Gate Assignment Problem: a case study of Lisbon airport

João Manuel Santos Silva
joao.m.s.silva@tecnico.ulisboa.pt

Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal

December 2019

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)

1. Introduction

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 Gate Assignment Problem since the beginning of this industry. The motivation for this dissertation is to achieve a new way of thinking this GAP, by including passenger characteristics, experience and their money spending habits into an Mixed-Integer Linear Programming model. By having that information on passengers and creating different categories per type of passenger (departing, arriving or transferring passengers), the model will optimise the adequate flight attribution to gates so that those same passengers have a higher potential of money spending at the Terminal. The models consists in using a maximisation of a multi-objective function of money spending at the airport and minimisation of walking distance travelled by all passengers.

Nowadays, airports are vital infrastructures as they are a key place in the development of a region, allowing to indirect businesses to arise in their surroundings, and most of all, are the entrance to the world for all passengers that travel everyday. The infrastructure itself, has evolved from a mere transport provider into a full business with all commodities needed to satisfy passengers.

According to [1], just in Europe, the amount of passengers travelling by plane in 2018 hit a new record of 2.34 billion, 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 thus, it is completely feasible to understand why globally the airline industry revenues were worth 151.8 billion € in 2015.

2. Related Literature

Since this dissertation has two different focuses, Gate Assignment Problem and Passenger characteristics and behaviour, a description of what the literature has 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 and their operation as turned into a really complex problem. In order to improve their capacities, a lot of research has been made in the taxi and gate assignment problem, dealing with problems such as passenger walking distances, model robustness and remote gate usage. [7] introduced a Tabu Search and Memetic algorithms aiming to minimise walking distances and not considering fixed schedules but a time window approach where flights were supposedly allocated. [11] used non linear programming and meta-modelling models where there was a simultaneously management of gate and bus planning, as well as minimising passenger walking distance and congestions at security checkpoints. [9] had the same objective of minimising passenger walking distance and remote gate usage but using a Bee Colony Optimisation model. [6] was aware of the cost of delays had on aiports and the economy, representing 7.7 billions of dollars just for US airlines, and thus, created a model proposing minimising flight conflict probability and number of flights assigned to aprons.

2.2. Passenger characteristics and behaviour

Airports are the first and last operation a passenger experiences [3] and it consists in a totally different environment from anything else due to the psychological and environmental unique experiences linked to the travel process. If passenger information is correctly absorbed by an airport manager, the passenger experience may increase the passenger willing to spend more money. Similarly to the approach by [10], passengers characteristics that influence behaviour may be divided in: trip characteristics - for example, low cost carriers usually have passengers that spend less money [5], passenger travelling alone spend less money and passengers who arrived earlier at the airport are more likely to spend money [5]; personal characteristics - for example, younger passengers are more likely to shop while older passengers are more likely to use facility activities [8] and passengers with higher wage are more prone to perform shopping and dining [8]; and process characteristics - for example, arriving earlier at the airport has a high positive correlation with passenger consumption [12].

To obtain data on the characteristics described in the previous section, a survey was conducted and aimed at travellers that had already departed, arrived or did a transfer at Terminal 1 of Lisbon Airport, related to aspects such as time, personal, air-trip, activities performed and orientation information.

2.3. Passenger behaviour analysis using choice modelling

To decrease 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. [4] gives the example of Choice models which is able to predict individual choices by analysing a set of discrete choices (p.e. reason of travelling: working, holidays,visiting family, etc.) or categorical (p.e. minimum, medium, high level of stress regarding the flight). Then, it was decided to introduce a Discrete Choice Modelling (DCM) approach to the results obtained from the survey, due to the potential interest to airport managers in order to optimise their knowledge on their passengers and afterwards, to apply a more profitable gate assignment to the airport, which will be demonstrated when applied to the case study.

3. Mixed-Integer Linear Programming Model

This model was created and validated on an illustrative example and applied to a real life case study at Lisbon Portela Airport. The gate assignment problem has been a constant challenge for airports and airline companies, due to the complexity of the problem. Starting by all the operational variables regarding airline requests for gates, airlines wanting their passengers to have the best infrastructure possible when arriving at the airport, the large number of flights and the dynamic nature of the problem, passengers expectations and willingness to spend money and all the uncertainties related due to differences in age, gender, nationality, travel destination and so much more. The solution obtained for this problem intends to take the perspective of the airport manager, i.e., the main focus is to increase the airport profits by maximising the money spent by passengers inside the Terminal. At the same time, the model tries to minimise the walking distance travelled, using a conversion cost in order to achieve a final objective function with the same units. Now, the model is presented as follows:

3.1. Constants

- **NG** Number of gates
- **NF** Number of flights
- **NTP** Number of passengers categories

3.2. Sets

- **G** Set of gates
- **F** Set of flights
- **P** Set of passenger categories

3.3. 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 distance of transferring passengers of category p
cds_p	Cost per distance of arriving passengers of category p
cde_p	Cost per 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

3.4. Decision Variables

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

$$y_{j,j_2} = \begin{cases} 1 & \text{if flight } j \text{ departs no later than flight } j_2 \text{ lands,} \\ 0 & \text{otherwise} \end{cases}$$

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

b_j	Linear dependant variable of x equal to the time passengers are allowed to enter the terminal from flight j
c_j	Linear dependant variable of x equal to the time passengers are allowed to enter flight j

3.5. Objective Function

$$\text{Maximise } O_{Total} = O_1 + O_2 + O_3 - O_4 - O_5 - O_6 \tag{1}$$

3.6. Constraints

$$O_1 = \sum_{i=1}^{NG} \sum_{i_2=1}^{NG} \sum_{j=1}^{NF} \sum_{j_2=1}^{NF} npt_{p,j,j_2} \cdot rt_{p,i} \cdot z_{i,i_2,j,j_2} \tag{2}$$

$$O_2 = \sum_{i=1}^{NG} \sum_{j=1}^{NF} \sum_{p=1}^{NTP} nps_{p,j} \cdot rs_{p,i} \cdot x_{i,j} \tag{3}$$

$$O_3 = \sum_{i=1}^{NG} \sum_{j=1}^{NF} \sum_{p=1}^{NTP} npe_{p,j} \cdot re_{p,i} \cdot x_{i,j} \tag{4}$$

$$O_4 = \sum_{i=1}^{NG} \sum_{i_2=1}^{NG} \sum_{j=1}^{NF} \sum_{j_2=1}^{NF} \sum_{p=1}^{NTP} npt_{p,j,j_2} \cdot cdt_p \cdot wdt_{i,i_2} \cdot z_{i,i_2,j,j_2} \tag{5}$$

$$O_5 = \sum_{i=1}^{NG} \sum_{j=1}^{NF} \sum_{p=1}^{NTP} nps_{p,j} \cdot cds_p \cdot wds_i \cdot x_{i,j} \tag{6}$$

$$O_6 = \sum_{i=1}^{NG} \sum_{j=1}^{NF} \sum_{p=1}^{NTP} npe_{p,j} \cdot cde_p \cdot wde_i \cdot x_{i,j} \tag{7}$$

$$\sum_{i}^{NG} x_{i,j} = 1, \ \forall \ j \in F \tag{8}$$

$$z_{i,i_2,j,j_2} \leq x_{i,j}, \ \forall \ j \in F, j_2 \in F, i \in G, i_2 \in G \tag{9}$$

$$z_{i,i_2,j,j_2} \leq x_{i_2,j_2}, \ \forall \ j \in F, j_2 \in F, i \in G, i_2 \in G \tag{10}$$

$$x_{i,j} + x_{i_2,j_2} - 1 \leq z_{i,i_2,j,j_2}, \ \forall \ j \in F, j_2 \in F, i \in G, i_2 \in G \tag{11}$$

$$b_j = a_j + \sum_{i=1}^{NG} (rtg_i + ut_i) \cdot x_{i,j}, \ \forall \ j \in F \tag{12}$$

$$c_j = d_j - \sum_{i=1}^{NG} (rtg_i + ut_i) \cdot x_{i,j}, \ \forall \ j \in F \tag{13}$$

$$c_j - b_{j_2} + y_{j,j_2} \cdot M \geq 0, \ \forall \ j \in F, j_2 \in F \tag{14}$$

$$c_j - b_{j_2} - (1 - y_{j,j_2}) \cdot M \leq 0, \ \forall \ j \in F, j_2 \in F \tag{15}$$

$$y_{j,j_2} + y_{j_2,j} \geq z_{i,i,j,j_2}, \ \forall \ j \in F, j_2 \in F, i \in G \ \wedge \ j \neq j_2 \tag{16}$$

$$x_{i,j} \ is \ binary, \ \forall i \in G, j \in F \tag{17}$$

$$y_{j,j_2} \ is \ binary, \ \forall \ j \in F, j_2 \in F \tag{18}$$

$$z_{i,i_2,j,j_2} \ is \ binary, \ \forall \ j \in F, j_2 \in F, i \in G, i_2 \in G \tag{19}$$

$$cg_i \geq cf_j \cdot x_{i,j}, \ \forall \ j \in F, j_2 \in F \tag{20}$$

$$x_{i,j} = 0 \ \forall \ j \in F, i \in G \wedge \ cga_i \neq cfa_j, \tag{21}$$

$$c_{j_2} - b_j \geq tmint_{i,i_2} \cdot z_{i,i_2,j,j_2}, \ \forall \ j \in F, j_2 \in F, i \in G, i_2 \in G \ \wedge \ \sum_{p=1}^{NTP} npt_{j,j_2} \geq 0 \tag{22}$$

$$b_{j_2} - ut_i - tmino_i - c_j - ut_i \geq -M \cdot (2 - x_{i,j} - x_{i,j_2}), \ \forall \ j \in F, j_2 \in F, i \in G \ \wedge \ j \neq j_2 \ \wedge a_j \ \leq a_{j_2} \tag{23}$$

$$x_{i,j} \leq xp_{i,j}, \forall \ j \in F, i \in G \tag{24}$$

Starting with the objective function represented in equation 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).

Constraints 8 to 16 are similar to the ones introduced by [7]. Constraint 8 ensures that each flight is assigned only to a single gate. Constraint 9 to 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 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 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 14 and 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 16 impose that a transfer to occur, there must be a flight that departs later than the other flight lands. Constraint 17, 18 and 19 define the decision variables $x_{i,j}$, y_{j,j_2} and z_{i,i_2,j,j_2} as binary variables.

Constraint 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 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 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 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 12 and 13, as well as the minimum time the gate needs to be empty due to operational reasons.

Constraint 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.

4. Case study of Lisbon Portela Airport

Lisbon Airport, also known as Humberto Delgado Airport or Portela Airport is the biggest and most important Portuguese airport. 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 to 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.

The growth levels achieved in Portugal are high due to the low-cost carriers consolidating their market presence and development of touristic offer in Portugal. The numbers are clear and show the huge development of air traffic throughout the years. According to [2], 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 50.0% 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 €. In terms of non-aviation business, it represented 26.3% of the total turnover of the ANA Group, corresponding to 218.7 million €, with the retail business being responsible for 56.4% of the non-aviation income.

4.1. Survey statistics

In total, the survey had 650 full individual accepted answers, with 447 answers about a departure, 609 answers about an arrival at Lisbon Airport and 349 answers about a transfer done in any airport in Europe (this was added to the survey since it was almost impossible to guarantee a satisfactory number of answers of passengers transferring at Lisbon Airport). Following, some statistics from the survey will be provided.

Figure 1 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. Additionally, more male passengers have answered this survey (52.8%). 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.

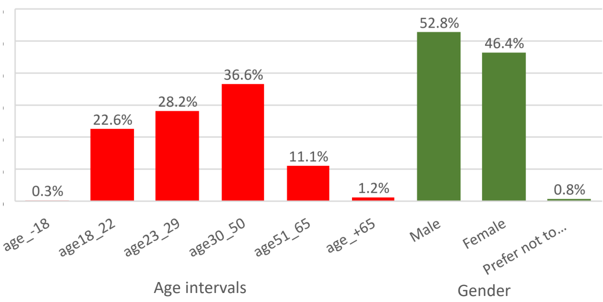

Figure 1: General personal characteristics from all passengers

The survey was separated in terms of type of passenger and each one will be shortly described.

4.1.1 Departing passengers

Around 32.0% answered feel completely relaxed regarding the time before the flight, and 46.1% regarding travelling by plane, which shows that people are becoming more and more comfortable and used to travel by plane. 60.6% of travellers used TAP Portugal as expected since the airport is the main hub of this airline company. In terms of flight destination 65.8% of answers were to Schengen countries. 56.0% had hold baggage and the average number of hand baggage per passenger was by far 1 with 77.6%. 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, as it was expected, the main reason for travelling was for holidays (44.3%), and afterwards personal reasons and due to work were the more frequent answers with 23.3% and 19.7% respectively. Contrary to what was expected, passengers arrived earlier at the airport, with 37.6% arriving between 1h30 min and 2h. Only 7.8% went to the business lounge and in total, the average money spending from departing passengers who spent something at the airport was around 30.0 €.

4.1.2 Arriving passengers

The most frequent airline company was again TAP Portugal (59.6%). 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%). Like in departing passengers, arriving passengers usually travel alone (37.4%) or with just one person (26.9%) and only respondents travel with children (8.2%). 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%. 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.

4.1.3 Transferring passengers

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. In terms of quantity of hand baggage, the most frequent answer was again 1 with 79.1%. Travelling alone and with one person was again the most frequent answer with 31.5% and 30.7% respectively, with only 6.9% travelling with children.

4.2. Category analysis

After analysing all statistics, the author created categories of passengers in order to achieve a separation of potential money spending per type of passenger, resulting in the following table 2. The Discrete Choice Model (DCM) (further explained in section 4.3) 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, also represented in table 2.

		Revenue per passenger
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€

Table 2: Representation of money spending per type of passenger to apply in the GAP

4.3. Modelling passenger behaviour

After creating categories of passengers, all the characteristics from the survey were analysed and checked to see which were more relevant (or not) for each category, using discrete choice modelling (DCM). Each model for departing, arriving and transferring passengers model were estimated with 80% of the dataset and 20% were reserved for model validation. The values of each parameter, associated to each variable in all utility functions from categories, can be observed in table 6.

Before knowing results from table 6, assumptions were made regarding what was expected from each variable. In the end, almost every assumption corresponded to the model results. Then, the same models were tested with the remaining 20% of the dataset of each type. Satisfied results were achieved, meaning that the created models for each type of passenger reflect the preferences of the answers from the survey.

4.4. Gate Assignment Problem

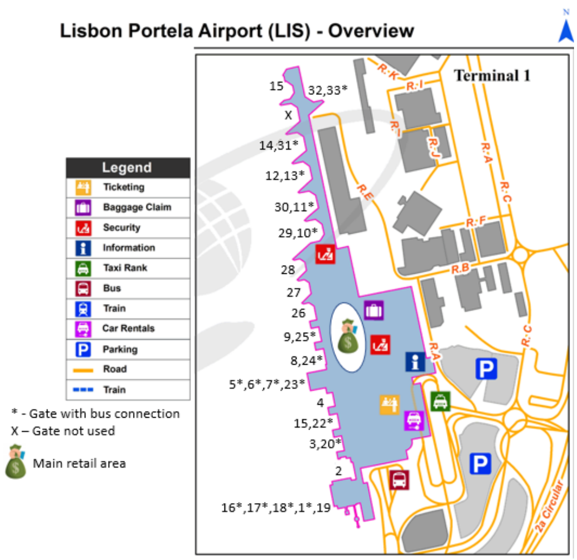

Figure 2: Overview of Lisbon Portela Airport (adapted from Airport Guide)

The problem has a total of 33 gates and it considered the flight planning horizon from 3pm-6pm on the 27th of August 2019. The 9 categories of passengers displayed in the previous section were used in this case study and all gates were assumed to be capable of receiving any flight. Regarding each gate, the walking distance needed to get from each gate to the main retail area (for departing passengers - wde_i), from each gate to the baggage claim area (for arriving passengers - wds_i) and between gates (for transferring passengers - wdt_{i,i_2}) were measured using "Google Maps", and gates were classified as if Schengen or non-Schengen cga_i (gates 1, 2, 3, 4, 5, 6, 7, 8, 9, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27 and 28 are Schengen; gates 10, 11, 12, 13, 14, 15, 29, 30, 31, 32 and 33 are non-Schengen).

In terms of capacity to receive certain sizes of airplanes, every gate was assumed to have the capability to receive any flight, and therefore cg_i and cf_j were assumed to be equal to 1. The unloading/loading time ut_i was considered 5 minutes for gates with jet-bridge connection and 20 minutes for gates that need a bus link in order to simulate the extra time needed when a bus connection is necessary. The time needed for the plane to go from the runway to each gate and vice-versa (rtg_i) was calculated assuming a taxi speed of 37 km/h. Still regarding gates, it was assumed that revenues decrease linearly with distance to the retail area, i.e. the closest gates located to the main retail area have full potential of money spending for each category of passenger, as shown previously in table 2, and the money spent by each category will decrease proportionally to the distance until reaching a 50% decrease in revenues on the farthest gate (15).

Regarding flights, information on arrival (a_j) and departure times (d_j), origin and destination, and classification of Schengen or non-Schengen (cfa_j) are presented in table 3. 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. Moreover, it was assumed that each flight had a medium occupation of 90% of capacity of each airplane and each category owns the percentage represented in table 2. In terms of transferring passengers, they were considered to occupy around 10% of the medium occupation of each flight.

In equations 5, 6 and 7, variables cdt_p, cde_p and

Table 3: Flights 1-22: Arrival (a_j) and departure time (d_j), origin and destination for each flight, classification of flight in terms of Schengen or non-Schengen (cfa_j)

Parameter	$a_j(min)$	$d_j(min)$	Origin	Destination	cfa_j
Flight1	3.36pm	5.02pm	Gran Canaria	Faro	1
Flight2	3.50pm	5.39pm	Rome	Ponta Delgada	1
Flight3	3.52pm	5.25pm	Frankfurt	Frankfurt	1
Flight4	4.17pm	5.21pm	Madrid	Madrid	1
Flight5	4.21pm	6.03pm	Vienna	Vienna	1
Flight6	4.22pm	5.45pm	Casablanca	Casablanca	2
Flight7	4.25pm	5.47pm	Hamburg	Brussels	1
Flight8	4.34pm	5.34pm	Amsterdam	—	1
Flight9	4.36pm	5.36pm	Ponta Delgada	—	1
Flight10	4.39pm	5.51pm	Athens	Athens	1
Flight11	3.54pm	4.54pm	—	Salvador	2
Flight12	4.12pm	5.12pm	—	Sao Paulo	2
Flight13	4.17pm	5.17pm	—	Fortaleza	2
Flight14	4.19pm	5.19pm	—	Recife	2
Flight15	4.29pm	5.29pm	—	New York	2
Flight16	5.05pm	6.29pm	Ponta Delgada	Ponta Delgada	1
Flight17	5.06pm	6.06pm	Eindhoven	—	1
Flight18	5.29pm	6.42pm	Brussels	Brussels	1
Flight19	5.38pm	6.38pm	Marrakesh	Marrakesh	2
Flight20	5.41pm	6.41pm	Bordeaux	Bordeaux	1
Flight21	5.43pm	6.43pm	London	London	2
Flight22	5.49pm	6.49pm	Paris	Paris	1

cds_p were all assumed as 0.012€/m after analysing the cost per delay of passengers at airports, in order to transform the walking distance performed by passengers into a cost to the objective function. Thus, there is only one unit in the objective function, in this case €, making it possible to achieve the best profitable solution while reducing the walking distance by passengers, at the same time.

5. Results

The model was run in 30 minutes time slots between 5pm and 6pm. Moreover, the model was also run in the entire hour from 5pm-6pm, and as an extreme event, the model was run for the entire hour, but knowing a priori that a determined flight had a different passenger composition, essentially with passengers willing to spend more money at the airport. In this document, the results from 5.30pm to 6pm will be further demonstrated. In order to take into account the flights that are already occupying gates at the airport, the first 18 flights are considered the flights already allocated, and therefore the model will assign the rest of flights arriving from 5.30pm to 6pm, i.e. flights 19 to 22, and compare with the actual gate allocation from the considered day, which is represented in table 4. The reader can also confirm that the model respects the Schengen/non-Schengen constraint and allocates the flights to the most rentable gates (closer to the main retail area).

In spite of the FICO Xpress model developed had a problem size of 528286 variables, the presolved model was able to reduce the number of variables of the problem to 2066, almost 256 times less. Then, the model was able to reach the optimal solution of 27304.60€ in 11.1 seconds with a optimality gap of 0%, meaning that the model was able to achieve the optimal solution. Each component value of the objective function can be observed in table 4.

Table 4: Demonstration of the optimal solution and its components

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**

Table 5: 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	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

The actual planning had revenues of 24337.30€ and the created model 27304.60€, meaning an increase in revenues of 12.2%, corresponding to 2967.30€.

6. Conclusions

Since airports yearly budgets are more and more dependant on non-aeronautical activities, investigations related to the GAP are becoming more important. In this case, the main objective of this dissertation was to introduce a framework that could help airport managers to allocate flights to gates in the most profitable way, by maximizing the potential commercial revenues from passengers. This MILP assigns flights to the most profitable gates, taking into account all the constraints from gates and flights, and by knowing a priori the composition inside each plane of each passenger category.

This work opens some future area research topics such as: the survey can be even more studied by adding new questions and answers in order to try to comprehend passengers in a more deeply approach; The number of answers can also be increased in order to be as close to the airport reality as possible; A new investigation on all the consumption criteria and distribution and how it influences and increases the potential revenues across the terminal.

This model has been an important contribution to the Gate Assignment Problem (GAP) due to the addition of Discrete Choice Modelling - with testing and forecasting the behaviour of the three existing types of passengers (departure, arrival and transferring). And lastly, the model is perfectly adjustable to any airport by a deep research and adaptation to the desired airport infrastructure.

References

[1] ACI Europe. Airport traffic report. December 2018.

[2] ANA Aeroportos de Portugal. Annual report 2018. 2018.

[3] 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.

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

[5] 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.

[6] 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.

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

[8] Y.-H. Lin and C.-F. Chen. Passengers' shopping motivations and commercial activities at airports - the moderating effects of time pressure and impulse buying tendency. *Tourism Management*, 36:426–434, 2013.

[9] 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.

[10] L. M. Rozema. Behavioural classification of passengers in an airport terminal. Master's thesis, Delft University of Technology, 2017.

[11] J. Spans. An integrated approach for efficient and resilient airport management. Master's thesis, Delft University of Technology, 2018.

[12] 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.

Table 6: Estimation results for modelling departing, arriving and transferring passengers money spending

Parameter name	**Parameter description**	**Parameter value**		
		Depart Model	Arrival model	Transfer model
$ASC\_nothing$		2.470		2.200
ASC_few		-2.920		2.630
ASC_more		-0.148		
$\beta_{leave_{b}us}$	1 if people leave the airport by bus		-1.460**	
$\beta_{dprt\_time\_afternoon}$	1 if the departure is during afternoon	-1.070*		-0.915**
$\beta_{dprt\_plan\_before\_airport\_yes}$	1 if passenger planned before which activities to do inside the airport	-1.260*		-1.590*
$\beta_{transf\_plan\_before\_airport\_yes2}$	1 if passenger planned before which activities to do inside the airport			-0.783**
β_{arrive_car}	1 if passenger arrives by own car	-1.050*		
β_{people_0}	1 if passenger travels alone	0.713*	0.613****	
β_{age30_50}	1 if passenger is between 30 to 50 years old	-1.200*	-0.973*	-1.140*
β_{age30_502}	1 if passenger is between 30 to 50 years old	-0.758**		
β_{age18_22}	1 if passenger is between 18 to 22 years old	1.210**		
β_{age18_222}	1 if passenger is between 18 to 22 years old	0.857****		
β_{age18_223}	1 if passenger is between 18 to 22 years old	0.791****		
$beta_{taxiuber\_shop}$	1 if passenger arrives by uber or taxi and shops after security	-1.980*		
$\beta_{holi\_peopleplus3}$	1 if passenger is travelling due to vacations and with more than 3 people	-1.610*		
$\beta_{dprt\_country\_International2}$	1 if passenger is travelling to an International destination	-0.604****		
$\beta_{dprt\_time\_morning2}$	1 if the departure is during morning	1.320*		0.664**
$\beta_{dprt\_time\_morning3}$	1 if the departure is during the morning	0.668**		
$\beta_{easy2move\_plus4}$	1 if passenger finds easy to move inside the airport	1.160*		
$\beta_{freq\_plane1\_3}$	1 if passenger travels by plane between 1 to 3 times per year	1.250*		
$\beta_{arrive\_personalise}$	1 if passenger arrives by taxi or uber	0.709**		
β_{motive_study}	1 if passenger is travelling due to studying abroad	1.060**		
$\beta_{children\_yes}$	1 if passenger is travelling with children	-1.900*		
$\beta_{dprt\_day\_Friday}$	1 if passenger is travelling on a Friday	-1.290**		
$\beta_{dprt\_delay\_yes2}$	1 if there was a delay in the departure	0.976*		
$\beta_{dprt\_delay\_yes3}$	1 if there was a delay in the departure	0.519***		
$\beta_{time\_airport\_bfcheckin\_schengen}$	1 if the passenger arrives at the airport before check-in opens for a schengen destination	0.520***		
$\beta_{aways\_daysless4}$	1 if passenger is travelling for less than 4 days	-1.000**		
$\beta_{income\_0difficulties}$	1 if passenger has no economic difficulties	0.988*		
$\beta_{child\_peopleplus3}$	1 if passenger is travelling with children and more than 3 people	-1.82*		
$\beta_{arrive\_country\_nonSchengen}$	1 if people arrive from a non-Schengen country		-1.140*	-0.754**
β_{arrive_lounge}	1 if people go to lounge after arrival		-3.500*	-0.945***
$\beta_{arrive\_lounge2}$	1 if passengers go to the business lounge at the airport			-1.840*
β_{leave_metro}	1 if people leave the airport by metro		-1.300*	
$\beta_{costs\_company}$	1 if people have their trip costs paid by their company		-0.715***	
β_{people_plus3}	1 if people are travelling with more than 3 people		-0.723**	
β_{age51_65}	1 if passengers are between 51 to 65 years old			-1.120*
β_{age51_652}	1 if passengers are between 51 to 65 years old			-1.650*
β_{fear_plus4}	1 if passengers feel fear regarding the time before their next flight			-1.330*
β_{stress_plus4}	1 if passengers feel stressed regarding travelling by plane			-0.954
Number of observations		358	487	279
Estimated parameters		29	9	14
Null log-Likelihood ($L(0)$)		-496.293	-337.563	-306.513
Log-Likelihood ($L(\beta)$)		-383.729	-155.974	-242.597
Likelihood ratio test		225.130	363.178	127.831
p^2		0.227	0.538	0.209
Adjusted p^2		0.168	0.511	0.163
Akaike Information Criterio		825.460	329.950	513.190

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