Gate Assignment Problem: a case study of Lisbon airport

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Dedicated to my family.

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Resumo

O número de viagens de avião não tem parado de aumentar, assim como as suas necessidades operacionais. De modo a conseguir acompanhar esta evolução, os aeroportos têm de garantir que as suas operações respondem eficazmente. Uma maneira de o fazer é através do Problema de Atribuição de Porta de Embarque associado ao aumento dos gastos no Terminal. Esta dissertação apresenta um modelo de Programação Linear Inteira Mista e implementa-o no software FICO Xpress. Foi ainda divulgado um inquérito para recolher informações relevantes para a modelação do comportamento dos passageiros nos seus gastos de dinheiro, o que levou à simulação de probabilidades de cada passageiro em contribuir para certos níveis de gastos de dinheiro, de acordo com o seu tipo de viagem (partida, chegada ou transferência), através de Modelação por Escolha Discreta. Deste modo, o modelo criado permite fazer a atribuição de voos a portas de embarque, combinando os resultados da modelação do comportamento dos passageiros e os constrangimentos operacionais do aeroporto. Como resultado, este modelo aumenta os gastos dos passageiros, ao atribuir um avião composto por passageiros de uma certa categoria de gastos de dinheiro, à porta de embarque mais rentável tendo em conta a proximidade à zona de maior concentração de retalho, assim como a diminuição da distância desde/até às portas de embarque atribuídas. Os resultados mostram um crescimento da função objetivo em 8.0% e 12.2%, correspondendo a 1732.7€ e 2967.3€, em intervalos de tempo de meia-hora das 17h às 18h, no dia considerado no caso de estudo.

Palavras-chave: Problema de Atribuição de Porta de Embarque, Modelação por Escolha Discreta, gestão aeroportuária, Programação Linear Inteira Mista

Abstract

Air trips keep increasing as the world population and its operational needs keep growing. In order to keep up with the increasing number of flights, airports must ensure that their operations efficiently respond by both considering the passenger experience and their economic viability. One way to achieve this is by optimising the Gate Assignment Problem (GAP) through revenue maximisation under passenger comfort restrictions inside the airport. This dissertation presents an original Mixed-integer Linear Programming (MILP) model that is implemented in FICO Xpress software. A survey to collect relevant information for the modelling of passenger money spending behaviour was performed, leading to the simulation of passenger probabilities of contributing to certain levels of revenues according to their flight type (departure, arrival, transfer), through Discrete Choice Modelling (DCM). The proposed gate assignment model allocates flights to gates, by combining the results from passenger behaviour modelling and the operational constraints of the airport. As a solution, the model increases the spendings of passengers at Lisbon Airport by matching a flight and their category of passengers to the most profitable gate, taking into account the proximity to the retail area and walking distance needed to get to the gate in a specified time-horizon. Results show an obvious increase in the objetive function of 8.0% and 12.2%, corresponding to 1732.7 € and 2967.3€, in half an hour time slots from 5pm to 6pm, respectively, in the considered day for the case study.

Keywords: Gate Assignment Problem (GAP), Discrete Choice Modelling (DCM), airport management, Mixed-integer Linear Programming (MILP)

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Acronyms

ACI Europe Airports Council International Europe.

BBO Biogeography-based optimization.

DCM Discrete Choice Modelling.

GAP Gate Assignment Problem.

GDP Gross Domestic Product.

IST Instituto Superior Técnico.

MILP Mixed Integer Linear Programming.

MIP Mixed Integer Programming.

MNL MultiNomial Logit.

Chapter 1

Introduction

In this chapter, the context of this dissertation is introduced. To begin with, a description is provided on the development in the airport industry globally since its beginning. Afterwards, the main objectives and the thesis outline are presented.

1.1 Motivation

Gate Assignment Problem (GAP) has been a long time problem that many researchers tried to solve and optimise. The airport industry is worth billions and a small improvement in the system may be worth a lot of money, leading to the existence of many ways of trying to solve the problem since the beginning of this industry. The motivation for this dissertation is to achieve a new way of thinking the GAP. The inclusion of passengers characteristics, experience and feedback will allow to create a pattern to identify which are the passengers that are willing to spend more money at the airport and consequently, an adequate attribution to proper gates will increase the possibility of those same passengers to spend more money. In the literature, it is possible to find a lot of researchers studying which characteristics are more important for this subject, however, to the best of author's knowledge there has not been a practical use of these characteristics on solving the Gate Assignment Problem.

1.2 Airport Industry

The airport industry started back in 1919, when the word ”airport” was first mentioned. Additionally, its first ever known definition was introduced as ”*an airport is said to be an area of land or water used or intended to be used for landing and takeoff of aircraft, including building and facilities*” (Zantke (1976)). Nowadays, airports are much more than that. Currently, the definition is different than in the past. Such a diversified industry that goes from catering, to intelligent gate assignment, to analysing passengers psychological satisfaction, to logistics. Besides, the added value by the airport industry to its surroundings, make it possible for other indirect businesses to arise and establish right next to them.

Airports are a key place in the development of the region they operate. They are responsible for giving mobility to everywhere and to serve as a first point of contact with the region for travellers. They largely define the economy of communities and cities and provide social cohesion. Besides, they can give the chance for passengers to travel to any point in the world, serving as the main door to any geography. By connecting the region with the outside world, airports are more than just transport infrastructure. An airport can lead to the region development and economic expansion by making it more attractive to outsiders (VINCI Airports (2014)).

1.2.1 Global Importance

Globally, ever since the air transportation appeared, it has been constantly increasing in its size either in terms of passengers or cargo. The airport structure itself, conforming to the main regulator of european airports Airports Council International Europe (ACI Europe), has evolved from mere transport providers into a full business with all the commodities needed to satisfy passengers.

According to ACI Europe (2018), just in Europe, the amount of passengers travelling by plane in 2018 hit a new record of 2.34 billion passengers, meaning an increase of 6.1% comparing to 2017 and a growth of 36% comparing to 2013. This trend has been evolving passenger numbers to unimagined quantities, and continuing like this, it is completely feasible to understand why globally the airline industry revenues were worth 151.8 billion € in 2015. In 2040, Eurocontrol (2018) estimates an increase of 53% comparing to today and due to the explosion of the global population and their necessities, more than 1.5 million of flights will not be able to fly if airport capacity remains the same. Moreover, Intervistas (2015) claim that, according to a 2015 study, the airport industry employs 12.3 million people and generate an income annually of 675 million euros, meaning around 4% of Gross Domestic Product (GDP) in Europe. Logically, it is one of the biggest industries that exists and continuous developments need to be done in order to meet capacity needs.

1.3 Objectives

The main goal of this dissertation is to develop a model that solves the Gate Assignment Problem (GAP), and incorporates information on passenger behaviour in the airport terminal. A survey is conducted revealing the main characteristics of passengers in terms of money spent and leading to the creation of passenger categories divided by the type of passenger and amount of money spent. Furthermore, the model will be applied in a case study on the Lisbon Airport Terminal 1, and an analysis of the improvements will be detailed, comparing the results from the MILP model with the actual planning from the considered day. Finally, this dissertation will allow to assess potential increase in money spending by passengers using the Gate Assignment Problem created with the contribution of Discrete Choice Modelling.

1.4 Thesis Outline

This dissertation is divided in 8 chapters:

1. Introduction - this first chapter presents some facts on aviation industry and importance and helps the reader to enter the context of this dissertation. Afterwards, the objectives and the structure of this master thesis are presented.

2. Related Work - State of the Art - this second chapter is a resume of all the relevant work for supporting this dissertation in both main themes of Gate Assignment Problem and Passenger Behaviour.

3. Airport passenger survey - this third chapter presents the survey design and explains the reasoning

behind some choices. Moreover, an explanation on how to employ this survey for discrete choice modelling is exhibited in order to give the reader a better comprehension on the subject.

4. Mixed-Integer Linear Programming - this fourth chapter is a full description of the optimisation model created during this dissertation, explaining all constraints and variables.

5. Demonstration – Model implementation and validation - this fifth chapter is a demonstration of the MILP model, using an illustrative example and explaining all inputs and results involved.

6. Application to a case study - in the sixth chapter, the case study is presented and the survey results are exhibited. Then, the survey results are combined into the MILP model and the operational gate allocation is presented. In addition, an extra event seen as an extreme event is presented in order to see how it influences the result of the mathematical model.

7. Results - in this seventh chapter, the results from the MILP model are compared with the actual planning from the airport. The results are compared in terms of revenues and operational results, leading to the demonstration on the benefit of using such a model.

8. Conclusion - in this last chapter, an overall conclusion of the dissertation is presented and the advantages of using this dissertation model to the airport is explained. Furthermore, an analysis of the limitations observed during this dissertation and a ”brainstorm” of ideas to explore in the future are exposed.

Chapter 2

Related Work - State of the Art

Through this chapter, it is intended to demonstrate a summary of the most relevant papers that were taken into account in this dissertation. Since this dissertation has two different focuses, the Gate Assignment Problem (GAP) and the passenger characteristics and behaviour, a description of what has been discussed in the literature on both subjects is presented.

2.1 Gate Assignment Problem

Throughout the years, airports all over the world are becoming busier due to the increase of population, the imposition of flying as one of the most safe means of transport and the increase of civil air-traffic. Thus, there is a higher probability of congestion either in the terminal or in the runaway and taxi segments.

Recently, to face this complex problem, ranging from landing to takeoff, airports are aiming to their inherent capacity problems, directly linked to passenger satisfaction, aircraft traffic and the environment.

Therefore, many researchers have tried to investigate the Gate Assignment Problem, through mathematical models with different objectives as is shown in table 2.1.

2.1.1 Walking distance

To enhance passenger satisfaction levels and airport experience, walking distance should always be an important matter to take into account. Every passenger is concerned with the time, and long walking distances mean less time to perform discretionary activities, which consist in optional activities dependent on the passenger freedom of choice (Popovic et al. (2009)). Thus, minimising walking distances allow for passengers to have time for their favourite activities, and, at the same time, it allows to have more time for themselves, either in terms of knowing and discovering new activities available at the airport, either to stay calmer while waiting for the boarding. Airports are seen as the beginning of the whole trip for departing passengers, and to do so, it should consist in a smooth experience. However, the passenger experience many times consists of long walks, no place to sit and little to do. Consequently, many have been the researchers that included the walking distance in their studies. Daş (2017) created three different models, looking to increase airport revenues, with the same second objective of minimising walking distance, highlighting again the importance of this factor. To compute the best solution, a hybrid algorithm was developed (Two PhaseLocal Search and Pareto Local Search) to seek which model had the best results. It was concluded that, from all models, the use of more specialised models aiming to maximise the number of passengers assigned to selected gates can obtain more income. Marinelli et al. (2015) using the same walking distance objective and remote gate

Table 2.1: Literature contribution for GAP

Reference	Methods / approach	Contribution
Daş (2017)	Two Phase Local search and Pareto Local search	Increase the number of passengers close to shopping facilities and decrease the passenger walking distance, in order for passengers to have more time to shop.
Zhang et al. (2017)	Heuristic BBO algorithm	Minimise flight conflict and number of flights assigned to aprons (also know as ramp, is the area of an airport where aircrafts are parked, unloaded or loaded, refueled, or boarded).
Kim et al. (2017)	Meta-heuristic algorithm Tabu Search	Minimise the transit time of passengers inside the terminal, minimise the taxi time on ramps and lastly to minimise disturbances in gate operations to maximise robustness of the gate assignment.
Behrends and Usher (2016)	Job shop scheduling solution	Combine aircraft taxi path with ground movement, leading to a final objective of increase customer satisfaction with revenues and operation cost recovery.
Marinelli et al. (2015)	Bee Colony Optimisation	Minimise passenger walking distance and remote gate usage
Neuman and Atkin (2013)	Mixed Integer linear programming model	Maximise time gaps between allocated flights in order to absorb potential delays induced by taxi conflicts, and minimise the utilisation of remote gates.
Jiang et al. (2013)	Integer non liner programming	Based on passenger walking distances and airlines' fairness.
Diepen et al. (2009)	Integer linear programming	Combination of gate and bus planning. In order to have a more efficient model, stabilised column generation and also column deletion were used. To gain robustness, the model tries to maximise idle times in order to absorb potential delays.
Lim et al. (2005)	Tabu Search and Memetic algorithms	Minimise walking distances and do not consider fixed schedules but a time window approach where flights are allocated.

usage, based on a Bee Colony Optimisation aims to find the best solution at Milano-Malpensa airport. The results showed that the actual scheduling of the airport was not as effective as the model proposed. Jiang et al. (2013) aims for a multiobjective gate assignment model based on passenger walking distance and airlines' fairness, using an Integer non Linear Programming model. Assuming passenger walking distance is divided in three parts: arrival passenger distance, distance from gate to baggage hall; departure passenger distance, distance from security check to gate; and transfer walking distance, distance from gate to transit counter and then to the gate of the next flight. Kim et al. (2017) mentions that not only in terms of costs, but also considering passenger satisfaction, the authors are aware that most air travelers have experienced long walking distances in an airport terminal to catch a flight.

2.1.2 Robustness

As mentioned and shown before, airports have high costs related to airplanes (not only due to the increase of fuel prices) and the more time they spend on the ground, the higher is the probability of colliding to other airplanes schedules, leading to a more expensive operation. So, airports try to create robust models in order to obtain smooth gate assignment operations. Moreover, with the increase of civil air-traffic and the corresponding growth of airports in the past decades, airplanes riding around the airport may collide with other airplanes taxiing, which means that gate assignment should predict in advance those collisions in order to reduce congestion and thus, increase the efficiency in the airport activity. To increase the overall robustness of an airport operation, Lim et al. (2005) considered an adjustable time window for the departure and arrival time of each flight. When flight schedules are fixed, minor delays or other problems would need for an urgent rescheduling of the initial plan, leading frequently to a solution far from optimal. With this model, minor delays can be absorbed, considering duration of transit as fixed and sliding them in a proper time window. Neuman and Atkin (2013) took into account possible conflicts at taxiways around gates and the expected traffic around certain gates and limited the number of aircrafts around them since they would create delays during their manoeuvres. Furthermore, the model proposed a function that maximises the time gaps between allocated flights, in order to absorb potential delays. Behrends and Usher (2016) developed a model where delays are minimised, that optimises the ability for flights to maintain their schedules. Zhang et al. (2017) tried to minimise flight conflict probability and number of flights assigned to aprons (also know as ramp, is the area of an airport where aircrafts are parked, unloaded or loaded, refueled, or boarded) using an Heuristic BBO algorithm. The robustness of the model could be evaluated by finding the right proportion of flights assigned to the aprons, leading to a subsequent flexibility of gate assignment. Kim et al. (2017) was aware that delay costs had a huge impact on airports and in the economy (just to the US passenger airlines delays costs accounted for 7.7 billions in 2011), and thus, created a model using a Tabu Search algorithm, focused on minimising the taxi time on ramps and disturbances in gate operations to maximise robustness of the gate assignment.

2.1.3 Remote gate usage

When an airplane arrives at an airport, it can either be allocated to a fixed gate or a remote gate. Fixed gates usually are connected to the terminal by jet-bridges (also known as jetways, which consists in a connector that extends from a gate to an airplane, allowing passengers to embark/disembark without going outside), which can mean less connecting time for passengers as well as less walking distance. On the other hand, remote gates imply a bus transfer to bring passengers to the terminal, meaning more connecting time and more walking distance, besides meaning a less desirable activity for passengers. Marinelli et al. (2015) analysed the remote gate usage in their approach, as well as Diepen et al. (2009) who dealed with gate and bus assignment at the same time, joining them together in order to find a better solution. Shareef (2016) evidences the operational disadvantage of remote gates, due to long waiting for aircrafts till all the passengers are moved from/to the aircraft by bus. Furthermore, the author points that in the US, remote gate allocation is not legal, while in Europe and Asia it continues to be a common usage, especially by low-cost carriers.

2.2 Passenger behaviour in airport terminals

As mentioned in chapter 1, nowadays airports are facing a high-speed development due to the increase of flights and passengers, meaning an enormous change in the way they operate (Gheorghe et al. (2016)). Furthermore, they are the first and last operation a passenger experiences (Bellizzi et al. (2018)) and a different environment from everything else, mainly due to the psychological and environmental unique experiences linked to the travel process (Crawford and Melewar (2003)). This information is essential to an airport manager, because if it is well absorbed, the passenger experience can increase the passenger willingness to pay for more products and services (Crawford and Melewar (2003)). As in every business, airport revenues are obviously one of the main focus of their managers. These revenues can come from aeronautical or non-aeronautical activities. The share of shopping revenues must be taken into account, which means, an airport should no longer be seen just as an intermediate building to flying, but as a touristic attraction due to all its activities and possibility of spending money. In recent years, big developments in the airports systems have happened, such as low-cost carriers have been introduced and gained a huge share in the market, making it cheaper for passengers to travel, meaning a decrease of revenues on airport earnings. Also, due to security reasons, a lot of investment from airports has been made to improve the passenger experience, making it a much smoother process since entering until leaving an airport (Gheorghe et al. (2016)).

Obviously, all these improvements require large investments and a huge percentage of the airport yearly budget. Thus, there is a need to look for more ways to increase their income from passengers, and nowadays air travel is much more affordable to a passenger, with really thin profit margins for airports in terms of aeronautical activities (Gheorghe et al. (2016)), meaning non-aeronautical activities are a better opportunity for airports to increase their revenues. These non-aeronautical activities, because of their contribution to airport revenues, have suffered a unique and amazing development in the last 10 years (Kalakou and Moura (2015)). According to Fasone et al. (2016), non-aeronautical revenues can represent more than 50% of incomes for an airport, and therefore, many different researches and developments in passenger experience have been made in order to take the best out of the passenger experience at an airport, both its own personal satisfaction and maximising their will to spend more money in its shops and services.

Finally, every barrier that can affect a passenger willingness to pay and to use airport non-aeronautical services needs to be overcome, by creating a controlled environment that minimises the stress and maintains the level of excitement of a passenger, while at the same time motivates the impulse of purchasing, leading to a increase in the airport performance and profitability.

2.2.1 Trip characteristics

This type of characteristics are based on the trip the passenger is doing, from the origin to its destination airport, and the several locations related to the trip itself. It includes check in method, group composition, airline company and more, as presented in table 2.2.

Table 2.2: Trip Characteristics and its relation to passenger behaviour

Passenger Characteristic	Relation to behaviour	Reference
Group composition	Passengers travelling in groups spend more time before security check-point. When someone stays behind, the rest of the group will slow down. This potentially leads to congestion and longer check-in dwell time. All these factors lead to a worse passenger experience inside a terminal.	Cheng et al. (2014)
	Passengers travelling alone will not spend as much money as accompanied, as well as people travelling with children.	Liu et al. (2014)
	Passengers travelling in group will spend more money in the dining area, unless they are travelling with children which decrease their money spent on dining activities.	Castillo-Manzano and López-Valpuesta (2013)
Travelling company	Passengers that arrived at the airport accompanied by people not travelling will perform more non-aeronautical activities before the security check-point.	Kalakou and Moura (2015)
Arrival time before flight	Passengers who arrive earlier at the airport will increase their likely to spend money on food and drinks.	Castillo-Manzano and López-Valpuesta (2013)
	Passengers who have more time at the airport before the flight are more likely to spend money in both activities and services.	Torres et al. (2005)
	Passengers who arrive earlier than 2 hours care much more about cleanliness of the airport since they will spend more time there.	Bellizzi et al. (2018)
Airline Type	Passengers who travel in low-cost carriers are less willing to spend money at the airport.	Castillo-Manzano and López-Valpuesta (2013)
Carry-on baggage	Passengers who bring more carry-on bags decrease linearly its probability of doing non-aeronautical activities.	Liu et al. (2014)
Check-in method	Passengers who do the online check-in will less likely spent money or time in activities before the security check-point.	Kalakou and Moura (2015)

2.2.2 Personal characteristics

Personal characteristics are composed and related to a single person. This includes information such as age, gender and nationality. Information about what they feel inside the airport and their thoughts on the whole airport experience is also considered as personal characteristics, and may be observed in table 2.3.

2.2.3 Process characteristics

Process characteristics are related to the different activities the passenger performs once inside the airport, it includes information about the aeronautical or non-aeronautical activities and also the time spent in each one. This information and its relation to passenger behaviour is presented in table 2.4.

Table 2.3: Personal Characteristics and its relation to passenger behaviour

Passenger characteristic	Relation to behaviour	Reference
Atmospheric environment	Passengers prefer a shopping area with high in-store visibility, cool colours for window display, floors, wall and ceiling and bright lighting for the airport display. More importantly, it was concluded that lighting has the most influence on consumer preferences.	Suzianti and Larasati (2017)
	Passengers travelling for vacations/leisure will care much more about comfort, while people travelling for work/studies care more about the technical aspects such as information inside the airport. On the other hand, people arriving two hours before their flight are more satisfied with cleanliness since they will spend more time there.	Bellizzi et al. (2018)
Place of residence	Passengers who do not live in the city of the airport are more likely to perform discretionary activities before the security check-point.	Kalakou and Moura (2015)
Age	Younger passengers are more likely to shop than middle aged travellers, which are more likely to use facility activities.	Liu et al. (2014)
Education level	Passengers that have a higher education level are more likely to perform inquiry activities.	Liu et al. (2014)
Gender	Male passengers are more likely to perform inquiry activities while female passengers are more likely to shop.	Liu et al. (2014)
Income	Passengers with a higher wage are more prone to perform shopping and dining activities.	Liu et al. (2014)

Table 2.4: Process characteristics and its relation to passenger behaviour

Reference	Process characteristics relation to behaviour
Liu et al. (2014)	Youngsters are more likely to perform discretionary activities than middle age people
	Frequent travellers shop less at the airport
	People with higher income are more likely to shop and dine at the airport
	People carrying more hand bags are less likely to dine at the airport
	People in large airports are less likely to spend time at the airport before check-in and consequently are more likely to perform discretionary activities afterwards
	In small airports, since they have fewer shopping facilities, people are less likely to shop at the airport
Kalakou and Moura (2015)	Passengers familiar with the airport and schengen passengers that check-in between 60-90min before the flight are more likely to perform non-auronautical activities
Castillo-Manzano and López-Valpuesta (2013)	People arriving earlier to the airport are more likely to dine at the airport
Torres et al. (2005)	Arriving earlier at the airport has a high positive correlation with passenger consumption

2.3 Different types of Passenger processes

Airports serve many different entities, passengers, airlines, security services, operators etc. It is fundamental that the configuration of airport buildings aim for all these components.

The passenger process is rather complex and diversified, ranging from the activities passengers perform, to the different kinds of passengers that exist. Passengers departing, arriving or transferring at an airport go through a number of mandatory steps in order to complete their journey. Thus, it can be really helpful to analyse and research the information about the passenger process in order to predict the next passenger activity. There are different kinds of activities, Popovic et al. (2009) differentiate them based on the process activities (e.g. check-in, security checkpoint, and passport control) and discretionary activities (done by the passenger to occupy their time such as coffee, shopping or exchanging money). Due to European regulations, the same passenger process is performed in every airport and can be ilustrated in figure 2.1.

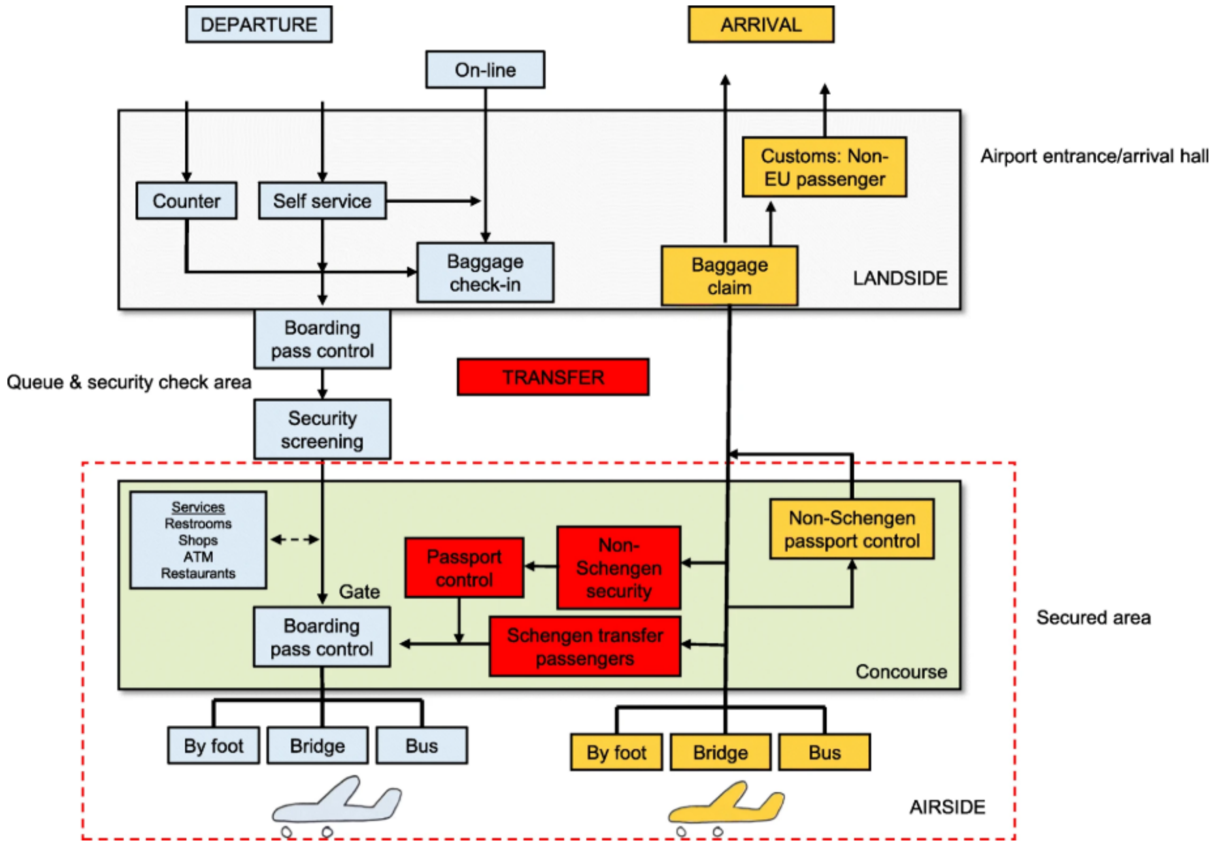

Figure 2.1: Passenger processes inside the airport (Source: Ikonen et al. (2018))

Next, the configuration and description of different types of passengers will be demonstrated:

Departing passengers

Considered to be the passenger with the most complicated process because there are three main phases in the terminal (Liu et al. (2014)). The phase before check-in, then, after check-in or in case the passenger has done an online check-in and only carries hand baggage, the passenger goes to the second phase, the security checkpoint, which can be considered to include the passport control phase, if needed. Lastly, the third phase before boarding to the aircraft. During all these steps, passengers can and usually perform discretionary activities, mostly after security checkpoint, since the passenger is not aware of the time needed to complete all the process activities and more importantly, they are always restricted to the time remaining until boarding.

Arriving passengers

Arriving passengers need to perform two different phases. Firstly, the phase before border control, this activity is only done if a passenger arrives at a Schengen airport and comes from a non-Schengen airport or vice-versa. This phase can last a considerable amount of time since, sometimes, many flights with the characteristics described before arrive at the airport, meaning a lot of people performing the passport control. At this stage the passengers are allowed to perform discretionary activities since, in many airports, they are allowed to access lounges.

The second activity is the before customs, which starts after the passport control. The passengers reach the baggage reclaim halls and in case a passenger has nothing to declare and only carries hand baggage throughout the whole trip, their time spent on this phase is approximately zero. At this stage, passengers can also perform limited discretionary activities since, purposely, there are not many activities available at this point. Actually, passengers at this stage are more concerned with searching for airport information about transportation to their final destination.

Transferring passengers

This type of passenger has a quicker passage through the airport processes, although they can spend a lot of time inside the terminal waiting for their next flight. In case the passenger comes from a Schengen airport and arrives at a non-Schengen airport or vice-versa, he/she needs to go to passport border control. If not, the passenger can go directly to lounges. In some airports, a security checkpoint is performed before passengers go to lounges.

2.4 Passenger segmentation

To achieve an optimal marketing strategy, the relationship between shopping and travellers, the constant development of air-traffic, and therefore more air passengers, and the huge quantity of shops and services offered at the airport need to be combined (Geuens et al. (2004)). Furthermore, the correct segmentation of passenger types is crucial in order to be close to the different customer expectations. It has been studied that passenger segmentation is performed according to personal and/or situation variables. It has been concluded by many researchers that only one passenger type is not the best approach since passengers are not a homogeneous group of individuals (D'Alfonso et al. (2013)).

Moreover, in case of a single passenger type, the socially optimal charge never exceeds the residual share of the marginal congestion cost (Zhang and Zhang (2003) and Basso and Zhang (2007)). On the other hand, in the case of two passenger types divided in terms of values of time, Czerny and Zhang (2011) found that the socially optimal charge may exceed the marginal congestion cost. These authors, as well as D'Alfonso et al. (2013) divided passengers into business (higher time-value) and leisure (lower time-value), and concluded that it can be useful to increase airport charges in order to protect business passengers from excessive congestion caused by leisure passengers. The congestion factor may lead to two different opinions, on the one hand, as congestion goes up, the dwell time (time available for shopping) decreases since passengers spend more time on queues. On the other hand, higher congestion may force passengers to arrive earlier at the airport since they expect longer waiting times in queues (Appold and Kasarda (2006) and Buendia and de Barros (2008)). Geuens et al. (2004) divided passengers in three segments: mood shoppers (a type of passenger that can only be found on an airport because his/her motivation and willing to shop is created due to the airport atmosphere passenger experience or other typical airport characteristics such as shopping due to boredom while waiting for the flight), shopping lovers (passengers that are always constant consumers, especially stimulated to shop by airport infrastructure) and apathetic shopper (not interested in shopping, either at airports and malls neither at home). In a different way, Geuens et al. (2002) suggests that exist six different types of passengers based on the available time the consumer has, the importance given to social interactions and the importance given to experiential elements: (1) Convenience shopper (time-poor, no social nor experiential interest), (2) Low-price shoppers (time-rich, neither social nor experiential interest), (3) Social shoppers (time-poor, social but no experiential interest), (4) Intense social shoppers (time-rich, social but no experiential interest), (5) Experiential shoppers (time-poor, experiential interest), and (6) Recreational shoppers (time-rich, experiential interest). Also, Harrison et al. (2015) identified a passenger segmentation based on time sensitivity and degree of passenger engagement: airport enthusiast (engaged and non-time sensitive), time filler (non-engaged and non-time sensitive), efficiency lover (non-engaged and time sensitive) and efficient enthusiast (engaged and time sensitive).

Chapter 3

Discrete Choice Modelling

In this chapter, a description on how the survey, used as base in the Discrete Choice Modelling (DCM), was created and what were the main aspects identified, is presented. Furthermore, a demonstration on how discrete choice modelling is settled and tested is exposed to the reader in order to achieve a better comprehension on the subject. In the end, a compilation on discrete choice modelling applications on airport planning is exhibited.

3.1 Survey description - Passenger Behaviour

As explained in chapter 2, researchers have for long associated passenger characteristics to behaviours, either from socio-demographic, trip and process characteristics. To obtain these characteristics a survey was conducted through a web-based revealed preference survey of airport travellers, which had already departed, arrived or did a transfer at Terminal 1 of Lisbon Airport. The choice of Terminal 1 was done due to the aim of this dissertation is to be applied at TAP Air Portugal, and therefore its flights only operate on this Terminal 1. The survey was designed using "Google Forms" and allowed to divide the respondents in three different groups (departure, arrival or transferring passenger) initially, but also to the same respondent to answer about any of the other processes. This allowed for a bigger perception of how for different processes, passenger activities change.

The structure of the survey follows the flowchart from figure 3.1 and all survey questions for departing, arriving and transferring passengers are presented in annexes, in table A.1, table A.2 and table A.3, respectively. In case the passenger has never done a transfer before, the survey questions are presented in table A.4. Moreover, general personal questions for all passengers are presented in table A.5.

The purpose of the survey is to gather useful information on how passengers behave inside the airport in order to stimulate modelling processes. Since passenger experience is the focus of this survey, the aim is to gather data on passenger "senses" and perception, which is done by groups of questions divided in:

- time-related information, which allows to understand what the passenger feels and does during the time at the airport;
- personal information, which allows to get to know better who the passenger is;
- air-trip information, allowing to understand what the passenger has opted for;
- activities and purchases performed by the passenger while at the terminal;
- orientation of the passenger inside the airport.

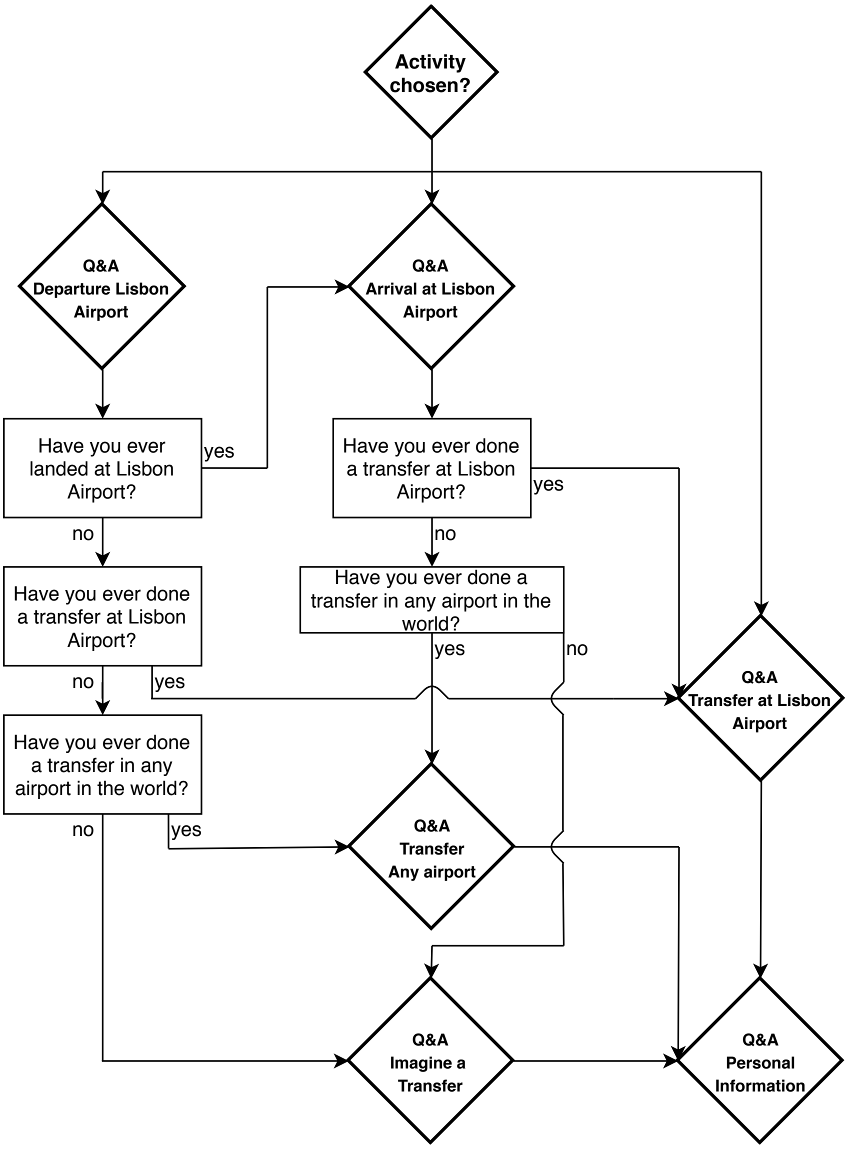

Figure 3.1: Flowchart of survey design

Moreover, each section above is proposed to reveal the following information which was identified in chapter 2 as important for passenger modelling and to help airport managers to identify important aspects for planning the airport operation.

- Time - The passenger is asked to reveal what day of the week and what time their flight was. In case of delay, how much it was, and time-related information on: time in advance they arrived at the airport and at the gate (departing passengers), time they waited for their hold baggage at the baggage claim area (arriving passengers) and time waited between the two flights (transferring passengers);
- Personal - The passenger is asked to answer questions regarding: age, gender, nationality, city of residence, monthly income, air travel frequency and Terminal 1 of Lisbon airport frequency, stress regarding the fear of travelling by plane, stress regarding the time before the flight;
- Air-trip information - The passenger is asked to describe their airline, which country were they

going (departing passengers), which country they came from (arriving passengers), and both (transferring passengers), mode of check-in, number of hold and hand baggage, mode of arrival at the airport, number of people they were travelling with, if there they were travelling with children, away days of their place of residence, reason of travelling and, in case for business motives, who paid for the cost of the trip;

- Activities - The passenger is asked to remember which activities they performed after passing the security control, such as: if they went to the business lounge, if they visited any place for having food/drinks and how much time and money they spent, if they visited any place for shopping and how much time and money they spent, as well as how many products they bought. To understand if their activities were planned or impulsive, a question was added to ask if the passenger had previously planned their activities inside the airport;
- Orientation - The passenger is asked their easiness of moving inside Terminal 1 of Lisbon Airport;

3.2 Forecasting passenger behaviour

For this dissertation, the human behaviour should be taken into account since the main objective of an airport is to fulfill their passenger movements and expectations. Consequently, airport planners should try to comprehend in the best achievable way how passenger characteristics can influence their needs. Kalakou and Moura (2015) mention that in transportation systems, this has been difficult to capture due to the heterogeneity of passengers and types of people, although it significantly affects the performance of any transport environment.

One way of trying to understand passenger behaviour is to try to group people according to certain characteristics or choices, and evaluate what pattern or characteristics influences people to opt for a certain option using Discrete Choice Modelling. In this dissertation, it was decided to divide passengers according to their money spending inside the airport. To introduce how this category division was made, and how choice modelling was modelled, the next subsections will be introduced to better explain to the reader how it works.

3.2.1 Passenger behaviour analysis using choice modelling

To reduce the consequences of an unpredictable passenger behaviour, there are mathematical models that allow to predict how a person is going to behave bearing in mind their personal and trip characteristics. Ben-Akiva and Lerman (1985) gives the example with Choice models which is able to predict individual choices by analysing a set of discrete choices (e.g. reason of travelling: working, holidays, visiting family, etc.) or categorical (e.g. minimum, medium, high level of stress regarding the flight).

Choice modelling was first mentioned by Thurstone (1927), who was studying the concept of discriminal process, by which an organism distinguishes and reacts to a given stimulus, and developed the first probit model that explained those choices. The first steps of the logit formula where done by Luce (1959), by analysing the assumptions about choice probabilities characteristics. Then, Marschak (1974) studied the utility maximisation and showed how it can be included in the evolution of the logit choice models. Then, it was introduced the error in the utility function and assumed to follow an extreme value distribution and consequently, introduced a logit formula of the choice probabilities. It was in this context that MultiNomial Logit (MNL) and Nested logit models were developed.

Discrete choice models are used to explain a user choice by an evaluation of a set of finite mutually exclusive alternatives. The utility of a choice tries to quantify the advantage and benefits of a user for choosing a specific choice. First, an individual gives information about his preferences by choosing an alternative i over a set of choices ($C_n = 1, 2, 3, ..., n \wedge n \in N$), attributes a certain utility value ($V_{j,n}$) to each of them and then evaluates which is the alternative that maximises his utility. The utility of the decision maker is then, a function of a combined set of explanatory variables chosen by the individual. When a decision maker chooses a certain choice, the observers that study the decision maker behaviour, are not completely sure of what influenced his final decision. Thus, Train (2002) introduced an error constant (ε) in the utility formulation to capture these uncertainties related to the lack of full information, due to omission of certain characteristics, unobserved alternatives, measurement errors. The utility function is then written as:

$$U_{i,n} = V_{i,n} + \varepsilon_{i,n} \tag{3.1}$$

Where:

$$V_{i,n} = \sum_k \beta_k \cdot x_{i,n,k} \tag{3.2}$$

where x is a vector of the variables (correspondent to each discrete choice) in the modelling process, either characteristics of the decision maker, trip choices, time related choices, and activities performed by the decision maker. β is the parameter that represents each choice importance for the model. The error term is assumed to be independent and each one is an identically distributed Extreme Value. This distribution is also known as Gumbel and type I extreme value (Train (2002)). The density for each unobserved component of utility is:

$$f(\varepsilon_{n,j}) = e^{-\varepsilon_{n,j}} \cdot e^{-e^{-\varepsilon_{n,j}}} \tag{3.3}$$

and the cumulative distribution, $F(\varepsilon_{n,j})$, is given by:

$$F(\varepsilon_{n,j}) = e^{-e^{-\varepsilon_{n,j}}} \tag{3.4}$$

It is important to notice that, in extreme value distribution, the concept of error Independence means that the error between two alternatives are completely independent.

To analyse the impact of variables for the choice of the decision maker, different aspects can be investigated. To identify the statistical significant variables for a choice, the observer should analyse the value of the parameter β for each variable. Afterwards, utility maximisation is used as the main criteria to decide the individual's choice by estimation of the maximum likelihood. According to Koppelman and Bhat (2006), the procedure for maximum likelihood estimation involves two important steps:

1. developing a joint probability density function of the observed sample, called the likelihood function;

2. estimating the parameter values which maximise the likelihood function. This likelihood function (L) is formed by the product of the N independent multinomial distributions:

$$L(\beta) = \prod_{n=1}^{N} \prod_{i=1}^{J_{C_n}} P_n \cdot (i|C_n)^{y_{i,n}} \tag{3.5}$$

where, $J_{C_n}$is the size of the choice set, C_n is the choice set of the decision-maker n and $y_{i,n}$ represents the decision-maker n choosing alternative i (where $y_{i,n}$=1 if i is chosen by individual n and $y_{i,n}$=0 otherwise). To obtain the maximisation of likelihood function (L) and the estimation of β, several softwares find the first derivative of the likelihood function (L) and equate it to zero. Since the maximisation of log of a function makes it easier to maximise by just equating it to zero, the log of the likelihood function (LL) is obtained by:

$$LL(\beta) = \sum_{n=1}^{N} \sum_{i=1}^{J_{C_n}} y_{i,n} \cdot ln(P_n(i|C_n)) \tag{3.6}$$

Then, the optimal solution is obtained by equating the log likelihood (LL) to zero.

Since each decision-maker is different, and each one has certain characteristics that distinguishes he/she from one another, we cannot take into account every factor that leads the decision-maker to choose a certain choice. Thus, this variability of a possible outcome is taken into account by creating a probabilistic choice theory, allowing observers to estimate the probability of different outcomes given a certain choice set and a decision-maker (McFadden (1974)).

As mentioned before, the decision rule for choosing a certain choice is to opt for the one with the highest utility:

$$P(i|C_n) = Pr(U_{i,n} \geq U_{j,n}, \forall\, j \in C_n) \tag{3.7}$$

where $U_{i,n}$ is the utility of alternative i for person n. The equation can be rewritten as:

$$P(i|C_n) = Pr(V_{i,n} + \varepsilon_{i,n} \geq V_{j,n} + \varepsilon_{j,n}, \forall\, j \in C_n) \tag{3.8}$$

or:

$$P(i|C_n) = Pr(\varepsilon_{j,n} - \varepsilon_{i,n} \leq V_{i,n} - V_{j,n}, \forall\, j \in C_n) \tag{3.9}$$

and can be rewritten to its logistical form by:

$$P_{i|C_n} = \frac{e^{\mu \cdot V_{i,n}}}{\sum_j^n e^{\mu \cdot V_{j,n}}}, \forall i \in C_n \tag{3.10}$$

where μ is a scale parameter of which "is usually based on a convenient normalisation of one of the variances of the random terms" (Ben-Akiva and Lerman (1985)).

In the utility form, some factors that affect the decision-maker choices are not taken into account due to the impossibility to know each user and what affects them. Therefore, an alternative-specific constant

(ASC) is added to include all those factors that are not taken into account in the model. One of the ASC of an utility is normalised to zero, and then the value of the other ASC from different utilities are compared to the one which was normalised.

3.3 Specification Testing

3.3.1 Specification of variables

After elaborating a model that can properly correlate the choices of the decision-makers, tests should be done to check the suitability of the specifications of variables and to check the model structure. In this dissertation, to check the specification of the model, tests such as the asymptotic t-test, the likelihood ratio test, test of generic attributes, tests of nonlinear specifications were done. Moreover, to check the structure of the model, tests for taste of variations and for heteroscedasticity were performed.

As any model, there are certain variables that we expect to have certain values and signs due to a priori assumptions, and therefore an informal test can be done just by evaluating the corresponding values and its variation according (or not according) to our assumptions. Another way to check the specification of variables is to check the parameter values with the equivalent values from similar models for the same set of choices. Besides these tests performed by simple analysis of results, other statistical tests may be performed, such as:

The asymptotic t-test

The asymptotic t-test is used to check the validity of a certain hypothesis (Ho). Firstly, a null hypothesis is created, usually claiming that a particular parameter in the model differs from a known constant (usually zero) or that two parameters β_k and β_l are equal. Then, a significance level (α) is chosen by the modeler, according to his/her intended level of accuracy for the model. This test is used to determine the likelihood of obtaining a sample outcome if the null hypothesis is true and, if Ho is accepted, give the probability value (p-value) of obtaining an outcome. The value of the t statistic is:

$$t_{\beta'} = \frac{\beta' - \beta_0}{\sigma_\beta} \tag{3.11}$$

where β' is the estimated value of the parameter, β_0 is a specified constant to serve as a reference value (usually 0) and σ_β is the standard error. The p-value is the probability to get a $t_{\beta'}$ as high as $t_{\beta'}$ from H_0 (the created null hypothesis). If the p-value is not greater than the chosen significance level (e.g. 1%, 5%, 10%), then the null hypothesis is rejected or, in other words, the variable that is being studied does not contribute to explain the decision-maker choice. Usually the most common values for significance levels are 0.01 and 0.05, which correspond to the values of the t-test ($t_{\beta'}$) of ± 1.65 and ± 1.96, respectively.

The likelihood ratio test

In statistics, the likelihood ratio test allows to check the goodness of fit of two models based on the ratio of their likelihoods, in which one model is a restricted model (after imposing some constraint, i.e, the null hypothesis) and the other is an enriched model, found by the maximisation over the entire parameter space. To test this, the modeler sets all coefficients from the null hypothesis to zero, except for the alternative-specific constant and solves:

$$\chi^2 = -2 \cdot [LL_U - LL_R] \tag{3.12}$$

where LL_U stands for the log likelihood of the enriched model and LL_R the log likelihood of the restricted model. Then, the likelihood-ratio test verifies if the restricted model is better than the enriched one by checking if the ratio is significantly different from zero.

3.4 Discrete choice modelling on airport planning

After concluding the model analysis, one of the main objectives of this dissertation, as mentioned before, is to give support for airports to attribute flights to gates in a way that maximises the probability of a passenger having expenses and thus, maximises the airport profits. To do so, discrete choice modelling can help to analyse and determine the main criteria to look for passenger characteristics, in order to better understand passenger choices and therefore, to better know which type of passengers are using the airport and consequently, to know how the maximisation of profits can be performed.

As explained in this chapter, general information of passenger behaviour are gathered on the performed survey. Aspects such as money spent on food/beverages and shopping. The integration of Discrete Choice Modelling with this data, allows for a more complete and comprehensive planning process, by analysing which are the main characteristics to get more money spent per passenger.

Based on the results from this kind of models, the information may be useful for different agents, such as:

- Transport Planners - these agents could benefit from the information provided by the model when dealing with the changes of passenger behaviour according to several personal characteristics, by analysing aspects such as, number of people travelling with, number of hand bags, nationality, reason for travelling, if the flight has an international or national destination, etc... The benefit for transport planners would be a better response to strategic decisions, by adapting models according to their interest, in order to have a convenient adjustment to passengers needs.

- Airport Managers - as mentioned in Kalakou and Moura (2015), international flights depart usually early in the morning or at late night, due to the time difference of origins and destinations. So, there is a possibility for airport managers to change their daily operation to better manage passenger flows, since certain passenger characteristic are known to be associated to, for example, arrival time at the airport, as well as, it is a good opportunity for airport managers to exploit retail area reconfigurations (for instance, changing airport layout or relocate passport control for Schengen flights) according to the time of day.

Concluding, discrete choice modelling is of high importance on airport planning since it reveals what characteristics influence passengers choices. Either in terms of operational planning, either in strategic decisions, these models with the correct data input, are able to add value to airports by incorporating passenger characteristics and adjust their strategies according to it.

Chapter 4

Mixed-Integer Linear Programming Model

In this chapter, the optimisation model is presented and described in detail. A Mixed Integer Linear Programming (MILP) model is fully defined and all the constraints, variables and objective functions are explained and discussed in detail. Many were the modifications to the initial model formulations, but to be closer to the case study and thus, to have more realistic results, this is the final model.

4.1 Model Formulation

The gate assignment problem is a challenge for airports and airline companies. On one hand, airports intend to allocate airplanes in the most efficient way, bearing in mind all the benefits of a perfect allocation such as: i) it corresponds to the airlines requests for a gate; ii) it increases passenger consumption and therefore profit inside the airport at stores, services, lounges, etc. On the other hand, airline companies want their passengers to feel secured inside the airport and with the most convenient infrastructures surrounding them. Besides having to take into account both operational parties, this problem is also relatively complex due to all the variables associated: large number of flights and the dynamic nature of the problem, passengers behaviour inside the airport, passengers expectations, passengers willingness to spend money and all the uncertainties related due to differences in age, gender, number of bags, nationality, place of residence, travel destination and so much more. Consequently, an optimisation model is presented in this chapter that will combine all the existing variables and obtain an optimised gate allocation.

The solution obtained for this problem intends to take the perspective of the airport manager, i.e., our main focus is to increase the airport profits by maximising the money spent by passengers inside the Terminal. The mathematical formulation is based on this approach, and thus, the walking distance that a passenger needs to walk to arrive at the desired gate should be decreased, and the amount of revenues from passengers should be increased. Three different passenger types are used in this formulation: departing, arriving and transferring passengers. Moreover, inside each segment, through the survey done to Lisbon airport passengers, an assignment is made to the probability of spending a certain amount of money per each passenger category inside each passenger type. The optimisation process will allow that all passengers with higher probability of spending money, to be the closest as possible to the center of retail area.

The present mathematical model is an adaptation of the model by Lim et al. (2005) which, as explained in chapter 2, allows a time window for each flight so that arriving and departure times do not have to be fixed to a certain schedule, but able to slide in the flight ”time-window”. Some constraints such as equations 4.9, 4.10, 4.11 and 4.16 (presented in the next section) were used as in Lim et al. (2005), and then the model was adapted to be closer to our case study, namely in the definition of the objective function and other constraints and variables.

The proposed model is a Mixed-Integer Linear Programming, which was implemented in an optimisation software FICO Xpress. Below, the next sections will fully define the model:

- Constants - provides the different constants used;
- Sets - presents the sets used;
- Parameters - distinguishes the meaning of the different variables used in the model;
- Decision variables - presents the binary decision variables;
- Objective function - introduces the several constituents of the multi objective function;
- Constraints - displays the several constraints used to define the limits of this model.

4.2 Constants

NG Number of gates

NF Number of flights

NTP Number of passengers categories

4.3 Sets

G Set of gates

F Set of flights

P Set of passenger categories

4.4 Parameters

a_j	The expected arrival time of flight j
d_j	The expected departure time of flight j
npt_{p,j,j_2}	Number of passengers in transfer from flight j to flight j_2, according to passenger category p
$nps_{p,j}$	Number of passengers arriving at the airport from flight j, according to passenger category p
$npe_{p,j}$	Number of passengers departing on flight j, according to passenger category p
wdt_{i,i_2}	Walking distance of transferring passengers between gate i and gate i_2
wds_i	Walking distance of arriving passengers from gate i to the baggage claim area

wde_i	Walking distance of departing passengers from the main retail area to gate i
$rt_{p,i}$	Revenues from transfer passengers of category p, arriving at gate i
$rs_{p,i}$	Revenues from arriving passengers of category p arriving at gate i
$re_{p,i}$	Revenues from departing passengers of category p, departing from gate i
cdt_p	Cost per walking distance of transferring passengers of category p
cds_p	Cost per walking distance of arriving passengers of category p
cde_p	Cost per walking distance of departing passengers of category p
cg_i	Classification of gate i per type of gate
cga_i	Classification of gate i if Schengen or no-Schengen
cfa_j	Classification of flight j if Schengen or no-Schengen
cf_j	Classification of flight j per type of flight
rtg_i	Time from runaway to gate i and vice versa
ut_i	Prepare time for departure or arrival between pilot and airport manager and time required for passengers to enter/leave the plane from/to gate i
$tmint_{i,i_2}$	Minimum time to allow transfer between gate i and gate i_2
$tmino_i$	Minimum time of free-gate between two flights in gate i
$xp_{i,j}$	Gate allocation of flight j at gate i staying on the ground before the time interval studied

4.5 Decision Variables

$$x_{i,j} = \begin{cases} 1 & \text{if flight } j \text{ is assigned to gate } i, \\ 0 & \text{otherwise} \end{cases}$$

$$y_{j,j_2} = \begin{cases} 1 & \text{if flight } j \text{ departs earlier than flight } j_2 \text{ lands}, \\ 0 & \text{otherwise} \end{cases}$$

$$z_{i,i_2,j,j_2} = \begin{cases} 1 & \text{if flight } j \text{ is assigned to gate } i \text{ and flight } j_2 \text{ is assigned to gate } i_2 \text{ ,} \\ 0 & \text{otherwise} \end{cases}$$

b_j	Linear dependent variable of $x_{i,j}$ equal to the time passengers are allowed to enter the terminal from flight j (this variable is displayed in minutes starting from 3pm)
c_j	Linear dependent variable of $x_{i,j}$ equal to the time passengers are allowed to enter flight j (this variable is displayed in minutes starting from 3pm)

4.6 Objective Function

$$\text{Maximise } O_{Total} = O_1 + O_2 + O_3 - O_4 - O_5 - O_6 \tag{4.1}$$

4.7 Constraints

$$O_1 = \sum_{i=1}^{NG}\sum_{i_2=1}^{NG}\sum_{j=1}^{NF}\sum_{j_2=1}^{NF} npt_{p,j,j_2} \cdot rt_{p,i} \cdot z_{i,i_2,j,j_2} \tag{4.2}$$

$$O_2 = \sum_{i=1}^{NG}\sum_{j=1}^{NF}\sum_{p=1}^{NTP} nps_{p,j} \cdot rs_{p,i} \cdot x_{i,j} \tag{4.3}$$

$$O_3 = \sum_{i=1}^{NG}\sum_{j=1}^{NF}\sum_{p=1}^{NTP} npe_{p,j} \cdot re_{p,i} \cdot x_{i,j} \tag{4.4}$$

$$O_4 = \sum_{i=1}^{NG}\sum_{i_2=1}^{NG}\sum_{j=1}^{NF}\sum_{j_2=1}^{NF}\sum_{p=1}^{NTP} npt_{p,j,j_2} \cdot cdt_p \cdot wdt_{i,i_2} \cdot z_{i,i_2,j,j_2} \tag{4.5}$$

$$O_5 = \sum_{i=1}^{NG}\sum_{j=1}^{NF}\sum_{p=1}^{NTP} nps_{p,j} \cdot cds_p \cdot wds_i \cdot x_{i,j} \tag{4.6}$$

$$O_6 = \sum_{i=1}^{NG}\sum_{j=1}^{NF}\sum_{p=1}^{NTP} npe_{p,j} \cdot cde_p \cdot wde_i \cdot x_{i,j} \tag{4.7}$$

$$\sum_{i}^{NG} x_{i,j} = 1,\ \forall\, j \in F \tag{4.8}$$

$$z_{i,i_2,j,j_2} \leq x_{i,j},\ \forall\, j \in F, j_2 \in F, i \in G, i_2 \in G \tag{4.9}$$

$$z_{i,i_2,j,j_2} \leq x_{i_2,j_2},\ \forall\, j \in F, j_2 \in F, i \in G, i_2 \in G \tag{4.10}$$

$$x_{i,j} + x_{i_2,j_2} - 1 \leq z_{i,i_2,j,j_2},\ \forall\, j \in F, j_2 \in F, i \in G, i_2 \in G \tag{4.11}$$

$$b_j = a_j + \sum_{i=1}^{NG}(rtg_i + ut_i) \cdot x_{i,j},\ \forall\, j \in F \tag{4.12}$$

$$c_j = d_j - \sum_{i=1}^{NG}(rtg_i + ut_i) \cdot x_{i,j},\ \forall\, j \in F \tag{4.13}$$

$$c_j - b_{j_2} + y_{j,j_2} \cdot M \geq 0,\ \forall\, j \in F, j_2 \in F \tag{4.14}$$

$$c_j - b_{j_2} - (1 - y_{j,j_2}) \cdot M \leq 0,\ \forall\, j \in F, j_2 \in F \tag{4.15}$$

$$y_{j,j_2} + y_{j_2,j} \geq z_{i,i,j,j_2},\ \forall\, j \in F, j_2 \in F, i \in G\ \wedge\ j \neq j_2 \tag{4.16}$$

$$x_{i,j}\ is\ binary,\ \forall i \in G, j \in F \tag{4.17}$$

$$y_{j,j_2}\ is\ binary,\ \forall\, j \in F, j_2 \in F \tag{4.18}$$

$$z_{i,i_2,j,j_2} \; is \; binary, \; \forall \; j \in F, j_2 \in F, i \in G, i_2 \in G \tag{4.19}$$

$$cg_i \geq cf_j \cdot x_{i,j}, \; \forall \; j \in F, j_2 \in F \tag{4.20}$$

$$x_{i,j} = 0 \; \forall \; j \in F, i \in G \wedge \; cga_i \neq cfa_j, \tag{4.21}$$

$$c_{j_2} - b_j \geq tmint_{i,i_2} \cdot z_{i,i_2,j,j_2}, \; \forall \; j \in F, j_2 \in F, i \in G, i_2 \in G \; \wedge \; \sum_{p=1}^{NTP} npt_{j,j_2} \geq 0 \tag{4.22}$$

$$b_{j_2} - ut_i - tmino_i - c_j - ut_i \geq -M \cdot (2 - x_{i,j} - x_{i,j_2}), \; \forall \; j \in F, j_2 \in F, i \in G \; \wedge \; j \neq j_2 \; \wedge a_j \; \leq a_{j_2} \tag{4.23}$$

$$x_{i,j} \leq xp_{i,j}, \forall \; j \in F, i \in G \tag{4.24}$$

Starting with the objective function 4.1, it consists in 6 factors (O_1, O_2, O_3, O_4, O_5 and O_6). The first three factors are a maximisation of money spending by passenger and thus, maximisation of profits for the airport. O_1 corresponds to profits from transferring passengers, O_2 from arriving passengers and O_3 from departing passengers. The last three factors, since have a minus in the objective function, correspond to a minimisation of walking distance for transferring passengers (O_4), for arriving passengers (O_5) and departing passengers (O_6). These last three components were converted to money by using cde_p, cds_p and cdt_p in order to have the same units in the objective function and therefore, to compare the values attributed to each part.

As mentioned before, constraints 4.8 to 4.16 are similar to the ones introduced by Lim et al. (2005). Constraint 4.8 ensures that each flight is assigned only to a single gate. Constraint 4.9 to 4.11 jointly define variable z (the first ensures that there can only be a transfer if flight j has been assigned to gate i, the second one that there can only be a transfer if flight j_2 has been assigned to gate i_2, and the third one that z is equal to one only if flight j is assigned to gate i and flight j_2 to gate i_2).

Constraint 4.12 ensures that the moment the plane is ready to disembark passengers needs to take into consideration the time the plane touches land, the time from the runway to the gate and the time needed for the plane to inform the tower of their arrival to the gate and other bureaucratic and security reasons.

Constraint 4.13 ensures in the same way, that the time the plane is expected to leave the ground needs to take into account the time needed for the plane to communicate their readiness to leave the gate to the tower and other bureaucratic and security reasons, as well as the time needed for the plane to go from the gate to the runway.

Constraints 4.14 and 4.15 are a combination to make sure that it is not possible for two different flights to occupy the same gate at the same time. Constraint 4.16 impose that a transfer to occur, there must be a flight that departs later than the other flight lands. Constraint 4.17, 4.18 and 4.19 define the decision variables $x_{i,j}$, y_{j,j_2} and z_{i,i_2,j,j_2} as binary variables.

Constraint 4.20 ensures that a flight can only be assigned to a gate capable of receiving a flight of such conditions (for example, on one hand, an Airbus A300 can not be assigned to a gate only indicated for smaller airplanes due to structural or operational restrictions. But, on the other hand, a smaller airplane can be assigned to a gate with a higher capability of receiving a bigger airplane).

Constraint 4.21 ensures that an arriving/departing flight from/to a Schengen origin/destination is assigned to a corresponding gate that has the infrastructure needed for this case, such as passport control. Moreover, a not-Schengen flight cannot be assigned to a Schengen gate.

Constraint 4.22 ensures that for a transfer to occur, there needs to be a minimum time between flights occupying in different gates. The amount of time needed for a passenger to walk from one gate to another, as well as the time for a passenger to leave and enter the plane needs to be taken into account.

Constraint 4.23 ensures that each gate can only take one flight at a time. To do so, all the expected amount of time needed for both airplanes to use the same gate consequently are introduced as described on constraints 4.12 and 4.13, as well as the minimum time the gate needs to be empty due to operational reasons.

Constraint 4.24 allows the user to enter the flights already staying on the ground before the gate assignment, i.e. it simulates the gates that are already occupied and thus, it disallows the model to use the same gate for another flight. To introduce this in the model, each value of the matrix $xp_{i,j}$ is equal to 1 when i and j are the gate and flight already occupied previous to the desired time horizon to be optimised, and 0 otherwise.

Chapter 5

Model implementation and validation

In chapter 5, a small-sized example is introduced to better clarify and give a better understanding of the concepts related to the chapter before, i.e., the optimisation process, the model implementation and its validation. In the first section, the optimisation software (FICO Xpress) is described and explained. Then, the parameters for the ”toy problem” are introduced and finally, the results are analysed and validated.

5.1 Optimisation process

Optimisation as the word itself, is specially focused on having a problem and solving it in the best way possible. It is a powerful tool that can achieve the best results with an objective defined, and respecting all the constraints introduced. Stewart (2015) defines optimisation as ”find the maximum (or minimum) value of some quantity Q under a certain set of given conditions”. The concept of optimisation can be associated with everything and every process, either from individual either company processes, including management of any kind of resources, such as people, infrastructures, energy, as well as minimising costs, maximising resources or revenues, improving performances.

The mathematical model presented in chapter 4 is one formulation of the complex problem of a gate assignment problem. In this particular case, the main airport objective is to increase profits to the airport, by doing an optimal management of gates, airplanes, people and the way they can all interact.

In every optimisation problem, a common multi-step approach is used to achieve the intended result (also resumed in figure 5.1):

- Identify the main goal of the optimisation, evaluate all the mid-processes that lead to the final goal, and analyse what can be changed and what cannot;
- Contact people to extract as much information as possible, as well as identifying already existing problems;
- Model the data in mathematical terms;
- Implement the model to check for possible mistakes, discover possible innovations;
- Check if there is an acceptable validation of the model, by satisfying all the goals and needs;
- Apply the mathematical model to optimise a real-business situation.

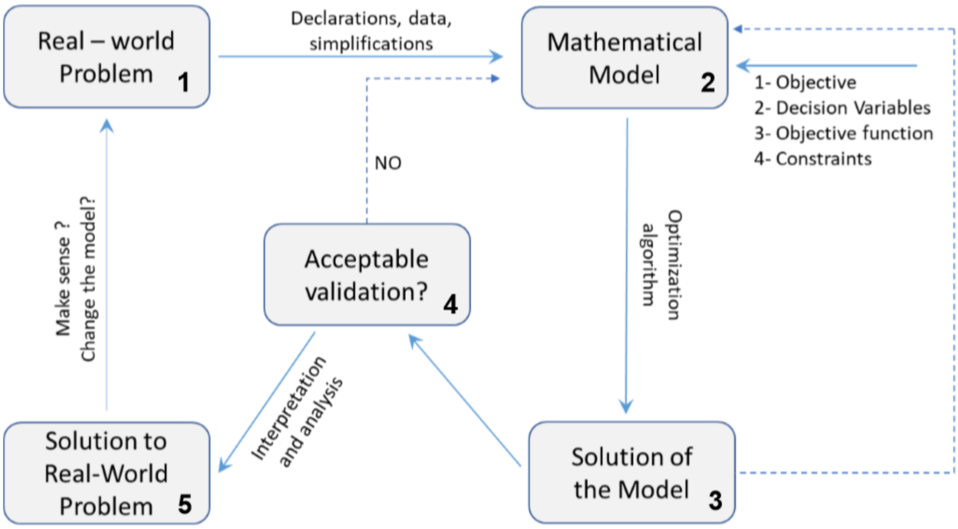

Figure 5.1: Optimisation problem approach (Source: Martins (2018))

5.2 Model implementation

An optimisation solver is needed for a problem of a dimension like a gate assignment, due to all the different variables involved, and the need to properly achieve an optimised time-table for airplanes to move inside an airport.

For this purpose, there are numerous softwares with optimisation solvers that can be found in the market, for example, LINDO, Microsoft Excel, IBM CPLEX, MATLAB, Gurobi or FICO Xpress.

For this present research, FICO Xpress was the chosen one. FICO Xpress is an optimisation solver from FICO (IBM), released in 1983, is used in both academic and industry purposes, and is currently available for the following models: ”large-scale, linear and mixed integer problems, as well as non-linear problems.” (source: FICO® Xpress website).

Moreover, “Solving large complex optimisation problems can be the difference between success and failure in today’s marketplace. FICO® Xpress Optimisation allows businesses to solve their toughest problems, faster. FICO’s deep portfolio of optimisation options enables users to easily build, deploy and use optimisation solutions that meet their needs.” (source: FICO® Xpress website).

A Mixed Integer Linear Programming (MILP) is the model chosen for this research since the model has a linear objective function, subject to linear equations and inequalities, and the decision variables are integers. Furthermore, there are continuous decision variables which are totally defined by binary variables, through equality conditions. The consequence of such a choice is the usage of more memory of the computer and more computing time, leading to a problem of higher complexity.

After choosing the appropriate solver for the problem, the MILP model is ”translated” to the software own language, Mosel. Mosel is the language used in FICO Xpress used as a modelling and solving language for the optimisation problem. In this case, for a MILP model optimisation, FICO Xpress uses a module called ”mmxprs” to solve the problem.

The transcription to the software language is divided into five different parts: i)Declarations, where all the constants, decision variables, parameters, sets are defined; ii) Input Data, where the necessary input information for the problem is inserted. In this case: the actual arrival time of flights "a_j"; the actual departure time of flights "d_j"; the number of passengers doing a transfer from one flight to another flight "npt_{p,j,j_2}"; the number of passengers arriving at the airport "$nps_{p,i}$"; the number of passengers entering the airport "$npe_{p,i}$"; the walking distance for transferring passengers from each gate to another gate " wdt_{i,i_2}"; the walking distance of passengers arriving at the airport from one gate to the baggage claim area "wds_i"; the walking distance of departing passengers, from the main retail area to each gate "wde_i"; the potential revenue from passengers doing a transfer per gate "$rt_{p,i}$"; the potential revenue from arriving passengers per each gate "$rs_{p,i}$"; the potential revenue from departing passengers per each gate "$re_{p,i}$"; cost per distance (euros per meter) for transferring, arriving and departing passengers "cdt_p", "cds_p" and "cde_p"; classification of each gate per capability of receiving flights of determined sizes "cg_i"; classification of flights per size of the plane "cf_j"; classification of gates and flights if Schegen or non-Schengen "cga_i" and "cfa_j"; time from runway to each gate "rtg_i"; time that a plane takes from the moment it arrives at the gate to the moment that passengers start to enter the terminal, including bus connection if necessary and the time required to be allowed to disembark passengers by the airport "ut_i" (the same time is considered for the time required to load all passengers and cargo and the plane is allowed to depart by the airport); minimum time to allow a passenger transfer to occur between two flights "$tmint_{i,i_2}$"; the time each gate must stay free between two consecutive flights "$tmino_i$"; gate allocation from flights that are already on the ground occupying certain gates before the desired planning horizon for gate assignment "$xp_{i,j}$"; iii) Objective Function, to be maximised by the model; iv) Constraints; and v) Output data, which allows to analyse the results provided by FICO Xpress for the case-study.

5.3 Model validation

To properly validate the model, a "toy size problem" should be illustrated. It is an example of a real problem, but on a smaller scale, able to easily demonstrate the model. These toy size problems aim to be really simple, so that they can test and validate a specific characteristic of the model, as well as test whether or not the implementation is correct. The representation of this example is presented in figure 5.2. G1 to G5 represent the 5 gates available, which are distanced 250 meters between each other, and the main retail area is assumed to be next to G1 (gate 1). Moreover, the exit point represents the point where the plane leaves the taxi area and goes to the runway (or vice versa) also drawn in the figure. In this example, it is not considered any flights on the ground previous to the gate assignment, i.e. all gates are free to use and thus $xp_{i,j}$ = 1.

In table 5.1, the constants used in the mathematical model are introduced. There are 5 gates available at the airport (NG) and 5 flights (NF). Moreover, there are 2 different sizes of gates (NTG), where each one can receive airplanes until a certain size and 9 categories of passengers (NTP) which were the result of the Discrete Choice Model (DCM), as it will be discussed in chapter 6. This initial toy-size problem, aims to demonstrate the operationality of the model. Thus, it will be verified that the model respects all the constraints in terms of allocation of gate assignment, already using the information provided by Discrete Choice Modelling.

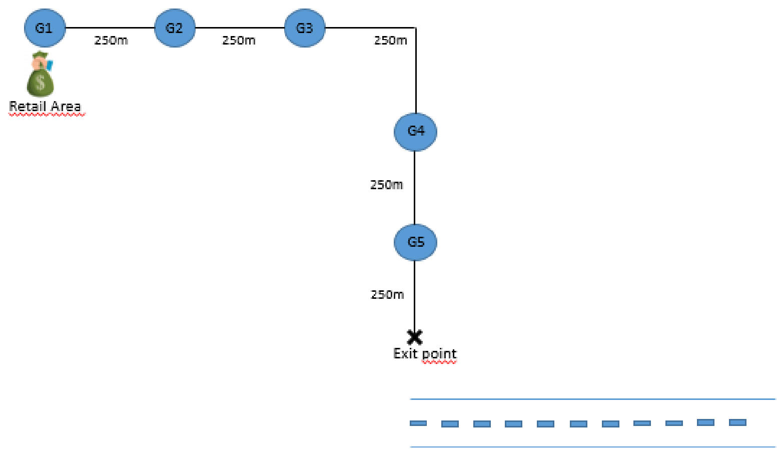

Figure 5.2: Simple representation of the illustrative example

Table 5.1: Constants used in the mathematical model for the illustrative example

Constant	Description	Units	Value
NG	Number of Gates	—	5
NF	Number of Flights	—	5
NTP	Number of categories of passengers	—	9
NTG	Number of type of gates	—	2

5.3.1 Parameters for the illustrative example

In table 5.2, information regarding flights is provided, such as the arrival (a_j) and departure time (d_j) of each flight, which were chosen to easily demonstrate to the reader the operation of the airport in the time-horizon used. More, classification of each flight (cfa_j) to divide between a Schengen and a non-Schengen flight, where 1 means Schengen and 2 non-Schengen. As can be seen, flight 2 is the only one which is a non-Schengen flight, meaning it will be allocated to a non-Schengen gate afterwards. In addition, classification of flights in terms of the size (cf_j) of the airplane is also demonstrated, where 1 is a normal size airplane and 2 a bigger airplane. Note that only flight 4 is a big size airplane and consequently will be allocated to a gate with the capability to receive an airplane as this.

Table 5.2: Arrival (a_j) and departure time (d_j), classification of flight in terms of Schengen or non-Schengen (cfa_j) and classification of flight in terms of size (cf_j)

Parameter	**Flight 1**	**Flight 2**	**Flight 3**	**Flight 4**	**Flight 5**
$a_j(min)$	5	15	15	20	25
$d_j(min)$	120	135	135	140	145
cfa_j	1	2	1	1	1
cf_j	1	1	1	2	1

In table 5.3, information regarding gates is provided, such as: the walking distance that arriving (wds_i) and departing (wde_i) passengers need to walk inside the airport from the gate to the center of the retail area, plus the distance from the retail area to the baggage claim area just for arriving passengers. Then, classification of each gate in terms of Schengen or non-Schengen (cga_i). Note that it can be concluded that since there is only one non-Schengen flight (Flight 2) and one non-Schengen gate (Gate 5), flight 2 must be assigned to gate 5 in the mathematical model. Furthermore, the minimum time a

Table 5.3: Walking distance of arriving and departing passengers "wds_i" and "wde_i", classification of gate if Schengen or non-Schengen "cga_i" and "cfa_j", classification of gate in terms of capability to receive certain sizes of airplanes "cg", minimum time that each gate must remain free between two flights "$tmino_i$", time the plane takes from the runway to each gate "rtg_i" and time the pilot takes from arriving at the gate until passengers start to leave to the terminal "ut_i" (the same is considered regarding the time passengers start to embark until leaving the plane leaves the gate

Parameter	Gate 1	Gate 2	Gate 3	Gate 4	Gate 5
$wds_i(m)$	180	430	680	930	1180
$wde_i(m)$	50	300	550	800	1050
cga_i	1	1	1	1	2
cg_i	1	1	1	2	1
$tmino_i(min)$	5	5	5	5	5
$rtg_i(min)$	2	1.6	1.2	0.8	0.4
$ut_i(min)$	5	5	5	5	5

gate needs to stay free between two flights ($tmino_i$) was set to 5, since it was considered an appropriate value for this constant. And finally, the time need for the airplane to go from the runway to the gate or vice versa (rtg_i), was calculated considering a taxi velocity of 37km/h, a common medium velocity in airplanes doing taxi.

In table 5.4, the walking distance between each gate is provided to show the distance travelled by transferring passengers (wdt_{i,i_2}), between the two considered gates.

Table 5.4: Walking distance of transferring passengers (wdt_{i,i_2})

$wdt_{i,i_2}(m)$	Gate 1	Gate 2	Gate 3	Gate 4	Gate 5
Gate 1	0	250	500	750	1000
Gate 2	250	0	250	500	750
Gate 3	500	250	0	250	500
Gate 4	750	500	250	0	250
Gate 5	1000	750	500	250	0

Table 5.5: Revenue per passenger per category of departing ($re_{p,i}$), arriving ($rs_{p,i}$) and transferring passengers ($rs_{p,i}$) for the illustrative example

Revenue per passenger	Passenger category	Gate 1	Gate 2	Gate 3	Gate 4	Gate 5
departure $re_{p,i}$(€)	**p1**	0	0	0	0	0
	p2	4	3.5	3	2.5	2
	p3	19	16.625	14.25	11.875	9.5
	p4	52	45.5	39	32.5	26
arrival $rs_{p,i}$(€)	**p5**	0	0	0	0	0
	p6	28	24.5	21	17.5	14
transfer $rt_{p,i}$(€)	**p7**	0	0	0	0	0
	p8	16	14	12	10	8
	p9	48	42	36	30	24

In table 5.5, the revenues from departing ($re_{p,i}$), arriving ($rs_{p,i}$) and transferring ($rt_{p,i}$) passengers dependent of the gate used are provided (the reasoning for the values of p1 to p9 will be further explained in section 6.1.2). It can be noted that Gate 1 was chosen as the gate closest to the main retail area of this airport, leading to higher revenues. Moreover, in order to simulate the longer distance between the gate and the main retail area, the less the passenger will spend in the airport, Gate 5 (the farthest from the retail area) has a revenue per type of passenger 50% less than in Gate 1. In between these gates, the revenue decreases proportionally to the distance to retail area.

Table 5.6: Number of departing ($npe_{p,i}$) and arriving passengers ($nps_{p,i}$)

Number of passengers		Flight1	Flight2	Flight3	Flight4	Flight5
Departing passengers $npe_{p,i}$	**p1**	54	54	54	54	54
	p2	27	27	27	27	27
	p3	52	52	52	52	52
	p4	29	29	29	29	29
Arriving passengers $nps_{p,i}$	**p5**	142	142	142	142	142
	p6	20	20	20	20	20

In table 5.6, the number of departing ($npe_{p,i}$) and arriving ($nps_{p,i}$) passengers is provided. The values used were obtained by considering all flights with a capacity of 180 seats, with a medium occupation of 90%. Then, the probability of each category of passenger was multiplied, leading to the values found in the table.

In appendix B.1 the number of passengers per category of transferring passengers is provided. Using the same approach as the previous table, the number of transferring passengers per plane was assumed to be around 10% of the medium occupation.

And finally, the cost per walking distance (euros per meter) travelled per category of passenger. cde_p(€/m), cds_p(€/m) and cdt_p(€/m) were assumed to be constant in every category of passengers and a value of 0.012 €/m was fixed to represent all these variables. This value will be further explained in section 6.1.4.

5.3.2 Results of the illustrative example

In this section the results of the illustrative example will be analysed and checked if there is a correct operation of the example airport, bearing in mind the parameters and constraints used, as explained in chapter 5.3.1, so that this mathematical model can be considered validated.

The model converged to an optimal solution of the objective function 4.1, with a total maximum revenue of 1829.4€, a result of the addition of revenues by all passengers minus the cost of walking distance travelled by those same passengers (converted to money by using cde_p, cds_p and cdt_p in order to have the same units and therefore, to compare the values attributed to each part).

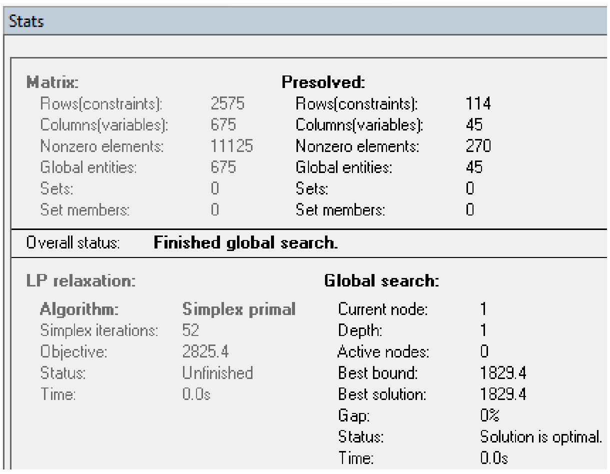

Figure 5.3: Statistics results of the illustrative example

Moreover, FICO Xpress is able to give additional information to the user such as the best bound, the gap and computational time. All these information can be seen at figure 5.3. The optimality Gap of 0% is a proof that the best solution was obtained by the model, with a best bound and best solution equal to 1829.4€. This optimality gap is defined as the difference between the best solution and the best bound, as expressed in equation 5.1, and in this case, since it is equal to zero, it is possible to confirm that the best solution for the example was achieved. Additionally, it is also important to point out that the computational time varies with the number of columns (variables), so it is expected that the presolved model with 45 variables will have a much lower computational time (less than 0.1s), demonstrated in figure 5.4, comparing to the one from the case study of Lisbon Airport.

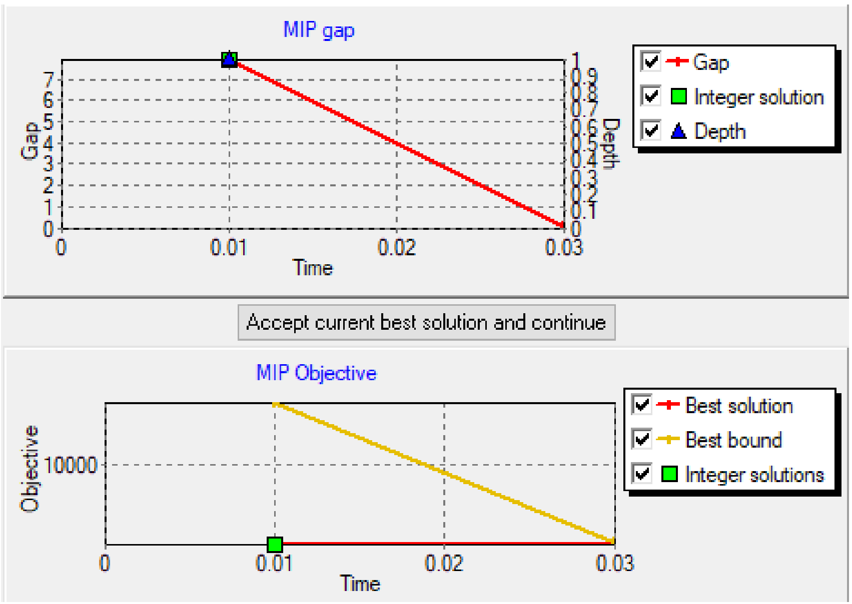

Figure 5.4: MIP search for the illustrative example

FICO Xpress obtains this optimal solution by a Branch-and-Bound technique that identifies many solutions (by a Mixed Integer Programming (MIP) search), which are differentiated in lower and upper bound comparing to relaxed solutions, so that in the end it is possible to find the optimal solution. In this model the best bound concept is an upper bound since the objective function is a maximisation of the objective function.

$$Optimality\ Gap = \frac{best\ solution - best\ bound}{best\ solution} \cdot 100 \tag{5.1}$$

This optimal solution and its related decision variables are crucial to give information as: which flight is assigned to each gate ($x_{i,j}$), the time each flight arrives at the gate (b_j), the time each flight leaves the gate (c_j), represented in figure 5.5. Moreover, which flights are not allowed to perform a transfer (y_{j,j_2}) which is not represented since all components of y_{j,j_2} are equal to zero, as it was intended in this illustrative example due to the large gap between the arrival of the last scheduled flight, and the departure of the first scheduled flight) and variable z_{i,i_2,j,j_2} which was also not represented since it is just important as an internal variable to the model.

By looking at figure 5.5 (left), the reader can understand that flight 1 was assigned to gate 2, flight 2

{i} G	{i} F	[ ] x
1	5	1
2	1	1
3	3	1
4	4	1
5	2	1

{i} F	[ ] b
1	11.6
2	20.4
3	21.2
4	25.8
5	32

{i} F	[ ] c
1	113.4
2	129.6
3	128.8
4	134.2
5	138

Figure 5.5: Table view from FICO Xpress of the decision variable $x_{i,j}$ (left), variable b_j (center) and variable $c_j(min)$ (right)

Table 5.7: Demonstration of the optimal solution and its components for the illustrative example

Objective function component	**Value (€)**
O_1 **- revenues from transferring passengers**	4080.0
O_2 **- revenues from arriving passengers**	2100.0
O_3 **- revenues from departing passengers**	9765.0
O_4 **- cost of walking from transferring passengers**	-2160.0
O_5 **- cost of walking from arriving passengers**	-6609.6
O_6 **- cost of walking from departing passengers**	-5346.0
Total	1829.4

to gate 5, flight 3 to gate 3, flight 4 to gate 4 and flight 5 to gate 1. As explained in section 5.3.1, flight 2 is a non-Schengen flight and thus, must be assigned to a non-Schengen, which is verified since gate 5 is also a non-Schengen gate. Moreover, flight 4 is a bigger size airplane and is correctly assigned to gate 4, which is also the only gate capable of receiving bigger airplanes.

Regarding time each flight arrived at the respective gate, figure 5.5 (center) shows that each value of b_j is the sum of the arrival time (a_j) plus time from runway to gate (rtg_i) and time for the pilot to successfully speak to the airport manager in order to let the passengers leave the airplane (ut_i). In terms of time each flight left the respective gate, figure 5.5 (right) shows that each value of c_j is the difference between the departure time (d_j) and time for the pilot to speak to the airport manager in order to successfully "check-out" the airplane and have the permission to leave the gate (ut_i) plus the time required for the airplane to go from the gate to runway (rtg_i). Finally, each component value of the objective function is presented in table 5.7.

In conclusion, the created model was verified with the illustrative example, then it is expected that the implementation of the model is correct, and thus, next chapter will be on applying the mathematical model to the case study of this dissertation.

Chapter 6

Application to a case study

In this chapter, the model is applied to a case study of Lisbon Portela Airport. Initially, a description of the airport and its organisation is provided, then the results from passenger categories are exhibited and the results of the model demonstrated and explained.

6.1 Lisbon Airport

Lisbon Airport, also known as Humberto Delgado Airport or Portela Airport is the biggest and most important Portuguese airport. Inaugurated on the 15th of October 1942 and located in Olivais, 7km away from Lisbon city centre, the airport has 2 runaways with 3805m and 2400m long, both with 45m in width. It has 2 civil terminals (T1 and T2) and also one military terminal also known as Figo Maduro Airport. The airport is the main hub of the Portuguese front-carrier TAP Air Portugal and is run by ANA Aeroportos de Portugal, S.A, which in combination with Portway - Handling de Portugal, S.A, comprise the ANA Group.

In 2013, ANA Aeroportos de Portugal, S.A was bought by VINCI Airports. Due to a 50-year Concession Contract signed with the Portuguese State, ANA is responsible until 2062 to provide public airport facilities and services in support of civil aviation at the Lisbon Airport. According to ANA Aeroportos de Portugal (2018) the growth in European air traffic and, in this case, at Lisbon Airport is driven by the continuing development of European global economies and the development of other drivers such as tourism. Also, the growth levels achieved in Portugal were due to the low-cost carriers consolidating their market presence and development of touristic offer in Portugal.

According to VINCI Airports (2019), it is the most crowded airport in Portugal. The numbers are clear and show the huge development of air traffic throughout the years. In 2018, there were 214,187 aircraft movements (plus 4.6% than 2017) and 29.284 million passengers (plus 6.5% than in 2017), meaning the airport was responsible for more than 50% of the entire country airport passengers (around 56 million).

In terms of aviation business, this sector contributed in 2018 with 73.7% of total ANA Group turnover, meaning 611.5 million€ (ANA Aeroportos de Portugal (2018)). The ANA Group's is divided in 5 different revenue streams as represented in figure 6.2, with the most important related to traffic, which meant 74.5% of the group's aviation income in 2018.

Overall, the non-aviation income meant 26.3% of the total turnover for the ANA Group considering all airports, corresponding to 218.7 million€ (an increase of 9.9% compared to 2017). With the retail business being responsible for 56.4% of the non-aviation income (Figure 6.3). The increase in consumption at Lisbon Airport in 2018 was particularly relevant due to the increase of the number of passenger at all ANA airports related to the continuing development of economy and the economic

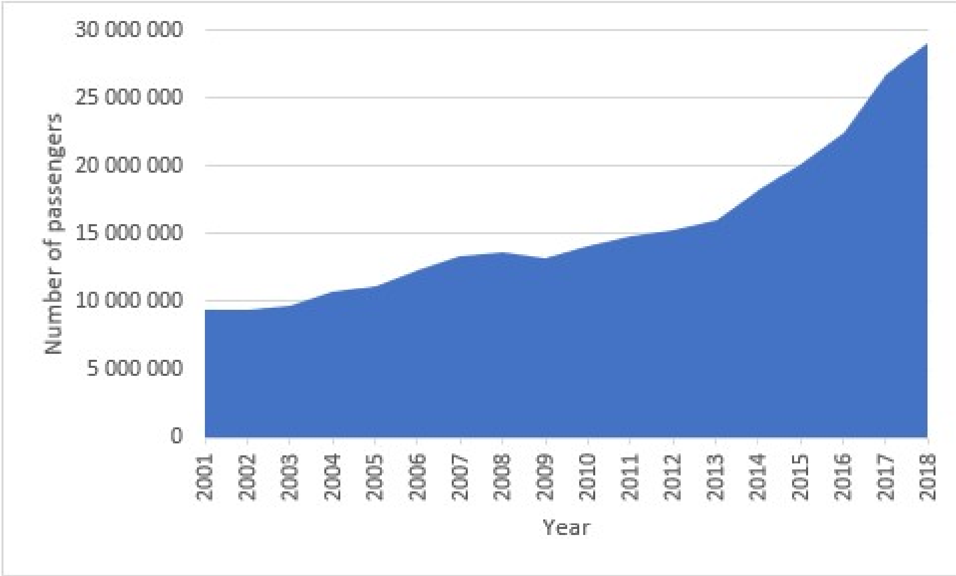

Figure 6.1: Evolution of the number of passengers at Lisbon Airport

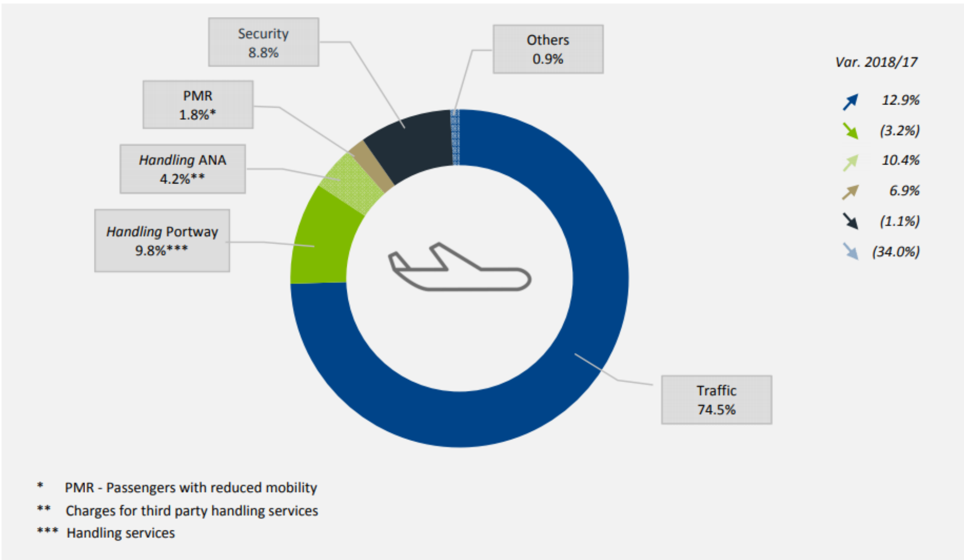

Figure 6.2: Distribution of the ANA Group's aviation business (Source: ANA Aeroportos de Portugal (2018))

recovery in two main traffic origin/destination markets: Brazil and Angola (ANA Aeroportos de Portugal (2018)). Moreover, the expansion and maximisation of occupancy rates in retail area at Terminal 2, also allowed for a reinforcement of the catering offer.

6.1.1 Survey statistics

The survey was developed using Google Forms and was spread using the Internet, where it was asked for people to remember their last Lisbon airport experience and answer according to it. The survey included answers of people from Instituto Superior Técnico (IST), their relatives, and was distributed by the author and his supervisors along all the scientific communities they belong. In total, the survey had around 650 full individual accepted answers. Between each type of passenger, there were 447 answers about a departure and 609 answers about an arrival at Terminal 1 of Lisbon airport. Regarding

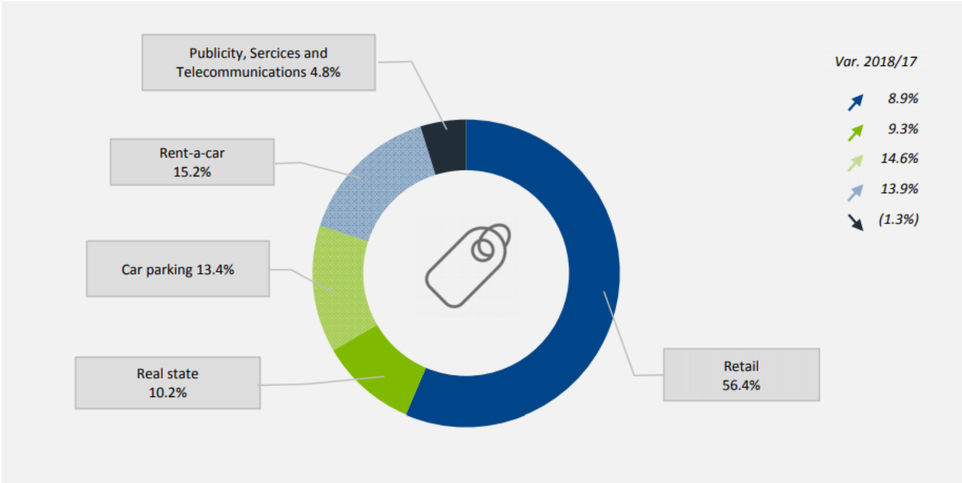

Figure 6.3: Distribution of the ANA Group's non-aviation business (ANA Aeroportos de Portugal (2018))

transferring passengers, 47 answers were completed about transferring at Terminal 1 of Lisbon Airport. Logically, it was expected that there would be a small number of answers about a transfer at Lisbon Airport and thus, since it was also intended to create a model for transfer passengers (knowing that this type of passenger is "obliged" to stay at the airport waiting for their next flight and consequently, have a higher chance of spending money inside the airport), the same questions were introduced regarding a transfer at any airport in the world, obtaining 476 full answers and for the case people had never made a transfer in their lives, three questions were made regarding, how much time would they wait inside the terminal, and what activities would they do during that time, obtaining 179 answers. Since a lot of answers from transferring passengers were performed about any airport in the world and the implementation model is related to the Lisbon Airport, it was decided to use only the answers from passengers that performed a transfer at European airports in order to have a modelcloser to the Lisbon airport case study, leading to a total of 349 full answers.

In this section, the survey statistics on departing, arriving and transferring passengers will be presented. As mentioned in chapter 3, the survey was a mix between question related to trip, personal and time information, activities performed and time and money spent on those activities. Besides, personal characteristics results from passengers in general will be presented.

Figure 6.4 shows that 36.6% of all passengers have between 30 and 50 years old and the statistics are almost divided in 50/50 in terms of >30 and <30 years old. More male passengers have answered this survey (52.8%) and as expected, due to being an online survey, there were much more Portuguese nationality answers (about 95.0%). Moreover, the number of answers from Lisbon residents is also expected since the survey was conducted at Instituto Superior Técnico (IST), located in Lisbon. Plus, as it can be seen, there is a high percentage of answers from people located in the center of Portugal (excluding Lisbon), since the author of this dissertation was born and raised in a city located in that area. The representation of passengers in this survey aimed to be as close as possible as the representation of passengers from the airport in order to be as close to reality as possible. However, this representation would be better if included more older people and from different nationalities. The time and effort needed

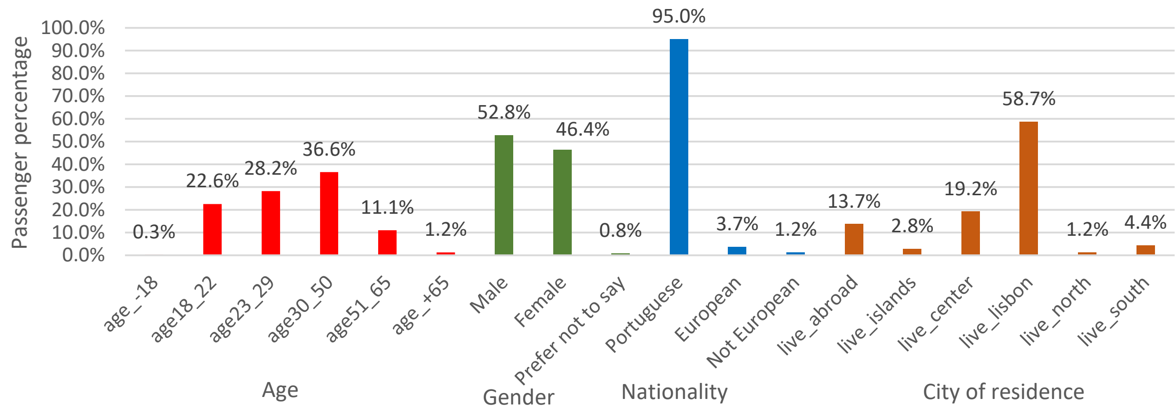

Figure 6.4: General personal characteristics from all passengers

to do this were not available at the time, but a total answers of 650 different individuals seem a consistent number of answers for this dissertation.

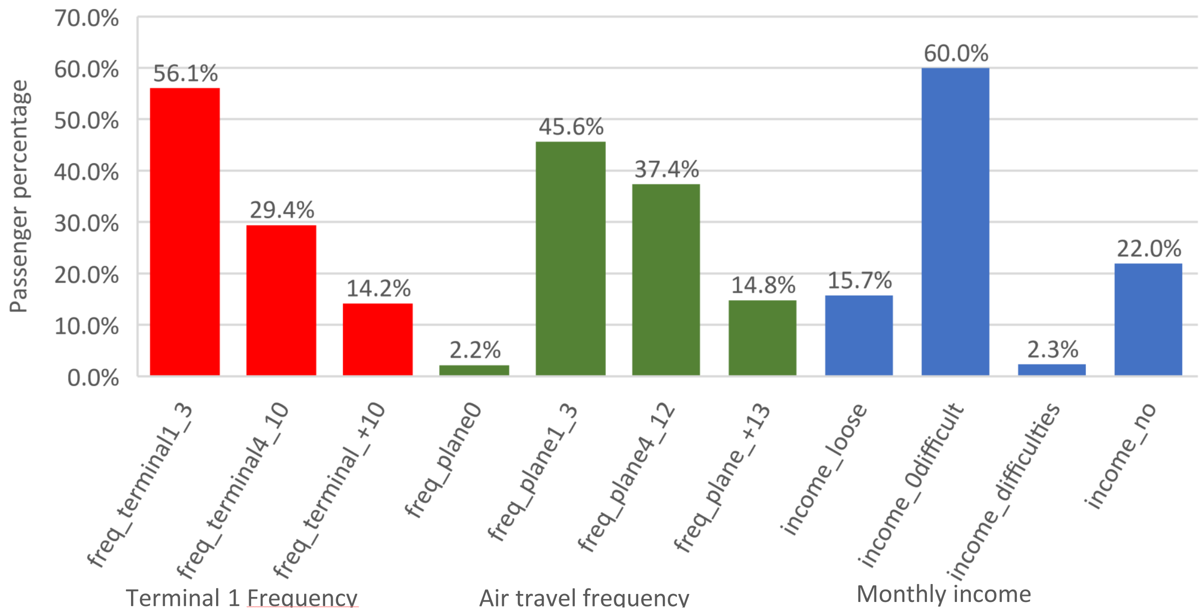

Figure 6.5: General personal characteristics from all passengers

Another graph presented in figure 6.5 shows that 56.1% of all passengers uses Terminal 1 between 1 and 3 times per year, 29.4% between 4 and 10 times per year, and 14.2% more than 10 times per year. In addition, 45.6% travel by plane between 1 and 3 times per year, 37.4% between 4 and 12 times per year, and 14.8% more than 13 times per year. Only 2.2% of respondents travel by plane 0 times per year, which means their survey was related to an experience that did not happen this last year.

In terms of monthly income, 60.0% answered to live without financial difficulties, 15.7% lives loosely and 22.0% have no monthly income, which are believed to be mainly students, since this survey had a lot of answers from youngsters.

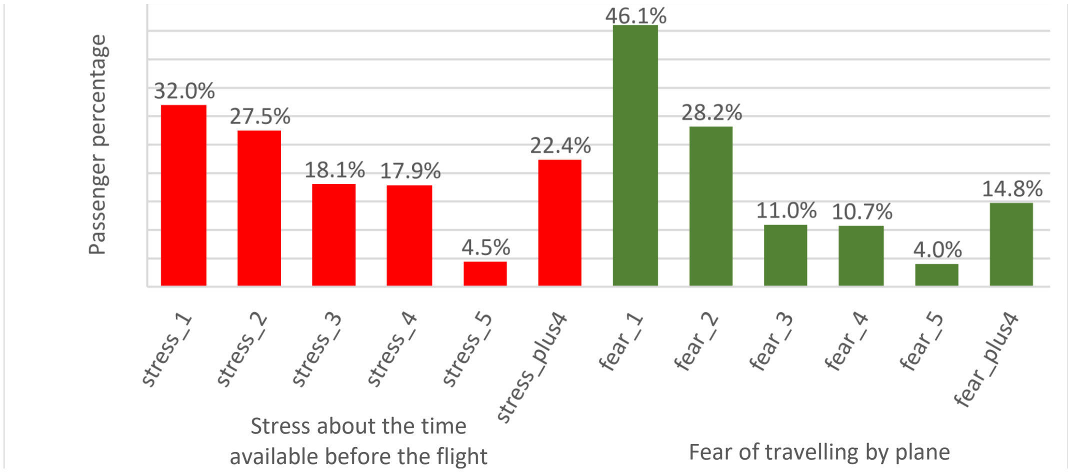

Figure 6.6: Personal characteristics from departing passengers

Departing passengers

On figure 6.6, around 32.0% answered to feel completely relaxed regarding the time before the flight (stress1), and 46.1% regarding travelling by plane, which shows that people are becoming more and more comfortable and used to travel by plane.

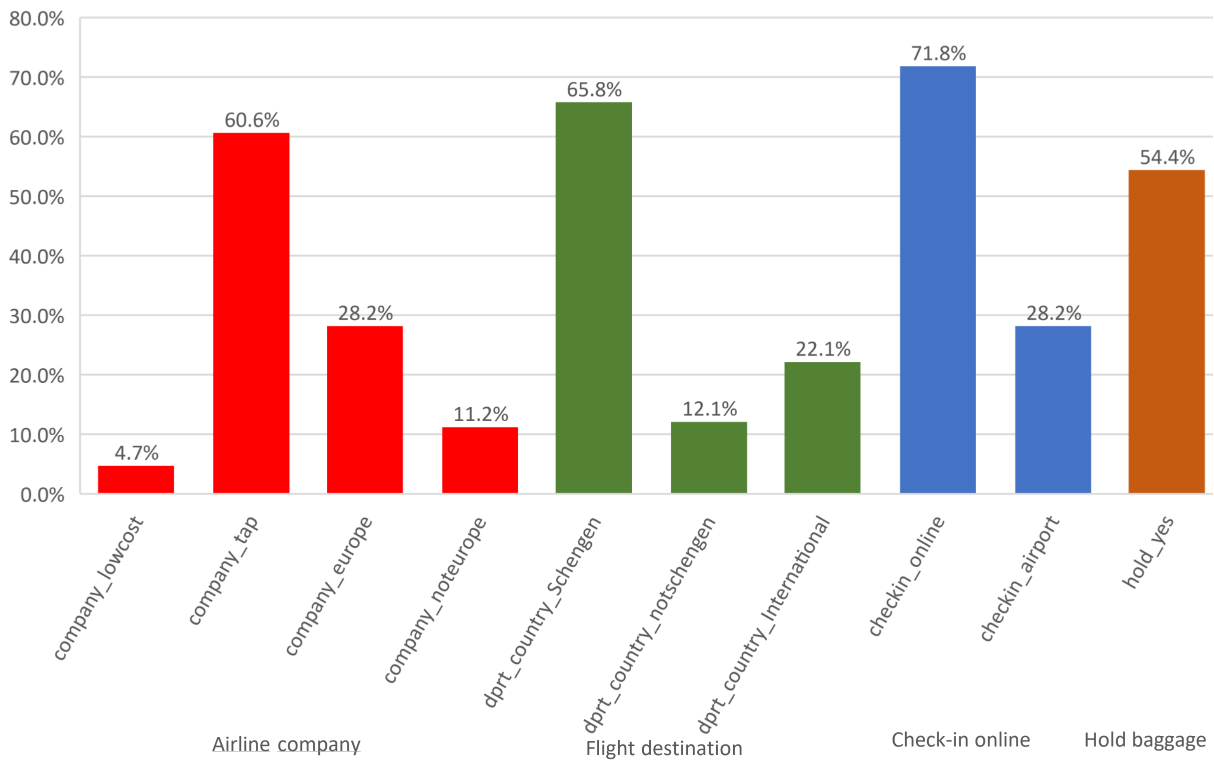

Figure 6.7: Air-trip characteristics from departing passengers

As the Lisbon Airport is the main hub of TAP Portugal, in figure 6.7, the results showed a huge percentage of flights from this airline company (60.6%) and since Terminal 2 is the terminal used for most low-cost airlines and the survey was conducted just for Terminal 1, just 4.6% were flights from low-cost airline companies. In terms of flight destination, it is normal that a huge percentage of destinations were to Schengen countries, representing 65.8% of all answers. Another aspect was the fact that nowadays more and more people check-in online, resulting in 72.0% from the survey. 56.0% of departing passengers had hold baggage and it is understood that these were the main responsibles for doing check-in at the airport. Moreover, the average number of hand baggage per passenger was by far 1 with 77.6% (Figure 6.8).

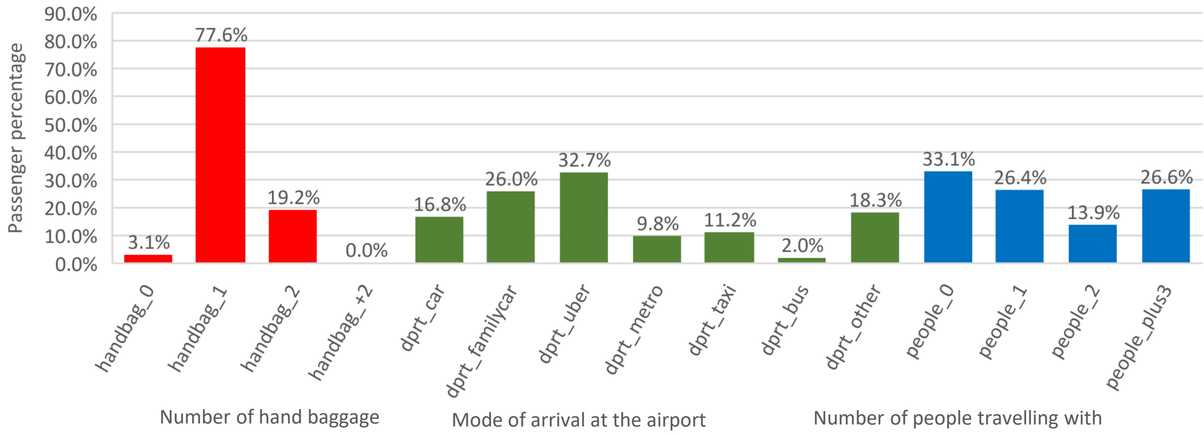

Figure 6.8: Additional Air-trip characteristics from departing passengers

Although the airport has a metro station, the ”uber or similar” option was the most chosen by passengers (32.7%).

In terms of number of people travelling with, the most usual number was zero with 33.0% and from the answers provided, just 9.6% travelled with children.

Besides, the main reason for travelling was for holidays (44.3%), and afterwards personal reasons and due to work were the more frequent answers with 23.27% and 19.69% respectively.

A common sense is that there are much more departing flights during the morning and the results confirm that 57.7% of the flights occurred before 12am. In terms of day of the week, 48.3% of answers consisted in flights happening between monday and thursday, 15.7% to friday and 16.8% during the weekend.

Figure 6.10 shows that passengers arrived earlier at the airport, with 37.6% arriving between 1h30 min and 2h before the flight departure. Not many passengers consumed any food/drinks or shopped before security at the airport (12.1% and 6.5%, respectively), with only 7.8% going to the business lounge. In total, the average money spending from departing passengers who spent something at the airport was around 30€.

In terms of orientation characteristics of departing passengers, presented in figure 6.11, it was found that people found easy to move around Terminal 1 (easy2move4 with 42.7%, on a scale of 1 to 5, where 1 means really difficult to move around, and 5 really easy to move around) which can be explained by the fact that most people were from portuguese nationality, and consequently more often frequent this airport.

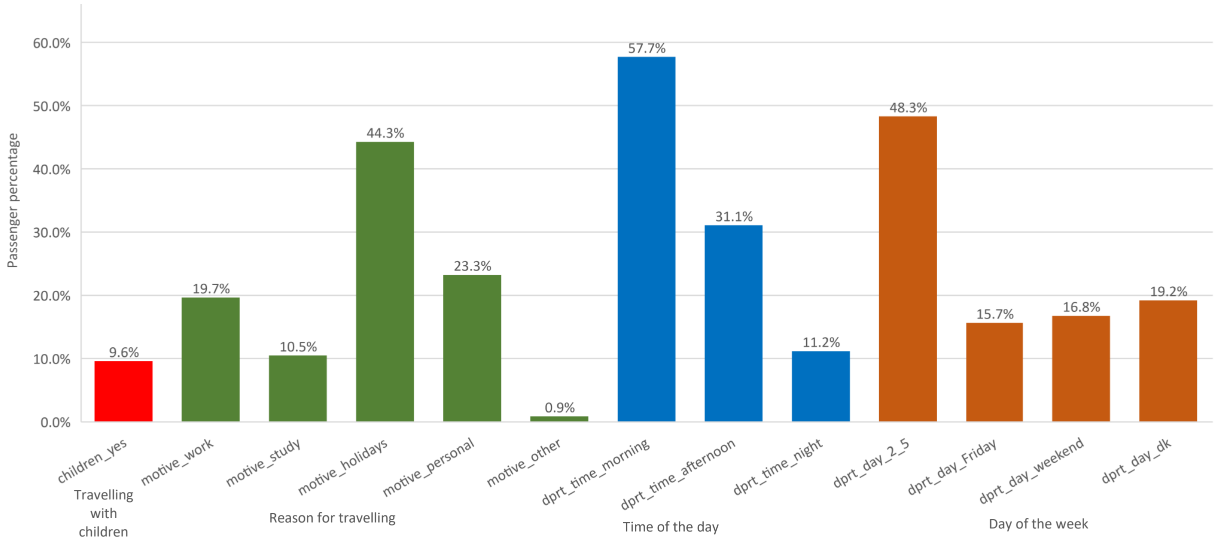

Figure 6.9: Air-trip and time related characteristics from departing passengers

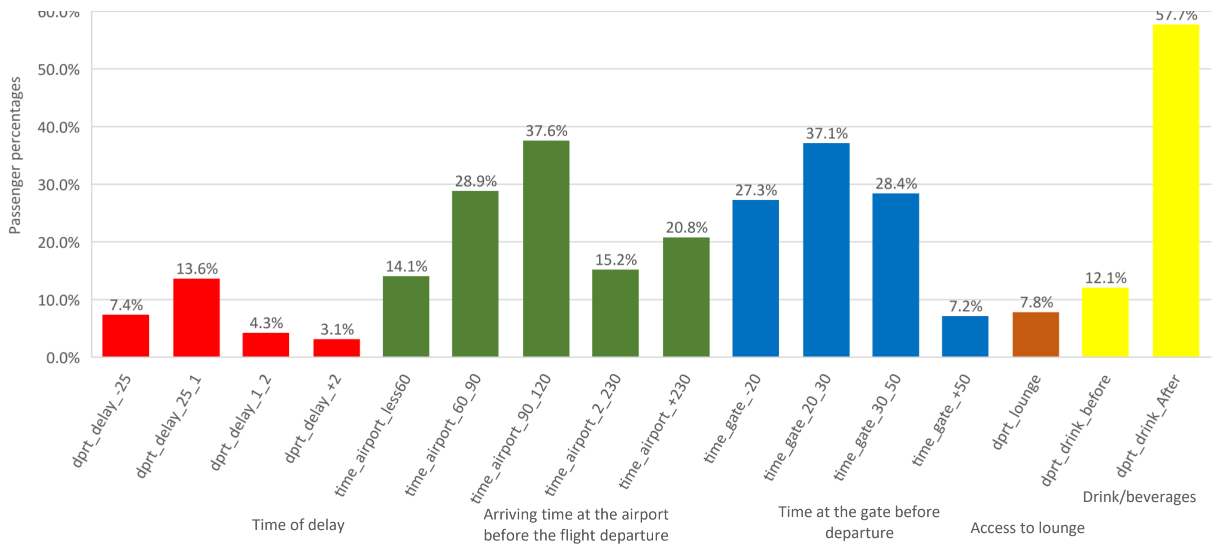

Figure 6.10: Time related characteristics from departing passengers

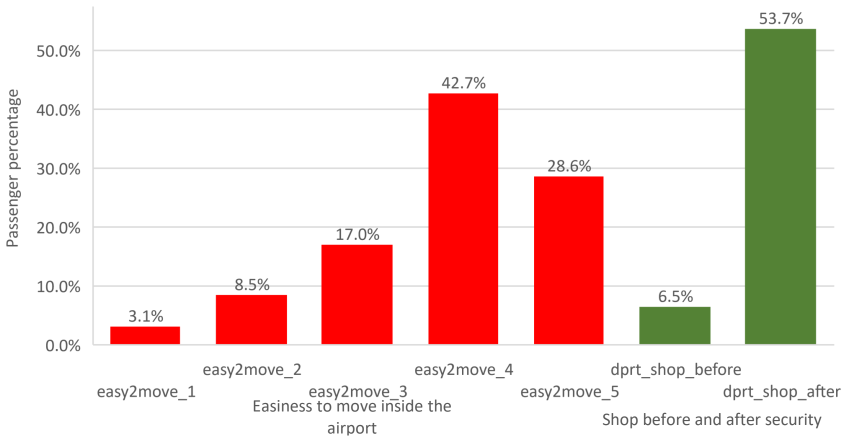

Figure 6.11: Activities and orientation at the airport from departing passengers

Arriving passengers

Figure 6.12 shows that the most frequent airline company is instinctively TAP Portugal (59.6%), as it was explained previously. Moreover, European airline companies hold 28.5% and non-european airline companies 11.9%.

Here, the most frequent mean of transport to leave the airport was a family/friend's car (36.4%), followed by uber or similar (23.0%) and own car (16.0%). In terms of flight origin, it was expectable that most of flight were from Schengen countries (69.0%).

Like in departing passengers, passengers usually travel alone (37.4%) or with just one person (26.9%) and only respondents travel with children (8.2%) which was expected since around 50.0% are youngsters, as it can be seen on figure 6.13

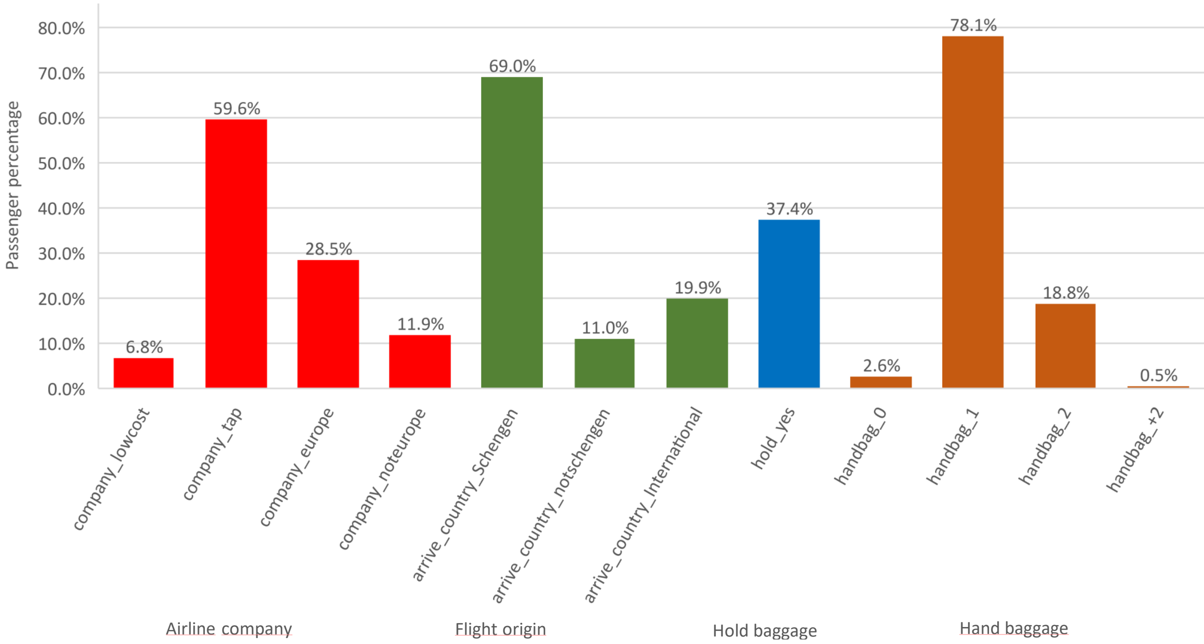

Figure 6.12: Air-trip characteristics from arriving passengers

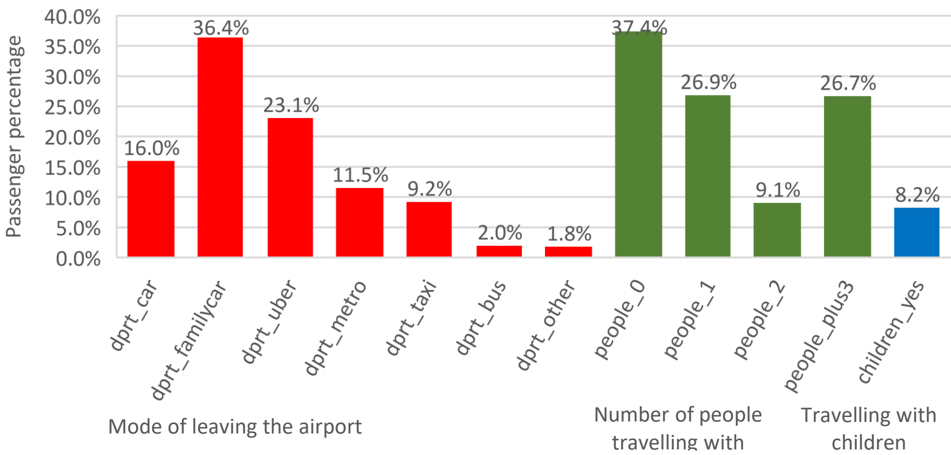

Figure 6.13: Additional Air-trip characteristics from arriving passengers

Logically, since most departing flights happen during the morning, figure 6.14 shows most of the arriving flights should arrive afterwards, which is confirmed by the survey statistics with 41.7% arriving in the afternoon and 35.3% arriving at night. In terms of time waited for passengers hold bags, the medium waiting time was 22 minutes, considering just the passengers with hold baggage (37.4%). In terms of reason for travelling, the same options as for departing passengers were the most chosen, holidays with

44.8% and personal with 22.6%.

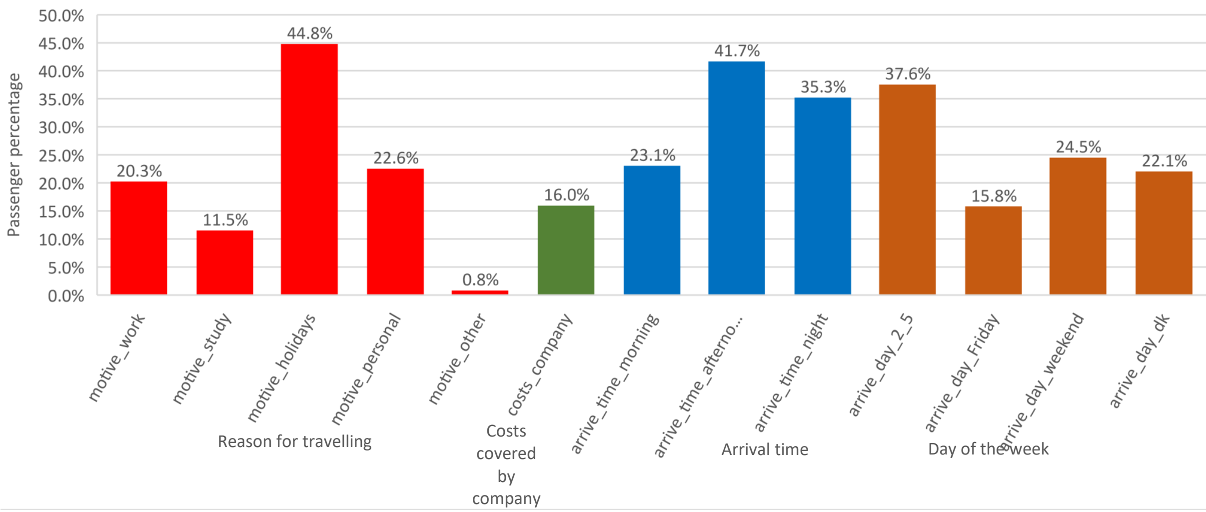

Figure 6.14: Air-trip and time related characteristics from arriving passengers

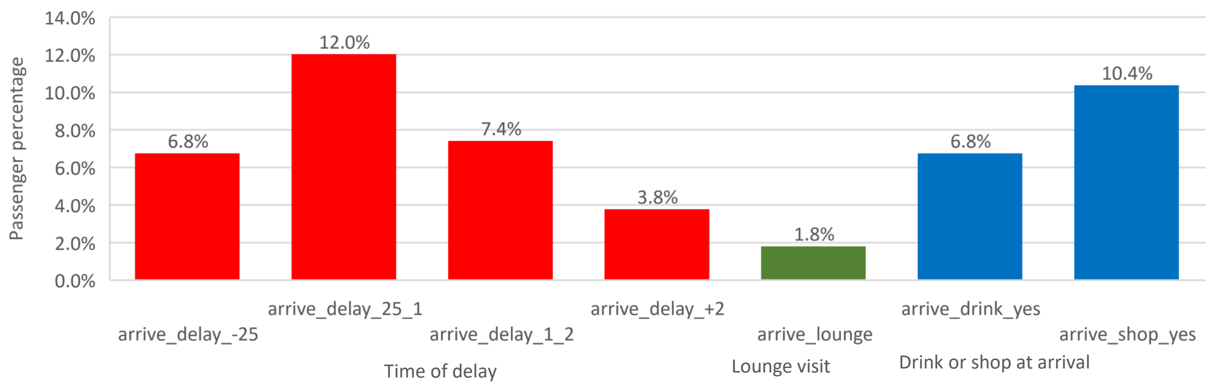

Figure 6.15: Time related characteristics from arriving passengers

In figure 6.15 it is reasonable to think that arriving passengers usually intend to leave the airport as soon as possible, to continue their journey, and it explains why only 6.8% had food/drinks at the airport and 10.4% did some shopping before leaving the airport, leading to an average of 28.5€ spent considering only the passengers that spent something at the airport and an average of 3.5€ considering all the answers. Moreover, only 1.8% of arriving passengers went to the business lounge.

As mentioned before, another proof of people being more and more used to travel, is the high percentage from easiness to move inside Terminal 1 (easy2moveplus4 with 72.2% on figure 6.16).

Transferring passengers

Lastly, the transferring passengers answers about an experience in Europe. Starting in figure 6.17, a lot of people still feel relaxed on doing a transfer regarding the time available (stress1 = 25.8%), but less relaxed compared to departing passengers, which is normal since passengers in this case need to

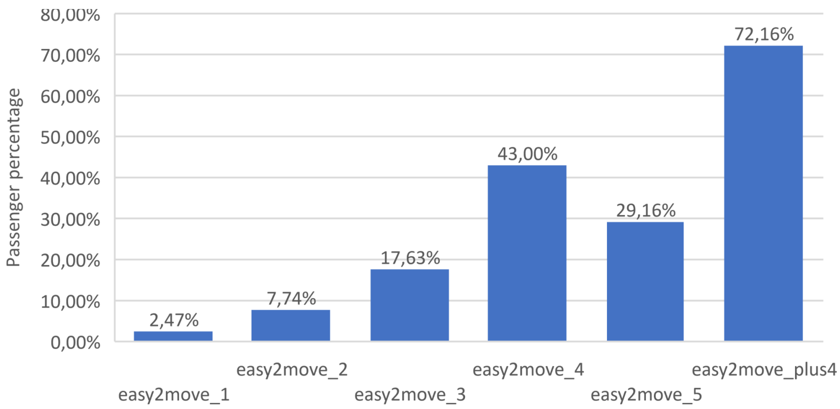

Figure 6.16: Orientation at Terminal 1 from arriving passengers

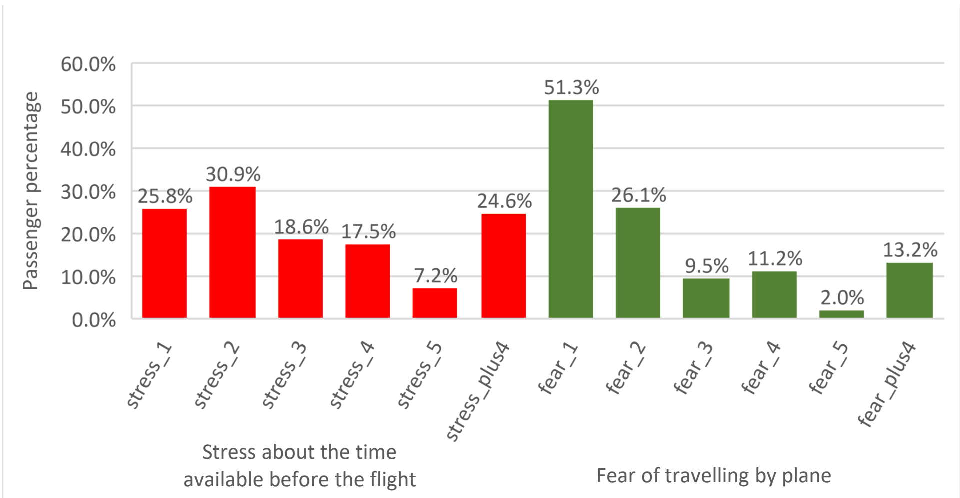

Figure 6.17: Personal characteristics from transferring passengers

travel by plane two times, and therefore, a higher possibility of losing one of the flights exists. In terms of fear of travelling by plane, 51.3% is really comfortable with their flight, which reinforces that people are becoming more used to travel by plane.

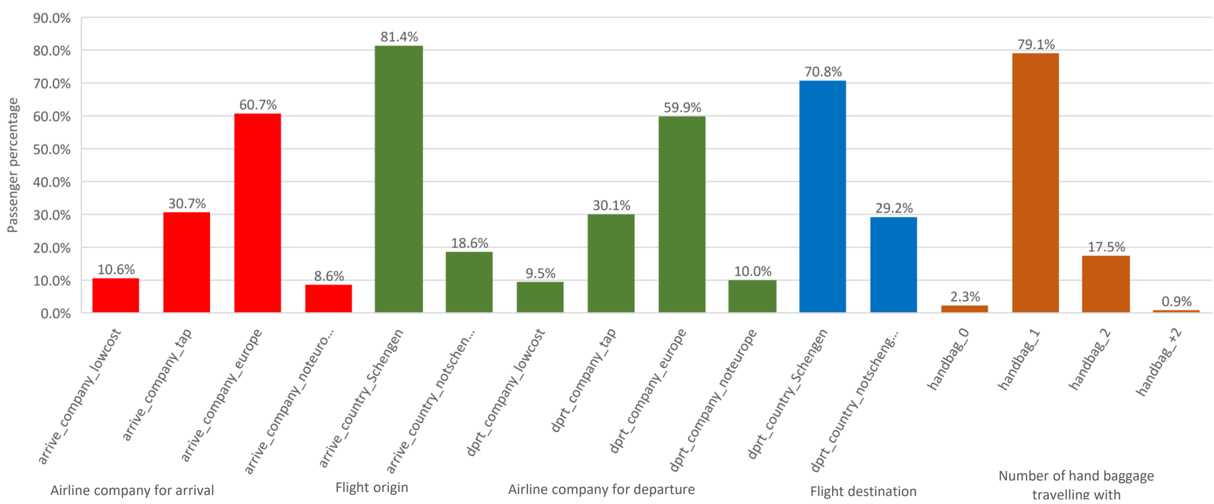

Figure 6.18: Air-trip characteristics from transferring passengers

On figure 6.18 and looking for the airlines used, it is also normal that there is a lower percentage of TAP Portugal (30.7% and 30.1%) and an increase of low-cost carriers (10.6% and 9.5%) on the arrival and departing flights. Since the answers only focused on European airports, it is normal that 81.4% and 70.8% from the flights were from and to Schengen countries, respectively. Here, the hold baggage was not questioned since it goes directly to the flight destination, but in terms of quantity of hand baggage, the most frequent answer was again 1 with 79.1%.

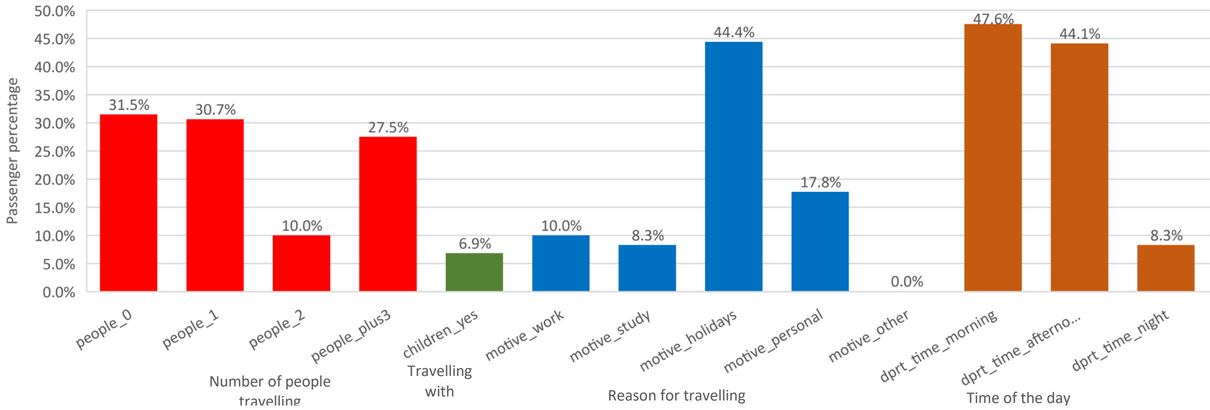

Figure 6.19: Air-trip and time related characteristics from transferring passengers

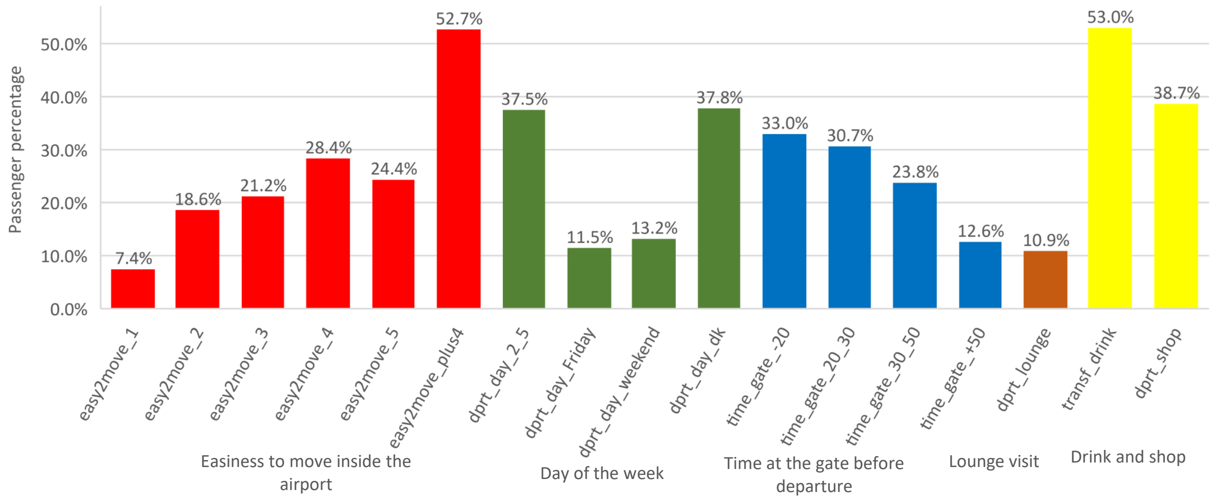

Figure 6.20: Time and orientation characteristics from transferring passengers

Furthermore, on figure 6.19 the number of people travelling followed the previous type of passengers with 31.5% and 30.7% answering to travel alone and with one person, respectively, with 6.9% travelling with children. Relatively to reason for travelling, 44.4% were on holidays and only 10.0% travelled due to work which is explained by the fact that companies usually try to book direct flights in order to reduce the travel time for their workers.

Also, it is expected for transfers to occur during the day since airline companies want to gather the highest amount of people to fulfill their flight, which can be seen on figure 6.19 with only 8.3% occurring during the night, and the rest occurring during the morning and the afternoon.

Since passengers are "obliged" to stay at the airport waiting at the airport, as explained during this dissertation, it is expected a high probability of shopping and eating at the Terminal. On figure 6.20 it is shown that 53.0% had drinks/beverages and 38.7% went shopping while waiting for their next flight, and 10.9% went to the business lounge. In total, restricting to just the transferring passengers that spent any money at the airport, the average of money spending was 32€.

In terms of orientation inside the airport, it is normal that people feel less oriented comparing to departing and arriving passengers from Lisbon airport since most of passengers were Portuguese people answering about foreigner airports (easy2moveplus4 = 52.7%).

6.1.2 Category analysis

After analysing all statistics, categories of passengers were created according to their total money spending inside the airport. Through a severe search for passenger categories in terms of money spending and to the best of the authors' knowledge, these type of categories have not been used in the past, meaning a correct passenger separation had to be chosen according to the results. Then, a sum of the total of money spent at the airport per each passenger was performed and bellow, in figure 6.21, a representation of categories of passengers inside each type of passenger will be demonstrated and explained.

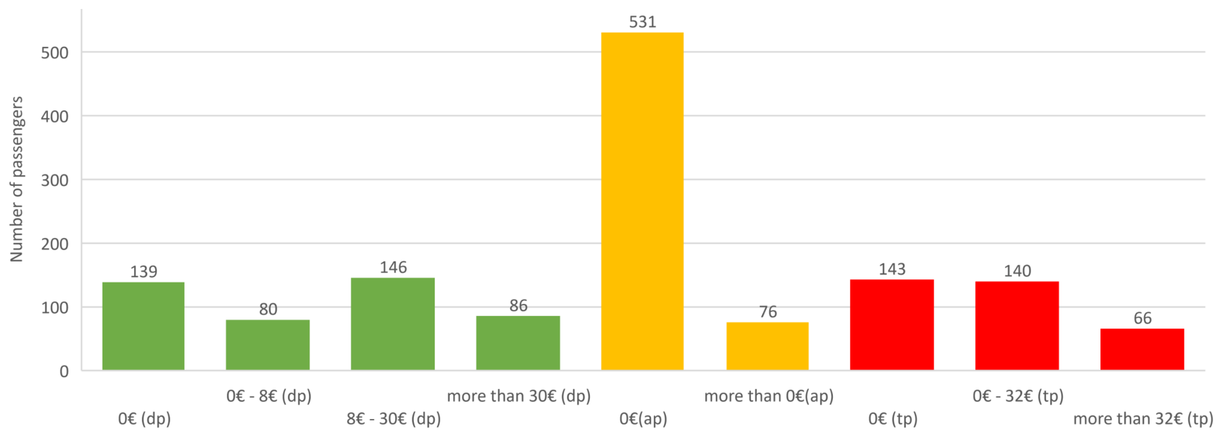

Figure 6.21: Passenger category per money spending per type of passenger

Departure passengers (dp) were divided in 4 groups; spending nothing (p1), 0 to 8€(p2), 8 to 30€ (p3) and more than 30€ (p4). The value of 8€ was chosen since many reports mentioned the average retail money spending from departing passengers to be around this value (Pentol (2019), Ikusi Airports (2018), Torres et al. (2005)). And 30€ was chosen since it was the average of money spending of passengers which actually spent something at the airport.

In terms of arrival passengers (ap), 2 groups were created: spending nothing (p5) or something (p6). This division was chosen since there were a lot of answers with 0€ spent at the airport, and to create a model according to passengers reports, these 2 groups were created.

And lastly, for transfer passengers (tp), 3 groups were created: spending nothing (p7), 0 to 32€ (p8) and more than 32€ (p9). 32€ was chosen since is also the average of money spending, considering only the passengers that spend anything at the airport.

The Discrete Choice Model (DCM) (further explained in section 6.1.3) was applied to these categories with 100% of dataset in order to simulate what percentage each category of passenger owns inside each type of passenger, represented in table 6.1.

It is important to notice that these categories have a margin of revenues inside each one. However, in order to apply these categories to the gate assignment problem, for these categories a fixed constant value needs to be assumed to each category. Consequently, it was decided to apply different methods to change the margin values to fixed values. For departing passengers, the 1st category (p1) was maintained to 0€, the 2nd category (p2) was changed from 0€-8€ to 4€ (the medium of the margin), the 3rd category(p3) was changed from 8€-30€ to 19€ (the medium of the sum of 8+30) and the 4th category (p4) was changed from more than 30€ to 52€ (the sum of 30 plus the margin of the prior category). For arriving passengers, the 5th category remains 0€, the 6th category (p6) is changed from more than 0€ to 28€ which is the average of money spending of passengers, considering only passengers that spend anything at the airport. And for transferring passengers, the 7th category (p7) remains 0€, the 8th category (p8) was changed from 0€-32€ to 16€ (the medium of the margin) and the 9th category (p9) was changed from more than 32€ to 48€ (the sum of 32 plus half the margin of the prior category). This conversion is better illustrated in table 6.1.

The resultant percentages of each category of departing, arriving and transferring passengers shown in table 6.1 will be used in the case study in variables "$npe_{p,i}$", "$nps_{p,i}$" and "npt_{p,j,j_2}", respectively, according to each plane capacity. Moreover the fixed revenue per passenger category from departing, arriving and transferring passengers shown will be attributed to variables "$re_{p,i}$", "$rs_{p,i}$", "$rt_{p,i}$", respectively, according to the distance between the gate and the main retail area.

Table 6.1: Representation of the revenue conversion to apply in the GAP

		Revenue per passenger per category
Departing passengers	**p1 (33.1%)**	0€
	p2 (16.8%)	4€
	p3 (32.3%)	19€
	p4 (17.8%)	52€
Arriving passengers	**p5 (87.8%)**	0€
	p6 (12.2%)	28€
Transferring passengers	**p7 (40.5%)**	0€
	p8 (42.0%)	16€
	p9 (17.5%)	48€

6.1.3 Modelling passenger behaviour

After creating categories of passengers, they were used in modelling passenger behaviour, in order to identify which characteristics were more relevant to each category inside each type of passenger. It is aimed to understand what drives passenger behaviour and decisions inside the airport terminal for each passenger category, and to do that, Biogeme software was used (Bierlaire (2003)).

Behaviour model for Departing passengers

Starting with departing passengers and using the categories presented in section 6.1.2, an initial judgement of what is expected for each characteristic to affect each category of departing passenger is presented as well as the corespondent variable code:

- Age - from 18 to 22 years old is expected to be more preponderant in spending less money since is assumed that youngsters usually have less money to spend comparing to adults (variable code: "age18_22", "age18_222" and "age18_223"). People from 30 to 50 years old are more likely to spend more money, as explained before (variable code: "age30_50", "age30_502").

- Mode of arrival - Arriving by own car is expected to affect positively spending more money since people plan their arrival at the airport previously to allow them to perform their intended activities and consequently have more time to spend money (variable code: "arrive_car"). Arriving by taxi or uber, as explained in chapter 2, is expected to affect positively spending more money since people arrive earlier than people who use public transports and consequently have more time to spend money (variable code: "arrive_personalise").

- Away days - It is assumed that passengers that are away for less days will spend less money than passengers that go on a long time trip (variable code: "away_days_less4").

- Country destination - people travelling to outside of Europe are more likely to spend more money, since they have to arrive at the airport earlier to perform the check-in, and consequently have more time to spend money (variable code: "dprt_country_International2").

- Day of departure - this parameter was not foreseen by the author due to lack of references in the literature (variable code: "dprt_day_Friday").

- Delay - If a flight has a delay, then is more likely to people spend money, since they will have more time to perform activities inside the airport (variable code: "dprt_delay_yes2" and "dprt_delay_yes3").

- Plan before arriving - people who plan their activities before arriving at the airport are less likely to spend nothing at the airport, since almost all activities inside the terminal involve spending some money such as eating or shopping (variable code: "plan_before_airport_yes").

- Travelling with children - people travelling with children are more likely to arrive earlier at the airport and thus, will have more time to spend money. Moreover, travelling with a child involves an extra money spending due to the child needs (variable code: "children_yes"). In case of travelling with children and in a group of more than 3 people, is more likely to spend money since, besides what was explained before, travelling in a group of people increases the likelihood to spend more money as mentioned in chapter 2 (variable code: "children_yes · people_plus3").

- Time of departure - it is assumed that people that travel during the morning are more likely to spend money (at least on breakfast) than passengers travelling during the afternoon or night (variable code: "dprt_time_afternoon", "dprt_time_morning2" and "dprt_time_morning3").

- Orientation - if a person knows well the inside of the Terminal or is capable of easily walking inside the airport, is more likely to spend money since they spend less time being lost and more time doing what they want (variable code: "easy2move_plus4")

- Travel frequency - people who are more used to travel by plane, have a better perception of inside the airport terminal and what activities are available. Then, they are more likely to perform just the activities they usually perform and do not spend huge quantities of money (variable code: "freq_plane1_3").

- Motive of travelling - people travelling on holidays are more likely to spend money at the airport since they want to increase their happiness during their planned trip. This factor united with traveling in a group of people increases even more the probability of spending money, since it is known that single travellers spend less money than people travelling in groups (variable code: "holi_peopleplus3"). People travelling due to studying abroad are likely to spend some money and most probably will do their last minute shopping (variable code: "motive_study").

- Income - people living without economic difficulties are expected to spend more money at the airport since their wage is bigger comparing to people who have less money (variable code: "income_0difficult").

- Group composition - people travelling alone are more likely to spend less money at the airport as mentioned in chapter 2.

- Shopping - people who shop after security will for certain spend money at the airport. This characteristics united with arriving at the airport by taxi or uber increases even more their likelihood of spending money (variable code: "taxiuber_shop").

- Arrival time before flight - If a passenger arrives before the opening of check-in is more likely to spend more money inside the airport since he has more time to perform discretionary activities. (variable code: "time_airport_bfcheckin_Schengen") This was calculated after the survey, since Lisbon Airport website mentions that check-in for Schengen countries opens 90 minutes before the departure time, for non-Schengen countries opens 120 minutes before and for international destinations check-in opens 180 minutes before the departure time.

As mentioned in section 3.2.1, some factors that affect the decision-maker choices are not taken into account due to the impossibility to know each user and what affects them and therefore, an alternative-specific constant (ASC) is added in the utility form to capture all those unknown factors. For departing passengers, there are 4 categories and thus, 4 alternatives - spend 0 euro (code: "nothing"), spend 4€ (code: "few"), spend 19€ (code: "more") and spend 52€ (code: "moremore"). The specification of the "moremore" alternative is only composed by the ASC and the deterministic utility is fixed to zero. The equivalent ASC is used in the utility form of the rest of the alternatives as well as all the parameters related to the relevant variables. Finally, the utility function and its variables that explain the money spent by departing passengers are the following:

$$V_{nothing} = ASC_{nothing} + \beta_{dprt\_time\_afternoon} \cdot dprt\_time\_afternoon + \beta_{dprt\_plan\_before\_airport\_yes} \cdot dprt\_plan\_before\_airport\_yes + \beta_{arrive\_car} \cdot arrive\_car + \beta_{people\_0} \cdot people\_0 + \beta_{age30\_50} \cdot age30\_50 + \beta_{age18\_22} \cdot age18\_22 + \beta_{taxiuber\_shop} \cdot arrive\_personalise \cdot dprt\_shop\_after + \beta_{holi\_peopleplus3} \cdot motive\_holidays \cdot people\_plus3$$

V_{few} = ASC_{few} + $\beta_{dprt\_country\_International2}$ · $dprt\_country\_International$+$\beta_{dprt\_time\_morning2}$ · $dprt\_time\_morning$ + $\beta_{easy2move_plus4}$ · $easy2move_plus4$ + $\beta_{freq\_plane1\_3}$ · $freq\_plane1\_3$ + $\beta_{arrive\_personalise}$ · $arrive\_personalise$ + β_{motive_study} · $motive\_study$ + β_{people_0} · $people\_0$ + β_{age18_222} · $age18\_22$ + $\beta_{children\_yes}$ · $children\_yes$ + $\beta_{dprt\_day\_Friday}$ · $dprt\_day\_Friday$ + $\beta_{dprt\_delay\_yes2}$ · $dprt\_delay\_yes$

V_{more} = ASC_{more} · $\beta_{dprt\_time\_morning3}$ · $dprt\_time\_morning$ + $\beta_{time\_airport\_bfcheckin\_Schengen}$ · $time\_airport\_bfcheckin\_Schengen$ + $\beta_{away\_daysless4}$ · $away\_daysless4$ + β_{age30_502} · $age30\_50$ + β_{age18_223} · $age18\_22$ + $\beta_{income\_income0difficult}$ · $income\_income0difficult$ + $\beta_{dprt\_delay\_yes3}$ · $dprt\_delay\_yes$ + $\beta_{child\_peopleplus3}$ · $children\_yes$ · $people\_plus3$

$V_{moremore}$ = $ASC_{moremore}$

The final results of the Multinomial Logit (MNL) Model, after several tests to specifications are presented in table 6.2 and compare its log-likelihood with that of a base model. Among the different variables, there was no evidence of significant correlations besides the variables used in more than one utility form as expected, meaning that variables are fairly independent. The values of the parameters are according to the a priori assumptions, except for $\beta_{child\_peopleplus3}$, since we expected to affect positively money spending inside the airport. Since there are no similar studies in literature for departing passengers, we cannot compare our results with previous studies. The model was estimated with 80% of the dataset and 20% were reserved for validation of accuracy of the model, namely to check what percentage of the choices from the 20% of the dataset match with the estimated choice probabilities of the observations as estimated by the model, with the validation results presented in table 6.22. In this case, 22.3% of our observations were correctly predicted by the model (with a probability higher than 50%), which was expected due to the higher number of categories in terms of departing passengers, in comparison with the 2 categories from arriving passengers and the 3 categories from transferring passengers.

Table 6.2: Estimation results for modelling departing passengers money spending

Parameter name	Parameter description	Parameter value	
		Base Model	Enriched Model
$ASC\_nothing$		-2.130	2.470
ASC_few		-0.547	-2.920
ASC_more		0.317	-0.148
$\beta_{dprt\_time\_afternoon}$	1 if the departure is during afternoon in $V_{nothing}$	-0.812*	-1.070*
$\beta_{dprt\_plan\_before\_airport\_yes}$	1 if passenger planned before which activities to do inside the airport in $V_{nothing}$		-1.260*
β_{arrive_car}	1 if passenger arrives by own car in $V_{nothing}$		-1.050*
β_{people_0}	1 if passenger travels alone in $V_{nothing}$ and V_{few}		0.713*
β_{age30_50}	1 if passenger is between 30 to 50 years old in $V_{nothing}$		-1.200*
β_{age30_502}	1 if passenger is between 30 to 50 years old in V_{more}		-0.758**
β_{age18_22}	1 if passenger is between 18 to 22 years old in $V_{nothing}$		1.210**
β_{age18_222}	1 if passenger is between 18 to 22 years old in V_{few}		0.857****
β_{age18_223}	1 if passenger is between 18 to 22 years old in V_{more}		0.791****
$\beta_{taxiuber\_shop}$	1 if passenger arrives by uber or taxi and shops after security in $V_{nothing}$		-1.980*

$\beta_{holi\_peopleplus3}$	1 if passenger is travelling due to vacations and with more than 3 people in $V_{nothing}$		-1.610*
$\beta_{dprt\_country\_International2}$	1 if passenger is travelling to an International destination in V_{few}	-0.682**	-0.604****
$\beta_{dprt\_time\_morning2}$	1 if the departure is during morning in V_{few}	1.170*	1.320*
$\beta_{dprt\_time\_morning3}$	1 if the departure is during the morning in V_{more}	0.597**	0.668**
$\beta_{easy2move\_plus4}$	1 if passenger finds easy to move inside the airport in V_{few}		1.160*
$\beta_{freq\_plane1\_3}$	1 if passenger travels by plane between 1 to 3 times per year in V_{few}		1.250*
$\beta_{arrive\_personalise}$	1 if passenger arrives by taxi or uber in V_{few}		0.709**
β_{motive_study}	1 if passenger is travelling due to studying abroad in V_{few}		1.060**
$\beta_{children\_yes}$	1 if passenger is travelling with children in V_{few}		-1.900*
$\beta_{dprt\_day\_Friday}$	1 if passenger is travelling on a Friday in V_{few}		-1.290**
$\beta_{dprt\_delay\_yes2}$	1 if there was a delay in the departure in V_{few}		0.976*
$\beta_{dprt\_delay\_yes3}$	1 if there was a delay in the departure in V_{more}		0.519***
$\beta_{time\_airport\_bfcheckin\_Schengen}$	1 if the passenger arrives at the airport before check-in opens for a Schengen destination in V_{more}		0.520***
$\beta_{aways\_daysless4}$	1 if passenger is travelling for less than 4 days in V_{more}		-1.000**
$\beta_{income\_0difficulties}$	1 if passenger has no economic difficulties in V_{more}		0.988*
$\beta_{child\_peopleplus3}$	1 if passenger is travelling with children and more than 3 people in in V_{more}		-1.820*
Number of observations	358		
Estimated parameters		7	29
Null log-Likelihood ($L(0)$)		-496.293	-496.293
Log-Likelihood ($L(\beta)$)		-469.995	-383.729
Likelihood ratio test		52.596	225.130
p^2		0.053	0.227
Adjusted p^2		0.039	0.168
Akaike Information Criterio		953.990	825.460

Notes: * Significant at 1%; ** Significant at 5%; *** Significant at 10%; ****Significant at 15%

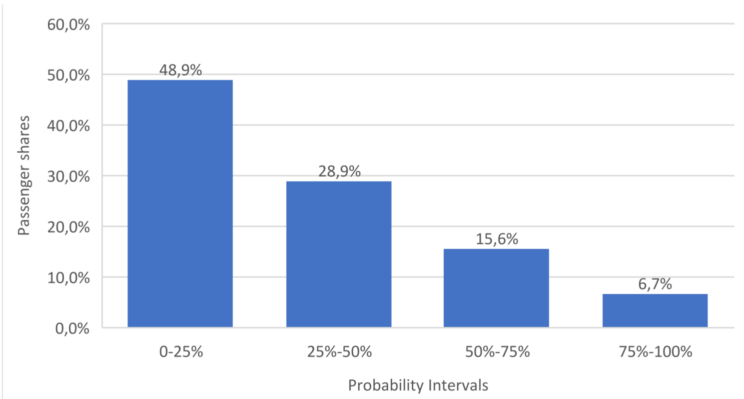

Figure 6.22: Histogram of the MNL Choice probabilities of departing passengers

Behaviour model for Arriving passengers

Similar to departing passengers, and using the correspondent categories for arriving passengers presented in section 6.1.2, an a priori judgement to what is expected for several characteristics to affect each category of arriving passenger is presented as well as the correspondent variable code:

- Age - similar to departing passengers, it is more likely for adults between 30 to 50 years old to spend money at the airport (variable code: "age30_50").

- Mode of leaving the airport - people leaving the airport by bus and metro are expected to spend less money than other people that do not use public transports (variable code: "leave_bus" and "leave_metro").
- Country origin - it is assumed that people who come for long distance flights are more likely to spend money at the airport (variable code: "arrive_country_notSchengen").
- Costs of the trip - people travelling with costs paid by their company are more likely to spend money when arriving at the airport since they have more money to spend in comparison to people travelling with costs paid by themselves (variable code: "costs_company").
- Group composition - people travelling alone are less likely to spend money at the airport comparing to people travelling with more people (variable code: "people_0" and "people_plus3").
- Lounge - a passenger is less likely to spend money at the airport if they go to the lounge since food and beverages are free (variable code: "arrive_lounge").

As explained in section for departing passengers, here there are 2 categories and thus, 2 alternatives - spend 0€ (code: "nothing") and spend 28€ (code: "more"). The specification of the "more" alternative is only composed by the ASC and the deterministic utility is fixed to zero. The equivalent ASC is used in the utility form of the rest of the alternatives as well as all the parameters related to the relevant variables. Finally, the utility function and its variables that explain the money spent by arriving passengers are the following:

$V_{nothing} = ASC_{nothing} + \beta_{dprt\_metro} \cdot dprt\_metro + \beta_{dprt_bus} \cdot dprt_bus + \beta_{costs\_company} \cdot costs\_company + \beta_{people\_0} \cdot people\_0 + \beta_{arrive\_lounge} \cdot arrive\_lounge + \beta_{age30\_50} \cdot age30\_50 + \beta_{people\_plus3} \cdot people\_plus3 + \beta_{arrive\_country\_notSchengen} \cdot arrive\_country\_notSchengen$

$V_{more} = ASC_{more}$

For arriving passengers, the MultiNomial Logit (MNL) Model is presented in table 6.3 and compared its log-likelihood with this of a base model. In a similar way, there was no evidence of significant correlations between variables besides the variables used in more than one utility form as expected, meaning that variables are fairly independent. The values of the parameters are also according to the a priori assumptions. Since there are no similar studies in literature for arriving passengers, we cannot compare our results with previous studies. The model was estimated with 80% of the dataset and 20% were reserved for model validation, with the validation results presented in table 6.23. In this case, 88% of our observations were correctly predicted by the model (with a probability higher than 50%), which ensures the validation of the model for arriving passengers.

Table 6.3: Estimation results for modelling arriving passengers money spending

Parameter name	Parameter description	Parameter value	
		Base Model	Enriched Model
$ASC_{nothing}$		2.230	3.150
β_{age30_50}	1 if people are between 30 to 50 years old in $V_{nothing}$		-0.973*
β_{leave_bus}	1 if people leave the airport by bus in $V_{nothing}$	-1.720**	-1.460**
$\beta_{arrive\_country\_nonSchengen}$	1 if people arrive from a non-Schengen country in $V_{nothing}$		-1.140*
β_{arrive_lounge}	1 if people go to lounge after arrival in $V_{nothing}$	-2.920**	-3.500*
β_{leave_metro}	1 if people leave the airport by metro in $V_{nothing}$	-0.778**	-1.300*
$\beta_{costs\_company}$	1 if people have their trip costs paid by their company in $V_{nothing}$		-0.715***
β_{people_0}	1 if people are travelling alone in $V_{nothing}$		0.613****
β_{people_plus3}	1 if people are travelling with more than 3 people in $V_{nothing}$		-0.723**
Number of observations	487		
Estimated parameters		4	9
Null log-Likelihood ($L(0)$)		-337.563	-337.563
Log-Likelihood ($L(\beta)$)		-170.471	-155.974
Likelihood ratio test		334.183	363.178
p^2		0.495	0.538
Adjusted p^2		0.483	0.511
Akaike Information Criterio		348.940	329.950

Notes: * Significant at 1%; ** Significant at 5%; *** Significant at 10%; ****Significant at 15%

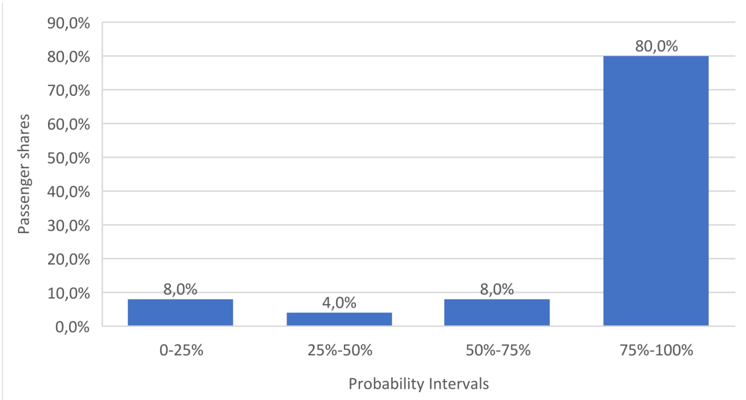

Figure 6.23: Histogram of the MNL Choice probabilities of arriving passengers

Behaviour Model for Transferring passengers

In terms of transferring passengers, a pre judgement may be performed and it consists in the following variables:

- Age - As explained throughout this paragraph, adults and older people are expected to spend more money at the airport, comparing to youngsters (variable code: ”age30_50”, ”age51_65” and ”age51_652”).
- Country origin - it is assumed that people who come for long distance flights are more likely to spend money at the airport (variable code: ”arrive_country_notSchengen2”).
- Stress of travelling by plane - usually people with fear of travelling by plane, try to arrive earlier at the airport, since their stress regarding their trip is already high, and arriving earlier allows them

to have more control at least about the time available to perform their desired activities, leading to spend more money (variable code: "stress_plus4").

- Fear regarding the time before next flight - people who are anxious to get in the plane and fear losing their flight, plan to arrive earlier at the gate to decrease their fear, and consequently spend less time at the retail area and more near their gate (variable code: "fear_plus4").

- Lounge - passengers who use the business lounge when transferring at the airport, usually spend less money at the retail area, since most of food and beverages are free in the lounge. (variable code: "transf_lounge" and "transf_lounge2").

- Pre-planned activities - passengers who have their plan of activities before arriving at the airport are less likely to spend more money than what they initially planned (variable code: "plan_before_airport_yes" and "plan_before_airport_yes2").

- Time of departure - it is assumed that people that travel during the morning are more likely to spend money (at least on breakfast) than passengers travelling during the afternoon or night (variable code: "transf_time_afternoon" and "transf_time_morning").

Similar to the other types of passengers, in transferring passengers there are 3 different categories and consequently, 3 alternatives - spend 0€ (code: "nothing"), spend 16€ (code: "few") and spend 48€ (code: "more"). In this case, the specification of the "more" alternative is only composed by ASC and its utility form is fixed to zero. Again, the equivalent ASC is used in the utility form of the rest of the alternatives as well as all the parameters related to the relevant variables. The utility function and its variables that explain the money spent by transferring passengers are the following:

$V_{nothing} = ASC_{nothing} + \beta_{age30\_50} \cdot age30\_50 + \beta_{fear\_plus4} \cdot fear\_plus4 + \beta_{transf\_plan\_before\_airport\_yes} \cdot transf\_plan\_before\_airport\_yes + \beta_{transf\_time\_morning} \cdot transf\_time\_morning + \beta_{transf\_lounge} \cdot transf\_lounge + \beta_{age51\_65} \cdot age51\_65$

$V_{few} = ASC_{few} + \beta_{arrive\_country\_notSchengen2} \cdot arrive\_country\_notSchengen + \beta_{stress\_plus4} \cdot stress\_plus4 + \beta_{transf\_time\_afternoon} \cdot transf\_time\_afternoon + \beta_{transf\_lounge2} \cdot transf\_lounge + \beta_{age51\_652} \cdot age51\_65 + \beta_{transf\_plan\_before\_airport\_yes2} \cdot transf\_plan\_before\_airport\_yes$

$V_{more} = ASC_{more}$

Finally for transferring passengers, the Multinomial Logit (MNL) Model is presented in table 6.4 and compared its log-likelihood with this of a base model. Like in departing and arriving passengers, there was no evidence of significant correlations between variables besides the variables used in more than one utility form as expected, meaning that variables are fairly independent. The values of the parameters are according to the a priori assumptions, except for β_{stress_plus4} and $\beta_{transf\_time\_morning}$. The values of the parameters are also according to the a priori assumptions. Since there are no similar studies in literature for transferring passengers, we cannot compare our results with previous studies. The model was estimated with 80% of the dataset and 20% were reserved for model validation, with the validation results presented in table 6.24. In this case, 44.3% of our observations were correctly predicted by the model (with a probability higher than 50%), which is a satisfying value for validation.

Table 6.4: Estimation results for modelling transferring passengers money spending

Parameter name	**Parameter description**	**Parameter value**	
		Base Model	Enriched Model
$ASC_{nothing}$		1.670	2.200
ASC_{few}		1.410	2.630
β_{age30_50}	1 if passengers are between 30 to 50 years old in $V_{nothing}$	-1.070*	-1.140*
β_{age51_65}	1 if passengers are between 51 to 65 years old in $V_{nothing}$	-1.380*	-1.120*
β_{age51_652}	1 if passengers are between 51 to 65 years old in V_{few}	-1.900*	-1.650*
$\beta_{arrive\_country\_notSchengen2}$	1 if passengers arrive at the airport from a non-Schengen country in V_{few}		-0.754**
β_{fear_plus4}	1 if passengers feel fear regarding the time before their next flight in $V_{nothing}$	-1.430*	-1.330*
β_{stress_plus4}	1 if passengers feel stressed regarding travelling by plane in V_{few}	-0.838**	-0.954
β_{transf_lounge}	1 if passengers go to the business lounge at the airport in $V_{nothing}$		-0.945***
$\beta_{transf\_lounge2}$	1 if passengers go to the business lounge at the airport in V_{few}		-1.840*
$\beta_{transf\_plan\_before\_airport\_yes}$	1 if passengers plan their activities before arriving at the airport in $V_{nothing}$		-1.590*
$\beta_{transf\_plan\_before\_airport\_yes2}$	1 if passengers plan their activitiesbefore arriving at the airport in V_{few}		-0.783**
$\beta_{transf\_time\_afternoon}$	1 if their next flight is during the afternoon in V_{few}		-0.915**
$\beta_{transf\_time\_morning}$	1 if their next flight is during the morning in $V_{nothing}$		0.664**
Number of observations	279		
Estimated parameters		7	14
Null log-Likelihood ($L(0)$)		-306.513	-306.513
Log-Likelihood ($L(\beta)$)		-264.572	-242.597
Likelihood ratio test		83.882	127.831
p^2		0.137	0.209
Adjusted p^2		0.114	0.163
Akaike Information Criterio		543.144	513.190

Notes: * Significant at 1%; ** Significant at 5%; *** Significant at 10%; ****Significant at 15%

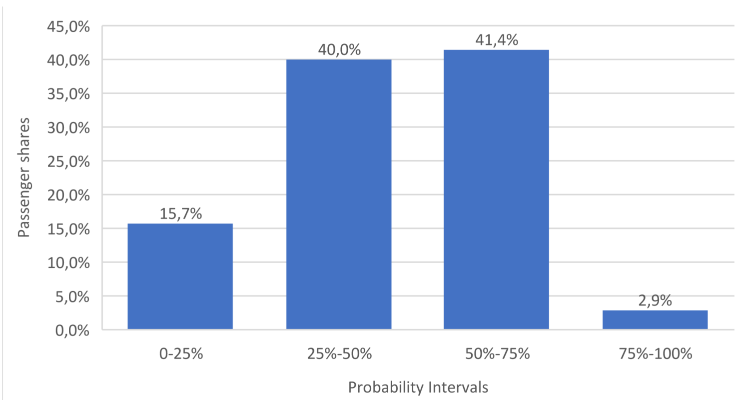

Figure 6.24: Histogram of the MNL Choice probabilities of transferring passengers

6.1.4 Gate Assignment Model for case study

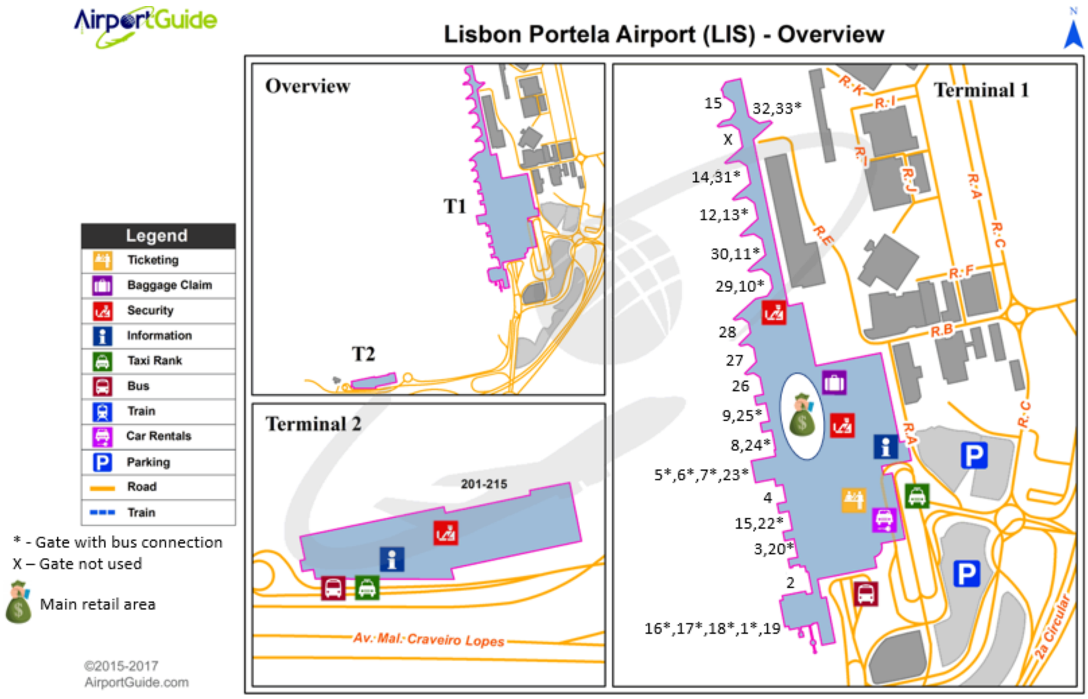

Figure 6.25: Overview of Lisbon Portela Airport (adapted from Airport Guide)

As mentioned in section 3, the model will be applied to Terminal 1 since TAP Portugal only operates on this Terminal. From the existing 47 gates (17 of which equipped with jet-bridges), only 33 gates were considered (all the 17 jet-bridges were considered). The exclusion of the rest of gates was executed by choosing only gates used in the time interval from 3pm to 6pm on the 27^{th} of August of 2019, which was used as our case study time interval. All these decisions are aimed at reducing the complexity of the problem, but keeping the quality of solutions and the inherent complexity of the problem. The main differences for the illustrative example are the number of gates and flights used. The illustrative example had 5 flights and 5 gates and our case-study 22 flights and 33 gates, keeping the same 9 passenger categories and 2 types of gates, as presented in table 6.5.

All the information needed to implement this case study was investigated and discovered from the Internet, since there was not a direct contact with ANA or TAP. To do so, all information regarding distances were taken from aerial footage of Lisbon Airport using Google Maps, and the actual planning of the airport for the considered time-window between 3pm-6pm were checked consecutively on the official app and website from ANA.

Table 6.5: Constants used in the mathematical model for the case study

Constant	Description	Units	Value
NG	Number of Gates	—	33
NF	Number of Flights	—	22
NTP	Number of categories of passengers	—	9
NTG	Number of type of gates	—	2

From the 33 gates, it is presented in table 6.6 that 22 were identified as allowed to allocate Schengen flights and 11 as non-Schengen due to access to passport control facilities, which is an activity needed for passengers departing or arriving from non-Schengen countries. Moreover, information is provided regarding walking distances that passengers must do to go from retail area to a certain gate (wde_i) and from gate to baggage claim area (wds_i). Note that, the difference between "wds_i" and "wde_i" is 130 meters, which is the extra distance travelled from the retail area to the baggage claim area. The walking distance transferring passengers (wdt_{i,i_2}) need to walk between two gates is provided in table B.6. All these walking distances were calculated using Google Maps and using aerial footage of the airport.

Furthermore, note that in table 6.6 all non-Schengen gates that require a bus link (i.e. gates 10, 11, 13, 20, 22, 24, 25, 31 and 33) have the same "wds_i" of gate 28 since it was considered that when arriving at the airport, the bus link always drops passengers near that gate. In this case study, it was considered that all gates have the capability of allocating any plane, so "cg_i" was considered to be 1 for each one. Similar to the illustrative example, a minimum time of free-gate was assumed to be 5 minutes ($tmino_i$). Moreover, the unloading time (ut_i) is the time the plane needs from arriving at the gate to allow passengers to enter at the airport (or vice-versa, i.e. the time the plane needs to leave the gate after all passengers are on board) depends if the gate has a jet-bridge or needs a bus connection. In case there is a jet-bridge the unloading time was assumed to be 5 minutes and in case of a bus connection the unloading time was assumed to be 20 minutes. Besides, the time needed from runaway to gate and from gate to runaway is also presented, and is the result of the distance measured in Google Maps and a velocity of 37 km/h. And finally, in table B.7 is presented the minimum time to allow a passenger transfer to occur between two gates ($tmint_{i,i_2}$), which was calculated assuming a passenger walking velocity of 60 meters per minute, in accordance with Young (1999).

Regarding flights, from the 22, 14 were identified as Schengen ("cfa_j" = 1) and 8 as non-Schengen ("cfa_j" = 2) due to their trip origin/destination. 8 different airline companies and 21 origins/destinations airports are included in our case study and information regarding actual arrival and departing time is also provided in table 6.7. Note that, flights 11, 12, 13, 14 and 15 do not have any flight origin since they were at the airport since the previous day, and to simulate these situations in our model, it was subtracted 60 minutes to their departure time. Additionally, flights 8, 9 and 17 do not have any flight destination since they will stay in the airport until the next day, and to simulate that in the model the departure time was considered to be 60 minutes after the arrival time.

In table 6.8, information regarding each expected revenues for the 9 different categories of passengers is provided. Initially, gates 8 and 24 were defined as being the closest to the retail area, meaning that revenues are the highest possible in both gates, in case of departing passengers. Then, the distance between all gates and these two central gates were measured, and it was assumed that revenues decrease linearly with distance to the retail area in comparison with the farthest gate, which was identified as gate 15 and assumed to have 50% decrease in revenues. Thus, gates 8 and 24 have an expected revenue of 0€, 4€, 19€ and 52€, while gate 15 has an expected revenue of 0€, 2€, 9.5€ and 26€ for the 1st (p1), 2nd (p2), 3rd (p3) and 4th (p4) category, respectively, for departing passengers. In case of arrival passengers, the same assumption was made and gate 15 (0€ and 14€ for the 5th and 6th (p6) category, respectively) was identified as being the farthest from retail area, meaning a revenue decrease of 50% in comparison to gates 8 and 24 (0€ and 28€ for the 5th and 6th (p6) category, respectively). In terms of transferring passengers, their revenues were simulated by taking into account only the gate of arrival, meaning that, like for arrival passengers, gate 15 (0€, 8€ and 24€ for the 7th (p7), 8th (p8) and 9th (p9) category, respectively) is considered to be the farthest from retail area and consequently has a decrease of 50% in revenues in comparison to gates 8 and 24 (0€, 16€ and 48€ for the 7th (p7), 8th (p8) and 9th (p9) category, respectively).

In table 6.9, information regarding the number of departing ($npe_{p,i}$) and arriving passengers ($nps_{p,i}$) for each flight is provided. Note that flights 8, 9 and 17 do not have any departing passengers since these planes arrived at Lisbon airport in our time margin between 3pm and 6pm, but only had another flight on the next day. In another way, flights 11, 12, 13, 14 and 15 do not have any arriving passengers because this plane was already at the airport since the previous day. As mentioned before, the total capacity of each flight was assumed to be 90% of the maximum capacity of each plane, and the total number of transferring passengers from each flight is around 10% of the mentioned capacity. Then, the arrival and departure time of each flight was compared and as mentioned in Neufville et al. (2013), a transfer can only occur if there is a 60 min gap between flights. To increase this margin security, since some gate need a bus connection, the minimum value between arrival and departure time was set to 120 min. Finally, on the possible transfers, random numbers of passengers were introduced. In tables B.4 and B.5, information regarding the number of transferring passengers (npt_{p,j,j_2}) between each flight is provided.

Table 6.6: Gates 1-33: Walking distance of arriving (wds_i) and departing passengers(wde_i), classification of gate if Schengen (cga_i=1) or non-Schengen (cga_i=2), classification of gate in terms of capability to receive certain sizes of airplanes (cg_i), minimum time that each gate must remain free between two flights ($tmino_i$), unloading time (ut_i) and distance from runaway to gate(rtg_i)

Parameter	**Gate1**	**Gate2**	**Gate3**	**Gate4**	**Gate5**	**Gate6**	**Gate7**	**Gate8**	**Gate9**	**Gate10**	**Gate11**	**Gate12**	**Gate13**	**Gate14**	**Gate15**	**Gate16**
$wds_i(m)$	370	420	370	280	370	370	370	170	220	370	370	560	370	625	750	370
$wde_i(m)$	405	290	240	150	115	115	115	40	90	300	365	430	430	495	620	405
cga_i	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	1
cg_i	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
$tmino_i(min)$	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
$ut_i(min)$	20	5	5	5	20	20	20	5	5	20	20	5	20	5	5	20
$rtg_i(min)$	3	3	3	3	3	3	3	3	3	2	2	2	2	2	2	3

Parameter	**Gate17**	**Gate18**	**Gate19**	**Gate21**	**Gate22**	**Gate23**	**Gate24**	**Gate25**	**Gate26**	**Gate27**	**Gate28**	**Gate29**	**Gate30**	**Gate31**	**Gate32**	**Gate33**
$wds_i(m)$	370	370	370	320	370	370	370	370	270	330	370	430	495	370	680	370
$wde_i(m)$	405	405	405	190	190	115	40	90	140	200	250	300	365	495	550	550
cga_i	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2
cg_i	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
$tmino_i(min)$	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
$ut_i(min)$	20	20	5	20	5	20	20	20	20	5	5	5	5	5	20	5
$rtg_i(min)$	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	3

Table 6.7: Flights 1-22: Arrival (a_j) and departure time (d_j), origin and destination for each flight, airline company, classification of flight in terms of Schengen or non-Schengen (cfa_j), classification of flight in terms of size (cf_j)

Parameter	**Flight1**	**Flight2**	**Flight3**	**Flight4**	**Flight5**	**Flight6**	**Flight7**	**Flight8**	**Flight9**	**Flight10**	**Flight11**
a_j	3.36pm	3.50pm	3.52pm	4.17pm	4.21pm	4.22pm	4.25pm	4.34pm	4.36pm	4.39pm	3.54pm
d_j	5.02pm	5.39pm	5.25pm	5.21pm	6.03pm	5.45pm	5.47pm	5.34pm	5.36pm	5.51pm	4.54pm
Origin	Gran Canaria	Rome	Frankfurt	Madrid	Vienna	Casablanca	Hamburg	Amsterdam	Ponta Delgada	Athens	—
Destination	Faro	Ponta Delgada	Frankfurt	Madrid	Vienna	Casablanca	Brussels	—	—	Athens	Salvador
Airline Company	TAP	TAP	Lufthansa	Iberia	TAP	Royal Air Maroc	TAP	TAP	White	Aegean	TAP
cfa_j	1	1	1	1	1	2	1	1	1	1	2
cf_j	1	1	1	1	1	1	1	1	1	1	1

Parameter	**Flight12**	**Flight13**	**Flight14**	**Flight15**	**Flight16**	**Flight17**	**Flight18**	**Flight19**	**Flight20**	**Flight21**	**Flight22**
a_j	4.12pm	4.17pm	4.19pm	4.29pm	5.05pm	5.06pm	5.29pm	5.38pm	5.41pm	5.43pm	5.49pm
d_j	5.12pm	5.17pm	5.19pm	5.29pm	6.29pm	6.06pm	6.42pm	6.38pm	6.41pm	6.43pm	6.49pm
Origin	—	—	—	—	Ponta Delgada	Eindhoven	Brussels	Marrakesh	Bordeaux	London	Paris
Destination	Sao Paulo	Fortaleza	Recife	New York	Ponta Delgada	—	Brussels	Marrakesh	Bordeaux	London	Paris
Airline company	TAP	TAP	TAP	TAP	TAP	TAP	TAP	TAP	TAP	British Airways	Air France
cfa_j	2	2	2	2	1	1	1	2	1	2	1
cf_j	1	1	1	1	1	1	1	1	1	1	1

Table 6.8: Gates 1-33: Revenue per passenger per category of departing ($re_{p,i}$), arriving ($rs_{p,i}$) and transferring ($rt_{p,i}$) passenger

Revenue per passenger	category	Gate1	Gate2	Gate3	Gate4	Gate5	Gate6	Gate7	Gate8	Gate9	Gate10	Gate11	Gate12	Gate13	Gate14	Gate15	Gate16
departure $re_{p,i}$ (€)	**p1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	p2	2.8	3.2	3.36	3.64	3.76	3.76	3.76	4	3.84	3.04	2.84	2.64	2.64	2.4	2	2.8
	p3	13.3	15.2	15.96	17.29	17.86	17.86	17.86	19	18.24	14.44	13.49	12.54	12.54	11.4	9.5	13.3
	p4	36.4	41.6	43.68	47.32	48.88	48.88	48.88	52	49.92	39.52	36.92	34.32	34.32	31.2	26	36.4
arrival $rs_{p,i}$ (€)	**p5**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	p6	19.6	22.4	23.52	25.48	26.32	26.32	26.32	28	26.88	21.28	19.88	18.48	18.48	16.8	14	19.6
transfer $rt_{p,i}$ (€)	**p7**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	p8	11.2	12.8	13.44	14.56	15.04	15.04	15.04	16	15.36	12.16	11.36	10.56	10.56	9.6	8	11.2
	p9	33.6	38.4	40.32	43.68	45.12	45.12	45.12	48	46.08	36.48	34.08	31.68	31.68	28.8	24	33.6

Revenue per passenger	category	Gate17	Gate18	Gate19	Gate20	Gate21	Gate22	Gate23	Gate24	Gate25	Gate26	Gate27	Gate28	Gate29	Gate30	Gate31	Gate32	Gate33
departure $re_{p,i}$(€)	**p1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	p2	2.8	2.8	2.8	3.36	3.52	3.52	3.76	4	3.84	3.68	3.48	3.32	3.04	2.84	2.4	2.24	2.24
	p3	13.3	13.3	13.3	15.96	16.72	16.72	17.86	19	18.24	17.48	16.53	15.77	14.44	13.49	11.4	10.64	10.64
	p4	36.4	36.4	36.4	43.68	45.76	45.76	48.88	52	49.92	47.84	45.24	43.16	39.52	36.92	31.2	29.12	29.12
arrival rs (€)	**p5**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	p6	19.6	19.6	19.6	23.52	24.64	24.64	26.32	28	26.88	25.76	24.36	23.24	21.28	19.88	16.8	15.68	15.68
transfer rt (€)	**p7**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	p8	11.2	11.2	11.2	13.44	14.08	14.08	15.04	16	15.36	14.72	13.92	13.28	12.16	11.36	9.6	8.96	8.96
	p9	33.6	33.6	33.6	40.32	42.24	42.24	45.12	48	46.08	44.16	41.76	39.84	36.48	34.08	28.8	26.88	26.88

Table 6.9: Flights 1-22: Number of departing ($npe_{p,i}$) and arriving ($nps_{p,i}$) passengers per category of passengers

	Total Capacity	116	116	226	141	133	92	175	116	141	141	242
Number of passengers		**Flight1**	**Flight2**	**Flight3**	**Flight4**	**Flight5**	**Flight6**	**Flight7**	**Flight8**	**Flight9**	**Flight10**	**Flight11**
Departing passengers $npe_{p,i}$	**p1**	39	39	75	47	44	31	58	0	0	47	80
	p2	20	20	38	24	22	16	29	0	0	24	41
	p3	38	38	73	46	43	30	57	0	0	46	78
	p4	21	21	40	25	24	16	31	0	0	25	43
Arriving passengers $nps_{p,i}$	**p5**	102	102	198	124	117	81	154	102	124	124	0
	p6	14	14	28	17	16	11	21	14	17	17	0

	Total Capacity	218	218	218	242	175	153	116	116	96	116	128
Number of passengers		**Flight12**	**Flight13**	**Flight14**	**Flight15**	**Flight16**	**Flight17**	**Flight18**	**Flight19**	**Flight20**	**Flight21**	**Flight22**
Departing passengers $npe_{p,i}$	**p1**	72	72	72	80	58	0	39	39	32	39	42
	p2	37	37	37	41	29	0	20	20	16	20	22
	p3	70	70	70	78	57	0	38	38	31	38	41
	p4	39	39	39	43	31	0	21	21	17	21	23
Arriving passengers $nps_{p,i}$	**p5**	0	0	0	0	154	134	102	102	84	102	112
	p6	0	0	0	0	21	19	14	14	12	14	16

In terms of costs per distance travelled, since it was not found any value in literature similar to the cost of distance per passenger need for this dissertation, some assumptions were made. Initially, cost of delay was found to be 72€ per minute per plane according to Neufville et al. (2013). Assuming a 100 seat capacity plane, each passenger has a cost of delay of 0.72€ per minute. Then, a velocity of 60 meters per minute was used, in accordance with Young (1999). Finally, using the following expression, a cost of 0.012€ per meter travelled by each passenger was achieved:

$$\frac{0.012€}{meter} = \frac{0.72€}{min} \cdot \frac{1min}{60meter} \tag{6.1}$$

This value of 0.012 €/m was assumed to be equal to any type o passenger of any category.

Gate allocation from 5pm to 5.30pm

In order to evaluate the usefulness of this gate assignment model some experiments will be documented and then the results evaluated. In this case, gathering all flights and gates information from our time interval from 3pm to 6pm, the mathematical model will attribute 3 flights (flights 16,17 and 18 arriving between 5pm and 5.30pm) to certain gates, knowing a priori, that there are still planes on ground occupying gates (flights 1, 11, 12, 13 and 14 since they have not left the gates before 5pm) as presented in table 6.10. Note again that variables b_j and b_j are displayed in minutes starting from 3pm.

Flight allocation before 5pm	Gate	Flight	$b_j(min)$	$c_j(min)$
$xp_{6,1} = 1$	6	1	59	99
$xp_{8,2} = 1$	8	2	58	151
$xp_{1,3} = 1$	1	3	75	122
$xp_{9,4} = 1$	9	4	85	133
$xp_{2,5} = 1$	2	5	89	175
$xp_{15,6} = 1$	15	6	89	158
$xp_{7,7} = 1$	7	7	108	144
$xp_{5,8} = 1$	5	8	117	131
$xp_{4,9} = 1$	4	9	104	148
$xp_{3,10} = 1$	3	10	107	163
$xp_{12,11} = 1$	12	11	61	107
$xp_{10,12} = 1$	10	12	94	110
$xp_{13,13} = 1$	13	13	99	115
$xp_{11,14} = 1$	11	14	101	117
$xp_{14,15} = 1$	14	15	96	142

Table 6.10: A priori filght allocation before 5pm

Gate allocation from 5.30pm to 6pm

In this case, the mathematical model will assign 4 flights (flights 19, 20, 21 and 22) knowing a priori that all flights staying on gates before 5.30pm are already allocated (represented in table 6.11) and thus, cannot use the same gates at the same time for this interval.

Gate allocation from 5pm to 6pm

This scenario will allow to understand what are the improvements in revenues if the gate allocation is performed for the whole time horizon from 5pm to 6pm. In this case, the a priori gate allocation is the same as in table 6.10 and the model will assign flights 16 to 22 to the corresponding gates.

Table 6.11: A priori flight allocation before 5.30pm

Flight allocation before 5.30pm	Gate	Flight	$b_j(min)$	$c_j(min)$
$xp_{6,1} = 1$	6	1	59	99
$xp_{8,2} = 1$	8	2	58	151
$xp_{1,3} = 1$	1	3	75	122
$xp_{9,4} = 1$	9	4	85	133
$xp_{2,5} = 1$	2	5	89	175
$xp_{15,6} = 1$	15	6	89	158
$xp_{7,7} = 1$	7	7	108	144
$xp_{5,8} = 1$	5	8	117	131
$xp_{4,9} = 1$	4	9	104	148
$xp_{3,10} = 1$	3	10	107	163
$xp_{12,11} = 1$	12	11	61	107
$xp_{10,12} = 1$	10	12	94	110
$xp_{13,13} = 1$	13	13	99	115
$xp_{11,14} = 1$	11	14	101	117
$xp_{14,15} = 1$	14	15	96	142
$xp_{26,16} = 1$	24	16	133	201
$xp_{6,17} = 1$	26	17	149	178
$xp_{17,18} = 1$	9	18	172	199

Gate allocation from 5pm to 6pm during an extreme event

This experiment will allow to see how the mathematical model adjusts in case an extreme event happens. In this case, flight 20 will be our main focus. Due to an extraordinary event in Lisbon, the airport planner knows a priori, that this flight will have an unusual category probability distribution of passengers arriving and departing. Once again, the a priori flight allocation is the same as represented in table 6.10. For this case, the number of passengers from category p1 to p6 were changed, and an increase of passengers that will spend more money at the airport will be affected by increasing to numbers such as presented in table 6.12, comparing to the initial number of passengers of flight 20 presented in table 6.9.

Table 6.12: Number of departing and arriving passengers for flight 20 for the extraordinary event

	New total capacity	106
Type of passengers		Number of passengers for Flight20 per category
Departing passengers $npe_{p,i}$	p1	14 (less 56%)
	p2	12 (less 25%)
	p3	42 (more 35%)
	p4	36 (more 47%)
Arriving passengers $nps_{p,i}$	p5	54 (less 36%)
	p6	50 (more 76%)

For this case, there is a huge difference in the number of passengers for each category, namely p1 from 32 to 14, p2 from 16 to 12, p3 from 31 to 42, p4 from 17 to 36, p5 from 84 to 54, p6 from 12 to 50. It is easy to see that there is an increase in categories that spend more money (p2, p3, p4 and p6) and a decrease in categories that spend less money (p1 and p5).

Chapter 7

Results

Gate allocation is a mathematical problem that has to be solved for a limited time interval (e.g. 15 minutes, 30 minutes, 1 hour) depending on the size of the problem and whether or not we can achieve an optimal solution in useful time to make a decision. In the next subsection, useful computational times from the model solutions will be achieved (e.g. less than 1 minute) and presented to the reader.

7.1 Results of the case study

In this section, the computational results for Lisbon airport case study are provided, as well as some statistic results regarding each time section studied (5pm to 5.30pm, 5.30pm to 6pm, 5pm to 6pm and 5pm to 6pm in case of an extreme event) such as: the problem size, computational time and the optimal solution for each case.

Gate allocation from 5pm to 5.30pm

Firstly, an analysis of the problem size will be performed. Looking at figure 7.1, this case has a much bigger size than the illustrative example as can be found in table 7.1, by looking at the number of columns of the matrix. Thus, the bigger the size of the problem, the more computational time is needed to obtain the optimal solution (7.5s in this case and less than 0.1s in the illustrative example as can be found in section 5.3.2).

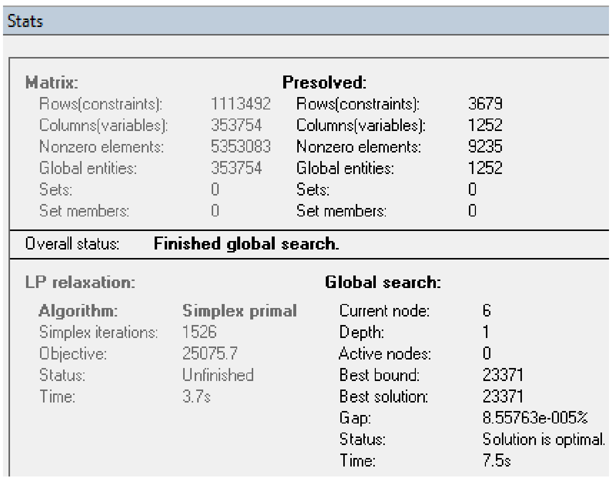

Figure 7.1: Statistics results for time section 5pm-5.30pm

Table 7.1 shows how to calculate the problem size and how it depends on the number of decision variables ($x_{i,j}$, y_{j,j_2} and z_{i,i_2,j,j_2}) and the size of sets (G, F, NTP and NTG). It is important to note that although the problem has 353754 variables, the presolved results shown in figure 7.1 show that the model is able to reduce the number of variables of the problem to 1252, almost 283 times less. Thus, the model is able to solve the problem much faster than with the initial problem size.

Table 7.1: Calculation of the problem size for planning horizon 5pm-5.30pm

Sets	Size	Decision variables	Size	Column's Size
G=1,... 33	33	$x_{i,j}$	$33 \times 18 = 594$	$594 + 324 + 352836 = 353754$
F=1,...18	18	y_{j,j_2}	$18 \times 18 = 324$	
NTP=1,...9	9	z_{i,i_2,j,j_2}	$33 \times 33 \times 18 \times 18 = 352836$	
NTG=1	1			

Regarding the optimality gap, the mathematical model was able to reach a gap of $8.55{\times}10^{-005}\%$ in 7.5 seconds, which means the solution obtained is the optimal one, corresponding to a revenue of 23371.00€. The optimality gap is not equal to zero as it should be due to the Mixed Integer Programming (MIP) solver and its linear programming relaxation that results from the use of a constraint that implies that each variable belongs to the interval between 0 and 1, instead of a binary.

In figure 7.2 is represented the evolution of the best feasible solution until the model is able to reach the optimal solution for this case study. The xx axis is the time in seconds and the yy axis is the objective function value. Green squares represent feasible solutions and the best bound (in this model is the upper bound) is represented by the yellow line.

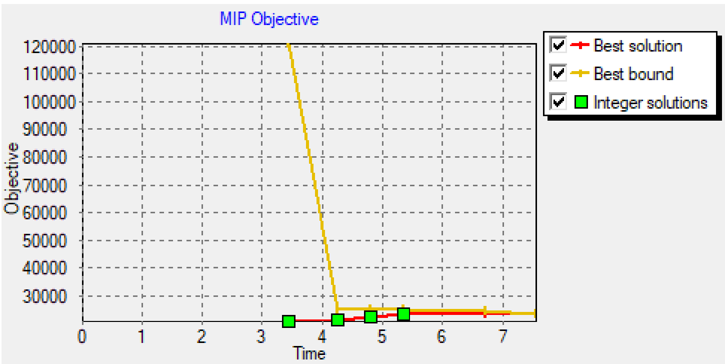

Figure 7.2: MIP Objective search for 5pm-5.30pm case study

In table 7.2, the composition of the optimal solution is provided. As expected, the main focus of revenues comes from revenues from departing passengers as referenced in chapter 2. Transferring passengers have the smallest impact in both revenues and cost of walking distance since they represent only 10% of each plane and lastly, arriving passenger have a considerable impact in the optimal solution.

Table 7.2: Demonstration of the optimal solution and its components from 5pm-5.30pm

Objective function component	Value (€)
O_1 - revenues from transferring passengers	2747.36
O_2 - revenues from arriving passengers	5486.60
O_3 - revenues from departing passengers	32379.70
O_4 - cost of walking distance from transferring passengers	-607.68
O_5 - cost of walking distance from arriving passengers	-7596.48
O_6 - cost of walking distance from departing passengers	-9038.58
Total	23371.00

In figure 7.3, a display of the results from the mathematical model regarding the time interval from

5pm to 5.30pm are presented, as well as the actual gate assignment in the Lisbon Airport. Also, in figure B.2 from annexes, an easier representation of the resultant gate allocation 5pm-5.30pm is provided, together with figure B.1 from annexes, that displays the a priori flight allocation. In the dissertation approach, note that from flight 1 to 15, the model respects the previous attribution corresponding to flights being on the ground at the same time as this time horizon. Moreover, note that flights 16, 17 and 18 respect the attribution to Schengen gates as intended and are the closest to the main retail area, respecting the gates already occupied with previous flights. Flight 18 occupies gate 9 which had been previously occupied but when the first arrives, the gate is already available.

Differences were expected between the actual planning with the mathematical model attribution, since the most profitable gates were not used when flights 16 to 18 arrived, in the actual planning. Therefore, the result is an attribution to the correspondent most profitable gates, respecting if the plane was from a Schengen country or not, in the mathematical model.

Table 7.3: Results for gate allocation 5pm-5.30pm and comparison to actual planning

Mathematical model				**Actual planning**			
Flight	**Gate**	$b_j(min)$	$c_j(min)$	**Flight**	**Gate**	$b_j(min)$	$c_j(min)$
1	6	59	99	1	6	59	99
2	8	58	151	2	8	58	151
3	1	75	122	3	1	75	122
4	9	85	133	4	9	85	133
5	2	89	175	5	2	89	175
6	15	90	157	6	15	90	157
7	7	108	144	7	7	108	144
8	5	117	131	8	5	117	131
9	4	104	148	9	4	104	148
10	3	107	163	10	3	107	163
11	12	62	106	11	12	62	106
12	10	95	109	12	10	95	109
13	13	100	114	13	13	100	114
14	11	102	116	14	11	102	116
15	14	97	141	15	14	97	141
16	**24**	147	187	**16**	**26**	133	201
17	**26**	133	178	**17**	**6**	149	163
18	**9**	157	214	**18**	**17**	172	199

Gate allocation from 5.30pm to 6pm

In this case, there is a priori allocation of 18 flights (flights 1 to 18, all arriving before 5.30pm), and the mathematical model should allocate the rest of flights 19 to 22 to the best potential revenue gates. Since there is a bigger problem size comparing to previous results, it is normal that the model takes more time to achieve the best possible solution. In fact, for this time horizon it was achieved a computational time of 11.1 seconds to achieve the optimal solution of 27304.60€ with an optimality gap of 0%, as presented in figure 7.3.

The problem size for this time horizon is different and can be investigated in table 7.4. It is important to note that although the problem has 528286 variables, the presolved results shown in figure 7.3 show that the model is able to reduce the number of variables of the problem to 2066, almost 256 times less. Thus, the model is able to solve the problem much faster than with the initial problem size.

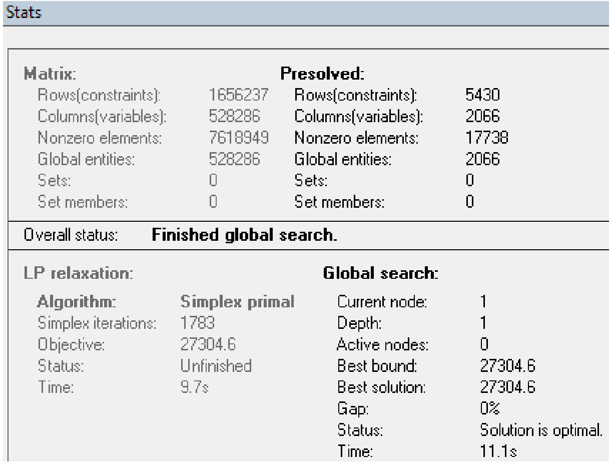

Figure 7.3: Statistics results for time section 5.30pm-6pm

Table 7.4: Calculation of the problem size for the planning horizon 5.30pm-6pm

Sets	Size	Decision variables	Size	Column's Size
G=1,... 33	33	$x_{i,j}$	$33 \times 22 = 726$	$726 + 484 + 527076 = 528286$
F=1,...22	22	y_{j,j_2}	$22 \times 22 = 484$	
NTP=1,...9	9	z_{i,i_2,j,j_2}	$33 \times 33 \times 22 \times 22 = 527076$	
NTG=1	1			

Using the same approach, the evolution of the best feasible solution until the optimal is reached using the MIP search is represented in figure 7.4 and the composition of the optimal solution in table 7.5.

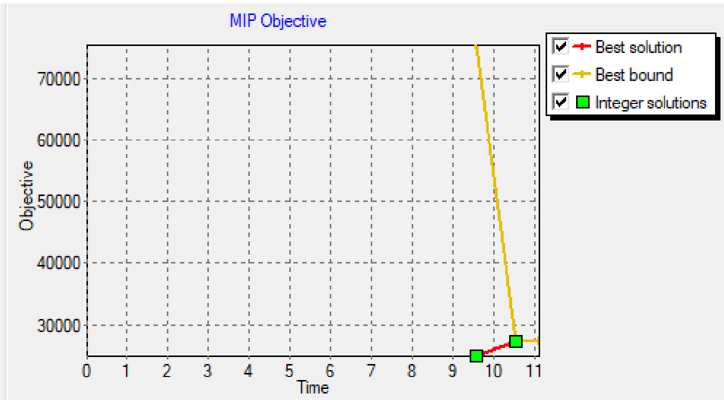

Figure 7.4: MIP Objective search for 5.30pm-6pm case study

Table 7.5: Demonstration of the optimal solution and its components from 5.30pm-6pm

Objective function component	Value (€)
O_1 - revenues from transferring passengers	3572.48
O_2 - revenues from arriving passengers	6587.00
O_3 - revenues from departing passengers	38079.80
O_4 - cost of walking distance from transferring passengers	-818.34
O_5 - cost of walking distance from arriving passengers	-9407.04
O_6 - cost of walking distance from departing passengers	-10709.30
Total	27304.60

And finally, the results for this time horizon are displayed in table 7.6. Also, in figure B.3, an easier representation of the resultant gate allocation 5.30pm-6pm is provided, together with figure B.1 that displays the a priori flight allocation. Note that, once again, the model respects the gate attibution from flight 1 to 18, and allocates flights 19 to 22 respecting if the flights are from Schengen or non-Schengen countries, as can be observed by looking at flight 19 and 21 (from non-Schengen countries) allocated at gates 10 and 29 (allowed to receive non-Schengen flights), respectively. Moreover, they are the closest possible to the main retail area respecting the gates already occupied by flights still on the ground.

Table 7.6: Results for gate allocation 5.30pm-6pm and comparison to actual planning

Mathematical model				**Actual planning**			
Flight	**Gate**	$b_j(min)$	$c_j(min)$	**Flight**	**Gate**	$b_j(min)$	$c_j(min)$
1	6	59	99	1	6	59	99
2	8	58	151	2	8	58	151
3	1	75	122	3	1	75	122
4	9	85	133	4	9	85	133
5	2	89	175	5	2	89	175
6	15	90	157	6	15	90	157
7	7	108	144	7	7	108	144
8	5	117	131	8	5	117	131
9	4	104	148	9	4	104	148
10	3	107	163	10	3	107	163
11	12	62	106	11	12	62	106
12	10	95	109	12	10	95	109
13	13	100	114	13	13	100	114
14	11	102	116	14	11	102	116
15	14	97	141	15	14	97	141
16	26	133	201	16	26	133	201
17	6	149	163	17	6	149	163
18	17	172	199	18	17	172	199
19	**10**	181	195	**19**	**31**	180	196
20	**9**	169	213	**20**	**16**	184	198
21	**29**	170	216	**21**	**33**	185	201
22	**8**	177	221	**22**	**4**	177	221

Gate allocation from 5pm to 6pm

As explained before, this scenario allows to see how is the gate allocation done if the mathematical has the opportunity to allocate a time horizon of one hour from 5pm to 6pm. Thus, there is a priori gate allocation from flights 1 to 15, and the model will assign 7 flights (3 relative to the 1^{st} half an hour and 4 relative to the 2^{nd} half an hour to the respective gates). In this case and observing figure 7.5, the problem size is the same as in table 7.4, although this case has more flights to allocate and consequently, the model is only able to reduce the number of variables to 8795, around 60 times less. In fact, the computational time achieved was 41.6 seconds with a optimality gap of $10.29\times 10^{-5}\%$, which allows us to confirm that the best bound is in fact the best and optimal solution with a revenue of 29144.20€.

The evolution of the MIP search is also presented in figure 7.6 and the composition of the best solution in table 7.7.

Lastly, the results are displayed in table 7.8, where the reader can confirm that the model once again respects the Schengen/non-Schengen constraint and allocates the flights to the appropriate gates considering maximisation of potential revenues. In figure B.4, an easier representation of the resultant gate allocation 5pm-6pm is provided, together with figure B.1 that displays the a priori flight allocation.

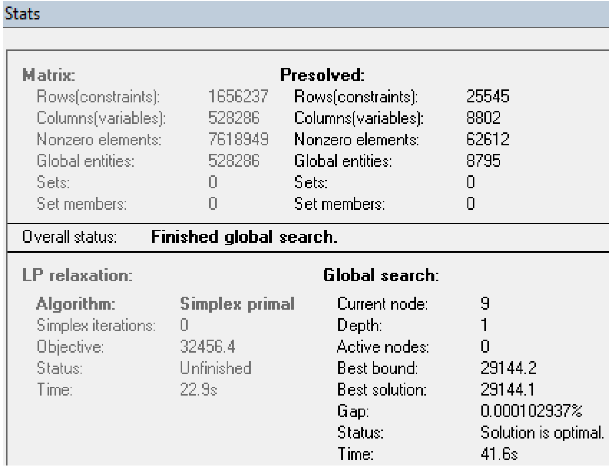

Figure 7.5: Statistics results for time section 5pm-6pm

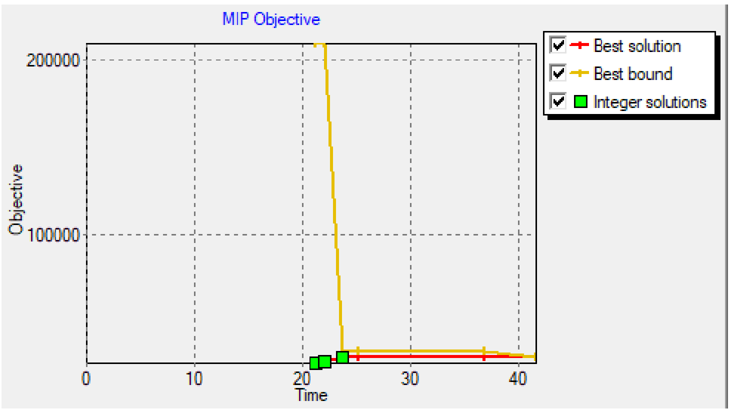

Figure 7.6: MIP Objective search for 5pm-6pm case study

Table 7.7: Demonstration of the optimal solution and its components from 5pm-6pm

Objective function component	**Value (€)**
O_1 **- revenues from transferring passengers**	3694.08
O_2 **- revenues from arriving passengers**	6853.00
O_3 **- revenues from departing passengers**	38797.10
O_4 **- cost of walking distance from transferring passengers**	-749.34
O_5 **- cost of walking distance from arriving passengers**	-9397.44
O_6 **- cost of walking distance from departing passengers**	-10053.30
Total	29144.10

Table 7.8: Results for gate allocation 5pm-6pm and comparison to actual planning

Mathematical model				**Actual planning**			
Flight	**Gate**	$b_j(min)$	$c_j(min)$	**Flight**	**Gate**	$b_j(min)$	$c_j(min)$
1	6	59	99	1	6	59	99
2	8	58	151	2	8	58	151
3	1	75	122	3	1	75	122
4	9	85	133	4	9	85	133
5	2	89	175	5	2	89	175
6	15	90	157	6	15	90	157
7	7	108	144	7	7	108	144
8	5	117	131	8	5	117	131
9	4	104	148	9	4	104	148
10	3	107	163	10	3	107	163
11	12	62	106	11	12	62	106
12	10	95	109	12	10	95	109
13	13	100	114	13	13	100	114
14	11	102	116	14	11	102	116
15	14	97	141	15	14	97	141
16	**24**	147	187	**16**	**26**	133	201
17	**26**	133	179	**17**	**6**	149	163
18	**9**	157	214	**18**	**17**	172	199
19	**29**	165	211	**19**	**31**	180	196
20	**25**	183	199	**20**	**16**	184	198
21	**10**	186	200	**21**	**33**	185	201
22	**8**	177	221	**22**	**4**	177	221

Gate allocation from 5pm to 6pm during an extreme event

This scenario will allow the reader to see the potential benefits of the current model from the perspective of the airport manager. In this case flight 20 was chosen due to its Schengen origin and since it was not already allocated to the closest gate to the retail area in the time-horizon from 5pm-6pm as presented in table 7.8. This extreme event consists of the scenario corresponding to an extraordinary event that gathers several people that will spend a lot of money at the airport. Knowing this information a priori, the airport manager is capable of doing a profitable gate allocation using the mathematical model so that flight 20 is closer to the retail area. For this situation, the a priori gate allocation is the same to flights 1 to 15, as shown in table 6.10.

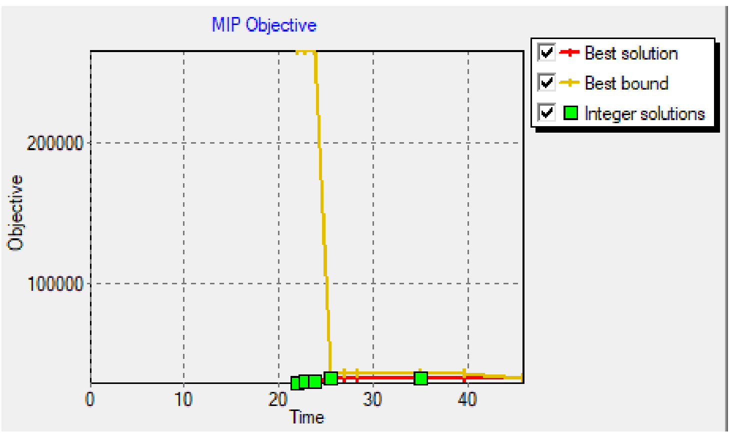

Figure 7.7: MIP Objective search for 5pm-6pm case study in an extreme scenario

Table 7.9: Demonstration of the optimal solution and its components from 5pm-6pm in case of an extreme event

Objective function component	Value (€)
O_1 - revenues from transferring passengers	3694.08
O_2 - revenues from arriving passengers	7800.52
O_3 - revenues from departing passengers	41610.10
O_4 - cost of walking distance from transferring passengers	-752.34
O_5 - cost of walking distance from arriving passengers	-9452.64
O_6 - cost of walking distance from departing passengers	-10076.30
Total	32823.40

For this case, the problem size is exactly the same as the previous scenario, also represented at table 7.4, where the model is able to reduce the number of variables to 8795, around 60 times less. Similar to the previous scenario, the model will allocate flights 15 to 22 in the most profitable way. The statistical results are presented in figure 7.8, and is noted that the best bound was achieved in 45.8 seconds with a optimality gap of $9.14{\times}10^{-5}$%, which confirms that the best bound found is the optimal solution with a revenue of 32823.40€ (which was expected to be higher than the "normal" time horizon from 5pm-6pm since there are much more passengers willing to spend more money on flight 20). The evolution of the MIP search is given in figure 7.7 and the composition of the best solution in table 7.9.

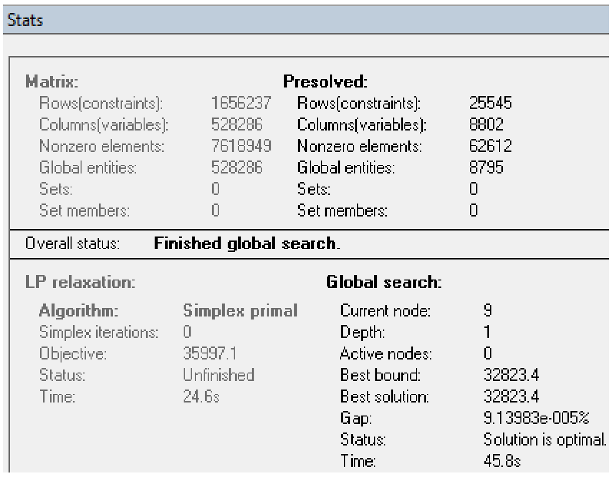

Figure 7.8: Statistics results for time section 5pm-6pm in an extreme scenario

Finally, the results are presented in table 7.10, and in figure B.5, an easier representation of the resultant gate allocation is provided, together with figure B.1 that displays the a priori flight allocation. From flights 16 to 22, it is clear that comparing to table 7.8, there is a change in the gate allocation of some flights (take a closer look at flights 18,20 and 22), which shows how the model can adapt to different scenarios, in order to achieve an increase in revenues.

These results allow to conclude that the MILP model proposed in this dissertation maximises airport revenues and consequently, that the created framework can allocate flights to gates, considering all the variables, in the most profitable way.

Table 7.10: Results for gate allocation 5pm-6pm in an extreme scenario and comparison to actual planning

Mathematical model				Actual planning			
Flight	**Gate**	$b_j(min)$	$c_j(min)$	**Flight**	**Gate**	$b_j(min)$	$c_j(min)$
1	6	59	99	1	6	59	99
2	8	58	151	2	8	58	151
3	1	75	122	3	1	75	122
4	9	85	133	4	9	85	133
5	2	89	175	5	2	89	175
6	15	90	157	6	15	90	157
7	7	108	144	7	7	108	144
8	5	117	131	8	5	117	131
9	4	104	148	9	4	104	148
10	3	107	163	10	3	107	163
11	12	62	106	11	12	62	106
12	10	95	109	12	10	95	109
13	13	100	114	13	13	100	114
14	11	102	116	14	11	102	116
15	14	97	141	15	14	97	141
16	**24**	147	187	**16**	**26**	133	201
17	**26**	133	179	**17**	**6**	149	163
18	**25**	171	200	**18**	**17**	172	199
19	**29**	165	211	**19**	**31**	180	196
20	**8**	169	213	**20**	**16**	184	198
21	**10**	186	200	**21**	**33**	185	201
22	**9**	177	221	**22**	**4**	177	221

7.2 Analysis of results

Comparison of Gate allocation from 5pm to 5.30pm, 5.30pm to 6pm and 5pm to 6pm to the actual planning

Returning to tables 7.3, 7.6 and 7.8, it is noticeable that flights have a different assignment and thus, the resultant revenues are also different.

The objective to an airport manager would be to give the inputs to the model from prior gate allocations and the expected time of arrival of the next half an hour flights and run the model, resulting in the best lucrative gate assignment to the airport.

In table 7.11, it is finally showed the opportunity of revenues increase that this dissertation allows an airport to have. An increase of 8.0% and 12.2%, corresponding to 1732.70€ and 2967.30€, respectively, in a time horizon of half an hour using the exact same number of passengers, manifests the opportunity of this dissertation method to increase considerably the revenues just by reallocating flights to certain gates.

Also in table 7.11, it is possible to analyse the applicability of the model to one hour time periods, in this case with an increase of 18.9%, corresponding to 4641.90€ in the total revenues.

The result of the actual planning was performed by attributing variable $xp_{i,j}$ to 1 in case flight j and gate i were attributed in the actual planning, and afterwards the objective function was calculated.

In practice, the announcement to passengers of what gate they need to go to is performed between every 15 to 30 minutes, and for this model, half an hour periods of gate allocation were seen as adequate to the case study. The final model was then capable of performing half an hour gate allocations as showed in results, in just some seconds of computational time.

In table 7.12, the first 3 cases (5pm-5.30pm, 5.30pm-6pm and 5pm-6pm) are compared in terms of number of variables, optimality gap and computational time. As demonstrated, the model is able to reduce the number of involved variables in 282, 256 and 69 times, respectively for each case. In terms of the optimality gap, all results are practically zero, which means all solutions are the optimal solution for each case. And in terms of computational time, all results are less than 1 minute which is a compatible result with the time required for allocating planes to gates at airports.

Lastly, in table 7.10 and annexe B.5, it is intended to show the reader the advantage of using this dissertation method in case an extreme event happens and how it can affect the gate allocation of all flights just by knowing a priori that one of the flights is carrying passengers willing to spend more money at the airport.

Table 7.11: Comparison between the actual planning to the mathematical model in terms of objective function value

Revenue per time slot	**Actual planning result**	**Mathematical model result**	**Variation**
Gate allocation from 5pm-5.30pm	21638.30€	23371.00€	+ 1732.70€ (increase of 8.0%)
Gate allocation from 5.30pm-6pm	24337.30€	27304.60€	+ 2967.30€ (increase of 12.2%)
Gate allocation from 5pm-6pm	24502.30€	29144.20€	+ 4641.90€ (increase of 18.9%)

Table 7.12: Comparison between the actual planning to the mathematical model

Gate allocation time-slot	**Initial number of variables**	**Presolved number of variables of the model**	**Optimality Gap**	**Computational time**
5pm-5.30pm	353,754	1,252(282 times less)	8.55 \times 10^{-5}	7.5 seconds
5.30pm-6pm	528,286	2,066 (256 times less)	0%	11.1 seconds
5pm-6pm	528,286	8,795 (69 times less)	10.29 \times 10^{-5}	41.6 seconds

Chapter 8

Conclusions

This final chapter is dedicated to highlight the main conclusions of this dissertation, as well as to identify the existing limitations and future areas that are worth studying further.

8.1 Conclusions

This dissertation examines the research conducted in a master's thesis on a Gate Assignment Problem, with a practical case study of Lisbon Portela Airport.

Due to the fact that non-aeronautical revenues are becoming more and more valuable for airports global revenues, the main objective of this dissertation was to introduce a framework that could support airport managers to allocate flights to gates in the most profitable way, by maximising the potential commercial revenues from passengers' spendings. The proposed framework is an innovative MILP model that allows to allocate flights to gates where there is a higher probability of spending money, respecting all the related variables (for instance Schengen/non-Schengen flights, the size of the plane). This assignment is based on knowing a priori the number of passengers for each flight so that the combination of passengers and more rentable gates is adjusted to the main goal of increasing airports profits.

Therefore, in retrospective, passengers' characteristics travelling in each flight are an opportunity to airport managers, and thus, should be shared between airline companies and the airport. In order to show the value of this information, the case study with an extreme event evaluates how the airport may increase their profits.

This model was adapted to a determined time horizon and to Lisbon Portela airport, but is perfectly capable of being adjusted to a different time horizon and to different airports if the user inserts the corresponding inputs into the MILP model.

This dissertation is a result of a long investigation, composed of several steps. Initially, the problem was presented and a review of the state of the art aimed at getting a deeper understanding of how far has this field gone and how could be improved with this dissertation approach. Then, an intense deep learning on discrete choice modelling was done leading to the use of this method in discovering what different categories of passengers exist and in what proportion, using the results of a survey directed at passengers from Lisbon Portela airport. Afterwards, the formulated optimisation model was applied to the Lisbon Portela case study and to a specific planning horizon, demonstrating that this model could find better and more profitable gate assignments than the actual planning. More precisely, the potential passenger revenues were increased in 8.0% and 12.2% on half an hour time horizons and 18.9% in an one hour time horizon, comparing to the actual planning at the airport.

However, an airport manager should not be totally dependent on the proposed gate assignment from this optimisation model, since there are unlikely and unexpected events that may change the existing constraints, such as an accident on a specific plane, or a problem in a bus connection. Nonetheless, this model can help to justify a decision that allows to support the airport manager in the gate assignment, contributing to speed up the decision time from the manager and to achieve a more clear and a higher quality problem's solution.

In terms of contribution to the scientific literature, this model is an important addition to the Gate Assignment Problem (GAP) since it includes the modelling, testing and forecasting the behaviour of the three existing types of passengers (departure, arrival and transferring). Furthermore, the model is as close to reality of Lisbon airport as possible and can be perfectly adjustable to any airport by a deep research and adaptation to the desired airport infrastructure.

8.2 Limitations

The major limitation of this dissertation research is the fact that inputs must be precisely inserted in the optimisation model according to a real world situation. If these inputs do not represent precisely the real world case study and even if there are feasible solutions found, the solutions cannot be applied in reality.

Another limitation of this optimisation model is the bus assignment. This feature was not modelled into the model and it was simulated by increasing the "ut_i - loading/unloading time" by 15 min in the respective gates that need a bus connection to the terminal. This situation decreases the model's accuracy due to the estimated increase, since each gate should have its particularities and can be either faster or slower to get passengers from the terminal to the gate and vice-versa. Therefore, this parameter should be carefully chosen for each situation, in order to achieve feasible and applicable solutions to the real world.

The fact that the objective function is formed by two different parts, revenues and walking distance implied there had to be a unification in the units used in the objective function, leading to a conversion of walking distance to cost per distance, which is done by a series of assumptions base on known values of cost per delay of airplanes.

The revenues from transferring passengers were considered to be fully dependent of the arriving gate and not the departure gate. This approximation was done since there was not enough time to fully investigate what should be the main criteria in this case and there was not any related scenario in literature to be comparable.

In discrete choice modelling, the answers to the survey are based in people's sincerity and can change depending on the mood of the person. Moreover, a survey of around 600 answers was used as a representation of Lisbon airport with almost 30 million passengers per year, and consequently, this survey is an approximation of reality but does not fully represent it. Moreover, in order to model transferring passengers and since the survey was not capable of reaching too many transferring passengers at Lisbon airport, all answers used included the passenger experience and activities in any European airport.

In terms of the survey validation, it might be argued that the survey was not capable of reaching every kind of people, since most of answers were collected using the internet, and therefore, some people might not have been considered to participate in this survey. Moreover, most of the answers were from Lisbon residents and therefore, do not fully represent the characteristics of passengers that live in other parts of the country.

The creation of categories of passengers is highly dependent on the mood of the person buying or using airport facilities. Plus, the conversion of categories from a range of money spending to a specific number is also a matter to discuss. The method used was seen as the best at the time even though there might be a matter of discussion in there.

And lastly, one of the major difficulties during this dissertation was the access to the Lisbon Portela Airport data. It was not possible to gain access to the desired information in useful time, leading to an extra effort in order to find, simulate and discover all the data needed in order to fulfill the inputs needed in the dissertation model and framework, such as distances between gates, distances needed for passengers to walk from/to gates and the gates used by each plane in the considered day for the case study.

8.3 Future work

As referred across this dissertation, this research may be explored in future works in several aspects. Starting by its applicability to more complex airports and with more flights to assign, include airplanes and gates with its own characteristics that need to be taken into account in a future optimisation model and in sum, a more complex case study that would test the model performance.

In the optimisation model itself, and as introduced in the section before, a relevant area of future work would be to investigate how the potential money spending from passengers may be affected during a transfer, looking at the walking distance needed to do in comparison to the potential revenues if the passenger needs to pass through the main retail area or not. Moreover, all the consumption criteria that influence and increase the potential revenues to the airport should also be considered as an aspect to develop. Since it depends from case to case, a future area of work might be to fully investigate Lisbon airport and its consumption distribution across the terminal.

A future area of work may also be to create a survey that might be spread across a higher number of people, in order to achieve solutions as close to reality as possible. Furthermore, an analysis to passenger characteristics on time spending at the airport and its importance should also be included in future researches. And in an extra performance, an analysis of the passenger characteristics that influence and explain a higher potential of money spending, as introduced during this optimisation model in the extreme event where there was a considerable increase of passengers willing to spend money at the airport. However, this was merely assumed and not fully explained by the passenger behaviour model (e.g. which characteristics lead to changing the number of passengers of the influenced passenger categories, when occurring an extreme event). This should be regarded as an additional effort to identify which are the characteristics and factors that contribute to lead passengers to spend more money at the airport.

Bibliography

ACI Europe. Airport traffic report. December 2018.

ANA Aeroportos de Portugal. Annual report 2018. 2018.

S. Appold and J. Kasarda. The appropriate scale of us airport retail activities. *Journal of Air Transport Management*, 12:277–287, 2006.

L. Basso and A. Zhang. Congestible facility rivalry in vertical structures. *Journal of Urban Economics*, 61(2):218–237, 2007.

J. A. Behrends and J. M. Usher. Aircraft gate assignemnt: Using a deterministic approach for integrating freight movement and aircraft taxiing. *Computers & Industrial Engineering*, 102:44–57, 2016.

M. G. Bellizzi, L. Eboli, C. Forciniti, and G. Mazzulla. Air transport passengers' satisfaction: an ordered logit model. *Transportation Reasearch Procedia*, 33:147–154, 2018.

M. Ben-Akiva and S. Lerman. *Discrete choice analysis*. Cambridge: The MIT Press, 1985.

M. Bierlaire. Biogeme: a free package for the estimation of discrete choice models. 2003.

M. Buendia and A. de Barros. Critical update of the post-security retail space design in passenger departure terminals. *Aerlines Magazine*, 40, 2008.

J. I. Castillo-Manzano and L. López-Valpuesta. Analysing passenger behaviour towards the catering industry: Implications for airport management. *International Journal of Hospitality Management*, 35: 258–260, 2013.

L. Cheng, C. Fookes, V. Reddy, and P. K. Yarlagadda, editors. *Analysis of Passenger Group Behaviour and Its Impact on Passenger Flow using an Agent-based Model*, 2014. SIMULTECH - 4th International Conference on Simulation and Modeling Methodologies, Technologies and Applications.

G. Crawford and T. C. Melewar. The importance of impulse purchasing behaviour in the international airport environment. *Journal of Consumer Behaviour*, 3(1):85–98, 2003.

A. I. Czerny and A. Zhang. Airport congestion pricing and passenger types. *Transportation Research Part B: Methodological*, 45(3):595–604, 2011.

T. D'Alfonso, C. Jiang, and Y. Wan. Airport pricing, concession revenues and passenger types. *Transport Economics and Policy*, 47(1):71–89, January 2013.

G. S. Daş. New multi objective models for the gate assignment problem. *Computers & Industrial Engineering*, 109:347–356, 2017.

G. Diepen, J. van den Akker, and J. Hoogeveen. Integrated gate and bus assignment at amsterdam airport schipol. *Robust and Online Large-Scale Optimization*, 5868:338–353, 2009.

Eurocontrol. European aviation in 2040 - challenges of growth'. 2018.

V. Fasone, L. Kofler, and R. Scuderi. Business performance of airports: Non-aviation revenues and their determinants. *Journal of Air Transport Management*, 53:35–45, 2016.

M. Geuens, M. Brengman, and R. S'Jegers. An exploratory study on grocery shopping motivations. *European advances in consumer research*, 5:135–140, 2002.

M. Geuens, D. Vantomme, and M. Brengman. Developing a typology of airport shoppers. *Tourism Management*, 25:615–622, 2004.

C. M. Gheorghe, M. Sebea, and C. Stoenescu. From passengers to airport customers - how should airports relate to their target groups?, 2016.

A. Harrison, V. Popovic, and B. Kraal. A new model for airport passenger segmentation. *Journal of Vacation Marketing*, 21(3):237–250, 2015.

N. Ikonen, C. Savolainen-Kopra, J. E. Enstone, I. Kulmala, P. Pasanen, A. Salmela, S. Salo, J. Nguyen-Van-Tam, and P. Ruutu. Deposition of respiratory virus pathogens on frequently touched surfaces at airports. *BMC Infectious Diseases*, 18, 5 2018.

Ikusi Airports. What are the main sources of nonaeronautical revenue at an airport? May 2018.

Intervistas. Economic impact of european airports - a critical catalyst to economic growth. January 2015.

Y. Jiang, L. Zeng, and Y. Luo. Multiobjective gate assignment based on passenger walking distance and fairness. *Mathematical Problems in Engineering*, 2013, 2013.

S. Kalakou and F. Moura. Modelling passenger's activity choice in airport terminal before the security checkpoint: the case of portela airport in lisbon. *Transportation Research Procedia*, 10:881–890, 2015.

S. H. Kim, E. Feron, J.-P. Clarke, A. Marzuoli, and D. Delahaye. Airport gate schedulling for passengers, aircraft, and operation. *Journal of Air Transportation*, 25(4):109–114, 2017.

F. S. Koppelman and C. R. Bhat. A self instructing course in mode choice modeling: Multinomial and nested logit models. 2006.

A. Lim, B. Rodrigues, and Y. Zhu. Airport gate scheduling with time windows. *Artificial Intelligence Review*, 24:5–31, 2005.

X. Liu, J. M. Usher, and L. Strawderman. An analysis of activity schedulling behaviour of airport travelers. *Computers and Industrial Engineering*, 74:208–218, 2014.

R. Luce. Individual choice behavior: A theoretical analysis. New York, 1959.

M. Marinelli, M. Dell'Orco, and D. Sassanelli. A metaheuristic approach to solve the flight gate assignment problem. *Transportation Research Procedia*, 5:211–220, 2015.

J. Marschak. Binary-choice constraints and random utility indicators (1960). *conomic Information, Decision, and Prediction. Theory and Decision Library (An International Series in the Philosophy and Methodology of the Social and Behavioral Sciences)*, 7(1):312–329, 1974.

R. A. Martins. Planning maintenance in bus operating companies, October 2018.

D. McFadden. The measurement of urban travel demand. *Journal of Public Economics*, 3(4):303–328, 1974.

R. Neufville, A. Odoni, P. Belobaba, and T. Reynolds. *Airport Systems - Planning, Design and Management*. Mc Graw Hill Education, second edition, 2013.

U. M. Neuman and J. A. Atkin. Airport gate assignment considering ground movement. *4th Int'l Conf. on Computational Logistics*, 8197:184–198, 2013.

A. Pentol. Ams spend per passenger drops -1.6% to 13.18€ in 2018. Travel Retail Business, February 2019.

Popovic, Vesna, Kraal, B. J., Kirk, and P. J., editors. *Passenger experience in an airport: an activity-centred approach*, October 2009. IASDR 2009 (International Association of Societies of Design Research).

K. S. Shareef. Common problems of airport passenger terminal operations, Summer 2016.

J. Stewart. *Study Guide : Calculus*. Cengage Learning, 8 edition, 2015.

A. Suzianti and H. N. Larasati. Designing shopping area atmospheric using choice-based conjoint analysis: Case study at soekarno-hatta international airport. *MATEC Web of Conferences*, 104, 2017.

L. L. Thurstone. A law of comparative judgement. *Pychological Review*, 340(4):273–286, 1927.

E. Torres, J. Domínguez, L. Valdés, and R. Aza. Passenger waiting time in an airport and expenditure carried out in the commercial area. *Journal of Air Transport Management*, 11:363–367, 2005.

K. Train. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press, 2002.

VINCI Airports. Opening your world. October 2014.

VINCI Airports. Resultados de tráfego do primeiro trimestre de 2019. 2019.

S. B. Young. Evaluation of pedestrian walking speeds in airport terminals. *Transportation Research Record*, 1674(1):20–26, 1999.

S. Zantke. "flughafen". *ABC des Luftverkehrs*, 1976.

A. Zhang and Y. Zhang. Airport capacity and congestion when carriers have market power. *Journal of Urban Economics*, 60(2):229–247, 2003.

H.-H. Zhang, Q.-W. Xue, and Y. Jiang. Multi-objective gate assignement based on robustness in hub airports. *Advances in Mechanical Engineering*, 9(2):1–13, 2017.

Appendix A

Survey demonstration

Table A.1: Survey questions about departing from Terminal 1 of Lisbon Airport

Question	Answer	Question	Answer
Was this the first time you used Terminal 1 of Lisbon Airport?	Yes		
	No		
From 1 to 5, how easily do you think you can move within the Terminal without getting lost?	ex: 3		
How frequently do you use Lisbon airport per year (departures or arrivals) ?	1 to 3 times per year		
	4 to 10 times per year		
	more than 10 times per year		
How frequently do you travel by plane per year ? (departures or arrivals)	0		
	1 to 3 times per year		
	4 to 12 times per year		
	more than 13 times per year		
Which airline company did you travel with?	ex: TAP Portugal		
How did you arrive at the airport?	Own car		
	Friend's/ family member car		
	Metro		
	Bus		
	Taxi		
	Uber		
	Other		
What was the reason of your trip?	Business	**Who paid the costs of the trip?**	Yourself
	Study		The company you work for
	Personal (Visiting family / friends, etc)		
	Holidays		
	Other		
Did you have hold baggage to check-in?	Yes		
	No		
How many hand baggage did you take?	0		
	1		
	2		
	more than 2		
How many people were you travelling with?	0		
	1		
	2		
	3		
	4		
	5		
	6		
	more than 6		
Were there any children with you?	Yes		

Table A.1: Survey questions about departing from Terminal 1 of Lisbon Airport

Question	Answer	Question	Answer
	No		
From 1 to 5, select the stress level you felt of losing your flight?	1 to 5		
From 1 to 5, select the stress level you felt regarding the fear of travelling by plane?	1 to 5		
How much time before the scheduled flight departure time did you arrive at the airport?	less than 30 min		
	30 min to 45 min		
	45 min to 1 h		
	1 h to 1h15min		
	1h15min to 1h30min		
	1h30min to 1h45min		
	1h45min to 2h		
	2h to 2h15min		
	2h15min to 2h30min		
	more than 2h30min		
How much time before the scheduled flight departure time did you go to your gate?	less than 20 min		
	20 min to 30 min		
	30min to 50min		
	more than 50min		
How did you checked-in?	Online		
	At the airport		
Which country was your destination?	ex: Spain		
On this trip, how many days were you away from your place of residence?	ex: 2		
What was the week day of departure?	Monday to Thursday		
	Friday		
	Weekend		
What time of the day was your flight scheduled to depart?	6am to 8am		
	8am to 10am		
	10am to 12am		
	12am to 2 pm		
	2pm to 4pm		
	4pm to 6pm		
	6pm to 8pm		
	8pm to 10pm		
	10pm to 1am		
Was there any flight delay?	Yes	**How long was the flight delay?**	less than 25min
	No		25min to 1h
			1h to 2h
			more than 2h
Planned the activities inside the Terminal before arriving at the Airport?	Yes		
	No		
Use of the business lounge?	Yes		
	No		
Did you visit any beverage area at Terminal 1, before security?	Yes		
	No		
Did you visit any beverage area at Terminal 1, after security?	Yes	**Time spent**	ex: 10 minutes
	No	**Money spent**	ex: 20 euros

Table A.1: Survey questions about departing from Terminal 1 of Lisbon Airport

Question	Answer	Question	Answer
Did you visit any shopping area at Terminal 1, before security?	Yes		
	No		
Did you visit any shopping area at Terminal 1, after security?	Yes	**Time spent**	ex:30 minutes
	No	**Money spent**	ex: 40 euros
		Number of products bought	ex: 2

Table A.2: Survey questions about arriving at Terminal 1 of Lisbon Airport

Question	Answer	Question	Answer
Was this the first time you used Terminal 1 of Lisbon Airport?	Yes		
	No		
From 1 to 5, how easily do you think you can move within the Terminal without getting lost?	1 to 5		
How frequently do you use Lisbon airport per year (departures or arrivals) ?	1 to 3 times per year		
	4 to 10 times per year		
	more than 10 times per year		
How frequently do you travel by plane per year ? (departures or arrivals)	0		
	1 to 3 times per year		
	4 to 12 times per year		
	more than 13 times per year		
Which airline company did you travel with?	ex: TAP Portugal		
How did you arrive at the airport?	Own car		
	Friend's/ family member car		
	Metro		
	Bus		
	Taxi		
	Uber		
	Other		
What was the reason of your trip?	Business	**Who paid the costs of the trip?**	Yourself
	Study		The company you work for
	Personal (Visiting family / friends, etc)		
	Holidays		
	Other		
Did you have hold baggage?	Yes	**Time waiting at the baggage claim area ? (in minutes)**	ex: 20 minutes
	No		
How many hand baggage did you take?	0		
	1		
	2		
	more than 2		
How many people were you travelling with?	0		
	1		
	2		
	3		
	4		
	5		
	6		

Table A.2: Survey questions about arriving at Terminal 1 of Lisbon Airport

Question	Answer	Question	Answer
	more than 6		
Were there any children with you?	Yes		
	No		
Which country did you come from?	ex: Spain		
In this trip, how many days were you away from your place of residence?	ex: 2		
What was the week day of arrival?	Monday to Thursday		
	Friday		
	Weekend		
What time of the day was your flight scheduled to arrive?	6am to 8am		
	8am to 10am		
	10am to 12am		
	12am to 2 pm		
	2pm to 4pm		
	4pm to 6pm		
	6pm to 8pm		
	8pm to 10pm		
	10pm to 1am		
Was there any flight delay?	Yes	**How long was the flight delay?**	less than 25min
	No		25min to 1h
			1h to 2h
			more than 2h
Planned the activities inside the Terminal before arriving at the Airport?	Use of the business lounge?		
	No		
Use of the business lounge?	Yes		
	No		
Did you visit any beverage area at Terminal 1?	Yes	**Time spent**	ex: 10 minutes
	No	**Money spent**	ex: 20 euros
Did you visit any shopping area at Terminal 1?	Yes	**Time spent**	ex:30 minutes
	No	**Money spent**	ex: 40 euros
		Number of products bought	ex: 1
Have you ever done a transfer at Terminal 1 of Lisbon Airport?	Yes		
	No		
Have you ever done a transfer at any airport in the world?	Yes		
	No		

Table A.3: Survey questions about doing a transfer in any airport in the world

Question	Answer	Question	Answer
In which airport did you do a transfer?	ex: Madrid		
First time at the Airport?	Yes		
	No		
From 1 to 5, how easily do you think you can move within the Terminal without getting lost?	1 to 5		
How frequently do you use this airport per year (departures or arrivals) ?	1 to 3 times per year		
	4 to 10 times per year		
	more than 10 times per year		

Table A.3: Survey questions about doing a transfer in any airport in the world

Question	Answer	Question	Answer
How frequently do you travel by plane per year ? (departures or arrivals)	0		
	1 to 3 times per year		
	4 to 12 times per year		
	more than 13 times per year		
What was the reason of your trip?	Business	**Who paid the costs of the trip?**	Yourself
	Study		The company you work for
	Personal (Visiting family / friends, etc)		
	Holidays		
	Other		
How many hand baggage did you take?	0		
	1		
	2		
	more than 2		
How many people were you travelling with?	0		
	1		
	2		
	3		
	4		
	5		
	6		
	more than 6		
Were there any children with you?	Yes		
	No		
From 1 to 5, select the stress level you felt of losing your flight?	1 to 5		
From 1 to 5, select the stress level you felt regarding the fear of travelling by plane?	1 to 5		
Which country did you come from?	ex: Portugal		
With which airline company did you depart from the Airport?	ex: TAP Portugal		
Which country did you go to?	ex: Barcelona		
Airline company departing from the airport	ex: Iberia		
In this trip, how many days were you away from your place of residence?	ex: 4 days		
What was the week day of arrival?	Monday to Thursday		
	Friday		
	Weekend		
What time of the day was your flight scheduled to depart from the airport?	6am to 8am		
	8am to 10am		
	10am to 12am		
	12am to 2 pm		
	2pm to 4pm		
	4pm to 6pm		
	6pm to 8pm		
	8pm to 10pm		
	10pm to 1am		
How much time available did you have from arrival until the departure of your next flight at the airport? (in hours)	ex: 2 hours	**Satisfied?**	Yes
			If no, how much time would you like to have

Table A.3: Survey questions about doing a transfer in any airport in the world

Question	Answer	Question	Answer
			inside the Terminal? (in minutes)
How much time before your next scheduled flight departure time were you at the gate?	less than 20 min		
	20 min to 30 min		
	30min to 50min		
	more than 50min		
Planned the activities inside the Terminal before arriving at the Airport?	Yes		
	No		
Use of the business lounge?	Yes		
	No		
Did you visit any beverage area at the Terminal?	Yes	**Time spent**	ex: 10 minutes
	No	**Money spent**	ex: 20 euros
Shopping area at the Terminal ?	Yes	**Time spent**	ex:30 minutes
	No	**Money spent**	ex: 40 euros
		Number of products bought	ex: 1

Table A.4: Survey questions when the passenger has never done a transfer in life

Question	Answer
How much free time would you like to have inside the Terminal, before boarding your next flight? (in minutes)	ex: 1 hour
Which activities would like to do regarding this time?	Toilet
	Food/drinks
	Products/services
	Common free area
	Wait at the gate
	Leave the airport and go to the city

Table A.5: Survey questions regarding personal information for all passengers

Question	Answer	Question	Answer
Do you live in Portugal?	Yes	**Where?**	Aveiro
	No		Beja
			Braga
			Bragança
			Castelo Branco
			Coimbra
			Évora
			Faro
			Guarda
			Leiria
			Lisboa
			Portalegre
			Porto
			Madeira
			Açores

Table A.5: Survey questions regarding personal information for all passengers

Question	Answer	Question	Answer
			Santarém
			Setúbal
			Viana do Castelo
			Vila Real
			Viseu
How old are you?	Less than 18 years old		
	18 to 22 years old		
	23 to 29 years old		
	30 to 50 years old		
	51 to 65 years old		
	more than 65 years old		
What is your gender?	Male		
	Female		
	Prefer no to say		
What is your gross monthly income?	My income allows me to live loosely		
	My income allows me to live without difficulties		
	I live with financial difficulties		
	I do not have any income		
What is your nationality?	ex: Portuguese		

Appendix B

Gate Assignment Problem (GAP)

B.1 Illustrative example

Table B.1: Number of transferring passengers of category p7 (npt_{p7,j,j_2})

p7	Flight 1	Flight 2	Flight 3	Flight 4	Flight 5
Fligh 1	0	7	7	7	7
Flight 2	7	0	7	7	7
Flight 3	7	7	0	7	7
Flight 4	7	7	7	0	7
Flight 5	7	7	7	7	0

Table B.2: Number of transferring passengers of category p8 (npt_{p8,j,j_2})

p8	Flight 1	Flight 2	Flight 3	Flight 4	Flight 5
Flight 1	0	8	8	8	8
Flight 2	8	0	8	8	8
Flight 3	8	8	0	8	8
Flight 4	8	8	8	0	8
Flight 5	8	8	8	8	0

Table B.3: Number of transferring passengers of category p9 (npt_{p9,j,j_2})

p9	Flight 1	Flight 2	Flight 3	Flight 4	Flight 5
Flight 1	0	3	3	3	3
Flight 2	3	0	3	3	3
Flight 3	3	3	0	3	3
Flight 4	3	3	3	0	3
Flight 5	3	3	3	3	0

B.2 Case study Lisbon Airport

Table B.4: [Number of transferring passengers from category p7 (npt_{p7,j,j_2}) and p8 (npt_{p8,j,j_2})

p7	Flight1	Flight2	Flight3	Flight4	Flight5	Flight6	Flight7	Flight8	Flight9	Flight10	Flight11	Flight12	Flight13	Flight14	Flight15	Flight16	Flight17	Flight18	Flight19	Flight20	Flight21	Flight22
Flight1	0	0	0	2	0	0	0	2	0	0	0	0	2	0	0	0	0	0	0	2	0	0
Flight2	0	0	2	0	0	2	0	0	2	0	0	0	0	0	0	0	0	0	2	0	0	0
Flight3	0	0	2	0	0	2	0	0	2	0	0	0	0	2	0	2	0	0	0	0	2	0
Flight4	0	0	0	0	2	0	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2
Flight5	0	0	0	0	0	0	2	0	0	2	0	0	0	0	0	0	2	0	0	2	0	0
Flight6	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2	0	0	2	0	0	0
Flight7	0	0	0	0	2	0	2	0	0	2	0	0	0	0	0	2	0	0	0	0	2	0
Flight8	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	2	0	0	2	0	0
Flight9	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	2
Flight10	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0
Flight11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	2	0
Flight17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	0	0
Flight18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

p8	Flight1	Flight2	Flight3	Flight4	Flight5	Flight6	Flight7	Flight8	Flight9	Flight10	Flight11	Flight12	Flight13	Flight14	Flight15	Flight16	Flight17	Flight18	Flight19	Flight20	Flight21	Flight22
Flight1	0	0	0	2	0	0	0	2	0	0	0	0	2	0	0	0	0	0	0	2	0	0
Flight2	0	0	2	0	0	2	0	0	2	0	0	0	0	0	0	0	0	0	2	0	0	0
Flight3	0	0	2	0	0	2	0	0	2	0	0	0	0	2	0	2	0	0	0	0	2	0
Flight4	0	0	0	0	2	0	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2
Flight5	0	0	0	0	0	0	2	0	0	2	0	0	0	0	0	0	2	0	0	2	0	0
Flight6	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2	0	0	2	0	0	0
Flight7	0	0	0	0	2	0	2	0	0	2	0	0	0	0	0	2	0	0	0	0	2	0
Flight8	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	2	0	0	2	0	0
Flight9	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	2
Flight10	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0
Flight11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	2	0
Flight17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	0	0
Flight18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.5: Number of transferring passengers from category p9 (npt_{p9,j,j_2})

p9	Flight1	Flight2	Flight3	Flight4	Flight5	Flight6	Flight7	Flight8	Flight9	Flight10	Flight11	Flight12	Flight13	Flight14	Flight15	Flight16	Flight17	Flight18	Flight19	Flight20	Flight21	Flight22
Flight1	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0
Flight2	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
Flight3	0	0	1	0	0	1	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0
Flight4	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
Flight5	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0
Flight6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0
Flight7	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0
Flight8	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0
Flight9	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1
Flight10	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
Flight11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	1	0
Flight17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	0	0
Flight18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flight22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table B.6: Walking distance of transferring flights between two gates wdt_{i,i_2} (in meters)

		Gates																																
	wdt_{i,i_2} (m)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**
	1	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	2	115	0	50	140	175	175	175	250	300	580	645	710	710	775	900	115	115	115	115	50	100	100	175	250	300	340	400	450	580	545	775	830	830
	3	165	50	0	90	125	125	125	200	250	530	595	660	660	725	850	165	165	165	165	0	50	50	125	200	250	290	350	400	530	595	725	780	780
	4	255	140	180	0	35	35	35	110	160	440	505	570	570	635	760	255	255	255	255	90	40	40	35	110	160	200	260	310	440	505	635	690	690
	5	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	6	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	7	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	8	365	250	200	110	75	75	75	0	50	330	395	460	460	525	650	365	365	365	365	200	150	150	75	0	50	90	150	200	330	395	525	580	580
	9	415	300	250	160	125	125	125	50	0	280	345	410	410	475	600	415	415	415	415	250	200	200	125	50	0	40	100	150	280	345	475	530	530
	10	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	11	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	12	825	710	660	620	585	585	585	510	460	130	65	0	0	65	190	825	825	825	825	660	610	610	575	500	450	410	350	300	65	65	65	120	120
	13	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	14	890	775	725	685	650	650	650	575	525	195	130	65	65	0	55	890	890	890	890	725	675	675	640	565	515	475	415	365	130	130	0	55	55
	15	1015	900	850	810	775	775	775	700	650	320	255	190	190	125	0	1015	1015	1015	1015	850	800	800	765	690	640	600	540	490	255	255	125	70	70
	16	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
Gates	**17**	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	18	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	19	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	20	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	21	215	100	50	40	75	75	75	150	200	480	545	610	610	675	800	215	215	215	215	50	0	0	75	150	200	240	300	350	480	545	675	730	730
	22	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	23	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	24	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	25	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	26	455	340	290	250	215	215	215	90	40	320	385	450	450	515	640	455	455	455	455	240	190	190	165	90	40	0	60	110	240	305	435	490	490
	27	515	400	350	310	275	275	275	150	100	180	245	310	310	375	500	515	515	515	515	300	250	250	225	150	100	60	0	50	180	245	375	430	430
	28	565	450	400	360	325	325	325	200	150	130	195	260	260	325	450	565	565	565	565	350	300	300	275	200	150	110	50	0	130	195	325	380	380
	29	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	30	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380
	31	890	775	725	685	650	650	650	575	525	195	130	65	65	0	55	890	890	890	890	725	675	675	640	565	515	475	415	365	130	130	0	55	55
	32	945	945	945	945	945	830	780	780	730	730	690	725	725	725	725	580	580	530	530	490	430	380	250	250	185	185	120	120	55	55	70	0	0
	33	565	450	400	310	275	275	275	200	150	130	195	260	260	325	450	565	565	565	565	400	350	350	275	200	150	110	50	0	130	195	325	380	380

Table B.7: Minimum time to allow transfer between two gates $tmint_{i,i_2}$ (in minutes)

		Gates																																
$tmint_{i,i_2}$ (min)		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**
	1	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	2	1	0	1	2	2	2	2	3	4	7	8	9	9	10	11	1	1	1	1	1	1	1	2	3	4	4	5	6	7	7	10	10	10
	3	2	1	0	1	2	2	2	3	3	7	7	8	8	9	11	2	2	2	2	0	1	1	2	3	3	4	4	5	7	7	9	10	10
	4	3	2	2	0	0	0	0	1	2	6	6	7	7	8	10	3	3	3	3	1	1	1	0	1	2	3	3	4	6	6	8	9	9
	5	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	6	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	7	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	8	5	3	3	1	1	1	1	0	1	4	5	6	6	7	8	5	5	5	5	3	2	2	1	0	1	1	2	3	4	5	7	7	7
	9	5	4	3	2	2	2	2	1	0	4	4	5	5	6	8	5	5	5	5	3	3	3	2	1	0	1	1	2	4	4	6	7	7
	10	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	11	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	12	10	9	8	8	7	7	7	6	6	2	1	0	0	1	2	10	10	10	10	8	8	8	7	6	6	5	4	4	1	1	1	2	2
	13	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	14	11	10	9	9	8	8	8	7	7	2	2	1	1	0	1	11	11	11	11	9	8	8	8	7	6	6	5	5	2	2	0	1	1
	15	13	11	11	10	10	10	10	9	8	4	3	2	2	2	0	13	13	13	13	11	10	10	10	9	8	8	7	6	3	3	2	1	1
	16	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
Gates	**17**	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	18	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	19	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	20	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	21	3	1	1	1	1	1	1	2	3	6	7	8	8	8	10	3	3	3	3	1	0	0	1	2	3	3	4	4	6	7	8	9	9
	22	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
	23	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
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	25	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5
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	28	7	6	5	5	4	4	4	3	2	2	2	3	3	4	6	7	7	7	7	4	4	4	3	3	2	1	1	0	2	2	4	5	5
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	31	11	10	9	9	8	8	8	7	7	2	2	1	1	0	1	11	11	11	11	9	8	8	8	7	6	6	5	5	2	2	0	1	1
	32	12	12	12	12	12	10	10	10	9	9	9	9	9	9	9	7	7	7	7	6	5	5	3	3	2	2	2	2	1	1	1	0	0
	33	7	6	5	4	3	3	3	3	2	2	2	3	3	4	6	7	7	7	7	5	4	4	3	3	2	1	1	0	2	2	4	5	5

Figure B.1: Demonstration of gate allocation before 5pm

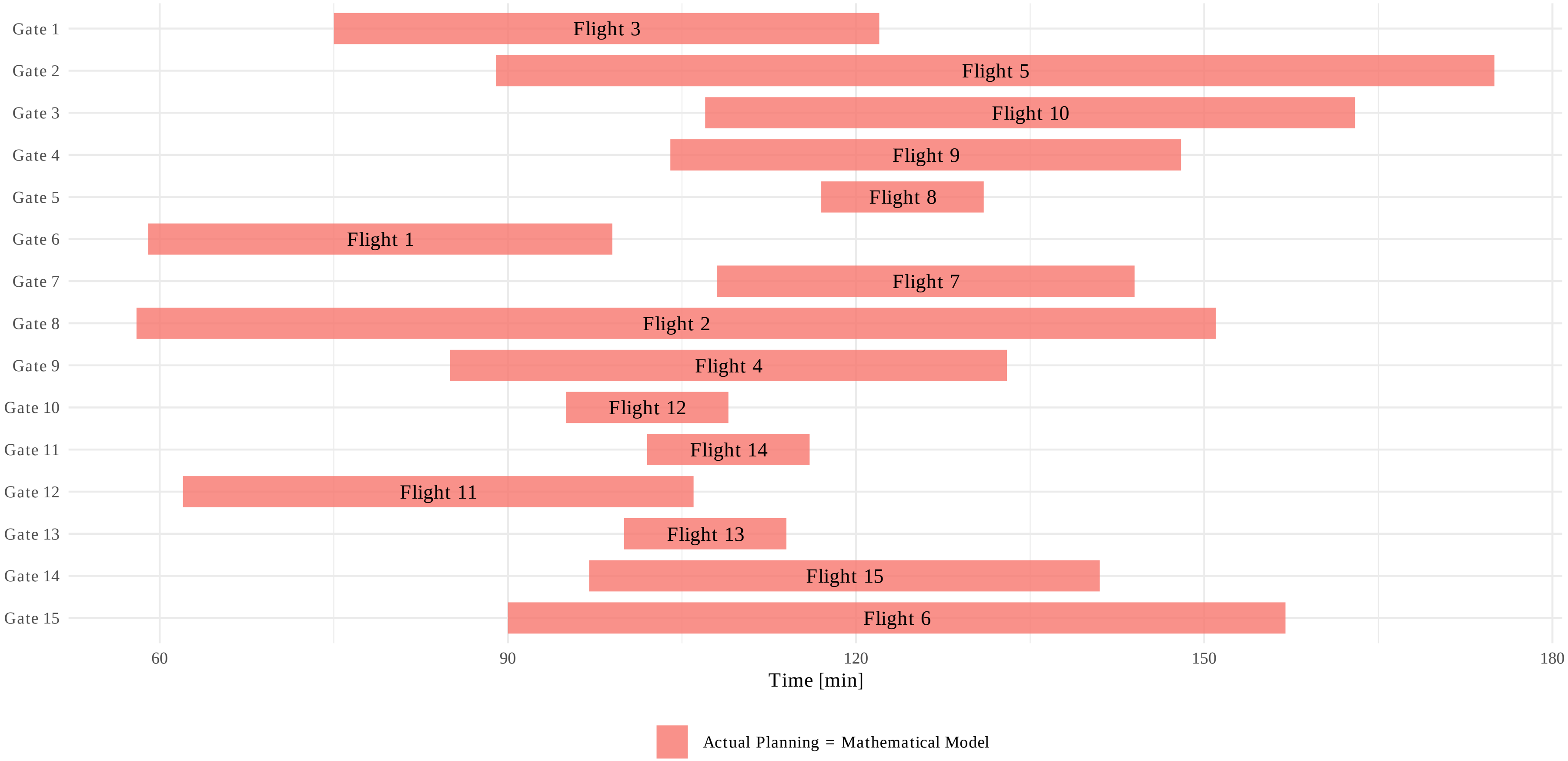

Figure B.2: Demonstration of the resultant gate allocation 5pm-5.30pm

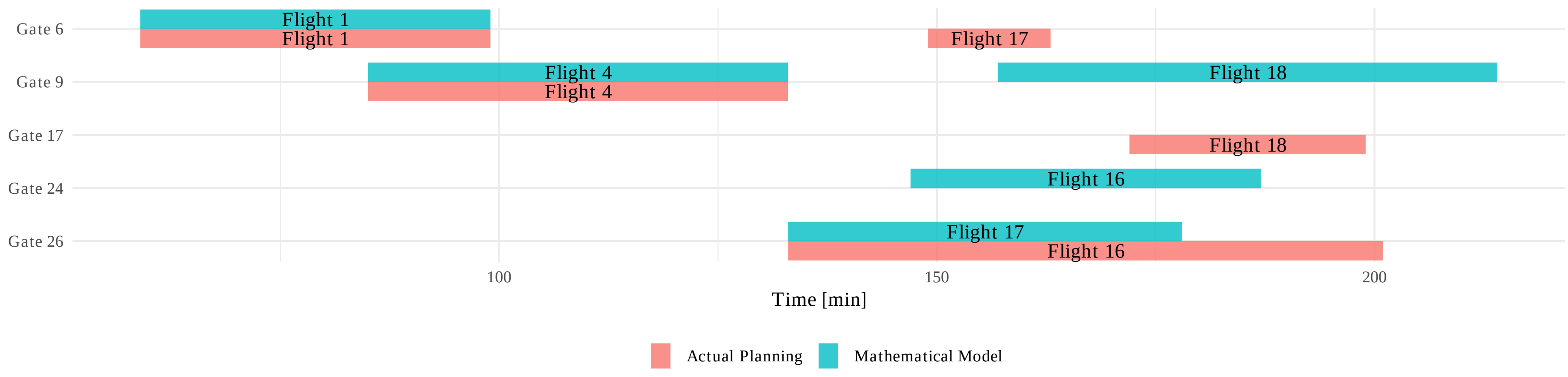

Figure B.3: Demonstration of the resultant gate allocation 5.30pm-6pm

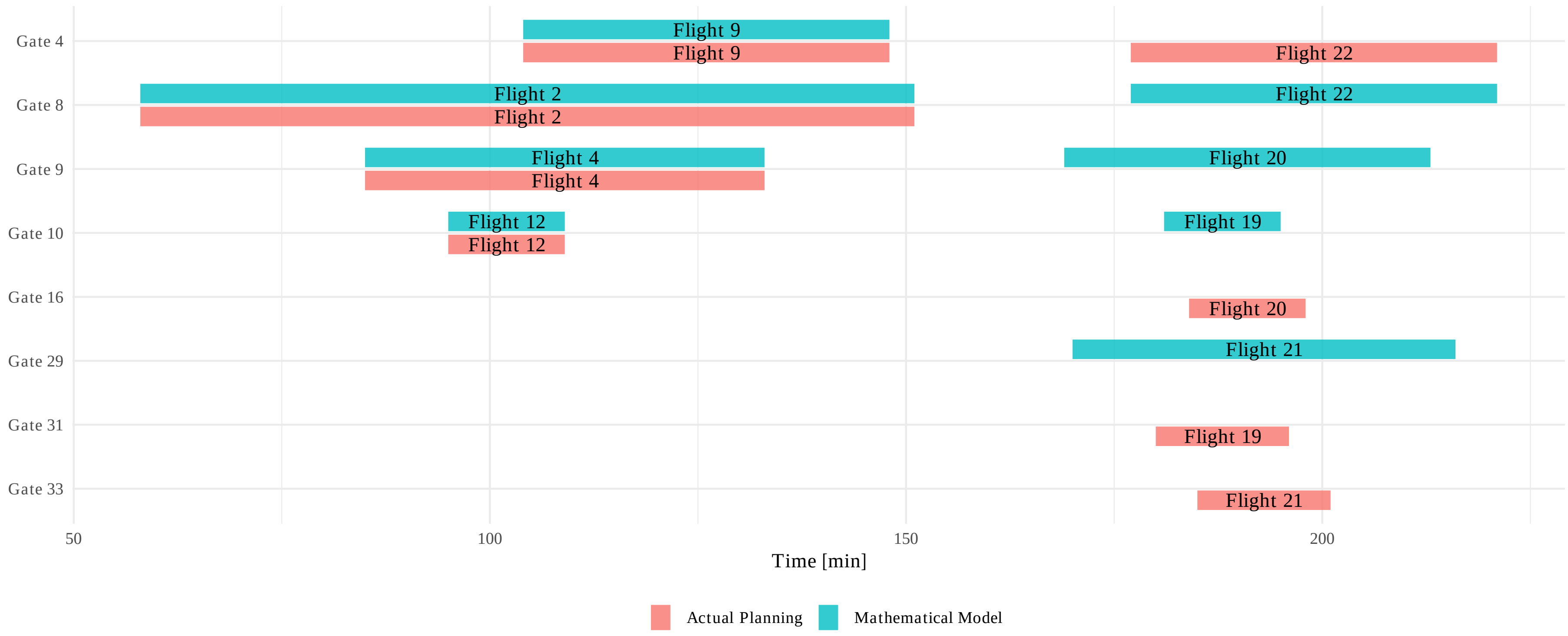

Figure B.4: Demonstration of the resultant gate allocation 5pm-6pm

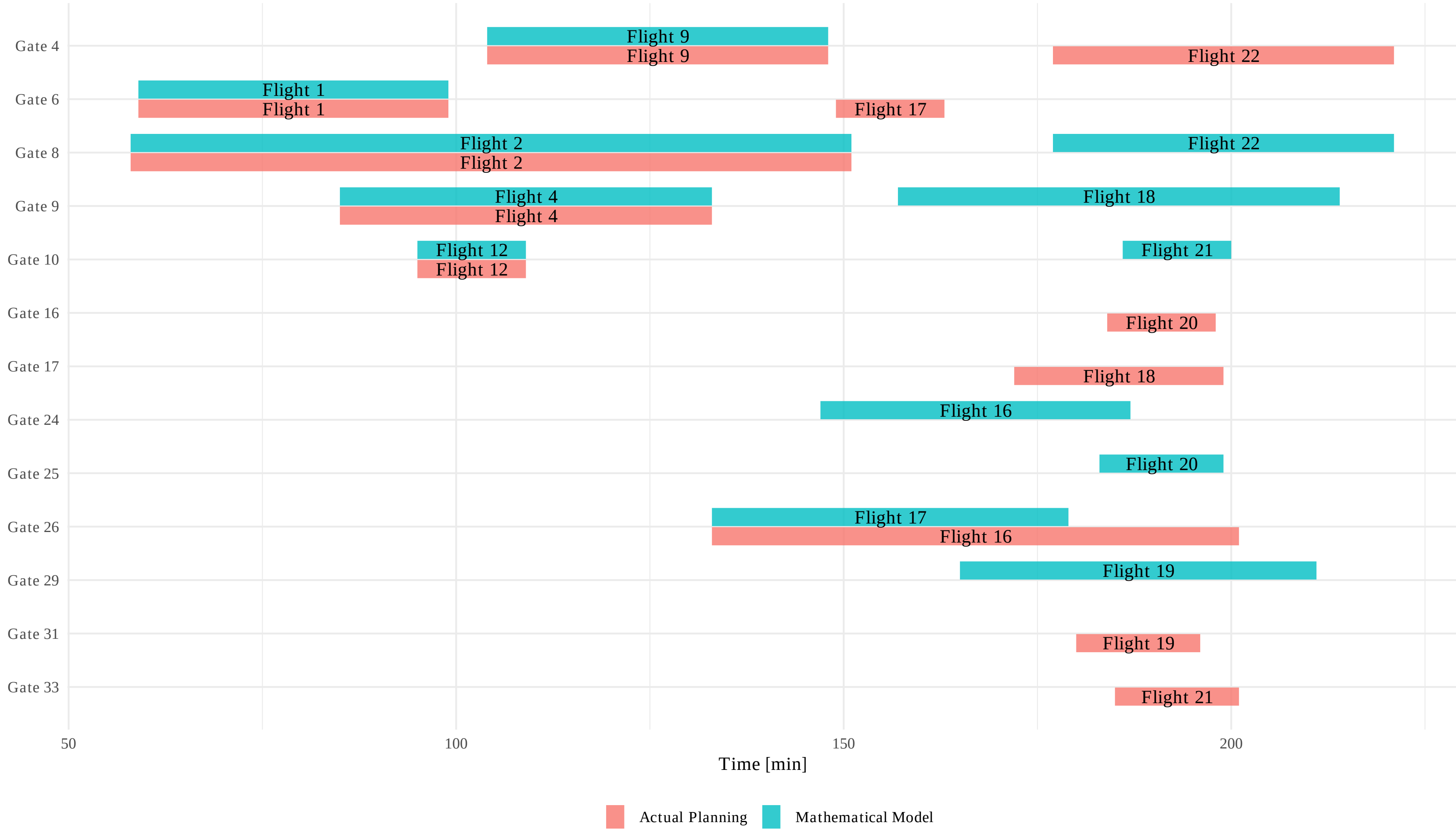

Figure B.5: Demonstration of the resultant gate allocation 5pm-6pm during an extreme event