Accessibility score for airport i in year k, available from Equation 3.11
τ = Coefficient for airfare
$F_{i,k}$ = Airfare score for airport i in year k, available from Equation 3.14
σ = Coefficient for connectivity
$C_{i,k}$ = Connectivity score for airport i in year k, available from Equation 3.21

Second, the air traffic passengers that utilise an airport in the MAR in a certain year can now be modelled using the equation below.

$$P_{i,k} = MAR\ ATD_k \cdot Y_{i,k} \tag{3.23}$$

Where:

$P_{i,k}$ = Air traffic passengers using airport i in year k
$MAR\ ATD_k$ = MAR air traffic demand in year k, which results from regional air traffic demand forecast
$Y_{i,k}$ = Market share of airport i in year k available from Equation 3.22

3.5. Coding Methodology

The quantitative model that has been set up in this research can be applied to every multi-airport region around the world if the minimum required data is provided. The quantitative model has been set up using Python (version 3.8) programming which needs two formatted data files. So, if the model is to be applied to a multi-airport region, the following data is necessary.

1. Sabre air traffic datasets for the years 2010 - 2019 for all airports considered. This is a .csv format and should contain the column names as mentioned in subsection 3.3.2.
2. A formatted MAR data-set in .xlsx format. This dataset is split into seven tabs that represent a data category:
    - Population. Contains population data for all sub-regions/districts for 2010 - 2019.
    - Income. Contains income data for all sub-regions/districts for 2010 - 2019.
    - Historical market shares. Contains market shares of airports serving the MAR for 2010 - 2019 in terms of air traffic passengers and percentages..
    - Geography airports. Contains identification names and coordinates of airports in question.
    - Geography region. Contains regional information on sub-regions (districts and wards) and their coordinates.
    - Connectivity. Contains connectivity indices for airports in question, resulting from the SEO NetScan Connectivity Model.
    - Access Times. Contains the result of the airports' access times computations.

4 Case Study Greater London

The analysis framework of this research can be performed on any MAR. However, several methodological steps can not be solely presented on a generic level and must be illustrated for a specific multi-airport region. Therefore, the analysis framework is illustrated and analysed on MAR *"The Greater London Area"*, which is one of Europe's major aviation hubs, located in the Southeast of the United Kingdom, and served by six airports. This chapter introduces the MAR by presenting its geographics, airports, and strategy. Then, the methodology is illustrated in detail for The Greater London Area, which from now on is refered to as Greater London.

This chapter focuses on four major aspects of Greater London. First, the geographics of the region are analysed. Second, the airports are presented with detailed information regarding their history, layout, markets served and passenger profiles. Third, the strategy of the region is briefly introduced which is returned in the forecasting framework in chapter 6. Fourth and final, the quantitative model is illustrated for Greater London.

4.1. Greater London Geographics

Greater London is an administrative area in England governed by the Greater London Authority (GLA), and a ceremonial county that covers the bulk of the same area, with exception of the City of London, which forms a separate ceremonial county. The administrative area, which has the same scope as the region of London, is organised into 33 local governmental districts, the 32 London boroughs and the City of London. In this research, the City of London and the 32 London boroughs have the same function. Therefore, the City of London is referred to as a 33rd 'borough'. The layout of these 33 local governmental districts that make up Greater London can be seen in Figure 4.1.

Each of these districts supplies and attracts air traffic passengers to and from airports that serve this region. It is assumed that a district's supply of departing air traffic demand is similar to its demand of arriving air traffic passengers because arriving traffic numbers are similar to departing traffic numbers [135]. This entails air traffic demand concerning a district depends on the characteristics of that district. Districts with more and wealthier inhabitants are more likely to contribute to a higher air traffic demand compared to a district with fewer and less wealthy inhabitants [54, 38, 112, 158]. Therefore, it is important to comprehend such characteristics of districts supplying air traffic demand to airports serving the region.

London districts, its 32 boroughs and the City of London are made up of wards. The wards in the United Kingdom are electoral districts at the sub-national level represented by one or more councillors and are made up of postcodes. Socio-economical and geographical data of these postcodes, grouped in wards and districts, provide vital information for air traffic modelling. Therefore, this has been researched and structured as can be seen in Table 4.1.

Greater London has experienced significant urbanisation, resulting in a 41% rise in its population since 1980 [132]. This shows a considerably larger percentage increase compared to the 22% for United

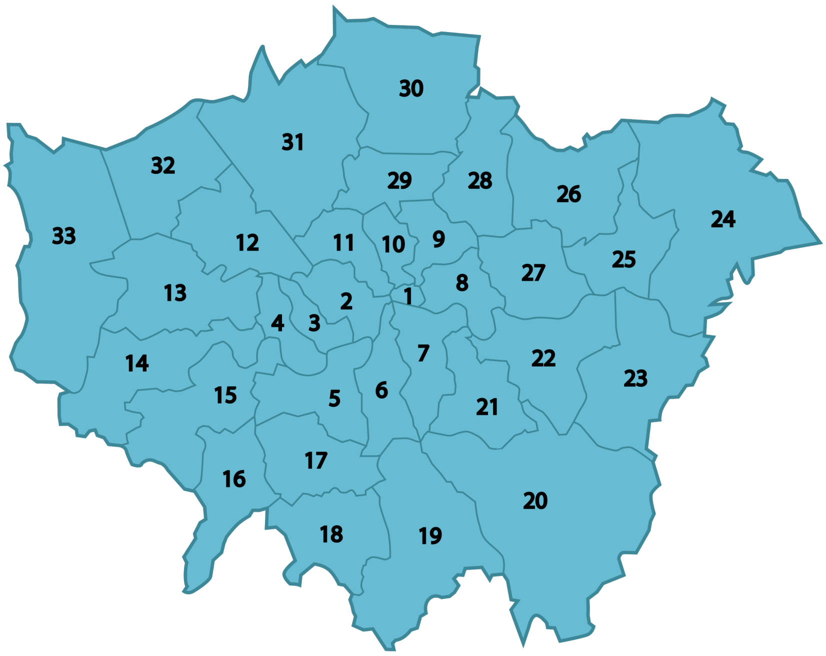

Figure 4.1: Overview of London's 33 governmental districts (Boroughs + City of London)

Districts	Map Nr	Number of Wards	Total Inhabitants (2019*)	Average Income (2019*) (GBP)
Barking and Dagenham	25	17	214,858	24,553
Barnet	31	21	402,363	27,963
Bexley	23	17	252,885	28,849
Brent	12	21	340,710	27,316
Bromley	20	22	334,292	33,275
Camden	11	18	255,526	34,510
City of London	1	25	7,953	49,076
City of Westminster	2	20	258,511	36,694
Croydon	19	28	396,548	29,281
Ealing	13	23	354,184	27,744
Enfield	30	21	339,480	25,549
Greenwich	22	17	289,650	30,209
Hackney	9	21	286,425	29,970
Hammersmith and Fulham	4	16	186,075	37,951
Haringey	29	19	285,949	28,546
Harrow	32	21	258,861	30,334
Havering	24	18	258,655	29,636
Hillingdon	33	22	312,567	28,458
Hounslow	14	20	281,339	28,546
Islington	10	16	241,589	36,444
Kensington and Chelsea	3	18	160,531	39,812
Kingston upon Thames	16	16	180,598	32,738
Lambeth	6	21	338,028	33,092
Lewisham	21	18	314,027	28,776
Merton	17	20	210,452	30,178
Newham	27	20	359,470	26,977
Redbridge	26	22	307,690	29,485
Richmond upon Thames	15	18	200,703	37,591
Southwark	7	23	327,271	32,738
Sutton	18	18	209,666	28,619
Tower Hamlets	8	20	323,696	35,912
Waltham Forest	28	20	286,776	29,970
Wandsworth	5	20	328,828	37,581

* 2019 data is taken ot provide uniform input with model

Table 4.1: Overview of Greater London District Characteristics of 2019 [12, 103]

Kingdom population for the same period [107]. UK's and Greater London's population growth since 1980 and its projections up to 2035 can be observed in Figure 4.2 and Figure 4.3.

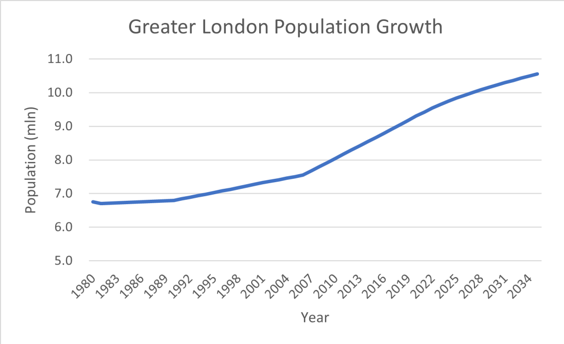

Figure 4.2: Greater London Population Growth 1950-2035

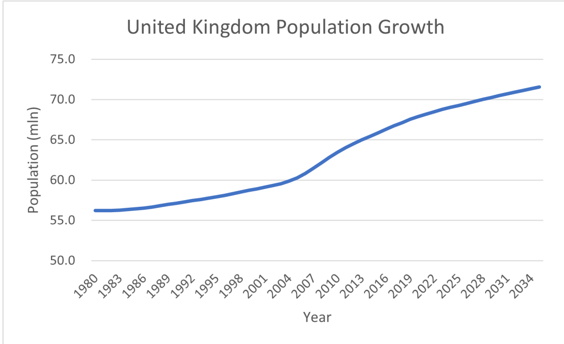

Figure 4.3: United Kingdom Population Growth 1950-2035

Greater London is surrounded by the so-called 'London Metropolitan Area', which includes Greater London and its surrounding commuter zone. This is the area in which it is practicable to commute to work in London and is also known as 'the London commuter belt' or 'Southeast metropolitan area'. Greater London produced £503 billion in 2019 while its metropolitan area - being the largest in Europe - generated £730 billion, contributing 33% to the UK's GDP of £2.2 trillion [104, 15, 58, 59].

4.2. Greater London Airports

This Greater London Area is served by the airports listed below and their distribution within the region can be observed in Figure 4.4.

1. London Heathrow Airport (LHR)
2. London Gatwick Airport (LGW)
3. London City Airport (LCY)
4. London Luton Airport (LTN)
5. London Stansted Airport (STN)
6. London Southend Airport (SEN)

The London airport system is one of the busiest transportation nodes by passenger volume worldwide. Combined, the six international airports handled over 180 million passengers in 2019.

London Heathrow Airport (LHR) is the busiest airport in the UK and one of the busiest in Europe with 81 million passengers in 2019, operating near full capacity for a decade now. It is located west of London's city centre, which can be accessed within 15 minutes with public transport. It is focused on intercontinental and long-haul O&D passengers served by full-service carriers.

London Gatwick Airport (LGW) is the second busiest airport in London and served 46.6 million passengers in 2019. It is located south of London's city centre and can be reached through public transport within 42 minutes. It is focused on tourism traffic and low-cost operators.

London City Airport is located near the heart of the financial district of London and served 5.1 million passengers in 2019. Owing to its convenient location in the financial district, also referred to as the commercial business district (CBD), London City Airport accommodates business traffic arriving from major cities in Europe. 80% of traffic is international and British Airways is the main airline serving the airport.

London Luton (LTN), Stansted (STN) and Southend Airport (SEN) are all located roughly 50 km from the city centre. These airports served 18, 28 and 2 million annual passengers in 2019 respectively, of

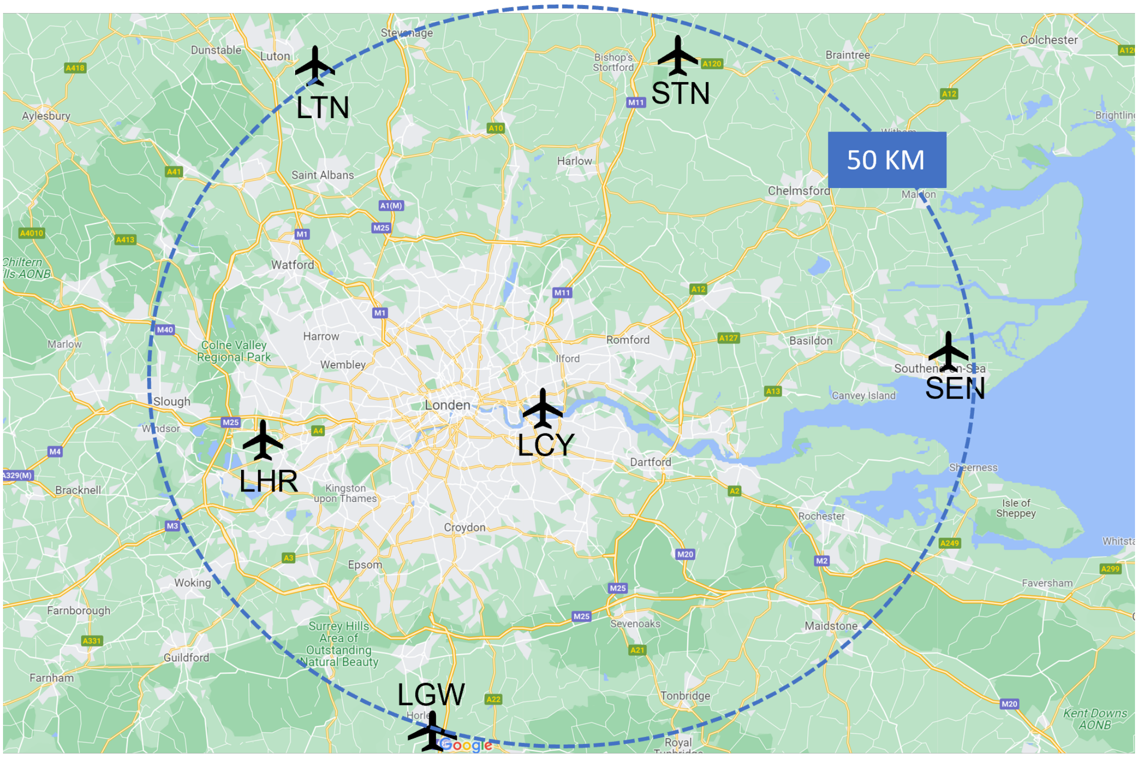

Figure 4.4: MAR Overview

which 90% were international passengers. They all focus on tourism traffic and low-cost carriers. An overview has been made of relevant airport data as can be seen in Table 4.2.

	LHR	LGW	LCY	LTN	STN	SEN
Annual passengers [mln]	80.9	46.6	5.1	18.0	28.1	2.0
Cargo [thousand metric tonnes]	1.700	150	n.a.	28	258	n.a.
Location w.r.t. city centre	West	South	Center	Northwest	Northeast	East
Focus	International long-haul	International	Business	Tourism LCC	Tourism	Tourism LCC
Nr of terminals	5 (3 operating)	2	1	1	1	1
Nr of runways	2	2 (1 operational)	1	1	1	1
Nr of annual aircraft movements	475.000	280.700	80.751	141.481	181.100	36.979

Table 4.2: Overview of London Airports [4, 5, 111, 3, 94]

Due to urbanisation, rising air traffic demand has resulted in a 41% rise in air traffic passengers using these airports in the last decade. This has resulted in pressure on airport capacity. Especially airports that focus on international traffic have shown a strong increase in air traffic passengers. Major factors driving this besides urbanisation are the rising amount of companies and their size in the commercial business district of London, and the increased tourism destinations Southeast London offers. In Figure 4.5, the rise in air traffic demand in the Greater London Area since 2010 can be observed.

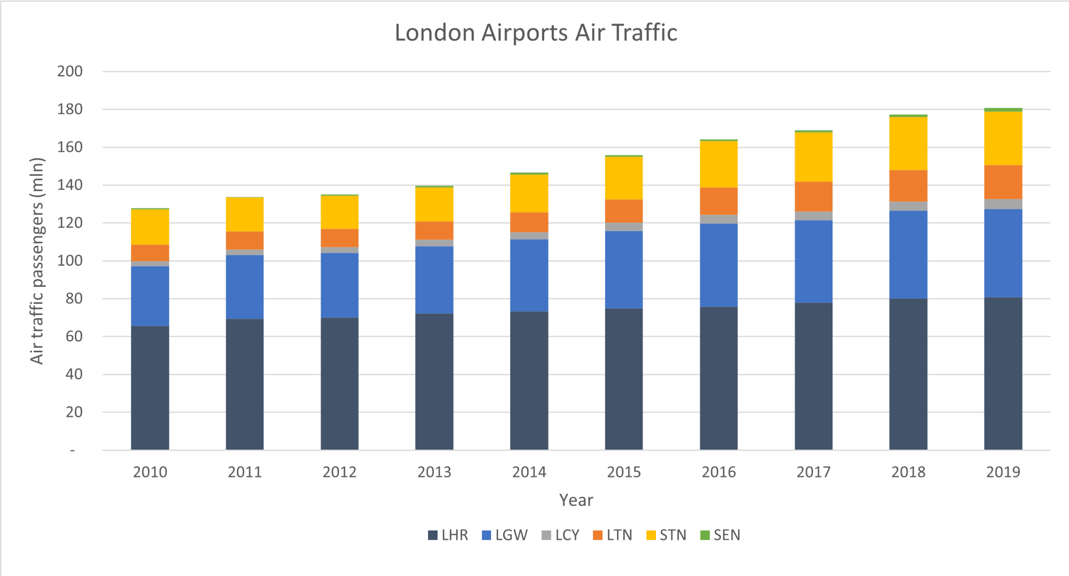

Figure 4.5: London Airport's Air Traffic 2010-2019

4.3. Greater London Strategy

The UK has the largest aviation network in Europe and the third-largest in the world. Aviation directly contributes at least £22 billion to the economy and supports 0.5 million jobs. The government supports the growth of aviation and the benefits this could deliver, provided that growth sustainably takes place, with actions to mitigate the environmental impacts.

Despite many advantages of a growing UK aviation, it faces various challenges that need to be overcome to take advantage of the opportunities the future holds, and to realise the benefits of sustainable growth while remaining at the forefront of aviation. All of these challenges are applicable to the aviation market in the Greater London Area, being UK's global hub. These challenges include:

- Global change and shifting markets;
- Impact of competition on business models;
- Increasing air traffic demand;
- Changing expectations of passengers;
- Effects of international climate change;
- Unlocking the full potential of modern technology.

As a result of increasing air traffic demand and a lack of capacity, the London airspace is full of holding stacks, which are circular flight paths where arriving aircraft often need to hold in before landing, resulting in delays and extra noise and carbon emissions. To safeguard its role as a major international hub and one of the leading aviation and aerospace sectors, the UK and Greater London must be well-positioned to take advantage of new opportunities while managing the potential economic, political and environmental challenges along the way. The UK Transport Department has set up an aviation strategy based on seven themes that will aid in achieving this.

1. Build a global and connected Britain;
2. Ensure aviation can grow sustainably;
3. Support regional growth and connectivity;
4. Enhance the passenger experience;

5. Ensure a sage and secure way to travel;
6. Support general aviation;
7. Encourage innovation and new technologies.

Build a global and connected Britain
Greater London plays a prominent role on the world stage being the largest international aviation network in Europe and the third largest worldwide. To keep this role, new connecting markets must emerge, and rising air traffic demand must be facilitated. Hereby, it is important to improve global standards, maintain and improve UKs connectivity, and support UK aviation export.

Ensure aviation can grow sustainably
To facilitate rising air traffic demand, the MAR should increase capacity and optimise operations. This should be done in partnership with governments, regulators and the industry to provide a comprehensive policy framework to better manage the environmental impacts of the sector. This framework is summarized in Figure 4.6. It concludes an extra Northwest runway at Heathrow and optimising runway use at surrounding airports will meet forecasted aviation demand up to 2030.

Figure 4.6: Partnership for sustainable growth

Support regional growth and connectivity
Airports are vital hubs for local economies, providing connectivity, employment and a hub for local transport schemes. To maximise these benefits, the following must be ensured:

- Markets are functioning effectively for consumers and local communities;
- Airports are delivering the connectivity that regions need to maximise their potential;
- The industry continues to provide high-quality training and employment opportunities;
- Barriers to the air freight industry are reduced.

Enhance the passenger experience
The industry is responsive to the needs of consumers but improvements can be made for passengers with additional needs. The UK government is working on a new 'Passenger Charter' to promote good practice in the sector, create a shared understanding of the level of service passengers should expect, and communicate roles and accountability clearly. The government proposes to take necessary action to improve the experience at the border and tackle problems caused by disruptive passengers. It will also consider strengthening the Civil Aviation Authority's range of enforcement powers across the consumer agenda. Aviation strategic plans focus on:

1. Sets out the proposed standards that could be included as part of a new Passenger Charter for aviation;
2. Sets out a range of new measures for passengers with additional needs;
3. outlines measures to tackle the problem of disruptive passengers associated with alcohol describes the government's approach to improving the operating model at the border to enhance the passenger experience;
4. Details proposals for simplifying and improving complaints and compensation procedures;
5. Sets out the government's proposals for ensuring that consumers have timely access to the information they need to make informed choices.

Ensuring a safe and secure way of travel
The UK is a global leader in aviation security and safety, having one of the best and safest aviation systems in the world. The government and CAA share knowledge and expertise with other nations, encouraging them to adhere to international standards and implement improvements with the industry to make the skies safer for everyone. To maintain UK's safety record, the aviation strategy focuses on:

- Addressing concentration of safety risks;
- Targeting emerging safety risks;
- Improving data and reporting;
- Addressing global variations in safety standards.

Support General Aviation
General Aviation (GA) sector contains non-scheduled civil aviation; business jets, pilot training, emergency service flights, air displays and aerial photography as well as private flying. Aircraft include single and multi-engine fixed-wing aeroplanes, helicopters, gliders, balloons, microlights, paragliders and model aircraft. UK's aviation strategy proposes to encourage growth in GA and indicates where GA should seize the initiatives and capitalise on its opportunities. It's focused on:

- How to reduce regulation;
- Strategic networks;
- Support for new existing commercial activities;
- Airspace;
- Safety;
- Safeguarding of aerodromes.

Encourage innovation and new technology
Innovation is key to delivering the outcomes of the UK governmental aviation strategy. They want to capture the benefits of innovation for consumers by unlocking mobility and offering new options on how people and goods can move around; and for the aerospace and aviation sectors, to maintain the UK's global leadership, help support jobs, increase productivity, and boost our trade and export capabilities. Focus-points are:

- Set out areas of opportunity for innovation in aviation - automation, electrification, digitisation and data sharing;
- Identify barriers to innovation and how these can be addressed by the government in its enabling role, working in partnership with the sector;
- Propose measures to better align policy and investments.

4.4. Methodology Illustration

This section presents and quantifies the methodology for The Greater London Region.

4.4.1. Regional Air Traffic Demand Forecast

The regional air traffic demand forecast analyses the correlation between socio-economic variables and air traffic activity, and uses projections of these variables and their correlation with air traffic activity to project air traffic activity in the MAR. Two variables have been proven to drive air traffic demand; GDP and oil prices. Data and projections of these variables are only available on a national level, and therefore, an initial analysis is performed using UK air traffic data. Then, using the correlation of UK air traffic and Greater London air traffic, national GDP and oil price data will be linked to Greater London air traffic activity.

First, UK's GDP relationship with UK's and Greater London's air traffic demand was researched, in which three types of data have been used:

- UK historical and projected annual GDP in real GBP [1980 - 2050] [104]
- UK annual air traffic passengers [1980 - 2019] [13]
- Greater London annual air traffic passengers [2010 - 2019]

The relationship between UK's GDP and UK's air traffic demand (ATD) was analysed and can be observed in Figure 4.7. Regression analysis shows UK air traffic demand can be modelled using Equation 4.1 with an R-squared of 0,9912.

Then, it was analysed how UK air traffic demand is correlated to Greater London (GL) air traffic demand, of which the result can be observed in Figure 4.8. Greater London air traffic demand can be modelled using Equation 4.2 with an R-squared of 0,9923.

Combining Equation 4.1 and Equation 4.2, Greater London air traffic demand can be computed from UK GDP using Equation 4.3.

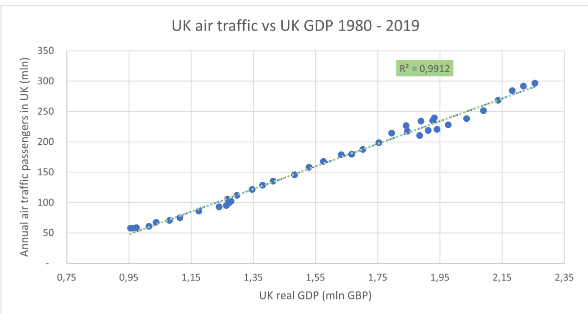

Figure 4.7: UK air traffic vs UK GDP 1980 - 2019

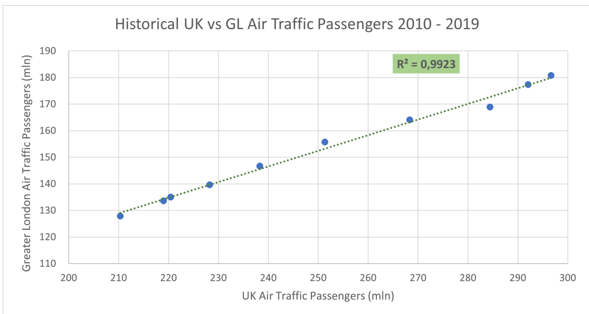

Figure 4.8: UK air traffic vs GL air traffic 2010 - 2019

$$UK\ ATD_k = -129,386,474 + 186.4573942 \cdot GDP\ UK_k \tag{4.1}$$

$$GL\ ATD_k = 5.7138 + 0.587 \cdot UK\ ATD_k \tag{4.2}$$

$$GL\ ATD_k = 5.7138 + 0.587(-129,386,474 + 186.4573942 \cdot GDP\ UK_k)$$
$$GL\ ATD_k = -75,949,854.52 + 109.45049 \cdot GDP\ UK_k, \tag{4.3}$$

Where:

k = Year
$UK\ ATD_k$ = United Kingdom air traffic demand in year k
$GDP\ UK_k$ = Gross Domestic Product of United Kingdom in year k
$GL\ ATD_k$ = Greater London air traffic demand in year k

Besides, over the years 2010 - 2019, it was observed 61.00% of UK air traffic demand used Greater London airports, which can be observed in Figure 4.9. Therefore, Greater London air traffic demand was assumed to be 61.00% of UK air traffic demand. This assumption is more accurate in modelling Greater London air traffic demand compared to the method described by Equation 4.3. Therefore, the 61% assumption is used for the Regional Air Traffic Demand Forecast.

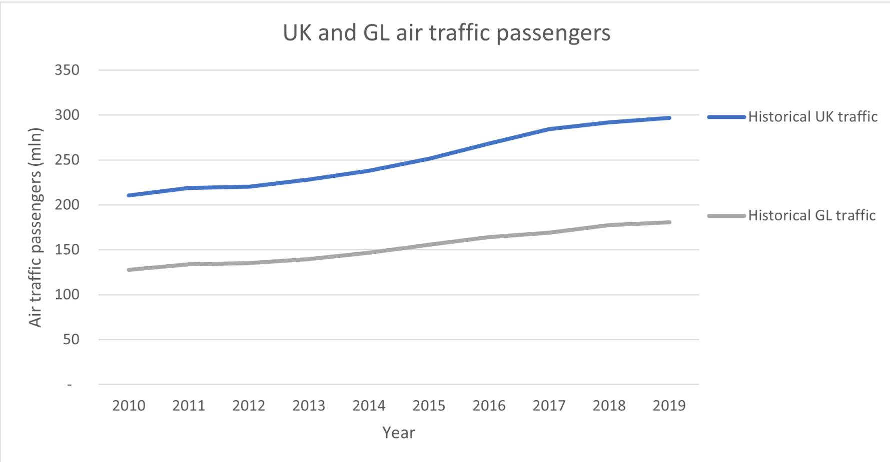

Figure 4.9: UK and Greater London air traffic demand from 2010 - 2019

Another variable that has proven to be related to air traffic demand is oil prices [33]. So, a regression analysis was performed using real oil prices as independent variables and UK air traffic demand as dependent variable. The results are presented in Figure 4.10 and show insufficient correlation and therefore oil prices are not used as predictor variables for UK air traffic demand, nor for Greater London air traffic demand.

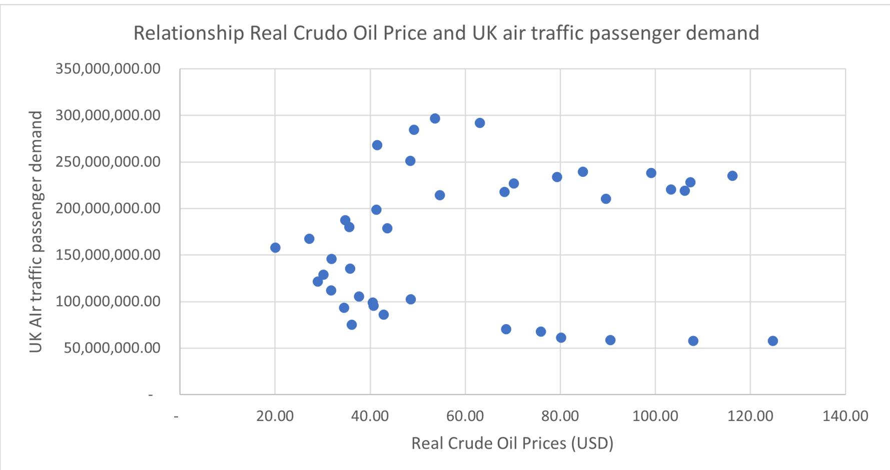

Figure 4.10: Relationship between real crude oil price and UK air traffic passenger demand

So, historical UK GDP was found to be correlated with UK air traffic demand, which was found to be correlated with Greater London air traffic demand over the years 2010 - 2019. Projections of UK GDP up to 2050 were used to project UK air traffic levels, which were used to project Greater London air traffic levels up to 2050. Its results can be found in chapter 5.

4.4.2. Airport Performance

The relative performance of airports is characterised by their attractiveness for air traffic passengers relative to other airports in Greater London. Airport performance is measured based on three key performance indicators; accessibility, airfare and connectivity.

For the accessibility computation, travel times for each airport district combination are weighted by the wealth adjusted population of those districts. Greater London has 33 districts and six airports, which means a list of 6 by 33 is created. For the travel time computation in Equation 3.4, the ratio of public transport ($R_{public\ transport}$) and private vehicles ($R_{private\ vehicle}$) access to airports has to be determined. The portion of air traffic passengers accessing the largest four London airports using private vehicles and public transport can be observed in Figure 4.11:

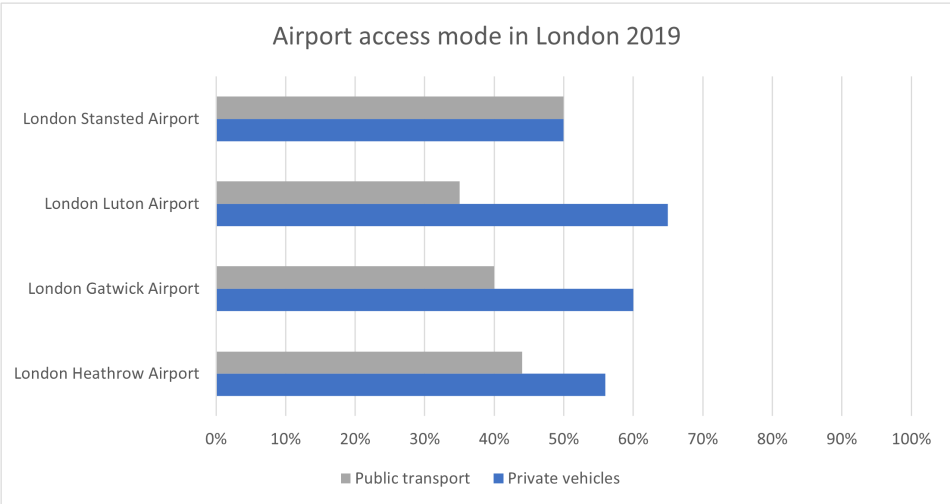

Figure 4.11: Airport access mode 2019

Taking the average for these London airports in 2019, 58% of air traffic passengers access airports using private vehicles and 42% access through public transport. Car transport is considered for the classification of private vehicles. Using these values for $R_{private\ vehicle}$ and $R_{public\ transport}$, travel times for each airport-district combination can now be computed using Equation 3.4 and compared with straight-line distances using Equation 3.3 for each airport-district combination.

For both methods, the mean value for the six London airports was computed to compare them. The hypothesis stated travel times show a smaller disparity than straight-line distance, which can be accepted in the case of Greater London. In Figure 4.12 and Figure 4.13, the results can be observed. To analyse the disparity between the values within average airport travel times and average airport distances, the maximum value from each series was divided by the minimum value of each series. This is 1.76 and 3.49 for travel time and distance respectively, which shows the disparity between travel time values is smaller compared to distances. This is because transport modes generally offer higher velocities for longer distances.

Travel time results in a more representative measure for accessibility than straight-line distance and is therefore taken into the computational method together with population and income.

The second variable that was included in the computation of airport accessibility is population. Population data was gathered at the London district level, of which the results can be observed in

Table 4.3. Summing up these values shows the population in London districts combined has risen 13,0% from 2010 to 2019, as can be observed in Figure 4.14.

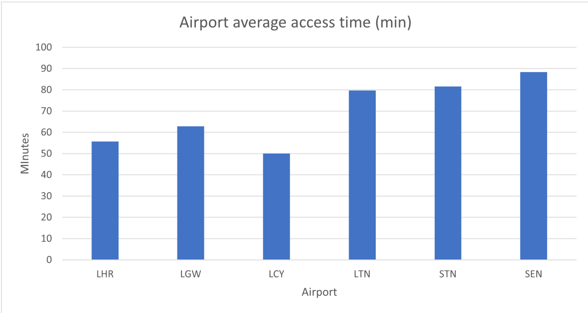

Figure 4.12: Average airport access time in minutes

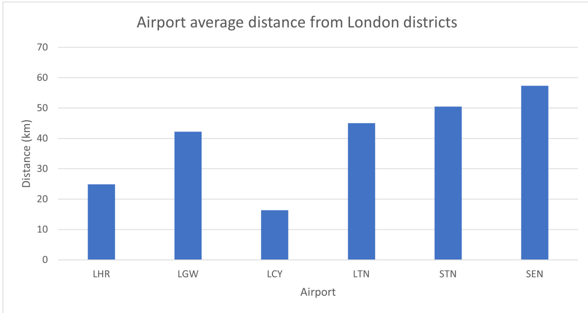

Figure 4.13: Average airport distance from London districts

District	Population 2010	Population 2011	Population 2012	Population 2013	Population 2014	Population 2015	Population 2016	Population 2017	Population 2018	Population 2019
Barking and Dagenham	182,838	187,418	190,949	194,741	198,683	202,368	206,849	210,513	212,773	214,858
Barnet	351,438	357,653	364,071	369,203	375,030	379,806	386,198	391,446	397,049	402,363
Bexley	230,711	233,002	234,499	236,915	240,093	242,370	244,988	247,179	249,999	252,885
Brent	304,785	313,084	315,499	318,103	321,601	324,851	329,093	332,750	336,859	340,710
Bromley	308,560	311,110	314,592	318,455	321,834	325,413	327,445	330,909	332,733	334,292
Camden	214,725	220,087	224,961	229,718	234,845	241,058	246,180	249,556	252,637	255,526
City of London	7,338	7,412	7,204	6,848	6,872	7,160	7,401	7,405	7,681	7,953
City of Westminster	217,187	219,582	223,858	226,841	233,292	242,299	247,614	250,049	254,375	258,511
Croydon	357,951	364,815	368,886	372,752	376,040	379,031	382,304	386,346	391,296	396,548
Ealing	334,073	339,665	341,022	342,845	342,469	343,410	343,547	347,126	350,784	354,184
Enfield	307,648	314,011	317,363	320,600	324,650	328,509	331,471	335,647	337,697	339,480
Greenwich	249,171	255,483	260,068	264,008	268,678	274,803	279,766	282,774	286,322	289,650
Hackney	241,739	247,578	252,515	257,775	263,546	269,405	273,922	277,475	281,740	286,425
Hammersmith and Fulham	180,842	182,790	180,195	179,030	178,710	179,754	179,998	181,889	184,050	186,075
Haringey	252,742	256,438	259,810	264,284	268,439	273,762	279,349	282,397	284,288	285,949
Harrow	237,451	241,063	242,941	243,937	246,575	247,694	249,316	252,052	255,369	258,861
Havering	236,234	238,281	240,087	242,434	246,328	249,439	253,137	256,162	257,511	258,655
Hillingdon	269,465	276,134	282,391	287,443	293,325	298,370	303,106	307,040	309,926	312,567
Hounslow	249,236	255,334	259,459	262,814	265,975	269,177	271,546	274,970	278,264	281,339
Islington	200,129	206,639	211,400	216,024	221,383	228,045	233,218	235,370	238,267	241,589
Kensington and Chelsea	160,463	158,652	156,331	155,995	156,591	158,112	157,127	157,954	159,301	160,531
Kingston upon Thames	158,648	160,469	163,939	166,826	169,991	173,558	176,140	178,419	179,581	180,598
Lambeth	297,650	304,808	310,527	314,569	318,543	324,758	328,237	331,157	334,724	338,028
Lewisham	272,525	277,525	282,143	286,767	292,520	297,912	302,454	306,380	310,324	314,027
Merton	199,136	201,226	202,908	203,906	204,198	205,248	205,712	208,225	209,421	210,452
Newham	299,171	311,912	315,536	319,679	325,774	334,269	342,430	347,448	353,245	359,470
Redbridge	275,088	281,521	284,743	288,398	293,181	296,919	299,375	303,887	305,910	307,690
Richmond upon Thames	186,304	187,527	189,145	191,365	193,585	194,730	195,846	197,988	199,419	200,703
Southwark	283,777	289,361	294,174	299,109	303,182	309,545	313,867	317,735	322,302	327,271
Sutton	189,321	191,515	194,022	196,306	198,526	200,537	202,612	204,933	207,378	209,666
Tower Hamlets	248,520	256,685	263,676	273,563	284,688	295,909	305,527	311,044	317,203	323,696
Waltham Forest	254,009	260,397	263,221	266,452	268,675	271,825	276,498	280,050	283,524	286,776
Wandsworth	302,620	308,300	308,902	311,106	312,735	315,134	316,686	319,731	324,400	328,828

Table 4.3: London District Population 2010 - 2019 [11]

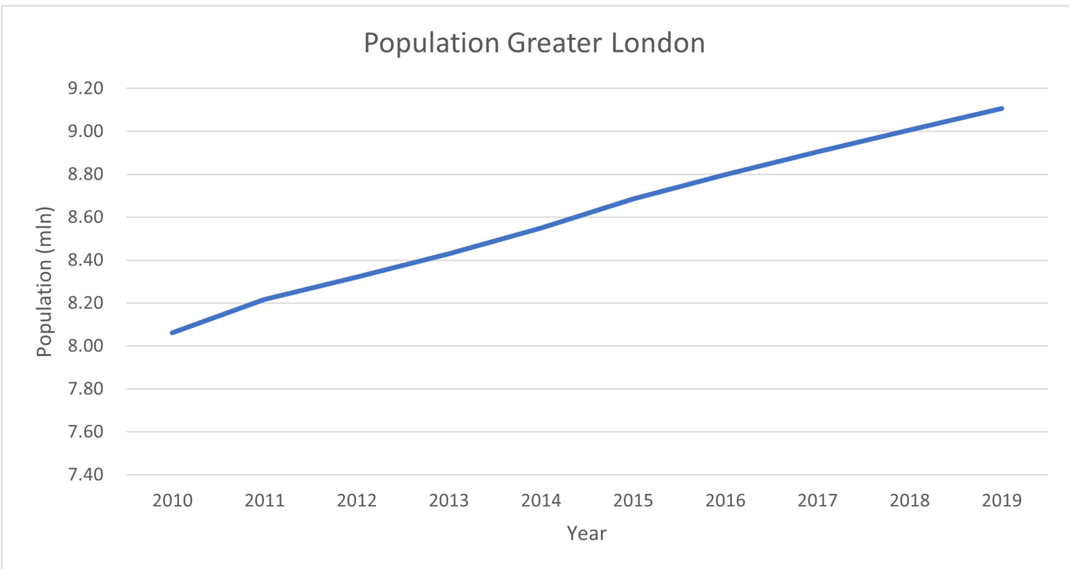

Figure 4.14: Greater London population development 2010 - 2019

The third variable included in the airport accessibility computation is wealth. This research has gathered average income data, in the form of average gross earnings (GBP) per London district through the years 2010 - 2019, which can be observed in Table 4.4. No data was available to analyse the exact elasticity of income to air traffic demand. Therefore, it was assumed population and income contribute equally to the performance of an airport's accessibility.

District	Income 2009	Income 2010	Income 2011	Income 2012	Income 2013	Income 2014	Income 2015	Income 2016	Income 2017	Income 2018	Income 2019
Barking and Dagenham	23,396	22,379	23,568	23,459	23,000	22,025	22,760	24,095	24,032	24,976	24,553
Barnet	27,530	26,148	25,976	26,227	26,977	24,976	25,596	25,314	27,243	27,973	27,963
Bexley	25,351	27,009	26,331	26,539	25,956	26,722	25,601	25,387	26,743	26,727	28,849
Brent	22,890	22,056	21,629	23,041	23,031	23,031	23,855	24,345	24,553	25,017	27,316
Bromley	28,442	27,483	28,760	29,537	30,293	30,157	30,434	30,460	31,695	32,983	33,275
Camden	32,378	30,392	31,904	31,904	32,816	31,961	30,658	32,972	32,023	33,071	34,510
City of London	39,744	43,662	43,163	43,396	43,314	43,125	43,923	44,547	46,392	47,407	49,076
City of Westminster	35,042	37,466	34,969	36,543	32,581	34,385	34,197	34,797	38,097	39,468	36,694
Croydon	25,856	26,873	25,111	25,711	25,095	26,013	25,658	26,706	28,072	28,703	29,281
Ealing	26,008	25,778	25,366	25,804	26,174	25,982	25,841	25,976	26,962	27,332	27,744
Enfield	23,990	22,906	24,803	23,740	23,474	24,126	24,689	24,183	25,012	24,230	25,549
Greenwich	26,753	25,476	25,439	24,527	26,925	26,539	27,759	28,114	28,828	29,506	30,209
Hackney	26,258	26,133	26,972	26,659	27,055	26,743	27,864	27,514	29,094	28,953	29,970
Hammersmith and Fulham	30,501	31,116	30,970	31,971	31,836	31,794	33,712	33,462	33,942	35,553	37,951
Haringey	25,507	25,841	24,595	25,497	24,220	24,381	26,065	25,121	27,384	28,745	28,546
Harrow	25,768	26,383	25,424	24,590	24,965	25,664	26,331	27,254	28,327	27,884	30,334
Havering	25,320	25,737	26,341	26,112	25,528	26,018	26,977	27,764	27,848	28,400	29,636
Hillingdon	25,022	26,055	25,929	26,571	27,222	25,674	26,002	26,055	26,086	27,718	28,458
Hounslow	24,465	24,970	24,668	24,976	24,976	24,162	25,836	26,112	26,951	27,817	28,546
Islington	30,663	31,226	31,200	31,544	31,591	31,982	31,471	31,971	33,681	35,850	36,444
Kensington and Chelsea	41,975	41,261	41,386	34,145	37,883	33,431	32,967	33,968	40,891	34,958	39,812
Kingston upon Thames	29,516	28,380	30,225	31,335	31,497	29,010	29,954	29,542	30,230	32,826	32,738
Lambeth	27,233	29,970	27,978	29,964	27,973	28,515	28,301	28,760	30,997	32,169	33,092
Lewisham	25,382	25,684	24,668	26,044	27,394	27,029	26,977	27,139	27,900	28,734	28,776
Merton	27,613	27,707	27,989	28,067	27,473	28,301	28,572	30,512	29,871	30,970	30,178
Newham	21,978	22,020	19,940	19,278	20,206	20,524	21,978	22,765	24,569	24,809	26,977
Redbridge	27,029	26,383	24,996	27,457	26,268	26,983	27,791	27,201	28,505	28,974	29,485
Richmond upon Thames	32,201	34,859	34,666	34,969	34,953	34,103	33,780	35,907	34,713	35,323	37,591
Southwark	27,457	27,170	27,655	27,973	27,337	27,577	29,036	28,307	30,606	30,725	32,738
Sutton	26,232	25,820	25,956	26,977	27,003	26,498	25,976	27,780	26,857	28,604	28,619
Tower Hamlets	28,995	28,520	28,270	29,547	29,980	29,970	28,927	29,083	30,861	32,717	35,912
Waltham Forest	24,824	24,798	24,209	24,637	23,031	23,187	24,830	25,200	26,034	27,613	29,970
Wandsworth	32,936	33,520	33,968	32,962	33,577	34,463	34,932	35,693	35,511	36,267	37,581

Table 4.4: Average household income in London 2010 - 2019 [105]

The steps for airfare and connectivity do not need any case illustration, since their results can be directly presented in chapter 5.

4.4.3. Airport Allocation and Market Shares

The final step of the quantitative model contains the airport allocation and computation of its market shares. A multivariate regression model mathematically correlates historical airport performance regarding their relative accessibility, airfares, and connectivity, to their historical market shares. The results are used to compute the number of air traffic passengers that utilise an airport in the MAR Greater London in a specific year using Equation 4.4, which can be observed below. This formula is similar to Equation 3.23, which uses the results of Equation 3.22.

$$P_{i,k} = GL\ ATD_k \cdot Y_{i,k} \tag{4.4}$$

Where:

$P_{i,k}$ = Air traffic passengers using airport i in year k
$GL\ ATD_k$ = Greater London air traffic demand in year k, as can be calculated in Equation 4.3
$Y_{i,k}$ = Market share of airport i in year k

5

Modelling Results

This chapter provides the results of the quantitative model. First, the results of the regional air traffic demand forecasts will be shared. Second, the scores for the airport's key performance indicators will be displayed. Third, the results of the regression analysis, airport allocation and market shares will be visualised and explained. Fourth and final, a scenario in the MAR using the quantitative model will be analysed.

5.1. Regional Air Traffic Demand Forecast

In this first step of the quantitative model, it was found UK GDP was correlated with UK air traffic demand, which was found to be correlated with Greater London air traffic demand over the period 2010 - 2019. This correlation was found using a regressions analysis, which in combination with UK's GDP projections, could project Greater London air traffic levels up to 2050.

First, the statistical results of the regression with UK GDP as independent (explanatory) variable and UK air traffic demand as dependent (response) variable are presented in Table 5.1.

Regression Statistics	
Multiple R	0.99561
R Square	0.99123
Adjusted R Square	0.99100
Standard Error	7,068,516
Observations	40

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-129,386,474	4,636,182	-27.9080	6.36998E-27	-1.39E+08	-1.20E+08	-1.39E+08	-1.20E+08
GDP	186.4574	2.8448	65.5434	1.062E-40	180.6984	192.2164	180.6984	192.2164

Table 5.1: Regression analysis results: UK GDP - UK air traffic demand 1980 - 2019

The correlation between UK GDP and UK air traffic demand can thus be captured by Equation 5.1.

$$UK\ ATD_k = -129E6 + 186.45739 \cdot UK\ GDP_k \tag{5.1}$$

Where:

$UK\ ATD_k$ = UK air traffic demand in year k
$UK\ GDP_k$ = UK GDP in GDP in year k

Second, the correlation between UK air traffic demand and Greater London (GL) air traffic demand was analysed. Two mathematical correlations were identified as accurate. The first correlation was computed using a regression and the second identified that GL traffic was a 61.00% fraction of UK traffic. It was concluded that the 61.00% assumption was implemented in the model. Therefore the following formula mathematically explains their correlation.

$$GL\ ATD_k = 0.61 \cdot UK\ ATD_k \tag{5.2}$$

Where:

$GL\ ATD_k$ = Greater London air traffic demand in year k

Combining Equation 5.1 and Equation 5.2 with UK GDP projections results in Figure 5.1.

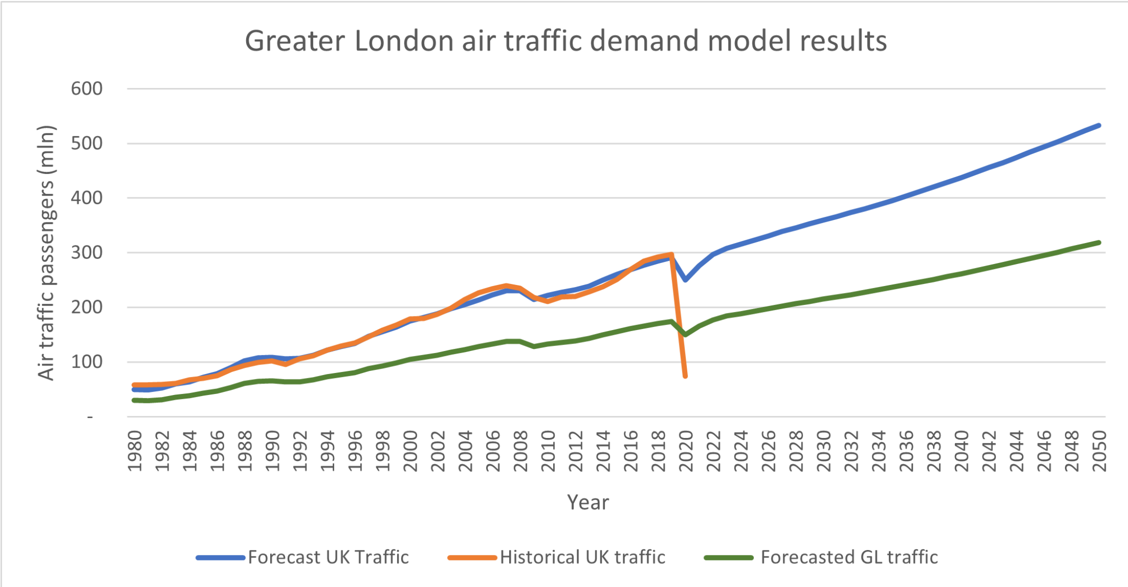

Figure 5.1: Results Regional Air Traffic Demand Forecast

5.2. Airport Performance

The next step in the quantitative model was to model airport performance through its three key performance indicators; accessibility, airfares and connectivity. This section will analyse the intermediate and final results of this scoring methodology.

Accessibility

The accessibility of airports was computed using wealth adjusted population and airport access time computations from London districts. For each airport each year, the accessibility $(A_{i,k})$ was computed using Equation 3.11. The scoring mechanism from accessibility index $(AI_{i,k})$ to points $(AP_{i,k})$ to final score $(A_{i,k})$ for the six London airports in 2019 can be observed in Table 5.2.

Scoring mechanism for 2019			
Airport	Accessibility Index (AI)	Accessibility Points (AP)	Accessibility (A)
LHR	1724.55	2668.83	9.60
LGW	1980.24	2413.15	8.78
LCY	1601.96	2791.43	10.00
LTN	2490.87	1902.51	7.13
SEN	2791.43	1601.96	6.16
STN	2554.52	1838.87	6.93

Table 5.2: Scoring mechanism for accessibility in 2019

The final accessibility results, being the values $A_{i,k}$ for 2010 - 2019 can be observed in Figure 5.2. The results for $A_{i,k}$ show a stable behaviour and therefore, not every year is plotted.

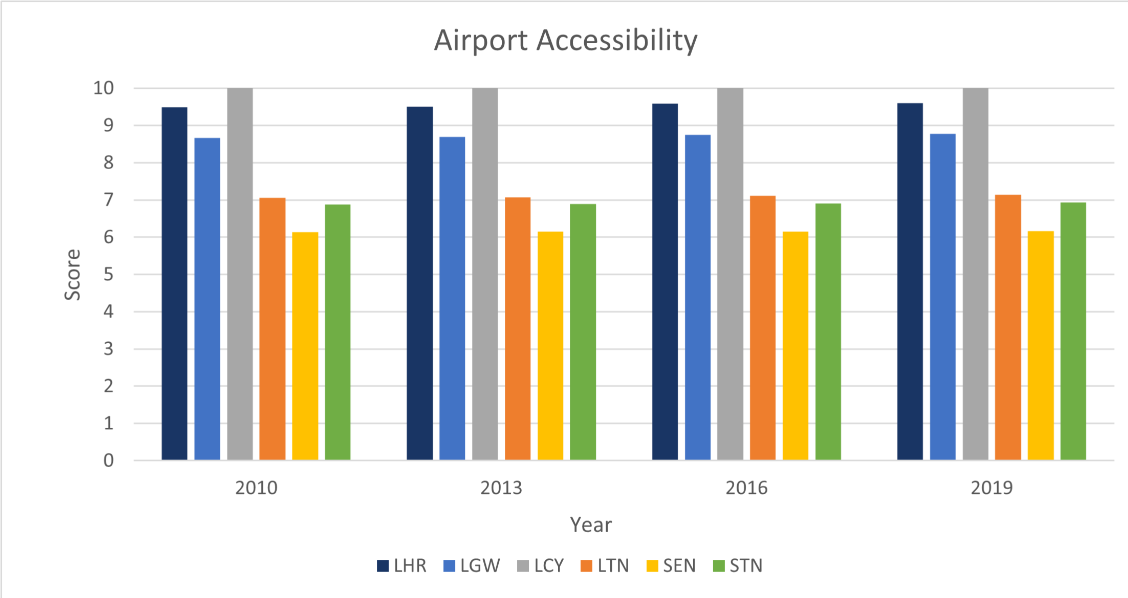

Figure 5.2: Results Airport Accessibility

The scores throughout the years do not change much. For example, LGW obtained 8,67 in 2010 and 8,78 in 2019. Airport-district distances have not changed from 2010 to 2019, and it has been proven that the infrastructural facilities have not been significantly improved in transporting people faster through this infrastructural network. Therefore, the travel time computations have been assumed to be constant.

Total population has increased 11% over nine years, in which total income has increased 13%. However, the relative distribution of population and income within each year has remained stable. For income, the standard deviation was £5047.66 and £4998.83 for 2010 and 2019 respectively. This means that 95% of the income values are captured in [£18,122 - £38,313] and [£21,771 - £41,767] for 2010 and 2019 respectively. For population, the standard deviation was 68.074 and 77.977 in 2010 and 2019 respectively. This means 95% of the population values are captured in [108,139 - 380,436] and [119,989 - 431,899] for 2010 and 2019 respectively. This tells us that the data is comparably dispersed for income and population within each year from 2010 to 2019. Together with the constant travel time computation, this explains the stable behaviour of airport accessibility performance.

It can be seen that the following rank emerges in terms of airport accessibility performance. This shows that the most centre-located airport, LCY, has indeed the highest accessibility. Also, it shows London Southend Airport, located far away from the majority of districts, scores the lowest every year.

1. London City Airport (LCY)
2. London Heathrow Airport (LHR)
3. London Gatwick Airport (LGW)
4. London Luton Airport (LTN)
5. London Stansted Airport (STN)
6. London Southend Airport (SEN)

Airfare

Airfares have been analysed on aggregate - and trip level, either being domestic, regional, continental or intercontinental. The results on aggregate level (for t = 5) are computed in Equation 3.14 and result in values for $F_{i,k}$, which are visualised in Figure 5.3. These are used in the third modelling block considering the regression analysis for airport allocation using Equation 3.22. Airport airfare results per trip level for 2019 can be observed in Figure 5.4.

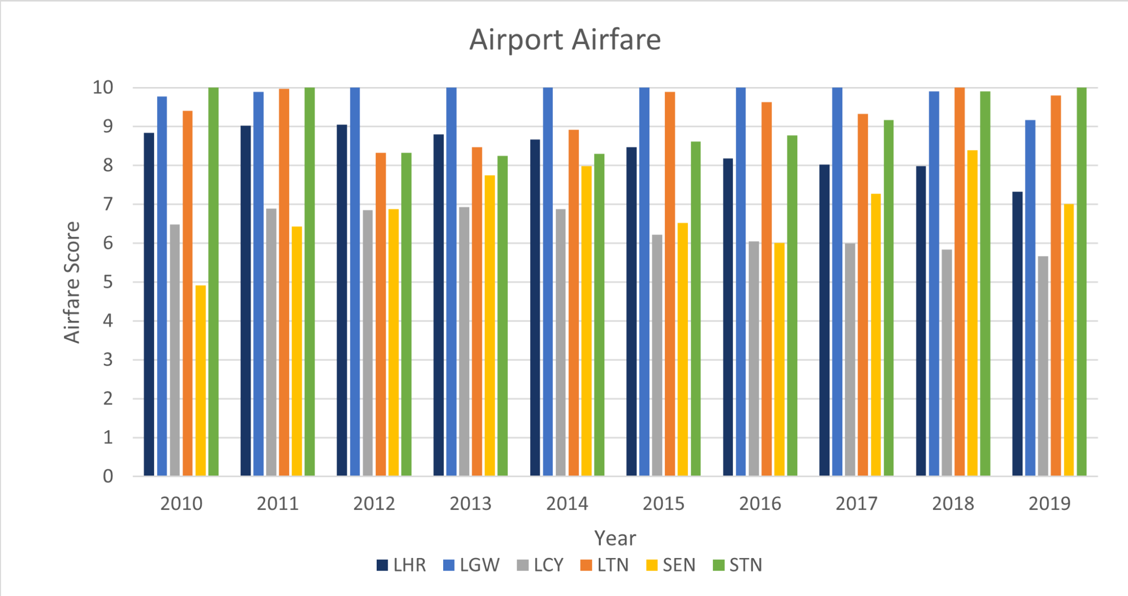

Figure 5.3: Results Airport Airfare

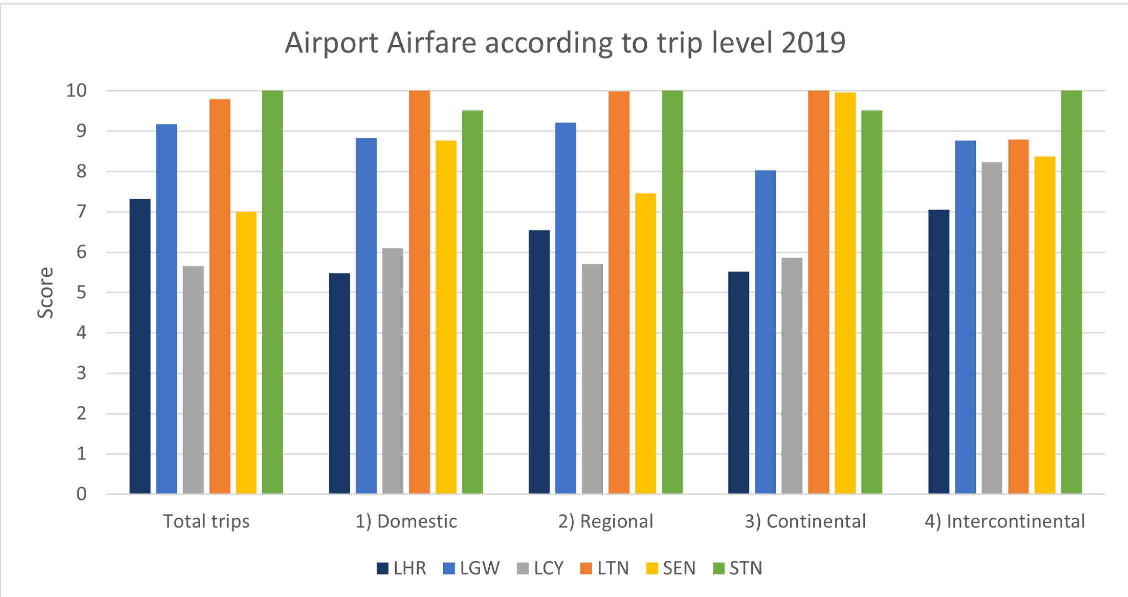

Figure 5.4: Airfare per trip level

It can be observed airport airfare performs much more volatile than airport accessibility, which in essence is caused by the fluctuating balance of supply and demand. Airlines drive their airfares based on real-time algorithms that fluctuate prices based on shifts in demand and available seats. The demand is captured by web-browsing activity capturing the popularity of destinations.

Several common factors influence airfare. First, airlines look at two types of consumers, early - and last-minute purchasers. An early purchase generally can wait some time to find the best deal, but often will simply buy relatively affordable tickets, since predicting the exact lowest price point is difficult. Last-minute purchasers often pay a relatively high price for a ticket since airlines know some consumers have no other option. The ratio of these type of passengers changes continuously. Second, airlines anticipate their prices based on the forecasted popularity of destinations, which changes throughout the years.

The following rank can be observed from the 2019 data.

1. London Stansted Airport
2. London Luton Airport
3. London Gatwick Airport
4. London London Heathrow Airport
5. London Southend Airport
6. London City Airport.

London City Airport is in the heart of the financial district which makes it attractive for business travellers. This makes the airport expensive which is shown in the results. Stansted Luton and Gatwick are located further away but focus on low-cost carriers, which make them relatively less expensive.

Connectivity

Airport connectivity ($C_{i,k}$) is computed using ACI's NetScan method in Equation 3.21 and its results are presented here. First, the evolution of London's largest international airport Heathrow is presented in Figure 5.5, after which the evolution of the remaining five airports is shown in Figure 5.6. The total connectivity scores for each airport for the years 2010 - 2019, being $C_{i,k}$, can be observed in Figure 5.7. The values for $C_{i,k}$ are used for the regression analysis for airport allocation in Equation 3.22.

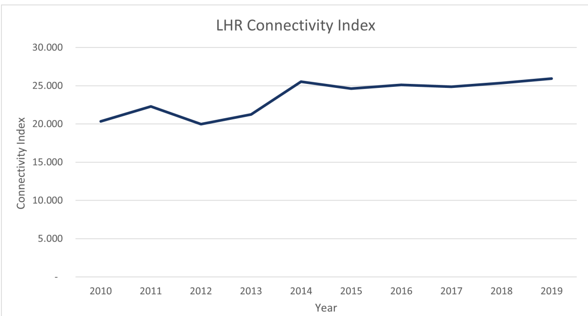

Figure 5.5: LHR Connectivity Index 2010 - 2019

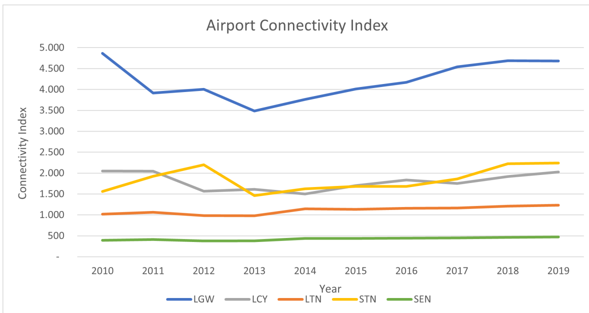

Figure 5.6: Airport Connectivity Indices 2010 - 2019

From Figure 5.6, it can be observed that all airports except London Gatwick have a stable airport connectivity performance over time. London Gatwick is London's second-largest airport in terms of air traffic passengers, after London Heathrow, which has been operating at 98% for a decade already. From Figure 5.5, it can be observed the number of destinations, and thereby the connectivity index of Heathrow has increased from 2010 to 2013, after which expanding its operations to even more destinations was not possible due to capacity constraints. However, the demand for international transport kept rising, which has since been facilitated by London Gatwick, resulting in an increase in its connectivity since 2013.

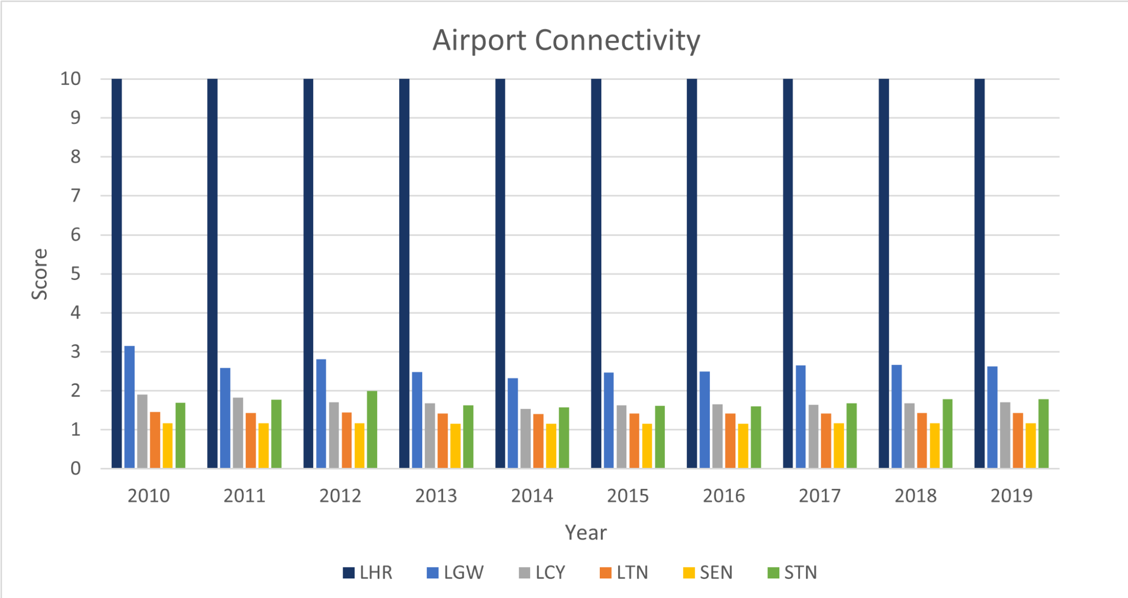

Figure 5.7: Results Airport Connectivity

The following ranking can be made concerning airport connectivity:

1. London London Heathrow Airport
2. London Gatwick Airport
3. London Stansted Airport
4. London City Airport.
5. London Luton Airport
6. London Southend Airport

5.3. Airport Allocation and Market Shares

Airport market shares can be modelled using Equation 3.22, and together with Equation 3.23, the allocation of air traffic passengers amongst airports in the MAR can be completed. This section provides the results of the airport key performance indicator computation and aggregate multivariate regression analysis, necessary to fill in these equations.

These results are presented in the following structure:

1. Results for airport key performance indicator computation; (Figure 5.8 - Figure 5.17)
2. Historical market shares of airports in the MAR; (Figure 5.18)
3. Statistical results of multivariate regression analysis, correlating airport key performance indicators to airport market shares; (Table 5.3)
4. Comparing modelled and actual historical market shares (Figure 5.19 and Figure 5.20)
5. Final results of air traffic allocation. (Figure 5.21)

First, the results for airport key performance indicator computations for the period 2010 - 2019 is presented.

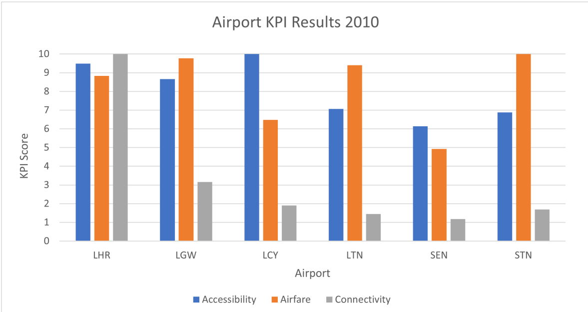

Figure 5.8: Airport KPI Results 2010

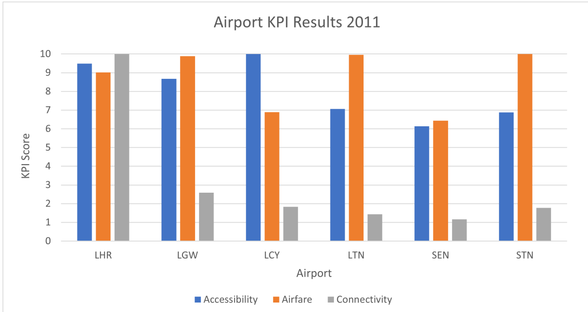

Figure 5.9: Airport KPI Results 2011

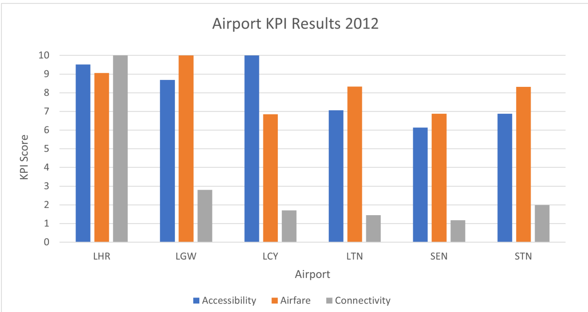

Figure 5.10: Airport KPI Results 2012

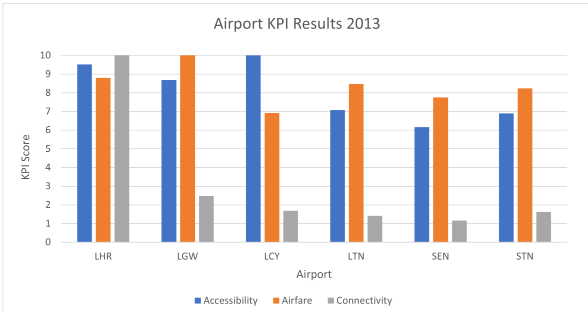

Figure 5.11: Airport KPI Results 2013

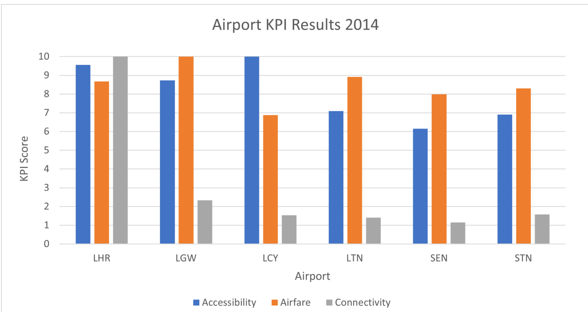

Figure 5.12: Airport KPI Results 2014

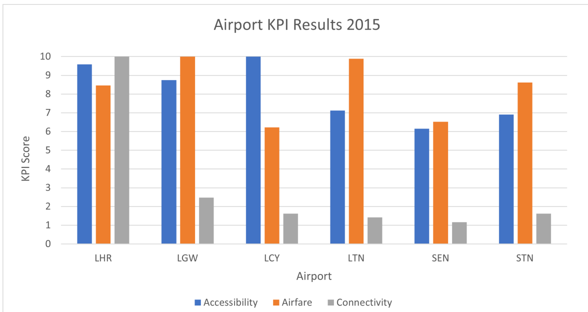

Figure 5.13: Airport KPI Results 2015

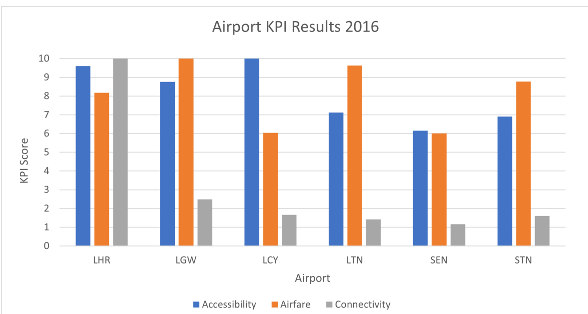

Figure 5.14: Airport KPI Results 2016

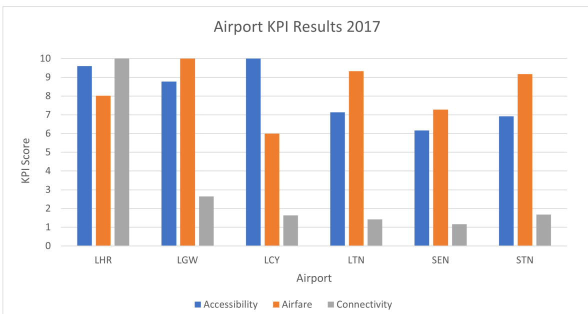

Figure 5.15: Airport KPI Results 2017

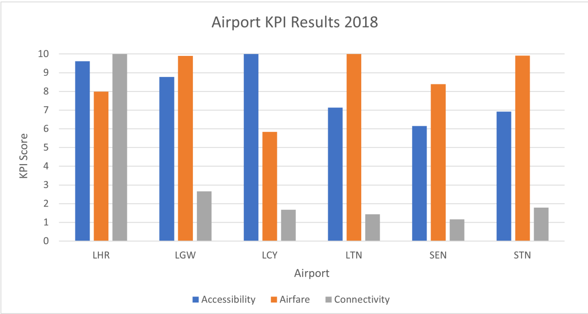

Figure 5.16: Airport KPI Results 2018

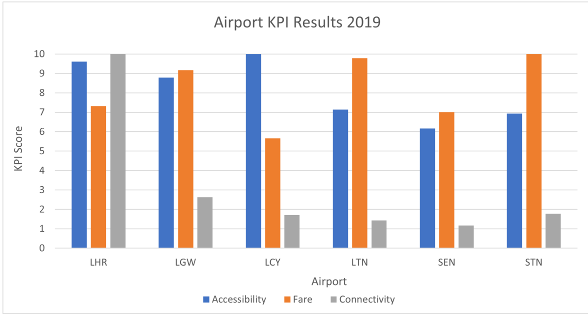

Figure 5.17: Airport KPI Results 2019

Second, the historical market shares of airports serving the MAR from 2010 to 2019 are presented. The multivariate regression model attempts to correlate the historical airport performance, in terms of accessibility, airfare, and connectivity, to these historical market shares.

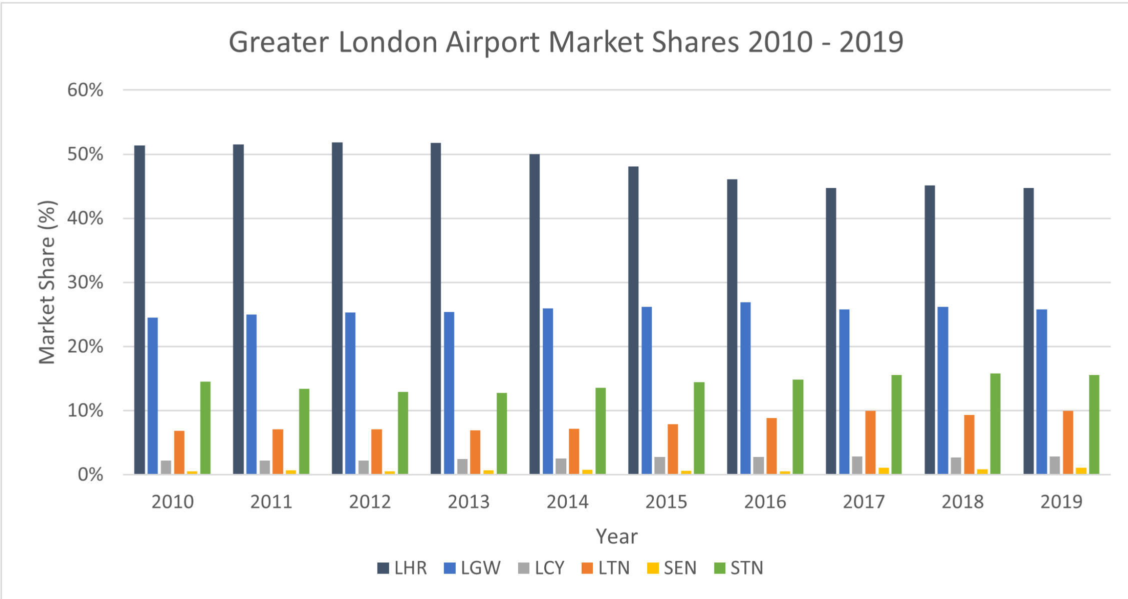

Figure 5.18: Greater London's historical market shares

Third, the statistical results of the multivariate regression analysis is presented. In total, there are now 60 observations, for a period of ten years in which six airports have been analysed according to three key performance indicators.

Regression Statistics	
Multiple R	0.975543
R Square	0.951684
Adjusted R Square	0.949095
Standard Error	0.037632
Observations	60

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-0.3803	0.0468	-8.1236	4.8426E-11	-0.4741	-0.2865	-0.4741	-0.2865
Accessibility	0.0095	0.0041	2.3086	2.4679E-02	0.0013	0.0177	0.0013	0.0177
Fare	0.0398	0.0035	11.3340	4.0293E-16	0.0328	0.0468	0.0328	0.0468
Connectivity	0.0445	0.0019	23.7439	6.4931E-31	0.0408	0.0483	0.0408	0.0483

Table 5.3: Regression Results

These results tell us that the model is able to predict airport market shares with an R-squared of 0,951, which means 95,1% of the variation in market shares can be explained by the KPI scores. Each KPI shows a logical coefficient sign, where connectivity is the most dominant KPI, followed by airfare and accessibility. All P-values are lower than 0.0247, which indicates that at a significance level of 97%, the null-hypothesis, being that the explanatory variables have no effect or relationship on the response variable, is rejected. So, the airport's key performance indicators are all well-correlated with the market shares of these airports. Especially airfare and connectivity show good values.

With the results from the multivariate regression analysis, Equation 3.22 can be filled in resulting in Equation 5.4, as shown below.

$$Y_{i,k} = \beta + \alpha \cdot A_{i,k} + \tau \cdot F_{i,k} + \sigma \cdot C_{i,k} \tag{5.3}$$

$$Y_{i,k} = -0.3803 + 0.0095 \cdot A_{i,k} + 0.0398 \cdot F_{i,k} + 0.0445 \cdot C_{i,k} \tag{5.4}$$

Where:

$Y_{i,k}$ = Market share of airport i in year k
β = Interception point = -0.3803
α = Coefficient for accessibility = 0.0095
$A_{i,k}$ = Accessibility score for airport i in year k
τ = Coefficient for airfare = 0.0398
$F_{i,k}$ = Airfare score for airport i in year k
σ = Coefficient for connectivity = 0.0445
$C_{i,k}$ = Connectivity score for airport i in year k

Now, $Y_{i,k}$ can be computed if values for $A_{i,k}$, $F_{i,k}$, and $C_{i,k}$ are known. This has been done for the historical years 2010 - 2019 to test the model's performance. In Figure 5.19, the modelled and actual airport market share for 2019 is presented. Another comparison between modelled and actual historical market shares has been made for 2010 - 2019 by visualising the difference in terms of percentage between them in Figure 5.20.

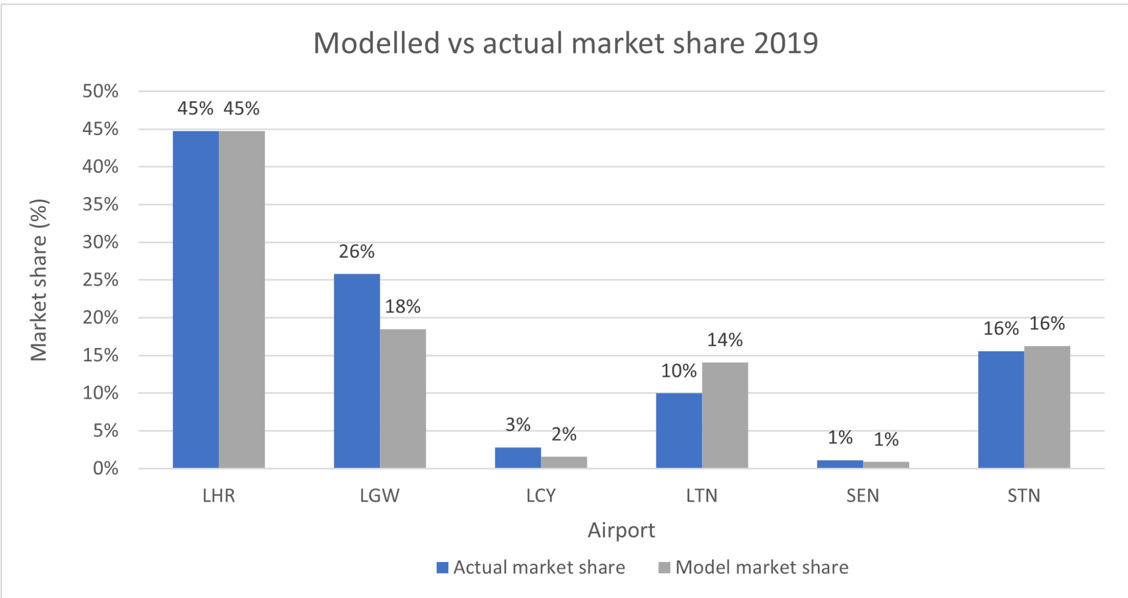

Figure 5.19: Modelled vs actual market share for London airports in 2019

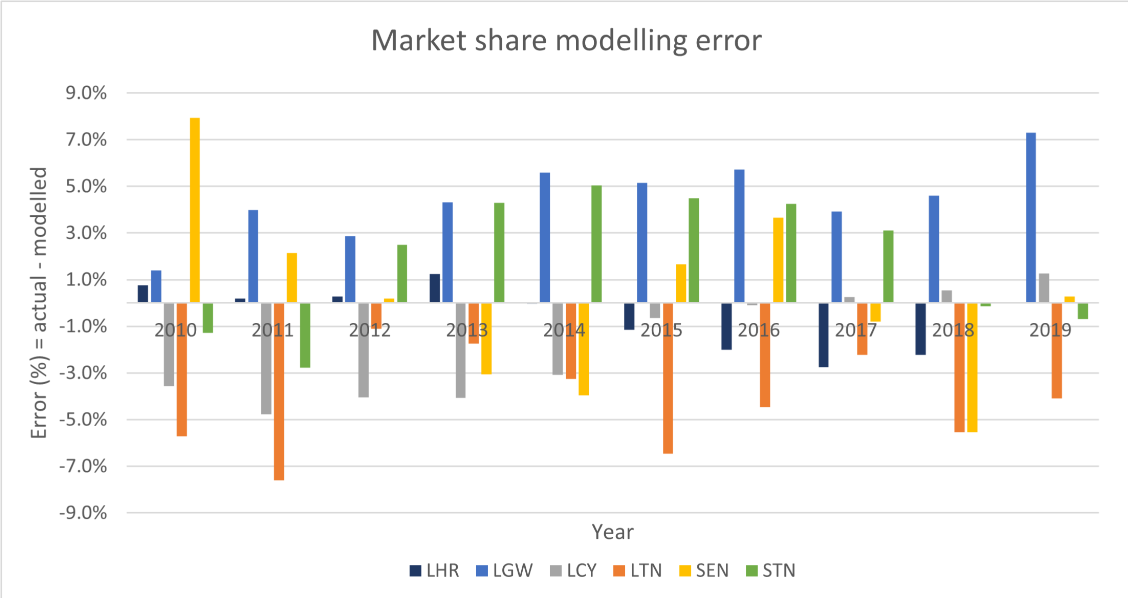

Figure 5.20: Modelled vs actual market share for London airports 2010 - 2019

Both from Figure 5.19 and Figure 5.20, it can be observed that the model over predicts the market share for Luton and under predicts the market share for Gatwick. This is caused by the omission of airport capacity constraints in the market share modelling. Luton airport performs at such a level, that the model assigns a higher market share, and thus more air traffic passengers than it can facilitate. Luton airport has been operating at 95% in 2019. It is likely that air traffic demand, which can not be facilitated at Luton, is 'diverted' to another airport with capacity, such as Gatwick, which has been operating only at 62% in 2019. So, the model assigns more air traffic passengers, and thus a higher market share to Luton, which it cannot facilitate based on its capacity. Therefore, air traffic demand that can not use Luton, will likely use Gatwick in reality, which is not captured by the model, resulting in a lower modelled market share for Gatwick.

For forecasting use of this model, it is assumed $A_{i,k}$, $F_{i,k}$, and $C_{i,k}$ remain constant. These values can be adapted such that, for example, an improved railway connection to airport 1 results in an increased $A_{i,k}$ for $i = 1$ and a decreased $A_{i,k}$ for $i \neq 1$. These adapted airport accessibility scores will translate to an adaptation in the projected airport market shares. For this model, key performance indicator scores can be improved through a scalar value. Calibrating these scalars is left for future research.

As fifth and final step, the number of air traffic passengers utilising airports in the MAR in a given year can be modelled using Equation 3.23, which is again shown below, but now Greater London (GL) represents the MAR

$$P_{i,k} = GL\ ATD_k \cdot Y_{i,k} \tag{5.5}$$

This formula can now be applied since $Y_{i,k}$ is known from the multi-variate regression results and airport key performance indicators, and $GL\ ATD_K$ has been obtained from the regional air traffic demand forecast. The results can be observed in Figure 5.21.

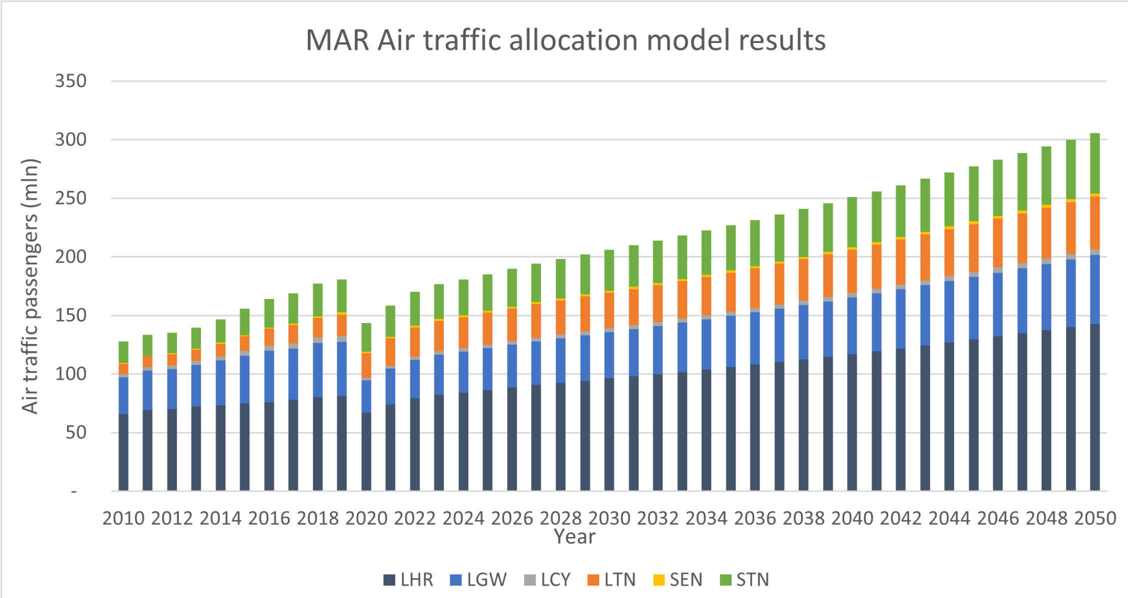

Figure 5.21: Air traffic allocation model results

5.3.1. Scenario: Airport Removal

The quantitative model can be used to compute/simulate how the performance of airports and therefore the allocation of air traffic passengers in the MAR adapt to strategic implementations in the region. Using the results of the regression model, which can be observed in Equation 5.4, such simulations can be performed. To illustrate this, several scenarios of strategic implementations have been identified:

1. The MAR is extended with an additional airport;
2. One MAR airport is closed for operations;
3. The region's infrastructure is improved which can result in various airports receiving an improved relative accessibility performance;
4. Airlines implement lower and thus more attractive fares for their flights, which can result in various airports receiving an improved relative airfare performance;
5. Airports expand their operations, perhaps by adding a new runway, which allows current and/or new airlines to expand their air traffic movements at that airport resulting in additional destinations. This can result in that airport receiving an improved relative connectivity performance.

Scenario two, the removal of an airport, is chosen as a scenario to simulate with the quantitative model because of several reasons. Scenario 1 will be inaccurate since imaginary data must be implemented for the additional airport. Scenarios 3, 4, and 5 present a more realistic scenario than scenario 2 but also present some difficulties. It is yet to be substantiated what the quantitative benefit of strategic implementations in the region is on accessibility, airfare and connectivity, since this is left outside the scope of this research.

An improved railway connection can increase an airport's accessibility. To quantify this, the improved travel time in minutes must be computed, which is only known after the infrastructural improvement is realised, except when accurate computations have already been made simulating the reduced travel times to airports. Airlines lowering their airfares can result in an improved airport airfare performance, but exactly to what extent this improves the airfare scoring depends on the evolution of prices, which are driven by many variables. The behaviour of airline prices and their predictions are left outside the scope of this research. Improved airport connectivity performance can only be computed when the data on planned additional destinations are available.

Because of these reasons, scenario 1 was chosen to be simulated by the model. Greater London is served by six airports. London Heathrow is UK's most crucial international hub airport and is therefore not chosen to 'be closed'. London City, Luton, Southend, and Stansted are the smallest four airports in Greater London, and removing them would not show significant adaptations in the performance of other MAR airports, thus neither for the adapted allocation of air traffic passengers. Therefore, London Gatwick Airport was chosen to 'be closed'. The quantitative model has been performed over the new MAR without Gatwick for 2019 using the results of the quantitative model with in Equation 5.4. This results in the adapted relative performance of the remaining five London airports, and also an adaptation in the allocation of air traffic passengers since traffic at London Gatwick now must be re-allocated. The adapted performance can be observed in Figure 5.22.

Having the adapted performance scores for Equation 5.4, the adapted market shares $Y_{i,2019}$ can be computed. These are shown and compared with the 'original' market shares when Gatwick was still included in Figure 5.23. Heathrow Airport (LHR) will grow by 12%, which equals a rise of 27% compared with its original market share, and City (LCY), Luton (LTN), Southend (SEN), and Stansted (STN) will rise by 0%, 80%, 49%, and 32% compared with their original market share respectively. This means that from the 46.6 million air traffic passengers that would use Gatwick, 22.6 million will re-allocate to Heathrow, 14.4 million to Luton, 9.1 million to Stansted and the remaining 0.5 million will be re-allocated to City and Southend combined.

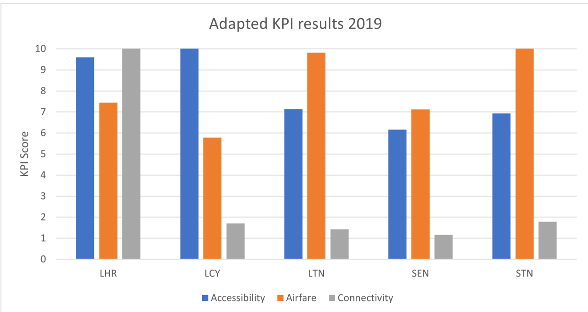

Figure 5.22: Adapted KPI results 2019

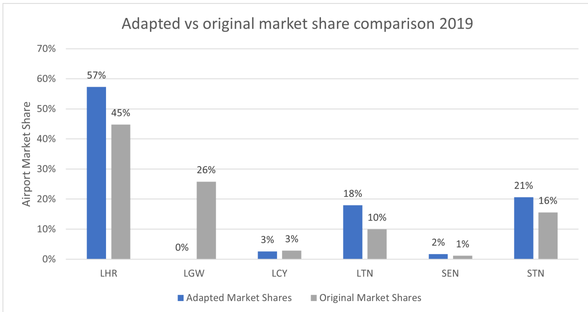

Figure 5.23: Adapted vs Original Market Shares 2019

Using Equation 5.5, the allocation of air traffic passengers over airports can be computed. Assuming London Gatwick Airport is closed after 2019, the number of air traffic passengers utilising airports in the MAR up to 2050 can be observed in Figure 5.24.

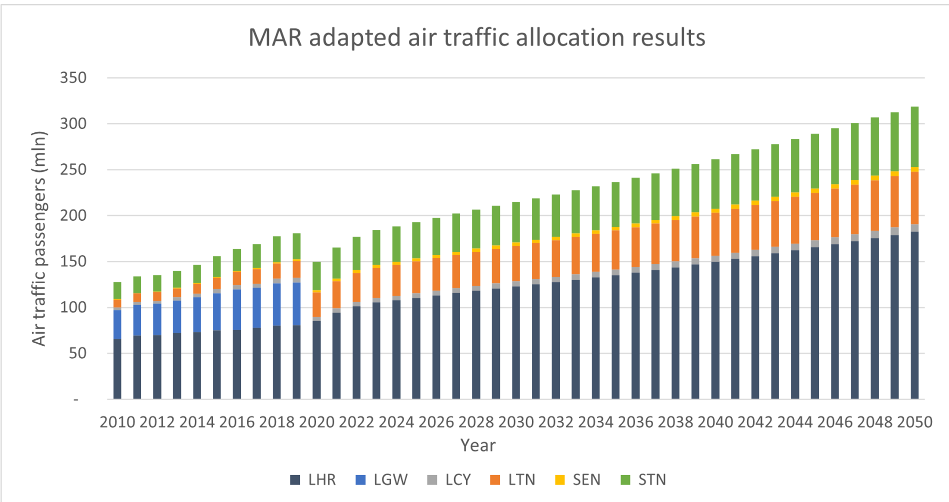

Figure 5.24: Adapted air traffic passenger allocation over MAR airport

6
Forecasting Framework

The results of the quantitative model are progressed with the Forecasting Framework. This part of the research is concerned with the second sub-goal of this research; *'Understand market dynamics of passenger integrated transport systems in a MAR. Forecasting its underlying determinants can provide estimates for the future transport system in a MAR, which accommodate and facilitate smooth future operations of used logistical components.'* The forecasting framework investigates the opportunities to use the quantitative model for strategic implementations in a multi-airport region. Therefore, this chapter is divided into two main sections.

Urbanization leads to rising air traffic demand, but is there enough capacity to facilitate this. Therefore, the first section covers capacity limiting factors for air traffic in the region. The quantitative model can be used to forecast the amount of air traffic passengers utilising airports in the MAR, which helps identify when airports (will) operate at their limit.

To ensure aviation in Greater London can grow with the expected demand sustainably, this research has investigated the major topics that are involved here and identified methods of how the forecasting framework can aid in delivering more accurate substantiations for political and strategic implementations. Therefore, the second section of this research concerns the future growth of the Greater London Area.

6.1. Capacity Limit

The capacity in terms of facilitating air traffic in a MAR is determined through three factors:

1. Airport capacity;
2. Airspace capacity;
3. Infrastructural capacity.

These three factors can constrain the facilitation of air traffic demand growth, which is assumed to grow according to the regional air traffic forecast. If the region would remain unconstrained, air traffic demand is expected to rise 82% from ±180 million to ±320 million passengers in the next 31 years, as can be seen in Figure 6.1.

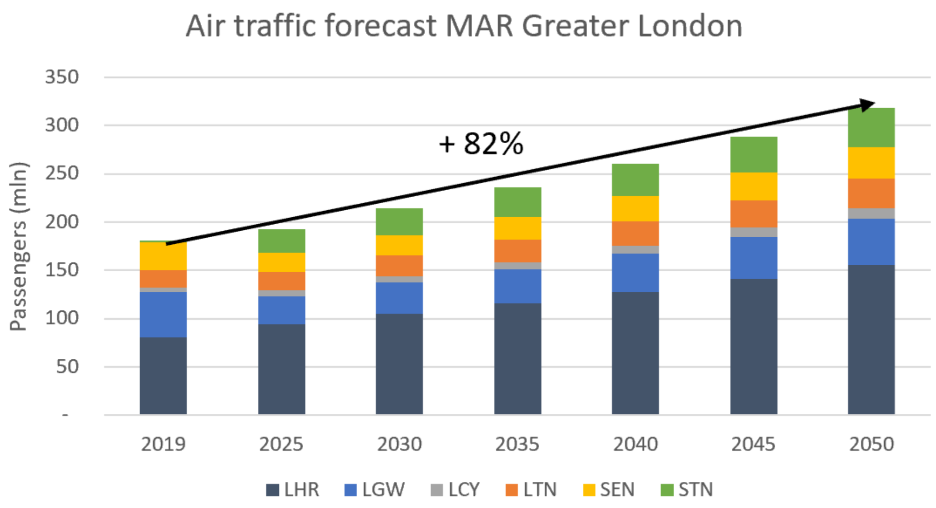

Figure 6.1: MAR expected growth next 31 years

6.1.1. Airport Capacity

Airport capacity is defined as *'a measure of the maximum number of aircraft operations that can be accommodated on the airport or by an airport component within a given period of time'* [152]. Aircraft operations in terms of air traffic movements can be converted to air traffic passengers through the aircraft seat capacity and load factors. To evaluate the potential growth The Greater London Area can handle, the level of airport utilisation and capacity was analysed and presented in Figure 6.2 and Figure 6.3.

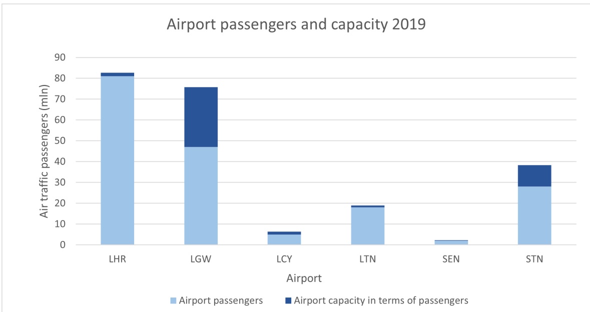

Figure 6.2: London airports utilisation in 2019

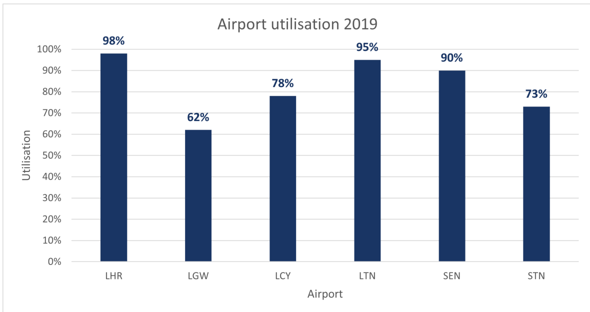

Figure 6.3: London airports utilisation percentage in 2019

London Heathrow, Luton and Southend airport have been operating above 90% in 2019, with Heathrow operating at 98% for the last decade. Future air traffic demand growth is likely to not be facilitated by these airports, which will be analysed in section 6.2.

6.1.2. Airspace Capacity

FIRs

All airspaces around the world are divided into Flight Information Regions (FIRs). Each FIR is managed by a controlling authority that has responsibility for ensuring that air traffic services are provided to the aircraft flying in them. The Civil Aviation Authority (CAA) is the controlling authority in the UK and National Air Traffic Services (NATS) provides air traffic services to them.

FIRs vary in size. Smaller countries may have one FIR in the airspace above them and larger countries may have several. Airspace over the ocean is typically divided into two or more FIRs and delegated to controlling authorities within countries that border it. In some cases, FIRs are split vertically into lower and upper sections. The lower section remains referred to as an FIR, but the upper portion is referred to as an Upper Information Region (or 'UIR').

Airspace within an FIR (and UIR) is usually divided into pieces that vary in function, size and classification. Classifications determine the rules for flying within a piece of airspace and whether it is 'controlled' or 'uncontrolled'. Aircraft flying in controlled airspace must follow instructions from Air Traffic Controllers. Aircraft flying in uncontrolled airspace are not mandated to take air traffic control services but can call on them if and when required (e.g. flight information, alerting and distress services).

UK FIRs

UK Airspace is divided into three FIRs: London, Scottish and Shanwick Oceanic, as can be seen in Figure 6.4

Figure 6.4: UK FIRs [109]

The London FIR covers England and Wales. The Scottish FIR covers Scotland and Northern Ireland. The Shanwick Oceanic FIR covers a region of airspace totalling 700,000 square miles over the North-East Atlantic. NATS manages the airspace within these FIRs from two air traffic control centres – one in Swanwick (Hampshire) and the other in Prestwick (Ayrshire).

NATS Swanwick Centre operates since 2002 and combines:

- The London Area Control Centre (LACC) which manages en-route traffic in the London Flight Information Region. This includes en-route airspace over England and Wales up to the Scottish border.

- The London Terminal Control Centre (LTCC) handles traffic below 24,500 feet flying to or from London's airports. This area, one of the busiest in Europe, extends south and east to the borders of France and the Netherlands, west towards Bristol and north to near Birmingham.

- Military Air Traffic Control which provides services to military aircraft (and civil aircraft when required) operating outside of controlled airspace. They work closely with civilian controllers to ensure the safe coordination of traffic.

NATS Prestwick Centre operates since 2010 and combines:

- The Manchester Area Control Centre (MACC), which controls aircraft over much of the north of England, the Midlands and North Wales from 2,500 feet (762m) up to 28,500 feet (8,687m).
- The Scottish Area Control Centre (SCACC), which controls aircraft over Scotland, Northern Ireland, Northern England and the North Sea from 2.,00 (762m) feet up to 66,000 feet (20,117m).
- The Oceanic Area Control Centre (OACC), which controls the airspace over the eastern half of the North Atlantic from the Azores (45 degrees north) to a boundary with Iceland (61 degrees north).

UK Airspace Classes
In the UK there are currently five classes of airspace; A, C, D, E and G. The classification of the airspace within an FIR determines the flight rules which apply and the minimum air traffic services which are to be provided. Classes A, C, D and E are areas of controlled airspace and G is uncontrolled airspace.
Controlled airspace is provided primarily to protect its users, mostly commercial airliners, and as such, aircraft that fly in controlled airspace must be equipped to a certain standard and their pilots must hold certain flying qualifications. Pilots must obtain clearance from Air Traffic Control (ATC) to enter such airspace and, except in an emergency, they must follow ATC instructions implicitly.

1. Class A. In class A airspace, only Instrument Flight Rules (IFR) flying is permitted. It is the most strictly regulated airspace where pilots must comply with ATC instructions at all times. Aircraft are separated from all other traffic and the users of this airspace are mainly major airlines and business jets.
2. Class C. Class C airspace in the UK extends from Flight Level (FL) 195 (19,500 feet) to FL 600 (60,000 feet). Both IFR and Visual Flight Rules (VFR) flying is permitted in this airspace but pilots require clearance to enter and must comply with ATC instructions.
3. Class D. Class D airspace is for IFR and VFR flying. An ATC clearance is needed and compliance with ATC instructions is mandatory. Control areas around aerodromes are typically class D and a speed limit of 250 knots applies if the aircraft is below FL 100 (10,000 feet).
   An aerodrome is a location from which flight operations take place such as large commercial airports, small General Aviation airfields and Military Air Bases. The term airport may imply a certain stature (having satisfied certain certification criteria or regulatory requirements) that an aerodrome may not have. So whilst all airports are aerodromes, not all aerodromes are airports.
4. Class E. Class E airspace is for IFR and VFR use. IFR aircraft require ATC clearance and compliance with ATC instructions is mandatory for separation purposes. VFR traffic does not require clearance to enter class E airspace.
5. Class G. In class G airspace, aircraft may fly when and where they like, subject to a set of simple rules. Although there is no legal requirement to do so, many pilots notify Air Traffic Control of their presence and intentions and pilots to take full responsibility for their own safety, although they can ask for help.
   Air Traffic Control can provide pilots in Class G with basic flight information service to support their safe flying. An Alerting Service is also provided if necessary to notify appropriate organisations regarding aircraft in need of assistance (e.g. search and rescue).

UK Airspace Types
In addition to being given a class, which specifies rules for flying, controlled airspace may be further defined by its ‘type’ depending on where it is and the function it provides. These can be observed in Figure 6.5.

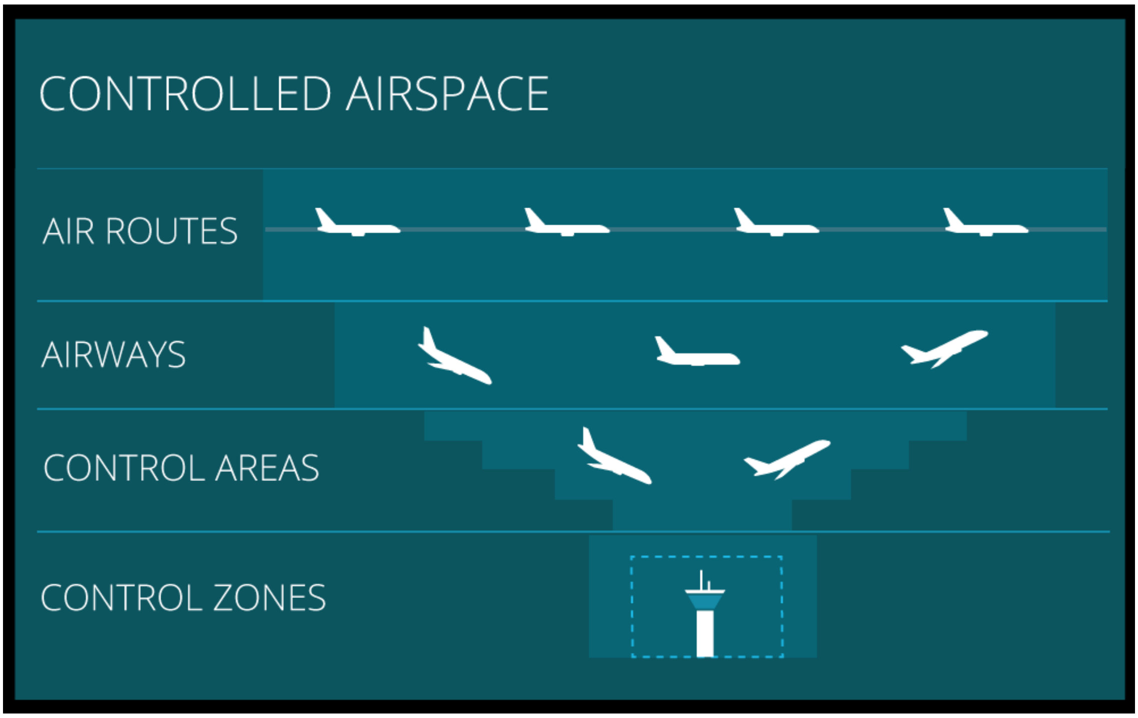

Figure 6.5: UK Airspace Types [109]

1. Control Zones (CTZ). Aerodrome Control Zones afford protection to aircraft within the immediate vicinity of aerodromes.

2. Control Areas (CTA). Control Areas are situated above the Aerodrome Traffic Zone (ATZ) and afford protection over a larger area to a specified upper limit. Terminal Control Areas are normally established at the junction of airways in the vicinity of one or more major aerodromes. The London Terminal Control Area is an example of this and deals with air traffic arriving and departing from London Heathrow, Gatwick, Luton, Stansted, London City, Northolt, Biggin Hill, Southend, Farnborough and other minor airfields in the London area.

Airways are corridors of airspace connecting the Control Areas and link up with airways in other countries too. Airways are normally 10 miles wide and have bases usually between 5,000 feet and 7,000 feet and they extend upward to a height of 24,500 feet.

Upper air routes (UARs) sit above airways. Their vertical limits are usually FL 250 (25,000 feet) – FL 460 (46,000 feet). Civil and military aircraft operating above FL 245 (24,500 feet) are subject to a full and mandatory Air Traffic Control Service. All airspace above 24,500 feet is Class C controlled airspace.

Restricted areas (sometimes called 'Danger areas') prevent aircraft from staying into dangerous places. Danger can come from airborne activities, such as military aircraft training or air-to-air refuelling. It can also come from the ground, such as from weapons testing ranges. To ensure efficient use of the airspace, most Restricted areas can be deactivated when they are not in use, allowing other aircraft to then use the airspace.

UK Airspace Sectors
To manage the airspace in an FIR, the company providing air traffic control services – often referred to as the 'Air Navigation Service Provider (ANSP)'– will divide it into 'Sectors'. These Sectors are like 3D jigsaw puzzle pieces with differing heights and sizes that interlock to cover the sky. These can be observed in Figure 6.6.

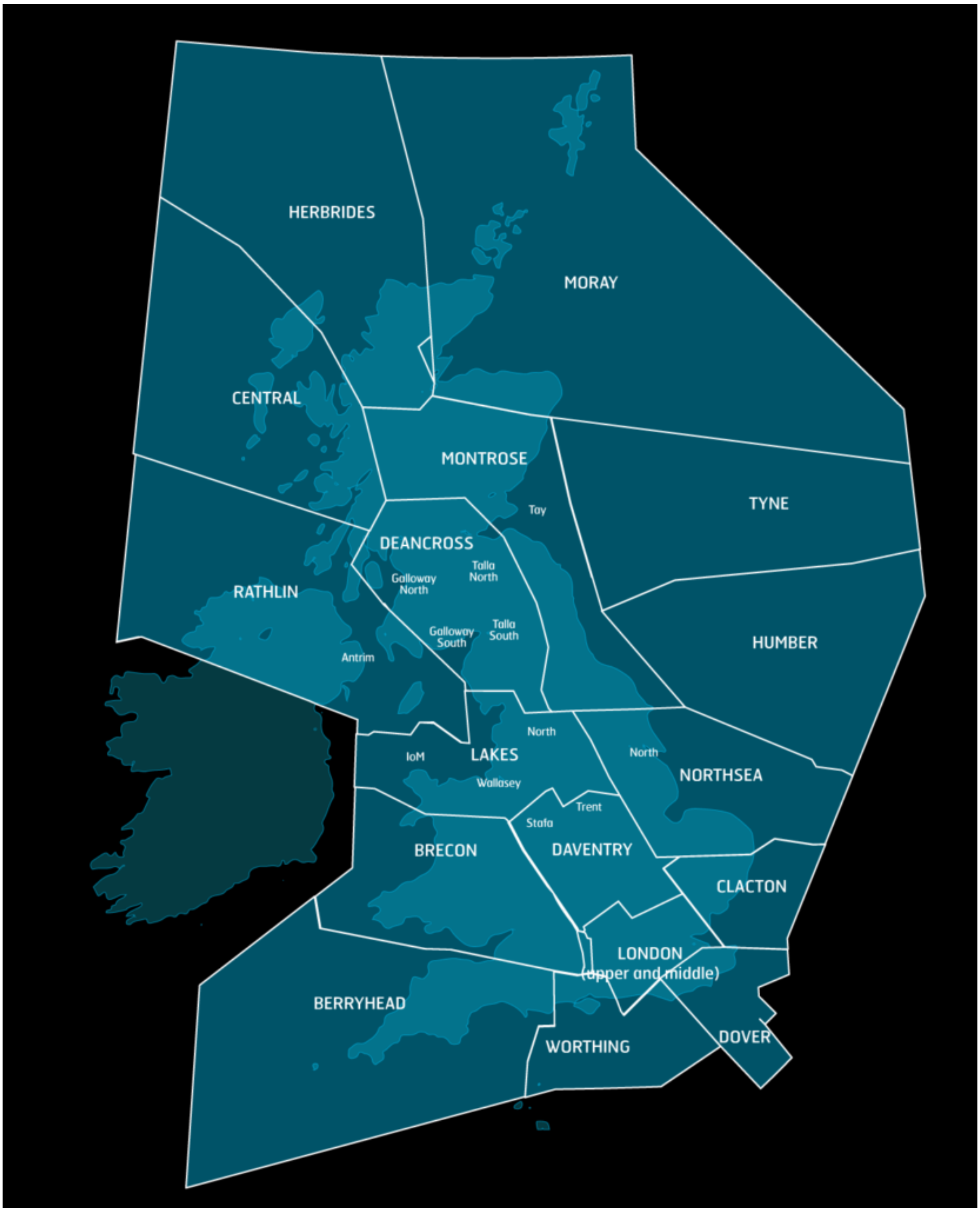

Figure 6.6: UK Sector Map [109]

Air Traffic Controllers (ATCOs) and Flight Information Services Officers (FISOs) are allocated to Sectors to advise and guide the aircraft flying in them. The number, type and skills of those allocated to a Sector will vary depending on the nature of airspace it covers (e.g. Class and Type as described above as well as how busy or complex it is). Airspace Sectors can be created and reduced dynamically to deal with demand. For example, in times when there are high levels of air traffic, more sectors may be opened with more Controllers allocated to manage the aircraft within an area of airspace. This is done to maintain safety as a Controller can only manage a certain number of aircraft at one time. In less busy periods, when there are low levels of air traffic, such as throughout the night, Sectors may be grouped or 'band-boxed', with fewer Controllers managing a larger area

Holding Stacks
Inbound aircraft in the London Airspace do not always have direct access to their runway. This is caused by airport delays, and as a result, these aircraft need to wait in so-called 'holding stacks'. Aircraft fly in circular motions above the airport waiting to land. A visualisation of these London holding stacks can be observed in Figure 6.7.

Figure 6.7: London Holding Stacks [108]

These stacks result in an increased noise footprint, higher emission levels, and further delays. It is important to limit these holding stacks by optimising London airspace and airport landing and take-off throughput.

6.1.3. Infrastructure Capacity
Infrastructural capacity concerns infrastructural facilities that facilitate air traffic passenger transport to and from airports in the multi-airport region. This includes:

1. Rail. Railway connections like trains and metros are crucial for airport access and transport from airports to the city. It is shown an average of 61% of air traffic passengers access London airports by public transport. The frequency of service and passenger capacity of these trains is important for their total capacity. The benefit of rail connections is that they are not prone to traffic jams during peak-hour traffic.

2. Road. Private vehicles, taxis, busses and coach services make use of public roads to facilitate airport-city transport.

Airports should always consider the maximum throughput of air traffic passengers to their terminal when expanding their operations. If the input of passengers in a terminal for a specified time frame is smaller than the expected output of passengers, then the expansion is not viable or the accessibility of that airport/terminal should be increased. In Greater London, public transport schemes currently provide sufficient capacity to supply the airport with air traffic passengers.

6.2. Future Growth
To facilitate rising air traffic demand in The Greater London Area, several developments have been identified that started to take shape already. These developments can be grouped into airport developments and airspace developments since Greater London's infrastructure are assumed to not limit air traffic growth at the moment.

This chapter analyses the potential growth of air traffic in the region using the quantitative model and identifies whether or not expansion plans will be enough for the expected growth in air traffic demand

6.2.1. Airport Developments

This section analyses Greater London airport expansion plans. First, London Heathrow Airport is analysed because it is Greater London's most important airport. Then, developments at the other five London airports are discussed, after which an aggregate regional demand capacity forecast is made.

London Heathrow Airport

Heathrow is the UK's only hub airport and the UK's biggest port by value for trade with countries outside the EU. Heathrow currently serves more than 200 destinations in more than 80 countries, connecting the UK to the world and the world to the UK.

It is not just passengers that travel through Heathrow; over £100bn worth of imports and exports from countries outside the EU were shipped through Heathrow in 2018, helping British businesses access customers in every corner of the globe. But Heathrow's existing runways are full and have been for over a decade. International airlines have grown their route networks at European airports like Paris and Frankfurt instead. These airports have capitalised on opportunities from new connections to growing economies in Asia and the Americas.

The airport currently consists of four terminals and two runways, which serve approximately 82 million passengers per annum. The terminals are accessed from the M25 and M4 and via the local road network. Rail, London Underground, coach and bus stations are also located in all terminal areas. Passenger and colleague car parking areas are located around the airport, with frequent bus services linking these areas to the terminals.

In July 2015, the independent Airports Commission reported the conclusion of its three-year study examining the need for additional capacity to maintain the UK's position as Europe's most important aviation hub [74]. It found that there is a need for additional runway capacity in The Greater London Area and unanimously concluded that a new north-west runway at Heathrow airport, combined with a package of measures to address environmental and community effects, presented the best set of measures for meeting that need and offered the greatest strategic and economic benefits.

In October 2016, the UK's Government announced that it endorsed the Airports Commission's recommendation, and backed the plan for the new third runway at Heathrow [74]. Besides, it announced that an Airports National Policy Statement (NPS) would be brought forward to provide policy for the preferred scheme and that a draft version would be open to public consultation and scrutiny by Parliament. National Policy Statements are put in place by Government to provide the policy framework for nationally significant infrastructure projects, such as the expansion of Heathrow.

In June 2018, after being approved by Parliament, the Secretary of State for Transport designated the Airports NPS, which confirms policy support for a new north-west runway at Heathrow, and establishes the primary policy framework for deciding whether our proposals to expand Heathrow should be granted development consent [74]. It also recognises the important role that the expansion of Heathrow has to play in supporting the wider UK economy. The proposed new layout of London Heathrow Airport can be observed in Figure 6.8.

Figure 6.8: London Heathrow Airport layout including the proposed new third runway [74]

London Heathrow is expected to serve additional air traffic passengers because of its expansion plan including the third runway. Using the quantitative model, projections of air traffic passengers at Heathrow can be computed. These projections were compared with the additional capacity Heathrow will create by executing its expansion, which can be observed in Figure 6.9.

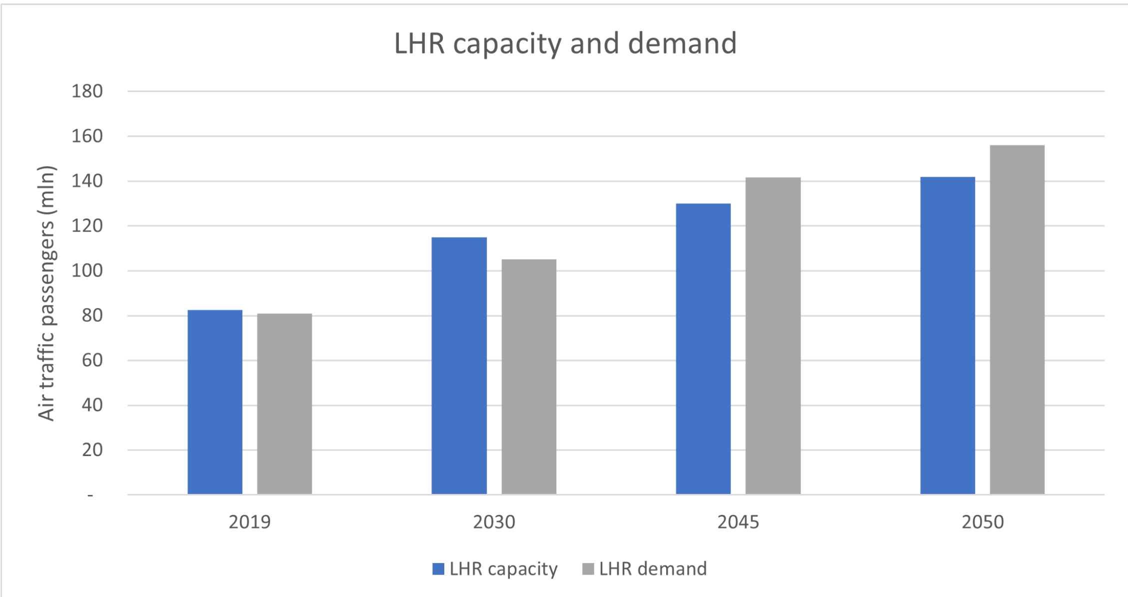

Figure 6.9: Heathrow Expansion projected demand and capacity

From this figure, it can be observed that the projected demand growth will outgrow the projected capacity growth by 2045. This means, based on air traffic passenger projections from the quantitative model, and the expected capacity increase by the expansion plans, Heathrow will reach its limit again by 2045.

There is some debate concerning the planned expansion at Heathrow. The original plan states that the newly planned runway will be fully operational by 2026. The cost of abating the carbon impact of the proposed third runway has doubled since parliament approved the expansion. A study by New Economics Foundation suggests the carbon value of the runway has increased from £50bn to £100bn, twice the value presented to ministers and parliamentarians by the Department for Transport in the Airports National Policy Statement [67]. As a result, Spanish infrastructure firm Ferrovial, which owns 25% of Heathrow, is tempted to cut funding after the CAA have presented that rising carbon cost will result in higher landing fees, making the investment returns too low [30].

Greenhouse gas emissions values (“carbon values”) are used across governments for valuating impacts on GHG emissions resulting from policy interventions. They represent a monetary value that society places on one tonne of carbon dioxide equivalent (£/tCO2e). They differ from carbon prices, which represent the observed price of carbon in a relevant market (such as the UK Emissions Trading Scheme). The government uses these values to estimate the monetary value of the greenhouse gas impact of policy proposals during policy design, and also after delivery [64].

The UK has a legal commitment to cut carbon emissions to zero. Therefore, most options for reducing emissions and removing carbon from the atmosphere are already being utilised. That is why the cost of abating new emissions gets higher as the climate ambition rises.

Expansion plans at other Greater London Airports
At the five other Greater London airports, several airport developments have also been planned, or are already being executed, to increase their capacity and facilitate rising air traffic demand.

1. London Gatwick Airport currently has two runways that can not be used simultaneously due to their proximity to each other. They plan to allow dual runway operations enabling 29 million annual air traffic passengers by 2038.

2. London City Airport has just completed eight new aircraft stands, a renewed parallel taxiway facilitating 45 atm’s/hour, an extension of the terminal, and a more efficient digital air traffic control tower that has facilitated 2 million new annual air traffic passengers.

3. London Luton Airport is planning to optimise its existing runway and renew its terminal building. This allows for 13 million new annual passengers in 2039.

4. London Stansted Airport is planning a new arrival terminal and arrival check-in, upgrading existing terminals, implementing new baggage and security systems, and making new taxiways and -stands. This all will result in 8 million new annual passengers in 2022.

5. London Southend Airport is planning to upgrade its runway, expand departure and arrival terminals, build a new hotel on site, and optimise car parking facilities leading to 7 million new annual air traffic passengers in 2023.

The quantitative model can project annual air traffic passengers at these airports at any year in terms of ($P_{i,k}$) using Equation 3.23, and thus also Equation 4.4. These expansion plans were compared with these projected air traffic passenger demand levels, of which the results can be seen in Figure 6.10. Then, the capacity expansion plans and projected air traffic demand for all London airports combined were analysed, of which the results are presented in Figure 6.11.

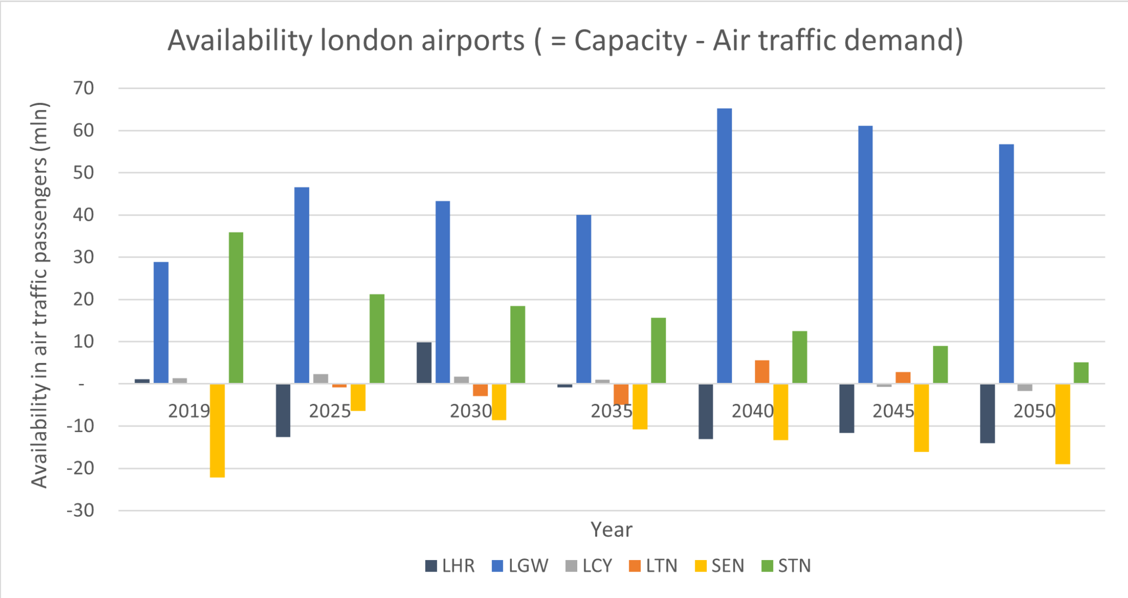

Figure 6.10: London Airports Capacity

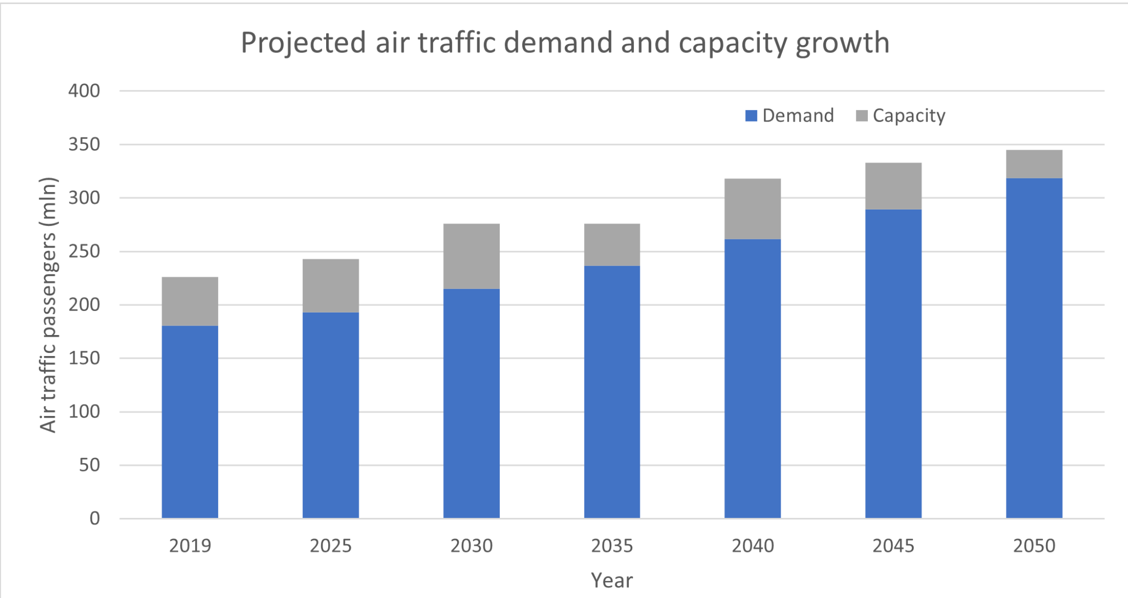

Figure 6.11: Projected availability of MAR Greater London

From Figure 6.10, it can be observed that London Gatwick and Stansted airport will handle air traffic demand growth well and that London Heathrow and Southend airport will not. London City and Luton airport do not present significant enough results, which is a result of random noise in the model. The MAR at the aggregate level can facilitate the expected air traffic demand growth.

The quantitative model in combination with expansion plans can be used as a warning system to detect the capacity limit for airports, cities and multi-airport regions. Therefore, the model is useful for airports and governments as a tool to identify the timing for and the dimension of strategic developments in the region to increase capacity. For example, if the development of a third runway at London Heathrow is realised, the airport's performance will rise, especially in terms of connectivity. This is likely to result in a higher market share and more air traffic passengers travelling to and from Heathrow, which means the infrastructure to and from Heathrow should be adapted to facilitate this rise. Also, the airspace is likely to get more crowded. In conclusion, the model can be used to quantify the expected growth in air traffic passengers, which forms the basis for expanding and optimising its surrounding infrastructure for governments and airspace for air traffic control.

6.2.2. Airspace Developments

London airspace developments mainly consider route optimization plans. If no action is taken regarding London's air traffic capacity, delays will be 30 minutes for every 1 in 30 flights by 2030. New technologies provide the opportunity for quicker, cleaner and quieter flights.

More than 2.6 million aircraft fly through UK airspace every year, carrying over 300 million passengers all over the world. But it's not just commercial aircraft that fly through our skies, there are military aircraft, private pilots, leisure flyers, drones and many others too — and everyone who wants to be there has a right to be. To meet these challenges, NATS is continuously working to modernise UK airspace to structure and transform the technology our controllers use to manage air traffic.

The UK's airspace is some of the most complex in the world, with its design dating back to the 1950s for aircraft which have long since stopped flying. The need to modernise it has now been recognised by the UK Government which tasked the Civil Aviation Authority (CAA) to coordinate how it happens. Modernising airspace, which means both route design and new tools and technologies, will make air traffic management more efficient, helping reduce the impact air traffic has on local communities and the environment and supporting future growth.

At the heart of the Airspace Modernisation Strategy is an airspace redesign programme to 'systemise' our airspace. This means creating a structured route network where aircraft follow defined routes between their departing airport and a point of exit from UK airspace, or the point of entry in UK airspace to their arrival airport. Systemised airspace will enable more efficient flight profiles and reduce the number of tactical interventions Air Traffic Controllers need to make. Performance-Based Navigation (PBN) and the Airspace Change Organising Group (ACOG) are keys to modernising airspace:

1. Performance-Based Navigation. PBS is a very accurate way of flying aircraft which uses satellite technology to allow aircraft to fly routes with more precision and consistency. Previous generations of aircraft could not fly as precisely as they can today, which meant navigating the skies using ground-based beacons and routes having a wide envelope of airspace surrounding them. In the future, NATS will be able to create new, more closely spaced routes which will reduce vectoring and which can be alternated on an agreed basis to provide noise respite for communities below. PBN can bring an end to holding stacks as we know them today. Instead, we'll be able to use new concepts such as Point Merge and enable more continuous climbs and descents. While these are not new concepts — they have been used for decades — continuous climbs and descents are not always achievable in the airspace around busy airports. Changing how arriving aircraft are managed will improve procedures for departing traffic which will no longer need to level off to safely pass underneath the stacks. In the future, aircraft will more quickly reach altitudes where they are more efficient, and this will make it easier to manage the impact of noise on people who live near airports [109].

2. Airspace Change Organising Groups. NATS is responsible for modernising the higher-level route network (what we call 'en-route'), and airports are responsible for their low-level departure and arrival routes. To coordinate the changes required, an independent body has been set up — ACOG. To change airspace, a process is set out by the CAA called CAP1616, which provides guidance when consultation is required with people who may be affected, whether they are airspace users or the wider public [109].

Aircraft waiting to land close to airports at low levels result in holding stacks, which are necessary to ensure safety and resilience within the airspace. In the past few years, ways to reduce this has been investigated through queue and capacity management enhancements. In the near term, NATS is planning to introduce changes to procedures for existing holding stacks to increase operational efficiency. The list below explains the main concepts worked on.

1. Demand Capacity Balancing (DCB). Forecasting demand, capacity, performance, infrastructure and weather ahead of time for effective capacity profile estimation.
2. Cross Border Arrival Management (XMAN). Work with neighbouring ANSPs (Maastricht upper airspace centre) to slow aircraft down up to 550 nm from landing. This aims to better manage the flow of aircraft into UK airspace by absorbing delays en-route.
3. Intelligent Approach (IA). Dynamically adjusts separation distances using time, rather than distance to keep landing rates consistent in strong headwinds.
4. Point Merge (PM). Aircraft queuing to land fly an extended flight path around an arc instead of holding circles (stacks). This allows aircraft to stay higher for longer with less noise.

These developments lead to reduced holding stacks, reduced aircraft fuel burns, reduced emissions and increased throughput of arriving and departing aircraft.

6.2.3. Greater London Growth Strategy

This section progresses on the Greater London Strategy explained in section 4.3 with the previously explained details regarding developments in the MAR. Growth in UK's aviation sector is a result of considerations made between its economic enhancements/importance and environmental impact. UK's aviation sector has a turnover of £60 billion, contributes over £52 billion to its GDP and facilitates around one million jobs in the UK [153]. In addition, the aerospace manufacturing sector generates annual exports of £26 billion and has a global market opportunity of £3.5 trillion over the next twenty years. It also employs over 100,000 highly skilled British workers and provides technology and research that has significant catalytic spin-off benefits to the wider UK economy. Besides, enhancing UK's aviation sector through its airports is crucial for the UK to maintain their position as a global aviation hub. [63, 100].

However, these economic benefits do come at a cost. Aviation has caused 7% of the UK's emissions in 2018 [69]. Due to UK's desire to reach net-zero in 2050, most options for reducing emissions and removing carbon from the atmosphere have already been utilised. Therefore, the cost of cleaning up, or 'abating', new emissions gets higher as climate ambitions rise. Therefore the carbon value recently tripped from £77 to £245 per tonne of carbon [151].

7

Discussion and Conclusion

This chapter discusses and concludes the research on airport market share forecasting in multi-airport regions.

7.1. Achievements of Goals

The main goal of this research was to *"Develop an analysis framework for the market dynamics driving airport activity levels, focusing on multi-airport regions, and analyse how this provides a base for strategic decisions in the region.* To realise this, two sub-goals were identified:

I Understand the evolution of airport market shares based on the allocation of air traffic passengers amongst airports in a chosen MAR;

II Understand market dynamics of passenger integrated transport system in a MAR. Forecasting its underlying determinants can provide estimates for the future transport system in a MAR, which accommodate and facilitate smooth future operations of used logistical components.

To achieve these goals, the research develops an analytical framework that consists of a quantitative model, which concerns sub-goal one, and a forecasting framework, which progresses the results of the quantitative model and thereby realises sub-goal two. The Greater London Area was selected as multi-airport region, which is located in the southeast of the United Kingdom and is served by six airports.

The quantitative model starts by modelling the regional air traffic demand in the Greater London Area for 2010 - 2050. A correlation was found between UK's GDP, UK's air traffic levels, and Greater London air traffic levels from 2010 to 2019. Projections of the UK's GDP formed the basis for projections of Greater London air traffic demand up to 2050, which concluded an 82% rise. The COVID-19 demand drop after 2019 forms the start of the forecasting period, which assumes air traffic demand grows unconstrained in correlation with UK GDP projections. However, online meetings have become the standard for many foreign business interactions, and together with the reduction of travel emissions, many companies have announced to reduce their air travel trips by 25% to 50% [75]. This trend is expected to result in air traffic levels recovering ±80% in 2022, compared to 2019 levels [52]. Air traffic levels in 2022 will provide insight into whether or not this bounce-back is realised, and to what extent the projections of air traffic levels should be adapted.

The second step of the quantitative model concerns allocating the modelled regional air traffic demand over airports serving The Greater London Area. This was done based on the relative performance of these airports amongst each other on three key performance indicators. First, airport accessibility concerns the access time from the regional sub-districts, weighted by the wealth and population size of these sub-districts. Second, airport airfares analysed the relative pricing of tickets per trip level, which is based on trip length. This allows the model to compare airports not only on an aggregate level but also on domestic, regional, continental and intercontinental level. The third and final key performance indicator is airport connectivity, which concerns the level at which an airport is connected to other regions and airports of the world. All key performance indicators were analysed relative to each other, from which a final grade on a scale from 1 to 10 was computed for each key performance indicator for each airport for each year.

The model assumes airport performance is directly linked to their market shares through the three key performance indicators. So, the third and final step of the quantitative model was correlating historical airport performance to their historical market shares, in terms of annual air traffic passengers as a portion of the total air traffic passengers utilising Greater London airports. This was done through a multivariate regression model, which concluded an R-squared of 0.95 based on 60 observations. Also, its results concluded that the order of influence on total airport performance was connectivity, airfare and accessibility respectively.

So, the quantitative model can predict airport market shares based on their key performance indicators and projections of the UK's GDP up to 2050. Changes in an airport's accessibility, airfare or connectivity can be implemented in the model, which translates to an adapted market share projection of all airports in the region.

The forecasting framework indicates capacity limiting factors in The Greater London Area and analyses how the model can be used to evaluate future growth developments and strategic implementations in the region. Air traffic demand is expected to grow, and three factors have been identified to potentially limit the facilitation of this growth in The Greater London Area. UK airports and their government are working on developing and improving their aviation sector based on these three factors.

1. Airport. Heathrow airport has already been operating at 98% for the last decade. The quantitative model can be used to model annual air traffic passengers at airports. Together with projections of future expansion plans at airports, it can be concluded that Gatwick, City and Stansted airport will be able to facilitate rising air traffic demand, and Heathrow, Luton and Southend airport will not. However analysing its aggregate projections, the region is successfully able to facilitate the rising demand.

2. Airspace. As a result of highly utilised airports and rising air traffic movements due to increase air traffic demand, London's airspace is busy. Arriving aircraft often need to hold in circular holding stacks before being granted to land to ensure safe landing operations. This results in increased noise and carbon emissions and creates further delays. If no action is taken, delays are likely to be 30 minutes for every one in three flights. NATS (National Air Traffic Services) is continuously working to modernise UK airspace to structure and transform the technology our controllers use to manage air traffic.

3. Infrastructure. London's infrastructure allows air traffic passengers to travel between the city and airports. Since its infrastructural operators like public transport and highways are well organised, this factor is not (expected) to limit air traffic demand growth in the region.

The UK's desire to keep its position as a global aviation hub demands that planned airport and airspace developments are realised. The sector already contributes 3.4% of the UK's total GDP and provides around 1 million jobs in the UK. Its expansion plans will increase air traffic movements but it will also decrease the presence of holding stacks, which decreases unnecessary emissions of carbons and noise. However, due to increased environmental awareness, abating additional (expected) carbon emissions, which result from these expansions, becomes more and more expensive risking the realisation of such expansion developments at London airports.

7.2. Research Value

The added value of this research can be concluded by its main results and their purposes. The main results consist of;

1. Annual air traffic demand of the UK and the multi-airport region Greater London up to 2050;

2. The relative performance of airports within the multi-airport region regarding their accessibility, airfares and connectivity;
3. Allocation of the projected multi-airport region air traffic passengers over airports serving the region up to 2050;
4. Utilisation levels of airports in the multi-airport region up to 2050.

Which can be used for the following purposes:

1. Quantify airspace activity. This is necessary for air traffic management systems, strategic implementations, and policy changes;
2. Quantify necessary airport capacity expansion given projected demand growth;
3. Compare performance relative to other airports in the multi-airport region;
4. Quantify how a strategic change in the multi-airport region or at the airport, in terms of accessibility, airfare, or connectivity, results in a change in the market shares of all airports serving the multi-airport region;
5. Identification of constraining factors in facilitating rising air traffic demand;
6. Detection of expected capacity limit both on multi-airport region and airport-specific level;
7. Quantify adjusted market shares after capacity expansion.

8

Recommendations for Future Research

This research was performed under several assumptions and limitations. This chapter proposes various enhancements that could be made to improve the applicability and accuracy of this research. This is done on the three components that make up the quantitative model; Regional Air Traffic Forecast, airport performance, and air traffic allocation, and regarding the forecasting framework.

8.1. Regional Air Traffic Demand Forecast

The Regional Air Traffic Forecast shows UK GDP, UK air traffic and Greater London air traffic are correlated. Projections of UK GDP from the basis that eventually leads to Greater London air traffic demand projections. An interesting first addition would be to analyse other explanatory variables for air traffic demand than UK GDP and oil prices. Second, implement and model the change in air traffic demand as a result of increased environmental awareness. It would be likely that, with the rise of greener alternative transport options for longer distances, the demand for air traffic will grow less strongly. Also, airlines are likely to increase prices when fuels become more expensive, which is currently happening as a result of the Russian-Ukrainian war. Third, if an airport within Greater London increases its capacity, the portion of UK air travel that flies to/from Greater London airports will increase. This means the 61.00% assumption would change. Fourth, apply the model to monthly data instead of annually. Fifth, perform the regional air traffic forecast on another multi-airport region. Necessary data includes projections of national and local (MAR) air traffic drivers, such as the UK's GDP in this research. Sixth and final, implement three scenarios of air traffic demand recovery from the COVID-19 demand drop. If a slow, medium and fast recovery scenario is implemented in the projected air traffic demand growth, future short-term air traffic levels will determine which of these recovery scenarios to use for the air traffic demand forecast from then on.

8.2. Airport Performance

Airport accessibility can be improved by replacing travel time computations with an automatic Google Maps API, that can calculate these travel times automatically. For the scale of this research, the Google API, or other comparable programs, require paid subscriptions and is therefore not used in this research. Second, the influence of population size and district wealth is assumed to equally influence airport accessibility. This is not the case in reality. It can be examined by analysing districts' passenger supply to airports, districts' population and gathered data on these passenger's wealth. Its results can be used to weigh population and wealth for the airport accessibility measure.

Airport airfares scores are assumed to behave linearly, meaning a twice as expensive ticket will be twice less attractive. However, in reality, when the wealth of an individual goes up, his/her sensitivity to price increases decreases. This means that the influence of price differences at lower income levels is higher than at higher income levels. Implementing this recommendation could lead to a more realistic influence of airport airfares on airport total performance.

Airport connectivity currently uses ACI's SEO NetScan method to compute airport-specific connectivity indices. This model, therefore, depends on the airports being in their analysis. For the six London airports, this is the case. When applying the model to another multi-airport region, it would be important to gain access to the ACI connectivity indices of those airports concerned, or use alternative complex network science. This can be done by ACI collaboration since an airport-specific report will be provided. This will then also give insight into the sensitivity of those indices, which will lead to insight into how the airport connectivity changes when an extra destination is added to an airport.

8.3. Air Traffic Allocation

The multivariate regression model shows statistically accurate and logical results. However, several changes could be investigated. First, as is recommended for the Regional Air Traffic Forecast, applying monthly data would increase the accuracy of the model.

Second, it could be analysed how potential air traffic passengers of Greater London airports weight accessibility, airfares and connectivity in their choice of airports. This can be achieved through mixed-logit modelling (MNL). Its results should be compared to the results (coefficients) of the multivariate regression model and analysed to what extend and why they align (or not).

Third, adding runway constraints to represent the scope of an airport can be useful in limiting additional traffic to airports that are operating above 98% in the future. This would mean that, despite the airport having the performance to attract more passengers, these additional passengers could not be allocated, and are thus distributed to other airports with capacity.

Fourth, in several multi-airport regions, air traffic passengers are not distributed logically based on relative airport performance but are largely influenced by the government. An example occurs in Russia, where some airlines are backed (indirectly) by their government or governmental officials, which force their airlines to operate at certain airports. This could be captured by a subjective dummy variable as the fourth key performance indicator.

8.4. Forecasting Framework

The forecasting framework provides insight into how the model can be used for strategic implementation in the region. In this analysis, it is assumed by air traffic passenger demand grows according to the regional air traffic demand forecast. This model does not take into account the variability in airfares, meaning that rising demand for a product (flights) does not result in a higher price of that product, which in reality does occur. Therefore, a good addition to the model would be to perform an econometric analysis of the change in airfares as a result of rising air traffic demand, probably under capacity en environmental pressure.

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